Understanding future changes in tropical cyclogenesis using Self-Organizing Maps

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\section*{Abstract}

Future changes in tropical cyclone (TC) genesis locations and frequency are explored by identifying relationships between TC genesis and dominant daily large-scale patterns, and evaluating the strength of these relationships under a climate change scenario. Self-Organizing Maps (SOMs) are used to characterize the dominant large-scale patterns in reanalysis data and in a regional climate model ensemble simulation of current climate. The main features on the resulting sea level pressure (SLP) SOMs are nodes that resemble both the negative and positive phases of the North Atlantic Oscillation, as well as blocking and ridging regimes. The frequency of the NAO-like nodes is strongly linked to TC genesis frequency and preferred genesis locations. This link is used to develop a statistical relationship between the frequency of large scale SLP patterns and TC genesis. The application of this relationship to an ensemble regional climate model simulation under a future climate forcing scenario predicts fewer TCs, which is consistent with the regional climate model that explicitly simulates fewer TCs. This demonstrates the strength of the relationships and their use in assessing future changes in TC genesis locations and frequency.

1. Introduction

In the climate change debate, tropical cyclones (TCs) receive much attention due to their sensitivity to the global climate and their potential to cause damage. Kunreuther and Michel-Kerjan (2009) and Smith and Katz (2013) indicate that losses due to TCs are currently doubling every 15 years. The majority of this increase is due to increasing exposure (e.g., Weinkle et al., 2012), but Estrada et al. (2015) estimated the climate change contribution to rising US hurricane costs to be roughly USD 136 m/yr.

Palmen (1948) linked TC responses to changes in climate on a variety of time scales. It is well known that warming generally leads to increasing thermodynamic potential for TCs (Emanuel, 1987), while changing atmospheric circulation is linked both to the potential of TC genesis and cyclone development (Emanuel, 2007; Vecchi and Soden, 2007). Caron et al. (2014) suggested that relatively higher frequency TC variations (sub-seasonal) are related to slowly varying thermodynamic conditions, such as changes in local sea surface temperatures (SSTs), while lower (annual) frequencies tend to be driven by large scale atmospheric conditions and teleconnections.

Current predictions of global and regional numbers of storms are highly uncertain. Even the sign of the change is not settled (e.g., Walsh et al., 2016; Knutson et al., 2010). TC counts are significantly more difficult to predict than large scale conditions. Therefore, this paper explores how large-scale environmental conditions can be used to understand and predict TC genesis with respect to the range of synoptic patterns that occur at the peak of storm season. Self-Organizing Maps (SOMs) are shown to be a powerful tool to advance our understanding of TC-environment relationships.

SOMs have been shown to be successful in the study of variability of large-scale synoptic conditions, especially in the North Atlantic (Reusch et al., 2007; Johnson et al., 2008; Hewitson and Crane, 2002). Non-linear interactions among modes of North Atlantic variability cannot be explored with traditional teleconnection patterns that are found using a rotated empirical orthogonal function (EOF) analysis. Instead of interpreting the loading vectors from the EOF analysis, a discrete mode of variability, they can instead be used as a basis for a continuum of functions that can describe more of the variability.

In this paper the dominant synoptic patterns in the current climate are characterized through a SOM analysis. Here, a SOM analysis is applied to observed historical climate (using ERA-I reanalysis, Dee et al., 2011 and IBTrACS, Knapp et al., 2010) and a 24-member Weather

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Research and Forecasting (WRF: Skamarock et al., 2008) regional ensemble simulation of current climate (Bruyere et al., 2017). This ensemble was designed to create a range of possible synoptic patterns (Prein et al., 2019) and TC responses to these patterns consistent with current climate. Next, the extent to which the dominant synoptic patterns can be used to model TC genesis is explored. Comparing relationships between the large-scale environments and the frequency and location of tropical cyclone genesis in model and observations allows us to understand the links between the large-scale environment and TC genesis.

The resulting statistical relationships are applied to an ensemble regional climate simulation under a future climate forcing scenario. Comparison between the statistical prediction of TC genesis and TC genesis explicitly simulated by the regional climate model allows us to understand the strength of the relationships and their utility in assessing potential future changes in TC genesis.

The paper is structured as follows: a background covering the experimental setup with regard to the WRF model configuration and SOM approach is provided in section 2. Section 3 covers a brief description of SOMs. Current climate results and discussion are covered in section 4 and future climate results are presented in section 5. Conclusions and future work are shown in section 6.

2. Methodology

2.1. Model configuration

The Weather Research and Forecasting (WRF: Skamarock et al., 2008) system is a versatile atmospheric model, which is used for a variety of functions in the scientific community, including meteorological research, operational weather forecasting, and regional climate simulations. The WRF system allows a large number of possible physical parameterization configurations, making it an ideal choice for physics ensemble simulations. Since the main research focus of this study is North Atlantic tropical cyclone frequency and genesis, a domain that includes both the Atlantic and Pacific Oceans around the Americas was selected. The relatively large domain, which ranges from 23.5° S to 60° N and from the West African Coast to the East Pacific (Fig. 1), was designed so that the simulations would be able to evolve day-to-day mesoscale systems independent from the driving data (Jones et al., 1995; Laprise et al., 2008; Done et al., 2015), while still capturing large scale systems entering through the boundaries. The selected model domain and resolution is consistent with what prior research has shown to be necessary to capture both TC formation and intensification (Kumar et al., 2011; Bender et al., 2010; Caron et al., 2010; Caron and Jones, 2011). WRF version 3.5.1 is used at a 36 km resolution, a resolution that has been previously shown to be sufficient to both simulate the large-scale climate conditions and tropical cyclones (Done et al., 2015), while still enabling multiple simulations within available resources.

In order to capture current climate variability, a twenty-four member physics ensemble was created (Bruyere et al., 2017), and run for the 11-year period from 1990 to 2000, with the first year used as spin-up (Karlicky, 2013). The 24 ensemble members were created by varying four different physics parameterization options: 1) radiation (CAM: Collins et al., 2006, and RRTMG: Mlawer et al., 1997), 2) cumulus (KF: Kain and Fritsch, 1990, NSAS: Han and Pan, 2011, and Tiedtke: Tiedtke,

![Fig. 1. WRF domain for physics ensemble, the inner grid is the extent of the SOM analysis.](image-url)
The physics parameterization combinations for the 24-ensemble members for the current climate. The three ensemble members chosen for future simulations are highlighted in grey.

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1989), 3) microphysics (WSM6: Hong et al., 2004, and Thompson et al., 2004), and 4) planetary boundary layer (PBL) (MYJ: Janjic, 1994; and YSU: Hong et al., 2006). Each possible combination of these options was used to create 24 ensemble members. All of these combinations of parameterizations are both commonly used and well-tested. Each ensemble used the same land surface scheme (NOAH: Chen and Dudhia, 2001), so the focus is on the representation of atmospheric processes only.

The 24 ensemble members are shown in Table 1, and abbreviated ensemble names for each of the members are shown. The radiation scheme is represented by the first character, the cumulus the second, microphysics the third, and the PBL the fourth. For example, CK6M corresponds to the CAM, KF, WSM6, and MYJ schemes.

The driving data used for the 24-member ensemble was the European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Reanalysis (Dee et al., 2011; ECMWF, 2009). This dataset uses a four-dimensional variational assimilation (4D-Var) system with a horizontal resolution of around 80 km. The Sea Surface Temperature (SST) data used was the Reynolds optimum interpolated (Olv2) analysis (Reynolds, 1988, Reynolds and Marsico, 1993), with a temporal resolution of a week and a horizontal resolution of 1.

Bruyere et al. (2017) used additional reanalyses and observational data sets to evaluate the 24 ensemble members based on their ability to accurately simulate the current climate, as well as provide a sufficient sample range for the future climate. Based on these criteria, Bruyere et al. (2017) selected three (see shaded boxes in Table 1) of the twenty-four ensemble members, and simulated the current climate, two near-future, and two far-future time slices, (nominally: 1990–2000, 2020–2030, 2030–2040, 2050–2060 and 2080–2090).

These current and future ensembles were driven with a single free-running (i.e., models that simulate the climate in a statistical sense, but does not predict the weather for any given year) Community Earth System Model (CESM: Hurrell et al., 2013) climate run. This global climate model (GCM) was performed as part of the Coupled Model Intercomparison Experiment Phase 5 (CMIP5: Taylor et al., 2012) under the RCP 8.5 future emissions scenario. RCP8.5 is a high emission scenario, where minimal actions are taken to curb greenhouse gas emissions (Riahi et al., 2011). Because GCMs are known to contain biases, these were removed from the CESM fields following Bruyere et al. (2014, 2015) prior to using these datasets to drive the WRF model for the current and future simulations.

2.2. Storm tracking

Each tropical cyclone developed by the model was tracked using the object tracking algorithm developed by Hodges (1995, 1999). The algorithm tracks vorticity centers at the 700 hPa level throughout the

![Fig. 2. Illustrations showing how large-scale features in a daily timeseries are matched to a SOM feature map.](image-url)
simulation period, filtering the selection to only track storms that have features that are representative of tropical cyclones. Tracks that met the following six criteria, were retained: 1) the sum of the horizontal temperature difference between the storm and its surrounding environment at 700 hPa, 500 hPa, and 300 hPa must be greater than 2 K; 2) the mean 850 hPa wind speed must be greater than the mean 300 hPa wind speed; 3) the 300 hPa horizontal temperature difference between the storm and its surrounding environment is greater than that at 850 hPa; 4) the genesis location must be south of 40 N; 5) the storms must retain tropical storm strength intensity for a minimum of 36 h; and 6) a wind speed criteria threshold. Walsh et al. (2007), showed that this threshold is dependent on model resolution, physics and basin of interest. Following their method, a threshold of 12 m/s was used for all KF simulations and 10 m/s for all other simulations (Bruyere et al., 2017). This method has been shown to work well in WRF simulations at 36 km resolution (Done et al., 2015).

3. Self-Organizing Maps

Self-organizing maps (SOMs) are powerful tools that can be used to identify dominant synoptic patterns in large datasets with an arbitrary number of dimensions (Kohonen, 1989). SOMs are one of several clustering techniques that can be used to isolate and group recurring patterns from a large atmospheric dataset. Unlike other clustering methods, SOMs use a neighborhood function that relates samples to each other in a two-dimensional matrix, known as a feature map (Fig. 2). SOMs are excellent at capturing nonlinearities in the data that can fill in gaps in the data space. The feature maps create a clear and instinctual way to interpret the results and promote process-level understanding (Hewitson and Crane, 2002; Kennedy et al., 2015). In addition, patterns identified by SOMs cover the entire scale of events depicted in the training data, indicating that the feature map is capturing the entire spectrum of possible synoptic patterns and treating the data as a continuum, unlike other clustering techniques. SOM analysis clusters the nodes in a two-dimensional grid with similar patterns near each other and the most extreme patterns at opposite corners of the feature map. The nodes at the ends of one diagonal are often similar to the positive and negative states of the first principal component of the input data, with the second principal component corresponding to the corners of the other diagonal (Reusch et al., 2007).

The analysis of the ensemble members was performed using the software package, SOM_PAK (Kohonen et al., 1996). This package creates reference vectors using a linear initialization as opposed to a random initialization. SOM results are not sensitive to the selected initialization method, but linear initializations tend to achieve faster convergence than a random initialization. The node reference vectors here are initialized with values from the covariance matrix of the input sea level pressure based on the first two eigenvectors with the largest eigenvalues and let them span the two-dimensional subspace (Kohonen, 2001). By initializing a SOM in this way, the clustering procedure starts at an already ordered set of weights and training can start with the convergence phase.

Next, an iterative process known as training is conducted until stable values are reached. During the training, each data sample, for example a daily map of sea level pressure, is presented to the SOM in the order it occurs in the original data set. Each data sample is then matched to the reference vectors. The best match node is identified as that with the smallest Euclidean distance between the reference vector and the data sample. Vectors for the best-matching node and those that are close in the two-dimensional array are then updated. This continues until all samples are tested and the final reference vectors are then mapped onto a two-dimensional grid with their locations in the matrix corresponding to their matching nodes (Skillic and Francis, 2012). The maps in the resulting feature map (schematic illustration shown in Fig. 2) represent the predominant synoptic patterns of the atmosphere. This iterative training procedure allows the SOM to account for the non-linear data distributions (Hewitson and Crane, 2002).

4. Current climate results and discussion

4.1. Simulated tropical cyclone frequency

The North Atlantic basin produces 10–13 named tropical cyclones per year. With a total of 264 simulated years, it is expected that the 24-member ensemble should conform to this average and spread. The 24-member ensemble had an average of 10 TCs per year with a spread of 7. Not all of the ensemble members performed equally well. However, 19 of the 24 members produced TC totals within one standard deviation of observations. Observed TC numbers range from a minimum of 4 to a maximum of 28 a year, while the ensemble has a range of 3–26. For the three chosen future ensemble members (grey shading in Table 1) the average TCs per year were 10–13 and 9–13 for the runs driven with reanalysis and climate data, respectively. This shows that the simulations were successful in reproducing both overall TC frequency and year-to-year variance (refer to Bruyere et al., 2017 for more details on the overall performance of the simulations). Next, the large-scale driving factors behind TC genesis are investigated using a SOM.

4.2. SOM construction

As the primary interest of this analysis is TCs in the North Atlantic basin, all SOM calculations were performed on a smaller subset of the WRF domain centered over the North Atlantic Basin (Fig. 1). The domain used to create the SOM feature maps ranges from 0 to 48 N and 98 W to 20 W, which encompasses the entire North Atlantic basin (Fig. 1, inner grid). For the SOM feature maps made from the original 24-member ensemble, all ensemble members and the ERA-Interim reanalysis were included in the SOM analysis using daily averages of sea level pressure (SLP) for August, September, and October (hereafter, ASO) for all eleven years. Because the interest here is mainly tropical cyclone genesis in the Atlantic, SLP was the chosen field selected for SOM training, as it reflects large scale environmental conditions without small scale variance commonly observed in other environmental fields such as wind and moisture. Application of SOMs to meteorological data has been shown to be very successful in clustering large spatial and temporal datasets, especially using SLP (Richardson et al., 2003; Nigro et al., 2011; Sheridan and Lee, 2011; Cassano et al., 2015). Training the SOMs was also tested on geopotential at 850 mb, 500 mb and 200 mb generally producing similar large-scale features. Sea surface temperature, although extremely important for tropical cyclone genesis, was not considered because it was prescribed in the ensemble.

The SOM_PAK software was applied to a total of 25,300 time slices of SLP from the smaller SOM grid. A number of sizes of feature maps (5x5, 6x4, and 7x5) were tested to determine the size map that would represent the variety of SLP patterns without multiple nodes showing patterns that are too similar. For each map size, numerous SOM feature maps were created using a variety of settings available in the software. Final maps for each size were then chosen by selecting the maps with a combination of the lowest qerror (a measure of the cumulative squared difference between the training data and the result of SOM values), having a flat Sammon map, and a feature map that shows a variety of representative nodes. The Sammon map (Sammon, 1969) is a two-dimensional representation of the relationship of the higher dimensional SOM space. The distances between the vectors rendered in a 2-D space show the dissimilarity between different nodes and helps visualize the relationship between nodes. Fig. 3a shows the Sammon map for the SOM that is eventually chosen (Fig. 4) and shows that the nodes 1,1 and 7,1 are more similar than the nodes across the bottom (nodes 1,5 and 7,5). In addition, the map shows a stable learning process in its ‘flatness’. If a Sammon map folds over onto itself (Fig. 3b) this shows an unstable learning process.

If the feature map matrix is too small, some patterns may not be
represented; if too big, adjacent patterns will be too similar (Skific and Francis, 2012). Based on these methods, a 7x5 SOM was chosen resulting in 35 nodes.

4.3. Current climate SOM

Fig. 4 shows a SOM feature map of daily sea level pressure (SLP) anomalies. The top left and bottom right nodes show opposite states of the first eigenvector while the nodes in the other corners are opposite states of the second eigenvector. Together these four corners represent the extremes of the total linear space of all possible synoptic patterns. Even accounting for the relatively small domain on which the SOM analysis was made, the strong low/high pressure anomalies in the upper left and lower right corners of the feature map (Fig. 2) have a strong
resemblance to the negative and positive phases of the North Atlantic Oscillation (Cassou et al., 2011; Hurrell et al., 2003). In the transitioning phases between NAO- and NAO+ like patterns, some of the SOM nodes represent what Cassou et al. (2011) termed Blocking and Ridging. Both phases of the NAO are favorable of TC genesis (Elsner and Kocher, 2000a; Elsner et al. 2000b, 2000c; Kossin et al., 2010; Villarini et al., 2012), with the positive phase resulting in TC tracks shifting westward and resulting in more landfalling TCs in North America (Kossin et al., 2010). Blocking and Ridging on the other hand result in less favorable conditions for TC genesis (Knaff, 1997; Murakami et al., 2016; Elsner, 2003). Therefore, it should follow that TC genesis will be higher for the nodes in the corners and on the edges of the feature map (Fig. 4) and lower for the center nodes. To explore this hypothesis, the sea surface temperature (SST) and TC frequency were examined for each node. For both the reanalysis driven and climate driven (see section 5 for more details) simulations the node frequencies are similar to observations (refer to the red and white bars in Fig. 8). The simulated frequency (Fig. 4) of occurrences of each node is relatively uniform, with nearly 80% of the node frequencies within one standard deviation of the mean. The lower left node with the strong low pressure shifted westward has the highest frequency in the ensemble, accounting for 4.8% of all days. The second-most frequent node is the negative NAO-like node at the upper left accounting for 4.1% of days.

Fig. 6. Heat map showing Normalized TC frequency per node. Colors correspond to: light blue/red is less than one standard deviation below/above the mean, and darker colors are more than one standard deviation from the mean values.

Fig. 5. a. Node SST anomalies based on the SLP anomaly SOM in Fig. 4. Dots are TC genesis locations associated with each node. b. Node Shear 200–850 hPa shear based on the SLP SOM. Dots are TC genesis as in 5a.
4.4. Relationships between SOMs and tropical cyclogenesis

Fig. 5a shows the composite Sea Surface Temperature Anomaly and simulated storm genesis points for each node displayed in Fig. 4. Fig. 6 depicts a corresponding heatmap of normalized TC counts for each node. As can be expected with nodes dependent on atmospheric phenomena which are connected to the ocean, SSTs vary significantly from node to node, as does tropical cyclogenesis.

When comparing the SST anomaly map (Fig. 5a) and TC numbers per node (Fig. 6) with the SLP anomaly SOM feature map (Fig. 4) it is clear that for synoptic conditions where either a strong high or low pressure system is present over the Atlantic Ocean (nodes located at the top and bottom of the feature map) there is a warm SST anomaly in the main development region (MDR: an area located just off the coast of West Africa that is associated with a high level of TC development: Bruyere et al., 2012). These nodes are also associated with higher than average TC frequency, indicating that these nodes represent favorable conditions for TC development.

Although the SST patterns for these edge nodes are similar, and they all favor cyclogenesis, these nodes have very different spatial cyclogenesis patterns. These patterns can to a large extent be explained by the associated shear patterns (Fig. 5b). For the NAO- phase, the highest shear values are located over the continent and the east coast, while for the NAO+ phase the region of highest shear shifts south east, with an accompanying shift in TC genesis locations. This shift results in cyclogenesis farther west for the NAO+ phase, which accounts for more landfalling cyclones observed during the NAO+ phase (Kossin et al., 2010).

Transition periods, which can be seen in the middle nodes of the feature map, are commonly associated with cool SST anomalies in the MDR, and less TC genesis. Although these nodes generally have low shear values (Fig. 5b), low shear is a necessary but not sufficient condition for cyclogenesis. Nodes with a strong low-pressure system do not favor genesis, and thus low shear adds no benefit for the production of cyclones under these conditions. Combining the favorable conditions of the corner and edge nodes with the higher than average node frequency results in higher TC numbers associated with these nodes. Conversely, the unfavorable center nodes combined with their lower than average node occurrence results in lower overall TC numbers associated with the center nodes.

5. Future climate results

5.1. Simulated tropical cyclone frequency change

Fig. 7 shows the simulated future North Atlantic TC frequencies from the three selected ensemble members. The RKTM (red) simulation shows the largest change in annual TC frequency. By the 2020s, the ensemble member produces on average four fewer TCs per year than the current climate. By the 2080s, there are approximately seven fewer TCs per year. It should be noted that this ensemble member produces fewer TCs under current climate conditions, but also continues to reduce TC frequency in the future. RNTY (blue) follows a similar pattern with decreases ranging from one to two TCs annually for the predicted periods. RTTY (green) was the only member to show a neutral to slightly positive change to future TC genesis. On average (black line) the three members reduce TC frequency by two storms per year by the end of the 21st Century. Next, these changes are interpreted through changes to the large-scale patterns as characterized by a SOM analysis.

5.2. Future climate SOM change

Fig. 8a shows the frequencies of occurrence of each node (from Fig. 4) for the reanalysis (red bars), as well as the 3 current and future climate ensemble members (white/grey bars). The white bars are the current ensemble members (1990–2000), the light grey bars are the near future ensemble members (2020–2030 and 2030–2040), whereas the dark grey bars show simulations farther into the future (2050–2060, and 2080–2090). Comparing the red bars (reanalysis) with the three white bars (ensemble members RKTM, RNTY, and RTTY for the current climate simulation) in Fig. 4 gives an indication of how well the model simulations perform in simulating the synoptic scale variability in the current climate in the region of interest. Looking out to the future (light and dark grey bars), the frequency map indicates that the SOM nodes associated with a strong high pressure over the North Atlantic (nodes in the lower right) are increasing in frequency in the future while the SOM nodes with a lower pressure over that same area (top and bottom left nodes) show a decrease in frequency. The numbers in the upper left corner of the nodes in Fig. 8a show the percentage change of the ensemble average frequency from 1990 to 2080. Fig. 8b shows the changes in frequency for each of the three ensemble members (colored lines) and the ensemble average frequency change (black line). Although individual ensembles members do not always have similar percent changes, all members and the ensemble average agree on the nodes where substantial changes are predicted for the future, indicating a future state where positive NAO phases are more common. There is also a shift away from corner nodes to center nodes in the future, pointing to a possible reason for the decrease in simulated TC frequency.

5.3. Understanding future changes in tropical cyclogenesis using SOMs

As previously discussed, the average simulated number of TCs per year decreased by just over two by the end of the century (Fig. 7). Per ensemble member the change in simulated TCs are relatively large, with predictions that range from a decrease of almost 7 (simulation RKTM) to an increase of just under two (simulation RTTY) cyclones a year. This predictive difference in sign is typical of current day climate predictions (see, for example, the summary by Walsh et al. (2016)), in which this case gives us the opportunity to further evaluate the link between node frequency and TC genesis. The simulation with the biggest decrease in cyclones (RKTM) uses the Mellor–Yamada–Janjic (MYJ: Janjic, 1994) PBL scheme which is a one-and-a-half order prognostic TKE (turbulent kinetic energy) scheme with local vertical mixing. The simulations that predicted less (or positive) changes, RNTY (decrease of 2 cyclones per
RTTY (increase of 2 cyclone per year) use the Yonsei University (YSU: Hong et al., 2006) PBL scheme, a first-order, non-local scheme with an explicit entrainment layer. Bruyere et al. (2017) showed that RTTY and RNTY both had higher sea level pressure biases than RKTM. In terms of SOM node frequencies, this sea level pressure bias resulted in RTTY having significantly lower frequencies for the upper right nodes, and higher frequencies for the lower right and middle (transition) nodes. In other words, the RTTY simulation shifts away from

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**Fig. 8.** a. Frequencies over the SOM for ERA-I (red) and near-term and future climate runs from CMIP5. First three white bars represent ensemble members RTTY, RNTY, and RKTM for the current climate (1990). Ensemble members are in the same order for the next two sets of three light grey bars for the near future climate runs (2020 and 2030). The far-future climate runs (2050 and 2080) represent the final six dark grey bars. The percentage change of the ensemble average frequency between 2080 and 1990 is shown in the upper right-hand corner of each node. Specific nodes are bolded. b. Percent change in frequency between 2080 and 1990 for each member and the ensemble average. White and grey sections correspond with rows from (a), with rows 1, 3, and 5 in white and rows 2 and 4 in grey. The numbers indicate the column of each row where a substantial change is predicted, these nodes have also been bolded in (a).

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**Fig. 9.** Future node frequency change (left) and TC count change (right). Red dots show significance of one standard deviation and red dots with black outline show significance of two standard deviations.
nodes that favor TC development, towards nodes that does not favor development, which thus accounts for the difference in future storms counts between the RTTY and RKTM simulations.

Fig. 9 shows node frequencies (left) and storm counts per node (right) anomalies (future – current) for the future decadal runs by node. The node changes per decade are depicted clockwise from 2020 (top triangle) to 2080 (left triangle). Changes that are larger than one standard deviation from the mean are indicated by red circles, while the changes larger than 2 standard divisions are depicted as red circles with a black outline. The nodes with significant changes are mainly in the upper left and lower left, where both node frequency and storm count per node show significant decreases into the future. The nodes that are associated with blocking/ridging (center of the frequency map) have significant changes in terms of node frequency, but not in terms of simulated cyclone numbers. Because the cyclone numbers are already quite low this indicates that increased frequency of these nodes does not necessarily lead to increases in cyclone genesis.

Fig. 10 shows 200–850 hPa shear changes for the future runs for the North Atlantic (25N–40N, 280E-320E). Shear in the North Atlantic goes down for most nodes except for some slight increases in the future for the upper left nodes. Thus, for the nodes that are favorable to TC genesis, future shear changes do not negatively impact TC genesis, with shear patterns staying similar or even more favorable towards the end of the century. But, because these nodes decrease in frequency in the future,
the more favorable shear environment does not necessarily lead to increased TC development overall. The nodes unfavorable for TC genesis, on the other hand, experience a significant drop in shear across the domain, but since shear is a necessary but not sufficient condition for TC genesis, the increase in node frequency (Fig. 9 left) and decrease in shear is not enough to affect the future TC count for these nodes in a significant way.

5.4. Comparing statistical and dynamical predictions of future changes

To explore the impact of changes in node frequency of corners and edges vs center nodes further, a simple model based on the TC genesis per node frequency for the 1990s was used to predict TC genesis under future climate conditions. First, all corner nodes (Fig. 11a: blue nodes) and all center nodes (Fig. 11a orange) are grouped together. Then, the 1990s TC genesis/node frequency relationships were used as predictors for the future climate. Fig. 11b shows that for the center nodes there is no relationship between node frequency and TC genesis, in fact regardless of the node frequency simulated TC genesis remains flat for blocking/ridging (center) nodes. Corner node frequency on the other hand explains more than 80% of TC genesis, thus accounting for the downward trend in TC genesis for future climate simulations where these node occurrences decrease in frequency.

5.5. Large scale climate change

Changes in the NAO index could be responsible for some of these changes in node frequency and TC count. To explore the impact of the large-scale changes, possible NAO changes in the future are investigated. An NAO-like index was calculated for the months of ASO for all of the future ensemble runs. It was not possible to calculate the actual NAO index (Hurrell, 1995) as Reyljka is not in the WRF domain used for this study (Fig. 1). A point as close to Reyjkavik as possible was chosen as a substitute. Because it is not an exact representation of the NAO and that it is over a season where the NAO is generally less active, the NAO values calculated are smaller than an actual NAO index would be in amplitude. Fig. 12 shows that not only is there a shift towards more positive NAO occurrence in the future (as Fig. 9 is also indicating), the amplitude of the positive events is becoming larger. It was noted previously that the accumulated effect of a shift from the left-hand nodes to the center and right-hand nodes results in less TC genesis. In addition to this, the increased frequency of nodes associated with the positive NAO phase means that cyclones that do develop will be shifted westward, and therefore increasing the likelihood that these will make landfall.

Fig. 13 shows, by node and decade, how the NAO changes. Again, these are differences relative to the NAO index in the 1990s climate runs. In general, the nodes that become more negative are the nodes that already had a negative NAO signature and the same goes for the nodes that became more positive. A larger number of nodes do show a positive change in the index, which is consistent with what is seen when compared with the NAO index for each modeled year (the three physics ensemble members were averaged) (Fig. 12). It shows a slight positive trend towards a more positive NAO for the whole SOM map. The middle nodes of the feature map, which were less favorable for TC development experience a slight increase in the NAO index that could make them more favorable, but did not correspond to an increase in TCs (Fig. 11). Additionally, the increasing strength of the NAO for both the upper left and lower right nodes did not result in a significant change in TC count. The largest change in count is attributed to the lower left nodes, where the negative NAO became stronger. This also did not have an impact on the overall storm count due to the decrease in frequency of those nodes (Figs. 8 and 9).

6. Conclusions

This paper explored future changes in tropical cyclone (TC) genesis locations and frequency by identifying relationships between TC genesis and dominant daily large-scale patterns, and evaluating the strength of these relationships under a climate change scenario. A SOMs analysis was used to link large scale SLP patterns to TC genesis in an ensemble regional climate simulation of current climate. The ensemble regional climate simulations are an appropriate dataset for this study because they are able to capture similar node frequencies to those in a reanalysis dataset, and simulated seasonal TC frequency distributions similar to historical observations. It is important to note that the 24-member ensemble was based off of a single reanalysis dataset and the results of the ensemble could be sensitive to other datasets. However, the evaluation of the ensemble by Bruyere et al. (2017) shows good agreement between the simulations and observations and indicates that the ensemble is appropriate for this study. Though some ensemble members departed from observations, the SOM analysis was shown to be a useful tool to highlight possible physical reasons for model error. For example, some members had a bias in SLP that contributed to different node frequencies and changing TC counts.

The extremes in SLP nodes (NAO-like nodes on the corners and edges of the feature map) are favorable for TC development, while the blocking/ridging nodes (center of the feature map) are less favorable. This is demonstrated by the attendant SST and shear patterns associated with the NAO positive and negative nodes. While SST patterns are similar, shear patterns are distinctly different, and explains the westward shift in TC genesis in the positive NAO node.

An ensemble regional climate simulation driven by a future climate scenario projects fewer TCs. Correspondingly, the frequency of nodes decreases for the left side, and increases for the right side of the feature map. Nodes associated with blocking/ridging and the positive NAO phase become more frequent. This corresponds to fewer TCs in the future with a higher potential for TCs making landfall. Application of a simple statistical model based on the node-TC relationships identified under current climate predicts fewer TCs. This is consistent with fewer TCs explicitly simulated by the regional climate model under the same scenario. This demonstrates the strength of the relationships and their utility in assessing potential future changes in TC genesis frequency and preferred locations.

It is important to note that this experiment used a single global model projection and is therefore one of many possible future SLP scenarios. However, our emphasis is on understanding future changes in TCs through the role of large-scale patterns, rather than exploring the full range of future possibilities. In addition, the use of a large regional model domain allowed for substantial internal variability of the large-scale patterns within the domain interior (Prein et al., 2019), thereby sampling more variability than provided by the forcing from a single global climate model projection.

The IPCC’s best estimate of TC changes in the future (Meehl et al., 2007) are for fewer but more intense TCs by the end of the century. This study also points to fewer TCs. This SOM approach has broader application to other aspects of TC behavior, such as intensity and landfall. For example, the westward shift in TC genesis has the potential to increase the probability of U.S. landfall in the future. In addition, if intensity increases in the future, combined with more landfalls, future damages associated with TCs could potentially be devastating.

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