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EXPERIMENTAL FOREST FIRE THREAT FORECAST

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ABSTRACT

Climate shifts due to El Niño (warmer than normal ocean temperatures in the tropical Pacific Ocean) and La Niña (cooler than normal) are well known and used to predict seasonal temperature and precipitation trends up to a year in advance. These climate shifts are particularly strong in the Southeastern United States. During the winter and spring months, El Niño brings plentiful rainfall and cooler temperatures to Florida. Recent los Niños occurred in 1997-1998, one of the strongest on record, with another mild El Niño in 2002-2003. Conversely, La Niña is associated with warm and dry winter and spring seasons in Florida. Temperature and precipitation affect wildfire activity; interannual drivers of climate, like ENSO, have an influence on wildfire activity. Studies have shown a strong connection between wildfires in Florida and La Niña, with the more than double the average number of acres burned (O'Brien et al 2002; Jones et al. 1999). While this relationship is important and lends a degree of predictability to the relative activity of future wildfire seasons, human activities such as effective suppression, prescribed burns, and ignition can play an equally important role in wildfire risks.

This study forecasts wildfire *potential* rather than actual burn statistics to avoid complications due to human interactions. This wildfire threat potential is based upon the Keetch-Byram Drought Index (KBDI). The KBDI is well suited as a seasonal forecast medium. It is based on daily temperature and rainfall measurements and responds to changing climate and weather conditions on time scales of days to months, and this index is high during dry warm weather patterns and low during wet cool patterns. The KBDI has been widely used in forestry in the Southeastern United States since its development in the 1970's, with foresters and firefighters have a good level of familiarity with the index and its applications. The KBDI is calculated daily and used as an index by wildfire managers.

This study calculates wildfire potential using a statistical method known as bootstrapping. Many datasets contain approximately a half-century of data, and the limited dataset will introduce biases. Bootstrapping can remedy bias by simulating thousands of years of data, which retain the climatology for the past half-century. Bootstrapping preserves the mean but not the variance. By incorporating this method, this study will improve long-term forest fire risks that will become useful for those living or working near forests and assist in managing forests and wildfires.

The Southeast Climate Consortium will also be issuing wildfire risk forecast for Florida and parts of Alabama and Georgia based on ENSO phase and the KBDI. Climate information and ENSO predictions are better served by incorporating them with known climate indices that are routinely used in the forestry sector. Wildfire managers and foresters operationally use the KBDI to monitor and predict wildfire activity (O'Brien et al. 2002). Meteorologists at the Florida Division of Forestry have demonstrated the validity of the KBDI as an indicator of potential wildfire activity in Florida (Long 2004). They showed that the value of the KBDI is not as important as the deviation from the monthly average. The wildfire risk forecast is based on the probabilities of KBDI anomalies and will present the probabilities associated with large deviations from the seasonal normal.

1. INTRODUCTION

Climatologists have studied the effects of variations in sea surface temperature in the equatorial Pacific on short-term climate variability (El Niño/Southern Oscillation). These variations are used to predict seasonal temperature and precipitation trends up to a year in advance. Previous studies have indicated that the El Niño/Southern Oscillation (ENSO) phase impacts climate in the United States and most of the world (Xue et al. 1997). The Southern Oscillation influences temperature, precipitation (Halpert and Ropelewski 1986), and upper-level winds (Nash 2002) during a particular year. The Southern Oscillation often results in droughts and wildfires by affecting temperature and precipitation for a given region, particularly Florida. The purpose of this study is to improve wild fire threat forecasts for southeastern United States using three ENSO phases.

Many datasets including the NOAA Cooperative (NOAA-COOPS) stations, however, contain less than 55 years of data, and the limited dataset introduces biases. These datasets contain only 13 years in the El Niño/warm phase, 14 years in the La Niña/cold phase, and 29 years in the neutral phase (Legler 2004) based on the JMA-SST definition of ENSO phases presented in section 2.2. Calculating statistics from only 13 years of data introduces errors. To remedy the problem, one may simulate thousands of years of data with only 55 years by using the method of bootstrapping. The Law of Large Numbers states that as the size of the sample increases, the difference between the sample estimate of variance and true variance approaches zero (Diaconis and Efron 1983). Bootstrapping selects random years of the same ENSO phase for the forecast month and year. Because only the data contains only 53 years, bootstrapping accounts for only the climate during the past 53 years (O'Brien et al. 2002). By incorporating the method of bootstrapping, this study will improve long-term forest fire risks that will become useful for those living or working near forests and is expected to assist in managing forests and forest fires.

This study assesses the risk of wildfires in Florida for El Niño, La Niña, and neutral years. The Keetch-Byram Drought Index (KBDI) is an appropriate index for measuring drought concerning the risks of forest fires because the index is a proxy for the dryness of vegetation and other fuels. Forest fire prediction is important to the Florida Division of Forestry, state and national parks, insurance companies, timber companies, and anyone living near or using our forests. The index uses the maximum daily temperature to assess the evapotranspiration from soil, fuels, and vegetation. It also uses daily precipitation measures to account for moisture returning to the soil (Keetch and Byram 1988). Droughts will increase the probability of forest fires because dry vegetation and organic material burns more easily than wet vegetation. The Southern Oscillation influences weather patterns that will increase or decrease the risk of droughts.

El Niño/Southern Oscillation impacts Florida, especially during the winter and spring months. The sea surface temperatures in the eastern Pacific affects climate by altering convection along the equatorial Pacific. The position of convection in the Pacific alters the sea level pressures (Diaz and Markgraf 1992) and upper level winds (Nash 2002) throughout the world. According to Douglas and Englehart, a teleconnection exists between autumn rains in the central Pacific and rainfall in Florida (Douglas and Englehart, 1981). The area of maximum rainfall in the Pacific is closer to Florida during an El Niño year than a La Niña year. During El Niño winters, sea level pressures in the central and eastern tropical Pacific are below average (Diaz and Markgraf 1992). These low-pressure anomalies affect the upper level winds, and these winds affect the development and track of middle latitude cyclones. El Niño teleconnections alter the jet stream causing middle latitude cyclones to develop and track into different locations (Douglas and Englehart 1981, Smith et al. 1998). Los Niños causes the polar jet stream to flow farther south than climatology allowing these frontal systems to reach Florida during the winter and spring, and these storms increase precipitation (Nash 2002). Las Niñas keep the polar jet stream and extratropical systems north of Florida (Douglas et al. 1981), thus keeping the state dry. Las Niñas tend to increase to probability of forest fires (Brenner 1999).

The ability to identify ENSO's impact on drought will lead to improvements in forest fire threat forecasts. Because the number of years available to calculate risks is limited, bootstrapping will enhance the forecast of drought by reducing bias. Bootstrapping will preserve the mean and not the variance. KBDI for Jacksonville and Belle Glade will be calculated from 1948 to 2002. After calculating KBDI for each day, the study will produce bootstrapped forecasts for each day (January 1 to July 31) and year (1950 to 2002). Bootstrapped forecasts will begin on January, April, and June, and the forecasts will end in July. Forecasts end in July because the forest fire season occurs primarily in late spring in Florida. Forest fires occur far less often in the autumn months than in the spring months (Brenner 1999). Selection of different lead times (January, April, and June) will test whether different outcomes and forecasts will result with use of bootstrapping. The bootstrapped KBDI will be calculated from temperature and precipitation obtained from bootstrapping. This study will calculate monthly drought risks and error bars for the cold, neutral, and warm ENSO phases using NOAA-COOPS data and the method of bootstrapping, and the Brier scores and odds ratio will compare the bootstrapped forecasts for the past 55 years with original KBDI dataset.

2. METHODOLOGY

2.1 Data

The National Weather Service collects daily observations from cooperative network stations. These stations typically observe daily maximum and minimum temperatures in degrees Fahrenheit and precipitation in inches, but some stations observe only temperature or only precipitation. The Florida Climate Center provides temperature and precipitation for the stations (Griffin and Zierden 2004). Most stations have observations beginning January 1, 1948 and end in December 2002, but a few stations have observations that begin as early as 1895 and end as late as 2003. To maintain consistency and account for antecedent conditions in KBDI calculations, this study will use observations beginning in 1950 and ending in 2002.

Stations selected for this study include Belle Glade in southern Florida and Jacksonville in northern Florida. Data from these cities begin in 1948 for Jacksonville and 1924 for Belle Glade, but date from 1950 to 2002 are used in calculations because KBDI calculations need to begin during a wet period. These two stations are located near national forests and state parks, and they are either outside of cities or in rural areas. The urban heat island effect impacts the temperature and precipitation of urban stations, and the heat island can skew high temperatures and over-predict high KBDI values. The two stations cover northern and southern Florida.

2.2 El Niño/Southern Oscillation Years

Table 1: List of La Niña, Neutral, and El Niño Years. ENSO years begin on October 1 of the posted year and end on September 30 on the subsequent year. For example, the 1997 El Niño year began on October 1, 1997 and ended on September 30, 1998.

La Niña Phase	Neutral Phase	El Niño Phase
1949, 1954, 1955, 1956 1964, 1967, 1970, 1971 1973, 1974, 1975, 1988 1998, 1999	1950, 1952, 1953, 1958, 1959, 1960, 1961, 1962, 1966, 1968, 1977, 1978, 1979, 1980, 1981, 1983, 1984, 1985, 1989, 1990, 1992, 1993, 1994, 1995, 1996, 2000, 2001	1951, 1957, 1963, 1965, 1969, 1972, 1976, 1982, 1986, 1987, 1991, 1997 2002

The Florida Climate Center provides ENSO phases for the above years determined by the Japanese Meteorological Agency mean annual sea surface temperature (JMA-SST) anomalies (Hanley et al. 2003). These anomalies are taken in the tropical Pacific between 4°S-4°N and 150°W-90°W. The JMA-SST index takes a 5-month running mean for each month. If six consecutive months between October of the posted year and September of the following year have mean anomalies of 0.5°C (-0.5°C) above (below) climatology, the year is classified as an El Niño (La Niña) year (Hanley et al. 2003). The El Niño/La Niña year is defined here as beginning in October of the posted year and ending in September of the following year. Los Niños have their greatest impact on the southeastern United States during the winter and spring months. For example, El Niño year of 1982 begins in October 1982 and ends in September of 1983. The ENSO phase for January through September would have the ENSO phase of the previous year as indicated in Table 1. Table 1 provides the list of El Niño, neutral, and La Niña years.

2.3 Bootstrapping

Bootstrapping is the process of making many of independent realizations with limited historical data (Diaconis and Efron 1983). For a particular day, month, and year, a random number generator selects a random year (not equal to the year forecasted) of the same ENSO phase and a random day within chosen month and year. After selection, the program uses temperature and precipitation for the corresponding day and month in the forecast year. The forecast calculates the KBDI using the selected temperature and precipitation. For example, to make a KBDI forecast for January 1, 1983 (El Niño year), one obtains the temperature and precipitation for any day in January for any other El Niño year. The program calculates the KBDI from the previous day's (December 31, 1982) KBDI, the current day's maximum temperature, and the current day's precipitation. With many possible combinations of unique bootstrapped months, it is possible to produce unlimited "bootstrapped" forecasts without having an identical forecast (Diaconis and Efron 1983). Because data for 53 years are used, bootstrapping will preserve the climatology of those 53 years. The technique of bootstrapping retains the climatology of the original data with slightly reduced variance while producing many samples.

Bootstrapping will begin at the beginning of each month and end on July. First, the model obtains the KBDI at the end of each month. After that, the program will forecast temperature and precipitation for each day by use of bootstrapping as explained earlier. Calculations will continue until July 31 of each forecast. For example, the model obtains the KBDI in the original non-bootstrapped data for December 31. KBDI for January 1 is predicted by using temperature and precipitation obtained by bootstrapping. Calculations will continue until July 31. The process begins again when the model obtains the original KBDI for January 31 to make forecasts from February through July. Forecasts beginning in January, April, and June will be analyzed in this study.

2.4 Keetch-Byram Drought Index Calculation

The Keetch-Byram Drought Index is a surrogate for the amount of moisture in the upper layers of the soil (Keetch and Byram 1988). It ranges from 0 to 800 with the value of 800 having no moisture in the upper layers of the soil. The KBDI uses the daily maximum temperature and precipitation to increment or decrement itself from one day to the next (Keetch and Byram 1988). The daily precipitation decreases the KBDI, and the daily maximum temperature increases the KBDI. The KBDI uses the maximum temperature as a proxy for evaporation. The dryness of the soil affects to the dryness of vegetation, and regions of drier the vegetation have a higher risk of forest fires than regions with moist vegetation. The KBDI, however, will not directly consider relative humidity, wind speed, or cloud cover in calculating evaporation. Along with daily precipitation and maximum temperature, the annual precipitation, and antecedent conditions are used to determine the factor to raise or lower the KBDI forecasts (Keetch and Byram 1988). KBDI is calculated for all days from 1949 to 2002. January through July are used in the forecast because Florida's wildfire season occurs during those months (Brenner 1999).

The first step in calculating KBDI is to find a day when the index is likely to have a value at or near zero. Because the drought index depends on antecedent conditions, the KBDI record must begin after a 7-day period of at least 6 inches of precipitation when the KBDI is assumed to be zero (Keetch and Byram 1988). To find a day with the index near zero, the program locates a seven-day period with a minimum of six inches of rain. The KBDI for the day after a week of at least six inches of rain is set to zero, and the model calculates the drought index for each day after the initial day. Luckily, both Belle Glade and Jacksonville have wet periods before 1949. To ensure consistency, KBDI dataset begins on December 31, 1949. The next two steps calculate the KBDI using temperature and precipitation.

The second step in calculating KBDI is to subtract the daily precipitation from the previous day's KBDI. The daily precipitation, measured in inches, is multiplied by a hundred. To account for canopy, precipitation from the previous day is used to determinate amount of moisture removed by the canopy. If less than 0.2 inches of rain fell during the previous day, the model subtracts 0.2 to the current day's precipitation. The daily precipitation is set to zero if it is less than 0.2 inches (Keetch and Byram 1988). If the KBDI is below zero (after subtraction), the index is set to zero. If the precipitation for a particular day is missing, the 1960-1990 monthly average precipitation divided by the number of days in that month substitutes the missing data.

The third step in calculating the KBDI is to add a KBDI value from tables using maximum temperature, annual temperature, and previous day's KBDI. The tables, included in the appendix, contain the adjusted previous day's KBDI and the maximum temperature ranges in columns and rows. To obtain the adjusted KBDI, subtract daily precipitation (in hundredths of an inch) from the previous day's KBDI. Annual precipitation ranges separate the tables. After obtaining the required information from calculations, the KBDI from the table is added to the previous day's KBDI to obtain the current day's KBDI.

2.5 Probability Calculation

The effects of The El Niño-Southern Oscillation on the Keetch-Byram Drought Index (KBDI) are tested by producing the probability of the monthly KBDI reaching or exceeding one standard deviation above the monthly mean (climatological) KBDI. Wildfire managers use the one standard deviation-threshold to assess risk of forest fires. The month of the year and the ENSO phase separates the forecast months. The program finds the average KBDI for each month in the samples, and the model compares the average KBDI for the tested sample month with the monthly climatology. The probabilities are calculated by counting all months exceeding one standard deviation above climatology, and this sum is divided by the total number of samples tested. In composite averages, the total sample size is the 1000 bootstrapped samples times the number of years in the ENSO phase. With twelve 1000-bootstraped samples, a range of 12 composite (average) probabilities can produce 95-percent confidence intervals for probabilities using 2 standard deviations above and below the mean forecast. The results are the probabilities of the monthly KBDI exceeding the one standard deviation threshold of a particular month of the year and ENSO phase.

2.6 Forecast Verification

Numerous methods of calculating error are available. Methods include the Brier scores (Mason 2004) and the odds ratio (Stephenson 1999). The Brier score finds the square of the difference between the probability forecast and the binary verification probability. The binary verification probability is either zero (no occurrence) or one (occurrence). Because the Brier score is a quadratic formula, one may decompose the Brier score into three components: uncertainty, reliability, and resolution (see next section). Both the odds ratio and Brier score will be used to compare bootstrapped forecasts with verification data; this verification will test whether lead-time has impact on the difference between bootstrapped forecasts and the original data.

2.7 Brier Score

Forecasts for binary events often have probabilities instead of deterministic values. Brier scores verify probabilistic forecasts. The Brier score is the mean of the square of the difference between probability forecast and verification forecast (Candille 2003). The equation for the Brier Score is given below:

$$B = \frac{1}{n}\sum_{i=1}^{n}(p_i - x_i)^2 \qquad (2.7.1)$$

The forecast probability, p, may have values between 0 and 1, but the verification probability can only have a value of one (the event occurred) or zero (the event did not occur). The variable, n, is the size of the sample, and Brier scores for samples larger than one are the average Brier score for the ensemble. Forecasts with lower Brier scores have stronger skill than forecasts with higher scores. When the Brier score is zero, the forecast is perfect. When the Brier score is one, the forecast has no skill.

The Brier skill score compares the Brier scores of the forecast and the Brier scores of climatology (2003). Unlike the raw Brier scores, increasing the forecast skill will increase the Brier skill score. The Brier skill score is equal to one minus the ratio between the Brier score for the forecast and the Brier score for climatology from one.

$$BSS = 1 - \frac{B_{\text{forecast}}}{B_{\text{climatology}}} \qquad (2.7.2)$$

The climatology forecast is the number of months exceeding the KBDI target in the 53-year sample and is independent of the ENSO phase. The distribution for KBDI anomalies is almost Gaussian; the climatology forecast for each month (exceeding one standard deviation above monthly climatology) is between fifteen to twenty percent. If the Brier skill score is one above zero, then the forecast is optimal. If the score is zero, then forecast has the same skill as the climatology forecast. When the Brier skill score is negative, the forecast performs worse than climatology.

The Brier score is composed of a quadratic formula; as a result, the score may be decomposed into three components. According to Mason, the Brier score includes uncertainty, reliability, and resolution (Mason 2004).

$$BS_k = \bar{o}(1 - \bar{o}) + (f_k - \bar{o}_k)^2 - (\bar{o}_k - \bar{o})^2 \qquad (2.7.3)$$

The terms given in order are uncertainty, reliability, and resolution. Because the Brier score is harsh and can often produce negative Brier skill scores or high raw Brier scores, one should analyze forecasts verified using Brier scores with caution (Mason 2004). Uncertainty is only influenced by the frequency of the event, $\bar{o}$, regardless of the quality of the forecast, and the frequency of the event lowers the Brier skill score. The uncertainty term is highest when the frequency is fifty percent, meaning that events occurring half the time will generally have lower skill scores than events occurring zero or hundred percent of the time.

Another variable, resolution, affects the skill of the forecast by finding the difference between the frequency of observed events at a certain level and the total frequency of observed events. Increasing the number of levels will generally increase skill. Levels may include temperature ranges or ENSO phases. Because each ENSO phase is analyzed separately, resolution will not be used in the analysis.

After accounting for uncertainty and resolution, Brier scores peak when the forecast probability of the event is equal to the percent of the occurrence of that particular event, but the maximum Brier skill score may not necessarily have a value near one. When events occur 50 percent of the time, the event has a high degree of uncertainty. Uncertainty increases the raw Brier score and decreases the Brier skill score (Mason 2004). Probabilistic forecasts rarely have values of zero or one; as a result, Brier scores of zero or one are rare due to uncertainty.

2.8 Finley Tables

Binary forecasts are forecasts for events that either occur or not occur. Examples include occurrence of precipitation, occurrence of a tornado, temperature reaching a threshold, or KBDI reaching a threshold. Because forecasts and verification for binary events each have two outcomes, binary forecasts are often verified using Finley's two-row and two-column table (Mason 2003). The table includes hits, correct rejections, misses, and false alarms. Correct forecasts are either hits or correct rejections, and incorrect forecasts are misses and false alarms. Hits occur when an event occurs, and the forecast predicts the same event. A correct rejection happens when both the forecast and the verification reject an event. A miss, a type I error, occurs when the event occurs and not forecasted. False alarms, type II errors, occur when the event was in the forecast, but event was not observed. The table below describes the four possible outcomes for binary events and forecasts.

Table 2: Finley Table of four possible forecast outcomes it their totals. Similar tables may be found in chapter 3: Binary Events in Forecast Verification by Ian Mason (Mason 2003).

Forecast	**Verification**	**Verification**	
	Yes	No	Total
Yes	Hit	False Alarms	Number of “yes” forecasts
No	Miss	Correct Rejection	Number of “no” forecasts
Total	Number of observed events	Number of non events	Sample Size

Often the binary tables include the sample size, total number of observed events, and number of forecasted events. The table, however, fails to include the total number of correct and incorrect forecasts. The number of correct forecasts are taken by summing the number of hits and correct rejections, and the number of incorrect forecast are taken by summing the number of misses and false alarms. Some tables include probabilities of each of the four possible combinations (Mason 2003), by dividing values in table 2 by the sample size. Many forecast verification methods, including the odds ratio, use variables in the Finley table.

2.9 Odds Ratio

The odds ratio score is the hit rate divided by the false alarm rate (Stephenson 1999). Odds are defined as the odds of an event occurring divided by the odds of an event not occurring *p/(1-p)* (Stephenson 1999). The odds of an event not occurring is simply the inverse *(1-p)/p*. The hit rate, *H*, is the odds of hits and the false alarm rate, *F*, is the odds of false alarms. The equation below states the odds ratio as the ratio between the hit rate and false alarm rate.

$$\theta = \frac{H}{1-H}\left(\frac{F}{1-F}\right)^{-1} \quad (2.9.1)$$

The score increases with increasing skill when the odds of a hit increase. The hit rate, *H*, is the hit rate divided by the total number of events occurred as given below:

$$H = \frac{hits}{hits + misses} \qquad (2.9.2)$$

The hit rate will increase when number of hits increase, and the hit rate will decrease when number of misses increase. Conversely, the false alarm rate is dependent on the number of false alarms and correct rejections as given below:

$$F = \frac{\textit{false alarms}}{\textit{false alarms} + \textit{correct rejections}} \qquad (2.9.3)$$

The false alarm rate will increase with number of false alarms and decrease with number of correct rejections. Odds of the false alarm will decrease the odds ratio. The odds ratio ranges from zero to infinity with equal odds at one. Forecasts of high skill will have the odds ratio greater than unity, and poor forecasts will have odds less than unity.

3. RESULTS

3.1 Forecasts

In both Jacksonville and Belle Glade, drought risks vary between ENSO phases. During the winter and spring months, high forest fire risks occur during La Niña years, and drought risks are minimal during El Niño winter and spring months. Drought risks reverse during the summer months; as a result, El Niño summers have higher drought risks than La Niña summers. Years with the neutral ENSO phase tend to have forecasts near the Gaussian climatological values, and the KBDI departures from the monthly mean have a Gaussian distribution. The summer season tends to have a smaller range in probability distribution than the spring and winter probability distribution. While forecasts for Belle Glade are similar to forecasts for Jacksonville, the drought risks reverse earlier in the year than in drought risks in Jacksonville.

3.1.1a Jacksonville – January

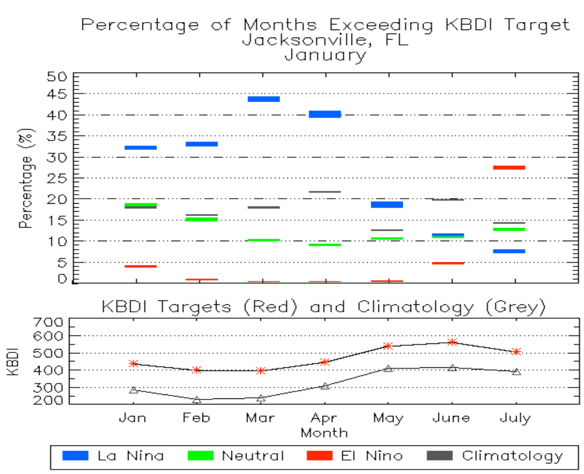


Figure 1: Jacksonville's composite forecast probabilities of monthly mean KBDI exceeding one standard deviation above the monthly climatology for each month starting in January. The date of initial KBDI is December 31. KBDI values are obtained by bootstrapping temperature and precipitation for each day of each month. The thickness of the bars is the 95% confidence interval for a range of probabilities in twelve sets of 1000 bootstrapped samples. The forecast is the average of forecasts of each year from 1950 to 2002.

3.1.1b Jacksonville – January The wildfire threat forecast varies considerably between La Niña, El Niño, and neutral phases for Jacksonville, FL. Variations in the probabilities of the KBDI exceeding the one-standard deviation above monthly climatology threshold are clear caused by ENSO-related trends (Figure 1). The 95 percent confidence intervals, as indicated by the widths of the bars, are tight for all forecasts and range from zero to two percent. The forecast predicts probabilities of KBDI anomalies not absolute KBDI. The figure predicts dry winters and wet summers during La Niña years and predicts wet winters and dry summers during El Niño years.

The majority of high KBDI forecasts tend to occur in La Niña years, especially during the winter and spring months. The results are consistent with La Niña's known effects on drought. According to the forecast, the probabilities of KBDI reaching the target for cold phase years exceed 25 percent during the winter and early spring months, with the greatest drought occurring in March with probabilities as high as 45% in March. After March, probabilities begin to decrease, and the forecast drops below 15 percent by June. The forecast is consistent with climatology in that probabilities decrease as weather patterns change in spring. Although the cold phase forecasts are consistent with La Niña's known influence short-term climate, however, probabilities exceeding a standard deviation above the average are smaller than 50 percent. To reduce uncertainty, the strength of La Niña and other systems determine whether a drought occurs during La Niña years. The figure still supports more droughts during the spring of El Niño years than other phases.

The model forecasts El Niño years to have low probabilities of drought throughout most of the forecast period. During the late winter and spring months, the probe-abilities remain near zero. The forecasts near zero or one hundred percent have minimal uncertainties. The results are consistent with the El Niño's known effects on the track of middle latitude cyclones. Probabilities begin to increase five percent for the June forecast, and the probability reaches 30 percent in July. Drought risks during El Niño summers, however, are lower than drought risks during La Niña spring; as a result, the forecast indicate ENSO has less influence on drought risks during summer. El Niño has the highest probabilities of the other two ENSO phases during the summer months and the lowest probabilities during the winter months.

Forecasts for the Neutral phase are between forecasts for the warm and cold phases, and probability trends for neutral phase years follows a similar trend to El Niño years.

Probabilities of drought in neutral phases are between ten and twenty percent; neutral phases have similar forecasts to climatology in January and February. KBDI anomalies and drought risks have a Gaussian distribution with a climatological risk around 17.5 percent. Climatological climate risks are between 14 and 22 percent according to Figure 1. Despite the neutral phase forecast remaining close to Gaussian probability, the forecast has variability from one month to another. Probabilities from March through July are lower than climatology. The neutral phase forecast is lower in the spring than in winter and summer. The neutral phase is near climatology, however, extreme droughts in the other phases may cause climatology predictions to have probabilities larger or smaller than probabilities in the neutral phase.

3.1.2a Jacksonville – April

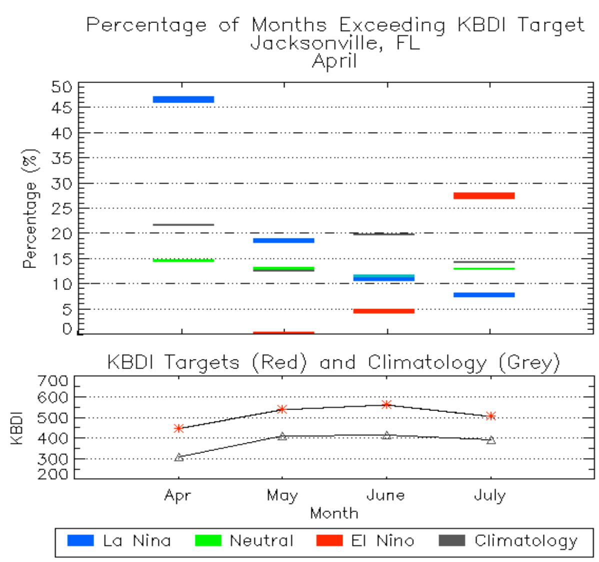


Figure 2: Jacksonville's composite forecast probabilities of monthly mean KBDI exceeding one standard deviation above the monthly climatology for each month starting in April. The date of initial KBDI is March 31. The composite forecast is the average forecast for all years between 1950-2002. Note that probability of drought during El Niño April is zero.

3.1.2b Jacksonville – April The wildfire threat forecast for April through July has changed little between forecasts in Figures 1 and 2. While forecasts for April have changed from Figures 1 and 2, the forecasts for May, June, and July have not changed. Like the forecasts beginning in January, probabilities of the KBDI exceeding the one-standard deviation threshold follow ENSO related influence in spring similar to Figure 2, and the confidence interval, as indicated by the widths of the bars, is still tight. La Niña years are dry in spring and wet in summer, and El Niño years are wet in the spring and dry in the summer.

High KBDI forecasts, in Figures 1 and 2, tend to occur in La Niña years, especially in April. The probabilities of KBDI reaching the threshold for cold phase years approach 50 percent in April (Figure 2), and the probabilities of droughts for April are significantly higher in Figure 2 than in Figure 1. Uncertainty, however, is high in April, and the model needs to include La Niña's strength or knowledge of other climatological features to determine drought.

The model forecasts El Niño years to have low probabilities of drought in April and May and increase to near 30 percent in July. Drought risks for July have not increased between Figures 1 and 2, and drought risks for El Niño summers remain lower than drought risks for spring in La Niña years. Changing the initialization time in the forecast has not changed the probabilities for El Niño years.

Forecasts for the neutral phase are between forecasts for the El Niño and La Niña phases in both figures. The drought risk increases in April, and forecasts for other months remain unchanged. The neutral phase forecast is lower in the spring than in other seasons.

3.1.3a Jacksonville – June

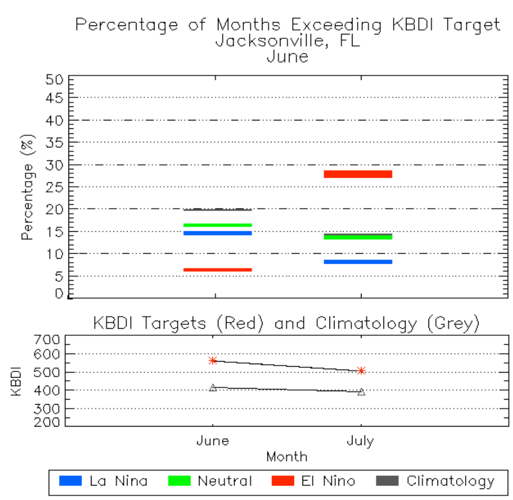


Figure 3: Jacksonville's composite forecast probabilities of monthly mean KBDI exceeding one standard deviation above the monthly climatology for each month starting in June. The date of initial KBDI is May 31. The composite forecast is the average forecast for all years between 1950-2002.

3.1.3b Jacksonville – June The wildfire threat forecast for June through July has increased by five percent in June and remained almost unchanged in July between forecasts beginning in January and April for Jacksonville, FL. Unlike the forecasts beginning in January and April, the probabilities of drought during the La Niña phase are lower than in the neutral phase. Generally, drought risks are higher during El Niño summers than La Niña summers.

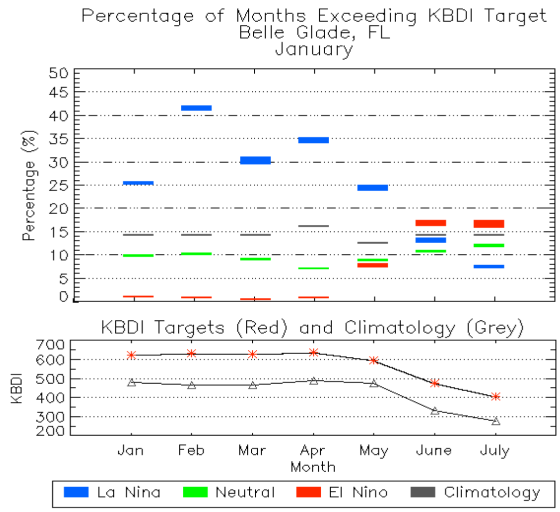
During the summer months, high KBDI indices rarely occur during La Niña years. The probability of drought during La Niña June has increased in Figures 2 and 3, but the probabilities remained unchanged in July. La Niña summers are wet in northern Florida according to the results in Figure 2.

The forecasts for El Niño years have minor changes between Figures 2 and 3. The forecast for June increased slightly, but the El Niño still has the lowest probability of the ENSO phases in June. July forecasts have remained unchanged with the El Niño probabilities the highest of all ENSO phases (Figure 3). Although summer droughts occur during El Niño years, the probability is lower than droughts predicted during La Niña winters. Lower probabilities in El Niño summers mean that probabilities of drought in other phases are higher than probabilities of drought in El Niño and neutral years during the winter.

Forecasts for the Neutral phase are between forecasts for the El Niño and La Niña phases in July and highest in June. Risks increased slightly in June from Figures 2 and 3, and July, like other ENSO phases, remains unchanged. The probabilities of all ENSO phases in June are lower than the climatological probability because June has a high number of misses in the bootstrapped forecasts. Probabilities of drought in neutral phases are between five and fifteen percent, making forecasts lower than climatology.

3.1.4a Belle Glade – January

Figure 4 (next page): Belle Glade's composite forecast probabilities of monthly mean KBDI exceeding one standard deviation above the monthly climatology for each month starting in January. The date of initial KBDI is December 31. The composite forecast is the average forecast for all years between 1950-2002.



3.1.4b Belle Glade – January The wildfire threat forecast remarkably varies between La Niña, El Niño, and neutral phases for Belle Glade, FL. Probabilities of the KBDI exceeding the one-standard deviation threshold tend to reverse from winter to summer according to Figure 4. Like previous figures, the widths of the bars (95 percent confidence intervals) are small for all forecasts and range from zero to two percent. Forecasts for both Jacksonville and Belle Glade have dry (wet) La Niña (El Niño) winters and wet (dry) La Niña (El Niño) summers, but the drought risks change earlier in the year in Belle Glade than the risks in Jacksonville.

The majority of high KBDI forecasts tend to occur in La Niña years, especially during the winter and early spring months. According to Figure 4, the probabilities of KBDI reaching the target for cold phase years exceed 25 percent during the winter and early spring months, and drop below 15 percent by June. Although probabilities are higher in winter than summer, January ranked lower than other months. Probabilities of drought are highest in February and April with probabilities of 45 and 35 percent respectively. Unlike drought risks in Jacksonville, the La Niña dry season peaks and ends earlier in the year. Errors in the forecast or influences by phenomena other than ENSO on climate may cause the probabilities to fluctuate from month to month.

The model forecasts El Niño years to have low probabilities of drought throughout the forecast period, and the probabilities remain near zero from February through April and increase to near 20 percent in July. Like forecasts in Jacksonville, warm phase years tend to have low probabilities of drought during the winter and spring months, but El Niño has the highest probabilities of the other two ENSO phases during the summer months. The El Niño summer drought risks, however, are lower than spring drought risks for La Niña, indicating ENSO's weaker influence on summer weather patterns. The El Niño summer dry season begins earlier in Belle Glade than in Jacksonville.

Forecasts for the neutral phase are between forecasts for the El Niño and La Niña phases. Probabilities of drought in Neutral phases are between five and fifteen percent, making forecasts lower than climatology. Belle Glade has lower probabilities of drought than Jacksonville during neutral phase. The neutral phase forecast is lower in the spring than in winter and summer.

3.1.5a Belle Glade – April

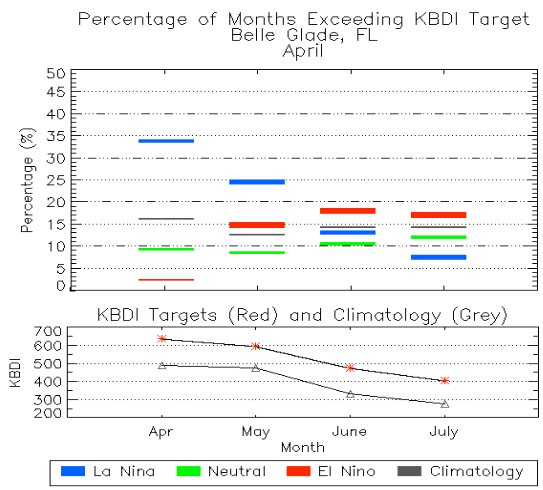


Figure 5: Belle Glade's composite forecast probabilities of monthly mean KBDI exceeding one standard deviation above the monthly climatology for each month starting in April. The date of initial KBDI is March 31. The composite forecast is the average of all forecasts between 1950-2002.

3.1.5b Belle Glade – April The wildfire threat forecast for April through July has changed little between forecasts beginning in January and forecasts beginning in April for Belle Glade, FL. Probabilities of the KBDI exceeding the one-standard deviation threshold indicate ENSO-related trends (Figure 5). Drought risks decline during the late spring of La Niña years and increase during the late spring of El Niño years.

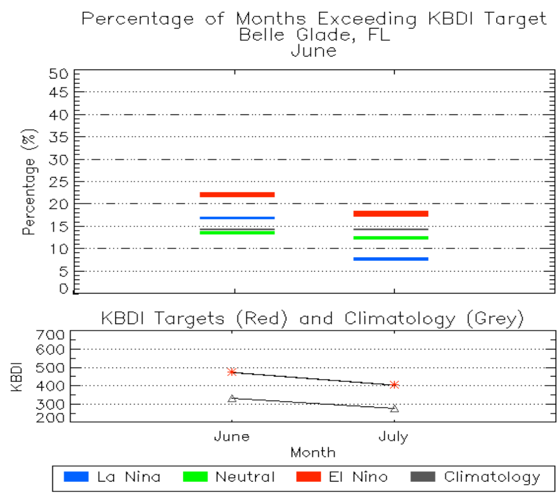
High KBDI forecasts tend to occur in La Niña years, especially in April and May. Like Figure 4, the probabilities of KBDI reaching the target for La Niña years reach or exceed 20 percent in April and May, probabilities and drop below 15 percent in June and July. Minor changes include a one to two percent decrease in April. Other months remained almost unchanged with steadily decline in risk from April to July.

The model forecasts El Niño years to have low probabilities of drought throughout the forecast period with probabilities below 20 percent for all months. Like Jacksonville, El Niño years tend to have low probabilities of drought during the spring months, but El Niño has the highest probabilities of the other two ENSO phases during the summer months. Changing the initial month has not increased risk of drought during El Niño summers, but risks have increased significantly in May according to Figures 4 and 5. The risk for May have increased by eight percent. The El Niño dry season begins earlier in Belle Glade than in Jacksonville.

Forecasts for the neutral phase are between forecasts for the El Niño and La Niña phases. Probabilities of drought in Neutral phases are between five and fifteen percent, making forecasts lower than climatology. Belle Glade has lower probabilities of drought than Jacksonville during neutral phases. Minor changes include an increase by two to three percent in April. The neutral phase forecast is lower in the spring than in winter and summer.

3.1.6a Belle Glade – June

Figure 6 (next page): Belle Glade's composite forecast probabilities of monthly mean KBDI exceeding one standard deviation above the monthly climatology for each month starting in June. The date of initial KBDI is May 31. The composite forecast is the average of all forecasts between 1950-2002.



3.1.6b Belle Glade – June The wildfire threat forecast for June through July has increased by five percent in June and remained almost unchanged in July between forecasts beginning in January and forecasts beginning in April for Belle Glade, FL. The distribution between ENSO phases, however, has remained unchanged. The risk of drought varies by ten percent from the ENSO phase of the lowest risk to the ENSO phase of the highest risk.

During the summer months, high KBDI rarely occur during La Niña Years. Forecasts in Figures 4, 5, and 6 agree that probabilities for La Niña years are between the probabilities of high KBDI in neutral and El Niño years in June and lowest in July. The risks or drought during the June of La Niña years, however, increased by four percent from Figures 5 and 6. La Niña summers are wet in both southern Florida and northern Florida according to the results for Jacksonville and Belle Glade.

The model forecasts El Niño years to have probabilities exceed 15 percent in June and July. Although the El Niño phase has the highest probabilities of drought in Figure 6, probabilities are still well below 50 percent. Probabilities for drought during June in El Niño years have increased by five percent from Figures 5 and 6. July forecasts have remained unchanged. Summer drought risks for La Niña and other ENSO phases are low.

Forecasts for the neutral phase are between forecasts for the El Niño and La Niña phases in July and the lowest probability in June. Probabilities of drought in Belle Glade are lower than probabilities of drought in Jacksonville during neutral phases. The June drought risks increased by three percent in June from Figures 5 and 6 and remained almost unchanged in July.

3.2 Verification

3.2.1A Brier score: Jacksonville – January

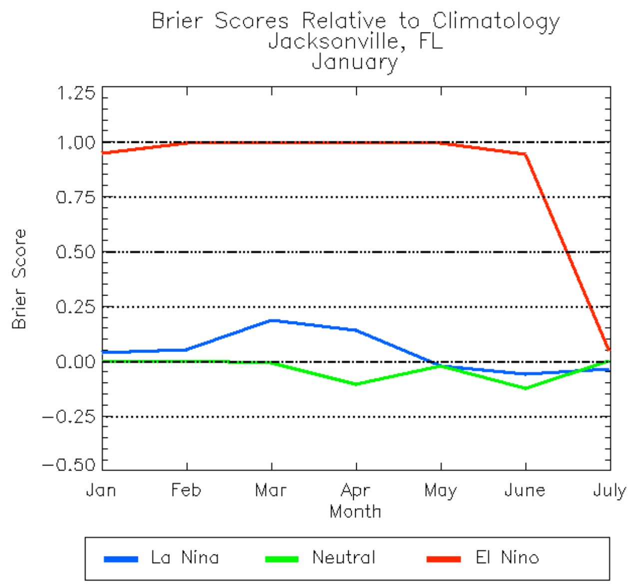


Figure 7: Jacksonville's composite Brier skill scores for each month starting in January. Perfect scores have values of one. Forecasts performing worse than climatology are less than zero.

3.2.1B Brier score: Jacksonville – January Generally, the Brier skill scores are high for El Niño years, moderate for La Niña years, and low for neutral years. La Niña scores peak in March, and are near climatology in early winter and summer. El Niño scores are high during the winter and spring months when droughts are non-existent, but decline in the summer. Neutral years have similar skills to climatology.

The Brier skill scores for La Niña years are low to moderate. Surprisingly, the skill score increases during the winter peaking in March, third month in the forecast. The delayed peak could mean that bootstrapping forecasts underpredicts droughts in the winter. The peak Brier skill score is only as high as 0.2, but this score is probably caused by uncertainties during La Niña years. As explained earlier, probabilities of drought are near fifty percent. If frequency is near fifty percent, scores will be reduced by uncertainty despite the probability values near verified frequency. As expected the skill scores decrease in time from March to

July. The skill scores drop below zero in early summer, meaning that the forecast performs worse than climatology. While skill scores for La Niña years are low compared to El Niño scores, values of 0.2 are typically excellent scores when considering uncertainty.

The Brier skill scores are perfect in El Niño winter and spring months, but the scores decline during the summer. Scores are almost unity during winter and spring months, and this high score may lead forecasters to question this score. Because probabilities are almost zero according to forecast figure, uncertainties are minimal. Both forecasts and verification indicate that droughts almost never occur during El Niño winters. During the summer, however, the scores decrease dramatically and drop below zero by July. Uncertainty increases as the probabilities of drought increase. The Brier scores and the forecasts prove that drought and forest fires during El Niño years almost never occur during winter and spring.

The Brier skill scores for the neutral phase are at or slightly worse than climatology. The scores indicate that the neutral phase has similar perform as climatology. According to figure 1, the probabilities are between 12 to 22 percent, near the climatological value of 17.5. Because the KBDI anomalies follow a Gaussian distribution, 17.5 percent of forecasts exceed one standard deviation above the mean. The neutral phase has a similar forecast as climatology because its probabilities are near 17.5 percent. The scores are lower in summer than winter, suggesting that forecasts for neutral years decline with increasing forecast time as well as forecasts for other ENSO phases.

Many would view the above Brier Score plot with criticism. Brier scores for most forecasts rarely reach unity. Although the study mainly concerns drought risks rather than lack thereof, warm phase scores of near unity will cause forecast scores to appear low for other ENSO phases. A brier score of 0.2 is considered an excellent forecast, and this often occurs during La Niña spring. The Brier score, however, is rather harsh for forecasts during the cold and neutral phases. Even though the forecast probability and frequency of occurrence are close in value for those phases, the Brier skill score is still low. If climatology and forecast probabilities have ten percent or less difference, Brier skill score would be low because the ratio between forecast Brier score and climatology skill score is near unity. For this reason, the odds ratio will replace the Brier skill score when verifying the forest fire threat forecasts.

3.2.2A Odds ratio: Jacksonville – January

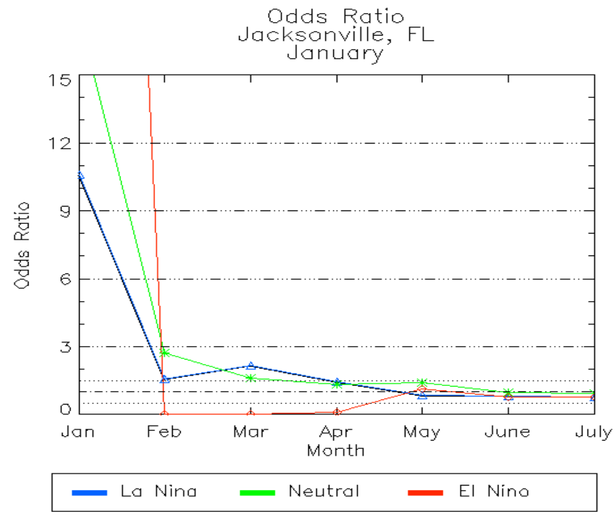


Figure 8: Odds ratio scores for Jacksonville, FL beginning in January. Odds ratio is the ratio between the odds of hits and odds of false alarms. Scores greater than unity indicate higher odds of hits than false alarms. Higher scores have better forecast skill. Dotted lines at 0.5 and 1.5 emphasize importance of scores near unity.

3.2.2B Odds ratio: Jacksonville – January The odds ratio for Jacksonville, FL varies significantly from each ENSO phase and forecast month. Each phase has the highest skill depending on the forecast month. As expected, earlier months have higher skill than later months because skill decreases with increasing forecasting time. Odds ratios for all ENSO phases converge to unity at the end of the forecast period. As the skill decrease, the hits decrease and/or false alarms increase.

The odds ratio for the La Niña phase is high in the winter but decreases to below unity during the spring. The score is above unity during January through April meaning that the hit rate is larger than the false alarm rate. During the other months, false alarms occur more than hits. Surprisingly, the odds ratio is lower in February than in January and March. Lower skill for the summer reflects lower skill at longer-range forecasts.

The odds ratio is poor during El Niño years and generally higher in summer than winter. Surprisingly, January has the highest odds ratio with score exceeding 25. January has a low false alarm rate with the number of correct rejections overwhelming the number of false alarms. From February through May, skill is zero meaning that no hits are observed. Lack of observed droughts causes lack of hits during the El Niño phase rather than low skill. Skill improves only slightly during summer when drought events are observed during summer, and the odds ratio is slightly below unity during the summer.

The neutral phase has variable skill. During the late spring/early summer months, the neutral phase has better skill than other ENSO phases. During other months, the skill is between the skill scores of La Niña and El Niño phases. The odds ratio follows for neutral years follows a similar trend to El Niño years during winter and spring and follows trends similar to La Niña years during the summer.

3.2.3A Odds ratio: Jacksonville - April

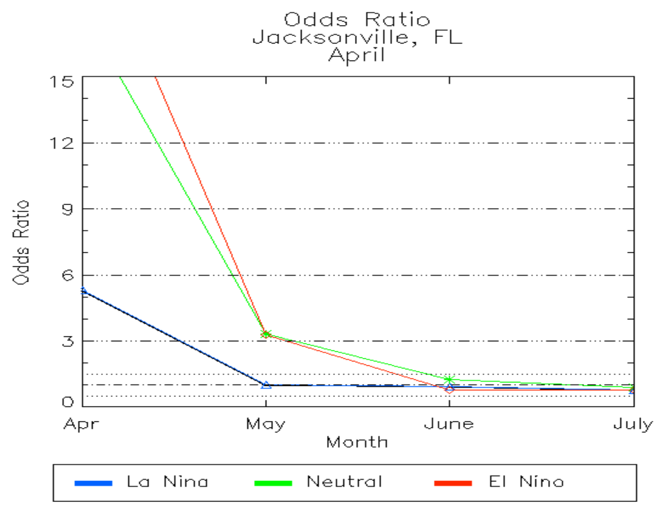


Figure 9: Odds Ratio for Jacksonville, FL beginning in April. Odds ratio is the ratio between the odds of hits and odds of false alarms. Higher scores have better forecast skill.

3.2.3B Odds ratio: Jacksonville – April The odds ratio for Jacksonville, FL for forecasts beginning in April have similar trends to the corresponding months in forecasts than began on January. The El Niño forecasts have the highest skill in the beginning of the forecast. As expected, earlier months have higher skill than later months because skill decreases with increasing forecasting time; as a result, the skills for April and May have improved. The hit rate decreases and/or false alarm rate increases, as skill decreases.

The odds ratio in the La Niña phase is highest in April and lowest in July. The score is well above unity in April meaning that hits occur more often than false alarms. Skill has improved in April and May from Figures 8 and 9. Skill, however, is not as high in April

(Figure 9) as in January (Figure 8). As the spring season progresses, the odds ratios for La Niña years decrease tremendously. During the summer months, the odds ratio decreases to slightly below unity meaning that false alarm rates are slightly higher than hit rates.

The odds ratio during the spring months of El Niño years has improved from Figure 8 and 9. In April and May, skill has improved and values are well above unity. This improvement is caused by lead-times in the forecast. During the late spring and summer, the odds ratio still collapses to slightly below unity indicating that decreasing forecast time improves skill slightly.

The odds ratio for neutral years are similar to El Niño years. Like the odds ratio for El Niño and La Niña phases, skill has improved for April and May. Neutral phase has better skill than other ENSO phases during May and June. Skill for July has not improved between Figure 8 and 9.

3.2.4A Odds ratio: Jacksonville - June

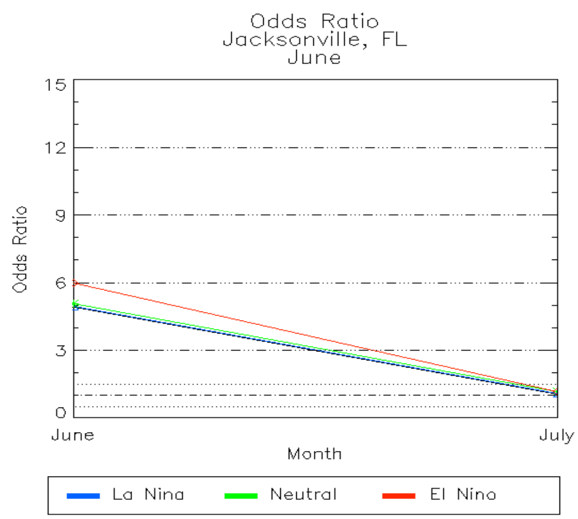


Figure 10: Odds ratio for Jacksonville, FL beginning in June. Odds ratio is the ratio between the odds of hits and odds of false alarms. Higher scores have better forecast skill.

3.2.4B Odds ratio: Jacksonville – June The odds ratio for Jacksonville, FL in June has improved significantly from Figures 9 and 10. The odds ratio for June forecasts are around five for all ENSO phases, but July forecasts are still low. As expected, earlier months have higher skill than later months because skill decreases with increasing forecast time. As the skill decrease, the hit rate decreases and/or false alarms rate increases.

The odds ratio is lowest in the La Niña phase for both June and July. In July, skill has improved from Figures 9 and 10, and its value is near five. In July, skill is near unity. Although skill improved in June, odds ratio in June is lower than the Odds ratio La Niña years in January (Figure 8) and April (Figure 9).

The odds ratio is high during June of El Niño years but low in July. Like the trend in the La Niña phase, the odds ratio decreases from June to July. The odds ratio slope from El Niño years is steeper than other phases because El Niño odds ratio is the largest of the three in June. Although skill improved in June, it is not as high as skill in April (Figure 9) and January (Figure 8). The odds ratio converges to unity in July for all three phases.

The neutral phase has slightly greater skill than La Niña years and follows the same trend as La Niña years. The odds ratio for neutral years during summer is consistent with forecasts beginning in January, April, or June. During other months, the skill is between the skill scores of La Niña and El Niño phases.

3.2.5A Odds ratio: Belle Glade - January

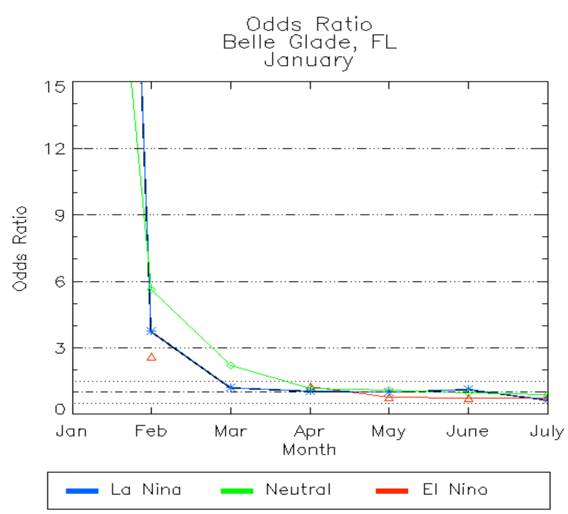


Figure 11: Odds ratio for Belle Glade, FL beginning in January. Odds ratio is the ratio between the odds of hits and odds of false alarms. Higher scores have better forecast skill. Odds ratios for El Niño January and March are not available.

3.2.5B Odds ratio: Belle Glade – January The odds ratio for Belle Glade, FL varies significantly from each ENSO phase and forecast month. Overall, the neutral phase has the highest skill. The odds ratio for the El Niño forecast is not available in January and March because the false alarm rate is zero. A zero false alarm rate causes an infinite odds ratio. As expected, earlier months have higher skill than later months because skill decreases with increasing forecasting time. Odds ratios for all ENSO phases converge to unity at the end of the forecast period. As the skill decrease, the hit rate decreases and/or false alarm rate increases.

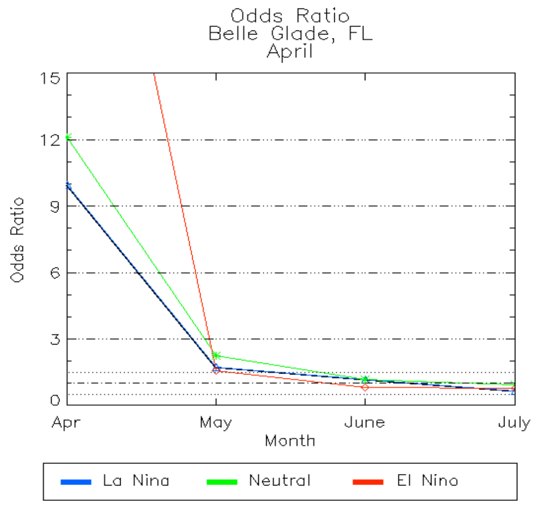
The odds ratio is for the La Niña phase is large in winter and low during summer. The score is well above unity during January and February. The January score for Belle Glade is much higher than the January score for Jacksonville, FL. This could mean that La Niña has greater influence on climate in Belle Glade than in Jacksonville. During the spring months, the odds ratio decreases to unity. Lower skill for the summer reflects lower skill at longer-range forecasts or lack of hits during wet La Niña summers.

The odds ratio for forecasts for El Niño years is near unity when odds ratio is available. In January and March, however, the odds ratio is not available because no false alarms were observed. In February, the odds ratio is about three times the false alarm rate, and other months have a ratio at or below unity. El Niño has slightly lower skill than the other ENSO phases during summer.

The neutral phase score is generally higher than the La Niña and El Niño odds ratios, and the neutral scores follow a similar trend as La Niña scores. January is the only month with odds ratio for neutral years lower than the odds ratio for La Niña years, but odds ratios are overwhelming high in January. While this ratio is higher than the odds ratio for other ENSO phases, the ratio for neutral phase still converge to near unity in the summer.

3.2.6A Odds ratio: Belle Glade – April

Figure 12 (next page): Odds ratio for Belle Glade, FL beginning in April. Odds ratio is the ratio between the odds of hits and odds of false alarms. Higher scores have better forecast skill.



3.2.6B Odds ratio: Belle Glade – April The odds ratio for Belle Glade, FL for forecasts in Figure 12 have similar trends to the corresponding months in forecasts in Figure 11. The El Niño forecasts have the highest skill in the beginning of the forecast and the forecasts for the neutral phase have the highest skill at the end of the forecast. As expected, earlier months have higher skill than later months because skill decreases with increasing forecasting time. April Scores improved dramatically from Figure 11 to Figure 12. The odds ratio for May have increased slightly. As skill decreases, the hits decrease and/or false alarms increase.

The odds ratio in the La Niña phase is highest in April and lowest in July. The score is around 10.0 in April, higher than the score in Jacksonville. While the odds ratio is moderately high, the odds ratio for January (Figure 11) is higher than in April (Figure 12). Odds ratio for May has improved slightly having a value near two. As the spring progresses, the skill for La Niña years decrease dramatically and drop to slightly below unity in July.

Like the La Niña forecast, the odds ratio for the El Niño forecast is highest in April. In June and July, skill for El Niño years is low meaning that the hit rate is low. The forecast for April has some improvement despite few observed hits, and this improvement is caused by lead-time. The odds ratio for May have slight improvements during El Niño years, but skill remains low in June and July.

The neutral phase follows the trend similar to La Niña in Figure 12. In April, the skill is between the skill scores of La Niña and El Niño phases. Skill has improved considerably in

April, but skill is not as high as in January. The skill for other months is slightly higher than the forecasts for the El Niño and La Niña phase. Skill remains low in June and July.

3.2.7A Odds ratio: Belle Glade - June

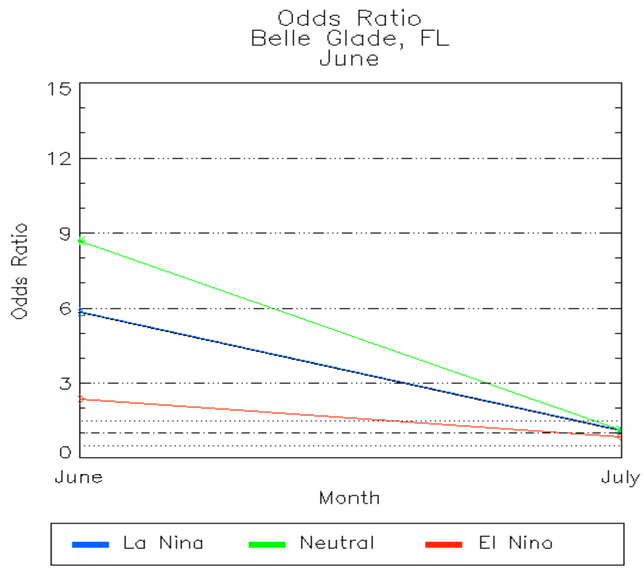


Figure 13: Odds ratio for Belle Glade, FL beginning in June. Odds ratio is the ratio between the odds of hits and odds of false alarms. Scores greater than unity indicate higher odds of hits than false alarms. Higher scores have better forecast skill.

3.2.7B Odds ratio: Belle Glade – June The odds ratio for Belle Glade have improved significantly from Figures 11, 12, and 13. The odds ratio for June forecasts is between two and nine for all ENSO phases, and July forecasts are still around unity. While the odds ratio for June increased from Figures 11, 12, and 13, the odds ratio is not as high as the odds ratio in April (Figure 12) and January (Figure 11).

The odds ratio from the La Niña phase is between the odds ratios for El Niño and Neutral phases for both June and July. The odds ratio is about six meaning than the odds of hits are six times larger than false alarms. In July, the odds ratio decreases to slightly above unity with equal hit and false alarm rates. Odds ratios for July in all forecasts are around unity despite lead-time and ENSO phase.

The odds ratio for the El Niño phase is lower than the odds ratios for the La Niña and neutral phases in both months (Figure 13). The odds ratio in June is slightly above two, and the odds ratio for the El Niño years decreases from June to July. The odds ratio slope from El

Niño years is not as steep as the other phases because El Niño odds ratio is the lowest of the three in June. The odds ratio converges to around unity in July for all three phases.

The neutral phase has greater skill than La Niña and El Niño years and follows the same trend as La Niña years. The odds ratio, however, is lower in June for in Figure 13 than the odds ratios for neutral years in April (Figure 12) and January (Figure 11). Like the odds ratios for other ENSO phases, the odds ratio converges at unity for the neutral phase in July.

4. Conclusion

In both Jacksonville and Belle Glade, drought risk forecasts vary between ENSO phases. During the winter and spring months, moderate forest fire risks (between 30 and 60 percent) occur during La Niña years. Drought risks are minimal during El Niño winter and spring months, and they reverse during the summer months. Summer months during the El Niño phase have higher risks of drought than summer months during the La Niña phase. The predicted risks are consistent with ENSO's known impact on weather patterns in Florida. During an El Niño (La Niña) winter, the jet stream is near (far) from Florida bringing enhanced (reduced) precipitation in Florida (Douglas and Englehart 1981). Years with the neutral ENSO phase tend to have forecasts near climatological probabilities. The summer season tends to have a smaller range in probability distribution than the spring and winter probability distribution. While Belle Glade has a similar forecast as Jacksonville, the drought risks change earlier in the year in Belle Glade than in Jacksonville. Verification schemes, like the odds ratio, verify the reliability of the potential forest fire threat forecasts.

The odds ratio generally demonstrate that forecasts are more reliable in winter than in summer. The wildfire threat forecast, like other forecasts, decrease in skill with forecast time. Forecast skill in summer is lower than winter regardless of lead time. The skill in each phase depends on month and location. In some instances, forecast skill during the warm ENSO phase is higher than other ENSO phases, and in other instances, the cold ENSO phase is higher than the other phases. In all forecasts, the odds ratios for all ENSO phases tend to converge to unity in July regardless of initial date of forecast. According to both forecasts and verification, one may use this report to assess wildfire risk in winter and spring, but summer forecasts are questionable.

The effects of ENSO on climate and forest fire threats is important to the Florida Division of Forestry and other agencies. By knowing the risks of forest fires, these agencies can mitigate the potential risks of fires by prescribed burns, fire alerts, and fire suppression. Public awareness of forest fire risks may also help reduce property damage associated with forest fires. The Southeast Climate Consortium will include more stations in Florida and some stations in Alabama and Georgia. Continued work will verify whether or not Jacksonville forest fire threats are typical of northern Florida, and Belle Glade forecasts are typical of southern Florida. Continued work may also include other oscillations like the North Atlantic Oscillation (NAO), the Pacific North American Pattern (PNA), and the Pacific Decadal Oscillation (PDO). More research on drought forecasts will allow operational meteorologists to provide better forecasts and understanding in long-range forest fire threats.

APPENDIX – KBDI TABLES

KBDI Increments for Sites with Annual Precipitation between 45 and 59 Inches

Table 3: Table of KBDI increment values with their respective temperature and previous day KBDI. This table can be found in the paper, "A Drought Index for Forest Fire Control" by Byram and Keetch (Byram and Keetch 1988).

KBDI → Temperature °F ↓	0-49	50-99	100-149	150-199	200-249	250-299	300-349	350-399	400-449	450-499	500-549	550-639	640-699	700-759	760-799
<53	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
53-55	2	2	2	1	1	1	1	1	1	1	1	1	1	0	0
56-58	3	2	2	2	2	2	1	1	1	1	1	1	1	0	0
59-61	3	3	3	3	3	2	2	2	2	1	1	1	1	1	0
62-64	4	4	4	4	3	3	3	2	2	2	2	1	1	1	0
65-67	6	5	5	4	4	4	3	3	3	2	2	2	1	1	0
68-70	7	6	6	6	5	5	4	4	3	3	2	2	1	1	0
71-73	8	8	7	7	6	6	5	5	4	4	3	2	1	1	0
74-76	10	10	9	8	8	7	6	6	5	4	4	3	2	1	1
77-79	12	11	11	10	9	8	8	7	6	5	4	3	2	1	1
80-82	15	14	13	12	11	10	9	8	7	6	5	4	2	1	1
83-85	17	16	15	14	13	12	11	10	8	7	6	5	3	2	1
86-88	21	19	18	17	15	14	13	11	10	9	7	5	3	2	1
89-91	24	23	21	20	18	16	15	13	12	10	9	6	4	2	1
92-94	28	27	25	23	21	19	17	16	14	12	10	7	4	3	1
95-97	33	31	29	27	25	23	20	18	16	14	12	9	5	3	1
98-100	39	37	34	31	29	26	24	21	19	16	14	10	6	4	1
101-103	46	43	40	37	34	31	28	25	22	19	16	12	7	4	1
104-106	53	50	46	43	39	36	33	29	26	22	19	14	8	5	1
>106	62	58	54	50	46	42	38	34	30	26	22	16	10	6	2

KBDI Increments for Sites with Annual Precipitation Greater than 59 Inches

Table 4: Table of KBDI increment values with their respective temperature and previous day KBDI. This table can be found in the paper, “A Drought Index for Forest Fire Control” by Byram and Keetch (Byram and Keetch 1988).

KBDI --> Temperature | °F V	0-49	50-99	100-149	150-199	200-249	250-299	300-349	350-399	400-449	450-499	500-549	550-639	640-699	700-759	760-799
<53	2	2	2	1	1	1	1	1	1	1	1	1	1	0	0
53-55	3	2	2	2	2	2	2	1	1	1	1	1	1	0	0
56-58	4	4	3	3	3	3	2	2	2	2	1	1	1	1	0
59-61	5	5	4	4	4	3	3	3	2	2	2	1	1	1	0
62-64	6	6	6	5	5	4	4	4	3	3	2	2	1	1	0
65-67	8	8	7	7	6	6	5	4	4	3	3	2	1	1	0
68-70	10	9	9	8	7	7	6	6	5	4	4	3	2	1	1
71-73	12	12	11	10	9	8	8	7	6	5	4	3	2	1	1
74-76	15	14	13	12	11	10	9	8	7	6	5	4	2	1	1
77-79	18	17	16	14	13	12	11	10	9	8	6	5	3	2	1
80-82	21	20	19	17	16	15	13	12	10	9	8	6	3	2	1
83-85	25	24	22	21	19	17	16	14	12	11	9	7	4	2	1
86-88	30	28	26	24	22	20	18	17	15	13	11	8	5	3	1
89-91	36	33	31	29	26	24	22	19	17	15	13	9	6	3	1
92-94	42	39	36	34	31	28	26	23	20	18	15	11	7	4	1
95-97	49	46	43	40	36	33	30	27	24	21	17	13	8	4	1
98-100	57	54	50	46	43	39	35	31	28	24	20	15	9	5	2
101-103	67	63	58	54	50	45	41	37	32	28	24	18	10	6	2
104-106	78	73	68	63	58	53	48	43	38	33	28	21	12	7	2
>106	91	85	79	73	68	62	56	50	44	38	32	24	14	8	2

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BIOGRAPHICAL SKETCH

Education: The Florida State University
Master of Science in Meteorology
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The Pennsylvania State University
Bachelor of Science in Meteorology
Minor in Geographic Information System
5/18/2003

Professional Experience:

8/20/2003-present Center of Ocean-Atmospheric Prediction Studies
Research Assistant
Produced and verified drought index for one to seven month forecast based on ENSO phase.
Contributed to the improvement of graphs.

5/15/2001-8/9/2003 The Pennsylvania State University
Undergraduate Researcher
Made Fortran and Excel Visual Basic Macro programs that verifies student forecasts.
Contributed to an early flash flood alert system based synoptic weather systems and presented results at the 2003 American Meteorological Society Annual Conference.
Produced a Flash graphical interface for the wheat scab model.

6/2/2002-8/1/2003	Zedx, inc. *Intern Programmer* Produced a decoder that decodes upper-level data. Drew habit-distribution maps for plant disease and pests.
5/20/2000-8/10/2000	Franklin Institute Science Museum *Intern* Presented tours of a model weather station to the public. Recorded weather observations.

Presentations:

2/11/2003	American Meteorological Society Annual Conference Presented my summer 2002 research on an early flash flood warning system for Pennsylvania.
11/5/2002	National Weather Service Fourth Northeast Regional Operational Workshop Presented my summer 2002 research on an early flash flood warning system for Pennsylvania.