

**JP2.16 THE RELATIONSHIP BETWEEN ENSO, PNA, AND AO/NAO AND EXTREME STORMINESS, RAINFALL, AND TEMPERATURE VARIABILITY DURING THE FLORIDA DRY SEASON: THOUGHTS ON PREDICTABILITY AND ATTRIBUTION**

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**1. INTRODUCTION**

Hagemeyer (2006, [http://www.srh.noaa.gov/mlb/enso/P2.4\\_18th\\_CLIVAR\\_AMS.pdf](http://www.srh.noaa.gov/mlb/enso/P2.4_18th_CLIVAR_AMS.pdf)) provided a comprehensive update of ongoing efforts to predict extreme storminess, rainfall, and temperature variability during the Florida dry season from the ENSO, PNA, AO, and NAO teleconnections using multiple linear regression (MLR) and logistical regression (LR, Wilks 1995) techniques. The author also reviewed a number of methods to assist decision makers in interpreting the utility of the statistical forecasts. This latest study continues the focus on improving the predictability of the most significantly impacting weather and climatic events of the Florida dry season: excessive stormy periods, excessively rainy and dry periods, and extreme cold weather outbreaks.

In an attempt to better assess intra-seasonal variability and improve predictability of these impacting weather events, the six month (November - April) predictand database and forecast methodology refined in Hagemeyer 2006 was divided into two three-month periods: November, December, and January (NDJ) and February, March, and April (FMA) for the Florida region and for a subregion of Florida, the Daytona Beach area. MLR and LR for the Florida dry season forecast parameters were recalculated for all new combinations for the 6-month dry season and two 3-month sub-seasons in an attempt to provide more detailed seasonal forecasts for decision makers. The updated MLR results are shown on Table 1.

The overall significance of the six-month relationships on Table 1 are very similar to those in Hagemeyer (2006). The updated LR results again clearly defined scenarios when the forecasts of extreme storminess, rainfall, and cold outbreaks work well and when they don't, which is valuable information for decision makers. A selection of the strongest LR relationships for each of the five predictands from Table 1 is shown as Figures 1a-e.

Narrowing down the dry season forecast in space and time should help close the gap between climate and weather as extreme sub-dry season variability is generally a result of the accumulated

passage of individual weather systems, or lack of weather systems, and can even be the result of the influence of one extreme weather system. However, attempting to narrow the sub-seasonal predictions to three month periods to improve timing gave results that were not significantly better than the six month results. The FMA correlations were slightly stronger than the NDJ correlations in most cases, but not to the point of significant differences in predictability. These results further validated the original thesis in Hagemeyer (2000a-b) and Hagemeyer and Almeida (H&A, 2002) that to achieve acceptable confidence intervals on extreme seasonal variability, and avoid inadvertent timing or localization errors, forecasts for the entire Florida six month dry season period are optimum, and any period less than three months gives poorer results due to sampling problems with the historical extreme database. Nevertheless, important insights into the predictability of extreme storminess, rainfall, and cold outbreaks were achieved as well as insights into the veracity of attribution of extreme weather events to phases of the major teleconnections indices.

Extremely stormy and/or wet periods were found to be almost exclusively related to El Nino. However, extremely quiescent and dry periods were found to be not only exclusively related to La Nina, but also to the influence of the PNA/NAO/AO in neutral or weak ENSO conditions. Indeed, the challenge of predictions during ENSO neutral conditions, which are most common, remains daunting. Extremes of temperature were most strongly related to the AO/NAO and the PNA. Additionally, the MJO has been found anecdotally to be related to excessive dry season rainfall, particularly when combined with El Nino. Figure 2 shows an example of the "Orange Blossom Express" moisture plume in December 2002 when an active MJO combined with a relatively weak El Nino to produce record rainfall in Central Florida (see H&A 2004). As found in Hagemeyer (2006), if the state of ENSO and the other major teleconnections could be accurately predicted well in advance, then remarkably accurate seasonal forecasts would likely result.

Indeed, after much investigation into the statistical relationships between Florida dry season extremes of weather and major teleconnections, it is clear that while continued mining of the data could result in more robust statistical methods of seasonal prediction, the fact is the relationships are generally good enough now. What is lacking is the ability to predict the underlying teleconnections and a fuller

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understanding of the physical relationships and the linkage between climate and weather.

Ultimately, an investigation such as the author has undertaken for many years runs up against the limits of predictability at various scales of space and time. So perhaps it is appropriate at this point to pause in the search for the perfect correlation and spend some time reflecting on where the greatest effort is needed next to deliver more reliable seasonal forecast products and some strategies that can make the most of the limited predictability of some strong relationships known today. Thus, the remainder of this paper will be devoted to summarizing the state of the statistical forecasts of extreme variability in the Florida dry season and consideration of how useful they are in current state, what really are the limits of predictability and attribution, and where we might go next.

## 2. THOUGHTS ON THE STATE OF STATISTICAL FORECASTS OF EXTREME DRY SEASON STORMINESS, RAINFALL, AND TEMPERATURE VARIABILITY

Hagemeyer (2006) illustrated how the MLR results of the common major teleconnections on dry season storminess, rainfall, and temperature could be interpreted to make physical sense by examining mean maps of the extreme phases of the ENSO, PNA, NAO, and AO in the context of Florida's physical geography.

Generally, it was found that each of the extreme phases of these teleconnections strongly favored a corresponding extreme seasonal response in climate and thus sensible weather in the Florida dry season and that the response and strong correlations were physically reasonable.

		SST (3.4/3.0)		PNA		NAO		AO		Best 3	
<b>JET STREAM</b>		.62		.40		.12		.22		.80	
<b>NDJ</b>	<b>FMA</b>	.23	.55	.35	.50	.18	.12	.28	.27	.66	.80
<b>STORMS</b>		.57		.32		.02		.11		.61	
<b>NDJ</b>	<b>FMA</b>	.36	.40	.05	.41	.04	.08	.07	.24	.44	.59
<b>MEAN TEMP</b>		.15		.38		.02		.12		.44	
<b>NDJ</b>	<b>DJF</b>	.02	.21	.24	.53	.14	.01	.20	.20	.36	.57
<b>MIN TEMP</b>		.07		.16		.24		.35		.49	
<b>NDJ</b>	<b>FMA</b>	.01	.11	.20	.33	.29	.10	.39	.33	.49	.47
<b>RAINFALL</b>		.38		.05		.05		.01		.42	
<b>NDJ</b>	<b>FMA</b>	.22	.38	.00	.04	.02	.00	.00	.03	.24	.40

**Table 1.** Correlation coefficients ( $R^2$ ) of regressions of predictor variables (top row) on the mean Florida grid (see Fig. 1 in Hagemeyer 2006) dry season 250 Mb U anomaly, storms, rainfall, mean temperature, and mean minimum temperature for the 1950-2004 dry seasons. The large horizontal grid cells are the results for an entire 6-month dry season, the smaller cells beneath are for the NDJ and FMA periods as indicated for each predictand. Crosshatched cells do not have significant relationships, grey shaded cells are significant at 95% level ( $F_{.05}$ ) and un-shaded and tan-shaded cells are significant at 99% level ( $F_{.01}$ ). Tan-shaded cells are the highest correlation for each variable and correspond to the logistic regression results on Figure 1. (**Note:** unless otherwise indicated in this paper, all referenced dry season data sets and correlations are for the 1950-2004 period).

The interpretation of these statistical relationships in Hagemeyer (2006) leads to three broad, but significant issues that are fundamental to improving long-range or seasonal forecasts of extreme climate and weather events. The first, and most fundamental, is the simple fact that none of the major teleconnections can be accurately forecast at long range. In the case of ENSO, Pacific SSTs are forecast out farther than a year by NOAA's Climate Forecast System (CFS) model and many other institutions ([http://iri.columbia.edu/climate/ENSO/currentinfo/SST\\_table.html](http://iri.columbia.edu/climate/ENSO/currentinfo/SST_table.html)). An observing network allows accurate

monitoring of the evolution of ENSO, but confidence in the forecasts, particularly the magnitude, is not great at lead times of more than a few months.

One advantage with El Nino is that the lag in Florida dry season response to ENSO can provide sufficient lead time for preparation. The historic El Nino of 1997-98 showed its hand in the summer of 1997 and was unlikely to abate and as such provided extended preparation time. However, the El Nino of 1982-83 was more difficult to assess in real time as an extensive observation network did not exist at the time and SSTs

rose steadily in the summer and then cooled in late summer before rising strongly in late summer and early fall. Even in hindsight, it did not become quite obvious until November that a major El Nino was in progress (Fig. 3). This type of major El Nino evolution could be problematic even today. Still, the Florida weather response lagged the rapid increase in SSTs in 1982 by several months. The storms, excessive rainfall and severe weather with the 1997-98 El Nino began in November and ended in early March with a rapid transition to extreme dryness. In 1982-83, the Florida response was delayed until January/February and continued through April as SSTs stayed high into early summer. So, no two El Ninos, even the two strongest on record, are alike.

The influence of Pacific SSTs on the impact of the jet stream to Florida is profound (Fig. 4) and highly reliable. The strength and location of the jet stream are fundamental to predicting mean and extreme climate and weather anomalies. Indeed, the Florida response to Pacific SSTs is so strong that the Pacific SSTs during the six months leading up to the beginning of the dry season (November - April) are more highly correlated with Florida dry season rainfall than the six months of SSTs during the dry season (Figs. 5a-b). Logistic regression results for predicting total dry season storminess exceeding  $\pm 1$  standard deviation (SD) from November through April using only August, September, and October (ASO) observations of Nino 3.4 is as good as almost any combination of SST index leads (Figure 6). This means that at the beginning of the dry season observed El Nino conditions provide a reliable forecast of above normal storminess without factoring in any forecast SST values. A simple review of the data reveals that of the 13 times since 1950 that the September Nino 3.4 index has been  $+0.50$  or greater, nine times, or about 70% of the time, the index was higher still in December or January. The serial correlation with Pacific SSTs in the NINO 3.0 and 3.4 areas is strong, and this simple illustrative predictive technique is probably as good as many sophisticated statistical or coupled dynamic models at predicting the continuance of El Nino into the Florida dry season when its impact is felt most in Florida.

The basic mechanism for impact is for warm Pacific SSTs to produce increased tropical convection and influence outgoing longwave radiation (OLR) and mid and upper tropospheric temperatures and impact mid latitude weather via influencing the position and strength of the jet stream. The author confirmed a strong statistical relationship between mean tropical OLR and 850 Mb wind in the NINO 3.0 area and Florida dry season weather in 1999 and 2000, but these relationships were not any stronger than that with the underlying SSTs. One reason SSTs provide such a long lead time is that, given warm Pacific SSTs, the jet stream will eventually respond and the resultant extra-tropical storms will impact Florida, maybe not in November or December, but in January and February, or March and April. Even the greatest El Ninos do not

continuously impact Florida's weather during a dry season. Much of the accumulated impact comes at time scales of a week or two interspersed throughout the dry season with significant periods of quiescent weather in between (H&A 2003 and 2004).

The flare-up of tropical convection and, in particular, an active MJO moving across the eastern Pacific could perhaps provide for useful intraseasonal forecasts of extreme storminess and rainfall which would be very beneficial. Figure 2 shows such an example for December 2002 when a moderate El Nino combined with a very active MJO to produce record rainfall in December. In contrast, the entire month of January 2003 was virtually rain free in Florida. A more direct predictive short-term link might be the actual development of tropical convection or model development of tropical convection, but it is a noisy field and difficult to parameterize in the short term. Also, data sets made of longer term averages would tend to mimic underlying SSTs in statistical analysis. This is an important area ripe for further research, because within a dry season forecast of extreme deviation, predicting the actual occurrence of the extreme weather events that make the season would be very beneficial at a time scale of 10 to 14 days out.

More aggressive outlooks of the impacts and possible actions to be taken to exploit the benefits and mitigate the costs of El Nino could be made if there was more confidence in the forecasts. There is also the most challenging issue of forecasting during weak or ENSO neutral conditions, the times when ENSO is not a major player, which are most common. During ENSO neutral conditions other teleconnections play a dominant role in extreme weather and climate. They are atmospheric variables (PNA, AO, NAO) that can operate on the time scale of weather and climate and are at the threshold of reasonably reliable short-term forecasts and reasonably accurate long-term forecasts. These other teleconnections can also modify the impact of El Nino and La Nina throughout a season and greatly affect intra seasonal variability.

Figure 1e and Table 1 illustrated the strong statistical relationship between the AO and minimum temperature in Florida. Figure 7 illustrates the spatial correlation of AO and surface air temperature for most of North America. The strongest positive correlations are over portions of Florida, meaning that as AO decreases the mean surface temperature decreases and vice versa. Extreme cold temperatures are a very serious threat to Florida citizens and the economy. Examples of mean MSLP maps for the months with the lowest average AO index (January 1977, Figure 8a) and highest average AO index (January 1993, Figure 8b) are presented to supplement the extreme positive and negative PNA, NAO, and ENSO mean MSLP maps from Figure 4 in Hagemeyer 2006. As with the case for NAO, there are very obvious reasons why AO- would be cold in Florida and AO+ would be warm. Updating Table 4 from Hagemeyer 2006 with the new AO statistical





Phenomena	Time Scale	Space Scale
Tropical Pacific SST	Months to seasons	Thousands of Km
PNA/NAO/AO	Weeks to months	Thousands of Km
Mean Storm Track/Jet Stream/LW Trough	Weeks to months	Thousands of Km
Short Wave Trough	Days to week	Hundreds to thousands of Km
ET Cyclone	Days to week	Hundreds to thousands of Km
Jet Streak	Days	Hundreds to thousands of Km
Severe Freeze/Cold Outbreak	Days	Hundreds to thousands of Km
MCC in Warm Sector	Hours to days	Hundreds of Km
Thunderstorms	Minutes to hours	Tens of Km
Excessive Convective Rainfall	Minutes to hours	Tens of Km
Mesocyclone/Super Cell	Minutes to hour	5 to10 Km
Tornado	Seconds to minutes	Hundreds of Meters

**Table 2.** Simple conceptual consideration of the time and space scales relating to the attribution and predictability of various cascading and inter-related weather and climate phenomena.

temperatures, devastating freezes are very rare. While La Nina generally leads to warmer mean temperatures, the singular occurrence of a freeze is more likely, but again not generally a devastating freeze. Indeed, there are two basic conditions needed to cause a severe freeze in Florida: very cold air in the northern source region and a storm track and ET cyclone with a trajectory to pull that air deep into Florida quickly and unmodified. This is most likely to occur under strongly negative AO/NAO conditions when ENSO does not dominate. So, the picture for predicting occurrences of extreme minimum temperature is complicated, but not so much so that scientists working with forecast users can not glean useful information.

An attempt to forecast storminess for a single location like Daytona Beach is not a realistic endeavor for reasons noted in Hagemeyer 2000, and H&A 2002 and 2003. The concept of storminess is the occurrence of a significant extratropical storm with all of its impacts, both negative and positive, influencing a broad area such as Florida so a storm count for a small area and the state is virtually identical. Of course the impact of an individual storm varies widely in phenomena and space and would be difficult to quantify and correlate.

The results of logistic regression for +/- 1 SD dry season rainfall at Daytona Beach on Nino 3.0 (Figure 13) is very similar to that for all of Florida, except that the relationship for extreme low rainfall and La Nina is a little stronger for Daytona Beach. It should be

expected that rainfall relationships for a smaller area will deviate from the larger aerial averages and among themselves, but not greatly when time averaged over a six-month season. To experiment with probabilistic prediction of the local occurrence of excessive rain or lack of rain from the ENSO signal, logistic regression was completed for the following five scenarios: maximum 24-hour rainfall at Daytona Beach in December exceeds 1, 1.5, and 2 inches, or does not exceed 0.25 or 0.50 inches (Figure 14).

The occurrence of excessive rainfall amounts within a given day in December in Daytona Beach, Florida, is inherently a mesoscale scale event. The nonconcurrence of heavy rainfall in December at Daytona Beach is inherently a synoptic scale climatic event - the consistent lack of weather systems conducive to producing rainfall. These assertions are certainly subject to debate. However, consider that if a forecast for a 6-month season or three month period of above/below normal rainfall is made - whether that forecast is right or not (verifies) - depends on the above two scenarios, either forces act to limit the conditions that cause rain, or act to focus heavy rainfall over Daytona Beach. So, if we spend all of our time focusing on verifying broad rainfall measures and correlations how does that get us any closer to linking climate and weather and providing more detail in a forecast? The results shown on Figure 14 can then be interpreted with the above discussion in mind.

Of the five scenarios, the >1-inch threshold is actually most common, occurring in 45% of the seasons between 1950 and 2004. Clearly, its occurrence is much more likely in strong El Ninos than strong La Ninas; but the relationship with the much rarer >1.5-inch threshold (18% of the seasons) is even more striking with a near zero chance of occurring in strong La Nina conditions versus near 80% chance of occurring in strong El Nino conditions. Indeed, the curve for the >1.5" in a day in December solution is very similar to the entire 6-month season solution for + 1SD rainfall. Should we be surprised that this is the case? Not if we remember what makes up the climate and seasonal averages. One can also see that at the very extreme ends of the daily rainfall spectrum, <0.25" and >2.0", the relationships are not as strong for ENSO. The >2.0" threshold is near zero for strong La Ninas, as would be expected, and rises to around 30% (versus 9% climatology) for strong El Ninos showing skill with what is actually a fairly high probability of a very rare event at a single point. The <.25" threshold is very low for El Nino conditions as would be expected, but it does not rise for La Nina conditions. There is a very good reason for this that is often overlooked. Strong La Ninas typically produce rather active winters, albeit with a northern storm track, and it is common to get cold frontal passages with rainfall in Florida in strong La Ninas. It is, however, uncommon to get heavy rain when the storm track is far to the north. Indeed, as found in Hagemeyer (2006) the driest conditions can come in ENSO neutral scenarios with positive AO/NAO and negative PNA and thus are not reflected on Figure 14.

The experiments illustrated on Figure 14 are an attempt to calibrate the limits of predictability for local rainfall extremes from the seasonal ENSO signal. For Daytona Beach the reliable limits of predictability are around the <0.50" and > 1.5" thresholds and these could be important to many users. If one compares the probability distribution for these two scenarios, it is evident that they are very similar to the overall seasonal rainfall +/- 1 SD extreme distribution (Fig. 13). Although the time scales are vastly different (24 hours versus six months) the results are perfectly in line with the linkage between climate and weather since an extreme wet or dry season is more than likely made up of the occurrence of rainfall days exceeding 1" or 1.5" or not exceeding 0.5". It's just a different way to think about the impact.

## 5. CONCLUDING REMARKS

This paper has presented a number of ideas and experiments on gaining more insights into the possibility of predicting extreme variability of storminess, rainfall, and temperature from large-scale teleconnections during the Florida dry season. The primary purpose of this paper is to perhaps stimulate interest in pushing the envelope in seasonal forecasting into unique impact variables relevant to specific areas and users. There are certainly potential benefits as well as risks to such approaches, but society continues to

become more sophisticated in their ability to understand the inter-relationships of weather and climate and the underlying uncertainties. The goal should be to broaden the constituency that can make educated decisions to exploit the evolving knowledge of climate and weather by taking advantage of benefits and reducing risks.

## 6. DISCLAIMER

The views expressed are those of the author and do not necessarily represent those of the National Weather Service.

## 7. REFERENCES

Please see: <http://www.srh.noaa.gov/mlb/research.html> for a complete list of references.

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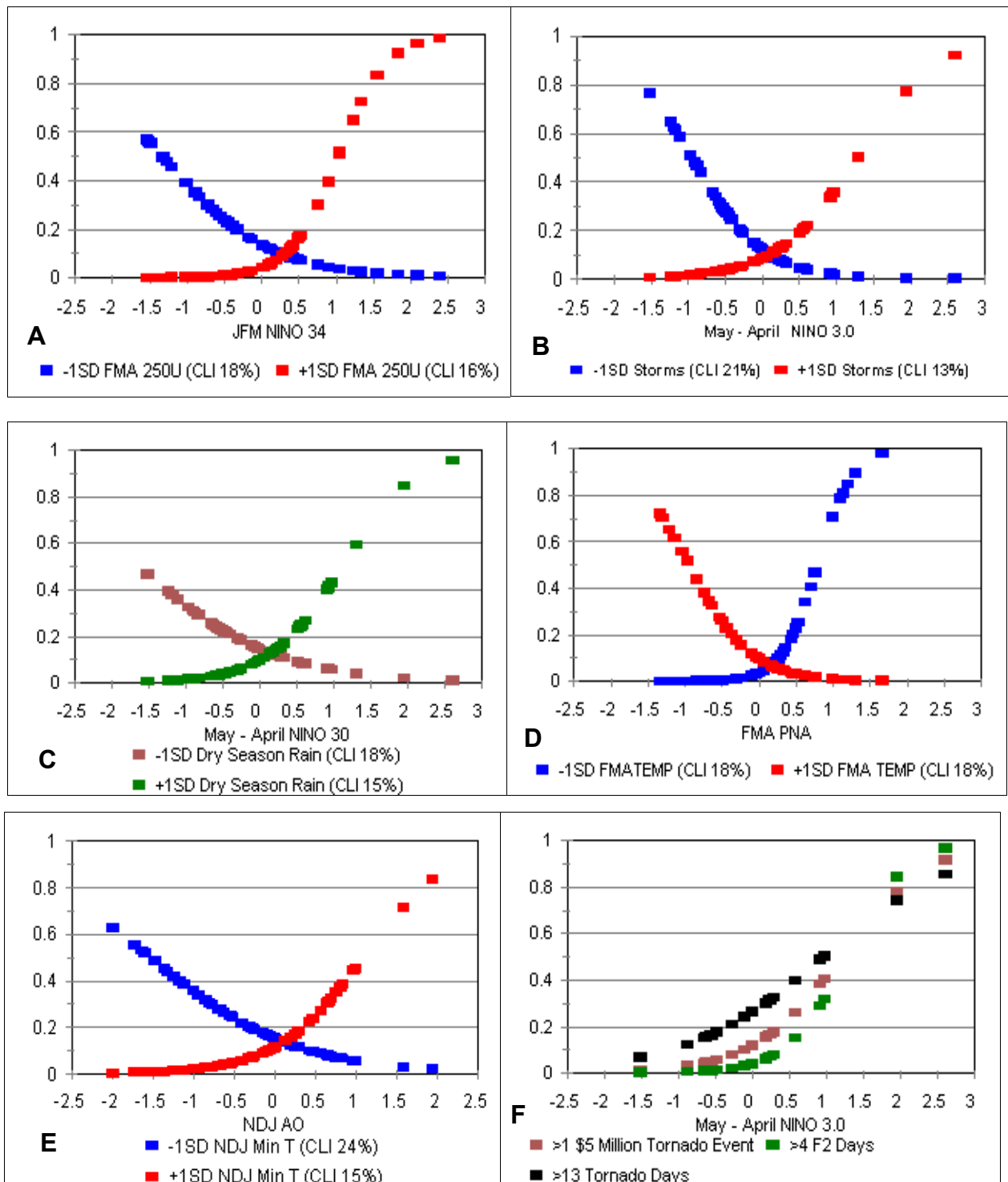
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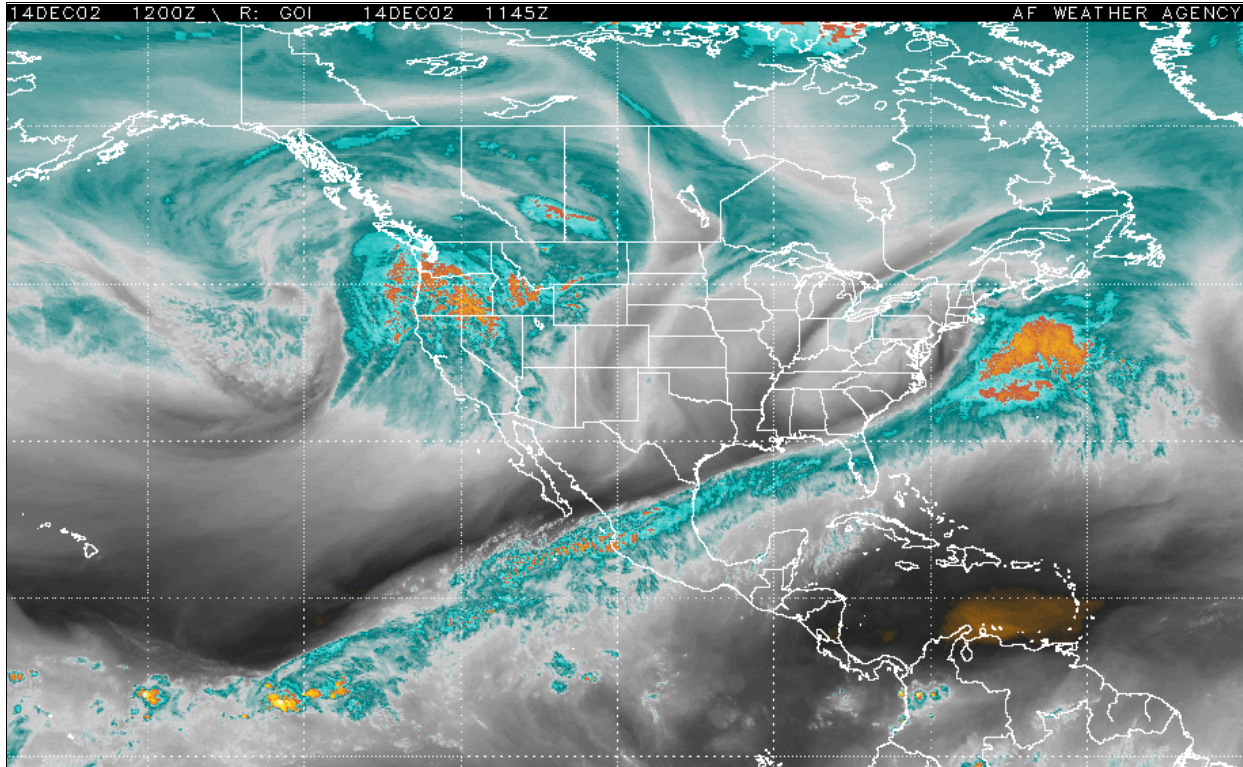
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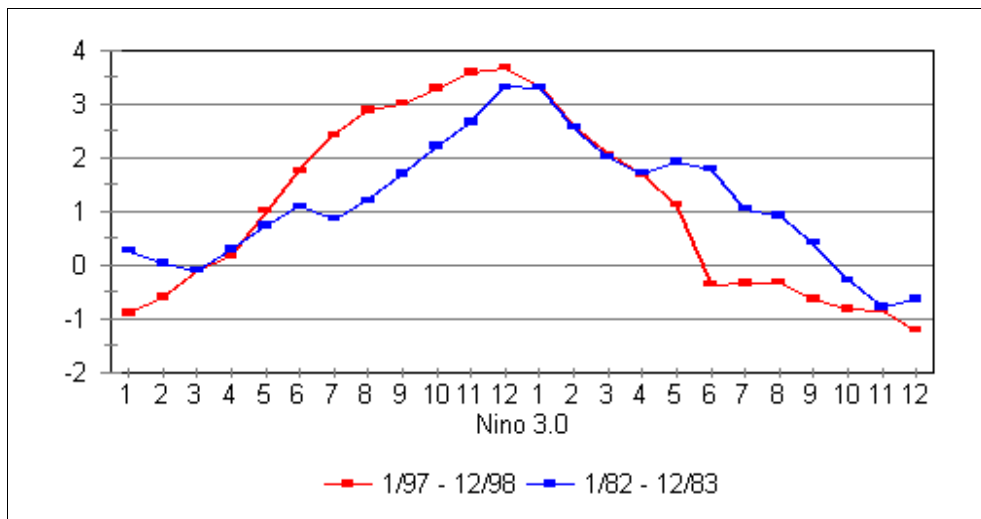
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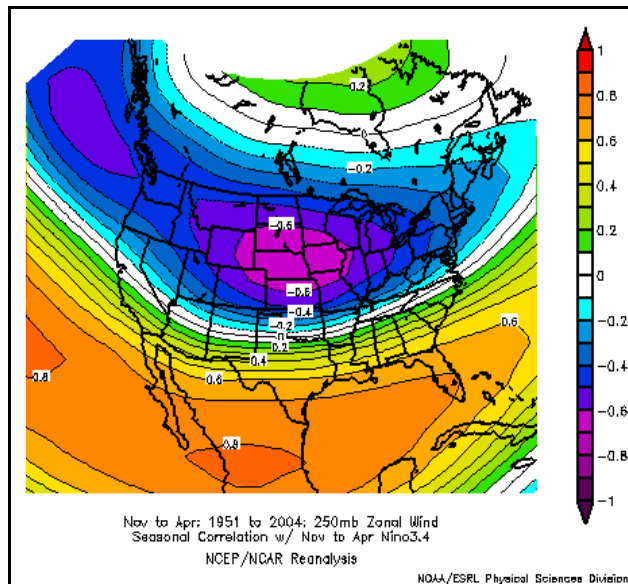
**Figures 1a-f.** Logistic Regression probability of exceedance results for NINO 3.4 on +/- 1 SD 250 mb U averaged over the Florida grid (A) , NINO 3.0 on +/- 1 SD Florida grid Storms (B), Nino 3.0 on +/- 1 SD Florida grid rainfall (C), PNA on +/- 1 SD Florida grid mean Temperature (D), AO on +/- 1 SD Florida grid mean minimum temperature (E), and NINO 3.4 on Florida dry season significant tornado measures ( F). For background on logistic regression see Hagemeyer 2006.



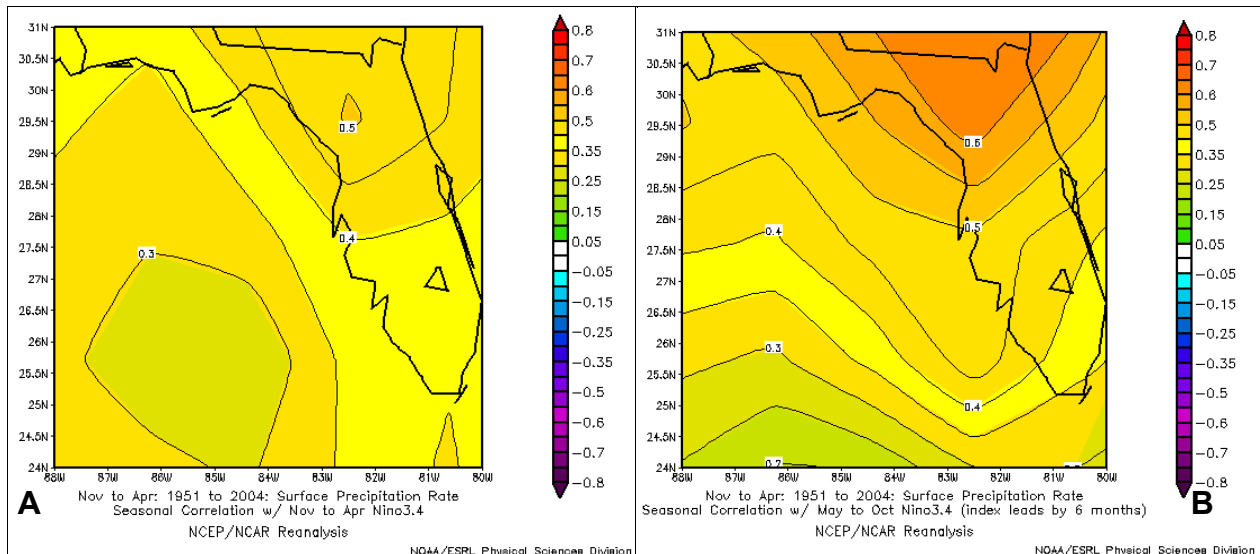
**Figure 2.** Enhanced water vapor imagery for 12 UTC 14 December, 2002 illustrating the Florida equivalent of the traditional “Pineapple Express”, the “Orange Blossom Express”, which persisted through much of December and contributed to record monthly rainfall in central Florida.



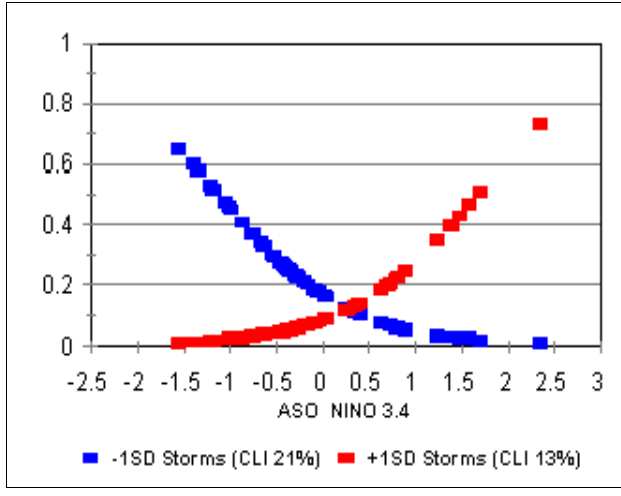
**Figure 3.** Plot of monthly mean NINO 3.0 anomalies for the 1982-83 and 1997-1998 El Niños. The Florida response started earlier and ended earlier in 1997-98 and started later and ended later in 1982-1983.



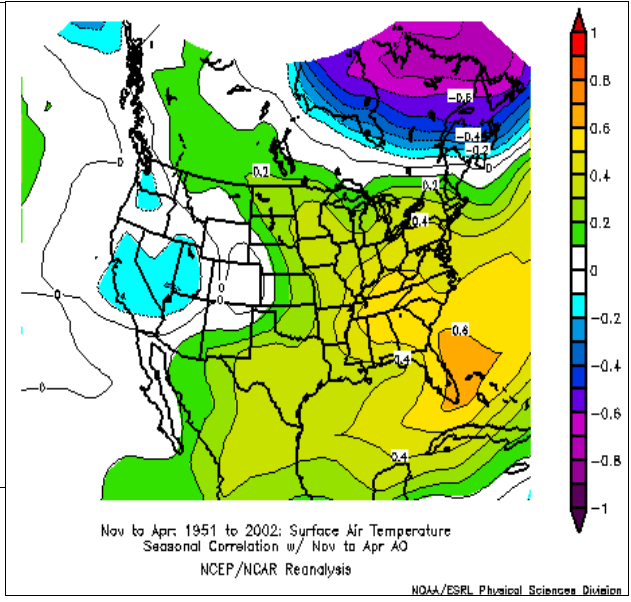
**Figure 4.** Plot of correlation coefficient of November to April Nino 3.4 regressed on November to April 250 Mb zonal wind (U).  
(Courtesy NOAA ESRL Physical Science Division).



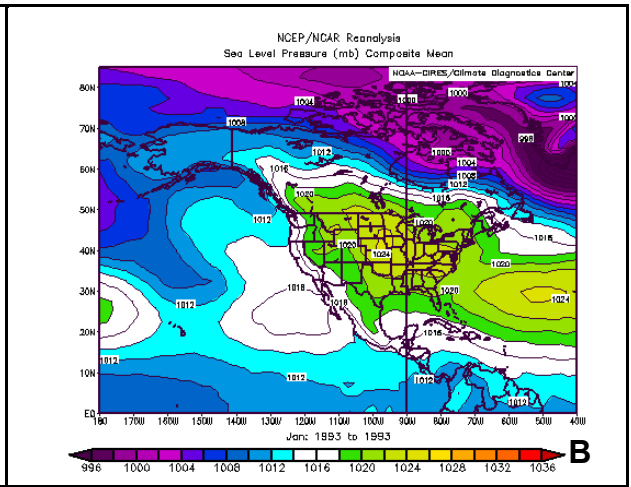
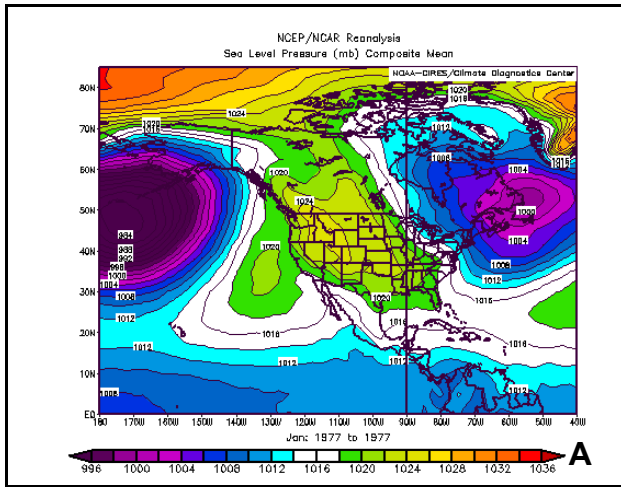
**Figures 5a-b.** Plots of correlation coefficients of November to April Nino 3.4 on November to April precipitation (0-month lead, Fig. 5a) and May to October Nino 3.4 on November to April precipitation (6-month lead, Fig. 5b).  
(Courtesy NOAA ESRL Physical Science Division).



**Figure 6.** Logistic Regression results for August, September, and October Nino 3.4 on +/- 1 SD Florida dry season storms.



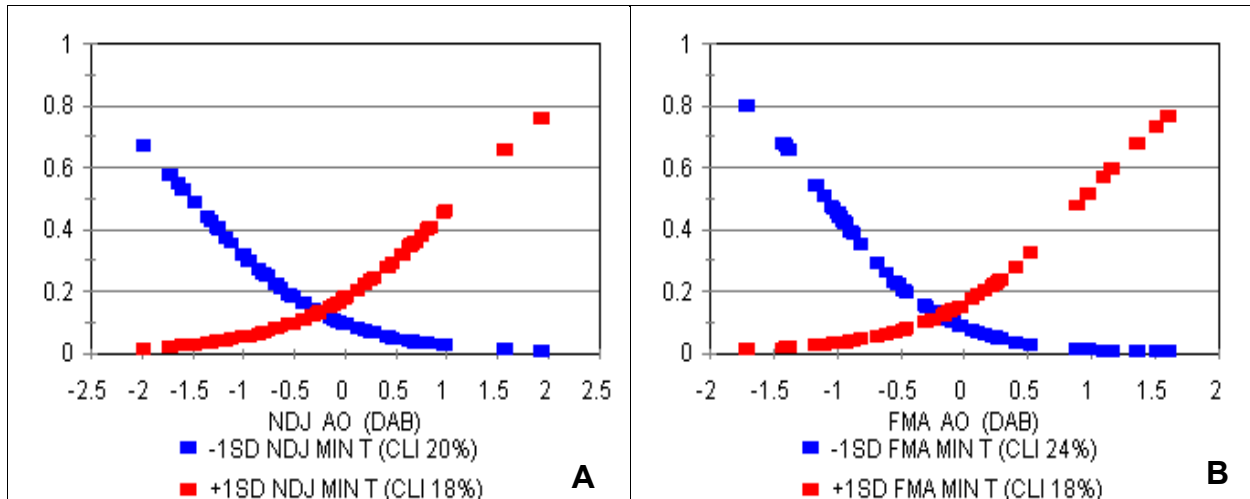
**Figure 7.** Plot of correlation of November to April AO with November to April surface air temperature. (Courtesy NOAA ESRL Physical Science Division).



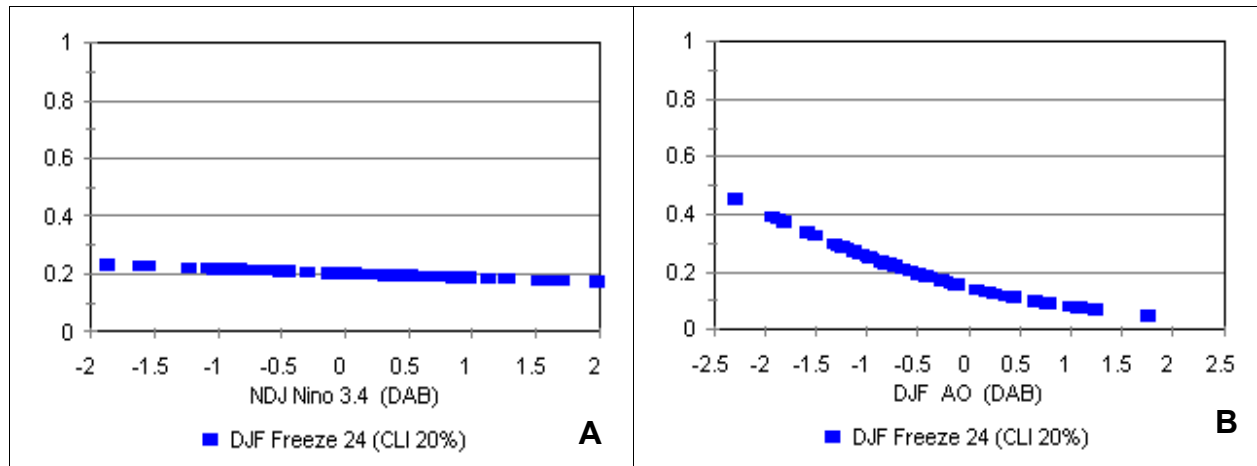
**Figures 8a-b.** Mean MSLP maps for record monthly negative AO (January 1977, 8a) and record monthly positive AO (January 1993, 8b). (Courtesy NOAA ESRL Physical Science Division).



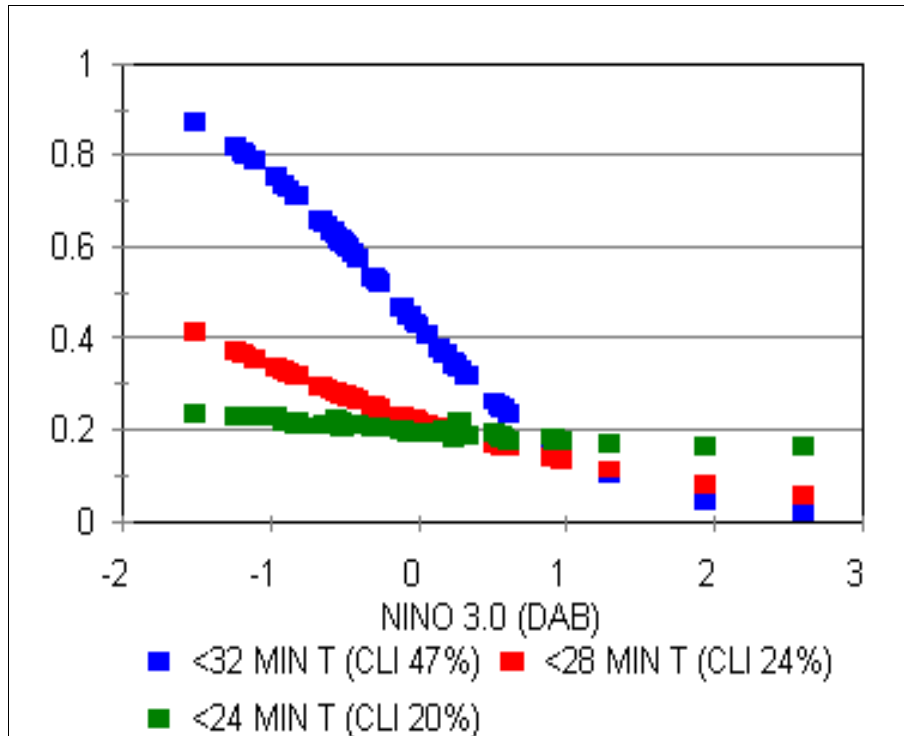
**Figure 9.** Front page of Miami Herald newspaper, 20 January 1977.



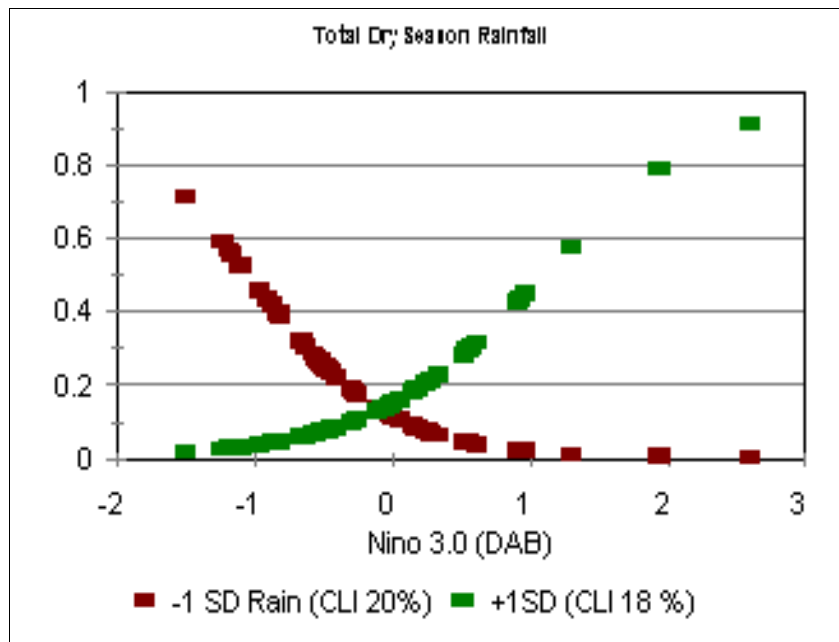
**Figure 10a-b.** Logistic regression results for +/- 1 SD mean minimum temperature for Daytona Beach, Florida, for NDJ (A) and FMA (B) on the NDJ and FMA mean AO index.



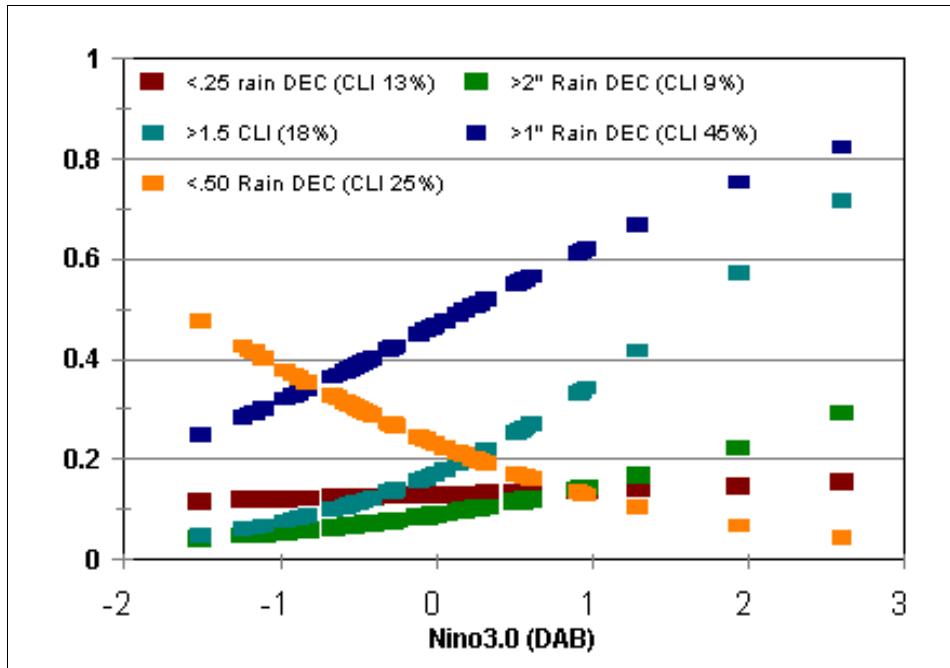
**Figure 11a-b.** Logistic regression results for the occurrence of at least one freeze in December, January or February (DJF) with minimum daily temperature # 24EF at Daytona Beach, Florida regressed on NDJ (one-month lead) Nino 3.4 (A) and DJF AO (B).



**Figure 12.** Logistic regression results for the occurrence of December minimum daily temperature falling below 32 EF, 28 EF, and 24 EF at Daytona Beach, Florida given the average value of NINO 3.0 for May through April (long lead forecast).



**Figure 13.** Logistic regression results for the occurrence of +/- 1 SD of dry season rainfall at Daytona Beach, Florida given the average value of NINO 3.0 for May through April (long lead forecast).



**Figure 14.** Logistic regression results for the occurrence of maximum daily rainfall in December at Daytona Beach, Florida exceeding 1", 1.5", and 2", and not exceeding 0.50" and 0.25" given average NINO 3.0 for May through April (long lead forecast).