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) 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	
JET STREAM		.62		.40		.12		.22		.80	
NDJ	FMA	.23	.55	.35	.50	.18	.12	.28	.27	.66	.80
STORMS		.57		.32		.02		.11		.61	
NDJ	FMA	.36	.40	.05	.41	.04	.08	.07	.24	.44	.59
MEAN TEMP		.15		.38		.02		.12		.44	
NDJ	DJF	.02	.21	.24.	.53	.14	.01	.20	.20	.36	.57
MIN TEMP		.07		.16		.24		.35		.49	
NDJ	FMA	.01	.11	.20	.33	.29	.10	.39	.33	.49	.47
RAINFALL		.38		.05		.00		.01		.42	
NDJ	FMA	.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). 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 +/- 1 standard deviation (SD) from November through April using only August, September, and October (ASO) <u>observations</u> 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 paramaterize 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 analysis presented in this paper provides for a theoretical worst-case scenario for extreme cold as strongly negative AO/NAO, positive PNA, and weak El Nino or ENSO neutral conditions. These conditions were present during much of the 1976-77 and 1977-78 seasons which rank as the second and first coldest, respectively, in Florida. In particular, January 1977 met all the criteria for extreme cold (Fig. 8a) and this was the only month in which snow is known to have fallen in south Florida (Fig. 9).

The problem with predictions of these obviously important teleconnections is the same as limitations with extended range weather predictions. If one could accurately predict extended range weather patterns dynamically, the same dynamic models would then provide estimates of PNA, AO, NAO indices, etc. In the case of the MJO, it is observable and can at times combine with El Nino to produce extreme rainfall in Florida (see Fig. 2 and Hagemeyer 2004 for discussion). The MJO is not predictable on the seasonal scale, but its observation can lead to improved forecasts of intra-seasonal rainfall extremes on the scale of 5 to 10 days in advance (Hagemeyer 2004). The same would apply to a devastating freeze, an event very unlikely to be predictable with any degree of confidence with seasonal lead times due to extreme rarity, but likely to give a reasonable signal of possibility some 10 to 14 days out in dynamic models. In summary, the first fundamental issue is the need for accurate predictions of the underlying teleconnections that have strong physical relationships to sensible weather and climate extremes.

The second fundamental issue is what is being forecast: mean atmospheric conditions. Outlooks of mean seasonal temperature and rainfall are valuable to a wide variety of users. Many interests such as agriculture, forestry, and water management can use mean seasonal outlooks of temperature and precipitation, but a wide variety of users, including those above, might also benefit from predictions of the occurrence of extreme weather within a season of means. Extremes of weather that are most impacting are typically hidden in the mean seasonal conditions. The author is in favor of forcing the issue of forecasting extreme weather from larger climatic signals and identifying strengths and weaknesses to focus future research. Extremes of seasonal measures of temperature and rainfall are made up of extreme weather events. If the deviations from the means are correlated, then it is likely the actual events contributing to the deviation may well be correlated. Interestingly, a seasonal forecast of 3-6 months is theoretically more accurate, as defined by the predictor/predictand relationships, than is a forecast of extreme weather, say 10 to 14 days in advance. But that doesn't always mean the existing predictor/predictand relationships are the most relevant. It is the author's opinion that shorter range forecasts should focus more on variables that define extreme events for a given area rather than above/below normal mean temperature and rainfall.

A major El Nino can rightly be thought of as an extreme climatic event, but its impact is really played out in a series of extreme weather events in some areas (such as Florida) that are predictable. El Nino is highly correlated with rainfall, the jet stream, and MSLP over Florida. So it is perhaps not surprising that the weather variable, significant extratropical storms over Florida in the dry season, that the author has been investigating for some time is also highly predictable. Storminess is an example of attempting to bridge the gap between climate and weather. The author has focused on a measure of seasonal storminess, the accumulation of major extratropical storms in the Florida dry season, as a significant impact variable that goes beyond traditional measures of temperature and rainfall and inherently combines climate and weather (Hagemeyer (1998, 2002, 2003, and 2004 etc.) with considerable success. However, there is considerable diversity of impact among a population of storms during a dry season. Not all extratropical storms are the same and some bring excessive flooding, rainfall, tornadoes, and misery; most beneficial rainfall; and some little promised rainfall. Later in this paper the author will present other examples of trying to squeeze extreme weather predictions of a probabilistic nature out of climate forecasts and large scale teleconnections. Examples of experiments to predict probabilistically the occurrence of extreme weather events at Daytona Beach within the broader seasonal forecast for mean temperatures and rainfall will be presented.

The third fundamental issue is attribution - and the storminess variable and severe local storm occurrence are good examples to consider. There has been a general reluctance by the atmospheric science community to attribute a singular extreme weather event to a climate phenomena such as El Nino. This debate was strong during the record-breaking El Nino of 1997-98, and the author was involved due to the occurrence of the deadliest tornado outbreak in Florida history on February 22-23 in Central Florida and the claims that it was “caused” by El Nino. Well, the answer depends on how the question is framed and is difficult to address in a short media interview. If the question is, is this killer tornado the direct result of El Nino, the answer is no. However, if the question is, did El Nino play a role in producing the conditions that spawned the killer tornado, then the answer is undoubtedly yes. The author developed a matrix in 2000 for use in explaining the predictability and attribution of various weather and climate phenomena in relation to Pacific SSTs (Table 2). This ultimately lead to the development of storminess as a variable that was a good proxy for severe weather typically associated with significant extratropical cyclones.

Hagemeyer (2000a&b) found the number of dry season F2 tornado days, the number of $5 million dollar tornado events, and the number of dry season tornado days from the 1980 through the 2000 dry seasons correlated quite well with NINO 3.0 and 3.4 (see also Fig. 1f). If one considers "seasonal" measures there is considerable scientific basis for a viable physical relationship to work with. The presence of a jet maxima is one of the key ingredients in producing an environment favorable for tornadogenesis. Hagemeyer and Matney (1993) found that the upper air parameter in proximity to Florida tornado outbreaks most highly correlated with reported tornado strength was the bulk mean wind. In other words, as the mean wind increases, the odds of stronger tornadoes increase. El Nino affects the location and strength of the jet stream and thus increases the odds of strong tornadoes in the Florida dry season.

There is a scientific conundrum regarding attribution and predictability that needs to be overcome. Not reacting to the obvious immediate issue of did El Nino cause this tornado, flash flood, landslide etc, but focusing instead on the appropriate issues and processes is crucial to making progress on forecasting extreme weather at the seasonal scale that people can take action on. The exact scientific answer to whether El Nino caused the tornado is no, due to the scales of motion. However, as scientists, we should have an obligation to reframe the question so it can be properly interpreted. To not have an open mind on attribution is to close doors on avenues of investigation that could lead to very useful information on potential impacts and mitigation even though the climate/weather theory is not perfect - and never will be.

For example, consider that what made the deadliest tornado outbreak in Florida history so important was that it killed a large number of people (42). There are at least two issues of attribution: the occurrence of the strong tornadoes, and the intersection of the tornadoes with society at its most vulnerable (RV's and mobile home parks). El Nino clearly has a role to play in setting the stage for violent tornadoes. Education and mitigating societal vulnerability are tools just as are tornado warnings or seasonal forecasts of extreme storminess. It is the author's opinion that there is much more to be gained in the study of attribution and public preparedness, education, and response. It can move forward in the absence of perfect theory and predictability without sacrificing scientific integrity. Society continues to become more sophisticated in understanding the inter-relationships of weather and climate and the underlying uncertainties. One of the biggest challenges is defining new impact variables that are most relevant and might be predictable. A few examples will be presented in the following section.

3. THOUGHTS ON PREDICTION OF SINGULAR EXTREME WEATHER EVENTS WITHIN THE FLORIDA DRY SEASON FROM MEAN TELECONNECTION INDICES

The author was intrigued by whether the exceptional relationships between some teleconnections and the probability of occurrence of extreme weather for Florida using LR techniques could be adapted for much smaller areas such as individual cities. The inherently probabilistic nature of LR is appealing and it can be used to identify a very specific extreme weather scenario and correlate the database produced for that variable with major teleconnections. First, LR was completed on the AO for NDJ and FMA with the NDJ and FMA +/- 1 SDs of mean minimum temperature at Daytona Beach, FL, in the same manner as for the entire Florida grid (NDJ example shown as Fig. 1e). The results for Daytona Beach (Figures 10a-b) were highly correlated with AO and virtually identical to those for Florida as a whole, which is not surprising since the variable is an extreme deviation of the mean minimum three-month temperature. This variable would be expected to show homogeneity across most of Florida, and Central Florida in particular.

LR was then conducted with Nino 3.4 (Fig. 11a) and AO (Fig. 11b) for the scenario of at least one devastating freeze occurring in Daytona Beach with minimum daily temperature # 24EF during December, January, or February, the traditional freeze months. In other words, given a certain value of Nino 3.4 or AO, what is the probability that a severe freeze would occur at Daytona Beach during DJF? The results show that NINO 3.4 (Fig. 11a) has literally no value at predicting major freezes. Indeed, the probability is nearly identical from historic strong La Nina to strong El Nino conditions and equal to climatology, indicating absolutely no skill. In contrast, the results for the AO show that there is about a 50% chance of an extreme freeze when extreme values of negative AO occur, and a near 0% chance of an extreme freeze when extreme values of positive AO occur. Of course, AO is not accurately predictable at long range. However, the impact of a consistent and strongly negative AO pattern for the winter in Florida is potentially so great that some critical customers could take action based on a low seasonal confidence forecast based on a prevailing negative AO. Interestingly, if ENSO is expected to be neutral or weak, the odds of a severe freeze should increase as ENSO would then be unlikely to prevent the other teleconnections from dominating. The most dramatic example of this is the January 1977 freeze/snow event with extreme negative AO during a weak El Nino.

Since ENSO is the one major teleconnection with a reasonable forecast track record, another experiment was conducted on the very specific criteria of the minimum daily temperature at Daytona Beach falling below 32 EF, 28 EF, and 24 EF in the month of December. Logistic regression results for these scenarios on May-April mean NINO 3.4 are shown on Figure 12. Interestingly, the results show a very strong relationship between the occurrence of a day of freezing temperatures and La Nina conditions, but this relationship becomes weaker as the freeze threshold is lowered to 28 EF and becomes totally insignificant at 24 EF. In contrast, positive NINO 3.0 conditions have no relationship whatsoever to freezing temperatures. These results clearly illustrate the long held anecdotal belief that while El Nino generally leads to cooler mean

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 telleconnections 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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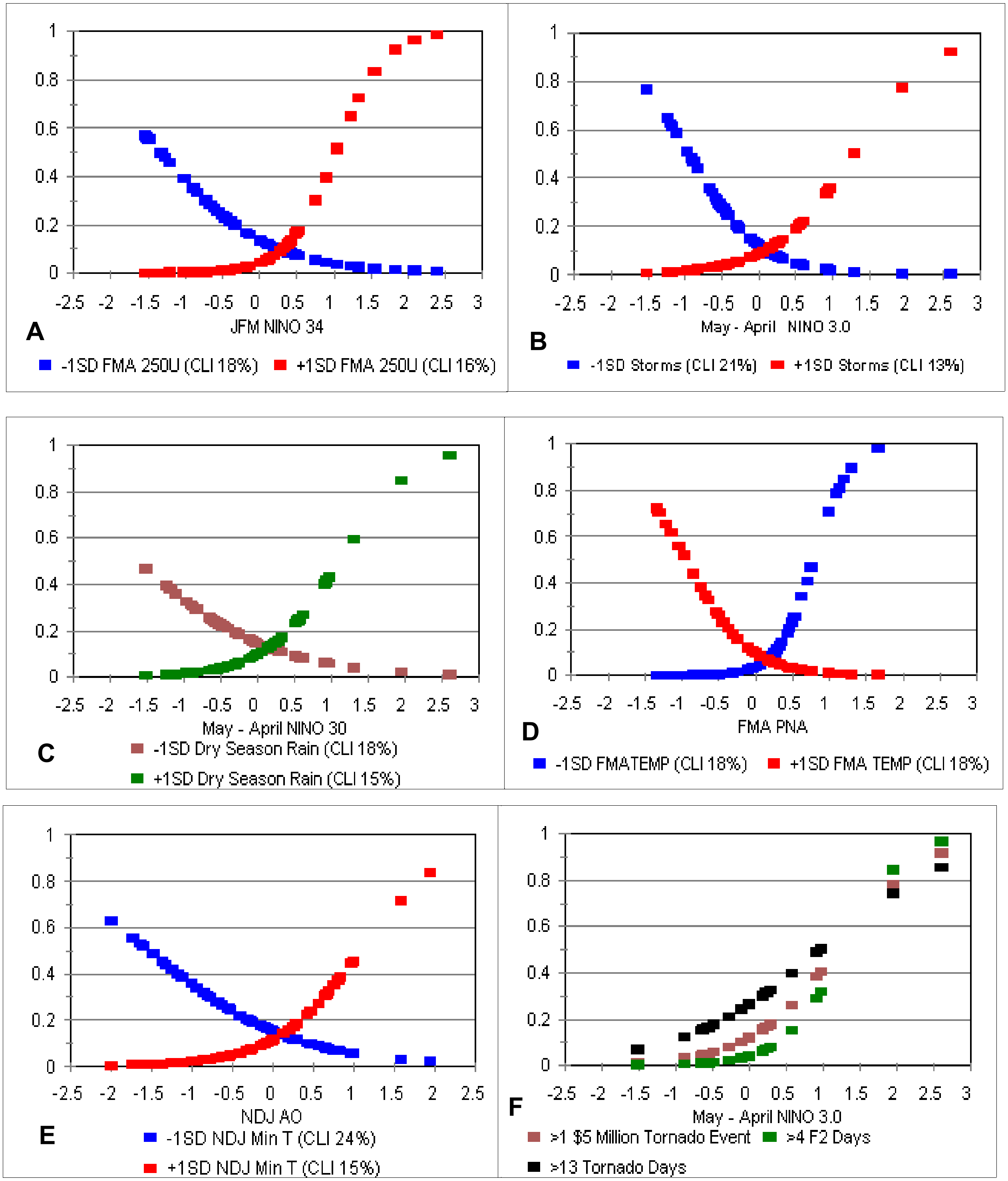


Figures 1a-f. Logistic Regression probability of exceedance results for NINO 3.4 on +/- 1 SD 250 mb U averaged over the Florida grid (A) , NINO 3.0 on +/- 1 SD Florida grid Storms (B), Nino 3.0 on +/- 1 SD Florida grid rainfall (C), PNA on +/- 1 SD Florida grid mean Temperature (D), AO on +/- 1 SD Florida 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.

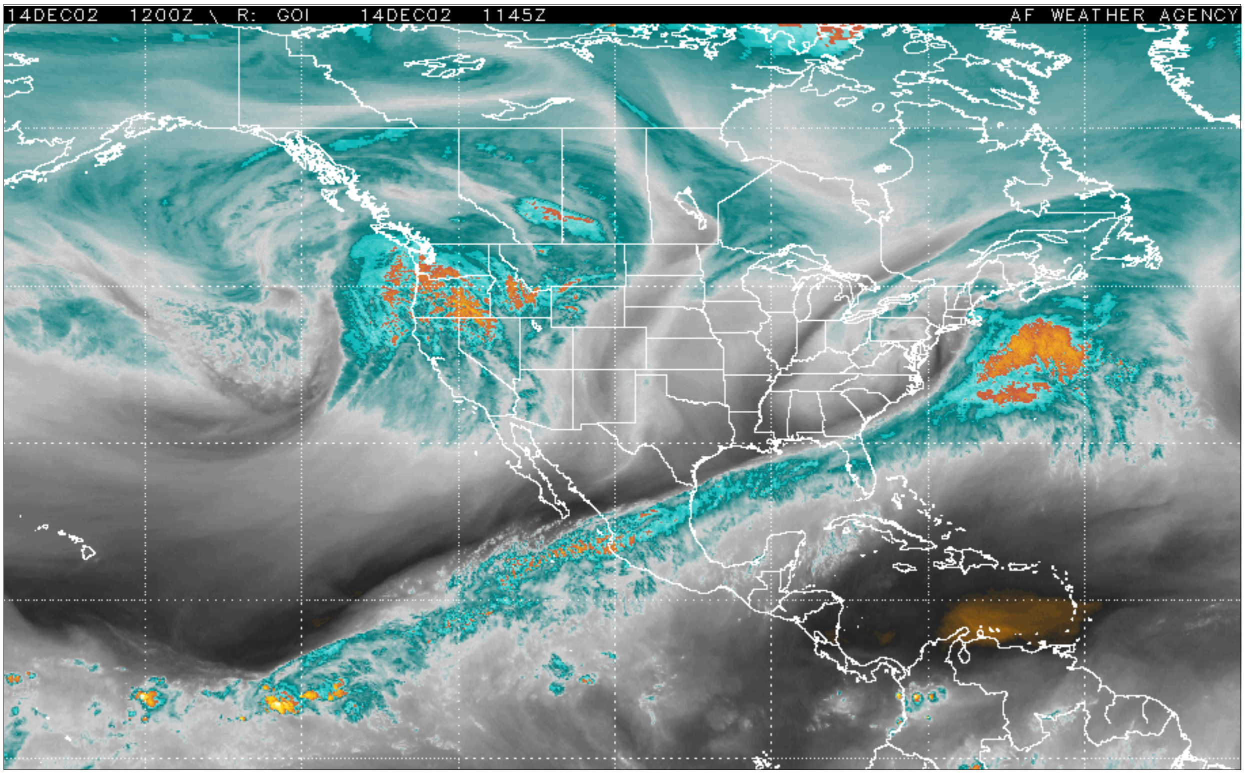


Figure 2. Enhanced water vapor imagery for 12 UTC 14 December, 2002 illustrating the Florida equivalent of the traditional "Pineapple Express", the "Orange Blossom Express", which persisted through much of December and contributed to record monthly rainfall in central Florida.

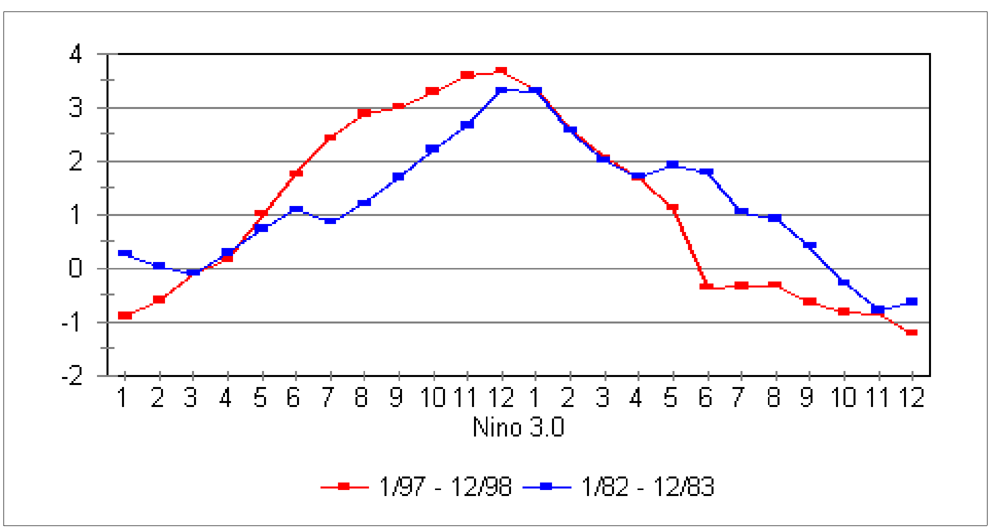


Figure 3. Plot of monthly mean NINO 3.0 anomalies for the 1982-83 and 1997-1998 El Ninos. The Florida response started earlier and ended earlier in 1997-98 and started later and ended later in 1982-1983.

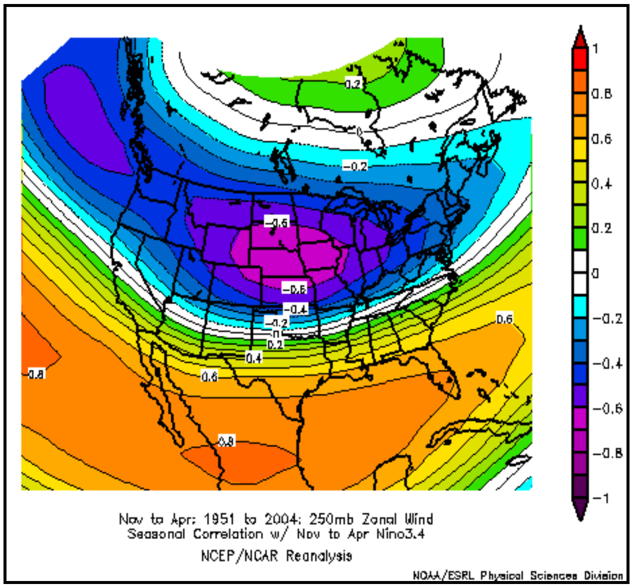
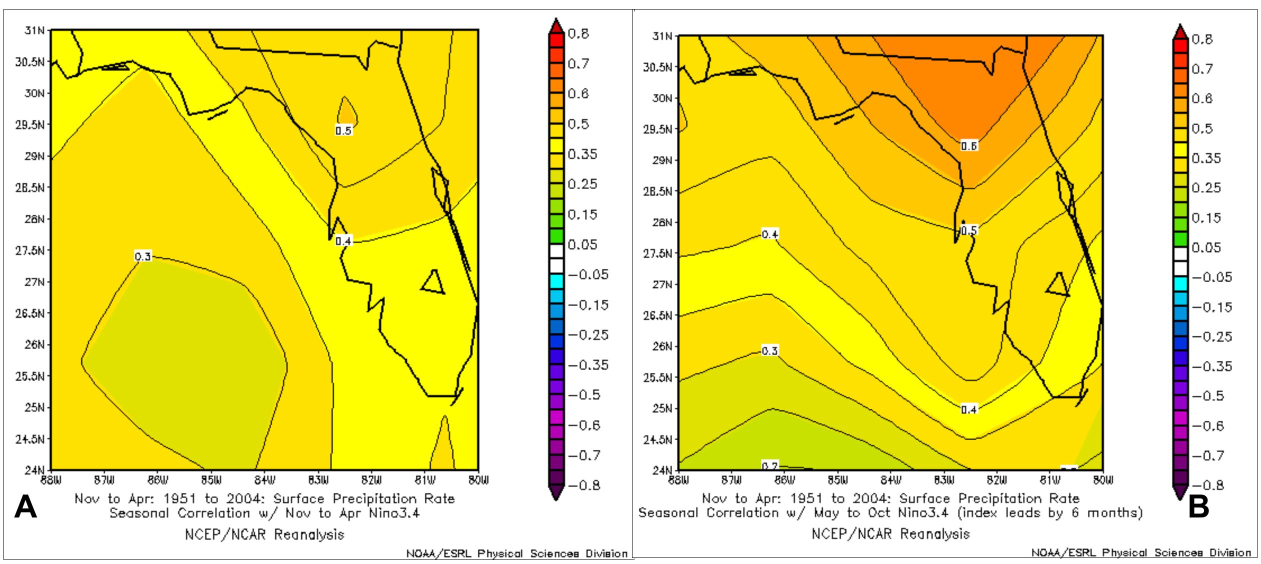


Figure 4. Plot of correlation coefficient of November to April Nino 3.4 regressed on November to April 250 Mb zonal wind (U).
(Courtesy NOAA ESRL Physical Science Division).



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).

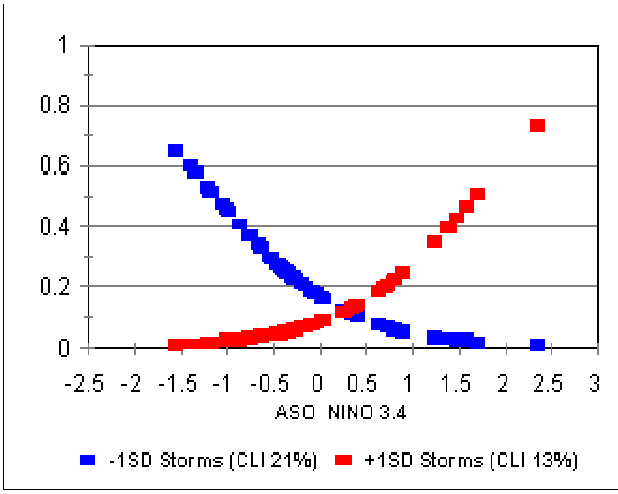


Figure 6. Logistic Regression results for August, September, and October Nino 3.4 on +/- 1 SD Florida dry season storms.

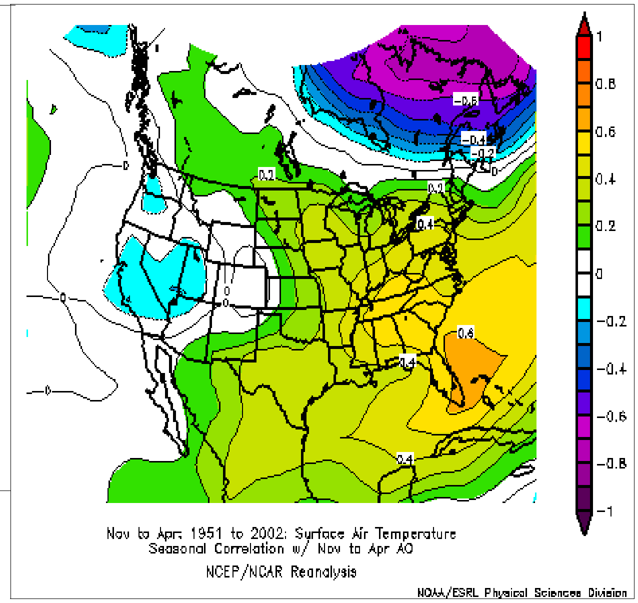
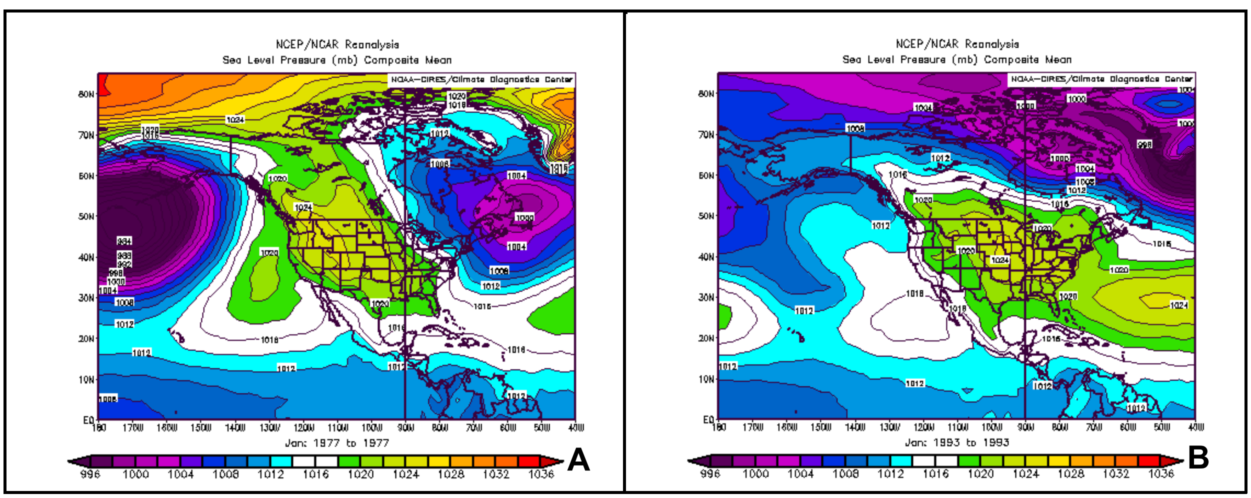


Figure 7. Plot of correlation of November to April AO with November to April surface air temperature. (Courtesy NOAA ESRL Physical Science Division).



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.

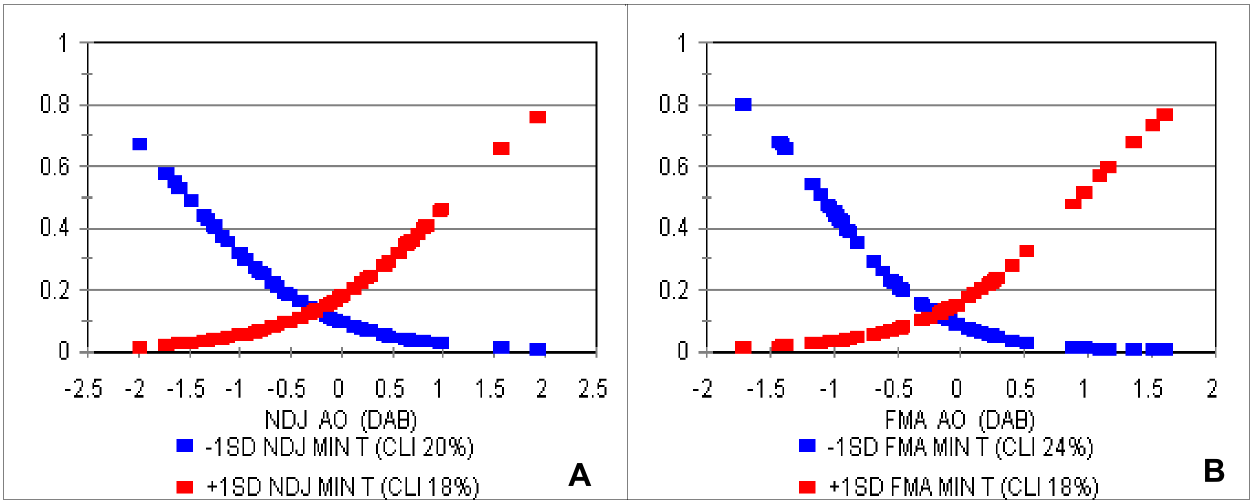


Figure 10a-b. Logistic regression results for +/- 1 SD mean minimum temperature for Daytona Beach, Florida, for NDJ (A) and FMA (B) on the NDJ and FMA mean AO index.

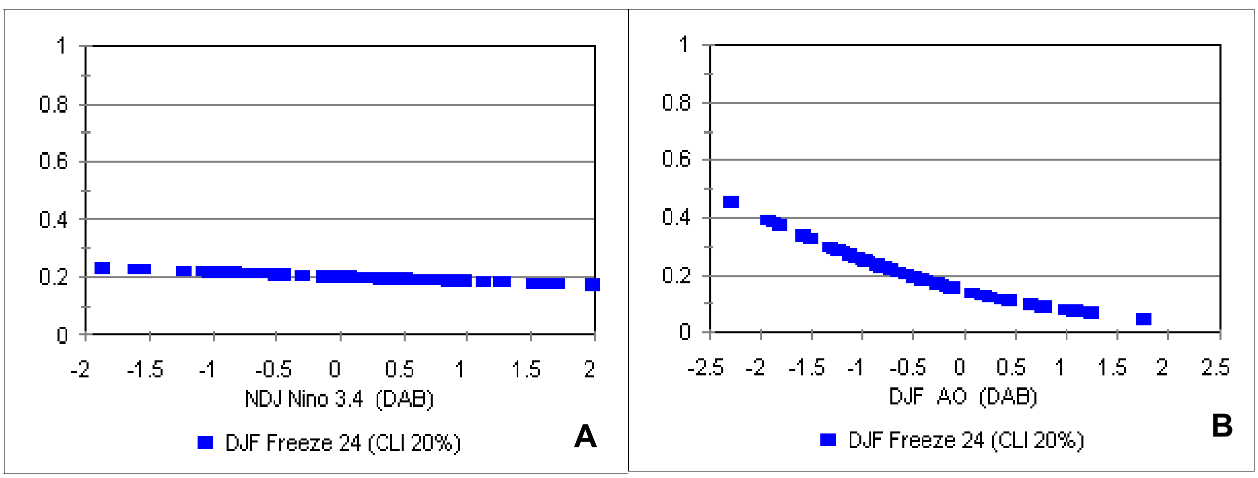


Figure 11a-b. Logistic regression results for the occurrence of at least one freeze in December, January or February (DJF) with minimum daily temperature # 24EF at Daytona Beach, Florida regressed on NDJ (one-month lead) Nino 3.4 (A) and DJF AO (B).

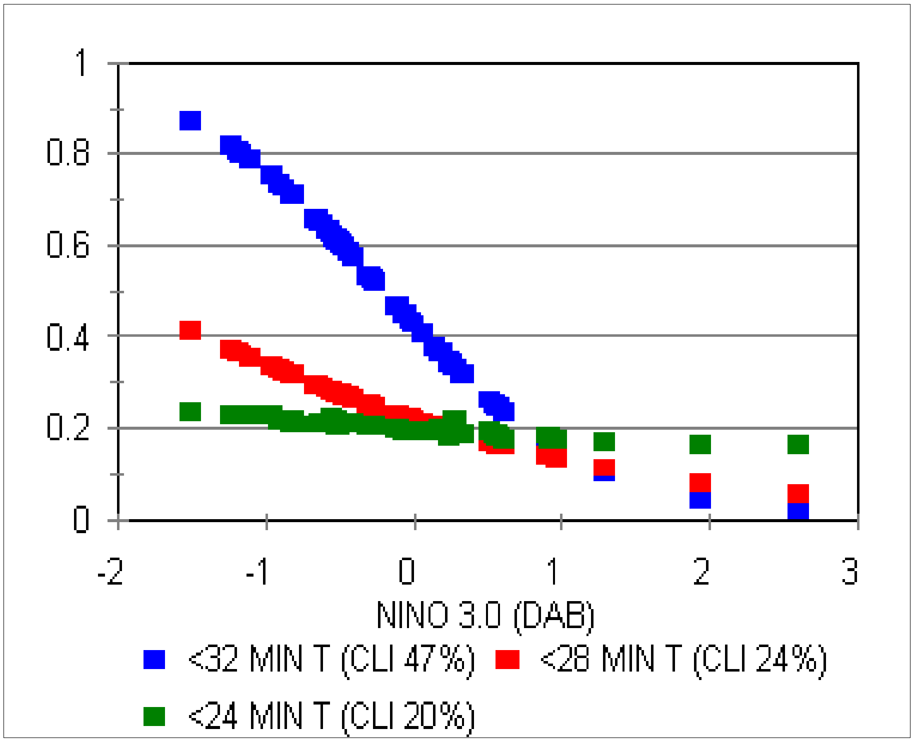


Figure 12. Logistic regression results for the occurrence of December minimum daily temperature falling below 32 EF, 28 EF, and 24 EF at Daytona Beach, Florida given the average value of NINO 3.0 for May through April (long lead forecast).

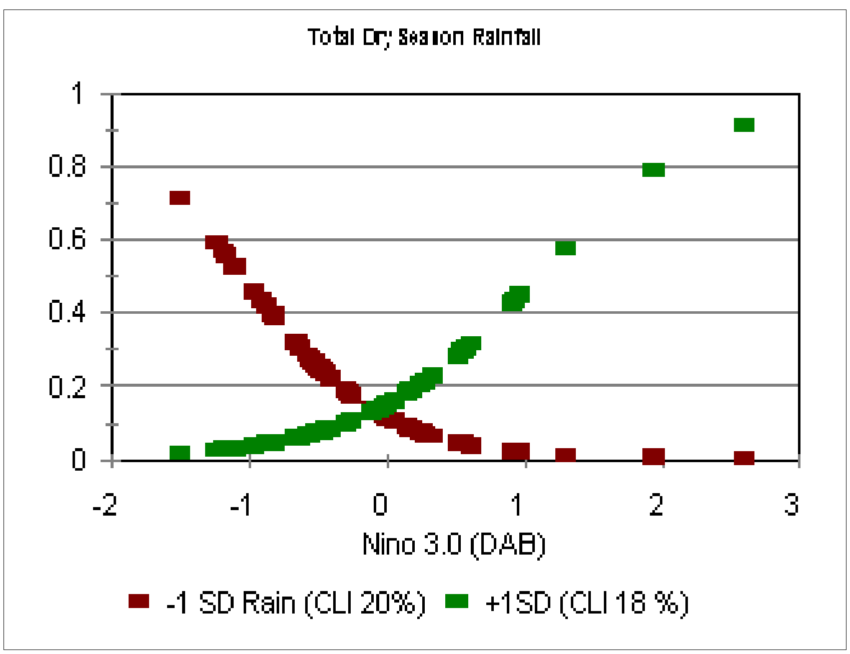


Figure 13. Logistic regression results for the occurrence of +/- 1 SD of dry season rainfall at Daytona Beach, Florida given the average value of NINO 3.0 for May through April (long lead forecast).

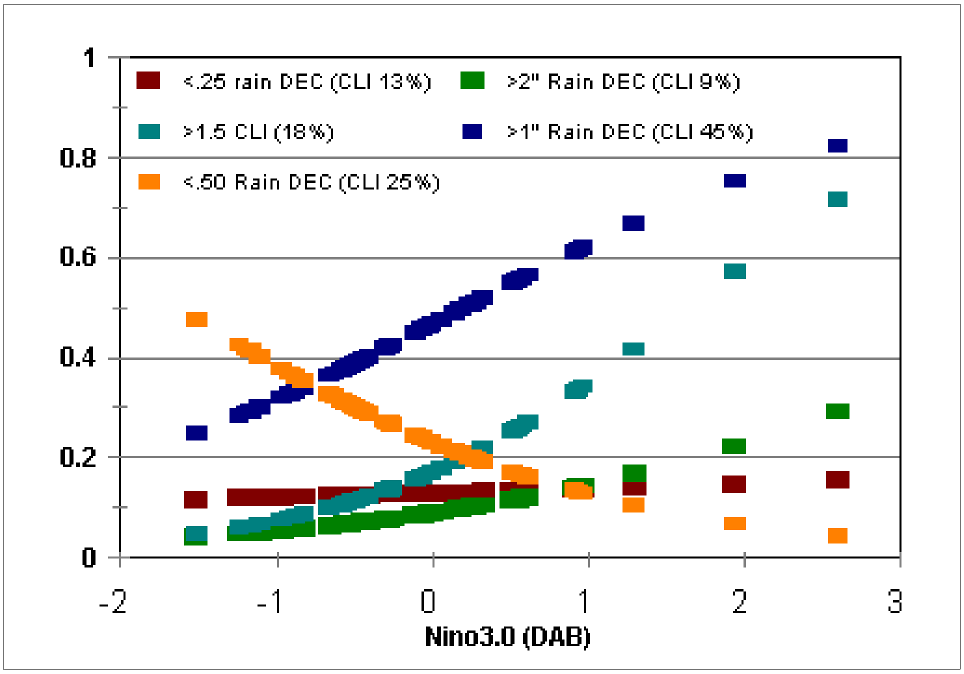


Figure 14. Logistic regression results for the occurrence of maximum daily rainfall in December at Daytona Beach, Florida exceeding 1", 1.5", and 2", and not exceeding 0.50" and 0.25" given average NINO 3.0 for May through April (long lead forecast).