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Part 2, Projected response to anthropogenic warming*

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Tropical Cyclones and Climate Change Assessment

Part II: Projected Response to Anthropogenic Warming

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ABSTRACT: Model projections of tropical cyclone (TC) activity response to anthropogenic warming in climate models are assessed. Observations, theory, and models, with increasing robustness, indicate rising global TC risk for some metrics that are projected to impact multiple regions. A 2°C anthropogenic global warming is projected to impact TC activity as follows. 1) The most confident TC-related projection is that sea level rise accompanying the warming will lead to higher storm inundation levels, assuming all other factors are unchanged. 2) For TC precipitation rates, there is at least medium-to-high confidence in an increase globally, with a median projected increase of 14%, or close to the rate of tropical water vapor increase with warming, at constant relative humidity. 3) For TC intensity, 10 of 11 authors had at least medium-to-high confidence that the global average will increase. The median projected increase in lifetime maximum surface wind speeds is about 5% (range: 1%–10%) in available higher-resolution studies. 4) For the global proportion (as opposed to frequency) of TCs that reach very intense (category 4–5) levels, there is at least medium-to-high confidence in an increase, with a median projected change of +13%. Author opinion was more mixed and confidence levels lower for the following projections: 5) a further poleward expansion of the latitude of maximum TC intensity in the western North Pacific; 6) a decrease of global TC frequency, as projected in most studies; 7) an increase in global very intense TC frequency (category 4–5), seen most prominently in higher-resolution models; and 8) a slowdown in TC translation speed.

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The question of how tropical cyclones (TCs) could change with future anthropogenic warming is an important issue, particularly owing to the large societal impacts from TCs. Previous global assessments include a WMO task team report (Knutson et al. 2010) and the IPCC AR5 (Christensen et al. 2013), with the latter reviewed in the supplemental material. Our report assesses mainly research published since the 2010 WMO report, focusing on the projected future response of TC activity to anthropogenic forcing. We assess confidence in projections, using IPCC AR5's framework for confidence levels as guidance. Walsh et al. (2016) reviewed TC–climate studies, including dynamical modeling, statistical modeling, theories, and evaluation of model present-day performance at simulating TC activity.

Models used for TC simulations and climate model-based projections of changes in TC-relevant environmental conditions are discussed in the “Model evaluation” section and the supplemental material. In the “Projections of TC responses to anthropogenic warming” section, we summarize future TC projections under various future climate forcing scenarios, and present multistudy aggregated results scaled to a 2°C global mean surface air temperature increase. In the “Paleoclimate perspectives” section, we review paleoclimate perspectives on the problem. The final section contains our summary and conclusions. The process used to develop the assessment and the distribution of author opinion on confidence levels for projections of various metrics are detailed in the supplemental material.

This assessment does not address some related topics such as changes in the occurrence of hurricane-force extratropical storms (e.g., Haarsma et al. 2013), changes in TC extratropical transition (Liu et al. 2017, 2018), changes in TC-related damages (e.g., Klotzbach et al. 2018), or changes in TC-related mortality risk (Pedeutzi et al. 2012).

Model evaluation

Projecting future changes in TC activity involves two problems: projecting changes in relevant environmental factors (e.g., SSTs, atmospheric circulation) that can affect TC activity and projecting changes in TC activity given a set of changes in the relevant environmental factors. Confidence in future TC projections relies on confidence in both of these tasks and will depend on three main factors: 1) level of scientific understanding of the physical mechanisms underlying the projected changes; 2) robustness of TC projections across models/studies and our confidence in the capability of models for making such TC projections and the related environmental projections, as discussed below; and 3) existence or not of supporting evidence for the future projected TC changes based on detection of anthropogenic signals in observations. The level of understanding of physical mechanisms is usually enhanced by the existence of a generally accepted theory or strong mechanistic understanding, as opposed to cases where such a theory or process understanding is at an earlier stage of development.

Evaluation of projections of TC-relevant environmental variables. Assessing the reliability of future projections of large-scale environmental changes that can influence TCs is a broad problem and is beyond the scope of this assessment. IPCC AR5 (IPCC 2013; Collins et al. 2013) contains some assessments of these projections (see the supplemental material). Their most confident statements were generally for global temperature and closely related variables, such as boundary layer moisture content and sea level rise, as opposed to detailed regional structure of SST and atmospheric circulation changes (e.g., regional steering flows, vertical shear) even though the latter often are important for TC genesis, intensity, tracks, translation speeds, and other TC characteristics.

Evaluation of TC simulation capabilities of current models. Model capabilities at simulating present-day TC climatology and variability for various TC metrics have been reviewed in Knutson et al. (2010), Walsh et al. (2015), Camargo and Wing (2016), and other references therein. Examples of TC metrics that are relatively well simulated by at least some models include: spatial distributions of TC occurrence and genesis (Walsh et al. 2015); seasonal cycles and interannual variability of either basinwide activity (Shaevitz et al. 2014; Zhao et al. 2009; Kodama et al. 2015; Murakami et al. 2015) or landfalling activity (Lok and Chan 2017); modulation of TC occurrence by El Niño (Kim et al. 2014; Wang et al. 2014; Han et al. 2016; Krishnamurthy et al. 2016; Zhang et al. 2016); U.S. landfalling-TC rainfall (Wright et al. 2015; Liu et al. 2018); composite TC rainfall-rate profiles over land (Liu et al. 2018) or the open ocean (Knutson et al. 2015); TC size distributions, including interbasin differences (Knutson et al. 2015; Schenkel et al. 2018); TC intensities, including maximum winds or central pressures (Bender et al. 2010; Zarzycki and Jablonowski 2014); occurrence frequency of intense TC winds for certain cities (Emanuel et al. 2008); and TC-induced SST cold wakes (Bender and Ginis 2000; Lloyd et al. 2011). Recent advances in seasonal hurricane prediction (Murakami et al. 2016, 2018) further support the use of dynamical models for TC climate change projections.

Some aspects of TC climate simulations improve with increased model resolution; for example, TC intensities and spatial structure tend to become more realistic (Wehner et al. 2015; Roberts et al. 2018). Coarse-grid climate models (~100–200-km grid spacing) generally cannot simulate category 4–5 TCs,¹ while higher-resolution global models (~10–100-km grid spacing) capture increasingly realistic structure of TCs, and in some cases even category 4–5 TCs (Murakami et al. 2015; Roberts et al. 2018). However, Davis (2018) has questioned whether 25-km-grid models should even be able to simulate category 4–5 TCs without having unrealistic wind field structure. Some regional models with ~1–10-km grid spacing, as well as statistical–dynamical frameworks, can simulate occurrence of such high-intensity storms. Other model characteristics, such as convective parameterization, can influence a model’s ability to simulate intense TCs (Kim et al. 2018). Global cloud-permitting models (1–10-km grid spacing) without convective parameterization can capture some eyewall structures of TCs (Kinter et al. 2013) and are becoming more useful for TC projection studies (Yamada et al. 2017). Satoh et al. (2015) used a 14-km-grid global convection-permitting model that explicitly calculates updrafts of deep convective circulations to explore the causes of reduced simulated TC frequency with climate warming.

TC projection studies include assumptions that potentially could degrade the reliability of the studies for projecting climate change influence on TCs. For example, many modeling studies use specified SSTs, where the atmosphere cannot affect the SSTs. This is an oversimplification of the real world, where TC-generated cool wakes, mixing, and salinity effects are examples of feedbacks onto the ocean. Ogata et al. (2016) reported that projected changes in

¹ Categories 1–5 in this report refer to the Saffir–Simpson TC intensity scale (Simpson and Riehl 1981; https://en.wikipedia.org/wiki/Saffir-Simpson_scale). We use category 0 to refer to TCs of tropical storm intensity, but not hurricane intensity (17–32 m s⁻¹).

intense TCs differ between an atmosphere-only model and an atmosphere–ocean coupled model, despite the models having identical monthly mean SSTs. The lack of SST coupling could have important modeling limitations (Trenberth et al. 2018); for example, the resulting surface energy imbalance presumably affects the reliability of TC potential intensity (PI) projections (Emanuel and Sobel 2013). We have summarized the type of ocean–atmosphere coupling used in various studies in the supplemental material.

The above summary provides some context and caveats on the multiple sources of uncertainty in future TC projections, which should be considered in assessing confidence levels.

Projections of TC responses to anthropogenic warming

In this section, we assess projected changes in TC activity associated with an anthropogenic warming of order 2°C. Given the difficulties in making confident projections, our assessment should be regarded as a broad, general, quantitative indication of future TC behavior. Here we are seeking to establish the *sign* of future change compared to present day if possible, followed by an estimation of the *general order of magnitude* of change expected under a 2°C anthropogenic global warming scenario. Placing a 2°C global warming in the context of future emission scenarios, CMIP5 models on average project a global mean surface temperature warming of 2°C, relative to 1986–2005 conditions, by around year 2055 under the RCP8.5 scenario. Meanwhile, for the RCP2.6 scenario, IPCC AR5 concludes with *medium confidence* that global warming will remain below 2°C during the twenty-first century (IPCC 2013).

To construct summary figures combining projections from studies that used different climate change scenarios (e.g., IPCC A1B, RCP4.5, RCP8.5), we rescaled the raw projections listed in Tables ES1–ES4 to be consistent with a 2°C global mean temperature increase. Some idealized studies have investigated the impact of a 2°C global SST increase with no CO₂ change, or a doubling of CO₂ with no SST change. These are not included in our aggregate results figures, since previous studies have shown that changing either CO₂ or SST alone can have substantial impacts on modeled TC activity (Yoshimura and Sugi 2005; Held and Zhao 2011; Sugi et al. 2012; Zhao et al. 2013; Walsh et al. 2015). Projections in our tables based on CO₂-only or SST-only experiments are denoted by green text.

The structure of atmospheric temperature changes, such as an amplified tropical tropospheric warming with height, can have important influences on TC activity, compared to SST increases alone, as shown in simulation studies (Shen et al. 2000; Hill and Lackmann 2011; Tuleya et al. 2016). For this reason, any published regional downscaling projections that do not incorporate atmospheric temperature changes along with SST changes in their boundary/initial conditions, or in their statistical regression parameters, are not included in our summary projection figures.

TC frequency (category 0–5). Projected changes in global TC frequency (tropical storm through category 5 combined) from various studies are summarized in Fig. 1. More detailed information, references, and projections data from individual studies and basins are contained in Table ES1. Figure 1 and Table ES1 indicate that the vast majority of individual studies (22 out of 27 studies) project a decrease in global TC frequency with greenhouse warming. (Some studies provide multiple estimates of projections by using different climate models, by using different model resolution versions or convection schemes, or by downscaling different global models or SST change patterns). The median change across all estimates in Fig. 1 is –14% with a range from –28% to +22%. The existing estimates typically project a reduction, with 87% of the 140 individual estimates being negative or zero. However, some studies project increases in global TC frequency (in some cases) including Murakami et al. (2014; 3 of 11 RCP8.5 CMIP5 coupled model projections), Camargo (2013; 6 of 12 RCP4.5 and RCP8.5 CMIP5 coupled model projections), Emanuel (2013; statistical–dynamical downscaling), Wehner et al.

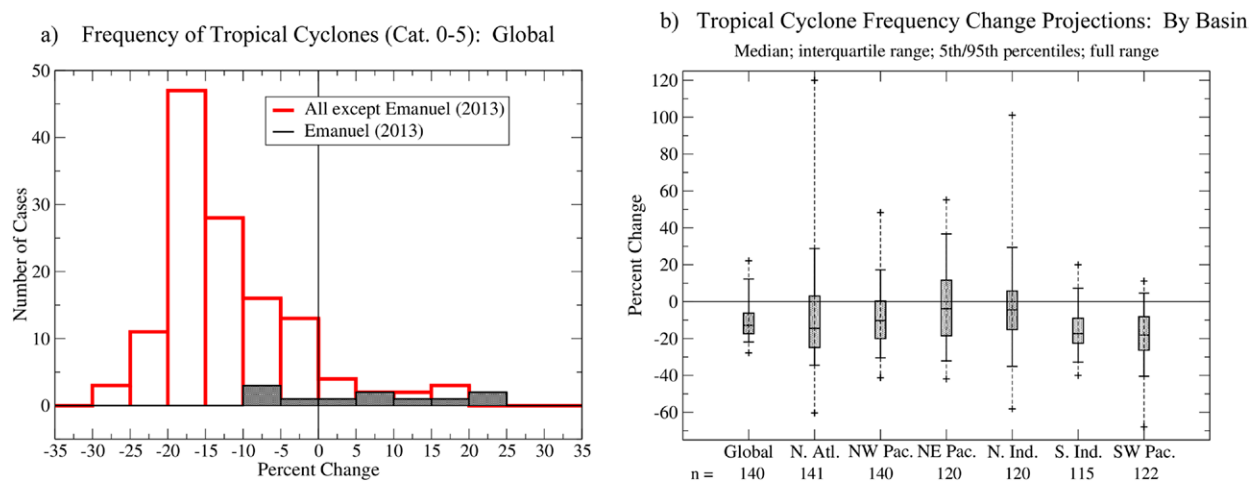


FIG. 1. Summary histograms and distributions of projected changes in TC frequency (%) from available studies, where the change in TC frequency for all Saffir–Simpson categories (0–5) combined is considered. Each case in the histogram/distribution represents a separate model estimate, with some individual studies contributing more than one model estimate (see Table ES1). All changes from Table ES1 have been rescaled prior to plotting to be consistent with a global mean temperature change of 2°C. (a) Global projection histogram: The red histogram is based on all available studies except Emanuel (2013); the gray-shaded histogram uses estimates from Emanuel (2013) only. (b) Global and basin-scale projected change distributions from Table ES1, for all studies including Emanuel (2013). Shaded boxes, whiskers, and plus signs in (b) denote the interquartile range, the 5th–95th percentiles, and the maxima and minima. Horizontal lines within shaded boxes are medians. Numbers listed along the bottom of the diagram in (b) are the number of separate estimates included within each distribution.

(2015; low-resolution version only), and Bhatia et al. (2018). In contrast to counting tropical storm–like features in model simulations, one study used an alternative TC detection method based on diagnosing storms from relatively large-scale dynamical and thermodynamical conditions (Tory et al. 2013) and found a global reduction in projected TC frequency in CMIP5 models, qualitatively consistent with most storm-counting studies.

As noted in Knutson et al. (2019, hereafter Part I), there is no clear observational evidence for a detectable human influence on historical global TC frequency (Maue 2011). Therefore, there is no clear observational evidence to either support or refute the notion of decreased global TC frequency with climate warming. This apparent discrepancy between model projections and historical observations could be due to a number of factors. Among these are the relatively short available global TC records, the relatively modest expected sensitivity of global TC frequency to global warming since the 1970s, errors arising from limitations of model projections, differences between historical climate forcings and those used for twenty-first-century projections, or even observational limitations. However, the growing TC observational databases may soon provide a means of distinguishing between some highly divergent modeled scenarios of global TC frequency (e.g., Emanuel 2013; Sugi and Yoshimura 2012).

One study projecting a global TC frequency increase (Emanuel 2013) used a statistical–dynamical TC downscaling framework, which assumes that the rate of seeding of random initial disturbances does not change with climate change—a possibly important assumption. However, there are other models projecting a global increase that do not use this assumption, so this assumption is not a necessary condition for a modeled global increase.

The physical mechanism responsible for reduced global TC frequency in the large majority of models remains uncertain (e.g., Mallard et al. 2013). Sugi et al. (2012) proposed an “upward mass flux hypothesis,” whereby reduced time-mean upward mass flux—a robust feature among climate model projections (Held and Soden 2006)—is unfavorable for TC genesis. Some progress can be seen in the framework of Sugi et al. as Satoh et al. (2015) further hypothesized that the projected reduction of global TC frequency results from reduced total convective mass

flux along with an increase of mass flux per TC. Idealized $2\times\text{CO}_2$ -only (fixed SST) and SST-only (+2-K uniform SST increase with fixed CO_2) experiments (Held and Zhao 2011; Sugi et al. 2012; Zhao et al. 2013; Walsh et al. 2015; Sugi et al. 2015) find a strong association between mass flux reduction and TC frequency reduction. The mechanism of the reduced mass flux is different in $2\times\text{CO}_2$ -only and SST-only experiments, being associated with reduced precipitation in $2\times\text{CO}_2$ -only experiments, and with increased dry static stability in SST-only experiments (Sugi et al. 2012). Another candidate mechanism to explain the TC frequency decrease is an increase in a nondimensional measure of midtropospheric saturation deficit as the climate warms (saturation deficit hypothesis). When this increase is artificially prevented in a down-scaling experiment, large increases in TC frequency are simulated (Emanuel et al. 2008). Camargo et al. (2014) find that the reduced global TC frequency with climate warming in the GFDL HiRAM model is best described statistically by a genesis index that combines column saturation deficit and PI. Tang and Camargo (2014) interpret reduced simulated TC frequency with climate warming in several models in terms of changes in a ventilation index combining vertical wind shear, midlevel entropy deficit, and PI. However, using genesis indices for TC projections introduces other uncertainties, as some studies report that the sensitivity of TC genesis to large-scale environmental parameters may differ between present-day and future climate states (Nolan and Rappin 2008; Murakami et al. 2013a).

How the various hypothesized mechanisms discussed above can be reconciled with the smaller set of models that project *increased* global TC frequency (e.g., Bhatia et al. 2018) remains to be determined. In any case, reconciling projection results with theories or mechanistic understanding of TC genesis may eventually lead to improved confidence in projections of TC frequency. As we will discuss later in this report, future projections for TC intensity and precipitation rates have a relatively stronger physical basis—and greater agreement among existing studies—than projections of global TC frequency.

Model TC frequency projections are less robust—in terms of the sign of projected change—for individual basins than for the globe (Fig. 1b; Table ES1). Comparing results across individual basins, relatively more robust decreases are projected for the southwest Pacific and south Indian Ocean. Projected TC season length changes have been examined (Dwyer et al. 2015), and the overall results are generally consistent with the changes in annual TC frequency, with models that produce fewer TCs also simulating shorter TC seasons, and vice versa.

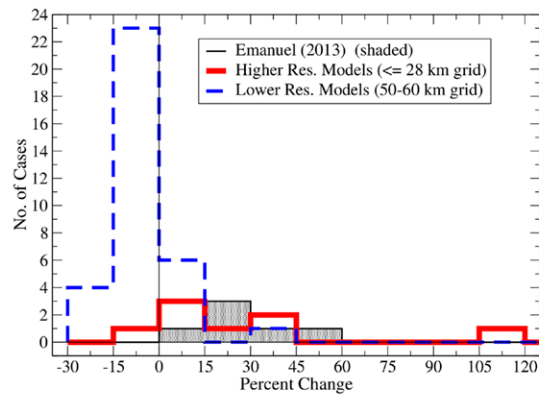
In our summary assessment, author team opinion was divided on how much confidence to place in a global TC frequency decrease with greenhouse warming. A decrease was rated as *low-to-medium* confidence by 7 of 11 authors, *medium confidence* (1 author), and *medium-to-high confidence* (3 authors).

Very intense (category 4–5) TC frequency. Very intense (i.e., category 4–5) TC frequency is a metric of great scientific and societal interest. For example, Pielke et al. (2008) report that category 4–5 TCs accounted for almost half of normalized economic damage from TCs in the United States despite representing only about 6% of TC occurrences.

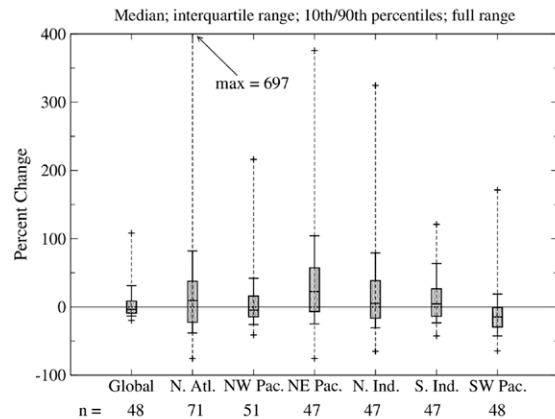
Figure 2 summarizes projections of very intense TC frequency from Table ES2. Since many models do not explicitly simulate category 4–5 TCs, in some cases we included in Fig. 2 the change in relatively intense classes of TCs for a given model. In some other cases, we report category 4–5 results as inferred from statistical refinement of model output, with the caveat that it is not based on explicit dynamical simulation.

Figure 2 contrasts sharply with the results for overall TC frequency (Fig. 1), showing no clear tendency for reduced very intense TC frequency, in comparison to overall TC global frequency (Fig. 1) which showed a marked tendency for a decrease. Most of the decreased very intense TC frequency projections originate from relatively coarse resolution models (grid spacing of about 50–60 km). Higher-resolution models (grid spacing of 28 km or finer) and Emanuel's

a) Very Intense Tropical Cyclone Freq. Change Projections: Global



b) Very Intense Tropical Cyclone Freq. Change Projections: By Basin



c) Percent Change in Proportion of Cat. 4-5 Tropical Cyclones: Global

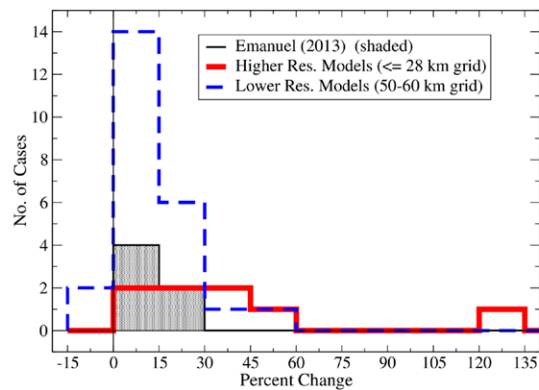


Fig. 2. As in Fig. 1, but for the change (%) in frequency of very intense TCs (e.g., category 4–5, or in some cases the most intense TCs in a given model; see Table ES2). (a) Percentage change in global very intense TC frequency. (b) Percentage change in very intense TC frequency by basin. (c) Percentage change in the global proportion of TCs that reach very intense levels (e.g., category 4–5, or in some cases the most intense TCs in a given model) relative to all TCs. In (a) and (c), the red histogram depicts relatively high-resolution dynamical model results (grid spacing of 28 km or finer); the blue dashed line depicts relatively lower-resolution model results (50–60-km grid spacing), including some refined with statistical downscaling; and the dark shaded area depicts results from Emanuel’s (2013) statistical–dynamical framework. In (b), shaded boxes, whiskers, and small plus signs denote the interquartile range, the 10th–90th percentiles, and the maxima and minima. Horizontal lines within shaded boxes are medians. All changes from Table ES2 have been rescaled prior to plotting to be consistent with a global mean temperature change of +2°C. See Fig. 1 caption for further details.

(2013) hybrid framework both generally project *increases* in very intense TC frequency (Fig. 2a). Results for individual basins (Fig. 2b) show an increasing tendency in the northeast Pacific basin and decreasing tendency in the southwest Pacific, but appear generally less robust than the global results.

We interpret the category 4–5 frequency projections as resulting from a combination of a general decrease in overall TC frequency and a generally increasing average TC intensity (discussed later). These competing influences lead to a less robust result for category 4–5 frequency than for TC intensity alone. The influence of the projected decrease in global TC frequency can be removed from the very intense TC frequency analysis by examining the *proportion* of TCs that reach category 4–5 intensity. For this proportion metric, almost all available projections (considering here models with grid spacing of 60 km or less) agree on a projected increase in category 4–5 proportion for the 2°C global greenhouse warming scenario (Fig. 2c; Table ES2; see also Holland and Bruyère 2014). The median projected change in the proportion of storms reaching category 4–5 is about +13% across available studies.

In summary, author opinion was divided on whether the global frequency of very intense (e.g., category 4–5) TCs will increase or not, with the confidence in an increase ranging from *low* (three authors), to *low-to-medium* (two), to *medium* (one), to *medium-to-high* (four) to *high* (one). There was higher confidence and stronger agreement that the proportion of TCs that reach very intense levels will increase, with 8 of 11 authors rating this as *medium-to-high confidence* and three authors rating it as *high confidence*. There is generally lower confidence in changes in these metrics at the individual basin scale than the global scale.

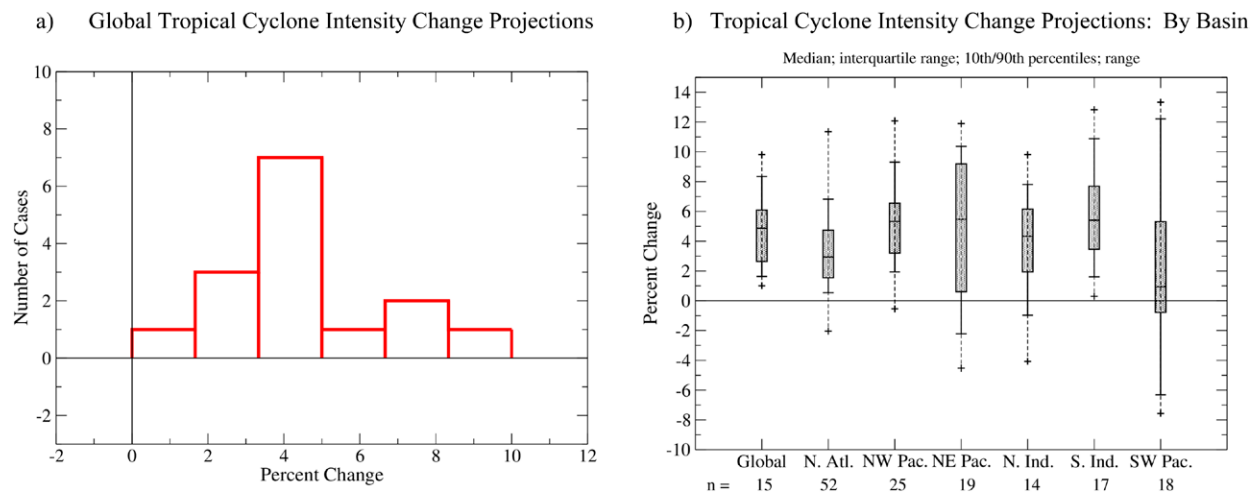


Fig. 3. (a) Summary global mean histogram and (b) individual basins and global mean distributions of projected changes in TC maximum intensities (surface wind speeds) from available studies (see Table ES3), expressed in percent. See Fig. 1 caption for list of metrics plotted and more details. Large whiskers in (b) indicate the 10th and 90th percentiles. In cases where a study reported only surface pressure changes, the plotted value is the percentage change in the square root of the central surface pressure drop relative to the large-scale environmental surface pressure.

TC intensity. Figure 3 summarizes TC intensity projections based on simulated lifetime maximum surface wind speeds. Fifteen individual scaled global estimates are all positive, with a mean and median increase (range) of about 5% (1%–10%). Average intensity at the global scale is projected to increase in all eight of eight studies that used dynamical models with grid spacing of 60 km or finer (Table ES3), and in Emanuel et al.’s (2008) statistical–dynamical framework. Thus, at least relatively higher-resolution models agree on a projected increase in global averaged maximum TC intensity.

A few studies using much coarser-resolution models (grid spacing of over 100 km) project no change in TC intensity; these are listed in Table ES3, but are not included in the Fig. 3 summaries. Several studies conclude that it is important to use higher model resolution for TC intensity change projections. Global model timeslice experiments by Manganello et al. (2014) simulate increased TC intensity with climate warming using a 16-km-grid model, but not with a 125-km grid spacing version of the model. Murakami and Sugi (2010) report that 60-km grid spacing is a critical resolution in projecting changes of intense TC frequency. These results suggest that projections of TC intensity change using very coarse-grid dynamical models (of order 100-km grid spacing or more) should be treated with caution.

A projected increase in TC intensity with climate warming is generally consistent with PI theory (e.g., Emanuel 1987) which also predicts such an increase in a greenhouse-warmed climate when applied to large-scale environmental fields from CMIP5 models (Sobel et al. 2016; Table ES3). PI theory provides a framework for interpreting TC intensity increases in dynamical models, accounting for enhanced upper-tropospheric warming influence—noted, for example, by Shen et al. (2000), Hill and Lackmann (2011), and Tuleya et al. (2016)—by assuming that the atmosphere remains moist adiabatic.

Huang et al. (2015) explored a variant of PI theory that replaces SST with upper-ocean-averaged temperature in the PI equations. They proposed that previous projections of the influence of greenhouse warming on TC intensity could be substantially overestimated, since ocean temperature changes in IPCC AR5 projections showed less warming at depth (e.g., top 100 m) than at the surface, implying an increased thermal stratification in a warming climate. The latter should enhance the cool wake induced by a given amount of mixing by a hurricane traveling over the ocean. Within their idealized framework, this mechanism substantially reduced the degree of intensification of TCs with climate warming. Subsequently, two studies

examined their proposed mechanism using a statistical–dynamical framework (Emanuel 2015) and a coupled hurricane ocean model (Tuleya et al. 2016). These two studies confirmed that Huang et al.’s proposed effect was present in their simulations, and they independently estimated that it reduced the projected intensification of TCs due to greenhouse warming by about 10%–15% compared to simulations without the effect. Balaguru et al. (2016) further propose that reduced near-surface salinity with climate warming will lead to a strengthening effect on TC intensification, all else equal, due to decreased mixing—an effect not included in Huang et al.

As discussed in Part I, the balance of evidence suggests that global TC intensity has undergone a weakly detectable increase, with most authors concluding that anthropogenic influence contributed to the increase. This suggestive finding provides some additional support for projections of global TC intensity increases.

In summary, most authors rated a future increase in the global average TC intensity as either *medium-to-high* (seven authors) or *high* (three authors) *confidence*, with one rating of *low-to-medium confidence*. The average increase projected for a 2°C global warming is about 5% (range 1%–10%) in available higher-resolution studies. At the individual basin scale, the author ratings were broadly similar though slightly less confident than for the global scale; the weakest signal was projected for the southwest Pacific basin.

TC rainfall rates. TC rainfall rate projections (Table ES4) are based on a variety of metrics used in different studies. TC rainfall rate in general is a particularly challenging metric for which to create multimodel aggregate projections, because different studies report results using a variety of averaging radii around the storm center. For our assessment, if multiple estimates were available from a given study (Table ES4) we used the estimate closest to 150-km radius. As a sensitivity test, we used the estimate closest to 500 km if multiple estimates were available. In either case, our aggregate results are based on a combination of results using averaging radii ranging from 1000 km to results based on the maximum precipitation rate anywhere within the storm. These multimodel aggregate results are referred to as “near-storm precipitation rate” projections in our report. With this caveat, we have combined TC rainfall projections from multiple studies to create the aggregate results shown in Fig. 4. We focus here on TC storm-relative *rainfall-rate* changes rather than accumulated rainfall at a given geographical location or total rainfall mass per storm; these latter two metrics have a strong dependence on storm size and on either translation speed or duration, for example.

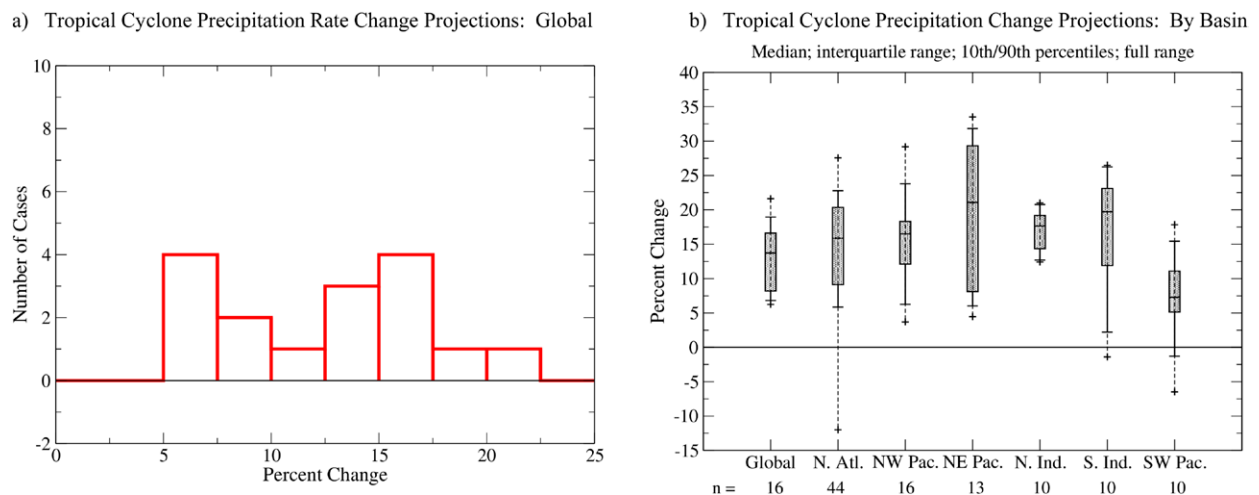


Fig. 4. (a) Summary global mean histogram and (b) distributions for individual basins and global of projected changes in near-storm TC rainfall rates from available studies (see Table ES4), expressed in percent. See Fig. 1 caption for list of metrics plotted and more details. Large whiskers in (b) indicate the 10th and 90th percentiles.

The TC precipitation-rate projections in Fig. 4 show the most robust projected increase across models of any TC metric we examined. All 16 global projections from eight studies indicate a global mean increase (median: +14%; range: +6% to +22%). For the sensitivity test where we used larger radius results (closest to 500 km) for the small number of studies where these were available, the overall results were fairly similar (median: +12.5%; range: +3.1% to +22%). TC precipitation rate metrics generally show positive changes for most individual basins as well (Fig. 4b), with only a few exceptions across the studies for some individual basin cases.

The projected 14% TC rain-rate increase for a 2°C global warming implies a slightly stronger than 7% increase per 1°C of tropical SST warming, since tropical SSTs generally warm less than global mean temperature in climate model projections. For example, an analysis of RCP4.5- and RCP8.5-scenario temperature projections from a sample of 10 CMIP5 models indicates that tropical SSTs warm at about 75% (range: 66%–93%) of the rate of global mean surface air temperature. Thus the Fig. 4 results indicate a fractional increase of near-storm precipitation rate that is at least as large as the fractional rate of water vapor increase associated with SST warming at constant relative humidity (i.e., about 7% per 1°C of tropical SST warming, as inferred from the Clausius–Clapeyron equation relating saturation vapor pressure to air temperature). Knutson et al. (2015), examining projected TC precipitation rates for individual basins, find that the increases in TC precipitation rates roughly approximate a 7% °C^{−1} scaling. The increasing rate appears to be modulated by the relative SST warming in a given basin (i.e., basin SST warming relative to the tropical average SST warming). Higher (lower) relative SST warming is associated with greater (less) than 7% °C^{−1} scaling of TC precipitation rates. Globally, they report that the rate of increase exceeds 7% °C^{−1} warming for averaging radii of 150 km or less, but declines to about 4% °C^{−1} at a radius of 500 km. Further, the percentage increase in precipitation rates also tends to decline with averaging radius in most individual basins. In contrast, Wright et al. (2015) report that for their model projected TC precipitation rates over U.S. land regions, the percentage increase in rain rate actually increases for larger averaging radius in more than half of the anthropogenic warming scenarios/cases they examined.

The physical mechanism producing the robust TC rainfall rate increases with climate warming is well understood (e.g., Allen and Ingram 2002; Wang et al. 2015). First, an extremely robust projection from climate models is that tropospheric water vapor content will increase in a warmer climate (IPCC 2013). This is a consequence of the relatively small projected changes in relative humidity, combined with an extremely robust projection of warming of both SST and the tropical troposphere. As a result, the large-scale atmospheric environment in which future TCs will evolve is projected to contain increased atmospheric water vapor at the rate of approximately 7% per 1°C of SST warming. Second, TC modeling studies consistently show that moisture convergence dominates over local evaporation as the primary moisture source for TC rainfall (e.g., Wang et al. 2015). Assuming no change in circulation characteristics, the moisture convergence scales directly with the total moisture content. Thus, with climate warming an increase in TC moisture convergence and precipitation rate is anticipated, unless the increase in atmospheric moisture content is offset by an (unexpected) substantial reduction in the dynamical convergence toward the TC center.

IPCC AR5 concluded that extreme precipitation from all sources (as opposed to just from TCs) over wet tropical regions is very likely to become more intense and more frequent with climate warming (Collins et al. 2013). This projection is supported by mechanistic understanding of the physical processes, as well as existing modeling and observational evidence for a detectable human influence on observed extreme precipitation. However, a detectable increase on TC rainfall rates has not yet been firmly established (Part I), which tempers confidence in future projections of an increase.

In summary, while existing modeling studies agree on a projected increase in global average TC rainfall rates, there is less agreement on details of this increase, such as whether it

will be greater or less than the $\sim 7\% \text{ }^{\circ}\text{C}^{-1}$ rate, and whether the fractional rain increase will increase or decrease as one moves away from the storm center by hundreds of kilometers. Available studies (e.g., Knutson et al. 2013; Wright et al. 2015; Knutson et al. 2015; Liu et al. 2018) provide conflicting results: there is dependence on the basin considered, relative SST warming, and whether land regions or oceanic regions are considered. Narrowing these uncertainties will be a challenge for future studies, and would benefit from observational guidance on TC precipitation rate changes.

Based on the above results, the author team concluded that globally averaged near-storm TC precipitation rates for individual TCs will increase with *medium-to-high confidence* (five authors) or *high confidence* (six authors). A representative quantitative estimate for the increase is about 14% for a 2°C global warming, or broadly close to the rate of tropical water vapor increase expected for warming at constant relative humidity. Confidence in an increase was assessed as broadly similar for individual basins, though uniformly slightly lower than for global projections, particularly for Southern Hemisphere basins.

TC tracks and areas of occurrence. Projected changes in TC tracks or areas of occurrence in climate warming scenarios are challenging to assess, as, for example, it can be difficult to compare results from various studies to obtain a consensus finding. However, if such TC track changes were to emerge due to anthropogenic climate change, they could be very important for societal impacts.

Some multimodel analyses have focused specifically on this issue. Nakamura et al. (2017) analyze metrics which combine TC track and occurrence data from multiple model ensembles over the western North Pacific. They find a statistically significant northward expansion of tracks, and in one of the multimodel ensembles they find an eastern shift in tracks in the central North Pacific suggesting a possible increase in TC risk to Hawaii. Another multimodel analysis (Chand et al. 2017) also projects increased TC activity in parts of the north-central and northeast Pacific, including near Hawaii, and projects that TC activity will be particularly enhanced over these parts of the North Pacific (and over parts of the southwest Pacific) during El Niño events in a warmer climate. Daloz et al. (2015) do not find robust changes in Atlantic TC tracks in an idealized warming scenario using a multimodel ensemble. Colbert et al. (2013, 2015) use a simplified TC track model to infer that weakened easterlies and weaker atmospheric circulations in CMIP3 and CMIP5 multimodel projections could lead to track shifts and favor fewer landfalling TCs for the western North Pacific and North Atlantic basins. Kossin et al. (2016) project a future poleward migration of the latitude of maximum TC intensity, which is broadly supported by evidence for a detectable poleward migration in the western North Pacific since the 1940s, thought to be related to the poleward expansion of the tropics. They examine both coarse-grid CMIP5 models (which have only limited TC simulation capability) and an empirical–statistical downscaling method.

A number of TC–climate studies project changes in TC track or occurrence, often in the form of maps or zonal/meridional averages for individual TC simulation models. Owing to space limitations and the difficulty in combining such information from individual studies into a summary quantitative distribution (as done for basinwide and global TC frequency, for example), we instead present a narrative summary of some track and occurrence findings from these publications in the supplemental material. Some of the changes summarized there have broadly similar characteristics seen across more than one study. We have organized some of these projected changes from different studies into several broad common categories or themes. These include a shift in TC activity in the northwest Pacific basin from the South China Sea region to the East China Sea region, an increase in TC activity in the central Pacific and near Hawaii, and poleward shifts of TC activity in the North Pacific and other basins.

In terms of mechanisms, Murakami et al. (2012) point out that a dynamical model tends to project increases in TC density where SSTs increase more than in other tropical ocean regions. Several previous studies report projected increases in TC density and PI where the SST increases more than in other open oceans. The tropical central Pacific and Arabian Sea are regions where a number of climate models robustly project larger relative future warming (Vecchi and Soden 2007a,b; Zhao et al. 2009; Murakami et al. 2012), consistent with projected increases in TCs near Hawaii (Murakami et al. 2012, 2013a, 2017a) and in the Arabian Sea (Murakami et al. 2013b, 2017b).

Despite the large number of studies that have explored the issue of future projections of TC tracks and occurrence changes, there is currently relatively limited overall confidence in these projections. The principal reasons for this include the difficulty in obtaining a clear model consensus in projected track/occurrence behavior, the lack of a clear detectable anthropogenic influence on such TC metrics in the historical data, and limited confidence in IPCC projections of regional circulation features and future SST pattern changes that could affect tracks (“Model evaluation” section and the supplemental material). Murakami et al. (2014) conclude that model biases in simulating present-day TC occurrence frequency affect projected future changes in TC occurrence frequency. Therefore, improving present-day TC climate simulations will be an important issue for reducing uncertainty in future TC projections.

To summarize, there is considerable diversity of results from available studies, making it difficult to identify a robust consensus projection for TC tracks/occurrence, although several studies project either poleward or eastward expansion of TC occurrence over the North Pacific region resulting in greater TC occurrence in the central North Pacific. Author opinion was divided on confidence in a projected further poleward expansion over the twenty-first century in the latitude of maximum TC intensity in the western North Pacific under scenario RCP8.5. Confidence levels in that projection ranged from *low* (one author) to *low-to-medium confidence* (four authors), to *medium* (three authors), to *medium-to-high* (three authors).

TC translation speeds. Recent studies investigating possible causes for some observed long-term declines in TC translation speeds (Kossin 2018, 2019; Moon et al. 2019; Lanzante 2019) have raised interest in model projections of this metric. Relatively few modeling studies to date have reported on changes in TC translation speed under climate change, and these studies do not collectively provide a strong consensus result. Two regional model downscaling studies find no robust projected changes in Atlantic (Knutson et al. 2013) or western North Pacific (Wu et al. 2014) translation speeds in either CMIP3 or CMIP5 multimodel downscaling experiments. Two of the 10 individual CMIP3 models that Knutson et al. (2013) downscaled project significant increases while one multimodel ensemble case they simulated (CMIP5/early twenty-first century only) projects a significant decrease. Kim et al. (2014) reports no significant change in translation speed of TCs globally or in any individual basin, based on a 50-km-grid coupled model $2\times\text{CO}_2$ experiment. Gutmann et al. (2018) projects a significant decrease of TC translation speed based on 22 Atlantic storms simulated under present-day and CMIP5/RCP8.5 late twenty-first-century conditions. A significant ($p = 0.05$) change (decrease) was simulated for the 22-member ensemble as well as for three of 22 individual cases in their study. We conclude that future projections of TC translation speed are uncertain.

TC size. TC size is an important determinant of storm surge risk (e.g., Powell and Reinhold 2007) and is correlated—along with TC intensity—to TC-related economic damages (e.g., Zhai and Jiang 2014). Several observational studies document the climatology of TC size (Kimball and Mulekar 2004; Dean et al. 2009; Chavas and Emanuel 2010; Chan and Chan 2012, 2018; Knaff et al. 2014; Wu et al. 2015; Schenkel et al. 2018). No detectable anthropogenic influences on TC size have been identified to date. Chavas et al. (2016) find that observed mean

TC size increases with relative SST (SST relative to tropical mean SST). Knutson et al. (2015) demonstrate that the interbasin variation of TC size can be captured, to a first approximation, in a dynamical downscaling framework driven by observed SSTs.

Several studies explore the characteristics of projected TC sizes under future climate change (Kim et al. 2014; Knutson et al. 2015; Yamada et al. 2017; Sun et al. 2017; Gutmann et al. 2018). Kim et al. (2014) simulate a 3% increase in TC size globally for a $2\times\text{CO}_2$ climate where they also simulate a 3% increase in mean storm intensity. Knutson et al. (2015) project that the median TC size (based on radius of 12 m s^{-1} winds) will remain approximately unchanged globally, as increases in most basins are offset by a decrease in the northwest Pacific basin (CMIP5/RCP4.5 scenario). Yamada et al. (2017) project TC size changes (IPCC A1B scenario) using a 14-km-grid global nonhydrostatic atmospheric model. Based on an 18-model CMIP ensemble (A1B scenario) climate change signal, they project a significant (10%) increase in radius of 12 m s^{-1} azimuthally averaged tangential TC wind speeds globally, with significant increases for the northwest Pacific, south Indian, and South Pacific basins, and significant decreases for the north Indian and northeast Pacific basins. Gutmann et al. (2018) simulated 22 Atlantic hurricane cases using a 4-km-grid regional model under present-day and future climate conditions and find no statistically significant changes in TC size, as measured by the average radius of hurricane force winds.

Future studies should further assess model capabilities at simulating present-day TC sizes, which has so far been done only to a limited extent. Better understanding of the mechanisms determining TC sizes in observations and models will be important, as will be the monitoring and accumulation of observed climate records of TC size.

A very strong increase in TC destructive potential is projected by Sun et al. (2017), including a large impact from a TC size increase as inferred using a new aggregate exposure approach. However, the basic design of their main model experiments does not incorporate atmospheric temperature warming in the initial or boundary conditions of their regional model along with the SST change.

In summary, several studies suggest an impact of anthropogenic warming on TC size characteristics, although not all studies find significant projected changes. While the projected TC size changes are generally on the order of 10% or less, these size changes are still highly variable, even in sign, among basins and studies.

Storm surges. Several studies (e.g., McInnes et al. 2003; Lin et al. 2012; Little et al. 2015; Garner et al. 2017; McInnes et al. 2014) have explored future storm surge risk in the context of anthropogenic climate change, where they consider the influence of both sea level rise and the changes in future hurricane climate (the latter being the focus of our assessment).

Lin et al. (2012) estimate flood return levels for New York City by coupling projected storms from Emanuel et al.'s (2008) downscaling model to a storm surge model. An idealized 1-m sea level rise increases surge risk dramatically, while the hurricane climate contributions, based on downscaling four CMIP3 models, are highly model dependent. Garner et al. (2017) examine New York City surge risk using sea level rise projections out to 2300. They find minimal influence of hurricane climate change on New York City surge risk, based on downscaling three CMIP5 models using Emanuel et al.'s framework, noting that a storm strengthening influence is offset by a shift of TC tracks away from the landfall region. Their model projects the 500-yr surge event to increase from 3.4 m (present estimate) to 4–5.1 m above mean tidal level by 2080–2100. Little et al. (2015) project changes in surge risk along the U.S. East Coast, incorporating both sea level rise and TC power dissipation index (PDI) changes—the latter derived from a 15-member ensemble of climate models following a statistical modeling approach (Villarini and Vecchi 2013). Most of the 15 models they assess project PDI increases; some model projections including both higher sea level and large projected increases in PDI have

compounded increases in projected flood risk. However, the projected increases in Atlantic PDI have considerable uncertainty, as several other TC modeling studies using dynamical, rather than statistical, downscaling approaches (Yamada et al. 2010; Kim et al. 2014; Knutson et al. 2015) project little change or decreases in PDI or accumulated cyclone energy (ACE), whereas Bhatia et al. (2018) project strong increases in Atlantic intense TC activity. McInnes et al. (2014) find that for Fiji the future projected increase in storm surge incidence is dominated by sea level rise, with only minor contributions from projected TC changes.

The above modeling studies confirm the intuitive notion that sea level rise leads to increased storm surge risk, all other factors equal (see also Sweet et al. 2013; Irish et al. 2014; Reed et al. 2015a), although occasional exceptions to this (for small sea level rises) due to nonlinear bay effects have been reported (e.g., Takayabu et al. 2015). However, the influence of TC climate changes on surge risk is much more uncertain than that of sea level rise (e.g., Woodruff et al. 2013), and the former is also not clearly evident from observational tide gauge studies to date (e.g., Marcos and Woodworth 2018; Wahl and Chambers 2015). Sea level rise projections for various locations have considerable uncertainties (IPCC 2013; Garner et al. 2017), although, global mean sea level rise will continue through the twenty-first century, at a rate that very likely will exceed that observed over 1971–2010 (IPCC 2013). While reducing uncertainty in future sea level rise is crucial for projecting future changes in surge risk, this topic is beyond the scope of our assessment.

In summary, our expectation is that projected increases in sea level, average TC intensity, and TC rainfall rates will each generally act to further elevate future storm surge risk. Changes in TC frequency, tracks, and intensity could contribute toward increasing or decreasing future storm surge risk (all other factors equal). Of the various influences on surge risk, we are most confident that sea level rise over the coming century will lead to higher average storm inundation levels for TCs that occur, assuming all other factors equal. Quantifying the relative contributions of these various influences, as well as other potential influences such as storm track changes, remains a significant challenge.

Paleoclimate perspectives

Paleostorm studies investigate prehistorical TC behavior using geologic proxy records or climate models. One use of such studies is to estimate the background level of climate variability using datasets that are longer than available instrumental records. This can help constrain the response of TC activity to past climate variations, which can serve as a guide to possible future changes caused by anthropogenic forcing [see Walsh et al. (2016) and Muller et al. (2017) for recent reviews].

An important branch of paleostorm research involves climate modeling. Simulations of TC behavior during very different past climate states (e.g., the Last Glacial Maximum) can be obtained using climate models, but only a limited number of such studies have been published. In general, these tend to reinforce the notion that cooler climates are not necessarily periods with fewer TCs, with some model experiments simulating *more* TCs (e.g., Kerty et al. 2012; Sugi et al. 2015), qualitatively consistent with projections of fewer TCs in a warmer climate, assuming a symmetry of TC frequency response between cooler and warmer climates. Yoo et al. (2016), however, simulate little difference between TC incidence for LGM conditions versus current climate. Examples of simulations of enhanced TC activity during past warm climates include Yan et al. (2016) and Federov et al. (2018). Millennial-scale TC simulations (Kozar et al. 2013; Reed et al. 2015b) can be used to explore TC–climate relationships; such studies suggest, for example, that Atlantic basin landfalling-TC records should be relatively good proxies for basinwide TC activity. Paleo-TC simulations can also be used to help interpret paleostorm activity records obtained from geologic proxy records (Woodruff et al. 2008), or to better estimate the hurricane surge risk for a given location (Lin et al. 2014). In summary,

Tropical Cyclone Projections (2°C Global Warming)

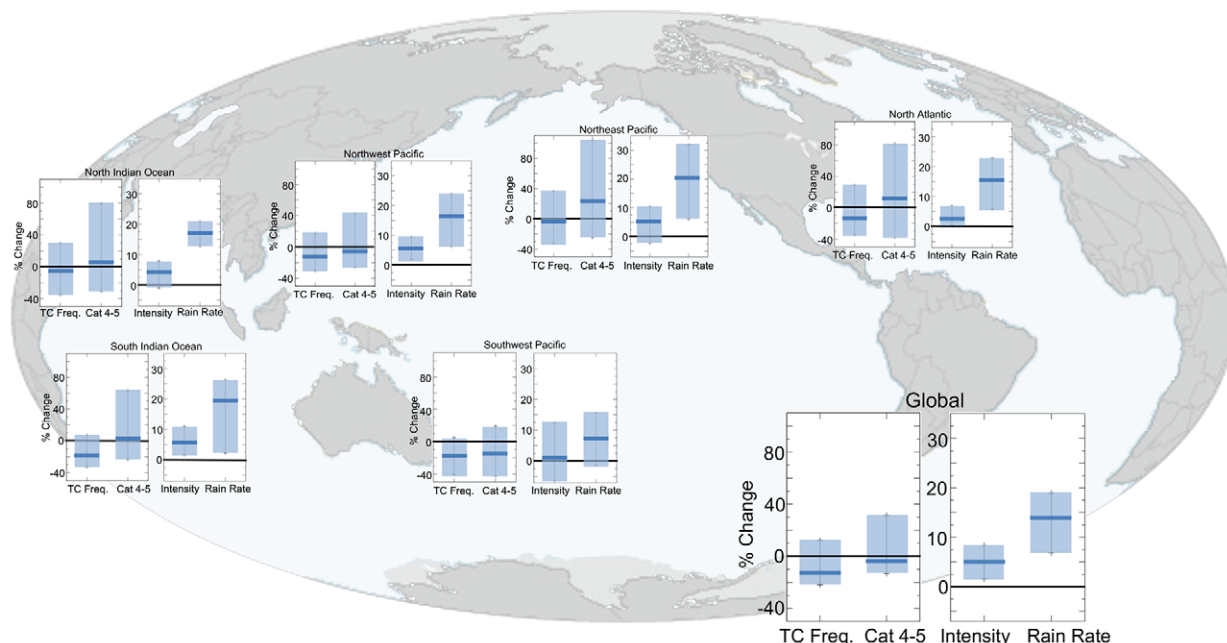


Fig. 5. Summary of TC projections for a 2°C global anthropogenic warming. Shown for each basin and the globe are median and percentile ranges for projected percentage changes in TC frequency, category 4–5 TC frequency, TC intensity, and TC near-storm rain rate. For TC frequency, the 5th–95th-percentile range across published estimates is shown. For category 4–5, TC frequency, TC intensity, and TC near-storm rain rates the 10th–90th-percentile range is shown. Note the different vertical-axis scales for the combined TC frequency and category 4–5 frequency plot vs the combined TC intensity and TC rain rate plot. See the supplemental material for further details on underlying studies used.

while climate model simulations and paleoclimate proxy evidence of past TC incidence have been published, from the viewpoint of our assessment, it is difficult at this stage to use these as quantitative guidance for future TC climatology.

Summary and conclusions

In this assessment, we have focused on the question of what changes in TC activity would be expected to accompany a 2°C anthropogenic global warming, according to current models. Confidence in several key TC projections has increased since the assessment of Knutson et al. (2010) due to support from additional studies, including new higher-resolution modeling studies. However, anthropogenic signals are not yet clearly detectable in observations for most TC metrics (Part I), a limiting factor for confidence in future projections.

A summary of modeled TC projections for a 2°C anthropogenic global warming is shown in Fig. 5 with the distribution of confidence levels across authors summarized in Table 1. The main projections can be summarized as follows:

- 1) The most confident TC-related projection is that sea level rise over the coming century will lead to higher storm surge levels on average for the TCs that do occur, assuming all other factors are unchanged. A TC climate change signal has not yet been convincingly identified in historical sea level extreme data.
- 2) For near-storm TC precipitation rates, there is at least *medium-to-high confidence* in an increase at the global scale. A representative quantitative estimate for the increase in TC precipitation rates is about 14% for a 2°C global warming, or close to the rate of tropical water vapor increase expected for atmospheric warming at constant relative humidity.
- 3) For TC intensity, 10 of 11 authors had at least *medium-to-high confidence* that the global average intensity will increase. The average increase projected for a 2°C global warming is

about 5% (range: 1%–10%) in available higher-resolution studies.

- 4) For the global proportion of TCs that reach very intense (category 4–5) levels there is at least *medium-to-high confidence* in an increase, with a median projected change of +13%. (This confident assessment of an increase in *proportion* of category 4–5 TCs does not apply for the actual frequency of category 4–5 TCs, which is discussed below.) An increase in this proportion metric is projected by almost all modeling studies we examined that simulated or statistically inferred category 4–5 frequency of TCs.

Table 1. Summary of author opinion on key tropical cyclone projections statements. The number in parentheses is the number of authors, out of 11, who responded with the given confidence level.

Precipitation rates of TCs are projected to increase globally. Confidence: high (6); medium-to-high (5)
Intensity of TCs is projected to increase globally. Confidence: high (3); medium-to-high (7); low-to-medium (1)
Proportion of category 4–5 TCs is projected to increase globally. Confidence: high (3); medium-to-high (8)
Frequency of category 4–5 TCs is projected to increase globally. Confidence: high (1); medium-to-high (4); medium (1); low-to-medium (2); low (3)
Frequency of all TCs (category 0–5) is projected to <i>decrease</i> globally. Confidence: medium-to-high (3); medium (1); low-to-medium (7)
Latitude of maximum TC intensity in western North Pacific will migrate poleward. Confidence: medium-to-high: (2); medium (4); low-to-medium (4); low (1)

Author opinion was more mixed and confidence levels generally lower for some other TC projections, including a further poleward expansion of the latitude of maximum intensity of TCs in the western North Pacific basin, a decrease of global TC frequency, and an increase in the global frequency (as opposed to proportion) of very intense (category 4–5) TCs. The vast majority of modeling studies project decreasing global TC frequency (median of about –13% for 2°C of global warming), while a few studies project an increase. It is difficult to identify/quantify a robust consensus in projected changes in TC tracks across studies, although several project either poleward or eastward expansion of TC occurrence over the North Pacific. Projected TC size metric changes are on the order of 10% or less, and highly variable between basins and studies. Confidence in projections of TC translation speed is low due to the potential for data artifacts in the observed slowdown and a lack of model consensus. Confidence in various TC projections in general was lower at the individual basin scale than for the global average.

We provide recommendations on TC metrics for future studies in the supplemental material. Reducing uncertainties in climate model projections of TC-related environmental variables will be important for reducing downstream impacts of these uncertainties on TC projections. Improved theories (e.g., for TC genesis), improved process understanding of TC responses to climate change, higher-resolution coupled model experiments, long-term observational programs, homogeneous climate-quality datasets, and combined model–observational analyses (e.g., detection and attribution) all should eventually help confirm or refute modeled projections and are important for future progress in the field.

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