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Modeling High-Impact Weather and Climate: Lessons from a Tropical Cyclone Perspective

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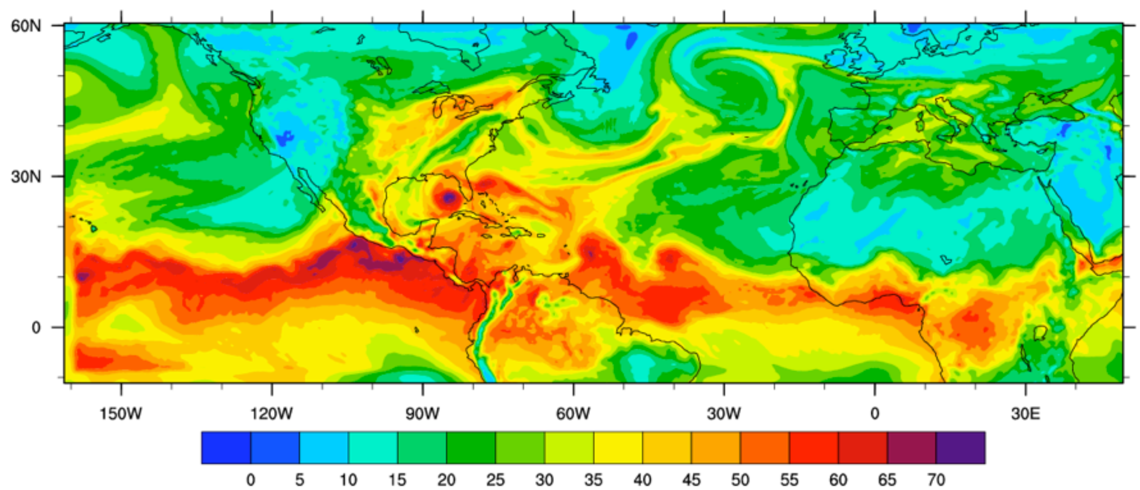

A snapshot of simulated vertically integrated water vapor (mm) using the NCAR Nested Regional Climate Model showing easterly waves tracking off the African coast out over the Atlantic and a Hurricane in the Gulf of Mexico.

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2. Acknowledgements

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3. Introduction

Society is well into a new era of catastrophes in which natural hazards, particularly weather and climate related hazards, are causing more damage than in the past (e.g. Kunreuther and Michel-Kerjan 2009). In recent years, society has faced a steep rise in economic and insured losses from weather and climate related hazards, largely due to significant increase in exposure (Höppe and Pielke 2006). Projections of a continuing trend towards more intense systems (see Bender et al. 2010; Knutson et al. 2010 for the case of tropical cyclones) point to a further increase societal vulnerability unless adequate planning and adaptation measures are implemented. More accurate information on high-impact events, defined (following Stephenson 2008) as either a short-lived intense weather event or an accumulation across a number of weather events in a given time period, is thus a critical need of society. This requires assessments of the statistics of high-impact events with regional clarity and on how they may change under climate variability and change together with estimates of uncertainty.

Meeting these demands requires a combination of dynamical and statistical components. The traditional dynamical approach combines the capacity of regional high resolution to simulate weather events with the capacity of global coarse resolution to simulate climate by embedding high resolution within the global mesh over regions of interest (e.g. Laprise et al. 2008; Knutson et al. 2007). Increases in computational capacity have enabled such simulations in unprecedented detail (e.g. Bender et al. 2010; Oouchi et al. 2006). Regional high resolution can provide trackable weather systems on decadal timescales, physical insights into their variability, physical response of weather systems to climate variability and change, and events outside the historical range in terms of location and scale. Despite these accomplishments, finite computational resources and overwhelming data volumes require considerations of the appropriate balance between sufficient detail to resolve the relevant physical processes, sufficiently long simulations to adequately sample climatology, and sufficient ensemble size to sample uncertainty. This often results in a truncation of the full distribution of high-impact events. Even if regional models could capture the full distribution then it may be necessary to treat error in location (e.g. storm track bias), error in frequency, and error in parameterized physical mechanisms.

In recognition of the limitations of the dynamical approach, a variety of statistical approaches have been explored. Uses of empirical relationships between weather systems and the large-scale environment have been successful in determining the weather system climate from coarse resolution data (e.g. Camargo et al. 2007). Statistical methods have also been used to post-process errors in frequency distributions of weather events from dynamical models, as discussed in Katz (2010). Although these two approaches add value to the dynamical approach, they are limited by the assumption of stationarity in the statistical relationships. Emanuel et al. (2008) provides an example of relaxing this assumption by increasing the connection between statistical and dynamical modeling components in assessing both tropical cyclone frequency and intensity.

Despite these initial recent developments, meeting the societal demand of assessing high-impact events with regional clarity remains extremely challenging. The purpose of this technical report is to present an overview of lessons learned over the past six years in modeling high-impact events on regional scales. Using the case of tropical cyclones as the archetypal high-impact event, the merits and limitations of the dynamical modeling approach are discussed and motivate, by way of illustrative examples, the need for combined dynamical-statistical approaches in order to provide credible and useful information.

Tropical cyclones represent a hard test case for simulating high-impact weather owing to their rarity in any one given region and highly uncertain future changes. For the North Atlantic, the past 15 years has seen activity well above the longer-term average in terms of intensity (Elsner et al. 2008) and frequency (Holland and Webster 2007; Vecchi and Knutson. 2008). Future global intensity increases are likely and there is model consensus on a decrease in global frequency (Knutson et al. 2010), yet changes on the scale of individual basins are far more uncertain with large variations between modeling studies (e.g. Knutson et al. 2007, 2010; Bengtsson et al. 2007; Oouchi et al. 2006).

The Nested Regional Climate Model (NRCM) is a dynamical downscaling tool designed specifically to contribute to assessments of high-impact events in current and future climates, and is utilized here to illustrate the current challenges. The next two sections describe simulation experiments with the NRCM: Section 4 examines NRCM simulations of global tropical cyclone activity in current climate, and Section 5 explores the capacity of the NRCM in limited area configuration to model both current and future North Atlantic tropical cyclone activity. These experiments are presented to illustrate current limitations and sensitivities of the dynamical model approach. The value of complementary statistical approaches is established by way of examples in Section 6. Section 7 highlights the importance of directly assessing the impacts of extreme events in order to generate information relevant to society. Finally, key findings are summarized in the discussion section.

4. Global Tropical Cyclone Activity

In this section, the ability of the NRCM to simulate global tropical cyclone activity is assessed. The NRCM is based on the Weather Research and Forecasting (WRF) model (Skamarock et al. 2008) nested into either a global reanalysis or a global climate model with options selected for long-term simulation, as described in Leung et al. (2005) and Done et al. (2011a). Here, results are presented from simulations using NRCM configured as a tropical channel model. The NRCM is driven by data from the NCEP/NCAR Reanalysis Project (NNRP, Kalnay et al. 1996) at 2.5° lat/lon grid spacing at the north and south lateral boundaries (45ºN and 45ºS, as shown in Fig. 1), as well as prescribed sea surface temperatures (Hurrell et al. 2008), albedo and vegetation fraction at the lower boundary. Model physical parameterizations (described in Done et al. 2011a) are chosen based on test simulations of seasonal rainfall totals and spatial distributions over the maritime continent when compared with Tropical Rainfall Measuring Mission Multisatellite Precipitation Analysis data (Huffman et al. 2007). The model is initialized on 1st January 2000 and runs though 1st January 2006 using a grid spacing of 36 km and 51 vertical levels up to 10hPa. An additional simulation is conducted with a two-way nest at 12 km grid spacing over the North Atlantic (Fig. 1) for the period 1st May 2005 through 1st Dec 2005 to probe the sensitivity of tropical cyclone simulation to model resolution. No nudging of the NRCM to NNRP data is applied in the interior of the domain. The NRCM is free to generate its own weather and climate and is constrained only by atmospheric data at the North and South boundaries and sea surface temperatures at the lower boundary.

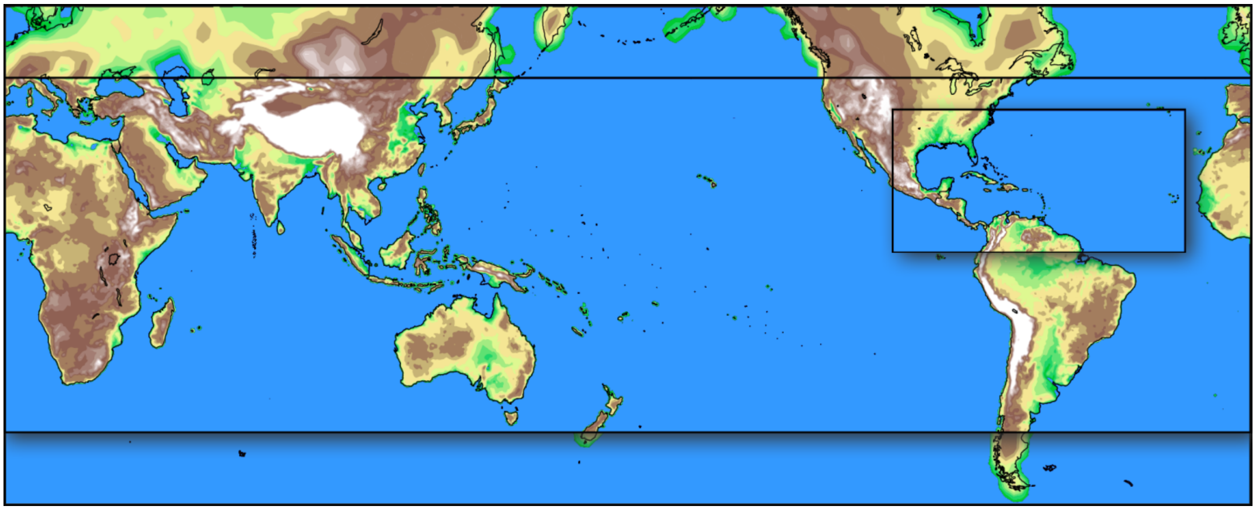


Figure 1: NRCM model domains at 36 km grid spacing (large black box) and 12 km grid spacing (small black box). Model terrain height (shaded) is shown at the different model resolutions and extends beyond the 36 km domain to indicate the resolution of the NNRP driving data.

Tropical cyclones are tracked automatically using the methodology described in Suzuki-Parker (2012). Local minima in surface pressure are first checked for 850hPa vorticity > $10^{-5}s^{-1}$ and 10m wind speed > $17ms^{-1}$ within 1º of the surface pressure minima. Next, vortex structure is checked for: sum of temperature anomalies at 300-, 500- and 700-hPa > 0K; temperature anomaly at 300hPa greater than the temperature anomaly at 850hPa; and, wind speed perturbation larger at 850hPa than 300hPa. In addition, the cyclone phase parameters of Hart (2003) are checked for B < 10, -VTL > 0 and –VTU > 0. Finally, a 2-day duration criterion is imposed.

The NRCM produces a reasonable temporal and spatial distribution of global tropical cyclone activity (Suzuki-Parker, 2012) but overproduces the total number by typically 20-30% depending on the year compared to observations (using IBTrACS data, Knapp et al. 2010). This bias is in part subject to details of the tracking algorithm (Suzuki-Parker, 2012); here the algorithm is not tuned to fit a specific model grid spacing to avoid interpreting the results of tuning as model skill. Rather, the same criteria are used across all model resolutions and experiments. Tulich et al. (2009) suggested that the bias is correlated to generally overactive easterly waves, particularly over the Northwest Pacific. Over the tropical North Atlantic, however, further examination shows that the easterly waves are generally too weak and dry, contributing to reduced tropical cyclogenesis in the eastern Tropical North Atlantic. The 12 km nested domain improves simulation of both the number and spatial distribution of tropical cyclones for the North Atlantic, with 20 storms at 12 km and 13 storms at 36 km compared to 25 tropical storms in the observations (using IBTrACS data, Knapp et al. 2010). Interestingly, at 12 km cyclogenesis occurs in the eastern tropical North Atlantic, but not at 36 km, suggesting the importance of local high resolution. Caron et al. (2010) and Caron and Jones (2011) noted a similar sensitivity of cyclogenesis in the eastern tropical North Atlantic to local resolution but found genesis to occur in this region at a grid spacing of 0.3° (approximately 30 km) rather than the higher resolution of 12 km found to be necessary in this study. This suggests local high resolution is not in itself sufficient. Cyclogenesis is influenced by large-scale, resolvable processes, (e.g. Gray 1968) but also by mesoscale processes below current model resolution. The multi-scale nature to cyclogenesis is a problem well suited to test emerging dynamical modeling techniques with global variable resolution meshes.

5. North American Climate Variability and Change

The capacity of the NRCM to simulate the current and future climate of high-impact weather of North America is now examined. The purpose of this section is to assess multi-year simulations of high-impact weather at high resolution using limited area domains; to identify the impact of domain size and resolution; and to explore and document critical sensitivities to this modeling approach. This experience also serves as guidance to determine priorities for further development with next generation modeling systems.

Global climate data are provided by Community Climate System Model (CCSM, Collins et al. 2006) version 3 integrations run under the A2 scenario (IPCC SRES SPM 2001), as submitted to the Coupled Model Intercomparison Project 3 (CMIP3, Meehl et al. 2007). The CCSM is a full Earth system model, including atmosphere, ocean, cryosphere, biosphere, and land surface. These data are then used to drive a NRCM 36 km domain using one-way nesting, which is then used to drive a 12 km domain (Fig. 2), again using one-way nesting. One-way nesting is chosen to avoid the unknown implications of using two-way nesting and also for the more practical reason of running each domain separately and checking the output for reasonable simulation prior to further downscaling. The model is run for three periods: a decade of 'current' climate conditions (1995-2005) referred to hereafter as 'base climate', and two future decades of 2020-2030 and 2045-2055[1]. The time periods are nominal since the driving CCSM model was initialized in 1950 with no additional assimilated data. Thus, for example, model interannual and multidecadal variations are not expected to match those in the real world, though the historical anthropogenic trend associated with greenhouse gases should be captured. All physical parameterizations are the same as used for the tropical simulations described in Section 4 (and described in Done et al. 2011a). This experiment provides key insights into domain size, location, horizontal resolution, climate bias, future changes in tropical cyclone frequency and intensity, and internal variability. These are each discussed in the following subsections.

[1] All NRCM data are held in storage at NCAR and are freely available for community use. The only caveat is that this involves several hundred terabytes of model output that require sophistication in the handling of large data sets.

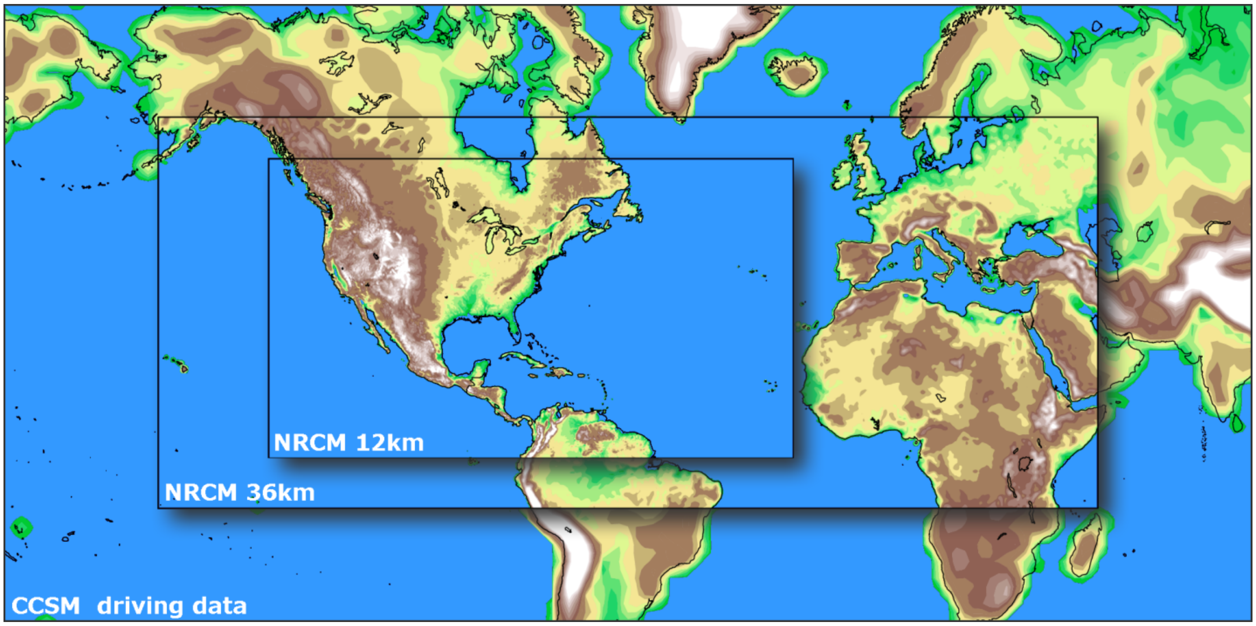


Figure 2: NRCM model domains at 36 km grid spacing (large black box) and 12 km grid spacing (small black box). Model terrain height (shaded) is shown at the different model resolutions and extends beyond the 36 km domain to indicate the resolution of the driving CCSM. Adapted from Done et al (2011b). Copyright 2011 OTC. Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Domain Size, Location and Horizontal Resolution

Domain size and horizontal resolution are key factors for regional climate simulation (Vannitsem and Chome 2005; Seth and Giorgi 1998; Seth and Rojas 2003) and tropical cyclone simulation (e.g. Landman et al. 2005; Kumar et al. 2011). In the previous section the sensitivity of cyclogenesis frequency to resolution was highlighted. Resolution also impacts cyclone structure (Fig. 3). At 36 km the simulated cyclone has a simple circular structure whereas at 12 km sub-system-scale structure emerges in the form of eye-wall asymmetries and spiral rain bands. These features have associated signatures in the surface wind fields important for impact assessments. Other cyclone characteristics will also be sensitive to model grid spacing including genesis mechanism (Kieu and Zhang 2008), eye-wall replacement cycles and rapid intensification (Davis et al. 2008), and upscale impacts through vertical redistributions of heat and momentum (as discussed in Leung et al. 2006). Caron et al. (2010) and Caron and Jones (2011) found that high resolution was also necessary for the intensity of easterly waves and even for accurate representation of the large-scale environment over the eastern Atlantic.

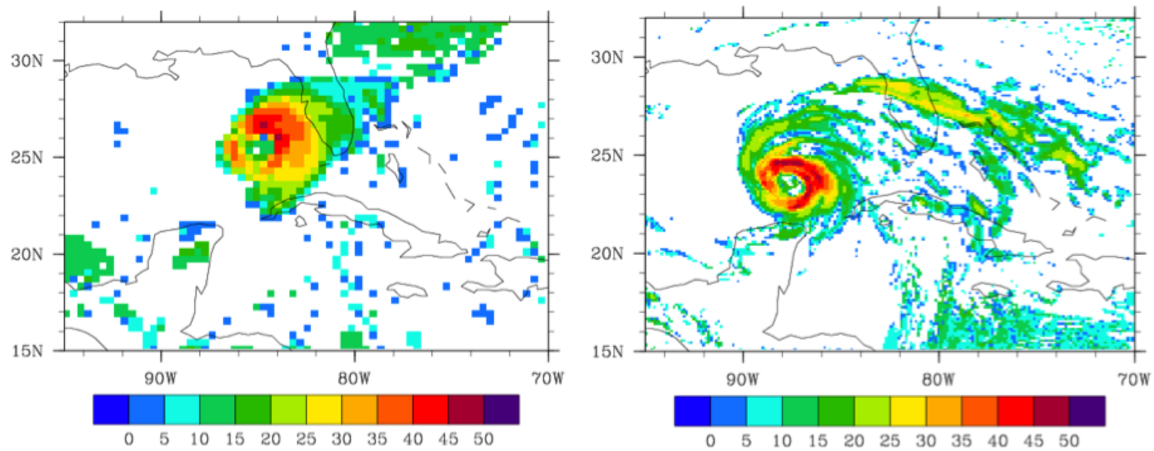


Figure 3: Snapshots of example NRCM tropical cyclones in the Gulf of Mexico generated on (left) the 36 km grid and (right) the 12 km grid, shown in model derived radar reflectivity (dBz).

Advantages of large domains include improved large-scales within the domain interior above those in the driving global data (Jones et al. 1995; Laprise et al. 2008) and a reduction in spatial spin-up issues by moving the inflow boundary far from the region of interest (Leduc and Laprise 2009). Critically, the choice of domain size and location must be guided by the need to capture regional physical processes (Giorgi and Mearns 1999) not only to assess high-impact weather in current climate but also to capture the correct climate response. A domain that is smaller than the main external modes of variability is closely coupled to the driving model (somewhat similar to nudging), and where small scales are important to these modes, the domain size needs to be sufficiently large to enable this upscale interaction to occur. For example, Caron and Jones (2011) constructed a domain to capture relationships between Atlantic SSTs, Sahelian rainfall and tropical cyclogenesis. Guided by these results, available resources for this study are directed to domain size at the expense of run length and ensemble size. The 36 and 12 km domains are therefore much larger than North America, our target region, to ensure the majority of atmospheric processes that impact the region are handled by the higher resolution model rather than the coarser climate model. As a specific example, African easterly waves are not well captured by the CCSM simulation (not shown), necessitating the inclusion of the African wave source and development region within the 36 km domain.

Climate Bias

Despite the large domain, errors in the lateral and surface boundary conditions can still impact the interior domain climate (e.g. Caron and Jones 2011). The NRCM-generated climate is significantly biased when driven directly by CCSM data. Anomalously strong large-scale flow at upper-levels over the tropical North Atlantic produces strong vertical wind shear, defined as the difference in winds between 200- and 850-hPa (Fig. 4a), thereby preventing tropical cyclogenesis. Sensitivity studies (not shown) reveal the bias transfers to the NRCM from CCSM, in part due to dynamical propagation from the east and west boundaries but mainly due to a warm eastern Pacific Ocean SST bias (Large and Danabasoglu 2006). This permanent El Niño-like condition is considered to be the cause of the high vertical shear in the NRCM over the tropical Atlantic through a modified Walker Circulation (e.g. Gray 1984). One solution to biased results is to statistically correct the NRCM model output (e.g. Dosio and Paruolo 2011) but here this post-processing approach is not suitable since the biased climate did not generate any tropical cyclones at all, thereby necessitating bias correction of the driving CCSM data prior to NRCM simulation.

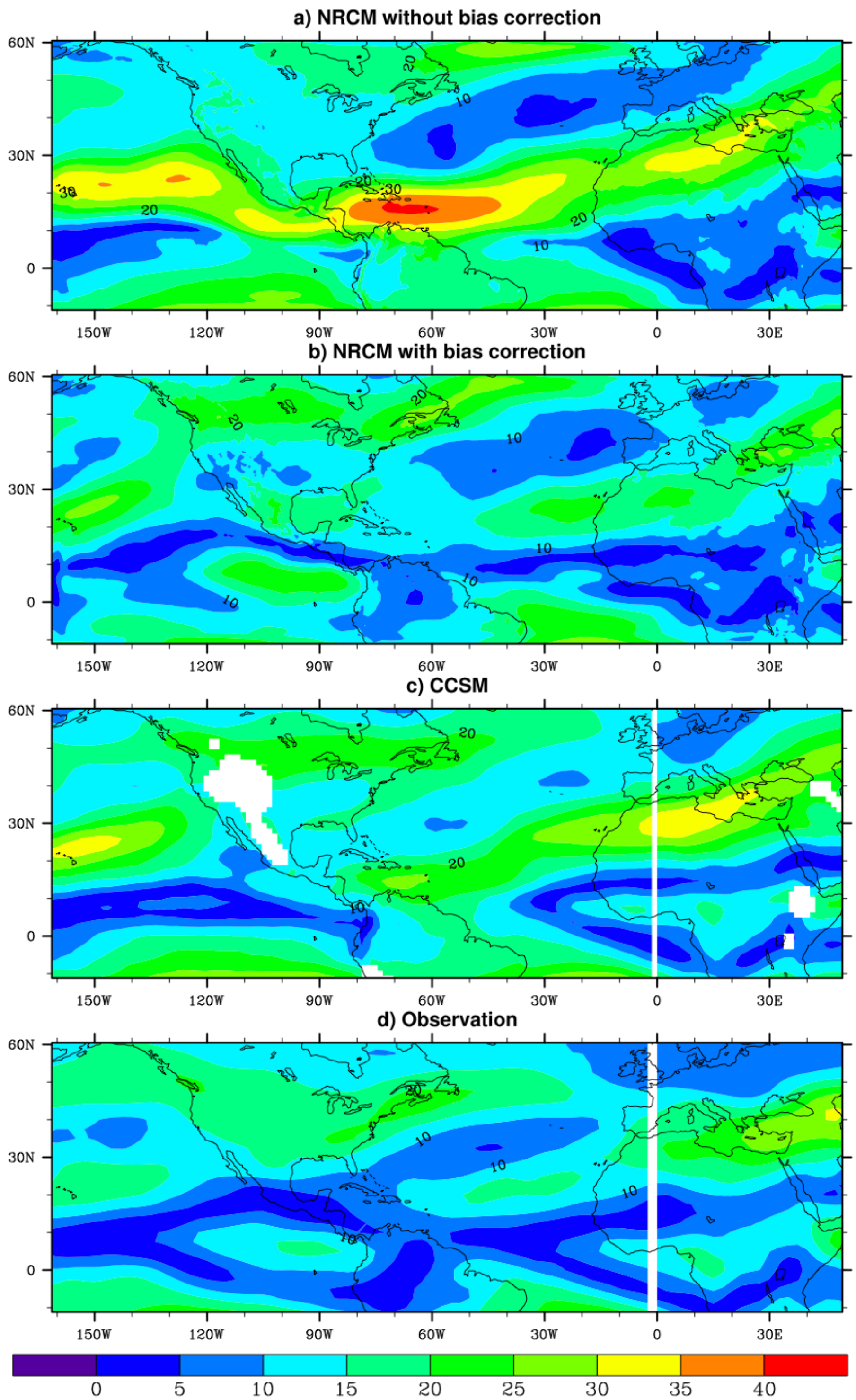


Figure 4: Three-month average vertical shear (200 – 850hPa, ms^{-1}) for the period August-October 1996 for (a) NRCM driven by raw CCSM data; (b) NRCM driven by revised CCSM data; (c) revised CCSM data, and (d) NNRP data. Adapted from Holland et al (2010). Copyright 2010 OTC.

A popular approach to assessing regional climate change that implicitly removes bias is the pseudo-global-warming approach (Schär et al. 1996; Rasmussen et al. 2011). In this approach, reanalysis data is used for current climate and future climate is constructed by adding a perturbation, intended to represent the mean climate change, to the reanalysis data. This approach assumes no change in variability at the domain boundaries and for small domains will constrain the frequency of weather events to current climate only. An alternative bias correction technique is used here that allows synoptic and climate variability to change in the future. Six-hourly CCSM data for the entire simulation (1950-2100) are broken down into an average annual cycle plus a perturbation term:

$$CCSM = \overline{CCSM} + CCSM', \tag{1}$$

where *CCSM'* varies in time throughout the entire 150-year CCSM simulation period and includes both high-frequency variability and climate trends. The average annual cycle is defined over a 20-year base period (to smooth out any influence of El Niño) from 1975 to 1994. Twenty years may not be sufficient to smooth out influence of multi-decadal variability but is chosen to avoid inclusion of any climate trends. Similarly, the 6-hourly NNRP data for 1975-1994 are broken down into an average annual cycle plus a perturbation term:

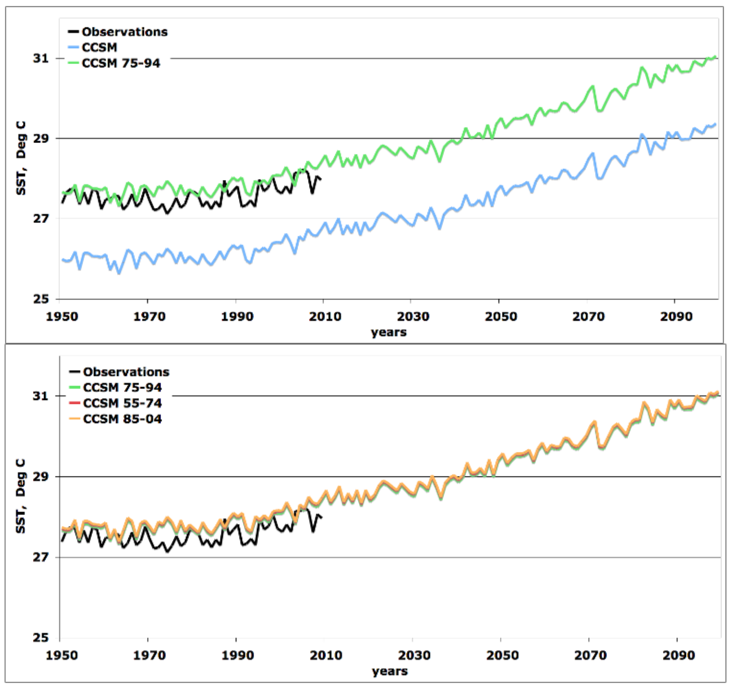
$$NNRP = \overline{NNRP} + NNRP', \tag{2}$$

The revised climate data, $CCSM_R$, are then constructed by replacing $\overline{CCSM}$ in Eq. 1 with $\overline{NNRP}$ in Eq. 2:

$$CCSM_R = \overline{NNRP} + CCSM'. \tag{3}$$

$CCSM_R$ for the entire period (1950-2100) therefore combines a base, seasonally varying climate provided by reanalysis data with day-to-day weather, climate variability (e.g. synoptic weather systems, ENSO) and climate change provided by CCSM. Equation 3 is applied to variables needed to generate the lateral and lower boundary conditions for NRCM; zonal and meridional wind, geopotential height, temperature, relative humidity, land and sea surface temperature and mean sea level pressure. To illustrate the procedure, the top panel in Fig. 5 shows a comparison between Aug-Sept-Oct average SST averaged over the tropical eastern North Atlantic between raw and revised CCSM data. The bias removal procedure brings the revised CCSM time series up to values within the observational error range for the Hurrell et al. (2008) surface analyses. When driven by bias-corrected boundary conditions (shown in Fig. 4c), the NRCM develops substantially improved wind shear over the tropical Atlantic (compare Fig. 4b with Fig. 4d). Although improvement in shear is only shown here for a single year, it is representative of the improvement over all years, and this improvement allows a reasonable simulation of the tropical cyclone climate (described later in this section).

There may be sensitivity of the revised climate to the choice of the base period arising from non-stationarity of the bias, but fortunately this is not the case here; as shown in the bottom panel in Fig. 5, choosing different base periods results in nearly identical bias corrections over the entire simulation period. This increases confidence that the bias will not change substantially in the future, though the validity of this assumption needs further consideration. Further justification for this approach is provided by Mote et al. (2011), who showed that for assessing *changes* between a current and future period, a biased model for current climate is as valid as an unbiased model (In the case here, however, bias correction is necessary primarily to capture tropical cyclone activity rather than to improve future predictions). On the other hand, Dosio and Paruolo (2011) showed the assumption of constant bias in time may only be appropriate for ensemble mean quantities rather than for individual model projections.



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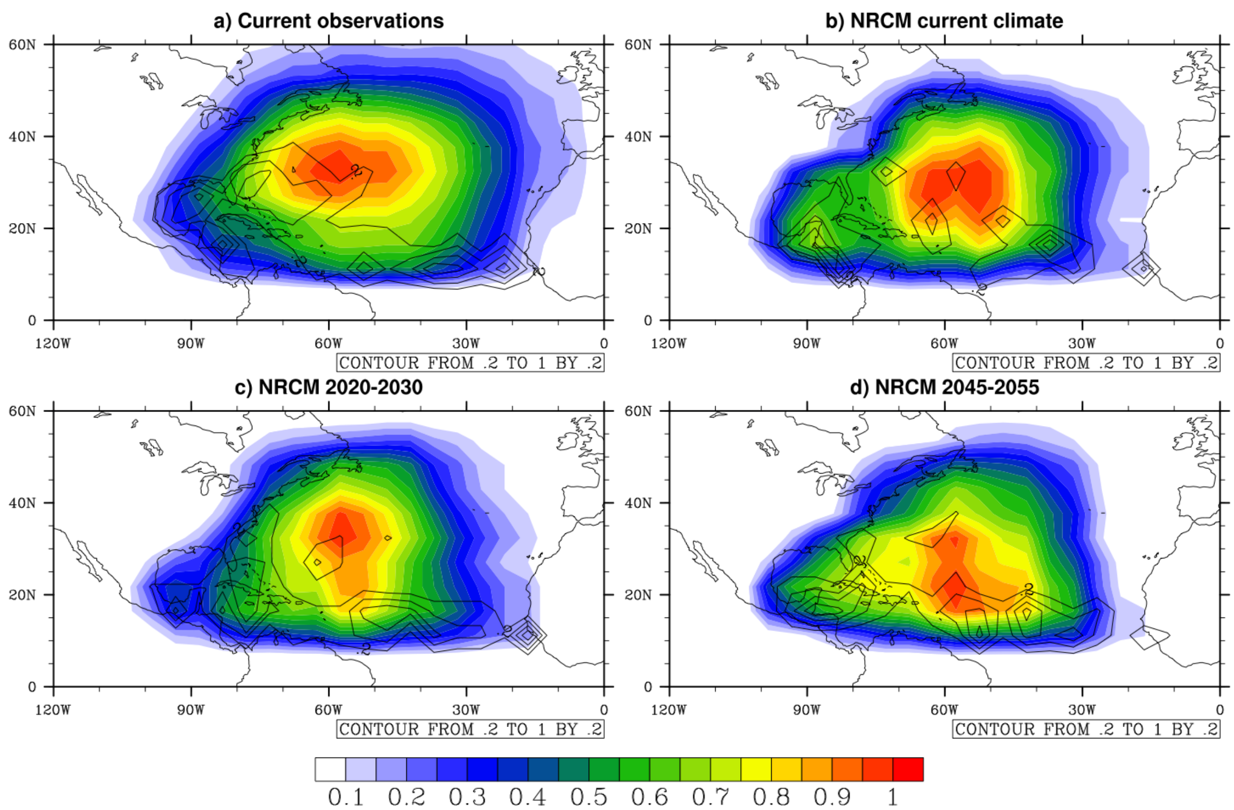
Future Changes in Tropical Cyclone Frequency

On the 36 km domain (Fig. 2), and using the same cyclone detection criteria as described in Section 4, the NRCM driven by bias corrected CCSM data produces an average of 7.6 North Atlantic tropical cyclones annually for base climate. As noted earlier the model base climate period 1995-2005 does not relate to 1995-2005 in the real world since CCSM is free running from 1950. This introduces ambiguity as to the selection of observational period used for model evaluation. The selection of 1975-1994 as base period for the bias correction leads to this being one logical choice. In this case the comparative annual number of observed North Atlantic tropical cyclones is 8.9 (using IBTrACS data, Knapp et al. 2010). Alternative choices are the average over, say, the recent 50 years (1958-2007) of 10.4, or the current (1995-2005) high period of 14.3 cyclones per year. Regardless of the choice of observational period for comparison, NRCM appears to underestimate the actual frequency. The frequency is also lower than produced by the NRCM when driven by reanalysis data using a channel domain presented in section 4, and the relative roles of the change in domain and change in driving data on tropical cyclone frequency have yet to be determined. However, the frequency could easily be corrected by tuning the detection criteria, but, as noted in Section 4, the detection parameters are deliberately frozen at fixed values. Of importance to this study, Suzuki-Parker (2012) showed that the future changes in cyclone frequency are not impacted by the choice of detection values (see also Done et al. 2011b).

In the next 50 years the NRCM predicts a statistically significant (at 90% using the two-sided Student's t-test) increase in North Atlantic tropical cyclone frequency, with annual numbers increasing from 7.6 in the base climate to 8.5 in 2020-2030 and 10.4 in 2045-2055. This implies a potential increase of ~37% in North Atlantic tropical cyclone frequency over the next 50 years. These results are different from those of other studies, which have tended towards predicting small changes and if anything a decrease in overall Atlantic tropical cyclone frequency over coming decades (e.g. Knutson et al. 2010; Bengtsson et al. 2007), and serves to highlight the large uncertainty in determining changes in high-impact events on regional scales.

The modeled North Atlantic tropical cyclone track and genesis densities on the 36 km domain for current climate are quite close to the observed long-term climatology (Fig. 6a,b). The future climate prediction exhibits a consistent southeastward shift in track density, from a maximum in the mid-Atlantic in base climate, to a low-latitude maximum in 2045-2055 (Fig. 6d). This prediction is a continuation of recent trends (Kimberlain and Elsner 1998; Holland and Webster 2007) and with Wu et al. (2010) who found that a relative increase in eastern Atlantic SSTs leads to changes in atmospheric circulation and near-equatorial tropical cyclone activity.



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Future Changes in Tropical Cyclone Intensity

Modeled tropical cyclone intensity distributions show that the most intense cyclones are weaker than observed (Fig. 7). This is a common problem due to the inability of the 12 and 36 km grid to resolve the inner core dynamics of a tropical cyclone (e.g. Knutson et al. 2008; Davis et al. 2010; Gentry and Lackmann 2010). Note also the related tendency to over-simulate moderate intensity systems, which to some extent is due to those storms that would have been more intense being held back in this region. Nevertheless, storms on both the 36 and 12 km domains experience a modest yet statistically significant (at 99% using the two-sample kolmogorov-smirnov test) future increase in mean wind speed of approximately 2 ms^{-1}. Note that this increase is less than observational errors in the historical record; meaning current observation systems could not detect this change in the mean intensity. A more marked increase, however, is seen in the number and intensity of the most intense hurricanes that can be resolved by the model (Fig. 7). This is in agreement with other dynamical modeling and theoretical studies (Henderson-Sellers et al. 1998; Knutson et al. 2010). These intensity increases may be due to future large-scale environment changes but also to the future southeastward shift of track density (Fig. 6) associated with potential changes in the proportion of tropical cyclones developing from easterly waves and cyclone track lengths. This is currently being investigated and results will be reported in a future study.

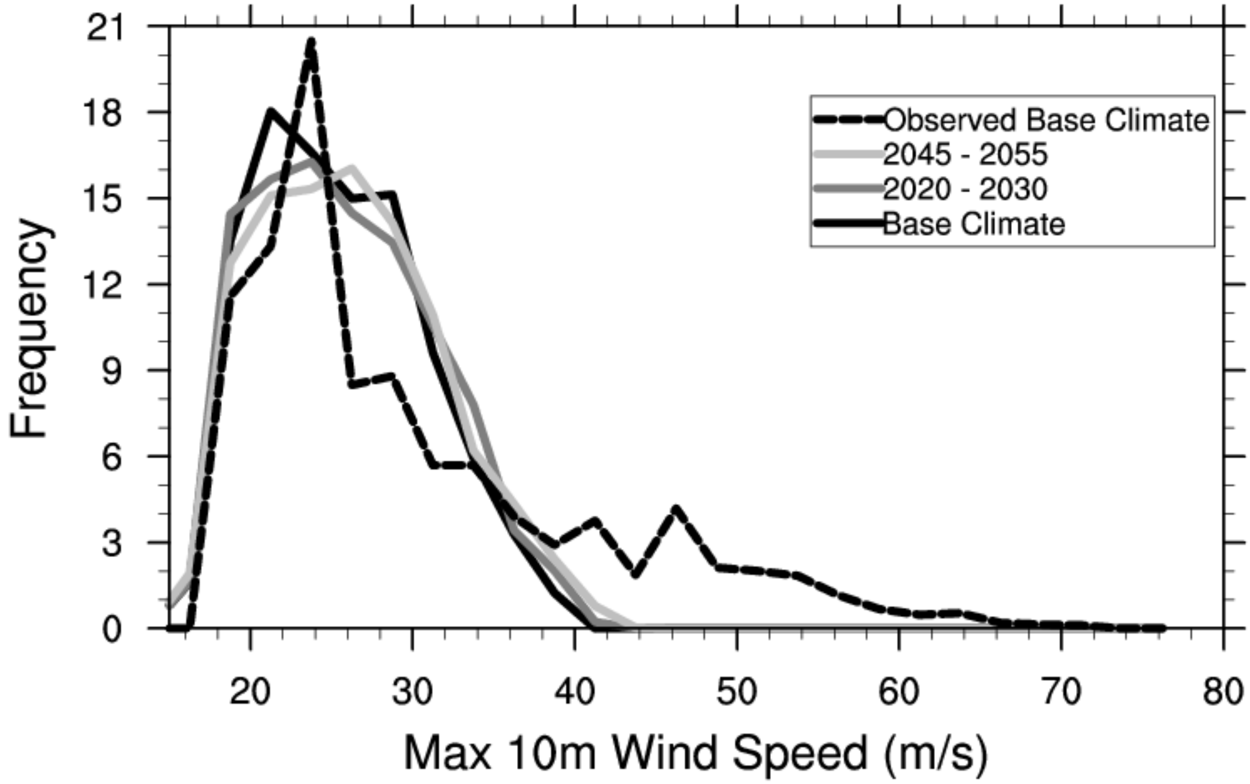

Figure 7: Frequency distributions of tropical cyclone intensity shown in wind speed (ms^{-1}) at 10m above the surface simulated by NRCM on the 36 km domain for base climate (black line), the period 2020-2030 (dark gray), and the period 2045-2055 (light gray). The dashed black line is the observed distribution using IBTrACS data for the period 1995-2005. Adapted from Holland et al (2010). Copyright 2010 OTC. Reproduced with permission of the copyright owner. Further reproduction prohibited without permission.

Internal Variability

Uncertainty due to internal variability becomes large for regional scales (Hawkins and Sutton 2009), and may be particularly acute for high-impact events and in particular for tropical cyclones owing to the stochastic nature of mesoscale convective activity. Jourdain et al. (2011) showed in a limited area domain modeling study that locally forced internal model variability was as important as the externally forced variability due to El Niño Southern Oscillation for interannual variability in South Pacific tropical cyclone frequency. Through a small initial condition ensemble of 20-year regional climate simulations over the Northwest Pacific Wu et al (2012) not only showed significant variability on annual and interannual timescales but also a small signal of internal variability of tropical cyclones on decadal timescales. Because of computational limitations on large domain, high-resolution simulations, internal variability of tropical cyclones on long timescales cannot currently be tested comprehensively with traditional dynamical approaches. Ongoing work to estimate internal variability of tropical cyclones using short-term initial condition ensembles will be reported in later studies.

6. Statistical Assessments

Confidence in the variability and trends of high-impact events obtained through dynamical downscaling is limited in part by the relatively short period and small number of events that can be simulated. Fortunately, sample size can be increased substantially through statistical approaches. Statistical downscaling applies large-scale empirical relationships to coarse-resolution model simulations to infer characteristics of the high-impact event, such as frequency, intensity or scale. Another approach applies extreme-value statistics to fill out the rare, high-impact tail of the distribution that has been truncated by coarse-resolution simulations.

Such statistical assessments are quick to run and can be applied to multiple coarse-resolution simulations, thereby enabling an assessment of consensus between future projections of high-impact weather. Examples of an empirical and an extreme value approach are used here to illustrate the benefits of statistical downscaling.

Statistical Assessment of Tropical Cyclone Frequency

A number of genesis potential indices have been developed to assess the frequency of tropical cyclones using empirical relationships with large-scale data taken from reanalysis datasets or global model simulations (e.g. Gray 1968, 1984; Emanuel and Nolan 2004; Emanuel et al. 2006). Such indices were typically designed to capture the hemispheric seasonal cycle but typically do not do well on regional and interannual scales. For example, Menkes et al. (2011) applied four genesis potential indices to different reanalysis datasets and found poor reproduction of interannual amplitude and phase variability on regional scales. The Emanuel and Nolan (2004) index combines low-level vorticity, mid-level relative humidity, potential intensity (a measure of the vertical instability of the atmosphere, Emanuel 2000), and vertical wind shear and has been used in recent studies (e.g. Camargo et al. 2007). Bruyere et al. (2012) showed that for interannual variability and longer-term changes, the relative humidity and vorticity terms contribute nothing to the skill, though this could be due to the specific formulation of the index rather than having a physical interpretation (a general limitation highlighted by Menkes et al. 2011). Indeed, Emanuel (2010) posed saturation deficit as an alternative to relative humidity and showed good interannual variability on regional scales when compared to other downscaling methods. Bruyere et al. had success omitting water vapor entirely by revising the Emanuel and Nolan (2004) index and formulating a Cyclone Genesis Index (CGI) to include only potential intensity (PI, ms^{-1}) and shear (V_{shear}, ms^{-1}), defined as the difference between winds at 200- and 850-hPa:

$$CGI = \left(\frac{PI}{70}\right)^3 (1 + 0.1V_{shear})^{-2} \qquad (4)$$

Bruyere et al. also found care needs to be taken when selecting an index averaging area: for the North Atlantic, a basin-wide average of CGI was not optimal in explaining total basin cyclone frequency, whereas an average taken over the eastern tropical Atlantic (5-20^{o}N, 60-15^{o}W), was able to explain 72% of the annual variance of total basin cyclone frequency. Application of the CGI over this eastern tropical Atlantic region using two different historical reanalysis datasets (NNRP and European Centre for Medium-Range Weather Forecasts Reanalysis (ERA)) shows

CGI is also able to reproduce the observed linear trend and multi-decadal variability in observed (using IBTrACS, Knapp et al. 2010) tropical cyclone frequency (Bruyere et al. and Fig. 8). Suzuki-Parker (2012) applied CGI to the same bias-corrected global data used to drive the NRCM simulations and produced results in agreement with the NRCM dynamical results that tropical cyclone frequency will increase by between 1 and 3 storms by the mid 21st century.

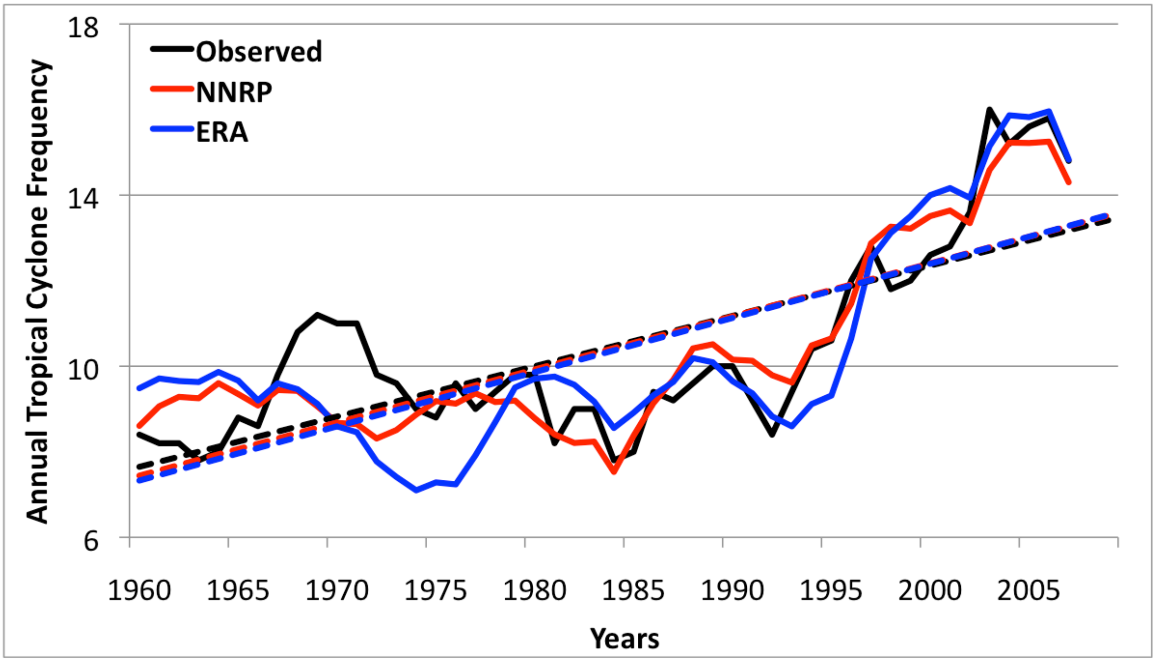

Figure 8: Five-year running mean of observed TC storm frequency (black), and that estimated from ASO CGI for NNRP (red) and ERA (blue), with dashed trend lines superimposed. Reproduced from Bruyere et al (2012). Permission pending from the American Meteorological Society.

Extreme Value Assessment of Tropical Cyclone Intensity

Current regional climate models do not resolve the most intense cyclones (Holland et al. 2010; Knutson et al. 2008). One complimentary approach to assess changes to the most intense cyclones from the truncated regional climate simulations is to utilize extreme value statistics (Coles 2001; Garrett and Muller 2008). The NRCM-generated cyclone intensity distribution has a much sharper decrease in the more intense cyclones than observed and is truncated at maximum winds of around 45 ms^{-1} for tropical cyclones on the 36 km grid (Fig. 7). However, as stated earlier the NRCM predicts a shift of the truncated distribution towards more intense storms over the next 50 years (Fig. 7). Applications of both the reverse Weibull distribution (Frechet 1927; Weibull 1939 hereafter simply Weibull) and the Generalized Pareto Distribution (e.g. Embrechts et al. 1997) have been experimented with to assess these associated changes in the intense cyclones. The Weibull is used here because of its history of application to modeling studies (e.g. Katz and Brown 1992, 1994; Mearns et al. 1984) and because it fits the entire distribution and has a bounded upper tail that lends itself to hurricane intensity assessment due to its bounded nature (Emanuel 1987; Holland 1997).

The Weibull Cumulative Distribution Function (CDF) and Probability Density Function (PDF) are:

$$\begin{aligned} &CDF: F(x) := 1 - e^{-(x/a)^b}, 0 \le x < \infty \\ &PDF: f(x) := \frac{\partial F(x)}{\partial x} = \frac{b}{a}\left(\frac{x}{a}\right)^{b-1} e^{-(x/a)^b}, 0 < x < \infty \end{aligned} \tag{5}$$

where *e* is the exponential function. The scale parameter *a* and the shape parameter *b* both lie in the range *(0,∞)*. b=1 corresponds to the exponential distribution, b=2 the Rayleigh distribution, b=3.5 an approximation of the normal distribution. The mean and the variance of the Weibull distribution are given by:

$$\begin{aligned} &Mean: \mu = a\Gamma\left(1 + \frac{1}{b}\right) \\ &Variance: \sigma^2 = a^2\Gamma\left(1 + \frac{2}{b}\right) - \mu^2 \end{aligned} \tag{6}$$

where *Γ* is the Gamma function. Thus, a first-order approximation to future changes in tropical cyclone extremes can be obtained by first applying the Weibull to current tropical cyclones (where *x* in Eqn. 5 corresponds to cyclone lifetime maximum 10m wind speed, using IBTrACS, Knapp et al. 2010) to obtain current shape and scale parameters. Model-resolved future changes in the mean and standard deviation of tropical cyclone intensity are then used to estimate changes to these current scale and shape parameters and provide an assessment of future full intensity distributions. Finally, the changes in probability of various tropical cyclone intensities can be calculated from the Weibull exceedence probability:

$$P(X > c) = 1 - F(c) = e^{-(c/a)^b}, \tag{7}$$

where c is the lower limit of the intensity range of interest (e.g. 69 ms^{-1} for Cat 5 hurricanes).

The small NRCM-predicted changes in the resolved distribution result in a much greater change in the most intense cyclones (Fig. 9). For example, Cat 5 hurricanes are predicted to increase by 60% from a base climate period of 1980-1994 and by 30% from a base climate period of 1995-2008. These results are essentially the same as obtained from application of the Generalized Pareto Distribution (Suzuki-Parker 2012). The increases are likely to be conservative due to the inability of the truncated NRCM distribution to properly define the full changes in mean and variance. One method to assess this possible underestimation of the changes is to further dynamically downscale the NRCM to a resolution capable of resolving the full intensity distribution. Although not attempted here, Bender et al. (2010) took this approach using the Geophysical Fluid Dynamics Laboratory operational hurricane model to downscale to a resolution that captured the full intensity distribution and showed similar future changes to the most intense storms as reported here. This suggests that the statistical correction of the intensity distribution is a promising line of research that warrants further exploration, particularly with regard to understanding how the model intensity distribution relates to the observed intensity distribution.

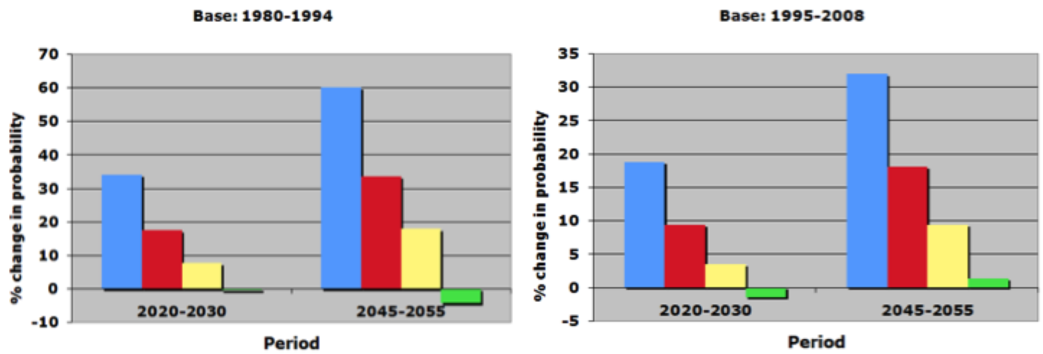

Figure 9: Estimated future changes to all hurricanes (green), category 3-5 (yellow), category 4-5 (red) and category 5 (blue) by applying a Weibull analysis to the truncated distributions in Fig. 7, and using a base climate of: left) 1980-1994 and right) 1995-2008.

The examples of empirical and extreme value approaches presented here serve to demonstrate the high potential of statistical approaches in assessing high-impact events under climate variability and change. The field is wide open to develop the concept further by utilizing more sophisticated approaches and extensions to couple with societal impact assessments.

7. Societal and Ecological Impact Assessments

The past two decades of regional climate research outputs have largely been exploratory in nature and not directly aligned to the requirements of the end user. Exceptions include ensemble regional downscaling programs such as the North American Regional Climate Change Assessment Program (Mearns et al. 2009), the Coordinated Regional Climate Downscaling Experiment (Giorgi et al. 2009), and the bias corrected and statistically downscaled CMIP3 archive (Maurer et al. 2007) that all aim to serve high resolution climate scenario needs. Recent work by Towler et al (2012) went a step further by incorporating NRCM-generated climate change data into a risk-based approach to assess ecological impacts and inform conservation efforts. One promising approach to directly relate meteorological data to impacts relevant to societal and industry planning is through the use of indices. Indices have proven to be an effective communication and decision-making tool through their ability to break the complex components down into quite understandable terms, albeit at the loss of some accuracy. One widely used tropical cyclone forecast example is the Saffir-Simpson scale (Simpson and Riehl 1981; Zhang et al. 2007) but this index is not well suited for impact assessments (as discussed in Kantha 2006). This has led to several alternative indices that incorporate other tropical cyclone variables. (e.g. Powell and Reinhold 2007; Malmstadt et al. 2009; Kantha 2008). Index development is a focus of current active research that aims to incorporate not only meteorological inputs but also socio-economic factors as drivers of societal impacts.

8. Concluding Discussion

Meeting the societal demand for assessments of variability and change in high-impact weather events with regional clarity is a challenge that extends well beyond simply improving climate simulations. The documentation of approaches used and lessons learnt in this report is intended to promote community discussion and collaboration on best practices in dynamical, statistical, and hybrid approaches of assessing weather and climate impacts; the goal being to develop a capability for assessing changes to high-impact events on regional scales under climate variability and change. Pursuing combinations of dynamical and statistical approaches and the development of methods for assessing impacts directly from the statistical/modeling predictions appears to be a key route to this progress as summarized below. One key area not mentioned here, simply because of lack of progress at this stage is data assimilation. Seasonal to decadal predictions require that the starting point is at the correct phase of a range of low-frequency climate variability and this requires new approaches to data assimilation.

In closing, key findings are summarized in these five points:

1) Treating bias: Regional climate simulations can be severely affected by biases in the driving global climate model, even when large domains are employed. Here, a successful technique has been shown to remove such bias in a manner that retains the day-to-day weather, climate variability and change components. As climate models improve, there still remains a need to treat regional biases (see for example the reduced but remaining Atlantic SST bias in CCSM4 versus CCSM3 shown by Muñoz et al. 2012). Further work is required to fully understand the implications of such techniques, to assess and remove changes in bias with time, and to develop new approaches to bias removal for emerging modeling tools such as regional atmosphere-ocean coupled models and global variable resolution meshes.

2) Assessing domain size, location and resolution: Regional climate physical processes and thus predictions are highly dependent on the domain size, location and resolution of the limited-area model. These aspects of model setup need careful consideration in order to capture accurate regional climate and high-impact weather. Experience with NRCM is that the regional domain should include those forcings and circulations that directly affect the regional climate over the area of interest. Larger is better, but this can only be done at the expense of resolution, simulation period, or ensemble size for assessing uncertainty. Interior nudging has been used in some studies to constrain larger scales in the interior domain to those of the global model. This may be valid for use with analysis data sets, but it can lead to a false sense of accuracy when applied to global climate models.

An important issue not addressed here is that of upscale modification of the global climate by mesoscale processes. One approach is to run the regional climate simulation in 2-way interactive mode with the global model. But this substantially increases computing time and limited experiments using NRCM indicates the impact is more on remote regions than on the local region of interest. Promising new directions into elegant variable resolution global models that inherently include two-way interaction between regional high resolution and global coarse resolution have the potential to overcome some of these restrictions (e.g. Jablonowksi et al. 2009; Skamarock et al. 2012) though there will still be a requirement to undertake a thorough assessment of each downscaling approach (Laprise et al. 2008).

Experience with NRCM at different resolutions indicates that higher resolution than is required to resolve the key characteristics of the high-impact events may produce little added value and may not be an optimal use of resources. Careful assessment of the required resolution for specific weather systems of interest is warranted.

3) Assessing simulation uncertainty: Internal stochasticity may be particularly acute for high-impact events and may mask the forced signal on annual and shorter timescales. Ensemble modeling is the obvious approach to identify the signal (see for example Chen and Lin (2011) who showed enhanced skill of the ensemble mean over that of individual members in seasonal forecasts of tropical cyclone frequency). Unfortunately, ensembles are computationally impractical for high resolution, large domain dynamical model simulations and will be for some time. A more practical approach is that of ensemble statistical downscaling techniques, either via direct application to multiple coarse-resolution simulations or through incorporating a stochastic component to the downscaling technique (as discussed in Wilks 2010).

4) Incorporating statistics: The potential of statistical techniques has been highlighted for both uncertainty estimation and filling out distributions of high-impact parameters that are only partly resolved by dynamical models. Statistical-dynamical approaches have been largely unexplored to date, and a comprehensive investigation into their limitations and opportunities is needed. Such techniques hold promise as powerful diagnostic tools (see for example, Wood et al. 2004) and offer a fertile ground for interdisciplinary collaboration. Moreover, the combined approach has potential to increase physical understanding of high-impact events. Future regional climate and high-impact weather studies with the NRCM and the next generation Model for Prediction Across Scales (Skamarock et al. 2012) will focus on the optimal combination of statistics and climate simulations to ensure the best use of available resources.

5) Direct impact assessments. Once the regional climate prediction has been made and the uncertainty quantified, there remains a huge gap regarding how this affects society. Use of impact indices is a powerful approach that can be applied directly to model output for both current and future scenarios. Impact indices also serve as highly effective, as well as a “two-way” communication mechanism, as an index developed on current data provides an excellent assessment of the parameters that need to be given priority in the statistical-dynamical modeling prediction process. There remains a need for detailed assessments, particularly of critical locations, and there is large potential for the development of more sophisticated, targeted approaches for a wide range of applications, e.g. ecology, industry, public planning, and society.

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