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ESTIMATING WATER DEPTHS USING ARTIFICIAL NEURAL NETWORKS

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The real-time Everglades Depth Estimation Network (EDEN) has been established in the Everglades of South Florida, USA, to support a variety of scientific and water-management purposes. The expansiveness of the Everglades, limited number of gauging stations, and extreme sensitivity of fauna to small changes in water depth have created a need for accurately predicting water depths at locations between the stations. This has been challenging because an ultra-low gradient makes interactions between meteorology, vegetation, topology, and hydrology complex. Linear techniques such as interpolation and ordinary least-squares regression have under-performed because of the system's non-linear dynamics. This paper presents an alternative approach that employs artificial neural network (ANN) models to perform multivariate, non-linear interpolation between gauging stations.

Using a combination of static and dynamic variables, predictions are generated in two modeling steps. The dynamic variables were 30-month time series of daily water depths at 16 stations and water levels (measured to the National Geodetic Vertical Datum of 1929) at 3 other stations. Static variable values were obtained from a previously developed GIS application having a 400-square-meter grid. Values included coordinates of cell centroids and percentages of vegetation types (slough, prairie, sawgrass, or upland) for approximately 2,300 cells, covering 370 square kilometers. The first ANN model interpolates mean water depths (for the period of record) from input static variables and mean water depths and levels at the gauging stations. The second ANN model predicts day-to-day variability about the interpolated means using a combination of static and dynamic variable inputs. A complete interpolation at a given cell is computed by summing the outputs of both models. Five of the water-depth gages were withheld from model development to validate model accuracy. Prediction accuracy was greatly improved, resulting in an average root-mean square prediction error at validation stations of only 3 centimeters (0.1 foot), or 4 percent of the dynamic range.

INTRODUCTION

The real-time Everglades Depth Estimation Network (EDEN) has been established in the Everglades of South Florida, USA, to support a variety of scientific and water-management purposes. The goals of EDEN are to help guide large-scale field operations, integrate hydrologic and biologic responses, and to support the monitoring assessments by scientists and principal investigators across disciplines. One objective of EDEN is to relate water-level data at real-time stage gages to unmonitored areas using ground-elevation data, so that water depths throughout the greater Everglades can be estimated [1].

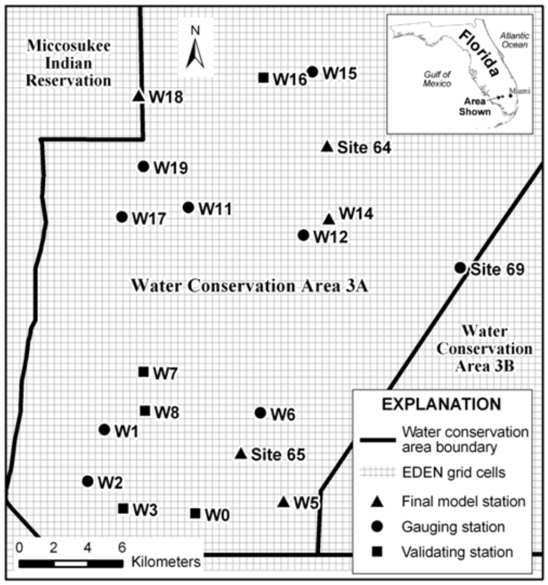

Figure 1. Map showing study area, gauging stations and the EDEN grid, proposed index stations, final model stations and validation stations.

Accurately predicting the hydrologic responses at unmonitored locations can be challenging because of the limited number of reference gauging stations and a limited understanding of complex topology and vegetation interactions. Techniques that are often used to estimate hydrologic responses at unmonitored locations include combinations of linear regression and interpolation, but often the dynamics between hydrology, topography, and vegetation are nonlinear. This paper presents the application of artificial neural network (ANN) models to predict water depths at unmonitored sites.

METHODS

ANN [1] models have been applied in western Oregon, USA, to estimate stream temperature at unmonitored sites [2]. In that study, dynamic clustering techniques were used to subset 142 temperature sites from 1st, 2nd, and 3rd order streams into three groups

[1] An ANN model is a flexible mathematical structure capable of describing complex nonlinear relations between input and output datasets. The architecture of ANN models is loosely based on the biological nervous system [4]. Although there are numerous types of ANNs, the most commonly used type of ANN is the multi-layer perceptron (MLP) [5].

of similar dynamic behaviors. Using static variables and time-series variables, water-temperature models were developed for unmonitored sites. A similar approach was used to predict water depths in a sub-domain of EDEN.

Datasets

Data for dynamic and static parameters were obtained for an area of Water Conservation Area 3A (WCA3a). Dynamic data included time series of water depths from 16 stations in the Snail Kite Study [3], and water levels from 3 U.S. Geological Survey (USGS) stations (Site 64, Site 65, and Site 69) for the period December 2002 to May 2005. Water depths for the Snail Kite Study are collected every 12 hours at 7:30 AM and 7:30 PM. The USGS data consist of daily mean water levels. The Snail Kite data were resampled and 7:30 AM data were used with the daily mean USGS data.

The static data were obtained from the 400-square-meter EDEN grid and included location of cell center (X-coordinate and Y-coordinate in meters) and percent vegetation type (slough, prairie, sawgrass, or upland). The location of the gaging station was associated with the center of the cell where the station is located and associated with the static variables for that cell. Figure 1 shows the study area of WCA3a, the location of the water-depth and water-level gauging stations, and the EDEN grid.

Data Preparation

The data from the Snail Kite network include water depths at the gauging stations. The USGS stations measure water levels to a known datum (National Geodetic Vertical Datum 1929). To set all the stations to a common datum for the analysis, Site 64 was used as a reference station and the difference between the measured data from the other stations was used as the time series for the analysis. Figure 2 shows the time series for the water level at Site 64, the water depth at W8, and the difference between the two time series (variable W8DIF). The variability of the difference between Sites 64 and W8 is clearly seen in Figure 2b where W8DIF is plotted on a separate axis. In addition to setting all the water-depth and water-level data to the same datum, using differences produces new signals that are less correlated than the original signals and reduces the multi-colinearity between the time series. The USGS sites are highly correlated and Sites 65 and 69 were decorrelated from Site 64. For the ANN modeling, a "stacked" dataset was generated that included the time series from USGS gaging stations, water-level differences from the Snail Kite network and the static variables for the 16 Snail Kite locations.

Selection of Index and Validation Sites

To evaluate the ability of ANN models to estimate water depths at unmonitored sites, stations to be used for index (model) stations and stations for water-depth validation (prediction) needed to be determined. Variables from the index stations are used as the explanatory variables and the water-level differences at the prediction stations are used as the response variable in model. The prediction stations are used to validate the

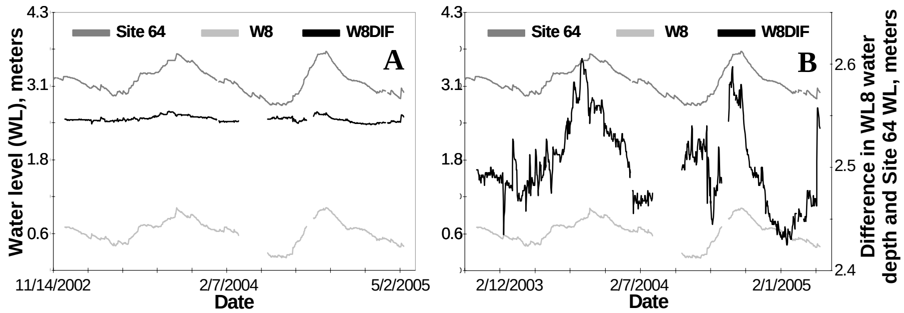

Figure 2. Plots showing water levels at Site 64, water depths at W8, and the difference between the two time series (W8DIF). In Figure 2b, W8DIF is plotted on a separate axis to show the detail of the variability between the two signals.

performance of the model. Because the three USGS water-level stations do not measure water depth and the land-surface elevation at the stations was not known, they were used as index stations. Rather than arbitrarily selecting which of the 16 water-depth stations would be used as index or predictions sites, a zone-averaging filter was used. The zone-averaging filter, or box filter, separates the dataset to be modeled into zones or boxes, each containing a user-specified number of input-output vectors. This de-biases the training dataset by placing uniform number vectors in each box to yield an ANN model that better represents less common behaviors and the full dynamic range of the predicted variables. The box filter was used to identify 11 water-depth stations as potential "index" stations, with the remaining other 5 stations were set aside as "validation" stations to independently evaluate the accuracy of a model. Figure 1 show the index and validation stations.

Modeling approach

A two-stage modeling approach was used to predict water-level differences at an unmonitored site (Figure 3). The first model (F_1) predicts the water-level difference (WLDIF-Site$_{pred1}$) using only the static variables of location and vegetation types. Obviously, this model (also called the "static" model) is not able to predict the dynamic variability of the water-level differences, but it is able to discriminate general differences in the WLDIF-Site variable based on differences in location (X_coord and Y-coord) and vegetation (slough, prairie, sawgrass, and upland). Figure 4 shows the water-level predictions from the static model. The static model is used to calculate the residual error (difference between the predicted and measured water-level difference, WLDIF-Site$_{residual}$), which is then modeled by a second model (F_2).

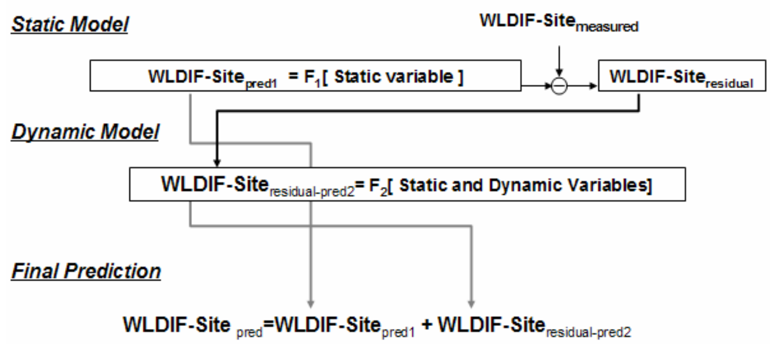

Figure 3. Schematic showing the two-stage model approach to making final water-level difference for a particular site (WLDIF-Site).

The second model (also call the "dynamic" model) uses time series of water-level and water-level difference variables along with static variables to predict the variability in water-level difference (WLDIF-Site$_{residual}$) at each site as characterized by the residual in the static model (F_1). The final prediction of water-level difference at each site is the summation of the water-level difference prediction from the static model and the prediction of the water-level difference residual from the dynamic model. To calculate predicted values for the water-depth gauging stations (or unmonitored sites), the

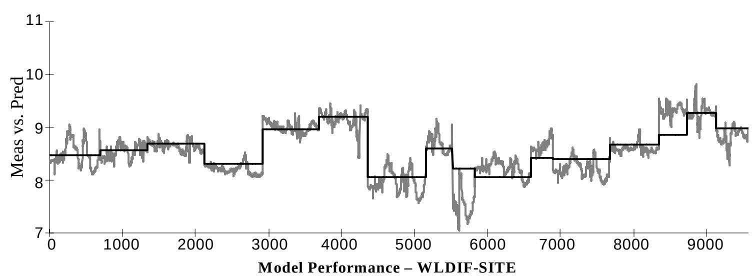

Figure 4. Plot showing predicted water-level difference (WLDIF-Site) for each site (black trace) and the measured water-level difference at each site (gray trace). The "step" in the black trace indicates the different sites. The ANN model used only the six static variables characterizing location and vegetation types. The model is able to generalize the water-level difference but unable to simulate the variability of the water-level difference. The plot shows the 16 sites in the training and testing datasets. The model was trained using only the 11 index water-depth sites.

predicted water-level difference is subtracted from the Site 64 water levels.

For the dynamic model (F_2), water-level difference time series from 11 sites were available to use as index sites along with the six static variables. To select variables and minimize the number of variables in the dynamic model, a cross-correlation matrix was generated to show the Pearson coefficients between the potential variables. By evaluating model results and sensitivity reports, higher correlated variables were removed from the final dynamic model. The final model uses 10 variables: 2 dynamic variables from the USGS water-level gauging stations, 3 dynamic variables from the Snail Kite water-depth stations, and 5 static variables. Figure 1 shows the EDEN grid with the final model stations used to train the model and validation stations used to evaluate the model results.

RESULTS

The ability of the model to predict water depths was evaluated using four "goodness-of-fit" statistics at the five validation sites and plots of measured and predicted water depths. The computed statistics include coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE), and percent model error (PME). Water depths for the five validation sites were predicted using the procedure outlined above and the statistics computed. Table 1a summarizes the statistical accuracy of the two-stage model using the five prediction sites.

Model accuracy is often reported in terms of R^2 and is commonly interpreted as the "goodness of the fit" of a model. A second interpretation is one of answering the question, "How much information does one variable or a group of variables have about the behavior of another variable?" In the first context, an $R^2 = 0.6$ might be disappointing, whereas in the latter, it merely is an accounting of how much information is shared by the variables being used. The R^2 for the five validation sites are high (0.980 – 0.995), and indicates that the model is able to explain much of the variability of the data and able to capture the overall trend of the data.

The RMSE is defined as the square root of the mean of the squared differences between the measured and predicted data. The RMSE for the validation sites varied from 0.017 to 0.048 meters. For the statistic to be relevant, RMSE should be evaluated with respect to the range of the output variable. A model may have a low RMSE, but if the range of the output variable is small, the model may be accurate, but for only a small range of conditions. Table 1a lists the MSE, RMSE and the range of the measured data for the validation stations. The PME statistic divides the RMSE by the range of the measured data to determine the percent of error over the full range of modeled data. For the water-depth ANN model, the PME ranges from 2.0 to 7.7 percent. The average RMSE is 0.028 meter and the PME for the model is 4.0 percent. The average absolute sensitivity of the variables in the final model is shown in Table 1b.

Station	N	R_{Square}	Mean square error (m)	Root mean square error (m)	Range of measured date (m)	Percent Model Error (%)
W0	453	0.995	0.0003	0.0172	0.86	2.0%
W3	97	0.994	0.0005	0.022	0.75	3.0%
W7	221	0.995	0.0023	0.048	0.63	7.7%
W8	453	0.995	0.0008	0.0286	0.82	3.5%
W16	176	0.980	0.0007	0.0259	0.91	2.8%

Table 1a. Statistical measure of prediction accuracy for ANN water-depth for the five validation sites.

Variable Name	Average absolute Sensitivity
SAWGRASS%	0.300
Y_COORD	0.191
UPLAND%	0.141
X_COORD	0.093
PRAIRIE%	0.078
WL18DIF	0.052
WL14DIF	0.049
WL5DIF	0.040
WL64	0.038
WL65DEC	0.021

Table 1b. Variables in the final dynamic model and their average absolute sensitivity.

A plot of measured and predicted water depths for Site W8 is shown in Figure 5. Site W8 provides performance results in the middle of the range. Site W8 (along with Site W0) also has the greatest amount of measured data (453 data points) and the plot shows that the model is able to simulate the full range of the measured data. For Site W8, the model generally underpredicts the water depths for the majority of the simulation. Predictions of water depths are not continuous due to missing data for one or more of the index stations. For complete predictions, the missing data at the index stations would need to be filled with estimated data.

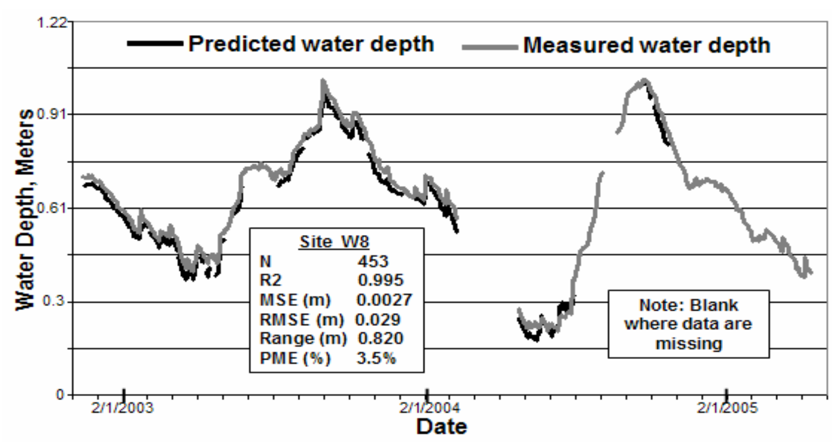

Figure 5. Plot showing measured (light trace) and predicted (dark trace) water depths for Site W8. Predictions are not continuous due to missing data for one or more of the index stations.

DISCUSSION

The final model accurately predicts water depths at unmonitored locations by combining information on location, vegetation, and hydrology. The ANN models are essentially performing a multi-variate kriging of water depths in the study area. The ANN models are able to interpolate spatially from the static variables and temporally from the dynamic variables. The sensitivity of the variables in the final model indicates that the final model is more sensitive to the static variables of the EDEN cell than the dynamic variables (Table 1b). The two most sensitive variables of the static variables are the percentage of sawgrass and the Y-coordinate, or the cell centroid.

A number of approaches may be taken to reduce the model error. Water flow and water depth in the Everglades are dependent on vegetation type and topography. In the model, there is not a static variable to describe and input topography, such as land-surface elevation at the center of the EDEN cell and/or a mean elevation of the cell. For the dynamic data, greater vertical control of the water-depth measurements would improve the data and, ultimately, the model results. The Everglades is a difficult environment for measuring water level and water depth to a known vertical datum. When small shifts in the vertical control of the water-level and water-depth data are not corrected, the ANN models will try to fit a multivariate surface to these erroneous small changes in water levels or water depths.

The preliminary results from applying ANN models to estimate water depths at unmonitored locations are encouraging. The spatial domain of the model is 370 square kilometers or about 2,300 cells in the EDEN grid network. The average root-mean square error for the prediction model at validation stations is approximately 0.03 meter or 4 percent.

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