Project MUSE®
Scholarly journals online

A Method for Estimating Pan Evaporation for Inland and Coastal Regions of the Southeastern U.S.

WILLIAM H. COOKE III, KATARZYNA GRALA, CHARLES L. WAX
Department of Geosciences, Mississippi State University

Regression models that estimate daily pan evaporation for inland and coastal regions of Southeastern U.S. were developed using observations of wind speed, solar radiation, minimum relative humidity, and maximum temperature. These weather elements are collected in numerous locations where measured pan evaporation records are not available, allowing an estimation of pan evaporation across large regions with higher point pattern density than is available using pan evaporation sites only. Sixteen models were developed and tested. An innovative model selection metric was developed, employing R square, Pearson's correlation coefficient, average difference between estimated and measured evaporation, root mean-squared error, and mean absolute error. Models selected included two validated for use in inland environments and one validated for use in coastal environments.

KEY WORDS: climate model, pan evaporation, water balance, weather

INTRODUCTION

Daily pan evaporation is an important factor in landscape-level water budget calculations. It is also an important dynamic variable that should be considered when modeling fire potential, making crop management decisions, and in other projects focusing on water management and conservation. Acquisition of pan evaporation data suitable for water budget calculations is a challenge because the data must be easily accessible, spatially well distributed, and collected regularly over extended time periods.

The predominant pan evaporation measurement method utilizes a 48-inch diameter pan that sits above ground, known as the Class-A evaporation pan. Exclusive adoption of these pans by the National Weather Service is considered to be the first attempt to unify evaporation data collection throughout the U.S. (Jones 1992). Evaporation pans and associated automated measurement devices are rather expensive and are located at a limited number of weather stations around the U.S. and the world. For example, in Mississippi evaporation pans are maintained at only nine locations and most of them are in the northern two-thirds of the state (Bell 2004).

In addition to the relative scarcity of collected pan evaporation data, the accuracy of pan evaporation estimates has been questioned by numerous researchers (Bruton et al. 2000a; Sumner and Jacobs 2005). For example, precipitation events interfere with accurate measurement of pan evaporation (Lindsey and Farnsworth 1997). Generally, the pan evaporation record must be corrected for any additions of rainfall to the pan. However, errors in

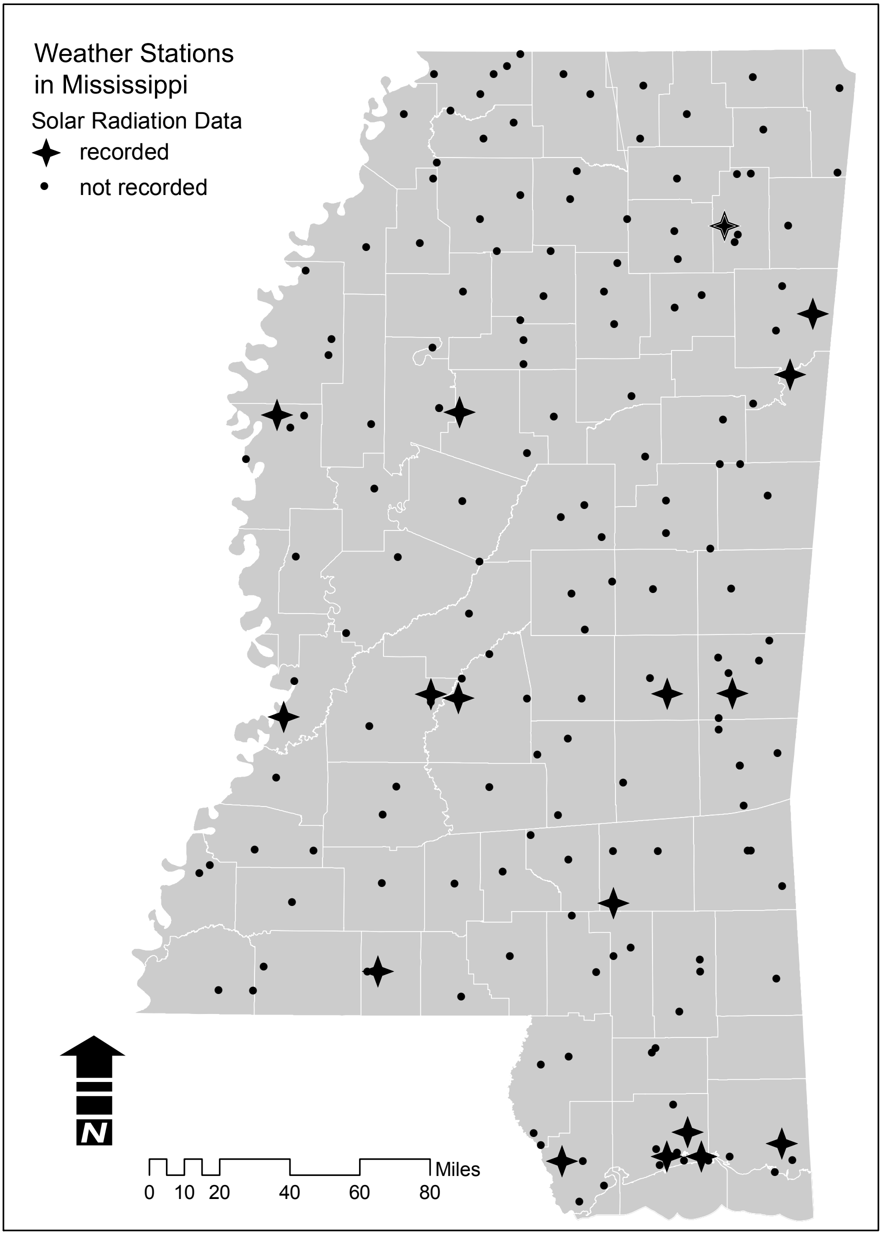


Figure 1. Map showing weather stations in Mississippi; stars indicate stations recording solar radiation.

rainfall measurement and inconsistency in rainfall capture add error to recorded pan evaporation data (Sumner and Jacobs 2005). Finally, pan evaporation records are often acquired seasonally, with more comprehensive data available in the summer months and during the growing season.

All these obstacles make good-quality daily evaporation data difficult to obtain at many locations across large regions. In order to fill this void, this study presents a method for estimating pan evaporation based on data from existing pan evaporation stations in Mississippi, Alabama, and Louisiana and other meteorological data that are readily available at numerous weather stations.

Many attempts have been made to develop empirical formulas that estimate potential evaporation and evapotranspiration. Thornthwaite (1942) stated, "The lack of a direct measure of losses by evaporation from natural surfaces has led to the development of many empirical formulas for expressing the effectiveness of evaporation." Historical formulas commonly used in the southeastern U.S. include Thornthwaite (1948), Blaney and Criddle (1950), Penman (1956), and Pote and Wax (1986). These formulas have varying degrees of complexity and some were developed for application at specific locations. Often, data necessary for formula calculations are simply not available. For example, the Penman equation, a commonly used estimator of evaporation from the free surface of a body of water (Penman 1948; Penman 1963; Shuttleworth 1993), requires measurement of net radiation, soil heat flux, air temperature, relative humidity, wind speed, vapor pressure, and other environmental variables (Sumner and Jacobs 2005). A complete set of these input elements at locations that are spatially well distributed over large geographic regions is rare. For example, Figure 1 shows the spatial distribution of weather stations in Mississippi with only 17 of 178 stations recording solar radiation.

With recent increased availability of hourly and daily meteorological data from a variety of observing networks, estimators of evaporation have been developed using "proxy" weather elements as inputs. Hanson (1989) used daily solar radiation, daily mean temperature, and wind run (daily average wind speed) to model class-A daily pan evaporation for southwest Idaho. Cahoon et al. (1991) used measured pan evaporation data to determine local coefficients for existing equations that estimate pan evaporation using data from 13 stations in the mid-south and southeastern U.S. Bruton et al. (2000b) developed artificial neural network (ANN) models to estimate daily pan evaporation using multiple measured weather variables as inputs. The ANN model included 14 different meteorological variables and resulted in r^2 of 0.717. ANN models were also developed by Terzi and Keskin (2005) to estimate evaporation for the Lake District in western Turkey using air temperature, water temperature, solar radiation, air pressure, wind speed, and relative humidity. Another recent method employed fuzzy logic models to estimate daily pan evaporation using air and water temperatures, sunshine hours, solar radiation, air pressures, relative humidity, and wind speed for Lake Egirdir in Turkey (Keskin et al. 2004).

While it is certainly possible to estimate pan evaporation at selected locations using any of these methods, the goal of this study is to estimate pan evaporation regionally, using numerous locations that meet four basic criteria: 1) data are readily available and easy to obtain; 2) data are spatially well distributed; 3) estimates are sensitive to regional climatic heterogeneity; and 4) data are easily implemented for interpolation of statistical surfaces within Geographic Information Systems (GIS).

While the simplest evaporation estimation methods are temperature based (Thornthwaite and Mather 1955), and these data are widely available across the Southeastern U.S., the dependence of more sophisticated evaporation estimation methods (Penman 1948) require net radiation, which is available at only approximately 10 percent of stations in Mississippi. Evaporation estimates derived from data obtained at the coarse resolution represented by stations that record net radiation are less likely to be sensitive to regional climatic variations. This coarse point resolution is less likely to capture environmental variability when data are interpolated using GIS (Hijmans et al. 2005). Consequently, none of the existing methods for calculating pan evaporation met all four criteria.

Pan evaporation estimates derived from a dense network of sites can play an important role in assessment of water budgets in areas frequently impacted by hurricanes. Environmental assessments will benefit from water budget calculations as they relate to fire hazard, water resource management, and rates of oxidation that affect vegetation decomposition and plant communities' recovery. Hurricanes frequently impact Gulf Coast weather station data streams (Graumann et al. 2005). In the aftermath of Hurricane Katrina, many of the existing weather observation sites were impacted, indicating the need for a spatially dense network of stations that measure pan evaporation or record data necessary for estimating pan evaporation.

MATERIALS AND METHODS

Study Area and Preliminary Analysis

The study focuses on areas of the southern region of the U.S. in the states of Louisiana, Mississippi, and Alabama that maintain pan evaporation stations (Figure 2). As shown in Figure 2, there are only a few stations in the region that record pan evaporation, and current daily pan evaporation data at these locations are not consistently available.

Because of the deficiency of actual daily pan evaporation data, substituting calculated daily historic average values for actual daily pan evaporation is an option for water budget applications and is currently used as an input in various models (Cothren et al. 2001; Ruley and Rusch 2004; Enciso and Wiedenfeld 2005). One drawback of using historic averages is the removal of short-term variability in evaporation via the averaging process.

In general, measured pan evaporation in the region was found to have total daily values ranging from a minimum of 2.54 mm to maximum of 7.62 mm over the period of the study (July–October). Therefore the overall mean values for historic and actual evaporation should be similar within this small range most of the time. Furthermore, evaporation is more spatially homogeneous than precipitation, so daily variability across the region is likely to be small (Bell 2004). The daily variation of precipitation is much more controlling

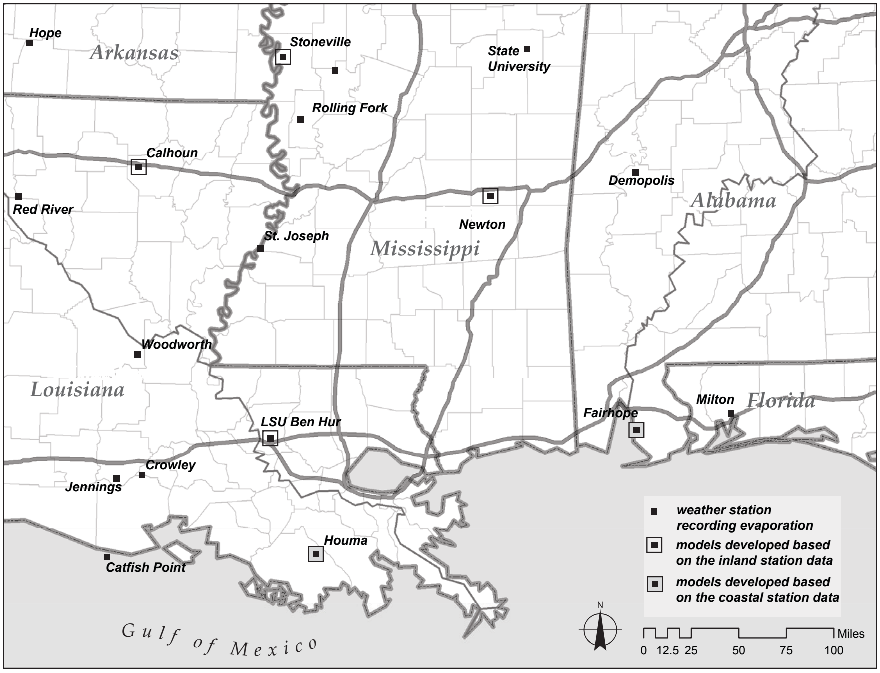
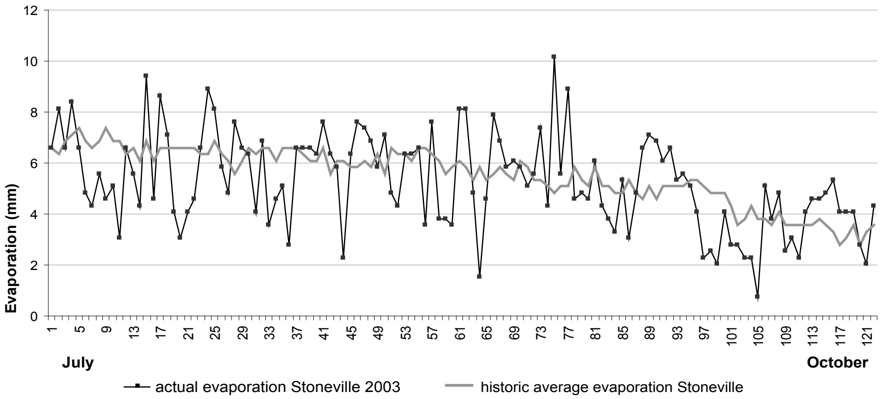


Figure 2. Map showing weather stations recording evaporation and locations for which evaporation models were created.

in a daily moisture assessment. According to Bell (2004), the average daily precipitation for July 15th in the southern region is 4.57 mm, and pan evaporation has an almost identical average of 4.82 mm on that same day. However, the standard deviation of the precipitation data is 9.39 mm, while the pan evaporation data have a standard deviation of only 1.52 mm. Precipitation is therefore over 6 times as variable on a given day as evaporation in the region. Nevertheless, the sparse coverage of pan evaporation stations makes it difficult to characterize small differences in evaporation, particularly during summer months when convective rainfall events can modify the microclimate and local water budgets. In addition, accurate characterization of the evaporation gradient and decay of coastal influences on evaporation is difficult to measure due to the limited number of pan evaporation stations that exist in both coastal and inland environments.

An initial comparison of actual measured and historic average records indicated numerous drawbacks. Figure 3 illustrates a comparison of the 2003 measured actual pan evaporation with the long-term historic average daily pan evaporation for an inland station (Stoneville, MS) and a coastal station (Houma, LA). The graph clearly illustrates that the derived average daily pan evaporation does not conform well to actual measured pan evaporation. It is apparent that the average pan



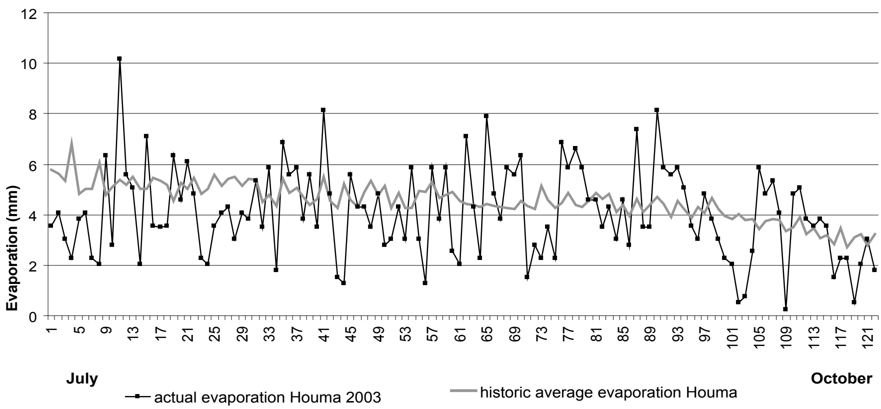


Figure 3. Comparison of actual measured (Stoneville 2003; Houma 2003) and historic average evaporation data (Stoneville 1977–2002; Houma 1977–2002).

evaporation fluctuates slightly around the mean value of 5 mm with a small decline at the end of the study period, while the actual measured pan evaporation is much more variable. Range and variance values are considerably different for historic average and actual pan evaporation, signifying the fact that average pan evaporation depicts neither low nor high pan evaporation values accurately (Table 1). This indicates that the average daily pan evaporation record poorly expresses the specific variability of actual daily pan evaporation as dictated by fluctuating weather conditions.

Estimation error can be significant when daily differences between historic averages and actual measured pan evaporation are cumulatively summed over a number of days. The cumulative differences are important criteria for identification of continuous dry periods that are associated with drought conditions.

Table 1. Comparison between actual and historic pan evaporation for coastal and inland stations (mm).

	Stoneville, MS		Houma, LA	
	Actual 2003	Historic	Actual 2003	Historic
Mean	5.25	5.52	4.06	4.54
Minimum	0.76	2.79	0.25	2.71
Maximum	10.16	7.37	10.16	6.80
Range	9.40	4.57	9.90	4.09
Std. Deviation	1.85	1.11	1.80	0.72
Variance	3.44	1.25	3.23	0.52

Finally, an important aspect of the pan evaporation estimation technique adopted in this research is the recognition of differences in pan evaporation rates between inland and coastal environments. In general, pan evaporation rates are higher inland than in the coastal zone (Wax and Pote 1996). This fact was initially confirmed by visual comparisons of means for actual and historic pan evaporation at Houma, Louisiana (coastal) and Stoneville, Mississippi (inland) stations (Table 1). In addition, vapor pressure deficits were calculated for Gulfport (coastal) and Tupelo (inland), MS, using 3:00 pm observation each July 15 from 1994 to 2006. The average vapor pressure deficit at the coastal location was 14.42 mb, and at the inland location was 21.60 mb, indicating that evaporation potential at coastal location is only about 67 percent of that at the inland location.

Methods

The study was carried out in three major stages. The first stage focused on the development of simple, representative regression models, capable of estimating daily pan evaporation for inland and coastal environments in the study region. The second stage included the selection of the 'best inland model' (BIM) and the 'best coastal model' (BCM). The third stage involved resolving whether modeled pan evaporation rates are more accurate than available historic averages. These three major stages are illustrated in more detail in the methodology flowchart (Figure 4). Finally, each selected "best" model was validated through an assessment of these models' accuracy when compared to actual measured pan evaporation.

Stage One: Model Development. Weather data used to develop and validate regression models were obtained from observation networks of the National Weather Service, the Louisiana Agriclimatic Information Center (http://www.lsuagcenter.com/weather/), the Mississippi State University Extension Service (http://ext.msstate.edu/anr/drec/), and the University of Utah 'Meso West' weather service (http://www.met.utah.edu/mesowest/). Data collected included daily observations of pan evaporation (inches), maximum temperature (Fahrenheit degrees), minimum relative humidity (percent), solar radiation (langleys), and wind speed

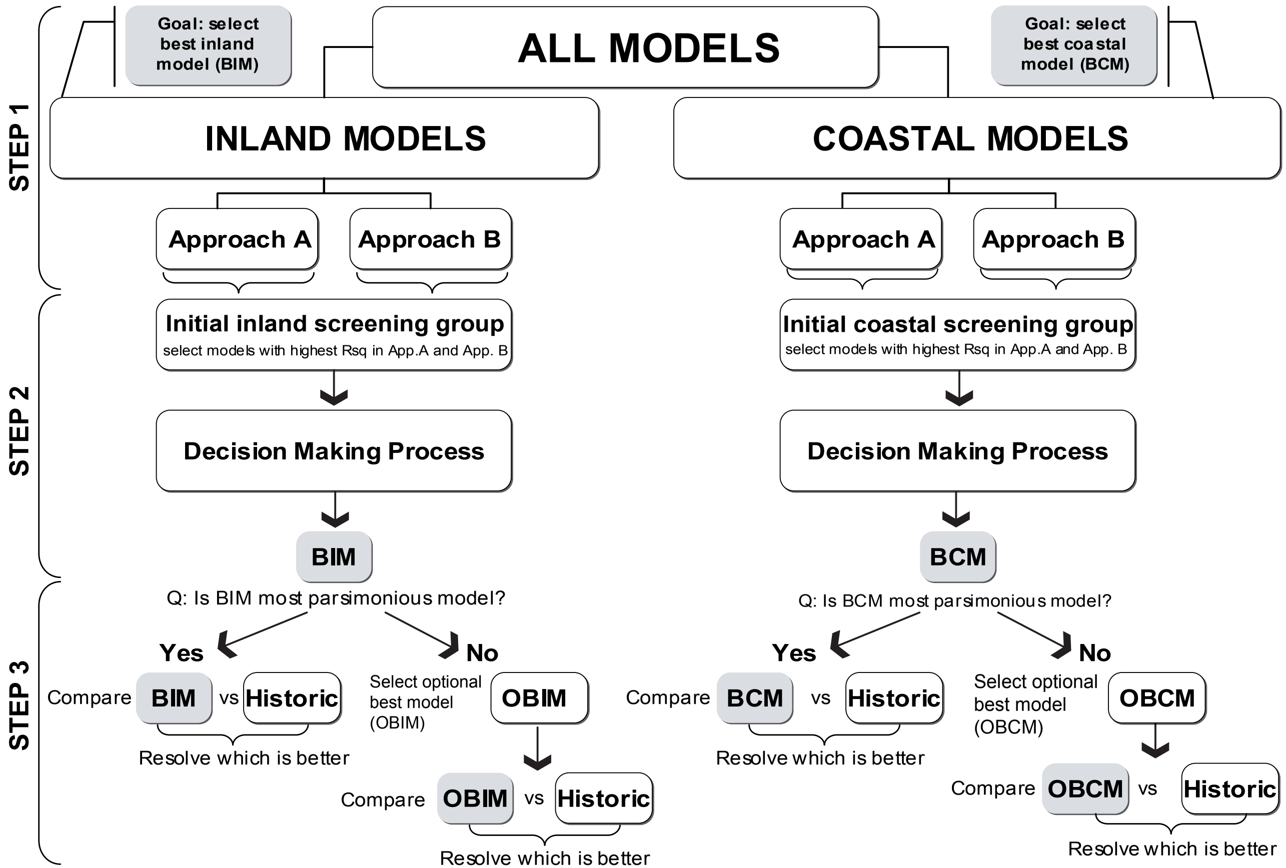


Figure 4. Stages of model development and selection.

(miles per hour) from July 1 through October 31 for 2002, 2003, and 2004. Data from these three years provided the most complete record of combined meteorological data and pan evaporation data available at the most sites in the region. The relatively short analysis period (July–October) was selected to represent periods of highest evaporative demand in the region. During the months from July through October irrigation demands, crop yield, fire hazard, and ground water depletion/replenishment are impacted most severely and this is the period when estimating pan evaporation is most useful. While it would have been advantageous to include data from a longer time period, thereby increasing the number of observations used to fit the models, these data were considered representative of the normal range of conditions expected in the southern gulf region. According to the National Climatic Data Center Mississippi, Alabama, and Louisiana experienced a range of conditions, slightly below or above normal in terms of temperature and precipitation between 2002 and 2004. The limited availability of complete data also re-emphasizes the problem addressed by this study; lack of a consistently available source of evaporation data.

The accuracy of pan evaporation estimation depends greatly on the quality of measured pan evaporation data as well as the statistical properties of the other meteorological variables used to develop models. Even though the data acquired for the modeling period were the most spatially and serially complete, numerous problems were still evident. For this reason, the data obtained were carefully examined before the modeling was attempted. The major data drawback observed was that serially complete and homogeneous data were often not available—weather stations in the study area do not consistently observe and archive similar elements. Also, daily pan evaporation records did not correspond with other measured meteorological variables due to difference in time of observation. Finally, numerous daily observations were either missing or incorrect.

Therefore, prior to the analysis, three data quality and variable properties issues were addressed. First, daily pan evaporation records were modified to correspond with other measured meteorological variables that differ in time of observation. For example, observations for temperature and minimum relative humidity usually occur the day before morning observations, not at the time of observation. Total solar radiation is summed over the period from midnight to midnight on the same day that maximum temperature, minimum relative humidity, and maximum wind speed are recorded. Also, evaporation is recorded at some sites over a 24-hour period from midnight to midnight on the day following the day of record for the other meteorological observations. Consequently, prior to modeling, pan evaporation measurements at these sites were shifted back by one day to insure consistency of observation period. Second, missing or obviously incorrect meteorological values (these not fitting within the range of normals) were identified and replaced with an average value calculated using records for the preceding and the following day. In general, less than 4 percent of pan evaporation data required editing (Wax and Pote 1996). Third, four major assumptions of multiple linear regression were tested. These assumptions included normal distribution of variables, assumption of a linear relationship between independent and dependent variables, variable measurement reliability, and assumption of homoscedasticity.

Using the corrected data sets, multiple linear regression (MLR) was used to develop evaporation models. Daily pan evaporation data for the years 2002 and 2004 were used as the dependent variable; 2003 data were used later for validation. Maximum air temperature, minimum relative humidity, and solar radiation for the corresponding years were used as independent variables. An 'all possible combinations' approach was used to assess variable relationships and variable interactions' contribution to pan evaporation predictions. From this approach, the optimal variable set was chosen on the basis of evaluation of adjusted R-square (RSQ) values and tests of assumptions for MLR. R-square is the coefficient of determination and is the proportion of variability in a data set that is accounted for by a statistical model. Adjusted RSQ is a modification of RSQ that adjusts for the number of explanatory terms in a model. Unlike RSQ, the adjusted RSQ increases only if the new term improves the model more than would be expected by chance. For, the optimal set of variables, outlier analysis was performed by assessing the values of the standardized residuals (e.g. values > 2.0 and values < -2.0) and using Cook's D outliers were removed from the data sets (Fox 1997).

Models were created for Louisiana stations (Ben Hur, Houma, Calhoun), Mississippi stations (Stoneville, Newton), and one Alabama station (Fairhope). These weather stations measure and archive daily pan evaporation that could be used for model fitting and cross-validation (Figure 2). These locations were also selected on the basis of weather data availability for the years 2002, 2003, and 2004, and to satisfy the spatial requirements for selectively estimating pan evaporation for both inland and coastal environments. Inland models were developed using Stoneville, Newton, Calhoun, and Ben Hur data, while coastal models were developed with Houma and Fairhope data.

Many weather stations only record a subset of the potential independent variables (Figure 1). In order to select the optimal combination of weather elements for both inland and coastal locations, two different "modeling approaches" were used. Approach A incorporated the optimal variable set selected on the basis of evaluation of adjusted RSQ. Approach B integrated only the two most commonly available elements as input variables—minimum relative humidity and maximum air temperature. Solar radiation was not included in the approach B models, since it is available only at a limited number of weather stations. Approach B requires the fewest number of variables, and models developed under this approach were compared with actual pan evaporation values to assess potential model under-fitting problem. A slightly under-fit model can be implemented at many locations that would not be used due an incomplete suite of explanatory variables.

Stage Two: Model Selection. Ultimately, the best inland and coastal models were selected to estimate pan evaporation for these two distinctively different environments. Modeled and historic evaporation rates were then tested against the actual 2003 measured pan evaporation in order to determine the most accurate method of estimating evaporation.

Table 2. Model performance measures, description, ranking, weights, and standardized values.

Performance measure	Description	Rank	Weight	Ideal value	Standardized value
RSQ	Explains the variance in the data. The higher the RSQ value the more versatile the model is.	1	0.5	1	RSQ
CC	Indicates trend agreement (model conformity) between actual and modeled evaporation. The higher the CC value the better model conforms with actual. Can have trend agreement, but different value range.	2	0.125	1	CC
AVG	Overcomes CC limitations of range value.	2	0.125	0	1-|AVG*10|
RMSE	Accepted standard model accuracy evaluation measure.	2	0.125	0	1-RMSE*10
MAE	Accepted standard model accuracy evaluation measure.	2	0.125	0	1-MAE*10

The second stage of the research involved the selection of the best inland model (BIM) and the best coastal model (BCM). Inland and coastal models were evaluated separately. Each potential model was evaluated by comparing the prediction results against actual pan evaporation measured in 2003. Inland models were evaluated against Stoneville 2003 pan evaporation data and coastal models were evaluated against Houma 2003 pan evaporation data. Both of these datasets were the most complete in the analyzed period.

The following performance measures were used to compare the predicted and measured pan evaporation. RSQ was used to measure how well each linear model under consideration fit the weather data to the measured pan evaporation data. Pearson's correlation coefficient (CC), average difference (AVG), root mean-squared error (RMSE), and mean absolute error (MAE) were used to measure how modeled predictions departed from the actual pan evaporation measurements. These performance measures were employed for all models in the initial inland and coastal screening groups and were used to compare each model to a hypothetical "perfect" model described with the following attributes: RSQ value = 1, RMSE and MAE values = 0, CC value = 1, and AVG value = 0. The performance measures were ordinated and weighted according to their perceived significance, and actual values were standardized (scaled between 0–1) to represent uniform value ranges as shown in Table 2. The perfect model for stage two

(PM2) can therefore be expressed with the following formula:

$$PM2 = 0.5\ (RSQ) + 0.125\ (CC) + 0.125\ (1\text{-}10|AVG|) + 0.125\ (1\text{-}10\ RMSE) + 0.125\ (1\text{-}10\ MAE) = 1 \quad (1)$$

The model RSQ that describes how well the predicted 'line' fits the data was considered the most important measure and assigned a weight of 0.5. The other measures (CC, |AVG|, RMSE, and MAE) measure the departure of the predicted pan evaporation values from the actual pan evaporation values. Individually, each 'departure' measure is assigned a weight of 0.125 and collectively are weighted equally (sum = 0.5) to RSQ. The total score for the perfect model is equal to 1, and scores for other models were calculated according to the same formula as shown above using the standardized measurement values (Table 2). The calculated scores were then compared, and models with highest scores were selected from inland and coastal screening groups respectively.

Stage Three: Model Comparison with Historic Average. The third stage evaluated whether modeled pan evaporation rates more accurately track actual pan evaporation than available historic averages. While it is expected that modeled daily pan evaporation rates should track actual daily pan evaporation rates better than historic averages, historic pan evaporation is currently used as an input in various models (Cothren et al. 2001; Ruley and Rusch 2004; Enciso and Wiedenfeld 2005).

Values for the performance measures from the best-selected models and performance measures calculated for the historic averages were used to validate the premise that modeled pan evaporation values are better estimates of daily evaporation than historic average values for pan evaporation. Determination of the hypothetical "perfect" model for stage three (PM3) did not include RSQ since historic data are actual pan evaporation measurements and not estimated by fitting a model to the data. All performance measures were weighted equally in stage three, and the following formula was used:

$$PM3 = 0.25\ (CC) + 0.25\ (1\text{-}10|AVG|) + 0.25\ (1\text{-}10\ RMSE) + 0.25\ (1\text{-}10\ MAE) = 1 \quad (2)$$

The estimation method (modeled or average historic values) that yielded the highest overall score and therefore the most accurate substitute for measured pan evaporation was selected.

Model Validation

The final phase of the study examined how closely model-estimated pan evaporation from the 'best' coastal and inland models approximated actual measured pan evaporation. To accomplish this, actual 2003 measured pan evaporation was compared with estimated pan evaporation derived from the 'best' models for validation. Modeling output units are inches and were later converted to millimeters for the purpose of this study.

RESULTS AND DISCUSSION

Stage One: Model Development

Multiple linear regression is a parametric analysis technique that was used to predict pan evaporation. While several assumptions that should be considered when using MLR were evaluated, it should be noted that moderate violations of parametric assumptions have little or no effect on substantive conclusions in most instances (Cohen 1969).

The Kolmogorov-Smirnov test (K-S) enables comparison of each independent variables' distribution with the theoretical normal distribution. The test statistic (Smirnov Z) is computed from the largest difference (in absolute value) between the independent variables distribution and the normal distribution. This test assesses whether the observations of the independent variable could reasonably have come from the normal distribution. Solar radiation showed evidence of a negatively skewed distribution and the K-S test resulted in confirmation of a non-normal distribution. Transforming solar radiation using a standard variable normalization technique (Equation 3) for the Ben Hur 2002 and 2004 data sets resulted in increases of approximately 0.01 in adjusted RSQ value and consequently, the decision was made not to transform solar radiation. K-S variable normality tests for maximum temperature and minimum relative humidity revealed that both variables were normally distributed with one exception; the Newton 2004 dataset where all three variables (maximum temperature, minimum relative humidity, and solar radiation) were determined to be non-normal.

$$newvalue = \sqrt{((\max value + 1) - SR_i)} \tag{3}$$

An Analysis of Variance (ANOVA) test of linearity was performed for all pairwise combinations of pan evaporation and each independent variable. The hypothesis that the relationship between each variable and pan evaporation was linear was not rejected for all datasets at all locations for solar radiation, maximum temperature, and minimum relative humidity. The hypothesis was rejected for wind speed for all datasets at all locations. The lack of a linear relationship between wind speed and pan evaporation is further evidenced by examination of the simple scatter plots. The scatterplot for the Newton 2004 data set (Figure 5) is typical of the relationship between wind speed and pan evaporation for all datasets at all locations.

A useful coefficient for assessing internal consistency of a variable's measurement scale is Cronbach's alpha (Cronbach 1951). Cronbach's alpha was estimated for standardized variable scales. Nunnally (1978) has indicated values of 0.7 and above are an acceptable level of reliability. Measurement scale reliability was generally high (near or above the 0.7 threshold) for solar radiation, maximum temperature, and minimum relative humidity for all datasets at all locations with a few exceptions. Cronbach's alpha values were below 0.7 for maximum temperature at Ben Hur 2004 (0.54), and Calhoun 2004 (0.61). Cronbach's alpha values were below 0.7 for minimum relative humidity at Fairhope 2004 (0.49) and Houma 2004 (0.64).

Homoscedasticity assumes that the variance of errors is the same across all levels of the Independent Variable (IV). Examination of plots of the standardized residuals (y-axis) by the regression standardized predicted value (x-axis) indicated that, in general, residuals were randomly scattered around 0 providing a relatively even distribution and no evidence of heteroscedasticity. Plots for solar radiation deviated slightly from a random scattering, probably due in part to the negative skew of the variable.

Multicollinearity in regression models

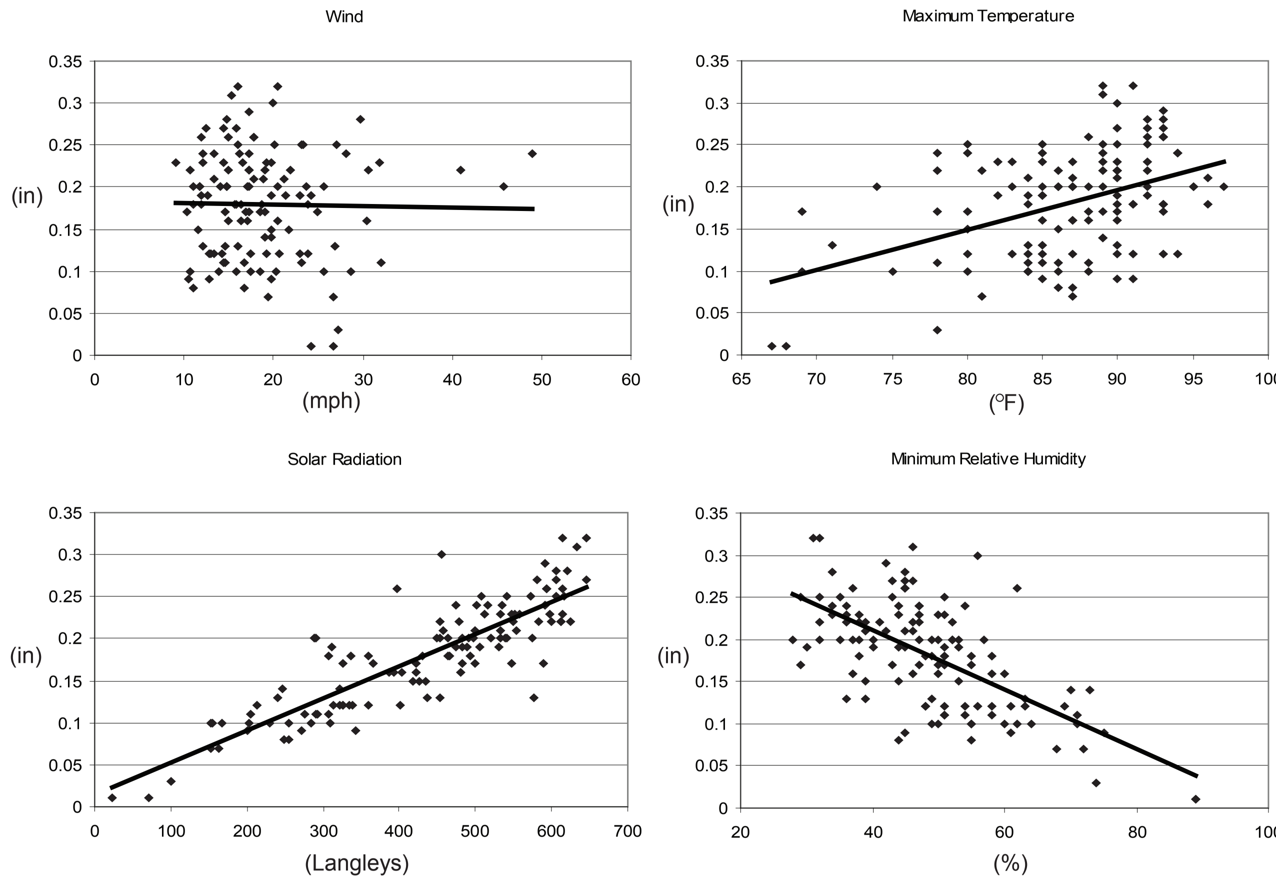


Figure 5. Newton, MS. 2004 scatterplots for wind speed (mph-miles per hour), max temperature (°F - Fahrenheit), solar radiation (Langleys), and minimum relative humidity (% - percentage) plotted against actual pan evaporation.

Table 3. Simple Linear Regression (SLR) R square (RSQ) values and all possible regression combinations for Multiple Linear Regression (MLR) with adjusted R square (ARSQ) listed.

Model name/ model combinations		Ben Hur 2002	Ben Hur 2004	Calhoun 2004	Newton 2004	Stoneville 2002	Stoneville 2004	Fairhope 2002	Fairhope 2004	Houma 2004
Temp	RSQ	0.432	0.135	0.191	0.187	0.582	0.225	0.438	0.509	0.257
RH	RSQ	0.486	0.471	0.166	0.418	0.499	0.261	0.403	0.158	0.265
SRad	RSQ	0.694	0.627	0.588	0.747	0.655	0.544	No data	No data	0.301
Wind	RSQ	0.003	0.025	0.005	0.000	0.000	0.004	No data	No data	0.034
Temp/RH	ARSQ	0.616	0.486	0.372	0.515	0.675	0.421	0.561	0.589	0.376
Temp/Srad	ARSQ	0.697	0.627	0.618	0.752	0.698	0.540	No data	No data	0.402
RH/SRad	ARSQ	0.686	0.625	0.587	0.744	0.685	0.588	No data	No data	0.310
Temp/RH/SRad	ARSQ	0.695	0.627	0.615	0.750	0.723	0.595	No data	No data	0.408

is evidenced by a high level of intercorrelation among independent variables. The Variance Inflation Factor (VIF) is often used as a measure of the degree multicollinearity of a particular independent variable. As a rule of thumb, a VIF greater than 4.0 indicates when multicollinearity of a particular independent variable becomes problematic (Belsley 1991). For this study, VIF values for all full models (maximum temperature, minimum relative humidity, and solar radiation) were calculated and evaluated. All VIF values for independent variables were less than 4.0 with one exception, Ben Hur 2002. For this dataset the VIF for solar radiation was 5.69. On the basis of these results, multicollinearity was not determined to be a noteworthy problem.

Four independent variables were initially considered as independent variables for modeling pan evaporation. The hypothesis that the relationship between wind speed and pan evaporation was linear was rejected for every location and every year. These results indicate that, for these stations and these data, wind speed has a random effect on pan evaporation. This finding coupled with low RSQ for wind speed (e.g. 0.034) led to the conclusion that wind speed should be eliminated as a potential independent variable.

Using the three remaining independent variables, the “all possible combinations” analyses enabled assessment of relationships between each variable and variable combinations with pan evaporation (Table 3). Solar radiation and maximum air temperature showed strong positive relationships with evaporation. The analyses also confirmed an inverse relationship between minimum relative humidity and measured pan evaporation.

Solar radiation had the highest RSQ among all variables and this result is consistent with previous studies (Sumner and Jacobs 2005). Marginal improvements were noted when maximum temperature or minimum relative humidity were combined with solar radiation. In general, highest adjusted RSQ values were obtained when all three variables were included. On the basis of these analyses, it was determined that when all three vari-

Table 4. MLR results of inland and coastal models (the highlighted models were further evaluated).

Station	App.	Year	Rsq	B	Temp.	Rel. hum.	Solar rad.
Stoneville	A	2002	0.730	−0.0412798	0.002754	−0.001408	0.000273
Stoneville	B	2002	0.681	−0.058047	0.004637	−0.002334	not used
Stoneville	A	2004	0.606	0.326	0.00147516	−0.0014418	0.00028
Stoneville	B	2004	0.475	−0.139	0.006	−0.003	not used
Newton	A	2004	0.756	−0.07912	0.001104	0.00007	0.000369
Newton	B	2004	0.523	0.02788	0.003586	−0.003236	not used
Calhoun	A	2004	0.625	−0.163	0.002	0.000069	0.00038
Calhoun	B	2004	0.383	−0.167	0.005	−0.003	not used
Ben Hur	A	2002	0.707	−0.113179	0.001965	−0.000436	0.000324
Ben Hur	B	2002	0.626	−0.117528	0.005147	−0.002723	not used
Ben Hur	A	2004	0.637	−0.0175437	0.001219	−0.006585	0.000348
Ben Hur	B	2004	0.495	0.181	0.0024353	−0.0038	not used
Fairhope	B	2002	0.569	−0.128	0.005	−0.002	not used
Fairhope	B	2004	0.587	−0.51	0.009	−0.002	not used
Houma	A	2004	0.427	−0.402	0.007	−0.001	0.00023
Houma	B	2004	0.389	−0.284	0.007	−0.003	no data

ables are available, they should be used for modeling pan evaporation. However, when solar radiation is not available, combining temperature and relative humidity resulted in adjusted RSQ values that indicate both variables should be included in the model. These results led to the development of tests of model efficacy for two different modeling approaches, with solar radiation (Approach A) and without solar radiation (Approach B). Once variable combinations were determined, model comparisons were made using RSQ rather than adjusted RSQ, since adjusted RSQ was only used to account for artificial inflation of potential variable combinations during the variable selection process.

Stage Two: Model Selection

Inland and coastal models were initially screened by RSQ values to reduce the total number of models for evaluation (Table 4). From all inland models, the following six were selected for further evaluation: Stoneville approach A 2002, Stoneville approach B 2002, Newton approach A 2004, Newton approach B 2004, Ben Hur approach A, and Ben Hur approach B 2002. From this group the best inland model (BIM) was selected using equation 1. Performance measures calculated for these models are shown in Table 5. The initial screening process for coastal models resulted in the selection of three models: Fairhope approach B 2002, Fairhope ap-

Table 5. Decision-making calculations carried out to select best inland model (BIM); weights (wght.) and standardized values (st.val.) are multiplied and then summed together (formula 1); values of performance measures are highlighted.

Inland Models	RSQ value		CC		AVG		RMSE		MAE		Total score
	wght.	st.val.	wght.	st.val.	wght.	st.val.	wght.	st.val.	wght.	st.val.	Σ
Stoneville	0.73		0.62		−0.057		0.082		0.070		
app. A 2002	0.5	0.73	0.125	0.62	0.125	0.44	0.125	0.18	0.125	0.30	**0.558**
Stoneville	0.68		0.45		−0.036		0.076		0.063		
app. B 2002	0.5	0.68	0.125	0.45	0.125	0.65	0.125	0.24	0.125	0.37	**0.554**
Newton app.	0.76		0.66		0.014		0.056		0.041		
A 2004	05	0.76	0.125	0.66	0.125	0.86	0.125	0.44	0.125	0.59	**0.699**
Newton app.	0.52		0.42		0.011		0.071		0.055		
B 2004	0.5	0.52	0.125	0.42	0.125	0.89	0.125	0.29	0.125	0.45	**0.516**
Ben Hur	0.71		0.65		−0.017		0.058		0.043		
app. A 2002	0.5	0.71	0.125	0.65	0.125	0.83	0.125	0.42	0.125	0.57	**0.664**
Ben Hur	0.63		0.45		−0.003		0.069		0.056		
app. B 2002	0.5	0.63	0.125	0.45	0.125	0.97	0.125	0.31	0.125	0.44	**0.586**

proach B 2004, and Houma approach A 2004 model. Performance measures determined for these models are shown in Table 6. These measures, highlighted in Tables 5 and 6, were used directly in the process of selecting the best inland models (BIM) and best coastal (BCM) models.

The best inland and coastal models were selected based on performance measure metrics using formula 1. In general, the best model was specified by a combination of the following characteristics: high RSQ and correlation coefficient values, low values of error measures, and a low value of average difference. Tables 5 and 6 show the decision-making calculations and total scores computed for selected inland and coastal models.

The highest total score among inland models was achieved by Newton approach A 2004 model (0.699). The optional model (Ben Hur approach B 2002, 0.586 score) was selected for use at locations where solar radiation data are not available. Therefore, the following models are recommended for use at inland sites:

With solar radiation: $BIM = -0.07912 + 0.0011(maxT) + 0.00007(minRH) + 0.00037(SR)$

Without solar radiation:

$OBIM = -0.117528 + 0.00515(maxT) - 0.00272(minRH)$

The highest total score among evaluated coastal models was achieved by Fairhope approach B 2004 model (0.579). An optional coastal model was not selected since solar radiation was not available at any sites with pan evaporation records. For use in all coastal sites (no solar radiation data required), the following model is recommended:

$BCM = -0.51 + 0.009(maxT) - 0.002(minRH)$

Table 6. Decision-making calculations carried out to select best coastal model (BCM); weights (wght.) and standardized values (st.val.) are multiplied and then summed together (formula 1); values of performance measures are highlighted.

Coastal Models	Performance measures: RSQ value		CC		AVG		RMSE		MAE		Total
	wght.	st.val.	wght.	st.val.	wght.	st.val.	wght.	st.val.	wght.	st.val.	Σ
Fairhope	0.57		0.54		−0.042		0.074		0.063		
app. B 2002	0.5	0.57	0.125	0.54	0.125	0.585	0.125	0.26	0.125	0.37	**0.504**
Fairhope	0.59		0.50		−0.009		0.067		0.055		
app. B 2004	0.5	0.59	0.125	0.50	0.125	0.991	0.125	0.33	0.125	0.45	**0.579**
Houma app.	0.43		0.59		−0.071		0.094		0.082		
A 2004	0.5	0.43	0.125	0.59	0.125	0.295	0.125	0.06	0.125	0.18	**0.356**

Stage Three: Model Comparison with Historic Average

The two best inland models and one best coastal model were evaluated to determine whether modeled pan evaporation rates more accurately track actual pan evaporation than available historic averages. Table 7 shows performance measures for best-selected models versus historic average records as well as final scores calculated using formula 2. The results indicate that for the best inland and coastal models, modeled estimates represent actual pan evaporation better than historic averages. These calculations indicated that for all "best" models, predicted pan evaporation is superior to historic averages.

Model Validation

Each "best" model was compared to actual 2003-measured pan evaporation for validation purposes. Figure 6A illustrates validation results of the best inland model (created based on Newton 2004 data using approach A) by plotting model results against pan evaporation measured at Stoneville in 2003. This inland model utilizes three variables: maximum air temperature, minimum relative humidity, and solar radiation. If solar radiation data are unavailable, the Ben Hur 2004 approach B model, which utilizes only maximum air temperature and minimum relative humidity, should be used. Figure 6B shows the validation results of this optional inland model. The best coastal model was created based on Fairhope 2004 data using approach B. This model uses maximum air temperature and minimum relative humidity data only. Figure 6C illustrates validation results of the model results plotted against pan evaporation measured at Houma in 2003. Overall, mean pan evaporation decreases during the fall months when daily temperature begins to decline. Since these models were developed for periods when temperature is high and precipitation is low, it is possible (when temperature is low and minimum relative humidity is high) to estimate a negative value for pan evaporation. This situation occurred twice in the selected coastal model (Figure 6C). To prevent this occurrence, negative model estimation

Table 7. Evaluation calculations carried out to compare results of the best-selected models and historic averages; weights (wght.) and standardized values (st.val.) are multiplied and then summed together (formula 2); values of performance measures are highlighted.

Selected models/ Historic	Performance measures: CC		AVG		RMSE		MAE		Total Σ
	wght.	st.val.	wght.	st.val.	wght.	st.val.	wght.	st.val.	
Newton	0.66		0.014		0.056		0.041		
app. B 2004	0.25	0.66	0.25	0.86	0.25	0.44	0.25	0.59	**0.638**
Ben Hur	0.45		−0.003		0.069		0.056		
app. C 2002	0.25	0.45	0.25	0.97	0.25	0.31	0.25	0.44	**0.542**
Historic	0.42		−0.0105		0.068		0.054		
inland	0.25	0.42	0.25	0.895	0.25	0.32	0.25	0.46	**0.524**
Fairhope	0.50		−0.009		0.067		0.055		
app. C 2004	0.25	0.50	0.25	0.991	0.25	0.33	0.25	0.45	**0.567**
Historic	0.20		−0.0187		0.074		0.062		
coastal	0.25	0.2	0.25	0.813	0.25	0.26	0.25	0.38	**0.414**

was constrained to equal zero, since negative evaporation is not possible.

Validation of model results confirmed initial expectations that pan evaporation rates predicted using selected models are superior to historic pan evaporation estimates. Modeled pan evaporation for both inland and coastal models reflected actual changes in daily weather conditions, while historic averages did not (compare Figure 3 to Figures 6A, B, and C).

CONCLUSIONS

The goal of this research was to estimate daily pan evaporation using readily available data at numerous locations for the southeastern region of the U.S. where such data are not routinely and consistently available. Although there is a large body of literature that indicates wind is correlated to pan evaporation, these results indicate a poor relationship for these datasets. This unexpected result might be explained by the fact that in these southern regions, wind is often accompanied by high humidity and rainfall.

The multiple regression models developed for this study combined actual measured solar radiation, maximum temperature, and minimum relative humidity to estimate pan evaporation. Pan evaporation estimations based on the best-selected models proved superior to available historic average pan evaporation data. As the number of input variables was reduced, the accuracy of the models was also reduced. However, inclusion of all variables as inputs significantly lowered the number of stations that have the potential for such estimation due to data availability. It was concluded that minimum relative humidity and maximum air temperature are the minimum required variables necessary to create satisfactory models. Even though reducing the number of input variables decreased model accuracy, it increased the number of stations

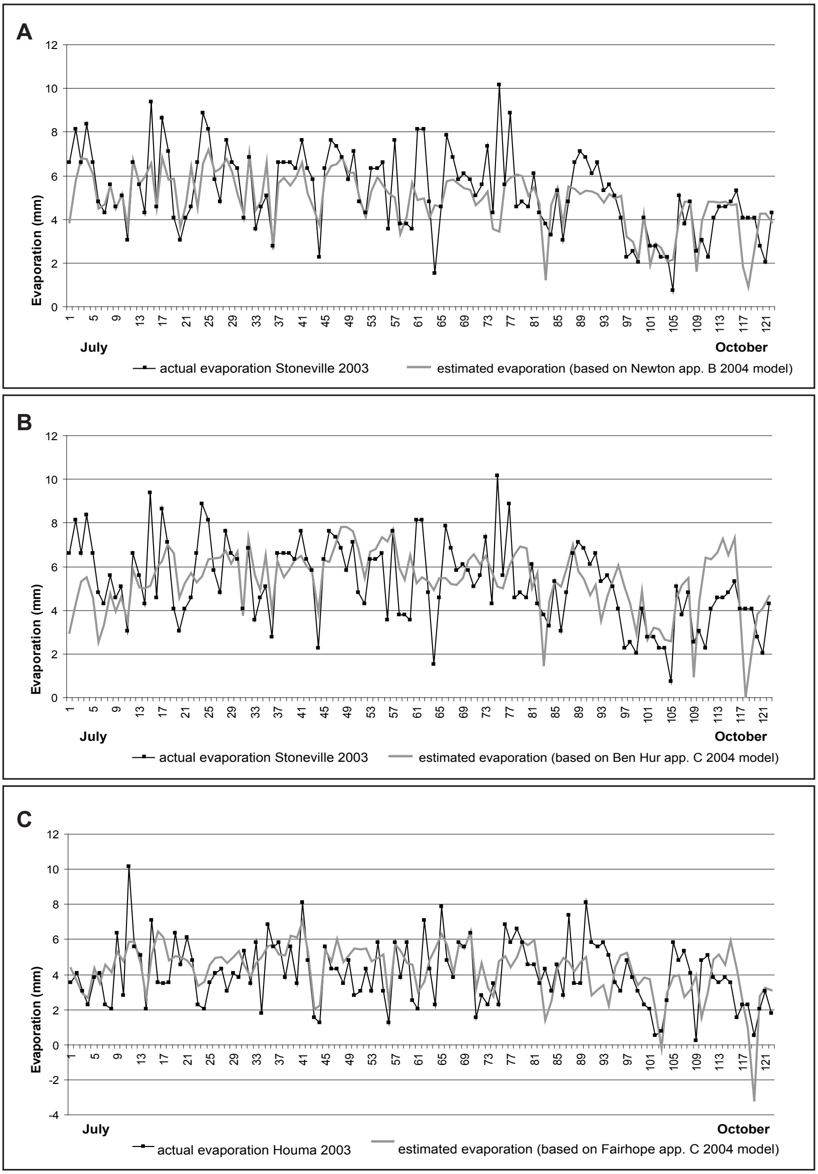


Figure 6. A. Comparison of actual measured (Stoneville 2003) evaporation and evaporation estimated for Stoneville 2003 using best inland model (Newton approach B 2004); B. Comparison chart of actual measured evaporation (Stoneville 2003) and evaporation estimated for Stoneville 2003 using optional best inland model (Ben Hur approach C 2004); C. Comparison chart of actual measured evaporation (Houma 2003) and evaporation estimated for Houma 2003 using best coastal model (Fairhope approach C 2004).

with weather data available for modeling pan evaporation. Maintaining a greater number of stations is considered of critical importance to the overall project goal, as it assures a large number of points are available for interpolation of evaporation across the entire region—important for the creation of dynamic water budget layers useful in GIS-based water budget applications. Regional climatic heterogeneity associated with coastal and inland processes are better characterized with these 'best' models. It is likely that with the increased number of stations available for interpolation, climatic heterogeneity due to landscape characteristics will be better measured.

The best pan evaporation prediction models were selected using a combination of different performance characteristics, as neither RSQ values nor error measures alone were determined to be satisfactory indicators of the best model. The decision-making process, as validated by comparison of predicted and actual pan evaporation rates, produced three easily-applied models—two inland and one coastal—that appear to provide reliable and useable daily pan evaporation estimates. Model choice depends on whether or not solar radiation data are available for use at an inland site. These selected best models are simple to use since they require minimal inputs and they are easy to update on a daily basis. Thus the models offer the opportunity to effectively estimate daily pan evaporation at multiple locations over a broad region using the best available input data.

The number of metrics employed in creating, testing, and validating selected models yields results that provide rigorous and credible estimates of pan evaporation. Use of these models results in pan evaporation estimates comparable to measured pan evaporation. In fact, it is possible that the predicted pan evaporation rates may produce a more useful regional assessment of evaporation because they are relatively free from recording errors or missing values, issues commonly found in measured and recorded pan evaporation data.

There are several model limitations and potential improvements that should be considered. The performance of coastal models could be improved by expanding the analysis region to include more weather stations that record solar radiation and develop more Approach A models for coastal environments. Also, it is not known how well the models will perform over time. The models should be continuously validated over time with actual pan evaporation data where available. Available records of actual pan evaporation that extend beyond the July–October time period should be compared with model-based estimates of pan evaporation to assess the precision of pan evaporation estimates that are extrapolated beyond the model development time period.

Evaporation derived from the Penman method could be used for further evaluation of the selected models' performance. The basic relationships between these variables and pan evaporation are not expected to undergo significant change over time; however, the coefficients could change in response to changing climatic conditions. Consequently, models should be recalibrated as more quality pan evaporation and weather station data becomes available. Additional analyses are planned that examine vapor pressure deficit as a possible substitute for minimum relative humidity in the models and for determining the extent of coastal influences over the inland environment. Analyses are also planned to compare predicted values at higher spatial densities with interpolated values from pan evaporation stations only.

Results of this study indicate that evaporation can be predicted at numerous locations with a few easy-to-obtain variables. This method of estimating missing or spatially deficient daily pan evaporation data should prove useful in regional GIS-based applications where a well-distributed pattern of stations used to estimate evaporation helps characterize the influence of convective precipitation events and coastal processes on evaporation.

REFERENCES

Bell, C.L. 2004. *Synthesis of a serially complete and homogeneous evaporation data set for the Southeastern region of the United States.* Department of Geosciences, Mississippi State University.

Belsley, D.A. 1991. A guide to using the collinearity diagnostics. *Computer Science in Economics and Management* 4:33–50.

Blaney, H.F., and W.D. Criddle. 1950. *Determining water requirements in irrigated areas from climatological and irrigation data*. ed. USDA, 48. Washington, D.C.: U.S. Soil Conservation Service.

Bruton, J.M., G. Hoogenboom, and R.W. McClendon. 2000a. A comparison of automatically and manually collected pan evaporation data. *Transactions of the Asae* 43:1097–1101.

Bruton, J.M., R.W. McClendon, and G. Hoogenboom. 2000b. Estimating daily pan evaporation with artificial neural networks. *Transactions of the Asae* 43:491–496.

Cahoon, J.E., J.A. Ferguson, and T.A. Costello. 1991. Estimating evapotranspiration using limited meteorological observations. *Agricultural and Forest Meteorology* 55:181–190.

Cohen, J. 1969. *Statistical power analysis for the behavioral sciences*. New York: Academic Press.

Cothren, G.M., S. Chen, M. Rahman, and R. Malone. 2001. Hydrologic modeling of aquatic plant treatment systems polishing dairy lagoon effluents. *Journal of Environmental Science and Health Part a-Toxic/Hazardous Substances & Environmental Engineering* 36:1905–1917.

Cronbach, L.J. 1951. Coefficient alpha and the internal structure of tests. *Psychometrika* 16:297–334.

Enciso, J., and B. Wiedenfeld. 2005. Irrigation guidelines based on historical weather data in the Lower Rio Grande Valley of Texas. *Agricultural Water Management* 76:1–7.

Fox, J. 1997. *Applied regression analysis, linear models, and related methods*. Thousand Oaks, Calif.: Sage Publications.

Graumann, A., T. Houston, J.H. Lawrimore, D. Levinson, N. Lott, S. McCown, S. Stephens, and D. Wuerts. 2005. *Hurricane Katrina Climatological Perspective. Preliminary Report* 1-28. Asheville, NC NOAA's National Climatic Data Center.

Hanson, C.L. 1989. Prediction of Class A pan evaporation in southwest Idaho. *J. Irrig. Drain. Eng.* ASCE 115(2):166–171.

Hijmans, R.J., S.E. Cameron, J.L. Parra, P.G. Jones, and A. Jarvis. 2005. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* 25:1965–1978.

Jones, F.E. 1992. *Evaporation of water: with emphasis on applications and measurements* Chelsea, Michigan: Lewis Publishers.

Keskin, M.E., O. Terzi, and D. Taylan. 2004. Fuzzy logic model approaches to daily pan evaporation estimation in western Turkey.

Hydrological Sciences Journal-Journal Des Sciences Hydrologiques 49:1001–1010.

Lindsey, S.D., and R.K. Farnsworth.1997. Sources of solar radiation estimates and their effect on daily potential evaporation for use in streamflow modeling. *Journal of Hydrology* 201:348–366.

Nunnally, J.C. 1978. *Psychometric theory*. New York: McGraw-Hill.

Penman, H.L. 1948. Natural evaporation from open water, bare soil, and grass. In *Proc. Roy. Soc. London* 120–146.

——. 1956. Estimating Evapotranspiration. *Trans American Geophysical Union* 37:43–46.

——. 1963. Vegetation and hydrology. In *Tech. Comm.*, 125. Harpenden, England: Commonwealth Bureau of Soils.

Pote, J.W., and C.L. Wax. 1986. Climatological Aspects of Irrigation Design Criteria in Mississippi. In *Mississippi Agricultural and Forestry Experiment Station Technical Bulletin* Mississippi State University: Mississippi State, MS.

Ruley, J.E., and K.A. Rusch. 2004. Development of a simplified phosphorus management model for a shallow, subtropical, urban hypereutrophic lake. *Ecological Engineering* 22:77–98.

Shuttleworth, W.J. 1993. Evaporation. In *Handbook of Hydrology,* ed. D. R. Maidments. McGraw-Hill.

Sumner, D.M., and J.M. Jacobs. 2005. Utility of Penman-Monteith, Priestley-Taylor, reference evapotranspiration, and pan evaporation methods to estimate pasture evapotranspiration. *Journal of Hydrology* 308:81–104.

Terzi, O., and M.E. Keskin. 2005. Modeling of Daily Pan Evaporation. *Journal of Applied Sciences* 5:368–372.

Thornthwaite, C.W. 1942. *Measurement of evaporation from land and water surfaces*, Washington, D.C.: U.S. Dept. of Agriculture. 143 p.

——. 1948. *An approach toward a rational classification of climate*. New York: American Geographical Society.

Thornthwaite, C.W., and J.R. Mather.1955. The Water Balance. *Publications in Climatology* VIII (1):1–104.

Wax, C.L., and J.W. Pote. 1996. The influence of climate on design of systems for land application of wastewater. *Climate Research* 6:71–78.

WILLIAM H. COOKE III is an Assistant Professor in the Department of Geosciences and GeoResources Institute at Mississippi State University, Mississippi State, MS 39762. Email: whc5@geosci.msstate.edu. His research interests include remote sensing, GIS multicriteria analysis, fire potential modeling, and vector-borne diseases.

KATARZYNA GRALA is a Research Associate in the Department of Geosciences and GeoResources Institute at Mississippi State University, Mississippi State, MS 39762. Email: kgrala@geosci.msstate.edu. Her research interests include GIS multicriteria analysis, natural resources management, fire potential modeling, and vector-borne diseases.

CHARLES L. WAX is a State Climatologist and Professor of Geography in the Department of Geosciences at Mississippi State University, Mississippi State, MS 39762. Email: wax@geosci.msstate.edu. His research interests include climatology, meteorology, hydrology, and natural resources.