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An Overview and Evaluation of SynthETC: A Statistical Model for Extra-Tropical Cyclones

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An Overview and Evaluation of SynthETC: A Statistical Model for Extra-Tropical Cyclones

By

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Abstract
Extratropical cyclones (ETCs) are the most common type of storms that affect northeastern North America. These storms generate precipitation and winds that can potentially produce serious hazards. Colle et al. 2010, Booth et al. (2015), and Booth et al. (2016) established that the path of the ETC is often very important for determining how and where the hazards associated with the ETCs occur. These results motivate the need to improve our understanding of ETC paths, especially the strongest ETCs. As such, this Master’s project is focused on understanding and improving a recently developed ETC track model, SynthETC.

SynthETC (i.e., Synthetic Extratropical Cyclone) is a statistical model for genesis, tracks, termination, and intensity of extratropical cyclones (ETCs) over eastern North America and the North Atlantic originally created by Hall and Booth (2017). It is purely statistical – that is, simulated storms and their features do not explicitly depend on any physics in the model. Instead, genesis of storms and storm features are modeled using probabilities that depend on historical data (both regionally and domain-wide), climate states, climatology, and in the case of storm tracks: memory. The climate states used in the model are the North Atlantic Oscillation (NAO), and El Nino/Southern Oscillation Index (ENSO), which are two of the dominant teleconnections that affect extratropical cyclones for the region of interest.

The ETC data used are tracks derived from the Sea Level Pressure (SLP) minima of the cyclones, using the Bauer et. al. (2015) tracking algorithm on ERA-Interim SLP data 1979-2015 (this is the same as Hall & Booth, 2017). Only intense storms are used, where “intense” is defined as a local
central pressure (CP) deficit of greater than 35 hPa (with respect to local climatology), and duration of at least six 6-hourly time steps. The domain of SynthETC simulation is the latitude (lat) by longitude (lon) grid of 1-by-1 degree boxes between 140W and 30W longitude, and 20N and 70N latitude. The climate state data used are monthly Nino 3.4 index available on NOAA’s website: (www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Nino34), and the monthly index available from the Climatic Research Unit of the University of East Anglia available at their website: (http://crudata.uea.ac.uk/cru/data/nao/nao.dat). All monthly data are interpolated to daily for use in the model, and are the same as data used by Hall & Booth, (2017).

The motivation for a statistical model is as follows. For assessment of risk and preparedness, individuals or insurance companies are often concerned with the predicted frequency or return periods of intense storms, which cause the most damage and pose significant threat to life. Such storms are not very common in the historical record, and as a result, being limited to the historical record poses serious limitations on prediction capability. One option is to run coupled general circulation models that resolve the physics of the ETCs. These integrations require large amounts of computation and take a long time to run. However, with a statistical model, we are able to re-run thousands of simulations of a historical period and generate a synthetic dataset that is much larger than the historical (this is of course assuming the model is an accurate representation of history and that ETC statistics are stationary). This statistical method is not specific to extratropical cyclones either, and was originally applied to tropical cyclones (Hall & Jewson, 2007), and was used to predict the return period of events like Hurricane Sandy (Hall & Sobel, 2013).

To illustrate some of this, figure 1 shows the 20 most intense (defined using Sea Level Pressure anomaly) storms generated from 50 simulations of the 1979-2015 (37 year) record that touch the green box shown. The two red tracks indicate storms more intense than any contained in the historical record. The ability to generate such tracks is unique to the statistical approach. Figure 2 shows the predicted (with 90% confidence bounds) and historical maximum storm intensity as a function of return rates for storms passing over three major metropolitan areas (Hall & Booth, 2017). Note the modeled return periods extend to higher intensities, giving us the ability to predict return rates of storms that are not in the historical record. Lastly, figure 3 shows the fractional change in annual ETC frequency based on the phase of NAO and ENSO. Thus, a particular combination of ENSO and NAO states could lead to a seasonal prediction of higher or lower storm frequency (or risk) for a particular time period.

The remainder of this Masters thesis is organized as follows:

- Chapter 2 will give an overview of the Hall & Booth (2017) model SynthETC, followed by a more detailed description of the model four model components (genesis, track, lysis, and intensity). These four components were developed over the course of five papers: Hall & Jewson, (2007), Yonekura & Hall (2011), Hall & Yonekura (2013), Hall & Yonekura (2014), and Hall & Booth (2017) (the first four being applied to tropical cyclones). This section shall serve as a comprehensive detailed description of the machinery in the final version of the model.
• Chapter 3 will present some evaluations of the model (including tests performed and not performed in Hall & Booth (2017)). The second part of chapter 3 will look at the effects of modifying the red-noise portion the track component of the model.
• Chapter 4 will address some issues found during evaluation and offers suggestions for future work.

One final note, because this document is meant to provide guidance to others that use SynthETC, and because I did not have time to make sense of every component of the model, there are a few places in where I add a comment that is either speculative or meant to provide guidance as to where to go for more information. For these comments, I use the following syntax: {RU: text/comments}. 
Figures for Chapter 1

Figure 1 - Tracks of the 20 most intense cyclones generated by 100 simulations of SynthETC, which originate or pass through the green box shown. Red tracks are storms which are more intense than any in the historical record meeting the same track criteria.

Intensity (central pressure deficit) vs return period curves for passage near DC, NYC, Boston (Hall & Booth, 2017).

Figure 2 - Intensity (as CP deficit, in mm Hg) as a function of return period for storm passage within 50 miles of three metropolitan areas in the northeast US. Figure from Hall & Booth (2017).

Figure 3 - Annual fractional change of storm passage frequency with CP deficit of 50mb Hg or greater, within 200 km of 1-degree gridpoint. Units of NAO and ENSO are in standard deviations with respect to the mean state. Figure from Hall & Booth (2017)
2. Description of SynthETC

2.A - Overview:

SynthETC generates synthetic extratropical cyclones by simulating four aspects: genesis, track, lysis (termination of storm), and intensity. Genesis is modeled as a Poisson process, with the Poisson mean rate determined by climate states and historical rates. Track-steps are modeled in two parts: the climate and climatological mean track step, plus a red-noise deviation from the step computed via lag-1 autoregression (AR(1)). Lysis also depends on climate states, and on regional lysis frequency. Intensity time series of each generated storm track is simulated using a resampling method of historical intensities, and perturbation of maximum intensities.

Simulations of genesis are carried out day by day; i.e., a start date is set for the statistical model, and then the model simulation evolves from one day to the next, testing for synthetic track genesis, until it reaches the predetermined simulation end date. On each day, a Poisson distribution is sampled to get the number of storms on that day. If a cyclogenesis is determined to occur on a given day, the storm is then located in the simulated domain. Then the evolution in space-time of that track is completed in its entirety. Its track is computed one step at a time (six-hourly time steps). At each step starting with step six, a lysis condition is checked. Once the storm is terminated, a “realistic” (defined later) intensity time series is selected for the storm from the set of historical time series. After all storms are simulated (with corresponding intensity time series), the maxima of each series is perturbed to allow simulated storms to have intensities not in the historical record.

2.B - Genesis

The genesis portion of the model has two parts. The full details are given in the following paragraphs, but we begin with a summary of the steps. First, the algorithm finds the number of storms generated on the particular simulated day by randomly drawing from a Poisson distribution that has a mean determined by climate predictors and historical trends. This is called the domain-wide genesis rate; it is calculated daily. Then, for each storm on this day (if any), the algorithm locates the storm using a lat by lon grid of local genesis rates which depend on a local, historically-determined probability density function, and climate states. This will be called the location-dependent genesis rate.

I. Domain-wide genesis rate:

The domain-wide genesis rate on a particular day, which is denoted by \( \Lambda(d) \), is found by multiplying three quantities. These are (1) the number of days in a simulated year (October-April months only, denoted by \( N \)), (2) the number of storms per day as predicted by ENSO and NAO states (denoted by \( C(d) \)), and (3) a basin-wide probability distribution of historical storm genesis spanning the entire year (365 days long, denoted by \( H(d) \)). Hence, the domain-wide rate is given by

\[ \Lambda(d) = N \cdot C(d) \cdot H(d) \] (1)
The daily genesis rates predicted by climate states, \( C(d) \), are calculated by regressing (using Poisson regression) daily storm genesis counts against daily NAO and ENSO indices. Poisson regression (as opposed to ordinary linear regression) allows the typically low number of daily storm genesis counts (0, 1, or 2) to yield significant regression results. Thus, \( C(d) \) is given by:

\[
C(d) = e^{a_0 + a_1 \cdot \text{NAO}(d) + a_2 \cdot \text{ENSO}(d)}
\]  

(2)

where \( a_0 \ldots a_2 \) are regression coefficients.

The historical probability density function (\( H(d) \)), is calculated by summing together, over lat an lon dimensions, a three-dimensional historical probability density function (pdf), \( K(\theta, \Phi, d) \). This will be explained in detail in the following paragraph, but essentially \( K(\theta, \Phi, d) \) is the local estimate of daily historical storm counts, normalized to a probability. The value \( H_d \) is thus given by

\[
H(d) = \frac{1}{A} \sum_{\theta, \phi} K(\theta, \phi, d) \cdot da(\theta, \phi)
\]

Where \( \theta \) and \( \Phi \) are lat and lon respectively, \( A \) is the area of the domain, \( da(\theta, \phi) \) is the area of the gridpoint (a 1° by 1° grid), and \( K(\theta, \Phi, d) \) is the probability density at location \((\theta, \Phi)\), on day \( d \), which is calculated as described below.

Probability Density Using Gaussian Kernel Weighting Technique:

At a given point in the domain \((\theta, \Phi)\) and given day \( d \), the number of historical storms counted at that point and time, \( K(\theta, \Phi, d) \), is estimated by counting the number of all historical storms in the entire domain and entire historical record, but with each storm count weighed inversely with its distance from \((\theta, \Phi)\), and its time-distance (in days) from day \( d \). The inverse weight applied is called a Gaussian kernel, and is given by

\[
w = e^{-\frac{d^2(\theta, \phi, i)}{2L^2} - \frac{T^2(d, i)}{2L_D^2}}
\]

where \( d(\theta, \Phi, i) \) is the distance from \((\theta, \Phi)\) to genesis site of storm \( i \), \( T(d, i) \) is the number of days between the current simulated day \( d \) and genesis day of storm \( i \), and \( L \) and \( L_D \) are length scale constants of distance and time, respectively. Thus \( K(\theta, \Phi, d) \) is given by:

\[
K(\theta, \phi, d) = Q \sum_i e^{-\frac{d^2(\theta, \phi, i)}{2L^2} - \frac{T^2(d, i)}{2L_D^2}}
\]  

(3)

The reasoning behind the Kernel weighting technique is as follows. When counting the number of storms at \((\theta, \Phi)\), there may not be enough data at that exact point to render reliable historical data of the number of storm genesis. One alternate would be to consider all storms within a fixed radius of \((\theta, \Phi)\). Larger radius allows the use of more data, but may blur important local variability in
storm genesis sites. Smaller radius may allow for such variability, but may once again result in insufficient local data availability. A Gaussian kernel such as the one in equation (3) gives us the ability to avoid using a harsh cut-off radius for counting “nearby” storms, by counting all storms in the basin but weighing the contribution of storms far away from (θ,Φ) much lower than those close to (θ,Φ). The constant L affects how steeply the weight declines with distance, and is the continuous analog of using a harsh cut-off radius. L is determined by \textit{out-of-sample likelihood maximization} (OSLM), and is equal to 140km. An example of a 2-dimensional Gaussian kernel centered at a point is given in figure 4. For the genesis count at point A, a genesis site at point A contributes a total of one, a genesis site at point B contributes a value close to one, and a genesis site at point C contributes a value close to zero. Increasing the length scale (L) would allow the genesis site at point C to contribute more significantly, but still less significantly than a genesis site at point B.

The Gaussian kernel given in (3) is just like this but also adds an inverse weight for the time dimension, so that historical storm genesis 6 months away from the current simulated day d contribute to the genesis count at day d significantly less than storms only a few days away from day d. \(L_D\) is also be optimized using OSLM. Here, \(L_D = 15\) days. After the kernel genesis count for all points in the domain and days of year is calculated, it is normalized by dividing each gridded value by the sum of all values. The result is a continuous, smoothly changing probability density function that resembles historical genesis trends. The resulting kernel probability density for each of the four seasons is plotted in figure 5, and resembles the well-known spatial distribution of ETC genesis.

Domain-wide genesis rate (continued):

After the 3-dimensional probability density function is generated, the historical domain-wide rate on a particular day \(H(d)\) is found by taking an area-weighted sum over the values along the lat and lon dimensions and dividing by the area of the domain, as mentioned earlier. During the simulation, on each day of the simulation, the values of N, C(d) and H(d) are combined as in (1) to find the mean genesis rate \(\Lambda(d)\) for that day. This rate is used as the mean of a Poisson distribution, which is randomly sampled to get the number of storms generated on that day.

\section*{II. Location-dependent Genesis Rate (locating the storms)}

After the number of storms on a given day is found (if that number is at least one), the storms must be given a genesis location on the grid. To locate the storms, a 3-dimensional grid of local formation rates scaled to be between 0 and 1 is generated. The value of the local formation rate at any lat, lon, and time (denoted by \(\lambda(\theta,\Phi,d)\)) is found by given by:

\[
\lambda(\theta,\phi,d) = N * c(\theta,\phi) * h(\theta,\phi,d)
\]  

(4)

where \(N\) is the number of days in the year again, \(c(\theta,\Phi)\) and \(h(\theta,\Phi,d)\) are the analogs of \(C_d\) and \(H_d\) in (1), but now are allowed to vary spatially in the domain. Hence, \(c(\theta,\Phi)\) is the local genesis rate predicted by climate states, and \(h(\theta,\Phi,d)\) is the local time-pdf of genesis. At any given location \((\theta,\Phi)\), \(c\) is found by computing a Poisson regression of daily storm genesis counts in the entire
spatial domain against daily ENSO and NAO indices, but with weighing each storm genesis inversely with its distance to \((\theta, \Phi)\). The weight is once again a Gaussian kernel, but with no weighing for the time domain. Hence, the weight is now:

\[
W_r = e^{-\frac{d^2(\theta, \phi, i)}{2L^2}}
\]

(5)

where \(d_{\theta, \phi, i}\) is the distance from \((\theta, \Phi)\) to the genesis site of storm \(i\), and \(L\) is a length scale equal to 140Km as before. Hence, \(c(\theta, \Phi)\) is given by

\[
c(\theta, \phi) = e^{a_0(\theta, \phi) + a_1(\theta, \phi)(\text{NAO}) + a_2(\theta, \phi)(\text{ENSO})}
\]

(6)

where \(a_0 \ldots a_2\) are regression coefficients as in (2), but are now variable spatially. The distance-weighted regression allows the impact of NAO and ENSO states on genesis frequency to vary spatially (for example, NAO may be positively correlated with genesis in one area of the Atlantic, but not in another). An example of spatially varying regression coefficients is given in Figure 6.

The value \(h(\theta, \Phi, d)\) at any given location \((\theta, \Phi)\) and day \(d\) is determined by dividing each value of the 3-dimensional probability density function \(K(\theta, \Phi, d)\) found in the previous section by the sum of probabilities across all times in that location, and then multiplying by a scale factor \(R\). The division by this sum normalizes \(h\) to a local time pdf. The purpose of \(R\) is to scale these probabilities to be rates per grid-point area, rather than rates per Gaussian kernel area (recall that \(\lambda\) involves all storm counts in a Gaussian circle, not a gridpoint). Hence, \(h(\theta, \Phi, d)\) is given by:

\[
h(\theta, \phi, d) = \frac{K(\theta, \phi, d)}{\sum_d K(\theta, \phi, d)} \cdot R(\theta, \phi, d)
\]

(7)

where \(R\) above is given by:

\[
R(\theta, \phi) = \frac{da(\theta, \phi)}{\sum_{\theta', \phi'} da(\theta', \phi') \cdot e^{-\frac{d^2(\theta', \phi', \theta, \phi)}{2L^2}}}
\]

(8)

where the primes indicate dummy variables, which are summed over.

Once the local genesis rate predicted by climate states, \(c(\theta, \Phi)\), and time-pdf of local genesis, \(h(\theta, \Phi, d)\) are found, they are plugged into equation (4) to find the local genesis rate. This rate is scaled to be between 0 and 1 across the whole domain by dividing by the maximum rate from the domain. During the simulation, a uniform-random latitude and longitude are picked for a candidate genesis site. This value of \(\lambda(\theta, \Phi, d)\) at this site is compared to a random number drawn from a uniform(0,1) distribution. If \(\lambda(\theta, \Phi, d)\) exceeds the random, this candidate site becomes an actual genesis site. If not, then a new random site is picked, and \(\lambda\) is compared to another number from a uniform(0,1) distribution. This process is repeated until the number of genesis sites found matches...
the number of storms in the domain in this day. Even though any point in the domain is equally likely to be picked (including points which rarely see storm genesis such as point B in figure 7), such points will rarely (but not never) have values of λ that exceed a draw from a uniform(0,1). Hence, such points will have a significantly lower frequency of storm genesis than those in regions where there is a high historical storm genesis (such as point A in figure 7) but not necessarily zero frequency.

2.C - Tracks

The tracks of SynthETC are constructed in 6-hourly increments (denoted by t). The increments depend directly on four variables: (1) climate states, (2) time of year as encoded by the seasonal cycle of 500-mb winds (U500 and V500), (3) local historical track activity, and (4) the track increments from the preceding track step (if any). Moreover, the strength of any of these dependencies is allowed to vary across the domain (ie: track direction may depend more strongly on one of the covariates in a particular part of the basin and have a strong dependence on another covariate in another part of the basin). Track increments here are quantified as the vector sum of zonal (x) and meridional (y) increments, and as a result, x and y track components are computed separately during simulations.

A track step is computed with the following two formulae:

\[
\begin{align*}
\Delta x_{\text{sim}} &= \bar{X} + \sigma_x * z_{x,t} \\
\Delta y_{\text{sim}} &= \bar{Y} + \sigma_y * z_{y,t}
\end{align*}
\]

(9)

The \(\bar{X}\) and \(\bar{Y}\) encode the track displacement dependence on NAO, ENSO, and climatology. Then, an anomaly (or perturbation) is added to the mean. The anomaly, \(z_{x,t}\) and \(z_{y,t}\), is the stochastic component of the track, with a memory of one 6-hourly step. The anomaly is made dimensional by multiplying by \(\sigma_x\) (or \(\sigma_y\) for y component), which is a local root-mean-square (rms) variance of track steps, with respect to the regression mean. Each of these components is explained in more detail below. From now on, I will refer to only the x-component of tracks for explanation, with the understanding that the same procedures are done for the y-component as well.

I. Dependence on Climate and Climatology: Linear Regression

First, to determine the dependence of track steps on NAO, ENSO, and climatological 500-hPa winds, regression coefficients (quantifying how tracks are influenced by climate states) at each location (\(\theta, \Phi\)) are computed. This is done by computing multiple linear regression of all the track displacements \(\Delta x\) in the x direction against NAO index, ENSO index, and U500 (V500), with each track displacement weighed inversely with its distance to the location (\(\theta, \Phi\)). The weight used is again a Gaussian weight: \(e^{-\frac{d^2}{2L^2}}\), where \(d\) is the distance from the point (\(\theta, \Phi\)) to the track step location, and \(L\) is a length scale determined using OSLM. Here, \(L=200\text{km}\). As a result of the Gaussian weight, track-steps close to (\(\theta, \Phi\)) will contribute significantly to regression coefficients at (\(\theta, \Phi\)) and track steps far away from (\(\theta, \Phi\)) will contribute very little. During the simulation, the regression-mean track displacement at a grid point (\(\theta, \Phi\)) is computed by:
\[
\overline{X} = a(\theta, \phi) + b(\theta, \phi) \cdot (NAO) + c(\theta, \phi) \cdot (ENSO) + d(\theta, \phi) \cdot (U500)
\]  
(10)

where \(a(\theta, \phi) \ldots d(\theta, \phi)\) are the local regression coefficients near where a storm is being simulated. As an example, grids of basin-wide distribution of NAO and ENSO regression coefficients in the x direction are shown in figure 8. Positive values indicate that larger climate state values correlate positively with track displacement (positive directions being east and north), and conversely for negative values.

II. Dependence on Local Historical Variability

For the next two portions of the model, along-track residuals are used. To find those residuals, first “along-track” mean track increments in the x and y directions (denoted by \(\bar{x}(i, j)\) and \(\bar{y}(i, j)\), respectively) are calculated. This is done again using distance-weighted multiple linear regression, but this time regression is done at each historical track point \((i, j)\), rather than each domain location \((\theta, \Phi)\). This is to allow for the length scale \(L\) for the Gaussian weight used for modeling track variability to be different from the weight used in calculating mean track steps. However, after computation of OSLM to find this length, the weight turns out to be equal to 200km, for both cases. The along-track means in the x direction is given by

\[
\overline{X}(i, j) = a_0(i, j) + a_1(i, j) \cdot (NAO) + a_2(i, j) \cdot (ENSO) + a_3(i, j) \cdot (U500)
\]  
(11)

where \(a_0 \ldots a_3\) are regression coefficients which may be different for each step \(i\) of each storm \(j\).

After the along-track means by \(\bar{x}(i, j)\) and \(\bar{y}(i, j)\) are calculated, along track residuals can be found by subtracting the along track means from the actual x and y displacements of step \(i\) of storm \(j\) (denoted by \(dx(i,j)\) and \(dy(i,j)\), respectively). Thus, the residual is given by

\[
rx(i, j) = \overline{X}(i, j) - dx(i, j)
\]  
(12)

Using the along-track variances, local track variances and covariances for each lat and lon grid can be calculated to provide a spatial distribution of how much tracks typically deviate (x and y components computed separately) from the climate-climatological mean. This is done by computing distance-weighted rms-variances: At each grid point \((\theta, \Phi)\) the rms-variance of all track residuals is computed, but with each track residual weighed inversely with its distance to \((\theta, \Phi)\) using a Gaussian weight (again) with OSLM-determined length scale \((L = 200m)\). Thus, x-component of the variance at \((\theta, \Phi)\) is given by the standard rms-variance formula:

\[
\sigma = \sqrt{\frac{1}{N} \sum_i x_i^2}
\]  
(13)

where \(x_i\) is replaced with \(rx(i, j) \cdot e^{-\frac{d(i,j)^2}{2L^2}}\) (the distance-weighted residuals), and \(N\) replaced with \(\sum_{i,j} e^{-\frac{d(i,j)^2}{2L^2}}\) (the sum of the weights). The sum is over all track steps \(i\) of each storm \(j\), and the resulting \(\sigma\) varies with each location \((\theta, \Phi)\). A similar formula holds for the y-component. An
example of the variances (x component only) is shown in figure 9. During the simulation, this is
the quantity plugged into the right-hand side of (9).

The covariance of x and y increments from the historical record at location \((\theta,\Phi)\) can also be
computed with this same principle, and is given by the standard rms-covariance formula:

\[
\sqrt{\text{cov}(x,y)} = \sqrt{\frac{1}{N} \sum_{i} x_i y_i}
\]

but with the term in the sum replaced by \(r_x(i,j) r_y(i,j) e^{-\frac{d(i,j)^2}{2L^2}}\), the weighted product of residuals,
and \(N\) replaced by \(\sum_{i,j} e^{-\frac{d(i,j)^2}{2L^2}}\), the sum of the weights. The sum is over all track steps \(i\) of each
storm \(j\). These covariances are used in the next portion of the model.

III. Stochastic Component of Tracks – AR(1).

Correlation coefficients from a multiple-regression analysis of along-track residuals against the
along-track residuals \(n\) steps prior to them \((n=1,2\ldots10)\) are plotted in figure 10. The plot suggests
that the dependence of a track increment only on the track increment 1 step prior to the current one
is significant. Thus, a lag-1 autoregressive (AR(1)) stochastic model is considered in modeling
track residuals.

Before being used separately to model x and y residuals in an AR(1) stochastic model, the residuals
must be dimensionless and have unit variance. However, for the residuals in the dataset, this is not
necessarily the case. Therefore, SynthETC uses a process of standardizing residuals, which was
originally done by Hall & Yonekura (2011). This process is illustrated in figure 11, (figure is from
the Hall & Yonekura paper). If we assume the residuals follow a non-isotropic correlated bi-normal
distribution, standardizing them is equivalent to shifting the scatterplot of the along-track x and y
residuals to have zero mean (figure 11b), rotating it into its principal axis (figure 8c), and then
dividing each principal component by its respective standard deviation (figure 8d). This results in
standardized residuals in the x and y directions.

Additionally, the AR(1) component of the increments is carried out at each \((\theta,\Phi)\) using distance-
weighted residuals. As a result, this process is also done at each \((\theta,\Phi)\) and applied to the distance-
weighted residuals. The AR(1) process is computed using these standardized residuals, rather than
the original \(r_x(i,j)\) and \(r_y(i,j)\).

At every point \((\theta,\Phi)\) in the domain, full AR(1) is computed using all calculated track step
residuals in the domain, but with each track step weighted inversely with distance using a Gaussian
weight with \(L=200\text{km}\). That is, the distance-weighted linear regression between all “along-track
distance-weighted standardized residuals” and all “along-track distance-weighted standardized
track residual” immediately prior to them is computed. The result is a lag-1 correlation coefficient,
but since this is done at each location using distance weights, there is a different autocorrelation
coefficient for each location (and for the x and y components separately). These are denoted by
\(ACC_x(\theta,\Phi)\) and \(ACC_y(\theta,\Phi)\), for x and y respectively. This once again allows the regression result
(this time, strength of auto-correlation) to vary in different points of the domain. Distributions of
ACC_x(\theta, \Phi) and ACC_y(\theta, \Phi) are shown in figure 12. Higher coefficient magnitudes indicate greater strength of memory, and as anticipated from figure 10, the vast majority of coefficients are positive and within range of 0.4 (some exceptions occur in data-sparse regions). An interesting result is that these coefficients are higher over the open ocean than land, suggesting that memory is stronger over the ocean. These autocorrelation coefficients are used in the simulation along with the other results described above, as described below.

IV. Simulation of Track-Step and Summary:

A simulation for the first step of a storm consists of the following: (1) Interpolating all of the regression coefficients and distance weighted rms variances calculated in steps above to the previously determined genesis point of the storm. (2) Interpolating the climate data (U500, V500, ENSO, NAO states) to the simulated time. (3) Plugging in the interpolated climate states and regression coefficients into the regression equation (10). And finally, (4) adding a random component Z. The random component Z is added by drawing an x and y displacement from a standard normal distribution, and then transforming the it into a dimensional quantity by performing the inverse of the standardization transformation described above. That is, it is multiplied by the local x or y standard deviation \sigma, rotated inversely of how it was in figure 8, and adding whatever was subtracted in figure 8). Hence, using the variables defined above, the first track increment in the x and y direction of a simulated storm is given by:

\begin{align}
    dx_{\text{sim}} &= X + \text{Trans}^{-1}\{N(0,1)\} \\
    dy_{\text{sim}} &= Y + \text{Trans}^{-1}\{N(0,1)\}
\end{align}

where Trans^{-1}\{\} indicates the application of the inverse of the above-described transformation, and N(0,1) represents a draw from a standard normal distribution. Note this is exactly equations (9), but with the \sigma being absorbed into the Trans^{-1}\{\} term, because it is used in the inverse transformation.

A simulation of all other steps of the storm consists of repeating steps 1-3 listed above, and then modifying step 4 as follows. First, interpolate ACC_x(\theta, \Phi) and ACC_y(\theta, \Phi) to the current storm point. Then, instead of simply applying the inverse transformation to a random draw from the standard normal, apply it to a quantity that varies in value depending on the strength of ACC_x(\theta, \Phi) and ACC_y(\theta, \Phi) at that point. This quantity is given by:

\begin{align}
    z_t = ACC(\theta, \phi) * z_{t-1} + \sqrt{1 - ACC(\theta, \phi)^2} * N(0,1)
\end{align}

where z_{t-1} is the standardized residual at time the previous time step. This is a standard AR(1) stochastic process, and predicts the future step by a mix of memory and randomness which is determined by the strength of the memory in the region (which in turn was determined by historical trends).

Finally, x and y displacements of the simulated track step are then given by
In summary, the model predicts the general direction and magnitude of a simulated storm track displacement as a regression mean, using multiple linear regression of regional historical displacements against NAO, ENSO, and climatological winds. Then, it perturbs that displacement by adding a residual which has a random and memory component, the strength of which depends on the historical strength of memory in storm tracks found in the simulated storm’s region.

2.D - Lysis:

The procedure for lysis is different from the Hall and Booth, (2017) approach. It is similar to the genesis and track approaches in that grids of regression coefficients are generated. This time, the coefficients are determined by logistic regression, where the predicted variable is the probability of occurrence of lysis (denoted by $P_L$), where occurrence of lysis is denoted by “1” in the data, and lack thereof is denoted by “0”. The regression at each location $(\theta, \Phi)$ is of “nearby” terminal storm points against the NAO and ENSO climate states on the dates of their termination, where “nearby” refers to all storm track points within 500 storm-track points of the current location being evaluated. [RU: I could not find a documented reason as to why 500 is used here, however it is likely some statistical optimization method was used]. Thus, the probability of lysis at a given point in the grid at a particular six-hourly step is given by

$$ p_{\theta, \Phi, t} = \frac{1}{1 + e^{a_0 + a_1 \times (\text{NAO}) + a_2 \times (\text{ENSO})}} , $$

(18)

where $a_0, a_1,$ and $a_2$ are the regression coefficients.

Simulation:

During the simulation, for each six-hourly step starting at step 6, the NAO and ENSO indices of the simulated day of year are combined with the regression coefficients interpolated to the storm point using equation (13), to generate a lysis probability. A random number $X$ from a uniform(0,1) distribution is drawn. If $X < p_{\theta, \Phi, t}$, then the storm is terminated. If not, the next step of the storm is simulated by the track component of the model.

2.E - Intensity

Intensity of a storm in the Hall and Booth model is defined as local central pressure (CP) deficit with respect to local SLP climatology. Hall and Booth (2017) have implemented a resampling method where after a synthetic storm track has been generated, a “realistic” (described below) CP time series is applied to the existing track. After being applied, it is rescaled to fit the length of the track. Then it is perturbed to allow for maximum intensities outside of the historical intensity range. Resampling historical intensities after a storm is fully generated works here because we are
not interested in the development of the intensity of any individual storm, but rather predictions of numbers of storms within certain regions and intensity ranges.

Selection of Intensity Time Series:

The selection of a CP time series for a simulated storm from the set of historical time series is random, but weighted towards the choosing a realistic time series for that storm. “Realistic” time series is defined as one whose special qualities (defined next) most closely resemble that of the historical storm. These special qualities are day of year, duration of track, and the locations of track formation, ¼-point, midpoint, ¾-point, and termination point of track. The weight applied to each of these seven qualities is given by $w_q = e^{-\frac{d_q^2}{2L_q^2}}$ where $d$ is the difference between the simulated storm’s quality and historical storm’s quality, and $L_q$ is the scale parameter (determined by OSLM). The values of the scale parameters are 30km each for storm track locations, 30 days for day of year, and 0.2 track-steps for duration of track. The probability of a CP series being selected for a simulated storm is then just the normalized product of all the weights $w_q$. During the simulation, a random CP series is selected (uniformly), and it’s probability $w$ is compared to that of a random number $X$ coming from a uniform(0,1) distribution. If $w > X$, this CP series is used for the track. If not, then another CP series is randomly selected, and the process repeats until the $w > X$ condition is met and a series is selected. The selected CP series is then shifted and scaled in time to match the start date and duration of the simulated storm track (if these qualities are in fact different).

Figure 13 is an example of a simulated track (in blue) with historical tracks (in red) whose CP time series have $w > 0.001$ (Hall and Booth, 2017). The solid track has $w = 0.2$. It is clear that sampled time series will have similar track shape and length (but not identical) to the simulated track.

Perturbation of Maximum Intensity:

Once the CP series is selected for the simulated storm, the maximum intensity is perturbed so that simulated maximum intensities are not limited to the historical values. The perturbation method is done in a way such that the distribution of the perturbed set conforms closely to the unperturbed set. This is done for a simulated track as follows. (1) Fit historical CP maxima to a generalized extreme value distribution (here, a Weibull($k=1.45, \lambda=15$)). (2) Find the p-value associated with each simulated track’s central pressure maximum as per this distribution. (3) Compute $z = \Phi^{-1}(p)$ for each storm, (where $\Phi$ represents the standard normal cdf). (4) Then add to each $z$ a value $M*z'$, where $M$ is the desired standardized perturbation magnitude and $z'$ is a random number from a standard normal. The choice of $M$ is 0.1 (units of standard normal), but is irrelevant to this study, since the intensity portion of the model is not being evaluated here. (RU: In my opinion, this value is critical, since it would effectively dictate the frequency of very intense storms. I was not able to ascertain how this value was selected) (4) Normalize across the new set of $z'$ so they form a normal distribution. (5) Then convert the $z$’s back to central pressures by performing the inverse of steps (1)-(3) for each simulated track. Finally, re-scale the central pressure series for each storm to fit the minimum and new maximum intensity without large jumps in intensity.
Figures for Chapter 2

Figure 4 - Generic example of Gaussian weighting kernel. L=30 grid-points.

Figure 5 - Historical genesis pdf, averaged over DJF (top left), MAM (bottom left), JJA (top right), and SON (bottom right) months. Units are normalized probability values.
Figure 6- Spatially varying genesis regression coefficients computed using local distance-weighted Poisson regression.

Figure 7- Example of a grid of mean genesis rates, scaled to the interval [0,1]. Points outside the most common genesis region near point B are much more likely to be selected by model for locating genesis of simulated storm, but will rarely (but not never) successfully produce a storm there, due to scaled values close to 0. Area near point B will be selected less frequently, but for each selection, storm genesis is far more likely.

Figure 8- Track regression coefficients multiplying NAO (left) and ENSO (right) states for the x-component of track displacement.
Figure 9: Local distance-weighted root-mean-square residuals for the x-component of the tracks.

Figure 10: Multiple linear regression of steps that are 1, 2... 10 steps behind the present track step residuals (or anomalies) against the present track step, for all steps.
Figure 11 - Scatterplot of distance-weighted storm track residuals at an arbitrary location in the domain (top left). The residuals are made dimensionless and de-correlated by subtracting out the means (top right), then rotating the data ellipse into it's principal axis (bottom left), and then dividing residuals by the standard deviation (bottom right).

Figure 12 - Grid of local AR(1) correlation coefficients. Higher values indicate strength of 1-step memory in influencing track steps.
Figure 13- Example of CP time series selection. Simulated storm track is in blue. Bold red historical track's CP time series has greatest probability of being selected for simulated track (p=0.35), thin red tracks are all historical tracks with probability > 0.001 of being selected for simulated track.
3. Model Diagnostics

3.A Preliminary Evaluation

A random sample of 40 synthetic tracks are plotted in figure 14. From this, it appears that SynthETC broadly reproduces the typical distribution of ETC tracks in the North Atlantic. A number of quantitative diagnostic measures are performed for SynthETC after running 50 simulations of the historical time period 1979-2015. The first are latitude and longitude crossings at 5-degree intervals of longitude and latitude, respectively (figure 15). For example, the red in the left-hand side of figure 15 shows the relative amount of storms crossing six fixed latitudes within 5-degree longitude bins. The reverse case (storms crossing fixed longitudes within 5-degree latitude bins) is shown on the right. The blue dashed lines show the upper and lower ends of the two standard deviation spread (2σ) of 50 model simulations.

The result largely matches that of Hall and Booth (2017). The latitude crossings show general agreement between model and simulations except in a region between the upper Midwest and lower Hudson Bay area, and in a region between New Brunswick and the western Labrador Sea, where the model underestimates norward-crossing storms. The longitude crossings in the model and simulations are also largely in agreement, except in a region between Boston and Newfoundland, where the model slightly under-predicts eastward storm crossings, and an area east of Newfoundland, where the model over-predicts eastward crossing storms.

It is likely that the lack of northward latitude crossings in the southern Labrador Sea region, and excess eastward longitude crossings south and east of this region is related to too many storms moving eastward in this region, and not enough northward. A commonly observed trend in extratropical cyclone activity in the North Atlantic is that storms tend to “hook” over the southern Labrador Sea, making a turn from the general northeast direction to a north-northwest direction. This hooking is particularly present during anomalously strong blocking events near Iceland, which is strongly coupled with NAO state. It is possible that the excess eastward tracking storms and lack of northward tracking storms, is due to the failure of the model to capture this hooking.

Figure 16 shows track-point density differences (history minus model) in units of standard deviations in color. Negatively valued (blue) areas suggest the model over-predicts the track-point density, and the reverse holds for positively valued (red) regions. Regions with a less than two standard deviation difference between model and history are suppressed. In the left panel there are contours of historical track point density, in the right panel contours of average simulated track point density are shown. Again, the main biases of concern are those near the Labrador Sea, with too few simulated storms points over the sea west of Greenland, and an excess of storm points east of Greenland. However, there are very few biases in the regions where storms traveling into these regions come from (off the coast of New England and Southern Canada). From the contours, there is a clear shift visible This is consistent with the above theory of not enough storms “hooking”, and taking a northwesterly turn over the southern Labrador Sea, and continuing to travel northeast past Greenland. (RU: one clear next task for this is to compare the propagation angle between the model and historical tracks using the metric from Booth et al. 2016. One could also compute changes in propagation angle.) From the contours, we can see there is a clear shift in storm track
points from a region to the immediate southeast of Greenland in the historical data, further to the east in the simulations. This could be due to simulated storms moving too fast zonally, relative to meridionally (addressed in the speed bias section).

Next, storm-step speeds are examined. This speed is the great-circle distance between successive six-hourly storm track points (in km), divided six hours. Histograms (normalized to probability distributions) of these speeds for 50 simulations of the model and history are plotted in figure 17. The histogram shows a clear bias in the model towards faster steps (p on the order of 10^-7 in a Kolmogorov-Smirnov test). Plotting such histograms for speeds averaged over entire storm lifecycles (figure 18), shows that there is also a discernable bias in the model (p=0.011 in a Kolmogorov-Smirnov test), but the difference is significantly smaller. Thus, the model may be accelerating or decelerating storms into (or out of) speeds within/below reasonable historical range, out of (or into) speeds outside the reasonable historical range. The track-step speed bias seems like the clearest bias in the model, and it was not discovered in Hall and Booth (2017). Thus, it will be a focus of this paper to assess this bias. However, since the core component of generating varying track steps is the stochastic component of the model, first, model behavior under varying amounts of stochastic signaling is examined.

### 3. B Exploring Modifications to the Stochastic Component

Recall equation (17), the formula for determining the step of a storm at time \( t + 1 \), for \( t > 1 \), which is reproduced below.

\[
\begin{align*}
\Delta x_{i, t+1} &= \bar{X} + \text{Trans}^{-1}[ACC_x(\theta, \phi) \cdot z_{t-1} + \sqrt{1 - ACC_x(\theta, \phi)^2} \cdot N(0,1)] \\
\Delta y_{i, t+1} &= \bar{Y} + \text{Trans}^{-1}[ACC_y(\theta, \phi) \cdot z_{t-1} + \sqrt{1 - ACC_y(\theta, \phi)^2} \cdot N(0,1)]
\end{align*}
\]

The formula could be intuitively modifying in the following ways: Set the memory to zero (\( ACC(\theta, \phi)=0 \) for both \( x \) and \( y \)). This is effectively a white-noise model for the residuals to the track mean, with randomness only (called “JRAND” here). The new formula for the track step is given by equation (19). Alternatively, the randomness can be set to zero (\( ACC(\theta, \phi)=1 \) for both \( x \) and \( y \)), which leaves only memory to be taken into account for computing the residuals (called “JMEM” here). The new formula for the track step is given by (20).

\[
\begin{align*}
\Delta x_{\text{JRAND}} &= \bar{X} + \text{Trans}^{-1}[N(0,1)] \\
\Delta x_{\text{JMEM}} &= \bar{X} + \text{Trans}^{-1}[z_{t-1}]
\end{align*}
\]

Instead of the above modifications, one can imagine eliminating parts of (17) without explicitly setting ACC to 0 or 1. Eliminating the left-hand term in the residual yields a quantity which is random, but the significance of randomness is increased or decreased at various points in the domain inversely with local strength of memory (AR(1) coefficient\( ACC(\theta, \phi) \)). The new formula for the track step given by (21), and this will be called “VRAND”, for varying amounts of randomness. Conversely, eliminating the right-hand term yields a quantity, which is determined by memory, but the strength of the memory is allowed to vary across the domain in proportion to
the local strength of memory. The new formula for the track step in this case is given by (22) here, and it is referred to as “VMEM” here, for varying amounts of memory.

\[
\begin{align*}
\mathbf{dx}_{\text{RAND}} &= \bar{X} + \text{Trans}^{-1}\left[\sqrt{1 - ACC_x(\theta, \phi)^2} * N(0,1)\right] \\
\mathbf{dx}_{\text{VMEM}} &= \bar{X} + \text{Trans}^{-1}\left[ACC_x(\theta, \phi) * z_{t-1}\right]
\end{align*}
\]

The model evaluation analyses above are repeated for each version of the track modification described above; first for JRAND and JMEM, then for VRAND and VMEM.

Results Using JRAND and JMEM:

The track point density, latitude/longitude crossings, and track speed distributions for the JRAND and JMEM model versions are shown in figure 19, 20, 21, and 22, respectively. JRAND is shown in the lower left panel, JMEM in lower right, and default SynthETC result is reproduced for comparison in the top panel.

Track-point density is not significantly different in the JRAND white noise model from the default, except for a slight increase in bias over the central North Atlantic and some small improvement in the biases near southeastern Greenland and the Hudson Bay area for the JRAND (white-noise) model, but other than that no clear differences appear. The JMEM model produces biases of stronger magnitude (but same in nature) than the default SynthETC model over the Labrador Sea and south east of Greenland. In figures 20 and 21, changing the model to JRAND does not improve model-history agreement in the latitude and longitude crossings. It worsens the bias in the eastern parts of the domain with too many storms crossing northward and eastward there, and fewer storms are crossing latitudes northward near the southern Labrador Sea where there was already a low model bias in the default SynthETC model. It is clear that strengthening white noise, or randomness is not likely to fix the potential lack of “hooking” over the south Labrador Sea. JMEM has a very different impact. It causes too few latitude and longitude crossings all throughout the eastern portions of the domain, suggesting perhaps that simulated storms are nearly stationary. Figure 22, lower right panel confirms this assertion, showing a sharp peak in track-step speed frequency near zero km/hr. Also, figure 22 shows that the bias in the track-step speed distributions is not improved in the JRAND model, and instead is made slightly worse.

Results Using VRAND and VMEM:

Results for the VRAND and VMEM models are shown in Figures 23-26 just as they were for JRAND and JMEM in figures 19-22. Figure 23 shows only minor changes in model-history agreement when changing the model to VRAND. Changing the model to VMEM results in increase in model-history agreement, with an increase in the excess storm track-points off the coast of Greenland, and low storm track-point counts over the central United States, eastern North Atlantic, and Labrador Sea. From figures 24 and 25, we see that the SynthETC biases in storm crossings are made worse by both JRAND and JMEM models. Both models also send too many storms northward in the eastern North Atlantic, while the JMEM model also has a large spike in eastward-crossing storms in the central and eastern North Atlantic. From figure 26, it is clear that the JMEM model makes the speed distribution bias significantly worse than the JRAND model, and adds a bi-modal characteristic in the speed distributions not observed in the historical set.
In summary, none of the four modified models perform better than the default SynthETC model by any of the discussed metrics, and the VMEM and JMEM models produce more disagreement with historical data than the JRAND and VRAND models do. In other words, suppressing the random component is worse than suppressing the memory component of the track model.

3.C Evaluating SynthETC’s Speed Bias

Next, the speed bias of SynthETC is addressed more directly. Figure 27 shows the local speed bias on a 2 by 2 lat-lon grid by averaging the track step speeds for all track steps that touch the gridpoint in the historical data and the model, and subtracting the historical average from the model average. This is done also for the zonal component (lower left of figure 27) and meridional component (lower right of figure 27). Note that the differences are not filtered by statistical significance, so not all of the biases are statistically significant. However, this shows that the high-speed bias is mainly located over the North Atlantic and Canada, and the bias is primarily in the zonal direction. Figure 28 plots the zonal and meridional track-step speed distributions, and confirms the assertion of higher bias in the zonal direction. This can be seen as being consistent with the latitude and longitude crossings, which showed too many storms crossing eastward and not too many crossing northward over the eastern North Atlantic.

Figure 29 plots the models local track-point density * local speed bias, minus the historical local track-point density * local speed bias. Thus, this is the combined bias of track-point density and track step speeds. Over northeastern Canada and Hudson Bay, there is a low bias in the model, but comparing this with track-point density of figure 16, this bias is primarily due to track point density, and not speeds. However in the region off the eastern US coast (which is also the primary region for extratropical cyclone development), the figure 29 bias is the strongest, and has no corresponding bias in track point density. Thus, the region where most cyclones develop is the region where one is most likely to find a simulated storm moving too quickly during any given time within a simulation. Figure 30 plots the 25 fastest storms from a random simulation and compares them with the 25 fastest historical storms, and shows that the model’s fastest storms are more concentrated in this same region than the historical storms, which compounds the bias in figure 29 to be very high.
Figures for Chapter 3

Figure 14 - First 40 simulated tracks from a random simulation.

Figure 15 - Relative number of storms crossing northward over fixed latitudes (left) and eastward over fixed longitudes (right), in 5-degree longitude/latitude bins. Red indicates historical record, and the pairs of blue dashed lines indicate the two standard deviation model spread. This is a re-production of figure 8 from Hamm & Booth (2017), and is largely in agreement.

Figure 16 - Track point density difference (50-simulation SynthETC average minus historical) on a 2-by-2 degree lat-lon grid, in units of model standard deviations. Colored areas are areas of domain where historical track-point density is more than two standard deviations outside model spread. Red contours show historical track point density, and purple contours show average simulated track point density, in units of $5 \times 10^{-4} \text{ km}^{-2}$. 
Figure 17- Probability distribution of mean track step speeds: 50 simulations of SynthETC model, and historical data.

Figure 18- Probability distributions of mean track speeds: 50 SynthETC simulations and historical data.
Figure 19: As in figure 16 (without contours), for default SynthETC (top), JRAND (bottom left), and JMEM (bottom right) versions of the model.

Figure 20: As in figure left side of 15, for default SynthETC (top), JRAND (bottom left), and JMEM (bottom right) versions of the model.
Figure 21: As in right side of figure 15, for default SynthETC (top), JRAND (bottom left), and JMEM (bottom right) versions of the model.

Figure 22: As in figure 17, for default SynthETC (top), JRAND (bottom left), and JMEM (bottom right) versions of the model.
Figure 23: As in figure 16 (without contours), for default SynthETC (top), VRAND (bottom left), and VMEM (bottom right) versions of the model.

Figure 24: As in figure left side of 15, for default SynthETC (top), VRAND (bottom left), and VMEM (bottom right) versions of the model.
Figure 25 As in figure right side of 15, for default SynthETC (top), VRAND (bottom left), and VMEM (bottom right) versions of the model.

Figure 26- As in figure 17, for default synthetic (top), VRAND (bottom left), and VMEM (bottom right) versions of the model
Figure 27- Local track step speed difference (50-run SynthETC model average minus history) calculated as km/hr on a 2-by-2 degree lat-lon grid. Zonal component (bottom left) and meridional component (bottom right).

Figure 28- As in figure 17, but zonal (left) and meridional (right) components of track-steps.
Figure 29- Product of speed difference and track point density of figures 16 and 28.

25 fastest tracks of 1 SynthETC simulation

25 fastest tracks of historical data

Figure 30- (Left) 15 fastest tracks of one random SynthETC simulation. (Right) 25 fastest tracks of historical record.
4. Conclusions and Discussion

SynthETC is a statistical model for genesis, tracks, lysis, and intensity of extratropical cyclones. Storm genesis is modeled as a Poisson process, tracks are modeled as a stochastic red-noise process, lysis is modeled with binomial probabilities determined with regression, and intensity was modeled using a resampling and perturbation method. Of these components, only the track component was modified and evaluated in detail.

The most prevalent model biases were at high latitudes: over northern Canada, Labrador Sea, and southern Greenland. Not enough simulated storms are moving northward into and over the Labrador sea, suggesting a possible lack of “hooking” which often occurs during periods of strong Icelandic blocking. Other results show that there is less SynthETC model bias over the east coast and central United States, which is more promising for prediction of storm frequencies over densely populated land.

One possibility for improving model-history agreement is resolving the lack of hooking that may be taking place. However, this hooking is strongly coupled with the NAO index, which is taken into account in the track component of the model. Perhaps then, it is the case that computing a mean track-step using climate states as a part of regression, and then separately computing a step-anomaly without using the climate states is not a sufficient way of encoding the impact of climate states (or NAO specifically) on the track component of cyclones. Perhaps it is necessary to also model the track-step anomaly as dependent on climate states in order to get the climate states to “cause” a turn (or hook in this case) in a storm track.

Figure 31 shows a set of 40 tracks simulated using only the mean track increment, and no anomaly (that is, only the first term on the right hand side of equation 17). The tracks mostly appear almost as straight or very smooth lines, with no sharp turns. This suggests that regardless of climate state, thus the only thing available to the model for turning tracks is the red-noise component (second term on the right hand side of equation 17), which does not depend on climate states. If the thing that leads to hooking is the NAO climate state (indirectly via Icelandic blocking), then the NAO climate state needs to have the ability to turn simulated storms, which may not be the case in SynthETC. A possibility for future research is to work such an effect more explicitly into the model.

Another possibility for future research is to account for statistical significance when computing local regression of climate states onto track displacements. Currently, regression coefficients are used for computing the track increments regardless of their statistical significance. It is possible that the effect of the NAO climate states at some points in the domain is being washed away in the regression, which is computed using two other predictors, which are possibly less relevant. In general, coefficients may be significant or insignificant at different parts of the domain as well. The method to improve this would be to check, during the computation of regression coefficients, if some or all of the coefficients confidence bounds include zero. If they do, those coefficients would not be used on the model, and only significant ones would be used. If no coefficients are
significant, a regional average track step can be computed (this is done already in areas where regression fails).

Another finding is that the model is sending storms too fast. This is especially true in the region where extratropical cyclones are more prevalent, suggesting that the bias may be systematic. This can be further assessed by introducing bias correctors into the model (i.e., for every simulated storm step – if the step is over some predetermined threshold, re-simulate the step), and observing to what extent this corrects the speed bias. It is possible also that regression with insignificant coefficients is over-predicting track features such as speed.

A second set of conclusions relates to modifying the red-noise component of the model. Neither the “more random” or “more memory” models improved model biases in any part of the domain. It was also clear that keeping the random portion of the red-noise model was more critical to maintaining model accuracy than keeping the memory portion of the model, which is a testament to the importance of randomness in the modeling of cyclone tracks (especially over land, since AR(1) coefficients in figure ---- were significantly lower over land).

Lastly, a possible route of investigation is clustering. Is SynthETC (perhaps in computing mean genesis rates or mean track steps) washing away certain characteristic clusters of storms characteristics? Evidence for clustering has been found by Mailier et al. (2006), and cluster analysis has not yet been considered in SynthETC. Cluster analysis of storm characteristics could provide some insight into this matter.
Figures for Chapter 4

Sample of 40 tracks from random simulation, mean track only

Figure 31- 40 tracks generated using only mean track component of SynthETC.
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