Integration of Hydrologic and Ecological Studies of the Snail Kite – Enhancements to the Snail Kite Decision Support System

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Introduction

Hydrologists and ecologists have been working on integrating a long-term hydrologic data network and a short-term ecological database to support ecological models of the habitat of the snail kite, a threatened and endangered bird of prey. Hydroperiods of water depths have a significant affect on the nesting and foraging of the snail kite. Data mining techniques, including artificial neural network (ANN) models, were applied to simulate the hydrology of snail kite habitat in the Water Conservation Area 3A of the Florida Everglades (Conrads and others, 2006). Seventeen short-term water-depth recorders were established in 2002 and are co-located at transects where extensive plant sampling is ongoing (fig. 1).

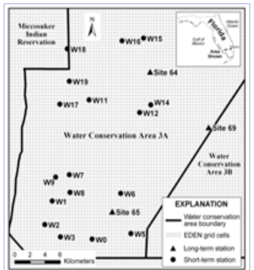


Figure 1. Short- and long-term water-depth and water-level stations in Water Conservation Area 3a used in this study.

Modeling Approach and Results

Using inputs representing the three long-term gages, very accurate ANN models were developed to predict the water levels at the 17 short-term sites. To decorrelate the water-depth data and to set all of the stations to a common datum for the analysis, Site 64 was used as the "standard" and the difference between Site 64 and each of the other water depths sites 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 Site 64 and W8 is clearly seen in figure 2b where W8DIF is plotted on a separate axis.

The predictions of water depths at the short-term sites are made in two steps. The first step is to develop ANN models to predict the water-depth difference (from Site 64) for each site. The second step is to subtract the predicted water-depth difference from Site 64 for the prediction at the short-term site.

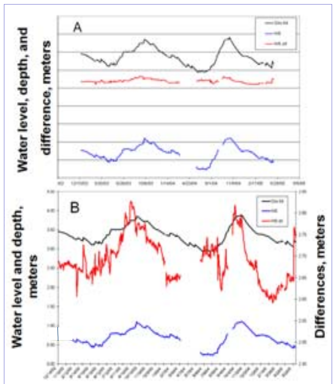


Figure 2. Plots showing water levels at Site 64, water depths at W8, and the difference between the two time series (W8DIF). In figure 2a, the three time series are plotted on the same axis. In figure 2b, W8DIF is plotted on a separate axis to show the detail of the variability between the two signals.

Table 1. Summary statistics for final water-depths predictions at short-term sites

[n, number of samples; R, Pearson coefficient; R^2, coefficient of determination; RMSE, root mean square error; PME, percent model error]

Statistic	n	R	R^2	Mean Error, meters	RMSE, meters	PME, percent
WL0	694	0.995	0.990	0.009	0.024	2.6%
WL1	352	0.999	0.997	0.000	0.013	1.5%
WL2	594	0.992	0.985	0.008	0.022	3.0%
WL3	301	0.996	0.992	-0.003	0.022	2.7%
WL5	563	0.999	0.997	0.002	0.015	1.5%
WL6	682	0.994	0.988	0.011	0.025	3.0%
WL7	222	0.997	0.994	0.001	0.012	1.8%
WL8	690	0.997	0.995	0.004	0.016	1.8%
WL9	567	0.993	0.986	0.002	0.027	3.1%
WL11	658	0.996	0.992	0.009	0.023	2.3%
WL12	603	0.998	0.996	0.008	0.018	1.6%
WL14	674	0.998	0.996	0.017	0.023	2.2%
WL15	659	0.997	0.994	0.004	0.021	1.9%
WL16	377	0.997	0.994	0.001	0.018	1.8%
WL17	392	0.991	0.982	0.000	0.029	2.8%
WL18	613	0.988	0.976	0.011	0.036	3.8%
WL19	426	0.994	0.988	-0.006	0.026	2.7%

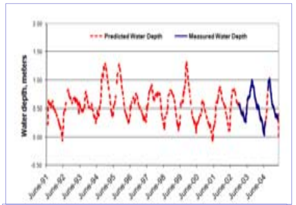
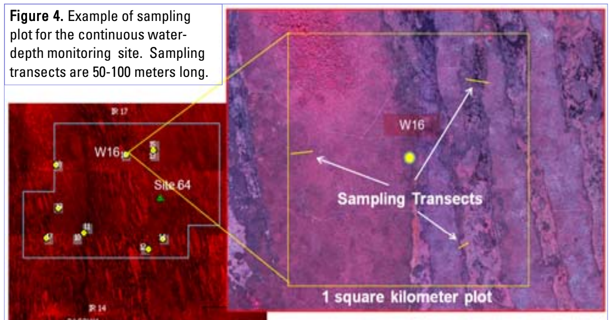


Figure 3. Measured (solid blue trace) and predicted (dashed red trace) water depth for Site W11. Period from June 1991 to June 2002 are the hindcasts from the model. Periods of missing predictions are due to missing data at one or more of the input stations.

Each model uses combinations of two general types of input signals from the three long-term sites, a water-level signal(s) (either the daily value or a moving window average) and a time derivative signal(s). The final water-depth predictions at the 17 short-term sites were evaluated using four "goodness-of-fit" statistics: coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE), and percent model error (PME) (Table 1).

The models were then used to hindcast water levels at the 17 short-term sites back to 1991 (fig. 3). A Decision Support System (DSS) was developed to disseminate the hindcast models in an easily used spreadsheet application that integrates the models and database with interactive controls and streaming graphics to run long-term simulations.

Figure 4. Example of sampling plot for the continuous water-depth monitoring site. Sampling transects are 50-100 meters long.



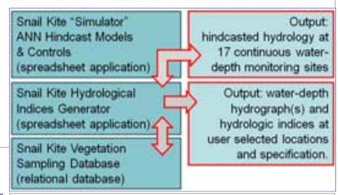


Figure 5. Architecture of the Snail Kite Decision Support System.

References

Conrads, P.A., Roehl, E.A., Daamen, R.C., and Kitchens, W.M., 2006, Using artificial neural network models to integrate hydrologic and ecological studies of the snail kite in the Everglades, USA, *in* Gourbesville, Philippe, Cunge, Jean, Guinot, Vincent, and Liong, Shie-Yui, eds., Proceedings of the 7th International Conference on Hydroinformatics, August 2006, Nice, France, v. 3, p. 1651–1658.

Enhancements to the Decision Support System

The 20 continuous monitoring sites are centered in a 1-km² plot representing different ecotones in the study area. For each plot, 2 or 3 belt transects (50-100 meters) were established and standing biomass are sampled every meter (fig. 4). Vegetation samples are collected twice a year and over 9,000 samples have been processed between 2002 and 2005. To better meet the needs of the plant ecologists, several enhancements have been made to the Snail Kite DSS:

- Hydrologic records are hindcasted back to 1962
- Water-depth hydrographs can be generated at any sampling location
- Additional statistics (hydrologic indices) with user controls including:
  - Days below a specified depth
  - Cummulative frequency distributions of water depth
  - Rate of change of high water pulses
  - Duration of increasing and decreasing pulses
- Reading and writing data to an external vegetation and hydrologic database
- Retraining of ANN models
- Generation of elevation profiles for sampling transects

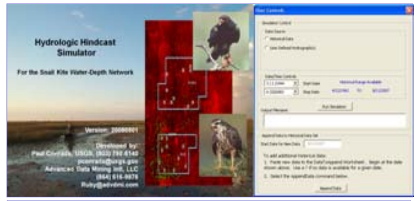


Figure 6. Screenshot of "About" worksheet of the Hydrologic Hindcast Simulator and User Controls for the spreadsheet application.

To accommodate the handling of hydrologic and sampling data, the architecture of the DSS was changed from a stand alone application to one integrating multiple applications (fig. 5). In the new DSS, the "Hydrologic Hindcast Simulator" is used to compute the hydrologic data for a user-specified period (fig. 6) and the "Hydrologic Indices Generator" computes the water-depth hydrographs and hydrologic indices at user selected locations and specification, respectively (fig. 7).

Figure 7. Screenshot of "About" worksheet for the Hydrologic Indices Generator and user controls for the spreadsheet application.

Summary

Hydrology has a significant effect on the nesting and foraging of the threatened and endangered snail kite. A DSS spreadsheet application that allows a broad range of users to have equal access to analytical tools for hindcasting hydrologic records was enhanced to generate hydrographs and hydrologic indices at locations of over 9,000 vegetation sampling sites. For ecologists, the DSS allows them to generate extended hydrologic records to increase the predictive capabilities for evaluating the snail kite habitat to changing hydrology. The application demonstrates how very accurate empirical models can be built directly from data and readily deployed to end-users to support interdisciplinary studies.