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Towards Dynamical Seasonal Forecast of Extratropical Transition in the North Atlantic

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Key Points:
- This study is one of the first attempts on the retrospective seasonal forecast of extratropical transition
- The global model shows good skill in predicting basin-wide and regional extratropical transition activity months in advance
- Limited skill in predictions of nontransitioning storms calls for improvements in future work

Supporting Information:
- Supporting Information S1

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Abstract Extratropical transition can extend the threat of tropical cyclones into the midlatitudes and modify it through expansion of rainfall and wind fields. Despite the scientific and socioeconomic interest, the seasonal forecast of extratropical transition has received little attention. The GFDL High-Resolution Forecast-Oriented Low Ocean Resolution (FLOR) model (HiFLOR) shows skill in seasonal forecasts of tropical cyclone frequency as well as major hurricanes. A July-initialized 12-member ensemble retrospective seasonal forecast experiment with HiFLOR in the North Atlantic is conducted, representing one of the very first attempts to predict the extratropical transition activity months in advance. HiFLOR exhibits retrospective skill in seasonal forecasts of basin-wide and regional ET activity relative to best track and reanalysis data. In contrast, the skill of HiFLOR in predictions of non-ET activity is limited. Future work targeted at improved predictions of non-ET storms provides a path for enhanced TC activity forecasting.

Plain Language Summary Extratropical transition (ET) is the process that tropical cyclones evolve from warm-core symmetric systems to cold-core asymmetric systems. Tropical cyclones undergoing transition can extend the threat of storms to midlatitudes by severe fresh flooding associated with enhanced rainfall (e.g., Hurricane Agnes, 1972) and storm surge associated with storm reintensification (e.g., Hurricane Sandy, 2012). Seasonal forecasts of ET activity have the potential to provide guide for storm preparedness and risk management. However, there have been few studies on this topic. This study provides the first attempts to predict ET activity months in advance in the North Atlantic using a global climate model. The model exhibits good skill in predicting basin-wide and regional ET storm frequency. In contrast, limited skill in predictions of non-ET storm frequency points to the need for improvement in future.

1. Introduction

Extratropical transition (ET) of tropical cyclones (TCs) is referred to as the process where TCs lose the tropical characteristics and become comparable to the structures of extratropical cyclones (EXs). This process is often associated with the interaction between the cyclone and midlatitude environment as the TC moves poleward. Comprehensive reviews of ET can be found in Jones et al. (2003) and Evans et al. (2017). A prominent feature of transitioning TCs is the spatial expansion of the gale-force wind fields (e.g., Evans & Hart, 2008), extending the threat of TCs to a larger area. This threat can be enhanced through rapid reintensification of the TC due to interaction between the cyclone and extratropical systems (Jones et al., 2003, and references therein). The reintensification associated with ET was a key element of the catastrophic storm surge of Hurricane Sandy in 2012 (Galarneau et al., 2013). In addition to wind and surge, heavy rainfall and associated flooding is another key component of the extreme weather conditions associated with ET (e.g., Atallah et al., 2007; Atallah & Bosart, 2003; Carr & Bosart, 1978; Colle, 2003; Jones et al., 2003; Liu & Smith, 2016). The prediction of ET activity is thus a topic of both scientific interest and socioeconomic significance.

Whereas prediction of ET for individual storms hours-to-days in advance can provide guidance for storm warning and evacuation, seasonal forecast that focuses on regionally specific ET activity aggregated over a season has potential utility to risk management and advancing our understanding of the climate controls on ET. However, there are few studies on the prediction and predictability of ET with a lead time of months. Most of the efforts on seasonal forecasts of TCs put little focus on ET activity. Recent advances in high-resolution dynamical modeling have enabled skillful seasonal prediction of basin-wide TC frequency (e.g., Alessandri et al., 2011; Camargo & Barnston, 2009; Camp et al., 2015; Chen & Lin, 2013; LaRow et al., 2010; Vitart et al., 2007; Zhao et al., 2010). Specifically, a recently developed global High-Resolution Forecast-Oriented Low Ocean Resolution (FLOR) version of the Geophysical Fluid Dynamical Laboratory's (GFDL) Coupled Model version 2.5 (Delworth et al., 2012) model has shown skill in simulation and seasonal prediction of regional TC activity (Vecchi et al., 2014) and extratropical storm activity (Yang et al., 2015) in the North Hemisphere. Hybrid statistical-dynamical models based on FLOR show promising results for predicting landfall TC frequency months in advance (Murakami, Villarini, et al., 2016; Zhang et al., 2017). Further, Liu et al. (2017) have shown that the FLOR model is capable of simulating ET activity in the North Atlantic. Recently, a version of FLOR with higher horizontal resolution for the atmosphere and land component (HiFLOR) shows improved seasonal prediction of tropical storms and hurricanes than FLOR, especially for major hurricanes (Murakami, Vecchi, et al., 2016). We follow on those promising results and use HiFLOR to evaluate the potential for skillful dynamical seasonal forecasting of ET activity in the North Atlantic. We introduce methods in section 2 and data in section 3, followed by results in section 4. Section 5 gives the summary and discussion.

2. Methods

2.1. Dynamical Model

We use the HiFLOR (Murakami et al., 2015), which has atmospheric and land components with horizontal grid spacing of approximately 25 km and horizontal grid spacing of approximately 1° for the ocean and sea ice components. HiFLOR was developed from FLOR by increasing the horizontal resolution of the land and atmosphere components, and shortening the time-step for calculation of atmospheric dynamics, but keeping all other elements of the model (including subgrid parameterizations) identical to FLOR. To evaluate the skill of HiFLOR in predicting ET activity in the North Atlantic, we evaluate a 12-member ensemble suite of 1 July initialized retrospective seasonal forecasts over the period 1980–2016. For each year, we focus on the core season (July–November) of ET activity (Hart & Evans, 2001; Liu et al., 2017). The 12-member ocean and sea ice components are initialized to observation-constrained conditions using GFDL's ensemble coupled data assimilation system (Chang et al., 2013; Zhang & Rosati, 2010). The atmosphere and land initial conditions are generated from a suite of HiFLOR atmosphere-land-only simulations driven by observed sea surface temperature (Vecchi et al., 2014; Yang et al., 2018). HiFLOR was also used in Murakami, Vecchi, et al. (2016) to explore seasonal TC predictability and Kapnick et al. (2018) to explore seasonal snowpack predictability. But they initialized the atmosphere and land components using an arbitrary year of a climate control simulation, which may represent a lower bound of the prediction skill of HiFLOR relative to the initialization in this study (Jia et al., 2016, 2017).

Tropical cyclone storms are tracked from instantaneous 4×-daily model output using the tracker developed by Harris et al. (2016) as implemented in Murakami et al. (2015). Briefly, this tracker uses a flood fill algorithm to identify storm centers with warm-core (localized 300- to 500-hPa temperature maxima of at least 2 K) and sea level pressure minima surrounded by closed contours at least 2 hPa higher than the minima. For each detected TC, the tracker also requires a lifetime duration of at least 72 hr, consecutive 36 hr of warm-core, and maximum surface wind higher than 17.5 m s^{-1}.

We use regional storm frequency to assess the skill of HiFLOR in predicting regional storm activity. We define the regional storm frequency in each 2° grid box as the total number of storm days in a season for which the storm centers of TCs are within 500 km from the box (similar to Liu et al., 2017; Vecchi et al., 2014). The use of 500-km storm size is consistent with observational assessments of typical TC size (e.g., Chavas & Emanuel, 2010) and the size used for ET studies (Evans & Hart, 2003; Hart, 2003). We compute the regional storm frequency for both HiFLOR predictions and observations and compare the two to explore the predictability of regional storm activity.

2.2. Cyclone Phase Space

We use the cyclone phase space (CPS) to determine the occurrence of ET events. This method has an objective definition of ET and requires only thermal geopotential heights at isobaric levels as inputs. It has been used in a range of individual storm analyses (e.g., Bao et al., 2015; Griffin & Bosart, 2014; Liu & Smith, 2016; Wang et al., 2012; Yang et al., 2017) and in ET climatology studies (Kitabatake, 2011; Song et al., 2011;

Table 1
The Rank Correlation and MSSS of Basin-Wide ET Frequency for the TC Group Among HiFLOR Retrospective Forecasts and HURDAT, JRA55_HURDAT, CFSR_HURDAT, and CFSR_CFSR in the North Atlantic During the 1980–2016 July–November Seasons

		HURDAT	JRA55_HURDAT	CFSR_HURDAT	CFSR_CFSR
RCOR	ET	0.49	0.51	0.45	0.45
	Non-ET	0.46	0.37	0.46	0.60
MSSS	ET	0.08	0.08	0.14	−0.02
	Non-ET	−0.64	−0.64	−0.34	−0.45

Wood & Ritchie, 2014; Zarzycki et al., 2017). CPS characterizes the thermal evolution of storms with three parameters: 900- to 600-hPa thermal thickness asymmetry (B), 900- to 600-hPa thermal wind ($-V_T^L$), and 600- to 300-hPa thermal wind ($-V_T^U$). One can refer to Evans and Hart (2003) and Hart (2003) for a detailed description of the three parameters. The onset of ET is triggered when B is larger than 10 m or $-V_T^L$ is lower than 0. The completion of ET is determined when the two conditions are both satisfied (Liu et al., 2017; Wood & Ritchie, 2014; Zarzycki et al., 2017). For HiFLOR, we employs a simplified version of the CPS method that uses 850- to 500-hPa thermal thickness asymmetry (B), 850- to 500-hPa thermal wind ($-V_T^L$), and 500- to 300-hPa thermal wind ($-V_T^U$) due to the availability of data. In spite of similar performance between the two versions of CPS, the use of the simplified CPS may represent a low bound of the prediction skill of HiFLOR for ET activity relative to the use of the standard version.

For convenience, a storm undergoing ET is called an ET storm. A storm that does not undergo ET is a non-ET storm. For an ET storms, the phase before the onset of ET is called TC phase. While the phase after the onset of ET is ET/EX phase where EX indicates that, after the completion of ET, the storm property more resembles an EX.

3. Data

We use observed TC "best tracks" from the National Hurricane Center hurricane database (HURDAT2; Landsea & Franklin, 2013) for the period 1980–2016. To be consistent with the tracker in FLOR, we use TCs with at least tropical storm intensity (i.e., wind speed ≥17.5 m s^{-1}) as well as 72-hr lifetime duration. Two reanalysis data sets are employed: the 6-hourly, 0.5° National Centers for Environmental Prediction Climate Forecast System Reanalysis (CFSR; Saha et al., 2010) and the 6-hourly, 1.25° Japanese 55-Year Reanalysis (JRA-55; Kobayashi et al., 2015). We combine the two reanalysis data sets separately with HURDAT tracks to find all storms undergoing ET over the period 1980–2016.

To compensate the inconsistency between TCs from reanalysis and HURDAT, we track storms in CFSR using the HiFLOR tracker but relaxing the criterion for warm-core and maximum surface wind speed due to the poor skill of CFSR in representing TC intensity. With these tracks, we apply CPS method in CFSR to find all ET storms over the period 1980–2016, referred to as CFSR_CFSR. The two ET data sets based on HURDAT tracks are named as CFSR_HURDAT and JRA55_HURDAT, respectively.

HURDAT gives an "EX" sign for a TC once its major energy source is baroclinic (McAdie et al., 2009), providing another ET data set. We use the four ET data sets (i.e., HURDAT, JRA55_HURDAT, CFSR_HURDAT, and CFSR_CFSR) as references to evaluate the forecast skill of HiFLOR for ET activity in spite of uncertainties associated with them. The contrasting properties of ET and non-ET storm tracks from the four references are well represented by HiFLOR (Figure S1 in the supporting information).

4. Results

We assess the retrospective forecast skill for basin-wide ET and non-ET storm frequency through the Spearman rank correlation (RCOR) and mean square skill score (MSSS). MSSS evaluates the prediction skill of the model against the climatological forecast. For both RCOR and MSSS, positive values indicate prediction skills with 1 pointing to perfect forecast, while negative values indicate failures in performance. The RCORs and MSSSs of predicted basin-wide ET frequency versus observational estimates of ET frequency from the four reference data sets over the period 1980–2016 (for the July–November season) indicate significant skill (Table 1). The comparison of HiFLOR prediction with CFSR_CFSR has lower MSSS than for the other three reference data sets. CFSR_CFSR detects TC storms by adopting the tracker for HiFLOR but with slight changes. On the one hand, CFSR_CFSR avoids the inconsistency between HURDAT tracks and atmospheric records as seen in CFSR_HURDAT. On the other hand, the deficiency of reanalysis data and the imperfection of tracking schemes in characterizing TC and ET activity may weaken the reliability of CFSR_CFSR (see Murakami, 2014; Schenkel & Hart, 2012). The two aspects highlight the uncertainties in both CFSR_CFSR and CFSR_HURDAT,

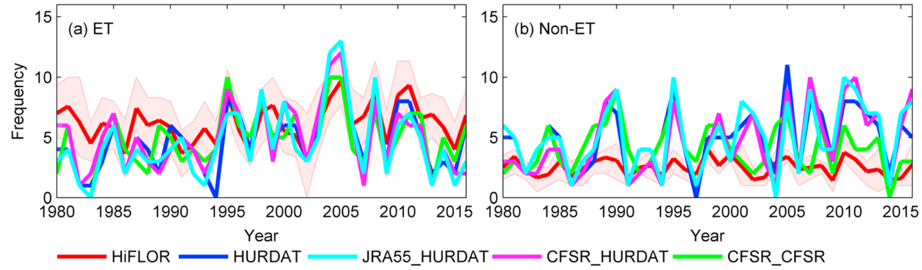

Figure 1. Annual frequency of (a) extratropical transition (ET) and (b) non-ET storms for the ensemble mean of the 12-member High-Resolution Forecast-Oriented Low Ocean Resolution model retrospective forecasts in the North Atlantic during the 1980–2016 July–November seasons. The upper and lower boundary of the pink area indicates the 90th and 10th quantiles of the interensemble spread, respectively. The annual storm frequency from HURDAT, JRA55_HURDAT, CFSR_HURDAT, and CFSR_CFSR is shown for comparison.

thus we use all the data sets as reference in evaluating the ET activity predicted by HiFLOR. Intercomparisons of the four references using RCORs indicate higher similarities for basin-wide ET frequency among data sets adopting HURDAT (Table S1 in the supporting information), suggesting a certain role of tracks in characterizing the ET activity.

In spite of comparable RCORs, negative values of MSSS suggest the deficiency of HiFLOR in predicting basin-wide non-ET storm frequency relative to ET frequency (Table 1). This is further highlighted in the contrast of predicted versus "observed" interannual variation of ET and non-ET storm frequency (Figure 1). HiFLOR predicts comparable ET storm frequency to the four references while substantial underestimation of non-ET storm frequency, implying that the prediction skill of HiFLOR in basin-wide TC frequency can be largely improved by enhancing the model's ability in forecasting non-ET storm activity.

Regional storm activity provides finer-scale information (e.g., coastal areas) than basin-wide storm frequency to guide storm risk management (Murakami, Vecchi, et al., 2016; Vecchi et al., 2014; Vecchi & Villarini, 2014). We use RCOR to examine the retrospective forecast skill of HiFLOR in regional storm activity. With CPS analyses, we divide the life cycles of ET storms to two phases: TC and ET/EX phase for which we expect to achieve a more comprehensive examination of the prediction skill of HiFLOR. The forecasts of regional storm activity for both non-ET events and TC phase of ET events from the mean of the reference data sets are paired to highlight the contrast of the prediction skills (Figure 2). HURDAT is excluded from the mean computing because it does not provide information of ET onset, only of ET completion. In spite of the TC nature of the two types of events, HiFLOR yields higher skill predicting TC phase of ET storms than non-ET storms over most areas. The regions of high RCORs north of the Gulf of Mexico indicate the potential predictability for the TC phase of landfalling ET events (Figure 2a). The promising skill for these landfalling storms extends to the ET/EX phase as seen in Figure 3. In contrast, the prediction skill for ET storms in the Gulf of Mexico coast is not clearly seen in predictions of non-ET storms. Similar contrasts of prediction skills are seen in the Caribbean islands (Figure 2). The comparison of HiFLOR prediction with each single reference show similar results (Figures S2 and S3). We speculate that the forecasting skill of HiFLOR for TC activity (see Murakami,

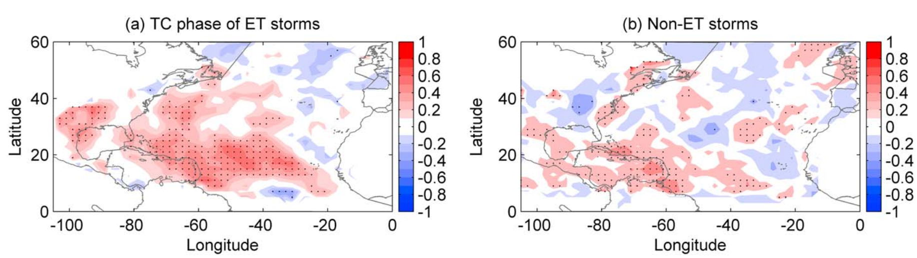

Figure 2. Retrospective forecast skill of 1980–2016 July–November storm frequency: (a) tropical cyclone phase of extratropical transition (ET) storms and b non-ET storms. The shading indicates the retrospective rank correlation of predicted versus reference storm frequency, stippled at a two-sided $p = 0.1$ level. The reference storm frequency is the mean of JRA55_HURDAT, CFSR_HURDAT, and CFSR_CFSR.

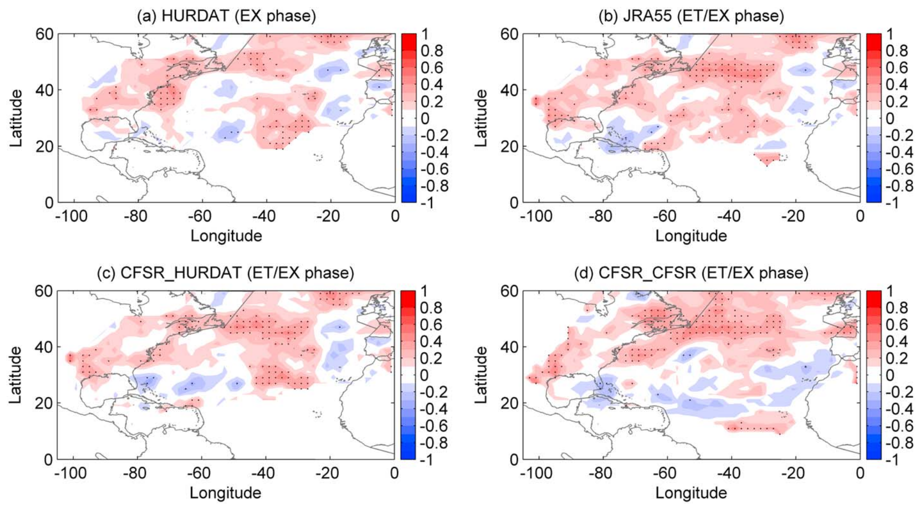

Figure 3. Retrospective forecast skill of extratropical transition (ET)/extratropical cyclone (EX) phase storm frequency for the 1980–2016 July–November period. The shading indicates the retrospective rank correlation of predicted versus (a) HURDAT, (b) JRA55_HURDAT, (c) CFSR_HURDAT, and (d) CFSR_CFSR storm frequency, stippled at a two-sided $p = 0.1$ level. The focus is on EX phase for HURDAT since HURDAT only provides the completion time of ET.

Vecchi, et al., 2016) primarily comes from the predictions of storms undergoing ET. This is explored by comparing the skill of HiFLOR for ET (including ET/EX phase) and non-ET storms through the percentage of area with significant prediction skill (roughly defined as rank correlation larger than 0.2 and significance level $p < 0.1$) over areas with annual storm frequency larger than 1. The area with skillful prediction for ET storms ranges from 28% to 32%, substantially higher than non-ET storms (13%–18%). These results suggest that improvement of the forecasting skill for non-ET storms provides an important path for refining the model's ability in predicting regional storm activity. For example, non-ET events account for major portions of the storms passing the Gulf of Mexico (Liu et al., 2017). Deficiency in predicting these storms would largely undermine the reliability of seasonal forecasts to support storm risk management.

The geographic contrast of the prediction skill of HiFLOR for the TC and ET/EX phase is rooted in the distinct storm properties of the two phases (Figures 2a and 3). It is worth noting that the comparison of HiFLOR prediction with HURDAT focuses on the EX phase because HURDAT only provides the completion time of ET (Figure 3a). In terms of the comparison with all the four references, HiFLOR exhibits good prediction skill in the northern portions of the eastern North Atlantic. The skill of HiFLOR is also seen in inland regions (see the Mississippi River basin north of the Gulf of Mexico and eastern Canada), highlighting the potential of dynamical models for predicting landfalling storms at ET/EX phase. The footprint of non-ET storms is constrained below ~40°N (Figure S4; Liu et al., 2017), highlighting the importance of the skill of HiFLOR for ET storms at high latitudes.

5. Discussion and Summary

In this study, we examine the retrospective seasonal forecasts of ET activity in the North Atlantic during the 1980–2016 July–November seasons with the GFDL HiFLOR global climate model. HiFLOR exhibits good skill in predicting basin-wide and regional ET activity (for both TC and ET/EX phase) including inland regions through the comparison with the four ET reference data sets. In contrast, we do not see skillful retrospective forecasts for non-ET storm activity in this experimental forecast system. This indicates that the seasonal prediction skill of HiFLOR for TC activity is primarily related to ET events rather than non-ET events. The contrast of skill for ET and non-ET storms may be partly explained by the performance of HiFLOR in the Gulf of Mexico. HiFLOR tends to underestimate the frequency of storm genesis in the Gulf of Mexico (Figure S5). Due to the dominance of non-ET storms in this region (Liu et al., 2017), this underestimation would mainly undermine the prediction skill for non-ET storms rather than ET storms. Improved forecasts of non-ET storm activity should yield enhanced skill for predictions of TC activity.

The successful seasonal forecast of TC activity by dynamical models is hypothesized to be associated with skillful predictions of two important aspects: large-scale climate conditions that influence TCs and response of TCs to the climatological and/or anomalous climate conditions (e.g., Vecchi et al., 2014). This hypothesis provides the physical basis for statistical-dynamical models for seasonal forecasts of TCs (see Murakami, Villarini, et al., 2016; Vecchi et al., 2011, 2013, 2014; Villarini & Vecchi, 2012; Wang et al., 2009; Zhang et al., 2016; Zhao et al., 2010). There are fewer studies on modulations of large-scale climate conditions on ET and non-ET activity relative to TC activity. Hart and Evans (2001) explored the relationship between three climate indices (North Atlantic Oscillation, Southern Oscillation Index, and Pacific-North American index) and observed ET frequency/rate from HURDAT over the period 1950–1996 in the North Atlantic. Hart and Evans (2001) found that these large-scale parameters accounted for less than 10% of the interannual variation of ET activity. More effort on understanding the climate control on both ET and non-ET activities are needed for improved understanding of the predictability of them. The contrasting responses of the two types of storms to climate may shed light on the development of statistical-dynamical prediction models, which may produce refined forecasting skill.

Grouping TCs to clusters in terms of tracks and genesis locations enables the finding that these clusters exhibit distinct responses to large-scale climate conditions (see Colbert & Soden, 2012; Kossin et al., 2010). This technique has been successfully used to develop statistical-dynamical models for the seasonal forecast of landfalling TCs in the North Atlantic (Murakami, Villarini, et al., 2016) and Western North Pacific (Zhang et al., 2016) through finding predictors for each TC cluster. Because tracks of ET and non-ET storms show distinct characteristics in many aspects (e.g., curvature and latitude coverage), the clustering technique may provide a useful path for improved understanding of climate modulation on ET and non-ET activity and seeking predictors to building hybrid models for seasonal forecasts.

This study represents one of the very first attempts to explore the ability of a dynamical model in predicting ET and non-ET activity at seasonal time scales, which also provides a tool to diagnose the strength and limitation of the prediction skill of the model. The limitation of the model in predicting non-ET activity requires future work on refining the forecast skill, which may involve a better understanding of the predictability and the development of statistical-dynamical prediction models.

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