P2.4 ENSO, PNA AND NAO SCENARIOS FOR EXTREME STORMINESS, RAINFALL AND TEMPERATURE VARIABILITY DURING THE FLORIDA DRY SEASON

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1. INTRODUCTION

Hagemeyer and Almeida (2005, http://www.srh.noaa.gov/mlb/enso/16th_climate.pdf) updated and improved the dry season (November 01-April 30) climatology of strong extra-tropical (ET) cyclones (or storms) affecting Florida, and expanded their forecast methodology for predicting dry season "storminess" (the accumulated passage of ET cyclones) from the El Nino-Southern Oscillation (ENSO) signal to include the North Atlantic Oscillation (NAO) and Pacific/North America (PNA) teleconnections. Their results confirmed that the addition of the NAO and PNA improved the dry season storminess forecast on average. However, the most significant improvements occurred in ENSO neutral seasons when the PNA and NAO can have the most influence, and entirely ENSO-based forecasts can fail badly.

While these forecast results seem to be good news, they raise more challenges for potential users to understand forecast uncertainty, assess impacts to society and take appropriate mitigation action. For example, a confident forecast of a strong El Nino can be relatively easily explained to, understood by, and acted upon by stakeholders to mitigate impact. However, during the majority of Florida dry seasons, the ENSO signal is either weak or neutral. Indeed, Hagemeyer and Almeida (H&A, 2005) documented that storm and rainfall variability can be as extreme in ENSO neutral dry seasons as during strong El Ninos or La Ninas. Understanding the interrelationships of the PNA and NAO is more challenging, and reliable seasonal predictions are not currently available.

Discussions of La Nina and El Nino have become commonplace in the Media and among users of seasonal forecasts, most of whom have a basic understanding of how ENSO influences Florida weather. As seasonal forecast users become more sophisticated, the focus will shift to other teleconnections like the NAO and PNA, especially in neutral or weak ENSO seasons. To facilitate the understanding and use of the seasonal forecasts, there is a need to provide more information on forecast uncertainty and the limits of predictability, factors controlling the range of climatic extremes that have been encountered in the past, and a guide to what extreme scenarios might be possible in the future.

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The primary hazards in the Florida dry season, important to a wide range of potential forecast users (decision makers), are damaging coastal storms, storms that spawn severe weather outbreaks and widespread flooding rains, a lack of storms and rainfall leading to drought and wildfire, and cold weather outbreaks. Because all of these hazards are not necessarily related to the occurrence or nonconcurrence of major extra-tropical cyclones, and to further examine the potential impact of the NAO and PNA, the author expanded the storminess investigation to include dry season rainfall and minimum temperature. The multiple linear regression (MLR) forecasts from H&A (2005) were also updated using improved NAO and PNA indices.

Much progress has been made on establishing the relationship between ENSO, PNA, and NAO and Florida dry season weather. The next step is to exploit this information for the benefit of society. All citizens of Florida should consider themselves in the context of decision-makers. The primary purpose of this paper is to demonstrate several ways to interpret and potentially exploit the dry season forecasts, including the use of Taylor-Russell diagrams and logistic regression analyses for probabilistic decision making.

2. MULTIPLE LINEAR REGRESSION FORECASTS OF STORMINESS, RAINFALL, AND MINIMUM TEMPERATURE

During the summer of 2005 the National Weather Service's (NWS) Climate Prediction Center (CPC) significantly revised the manner in which the PNA and NAO are calculated to eliminate inconsistencies between monthly and daily teleconnection indices. The historical archive of the NAO and PNA indices were also revised (http://www.cpc.ncep.noaa.gov/data/teledoc/telecontents.shtml). The storminess forecast equations from H&A (2005) were updated using the new NAO and PNA indices for the 1950 through 2003 Florida Dry Seasons.
Previously unpublished ENSO-based dry season rainfall forecasts were updated through the 2003 season and the new PNA and NAO indices were added as predictands. In addition, the author's database of average dry season minimum temperature for the 1958 through 1999 seasons was used to develop MLR equations for the prediction of minimum temperature from ENSO, PNA, and NAO. See H&A (2005) for development of the seasonal PNA and NAO indices and H&A (2002, 2003, and 2004) for

background on the development of the Nino 3.0 predictor index. All predictand data were obtained from the NWS's National Center for Environmental Prediction (NCEP) reanalysis data servers (Kalnay, et. al., 1996), and predictor indices were obtained from the CPC.

Figure 1 shows the Florida grid used to calculate dry season storms and rainfall. The smaller blue grid on Fig. 1 was used for calculation of dry season minimum temperature. Figure 2 show the sea surface temperature (SST) regions used as predictors. The relevant regression results for the 1950 through 2003 seasons are shown on Table 1. As in H&A (2005), Nino 3.0 and Nino 1+2 had the greatest correlation with storms, followed by Nino 3.4 and PNA. PNA (R^2 = .31) again outperformed Nino 4.0 (R^2 = .27, not shown). The PNA is significantly correlated with all the Nino indices, especially Nino 1+2 and Nino 3.0 which indicate that ENSO likely plays a significant role in the PNA pattern itself. In contrast, the NAO showed no correlation with any of the NINO SST indices, and its correlation with storms was not significant.

Although Nino 3.0 outperformed Nino 3.4, the results are statistically very similar (storms predicted by Nino 3.0 regressed on storms predicted by Nino 3.4 have a correlation coefficient of R^2 = 0.92). The combination of Nino 3.0, PNA, and NAO on storms produced R^2 = 0.63 versus R^2 = 0.67 in H&A (2005) using the old NAO and PNA indices. These results are comparable as storms predicted with the old NAO and PNA indices regressed on storms predicted using the new NAO and PNA indices produced a correlation coefficient of R^2 = 0.96. Figure 3 shows hindcasts of storminess predicted using the old NAO and PNA indices and the new NAO and PNA indices compared to actual and normal storms. There is no significant difference in the forecasts using the new and old indices. The mean absolute error using the new NAO/PNA indices was 1.82 storms and 1.95 storms using the old NAO/PNA indices.

The updated MLR seasonal storminess, rainfall, and minimum temperature forecasts are shown as Equations (1), (2), and (3), respectively.

$$\textbf{Storminess}_{\text{(NOV-APR)}} = \mathbf{6.3 + 3.2(Nino3.0_{\text{MAY-APR}}) + 1.0(PNA_{\text{NOV-APR}}) - 1.5\,(NAO_{\text{NOV-APR}})} \quad \mathbf{(1)}$$

$$\textbf{Rainfall}_{\text{(NOV-APR)}} = \mathbf{14.4 + 3.4(Nino3.0_{\text{MAY-APR}}) + 0.4(PNA_{\text{NOV-APR}}) - 1.4\,(NAO_{\text{NOV-APR}})} \quad \mathbf{(2)}$$

$$\textbf{Min Temp}_{\text{(NOV-APR)}} = \mathbf{15.6 + 0.1(Nino3.0_{\text{MAY-APR}}) - 0.8(PNA_{\text{NOV-APR}}) + 0.8\,(NAO_{\text{NOV-APR}})} \quad \mathbf{(3)}$$

The equations again confirm the author's original thesis that Nino 3.0 is the dominant signal for storminess and rainfall and that negative NAO and positive PNA act to increase the potential for storminess and rainfall, while negative PNA and positive NAO act to reduce storminess and rainfall potential. The results of equation (3) confirm PNA and NAO are the dominant signals for seasonal minimum temperature, that negative NAO and positive PNA are favorable for cooler temperatures, and that positive NAO and negative PNA are favorable for warmer minimum temperatures. Nino 3.0 could be left out of equation (3) due to its insignificance.

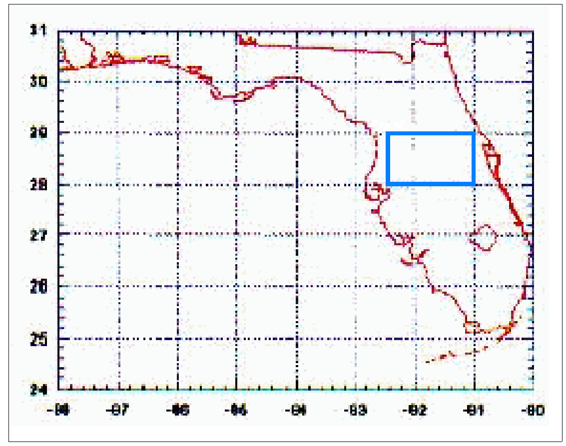


Figure 1. Grid used for computation of Florida dry season storminess and rainfall. The smaller blue inset grid over central Florida was used to compute average dry season minimum temperature.

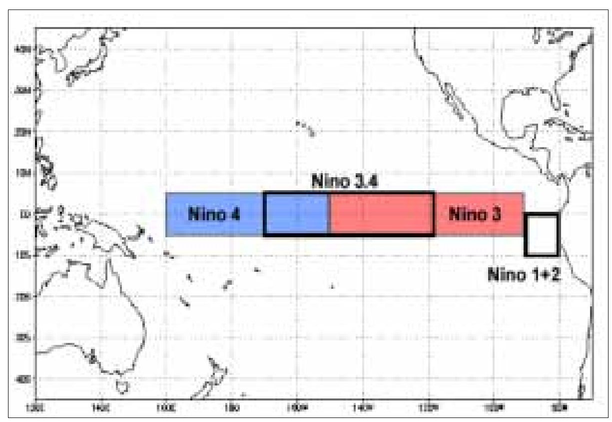


Figure 2. SST regions used as predictors in MLR.

	250 mb U	Storms	Rainfall	Mean Temp	Min Temp*
Nino 1+2	**.48**	**.55**	**.39**	**.11**	**.01**
Nino 3.0	**.62**	**.57**	**.35**	**.18**	**.03**
Nino 3.4	**.57**	**.47**	**.30**	**.18**	**.03**
NAO	**.12**	**.02**	**.00**	**.02**	**.31**
PNA	**.40**	**.31**	**.05**	**.38**	**.16**
3.0+PNA+NAO	**.80**	**.63**	**.42**	**.42**	**.55**

Table 1. Correlation coefficients (R^2) of regressions of predictor variables on the Florida grid (Fig. 1) dry season 250 mb U anomaly, storms, rainfall, and mean temperature for the 1950-2003 dry seasons, and for mean minimum temperature for the 1958-1999 dry seasons (*central Florida grid in blue on Fig. 1). Cells shaded dark do not have significant relationships, medium shaded cells are significant at 95% level (**$F_{.05}$**), and light shaded cells are significant at 99% level ($\mathbf{F}_{.01}$).

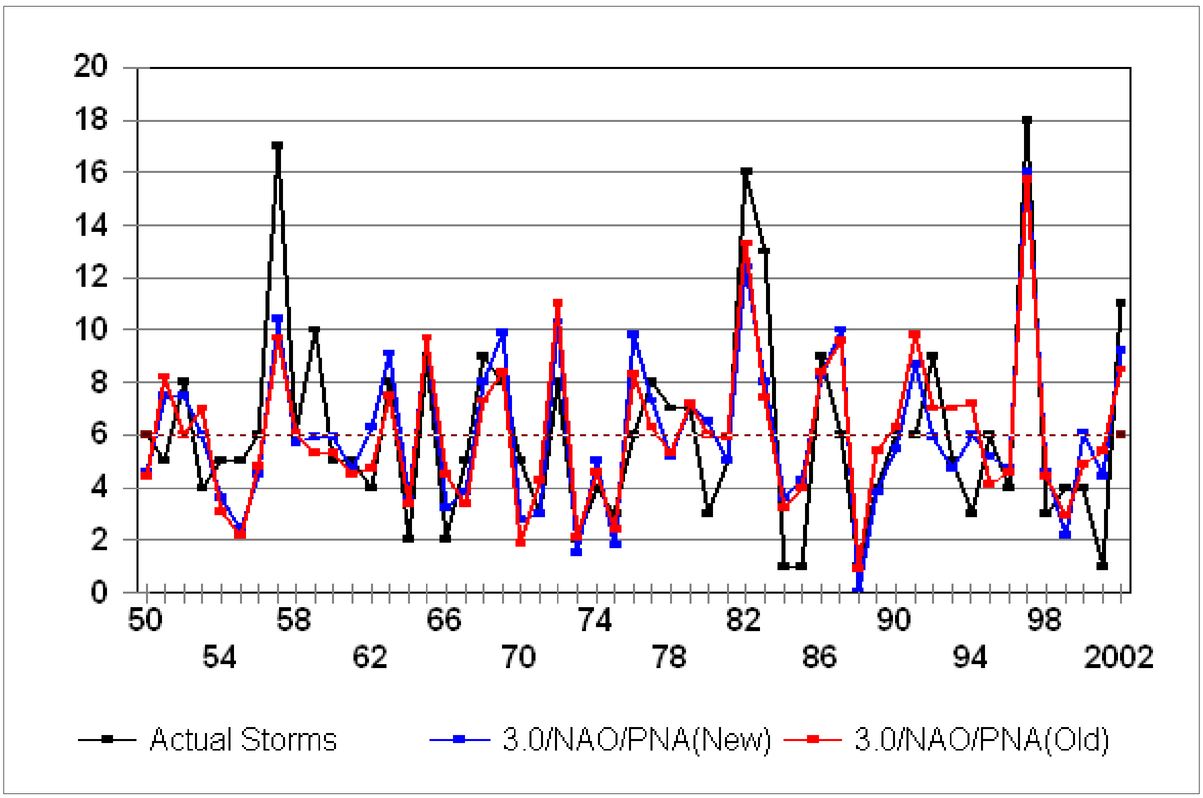
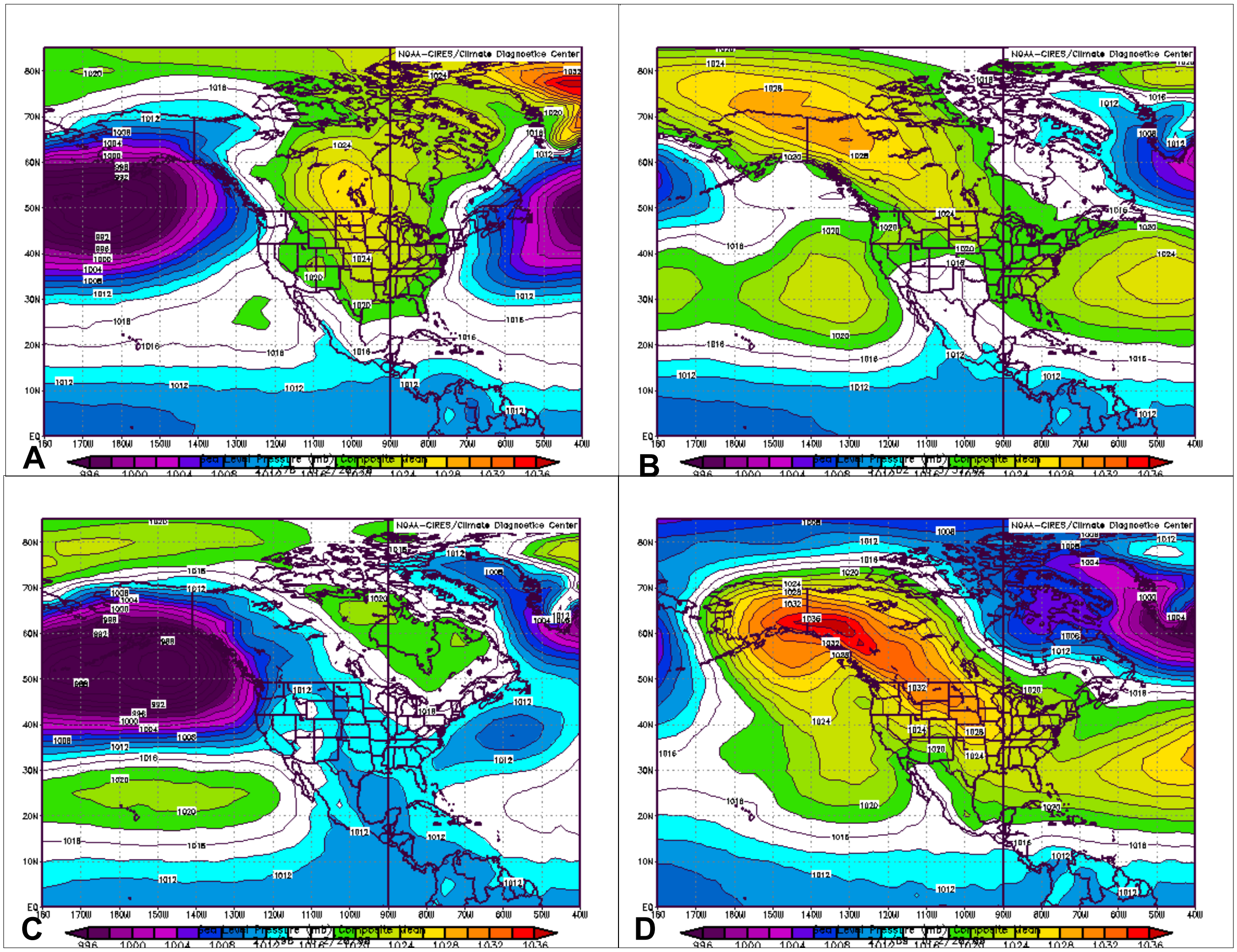


Figure 3. Number of Florida grid storms for the 1950 - 2002 dry seasons (black line) compared to dry season storms predicted by Equation 1 using new PNA and NAO indices (blue line) and storms from H&A (2005) using the old PNA and NAO indices (red line). The dashed line indicates average storms per season (6).



Figures 4a-d. Composite daily mean sea level pressure (mb) charts for the extreme PNA+ and NAO- conditions of February 1978 (4a) during ENSO-neutral conditions, extreme PNA- and NAO+ conditions of March 2002 (4b) during ENSO-neutral conditions, extreme El Nino conditions of February 1998 (4c), and extreme La Nina conditions of February 1989 (4d). Images provided by the NOAA-CIRES Climate Diagnostics Center, Boulder Colorado from their Web site at http://www.cdc.noaa.gov.

To reaffirm the physical reality of the storminess, rainfall, and minimum temperature forecast equations, brief reviews of the synoptic patterns associated with the extreme phases of ENSO, PNA, and NAO are in order. The extreme case of a strong negative NAO with a strong positive PNA, as in February 1978, is shown on Figure 4a. In this case, strong and extensive low pressure systems are found over the North Atlantic and North Pacific Oceans, while high pressure as a manifestation of the strongly positive PNA is centered over the plains of Canada and the United States. Surface pressure is lower than normal over Florida reflecting increased storminess, typically in the form of coastal storms developing north and east of Florida. Florida is wide open to the frequent intrusion of cold air masses from the north. The 1977-78 dry season had the lowest average minimum temperature of all seasons since 1950. The mean storm track is along the eastern seaboard from the vicinity of Florida northward. Rainfall, although perhaps more frequent than normal, is not necessarily excessive as the storms generally are more likely to intensify significantly downstream of Florida.

The extreme case of a strong positive NAO with a strong negative PNA, as in March 2002, is shown on Figure 4b. In this case, extensive high pressure ridges are found over the North Atlantic and North Pacific Oceans with the Atlantic high pressure ridge extending westward north of Florida. Strong continental high pressure is found over the high arctic of Alaska and Canada. This pattern quite simply limits the chances of storms and rainfall over Florida. A weaker mean storm track is found well north of Florida, extending from the desert southwest to the Great Lakes region. Minimum temperatures are quite warm on average as east to southeasterly surface flow modified by maritime influence prevails.

Figures 4c&d show the two extreme phases of ENSO for February 1998 (El Nino) and February 1989 (La

Nina), respectively. In the case of February 1998, the PNA was strongly positive in concert with high Nino 3.0, and the NAO was negative. Low pressure is predominant and a reflection of frequent storm passages on a southern track across or near the Gulf of Mexico into the Atlantic Seaboard. Rainfall is extreme across Florida. In the case of February 1989 (Fig. 4d), the PNA was strongly negative in concert with low Nino 3.0 and the NAO was positive. High pressure is predominating and the strong Atlantic subtropical ridge extends westward across Florida.

It is interesting to note the structural similarities between Figures 4a and 4c and Figures 4b and 4d. It is clear why extreme combinations of NAO and PNA in ENSO neutral seasons can rival all but the strongest El Ninos and La Ninas in impact on Florida. The relationship of ENSO, PNA, and NAO to Florida dry season weather is not linear, and they do not represent all possible teleconnections, but they explain most of the variability and approximate a quasi-linear relationship within the range of values normally encountered.

The results of equations (1), (2), and (3) are physically consistent with observations in nature. The first types of education and decision aides to be presented are tables of all possible combinations of Nino 3.0, NAO, and PNA with simulated forecast values from equations (1), (2), and (3) using historical data. These tables are meant to be quick references to assist users of the forecasts in understanding the interrelationships among Nino 3.0, PNA, and NAO and for developing scenarios.

2.1 *SST, NAO, and PNA on Storminess*

Table 2 displays all possible combinations of ENSO, PNA, and NAO. Each cell in Table 2 displays the theoretical number of storms predicted from Equation 1 using historical extreme ranges of the indices, except where neutral is indicated and the entry into the equation was zero. Combinations of teleconnections unlikely to be observed are shaded in light gray. For example, a negative seasonal PNA would not be observed in nature during a strong El Nino, a neutral PNA would be rare during a strong El Nino, and a positive seasonal PNA would not be observed during a strong La Nina. In contrast, all phases of NAO are found, even strongly positive during strong El Ninos such as 1982-83 (seasonal NAO +.78).

The most extreme storminess possibilities are a strong El Nino with positive PNA and negative NAO (18 storms) and a strong La Nina with negative PNA and positive NAO (0 storms). Three of the four strongest El Ninos which correspond to the three highest observed seasonal storm counts (worst case scenarios) are shaded in red in the upper right on Table 2 and correspond rather closely with theoretical storminess predictions. The three lowest seasonal storm counts, all with just one storm, are shaded in blue in the lower left on Table 2. Two of the cases are associated with strong La Ninas with PNA negative and NAO neutral or positive, exactly as theory predicts and close in number (1 versus 0). However, one case (2001-2002) is associated with ENSO neutral conditions with PNA negative and NAO positive, reaffirming what H&A (2005) found about the importance of PNA and NAO.

The variability accounted for by Equation (1) during ENSO neutral conditions is significant. Previously, ENSO-only forecasts would always forecast a normal six storms in neutral ENSO conditions. With the new forecast equation including NAO and PNA, the range of storm values under ENSO neutral conditions now is from 3 to 10 compared to an observed range in neutral conditions of from 1 to 13. The new forecast scheme is a significant improvement over the previous ENSO-only method, assuming some measure of seasonal NAO and PNA is predictable.

2.2 *SST, NAO, and PNA on Rainfall*

Table 3 displays all possible combinations of ENSO, PNA, and NAO. The conventions are the same as in Table 2 except that each cell in Table 3 displays the theoretical seasonal rainfall in inches from Equation (2). The most extreme rainfall possibilities are a strong El Nino with positive PNA and negative NAO (upper right, 25.4") and a strong La Nina with negative PNA and positive NAO (lower left, 6.9"). The four highest observed seasonal rainfall amounts (worst case scenarios), are shaded in green in the upper right on Table 3 in the expected locations and with amounts in line with theoretical predictions. The three lowest observed seasonal rainfall amounts (worst case scenarios) are shaded in brown on Table 2. Here the driest seasons are <u>not</u> found for the conditions predicted by equation (2), strong La Nina with neutral or positive NAO and negative PNA. Rather, two of them are found in ENSO neutral conditions, and the third in relatively weak La Nina conditions.

This clearly illustrates that La Nina and El Nino are not truly opposites with regard to rainfall, and simple assumptions are not valid. A very strong La Nina does not necessarily mean the least amount of rainfall; indeed, the strongest La Nina (1988-89) did not equate to the lowest rainfall. Actual rainfall was 175% of what was predicted (red text in lower left corner of Table 3). The very driest years tend to be ENSO neutral or weak La Nina years. A very strong La Nina can be associated with a strong northern jet stream and stormy conditions. It's just that most storms will pass north of Florida, but associated rainfall with trailing cold fronts or stalled cold fronts can still occur over Florida. It may be that the neutral phase is the most passive and the predisposition for Florida is to be dry in the dry season. This is a significant challenge for those whose primary concern is the occurrence of less than normal rainfall in the Florida dry season, especially if the preceding wet season rainfall has been below normal. The possibility table in this case helps define a significant forecast challenge that will be discussed in subsequent sections on decision aides.

Theoretical Predictions of Dry Season Storms				
	PNA (-)	PNA (0)	PNA (+)	
El Nino	15	16	18 (17 in 1957-58)	NAO (-)
	14	15	16 (18 in 1997-98)	NAO (0)
	11	13	14 (16 in 1982-83)	NAO (+)
Neutral	7	8	10	NAO (-)
	5	6	8	NAO (0)
	3 (1 in 2001-02)	4	6	NAO (+)
La Nina	2	3	5	NAO (-)
	0 (1 in1984-85)	1	3	NAO (0)
	0 (1 in 1988-89)	0	1	NAO (+)
	PNA (-)	PNA (0)	PNA (+)	

Table 2. The 27 possible combinations of the PNA, NAO, and ENSO and theoretical predictions of storms from Equation 1 using extreme historical values of ENSO, PNA, and NAO except for where neutral is indicated. Combinations that rarely exist in the historical record are shaded in gray. The combinations with the three highest and lowest observed number of storms are shaded red and blue, respectively.

Theoretical Predictions of Dry Season Rainfall				
	PNA (-)	PNA (0)	PNA (+)	
El Nino	24.4	24.8	25.4 (19.1 in 1957-58)	NAO (-)
	22.9	23.3	23.9 (22.3 in 1997-98)	NAO (0)
	21	21.4	22 (24.3 in 1982-83) *	NAO (+)
Neutral	15.5	15.9	16.5	NAO (-)
	14	14.4	15 (7.2 in 2000-01)	NAO (0)
	12.1 (8.8 in 2001-02)	14	13.1	NAO (+)
La Nina	10.3 (8.9 in 1967-68)	10.7	11.4	NAO (-)
	8.8	9.2	9.9	NAO (0)
	6.9 (12.1 in 88-89)	7.3	7.9	NAO (+)
	PNA (-)	PNA (0)	PNA (+)	

Table 3. The 27 possible combinations of the PNA, NAO, and ENSO and theoretical predictions of rainfall from Equation 2 using extreme historical values of ENSO, PNA, and NAO except for where neutral is indicated. Combinations that rarely exist in the historical record are shaded in gray. The combinations with the four highest (* 20.4" in 86-87 also in the El Nino, PNA+, NAO+ cell) and three lowest observed seasonal rainfall amounts are shaded green and brown, respectively.

Theoretical Predictions of Dry Season Average Minimum Temperature				
	PNA (-)	**PNA (0)**	**PNA (+)**	
El Nino	**15.9**	**15.1**	**13.7 (14.3 in 1976-77)**	**NAO (-)**
	16.8	**16.0**	**14.6**	**NAO (0)**
	17.9	**17.1**	**15.8**	**NAO (+)**
Neutral	**15.5**	**14.7**	**13.4 (14.0 in 1977-78)**	**NAO (-)**
	16.4	**15.6**	**14.3**	**NAO (0)**
	17.5 (17.1 in 1990-91)	**16.7**	**15.4**	**NAO (+)**
La Nina	**15.3**	**14.5**	**13.1**	**NAO (-)**
	16.2	**15.4**	**14**	**NAO (0)**
	17.3 (17.0 in 1971-72)	**16.5**	**15.2**	**NAO (+)**
	PNA (-)	**PNA (0)**	**PNA (+)**	

Table 4. The 27 possible combinations of the PNA, NAO, and ENSO and theoretical predictions of average minimum temperature from Equation 3 using extreme historical values of ENSO, PNA, and NAO except for where neutral is indicated. Combinations that rarely exist in the historical record are shaded in gray. The combinations with the two highest and lowest observed seasonal rainfall are shaded red and blue, respectively.

2.3 *SST, NAO, and PNA on Minimum Temperature*

Table 4 displays all possible combinations of ENSO, PNA, and NAO. The conventions are the same as in Tables 2 and 3 except that each cell in Table 4 displays the theoretical seasonal average minimum temperature (EC) from Equation (3). The most extreme minimum temperature possibilities are ENSO neutral or weak El Nino with a strong positive PNA and strong negative NAO (upper right 13.4 and 13.7 EC, respectively) and ENSO neutral or weak La Nina with a strong negative PNA and strong positive NAO (lower left, 17.5 and 17.3 EC, respectively) . The two highest observed seasonal minimum temperatures (worst case scenarios), shaded in red in the lower left on Table 4 are not only in the right location, but they are also very close to the values predicted by equation (3). However, the 1971-72 La Nina was quite weak (Nino 3.0 -.58). The two lowest observed seasonal minimum temperatures (worst case scenarios), shaded in blue in the upper right on Table 4, are also in the right location and close to predicted values. The 1976-77 El Nino was also quite weak (+.55). The two El Nino/La Nina cases on Table 4 were actually very close to being neutral, but had quite strong PNA phases (+0.93 and -1.05, respectively). The possibility table illustrates more clearly that ENSO is <u>not</u> a big player in seasonal minimum temperatures as the warmest and coldest temperatures are possible under weak and neutral ENSO conditions and driven by the PNA and NAO.

3. TAYLOR-RUSSELL DIAGRAMS AS DECISION AIDES

The possibility tables are useful for better understanding the relationship of teleconnections to impact weather and for developing scenarios. However, hard decisions must almost always be made in the face of uncertainty, and a degree of objectivity in the decision making process is desirable. The certainty/uncertainty of the predictions from equations (1), (2), and (3) can be evaluated by considering the correlation coefficients (such as on Table 1) and by various error calculations and significance tests. Value can also be evaluated by comparing historical predictions from the equations versus actual values (hindcasts) such as those on Figure 3. However, H&A (2002) found that graphical displays of predicted versus observed phenomena using a variation on the reliability diagram called a Taylor-Russell diagram (Stewart, 2000) can be valuable to better understand uncertainty in the context of decision making.

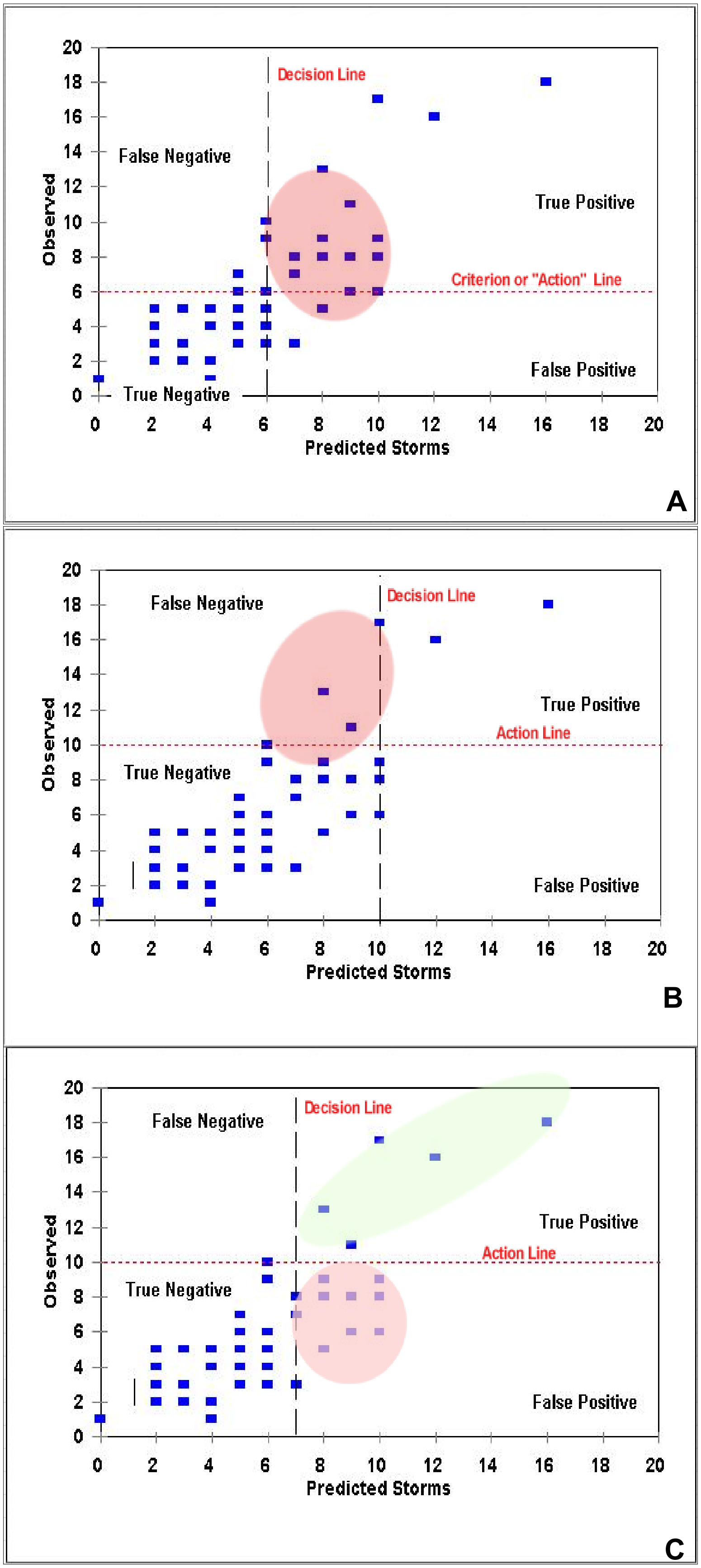
Taylor-Russell (TR) diagrams of Equation (1), the prediction of storms from Nino 3.0, PNA, and NAO for three different decision scenarios are shown as Figures 5a-c. On Fig. 5a, along the x-axis are the predicted dry season storms from 1950 -2003 (rounded to the nearest whole storm). Along the y-axis are the corresponding observed dry season storms. The diagram is then divided into two sections by a horizontal criterion or "action line." Above this line, based on past experience or scenarios and studies, action should be taken. In this case, above normal storms (>6) is selected as the action line. If above normal storms are going to occur, mitigation actions should be taken. The TR diagram is then further divided into four sections by the establishment of a vertical “decision line” based on a prediction from Equation (1). On Fig. 5a the decision line has also been selected as a prediction of >6 storms. The scenario is thus defined as needing to take action when a forecast of >6 storms is made. The resulting four regions of the TR diagram based on the definition of the scenario are: 1) true positive (upper right), a prediction of >6 is made and it is correct and preparations are proper and successful; 2) true negative (lower left), the prediction is <6 storms and it is correct and no preparations were made or needed; 3) false positive or, more commonly, false alarm, (lower right), action was taken on the prediction of >6 storms and it proved unnecessary; and 4) false negative (upper left), the prediction is <6 storms (below criterion line), but >6 storms occur and actions that should have been taken were not, leading to a negative impact. The false negative is generally the worst case scenario.

What should be clear from the pattern of scatter on Fig. 5a is that the forecast is good, but not perfect. The TR diagram can be adjusted by decision makers to account for the role of uncertainty and the cost benefit of the use of the forecast. For example, the selection of the simple criteria of above normal storms (>6) on Fig. 5a may result in too many seasons when actions are required. This depends, of course, on the sensitivity of users, but most users might find the normal threshold too low. The criterion could be raised to 1 standard deviation (SD) above normal storminess (horizontal line >10 storms on Fig. 5b), which would be highly impacting to most users and action should definitely be taken. If the decision line is also set at 10 storms on Fig. 5b, the implications are that the False Positives/Alarms would be reduced to near zero, but the false negatives or un-forecast events could be extremely costly, if not devastating, at this threshold level -- potential losses could be unacceptable. The decision makers could then move the decision line lower as in Fig. 5c to the point where the false negatives or unforecast losses are eliminated. In other words, the decision to take action to prepare for 10 storms will be made at a forecast of $7, storms providing more margin for error (hedging). However, this cannot be done without increasing the odds that more false alarms will occur and unnecessary action will be taken. The decision line is critical as it can be used to explore costs versus benefits for a particular user’s problem. The TR diagrams are thus useful in exploring the implications of actions taken to deal with uncertain forecasts.

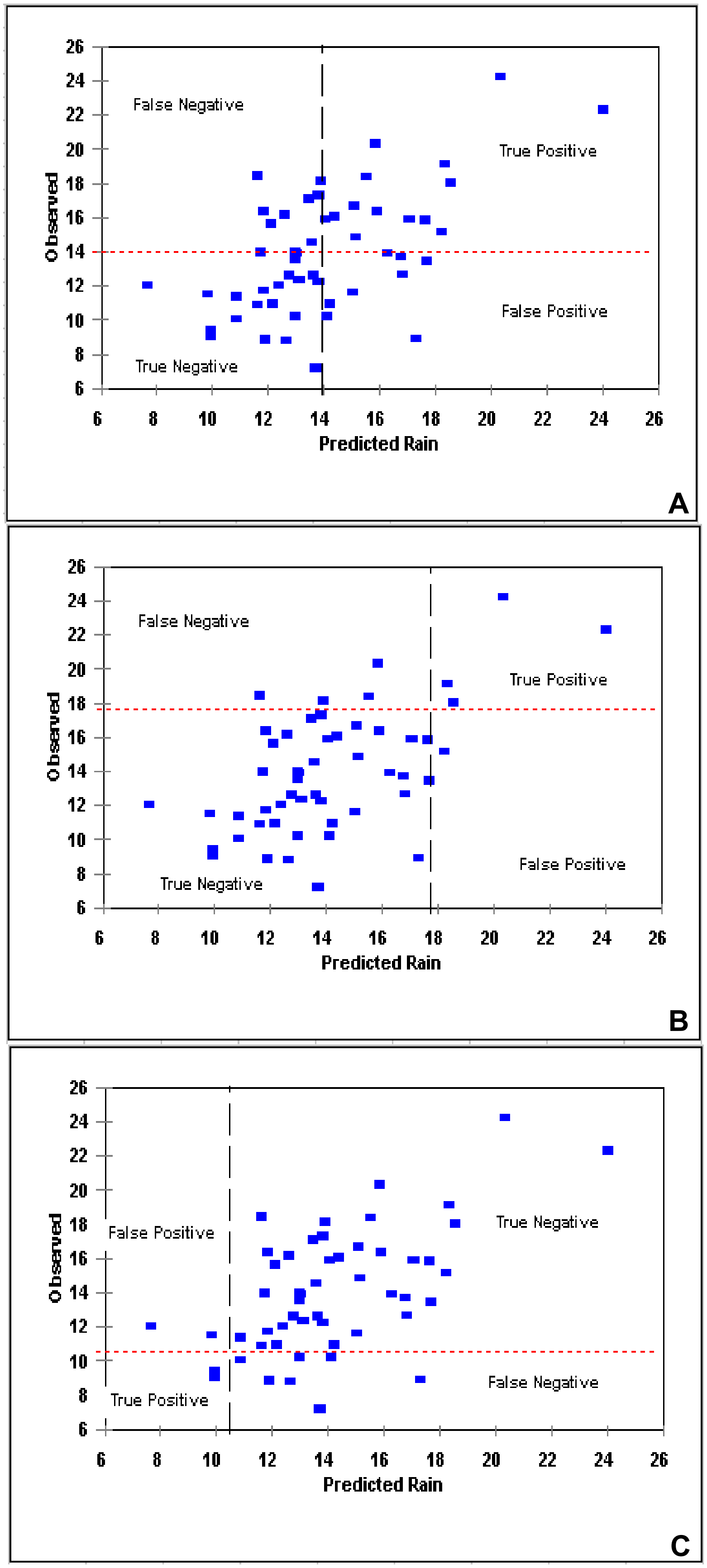
Figures 6a-c show TR diagrams for three different dry season rainfall scenarios based on equation (2). It should be evident that there is more uncertainty in the rainfall forecast due to the greater scatter of the predicted/observed pairs (R^2 = 0.42 for rainfall versus R^2 = 0.63 for storms). Figure 6a show the action/decision line set for above normal rainfall (> 14 inches). The cluster of values around normal in all four quadrants on Fig. 6a indicates this is probably not a good criteria choice (but it could be for some sensitive users). Fig 6b shows the TR diagram for criterion and decision thresholds set at >1 SD above normal rainfall (>17.6"). As in the case of storms, the user can experiment with cost benefit by adjusting the decision line to reach some balance between false alarms and missed events.

Lack of dry season rainfall is also a significant impact to many decision makers. Figure 6c shows a TR diagram for the opposite scenario of Fig 6b where the action and decision lines are set for <1 SD below normal rainfall (<10.3"). Note that in this case where the problem is defined as action taken when the event is less than some criteria, the four quadrants are reversed from Figs. 6a-b. In this scenario, the false negative, or missed forecast, for the impact of below normal rain is now in the lower right (rain forecast >1 SD below normal and rain < 1 SD below normal occurs). The user must move the decision line to the right (higher) to mitigate the potential negative impacts of a missed forecast. This scenario indicates that forecasts from equation (2) have some serious issues with over-forecasting seasonal rainfall at the lower end of the spectrum. For example, a user critically concerned about dry conditions would have to move the decision line so far to the right in Fig. 6c that the false alarms would very likely be untenable. Recall that this issue was first identified as a potentially serious problem on Table 3 where the theoretical lowest rainfall was not found under the conditions predicted by Equation (2). The use of the TR diagram in this case does not solve the problem, but helps clarify the issue for decision makers and brings it out into the open for consideration of alternatives for mitigation. The challenge of the below normal rainfall forecast will be explored further in the next section.

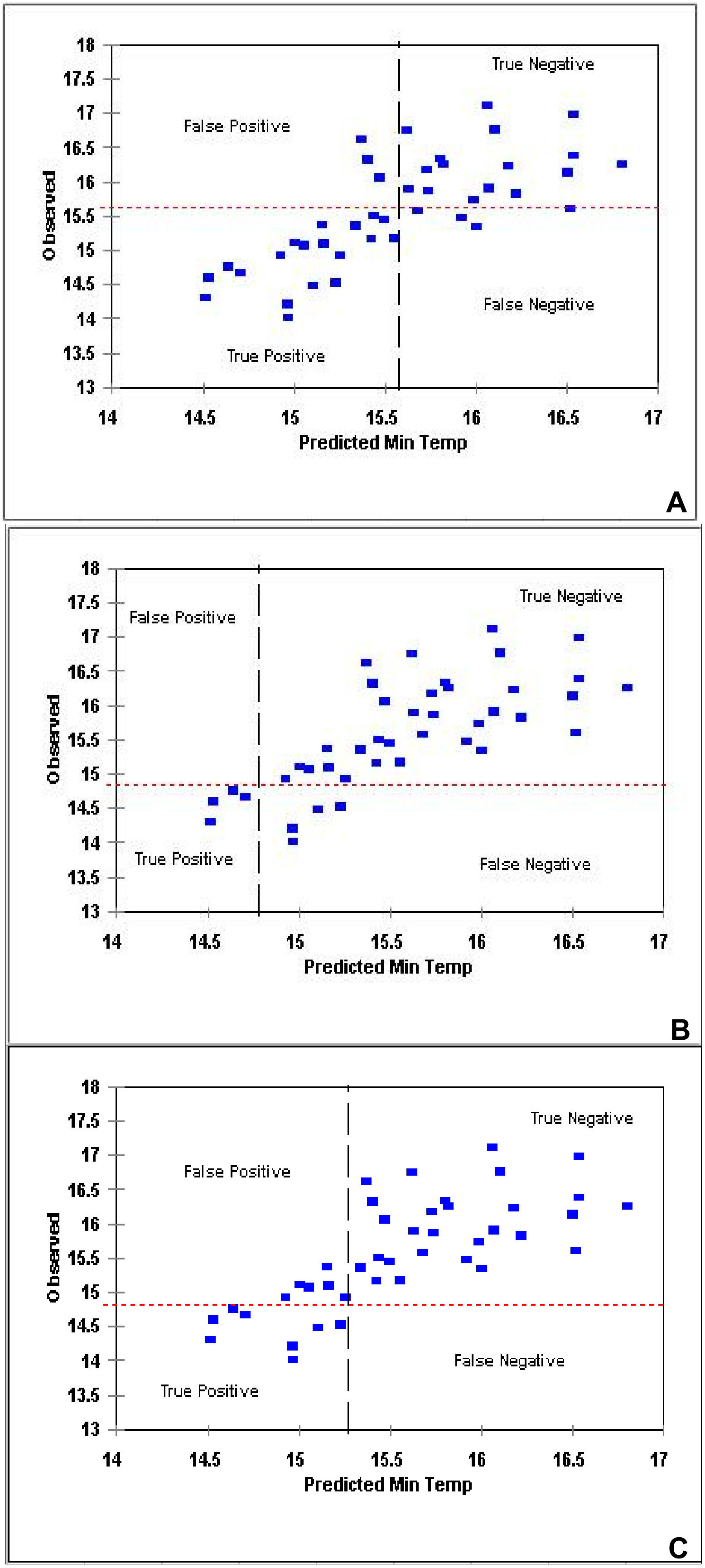
Figures 7a-c are the TR diagrams for dry season average minimum temperatures over central Florida (blue inset map on Fig.1) for 1958-99 from equation (3). Note that the plotted results from equation (3) have less scatter (R^2 = 0.55) than from equation (2) for rain (R^2 = 0.42). The example scenarios for minimum temperature are concerned with <u>below</u> normal temperature; the quadrant conventions are as in Fig.6c for below normal rainfall. Figure 7a shows the action and decision thresholds set for minimum temperatures below normal (<15.6 EC). The forecast is actually quite good with just a few false negatives close to the action line. A more impacting scenario is shown on Fig. 7b where the action/decision thresholds are set at 1 SD below normal minimum temperatures (<14.8 EC). This criterion results in no false positives/alarms, but some significant false negatives (missed events). The decision line has been moved to the right (<15.3 EC) in Fig. 7c to eliminate missed events at the expense of accepting some false alarms. However, in this case, all of the false alarms are relatively minor and still below normal. A cost benefit analysis of this scenario is likely to be favorable.



Figures 5a-c. Taylor-Russell diagrams of Florida dry season storms predicted by Equation (1) and rounded to the nearest whole storm plotted against observed storms for the 1950 through 2003 dry seasons for three different criterion/decision scenarios: 5a) greater than normal storminess for both decision and criterion line, 5b) greater than 1 standard deviation above normal storminess for both decision and criterion line, and 5c) greater than 7 storm decision line and greater than 1 standard deviation above normal criterion line.



Figures 6a-c. Taylor-Russell diagrams of Florida dry season rainfall (inches) predicted by Equation (2) plotted against observed rainfall for the 1950 through 2003 dry seasons for three different criterion/decision scenarios: 6a) greater than normal rainfall for both decision and criterion line, 6b) greater than 1 standard deviation above normal rainfall for both decision and criterion line, and 6c) less than 1 standard deviation below normal for both decision and criterion line.



Figures 7a-c. Taylor-Russell diagrams of Florida dry season average minimum temperature (EC) predicted by Equation (3) plotted against observed minimum temperatures for the 1950 through 2003 dry seasons for three different criterion/decision scenarios: 7a) less than normal minimum temperature for both decision and criterion line, 7b) less than 1 standard deviation below normal minimum temperature for both decision and criterion line, and 7c) less than 15.3 EC minimum temperature decision line and less than 1 standard deviation criterion line.

4. LOGISTIC REGRESSION TO IMPROVE DECISION MAKING

Logistic regression (Wilkes, 1995) is a variation of ordinary regression that can be used when the predictand is dichotomous (restricted to two values) and usually represents the occurrence or nonoccurrence of an event (coded as 1 for occurrence or 0 for nonoccurrence). Logistic regression (LR) fits a sigmoidal, or s-shaped, curve by taking the linear regression equation, which could produce any y-value between minus infinity and plus infinity, and transforming it with the function: $p = \mathrm{Exp}(y) / (1 + \mathrm{Exp}(y))$. LR is then a special kind of nonlinear regression that predicts the probability of the occurrence of an event of interest (scenario) as a function of the independent variables. The probability of the occurrence of the event (y) is then given by equation (4).

$$\mathbf{P(y) = 1 - (1/(1 + \mathit{exp}(C + C_1X_1 + C_2X_2....C_kX_k)))} \qquad \mathbf{(4)}$$

$$\mathbf{Storminess_{(NOV\text{-}APR)} > normal = -1.04 + 2.42(Nino3.0_{MAY\text{-}APR}) + 0.93(PNA_{NOV\text{-}APR}) - 1.72\,(NAO_{NOV\text{-}APR})} \qquad \mathbf{(5)}$$

$$\mathbf{P(Storminess_{(NOV\text{-}APR)} > normal) = 1 - (1/(1 + \mathit{exp}(-1.04 + 2.42(Nino3.0_{MAY\text{-}APR}) + 0.93(PNA_{NOV\text{-}APR}) - 1.72\,(NAO_{NOV\text{-}APR}))))} \qquad \mathbf{(6)}$$

$$\mathbf{Storminess_{(NOV\text{-}APR)} > 1SD = -3.69 + 1.36(Nino3.0_{MAY\text{-}APR}) + 2.76(PNA_{NOV\text{-}APR}) - 0.74\,(NAO_{NOV\text{-}APR})} \qquad \mathbf{(7)}$$

$$\mathbf{Rainfall_{(NOV\text{-}APR)} > 1SD = -2.24 + 2.01(Nino3.0_{MAY\text{-}APR}) - 0.09(PNA_{NOV\text{-}APR}) +\text{-}\ 0.64\,(NAO_{NOV\text{-}APR})} \qquad \mathbf{(8)}$$

$$\mathbf{Rainfall_{(NOV\text{-}APR)} < 1SD = -2.76 - 3.05(Nino3.0_{MAY\text{-}APR}) + 2.90(PNA_{NOV\text{-}APR}) - 0.25\,(NAO_{NOV\text{-}APR})} \qquad \mathbf{(9)}$$

$$\mathbf{Min\ Temp_{(NOV\text{-}APR)} < 1SD = -3.15 - 0\ .44(Nino3.0_{MAY\text{-}APR}) + 2.70(PNA_{NOV\text{-}APR}) - 3.32\,(NAO_{NOV\text{-}APR})} \qquad \mathbf{(10)}$$

LR can be a useful approach for decision making because it reframes the forecast issue to specifically address a given scenario in probabilistic terms. For example, in traditional MLR such as Equation (1) DS storminess is predicted using historical storminess data and Nino 3.0, PNA, and NAO indices. The result for any given hindcast (or forecast) of Nino 3.0, PNA, and NAO is the number of storms expected in a season, a deterministic forecast. Any number of statistics can be examined to assess the reliability of this forecast. Taylor Russell diagrams can be constructed from the observed and predicted storms to provide insights for decision making and the probability of detection and false alarm rates computed.

These methods can, if one is not careful, become "black boxes" where the signs and magnitudes of the original predictor variables are removed from the process of decision making and the focus is on the output. These methods also do not account for errors in the underlying predictor variables. Equation (1) must then serve all decision making challenges relating to predicted storms over the entire range of predictor variables. In contrast, LR requires the definition of the scenario of interest at the outset and a unique data set and equation for each scenario. For example, assume one needs to take action if above normal storminess is going to occur. The database of storms is analyzed for the 1950-2003 dry seasons and each season is coded either 1 for seasons with >6 storms or 0 for seasons with 6 or less storms. Then MLR is done on this dichotomus data set with Nino 3.0, PNA, and NAO predictor variables just as in Equation (1). The resulting >6 storm LR decision scenario is shown as equation (5). Predicted probabilities of >6 storms can then be calculated by inserting equation (5) into equation (4) as shown in the resulting equation (6). Equations (7), (8), (9), and (10) show LR scenarios (Fy) for >1 SD storms, >1 SD rainfall, <1 SD rainfall, and <1 SD minimum temperature, respectively, all significant at the 99% level ($\chi^2_{.01}$, $F_{.01}$).

The value of LR in decision making becomes obvious when probabilities **P**(*y*) are plotted against predictor variables. Figures 8a-c show the probabilities for four different storm scenarios as predicted from Nino 3.0, PNA, and NAO, respectively: 1) above normal storms, 2) below normal storms, 3) >1 SD above normal storms, and 4) < 1 SD below normal storms. The LR results for storm scenarios on Nino 3.0 are shown on Fig. 8a. All four scenario equations are highly significant (p=.001,$\chi^2_{.01}$, $F_{.01}$) as would be expected and in agreement with MLR results earlier. However, the wealth of decision making information is immediately obvious as addressing four distinct scenarios or action thresholds, depending on user needs where the traditional MLR approach has to satisfy all scenarios. If Nino 3.0 is predicted to average 1.0 (May-April) there is an 80% chance of >6 storms in the dry season, a 40% chance of >10 storms, and a near zero chance of <6 storms and < 2 storms.

It is important to remember that the seasonal forecasts contain an extra degree of uncertainty that is not always communicated well to the users. For example, the seasonal prediction equations of storms, rainfall, and minimum temperature using indices such as SST, PNA, and NAO contain uncertainties. However, the predictor variables themselves (SST, PNA, NAO) input into the forecast equations are based on observations and forecasts and their values also contain uncertainties. So first the predictor phenomena must be accurately forecast and then the teleconnection forecasts must accurately describe the relationship. With LR scenarios such as on Fig. 8a, decision makers can assess the implications of uncertainty in the underlying predictors. For example, if a Nino 3.0 forecast of 1.0 is used with an error range of, say, +/- 0.50 in May to predict storminess in the upcoming dry season it can be seen that the probability of below normal storminess is very low, the probability of above normal storms ranges from around 60% to near 95%, and the probability of >1 SD above normal storms ranges from 20% to 60%. A scenario of >1 SD above normal storms is likely to be very impacting for most users and the LR results highlight the rapid rise in probabilities from 0.5 to

1.5 Nino 3.0 that could alert sensitive users to focus on this possibility well ahead of time.

The LR results for storm scenarios on PNA (Fig. 8b) and NAO (Fig. 8c) are shown for comparison. To a large degree, the PNA results (all significant at $\boldsymbol{\chi}^2_{.01}$, $\mathbf{F}_{.01}$) duplicate Nino 3.0 results as the two are highly correlated (H&A, 2005) and seasonal PNA almost always follows the sign of Nino 3.0 when it is not neutral. There is currently no long range forecast of PNA other than that which would be based on the Nino 3.0 forecast itself. The results for storm scenarios on NAO on Figure 8c are not significant, especially for the >1 SD above normal scenario where p=0.98 and the "curve" is almost a straight line which would indicate absolutely no value. However, the above normal storm scenario does show increasing probability of storms as NAO decreases (p=0.14 and not quite significant at the 0.90 level).

Clearly, Nino 3.0 is the dominant factor in predicting dry season storminess, again confirming previous results (H&A, 2005). LR storm scenarios were also done with NAO and PNA during Nino 3.0 neutral seasons. In this case, the above/below normal storm cases were calculated for the 25 seasons from 1950-2003 when Nino 3.0 was -.5 to +.5. and LR on NAO and PNA was completed. LR for the +/- 1 SD storm scenarios was not completed because the occurrence of such extreme variability rarely occurs in Nino 3.0 neutral years. Figures 9a-b show that NAO and PNA are significant predictors of the probability of above normal storms during ENSO neutral seasons, reaffirming the results of H&A (2005). Negative NAO and positive PNA can combine to produce stormy conditions in the absence of significant Pacific SST anomalies. Note, however, that the range of +PNA is more limited in ENSO neutral years. The results for below normal storms were not significant for either PNA or NAO at $\boldsymbol{\chi}^2_{.10}$ or $\mathbf{F}_{.10}$, but do show that in general NAO+ and PNA- reduce storminess.

Figures 10a-c show the probabilities for two significant seasonal rainfall scenarios, >1 SD above normal rainfall (>17.6"), and < 1 SD below normal rainfall (<10.3"), as predicted from Nino 3.0, PNA, and NAO, respectively. The LR results for rainfall scenarios on Nino 3.0 are shown on Figure 10a. The >1 SD above normal equation is significant at p=.001, $\chi^2_{.01}$, and $F_{.01}$, while the <1 SD below normal equation is significant at p=.05, $\chi^2_{.05}$, and $F_{.05}$. As revealed earlier in the possibility tables and TR diagrams, dry season rainfall can be a significantly more challenging decision-making problem than storminess. The LR results on Figure 10a clearly show that the rainfall forecasts for La Nina and El Nino conditions are anything but mirror images or simply opposite forecasts. During a strong El Nino, excessive rainfall is a reliable occurrence with a probability of 70-100% for Nino 3.0 above +1.5. In contrast, the strongest La Nina with Nino 3.0 below -1.50 produces only a 50% chance of extreme dry conditions (<1 SD below normal rainfall). One way to consider the two phases in the context of Florida dry season weather is that El Nino is an active phase forcing storms and attendant hazards and rainfall while strong La Nina and neutral ENSO with positive NAO and negative PNA are passive phases that generally limit storms and rainfall by suppressing either storm development or steering storms away from Florida. This is inherently a more complicated and less predicable relationship.

The LR results for rainfall scenarios on PNA are shown on Figure 10b. The >1 SD above normal equation is significant at p=.05,$\chi^2_{.05}$, $F_{.05}$ and the <1 SD below normal equation is not significant. The LR results for rainfall scenarios on NAO (Fig. 10c) are not significant for either scenario. As was the case for storms, there were not enough occurrences of extreme rainfall deviation in ENSO neutral seasons to conduct LR on PNA and NAO on </> 1 SD scenarios. It is not surprising that Nino 3.0 is the dominant teleconnection for extreme dry season rainfall variability as is also the case for storms. However, the relationship between storms and rainfall generally diverges from neutral toward strong La Nina conditions as rainfall obviously still occurs even when few significant extratropical cyclones occur. Recall the greatest La Nina of all in 1988-89 had only one storm, but 12 inches of rainfall which was not 1 SD below normal.

The value of LR in the case of seasonal rainfall extremes is that it clearly identifies two distinct forecast challenges; one for excessive rainfall that is highly predictable, and one for extreme dryness that is not so predictable. For decision-makers, this means very dry conditions are not as predictable as very wet conditions, and ENSO neutral may well be the extreme driest state of all. This is valuable information, and at least these methods arm users with more context within which to balance decisions. In contrast, traditional MLR combines both scenarios into one forecast scheme that compromises both and can mask the underlying issues.

Figures 11a-c show the LR probabilities for two significant minimum temperature scenarios for Central Florida, >1 SD above normal (>16.4 EC) minimum temperature, and < 1 SD below normal (<14.8EC) minimum temperature as predicted from Nino 3.0, PNA, and NAO, respectively. The LR results for the minimum temperature scenarios on Nino 3.0 and PNA (Figs. 11a-b) are very similar. Both Nino 3.0 and PNA are significant for >1 SD above normal minimum temperature (p=.025, $\chi^2_{.025}$, and $F_{.025}$) and not significant for <1 SD below normal minimum temperature. As might be expected from the possibilities on Table 4, La Nina and negative PNA greatly increase the odds of warmer minimum temperatures, while the odds of cooler minimum temperatures are extremely low. Although not statistically significant at the 90% level, the PNA results do show that a positive PNA produces a higher probability of cooler temps as expected. Indeed, the relationship between PNA and Nino 3.0 and cooler minimum temperature probabilities remains low across the entire range of Nino 3.0 and PNA from strong La Nina to strong El Nino. This again shows the value of LR in refining forecast scenarios into those that are more robust for decision-making and those that are more problematic. As in the case of rainfall, El Nino and La Nina are not mirror images of each other with regard to minimum temperature. There is a very high probability of excessive rainfall with Nino 3.0 above 1.0, but the relationship to well below normal minimum temperatures is very weak. El Ninos are typically associated with cloudy, rainy conditions and a southern storm track. These conditions would overall keep average mean temperatures cooler than normal, but limit extreme cool temperatures as minimum temperatures would be moderated by the rain and cloud cover. Likewise, La Nina conditions would generally result in moderate to warmer minimum temperatures due to the influence of maritime or easterly surface flow associated with the subtropical ridge which would limit possibilities of extreme cold minimum temperatures.

The LR results for extreme minimum temperature scenarios on NAO are shown on Figure 11c. The relationship between NAO and <1 SD below normal minimum temperatures is highly significant (*p*=.001, $\chi^2_{.001}$, and $F_{.001}$). The relationship between NAO and >1 SD above normal minimum temperature is weak and not significant. Clearly, NAO is the most significant predictor of much colder than normal minimum temperatures in the Florida dry season. A negative NAO literally assures a colder dry season, while a positive NAO has nearly a zero percent chance of colder than normal seasonal minimum temperatures. This makes sense when one considers that a negative NAO implies the lack of a high pressure ridge over Florida, a northerly storm track, and predominant northerly flow, while a positive NAO implies a ridge building over or just north of Florida as an extension of the Atlantic subtropical ridge and moderate air masses of maritime influence. Table 4 indicates the two coldest dry seasons of all occurred in strong negative NAO seasons with either neutral or weak El Nino conditions and positive PNA. On the seasonal scale, strongly negative NAO and positive PNA can be found in neutral or El Nino conditions, but not in La Nina conditions. Interestingly, it would appear that strong phases of El Nino or La Nina are the least likely to produce extremes of below normal minimum temperatures.

Negative Nino 3.0 and PNA anomalies have a clear relationship to warmer than normal minimum temperatures and NAO a very strong relationship to colder than normal minimum temperatures. Major freezes are significant hazards in the Florida dry season and experimental LR was conducted on major Central Florida freezes for the 1958-1999 dry seasons to determine if Nino 3.0, PNA, and NAO had any predictive ability.

Figures 12a-c show the LR probabilities for a significant central Florida freeze in a dry season (average daily temp < 0EC over a grid from 28E to 29E N and 81E to 82.5E W, blue box on Figure 1) as predicted from Nino 3.0, PNA, and NAO respectively. In this case, the scenario is the occurrence of a singular event in a dry season, a major freeze. A major freeze occurred in nine of the 42 seasons, and the 1985-86 dry season had two freezes (for LR only coded as a freeze occurred). The LR results for the freeze scenario on Nino 3.0 (Fig. 12a) show no relationship to the state of ENSO. The probability of a major freeze is nearly the same for a strong El Nino as it is for a strong La Nina. The nearly uniform results of around 20% for the entire range of Nino 3.0 merely reflect the climatological odds of 21% (9 in 42 years) of a freeze occurring in any year. The results for PNA (Fig. 12b) are better, but not statistically significant. However, some skill is indicated with an 11% probability of a freeze with a strong negative PNA-, and a 33% probability of a freeze with a strong positive PNA. The results for NAO (Fig. 12c), while not significant at the 90% level, are considerably better than either Nino 3.0 or PNA, and range from a 43% probability of a freeze for a strong negative NAO to an 8% chance of a freeze for a strong positive NAO. The results are similar to, but less significant than, the results for the <1 SD minimum temperature scenario and in agreement with the MLR equation (3), Table 4, and the synoptic conceptual models of Figures 4a-d.

5. CONCLUDING REMARKS

The results of this latest study improve the understanding of the relationships of ENSO, PNA, and NAO to extreme variability scenarios of hazardous Florida dry season weather. Decision aides presented such as possibility tables, Taylor-Russell diagrams and logistic regression plots improve the ability to use the statistical results to develop dry season impact scenarios and exploit climate forecasts. These initial results indicate LR might be particularly useful in identifying impacting scenarios that are highly predictable using a probabilistic approach. Taylor-Russell diagrams are useful for revealing the level of uncertainly of the MLR forecasts and putting the decision making process into the context of cost and benefits. Perhaps the most useful achievement of this latest study is the realization that there is not one simple approach for all scenarios and the identification of scenarios when the seasonal forecasts work well and when they don't. This is useful information for decision makers that can be exploited.

This study also reveals ample areas for future work. First and foremost is the ability to forecast NAO on a seasonal scale. The economic value of reliable seasonal NAO forecasts could be great. The PNA is to a large degree implicit in the ENSO forecast in non-neutral years. The greatest challenge is likely predicting the higher frequency NAO signal. H&A (2004) noted that the NAO and PNA control to a large degree the intraseasonal variability of storms, rainfall, and temperature which then can accumulate to extreme interseasonal variability without the major involvement of an El Nino or La Nina. Indeed, season in and season out, there may be more economic benefit to be gained in NAO and PNA predictions made in ENSO neutral conditions.

Nino 3.0 is a measure of Pacific SST's that force atmospheric conditions while the NAO and PNA indices are direct measurements of atmospheric variables at different time scales. The NAO and PNA are only reliably predictable out to 14 days and these forecasts are available from the NWS CPC. H&A (2004) illustrated that the influence of the Madden-Julian Oscillation (MJO) can be significant at times, and most likely to increase rainfall and storminess over Florida in cooperation with El Nino and positive PNA and negative NAO conditions. It is unlikely that the MJO teleconnection will be able to be accounted for in a seasonal forecast.

This study and the author's past studies have found the Nino 3.0 SST index to be superior for forecasting during the Florida Dry Season compared to Nino 3.4, which is the official index for the definition of El Nino. However, as a practical matter for decision makers, and to avoid undue complication, the two indices are interchangeable to a large degree, especially during moderate to strong El Ninos that involve the entire tropical Pacific. There have been cases were El Ninos as defined by Nino 3.4 have not extended to the eastern Pacific (Nino 3.4 and Nino 1+2 regions) where SST's appear to have the greatest impact on Florida. These are most likely to be weaker El Ninos. The author is of the opinion it would be beneficial to define a moderate and strong El Nino based on Pacific SST anomalies, and impact strength could perhaps be calibrated locally/regionally using LR techniques such as on Figure 10a which identifies some logical cutoff points for El Nino and La Nina impact definitions.

Overall, the challenge now is perhaps not so much the prediction of seasonal anomalies, but getting the universe of potential users to realize that there may be some benefits to be gained and costs to be avoided if they can put various aspects of the conduct of their lives/business into the context of climate impacts that dry season predictions and decision aides can be applied to. This will be the focus of the author's future work.

6. ACKNOWLEDGMENTS

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

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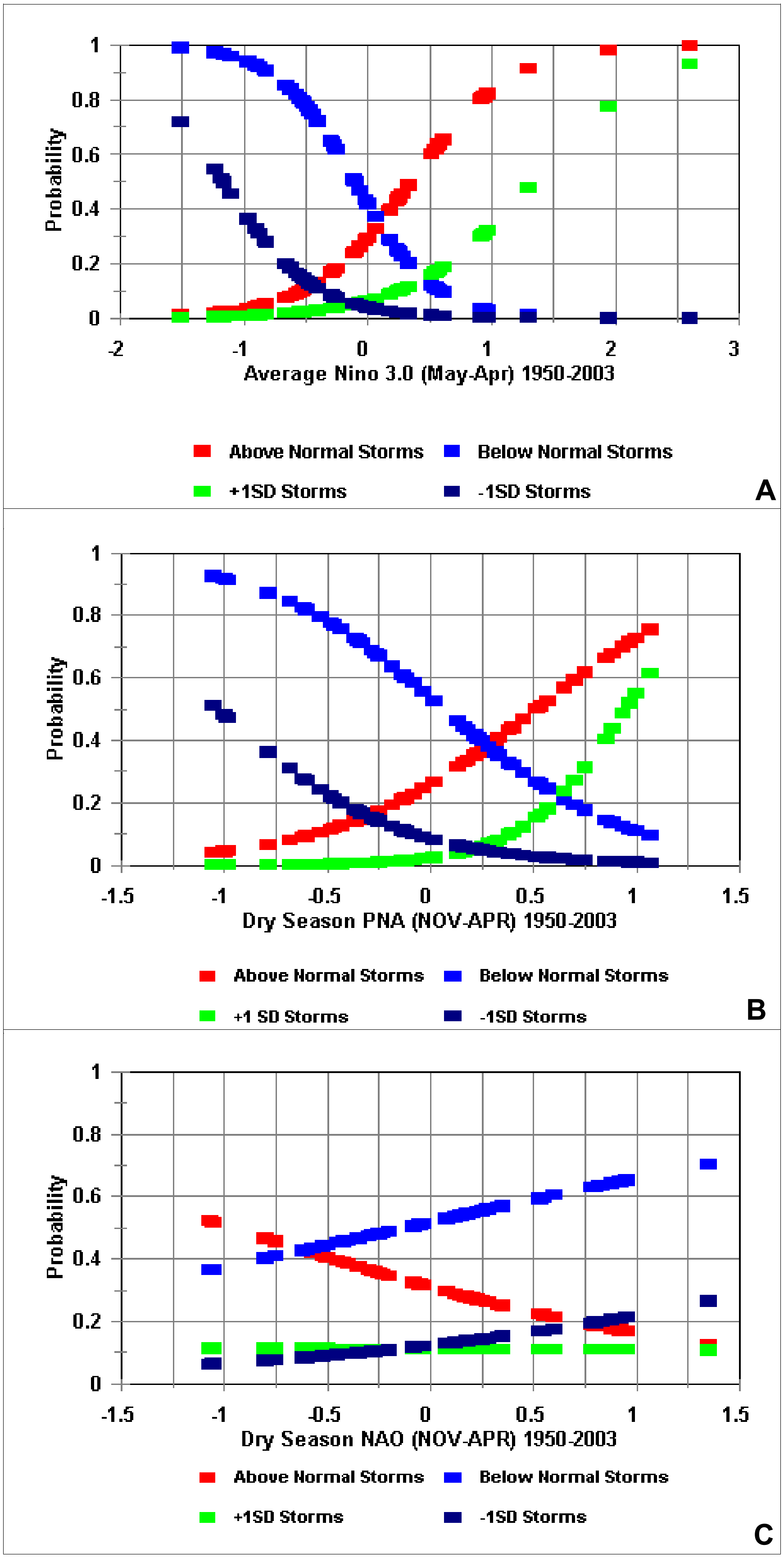
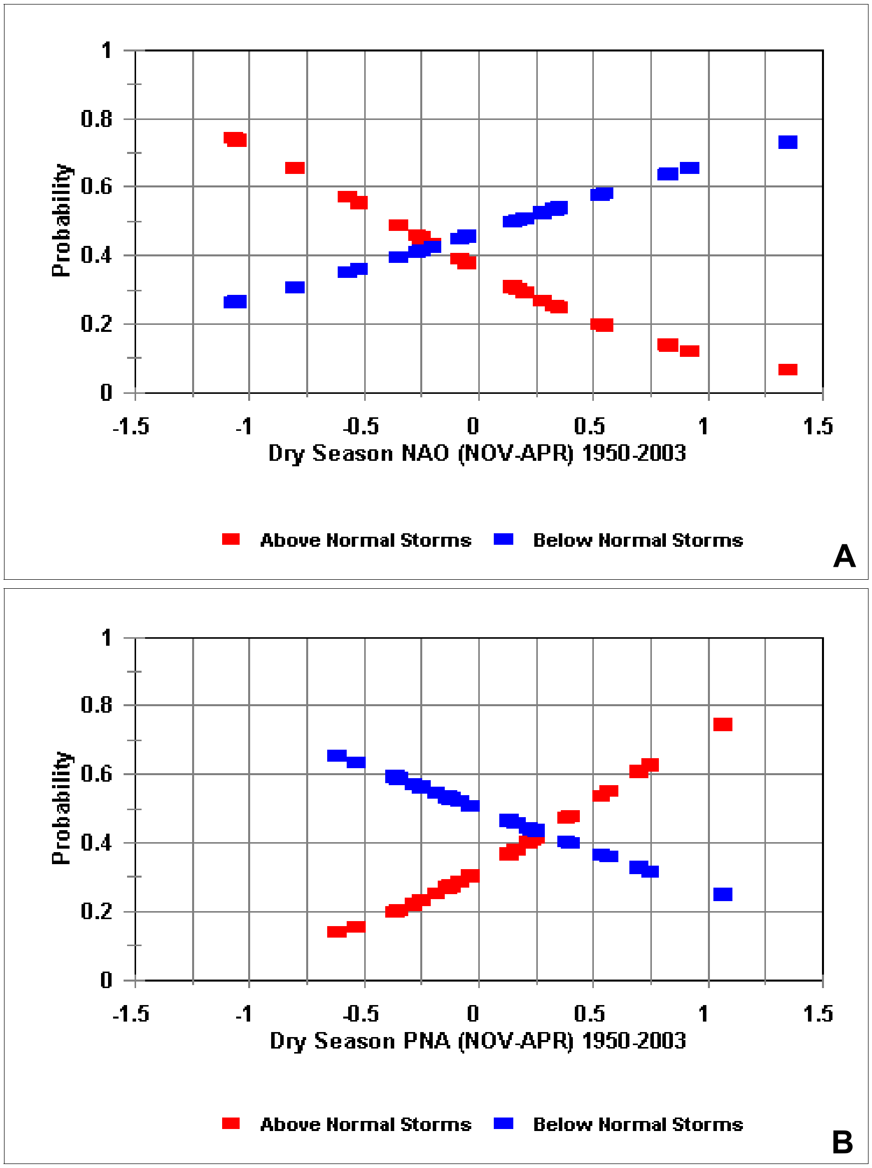
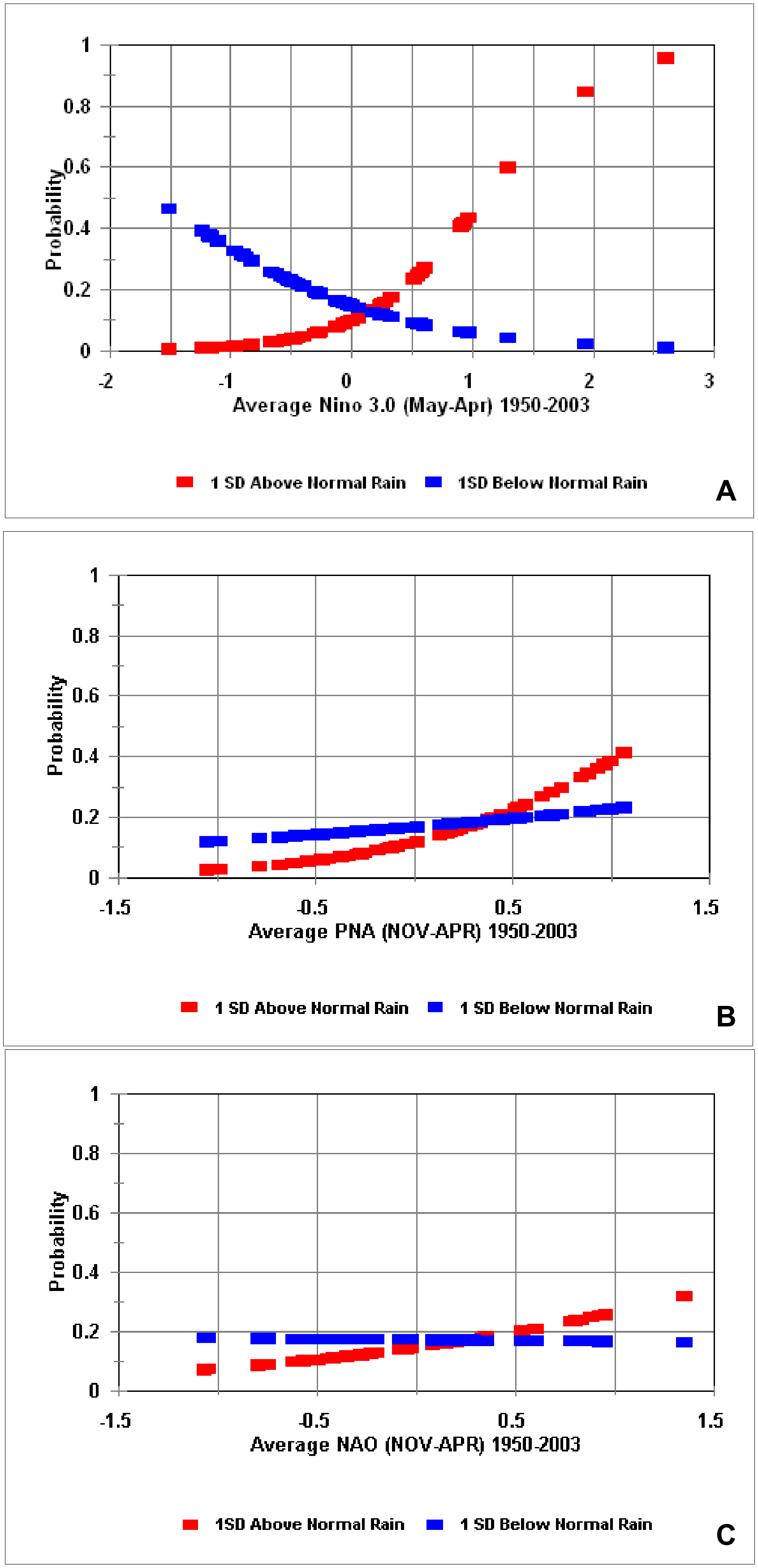


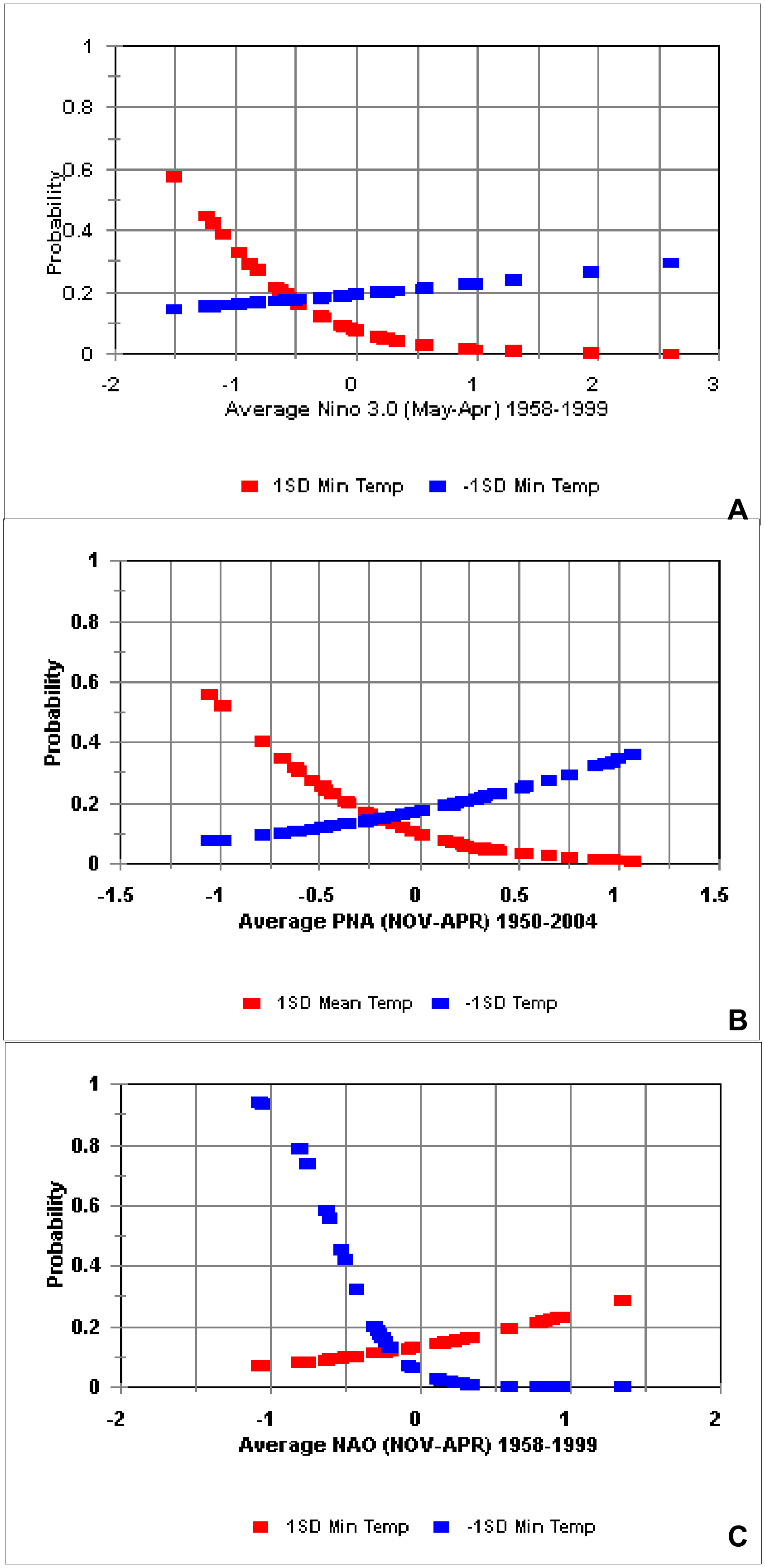
Figures 8a-c. Plots of predicted probabilities from logistic regression scenarios of above normal (>6) dry season storms, below normal (<6) dry season storms, 1 standard deviation below normal storms (<2), and 1 standard deviation above normal storms (>10) on Nino 3.0 (Fig. 8a), PNA (Fig. 8b), and NAO (Fig. 8c) indices for the 54 seasons from 1950 through 2003. The results for all four scenarios on Figs 8a-b are significant at p=.001,$\chi^2_{.01}$, and $F_{.01}$). Results for the scenarios on Fig. 8c are not significant.



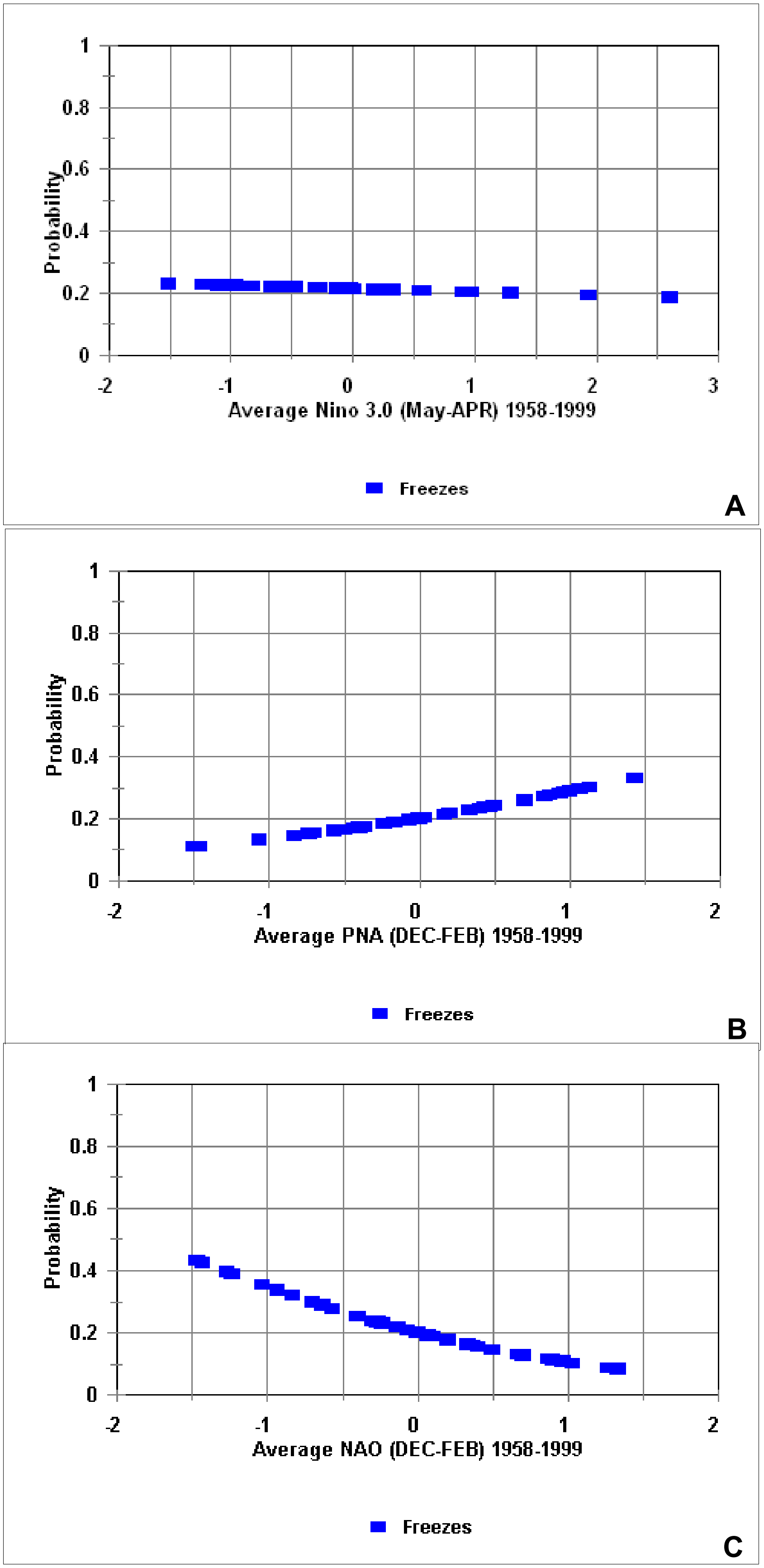
Figures 9a-b. Plots of predicted probabilities from logistic regression scenarios of above normal (>6) dry season storminess and below normal (<6) dry season storms during 25 seasons with neutral Nino 3.0 between 1950 and 2003 for NAO (Fig. 9a), and PNA (Fig. 9b) indices. The above normal storms equation was significant at (*p*=.05, $\chi^2_{.05}$ and, $F_{.05}$ for NAO and *p*=.010, $\chi^2_{.10}$, and $F_{.10}$ for PNA. The below normal storm equations were not significant. There were not enough cases of storms >/< 1 SD above/below normal during ENSO neutral conditions to conduct logistic regression.



Figures 10a-c. Plots of predicted probabilities from logistic regression scenarios of 1 SD below normal rainfall (<10.3") and 1 SD above normal rainfall (>17.6") on Nino 3.0 (Fig. 10a), PNA (Fig. 10b), and NAO (Fig. 10c) indices for the 54 seasons from 1950 through 2003. The results for Fig. 10a are significant at *p*=.001, $\chi^2_{.01}$, and $F_{.01}$ for 1 SD above normal and *p*=.05, $\chi^2_{.05}$, and $F_{.05}$ for 1 SD below normal. The results for Fig. 10b are significant at *p*=.05, $\chi^2_{.05}$, and $F_{.05}$ for above 1 SD and not significant for below 1 SD. The results for Fig. 10c are not significant.



Figures 11a-c. Plots of predicted probabilities from logistic regression scenarios of 1 SD below normal minimum temperature (<14.8 EC) and 1 SD above normal minimum temperature (>16.4 EC) on Nino 3.0 (Fig. 10a), PNA (Fig. 10b), and NAO (Fig. 10c) indices for the 54 seasons from 1950 through 2003. The results for Fig. 11a are significant at *p*=.025, $\chi^2_{.025}$, and $F_{.025}$ for 1 SD above normal and not significant at 1 SD below normal. The results for Fig. 11b are significant at *p*=.025, $\chi^2_{.025}$, and $F_{.025}$ for 1 SD above normal and not significant for 1 SD below normal. The results for Fig. 10c are not significant for 1 SD above normal and significant at *p*=.001 $\chi^2_{.001}$, and $F_{.001}$ for 1 SD below normal.



Figures 12a-c. Plots of predicted probabilities from the logistic regression scenario of the occurrence of a significant central Florida freeze in a given dry season on Nino 3.0 (Fig. 12a), PNA (Fig. 12b), and NAO (Fig. 12c) indices for the 1958-99 dry seasons. A significant freeze is defined as an average minimum daily temperature < 0 EC across the blue grid on Fig. 1. The results for Figs. 12a-b are not significant (ρ . 0.89 and ρ . 0.38, respectively). The results for Fig. 12c are not quite significant at the 90% level (ρ . 0.13).