ENSO's Spatial Patterns and Their Impact on Atlantic Tropical Cyclone Activity

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Abstract

hello

1 Introduction

Seasonal tropical cyclone (TC) forecasting has become an active field of research [5, 4, 3, 13]. While seasonal forecasts cannot inform us of the frequency or intensity of landfalling hurricanes, aggregate TC statistics such as counts, are valuable to the reinsurance industry as well as to forecast the environment's response to seasonal TC activity – for example ocean heat transport or phytoplankton bloom. A primary driver of seasonal TC activity are the large-scale conditions over the Atlantic basin and any reasonable attempt at skillful seasonal prediction should be able to reproduce the sufficient conditions for TC activity [9], even if synoptic-scale (*i.e.* African Easterly Waves, *etc.*) and stochastic events cannot be accounted for.

One of the well-documented influencers of Atlantic TC activity on seasonal timescales through large-scale conditions is the El-Niño Southern Oscillation (ENSO): the quasi-periodic cycle of warming and cooling of the near equatorial Pacific sea surface temperatures (SST). Enhanced convection as a result of anomalous Eastern Pacific Ocean warming is associated with strong westerly upper tropospheric wind over the Caribbean basin and tropical Atlantic, resulting in low TC activity during ENSO's warm phase (El Niño) and high TC activity during its cold phase (La Niña) [10]. Other studies have suggested that ENSO impacts Atlantic TC activity via tropospheric warming [18].

For the past 50 years, numerous attempts to abstract such a cycle using empirical warming-based indices have been made. Indices such as NINO1+2 and NINO3.4 are constructed by averaging the sea surface temperature (SST) anomalies of static oceanic regions and are subsequently related to Atlantic TC activity [19]. While such indices have been a staple of long-range teleconnection research, recent studies suggest that to fully capture ENSO activity, it is no longer sufficient to monitor the warm and cold phases of the Eastern Pacific. Some research proposes to monitor several regions concurrently [20, 16] or focus on the Central Pacific [1]. Warming in the Central Pacific, known as El Niño Modoki (or Central Pacific ENSO), where warm waters are surrounded by cold ones has been observed with increased frequency since the 1990s. Such changes have been attributed to anthropogenic global warming [23] as well as natural climate variability [22] and might impact Atlantic TC landfalling probabilities [12]. Given the increasing number of studies reporting a shift in the spatial warming patterns of the Pacific it is comes with no surprise that monitoring static East Pacific regions is less informative of Atlantic TC activity (see Figure 1).

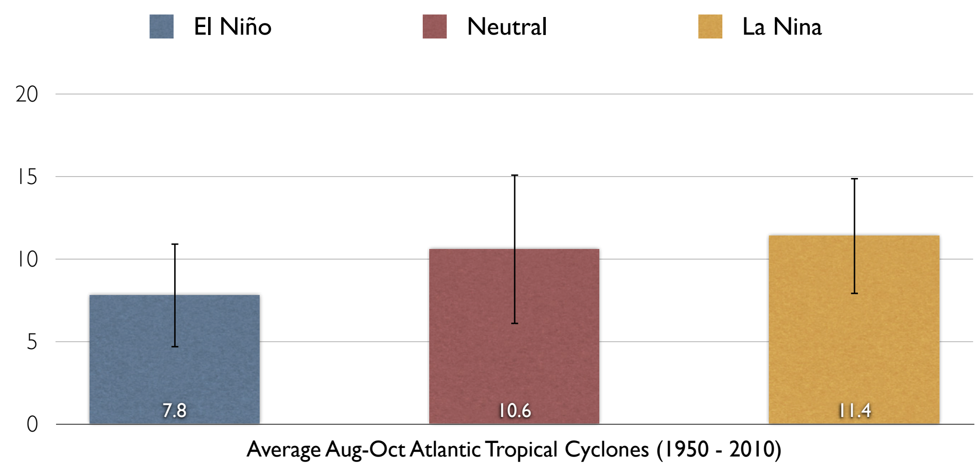

Figure 1: The mean August-October Atlantic TC counts. Error bars denote one standard deviation. This figure shows that while there are notable differences in TC counts based on the phase of ENSO, the large variability of TC counts make discerning ENSO's impact uncertain. NINO3.4 index was building using ERSSTV3. TC counts are from the Unisys best track archive.

Given that ENSO impacts the large-scale conditions over the Atlantic through anomalous warming and its resulting deep convection, it is not only important to monitor the intensity of warming along the equatorial Pacific – something traditional NINO indices do – but to also capture the location of the warming as well. We propose a distance-based ENSO index (S-ENSO for spatial ENSO) that tracks the longitude of highest SST anomaly in the tropical Pacific and show its robustness in predicting seasonal Atlantic TC activity as well as resolving the large-scale conditions over the Atlantic. Such an index, coupled with other seasonal prediction methods based on Atlantic variables (e.g. [14, 6]) can prove to be a significant addition to dynamical and statistical forecast models.

2 Shifting of ENSO

Given the increasing number of studies reporting a shift in ENSO's warming patterns [1, 11, 23, 15, 12], we examine empirically the extent of such a shift. For every month from January 1979 to November 2012, we monitor the longitude of the warmest 10° latitude by 40° longitude region in the Pacific (see methods for details). As it can be seen in Figure 2 there has been a distinct westward shift in the longitude of the warmest Pacific region. This may explain how traditional NINO indices were initially successful in abstracting the impact Pacific warming might have on Atlantic TCs, but as the warming gradually shifted westward they have grown less accurate.

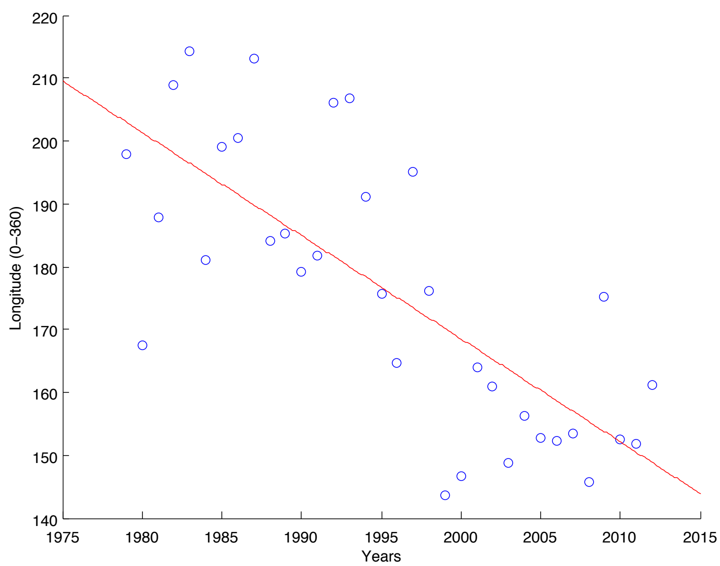

Figure 2: The annual mean longitude of the warmest SST anomaly region in the Pacific (1979 − 2012). The figure shows a clear westward shift the warmest region in the Pacific. $R^2 = 0.54$ $p < 0.01$

	TCs	Major Hurricanes	NTC	PDI	ACE
S-ENSO	**-0.75**	**-0.59**	**-0.74**	**-0.68**	**-0.73**
Nino1+2	-0.51	-0.46	-0.46	-0.4	-0.42
Nino 3	-0.51	-0.51	-0.48	-0.44	-0.45
Nino 4	-0.32	-0.47	-0.32	-0.3	-0.31
Nino 3.4	-0.47	-0.53	-0.46	-0.43	-0.45

Table 1: Linear correlation coefficients between the June-October S-ENSO and August-October Atlantic TC activity. The highest score for each category is highlighted in **bold**. All correlations are significant at 95% level

3 S-ENSO an index for a shifting warming patters

We propose that the spatial distribution of Pacific Ocean warming might provide better predictive insights into ENSO-Atlantic TC activity relationship than warming anomalies alone. For this analysis we use June-October S-ENSO index (see methods). Table 1 shows S-ENSO's linear correlation coefficients with various quantities that communicate August-October Atlantic TC activity: number of tropical cyclones, number of major hurricanes, potential dissipation index (PDI) [7], accumulated cyclone energy (ACE) [2], and net tropical cyclone energy (NTC) [8]. The significant improvement over traditional static NINO indices, especially with regards to cumulative statistics such as ACE and NTC, indicates that S-ENSO resolves the large-scale conditions over the Atlantic as well as the in-season TC precursors than traditional more accurately than static warming-base indices.

In addition to providing increased in-season accuracy than traditional NINO indices, S-ENSO is more robust to the ENSO spring predictability barrier [21]. Figure 3 shows the performance of each NINO index as well as S-ENSO as a function of lead time. While S-ENSO's performance drops with January lead time, it is nearly an order of magnitude stronger than that of some static NINO indices. In fact, give the 30 degrees of freedom in the data (N=32; df = N-2), the traditional NINO indices do not provide significant correlations until July as opposed to March for S-ENSO. Furthermore, the improved accuracy remains significant from January until October. Therefore, if dynamical models can resolve the spatial patterns of ENSO as represented by S-ENSO then dynamical models could potentially have significant skill in predicting August-October TC activity.

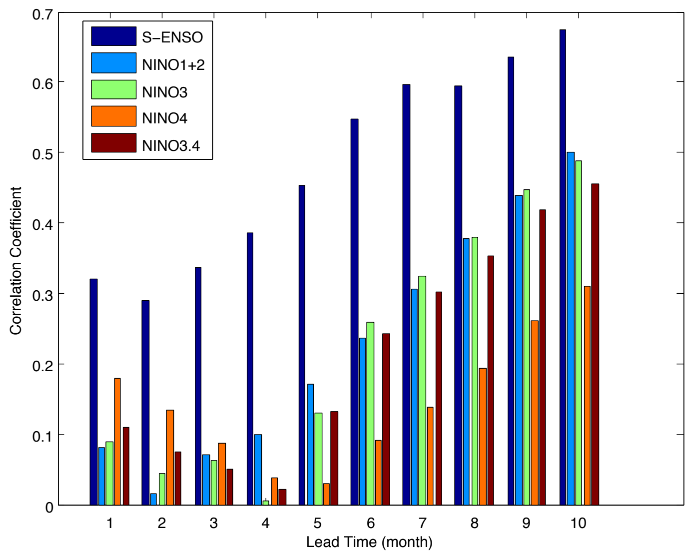

Figure 3: The linear correlation coefficients between different ENSO indices and Atlantic August-October TC counts. The x-axis denotes the last month used to build each index (see methods). The indices increase in accuracy as we move closer to the TC season, however S-ENSO performance is not as severely affected by the ENSO predictability barrier as traditional NINO indices.

4 Summary of Methods

4.1 S-ENSO

The S-ENSO index is computed by first averaging the SST anomalies over the June-October period to accurately capture ENSO's evolution prior to and during the Atlantic hurricane season (August-October). We then search the tropical Pacific (5°S-30°N) for a region of similar size to traditional ENSO indices that has the highest mean SST anomaly over the June-October period. We repeat this procedure for each year from 1979 to 2010. Monthly SST anomalies we computed from the ERSSTV3 monthly SST dataset [17]. See Figure 4.

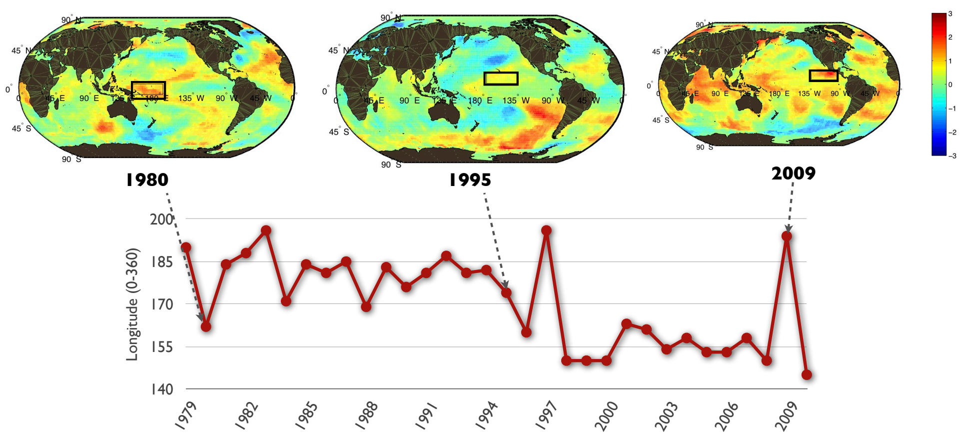

Figure 4: A schematic demonstrating how the S-ENSO index is built. First, SST anomalies over a certain month range are computed resulting in maps similar to those above. Next, we search the tropical Pacific for the region with the highest mean SST warming anomaly. Finally, we record the longitude of that region. We repeat this procedure for all years from 1979-2010.

4.2 Lead Times Analysis

Figure 3 shows the relative ability of each index to forecast Atlantic TC activity as a function of lead time. Each index (S-ENSO, NINO1.2, *etc.*) is computed by first averaging SST anomalies over a certain month range denoted by a start and end month. The resulting index is then correlated with August-October Atlantic TC counts. For each month on the x-axis, we average the performance of all variations of the indices that end in the month indicated on the chart (end month varies from January to October). For example, the first set of bars were obtained by averaging the performance of all indices end month was January. In this case, there is only one such index the January-January index. The values for the June lead month (number 6 on the x-axis) were obtained by averaging the performance of all indices that had a June end month. There are 6 such indices: January-June, February-June, March-June, April-June, May-June, and June-June. This procedure was repeated for all indices and end months ranging from January to October.

5 Appendix - Work in Progress

5.1 Increased seasonal predictability through monitoring the SST warming patterns and associated impact

In addition to monitoring the location of the largest warming anomaly in the Pacific, we have also monitored the resulting deep convection and other spatial patterns such as the mean SST empirical orthogonal function (EOF). A combination of such quantities may yield a significant improvement over the state-of-the-art statistical forecasting algorithms. We have already done an extensive analysis of this multi-variable index and have seen some improvements in performance. We are currently working on identifying the sources of accuracy for such an index.

5.2 Monitoring the spatial warming patterns in the Pacific allows us to by-pass the ENSO predictability barrier

While S-ENSO is more robust than tradition NINO indices to increased lead times, we are investigating how predictable such spatial patterns are. If we are able to predict the warming distribution several months in advance, then that would be a significant contribution to TC forecasting techniques. We have compiled results studying the evolution of both our S-ENSO index and EOF indices. There seems to be a predictable pattern that can be resolves using statistical methods. We are also investigating whether current SST forecast models such as ECMWF are able to reproduce S-ENSO.

5.3 Monitoring the spatial distribution of the warmest and coldest SST anomaly regions in the Pacific encapsulates the Pacific SST EOF

We also built an index that monitors the distance between the coldest and warmest SST region in the Pacific, which is similar to what the EOF does in terms of looking at extremes to explain variability. Such an analysis allows for a more detailed monitoring of ENSO's evolution. Our preliminary analysis shows that both the spatial distribution and the EOF's first principal component explain the same amount of TC variability.

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