2.4 ATLANTIC TROPICAL CYCLONES DURING STRONG AND MODERATE ENSO EVENTS

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1. INTRODUCTION

Atlantic tropical cyclones (TCs), and their most intense manifestations, the hurricanes, have a significant impact on the costal regions of Central and North America (Pielke and Landsea, 1998). The seasonal forecast of TCs activity aims to determine the frequency and intensity of storms (Gray et al., 1992, 1993, 1994; Landsea et al., 1992, 1993, 1994; Klotzbach and Gray, 2003, 2004; Klotzbach, 2007). Understanding the processes that influence TCs at seasonal time scale is accomplished by statistical analysis of observations as well as by numerical simulations (Knutson et al., 2010; Kossin et al., 2010; Vitart, 2006).

It has been shown that TCs activity at seasonal scale is influenced by: a) the sea surface temperature (SST) in the North Atlantic, especially in the Main Development Region (MDR) and in the Caribbean region; b) the vertical shear of the horizontal zonal wind; c) the moisture distribution, the vertical stability as well as the atmospheric pressure anomalies. Hurricanes need to develop vertically and strong vertical wind shear can tear them apart. When the wind shear is increased, there is a greater chance the storm will dissipate because it is pushed or spread over a larger area. Ocean temperatures greater than about 26.5 deg C through a depth of at least 50 meters are generally favorable for the formation of tropical cyclones. Higher SST lead to higher probability of TC genesis, and to stronger storms. Among the factors that impact TCs, the SST have been investigated extensively, in part due to the availability of long term measurements in the North Atlantic region (Reynolds and Smith, 1994; Smith and Reynolds, 2004; Smith et al., 2008).

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It has been argued that the SST Atlantic Multidecadal Oscillation (AMO) (Marshall et al., 2001; Knight et al., 2005) modulates the TCs activity at decadal time scale (Goldenberg et al., 2001). At shorter time scale, El Nino - Southern Oscillation (ENSO) events create large oceanic and atmospheric perturbations that enables TCs prediction at seasonal time scale (Gray, 1984; Landsea, 2000; Chu, 2004; Smith et al., 2007; Klotzbach, 2007). The recent progress in ENSO forecasting provides the means for successful short term climate predictions (Zebiak and Cane, 1987; Latif et al., 1998; Chen et al., 2004) with implications for the Atlantic TCs predictability.

It has been shown that the Oceanic Nino Index (ONI), based on the sea surface temperature anomaly (SSTA) in the Nino3.4 region of the tropical Pacific can be used to characterize ENSO. Thus, we adopt ONI as the primary ENSO time series to be linked to TCs activity. We show that TCs frequencies are statistically linked to ONI before and during the Atlantic hurricane season in years with strong and moderate ENSO events.

2. DATA AND METHOD

We use the NOAA ONI for the time interval 1950 - 2009 based on the most recent version of the Extended Reconstruction Sea Surface Temperature (ERSST.v3) analysis (Smith et al., 2008). These SST are based on the International Comprehensive Ocean – Atmosphere Data Set (ICOADS) release 2.4. The anomalies are computed with respect to a 1971-2000 month climatology (Xue et al. 2003). ONI is used for identifying El Nino (warm) and La Nina (cool) events in the tropical Pacific. ONI is the running 3-month mean SST anomaly for the Nino3.4 region (i.e., 5^o N – 5^o S, 120^o –170^o W). ENSO events are defined as 5 consecutive months at or above the +0.5 deg C anomaly for warm (El Nino) events and at or below the -0.5 deg C anomaly for cold (La Nina) events.

For the purpose of this study, an ENSO event is considered “intense” (i.e. moderate or strong) when ONI has an absolute value larger than 1 deg C, for at least 5 consecutive months. In our analysis we use only intense ENSO events because tests have shown that during weak events as well as during non-event years, the TCs activity is largely driven by other physical factors and the influence of the central equatorial Pacific is difficult to detect. Thus, using a subset of years with intense El Nino and La Nina events, it is more likely to detect a statistical relationship between TCs frequencies and ONI.

Besides the ONI time series, we use the global SST data to determine the spatial distribution of SSTA for years with intense ENSO events. Moreover, to test the role of the vertical wind shear, we use the NCEP/NCAR reanalysis and calculate the wind shear anomalies for the hurricane season during the years of interest. The NOAA HURDAT data are used for the TCs statistics (Landsea et al., 2004). The methodology used in this study can be summarized as: a) perform regression analysis between ONI and TCs frequencies; b) once the regression is established and found statistically significant, determine whether ENSO is predictable several months in advance the hurricane season; c) attempt to provide a mechanistic explanation of the TCs frequencies – ONI regression based on composite maps of SSTA and vertical wind shear, using the ERSST and the NCEP/NCAR data.

3. RESULTS AND DISCUSSION

During the time interval 1950 - 2009, there were 22 intense ENSO events. As we will show below, the correlation between ONI and TCs frequencies is significant, and thus, about one third of the time there is a good chance to forecast Atlantic TCs activity based on intense ENSO events.

3.1 Regression analysis

Our first step is to perform regression analysis (von Storch and Zwiers, 1999; Wilkis, 1995) between TCs frequencies and ONI. The TCs frequencies have the following notations: NS – frequency of named storms; H – frequency of hurricanes; MH – frequency of major hurricanes; and USH – frequency of US landfalling hurricanes. We note first that a similar regression analysis is possible between the accumulated cyclone energy (ACE) and ONI. Figure 1 shows that ACE correlates very well with the TCs frequencies, especially with the frequencies of hurricanes and major hurricanes. In view of this strong correlation, we limit our following presentation to correlations between ONI and TCs frequencies.

Figure 2 illustrates the linear regression between the frequency of named storms (NS) during the entire hurricane season and ONI for the specified three months. Thus, MAM indicates ONI for the months March – April – May, and so on. We note the significant negative correlation between NS and ONI. Analysis of the statistical output shows that ONI for JAS, ASO, and SON has the highest correlation with NS for the data set used here. The lowest correlation is between NS and ONI for MAM, which is also the earliest time interval considered, long before the hurricane season. Results indicate that if we can predict an intense ENSO before May or June for example, we can obtain a good estimate of the TCs frequencies in the following hurricane season.

Figure 3 shows the linear regression between the frequency of hurricanes (H) during the entire hurricane season and ONI for the specified three months. Similarly, Figure 4 shows the linear regression between the frequency of major hurricanes (MH) during the entire hurricane season and ONI for the specified three months. Both for H and MH, the correlation with ONI is significant during intense ENSO events. Somehow weaker correlation, yet statistically significant, is found for the correlation between USH and ONI (Figure 5). From a practical perspective, predicting USH as well as the frequencies of landfalling TCs in other island and coastal areas of the Gulf of Mexico is paramount.

3.2 ENSO statistical forecast

The utility of a regression model to predict TCs frequencies based on ONI values is largely dependent on the ability to predict ONI in advance of the hurricane season. There is significant progress in ENSO forecast, both using statistical methods and dynamic models (Chen et al., 2004). Here we follow a statistical approach, based largely on time series analysis and forecasting, as described in

Hamilton (1994), to predict the monthly Nino3.4 SSTA index for several months. The performance of such model is largely dependent on the remarkable SSTA persistence in specific oceanic regions (Andronache and Phillips, 2008; Andronache, 2009, 2010a, 2010b). The illustrations shown below are for SSTA predictions for one, two, three and six months. Figure 6 shows: a) Nino3.4 SSTA forecast one month in advance; b) the corresponding forecast error; c) Nino3.4 SSTA forecast two months in advance; and d) the corresponding forecast error. The forecast error is defined as the difference between the observed and the predicted SSTA value. In the graph showing the comparisons between the observed and predicted Nino3.4 SSTA values, the first 100 months are used to determine the parameters of the model. We note that the prediction error is less than 0.5 deg C, which is acceptable. Somehow larger errors are found in instances for the two months prediction. Similarly, Figure 7 shows: a) Nino3.4 SSTA forecast three months in advance; b) the corresponding forecast error; c) Nino3.4 SSTA forecast six months in advance; and d) the corresponding forecast error. In these cases, we note that for three months, predictions are still dominated by small errors, while for six months, the error of prediction becomes too large. Results suggest that a statistical approach to ENSO prediction can provide, several months in advance, the ONI values that can be used as predictor in our regression model.

3.3 Composite SSTA maps

Figure 8 shows the composite map of the global SSTA during the hurricane season (months June – November) for years with intense El Nino events. It illustrates that in the MDR and Caribbean region, SSTA is not favorable for more TCs, while in North Eastern Pacific, some positive SSTA are apparent. In Figure 9, we show the composite map of the global SSTA during the hurricane season (months June – November) for years with intense La Nina events. In this case, SSTA in North Atlantic is more favorable for TCs formation, while in North Eastern Pacific, SSTA is slightly negative. Our analysis of SSTA during intense ENSO events tends to support earlier findings that frequencies of TCs in Western North Atlantic are negatively correlated with North Eastern Pacific TCs (Wang and Lee, 2009). Nevertheless, SSTA appear to have small values overall, and it seems likely that the wind shear effects on TCs frequencies are more significant, as illustrated in the next subsection.

3.4 Composite wind shear maps

Figure 10 shows the composite map of the global vertical wind shear anomaly during the hurricane season (months June – November) for years with intense El Nino events. We note the positive wind shear anomaly extended over Caribbean region, confirming the work by Gray (1984) and other following studies that linked El Nino to the suppression of TCs formation due to enhanced wind shear. In contrast, Figure 11 shows the composite map of the global vertical wind shear anomaly during the hurricane season (months June – November) for years with intense La Nina events. It confirms that strong negative anomalies in MDR area are favorable for TCs development and intensification. Detailed analysis for each month of the hurricanes season (not shown) supports the overall relationship between vertical wind shear anomaly and TCs frequencies, while some variability from month to month is apparent.

4. CONCLUSIONS

In summary, we found that there is significant correlation between intense ENSO events and TCs frequencies in the North Atlantic, confirming results from previous analyses related to using ENSO as predictor of TCs activity at seasonal time scale. The vertical wind shear anomalies are likely to play a role in the North Atlantic TCs development and intensification during intense ENSO events. Also, our analysis suggests that seasonal hurricane outlook can benefit from accurate ENSO forecast, which has made remarkable progress over the last two decades. Finally, changes in AMO, ENSO, and other major factors due to climate warming, can alter the relationship between ONI and TCs frequencies based on past data (Webster et al., 2005; Emanuel, 2005; Mann and Emanuel, 2006). Continuous advances and refinements in data collection, analysis and model development remain paramount to improve TCs seasonal forecasts in a changing climate.

5. ACKNOWLEDGMENTS

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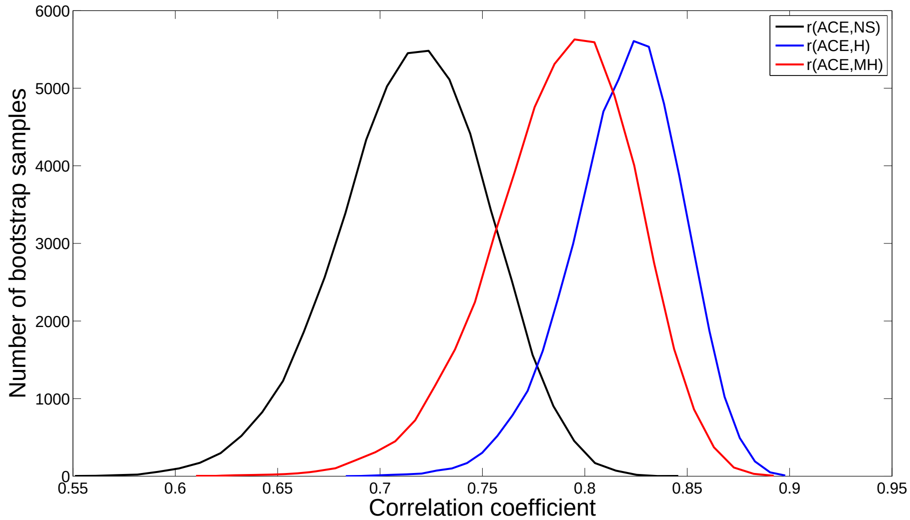

Figure 1. Distribution of the correlation coefficient between the accumulated cyclone energy (ACE) and frequencies of named storms (NS), hurricanes (H) and major hurricanes (MH) using the bootstrapping method.

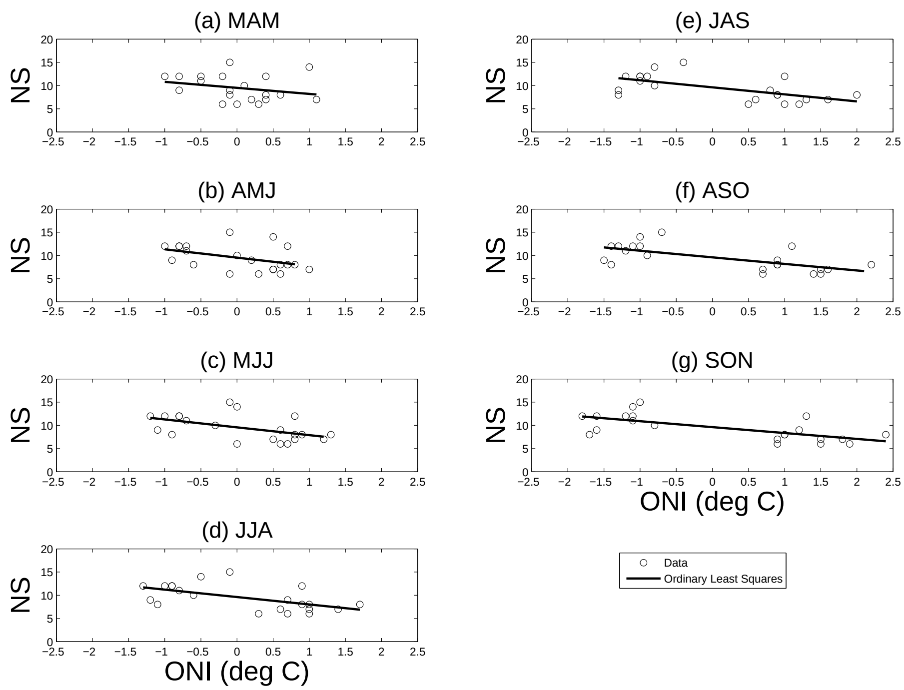

Figure 2. Linear regression between the frequency of named storms (NS) during the entire hurricane season and the Oceanic Nino Index (ONI) for the specified three months.

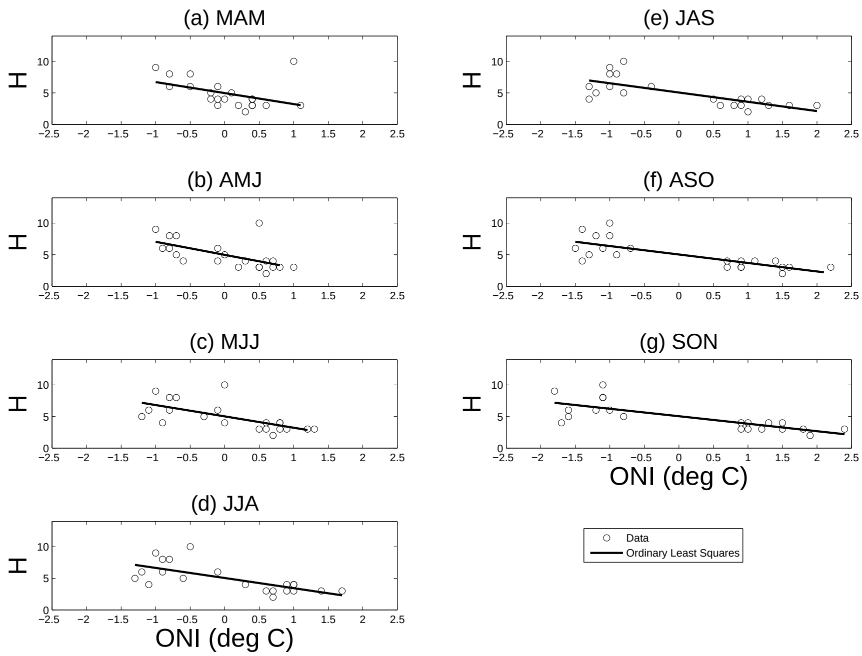

Figure 3. Linear regression between the frequency of hurricanes (H) during the entire hurricane season and ONI for the specified three months.

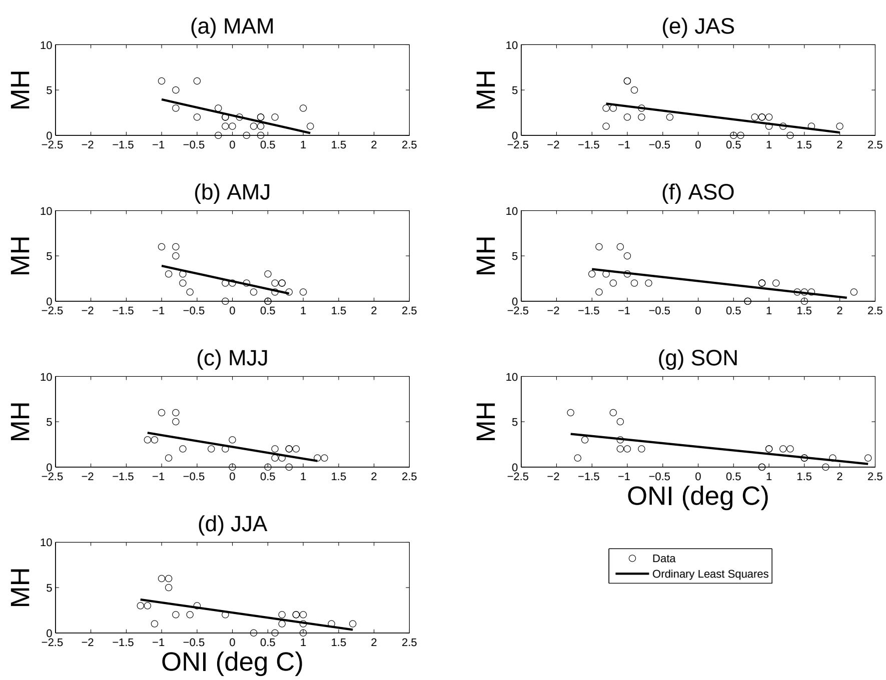

Figure 4. Linear regression between the frequency of major hurricanes (MH) during the entire hurricane season and ONI for the specified three months.

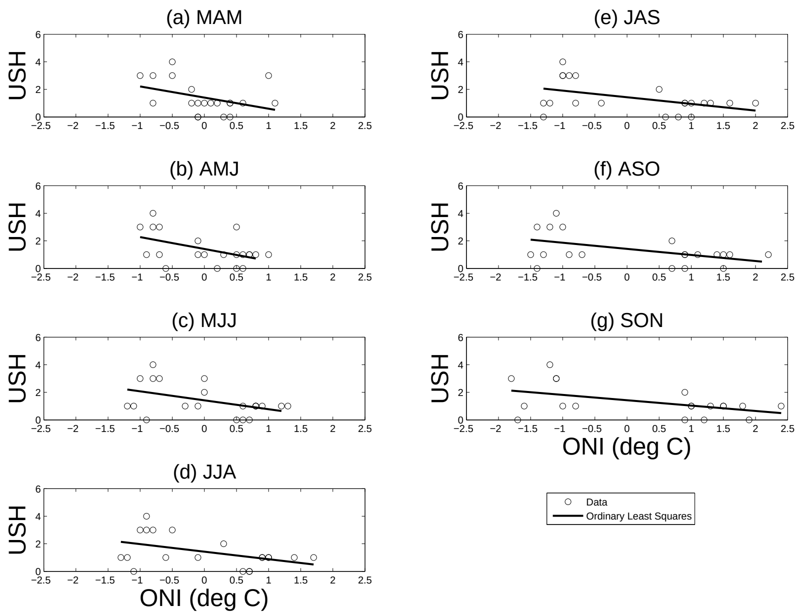

Figure 5. Linear regression between the frequency of US landfalling hurricanes (USH) during the entire hurricane season and ONI for the specified three months.

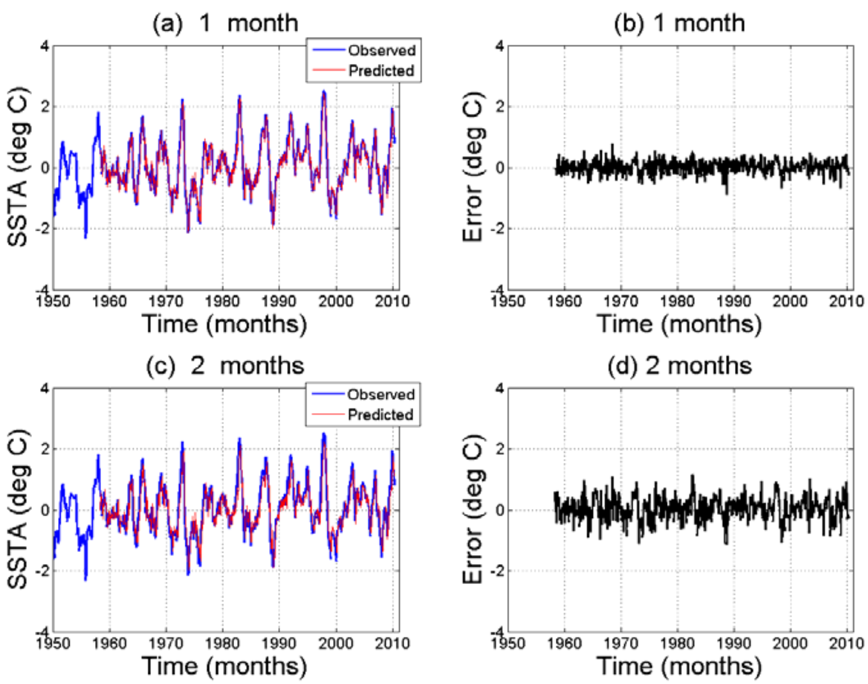

Figure 6. a) Nino3.4 SSTA forecast one month in advance; b) the corresponding forecast error; c) Nino3.4 SSTA forecast two months in advance; d) the corresponding forecast error. The forecast error is defined as the difference between the observed and the predicted value. The first 100 months are used for model parameter determination.

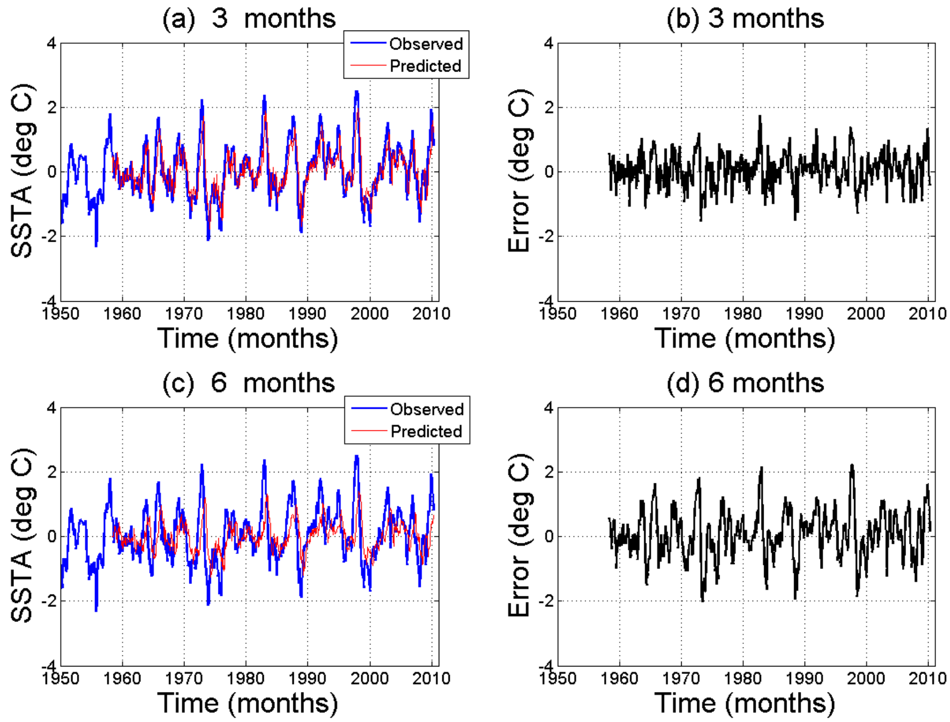

Figure 7. a) Nino3.4 SSTA forecast three month in advance; b) the corresponding forecast error; c) Nino3.4 SSTA forecast six months in advance; d) the corresponding forecast error. The forecast error is defined as the difference between the observed and the predicted value. The first 100 months are used for model parameter determination

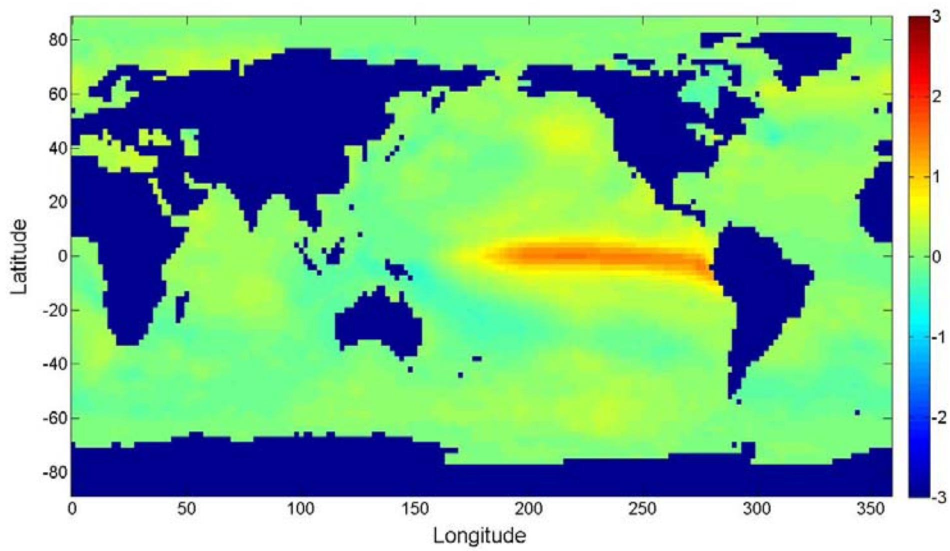

Figure 8. Composite map of the global SSTA during the hurricane season (months June – November) for years with intense El Nino events.

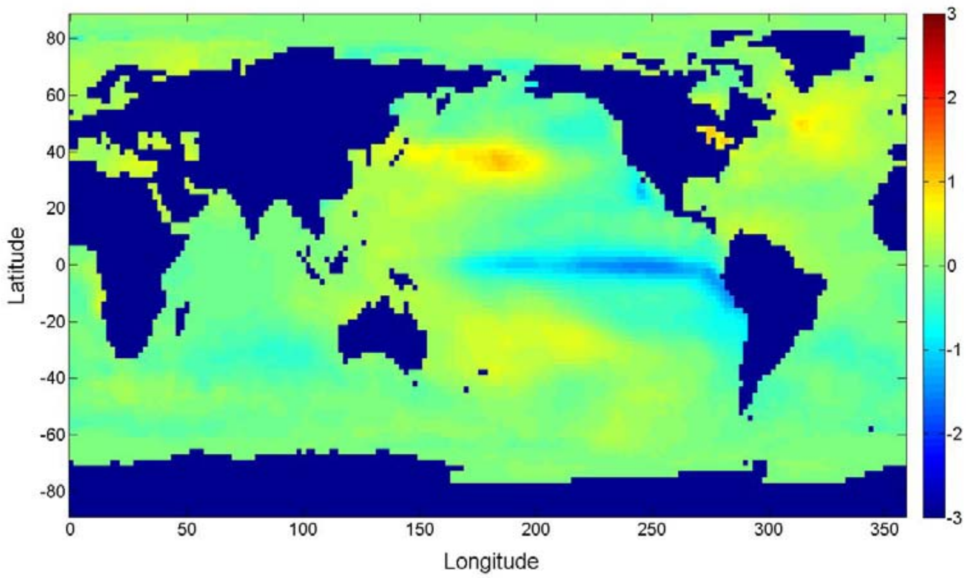

Figure 9. Composite map of the global SSTA during the hurricane season (months June – November) for years with intense La Nina events.

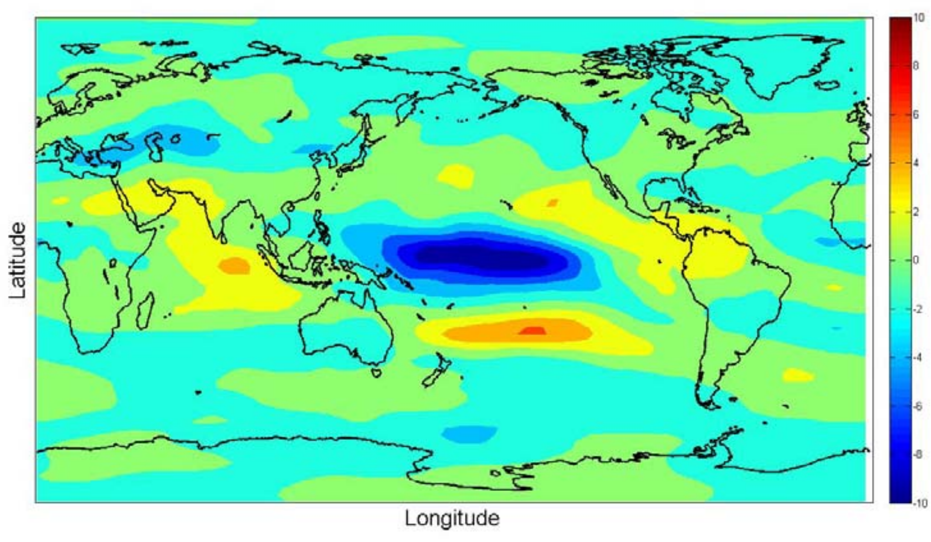

Figure 10. Composite map of the global vertical wind shear anomaly during the hurricane season (months June – November) for years with intense El Nino events.

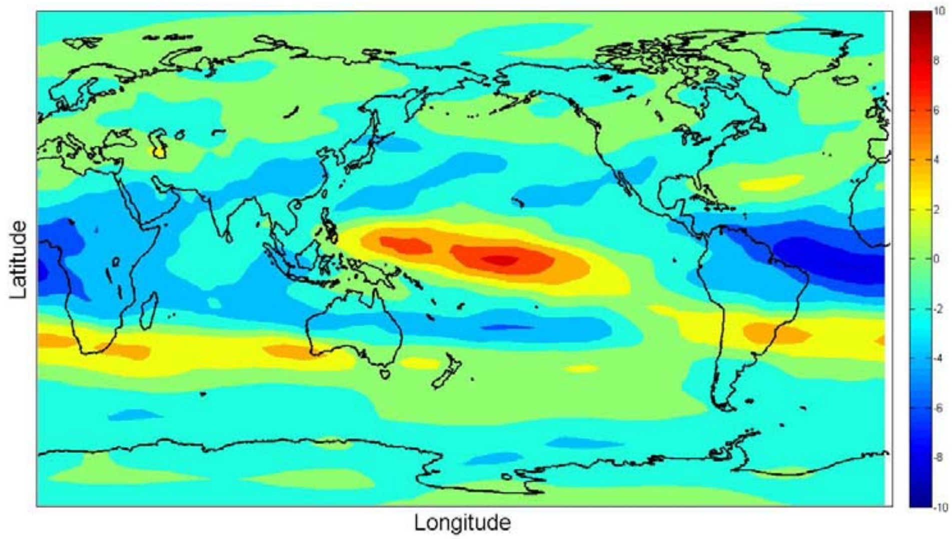

Figure 11. Composite map of the global vertical wind shear anomaly during the hurricane season (months June – November) for years with intense La Nina events.