P1.15 **DEVELOPING A STATISTICAL SCHEME TO PREDICT THE OCCURRENCE OF LIGHTNING IN SOUTH FLORIDA**

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1. INTRODUCTION

Cloud-to-ground (CG) lightning is a dangerous and potentially deadly natural phenomenon. 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 will lead to fewer injuries and deaths, with less time and money spent repairing damaged property and restoring electric services.

Various statistical models have been developed to predict thunderstorms and lightning. 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 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.

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. 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.

A few authors have developed statistical thunderstorm forecast guidance for the immediate area of the Kennedy Space Center (KSC). Neumann and Nicholson (1972) used non-linear, multivariate regression techniques to forecast thunderstorm activity at KSC. Their regression models were developed using radiosonde-derived training 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.

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. Screening techniques selected four of the predictors to comprise the lightning index, including maximum electric field mill strength, GPS Integrated Precipitable Water Vapor (IPWV), the 9-hour change in IPWV, and the K-index.

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. These areas are served by Florida Power and Light Corporation (FP&L) who are using the guidance in various manpower decisions. Data from the National Lightning Detection Network (NLDN) (Cummins et al. 1998) 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 the 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.

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2. METHODOLOGY

2.1 Study Period

The study area consists of two specific portions of two South Florida counties -- 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 selected by FP&L because they contain most of the population in these counties and contain most of FP&L's power generating facilities and transmission lines that serve these customers.

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 forecast 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 focused 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 during these months typically is weak, and the influence of mid-latitude systems is minimal. 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 described here is not suitable for those situations. The following section describes our cursory attempt to remove these days.

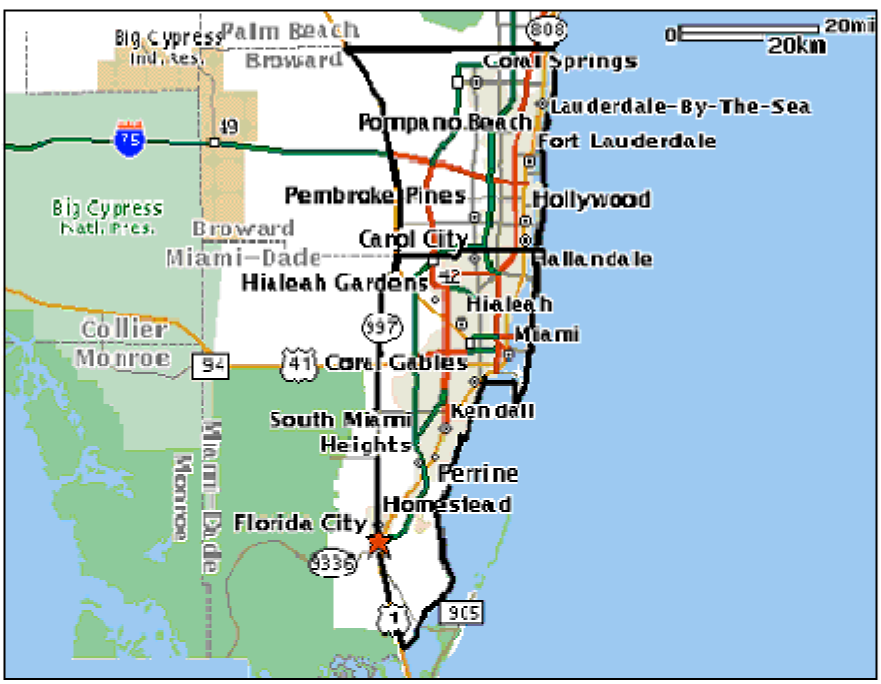


Figure 1. Map of South Florida Counties. Broward and Miami-Dade Counties are shown in their entirety. The two study areas in these counties are outlined in black. (Map taken from www.mapquest.com)

Separate guidance equations were developed for the two areas 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 than in Broward County, having more inlets and capes. 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 closer to Lake Okeechobee, suggesting that lake breezes will exert more influence on convective activity and lightning occurrence. Only results for Miami-Dade County are presented in this paper.

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., specifics concerning the network's operations and methodology are discussed in detail by Cummins et al. (1998).

The detection efficiency and location accuracy of the NLDN have improved substantially since its inception. During its early years, 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 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 of 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.

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 Lopez 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 were calculated for potential use in the algorithm. The original sounding data 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 fifty-four parameters considered here (Table 1).

Several potential parameters deserve a brief description. Layer averaged wind parameters were vector-averaged. Vector-averaged winds in the 1000-700 hPa layer were used because previous studies (e.g., Lopez 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 achieved using more shallow sub-layers within and above this steering layer. Layer averaged quantities other than winds were simple arithmetic means. Convective available potential energy (CAPE), the lifted index (LI) and related parameters were calculated using 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 temperature was based on the mean saturation mixing ratio in the mixed layer (surface to 825 hPa).

Table 1. Radiosonde-derived parameters considered 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

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 our final data set.

2.4 Logistic Regression

Binary logistic regression (BLR) was determined to be the best statistical procedure for the study. BLR 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.

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

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

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

$$g(P_j) = \ln[(P_j)/(1 - P_j)] = B_0 + B_j X_j. \qquad (2)$$

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).

Logistic regression has been used previously in the meteorological literature. Mazany et al. (2002) employed 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 Statistical Package for the Social Sciences (SPSS) Version 11.5 for Windows was used for the logistic regression in this study.

3. 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 was 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 was to select the step that 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. We 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. 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 lightning activity. Conversely, a p-value 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 covariates are assumed to be unchanged during this estimation (Mazany et al. 2002).

Table 2. Contingency table for forecast and observed lightning activity.

	Model Forecast	
	Yes	No
Observed		
Yes	A	B
No	C	D

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. 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. We 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.

We sought to develop the most parsimonious model possible because including 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.

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 model for eastern Miami-Dade County for the entire 14-year study period is given in Table 3. Both persistence variables, wind speed and direction, moisture, and stability parameters comprise the equations. All of the predictors appearing in the models make physical sense and are discussed below.

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

	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

The coefficients for both persistence parameters in Table 3 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.

We 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 2 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. We 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. We 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. 2). The equation in Table 3, 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 (not shown).

We 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.

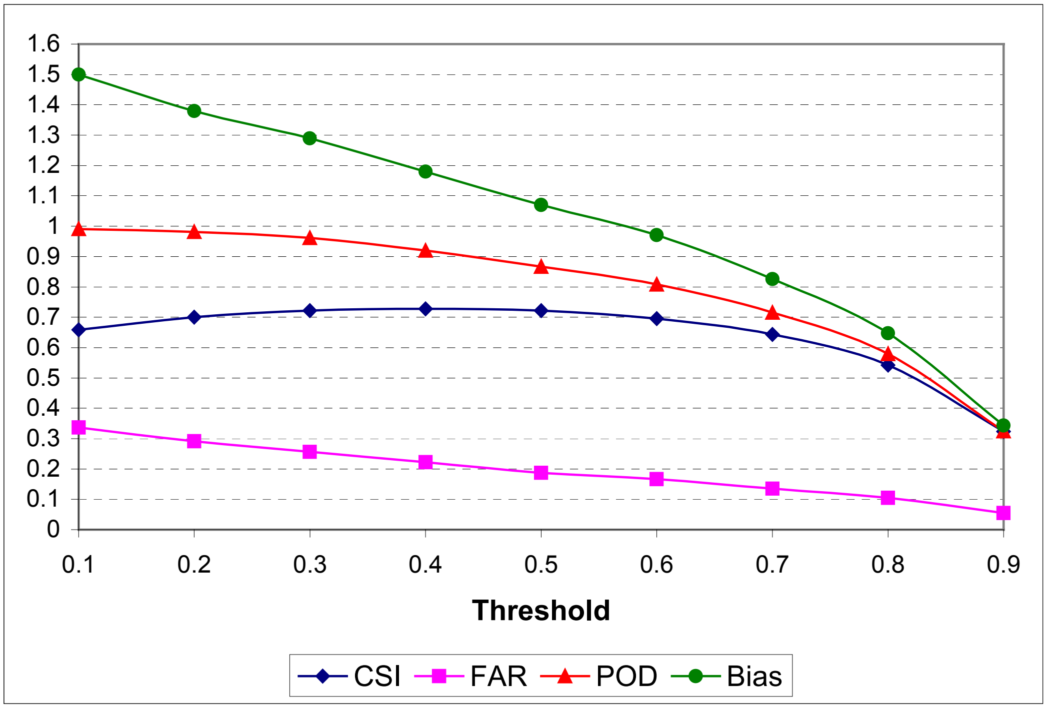


Figure 2. CSI, FAR, POD, and Bias for a range of threshold values for the eastern Miami-Dade County model.

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.

Observed	Model Forecast Yes	Model Forecast No	Statistic/ Forecast	Model 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 3 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, we 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).

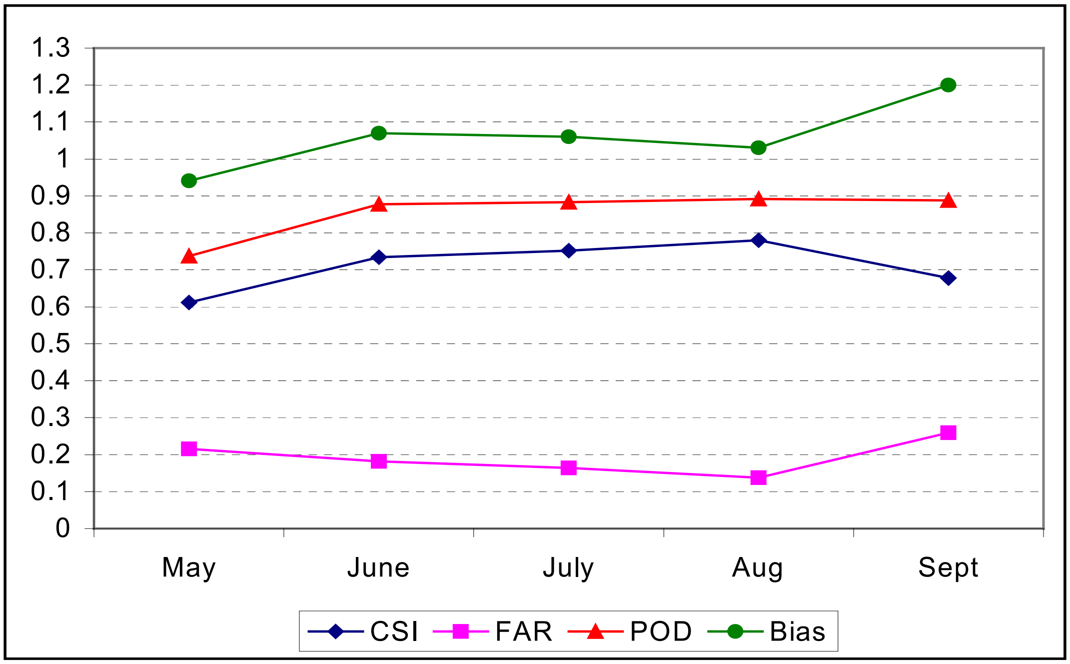


Figure 3. CSI, FAR, POD, and Bias by month for the warm season BLR model for eastern Miami-Dade County.

Figure 4 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 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. 3 and 4, 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.

4. 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. The number of terms in each model ranges between four and eight, depending on the month. For example, the June model contains four terms, and the August model contains eight terms. Although the types and number of terms in the models differ from month to month and 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).

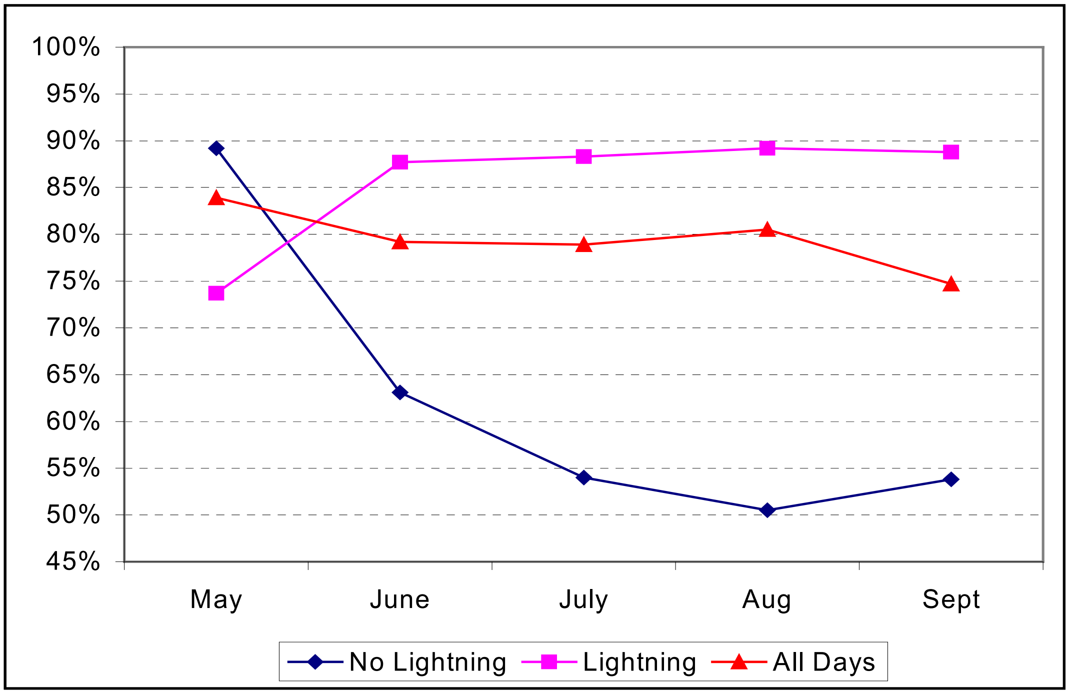


Figure 4. Graph by month for the percent of correctly forecast days with no lightning occurrence, days with lightning occurrence, and all days for the eastern Miami-Dade County model.

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

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

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

The predictors and their coefficients (Table 5) display some variation from month to month. And, the threshold values also vary, not always being 0.5 as before. This is expected because we are seeking to maximize the predictive skill of the BLR model for each month. The fact that each of the models is somewhat different supports our reasoning that forecasts for each month can be improved by deriving separate models.

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. Although a given monthly model may contain more than one wind term or more than one moisture term, it is important to note that each of the selected parameters is significant at at least the 95% test level, as determined by the p-value (not shown).

Since the August model consists of eight terms, more than any other model, it deserves a brief discussion. We sought to have the most parsimonious model possible. Therefore, a model consisting of only three terms first was considered, containing both persistence predictors and the u wind component in the 1000-700 hPa layer. This simple model 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 model, we increased 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, we could evaluate the performance of the separate monthly models against the full warm season model derived in the previous section.
.

Table 6 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 6 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 6. 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.

	Model Forecast		Statistic/	Model
Observed	Yes	No	Forecast	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%

5. CROSS VALIDATION PROCEDURES

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, we employed a cross-validation procedure.

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, we excluded data from 1989 and re-derived the BLR model using the remaining thirteen years of data. During the re-derivation, the entire process described in Section 3 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. Next, data from 1990 were excluded, and the model was re-derived 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 Table 5.

If the original models (Table 5) 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. Figure 5 graphs these statistics by month for eastern Miami-Dade County. Since no lightning was observed during May 1992 in eastern Miami-Dade County, none of the statistics could be computed. This was the only month when this occurred.

a) May

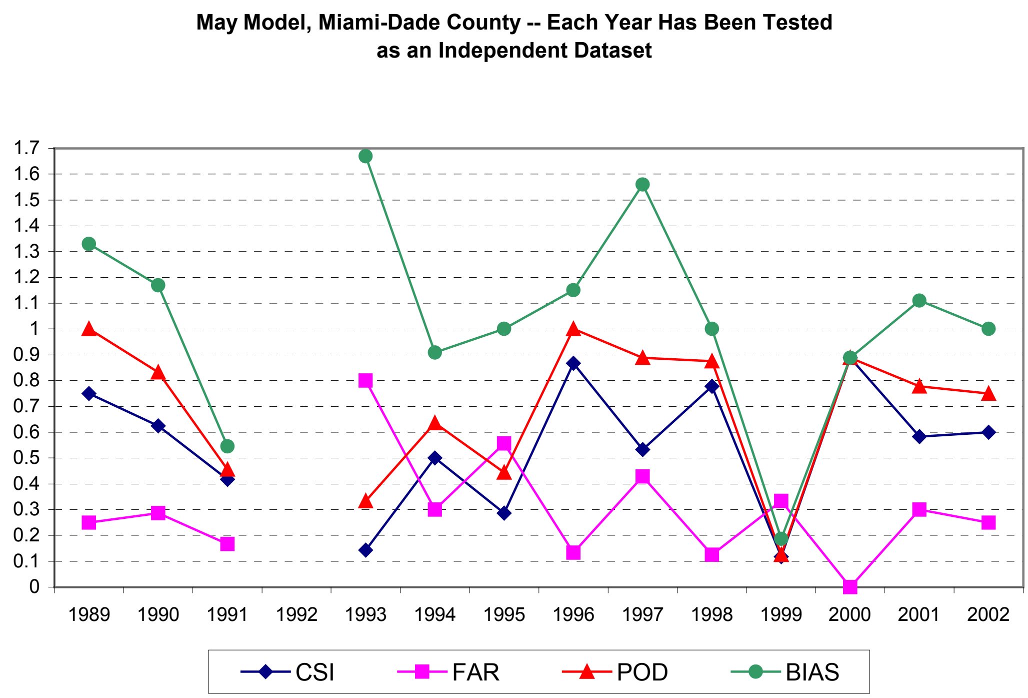
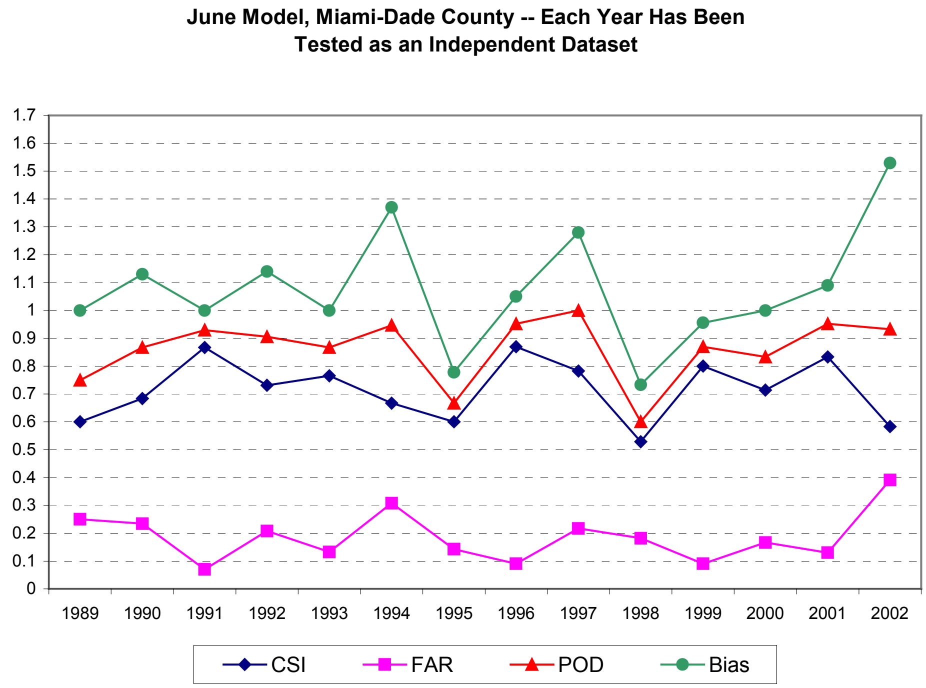


Figure 5. Plots of evaluation statistics for each cross-validation run for each of the monthly models in eastern Miami-Dade County.

b) June



c) July

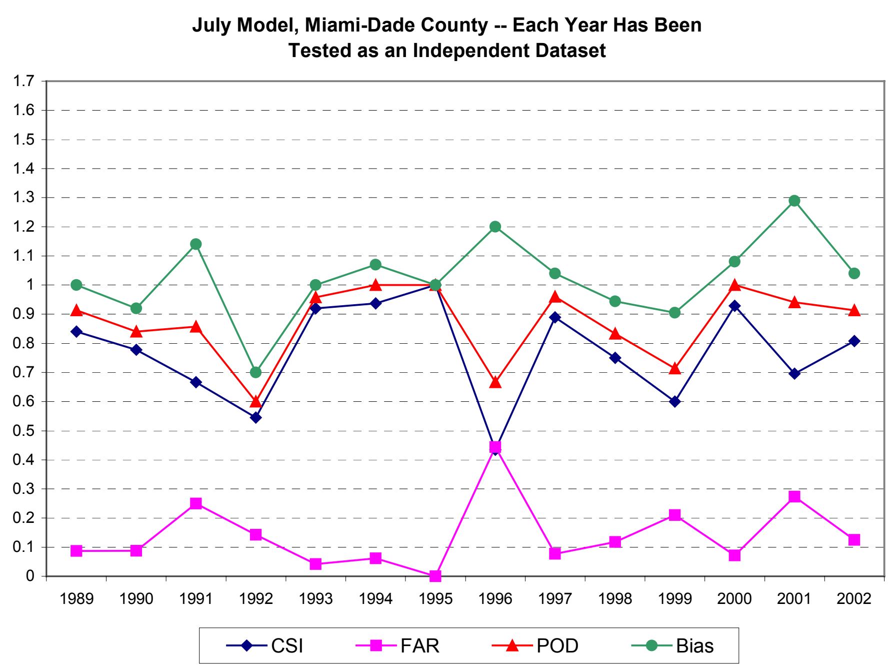
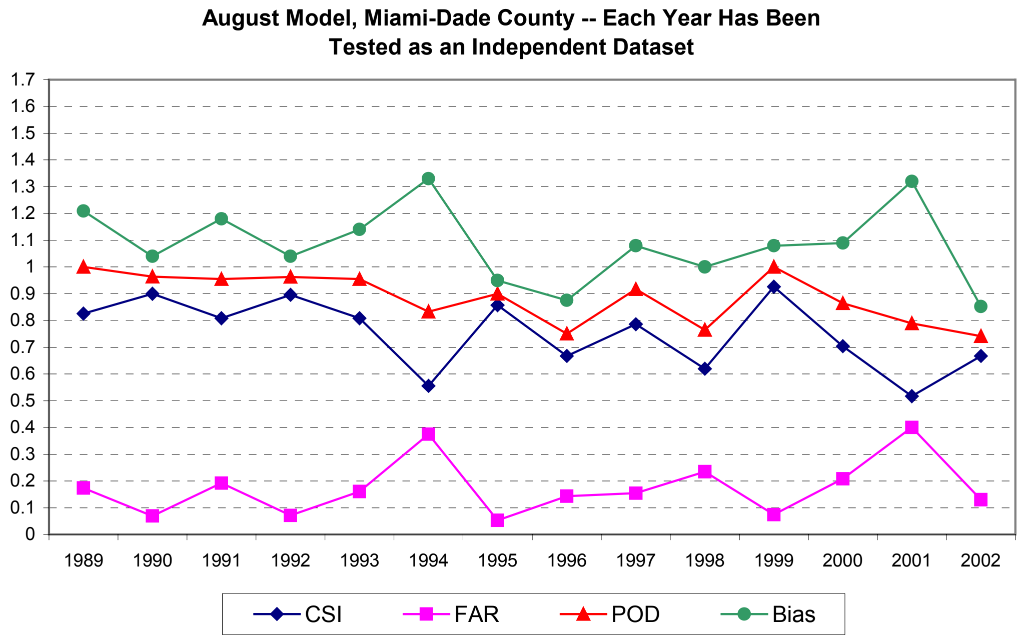


Figure 5. Continued

d) August



e) September

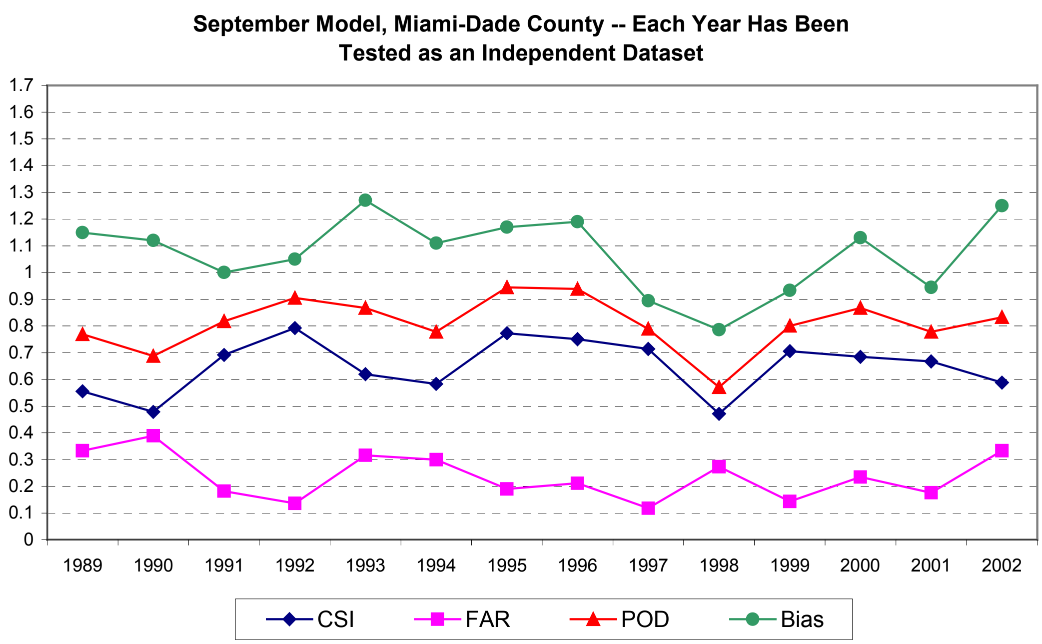


Figure 5. Continued

Figure 5 reveals considerable variation in the range of the statistics between months and between years (i.e., the independent tests). Within each monthly model, some years exhibit good forecasting skill while other years are worse. Table 7 contains contingency tables for the combination of the fourteen different cross-validated models for each month in eastern Miami-Dade County. The worst forecast statistics (i.e., CSI, FAR, and POD) occur during May, while the best results are obtained during July and August. This is supported by Fig. 5 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. 5a), 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. 5a). On the other hand, during July 1995 (Fig. 5c) 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 (i.e., CSI = 1, FAR = 0, POD = 1, and Bias = 1).

Table 7. 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%

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%

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. 5a).

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 8 gives the 2 x 2 contingency tables and evaluation statistics for eastern Miami-Dade County. These statistics are based on the independent testing using the cross-validation procedure discussed above. Thus, they constitute the final evaluation of model performance. CSI is approximately 71%, while FAR is 19%. Approximately two-thirds of the days without lightning and 85% of days with lightning are correctly forecast. Finally, more than 75% of all days are correctly forecast. As expected, these results are slightly worse than those cited earlier, based on the dependent data (Table 6).

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

	Model Forecast		Statistic/	Model
Observed	Yes	No	Forecast	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%

6. COMPARISON WITH PERSISTENCE

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) will yield reasonably accurate results. This assumption is supported by Table 9, which gives the 2 x 2 contingency table, evaluation statistics, and the percent of correctly forecast days using persistence alone for eastern Miami-Dade County. Comparing Tables 8 and 9, it is clear that the guidance developed in this study improves upon persistence alone. The CSI improves from 64% (Table 9) with persistence alone to 71% (Table 8) using the current models. The FAR improves from 22% (Table 9) to 19% (Table 8). The percent of correctly forecast days in eastern Miami-Dade County improves from 72% (Table 9) to 78% (Table 8). Thus, the guidance model yields a definite improvement over persistence. This is an important finding.

7. ANALYSIS OF INCORRECTLY FORECAST DAYS

It is informative to investigate days when the guidance model produced incorrect forecasts. The goal is to better understand the model's strengths and weaknesses so that forecasters can apply this information when interpreting model results during daily operational implementation. Two types of incorrect forecasts ("bust" days) are 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 but does not occur (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 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 9. 2 x 2 contingency table, evaluation statistics, and percent of correctly forecast days for Miami-Dade County using only persistence.

	Model Forecast		Statistic/	Model
Observed	Yes	No	Forecast	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%

Table 10 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.

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. However, 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 10. 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 to the guidance algorithm.

Table 10. 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

Table 11 is analogous to Table 10 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 11. 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

We 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. 6a and 6b are busted 0 days, while Figures 6c and 6d are busted 1 days. The two busted 0 days provide a stark contrast in conditions. On July 5, 1990 (Fig. 6a) 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. 6b). 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. 6b), the six observed flashes occurred only within the extreme western portion of the area of interest.

Figs. 6c and 6d are examples of busted 1 days. On May 16, 1999 (Fig. 6c) 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. 6d) 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. 6a) and June 17, 2002 (Fig. 6d) were worse busts than their counterparts in Fig. 6. On June 17th (Fig. 6d) the model forecast lightning in eastern Miami-Dade County but there was no lightning close to the 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.

a) 7/5/90 Busted 0

b) 9/22/93 Busted 0

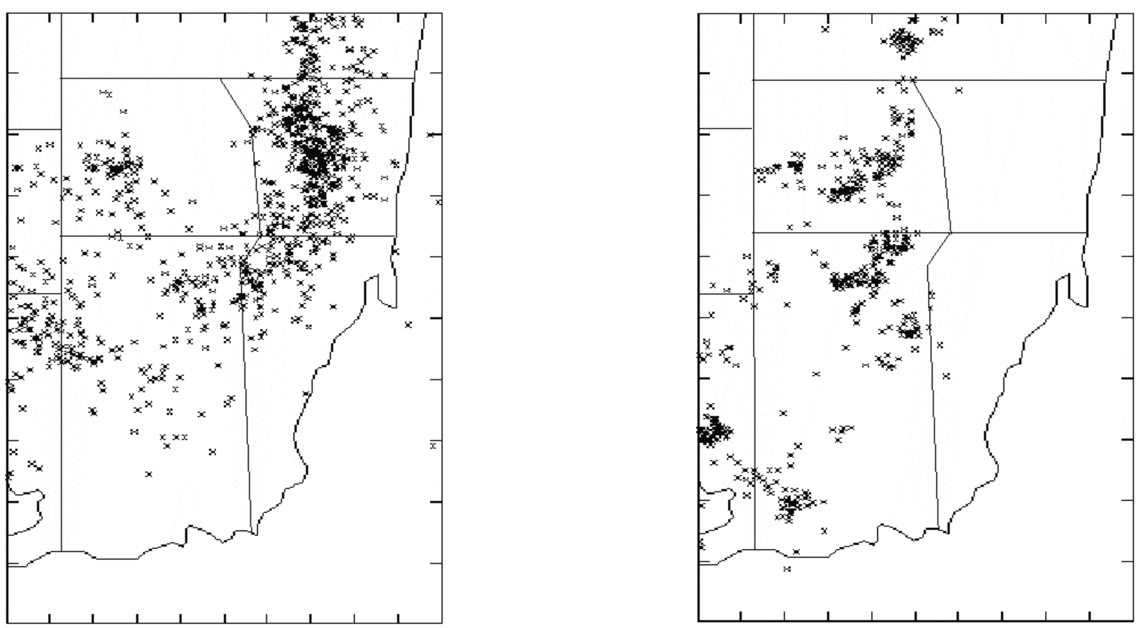


Figure 6. Cumulative noon to midnight plots of lightning flashes for (a) July 5, 1990, (b) September 22, 1993, (c) May 16, 1999, and (d) June 17, 2002. Panels (a) and (b) are busted 0 forecasts. Panels (c) and (d) are busted 1 forecasts. All bust days are based on the area of interest in eastern Miami-Dade County.

c) 5/16/99 Busted 1

d) 6/17/02 Busted 1

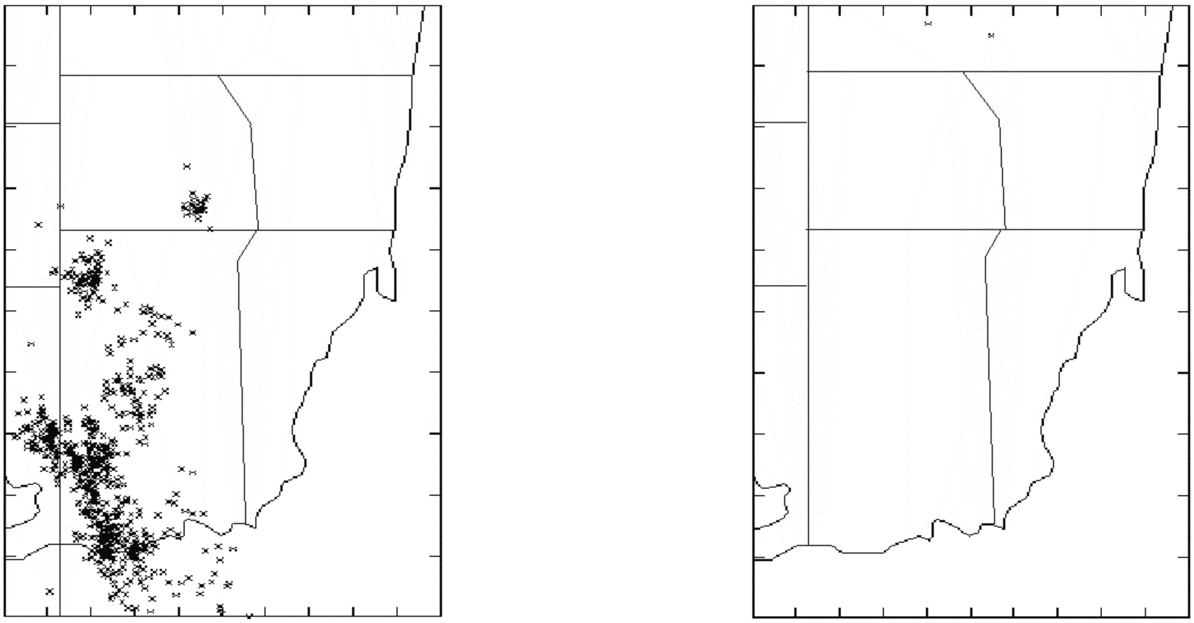


Figure 6. Continued

The last example of a busted forecast occurred on May 4, 1998 (Fig. 7). 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 suggested that no lightning would occur on this day. The probability of observing at least one flash was 0.28 with a threshold of 0.47 for determining the “yes” forecast. However, Fig. 7a-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.

8. RESULTS FOR SUMMER 2004

The lightning guidance models described in the previous sections were run daily during Summer 2004 to assess their effectiveness on a totally independent data set. Results were sent to FP&L officials by noon of each day for their consideration. Statistics for June-August 2004 are presented in Table 12. Results for May 2004 are not shown since the month was very dry, containing only two days with observed lightning within the study area. Conversely, September 2004 was highly anomalous since Central and South Florida were devastated by several major hurricanes. Those highly disturbed conditions violated the basic assumption behind our model guidance—that the sea breeze is the major forcing mechanism leading to convective development.

The guidance models performed well during the 2004 period (Table 12). Results for May were slightly worse than those derived from cross validation (Table 7). However, during July and August 2004, the results were somewhat better than from cross validation. Considering the combined three month period (Table 12-d), the model correctly forecast 90% of the lightning days, but only 44% of the non-lightning days, for an overall correct score of 82%. The CSI was 80%, the FAR was 12%, and the POD was 90%.

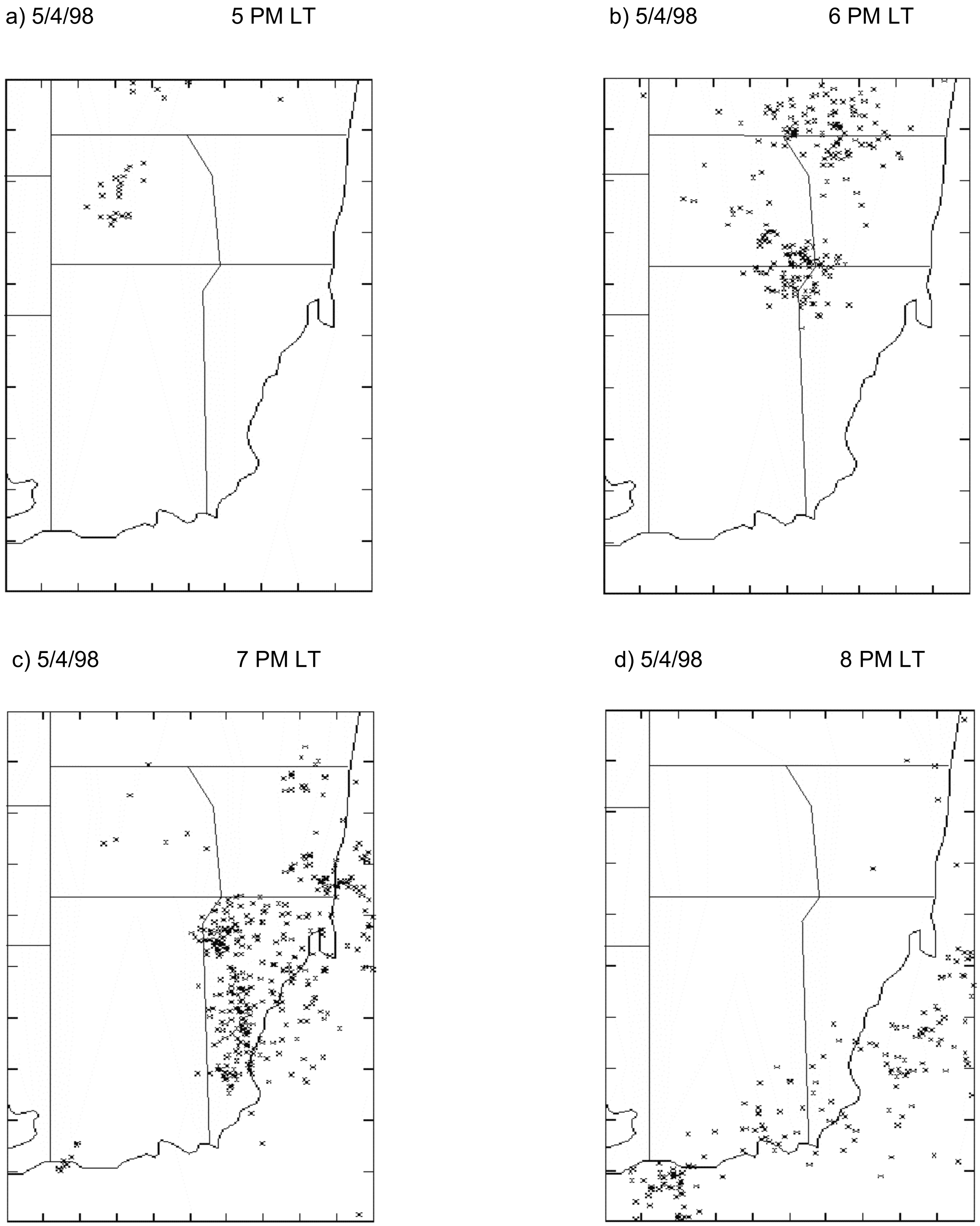


Figure 7. Hourly lightning plots for the hour starting at (a) 5 PM LT, (b) 6 PM LT, (c) 7 PM LT, and (d) 8 PM LT on May 4, 1998 as a cold front was moving southward into Florida.

Table 12. 2 x 2 contingency table showing results for Miami-Dade County during June-August 2004. Evaluation statistics, and percent correctly forecast days are included.

a) June Model

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model Performance
Yes	15	4	CSI	65.2%
			FAR	21.1%
			POD	78.9%
No	4	4	Bias	1.00
			No lightning	50.0%
			Lightning days	78.9%
			All days	70.4%

b) July Model

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model Performance
Yes	24	2	CSI	82.8%
			FAR	11.1%
			POD	92.3%
No	3	2	Bias	1.04
			No lightning	40.0%
			Lightning days	92.3%
			All days	83.9%

c) August Model

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model Performance
Yes	26	1	CSI	89.7%
			FAR	7.1%
			POD	96.3%
No	2	1	Bias	1.04
			No lightning	33.3%
			Lightning days	96.3%
			All days	90.0%

d) Combined June-August Results

Observed	Model Forecast Yes	No	Statistic/ Forecast	Model Performance
Yes	63	7	CSI	80.2%
			FAR	12.2%
			POD	90.3%
No	9	7	Bias	1.03
			No lightning	43.8%
			Lightning days	90.3%
			All days	81.8%

9. 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 forecast 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. Only results for Miami-Dade County were presented in this paper.

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. 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. Two persistence variables (the previous day's afternoon activity and the current day's morning activity) also were included as potential predictors. Binary logistic regression (BLR) was used to relate noon to midnight lightning activity to the pool of potential predictors.

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 final model, each of the fourteen years was removed one year at a time, and a "new" model was re-derived from the remaining thirteen years of 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.

The models were run during the warm season of 2004 to evaluate their performance on a totally independent data set. Results showed that the model skill during Summer 2004 was comparable to that obtained from the cross validated data used to develop the models.

It is encouraging that such favorable results have been achieved by using only a single morning radiosonde sounding together with persistence. Since the guidance products do improve over persistence alone, the models will serve as useful guidance for FP&L. By incorporating mesoscale model output to capture spatial and temporal changes in meteorological conditions that sometimes occur after 1200 UTC, it is believed that the forecast skill of future guidance equations can be improved further. That research currently is underway.

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