CHAPTER ONE
INTRODUCTION

Cloud-to-ground (CG) lightning is a dangerous, and potentially deadly natural phenomenon. It can disrupt human activities such as aviation and outdoor sporting events, damage property, and start fires. Electrical systems are particularly susceptible to lightning damage. Not only are power outages disruptive to customers, but they are costly to electric providers if not repaired in a timely manner. Improved CG lightning forecasts can result in fewer injuries and deaths, with less time and money spent repairing damaged property or restoring electric services. A better understanding of the physical processes that lead to convective activity and its attendant lightning production is essential to more accurately forecast CG lightning.

The National Lightning Detection Network (NLDN) (Cummins et al. 1998) consists of approximately one hundred sensors across the country. It has been in continuous operation since 1989. Data recorded by the NLDN include the latitude, longitude, time, peak current, polarity, and multiplicity of each stroke. Many studies have used these data to analyze lightning occurrence within the United States. Orville (1991, 1994), Orville and Silver (1997), Huffines and Orville (1999), Orville and Huffines (2001), and Orville et al. (2002) have shown that Florida experiences the greatest flash densities in the nation.

Most localized studies of lightning activity have focused on Florida. Maier et al. (1984) analyzed the diurnal variation of lightning near the Kennedy Space Center (KSC) and showed that lightning activity peaks between 2000 and 2100 UTC, approximately three hours after local solar noon. Their results were in good agreement with Wallace (1975), who showed that thunderstorm frequency over the peninsula peaks strongly between 1900 and 2100 UTC. Hodanish et al. (1997) compiled a 10-year monthly climatology of Florida lightning. They found that peak flash densities occurred during the summer (June-August) in the central portion of the state, particularly between Tampa and the KSC. This local maximum was found to result from sea breeze convergence zones along both the east and west coasts and their interaction with the low-level environmental flow.

Reap (1994), Camp et al. (1998), and Lericos et al. (2002) studied how lightning distributions in Florida are affected by the prevailing low-level winds. Reap (1994) found that when the low-level flow over the peninsula is from the southeast, maximum lightning frequencies occur along the west coast. Conversely, when the large-scale flow is southwesterly, greatest frequencies are along the east coast. For each flow regime, he also noted embedded secondary maxima associated with localized shoreline curvature effects. Camp et al. (1998) focused on the panhandle of Florida. Their results indicated that the prevailing low-level wind speed, in addition to its direction, affects lightning distributions. Moderate wind speeds of 2–5 m s^{-1} generally are more conducive to lightning occurrence than stronger speeds. Additionally, the direction of the synoptic flow was found to play a role in the timing of peak lightning occurrence. Lightning activity during southerly flow peaks earlier (1800-2000 UTC) than during northerly flow (2200 UTC). Lericos et al. (2002) compiled a 10-year climatology of warm season lightning distributions for the Florida peninsula related to the position of the subtropical ridge axis. Major differences in the distributions of the lightning maxima were found to depend on the location of the subtropical ridge axis, which determines the large scale flow during synoptically quiescent periods.

The sea breeze, a thermally direct circulation that develops due to differential heating between land and water, is critical to understanding lightning distributions in Florida during the warm season. Simpson (1994) gives a thorough description of the sea breeze, from basic definitions and concepts to analytic and numerical modeling results. Estoque (1962) was one of the first to numerically model the sea breeze in two dimensions. He assumed various types of prevailing large scale winds and thermal stratifications to study how the sea breeze circulation develops.

Pielke (1974) used a three dimensional model to describe the initiation and evolution of sea breeze convergence patterns in South Florida as a function of surface heating and large scale synoptic forcing. His results, when compared with observed cloud and precipitation patterns, revealed that sea breeze circulations provide the dominant control of thunderstorm location on synoptically undisturbed days. Blanchard and López (1985) obtained similar results from diagnostic studies. They noted that changes in the synoptic scale wind field corresponded closely to changes in thermodynamic conditions and observed radar-derived patterns of convection. Using a simple two dimensional numerical model in which only the large scale flow was allowed to vary, Arritt (1993) showed the effects of onshore versus offshore flow on sea breeze development. Onshore speeds greater than a few meters per second suppressed the sea breeze perturbation. However, offshore wind speeds as strong as 11 m s^{-1} were found to produce a well developed sea breeze circulation that remained near the coastline.

Several studies have taken a more localized view of CG lightning distributions, particularly how these distributions are affected by urban areas. Watson and Holle (1996) studied lightning patterns near Atlanta, Georgia in preparation for the 1996 Summer Olympics. They found a maximum over Atlanta that peaks during the late afternoon. Livingston et al. (1996) compiled a lightning climatology, synoptic assessment, and thermodynamic evaluation of Georgia, also for the 1996 Summer Olympics. They confirmed a diurnal progression of lightning, with peak activity near 2200 UTC. About 50 km inland, near Savannah, Georgia, a definite maximum in flash densities was attributed to the sea breeze.

Westcott (1995) studied summertime CG lightning activity near sixteen major Midwestern urban areas between 1989 and 1992. Enhancements of 40% or more were found over and downwind of many of these cities. These enhancements were greatest during the afternoon when urban-rural temperature differences are smallest, but when the atmosphere is most unstable. She suggested that the urban areas are not responsible for initiating new lightning storms, but contribute to greater lightning activity from those storms that do occur. Various physical and anthropogenic factors were investigated that could interact in diverse ways to account for the observed change in lightning frequencies.

Orville et al. (2001) and Steiger et al. (2002) examined CG lightning characteristics near Houston, Texas for the period 1989-2000. They found a 45%

enhancement in flash densities over Houston compared to the surrounding areas. These greater flash densities were found to result from the urban heat island effect, increased levels of air pollution, and complexities of the nearby coastline. As in Westcott's (1995) study, Steiger et al. (2002) noted that increased thunderstorm initiation is not the most significant cause of the enhancement. Orville et al. (2001) and Steiger et al. (2002) suggested that increased air pollution reduces mean droplet size, enabling more cloud water to reach the mixed phase region where it is involved in charge separation. This, in turn, leads to enhanced lightning activity and a change in the thunderstorm's charge distribution. This latter effect has been suggested as a means of altering the polarity of CG lightning flashes (Steiger et al. 2002).

Various statistical models have been developed to predict thunderstorms and lightning, e.g., Neumann and Nicholson (1972), Reap and Foster (1979), Mazany et al. (2002), and Burrows et al. (2004). Reap and Foster (1979) used Model Output Statistics (MOS) to develop probability equations for 12-36 hour thunderstorm forecasts over much of the nation east of the Rocky Mountains. The equations were derived by applying screening regression techniques to relate manually digitized radar (MDR) data and storm reports to large scale meteorological parameters. Burrows et al. (2004) developed statistical model guidance for lightning occurrence in Canada and the northern United States during the warm season. Their technique utilized a tree-based regression algorithm with input from the Canadian Meteorological Center's Global Environmental Multiscale (GEM) numerical forecast model. Their resulting statistical forecasts showed positive skill to 48 hours over this large geographic region, with the best results between 1800-0600 UTC. This was attributable to the well known diurnal variation in lightning activity.

Several studies have developed statistical guidance for considerably smaller areas. Reap (1994) used the National Meteorological Center's (NMC's) Nested Grid Model (NGM) and climatological lightning frequencies to develop statistical forecast equations for the Florida peninsula. The climatological frequencies were combined with the K stability index to form interactive predictors that take into account the temporal and spatial variations in lightning occurrence for different low-level flow regimes (e.g., southeasterly or southwesterly), but modulate the climatology based on the daily large-scale synoptic situation (Reap 1994). Brenner (2004) used multiple linear regression analysis to produce equations predicting average areal coverage and rainfall amount in West-Central Florida. His analysis used parameters extracted directly from the 1200 UTC radiosonde sounding that represent moisture, stability, temperature, and wind. The precipitation trend, and the magnitude of the change from the observed value of the previous day were reliable approximately 75% of the time. Average prediction error generally was within ±10% for areal coverage and ±0.10 in. for rainfall amount.

A few authors have developed statistical thunderstorm forecast guidance for the immediate KSC area. Neumann and Nicholson (1972) used non-linear, multivariate regression techniques to forecast thunderstorm activity at KSC. Their regression models were developed using twelve years of radiosonde-derived training data which then were applied to two years of independent data. Predictors found useful included orthogonal wind components at several levels, 900 hPa temperature, mean relative humidity in the 800-600 hPa layer, and the Showalter stability index. The statistical technique was shown to yield useful forecast guidance.

Logistic regression techniques were implemented by Mazany et al. (2002) to develop an index for predicting short term lightning occurrence at the KSC. They initially tested twenty-three predictors derived from a host of sources including Global Positioning System (GPS) sensors, electric field mills, surface observations, radiosonde data, and Eta model output. Screening techniques selected four of the twenty-three predictors to comprise the lightning index. These included maximum electric field mill strength, GPS Integrated Precipitable Water Vapor (IPWV), the 9-hour change in IPWV, and the K-index. Whenever the value of the index fell below a threshold of 0.7, lightning was observed within the next 12.5 hours.

To summarize, several of the previously mentioned studies found Florida to be the most active region in the country for CG lightning, while others have documented the relationship between lightning distributions, the sea breeze, prevailing low-level flow, and coastline shapes and irregularities. Other studies showed an enhancement of lightning due to the urban heat island effect and increased air pollution near major cities. And, statistical studies have related thunderstorm and lightning occurrence to large scale meteorological variables. Each of these concepts is applicable to the east coast of South

Florida where the sea breeze is the dominant mechanism for warm season thunderstorm development. The urban heat island effect and increased air pollution also may contribute to an increase in lightning activity in these heavily populated areas. Coastline irregularities may enhance or suppress lightning activity in specific portions of the area. Furthermore, South Florida can be affected by both the Atlantic and Gulf Coast sea breezes, and these breezes can interact with more subtle circulations due to nearby swamps and lakes.

The current study develops statistical model guidance for lightning occurrence in the eastern halves of Miami-Dade and Broward Counties in South Florida during the warm season. Both NLDN data and upper air soundings from Miami (West Palm Beach prior to 1995) are used to develop the statistical procedure. Screening regression techniques are employed to select those thermodynamic and kinematic variables that best explain the observed day-to-day variation in lightning occurrence. Statistical models then are developed to determine whether at least one flash will occur between noon and midnight local time (LT) in the two areas of interest. The guidance products that are developed in this study will be delivered to Florida Power and Light Corporation (FP&L) for possible use in their daily manpower and generating load deliberations.

Section 2 describes the data and how they were processed to produce a final, working dataset. It also explains the basic statistical methodology used in this study. A detailed account of the procedures implemented and the results obtained are discussed in Section 3. Finally, Section 4 summarizes the study, draws conclusions from the results, and explores how future studies might build upon the present work.

CHAPTER TWO
DATA AND METHODOLOGY

2.1 Introduction

This study focuses on two specific portions of two South Florida counties. The areas of interest are 1) east of highway US 27 in Broward County, and 2) east of State Route 997 (Krome Avenue) in Miami-Dade County (Fig.1). These areas were defined by FP&L because they contain most of the population in these counties and most of FP&L's power generating facilities and transmission lines that serve these customers.

Lightning is one of the main causes of power outages in South Florida during the warm season, and this study's forecast guidance will assist FP&L managers in their decision making processes. FP&L typically decides around 1:30 PM LT whether extra line crews will be needed after normal business hours. They defined noon to midnight as the time period when the risk of lightning is most costly to them. If lightning causes power outages after normal business hours, when most line crews already have left for the day, time and money are lost restoring services. Conversely, if extra line crews are kept after hours and no lightning occurs, FP&L suffers unnecessary overtime labor costs.

The study focuses on the warm season months of May to September when the sea breeze generally is the dominant forcing mechanism for afternoon convection. The period of study was 1989 to 2002, a total of fourteen warm seasons. Synoptic scale forcing typically is weak, and the influence of mid-latitude systems is minimal during these months. Instead, mesoscale phenomena such as sea and lake breezes interact with their environment, geographic features, and each other to produce complex patterns of convergence and resulting convection. Frontal passages and upper level waves are more likely during May and September, and tropical waves are a greater concern during late August and September than in the other summer months. The forecast guidance

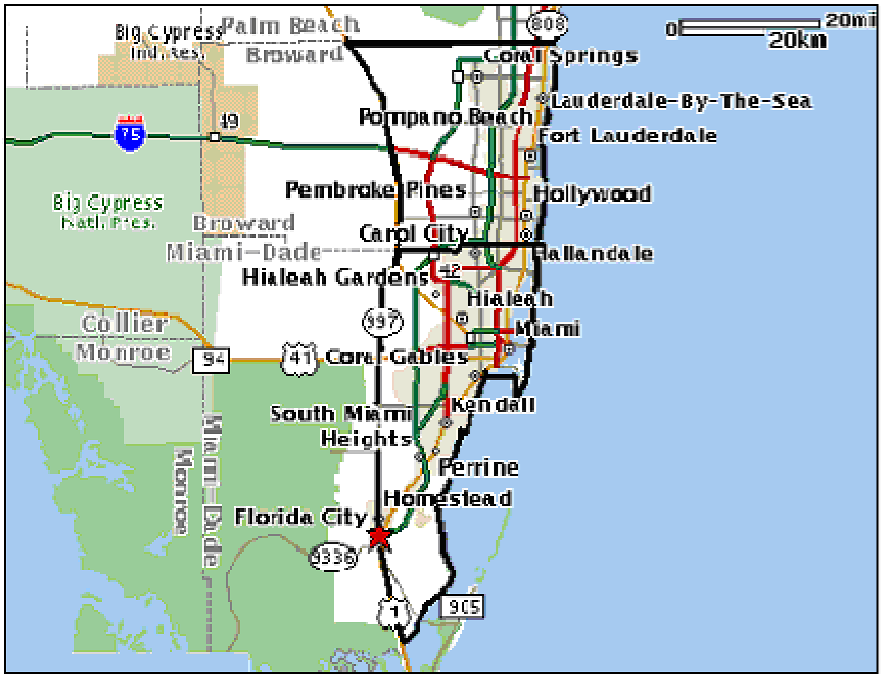


Figure 1. Map of South Florida Counties. Broward and Miami-Dade Counties are shown in their entirety. The two study areas in these counties are outlined in black. (Map taken from www.mapquest.com)

described here is not suitable for those situations. The following section will describe the cursory attempt to remove some of these days.

Separate guidance equations were developed for the two areas of interest in Miami-Dade and Broward Counties. The two counties were treated separately for a number of reasons. First, the coastline of Miami-Dade County is more complex, with more inlets and capes than in Broward County. And, the average orientations of the coastlines differ. Broward County's average coastline orientation is nearly north-south, while the Miami-Dade coastline is approximately 18º east of north. Second, the east to west extent of Broward County's area of interest is greater than in Miami-Dade County due to the coastline orientation. The total area of interest in Miami-Dade County is 1906 km^2, while in Broward County the area of interest is 450 km^2 smaller. Finally, Broward County is north of Miami-Dade County, closer to Lake Okeechobee. This closer proximity to the lake suggests that lake breezes will exert more influence on convective activity and lightning occurrence in Broward County.

2.2 Lightning Data

The NLDN detects and records CG lightning flashes over the contiguous United States and adjacent coastal waters. Owned and operated by Vaisala Inc., this network provides lightning data to commercial, government, and educational institutions. Specifics concerning the network's operations and methodology are discussed in detail by Cummins et al. (1998). The network consists of one hundred six ground-based sensors and utilizes the IMProved Accuracy from Combined Technology (IMPACT) method to detect lightning flashes. This method of flash recording incorporates two types of sensors: time-of-arrival (TOA) and IMPACT sensors. Both TOA and magnetic direction finder (MDF) methods are employed to determine the location, time, and other characteristics of each flash.

The detection efficiency and location accuracy of the NLDN have improved substantially since its inception. During its early years of operation, the detection efficiency ranged from 65% to 85%, while the location accuracy was 2 km to 8 km (Cummins et al. 1998). System upgrades between 1994 and 1995 greatly improved both the detection efficiency and location accuracy. Since these upgrades, the network's detection efficiency is 80-90%, and location is accurate to within 0.5 km over most of the country. However, in South Florida the detection efficiency is degraded due to a lack of NLDN sensors over the adjacent waters. Detection efficiency near the northern border of Broward County is approximately 70%, and is only 60% at the southern tip of Florida (Cummins et al. 1998). No corrections were applied to the data to compensate for variations in detection efficiency and location accuracy across the study area. This produces an underestimation of flash counts.

Due to the recent enhanced detection, lightning other than CG may be sensed and recorded. Following the suggestion by Cummins et al. (1998), weak positive flashes with strengths less than 10 kA were removed from the working dataset. Additionally, when two or more flashes were detected within 10 km and within the same second, only the first flash's data were retained, but their multiplicities were added (Cummins et al. 1998).

Lightning flashes were counted separately within the two domains in Fig. 1. If a flash occurred in the area of interest during the time period specified by FP&L (noon to midnight LT), it was included for analysis. The fourteen year warm season totals for both counties were obtained for each day that lightning data were available (2097 out of a possible 2142 warm season days).

2.3 Radiosonde Data

Lightning occurrence was related to parameters calculated from the 1200 UTC Miami (West Palm Beach prior to August 1995) radiosonde sounding. Since Miami and West Palm Beach are separated by only 108 km, both sounding sites were assumed to represent the study area (Blanchard and López 1985; Lericos et al. 2002). Radiosonde data from 1989 to 1999 were available on the "Radiosonde Data of North America" CD-ROM distributed by the National Climatic Data Center (NCDC) and the Forecast Systems Laboratory (FSL) (NCDC and FSL 1999). Data from the years 2000 to 2002 were obtained directly from FSL's website (http://raob.fsl.noaa.gov).

Various wind, moisture, temperature, and stability parameters used previously in the literature, and others that were considered to be of potential use, were calculated. The original sounding data were available at each baroswitch contact. These raw soundings were converted to 25 hPa increments using a logarithmic interpolation scheme. The interpolated soundings then were run through a series of FORTAN programs that calculated the parameters considered in this study. Fifty-four parameters were investigated in all (see Table 1).

Several potential parameters deserve a brief description. Layer averaged wind parameters were vector-averaged. This was done to account for winds passing through 360˚. Vector-averaged winds in the 1000-700 hPa layer were used because previous studies (e.g., López and Holle 1987, Camp et al. 1998, and Lericos et al. 2002) found that this layer best determines the motion of sea breeze fronts and thunderstorms over Florida during the warm season. Wind parameters calculated at other layers and levels (e.g., 850-700, 700-500, 950 hPa) were included to determine if more predictive skill could be

Table 1. Radiosonde-derived parameters used in this study

Mean 1000-700 hPa wind direction	Surface wet bulb temperature
Mean 1000-700 hPa wind speed	Precipitable water
Mean 1000-700 hPa u-wind component*	Mean mixing ratio in mixed layer**
Mean 1000-700 hPa v-wind component *	K-index
Sine of the mean wind direction in radians	Vertical totals
Sine of the wind direction at 950 hPa	Cross totals
Sine of the wind direction at 700 hPa	Wind speed at 900 hPa
Mean sfc-850 hPa u-wind component	Total totals
Mean sfc-850 hPa v-wind component	SWEAT index
Mean sfc-850 hPa wind speed	CAPE
Mean 850-700 hPa u-wind component	Modified CAPE***
Mean 850-700 hPa v-wind component	Lifted Index
Mean 850-700 hPa wind speed	Modified Lifted Index***
Mean 700-500 hPa u-wind component	Showalter Stability Index
Mean 700-500 hPa v-wind component	sfc-1000hPa temperature difference
Mean 700-500 hPa wind speed	sfc-850 hPa temperature difference
Dewpoint at surface	850-700 hPa temperature difference
Modified surface dewpoint	850-500 hPa temperature difference
Mean sfc-900 hPa relative humidity	500-300 hPa temperature difference
Mean 800-600 hPa relative humidity	1000 hPa height
Mean 700-500 hPa relative humidity	850 hPa height
Mean 600-400 hPa relative humidity	Equilibrium level
Mean sfc-500 hPa relative humidity	Freezing level
Mean 500-300 hPa relative humidity	Wet bulb zero height
Mean 800-600 hPa dewpoint depression	1000-500 hPa thickness
Mean sfc-500 hPa dewpoint depression	Convective temperature
Temperature at 900 hPa	Temperature at the Equilibrium level

* u and v components are perpendicular and parallel to an averaged coastline of 15˚
** mixed layer is taken to be the surface to 825 hPa
*** modified values are based on Convective temperature

achieved using more shallow sub-layers within and above this steering layer. Other layer averaged quantities were simple arithmetic means. Convective available potential energy (CAPE), the lifted index (LI) and related parameters were calculated using the surface data as the parcel to be lifted. Modified CAPE and LI also were computed based on assumed afternoon conditions. The convective temperature was obtained by following the dry adiabat from the convective condensation level (CCL) to the surface. The modified surface dewpoint is based on the mean saturation mixing ratio in the mixed layer (surface to 825 hPa).

Two types of persistence variables also were considered in the parameter pool. The first was the previous day's noon to midnight lightning activity (occurrence or non-occurrence). The second persistence variable was the current day's morning (6:00 AM to noon) lightning activity (also occurrence or non-occurrence).

There were 2092 days out of a possible 2142 days when 1200 UTC radiosonde data were available. Days with mean 1000-700 hPa wind speeds greater than three standard deviations above the mean (>25.53 kts) were removed. These 28 days were found to be synoptically disturbed due to tropical systems or mid-latitude systems (i.e., surface fronts or upper-level waves) in the vicinity of South Florida. Other synoptically disturbed days undoubtedly remain in the data set. In addition, some days contained missing data at various levels such that some or all of the radiosonde-derived parameters could not be computed. When this occurred, the day was removed from the dataset. Days on which lightning data were unavailable also were excluded. In all, 268 days (12.5% of the total possible days) either were synoptically disturbed or contained missing radiosonde and/or lightning data. This left 1874 days with complete radiosonde and lightning data. These days comprised my final data set.

2.4 Logistic Regression

Linear regression is an often used method for relating a predictor or set of predictors (x's) to one or more response variables (y's). The procedure requires that for each x, there exists a group of y-values which are normally distributed. To determine the relationship between the predictors and response variables, a scatter diagram of the (x,y) pairs can be plotted, and a straight line can be fit to the data. The resulting line, describing the linear regression, should explain most of the variation in the predictand.

The coefficient of determination (R^2) is a commonly used measure of the fit of a regression. It can be interpreted as the proportion of the variation in the predictand that is accounted for by the regression (Wilks 1995). With a perfect regression, R^2 equals one.

Conversely, a regression in which none of the observed variation in the predictand is explained by the regression line yields an R^2 value of zero.

With these points in mind, an initial data survey was conducted to determine whether or not linear regression should be used in this study. Scatter plots were made of each predictor versus observed lightning flash counts. Straight lines then were fit to the scatter plots, and R^2 values were computed to evaluate the degree of fit. In every case R^2 values were less than 0.1, implying that less than 10% of the variation in flash counts was explained by the linear regression.

Next, higher order polynomials (third, fourth, and fifth order) were fit to the scatter plots to incorporate some of the non-linearity between predictors and predictand. R^2 values again were computed to determine how well the higher order polynomials fit the observed data. The R^2 values improved, but still were less than 0.1. Figure 2 is an example of a scatter plot, linear regression line, fourth order polynomial, and R^2 values for CAPE, modified for the convective temperature. These figures clearly showed the non-linear relationships between the predictors and flash counts and the failure of higher order terms to explain more of the observed variation in these counts.

A histogram of noon to midnight lightning counts was made to check for a normal distribution. The histogram was found to be exponentially distributed, highly skewed to the right due to the large number of days with little or no lightning activity.

It is important to note that the goal of this research was not to forecast the amount of lightning, but only its occurrence or non-occurrence. Based on this consideration and the preliminary survey of the data described above, it became clear that linear regression was not an appropriate analysis method for this study, and that a more robust regression technique was needed.

Binary logistic regression (BLR) was determined to be the best procedure for the study. The procedure has several important attributes that differ from linear regression. First, logistic regression allows non-linear relationships between the independent and dependent variables. Second, it does not require normally distributed response variables. Finally, the outcome variable is bounded between zero (no) and one (yes) (Hosmer and Lemeshow 1989). Applied to the current study, the two outcomes are yes, at least one lightning flash was observed, or no, no lightning was observed.

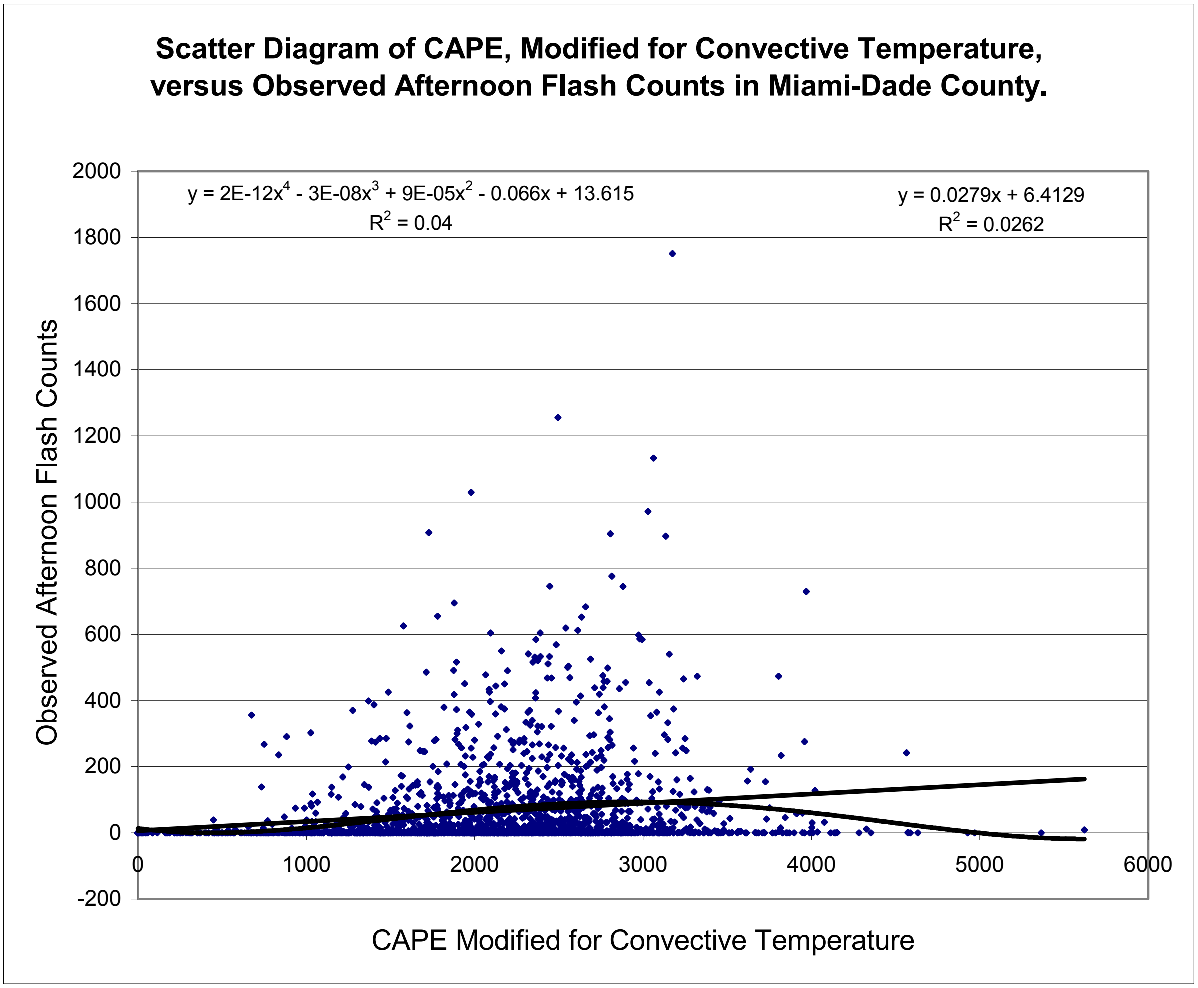


Figure 2. A sample scatter plot of CAPE, modified for afternoon convective temperature, versus observed flash counts in Miami-Dade County. A straight line and a fourth order polynomial are fit to the data. Also included are the equations and R^2 values for the fitted lines. The scatter plot and fitted lines illustrate the non-linear relationship between the predictor and lightning occurrence.

The quantity $P_j = E(Y \mid x_j)$ represents the conditional mean of a lightning flash (Y) given a predictor (x) when the logistic distribution is used (Hosmer and Lemeshow 1989). The specific form of the logistic regression model is

$$P_j = \frac{e^{(B_0 + B_j x_j)}}{1 + e^{(B_0 + B_j x_j)}}, \tag{1}$$

where P_j is the probability of a response for the j^{th} covariate, B_0 is the intercept, B_j is a vector of unknown coefficients associated with the predictor, and x_j is a predictor variable. A logit transformation of P_j then is applied, defined as

$$g(P_j) = \ln[(P_j)/(1 - P_j)] = B_0 + B_jX_j. \tag{2}$$

The link function, $g(P_j)$, has many desirable characteristics of a linear model, and it constrains the probability, P_j, to the meaningful values of zero to one inclusive (Hosmer and Lemeshow 1989).

There is precedent for the logistic regression scheme in the literature. Mazany et al. (2002) used logistic regression in their development of lightning guidance at the KSC. Additionally, Leyton and Fritsch (2003) implemented logistic regression in their probabilistic forecasts of ceiling and visibility for the Upper Midwest. The latter study found the logistic scheme to be superior to multiple linear regression because it can fit each predictor to the predictand in a non-linear way.

The Statistical Package for the Social Sciences (SPSS) Version 11.5 for Windows was used for the logistic regression in this study. This software package utilizes a spreadsheet format for data storage and processing that is similar to Microsoft Excel, but is more diverse and powerful in its statistical applications.

CHAPTER THREE
RESULTS

3.1 Model Development

The final 14-year data set was used to develop the statistical lightning guidance models. The model developed for eastern Miami-Dade County for the entire study period will be used to describe the procedures used in model development. Similar procedures were used for eastern Broward County. First, the dependent (56 calculated predictors, Table 1) and independent (lightning occurrence or non-occurrence) variables were declared. The independent variable is either yes (1), if one or more flashes are recorded between noon and midnight in the study areas, or no (0), if no flashes were recorded during this same period. Every calculated parameter was considered a potential predictor (dependent variables) for the screening regression that follows.

A forward stepwise procedure within SPSS was used to screen the dependent variables for the BLR equation. This procedure uses the p-value (Hosmer and Lemeshow 1989), also known as the rejection level or level of the test, to determine which of the dependent variables explains the most variation in the independent variable (lightning occurrence or non-occurrence) at each step of the development. The p-value is a probability ranging from zero to one. If this value is small, the difference in sample means is unlikely to be a coincidence, and that parameter may have statistical significance (Mazany et al. 2002). The test level (p-value) is chosen in advance, and if a predictor's p-value is less than or equal to this value, it is a candidate for inclusion in the BLR equation. An 85% test level (p-value = 0.15) was used in the initial stepwise screening process.

The forward stepwise procedure determines the p-value for each predictor at each step. During the first step, the predictor with the lowest p-value (less than or equal to the test level) is entered into the BLR equation. This is known as forward selection. During the next step, p-values of the remaining predictors are calculated. Again, the predictor with the lowest p-value that is less than or equal to the test level for forward selection is entered into the regression equation. Then, the p-values of these two terms are computed again to check if inclusion of the second term has caused either term to become statistically insignificant, i.e., if the p-value(s) exceed a certain, different test level, known as the test level for backward elimination. A p-value of 0.2 was used as the test for backward elimination. If both terms in the BLR equation still satisfy the p-value criteria, the stepwise procedure continues to the next step. Otherwise, the less significant term is removed. This process of forward selection with a test for backward elimination continues until all statistically significant terms are included in the model.

The next task is to select the step that has produced the best model. At each step of the screening process SPSS provides copious amounts of information that allow a complete evaluation of the statistical significance of each predictor and the model as a whole. I focused on the Hosmer and Lemeshow Goodness of Fit (HLGF) test, the estimated coefficient and its standard error, the Wald statistic, the p-value of each predictor, and a 2 x 2 contingency table (see Table 2). The focus on these tests was based on Mazany et al. (2002) and online support for the SPSS software. The tests are used to determine the appropriateness of the BLR and are discussed briefly below. Each of the tests or statistics is evaluated at each step of the screening regression.

The HLGF test is analogous to the R^2 value, providing a means to determine how well the regressed equation fits the data. The fit of the BLR to the data using the HLGF test is determined using the p-value of the test. A p-value that is too small (e.g., less than 0.1) implies that the equation does not adequately account for the observed variation in the lightning activity. Conversely, a p-value for the HLGF test that is too large (e.g., greater than 0.9) implies that the regressed equation has been overfit, i.e., it is too dependent on the data from which it was derived and likely will not perform well on independent data. HLGF p-values of 0.5 – 0.6 are considered ideal (Mazany et al. 2002).

The coefficient (and its standard error) of each predictor is estimated at each step of deriving the BLR model. The coefficient of each predictor is the estimated change in the link function (2) due to a one unit change in the predictor. All other factors and

Table 2. Contingency table for forecast and observed lightning activity. Quadrant A denotes occasions when lightning was forecast to occur and did occur. Quadrant B denotes occasions when lightning was forecast to occur but did not. Quadrant C denotes occasions when lightning was not forecast to occur but did occur. Quadrant D denotes occasions when lightning was not forecast to occur and did not occur.

	Model Forecast	
	Yes	No
Observed		
Yes	A	B
No	C	D

covariates are assumed to be unchanged during this estimation (Mazany et al. 2002).

The Wald statistic is the square of the t-ratio (Hosmer and Lemeshow 1989). The t-ratio, also known as the t test or z value, is obtained by dividing the predictor's coefficient by its standard error. The t-ratio is a direct measure of the meaningfulness of the fitted regression. Small standard errors result in large t-ratios. If the t-ratio is small, the standard error is large, implying uncertainty in determining the coefficient, and the regression is not informative. Only predictors with the largest Wald statistic are included in the model.

A 2 x 2 contingency table (Table 2) was used to evaluate how well the model at that step handled forecasting days with and without lightning. The percent of correctly forecast days with lightning and the percent of correctly forecast days with no lightning can be calculated from Table 2. The percent of correctly forecast days with lightning is calculated as A/(A+B), and the percent of correctly forecast days with no lightning is given by D/(D+C). Additionally, the overall percent of all days correctly forecast is given by (A+D)/(A+B+C+D). This value, also known as the hit rate, is a direct measure of the accuracy of the forecasts.

The p-value of each predictor at each step during the forward selection process also is used to determine that predictor's inclusion or exclusion. I used the 95% significance level (not the initial 85% used during screening), corresponding to a p-value of 0.05, for inclusion in the final model. This p-value was the upper limit to include a predictor in the BLR model, with terms having the lowest p-values chosen for the BLR model. All terms in the model for the entire 14-year study period had p-values less than 0.01.

The step of the screening regression that optimizes the various statistics described above is chosen as the best BLR model. It generally is not possible to satisfy all of the above conditions. However, the best model satisfies as many of these conditions as possible.

An important consideration during model development was to avoid including too many predictors. The inclusion of too many terms can result in the model being numerically unstable or yielding inferior results. Beyond a certain step in the screening regression, the inclusion of extra terms does not improve the forecast skill of the model. This happens because the screening procedure continues to add predictors to the model, regardless of the forecast skill that is achieved, until p-values exceed the predetermined test level as described above. I sought to develop the most parsimonious model possible.

In addition to the fifty-six dependent variables, higher order and interaction terms were investigated to add skill to the forecasts. Higher order terms were computed by standardizing each predictor and then raising it to the second, third, and fourth power. The standardization was accomplished by subtracting the mean and then dividing by the standard deviation (Wilks 1995). Interaction terms were computed by multiplying two or more terms together (Reap and Foster 1979; Reap 1994). As an example, low level u and v wind components are multiplied by low level moisture parameters to form moisture transport terms. Results showed that these higher order and interaction terms did not improve forecast skill, and they were not chosen during the screening process.

Based on the tests and statistics described above, the best models for eastern Miami-Dade and Broward Counties for the entire 14-year study period are given in Table 3. Both persistence variables, wind speed and direction, moisture, and stability parameters

Table 3. Predictors and coefficients of the final all-months model for a) eastern Miami-Dade County and b) eastern Broward County, based on the screening regression performed on the entire 14 year data set.

a) Eastern Miami-Dade County

	Parameter	Coefficient
B_0	Intercept	- 4.826
B_1	Morning persistence	1.017
B_2	Previous day's persistence	0.775
B_3	Sine of the vector mean wind direction (radians), 1000-700 hPa	- 1.093
B_4	Vector-averaged wind speed in the 1000-700 hPa layer	- 0.088
B_5	Precipitable Water	0.997
B_6	Modified Lifted Index	- 0.276

b) Eastern Broward County

	Parameter	Coefficient
B_0	Intercept	- 5.659
B_1	Morning persistence	0.979
B_2	Previous day's persistence	0.528
B_3	Sine of the wind direction at 950 hPa	- 1.225
B_4	Vector-averaged wind speed in the 1000-700 hPa layer	- 0.088
B_5	Precipitable Water	1.178
B_6	Modified Lifted Index	- 0.324

comprise the equations. All of the predictors that appear in the models make physical sense and are discussed briefly below.

The following discusses the equation for eastern Miami-Dade County (Table 3a). The coefficients for both persistence parameters are positive, indicating that lightning activity on the previous day and during the morning increase the probability of afternoon lightning activity. The previous day's persistence is included because meteorological conditions during the warm season in South Florida often change very little from day to day. Thus, if conditions were favorable for lightning on the previous day, conditions on the current day often are similar. Lightning activity during the morning of the current day means that convective activity has occurred and that outflow boundaries may be present. These boundaries can enhance low level convergence by interacting with the sea breeze circulation that may develop during the afternoon.

The coefficient for the sine of the vector-averaged wind direction (radians) in the 1000-700 hPa layer is negative. Since the sine of angles between π and 2π (i.e., between 180˚ and 360˚, a westerly wind) is negative, an offshore, low-level wind increases the probability of afternoon lightning activity. The coefficient of the mean low-level wind speed parameter also is negative, suggesting that as the wind speed increases, the probability of observing afternoon lightning in the study area decreases. This is consistent with the findings of Camp et al. (1998) and Arritt (1993) who found that onshore wind speeds exceeding a few m s^{-1} and offshore speeds greater than 11 m s^{-1} suppress sea breeze development. Conversely, weak offshore flow produces a strong sea breeze whose leading edge remains near the coastline. For example, in eastern Miami-Dade and Broward Counties this scenario can produce extensive, slow-moving thunderstorms if thermodynamic conditions are appropriate.

The final two parameters that comprise the BLR equation are precipitable water and the lifted index, modified for the convective temperature. The coefficient for precipitable water is positive. This means that as more moisture is present in the atmosphere, convection and lightning activity are more likely to occur. The lifted index is a stability parameter that decreases, or becomes more negative, as the atmosphere becomes less stable. The coefficient for this term is negative, implying that as atmospheric stability decreases, the probability of afternoon lightning increases.

The BLR models in Table 3 contain the most statistically significant parameters from our predictor pool. These predictors explain the physical processes that lead to convective activity and its attendant lightning occurrence in South Florida during the warm season.

I next sought to maximize the predictive skill of the model. The output of the BLR equation is a probability ranging between zero and one. To make a yes/no forecast based on this output, it is necessary to determine a threshold value of probability. This is necessary because a threshold of 0.5 does not necessarily yield the best results. If the model yields a probability that exceeds the selected threshold, afternoon lightning is forecast.

Determining the best threshold was based, in part, on verification scores derived from Table 2. Donaldson (1975), Reap and Foster (1979), Reap (1994), and Mazany et al. (2002) describe several statistics that often are used to test for the optimum threshold value. These are the critical success index (CSI), or threat score, given by A/(A+B+C), the false alarm ratio (FAR) given by C/(A+C), the probability of detection (POD) given by A/(A+B), and the bias given by (A+C)/(A+B). Bias indicates the degree of overforecasting (Bias > 1) or underforecasting (Bias < 1) associated with the threshold values (Reap 1994).

Figure 3 shows how these statistics vary for different threshold values for eastern Miami-Dade County. Except for CSI, values of the statistics decrease as the threshold is increased. Reap's (1994) lightning guidance equations used a threshold that maximized the CSI and had as high a POD and as low a bias as possible. This rationale was used as a general guideline in the present study. I also sought to minimize the FAR and obtain the highest percent correct days with no lightning occurrence. This latter consideration was used because results showed that the BLR scheme did a better job of forecasting days when lightning was observed, i.e., the percent of correctly forecast days with lightning was greater than for days without lightning. I found that the hit rate was improved by sacrificing some precision in forecasting days with lightning occurrence in order to improve the forecasts of days without lightning.

Based on the above considerations, a threshold of 0.5 was chosen for the BLR model for Miami-Dade County derived using the entire study period of data (Fig. 3). The

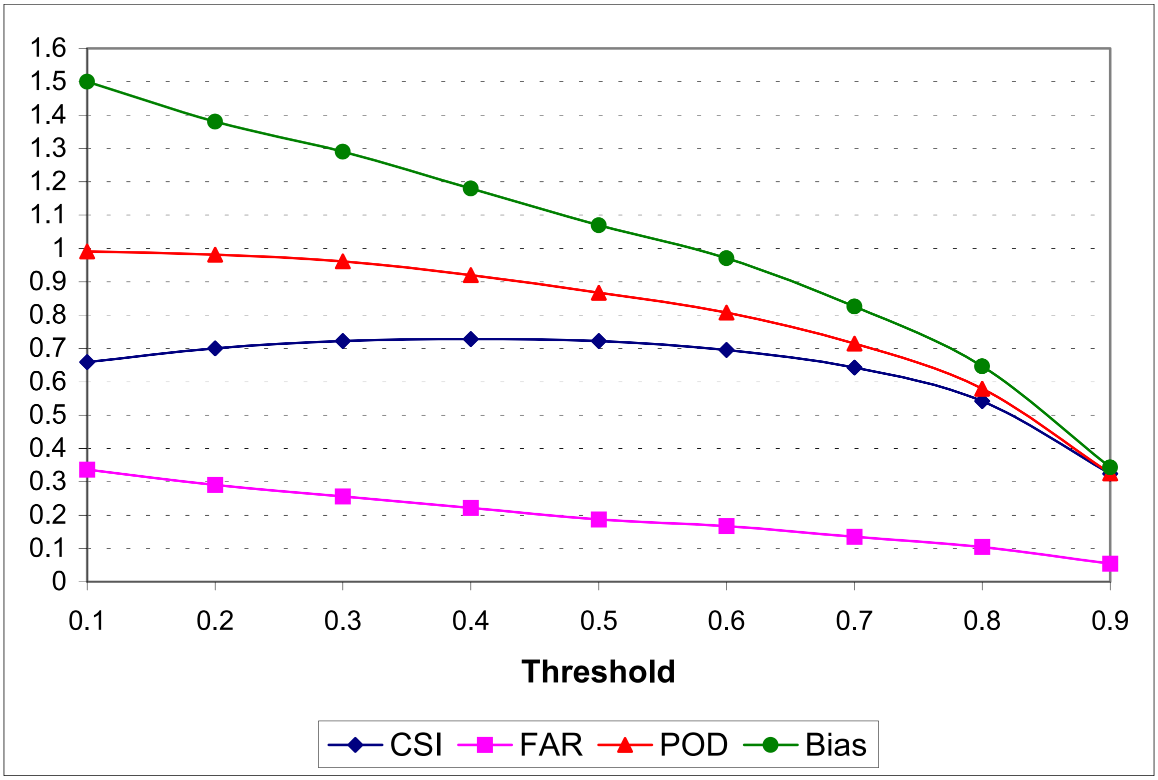


Figure 3. CSI, FAR, POD, and Bias for a range of threshold values for the eastern Miami-Dade County model.

equation in Table 3a, together with a threshold value of 0.5 for determining the yes or no forecast, constitutes the model for Miami-Dade County when all warm season months are considered together. Similar procedures were followed for eastern Broward County.

I next investigated how this model performed during each warm season month. The model just described was applied to each day in our final data set, producing a forecast for each day comprising the dependent data set. Contingency tables were made of these forecasts, and all previously mentioned quantities derived from this table were calculated.

Table 4 is the 2 x 2 contingency table for this final warm season model for Miami-Dade County. Evaluation statistics and percent correctly forecast days are shown in the table. The statistics and percent correct days from Table 4 show that the model handles the warm season as a whole rather well. The CSI is 72%, the FAR is 19%, and the POD is 87%, with 79% of all days being correctly forecast.

Table 4. 2 x 2 contingency table for the warm season model for Miami-Dade County, Evaluation statistics, and percent correctly forecast days are included.

	Model Forecast		Statistic/	Model
Observed	Yes	No	Forecast	performance
Yes	1018	156	CSI	72.2%
			FAR	18.7%
			POD	86.7%
No	235	465	Bias	1.07
			No lightning	66.4%
			Lightning days	86.7%
			All days	79.1%

Figure 4 graphs, by month, the various evaluation statistics. The statistics exhibit considerable variability between months, with the worst results during May and September. As an example, the CSI ranges from a high of 78% during August to 61% during May. As previously discussed, May and September are climatologically different from the other warm season months due, in part, to synoptic or tropical influences. Also, since May begins the warm season and September is near its end, I expect the sea breeze to be relatively weak compared to June, July, and August. During these middle three months CSI, FAR, POD, and bias show little variability from month to month. The best results are obtained late in the warm season, during July and August, when afternoon convection and lightning activity are forced almost entirely by the sea breeze circulation. Similar results were obtained for the Broward County model (not shown).

Figure 5 shows the percent of correctly forecast days with lightning, without lightning, and all days combined for the Miami-Dade County model. Again, it is clear

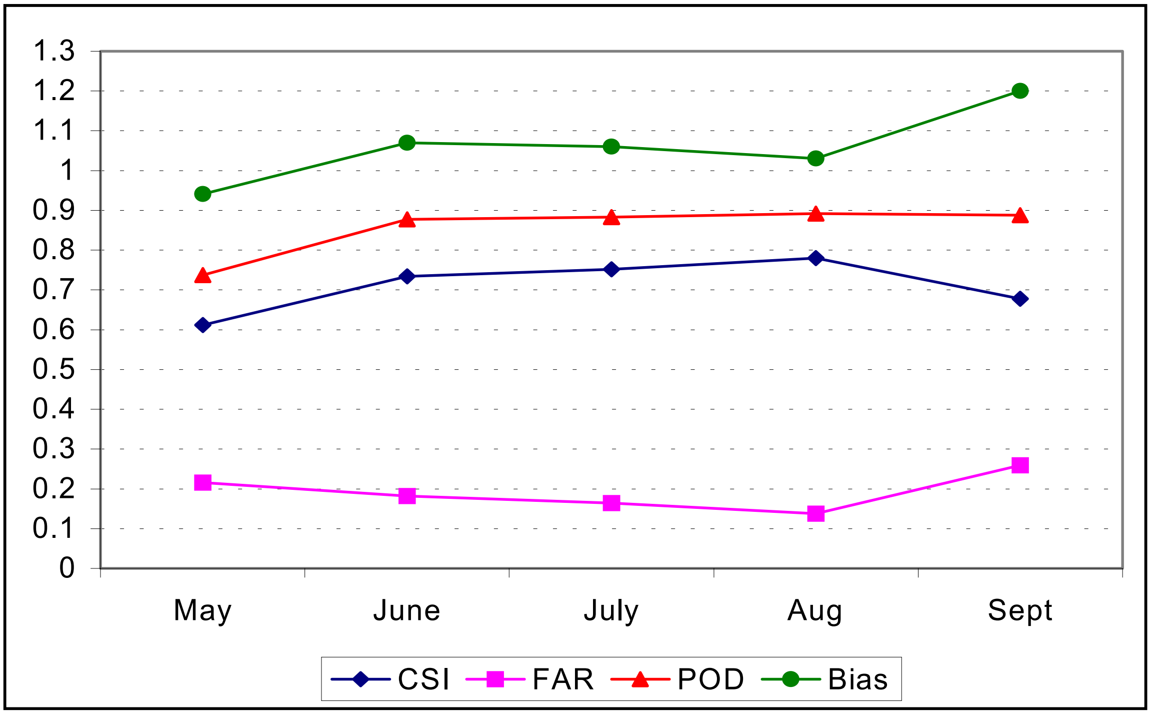


Figure 4. CSI, FAR, POD, and Bias by month for the warm season BLR model for eastern Miami-Dade County.

that the model performs differently during May than the rest of the warm season months. The model exhibits increasingly degraded performance with respect to forecasting days with no lightning activity as the warm season progresses. By August, the percent of correctly forecast days with no lighting drops to nearly half that of May (from ~90% to ~50%). Conversely, the model produces better forecasts of lightning days during this period (increasing from ~74% to 89%). Results were similar for Broward County (not shown).

Based on Figs. 4 and 5, and the climatological differences between the warm season months, it was appropriate to derive separate equations for each month during the warm season. The next section describes the monthly models that were developed for each county.

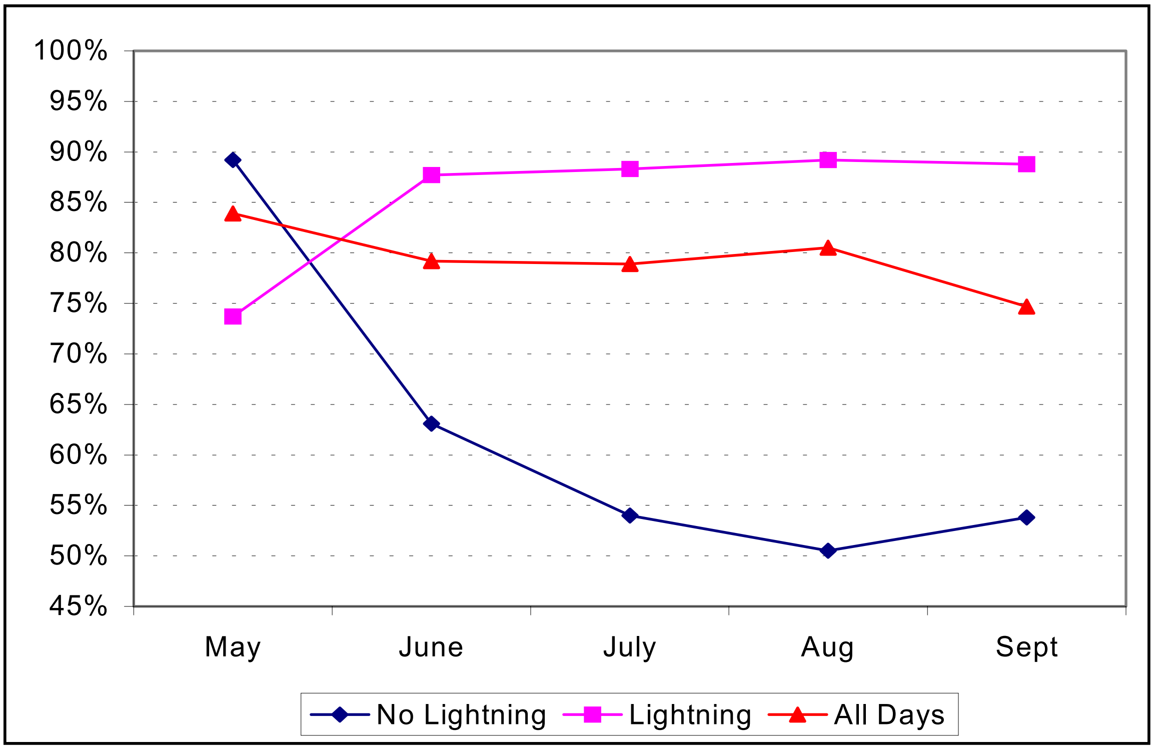


Figure 5. Graph by month for the percent of correctly forecast days with no lightning occurrence, days with lightning occurrence, and all days for the eastern Miami-Dade County model.

3.2 Monthly Models

The same process for model building described in the previous section was employed to derive the monthly models. Each month's data were treated separately during this process. Ten different models were derived in all, one for each of the five warm season months for each county.

The predictors and corresponding coefficients for each of the monthly models for eastern Miami-Dade County are given in Table 5. Table 6 lists the predictors and coefficients for each monthly model for eastern Broward County. The number of terms in each model ranges between four and eight, depending on the month. For example, both June models contain four terms, and both August models contain eight terms. Although the types and number of terms in the models differ from month to month and

Table 5. Monthly models for Miami-Dade County. Predictors and their coefficients are listed for each model.

a) May Model Threshold = 0.47

	Predictor	Coefficient
B_0	Intercept	-12.257
B_1	Sine of the mean wind direction, 1000-700 hPa	-1.470
B_2	Precipitable water	0.841
B_3	Lifted index	-0.363
B_4	Temperature at 900 hPa	0.391
B_5	Previous day's persistence	0.964

b) June Model Threshold = 0.50

	Predictor	Coefficient
B_0	Intercept	-5.043
B_1	Morning persistence	1.312
B_2	Sine of the mean wind direction, 1000-700 hPa	-1.147
B_3	Mean dewpoint depression, surface-500 hPa	-0.217
B_4	Mean temperature difference, 850-500 hPa	-0.467

c) July Model Threshold = 0.54

	Predictor	Coefficient
B_0	Intercept	9.410
B_1	Sine of the wind direction at 950 hPa	-1.218
B_2	Morning persistence	1.294
B_3	Mean dewpoint depression, surface-500 hPa	-0.212
B_4	Height of the 1000 hPa level	-0.037
B_5	Mean u-component, 850-700 hPa	1.575

Table 5. (continued)

d) August Model Threshold = 0.56

	Predictor	Coefficient
B_0	Intercept	8.844
B_1	Previous day's persistence	0.717
B_2	Mean u-component, 1000-700 hPa	0.142
B_3	Surface dewpoint	-0.679
B_4	Mean relative humidity, 600-400 hPa	0.027
B_5	Mean dewpoint depression, 800-600 hPa	-0.186
B_6	Wet bulb zero level	-0.002
B_7	Temperature at 900 hPa	0.574
B_8	Temperature at the equilibrium level	-0.078

e) September Model Threshold = 0.50

	Predictor	Coefficient
B_0	Intercept	-0.881
B_1	Morning persistence	1.129
B_2	Previous day's persistence	0.774
B_3	K index	0.072
B_4	Sine of the wind direction at 950 hPa	-1.007
B_5	Mean wind speed, surface-850 hPa	-0.116

Table 6. Monthly models for Broward County. Predictors and their coefficients are listed for each model.

a) May Model Threshold = 0.44

	Predictor	Coefficient
B_0	Intercept	-3.331
B_1	Sine of the mean wind direction, 1000-700 hPa	-0.935
B_2	Precipitable water	1.791
B_3	Modified lifted index	-0.471
B_4	Mean wind speed, 700-500 hPa	-0.088
B_5	Mean relative humidity, surface-900 hPa	-0.055
B_6	Surface wind speed	-0.159
B_7	Sine of the wind direction at 700 hPa	-0.738

Table 6. (continued)

b) June Model Threshold = 0.50

	Predictor	Coefficient
B_0	Intercept	-9.359
B_1	K index	0.078
B_2	Total totals	0.185
B_3	Sine of the wind direction at 950 hPa	-1.144
B_4	Temperature difference, surface-1000 hPa	0.451

c) July Model Threshold = 0.55

	Predictor	Coefficient
B_0	Intercept	10.002
B_1	Morning persistence	1.409
B_2	Sine of the wind direction at 950 hPa	-0.737
B_3	Wind speed at 900 hPa	0.219
B_4	Mean wind speed, surface-850 hPa	-0.388
B_5	Mean dewpoint depression, surface-500 hPa	-0.163
B_6	Height of the 1000 hPa level	-0.043

d) August Model Threshold = 0.58

	Predictor	Coefficient
B_0	Intercept	-179.413
B_1	Morning persistence	1.280
B_2	Mean wind speed, 1000-700 hPa	-0.429
B_3	Mean u wind component, 1000-700 hPa	0.169
B_4	Mean relative humidity, 600-400 hPa	0.062
B_5	Modified lifted index	-0.516
B_6	Wind speed at 900 hPa	0.358
B_7	Height of the 1000 hPa level	-0.136
B_8	Height of the 850 hPa level	0.125

Table 6. (continued)

e) September Model Threshold = 0.50

	Predictor	Coefficient
B_0	Intercept	0.287
B_1	Morning persistence	1.125
B_2	Modified CAPE	0.001
B_3	Sine of the wind direction at 950 hPa	-0.983
B_4	Mean u wind component, surface-850 hPa	0.764
B_5	Mean dewpoint depression, surface-500 hPa	-0.214
B_6	Mean v wind component, 1000-700 hPa	0.061

between the two counties, these terms explain the fundamental physical processes that govern warm season convective and lightning activity in South Florida. The monthly models generally contain persistence, wind speed and direction, moisture, and stability parameters. These same general parameters were chosen for the full warm season models discussed in the previous section (Table 3).

The predictors and their coefficients (Tables 5 and 6) display some variation from month to month and between the two counties. And, the threshold values also vary, not always being 0.5 as before. This is expected because I am seeking to maximize the predictive skill of the BLR model for each month. The fact that each of the ten models is somewhat different supports our reasoning that forecasts for each month can be improved by deriving separate models. Had the same predictors and coefficients appeared in all the monthly models, there would have been no need to derive a separate model for each warm season month.

The multiple wind, moisture, and stability parameters comprising the original fifty-six potential predictors (Table 1) describe these physical quantities at different levels and layers in the atmosphere. Thus, they are not completely independent. As an example, note that four of the seven predictors chosen for Broward County's May model (Table 6a) are wind related. Two of these predictors describe wind direction; the other two describe its speed. The first direction parameter is the sine of the vector averaged wind in a layer (1000-700 hPa), and the second is the sine of the wind direction at a single level (700 hPa). The two speed parameters are surface wind speed and the mean speed in the 700-500 hPa layer. It is important to note that each of these four parameters is significant at at least the 95% test level, as determined by the p-value (not shown).

In contrast, the May model for Miami-Dade County (Table 5a) contains only one wind term, the sine of the vector-averaged wind between 1000 and 700 hPa. This model also contains persistence, moisture, stability, and temperature. This contrast provides further evidence that deriving separate models for the two areas of interest is justified.

Since the two August models each consist of eight terms, more than any other model, they deserve a brief discussion. I sought to have the most parsimonious model possible. Therefore, models consisting of only three terms first were considered for both counties. These two models contained both persistence predictors and the u wind component in the 1000-700 hPa layer. These simple models forecast days with lightning very well (~95% correct, not shown). However, the percent of correctly forecast days with no lightning was only 32%. By incorporating additional terms into the models for this month, I was able to increase the skill of correctly forecasting days with no lightning to approximately 52%, while correctly forecasting days with lightning suffered only minimally. Specifically, POD, which is analogous to the percent of correctly forecast days with lightning, only fell from 95% to 93%. On the other hand, the three remaining evaluation statistics improved. For example, CSI increased from 79% to 82% by using the extra terms.

By applying each of the monthly models to the dependent data from which they were derived, I could evaluate the performance of the separate monthly models against the full warm season model derived in the previous section. Table 7 is similar to Table 4, but represents the combined statistics from the five monthly models for Miami-Dade County. Similar results were obtained for Broward County (not shown). Comparing Table 7 to Table 4, it is clear that there is improvement in correctly forecasting days with lightning, days without lightning, and all days combined. The greatest improvement is in correctly forecasting days without lightning, where the accuracy increases 3.5%. The four evaluation statistics also improve, with the CSI and FAR showing the greatest improvements. Thus, forecast skill is enhanced by deriving separate monthly models for both counties.

Table 7. 2 x 2 contingency table for the combination of the five monthly models for Miami-Dade County. Evaluation statistics and percent correctly forecast days are included.

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model performance
Yes	1034	140	CSI	74.7%
			FAR	16.9%
			POD	88.1%
No	211	489	Bias	1.06
			No lightning	69.9%
			Lightning days	88.1%
			All days	81.3%

The predictors and coefficients that appear in Tables 5 and 6 comprise the final models for eastern Miami-Dade and Broward Counties, respectively. At this point, all evaluation of model performance has been based on dependent data. Testing using independent data is conducted next to determine the stability of the models and to provide a more rigorous evaluation of their performance.

3.3 Cross-validation

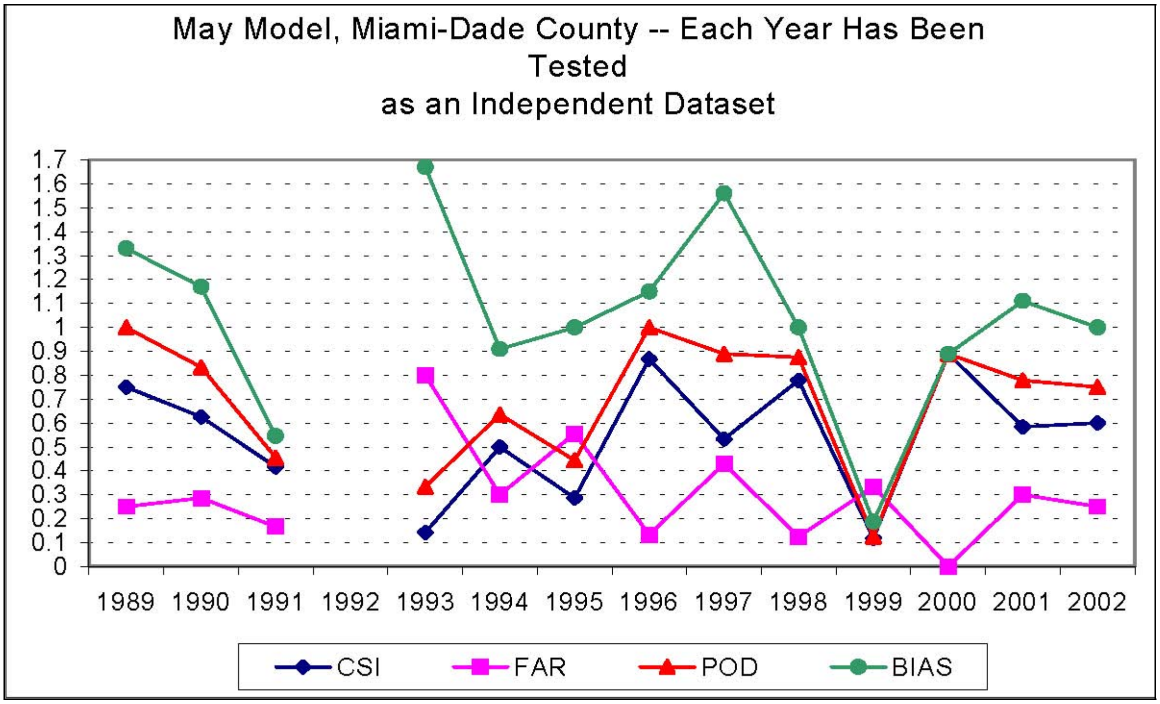
Regression equations used for weather forecasting usually are tested on an independent data set that has been held back during the model development phase (Wilks 1995). During the development of the models discussed previously, no independent data set was excluded for testing the models. Instead, all available data were used to achieve as much predictive skill in the final models as possible. To perform independent testing from a dependent data set, a cross-validation procedure was used.

Wilks (1995, p. 194) defines cross-validation in the following manner. “Cross-validation is carried out using developmental data sets of size $n - 1$, and verification data ‘sets’ containing the remaining single observation of the predictand. In this case there are n distinct partitions of the data. The regression model is recalculated for each of these partitions. The result is *n* similar forecast equations, each computed without one of the observations of the predictand."

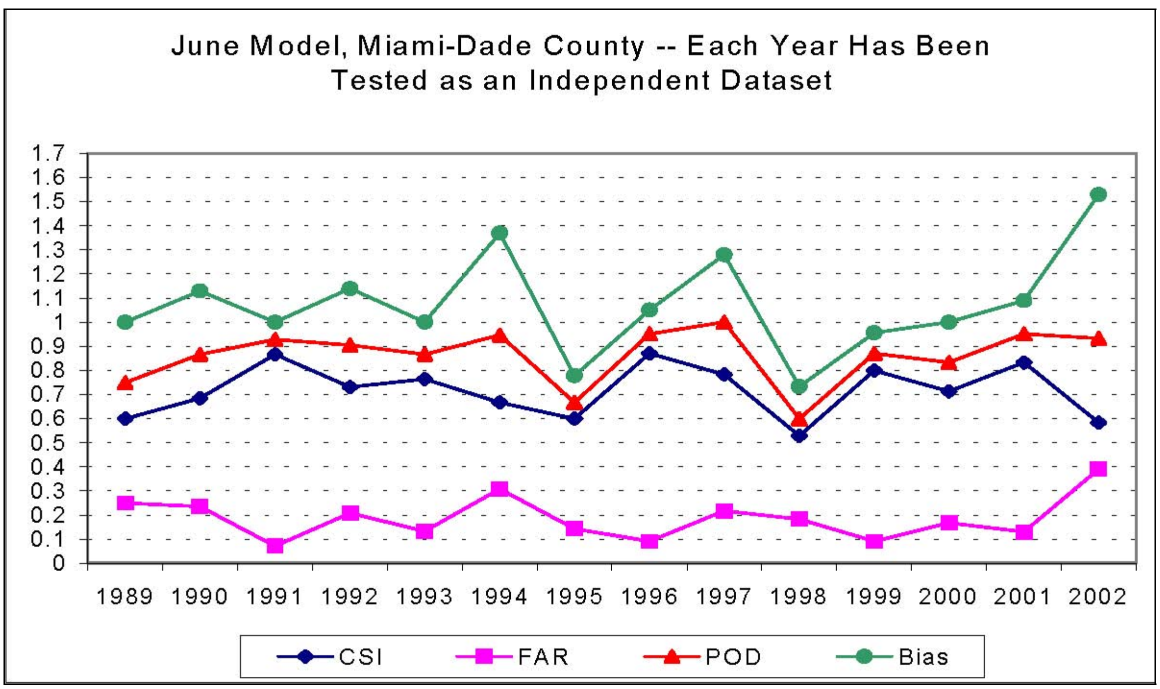
Applying this cross-validation procedure to the current study, fourteen partitions of the data set were used, one for each year in the study period. First, I excluded data from 1989 and rederived the BLR model using the remaining thirteen years of data. During the rederivation, the entire process described in Section 3.1 was repeated. This was done to allow the best model to be chosen as each year is excluded as the independent data set. Each resulting model then was compared to the original 14-year model to assess differences in the predictors and coefficients. The reason for this will be discussed shortly. Next, data from 1990 were excluded, and the model was rederived and compared to the original. This process continued until each of the fourteen years had been excluded, and fourteen separate models had been rederived. This was done for each of the ten monthly models listed in Tables 5 and 6.

If the original models (Tables 5 and 6) are stable, there should be little variation in the predictors and their coefficients chosen during the cross-validation. However, some variation is expected because the "new" model is derived from a different data set. Results (not shown) indicate that our original models were stable, i.e., there was little change in the various sets of chosen predictors and their coefficients (not shown). And, there was little difference between them and the original monthly models. In nearly every case, the same wind, moisture, and stability parameters appeared in the cross-validated models. Exceptions included an extra term sometimes being included, one of the original terms being excluded, or a slight variation in one of the terms from the original model, e.g., the mean u wind component in the 1000-700 hPa layer instead of the sine of the mean direction in the same layer.

Each of the fourteen model versions for each month was applied to the year that was withheld during the cross-validation. That process allowed all of the dependent data (each month) to be tested as independent data, providing a better evaluation of forecast skill. Evaluation statistics were computed from these "independent" tests. Figures 6 and 7 graph these statistics by month for eastern Miami-Dade and Broward Counties, respectively. Since no lightning was observed during May 1992 in eastern Miami-Dade

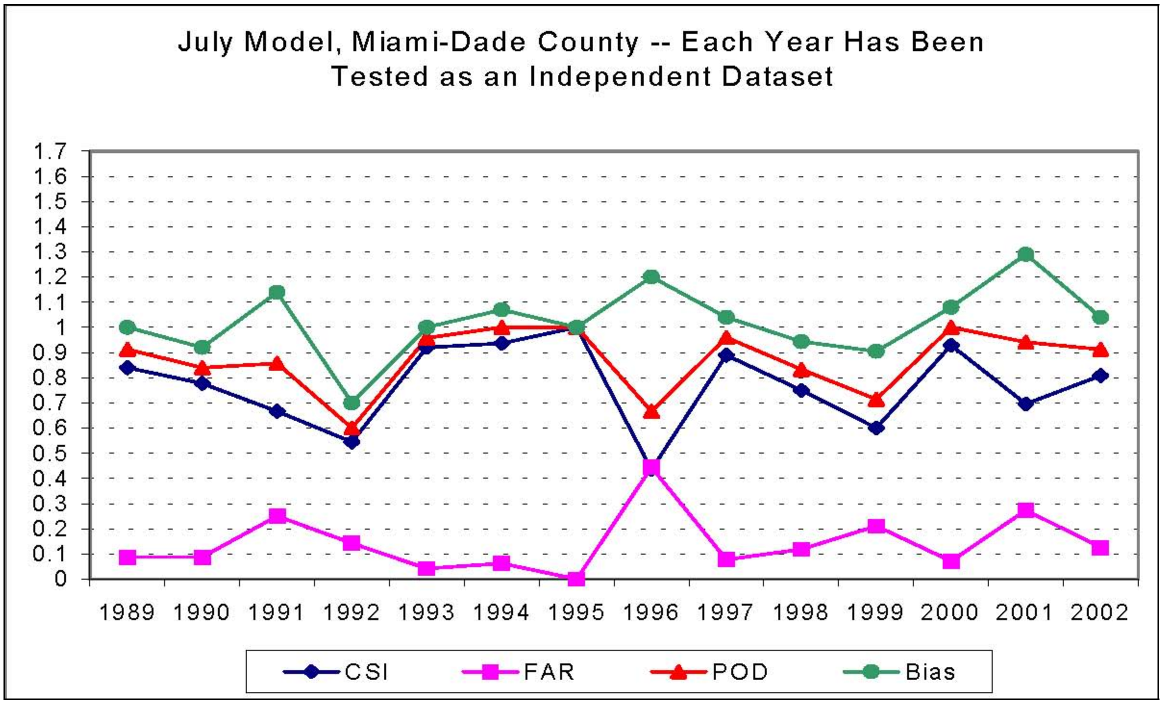


a) May

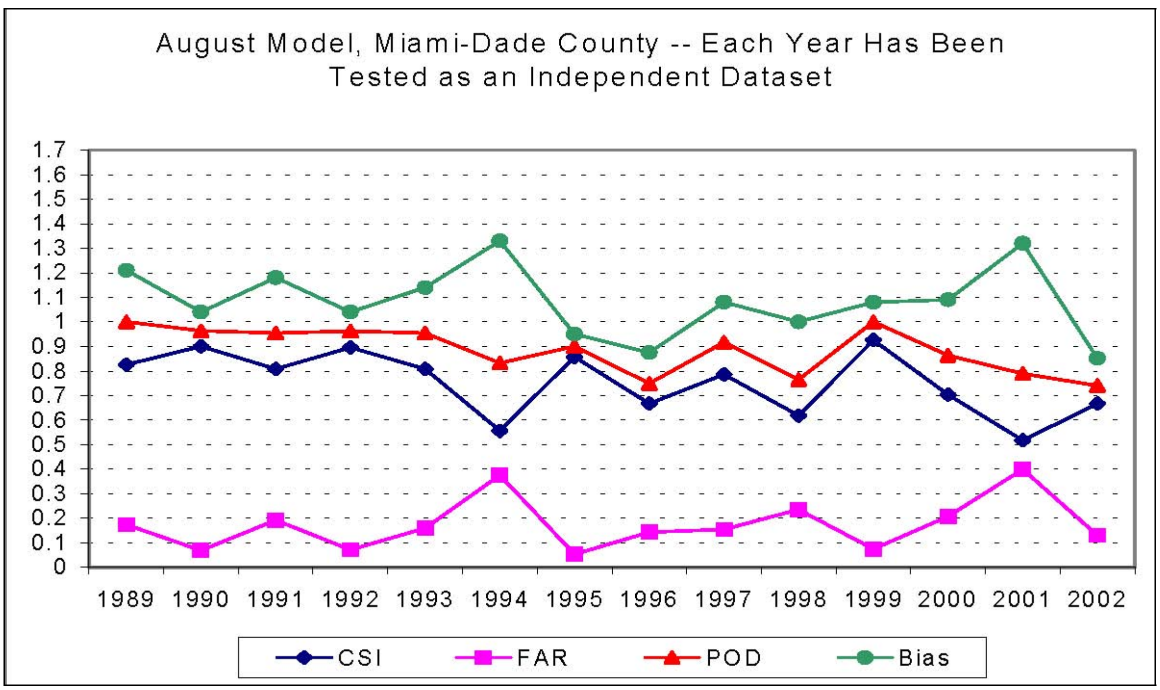


b) June

Figure 6. Plots of evaluation statistics for each cross-validation run for each of the monthly models in eastern Miami-Dade County.

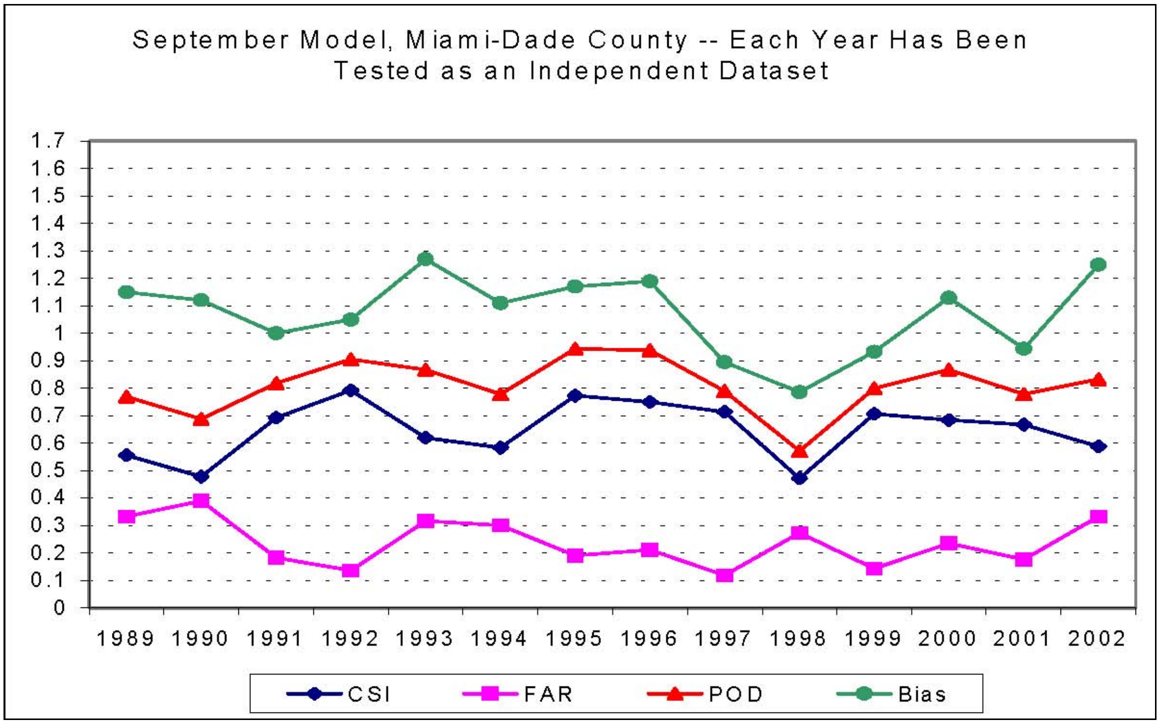


c) July



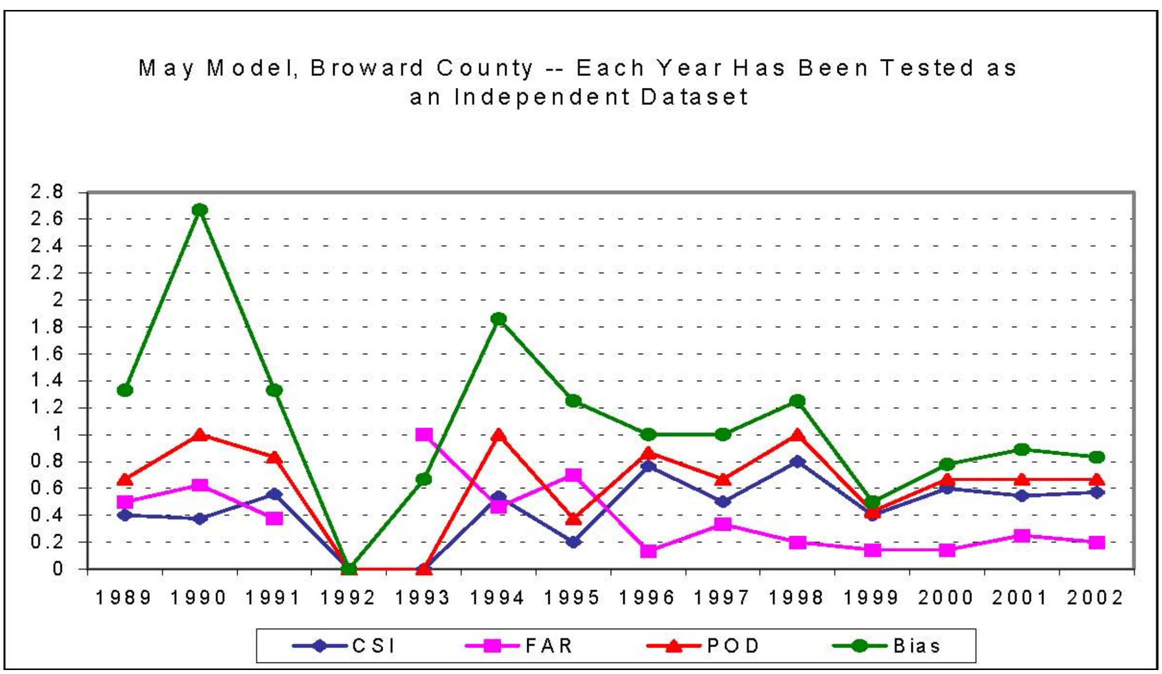
d) August

Figure 6. (continued)



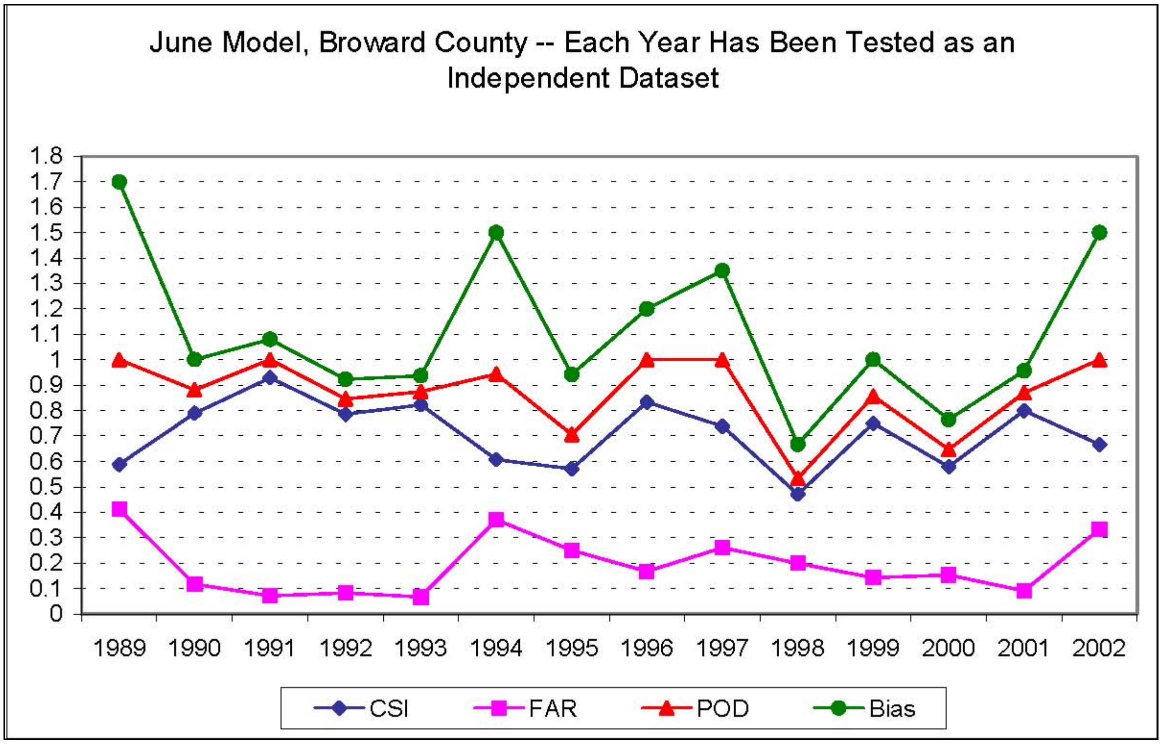
e) September

Figure 6. (continued)

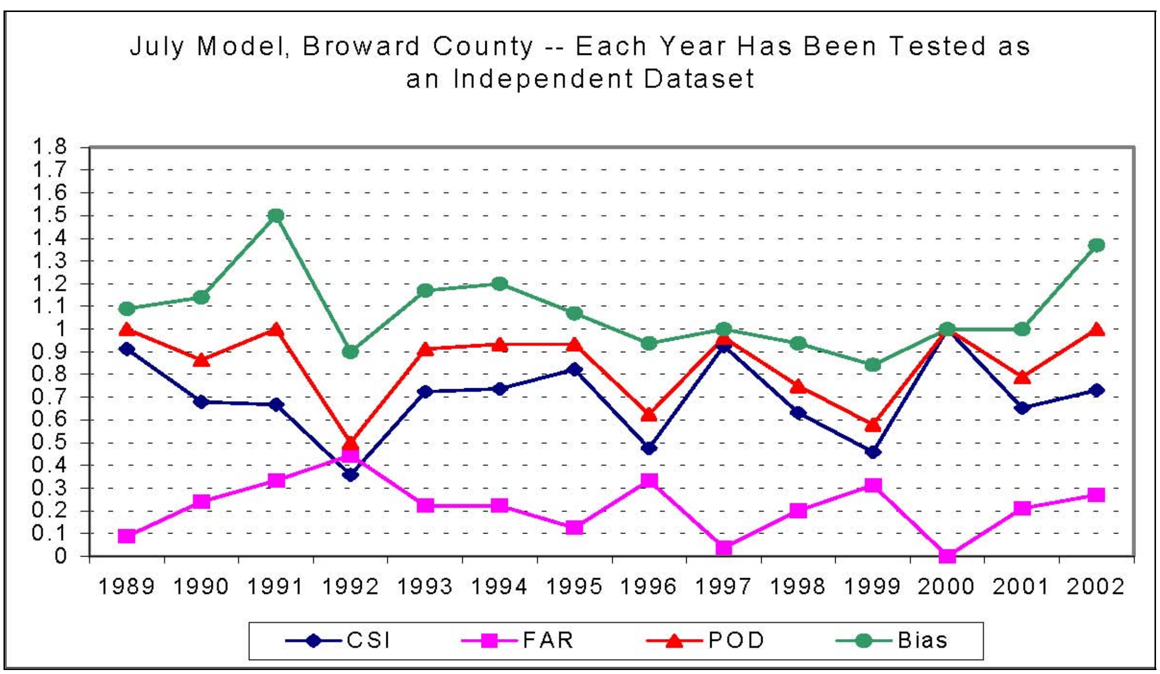


a) May

Figure 7. Same as Figure 6 but for Broward County.

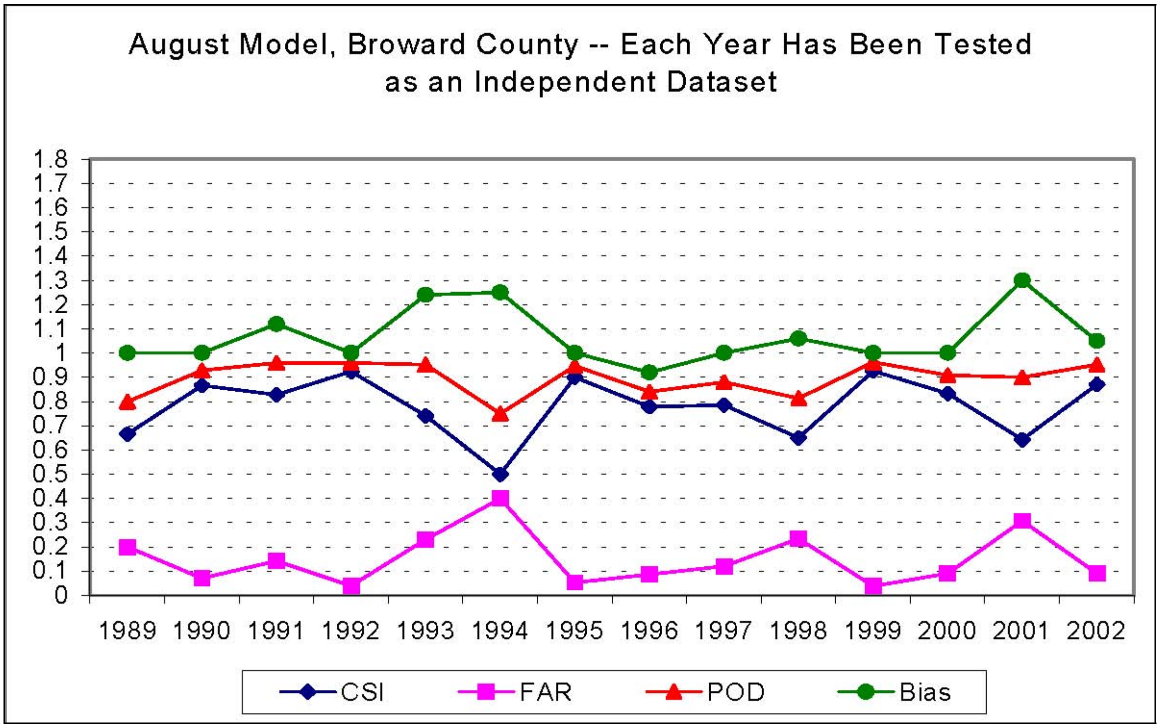


b) June

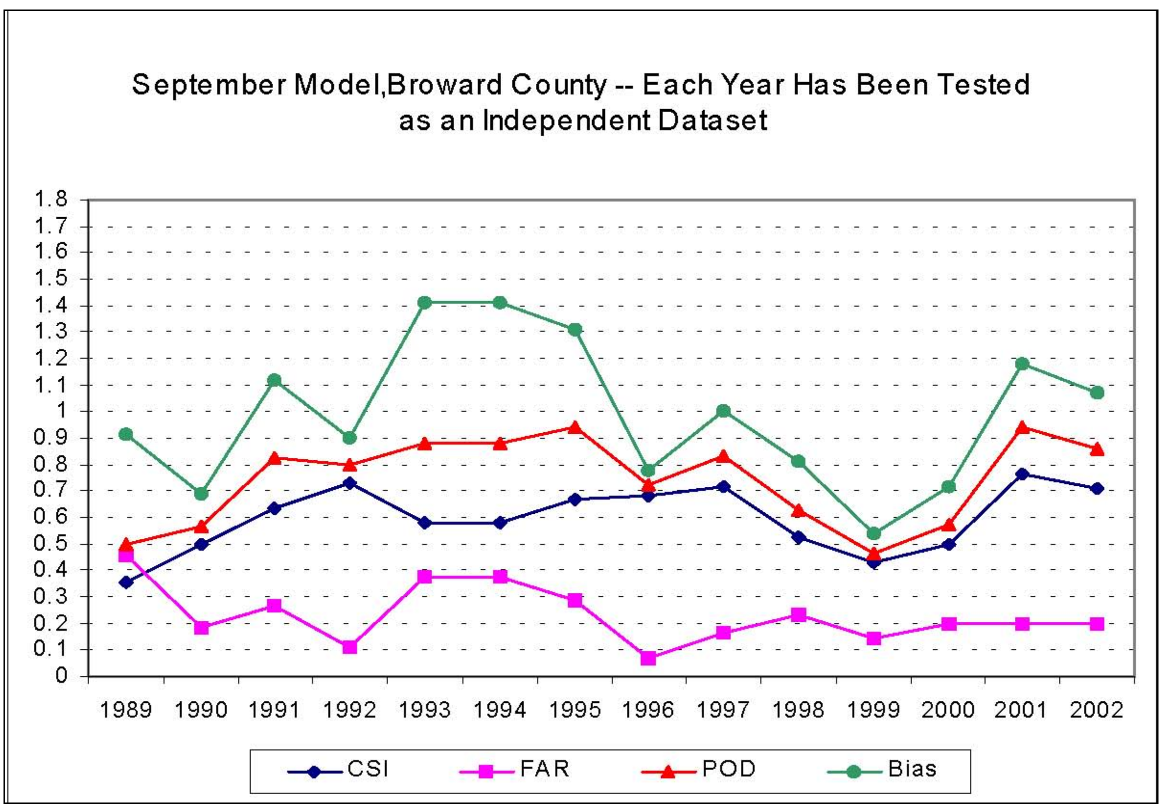


c) July

Figure 7. (continued)



d) August



e) September

Figure 7. (continued)

County, none of the statistics could be computed. This was the only month when this occurred.

Figures 6 and 7 reveal considerable variation in the range of the statistics between months and between years within the months themselves (i.e., the independent tests). Within each monthly model, some years exhibit good forecasting skill while other years are worse. Tables 8 and 9 contain contingency tables for the combination of the fourteen different cross-validated models for each month in eastern Miami-Dade and Broward Counties, respectively. The results for eastern Miami-Dade and Broward Counties generally show the same trends. Statistics for Miami-Dade County (Table 8) will be used to illustrate several major points.

The worst forecast statistics (i.e., CSI, FAR, and POD) occur during May, while the best results are obtained during July and August (Table 8). This is supported by Fig. 6a which shows the largest year to year variations in the statistics during that month. Conversely, the plots of CSI, FAR, and POD exhibit the smallest range during July and August. After May, September is the next most difficult month to forecast. As an example, typical CSI values range between 0.4 and 0.8 during May (Fig. 6a), with a smaller range of approximately 0.6 to 0.9 during July, and August. In general, the magnitude of this statistic also increases from May to July and August.

During each month there are some years when the lightning guidance models perform poorly and others when they perform very well. One reason the model can perform poorly is that some individual years contain only a very small number of days with lightning (often occurring in May) or without lightning (often occurring in July and August). If the model forecast some of these days incorrectly, the evaluation statistics are greatly affected. An example is May 1993 when lightning was observed on only three days. Two of these days were incorrectly forecast, causing CSI, FAR, and POD to be very poor (Fig. 6a). On the other hand, during July 1995 there were only two days when lightning was not observed. In this case the model correctly forecast these two days in addition to every other day when lightning was observed, i.e., all days were correctly forecast. The result was perfect scores for all evaluation statistics (i.e., CSI = 1, FAR = 0, POD = 1, and Bias = 1; Fig. 6c).

Table 8. 2 x 2 contingency tables for cross-validation of the five monthly models for Miami-Dade County. Evaluation statistics and percent correctly forecast days are included.

a) May model

Observed	Model Forecast Yes	Model Forecast No	Statistic/ Forecast	Model performance
Yes	79	39	CSI	52.7%
			FAR	28.8%
			POD	66.9%
No	32	174	Bias	0.941
			No lightning	84.5%
			Lightning days	66.9%
			All days	78.1%

b) June model

Observed	Model Forecast Yes	Model Forecast No	Statistic/ Forecast	Model performance
Yes	213	32	CSI	72.0%
			FAR	19.3%
			POD	86.9%
No	51	79	Bias	1.08
			No lightning	60.8%
			Lightning days	86.9%
			All days	77.9%

Table 8. (continued)

c) July model

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model performance
Yes	235	30	CSI	78.1%
			FAR	13.3%
			POD	88.7%
No	36	64	Bias	1.02
			No lightning	64.0%
			Lightning days	88.7%
			All days	81.9%

d) August model

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model performance
Yes	279	35	CSI	75.0%
			FAR	15.6%
			POD	88.8%
No	58	33	Bias	1.07
			No lightning	36.3%
			Lightning days	88.8%
			All days	77.0%

e) September model

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model performance
Yes	189	43	CSI	65.2%
			FAR	23.5%
			POD	81.5%
No	58	98	Bias	1.06
			No lightning	62.8%
			Lightning days	81.5%
			All days	74.0%

Table 9. Same as Table 8, but for Broward County.

a) May model

Observed	Model Forecast Yes	Model Forecast No	Statistic/ Forecast	Model performance
Yes	73	34	CSI	49.7%
			FAR	35.4%
			POD	68.2%
No	40	194	Bias	1.06
			No lightning	82.9%
			Lightning days	68.2%
			All days	78.3%

b) June model

Observed	Model Forecast Yes	Model Forecast No	Statistic/ Forecast	Model performance
Yes	213	34	CSI	70.8%
			FAR	20.2%
			POD	86.2%
No	54	75	Bias	1.08
			No lightning	58.1%
			Lightning days	86.2%
			All days	76.8%

Table 9. (continued)

c) July model

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model performance
Yes	220	35	CSI	71.7%
			FAR	19.1%
			POD	86.3%
No	52	58	Bias	1.07
			No lightning	52.7%
			Lightning days	86.3%
			All days	76.2%

d) August model

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model performance
Yes	279	30	CSI	78.2%
			FAR	14.7%
			POD	90.3%
No	48	48	Bias	1.06
			No lightning	50.0%
			Lightning days	90.3%
			All days	80.7%

e) September model

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model performance
Yes	170	55	CSI	60.7%
			FAR	24.4%
			POD	75.6%
No	55	108	Bias	1.00
			No lightning	66.3%
			Lightning days	75.6%
			All days	71.6%

Poor performance was not due solely to too few days with or without lightning. In some cases, the model simply did a poor job of forecasting lightning during an individual month. For example, during May 1999 there were an adequate number of days with and without lightning, but some of our worst evaluation scores occurred during this month (CSI ≈ 0.1, FAR ≈ 0.3, POD ≈ 0.1, Bias ≈0.2). On the other hand, during May of the next year, these same statistics were the best for this month (Fig. 6a).

Poor performance of the model during the cross-validation procedure also occurs during the "best" months of July and August. July 1996 and August 2001 were the two years during their respective months when the evaluation statistics were the poorest. This was not due to a lack of days with no lightning; the model simply handled these years poorly, probably because synoptic conditions were atypical of those during the training period.

Table 9 and the monthly plots in Fig. 7, for eastern Broward County, show the same general features as discussed for eastern Miami-Dade County. May exhibits the greatest year to year variability of the evaluation statistics, followed by September. Conversely, July and August are the most stable models, as evidenced by the yearly variations in CSI, FAR, and POD. One should note the large bias during May 1990 that is ~50% larger than for any other year. And, statistics for 1992 and 1993 are the worst of all 140 cross-validation runs. During these three years, there were too few days with lightning to calculate reliable statistics (as discussed above).

Table 10 gives the 2 x 2 contingency tables and evaluation statistics for eastern Miami-Dade and Broward Counties. These statistics are based on the independent testing using the cross-validation procedure discussed above. Thus, they constitute the final evaluation of model performance in eastern Miami-Dade and Broward Counties. Although the differences are small, results generally are slightly better in Miami-Dade County. CSI is approximately 71% in eastern Miami-Dade County, whereas it is ~69% in eastern Broward County. FAR is 19% and 21% in eastern Miami-Dade and Broward Counties, respectively. Approximately two-thirds of the days without lightning and 84% of days with lightning are correctly forecast in both counties. Finally, more than 75% of all days in both areas of interest are correctly forecast. As expected, these results are slightly worse than those cited earlier, based on the dependent data (Table 7).

Table 10. 2 x 2 contingency tables for the combined cross-validated five monthly models for Miami-Dade and Broward Counties. Evaluation statistics and percent correctly forecast days are included.

a) Miami-Dade County

Observed	Model Forecast Yes	Model Forecast No	Statistic/ Forecast	Model performance
Yes	995	179	CSI	70.6%
			FAR	19.1%
			POD	84.7%
No	235	448	Bias	1.05
			No lightning	65.6%
			Lightning days	84.7%
			All days	77.7%

b) Broward County

Observed	Model Forecast Yes	Model Forecast No	Statistic/ Forecast	Model performance
Yes	955	188	CSI	68.6%
			FAR	20.7%
			POD	83.5%
No	249	483	Bias	1.05
			No lightning	66.0%
			Lightning days	83.5%
			All days	76.7%

Meteorological conditions often change little from day to day in South Florida during the warm season. Therefore, making a forecast for afternoon lightning activity on the current day based on the previous day's activity (i.e., using only persistence) would yield reasonably accurate results. This assumption is supported by Table 11, which gives 2 x 2 contingency tables, evaluation statistics, and the percent of correctly forecast days using persistence alone for the two areas of interest. Comparing Tables 10 and 11, it is clear that the guidance developed in this study improves upon persistence alone. For eastern Miami-Dade and Broward Counties, respectively, the CSI improves from 64% (Table 11a) and 61% (Table 11b) with persistence alone to 71% (Table 10a) and 69% (Table 10b) using the current models. The FAR improves from 22% (Table 11a) to 19% (Table 10a) in eastern Miami-Dade County, and from 24% (Table 11b) to 21% (Table 10b) in eastern Broward County. The percent of correctly forecast days in eastern Miami-Dade County improves from 72% (Table 11a) to 78% (Table 10a). Similarly, for eastern Broward County the percent of correctly forecast days improves from 70% (Table 11b) to 77% (Table 10b). Thus, the guidance models yield a definite improvement.

3.4 Analysis of Incorrectly Forecast Days

It is informative to investigate days when the guidance model produced incorrect forecasts. The goal is to gain a better understanding of the model's strengths and weaknesses so that forecasters can apply this information when interpreting model results during daily operational implementation. Since results for eastern Miami-Dade and Broward Counties are similar, only the Miami-Dade area will be discussed in detail.

Two types of incorrect forecasts ("bust" days) will be discussed. The first is when no lightning is forecast but is observed nonetheless (a "busted 0" day). The second type of incorrect forecast is a day on which lightning is forecast to occur but does not (a "busted 1" day).

When examining busted 0 days, the amount of lightning observed should be considered. The motivation, from an operational standpoint, is that the risk of damage to power generating facilities and transport lines increases as more lightning occurs. Thus, a busted 0 day when many strokes (e.g., more than 100) are observed is worse than a busted 0 day with only a few strokes (e.g., 5 – 10).

All days with lightning occurrence between noon and midnight were categorized into groups (quartiles) with approximately equal numbers of days in each quartile. This procedure was performed within SPSS. For eastern Miami-Dade County there are approximately 300 days in each quartile. The number of afternoon/evening flashes in each quartile is as follows: Quartile One (Q1) ≤ 7, Quartile Two (Q2) 8 – 40 flashes, Quartile Three (Q3) 41 – 125 flashes, and Quartile Four (Q4) >125 flashes.

Table 11. 2 x 2 contingency table, evaluation statistics, and percent of correctly forecast days for Miami-Dade and Broward Counties using only persistence.

a) Miami-Dade County

Observed	Model Forecast Yes	Model Forecast No	Statistic/ Forecast	Model performance
Yes	910	263	CSI	63.7%
			FAR	21.9%
			POD	77.6%
No	255	446	Bias	0.993
			No lightning	63.6%
			Lightning days	77.6%
			All days	72.4%

b) Broward County

Observed	Model Forecast Yes	Model Forecast No	Statistic/ Forecast	Model performance
Yes	857	285	CSI	60.7%
			FAR	24.0%
			POD	75.0%
No	270	462	Bias	0.987
			No lightning	63.1%
			Lightning days	75.0%
			All days	70.4%

Table 12 lists by month the percentage of days having lightning that was not forecast (a busted 0 day). Overall statistics are presented, and they are subdivided by quartile. The results from this table are encouraging. The overall percentage of incorrectly forecast days ranges from 22% during May to only 9% in August. Thus, the percentage of busted 0 days decreases from May to July and August. The greatest percentage of busted 0 days generally occurs with Q1 events. Conversely, the extreme Q4 days are most often correctly forecast. The exception is May when a higher percentage of busted 0 days occurs during Q2 activity than during Q1 activity. The percentage of busted Q1 days ranges from 20% in July and August to 29% in September, while the percentage of busted Q4 days ranges from 12% in May to only 1% in July and August.

Table 12. Analysis of days having lightning that was not forecast for Miami-Dade County.

	May	June	July	August	September
Lightning Observed/ Not Forecast	22%	11%	10%	9%	15%
Q1 Observed/ Not Forecast	23%	21%	20%	20%	29%
Q2 Observed/ Not Forecast	31%	17%	12%	12%	12%
Q3 Observed/ Not Forecast	17%	3%	8%	8%	8%
Q4 Observed/ Not Forecast	12%	4%	1%	1%	9%
Threshold Probability	0.47	0.5	0.54	0.56	0.5
Median Probability on "Busted 0" Days	0.26	0.34	0.39	0.5	0.35

These results again suggest that the models perform well, and are especially good at forecasting days with the greatest lightning activity. It is important to state that the goal of this study is not to forecast the amount of afternoon lightning, but simply its occurrence or non occurrence. The fact that the fewest busts occur on high activity (i.e., Q4) days is encouraging in that as thermodynamic and kinematic conditions become optimum for high lightning activity they are handled well by the models via the physical predictors comprising them.

The threshold probability for forecasting lightning (seen earlier in Table 5) and the median forecast probability on the busted 0 days is given for each month at the bottom of Table 12. Comparing the median probability to the threshold value is a way of indicating how far the model was from predicting lightning. The difference between the threshold and median forecast probabilities decreases from May (0.17) to August (0.06). This indicates that even though the models have produced busted 0 days, the forecast probabilities during these busts are not as far from the threshold during July and August as during May. As noted earlier, synoptic scale forcing often causes convection over South Florida during May, and these situations are not handled well by the guidance models or by the 1200 UTC soundings that are used as input.

Table 13 is analogous to Table 12 but for busted 1 days. The previously mentioned quartiles have no relevance on these days since no lightning occurred. May exhibits the greatest percentage of incorrect forecasts (23%), while July has the best forecasts, again showing that results generally improve from May to July and August. The median forecast probability on busted 1 days along with each month's threshold probability also are given. However, unlike the busted 0 days, the median forecast probabilities do not approach the threshold value as the warm season progresses.

Table 13. Analysis of days with no lightning although lightning had been forecast for Miami-Dade County.

	May	June	July	August	September
Lightning Forecast/ Not Observed	23%	19%	13%	16%	21%
Threshold Probability	0.47	0.5	0.54	0.56	0.5
Median Probability on "Busted 1" Days	0.67	0.75	0.72	0.79	0.68

Days when the models produced a busted 0 forecast were examined in search of similarities among the predictors and the overall meteorological setting. This was done in an effort to develop general insight that might provide guidance to FP&L personnel in their decision making processes. The first finding regards persistence. Specifically, every monthly model for Miami-Dade County contained at least one of the persistence variables. For each of these models, persistence on approximately 90% of the busted forecast days was zero (no lightning). Thus, the forecast day producing lightning was a departure from the previous day. This change in conditions may have occurred after the morning 1200 UTC sounding that is used in the guidance models. Additionally, every monthly model except August contained the sine of the wind direction at either a single level or vector-averaged over a layer. On nearly 90% of the days that the model busted a 0 forecast during these four months, the sine of the wind direction was positive, indicating onshore, easterly flow which is considered detrimental to sea breeze development.

Since onshore flow in the morning sounding was so common during busted 0 days, that day's evening sounding (0000 UTC) was investigated on the approximately dozen days with the largest afternoon flash totals (Q4 days) to check if the wind direction had shifted to offshore flow. I hypothesized that the morning easterly flow had shifted to westerly later in the day, contributing to the development of an east coast sea breeze that might explain the busted forecast. However, only one of the investigated days displayed this easterly to westerly wind shift, and this was due to a frontal passage. A more detailed explanation of this one case is presented later. More thorough investigations will be required to explain why the other major 0 busts occurred.

Other generalities among terms of the individual monthly models also were observed on the combination of all busted 0 days, but they were not as widely observed as those discussed above. For example, during May, LI values greater than – 4 were observed on 77% of the busted 0 days. During July, the vector-averaged u wind component between 850 and 700 hPa indicated onshore flow on all busted 0 days. Similarly, during August the 1000-700 hPa vector-averaged u wind component was onshore in every case of a busted 0 forecast. Moreover, the magnitude of this cross-shore wind component exceeded 5 m s^{-1} on approximately half of the busted 0 days during this month. The generalities mentioned above that are based on past situations hopefully will assist FP&L personnel in their interpretation of the lightning guidance product.

Generalities describing busted 1 days were much more difficult to distinguish compared to the busted 0 days. The most notable generalization is that previous day lightning activity during May, August, and September occurred on ~ 70% of the busted 1 days in Miami-Dade County. Further research will be required to understand the factors leading to this departure from persistence.

I next examined spatial plots of lightning flashes for several cases of busted 0 and busted 1 forecasts. These cases illustrate some of the challenges in forecasting lightning over small areas. Figures. 8a and 8b are busted 0 days, while Figures 8c and 8d are busted 1 days. The two busted 0 days provide a stark contrast in conditions. On July 5, 1990 (Fig. 8a) one hundred seventeen flashes occurred in eastern Miami-Dade County during the noon to midnight period, while only six flashes occurred on September 22, 1993 (Fig. 8b). As mentioned previously, a busted day when so many flashes were observed like July 5, 1990, is a more serious error because lightning was observed across a much greater portion of the area of interest. Conversely, on September 22, 1993 (Fig. 8b), the six observed flashes occurred only within the extreme western portion of the area of interest.

Figs. 8c and 8d are examples of busted 1 days. On May 16, 1999 (Fig. 8c) the model forecast lightning for eastern Miami-Dade County, but no lightning occurred in the area of interest during the noon to midnight period. However, there was abundant lightning activity in the western portion of Miami-Dade County, just outside the area of interest. A slight change in the location of this sea breeze-induced convection would have yielded a correct forecast. On the other hand, on June 17, 2002 (Fig. 8d) lightning was forecast for eastern Miami-Dade County, but no lightning was observed anywhere near the county.

The busted forecast days of July 5, 1990 (Fig. 8a) and June 17, 2002 (Fig. 8d) were worse busts than their counterparts in Fig. 8. On June 17th (Fig. 8d) the model forecast lightning in eastern Miami-Dade County but there was no lightning close to the

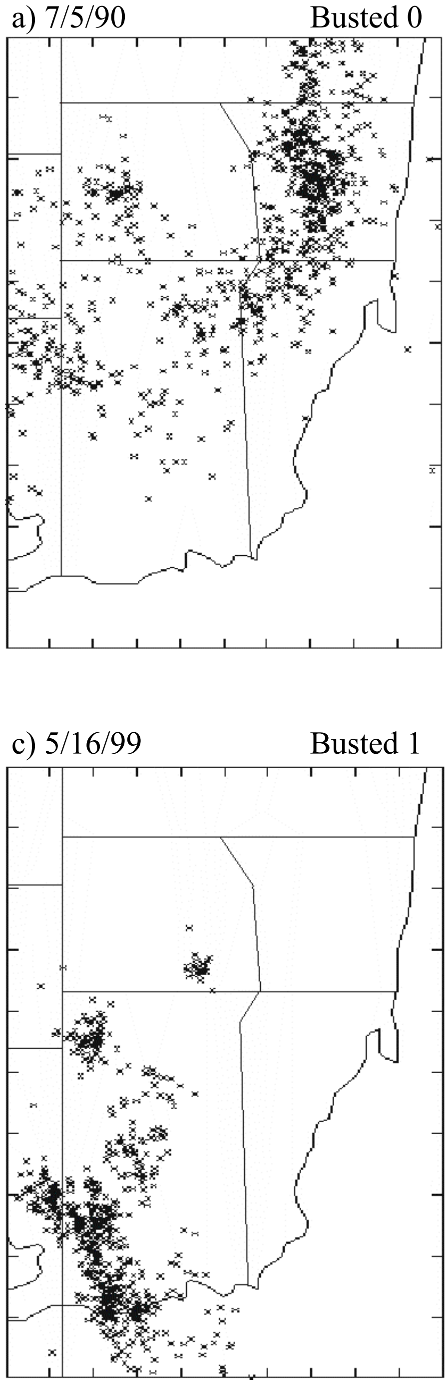


Figure 8. Cumulative noon to midnight plots of lightning flashes for (a) July 5, 1990, (b) September 22, 1993, (c) May 16, 1999, and (d) June 17, 2002. Panels (a) and (b) are busted 0 forecasts. Panels (c) and (d) are busted 1 forecasts. All bust days are based on the area of interest in eastern Miami-Dade County.

area of interest. On July 5th no lightning was forecast for eastern Miami-Dade County but lightning occurred across the entire east-west extent of the area of interest.

The last example of a busted forecast occurred on May 4, 1998 (Fig. 9). This day emphasizes the point that the models are not suited for synoptically disturbed situations. At 1200 UTC a cold front was positioned just north of Florida. Based on the 1200 UTC Miami sounding data, the model output for this day suggested that no lightning would occur. The probability of observing at least one flash was 0.28 with a threshold of 0.47 for determining the "yes" forecast. However, Fig. 9a-d shows the progression of storms and lightning ahead of the frontal boundary as it moved southward into Florida throughout the evening. Conditions obviously changed after 1200 UTC.

The statistical forecast equations developed in this study are meant to be a source of guidance that should be used in conjunction with other guidance products. Other guidance on this day would have indicated the expected frontally induced convection. As an extension to this study, it is hoped that incorporating mesoscale model output will improve the forecast skill of this guidance product by capturing changes in the meteorological conditions that sometimes occur after the morning 1200 UTC sounding.

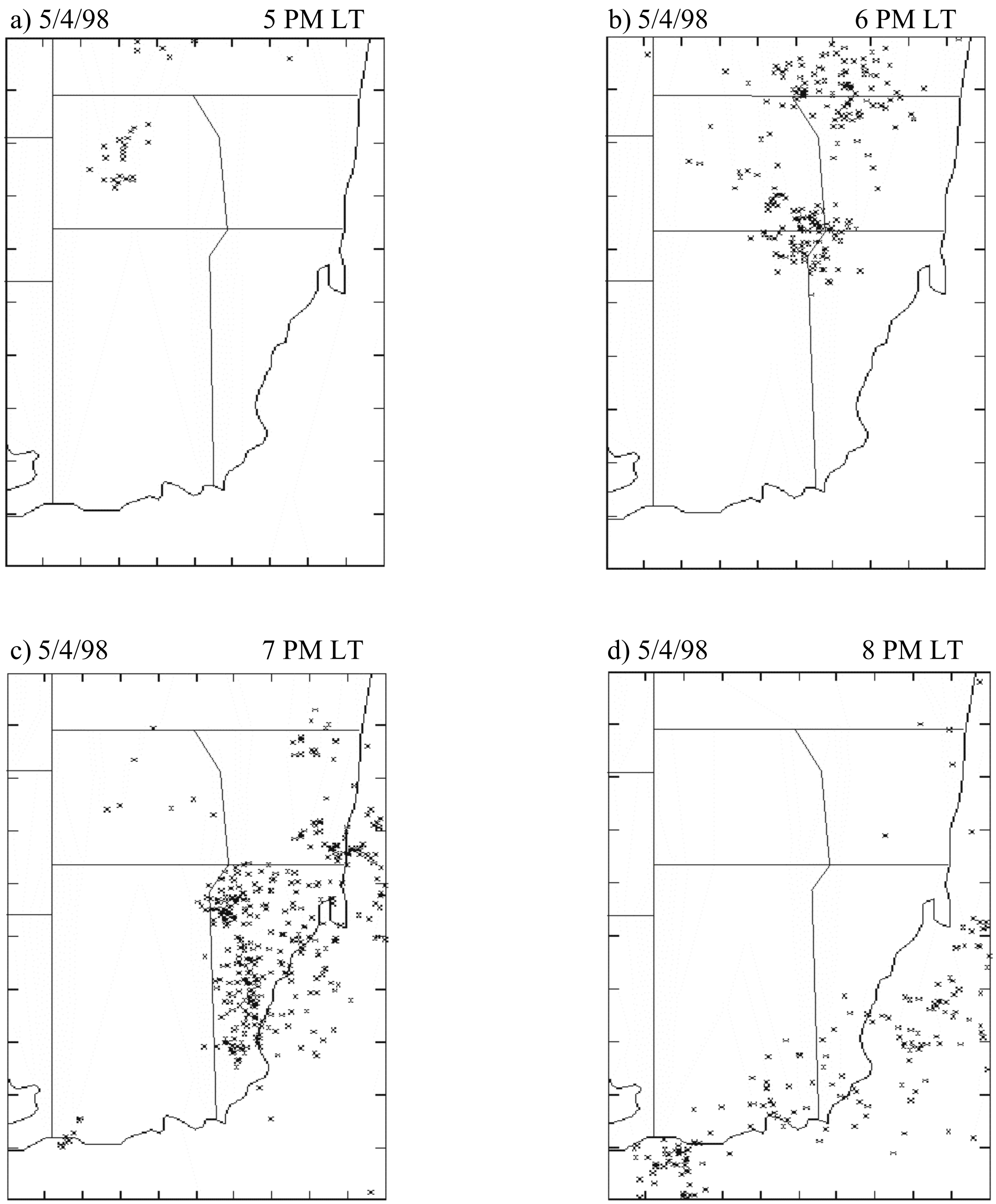


Figure 9. Hourly lightning plots for the hour starting at (a) 5 PM LT, (b) 6 PM LT, (c) 7 PM LT, and (d) 8 PM LT on May 4, 1998 as a cold front was moving southward into Florida.

CHAPTER FOUR

SUMMARY AND CONCLUSIONS

This study has developed statistical guidance equations to determine the probability of noon to midnight lightning activity (the occurrence or non occurrence of at least one flash) in eastern Miami-Dade and Broward Counties during the warm season (May-September). The guidance assumes that the sea breeze provides the dominant forcing for afternoon convective and lightning activity. This is most often true during June, July, and August. The guidance product was developed to assist personnel at Florida Power and Light Corporation (FP&L) in their decisions concerning whether extra line crews will be needed after normal business hours.

The areas of interest in both counties and the noon to midnight time period were defined by FP&L. The specific areas (east of US 27 in Broward County and east of State Route 997 in Miami-Dade County) contain the majority of FP&L's customers and service lines in these counties. The noon to midnight period was selected because the risk of lightning activity is most costly to FP&L.

Fourteen years (1989-2002) of warm season lightning and radiosonde data were used to develop and test the guidance equations. The lightning data were obtained from the National Lightning Detection Network. They were used to determine whether lightning occurred within the areas of interest during the noon to midnight period. Lightning data were available for 2097 out of a possible 2142 warm season days. The 1200 UTC Miami (West Palm Beach prior to August 1995) sounding served as the major input to model development. These radiosonde data were used to calculate approximately fifty potential predictors, including various wind, moisture, stability and temperature parameters. All days with any missing radiosonde-derived parameters were excluded from the final data set. Two persistence variables (the previous day's afternoon activity and the current day's morning activity) also were included as potential predictors. A total of 1874 warm season days over the 14-year study period provided both radiosonde and lightning data.

Binary logistic regression (BLR) was used to relate noon to midnight lightning activity to the pool of potential predictors. This method is advantageous to linear regression for several reasons. First, BLR does not require linear relationships between the dependent and independent variables. Second, it does not require normally distributed response variables. Finally, the outcome variable is dichotomous (yes or no). Each of these conditions was applicable to the data, making BLR the most appropriate choice for regression analysis.

A single model for the entire warm season was derived by applying a stepwise screening procedure to determine which of the potential predictors were most important in describing the observed variation in lightning activity. The parameters selected for this model were the vector-averaged sine of wind direction, and wind speed (both in the 1000-700 hPa layer), precipitable water, LI modified for assumed afternoon conditions, and both persistence variables. Each of these independent variables is known to be physically related to the strength and movement of the sea breeze or to convective initiation. This model then was applied to the dependent data from which it was derived, and the percent of correctly forecast days, along with various evaluation statistics, were computed for the individual months comprising the warm season. Results revealed that the model performed differently during each month. Specifically, the evaluation statistics were worst in May, followed by September. These two months are the first and last months of the warm season in South Florida, and synoptic scale influence is more likely than during June, July, and August.

Based on these results, it was determined that deriving a separate model for each month would increase forecast skill compared to using only a single model for the entire warm season. The five monthly models for each county generally contained similar independent variables. Once the individual monthly models were developed, they too were applied to the data from which they were derived. Compared with the entire warm season model, the evaluation statistics and percent of correctly forecast days improved for each month.

To test the monthly models on independent data, a cross-validation procedure was employed. For each of the ten final models, each of the fourteen years was removed one year at a time, and a "new" model was rederived from the remaining thirteen years of data. The cross-validation process served two purposes. First, it revealed that the final monthly models were stable, i.e., the predictors and their coefficients chosen during each of the fourteen cross-validation runs for each monthly model exhibited little change from the original 14-year model. Second, it allowed each of the models to be tested on independent data.

The various evaluation statistics and percent of correctly forecast days varied for each individual month within the warm season. For eastern Miami-Dade County, the POD ranged from a low of 67% in May to a high of 89% during July and August. The FAR varied from 29% in May to only 13% in July, and the CSI, which is a combination of these two statistics, ranged from 53% in May to 78% during July. Results were similar for Broward County.

Results from the independent tests of the monthly models revealed that the guidance developed in this study outperformed persistence. This was an important achievement since persistence is a strong predictor of lightning activity during the warm season in South Florida. When results for the monthly models were combined, the CSI was 71% in eastern Miami-Dade County, compared with 64% using persistence alone. Similarly, the percent of correctly forecast days with lightning beat persistence alone by 7% (85% versus 78%). Additionally, the hit rate improved from 72% using just persistence to 78% using the monthly models. Similar results were obtained for eastern Broward County.

Days when the models produced an incorrect forecast (bust days) were examined. On days when no lightning was forecast but occurred anyway (busted 0 days), the amount of lightning observed was considered. The amount of noon to midnight lightning was assessed by grouping days with lightning into quartiles. This was done to evaluate how well the models handled days with minimal lightning activity (e.g., Q1 days, 1-7 flashes) versus days with large lightning activity (e.g., Q4 days, >125 flashes). Considering all busted 0 days for eastern Miami-Dade County, the percent of incorrect forecasts improved as the warm season progressed, ranging from a high of 22% during

May to a low of only 9% during August. Moreover, a smaller percentage of Q4 days was incorrectly forecast than Q1 days for each warm season month. For example, in July and August 20% of Q1 days were incorrectly forecast, whereas only 1% of Q4 days were busts. This indicates that the models are best able to forecast days when many strokes occur. On days when no noon to midnight lightning was observed, but had been forecast, results again showed that the percentage of incorrectly forecast days decreased as the warm season progressed, ranging from 23% during May to 13% in July.

Since the guidance products do improve on persistence alone, the models will serve as useful guidance for FP&L. It is believed that by incorporating mesoscale model output to capture spatial and temporal changes in meteorological conditions that sometimes occur after 1200 UTC, the forecast skill of future guidance equations can be improved further.

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BIOGRAPHICAL SKETCH

Justin Marsh Winarchick was born in Allentown, Pennsylvania, on September 16, 1979. Justin became fascinated with thunderstorms at an early age, but it wasn't until the summer of 1990 that he whole heartedly fell in love with the weather. That summer, during his first airplane ride, he decided he wanted to be a pilot, and he wanted to study meteorology.

Justin and his family moved to the Jacksonville, Florida area in the spring of 1996, when he was 16 years old. Justin graduated in the top ten percent of his high school class the following summer. Instead of going directly into a four year school, Justin stayed in the Jacksonville area to complete his first two years of college while pursuing his dream of flying, by taking flying lessons at the local airport.

In the fall of 1999, Justin transferred to the Florida State University to finish his college education. On December 15, 2001, he received a Bachelor of Science degree in meteorology, with minors in mathematics and physics. In the fall of 2002, Justin started graduate school at the Florida State University to receive his Master of Science degree, again in meteorology. He was hired by Dr. Henry Fuelberg to conduct lightning research.