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National Park Service
Everglades National Park

PROJECT TITLE: SYNTHESIS OF EXISTING DATA ON AQUATIC COMMUNITIES IN EVERGLADES NATIONAL PARK IN A FRAMEWORK FOR ECOSYSTEM ASSESSMENT AND EVALUTION

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IV. Presentations and Posters

A.	Taylor Slough Review (Presentation)	Attached
B.	GEER (presentation)	Attached
C.	GEER poster	Attached

I. Executive Summary

This project provided for a full-time data analyst to assist in development of methods to better use existing databases on aquatic fauna in planning and assessing management and restoration of the Everglades. Charles Goss was hired to assist Joel Trexler in these analyses. A number of advances were made through the help of Mr. Goss that are described in this report. The primary advance was in development of a protocol to assess management impacts when no reference sites are available for comparison, which is a common situation the Everglades because of its large size with open flow of both surface and ground water. The resulting method was illustrated by assessment of impacts by ISOP/IOP hydrological schedules that were begun in late 1999. Comparisons to a pre-ISOP/IOP period with model forecasts of the impact of changing management given rainfall in the years 2000 – 2008 indicated that more drying events were observed in Taylor Slough, and in some portions of Shark River Slough, than would be expected if ISOP/IOP had not be implemented. This work was reported in a peer-reviewed paper published as part of a collection of papers on assessment of Everglades restoration. A Performance Measure documentation sheet elaborating on this method was developed with Doug Donalson for use in the DECOMP program and is currently under review by RECOVER. In addition, a presentation was developed for a special meeting on management of Taylor Slough that further evaluated the changes in management that could account for the observed increase in drying frequency in that region of Everglades National Park. Those analyses suggested that though the annual water budget has not been so impacted by ISOP/IOP, the bulk of flow under Taylor Slough bridge was pushed to earlier in the dry season, possibly leading to dryer dry seasons than would have been experienced without that change. For aquatic fauna, if a 'dryer' dry season means that marsh surfaces dry that would not have otherwise dried, high mortality with multi-year impacts are noted. For these organisms, annual water budgets are not as important as the annual minimum stage relative to ground surface at key points in the slough.

A number of related topics tied to improving statistical modeling of aquatic fauna data are covered by sections of this report. These include evaluation of alternative hydrological models (EDEN, 2 mile x 2 mile, 500m x 500m) for use in assessments, documentation of multi-year cycles in rainfall that confound analysis of hydrological management in the Everglades, development of a new independent variable for assessment based on the size of flooded habitat surrounding aquatic animal sampling sites, and a discussion of lessons learned in fitting temporal autocorrelation in time series models used for these assessments. Also, we explored seasonality in juvenile and adult population dynamics of key fish species and documented how it changes among years. Finally, we developed a quality assurance – quality control (QA/QC) protocol for management of aquatic fauna data sets.

II. Project Management

A. Overview

During the first year of this project we completed creation of our database, including updates through the end of 2006 and assemblage of extensive metadata. All data types (fish, invertebrate, crayfish, vegetation, physical and biomass) were in their finished forms and ready for analysis and interpretation. Additional years were added as the project progressed and current assessments use data through the 2007-2008 wateryear (May through April).

Using the finalized data sets, we continued to update our analyses to determine the effects of the Interim Operating Plan (IOP) on the biota of the Everglades. To illustrate the impacts of IOP, we analyzed time-series of the population dynamics of both fish and crayfish before IOP and after IOP. We used species that vary in their sensitivity to hydrology to illustrate how changes in water management practices (i.e. IOP) impact Everglades' animal communities. These data were then used for presentations at the Krome Center and other venues (see presentations list, below). To accomplish this we created models that use rainfall to predict water depths at a given site under pre-IOP water management conditions (1992-1999). These models were then be used to predict fish densities in the post-IOP period (2000-2007), assuming that pre-IOP management remained with the observed rainfall. We compared the results from the model simulation to the observed data and quantified the differences between the observed data and the predicted data. This analysis yielded insights into the ramifications of IOP with a potential to inform future water management decisions. A version of this description was used by Doug Donalson in his DECOMP Performance Measures Documentation Sheet produced in September this year, and updated recently (copies of the original are included in this report and the most recent draft is included as a file supporting the report).

B. Publications and Presentations

Publications

Doren, R. F., J. C. Trexler, A. D. Gottlieb, and M. Harwell. 2009. Ecological Indicators for System-wide Assessment of the Greater Everglades Ecosystem Restoration Program. Ecological Indicators 9:S2-S16

Trexler, J. C., and C. W. Goss. 2009. Aquatic Fauna as Indicators for Everglades Restoration: Applying Dynamic Targets in Assessments. Ecological Indicators 9S:S108-S119.

Doren, R.F., Trexler, J.C., Harwell, M., and Best, G.R., Editors, 2008. System-wide Indicators for Everglades Restoration 2008 Assessment. So. FL. Everglades Restoration Task Force, US Dept. Interior, Technical Report. 39pp.

Meetings with So Florida Environmental Managers and Science Coordinators:

South Florida Natural Resources Center (ENP)	April 16, 2007
South Florida Natural Resources Center (ENP)	Sept 12, 2007
Indicator Program (DOI Task Force, led by Bob Doren)	April 9, June 13, Oct 22, 2007
SCG Meeting, Presentation of Indicator Tool	Oct 18, 2007
RECOVER Leadership Group (RLG)	Jan 8, 2008

Presentations of Results from this project to professional groups:

Ecological Society of America, Symposium on setting targets for restoration	August 8, 2007
Estuarine Research Federation	Nov 8, 2007
Florida Institute of Technology	Oct 11, 2007
Greater Everglades Ecological Restoration meeting	July, 2008

C. Collaborators

We have sent data to William F. Loftus, Shawn Liston, Jennifer Rehage, Jerry Lorenz. Trexler met with Don DeAngelis, Troy Mullins, and Doug Donaldson to discuss development of a new fish model for use in evaluation projects. Don is gave a presentation of early aspects of this model at the 2nd National Conference on Ecosystem Restoration in April, 2007.

D. Future Directions

Synthesis of existing data is an ongoing project because new data are always being added to our collection and further improvements are always being made to the existing protocols. Our most immediate future direction will be to use new hydrological scenarios that are expected soon, in concert with our current parameters estimates for Performance Measure responses to hydrological variation (see DECOMP PM doc sheets), to project a wider array of possible restoration futures. This is a project being undertaken by RECOVER with the trophic hypothesis team. In addition, we hope to add local nutrient status to our PM models to expand the range of impacts we assess to include the two major drivers affected by management: hydrology and nutrient status. However, the Everglades Landscape Model (ELM) is the only simulation tool that provides both hydrological and nutrient scenarios. This means that development of aquatic fauna performance measures that address both hydrology and nutrients, while desirable, will not be actionable until future work is completed by modelers of the physical drivers.

VI. PROJECT RESULTS

A. **Assessing Management Impacts to Aquatic Fauna in the Everglades** (see also Trexler and Goss 2009 submitted with this report)

A key goal for Everglades restoration is to 'get the water right' with the expectation that other components of the ecosystem will be restored as a result. An implication of 'getting the water right' is that operations of the water distribution system lead to water-level fluctuation that reflect historical patterns resulting from rainfall, and that linking surface-water dynamics to rainfall will recapture historical patterns of hydroperiod, including frequency and periodicity of marsh drying. Ecologists agree that frequency and periodicity of drying across the landscape, along with oligotrophic water quality, are key elements to restoring ecosystem function in the Everglades. Thus, assessing performance measures of Everglades management should include rainfall-based targets that adjust expectations for seasonal and inter-annual patterns of regional rainfall. In this assessment, we use a protocol that incorporates **dynamic targets** for performance measures of aquatic consumers that are designed to remove variation resulting from rainfall and focus evaluation on the residual variation resulting from water management choices.

Aquatic fauna are included as indicators of Everglades management and restoration because of their central role in the food web, supporting emblematic Everglades animals such as wading birds and alligators. In Everglades monitoring and assessment, aquatic consumers refers to small fish and crustaceans that are directly consumed by wading birds and juvenile alligators. The linkage of these organisms to water management is well established in the published literature, permitting evaluation of the impact of changing water delivery and quality on their numbers (Fig. 1). Also, their life cycles are generally one year or less, providing relatively rapid responses to changing conditions that can be assessed through standard sampling protocols. Unlike flagship species with high visibility and public support such as wading birds or alligators, aquatic consumers are included in ecosystem assessment solely because of their place in a chain of causality, linking water management and animals of high value to society.

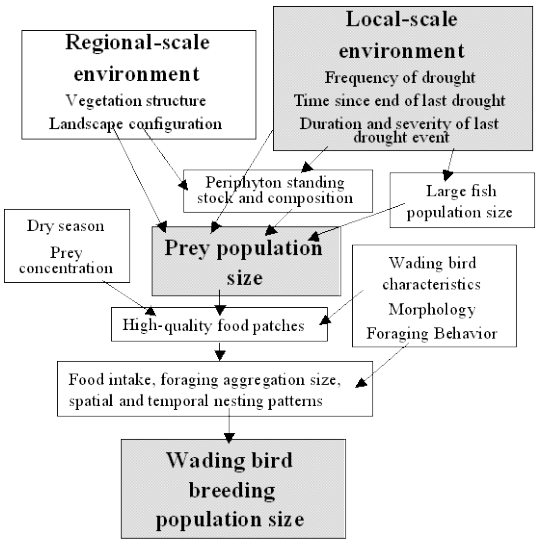


Figure 1. Conceptual model illustrating the linkage of environmental drivers controlled by managers to aquatic consumer performance measures, and their linkage to wading bird population dynamics.

We have a relatively good understanding of the linkage of hydrological dynamics to aquatic fauna, making target setting based on idealized and realized hydrological management feasible. Exactly how regional patterns of aquatic fauna production is linked to nesting success of our apex species (wading birds in this case) is not as well established, but is the target of ongoing research. In this assessment, we ask if hydrological operations are producing the expected spatial and temporal patterns of aquatic consumers given rainfall and desired hydrological variation. Future assessments should identify targets for aquatic consumers tied to wading bird productivity, which in turn will permit identification and resolution of discrepancies, if they exist, between goals for hydrological management and restoration of animals that are highly valued by society.

Aquatic Fauna Performance Measures.- We have identified four patterns of population-level responses to marsh drying in wading bird prey species of the Everglades. We believe that these responses represent different life-history strategies for coping with drought stress (DeAngelis et al. 2005) and have selected indicator species to represent groups of species with similar strategies. Three patterns are found in fish and grass shrimp (Trexler et al. 2001; Ruetz et al. 2005; Trexler et al. 2005; DeAngelis et al. 2005). These are: 1) slow recovery following marsh drying, possibly taking years to regain pre-drought density (typical of bluefin killifish *Lucania goodei*, least killifish *Heterandria formosa*, grass shrimp Palaemonetes paludosus); 2) maximum density attained soon after drying events and lower densities a year or longer after drying (typical of flagfish *Jordanella floridae* and marsh killifish *Fundulus confluentus*); and 3) a moderate relationship between density and time since drying at a regional site, presumably because of medium-scale movement (10's of kms) from areas that are drying (unique in the Everglades to eastern mosquitofish *Gambusia holbrooki*). A fourth relationship is seen in crayfish and probably differs from fish and grass shrimp parameters because of their ability to burrow and tolerate moderate amounts of marsh drying (Dorn and Trexler 2007). Everglades crayfish (*Procambarus alleni*) display little or no relationship between local time since flooding and density, but regional drying and average water depth over the past 6 months do explain moderate amounts of variability in their density (Dorn and Trexler 2007). Everglades crayfish are more abundant when recent water depths have been shallow or drying is frequent, and slough crayfish (*Procambarus fallax*) are more abundant in deeper water and longer-hydroperiod sites (Dorn and Trexler 2007). We are not currently using slough crayfish as a performance measure because no clear relationship has been identified between their numbers and hydrological parameters; their density may be most strongly affected by biotic interactions indirectly tied to hydrology (Dorn and Trexler, unpublished data). We have selected bluefin killifish, flagfish, eastern mosquitofish, and Everglades crayfish to make assessments because they represent the four life-history strategies and are frequent enough in our samples to provide adequate statistical power to detect effects we believe are important. As a fifth performance measure, we use the summed density of all fish species. This is an index of fish productivity and is positively correlated with time since a site reflooded after the most recent drying event; density is better correlated to hydrological parameters than biomass. A sixth performance measure used is the percent of fish that are non-native. Though the direct impacts of non-native fishes on Everglades ecosystem function are not well

understood, their presence conflicts with management criteria for Everglades National Park and there is ongoing concern about their potential impacts on native taxa.

Hydrological Goals used for this Assessment.- We used the same hydrological goals for this assessment as employed in the IOP Project Evaluation Report (SFNRC 2005). Those goals were to match the relationship between rainfall and water-depth fluctuation observed in the period between 1993 and 1999. These years included several with very high regional rainfall (1996, 1997), and some with relatively lower levels (1993 and 1998). The high rainfall years may have provided high water levels similar to those found historically and prior to implementation of water drainage programs in the Everglades. Additional hydrological scenarios should be used to construct performance measure targets in future assessments. The Natural System Model (NSM) is a natural choice for such a scenario, as are hydrological models used for evaluation exercises and planning, for example the D13R (USACOE 1999). Any applicable hydrological model can be used, as long as it is run with rainfall data that includes the years being assessed. Some preliminary examination of NSM output run through 2005 and provided on an experimental basis by staff of the South Florida Water Management District indicates that it predicted higher water levels and less frequent marsh drying than simulated in the 1993-1999 goals used in this report. Thus, impacts identified in this report are probably conservative when compared to current thinking about hydrology of the historical Everglades.

Assessment Methods

Overview of Modeling Strategy- We used the years 1993 through 1999 as a baseline to establish phenomenological relationships between water depth measured at our study sites and rainfall from gauges across three regions: Shark River Slough (SRS), Taylor Slough (TSL), and Water Conservation Areas 3A and 3B (WCA3A and WCA3B). We then used these relationships and the observed rainfall in years 2000 through 2006 to project water depths for those years. The resulting projections simulate water depths expected if no change in water management occurred following the baseline period. We used these hydrological projections to forecast performance measures (PM) at each monitoring site. Finally, the PM forecasts were used as targets for comparison to observed values for each PM in order to assess how implementation of new water management operations may have affected aquatic-system function. The following sections give a methodological overview of the modeling process, and present key findings. Our modeling procedure is divided into three different sections to illustrate the steps that we went through to determine our final impact assessments. A step-by-step description of the modeling reported here is provided in Appendix A.1, and all programs are provided on a CD that accompanies this report.

Modeling Methodology and Key Findings

Hydrological Models- We used daily rainfall data to derive a statistical relationship between rainfall and surface-water depth at a given long-term monitoring plot in the goal period (November 1, 1993 – November 1, 1999). This period was modified from assessments requested by personnel from the South Florida Natural Resources Center and

corresponds to a range of relatively dry and wet years based on rainfall records for the southern Everglades region (Fig. 2). We generated several different rainfall parameters corresponding to the cumulative amount of rainfall over a given period of time. To select parameters to predict field water depths we used two criteria: 1) cross-validation predicted residual sums of squares (CVPRESS) and 2) proportion of times we correctly classified observed marsh drying events (classification rate). Marsh drying events are particularly important for this modeling effort because drying (defined here as water depth less than 5 cm) represents a threshold for many aquatic fauna, especially fish. Once our final hydrological model was selected, we used its parameters to predict surface-water depth in the assessment period (January 1, 2000 through December 31, 2006). This simulates surface water depths if water management operations of the 'target setting period' were maintained during the 'assessment period.'

Our models predicted wetter marshes and fewer drying events in many areas south of the Tamiami Trail than were observed during the assessment period; results were mixed for Water Conservation Areas 3A and 3B (Fig. 3). Additionally, we were able to predict the majority of drying events in the goal period, but the same model using rainfall in the assessment period predicted less than half of the drying events observed. These results indicate that water management operations in the assessment period were responsible for the change in surface water when compared to the target period, not differences in rainfall. In the following sections of this report, our assessment of consumer performance measures illustrates the impact of this difference on aquatic consumer density.

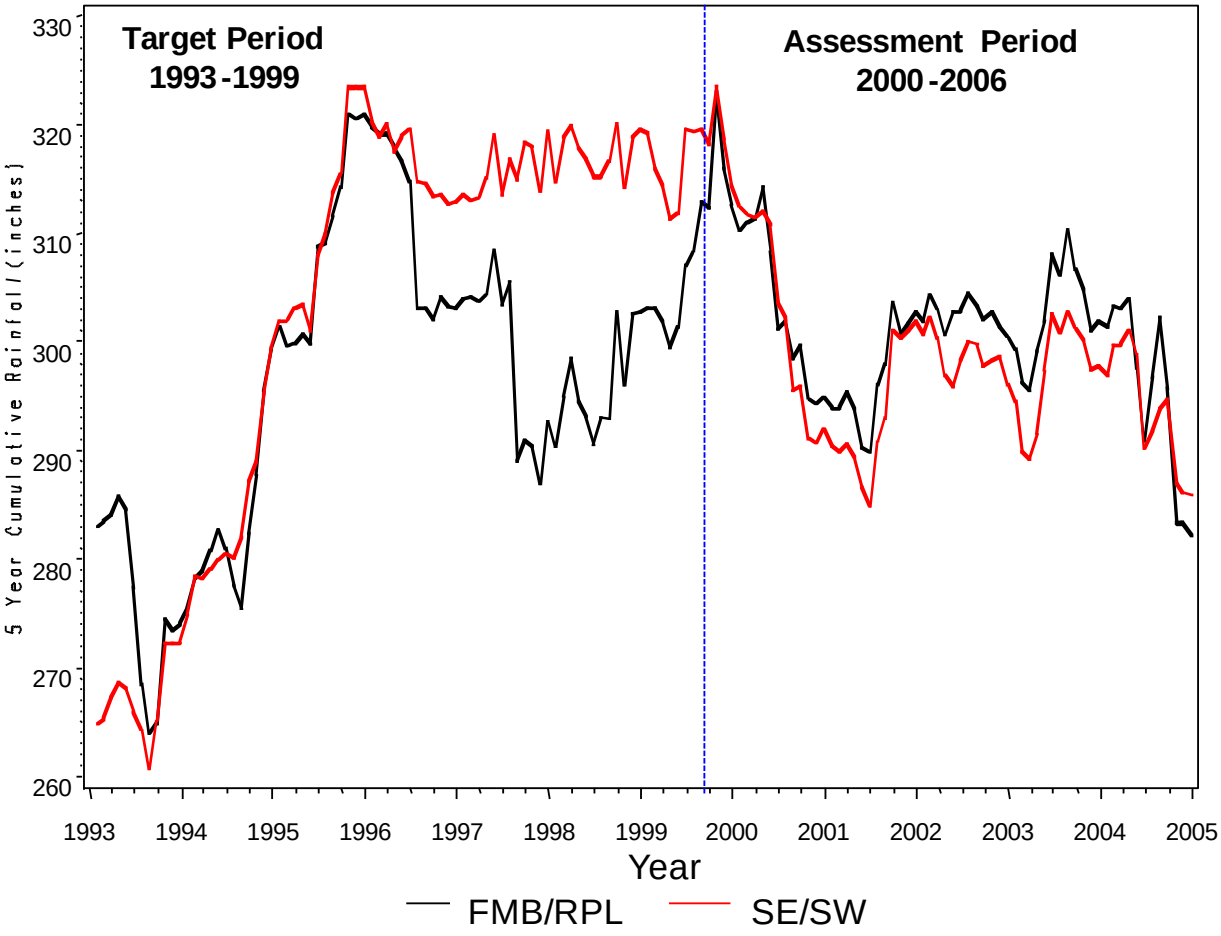


Fig. 2. Time series for the daily 5-year cumulative sum of rainfall (inches) from 1993 to 2006 extract from a time series of running cumulative values starting in 1905 (not shown). The black line corresponds to the average of rainfall record from Forty Mile Bend Ranger Station (FMB) and Royal Palm (RPL), and the red line corresponds to the average of rainfall record from SE and SW gauges. Hydrological goals were set from the time highlighted in red (1993-1999), and assessments were made for the years highlighted in green (2000-2006).

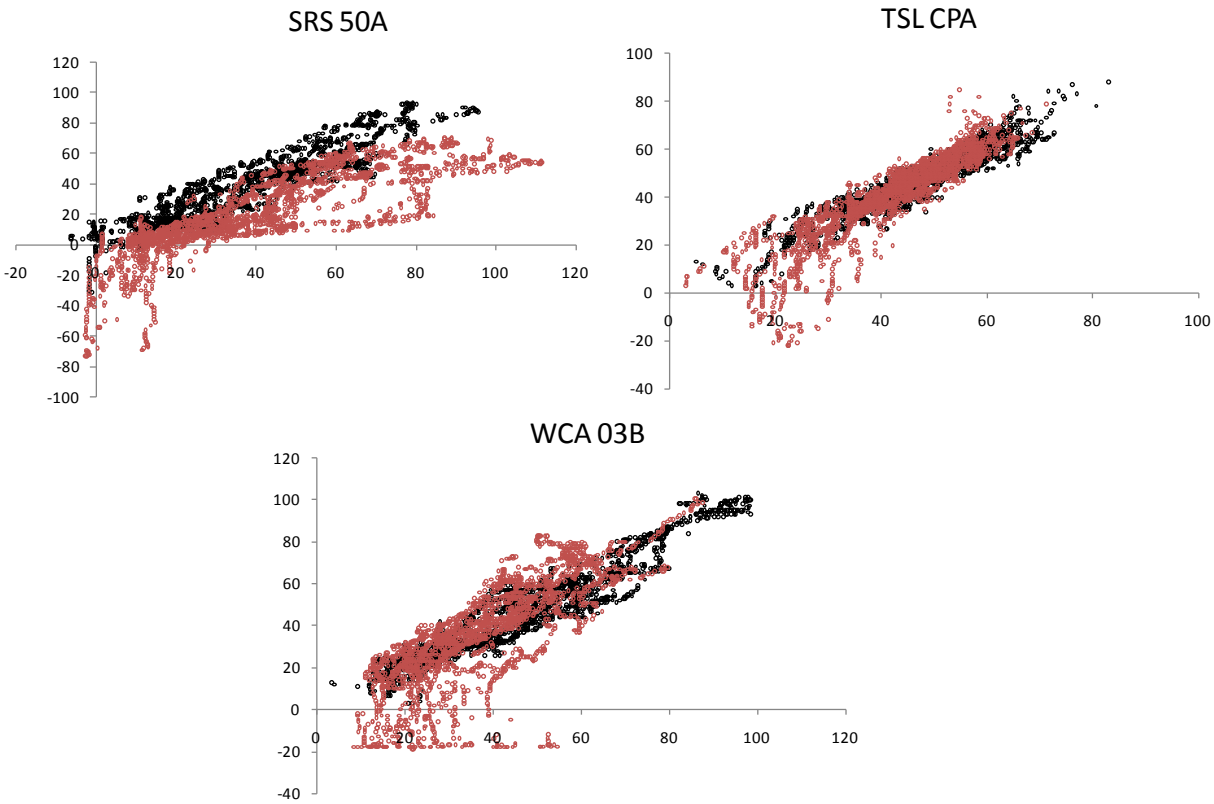


Fig. 3. Hydrological model predictions in the target (black) and assessment (red) periods. Observed depth is plotted on the y-axes and predicted depth is on the x-axes for three exemplary monitoring plots (SRS50A is in Shark River Slough near Shark Valley; TS CPA is in Taylor Slough at Craighead Pond; WCA 03B is in western WCA 3A, south of the L28 Interceptor Canal). Below ground water depths are not well predicted, possibly because of inaccuracies in the observed data.

Ecological Data and Models- Monitoring programs for aquatic consumers focus on small aquatic animals (fish < 8-cm standard length; fish and macroinvertebrates routinely retained on 2-mm mesh sieves) and are conducted in the Everglades by use of a 1-m^2 throw trap (Kushlan 1981; Loftus and Eklund 1994). Several papers support use of this technique based on comparative evaluations with alternative methods that examined bias and efficiency in sampling fishes (Chick et al. 1992; Jordan et al. 1997) and macroinvertebrates (Turner and Trexler 1997; Dorn et al. 2005) in Everglades marshes. Wolski et al. (2004) found little impact of long-term visitation that accompanies throw-trap sampling at fixed sites in the Everglades, further justifying the technique's use for monitoring. A history of PM development and fish monitoring in Everglades National Park is provided in Trexler et al. (2003). Data used for this assessment were obtained from long-term monitoring of the Modified Water Delivery Program (Fig. 4). Future assessments will use data from the Monitoring and Assessment Program of CERP; a brief discussion and assessment using those data for 2005 are given at the end of this report.

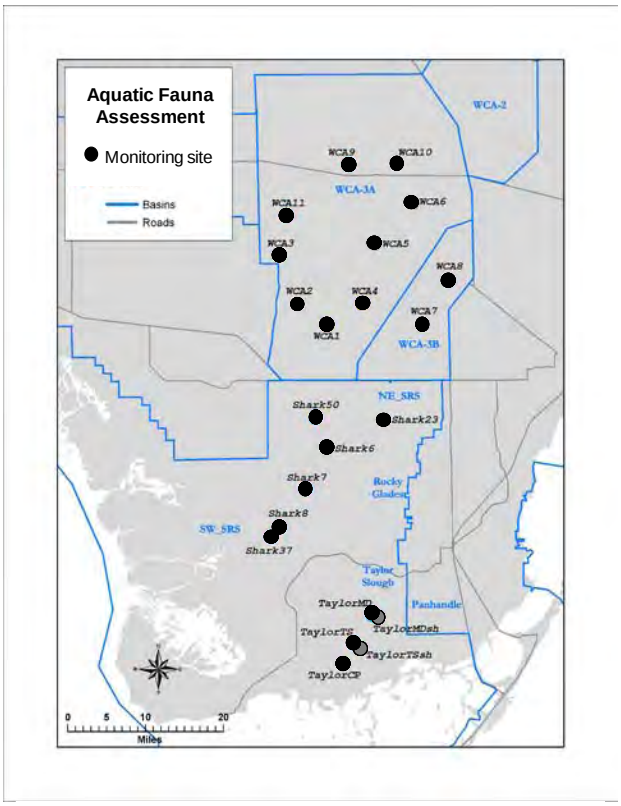


Figure 4. Map of long-term monitoring sites used for this assessment.

We modeled five different performance measures: total fish density (all species of fish summed), eastern mosquitofish, flagfish, and bluefin killifish, and Everglades crayfish. Past work has demonstrated that these fish are representative of the variety of life-history responses to drying events (Trexler et al. 2005; DeAngelis et al. 2005). Flagfish and eastern mosquitofish typically recover quickly from marsh drying, while bluefin killifish recover more slowly (DeAngelis et al. 2005). Additionally the Everglades crayfish has been shown to survive marsh drying conditions and is typical of short-hydroperiod marshes in the southern Everglades (Hendrix and Loftus 2000; Dorn and Trexler, unpublished data). We analyzed these data using hydrological parameters that estimate the time passed since re-flooding from most recent drying event. We define drying as water depth dropping below 5 cm and flooding as when previously low water levels rise above 5 cm. To account for ecological responses driven by hydrology operating at different spatial scales, we created three different hydrological parameters: local days since flooding (LDSF), local days since flooding adjusted for regional drying (ADSF), and regional days since flooding (RDSF). We used linear regression to capture patterns of recovery following marsh flooding and evaluated our models using Akaike's Information Criterion (AIC) to select a preferred model from a hierarchy of models. Our final models generally described the data well, although fit varied across species and regions.

Consistent with previous studies, we found that bluefin killifish and total fish typically increased in density following marsh flooding (Fig. 5). In contrast, flagfish and eastern mosquitofish decreased with time following marsh flooding at some sites, though not at the same rate or to the same extent; eastern mosquitofish are almost always much more abundant that flagfish (Fig. 5). Our models were also consistent with published results indicating that Everglades crayfish tend to decrease in density the longer a marsh is inundated. In fact, this species is extremely rare in WCA 3A and 3B, most likely because there are several areas that in those regions that rarely dry. Everglades crayfish could not be assessed in these water conservation areas.

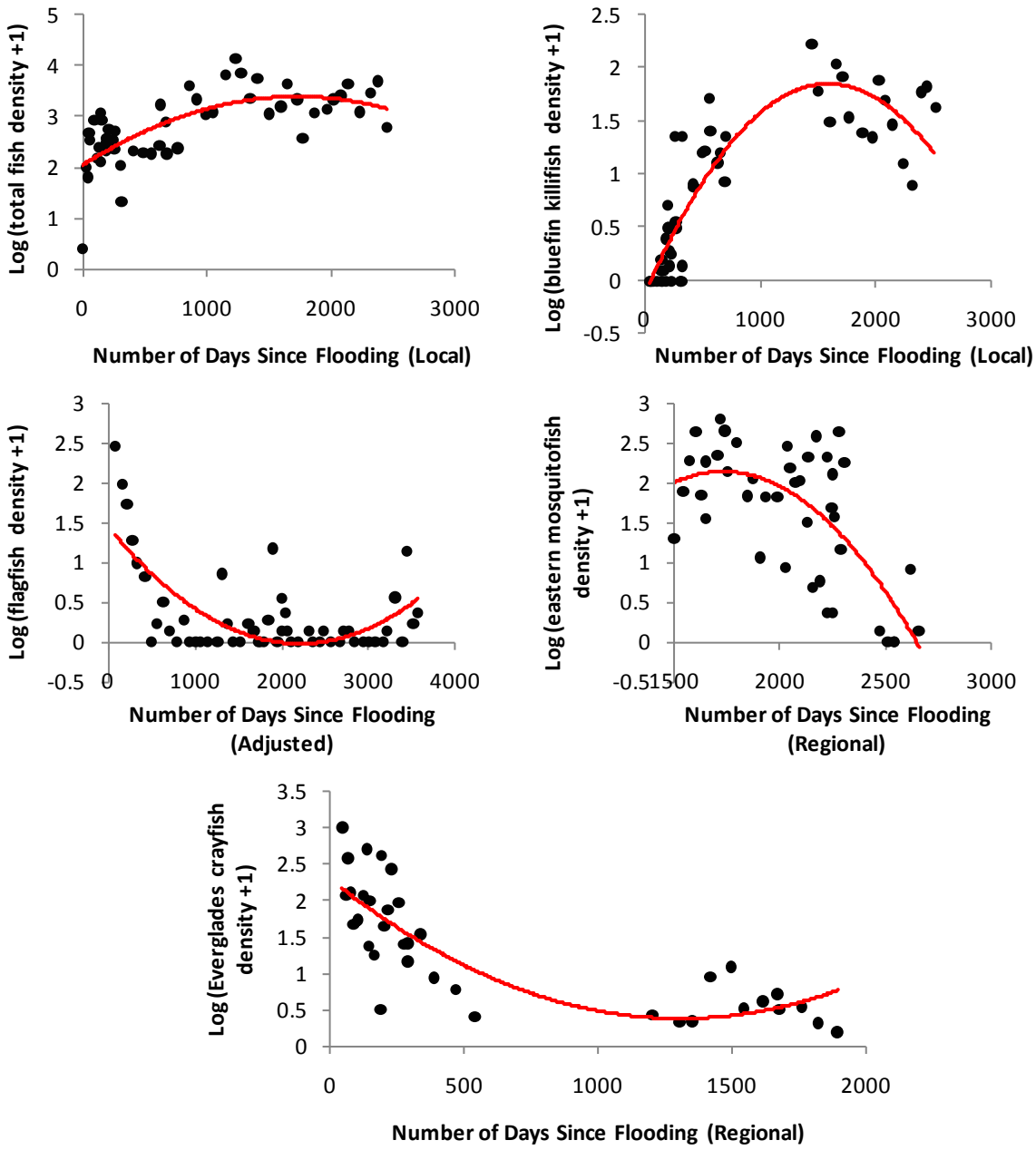


Fig. 5. These graphs are quadratic regressions illustrating our model fits for each fish species at specific sampling sites. Starting in the upper left and preceding right the sites are as follows: SRS 08A, TSL CPA, WCA 02B, WCA 05 B, and TSL MDD.

Water Depth and Ecological Synthesis Models- Using the predicted data from our hydrological model and the parameter estimates from our ecological model, we projected fish densities into the assessment period. This gives us an estimate of aquatic consumer densities if water management were consistent with the goals and targets as defined for this assessment. We found many instances where there was substantial deviation of the

observed fish density when compared to predictions by the hydrological goals (Fig. 6). This suggests that the deviation in the relationship between rainfall and water depth in the assessment period, translated to a change in aquatic fauna densities that resulted from water management activities. In the next section we describe how to interpret the results in Figure 4 and summarize the findings in regional assessments.

Fig. 6 (Below and next page). Illustrations from selected sites of observed time series data and model predictions (left) and the objective limits and targets (right) for five performance measures. There are 64 plots in our database, so the results are aggregated for each performance measure to yield a robust regional assessment using methods discussed in the next section. Upper and lower objective limits are the 95% confidence limits from our ecological targets (this captures uncertainty in fit of our assessment model); the target confidence intervals are derived from deviations for the observed and target data on an annual basis (there are seven groups for the seven annual assessments). The widths of those intervals (1.5, 2.0, and 3.0 standard errors) correspond to different criteria for assessment discussed in the next section. Impacts are evaluated based on overlap of intervals with the upper and lower bounds of uncertainty for fit of the model generating assessment goals (i.e., if the black bars are outside the blue and red bars, we judge that as a negative impact; if they overlap, we assess based on the amount of overlap).

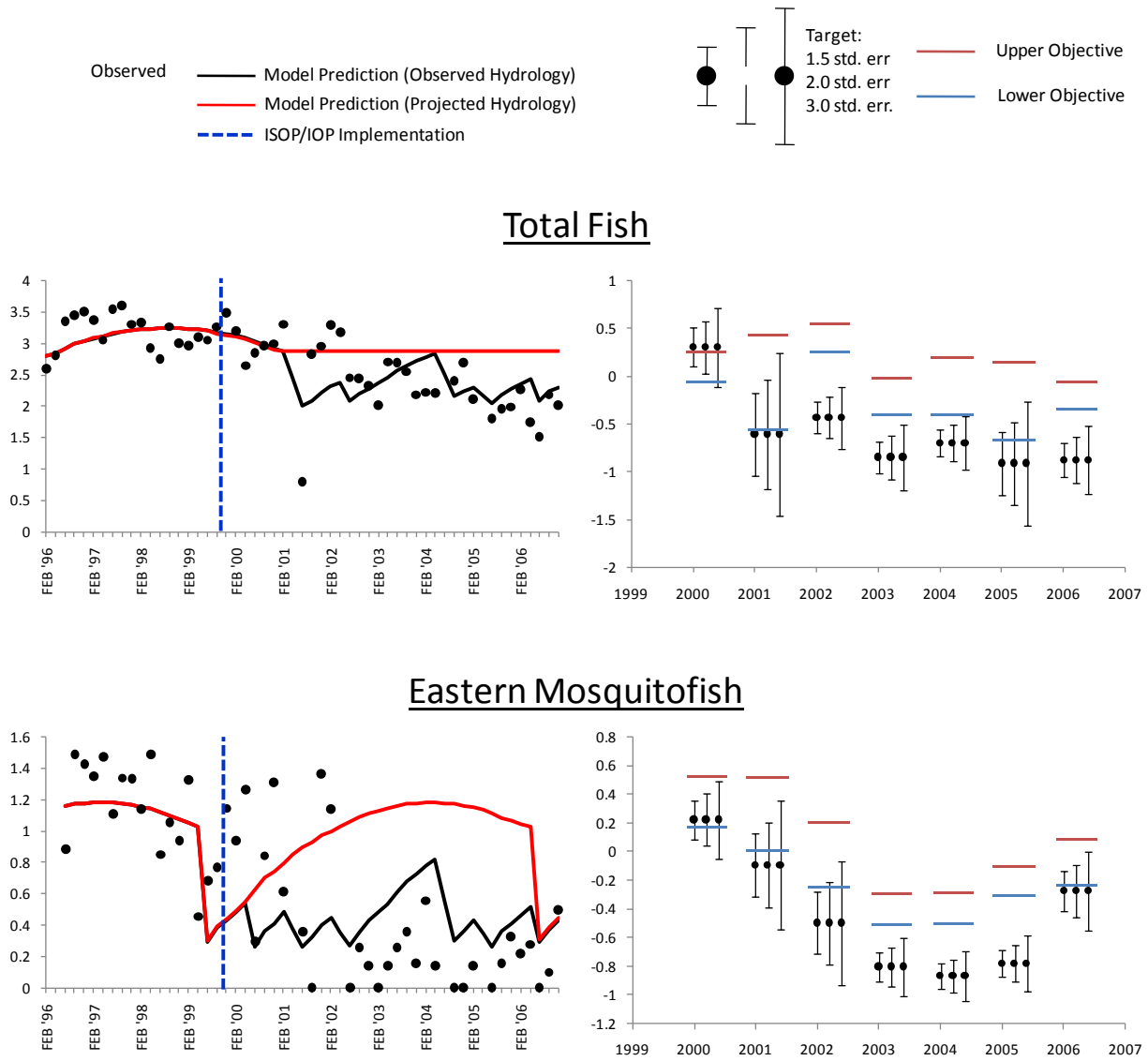
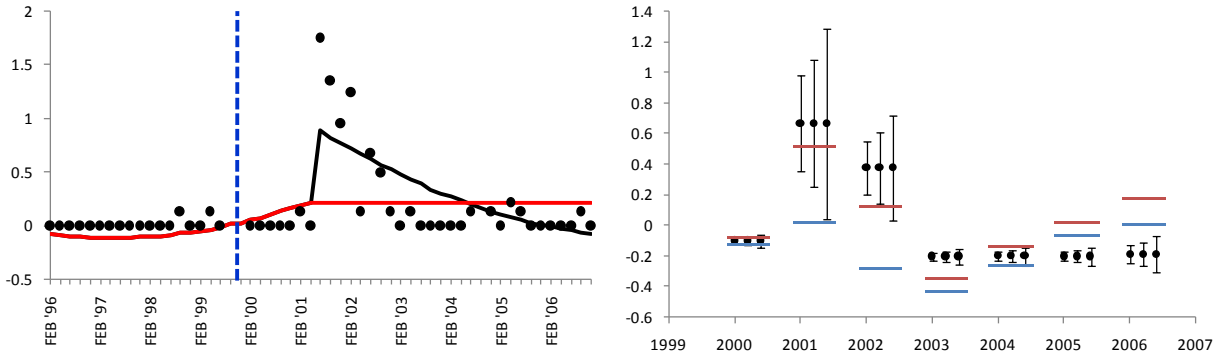
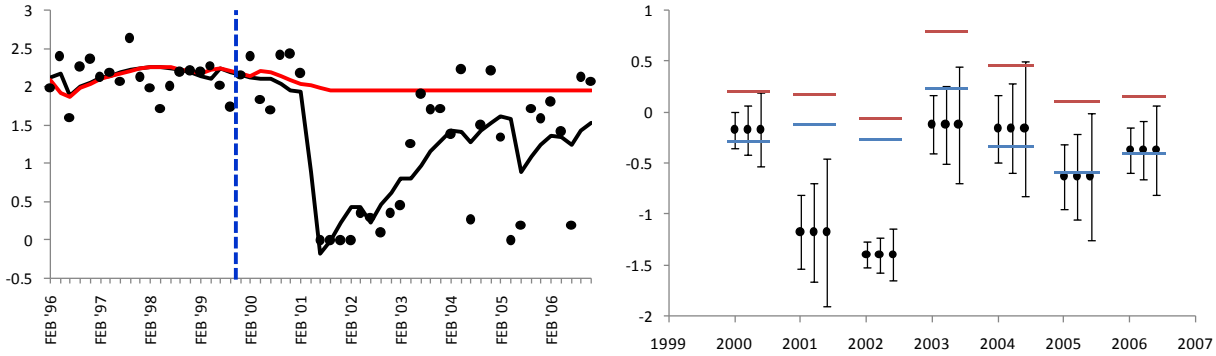


Fig. 6 (continued from last page)

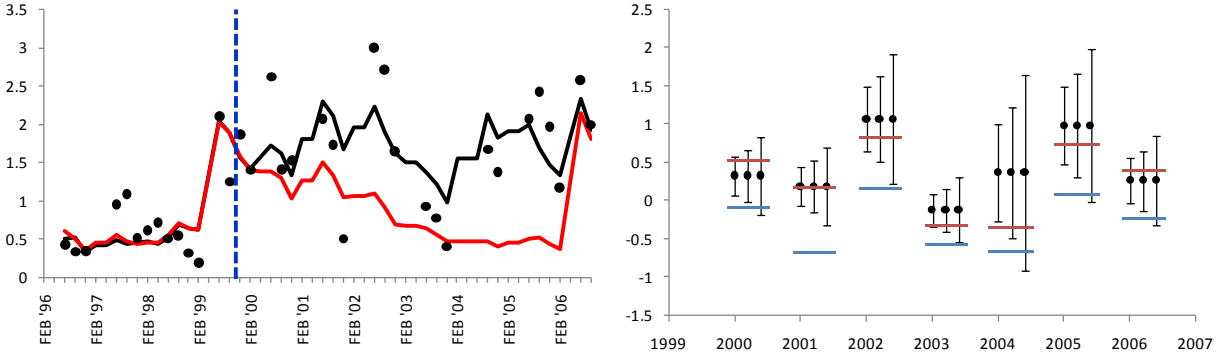
Flagfish



Bluefin Killifish



Everglades Crayfish



Assessing Impacts to Aquatic Consumers.- In order to assess if management is 'getting the water right', we identified impacts based on deviation between our observed values for each performance measure and goals for hydrological management. We identified two primary sources of uncertainty in this process: uncertainty in the fit of our hydrological and ecological models; and uncertainty in our comparison of sampling data to the targets. To account for uncertainty in our modeling, including systematic (lack-of-fit) and random variability in the models, we estimated an objective interval (mean +/- 2 standard errors) for use as upper and lower limits our targets (blue and red bars in Fig. 4). Assessing the magnitude in deviation between our observed data and ecological targets requires defining an 'impact' based on the magnitude of deviation. We did this by use of estimates of the standard error of deviations between observed and target values calculated on an annual basis (black confidence intervals in Fig. 4). Interpretation of these confidence intervals was based on criteria from Decision Theory used to evaluate time series of data on industrial processes.

We defined two classes of impact: individual years with extreme deviations (type A); and runs of consistent deviations from the ecological targets (types B and C). We followed criteria from Allen et. al (1997) using Shewhart Control Chart Theory and define different criteria for defining an impact:

> Type A: one year at least three standard errors above the upper limit of the objective interval, or three standard errors below the lower limit of the objective interval.
> Type B: two out of three consecutive years at least two standard errors above the upper limit of the objective interval, or two standard errors below the lower limit of the objective interval.
> Type C: four out of five consecutive years with at least 1.5 standard errors above the upper limit of the objective interval, or 1.5 standard errors below the lower limit of the objective interval.

This method ensures that we take into account any lack of fit of the original model to the data when assigning an impact, yielding conservative estimates of impacts that are coded as red stoplights (i.e., we have attempted to minimize misclassifying areas without impacts by setting a high standard to assign red stoplights). In contrast, we assign yellow stoplights more liberally because they are simply indicative of sites deserving additional attention (i.e., we have attempted to minimize misclassifying impacted areas as meeting targets by assigning yellow lights with less rigor; see criteria below).

We selected several monitoring sites to illustrate typical patterns of impact for each PM (Fig. 6). In these time-series graphs (Fig. 6, left panels), we capture hydrological variation well in the target setting (or baseline) period. Following 2000, it is clear that our predictions based on the observed hydrology deviate dramatically from our predictions based on the projected hydrology. The graphs on the right panels of Figure 6 illustrate the objective upper and lower limits of the targets with the three confidence intervals representing our three criteria for assessing impacts. These graphs show that,

for the plots reported in this figure, we tended to predict more total fish, eastern mosquitofish and bluefin killifish based on our projected hydrology than were observed. At these sites the patterns were relatively consistent with the mean typically falling outside the objective limits, and several instances where the 3 standard error interval falls below the objective limits. These patterns are typical of Shark River Slough and Taylor Slough. Results for Water Conservation Area 3A are more complex, with impacts depending on the species assessed and location within the landscape. Note that we observed more flagfish and Everglades crayfish than predicted, as expected with drier conditions.

We use assigned stoplights at the regional level (Shark River Slough, Taylor Slough, Water Conservation Area 3A, Water Conservation Area 3B) to communicate the state of aquatic communities in each year beginning in 2000 and ending in 2006 (Table 1). Red stoplights indicate that there is an impact and correspond to Type A, Type B, and Type C impacts. Yellow lights indicate caution and correspond to years where our target is 1.5 standard errors above or below our objective. Finally, green stoplights correspond to years where there is no impact, and the target falls within 1.5 standard errors of the objective. To obtain a regional assessment for each species, we ranked the stoplights: 1=Green, 2=Yellow, and 3=Red, and took the means of the yearly ranks for sites within regions; we rounded to the nearest integer to get a stoplight estimate for each region in each year. Impacts (red lights) were more common in assessments after 2002 because we were able to apply time series criteria with three years of data, and had three ways to detect impacts by 2004. Our ability to assign impacts with confidence increased as more years of data were available, with threshold points after 3 and 5 years because of cumulative information available to interpret findings.

Shark River Slough and Taylor Slough yielded the most striking examples of failure to meet our *a priori* targets (Table 1), with fewer fish and more Everglades crayfish than expected (Table 2). These patterns were most apparent for total fish and bluefin killifish, while eastern mosquitofish tended to yield weaker responses. The only two impacts for flagfish in Shark River Slough indicated that we observed more fish than predicted by our model. In Taylor Slough, our hydrological models described flagfish population dynamics poorly at most study plots, though they were collected, so we were unable to make an assessment. All impacts for Everglades crayfish resulted from observing more specimens than were predicted for the targets (Tables 1 and 2). This suggests that when marshes are drier overall, Everglades crayfish increase their range and abundance. Overall, patterns of impact for bluefin killifish and total fish in WCA 3A were more complex. There were fewer impacts in WCA 3A than in Everglades National Park, and the yearly regional assessments were generally all green (total fish), or a mixture of green, yellow and red, with the current status of bluefin killifish either yellow (WCA 3A) or green (WCA 3B). For flagfish and eastern mosquitofish, most of the impacts resulted because we observed higher density than expected. We believe this resulted from movement of fish from western areas of WCA 3A that dried, and concentrated at sites in the southeast. The current status for either of these species does not indicate an impact. Everglades crayfish is extremely rare in these water conservation areas, so we were unable to make an assessment. Water Conservation Area 3B revealed

few deviations from expectations, consistent with its status of isolation from other parts of the ecosystem and limited capacity for impacts from operations (though ground water seepage is a potential mechanism to transfer management impacts to this region from upstream).

Table 1. Regional stoplight summary of all PMs. Current status refers to 2006.

Performance Measure	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**Current status**
Shark River Slough							
eastern mosquitofish	🟢	🟢	🟡	🔴	🔴	🟡	🟡
flagfish	🟢	🟢	🟢	🟡	🟢	🟢	🟢
bluefin killifish	🟢	🟡	🟡	🔴	🟡	🟡	🟡
total fish	🟢	🟢	🔴	🔴	🔴	🔴	🔴
Everglades crayfish	🟢	🟡	🟢	🟡	🔴	🟡	🟡
Non-native fishes	🟡	🟡	🟡	🟡	🟡	🟡	🟡
Taylor Slough							
eastern mosquitofish	🟢	🟢	🟢	🟡	🟡	🟡	🟡
flagfish	⚪	⚪	⚪	⚪	⚪	⚪	⚪
bluefin killifish	🟢	🟡	🔴	🔴	🔴	🔴	🔴
total fish	🟢	🟢	🟡	🟡	🔴	🔴	🔴
Everglades crayfish	🟢	🟢	🟢	🟡	🔴	🟡	🟡
Non-native fishes	🟡	🟡	🟡	🟡	🟡	🟡	🟡
Water Convservation Area 3A							
eastern mosquitofish	🟢	🟢	🟡	🟡	🟡	🟢	🟢
flagfish	🟢	🟢	🟢	🟢	🟢	🟡	🟡
bluefin killifish	🟢	🟢	🟡	🟡	🟡	🟡	🟡
total fish	🟢	🟢	🟢	🟢	🟢	🟢	🟢
Non-native fishes	🟡	🟡	🟡	🟡	🟡	🟡	🟡
Water Convservation Area 3B							
eastern mosquitofish	🟢	🟢	🔴	🔴	🔴	🔴	🟡
flagfish	🟢	🟡	🟡	🟡	🟡	🟡	🟡
bluefin killifish	🟢	🔴	🔴	🟡	🟢	🟢	🟢
total fish	🟢	🟢	🟢	🟢	🟢	🟢	🟢
Non-native fishes	🟡	🟡	🟡	🟡	🟡	🟡	🟡

Table 2. Summary of the number of site-level impacts (red stoplights) in a given region as a result of observing fewer animals than expected, more animals than expected, or a mixture of the two. Counts of the number of red stoplights between 2000 and 2006 are listed, reported by the direction of deviations.

Region	Species	More than Expected	Fewer than Expected	Mixture
SRS	Everglades crayfish	16	0	0
SRS	eastern mosquitofish	0	7	0
SRS	flagfish	2	0	0
SRS	bluefin killifish	0	20	1
SRS	total fish	0	24	0
TSL	Everglades crayfish	13	0	0
TSL	eastern mosquitofish	0	10	0
TSL	flagfish	0	0	0
TSL	bluefin killifish	0	22	0
TSL	total fish	0	17	0
WCA3A	eastern mosquitofish	7	0	0
WCA3A	flagfish	3	5	0
WCA3A	bluefin killifish	0	10	0
WCA3A	total fish	0	2	0
WCA3B	eastern mosquitofish	9	0	0
WCA3B	flagfish	6	0	0
WCA3B	bluefin killifish	0	4	0
WCA3B	total fish	0	0	0

Non-native Fishes. In the absence of any ecological data on threshold densities for biological impacts of non-native fishes on aquatic ecosystem function of the Everglades, we used a criterion of relative abundance to assign annual impacts. If non-native taxa comprised at least 2% of all fishes collected in a year at a monitoring site, we assigned a value of caution (yellow) to the site for that year. We also considered evidence of a trend of increasing absolute abundance as a source of concern. Based on unpublished data on Mayan cichlid (*Cichlassoma uropthalmus*) density in the Southern Everglades, we assigned a value of exceeds targets (red) if the summed density of non-native fishes (including Mayan cichlids) exceeded 10%. We also assigned 'exceeds target' if the relative abundance of non-native species exceeded 5% for three or more years in a row.

These targets are arbitrary in the absence of much-needed experimental studies of biotic interactions of these taxa indicating detrimental effects on native taxa or other measures of ecosystem function. At present, one or more non-native fish species can be considered present in all areas of the Everglades, and eradication is not currently possible. For this reason, we set a lower boundary greater than zero, though management criteria for the Everglades National Park would require this. Assessing non-native species requires careful consideration because of known gear bias in fish collections, and impacts of sample size in estimating population parameters (sample size refers to both the number of samples AND the total number of animals collected). Assessments must be made with consistent methods for comparisons, either across space or through time, and emphasize relative differences. For example, minnow-trap sampling in Everglades marshes by placement of traps on the substrate typically yields a higher relative abundance of non-native taxa than throw-trap sampling. Minnow traps are preferable to throw traps to determine if species of non-native fishes are present in an area, but throw traps are preferable to obtain a quantitative measure of their relative abundance in the community at a location (assuming that other conditions are appropriate for throw-trap sampling, such as vegetation cover and water depth). We anticipate much interest in refining this target for future assessments.

We found that non-native fishes were typically between 2 and 4% of the fishes collected by throw trap at all of our monitoring sites over the 7 years of this assessment (Fig. 7). In Shark River Slough, one site produced more than 10% non-native fishes in 2003, and slightly less in 2004. This monitoring site is adjacent to the Shark Valley tram road and near a borrow pit which appears to serve as a reservoir of non-native taxa. However, these two years were also relatively dry at this site and few fish of any species were collected. In fact, the most non-native specimens by far are collected at Rookery Branch, a site near the mangrove zone and close to the headwater creeks of the Shark River. However, this site is generally productive for fishes, so the high numbers of non-native taxa (mostly Mayan cichlids) remains a relatively small proportion of the community. A similar pattern is seen in Taylor Slough, where a short-hydroperiod site on the edge of the main slough harbored the highest frequency of non-native fishes, but the most specimens were collected at the southern end of the slough in Craighead Pond, and at a site near the Madeira Ditch, an artificial permanent water refuge. There were no trends of increasing (or decreasing) frequency or density of non-native taxa at these

monitoring sites. We assigned yellow stoplights throughout for non-native taxa because of their persistent low frequency and uncertainty about their impacts.

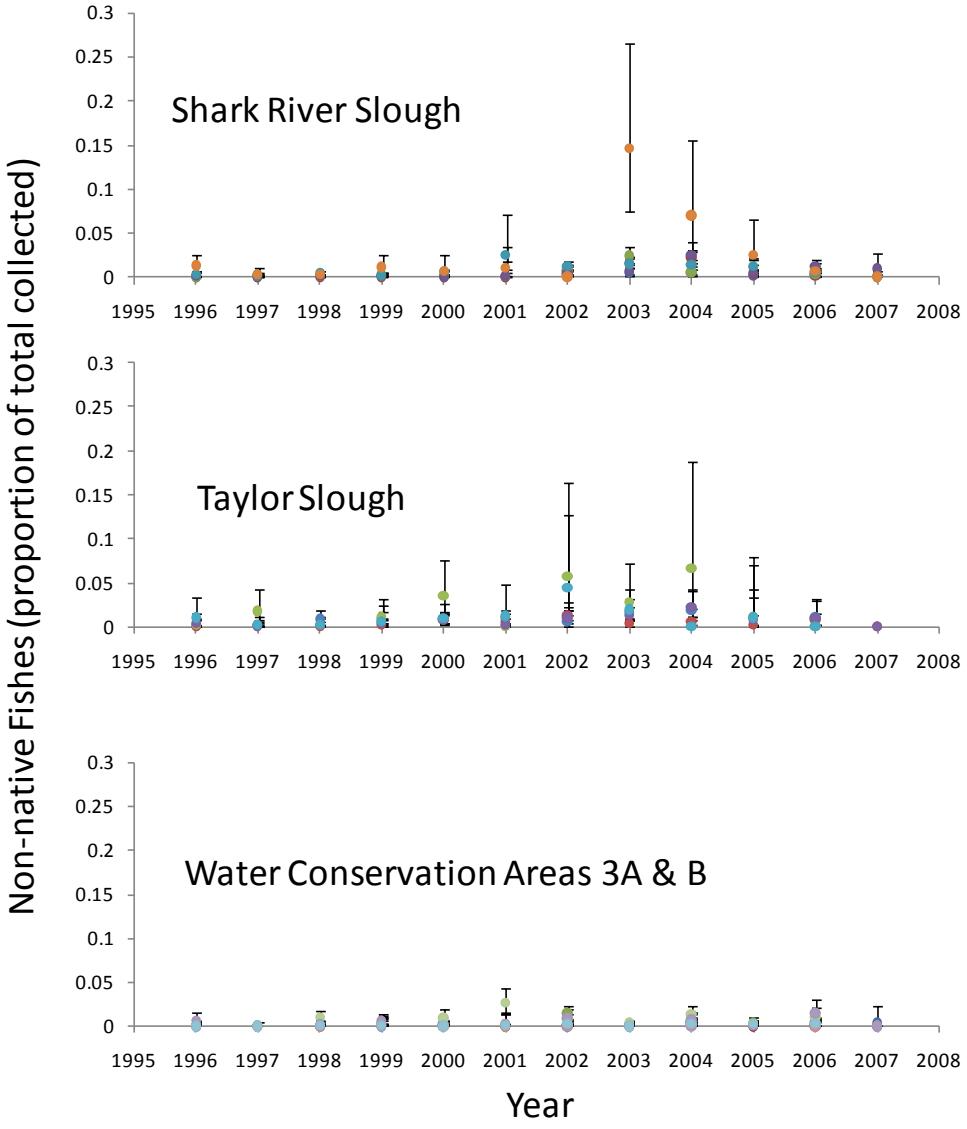


Figure 7. Proportion of non-native fishes collected at each study site in each year, reported separately for regions. Means and 95% confidence intervals were derived by GLM with logit linking function. High values in Shark River Slough and Taylor Slough correspond to site/year combinations when relatively few fish were collected.

Future Assessments and Lessons

Future assessments should be made system-wide using data collected for CERP-MAP. At present, three system-wide surveys have been completed through wet-season sampling (September through November). Assessments reported here indicate that at least three years of data are needed to implement a robust analysis accounting for trends, and five years is best. An impediment to applying dynamic targets in assessment with the CERP-MAP data is in the lack of landscape-scale hydrological targets for evaluating the monitoring data. Evaluating impacts of hydrological operations requires assessments that account for rainfall patterns, particularly for fishes.

We created a preliminary assessment for 2005 using CERP-MAP data and the performance measure total fish (density of all fish summed). To accomplish this, we used a trial version of the Natural System Model that has been run using rainfall data through the end of 2005. This permitted calculation of the days since last re-flooding parameter for modeling total fish density, in a similar manner used elsewhere in this report. *Note: Use of NSM in this case is on a trial basis only as this version has not undergone full QA/QC.* We assigned red stoplights by observed fish density at least three standard errors beyond the target and yellow when observations were between 2 and 3 standard errors from expected. For these data, we used the relationship between fish density and days since the marsh last re-flooded estimate from Shark River Slough as our target. The observed relationship deviates significantly between Shark River Slough, Taylor Slough, and Water Conservation 3A, probably because of different histories of drying and access to permanently inundated refuges (both of which affect patterns of predation, in addition to direct effects of mortality). We opted to use the Shark River Slough relationship as an ecosystem-wide target because it area has less impact of artificial deep-water refuges compared to Water Conservation Area 3A, but has not experienced repeated slough-wide drying as in Taylor Slough.

Most of our collections deviated markedly from NSM-derived expectations and garnered a red stoplight (Fig. 8). The direction of deviations is of interest, with fewer fish than expected in the south (Shark River Slough and Taylor Slough) and more in the north (WCA-2A and Loxahatchee National Wildlife Refuge); there is a mixture of directions in Water Conservation Area 3A. Some of the results are odd, such as in WCA 3A, where we generally caught more fish than were expected at four out of six sampling points. We will not expend more space evaluating this graph because of the tentative nature of the hydrological model results. However, this illustrates that assessments of aquatic consumers with application of dynamics targets is feasible at the ecosystem scale once appropriate hydrological models are made available.

Additional ecological studies are needed on impacts of non-native fish species to develop targets better linked to ecological impacts, if impacts are documented. Experimental studies are of special importance because impacts cannot be effectively assessed by abundance alone; abundant non-native species could be benign and rare species could act through indirect routes to alter feeding opportunities for wading birds or alligators.

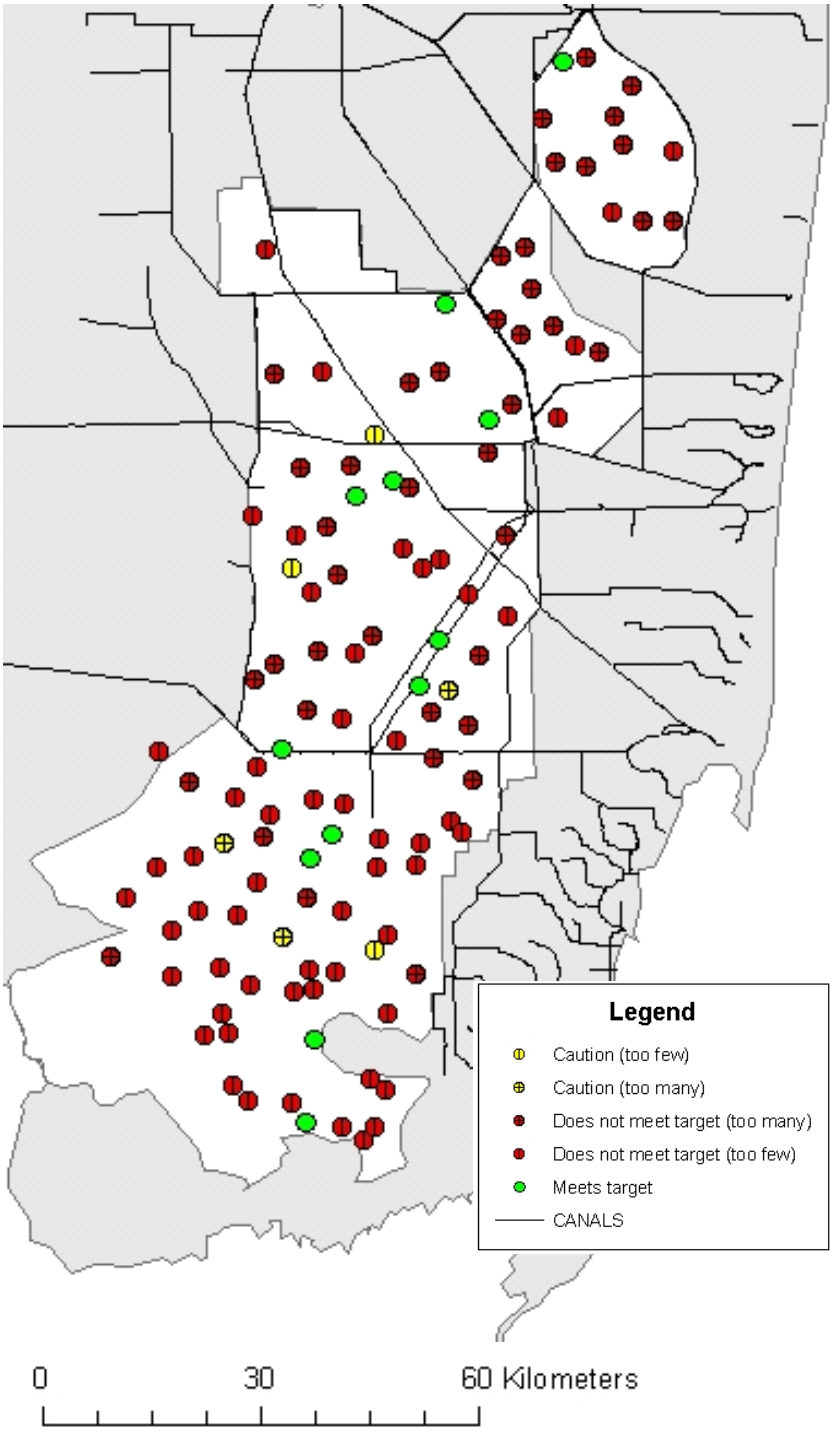


Figure 8. Map of results of assessment using total fish density from 2005 CERP MAP wet-season collections. Targets were derived from an experimental version of NSM used for illustrative purposes.

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A.1 Appendix: Overview of steps for an Ecological Assessment
Prepared by Charles Goss, Mandy Banet, and Joel Trexler

We use nonlinear models and the program Statistical Analysis System (SAS) to assess management impacts for fish Performance Measures. This is a two-step process that begins with setting targets based on hydrological modeling, followed by comparing field data to targets for the actual assessment. In future assessments, the hydrological targets will be provided by managers, eliminating a step that is covered here.

This assessment should be considered an example, and describes the steps conducted for the IOP assessment that was included in the deliverables for this project. All files described here are included on a CD submitted with this report. You will need to modify the file locations and libraries to match with the organization of your computer, or the programs will not run properly. For example, if you copy the directory IOP_CODE from the CD to a D: drive on your computer, you will need to add the D: drive address to the file addresses listed below.

Modeling steps:

A. Hydrological model: dataset creation and cross validation analysis

1. Import rainfall data and concatenate file to create final rainfall data set for use in hydrological analyses.

IOP_CODE\1_datasets\iop_rainfall_data_creation

2. Merge the rainfall data with long-term monitoring hydrological data to produce dataset used for the hydrological analyses.

IOP_CODE\1_datasets\iop_hydrology_dataset_creation program

3. Use cross-validation methods to determine relationship between rainfall and observed water depths.

IOP_CODE\1_datasets\iop_hydro_cross_validation

Dataset created: iop_hydr.pred_hydrology_dsd_final

4. Merge predicted hydrology dataset with NSM hydrology data. The dataset that results will be merged with fish data for assessment.

IOP_CODE \1_datasets\iop_hydro_nsm_merge

Dataset created: iop_hydr.hydro_nsm_rainpred_merge

B. Ecological dataset and nonlinear modeling of fish data

1. Calculate the predicted fish and crayfish density at each plot based on hydrological targets. Open and run the following SAS program to create a dataset for analysis.

IOP_CODE\1_datasets\iop_fishcray_data_creation_nsm

2. The 2_analyses folder contains programs that estimate fish and crayfish parameters based on the relationship between fish/crayfish and DSD. The program then creates a file with the fish predictions using the nonlinear parameters to predict the expected fish density using both observed and predicted hydrology. Run the following SAS programs:

IOP_CODE\2_analyses\1_jorflo_nlin_analyses
IOP_CODE\2_analyses\1_lucgoo_nlin_analyses
IOP_CODE\2_analyses\1_proall_nlin_analyses
IOP_CODE\2_analyses\1_totfish_nlin_analyses

3. Finally we use mixed model analysis (modeling covariance structure) to do a Before-After-Control-Impact (BACI) analysis of the residuals of the analyses from the last step. In this analysis we test whether there is evidence of an impact in the before period vs. the after period.

In species that are found less frequently, such as flagfish, the number of zeros in the dataset leads to heterogeneity of variance. In these cases, a permutation test is performed on a random subset of the data in order to assess the legitimacy of the results. A macro for this test is in the wrapper_macro program.

Run the following SAS programs:

IOP_CODE\2_analyses\Wrapper_Macro
IOP_CODE\2_analyses\2_Autocorr_model_jor *uses permutation test
IOP_CODE\2_analyses\2_Autocorr_model_proall *uses permutation test
IOP_CODE\2_analyses\2_Autocorr_model_luc
IOP_CODE\2_analyses\2_Autocorr_model_tot

4. To create summary stats of our analyses for publication, run the appropriate SAS programs for the hydrological analyses and the nonlinear analyses in the 3_summstats folder:

IOP_CODE\3_summstats\hydrology_summary_stats
IOP_CODE\3_summstats\IOP_fish_nonlin_graphs
IOP_CODE\3_summstats\ IOP_fish_nonlin_summstats
IOP_CODE\3_summstats\ IOP_hydro_nsm_graphs
IOP_CODE\3_summstats\ IOP_hydro_val_summ_stats_final

B. Fish Performance Measure Document Sheet

For final see: Donalson, D., J. Trexler, D. Deangelis, A. Logalbo. 2009. Small-Sized Freshwater Fish Density Performance Measure. Draft DECOMP Performance Measure, Greater Everglades Aquatic Trophic Levels. Documentation Sheet. 14pp.

DRAFT

Greater Everglades Aquatic Trophic Levels
Small Fishes Density Sub-unit

Last Date Revised: 08-31-07

Acceptance Status: draft performance measure

Desired Restoration Condition
The desired restoration conditions for small fish density are to achieve late wet season population densities and taxonomic compositions consistent with pre-drainage hydrologic patterns in the Everglades wetlands and to provide high-density patches of prey-availability so that wading birds can feed effectively as water levels recede during the dry / nesting season.

1.1 Predictive Metric and Target

Two spatially explicit predictive metrics will be included in this performance measure. The first is an updated version of the Trexler et. al. fish habitat suitability index (HSI) model (http://my.sfwmd.gov/pls/portal/docs/PAGE/PG_GRP_SFWMD_HESM/PORTLET_HABITAT/PORTLET_HSI_SUBTABS_2/TAB1392141/HSI_DEC_2004_CHAPTER6.PDF) . This model represents fish density as a function of days since last dry-down for three different landscape dry-down frequencies, short, medium, and long. The second is a new model presently in development that is a true trophic food chain model. Both models will be spatially explicit and will be driven by 500 meter resolution hydrology. The same simulation "engine" that is used for the NPS's Hydrologic Impact Evaluator (HIE) will also be used to drive these two models.

1.1.1 The Trexler fish density model

Dr. Joel Trexler's lab used a 10-year time series (1996-2006) of aquatic consumer data to identify relationships between performance measures indicative of aquatic food-web dynamics and hydrological management. The data were gathered with a 1-m^2 throw trap and standard sampling protocol carried out at 20 monitoring sites in Taylor Slough, Shark River Slough, and Water Conservation Areas 3A and 3B (map of sites in Trexler et al. 2001). Samples were collected at each study site in five months of each year (February, April, July, October, December), yielding over 17,000 community samples with over

250,000 fish records for establishing relationships between biota and hydrological conditions. Quantitative data on fish and aquatic invertebrates (crayfish, shrimp, snails, and aquatic insects) were recorded from all samples, along with environmental data on emergent-plant stem density, floating mat volume (periphyton and floating vascular plants and macroalgae), and water depth. The methods, including estimates of sampling efficiency and evaluation of sources of bias, are described in several papers (Jordan et al. 1997; Wolski et al. 2002; and papers cited therein). The study sites and sample design are also described in detail in other publications (Trexler et al. 2001, 2003, 2005).

Trexler et al have been working on approaches using monitoring data to derive statistical relationships between biotic performance measures and hydrological parameters for ecological assessments of management. At present, models have been developed for several aquatic consumers indicative of Everglades trophic dynamics. Two are discussed here: total fish density (all species summed, number per meter square) and Bluefin Killifish (number per meter square). Both of these indicators display strong monotonic relationships with the number of days between the time of sampling and re-wetting of the site after the most recent drying event. Certainly, other factors also influence the values of these indicators (e.g., Trexler et al. 2005; Chick et al. 2004), but generally more than 60% of the sampling variation (and often more than 70%) can be explained by this single parameter (hereafter, days since dry down [DSDD]).

A logistic equation has been used to model this relationship; separate parameterization is desirable for data from Taylor Slough, Shark River Slough, and Water Conservation Areas 3A and 3B. Separate parameterization was not needed for the data gathered within these areas. Further discussion of the biology of these fits is beyond the scope of this document, however, a key caveat is that caution should be exercised in using these relationships at sites with a history of substantially shorter hydroperiods than those where the data were gathered (Table 1). There is no particular reason to use a logistic model to describe these relationships, though this and related non-linear models better described the data than simple polynomials. Ecologists have often used the logistic equation to describe population growth and the parameters have traditional interpretations (r and K). Possibly an argument against using such a model is the temptation to interpret parameter estimates in this way when caution is necessary because immigration and emigration have not been independently accounted for and are certainly important factors influencing aquatic animals in the Everglades. However, excellent data descriptions from a phenomenological fit of this model have been found. Future work may lead to replacing the logistic model with a Gompertz model, because of limitations in the former (assumes symmetrical population growth at low and high ends of the relationship), but current work has revealed only minor benefit to the latter and only in some data sets.

Table 1. Range of average hydroperiod in days between 1996 and 2006 at Trexler's long-term monitoring sites. There were 6 sites in Shark River Slough, 3 in Taylor Slough, and 11 in Water Conservation Areas 3A and 3B. Averages are over the

10-year interval and minimum and maximum are the shortest and longest average annual hydroperiods at the sites where aquatic consumer data were collected.

	Region		
	Shark River Slough	Taylor Slough	Water Conservation Areas 3A & 3B
Minimum	306	244	318
Maximum	362	357	365

The data were fit to three distinct areas with different frequencies of dry down, Taylor Slough (high), Shark River Slough (intermediate), and Water Conservation Areas 3A and 3B (low). There are presently six sets of parameters, total densities of fish in the three regions and density of Bluefin Killifish (a species that is especially sensitive to hydrologic conditions) in each of the three regions. We will also look into the possibility of separating WCA 3A and 3B into two separate regions.

The logistic equations will be embedded into the same model infrastructure that drives the HIE constraint. The field sites may be classified as three different indicator regions representing three different dry down frequencies or various individual cells in the landscape may be classified according to dry down frequency. At least initially, both the Total Fish and the Killifish will be computed.

The Trexler Equation follows. Table 2 provides the initial parameterization for the three areas and two different indicators.

LOG(TOTFISH +1)=K/(1+((K-Y0)/Y0)*EXP((-r*DSLDD)))

Where:

DLSDD is days since last dry down
r is the growth constant
TOTFISH is the total fish density (number) per meter^2
K=asymptotic density
Y0=Y intercept

Table 2. Parameters from Trexler Logistic Regression for 3 spatially distinct regions for both total fish density and density of Bluefin Killifish.

	Taylor Slough		Shark Slough		WCA 3A/B	
Parameter	Total Fish	Killifish	Total Fish	Killifish	Total Fish	Killifish
K	2.625	1.582	2.757	1.644	2.901	1.491
R	0.003	0.010	0.006	0.007	0.097	0.006
D0	1.08	0.077	1.486	0.232	0.300	0.401

Figure 1 shows the positions of the Trexler monitoring sites. Figure 2 shows the cells used by the older Fish HSI for comparison. Figures 3a-c shows recovery since last dry down over time for total fish in all three areas (Table 1). Figure 4 is a demonstration run of the new Trexler model. The range is 3.4-7.4 fish/m^2 where greens are low values and reds are high values. It is not meant as a scientific report by any stretch, it is simply a proof of concept and speed test. The HIE Landscape was seeded by the Trexler logistic equations using the parameters representing total fish in Shark River Slough. The code does just two things, calculate the days since last dry down, and thereby fish density, and the sum over time of the fish density. This was the simplest implementation for a quick demo. The map shows the result from the SFWMM Verification run 1996-1997. Approximately 77,000 cells are processed per day and the one year run took 15 seconds.

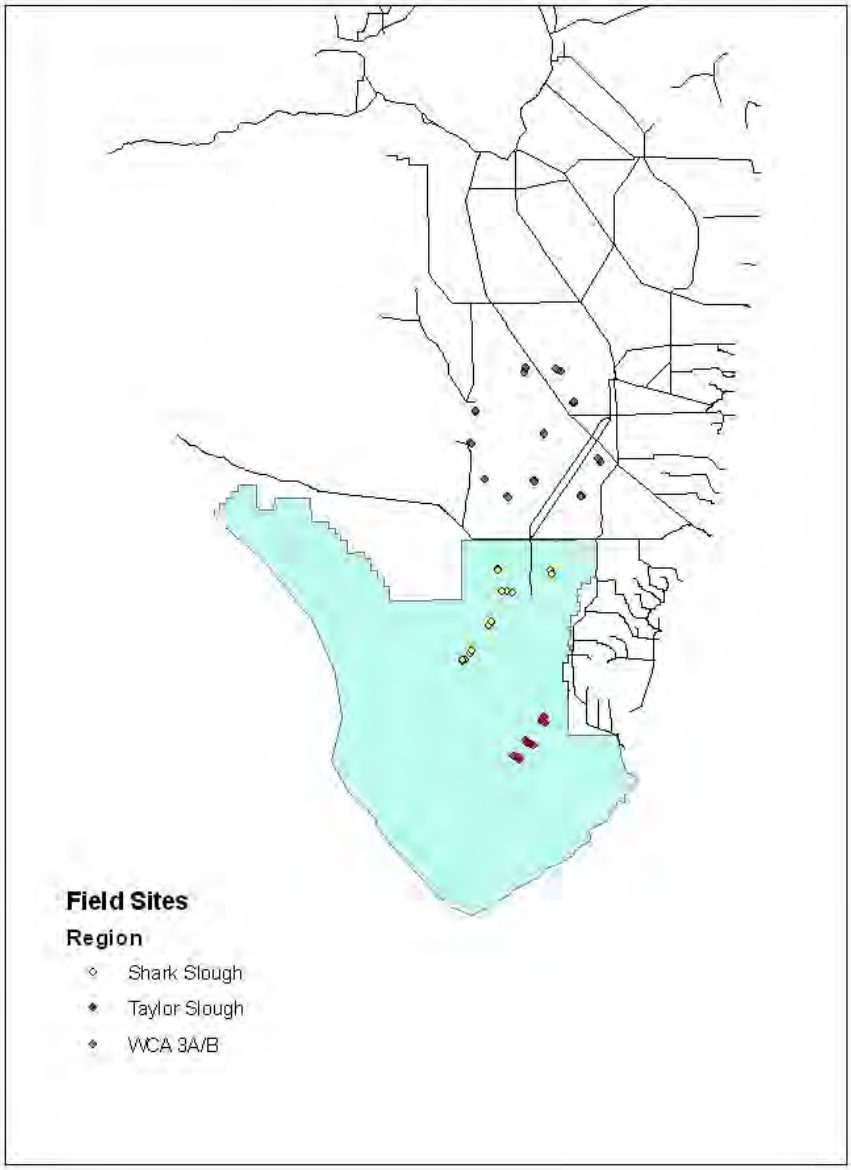

Figure 1 Trexler monitoring sites

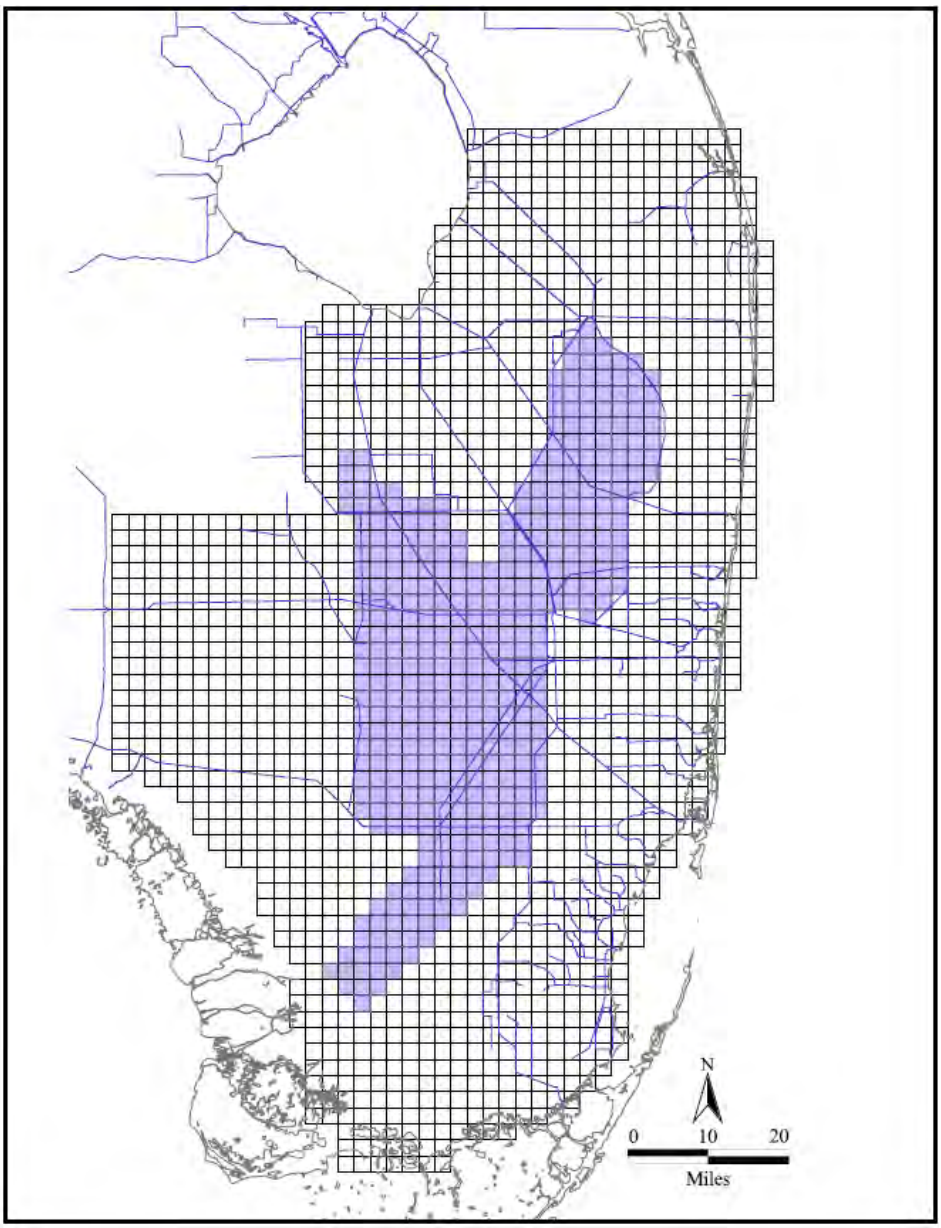

Figure 2 Cells (shaded) used by Fish HSI

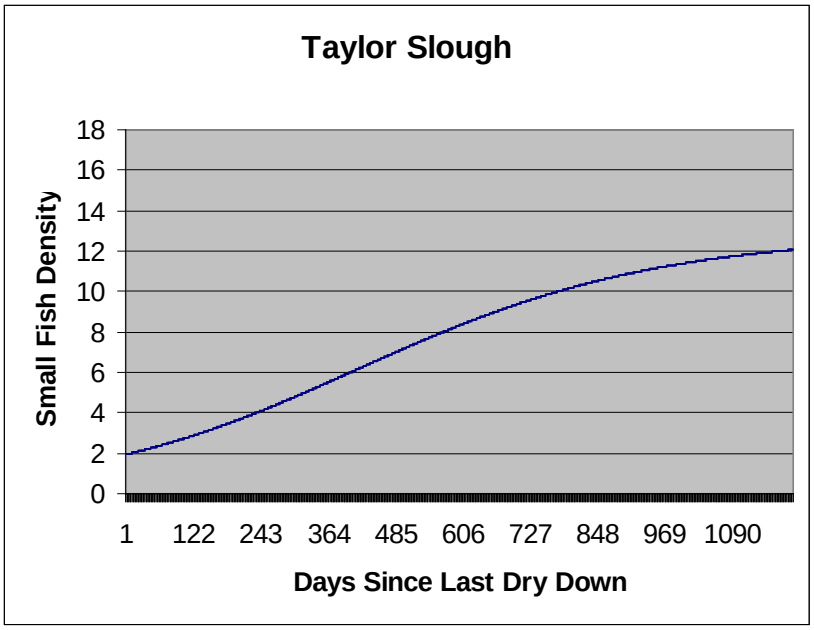

Figure 3a Total Fish recovery since last dry down in Taylor Slough

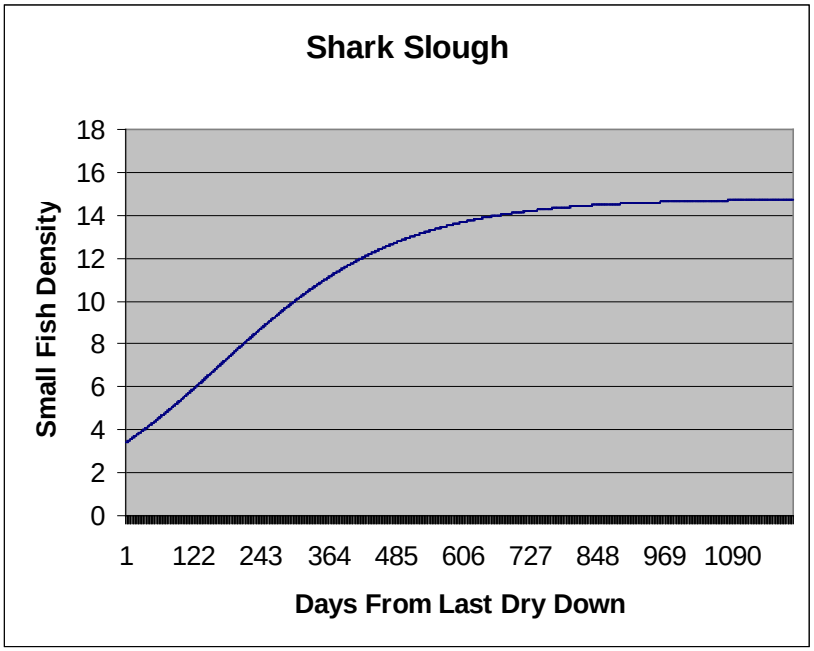

Figure 3b Total Fish recovery since last dry down in Shark Slough

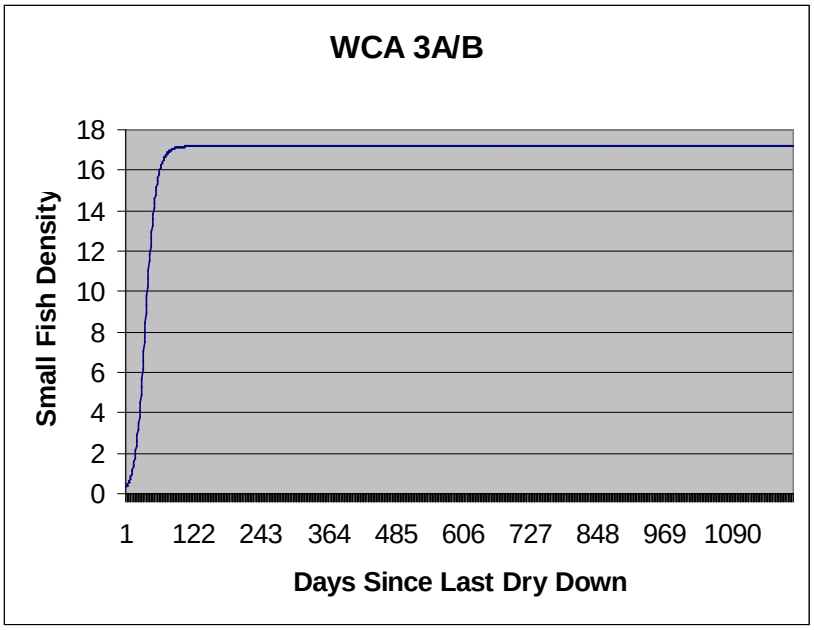

Figure 3c Total Fish recovery since last dry down in WCA 3A/3B

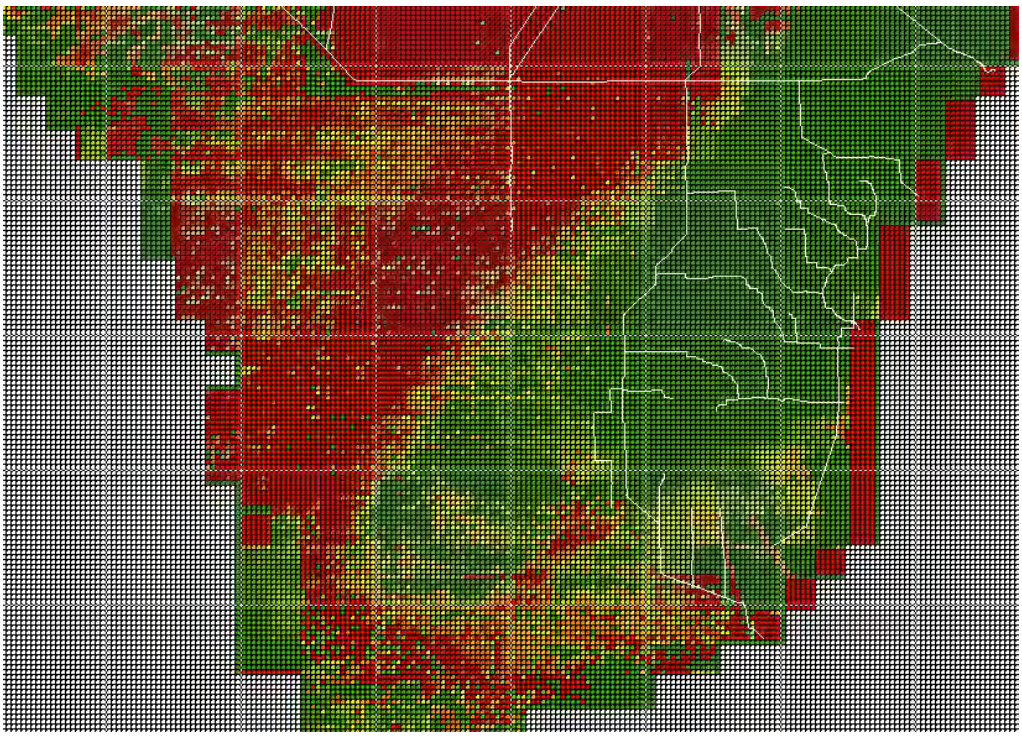

Figure 4 Demonstration of Trexler model – red tones represent the highest values, green the lowest

1.1.1 DeAngelis, Donalson, Trexler (DDT) trophic food web model

This model is presently in development. Unlike the previous model, DDT is a process driven model. Biomass moves up and down the food chain from predation and deaths. Also, movement of all represented species/guilds is explicit with changes in water depth. This represents a sort of rescue effect, where dried out cells do not start barren when reflooded, but rather new colonists arrive with the increasing water.

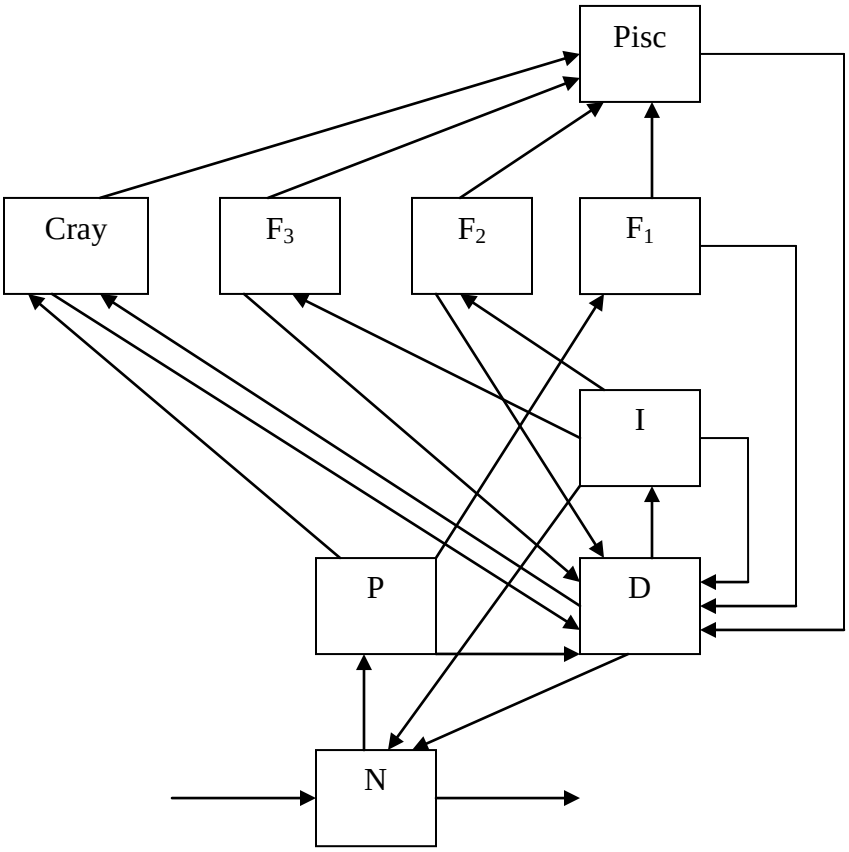

Figure 5 Conceptual Ecological Model of the DDT model. N=Nutrients, D=Detritus, P=Periphyton, I=Invertebrates, Cray=Crayfish, F1=Periphyton feeding fish, F2 and F3=Invertebrate feeding fish, Pisc= Piscivorous fish. A (work in progress) document that describes the present version of the equations and parameters comprising the model is available by request.

1.2 Assessment Parameter and Target

Continued field work by Dr. Joel Trexler's FIU research group will provide assessments and comparisons of model results and aid in the refinement of both models being used for

this performance measure. Funding for Dr. Trexler's research was provided under Cooperative Agreement J5284060020, "Synthesis of Existing Data on Aquatic Communities in Everglades National Park in a Framework for Ecosystem Assessment and Evaluation" through the CESI program.

Justification

Fishes are the most abundant vertebrates in the Everglades and Big Cypress ecosystems of southern Florida. The small-bodied species, particularly livebearers and killifishes, dominate the community by numbers. They constitute an ecosystem component whose biomass is the major energy resource for higher trophic levels, especially wintering and breeding wading birds (Ogden 1994, Crozier and Gawlik 2003). Systematic, human-induced changes in hydrology over the last several decades have altered hydroperiods in most wetland areas, thereby diminishing this fish forage-base or changing the pattern of its availability. Lack of sufficient biomass and availability of prey is thought to be a major cause in the decline of wading bird nesting at traditional Everglades' rookeries (Ogden 1994), and recovery of historic fish productivity is a primary goal for restoration of southern Florida wetlands (Ogden et al. 2003).

The strongly seasonal rainfall pattern of this region creates a cycle of wet and dry seasons. Because of the flat landscape, relatively small differences in mean water level amplify into large differences in the amount of wetted area and flooding duration, which affect many plant and animal communities. The wetland small-fish community is strongly influenced by seasonal hydrologic fluctuations (Loftus and Kushlan 1987, Trexler et al 2002).

3.1 Relationship to Conceptual Ecological Models

Abundant large vertebrates and aquatic prey bases are listed as a defining ecosystem characteristic in the Total System Model (Ogden et al 2005) and marsh fishes are identified as key ecological attributes of that defining characteristic. A number of aquatic trophic levels are included as ecological attributes in the Everglades Ridge and Slough Conceptual Ecological Model (Ogden 2005). This performance measure is currently focused on a subset of both the Total System and Ridge and Slough models (marsh fishes).

3.2 Relationship to Adaptive Assessment Hypothesis Clusters

3.2.1 Greater Everglades Hypothesis Cluster – Predator-Prey Interactions of Wading Birds and Aquatic Fauna Forage Base

The collapse of wading bird nesting colonies in the southern Everglades is attributed to declines in population densities and seasonal concentrations of marsh fishes and other aquatic prey organisms. Restoration of natural hydrologic conditions will re-establish distributions of prey densities and concentrations across the landscape that in turn will support the return of large, successful wading bird nesting colonies to the southern Everglades.

Hypothesis 1 – Aquatic Fauna Wet Season Prey Population

The wet-season density, size structure, and relative abundance of marsh fishes and other aquatic wading bird prey are directly related to the time since the last dry-down and the length of time the marsh was dry. Aquatic prey populations are further affected by salinity in coastal ecotones and by site nutrient status. Responses are non-linear and species specific.

Hypothesis 2 – Aquatic Fauna Dry Season Prey Concentration
The concentration of marsh fishes and other wading bird prey into high-density patches where wading birds can feed effectively is controlled by the rate of dry-season water level recession and local topography/habitat heterogeneity.

Evaluation Application

4.1 Evaluation Protocol

The Everglades is a system adapted to constant flooding followed by dry-downs, and many of the species are dependent upon that cycle, including the wading birds that depend on the fish populations. Therefore, fish density alone is not sufficient to define an evaluation protocol for aquatic species in the Greater Everglades system. Instead, it must be a combination of fish density, water timing, and water depth.
Fish Density: Fish density should be maximized given the constraints on water timing.
Timing: The changes in water should be synchronized with the nesting season of the wading birds. Initially this will be January 1 to July 15, as is the default in the ATLSS SESI Wading Bird model.

Water Depth: Although hydroperiod is a favored evaluation parameter for many Everglades performance measures, it is not appropriate for fish evaluation. Deeper water provides more total fish biomass with the same density. The measure of fish density is two dimensional, but the deeper water in the wet season water provides much higher densities of fish for wading birds during dry downs. Therefore, water depth will be used as one of the evaluation protocols. Water in a range of 5-35 cm. during the nesting season is the initial target. However, this may be updated as more work is done on the Wading Bird performance measure.

4.2 Normalized Performance Output

The exact format of the output has yet to be developed. However, the final output will be done by post processing the data. In addition, triggers will be included in both the model and the post processing tools to flag any large discrepancies either in space or time. This will ensure that scientists are aware of any critical differences across space or time that might be lost during later averaging.

4.3 Model Output

Both models will provide output at a 500 meter^2 over a subset of the SFWMM cells. One possible choice is the same set of cells used in the present Fish HSI. Another is to categorize all the cells as either high, intermediate, or low frequency dry down and then assign the appropriate parameters accordingly. As much data as is reasonable will be

provided as model output because this provides better input for post processing efforts and makes data mining much easier in the event of anomalous output.

4.3.1 Trexler Model

Daily fish density/m^2.

4.3.2 DDT Model

Daily biomass estimations of the components shown in Figure 5.

4.4 Uncertainty

The growth dynamics of small fish populations under static conditions is relatively well understood. However, under the seasonally varying hydrology of the Everglades, where the amount of flooded area can change drastically with time, and where both the resource base of small fishes and the effects of interactions of small fishes with pisciverous fishes is difficult to assess, there is a high level of uncertainty in the predicting absolute values of fish population and biomass densities. The fish dynamics are also sensitive to the errors in both the water elevation and the reference elevation. This uncertainty is reduced and the performance measure provides very useful information when different scenarios are compared, the metrics aggregated into averages and when the general spatial patterns are considered.

MAP Module and Section

Greater Everglades Module Section 3.1.3.11

Assessment Approach

The strategy for the integrated assessment of wading bird/aquatic fauna predator prey relationships is to annually track the production of aquatic fauna populations during the wet season, the concentration of those populations during the subsequent dry season, and distribution and size of wading bird nesting colonies in response to the prey populations (RECOVER 2007).

Evaluation Tools Needed

Two evaluation tools are proposed, as detailed in section 1.1, the Trexler Fish model and the DDT aquatic food web model. In addition, software for post-processing the raw data will be developed.

Assessment Tools Needed

None have been identified.

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C. Hydrological cycles, management and assessment

To investigate the patterns and periodicity in the rainfall cycles, we analyzed time series of rainfall data (1895-2006) from four rainfall gauges in Everglades National Park. Two of the gauges, Forty Mile Bend (FMB) and Royal Palm (RPL), capture daily rainfall estimates from 1949 to 2006. The other two gauges, regional estimates for Southeast Everglades (SE) and the Southwest Everglades (SW), are cumulative monthly rainfall data from 1895 through 2004. We took the average of the rainfall gauges that were collected on the same timescale (avg. daily estimate for FMB and RPL, and the avg. monthly for SE and SW) to get two estimates of the regional monthly rainfall for the Everglades. In previous analyses we found that interpretable temporal patterns in rainfall do not emerge until the data are aggregated across multi-year temporal scales. In this analysis, patterns in rainfall tended to stabilize at cumulative daily/monthly rainfall over the previous 5 years. These patterns are illustrated in Figs 1 and 2. Because there are only a few readily apparent rainfall cycles in this time series, indicated by a trough-peak-trough sequence, we deemed that qualitative assessments were adequate to describe these data. In this time series, the general trend in rainfall cycles vary from about 7 to >14 year cycles. This suggests that our target period (1993-1999) was shorter than historical rainfall cycles, and may have captured only one part of the rainfall cycle that is currently underway. Additionally we found that in the assessment period there is a marked departure in our two rainfall estimates. This departure is most likely because there are numerous missing rainfall gauges in this analysis.

Our results from this analysis should be interpreted with caution because we did not have long term rainfall data for all of the gauges used. Also, we left out rainfall estimates from 1 of the regions in our study (Water Conservation Areas 3A and 3B) because we did not have long-term rainfall data from immediately upstream. Our goal here is to illustrate general trends in natural processes and relate them to the implementation of water management actions.

Fig. 1. Time series for the daily 5-year cumulative sum of rainfall (inches) from 1905 to 2006. The black line corresponds to the average of FMB and RPL, and the red line corresponds to the average of SE and SW. The Target period labeled TAR (1993-1999), and assessment period is labeled ASSE (2000-2006).

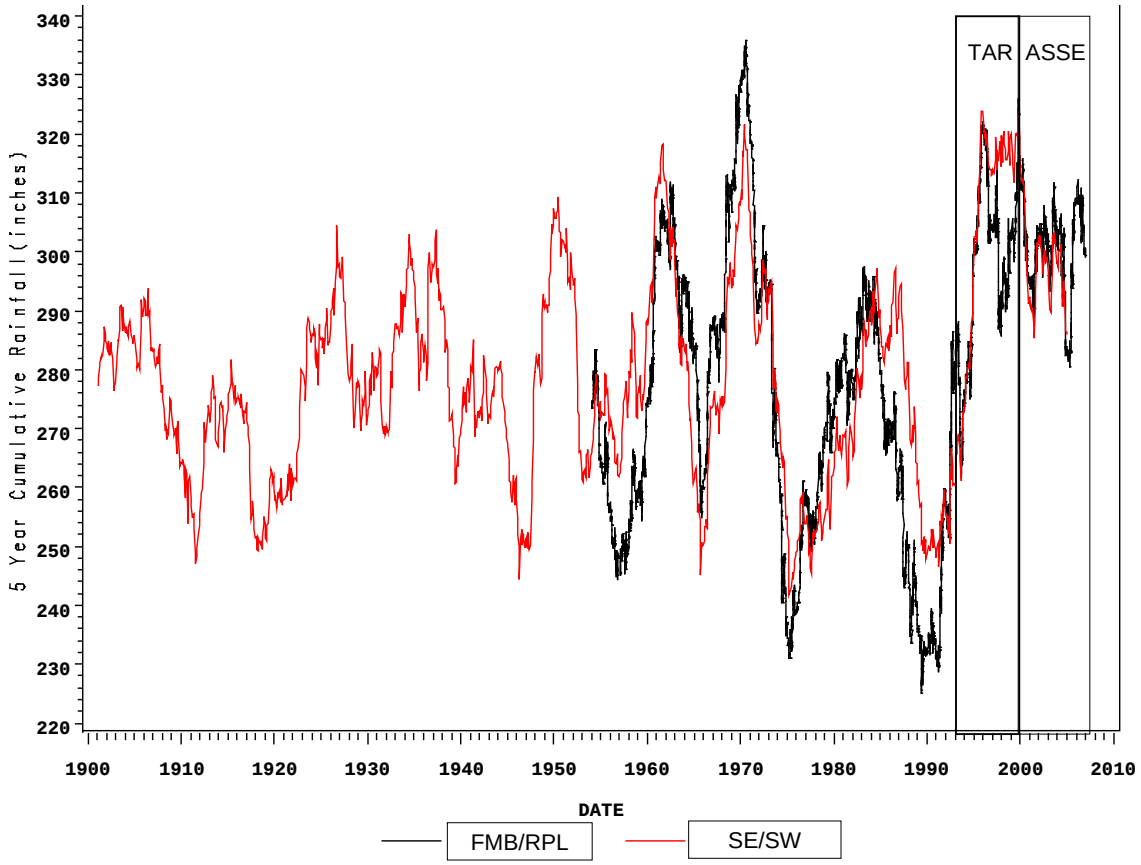
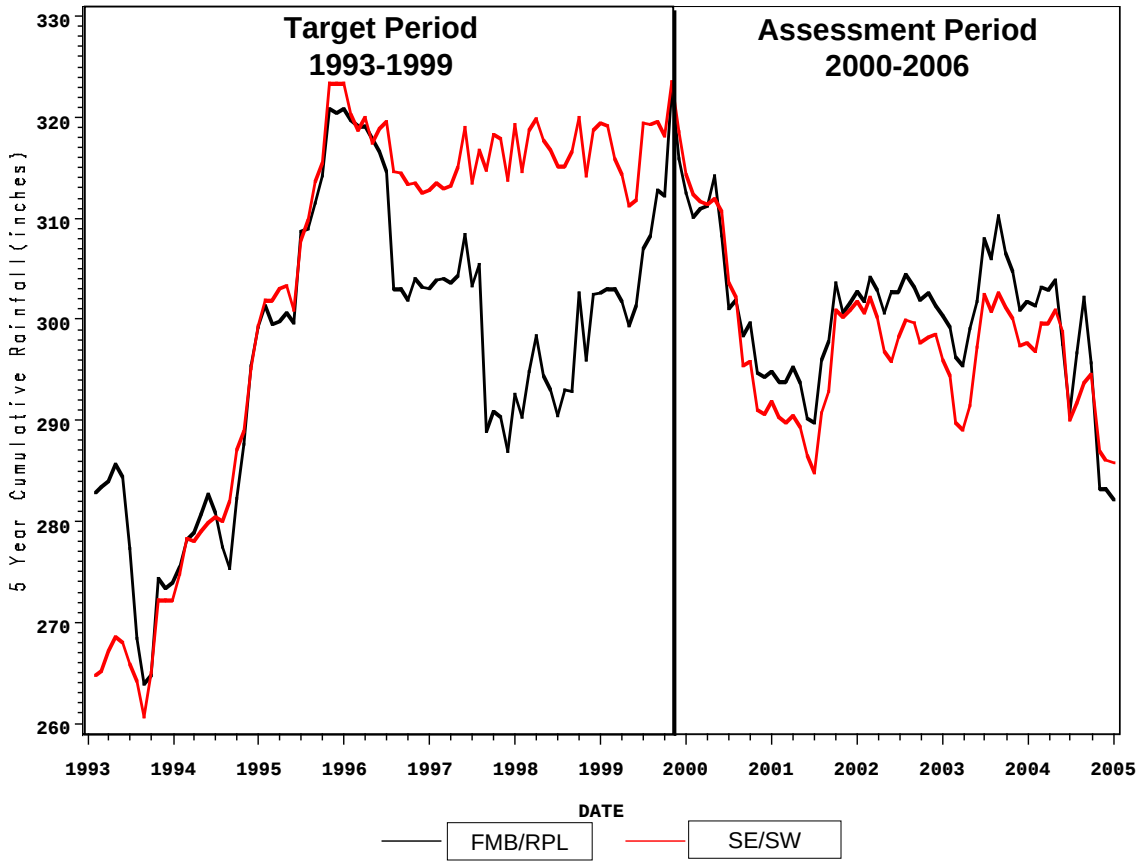


Fig. 2. Time series for the daily 5 year cumulative sum of rainfall (inches) from 1905 to 2006. The black line corresponds to the average of FMB and RPL, and the red line corresponds to the average of SE and SW. The Target period is highlighted in red (1993-1999), and assessment period is highlighted in green (2000-2006).



D. Modeling Temporal Autocorrelation in Time-Series Data: A Cautionary Note

Overview and Methodology

In time-series analysis it is generally the case that observations taken across time are correlated to some degree (samples taken close in time tend to be more similar than those taken further apart in time). This phenomenon is described as serial autocorrelation and is thought to be an indication of a missing predictor correlated with the dependent variable that varies through time (Neter, Wasserman, and Kutner 1990). An indication of serial autocorrelation is when there are systematic patterns in the residuals through time, suggesting either positive (more runs of consecutive residuals above or below zero than expected due to chance) or negative autocorrelation (too many alternating positive and negative fluctuations about zero than expected due to chance). When present, this phenomenon presents a problem because it violates assumptions of traditional statistical theory [Ordinary Least Squares (OLS)] that observations are independent of each other [i.e., off-diagonal estimates (covariance among observations) in the variance-covariance matrix are assumed to be zero]. A solution to this problem is to take into account serial autocorrelation by estimating the covariance of observations through time. This solution generally requires the use of maximum likelihood methodology to estimate the model parameters. The maximum likelihood approach to estimating population parameters is an iterative technique that can solve for fixed (and random) effects by explicitly modeling the structure of the variance-covariance matrix, and the probability distribution. There are a variety of statistical programs that allow practitioners to model their data and correct their estimates for autocorrelation in time-series data. Unfortunately, this methodology, while simple to implement, is subject to assumptions of the algorithms employed and may lead to unexpected and possibly misleading results.

An assumption underlying the theory for estimating autocorrelation parameters is that the observed data are a function of previous error terms in addition to a "disturbance" term. Failure to account for lags in a response variable because of autocorrelation may create a situation where ordinary least squares (OLS) regression under-estimates variance, leading to biased parameter estimates. When measures are taken to control for autocorrelation in an analysis the results can appear to exacerbate the problem (i.e., the residuals appear even more correlated through time), however the underlying theory assumes that adjusting for autocorrelation will provide more accurate estimates of the "true" population parameters. Our analyses focus on dependent variable that could be expected to demonstrate temporal autocorrelation because of resampling the same population of aquatic animals over time. Thus, modeling temporal autocorrelation is an important part of our statistical analysis. In this section we report a potential source of bias created by use of a commonly employed statistical method to model autocorrelation. We report analysis with a commonly used program (SAS mixed procedure), though we expect that other programs (R, for example) are likely to demonstrate the same problem we illustrate. We are not aware of any documentation alerting data analysts of the problem we illustrate, though SAS does include options that can overcome it. Probably, very experienced statisticians would not be led astray by the particular issues we report, but non-statisticians analyzing data very well could be.

To explore the effects of different options to model temporal autocorrelation in ecological data, we modeled the net replacement rate (R_o) for several species of fish with three covariance structures: 1) constant variance-covariance structure that is estimated assuming that covariance among observations decrease as a function of time; 2) heterogeneous variance-covariance structure that estimates different variance and covariance parameters for different groupings of data, and assumes that covariance decreases as a function of time; and 3) observations are independent across time (i.e., covariance is zero). For option 2, we had two groups: prior to a region-wide drought and after the drought. We estimated the covariance parameters (1 and 2) using a spatial power law function: Covariance $[Y_{t1}, Y_{t2}] = \sigma^2 \times \rho^{|t1-t2|}$, where ρ = autoregressive parameter ($|\rho|<1$) and σ^2 = variance. This function is a generalization of the first-order autoregressive (AR1) model, and permits modeling of autocorrelation in time-series that have unequally spaced observations (Littell et. al 2006). Using these model structures, we estimated the following parameters to describe R_o:

a) Response variable (natural log transformed): $R_o=N_t/N_{t-1}$
b) Endogenous factors (natural log transformed): N_{t-1}, N_{t-2}, N_{t-3}
c) Exogenous factors: the number of days since marsh flooding (DSF, DSF^2), and rate of marsh expansion/recession (EXP/REC)

Our model was $R_o= \beta_o + \beta_{Nt-1} + \beta_{Nt-2} + \beta_{Nt-3} + \beta_{DSF} + \beta_{DSF}^2 + \beta_{EXP/REC}$, with the variance-covariance matrix (Σ) equal to: $\Sigma= \sigma^2 \times \rho^{|t1-t2|}$; $\Sigma= \sigma^2_i \times \rho_i^{|t1-t2|}$, where i=1 in the pre-drought period, and i=2 in the post-drought period; or $\Sigma= \sigma^2 I$. We used the Akaike's Information Criterion$_c$ (AICc; AIC adjusted for small sample sizes) as an indication of overall model fit (models within 7 AICc's of the best model have equal empirical support). As an additional measure of model fit we estimated the amount of variance explained by the linear regression relationship between the observed data and the model predictions (Ad hoc R^2).

Results and Discussion

Overall, there were similar levels of empirical support for all model structures. According to the AICc fitstatistic, models with a Spatial Power parameter using a separate covariance structure for both the pre-and post-drought period had the most empirical support (74 models), followed by the Spatial Power structure assuming constant covariance structure across the time-series (64 models) and finally the models with no covariance structure (61 total models). Given that our data are were collected in a time-series format, the number of times that models assuming no covariance structure had equal or more empirical support as models with explicitly modeled covariance support was relatively large. We concluded that the AICc statistic does not adequately discriminate among these models, so we estimated the fit of the model predictions to the observed data using linear regression (OLS R^2) and compared the R^2 among models with equal empirical support (i.e., within AICc of the best model).

We found that among models with equal empirical support, those assuming independent covariance structures generally had a much higher R^2 than those including temporal autocorrelation in the covariance structure. The overall average difference in R^2

between independent and dependent autocorrelation models ranged from 0 to 0.26 with an average difference of about 0.03. Some discrepancy in R^2 among models is expected because the statistical model without explicit covariance structure should have parameter estimates that converge on those estimated by OLS; and OLS fits the data by minimizing the sums of squared error, thereby maximizing the R^2. However, discrepancies as large as 0.26 for models with essentially equal empirical support according to AICc values, suggests that there is an apparent lack-of-fit between the data and the model predictions for repeated measures models. While, we appreciate that the statistical theory motivating analysis of repeated measures data is generally not focused on minimizing the sums of squared deviations of the model predictions from the observations per se (as in OLS), we think the sometimes large discrepancy in R^2 values among the models suggests that in certain circumstances maximum likelihood estimation assuming covariance is a decreasing function of time can lead to dramatically different predictions than the maximum likelihood estimation (and implicitly OLS) that assumes that observations are independent. This discrepancy indicates a systematic lack-of-fit for models that estimate temporal autocorrelation. To further explore this we plotted the predicted and observed values for the different model types.

When we examined the relationship between the model predictions and the observed data through time, it became clear that there were many instances where the model predictions diverged greatly. An example of this phenomenon is illustrated in Figures 1 and 2. These plots illustrate that the independent covariance model matches the observed data much more closely than either of the models that explicitly estimate parameters for covariance. In Figure 1, there are the periods both at the beginning of the time-series and at the beginning of 2004, where the repeated measures predictions are consistently greater than the observed data, indicating a much more biased fit than the OLS prediction. Further we found evidence that there are instances where there may be a change in the covariance structure through time. Figure 2 illustrates an instance, where for one of our study species (least killifish) the predictions for the model that assumes a constant covariance structure across the time-series clearly has consistently higher predictions than the observed data following a 2001 drought. However, both the model assuming observations are independent and the model that has different covariance structure for pre- and post drought time periods matched the data much more closely.

In this study, we came to two general conclusions about modeling temporal autocorrelation in time-series data. Our first conclusion is that explicitly modeling autocorrelation in time-series data is not always necessary, and may actually lead to unexpected results. We found that using models that estimate parameters for autocorrelation can generate predictions that systematically predict values that are much higher or lower than the observed data. Further, these model predictions have a poorer fit to the observed data than a simpler model assuming independent errors. It appears as though the more complex models are laden with assumptions about the data generating process that are not as transparent as one would like when trying to apply statistical models in an applied context. This result may be due to aspects of the way our data were gathered and the type of analysis we used.

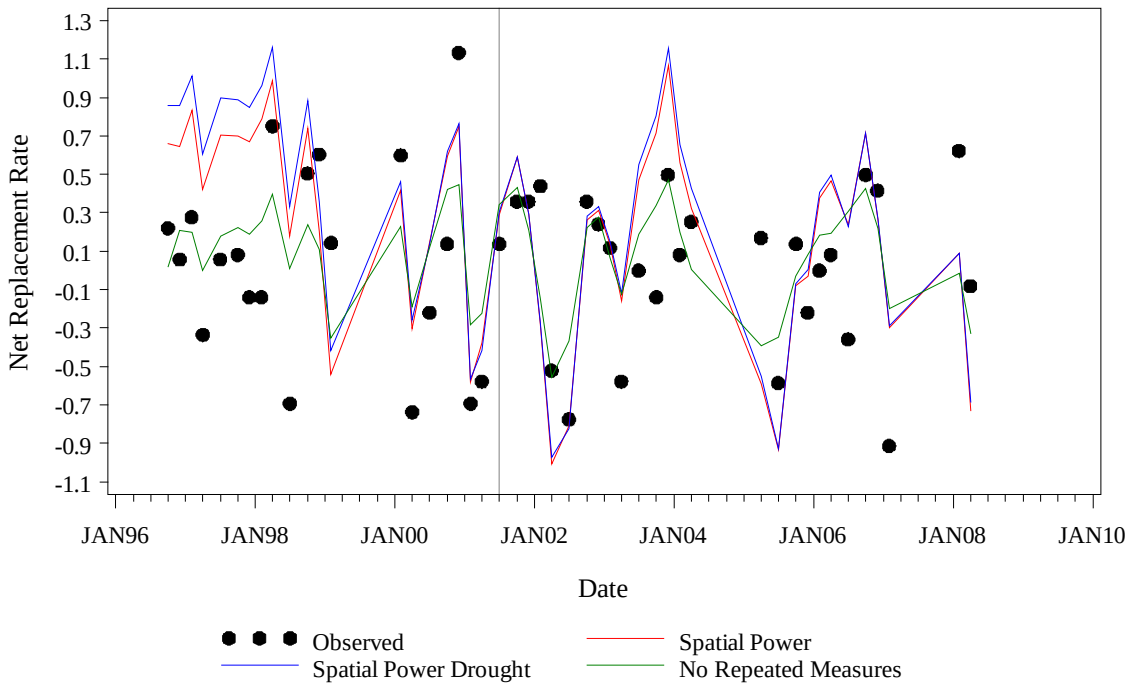
All of the predictors (5) in our models vary on the same time scale as the dependent variable. We have several variables that correspond to population cycles (endogenous variables) and variables that vary across seasons and years (exogenous variables). It is clear that the inclusion of these variables permits an adequate modeling of fish population dynamics. Additionally, our sampling protocol is structured such that there are 3 replicates per unit time for each spatial location. This spreads the replicates across space and reduces the chance that unmeasured variables simultaneously affect each of the replicates, reducing the risk of serial autocorrelation. Further, the structure of our analyses actually account for autocorrelation by inclusion of time-lagged independent variables.

Our second conclusion was that the structure of the covariance and variance can vary through time. This is clearly illustrated in Figure 2, where the model that has constant covariance structure systematically predicted densities that were much greater than the observed data, while a covariance structure estimated different parameters for pre and post drought was more consistent with the observed data. While it may not be surprising that the covariance structure changed following an extreme event such as a region-wide drought, we think that it is important to point out to those of us practitioners who commonly assume that the structure of the variance-covariance matrix does not change through time (possibly without realizing it because we include the AR1 option as a routine). In this instance, assuming a constant variance-covariance matrix lead to misleading predictions, as well as missing an important biological phenomenon of changing covariance structure coinciding with an environmental perturbation.

With the advent of statistical programs that make it easy to model complex ecological data with the click of a button, it is easy for practitioners to fit models to data that are more complex than are warranted in the data at hand. We think that this stems from a fundamental philosophical difference between OLS methods assuming no autocorrelation and methods that assume that population level autocorrelation can be detected in sample data. In our analyses it seems clear that estimating parameters to account for autocorrelation can produce predictions that systematically over or under predict the observed data. However, these apparently biased predictions are consistent with statistical theory on time-series data, in that the theory assumes that there is an unmeasured factor in the data that influences the sample data in such a way that it causes OLS to incorrectly estimate parameters and underestimate the overall error. Oftentimes, the default response for a practitioner when confronted with modeling a time-series dataset is to always include an estimator of autocorrelation

Figure 1. A) Time-series of observed and predicted data from all of our models for eastern mosquitofish at site WCA03A. Spatial power and spatial power drought refer to the repeated measures analyses with a constant covariance structure and a variable covariance structure respectively; no repeated measures refers to the model assuming independent observations. B) Time-series of residuals graph from each model type for eastern mosquitofish at site WCA03A.

A)



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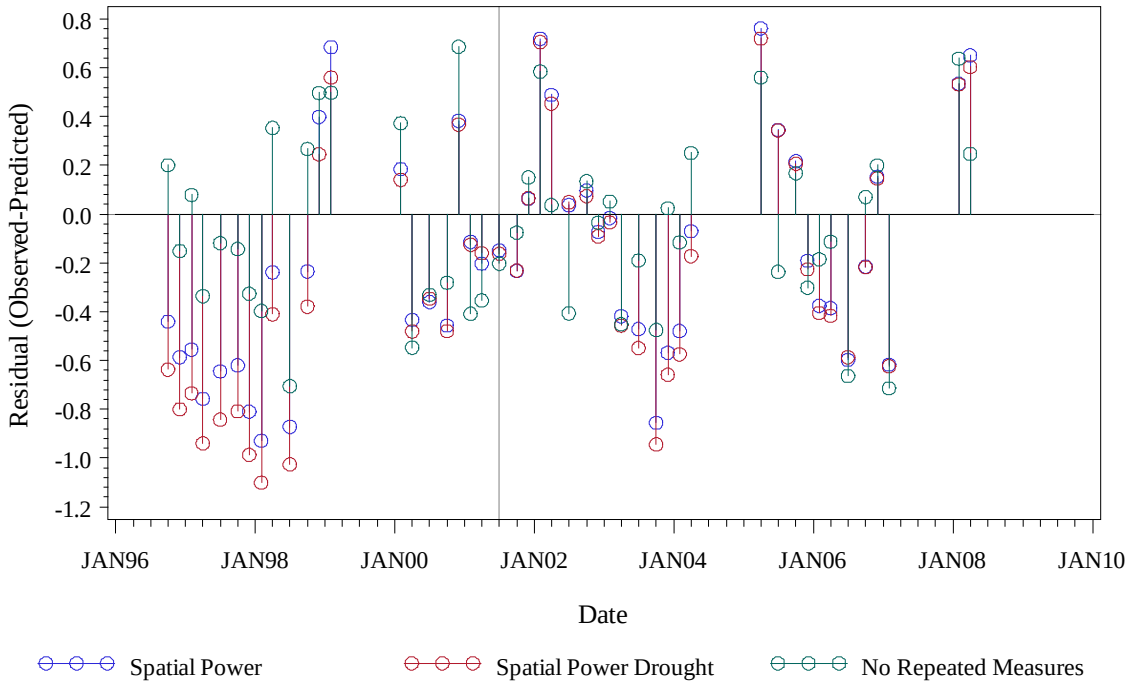
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JAN96
JAN98
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JAN02
JAN04
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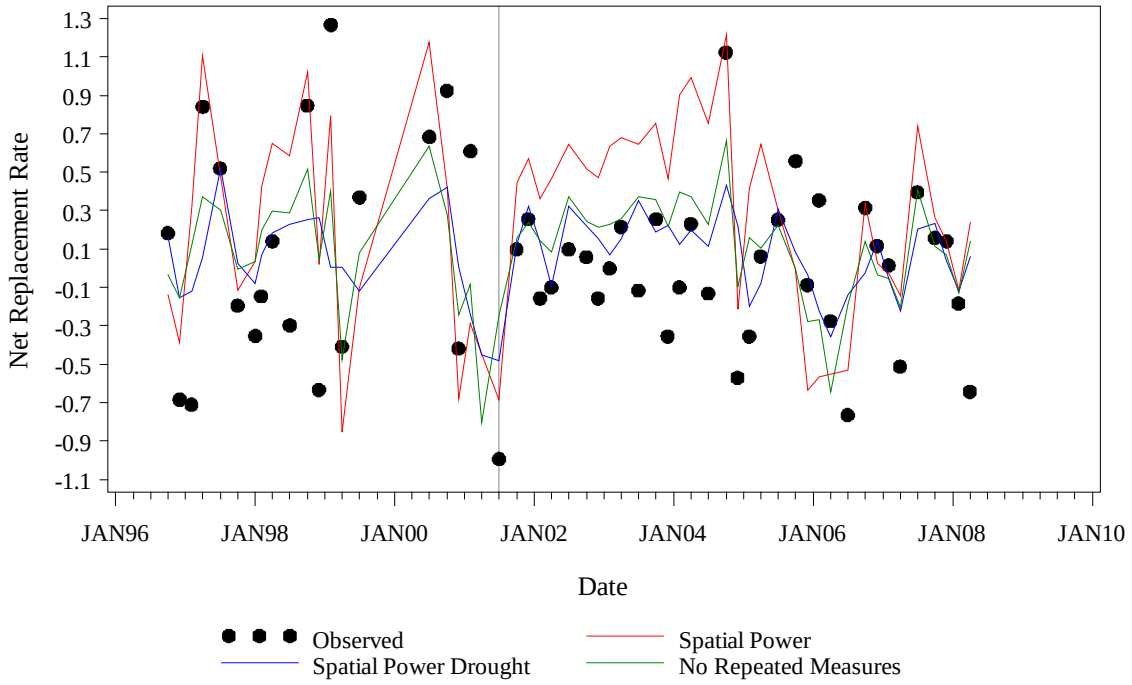
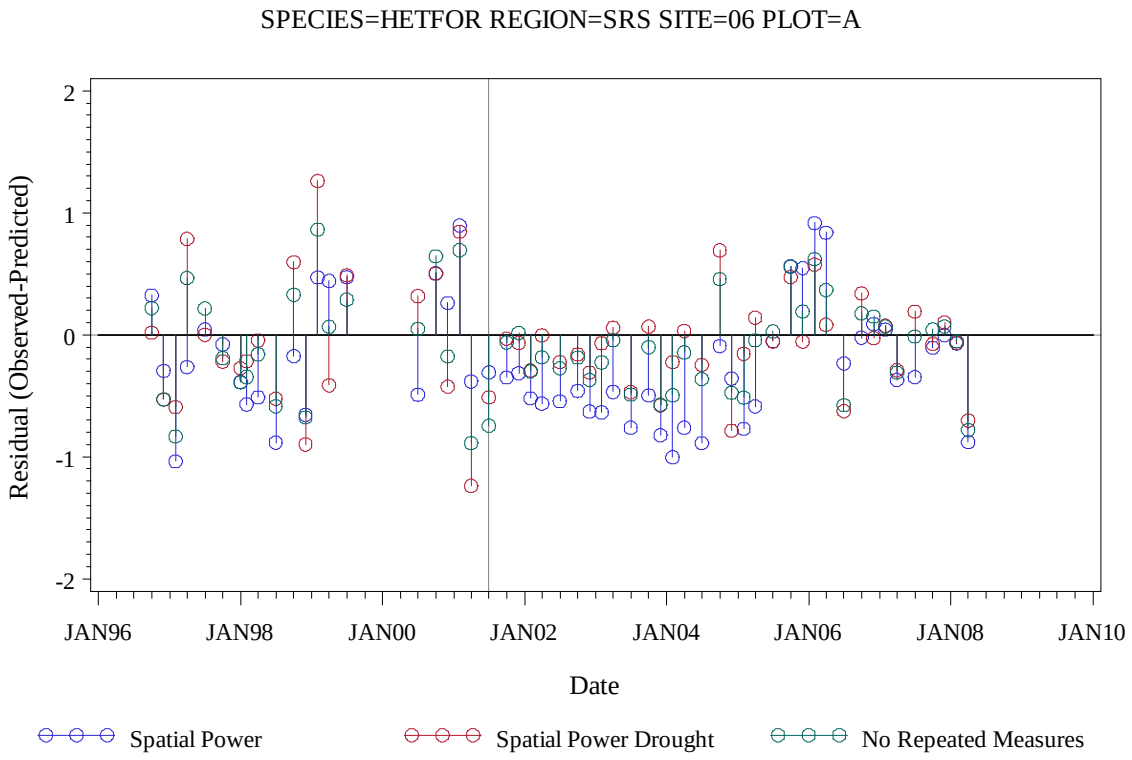
JAN08
JAN10
Date
Spatial Power
Spatial Power Drought
No Repeated Measures

Figure 2. A) Time-series of observed and predicted data from all of our models for least killifish at site SRS06A. Spatial power and spatial power drought refer to the repeated measures analyses with a constant covariance structure and a variable covariance structure respectively; no repeated measures refers to the model assuming independent observations. B) Time-series of residuals graph from each model type for least killifish at site SRS06A.

A)



B)


SPECIES=HETFOR REGION=SRS SITE=06 PLOT=A
Residual (Observed-Predicted)
2
1
0
-1
-2
JAN96
JAN98
JAN00
JAN02
JAN04
JAN06
JAN08
JAN10
Date
Spatial Power
Spatial Power Drought
No Repeated Measures

E. Regional Pool Size Analyses: Methods and Results

To evaluate aquatic animal responses to marsh drying, we asked Troy Mullins, South Florida Natural Sciences Center, Everglades National Park, to create a hydrology parameter that quantifies the area of marsh that is inundated with water (regional pool size). This parameter is derived from the Everglades Depth Estimation Network (EDEN) hydrology data (USGS fact sheet citation). EDEN hydrology data are estimated from a model that divides the Everglades landscape into a grid that is composed of 400 m^2 "cells". The regional-pool size is determined by using the locations (cells) of each of our monitoring sites and calculating the number of cells within a basin that are above a depth threshold (e.g. 0 cm). If a cell within a basin is linked to a monitoring site by a contiguous linkage of cells above the depth threshold, then the cell receives a value of 1, otherwise the cell gets a zero (see Figure 1 for a detailed map of each basin). The cells are tallied for each monitoring site to obtain the regional pool size estimate from 2000-2007 (EDEN begins in 2000). Unfortunately, this period of time is shorter than the records for our long-term aquatic biota and hydrological monitoring database (1996-present). Our hydrological data were derived by fitting regression relationships at each of our sites between the measured depth and nearby stages to obtain daily water depth estimates. To estimate the regional pool size prior to the onset of EDEN we use our daily water depth estimates from 1996 through the present to predict the regional pool size.

Due to local ground elevation variability at a scale less than 400 m^2, EDEN water depth estimates are not as accurate as our estimated water depths at our 100 m^2 sampling sites. This presents a challenge to our modeling effort because the regional pool size parameter is generated from EDEN depths. To adjust for the difference between EDEN water depths and our estimated daily water depths, we calculated the average difference between the EDEN water depth prediction and the measured water depths at our sites (measured depth-EDEN depth). We then took this difference and subtracted it from our estimates of daily water depths so that they were more similar to the EDEN depths. This new adjusted water depth value was then used to predict regional pool size.

Because there are a maximum number of possible cells in each basin, and each has a minimum of 0, models based on traditional linear least squares theory are inadequate to describe the relationship between water depth and regional pool size. Logistic regression permits modeling a response variable that is bounded at one and zero. To make the regional pool parameter amenable to logistic regression analysis, we calculated the proportion of maximum regional pool size response variable by dividing regional pool size by the total number of possible cells in each basin; this creates a response variable that has a minimum of zero and a maximum of 1. To predict regional pool size we split our data into three regions: Shark River Slough (SRS), Taylor Slough (TSL) and the Water Conservation Areas (WCA); and used the water depths from sites within a given region to predict the regional pool parameter at each site. Many of the intra-regional site water depth estimates have very high correlation coefficients (>.98), which can yield unstable parameter estimates in multiple regression. To distill the variation among predictors into orthogonal components (axes) we used a Principal Components Analysis (PCA). In turn we used these PCA axes as predictors in the

logistic regression analyses. Once we obtained the logistic regression parameter estimates for each axis, we used these parameters to predict the regional pool size across the entire time span of our study (1996-2008).

Results

The PCA analysis revealed that the majority of the variation in the data was well described by the first 2 axes: 96.8% (SRS), 99.9% (TSL), and 96.5% (WCA). However, when we used these axes as predictors in the logistic regression, they were not always able to capture the rarer occurrences of values close to zero. In order to more completely describe the lower end of the regional pool size gradient we included all axes that explained greater than or equal to .01 % of the variance. This resulted in using 5, 3 and 10 PCA axes for SRS, TSL and the WCA regions respectively. We then used these axes in the logistic regression analyses to predict the proportion of maximum regional pool size.

Overall the logistic regression analyses aptly described variation in the proportion of maximum regional pool size. The likelihood ratio statistics for the parameters (PCA axes) in all regions (SRS (5 parms), TSL (3 parms) and WCA (10 parms)), at our sites indicated that almost all of the parameters were different than zero ($P<.05$). The likelihood ratio statistic for PCA axis 10 at site 09A in WCA, indicated that it was not different was zero and was removed from the model. Diagnostic plots (observed vs. predicted and residuals vs. predicted) suggested that, in general, the models captured variation in the response variable well; however there were instances on the lower end of the gradient (esp. near zero) where the model did not describe the data as well. As illustrated in Figure 2, above zero there is generally close to a one-to-one relationship between the observed and predicted data, however the model becomes more positively biased when the observed data are close to zero. While this bias is potential cause for concern, examination of the relationship between the observed and predicted values across time revealed that the model captures the general decreasing trends in the data as the response variable approaches zero (Figure 3). Further, our interest lies in relating aquatic animal density to general trends in regional pool size and we are not as concerned with exact predictions. Therefore the bias exhibited these models is not of great concern for our purposes. Calculation of the strength of the linear relationship between the predicted values and the observed values using a linear least squares model further supported the adequacy of the model. The coefficient of determination, on average, indicated that the models explained between approximately 86% and 93% of the variation in the data (see appendix for R^2 estimates for each model). Although this analysis violates some of the assumptions of linear least squares, namely that the independent variable is measured without error, we believe that these statistics provide a more intuitive metric for measuring model fits than standard fit statistics used for generalized linear models.

Figure 1. EDEN basins used to calculate regional habitat area for each day we sampled. An algorithm was created that counted contiguous cells with depth greater than 5 or 10 cm starting with the cell where we sample. This created a time series of habitat area for the duration of our study.

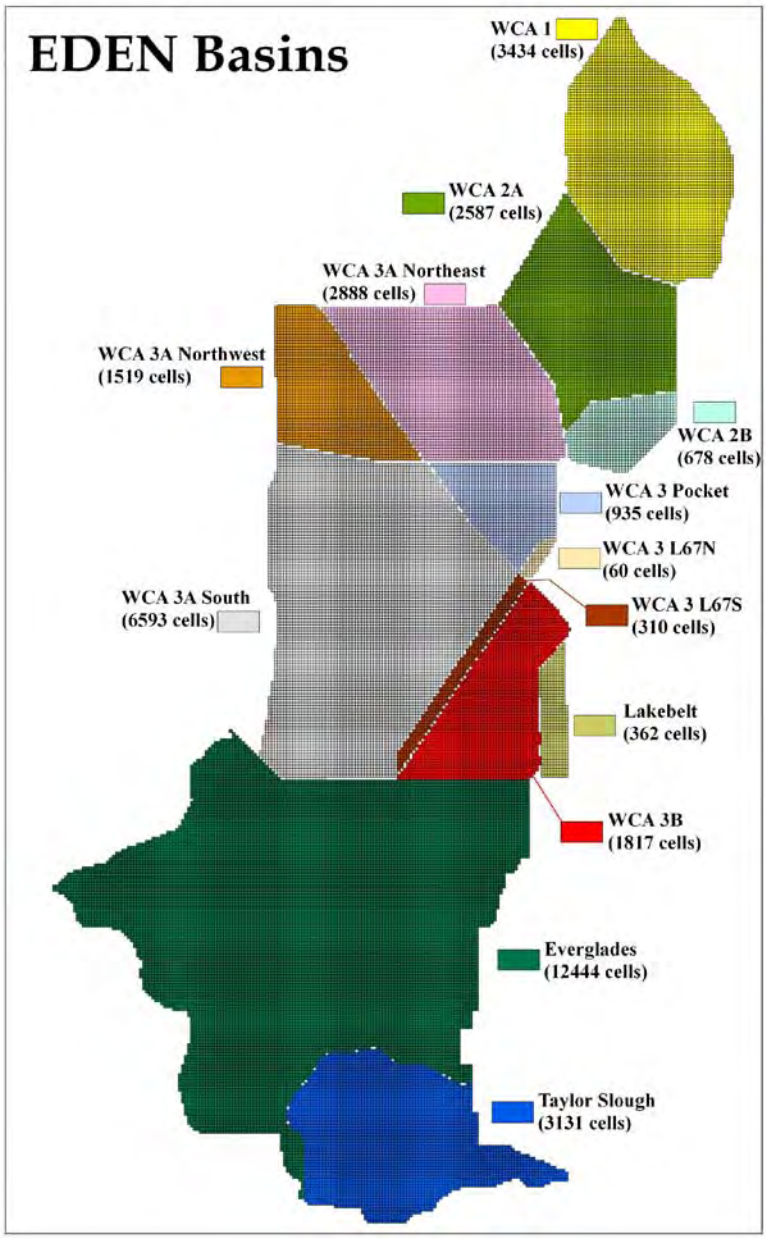


Figure 2. Plot of the observed data versus the model predictions at site TSB located in the Taylor Slough region. In this graph we converted the model predictions to the original scale of the data (# cells) by multiplying by the maximum number of cells in a basin. The black line corresponds to the expected relationship if the predicted values perfectly describe the observed data (i.e. a one-to-one relationship).

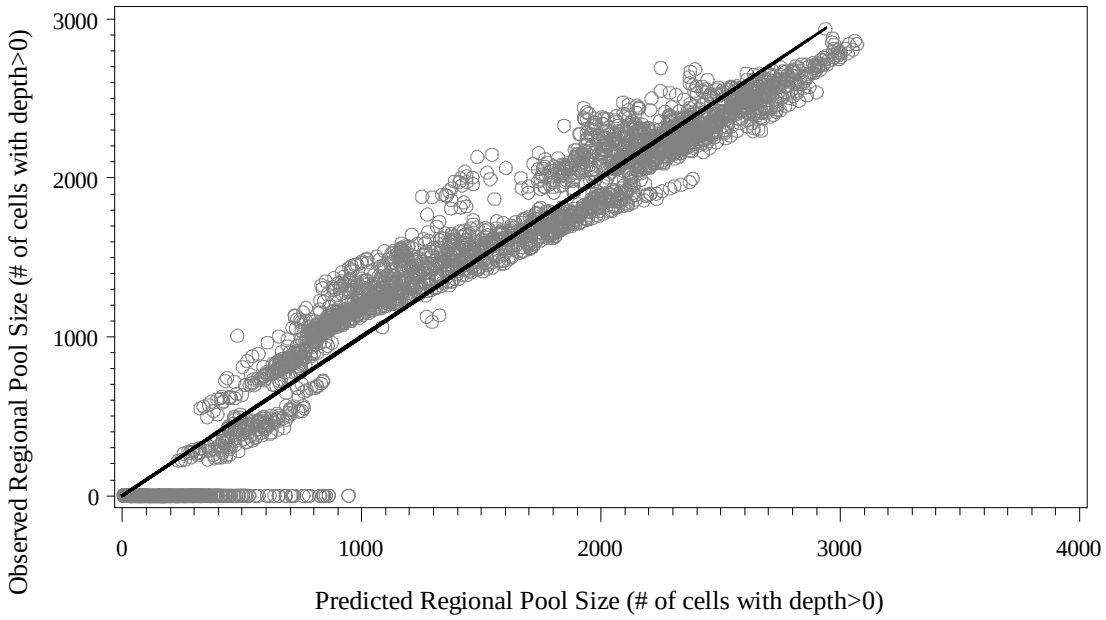
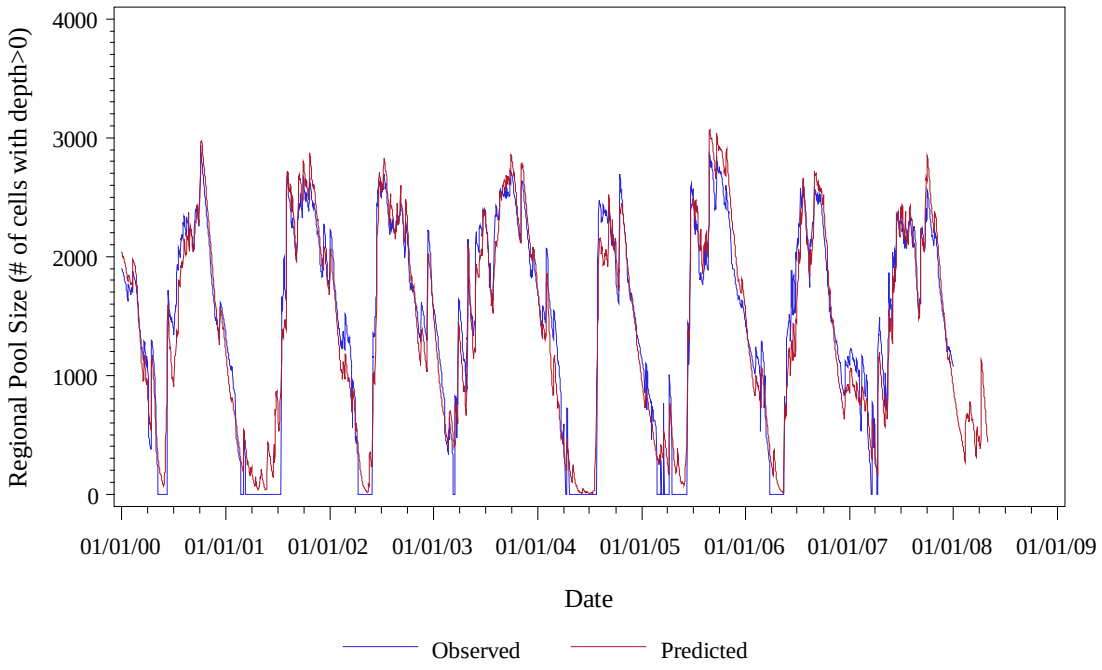


Figure 3. Time series plot of the observed data and the model predictions at site TSB located in the Taylor Slough region from 2000-2007. In this graph we converted the model predictions to the original scale of the data (# cells) by multiplying by the maximum number of cells in a basin.



Appendix 1. Model fits by site.

Region	Site	Plot	R^2	Region	Site	Plot	R^2	Region	Site	Plot	R^2
SRS	06	A	0.896	TSL	CP	A	0.944	WCA	01	A	0.932
SRS	06	B	0.898	TSL	CP	B	0.946	WCA	01	B	0.932
SRS	06	C	0.881	TSL	MD	A	0.904	WCA	01	C	0.932
SRS	07	A	0.876	TSL	MD	B	0.910	WCA	02	A	0.847
SRS	07	B	0.883	TSL	MD	C	0.911	WCA	02	B	0.847
SRS	07	C	0.876	TSL	MD	D	0.927	WCA	02	C	0.847
SRS	08	A	0.857	TSL	MD	E	0.902	WCA	03	A	0.909
SRS	08	B	0.871	TSL	TS	A	0.949	WCA	03	B	0.903
SRS	08	C	0.871	TSL	TS	B	0.942	WCA	03	C	0.909
SRS	23	A	0.865	TSL	TS	C	0.950	WCA	04	A	0.932
SRS	23	B	0.861	TSL	TS	D	0.905	WCA	04	B	0.932
SRS	23	C	0.865	TSL	TS	E	0.945	WCA	04	C	0.932
SRS	37	A	0.832					WCA	05	A	0.932
SRS	37	B	0.849					WCA	05	B	0.932
SRS	37	C	0.812					WCA	05	C	0.932
SRS	50	A	0.801					WCA	06	A	0.845
SRS	50	B	0.799					WCA	06	B	0.845
SRS	50	C	0.799					WCA	06	C	0.845
								WCA	07	A	0.772
								WCA	07	B	0.767
								WCA	07	C	0.784
								WCA	08	A	0.693
								WCA	08	B	0.818
								WCA	08	C	0.872
								WCA	09	A	0.923
								WCA	09	B	0.917
								WCA	09	C	0.917
								WCA	10	A	0.930
								WCA	10	B	0.925
								WCA	10	C	0.925
								WCA	11	A	0.887
								WCA	11	B	0.887
								WCA	11	C	0.897

F. Seasonality in Selected Species from the Everglades

Our ecological assessments generally focus at inter-year variation before and after a change in management. However, accounting for seasonal patterns of adult population dynamics and recruitment of juveniles is obviously important in properly interpreting multi-year impacts. In this section, we focus on changes in fish density across seasons by examining consistency of these patterns across years. We modeled juvenile and adult density separately for each species considered. To explore seasonal and yearly patterns we used two different parameters: 1) Wateryear: May through April; 2) Sampling Season: 1=July, 2=October, 3=December, 4=February, and 5=April. Because of the spatial complexity of our data, we analyze temporal trends separately for each spatial unit (Sites; replicates=plots, approx. 3 per sampling period). We used 10 hierarchical statistical models to test the questions about fish population dynamics. For models 1-9 season is treated as continuous. In model 10, season is treated as categorical.

1) Intercept: 1 parameter

2) Intercept + Season: 2 parameters

3) Intercept + Season + Season^2: 3 parameters

4) Intercept + Wateryear: 12 parameters

5) Intercept + Wateryear + Season: 13 parameters

6) Intercept + Wateryear + Season + Season^2: 14 parameters

7) Intercept + Wateryear + Season + Wateryear x Season: 24 parameters

8) Intercept + Wateryear + Season + Season^2 + Wateryear x Season: 25 parameters

9) Intercept + Wateryear + Season + Season^2 + Wateryear x Season + Wateryear x Season^2: 36 parameters

10) Intercept + Wateryear + Season(Wateryear): 60 parameters

We used Akaike's Information Criterion to evaluate the fit of each of these models to the data. We then ranked the models according to this fit statistic and calculated the AIC_C differences: $AIC_{C\text{model i}}$ - $AIC_{C\text{best model}}$. We used the AIC_C differences to derive Akaike weights for each of the models. Akaike weights are calculated as follows:

Model Likelihood=exp(-1/2 x (AIC_C Difference)), and the Akaike weight=Model Likelihood_i/Summation of Model Likelihood for all models in the set (Burnham and Anderson 1998).

We used these Akaike weights (*w*) to compute the weight for each model prediction (*Theta*) according to the strength of evidence for that model, calculate the "model average" prediction (*Theta**) by summing all of the weighted predictions across models

for each species, age-class and location. The model averaging equation for each of the *i* models is as follows:

*Theta**=Summation across all models in the set of w_i*$Theta_i$. We also calculated a pseudo-r^2 value as an indication of model fit: 1-exp(-2/N*(-2 Log Likelihood of Model-2 Log Likelihood of Intercept Only Model))/(1-exp(2/N*(-2 Log Likelihood of Intercept Only Model/-2))).

Ecologists commonly use ordinary least squares (OLS) theory to model their data and implicitly assume the response variable of interest is distributed normally, and that the variance is homoscedastic. A battery of standard transformation is available to force non-normal data into a normal distribution in order to take advantage of the simplicity and available software for analysis of normally distributed dependent variables. These analyses are readily interpretable and have a long history of use; however it is not uncommon for ecological data to fail meet normality assumptions, even after transformation. Generalized linear models provide a flexible framework for explicit modeling of probability distributions, and allow comparison of models with different distributional assumptions (McCullagh and Nelder 1989). Further, generalized linear models allow the inclusion of a linking function that links the systematic component (e.g., linear equation) to the stochastic component (i.e., the response variable on the original scale of the data). Two important purposes of the linking function are: 1) transform additive model components to multiplicative on the original scale of the data, 2) force the model to meet the assumptions of a given probability distribution. For example, data that follow a binomial probability distribution must fall between zero and 1; using the logit linking function forces the data to be bounded by 0 and 1. In this study our focus is on count data, i.e., integer data that cannot be below zero. Because of this structure, we chose to use the log linking function; this function prevents estimates from being less than zero, which is an impossible outcome for count data. Using the log linking function we assume that fish density is distributed according to a Poisson process.

We used a 12-year time series (1996-2007) of aquatic consumer data to identify robust seasonal patterns of juvenile and adult density at our study sites. The data were gathered with a 1-m^2 throw trap and standard sampling protocol carried out at 22 monitoring sites in Taylor Slough (TSL), Shark River Slough (SRS), and Water Conservation Areas (WCA) 3A and 3B. Samples were collected at each study site in five months of each year (July, October, December, February, April), yielding over 17,000 community samples with over 250,000 fish records for describing relationships between biota and time. Quantitative data on fish were recorded from all samples, along with environmental data on emergent-plant stem density, floating mat volume (periphyton and floating vascular plants and macroalgae), and water depth. The methods, including estimates of sampling efficiency and evaluation of sources of bias, are described in several papers (Chick et al. 1992; Jordan et al. 1997; Wolski et al. 2002). The study sites and sampling design are described in detail in other publications (Trexler et al. 2001, 2003, 2005).

Missing data can greatly hamper seasonal analyses because of caps in the time sequence. In Everglades aquatic fauna sampling, there are a variety of circumstances yielding missing data, many of which can be compensated for with minimal assumptions. For example, there are many instances in these data where the marsh was too dry to obtain a sample. In these instances we used previously derived regression relationships to predict water depths at these sites. If the water depth was <=5 cm we assume that the conditions are too stressful for fish and we input a zero for all of the study species. In this case, the entry of zero seems quite reasonable to us. Alternatively, there were instances where the marsh was too deep to sample, or the airboat trail was dry, but we know from our hydrological models that the site had water. In these instances we assume that there are fish, but we do not have sampling data (a true *missing* datum). In these cases and if only one observation from a time series is missing, we can use model predictions derived from the rest of the wateryear to predict fish density and avoid dropping the entire year of data. In the latter instances we extrapolated from the regression line to predict missing data, therefore we screened data that were obviously unrealistic given the intra-year seasonal trends from further analysis. If missing data were at the beginning or end of a time series, we excluded those cases because of the inability to interpolate reasonably.

Results

We found that the pseudo-R^2 and Akaike weights revealed marked inter-species and inter-age-class variation in the fit of models to the data. As expected from statistical theory, on average, the pseudo-R^2 value increased with increasing model complexity (i.e., the more parameters in the model the better the fit); it follows that the most complex model, fitting a separate parameter for Wateryear and for each season within each Wateryear for a total of 60 parameters, consistently yielded the highest mean pseudo-R^2 value across all of the response variables (Fig. 1). For all of the response variables the largest change in pseudo-R^2 generally occurred when during the transition from models that describe temporal variation using only parameters assuming a multiplicative relationship between season and fish density (3 parameter model) to models with a separate parameter estimate for each Wateryear (i.e., fitting a dummy variable to each year and estimating the intercept; 12 parameter model). This suggests that fish population dynamics vary much more among years than across seasons, ignoring differences among years. Following inclusion of the Wateryear parameters, the increases in pseudo-R^2 by adding more parameters were generally more modest. Because Akaike's Information Criterion (AIC) takes into account the number of parameters in the estimation of model fit, the patterns in model fit according the Akaike weights were much different than those indicated by the pseudo-R^2.

The mean Akaike weights for eastern mosquitofish models (both juveniles and adults) generally increased with increasing model complexity until the most complex model (60 parameter model), where it strongly declines (Fig.1). The model with the highest mean Akaike weight for eastern mosquitofish adults was the 14 parameter model (Wateryear + Season + Season2 + Wateryear x Season) and for juveniles it was the 36 parameter model (Wateryear + Season + Season^2 + Wateryear x Season + Wateryear x

Season^2). The models with the highest weight for least killifish adults and juveniles were the opposite of those eastern mosquitofish: the 14 parameter model described juvenile dynamics best, while the 36 parameter model best described the adults. Flagfish juveniles were best described by the 13 parameter model, while the adults were best described by models ranging from 12 to 14 parameters. The population dynamics of both juvenile and adult bluefin killifish were best described by the 14 parameter model. When we used the Akaike weights to generate the model averaged predicted value we found that there was marked temporal, spatial, species and age-class differences in the predictions.

Although there was marked variation among years and sites, we found relatively consistent response profiles for all species and age classes. To illustrate this we plotted the response profiles for eastern mosquitofish at one of our sampling sites across years, and at one of our sampling regions across sites (averaging across wateryears). As illustrated in figure 2, adult eastern mosquitofish density generally increases as the season progresses although the rate of change varies across years and sites. To estimate the general seasonal response profiles of each species and age-class, we calculated the mean and uncertainty (mean +/- 2 stdandard error) of the predicted values for each season over all years and sites. Figure 3 illustrates that both eastern mosquitofish and flagfish juveniles are relatively high at the beginning of the year (July/October) and decrease throughout the rest of the year, while adults for both species increase early on and reach an asymptote towards the end of the year (February/April). Further, eastern mosquitofish juveniles are predicted to be less than adults in April, while flagfish juveniles are predicted to be less than adults in both February and April. Bluefin killifish juveniles have a hump shaped relationship between season and density increasing from July to December, and then decreasing thereafter; alternatively adults increase throughout the year. Juvenile bluefin killifish are predicted to be lower than adults in April. Of all our study species, least killifish have is the only species where throughout the entire year the adult catch is greater than the juvenile catch. Our interpretation of this is that our sampling methodology is biased towards catching least killifish adults. Therefore our estimates of juvenile least killifish are not representative of the actual populations of juvenile density in the marsh.

Figure 1. Model fit as a function of the number of parameters. Increasing parameters increases model fit in each case, but the gain in complexity plataues around 12 for every species. Blue points indicated Akaike Weights and red are Pseudo-R^2. Circles with solid lines are for adults and triangles with dashed lines are for juveniles.

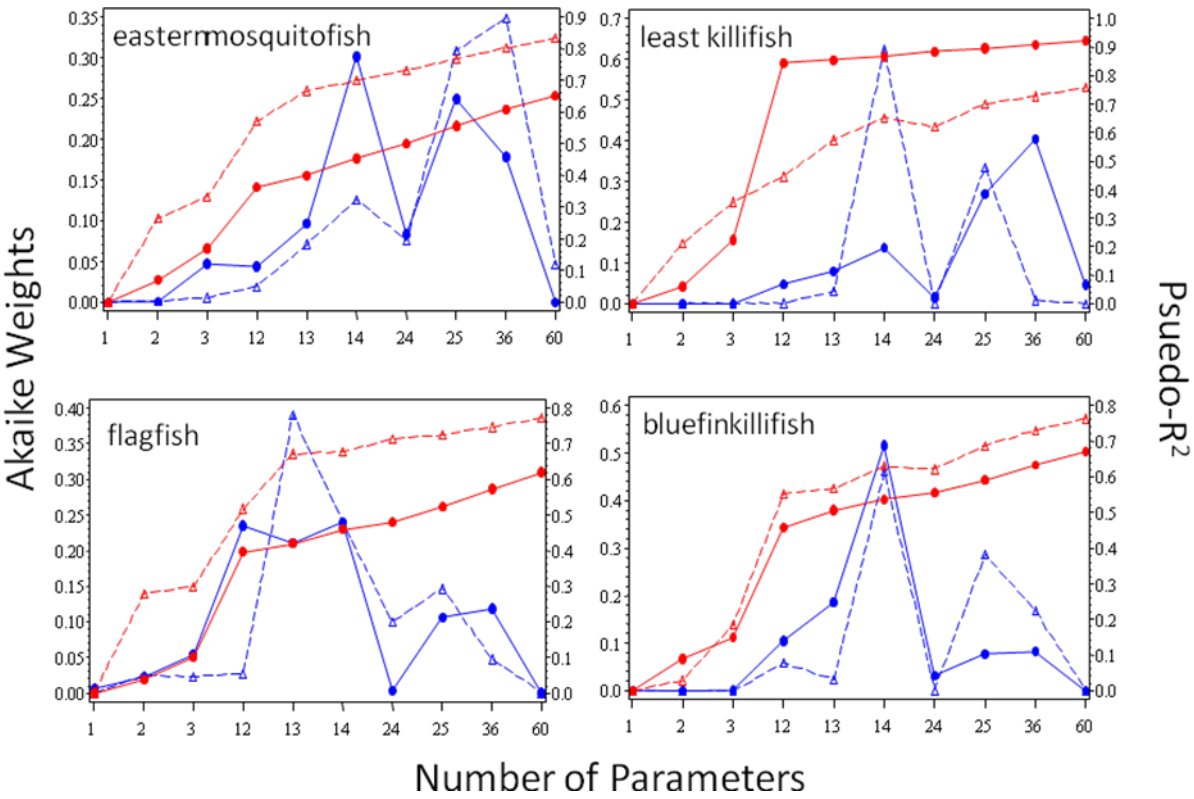


Figure 2. Plot of predicted eastern mosquitofish fish density for each season for site 06 across wateryears (panel A) and predicted fish density averaged across years for each site in the Shark River Slough region (panel B).

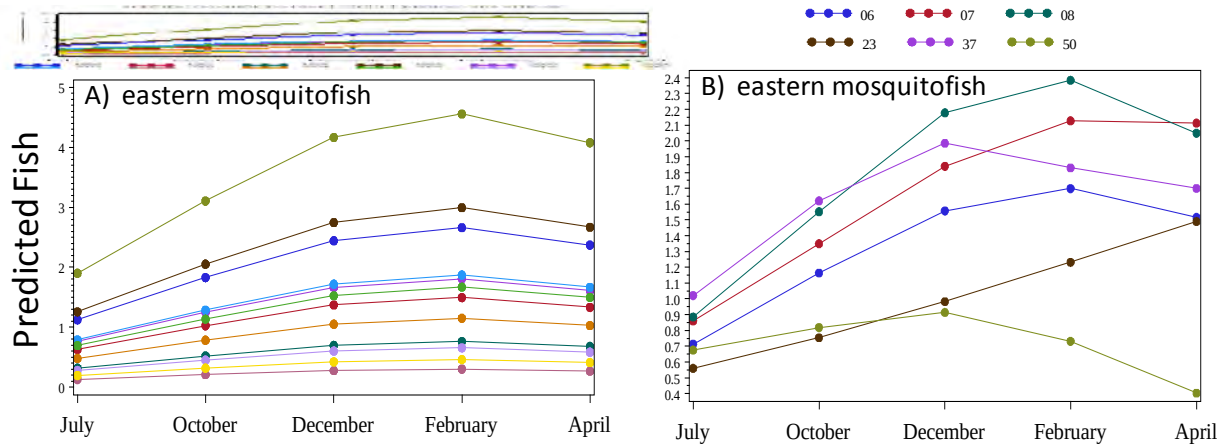
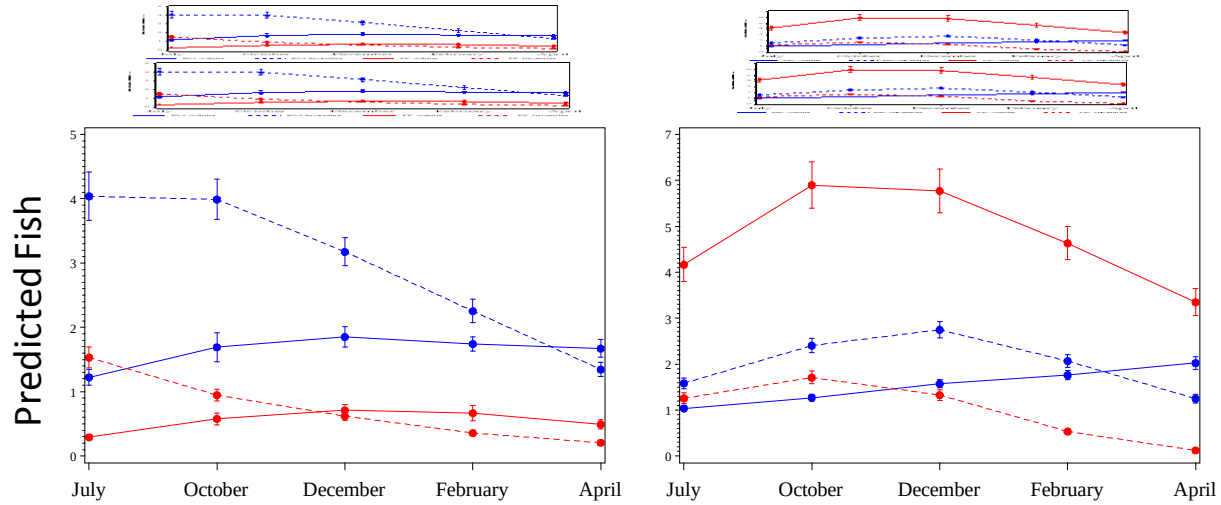


Figure 3. Plots of fish density for each species and age-class averaged across sites and wateryears (mean +/- 2 standard errors) for each season. EM = eastern mosquitofish; FF = flagfish; BK = bluefin killifish; LK = least killifish.



G. Hydrological Model Comparison Summary

Overview

Most ecological analyses of aquatic habitats conducted for Everglades management and restoration are dependent on estimates of hydrological parameters that must be inferred from in situ gauges through a model. In fact, the availability of high quality hydrological data at the proper scale of measurement is a limiting factor for much Everglades research. For our long-term monitoring program, we have measured water depth at 64 different locations 5 times per year over a 12 year period. While useful, these spot estimates cannot permit estimation of key hydrological parameters, such as 'days since reflooding'. To get daily water-depth estimates we use observed water depth data to estimated regression relationships with depths from nearby hydrological gauges (we will refer to these estimates as our Modified Water Model for this report). These regressions generally predict water depth well, most relationships having a R^2 of >0.90. These predicted values are then used to generate various hydrological parameters that are used in our ongoing efforts to study aquatic animal communities. State and Federal agencies have modeled Everglades hydrology at a different scales and time periods that are available for use by researchers. Here, we evaluate the comparability of three such alternatives, the 2 mile by 2 mile management model of SFWMD, a 500m x 500m model taken from the 2 x 2 by Doug Donalson, and the USGS's EDEN. We use our Modified Waters model output as a 'true' estimate for our study sites and compare the performance of these alternatives to see which match most closely.

The SFWMD's management model is a well-calibrated and widely used model for water management decision making. It predicts water depth at a 2 mile by 2 mile spatial scale (2x2 model – one depth estimate per 2 mile by 2 mile grid cell). While this scale is appropriate in a water management context, it smoothes over topographic variation that at the sub 2 mile scale that is widely considered to be ecological relevant. For example, discrepancies between the single large-scale estimate and local topographic relief can have important implications for aquatic animal communities because a change in water depth of a few centimeters can be the difference between persistence and local extirpation. To address these and other concerns related to the coarse spatial scale of the 2x2 model, Doug Donalson produced a modified version to predict water depths at a 500 meter scale (500 meter model) by using high resolution topography. Finally, the USGS has developed a new hydrological tool, the Everglades Depth Estimation Network (EDEN), which can predict water depths at a 400 meter spatial scale. Past analyses have confirmed that EDEN predictions are within an advertised 10 cm resolution to our Modified Waters model predictions (after applying a local correction based on our in situ repeated measurements).

There limitations to use of each of these models in ecological research because of the timeframe over which they have been run. The 2x2 and 500 meter models (here collectively referred to as the Donalson Models because he provided the 2x2 data to us) provide estimates from 1981 through the end of 2000, while the EDEN model begins in 2000 and has estimates through the present. Our monitoring data span from 1996 through the present, spanning the coverage of both model types. The first set of models

covers the first 4 years of our study, and EDEN covers the last 8 years of our study, with only 1 year of overlap between the models. It has been suggested that the 500 meter model can be used to complement the EDEN data and predict depths prior to 2000. Because of local topographical variation, we "correct" all of the SFWMD model estimates by the difference between the observed and model predictions: Corrected Depth=Model Prediction + {Mean per site (Observed Depth-Model Prediction)}. This correction adjusts for local topographic variation at our monitoring sites.

In this paper we compare these three hydrological models to our observed data and our model to address the following questions:

1. Is the 500 meter model an improved estimate of water depths at a smaller spatial scale?
2. How do the predictions from the EDEN models compare with those of the 2x2 and 500 meter models?
3. Do any of these models predict water depths at our monitoring sites as good, or better, than our than the Modified Waters model?

Result Summary

We found that the 500-meter model does not markedly improve the fit of the 2x2 model to the data from our monitoring sites. The time series graph in Figure 1 illustrates that the 500-meter model and the 2x2 model are very similar throughout our time series; further the predictions do not fit the observed data as well as the Modified Waters model. When we used all of the hydrological models to predict observed depths from 1996 through 2000, the overall average R^2 was 0.93, 0.82, and 0.82 for the Modified Waters Model, the 2x2 model and the 500-meter model, respectively. When we plotted a graph of output from 2x2 against the 500-meter model, there is clearly a very close relationship between the two models, with considerable overlap across the entire depth gradient (Figure 2). However, there is increased variation in the correspondence of the predictions as the depth approaches zero, indicating that the 500 meter model may diverge from the 2x2 at lower depths.

Although depth is an important factor shaping Everglades animal communities, a more critical parameter influencing their dynamics is the number of days since the marsh flooded following a drying event {Days Since Flooding (DSF); Depth<=5cm}. In general we found that the DSF predicted by the 2x2 and 500-meter models were almost identical across all sites. When there was deviation between the 2x2 and 500 meter models, there were both cases when the 2x2 matched more closely with the Modified Waters models (Figure 3A), and where the 500-meter matched more closely (Figure 3B). Further, as illustrated in the Figure 3 graphs, the 2x2 and 500-meter models oftentimes did not match well to the Modified Waters, model predicting either too few or too many drying events. These results indicate that the 2x2 and the 500-meter model are usually almost indistinguishable from each other after correcting for local topographical variation. Additionally, it is not clear which model would be preferable to modeling hydrological dynamics at our monitoring sites.

The time series plots in Figure 4, illustrate the general patterns in the model fits of all of the hydrological models to the observed data in 2000. In general we found a much closer match of the Modified Waters model and the EDEN model to the observed data than to the Donalson models. Because there was only one year of data, and the Modified Waters model is generally the best predictor of observed water depth, we used the Modified Waters model predictions as a surrogate for observed data and derived the regression relationship between the Donalson and EDEN models, and the Modified Waters model. Consistent with the time series plots, we found that the EDEN models were a much better match to the Modified Waters depths than the Donalson models, with a mean R^2 of 0.93 for EDEN and about 0.80 for both of the Donalson models.

Figure 1. Time series plot from 1996-2000 at site TSLCPA of the Modified Waters model, 2x2, and the 500 meter depth predictions, overlaid on the observed depth data.

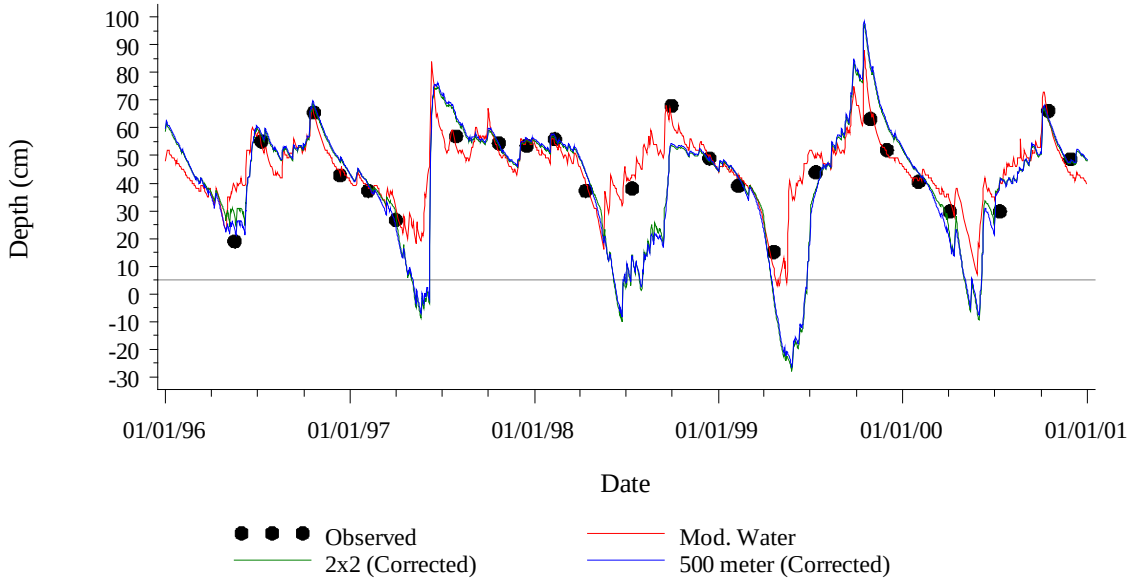


Figure 2. Plot of the 2x2 model predictions versus the 500 meter model depth predictions.

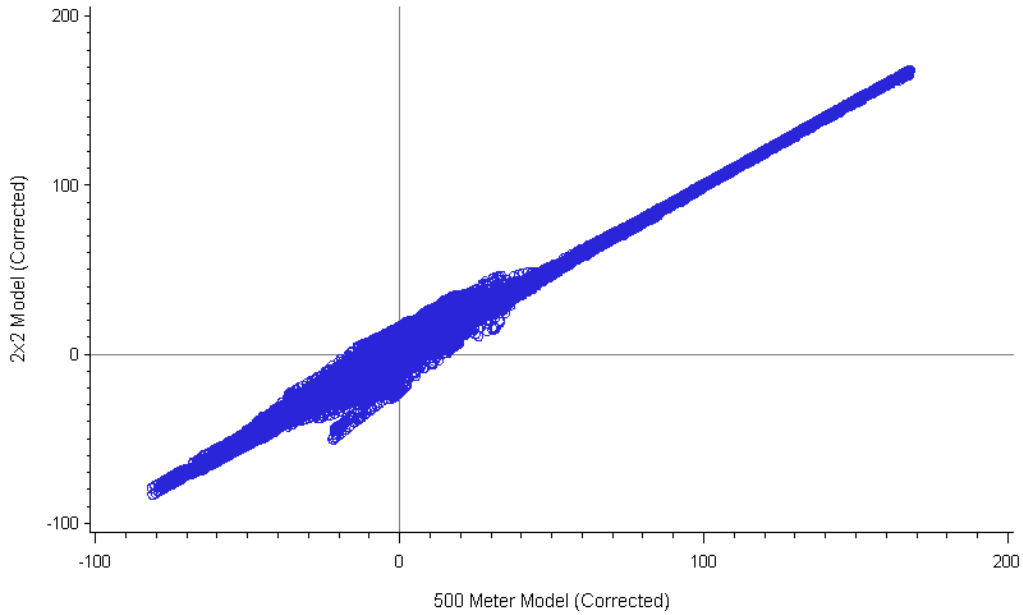
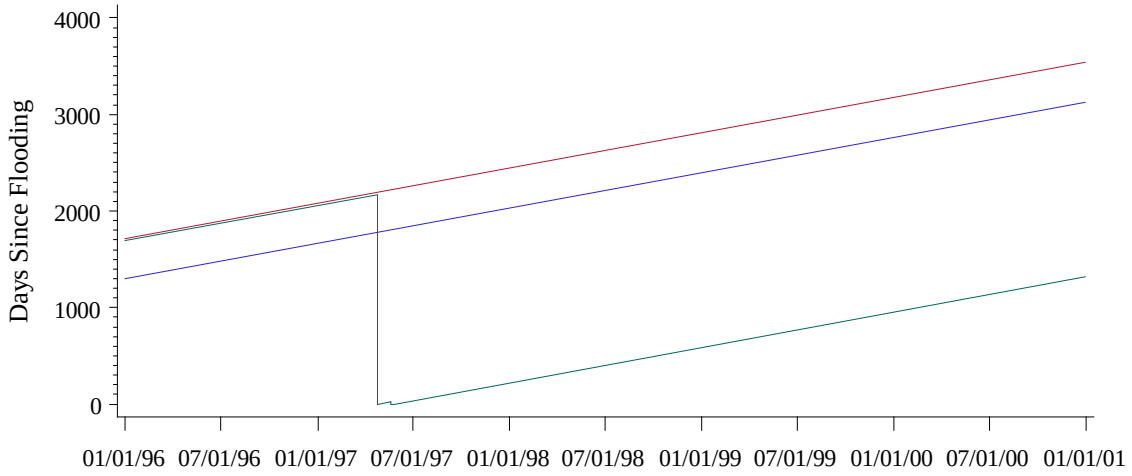


Figure 3. Time series plot from 1996-2000 at sites SRS23B (A) SRS37A (B) of the Modified Waters model, 2x2, and the 500 meter DSF predictions.

A)



B)

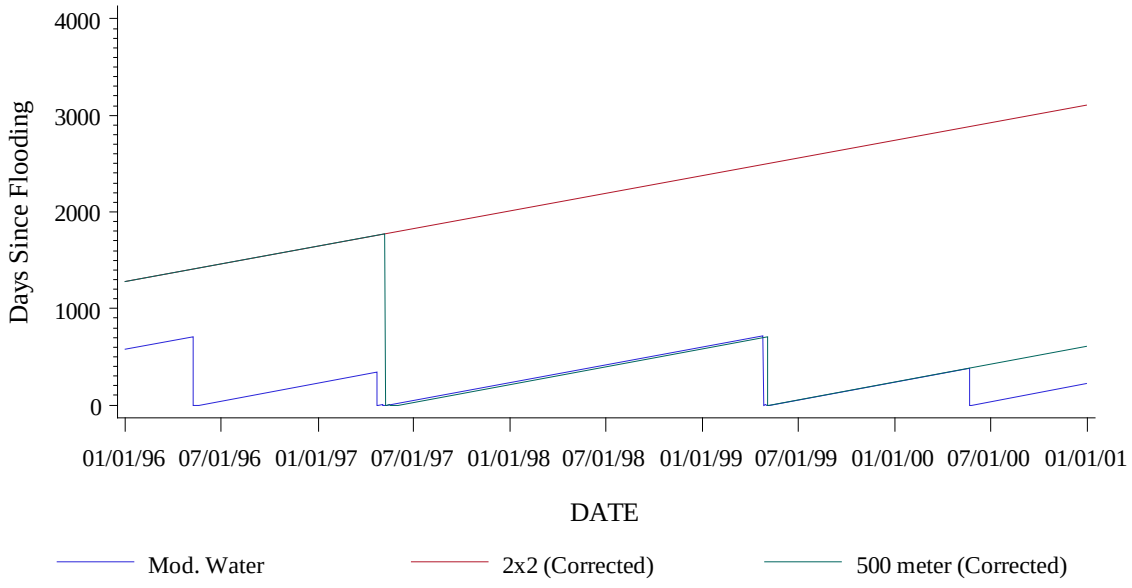
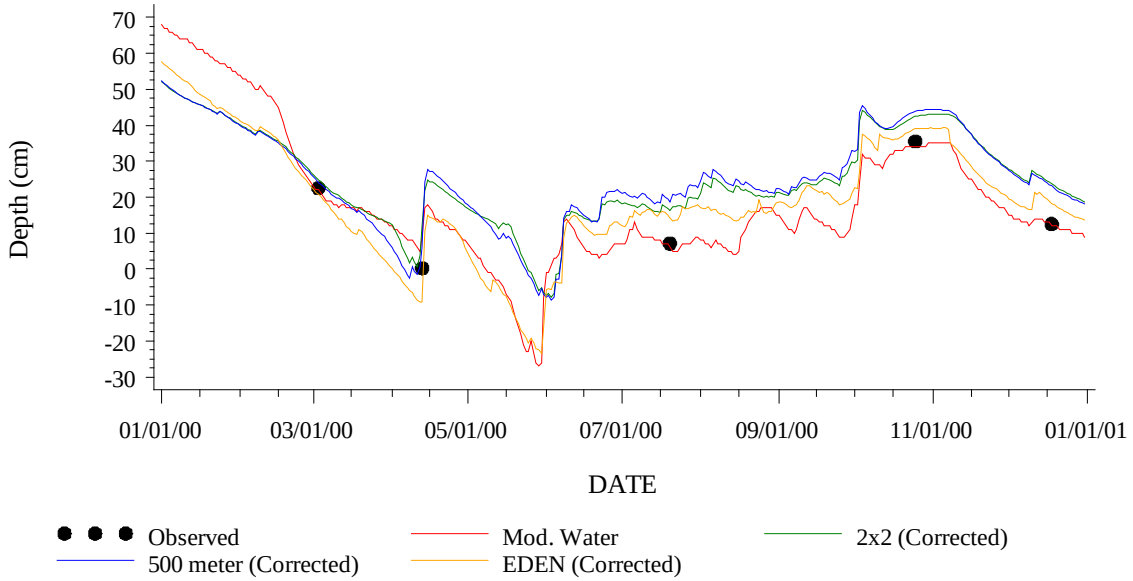


Figure 4. Time series plot of the year 2000 at site SRS50B of the Modified Waters model, 2x2, 500 meter, and the EDEN depth predictions overlaid on the observed depth data.



H. Aquatic fauna monitoring protocol: Data management QAQC

1. Lab Protocol for Error Checking Data Sets

Our lab protocol for data checking involves several steps that are aimed at minimizing the errors due to the transfer of data from "raw" hand-written data sheets to our database. The first step in entering and checking data is for a technician to enter the data. The data are then double-checked by a different technician and sent to the database manager. The database manager then imports the spreadsheets into the Statistical Analysis System (SAS) and runs a series of error-checks to ensure integrity and consistency of the data. Once these checks are completed, the new data are incorporated into the long-term database.

We have six different "data types" that are collected and stored in our long-term database. The data types are as follows: fish data, crayfish data, invertebrate & other vertebrate data, animal wet weight data, vegetation data, and physical data. These data are entered by technicians in a simple format to minimize the inevitable errors that occur when transferring information from the raw datasheets to computer spreadsheets. Unfortunately, this simple format does not structure the data in a way that is amenable to further analysis and interpretation. SAS offers an interface that permits importing and data manipulation via a high-level programming language. This language has the capability to restructure the data into any form we require. Additionally, SAS has analytical techniques that permit us to calculate descriptive statistics, and analyze the data in the same program.

Checking the integrity and consistency of the data in SAS involves a series of steps. Because the datasets are structured differently and contain different information, the programs we write for each data type are slightly different. The following describes the programs used for importing, checking and incorporating each data type into our database:

2. Excel Files (all data types)

   a) Convert Excel spreadsheets into a .csv file. To do this click "save as type" CSV.
   b) File names should be standardized as follows: REGION_DATATYPE_YEAR_SAMPLINGPERIOD; example: SRS_FISH_2008_PER3. This naming standardization should be followed when importing the data into SAS.
   c) Fill in blank cells with ".".
   d) Make sure that all of the column headings are consistent with the SAS import template.

3. Import and Error Checking SAS Programs

We have prepared import and error checking SAS programs that provide a general framework for importing and error checking files in SAS. These programs are submitted as accompanying electronic materials with this report and the directories listed below mirror our directory format; they will have to be modified accordingly for application on other computer platforms. These programs require the user to input information about the datasets. If the dataset is not from Modified Waters project, or if new information is added to the data, then the template should be modified accordingly.

Open SAS import templates:
D:\MONITORING_DATA\PROJECTS\DATA_QAQC\SAS_PROGRAMS\IMPORT_TEMPLATES

Fish and Crayfish Programs:

a) Import .csv files.
b) Combine datasets from different sampling periods into one dataset.
c) Check data for general spatial, temporal and data type specific errors. These checks are aimed at detecting misspellings, incorrect dates, and impossible values (e.g., crayfish length>1000mm).
d) Add data to long-term database. These datasets have information that is not contained in the "count" dataset, such as: length, sex, and form. Additionally these files may contain individual specific comments that are not relevant to the count dataset.
e) Create a "count" variable with a value of 1 for each individual caught. Then use PROC MEANS to sum the number of individuals for each species for a given sample (i.e. how many individuals of a given species were caught in a throw trap at a plot on a specific date). Be sure to keep any comments that are relevant to the count dataset in this file and eliminate comments that are only appropriate for the individual file (e.g., keep comment=TRLDRY, do not keep comment=PRTMIS; see list of comments in the metadata for a full list of comments).
f) Use PROC TRANSPOSE to transpose this dataset so that the species are columns and the value for each species is a count for the number of individuals caught in a sample. This dataset should have one row per sample. Transposition of the data will create missing values where a species was not caught in a sample.
g) If there are not unusual circumstances as indicated by a comment (e.g., comment=sitdry) then the missing values for each species are filled in with zeros. If no sample was taken, <u>do not</u> fill a missing value in with zero.
h) Check for duplicate entries.
i) Create a pre-merge count dataset. This dataset will be used in a merge check program to check spatial and temporal consistency among data types.

Invertebrate & Other Vertebrate and Vegetation Programs:

a) Import .csv files.
b) Combine datasets from different sampling periods into one dataset.
c) Check data for general spatial, temporal and data type specific errors. These checks are aimed at detecting misspellings, incorrect dates, and impossible values.
d) Use PROC MEANS to sum the number of individuals for each species for a given sample (i.e. how many individuals of a given species were caught in a throw trap at a plot on a specific date). Be sure to keep any comments that are relevant to the count dataset in this file and eliminate comments that are only appropriate for the individual file (e.g., keep comment=TRLDRY, do not keep comment=PRTMIS; see list of comments in the metadata for a full list of comments).
e) Use PROC TRANSPOSE to transpose this dataset so that the species are columns and the value for each species is a count for the number of individuals caught in a sample. This dataset should have one row per sample. Transposition of the data will create missing values where a species was not caught in a sample.
f) If there are not unusual circumstances as indicated by a comment (e.g., comment=sitdry) then the missing values for each species are filled in with zeros. If no sample was taken, <u>do not</u> fill a missing value in with zero.
g) Check for duplicate entries.
h) Create a pre-merge dataset. This dataset will be used in a merge check program to check spatial and temporal consistency among data types.

Wet Weight Program:

a) Import .csv files.
b) Combine datasets from different sampling periods into one dataset.
c) Check data for general spatial, temporal and data type specific errors. These checks are aimed at detecting misspellings, incorrect dates, and impossible values.
d) Use PROC TRANSPOSE to transpose this dataset so that the species are columns and the value for each wet weight type {FISWGT(Fish), CRYWGT(Crayfish), SHPWGT(Shrimp), MOLWGT(Mollusc), OITWGT(Other Invertebrate), OVTWGT(Other Vertebrate)} is a wet weight value (in grams) a sample. This dataset should have one row per sample. Transposition of the data will create missing values where a wet weight type was not caught in a sample.
e) If there are not unusual circumstances as indicated by a comment (e.g., comment=sitdry) then the missing values for each species are filled in with zeros. If no sample was taken, <u>do not</u> fill a missing value in with zero.
f) Check for duplicate entries.

g) Create a pre-merge dataset. This dataset will be used in a merge check program to check spatial and temporal consistency among data types.

Physical Program:

a) Import .csv files.
b) Combine datasets from different sampling periods into one dataset.
c) Check data for general spatial, temporal and data type specific errors. These checks are aimed at detecting misspellings, incorrect dates, and impossible values.
d) Check for duplicate entries.
e) Create a pre-merge dataset. This dataset will be used in a merge check program to check spatial and temporal consistency among data types.

4. Merge Check Program

Open Merge Check Program:
D:\MONITORING_DATA\PROJECTS\DATA_QAQC\SAS_PROGRAMS\MERGE_CHK

a) Obtain datasets for each of the different data types (6) and sort in the same order using all spatial and temporal variables as by variables.
b) Do a "match-merge" data step using all spatial and temporal variables as by variables.
c) If any of the temporal or spatial components of any of the datasets do not match then create an output dataset that has all instances where this occurs.
d) Once there are no discrepancies among datasets in spatial and temporal values, then check for discrepancies between the wet weights and the density data.
e) Once there are no discrepancies among the datasets in either spatial and temporal values or between wet weight and density, add each data type to the long term database.

5. Database and Hydrology Merge SAS programs

Open Database and Hydrology Merge Program:
D:\MONITORING_DATA\PROJECTS\DATA_QAQC\SAS_PROGRAMS\DATABASE_AND_HYDROLOGY_MERGE

a) Obtain "new" data from the "merge dataset" according to each specific data type.
b) Obtain the "old" data set; i.e., the data currently in the existing database.
c) Concatenate the old and new datasets to create the updated database.
d) Merge updated hydrology data with the database.

The following is a list of the directories for each data type. These directories include all of the data and SAS programs needed to (re)create the database.
Fish directory: D:\MONITORING_DATA\FISH_DATA
Crayfish directory: D:\MONITORING_DATA\CRAYFISH_DATA
Invertebrate & Other Vertebrate Directory:
D:\MONITORING_DATA\INVERTEBRATES
Vegetation Directory: D:\MONITORING_DATA\VEGETATION
Wet Weight Directory: D:\MONITORING_DATA\WET_WEIGHTS
Physical Directory: D:\MONITORING_DATA\PHYSICAL_DATA

All of the importing/error checking templates are located in the following directory:
D:\MONITORING_DATA\PROJECTS\DATA_QAQC

6. Tips and Tricks for data management

Excel

Keyboard shortcuts:
Windows: ctrl x=cut, ctrl c=copy, ctrl v=paste
SAS: ctrl e=clear log window

E. Using SAS

Checking the SAS error log: use the edit drop down menu to search for the following keywords that indicate that there is an error in the program:

a) error: there was an error in the SAS program
b) warning: something happened in the program that may be a problem, but isn't always a problem.
c) uninitialized: Usually the result of performing an operation on a variable that does not exist.

The SAS dataset names should have a common format. Therefore once the import template any of the data types is updated with new information for the data at hand, the other data types can be substituted into the new template via a search and replace. Ex: fish is the first data type imported; use search and replace to replace all "fish" file names with "invt" to create the invertebrate data sets.

Create a list of all of the values of a variable: sort the SAS dataset by the variable of interest. Use a data step on this sorted dataset and use the same by statement. Use a put statement to print the variable into the log.
Example:

```
PROC SORT DATA==dataset OUT=sorteddata;
        BY variable;
RUN;
```

```
DATA _null_; SET sorteddata;
        BY variable;
        IF FIRST.variable THEN PUT variable=;
RUN;
```

Create a list of all variables in a dataset: use the contents procedure
Ex:

```
PROC CONTENTS DATA=dataset SHORT;
RUN;
```

Perform multiple actions using one condition: use a do loop.
Ex:

```
DATA dataset; SET dataset;
        IF condition THEN DO;
                x=2;
                y=1;
                z=5;
        END;
RUN;
```

Perform an action on multiple variables: Use an array statement and a do loop. An array statement uses an index(i) to reference multiple variables. The do loop performs the same action for each variable.

```
DATA dataset; SET dataset;
        ARRAY NAME(*) variable1 variable2 variable3 variable4;
        DO I=1 TO DIM(NAME);
                IF condition THEN NAME(I)=0;
        END;
RUN;
```

If all of the variables are numeric then you can use the "_NUMERIC_" keyword instead of naming separate variables in the ARRAY statement.

Extract part of a string: Use a SUBSTR function.

Ex: This example extracts the site name from the following composite id variable that has region, site and plot combined: ID=SRS06B.

SUBSTR(character value, start, length).

```
DATA dataset; SET dataset;
        site=SUBSTR(id, 4, 2);
RUN;
```

Combine variables into one variable and remove spaces: CATS function.
CATS(variable1, variable2, variable3, ..., variablen)

Create a variable that accumulates: Use the retain statement. When SAS creates a new dataset the default behavior is to reset all of the variables to missing for each iteration of the data step loop. The retain statement overrides this behavior and retains the value for the last observation. This is a useful statement when we want to calculate variables that accumulate through time, e.g., days since flooding.