A Method for Regional Estimates of Evaporation for Use in GIS-Based Dynamic Forest Fire Potential Models

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ABSTRACT

Dynamic GIS-based spatial depictions of fire potential require daily measurements of precipitation and evaporation to characterize regional landscape moisture conditions. Regression models that estimate daily evaporation in the U.S. southern region 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 evaporation records are not available, allowing an estimation of evaporation across large regions. Sixteen models were developed and tested for use in both coastal and inland environments. 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 (Best Inland Model—BIM, and an Optional Best Inland Model—OBIM) and one validated for coastal environments (Best Coastal Model—BCM). The selected models are:

BIM=-0.07912+0.0011(maxT)+0.00007(minRH)+0.00037(SR)

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

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

Key words: climate model, evaporation, forest fire, 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. The widely used Keetch-Byram Drought Index (KBDI) is designed for assessing fire potential and is related to the flammability of organic material in the ground, yet the inputs (daily maximum temperature, daily total precipitation, and mean annual precipitation) do not directly account for losses of moisture due to evaporation (Janis, Johnson and Forthun 2002). By incorporating daily evaporation into fire potential models, more precise calculation of the dynamic water budget can be integrated into fire decision support systems. Spatially-explicit statistical surfaces derived from these precise water budget calculations can potentially provide decision information on a regional basis, allowing more effective allocation of personnel and equipment necessary for fire suppression activities.

Acquisition of evaporation data suitable for regional fire potential modeling is a challenge. Evaporation data must be easily accessible, spatially well distributed, and collected regularly over extended time periods. The predominant 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 located 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, Hoogenboom and McClendon 2000, 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 rainfall measurement and inconsistency in rainfall capture add error to recorded evaporation data (Sumner and Jacobs 2005). Finally, 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 a large region. In order to fill this void, regional estimates of evaporation are needed to produce spatial layers for use in Geographic Information Systems-based (GIS) analyses as a part of dynamic climate component in regional fire potential models. 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 are relatively complex or were developed for application at specific locations. For example, the Penman equation requires measurement of net radiation, soil heat flux, air temperature, relative humidity, wind speed, and other environmental variables (Sumner and Jacobs 2005). A complete set of these input elements that are spatially well distributed over large geographic regions is rarely available, which makes evaporation estimates based on the Penman method unfeasible for regional fire potential models.

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 to model class-A daily pan evaporation for southwest Idaho. Cahoon, Ferguson and Costello (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, McClendon and Hoogenboom (2000) 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 Rsq of 0.717. ANN models were developed also 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, Terzi and Taylan 2004).

Most of the previously cited attempts to estimate evaporation tend to be complex, requiring compound sets of input variables data and complicated calculations. Our goal is to obtain regionally-based evaporation estimates 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 within GIS-based models. Consequently, none of the existing methods for calculating evaporation meet all four criteria.

While numerous fire models have been developed in the U.S., efforts have generally been oriented towards the western U.S. (Pew and Larsen 2001, WhitlockShafer and Marlon 2003). The fire potential model referenced in this study is specifically designed to address distinctive conditions of the U.S. southeastern region. Although fire potential is generally regarded as lower in the eastern U.S., Mississippi has on average 3760 wildfires each year that require personnel and resources to extinguish (average number of wildfires calculated based on historic fire data acquired from Mississippi Forestry Commission). Eastern U.S. physical geography presents unique challenges to understanding the processes that result in patterns of fire occurrence. Potential process variables include climate, population density, landscape fragmentation, vegetation associations, and landforms. The referenced fire potential model for the U.S. southeastern region includes climate (assessment of water budget in the environment during the fire season), anthropogenic factors (ignition), vegetation (fuel hazard), and topography (modifies precipitation). Figure 1 illustrates the modeling variables and their interactions. The method for estimating the critical evaporation component for the model's dynamic water budget variable is the focus of this paper.

Daily water budget estimates are calculated by accumulating (summing) each day's precipitation minus evaporation (P-E) estimates and comparing these to long-term daily averages. Therefore, the water budget variable is an index that is calculated by measuring the daily departure of P-E from the historic P-E averages. While not a direct measure of fuel moisture, this index is representative of landscape moisture conditions critical for assessing fuel moisture in the various ‘hour’ fuels that exist in the state of Mississippi and the southeastern U.S. The spatial depiction of cumulative wet or dry landscape conditions, used in conjunction with vegetation, ignition, soil, and topography provide both a spatial and temporal view of patterns of fire potential.

Hurricane Katrina reduced billions of board feet of standing timber to ground clutter across the Gulf Coast. In the months and years following the event, this downed timber can potentially become a vast quantity of fuel for fires in the affected region. Availability of regional evaporation estimates resulting from this study can play an important role in any assessment of daily fuel moisture conditions. The water budget estimate can also support future efforts to model rates of climatically-driven oxidation processes that reduce fuels and aid in ecosystem recovery in the Hurricane Katrina impacted regions and throughout any area of the southeastern U.S. that is impacted by hurricanes.

MATERIALS AND METHODS

Study area and preliminary analysis

The study area consists of parts of the southern region of the U.S., focusing on the areas affected by Hurricane Katrina in the states of Louisiana, Mississippi and Alabama (Figure 2). As shown in Figure 2, there are only a few stations in the region that record evaporation, and current daily evaporation data at these locations are not consistently available.

Because of the deficiency of actual daily evaporation data, substituting calculated daily historic average values for actual daily evaporation was initially considered. In general, evaporation in the region was found to be a fairly constant element with most values occurring in an interval between 2.54 mm and 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 spatially homogeneous, so daily variability across the region should be small. The daily variation of precipitation is much more controlling in a daily moisture assessment. According to Bell (2004), the average daily precipitation for July 15th in the southern region is 4.572 mm, and evaporation had an almost identical average of 4.826 mm on that same day. However, the standard deviation of the precipitation data is 9.398 mm while the evaporation data have a standard deviation of only 1.524 mm. Precipitation is therefore over 6 times as variable on a given day as evaporation in the region.

An initial comparison of actual measured and historic average records indicated numerous drawbacks. Figure 3 illustrates a comparison of the 2003 measured actual evaporation with the long-term historic average daily evaporation for an inland station (Stoneville, MS) and a coastal station (Houma, LA). The graph clearly illustrates that the derived average daily evaporation does not conform well to actual measured evaporation. It is apparent that the average 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 evaporation is much more variable. Range and variance values are significantly different for average and actual evaporation, signifying the fact that average evaporation depicts neither low nor high evaporation values accurately (Table 1). This indicates that the average daily evaporation record poorly expresses the specific variability of actual daily evaporation as dictated by fluctuating weather conditions.

Estimation error can be significant when daily differences between historic averages and actual measured 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 increased fire potential.

Finally, it is recognized that differences in evaporation rates exist between inland and coastal environments. In general, evaporation rates are higher inland than in the coastal zone (Wax and Pote 1996). This fact, confirmed in preliminary findings (Table 1), was an important aspect of the evaporation modeling technique adopted in this research.

Methods

The study was carried out in three major stages. The first stage focused on the development of simple, representative models, capable of estimating daily 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 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 the actual measured evaporation.

Stage One: Model Development

Weather data used to develop and validate 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, maximum temperature, minimum relative humidity, solar radiation, and wind speed from July 1 through October 31 for 2002, 2003, and 2004. This period corresponds with the dry summer-fall season of increased fire potential in the region. In Mississippi for example, based on 14 years of historic fire occurrence data, September and October are the months with the most fires during the dry summer-fall season (Figure 5).

The accuracy of pan evaporation estimation depends greatly on the quality of measured pan evaporation data as well as the quality of other meteorological variables used to develop models. For this reason, the data obtained were carefully examined before the modeling was attempted. Numerous problems were evident with these data. The major drawback was that serially complete and homogeneous data are not available—weather stations in the study area do not consistently observe and archive similar elements. Also, daily pan evaporation records from many stations 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 it was necessary to address these data quality issues. First, all observations were corrected for time-of-observation. Second, missing or obviously incorrect values were identified and replaced with an average value calculated using records for the preceding and the following day. Third, data histograms and scatterplots were evaluated to identify extreme values and outliers in the data sets. Subsequently, atypical extreme values and outliers were removed from the data sets.

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. Maximum air temperature, minimum relative humidity, solar radiation, and average wind speed for the corresponding years were used as independent variables.

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, 2004, and to satisfy the spatial requirements for selectively estimating evaporation for both inland and coastal environments. Inland models were created using Stoneville, Newton, Calhoun and Ben Hur data, while coastal models were created with Houma and Fairhope data.

All four independent variables were included in the MLR models and tested in terms of their significance to the resulting evaporation estimation. In order to select the most optimal combination of weather elements for both inland and coastal locations, three different “modeling approaches” were used (Table 2). Approach A incorporated all four weather elements as inputs. Approach B incorporated only three input variables (average wind speed was excluded). Approach C 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 C models, since it is available only at a limited number of weather stations in the southeastern region of the U.S. Approach C requires the fewest number of variables, and models developed under this approach were assessed for under-fitting problems. In general, a slightly under-fit model that can be implemented at many locations is preferable to a model that has a complete suite of explanatory variables that are available at only a few locations in the analyzed region.

Ultimately, the best inland and coastal models were selected to estimate 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.

Stage Two: Model Selection

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. Models with highest RSQ values were selected and included in the initial selection groups. These models were then evaluated by assessing how accurately each specific model predicted evaporation measured in 2003. Inland models were evaluated against Stoneville 2003 data and coastal models were evaluated against Houma 2003 data.

The following performance measures were used to describe the similarity of the predicted and measured evaporation: R square (RSQ), Pearson's correlation coefficient (CC), average difference between predicted and measured evaporation (AVG), root mean-squared error (RMSE) and mean absolute error (MAE). These performance measures were determined 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 to represent uniform value ranges as shown in Table 3. The perfect model for stage two (PM2) can therefore be expressed with the following formula:

$$PM2=0.4\ (RSQ) + 0.15\ (CC) + 0.15\ (1\text{-}10|AVG|) + 0.15\ (1\text{-}10\ RMSE) + 0.15\ (1\text{-}10\ MAE) = 1 \quad (1)$$

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 3). 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 evaporation rates were more accurate than available historic averages. Values for the performance measures (RSQ, CC, |AVG|, RMSE, MAE) from the best-selected models and performance measures calculated for the historic averages were compared to determine if modeled or average values were a better estimation of the actual evaporation. Determination of the "perfect" model for stage three (PM3) did not include RSQ since RSQ was not calculated for historic 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 evaporation was selected. If a model was chosen over historic averages, and if that model was not the most parsimonious, the optional approach C model (OBIM for inland or OBCM for coastal environments) not requiring solar radiation data was chosen (Figure 4). The rationalization for this decision is that solar radiation data are not observed at most weather stations in the southeastern region of the U.S., especially in Mississippi and Alabama, so use of a model requiring this variable would significantly limit the number of potential locations where evaporation could be estimated. Using a model with fewer variables allows a greater number of point estimates of evaporation. Alternatively, when solar radiation data are available, an expanded model can be used.

Model Validation

The final phase of the study examined how closely model-estimated evaporation approximated actual measured evaporation. To accomplish this, actual 2003 measured evaporation was compared with estimated evaporation derived from the models for validation.

RESULTS AND DISCUSSION

Stage One: Model Development

Four independent variables were initially used and tested in three different modeling approaches to find the most optimal combination of input variables. These modeling approaches, as shown in Table 4, resulted in considerably different RSQ values. Approach A, where all four independent weather variables were included, produced highest RSQ values. Approach B, where the average wind speed variable was excluded, resulted in only slightly lower RSQ values than approach A. In approach C, however, the exclusion of solar radiation caused a significant decline in RSQ values. Variables' coefficients and RSQ values are shown for all models in Table 4. Declining RSQ values were associated with the removal of wind and solar radiation as independent variables. Coefficients were similar in sign and magnitude.

In addition to testing different combinations of input variables, scatterplots were created to compare each independent variable to evaporation. Maximum air temperature, minimum relative humidity, solar radiation, and average wind speed were plotted against the evaporation data. Based on the scatterplot analyses, a strong positive relationship was observed between evaporation and solar radiation and maximum air temperature. The analyses also confirmed an inverse relationship between minimum relative humidity and measured pan evaporation. Finally, these analyses indicated no clear relationship between average wind speed and measured pan evaporation.

Approach A was abandoned at this point because wind was measured differently among stations and was non-significant as a predictor variable. Its inclusion resulted in marginal improvement in RSQ, and likely resulted in model over-fitting (artificially inflated RSQ). With the elimination of approach A, the objective was narrowed to create models for 2002 and 2004 using approaches B and C. However, at locations where only minimum relative humidity and air temperature were available, only approach C models were feasible. For instance, Fairhope 2002 and 2004 models were approach C models, created without solar radiation data, as these data were unavailable at that location.

Numerous evaporation models of approaches B and C were developed to estimate inland and coastal evaporation within the study region. The results vary considerably in terms of RSQ values. In general, approach B models produced higher RSQ values than approach C models, indicating strong contribution of solar radiation as an input variable to the models. Even though the approach C models produced higher error of the estimates (Table 5), indicating model under-fitting, they have a significant spatial advantage over the approach B models, guaranteeing the highest possible number of locations where an evaporation estimate can be produced.

Twelve inland and four coastal models were developed. Fewer coastal models were developed due to limited evaporation data at the coastal location (available from only two reporting stations). Also, solar radiation data were unavailable for one of these coastal stations. The results for inland models are presented in Table 5 and for coastal models in Table 6.

Inland models resulted in comparatively higher RSQ values than coastal models, with most values exceeding 0.6 and the highest value of 0.756 for the Newton approach B 2004 model. RSQ values for coastal models ranged from 0.587 (Fairhope C 2004) to 0.389 (Houma C 2004). These inferior results of coastal models are most likely associated with poorer data availability, lower data quality, and a larger number of missing records.

Stage Two: Model Selection

Inland and coastal models were initially screened by RSQ values to reduce the total number of models for evaluation. From all inland models, the following six were selected for further evaluation: Stoneville approach B 2002, Stoneville approach C 2002, Newton approach B 2004, Newton approach C 2004, Ben Hur approach B and Ben Hur approach C 2002. From this group the best inland model (BIM) was selected using equation 1. Performance measures calculated for these models are shown in Table 7. The initial screening process for coastal models resulted in the selection of three models: Fairhope approach C 2002, Fairhope approach C 2004, and Houma approach B 2004 model. Performance measures determined for these models are shown in Table 8. These measures, highlighted in tables 7 and 8, were used directly in the process of selecting the best inland (BIM) and 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 7 and 8 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 B 2004 model (0.687). However, this was not the most parsimonious model, so the optional model (Ben Hur approach C 2002, 0.578 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 C 2004 model (0.576), which was also the most parsimonious model, so an optional coastal model was not selected. 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)

Stage Three: Model Comparison with Historic Average

The two best inland models and one best coastal model were further evaluated to resolve whether modeled evaporation estimations are superior to historic averages. Table 9 shows performance measures for best-selected models versus historic average records as well as final scores calculated using formula 2. The results indicate that in all cases, modeled estimates represent actual evaporation better than historic averages. These calculations indicated that for all "best" models, predicted evaporation is superior to historic averages.

Model Validation

Each "best" model was compared to actual 2003-measured evaporation for validation purposes. Figure 6 illustrates validation results of the best inland model (created based on Newton 2004 data using approach B), by plotting model results against pan evaporation measured at Stoneville in 2003. Predicted evaporation is much closer to measured pan evaporation than the historic average (compare to Figure 3). 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 C model, which utilizes only maximum air temperature and minimum relative humidity, should be used. Figure 7 shows the validation results of this optional inland model. Correlation coefficients (Pearson's R) are higher for both "best" inland models than historic averages, and the predicted values conform to changes in actual evaporation better than historic averages.

The best coastal model was created based on Fairhope 2004 data using approach C. This is also the most parsimonious model, using maximum air temperature and minimum relative humidity data only. Figure 8 illustrates validation results of the model results plotted against pan evaporation measured at Houma in 2003. Predicted evaporation is closer to measured pan evaporation than the historic average. Also, the correlation coefficient for this model is significantly higher than that of the historic average (0.49 versus 0.199), and evaluated error measures of the model are lower than that of the historic average. The combination of higher CC and lower error measures indicates that it is better to use predicted evaporation estimated from the Fairhope 2004 model than to use historic average evaporation.

Overall, mean evaporation decreases during the fall months when daily temperature begins to decline. Since these models were developed for the climatologically controlled fire season, it is possible (when temperature is low and minimum relative humidity is high) to estimate a negative value for evaporation. This situation occurred twice in the selected coastal model (Figure 8). To prevent this occurrence, negative model estimation was constrained to equal zero, since negative evaporation is not possible.

Validation of model results confirmed initial expectations that evaporation rates predicted using selected models are superior to historic evaporation estimates. Modeled evaporation for both inland and coastal models reflected actual changes in daily weather conditions, while historic averages did not (compare Figure 3 to Figures 6, 7, and 8).

CONCLUSIONS

The goal of this research was to estimate daily pan evaporation at numerous locations for the southeastern region of the U.S. where such data are not routinely and consistently available. Multiple regression models developed using combinations of actual measured solar radiation, maximum temperature, and minimum relative humidity resulted in useful evaporation estimations. Evaporation estimations based on the best-selected models proved superior to available historic average 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 with weather data available for modeling evaporation. Maintaining a greater number of stations was considered of critical importance to the overall project goal, as it assured a sufficient number of points for interpolation of evaporation across the entire region—needed to create a dynamic layer for use in a fire potential model.

The best evaporation 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 evaporation rates, produced three easily-applied models—two inland and one coastal—that appear to provide reliable and useable daily evaporation data. Depending on whether or not solar radiation data are available for use at an inland site (approach B or C), the following models are recommended:

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)

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)

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 evaporation at multiple locations over a broad region.

The number of metrics employed in creating, testing, and validating selected models yields results that provide rigorous and credible estimates of evaporation. Use of these models results in evaporation estimates comparable to measured pan evaporation. In fact, it is possible that the predicted 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. This method of estimating missing or spatially deficient daily evaporation data should prove useful in regional applications such as a dynamic fire potential assessment for large areas of forest affected by Hurricane Katrina in the southeastern U.S., and for the southeastern region in general.

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LIST OF ACRONYMS

ANN - artificial neural network

AVG - average difference between estimated and measured evaporation

BCM - Best Coastal Model

BIM - Best Inland Model

CC - Pearson's correlation coefficient

GIS - Geographic Information Systems

KBDI - Keetch-Byram Drought Index

MAE - mean absolute error

maxT - maximum temperature

minRH - minimum relative humidity

MLR - multiple linear regression

OBCM - Optional Best Coastal Model

OBIM - Optional Best Inland Model

PM2 - perfect model for stage two

PM3 - perfect model for stage three

RMSE - root mean-squared error

RSQ - R square

SR - solar radiation

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	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	6.8
Range	9.4	4.57	9.9	4.09
Std. Deviation	1.85	1.11	1.8	0.72
Variance	3.44	1.25	3.23	0.52

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

Modeling	Variable				Data availability
	Average wind	Solar radiation	Min. relative humidity	Max. air temperature	
Approach A	+	+	+	+	Ben Hur, Houma, Calhoun, Stoneville, Newton
Approach B	+	+	+		Ben Hur, Houma, Calhoun, Stoneville, Newton
Approach C	+	+			Ben Hur, Houma, Calhoun, Stoneville, Newton, Fairhope

Table 2. Combinations of weather input variables used in the modeling approaches and data availability

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	0.4	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	0.15	1	CC
AVG	Overcomes CC limitations of range value	2	0.15	0	1- |AVG*10|
RMSE	Accepted standard model accuracy evaluation measure	2	0.15	0	1- RMSE*10
MAE	Accepted standard model accuracy evaluation measure	2	0.15	0	1- MAE *10

Table 3. Model performance measures, description, ranking, weights and standardized value

Weather Station Model	RSQ	Coefficients				
		B	**Temp.**	**Rel. hum.**	**Solar rad.**	**Wind**
Stoneville app.A	0.777	-0.132	0.003	-0.0011	0.0003	0.001
Ben Hur app. A	0.761	-0.147	0.0022	-0.0006	0.0003	0.0079
Stoneville app.B	0.730	-0.041	0.0028	-0.0014	0.0003	Not used
Ben Hur app. B	0.707	-0.113	0.002	-0.0004	0.0003	Not used
Stoneville app. C	0.681	-0.058	0.0046	-0.0023	Not used	Not used
Ben Hur app. C	0.626	-0.1175	0.0051	-0.0027	Not used	Not used

Table 4. Results of 2002 models illustrating the difference of inclusion and exclusion of wind and solar radiation variables

Station	App.	Year	Rsq	Adj. Rsq.	Error of the Estimate	B	Temp.	Rel. hum.	Solar rad.
Stoneville	B	2002	0.730463	0.723	0.0458	-0.0412798	0.002754	-0.001408	0.000273
Stoneville	C	2002	0.681097	0.675	0.0496	-0.058047	0.004637	-0.002334	not used
Stoneville	B	2004	0.606	0.595	0.0454	0.326	0.00147516	-0.0014418	0.00028
Stoneville	C	2004	0.475	0.465	0.0509	-0.139	0.006	-0.003	not used
Newton	B	2002	no data	no data	no data	not developed	not developed	not developed	not developed
Newton	C	2002	no data	no data	no data	not developed	not developed	not developed	not developed
Newton	B	2004	0.756128	0.7499	0.0325	-0.07912	0.001104	0.00007	0.000369
Newton	C	2004	0.52291	0.5149	0.0452	0.02788	0.003586	-0.003236	not used
Calhoun	B	2002	no data	no data	no data	not developed	not developed	not developed	not developed
Calhoun	C	2002	no data	no data	no data	not developed	not developed	not developed	not developed
Calhoun	B	2004	0.625	0.615	0.0397	-0.163	0.002	0.000069	0.00038
Calhoun	C	2004	0.383	0.372	0.0506	-0.167	0.005	-0.003	not used
Ben Hur	B	2002	0.706919	0.6947	0.0371	-0.113179	0.001965	-0.000436	0.000324
Ben Hur	C	2002	0.625995	0.6157	0.0416	-0.117528	0.005147	-0.002723	not used
Ben Hur	B	2004	0.637	0.6273	0.0439	-0.0175437	0.001219	-0.006585	0.000348
Ben Hur	C	2004	0.495	0.4863	0.0515	0.181	0.0024353	-0.0038	not used

Table 5. RSQ results of inland models

Station	Approach	year	Rsq	B	Temp.	Rel. hum.	Solar rad.
Fairhope	B	2002	no data	not developed	not developed	not developed	not developed
Fairhope	C	2002	0.569	-0.128	0.005	-0.002	not used
Fairhope	B	2004	no data	not developed	not developed	not developed	not developed
Fairhope	C	2004	0.587	-0.51	0.009	-0.002	not used
Houma	B	2002	no data	not developed	not developed	not developed	not developed
Houma	C	2002	no data	not developed	not developed	not developed	not developed
Houma	B	2004	0.427	-0.402	0.007	-0.001	0.00023
Houma	C	2004	0.389	-0.284	0.007	-0.003	no data

Table 6. RSQ results of coastal models

Inland Models	**Performance measures**										**Total score**
	RSQ value		CC		AVG		RMSE		MAE		
	wght.	St.val.	wght.	St.val.	wght.	St.val.	wght.	St.val.	wght.	St.val.	∑
Stoneville app. B 2002	0.73		0.62		-0.057		0.082		0.070		
	0.4 *	0.73	0.15 *	0.62	0.15 *	0.44	0.15*	0.18	0.15*	0.30	**0.522**
Stoneville app. C 2002	0.68		0.45		-0.036		0.076		0.063		
	0.4*	0.68	0.15 *	0.45	0.15 *	0.65	0.15 *	0.24	0.15 *	0.37	**0.529**
Newton app. B 2004	0.76		0.66		0.014		0.056		0.041		
	0.4*	0.76	0.15 *	0.66	0.15 *	0.86	0.15 *	0.44	0.15 *	0.59	**0.687**
Newton app. C 2004	0.52		0.42		0.011		0.071		0.055		
	0.4*	0.52	0.15 *	0.42	0.15 *	0.89	0.15 *	0.29	0.15 *	0.45	**0.516**
LSU Ben Hur B 2002	0.71		0.65		-0.017		0.058		0.043		
	0.4*	0.71	0.15 *	0.65	0.15 *	0.83	0.15 *	0.42	0.15 *	0.57	**0.655**
LSU Ben Hur C 2002	0.63		0.45		-0.003		0.069		0.056		
	0.4*	0.63	0.15 *	0.45	0.15 *	0.97	0.15 *	0.31	0.15 *	0.44	**0.578**

Table 7. Decision-making calculations carried out to select best inland model (BIM); values of performance measures are highlighted

Coastal Model	Performance measures										Total
	RSQ value		CC		AVG		RMSE		MAE		
	wght.	St.val.	wght.	St.val.	wght.	St.val.	wght.	St.val.	wght.	St.val.	∑
FH C 2002	0.57		0.54		-0.042		0.074		0.063		
	0.4 *	0.57	0.15 *	0.54	0.15 *	0.585	0.15*	0.26	0.15*	0.37	**0.491**
FH C 2004	0.59		0.50		-0.009		0.067		0.055		
	0.4*	0.59	0.15 *	0.50	0.15 *	0.991	0.15 *	0.33	0.15 *	0.45	**0.576**
HM B 2004	0.43		0.59		-0.071		0.094		0.082		
	0.4 *	0.43	0.15 *	0.59	0.15 *	0.295	0.15*	0.06	0.15*	0.18	**0.340**

Table 8. Decision-making calculations carried out to select best coastal model (BCM); values of performance measures are highlighted

Figures

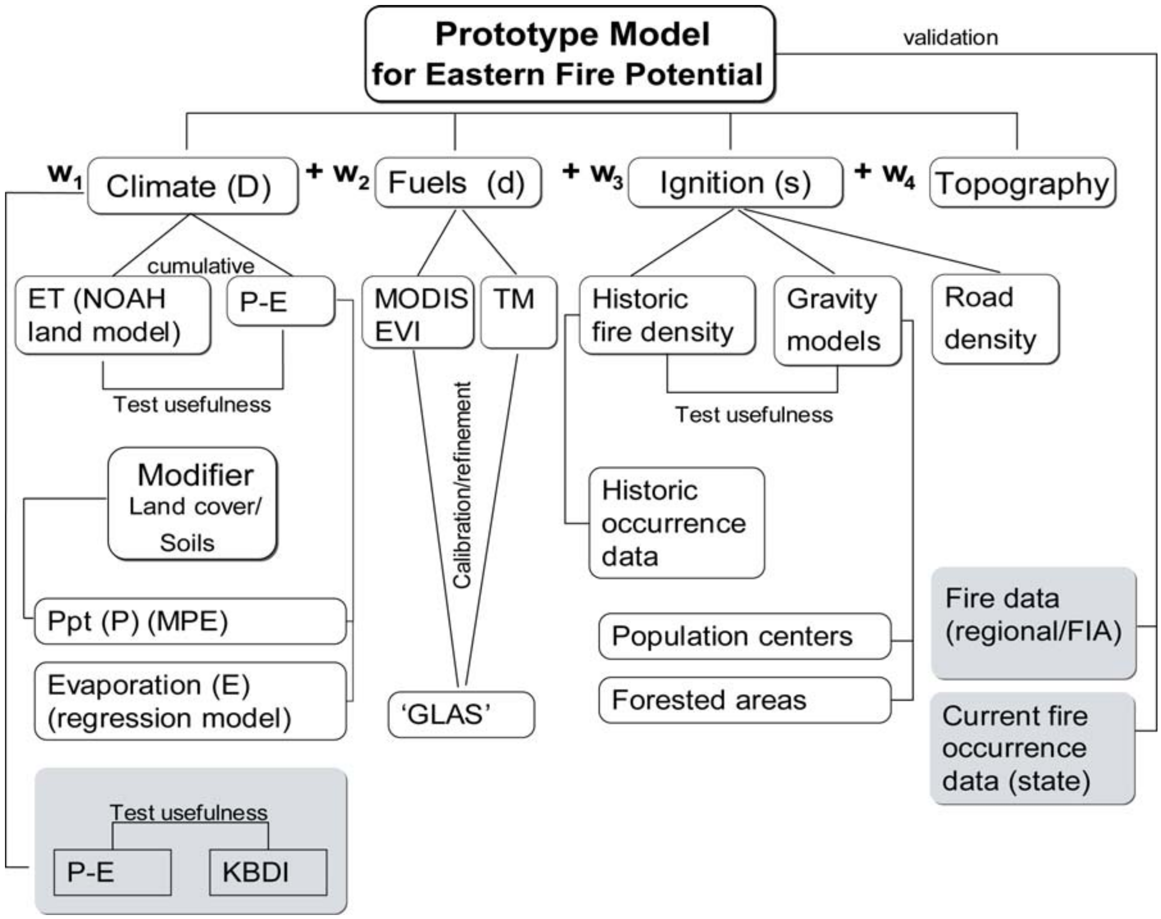

Figure 1. Flowchart illustrating major input variables, data components and processes in the fire potential model

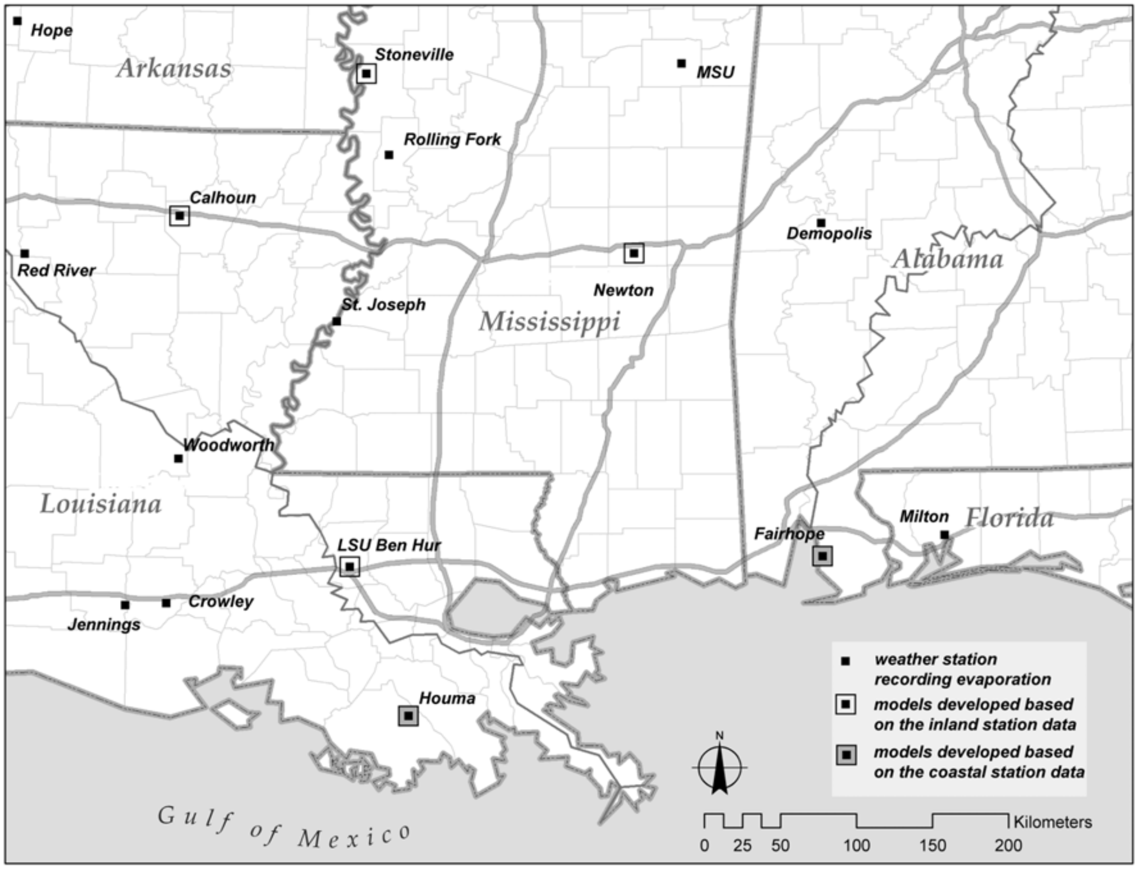

Figure 2. Map of the study area showing weather stations recording evaporation and locations for which evaporation models were created

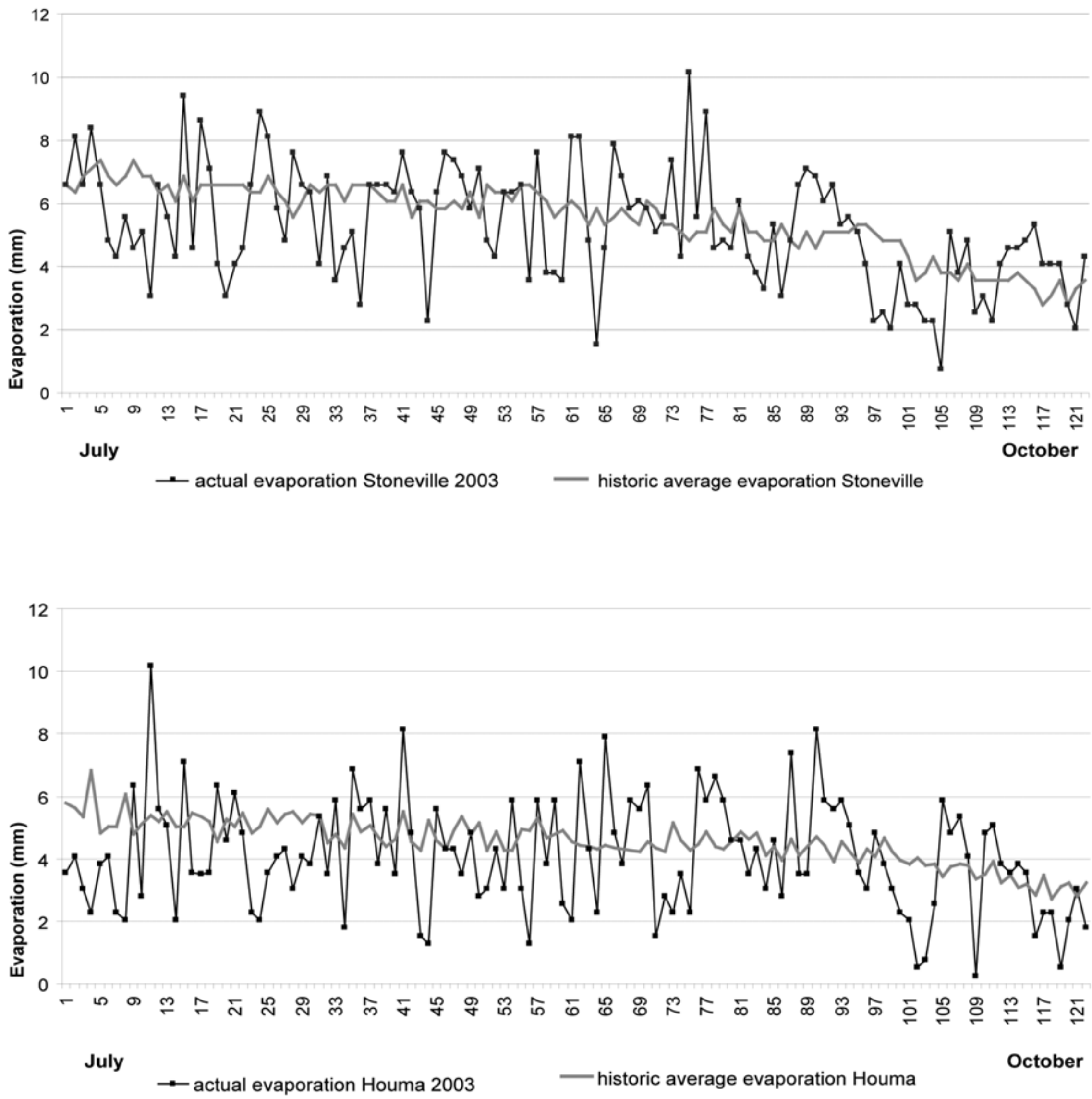

Figure 3. Comparison of actual measured (Stoneville 2003, Houma 2003) and historic average evaporation data (Stoneville 1977-2002, Houma 1977-2002)

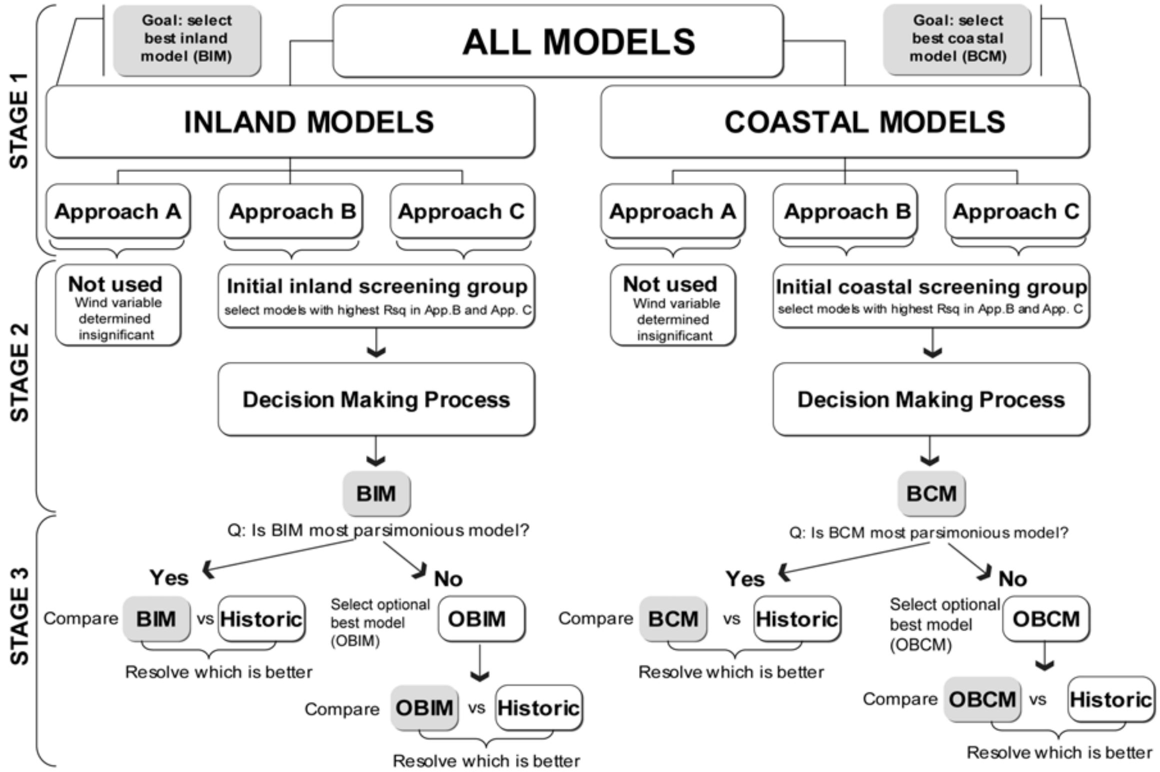

Figure 4. Stages of model development and selection

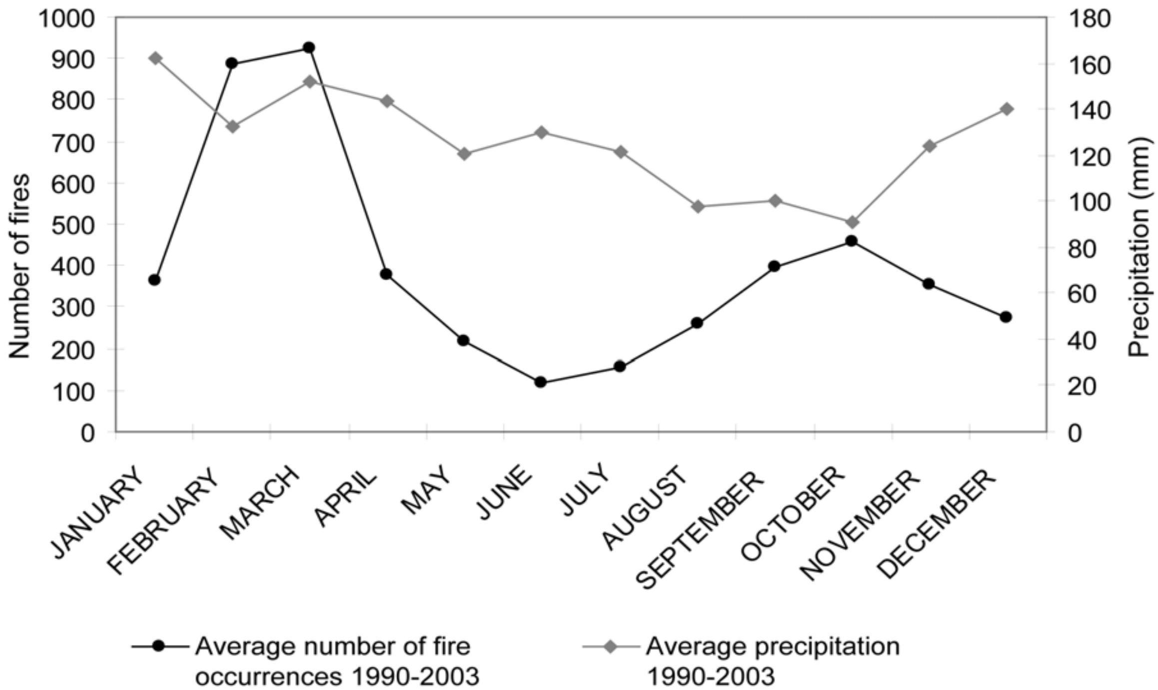

Figure 5. Comparison of average monthly precipitation and average number of fire occurrences in Mississippi between 1990 and 2003 (Data sources: National Weather Service, Mississippi Forestry Commission)

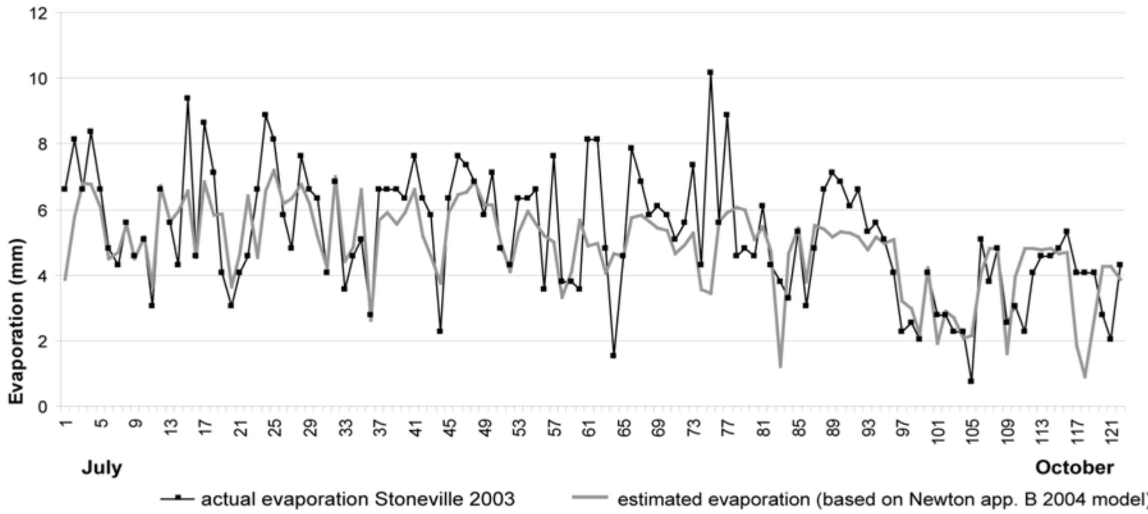

Figure 6. Comparison of actual measured (Stoneville 2003) evaporation and evaporation estimated for Stoneville 2003 using best inland model (Newton approach B 2004)

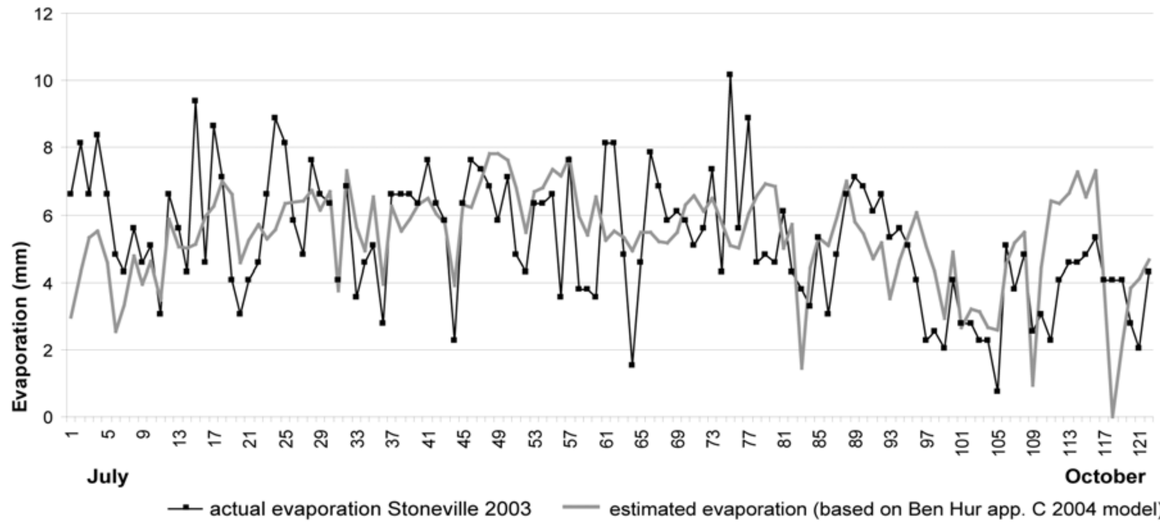

Figure 7. Comparison chart of actual measured evaporation (Stoneville 2003) and evaporation estimated for Stoneville 2003 using optional best inland model (Ben Hur approach C 2004)

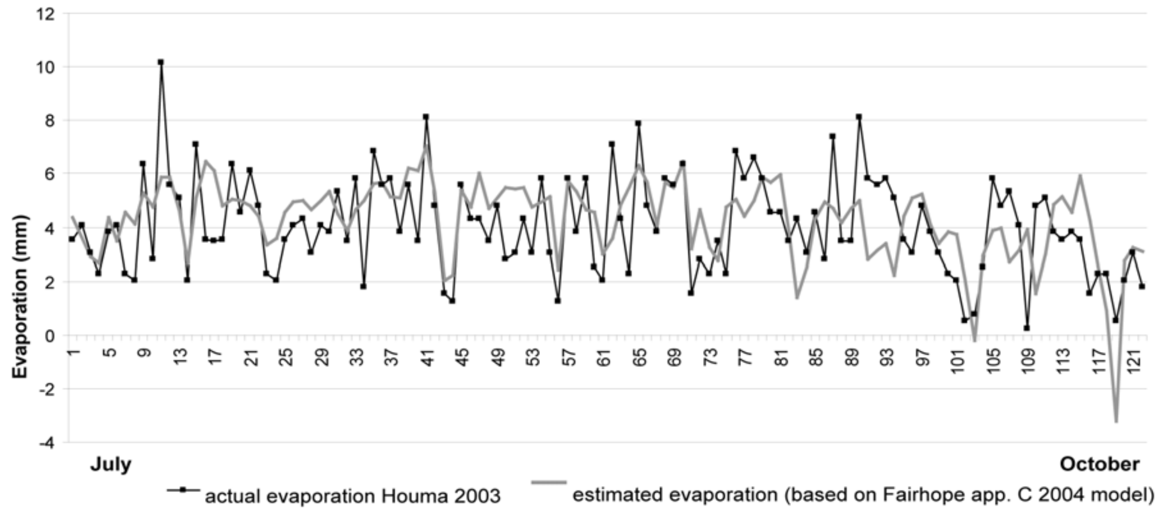

Figure 8. Comparison chart of actual measured evaporation (Houma 2003) and evaporation estimated for Houma 2003 using best coastal model (Fairhope approach C 2004)

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

Table 9. Evaluation calculations carried out to compare results of the best-selected models and historic averages; values of performance measures are highlighted