

## Predicting foraging wading bird populations in Everglades National Park from seasonal hydrologic statistics under different management scenarios

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[1] The ability to map relationships between ecological outcomes and hydrologic conditions in the Everglades National Park (ENP) is a key building block for their restoration program, a primary goal of which is to improve conditions for wading birds. This paper presents a model linking wading bird foraging numbers to hydrologic conditions in the ENP. Seasonal hydrologic statistics derived from a single water level recorder are well correlated with water depths throughout most areas of the ENP, and are effective as predictors of wading bird numbers when using a nonlinear hierarchical Bayesian model to estimate the conditional distribution of bird populations. Model parameters are estimated using a Markov chain Monte Carlo (MCMC) procedure. Parameter and model uncertainty is assessed as a byproduct of the estimation process. Water depths at the beginning of the nesting season, the average dry season water level, and the numbers of reversals from the dry season recession are identified as significant predictors, consistent with the hydrologic conditions considered important in the production and concentration of prey organisms in this system. Long-term hydrologic records at the index location allow for a retrospective analysis (1952–2006) of foraging bird numbers showing low frequency oscillations in response to decadal fluctuations in hydroclimatic conditions. Simulations of water levels at the index location used in the Bayesian model under alternative water management scenarios allow the posterior probability distributions of the number of foraging birds to be compared, thus providing a mechanism for linking management schemes to seasonal rainfall forecasts.

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### 1. Introduction

[2] Many of the adverse impacts on ecosystem function in the Everglades National Park (ENP; Figure 1) are caused directly or indirectly by altered regional hydrology [Bancroft *et al.*, 2002; Craighead, 1971; Davis, 1943; Gleason, 1984; Loveless, 1959; Powell *et al.*, 1989]. However, it is difficult to identify cause-and-effect relations between altered hydrologic patterns and ecosystem function because of the many factors involved and the paucity of long-term data on each of the putative notions. Consequently, modeling studies [Cline *et al.*, 2006; Gaines, 2000; Wetzel, 2001] have been undertaken to create synthetic records that could represent the hydroecology of the region. Since the relationships in such models are largely prescribed or empirically estimated from relatively short records, it is

difficult to rely solely on them as tools for understanding or predicting the ecological outcomes in the ENP consequent to hydroclimatic variations. A few authors [Bancroft *et al.*, 2002; Russell *et al.*, 2002] have tried to directly use data on a few species and hydrologic or climatic indicators to infer such relationships that could be used for subsequent management of the ENP. This paper contributes to this literature.

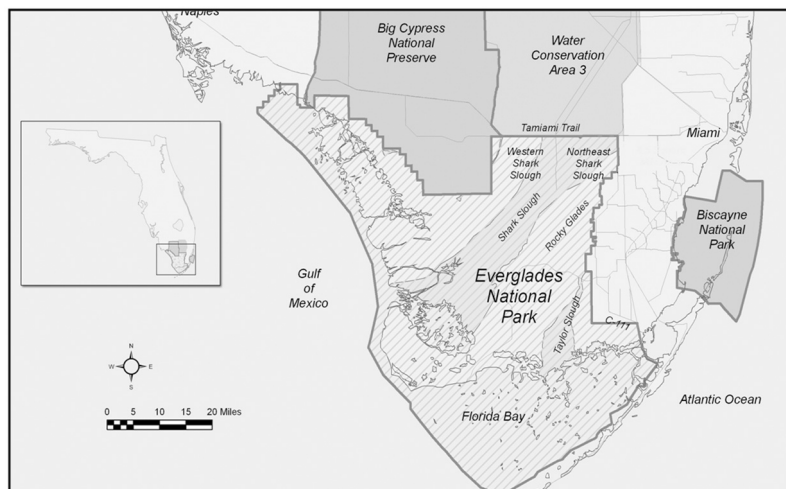
[3] A goal of the restoration project is to ensure that the ecological health of the ENP improves as a direct result of management activities. Achieving hydrologic targets through the proper timing and amount of releases from control structures is a first step in the management process. Significant climate and weather variations in the region [Kwon *et al.*, 2006, 2009] influence the ability to make releases and determine the ecological outcomes. A predictive model for ecological outcomes given anticipated climate conditions and proposed releases is a basic building block for an adaptive management process. The development of such a model with a capacity for uncertainty analysis is the goal of the larger research project to which this paper contributes.

[4] Seasonal water depths in the ENP depend on managed surface water releases from control structures and on direct rainfall. On an annual basis and for the ENP as a

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**Figure 1.** Everglades National Park is located at the southern tip of the state of Florida. The hydrologic monitoring station P33 is identified by the star near the center of Shark Slough.

whole, direct rainfall is the dominant component of the two water sources. However, the importance of the discharges through the control structures increases during the dry season. These discharges are concentrated along the northern boundary of the ENP and they have their largest influence in the region directly downstream called Shark Slough (Figure 1). The ecological responses to these discharges must be quantified to effectively manage the park and to guide the restoration effort. However, given the large influence of rainfall on the system, the ecological responses to the managed discharges must be placed within the context of larger-scale climatic factors. Here we link the variations in the foraging populations of two wading bird species, key indicators of the Everglades' ecology, to hydrologic conditions in the national park that result from rainfall and managed releases.

[5] Foraging patterns of wading birds have been a key issue in the Comprehensive Everglades Restoration Plan (CERP), and the monitoring of wading bird nesting success is a coordinated effort between many agencies in Florida. Although other factors (e.g., prey conditions, migrations from remote areas) may influence the foraging patterns of wading birds in ENP [Cristol and Switzer, 1999; Gawlik, 2002; Houtman and Dill, 1998; Krebs and Cowie, 1976; Lima and Dill, 1990; Safina and Burger, 1985], it is likely that hydrologic conditions are a major driver that dominate the underlying population dynamics in the park [Cezilly et al., 1995; Frederick and Collopy, 1989; Gawlik, 2002; Powell, 1987; Russell et al., 2002; Smith, 1995; Spalding et al., 1993; Strong et al., 1997]. Previous studies [Russell et al., 2002] have shown an inverse relationship between the number and degree of dry season disruptions (short-term reversals in the recession of surface water) and bird abundance.

[6] This paper develops a hierarchical Bayesian model that first relates the population of two dominant wading birds, the Great Egret (*Casmerodius albus*) and White Ibis (*Eudocimus albus*), to key seasonal statistics of the water levels at P33. The relatively long record (>50 yrs) at this gage provides a basis for linking wading bird foraging

patterns in ENP to interannual to decadal climate variability. Water levels at P33 and potential wading bird foraging populations are then predicted, again in a Bayesian framework, on the basis of rainfall and inflow volumes under different management scenarios for the park. The Bayesian posterior probability densities of bird populations conditional on management scenarios embody the uncertainty because of both sampling and parameter estimation. Their comparative analysis allows for the selection of ecologically favorable water release strategies.

## 2. Study Area and Data

[7] The greater Everglades ecosystem extends from the southern edge of Lake Okeechobee to Florida Bay. The southern terminus of the system has been preserved as ENP, one of the most widely recognized wetlands in the world. The historic ecosystem was once characterized by large expanses of shallow, slowly moving surface water (called sheetflow) with seasonally fluctuating water levels controlled primarily by rainfall and runoff from Lake Okeechobee. Hydropatterns over much of this region have been altered through various forms of land use change and management practices related to regional water supply and flood control. The once contiguous wetlands have been compartmentalized by a series of canals and levees that, along with a network of pumps, weirs, and gated culverts, are the primary means by which water levels are controlled and deliveries are made to the population centers and natural areas. As a result of these modifications, sheetflow patterns in the system have been altered, causing deviations from historic water level fluctuations and an overall decline of ecosystem function within ENP. Most notably, wading bird populations are estimated to have declined by 90% relative to their historic levels [Ogden, 1994]. ENP has a subtropical climate with a distinct wet season in the summer and a dry season in the winter. Almost 75% of the annual precipitation falls during May–October with monthly precipitation amounts ranging between 0.0 and 20.0 inches. Overland sheetflow from northern contributing zones into

the ENP is a fraction of the historical amounts. Ecologic restoration of ENP brings to the fore the challenge of how to deliver the right amount of water to the park at the right times to the right locations.

[8] The primary data considered are historical rainfall records, water stages, and the foraging abundance of the Great Egret and White Ibis. Water level data are taken from the P33 gage, which is shown below to be directly related to overall hydrologic conditions in the park, and for which long-term reliable data are readily available from 1952 to 2007. The seasonal variation in the water stage at P33 is illustrated in Figure 2a.

[9] Wading bird foraging data from the systematic reconnaissance survey flights (SRF) [Norton-Griffiths, 1978; Russell et al., 2001] were used. The SRF involve flying at a fixed altitude and speed across a study area on a predetermined transect while observers count animals in a strip of land on either side of the aircraft. The SRF surveys were initiated to give South Florida's operational resource managers a tool to assess wildlife populations. Past work to explore the effects of hydrology on SRF-derived wading bird distribution and abundance data is documented by Bancroft et al. [1992, 2002] and Porter and Smith [1984]. The SRF wading bird survey was initiated in 1985. The data are updated every month from December through May, the dry season in south Florida, and once in August. Russell et al. [2001] provide details of the SRF wading bird surveys. In the present work the wading bird data were derived by aggregation from any grid cell in which each species was ever recorded by SRF from 1985 to 2006. The seasonal variations in Great Egret and White Ibis populations are shown in Figures 2b and 2c.

### 3. Preliminary Analyses

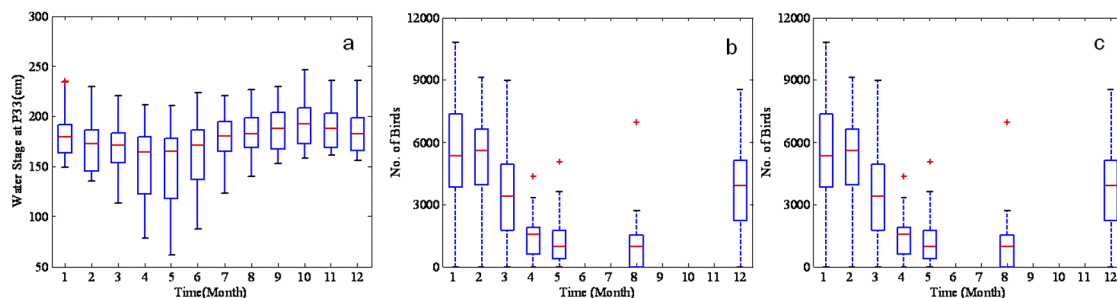
#### 3.1. Relationship Between P33 Stage and Water Depths in ENP

[10] During the dry season, large numbers of wading birds forage within the ENP and tend to concentrate along Shark Slough. Aerial survey records (1985–present) show the numbers of wading birds foraging in the Slough and throughout the ENP fluctuate on an annual basis. These fluctuations have been linked to water depths at the beginning of the dry season and the subsequent recession rates by Russell et al. [2002]. However, the hydrologic data used

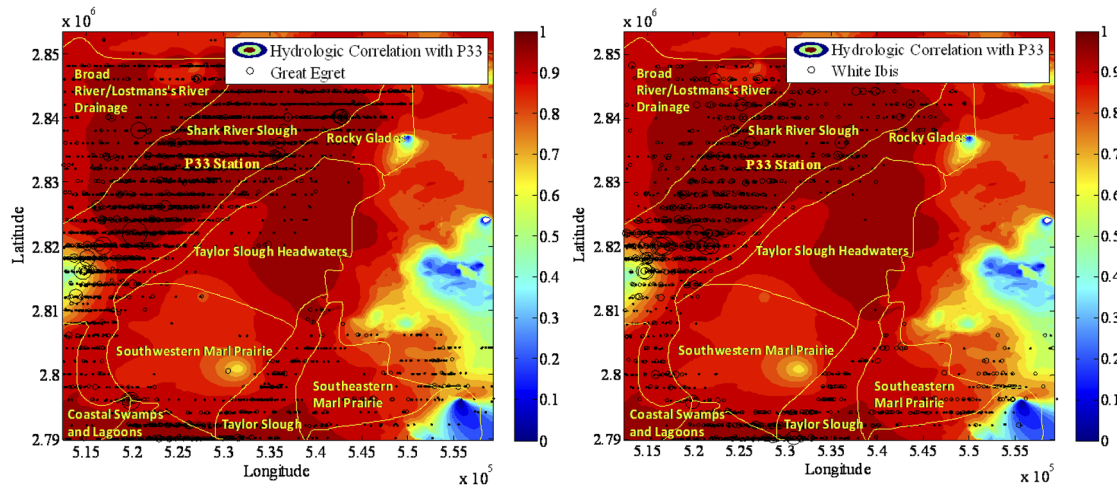
by Russell et al. [2002] were derived from qualitative aerial observations and not on the basis of actual gage data. This is because water level recorders have been scattered nonuniformly in the park and operational for different time periods. Synoptic water depths for the entire park were therefore not available for the period of record matching the bird surveys. Recent installations of automated gage stations have increased the spatial coverage of water level measurements and allowed for interpolation between these stations. Updated, grid-based (400 m<sup>2</sup>) topography data [Desmond, 2003] facilitates the conversion of the interpolated water levels to water depths for most of the ENP.

[11] Water level fluctuations across the ENP are highly correlated. A linear correlation map between daily water stages from January to April 2006 at P33 and daily water depths derived from interpolation of gauge data throughout the ENP is illustrated through the colored contour maps in Figure 3. A high correlation is observed between stages at P33 and water depths throughout ENP over this period. The correlations are highest along the longitudinal axis of Shark Slough, trending from NE to SW across ENP, and in areas of similar elevations during both the dry and wet seasons such as the Broad and Lostman's River drainages. Control structures discharge water across the northern boundary of ENP directly into the Slough and have less effect on water levels in adjacent areas of higher elevation, or in areas close to the border canals. Thus, there is some decrease in correlation between stages at P33 and water depths outside of the Slough, such as in some of the marl prairie regions. For the period from 2000–2007 we found an average  $r^2$  correlation coefficient of 0.75 (ranging from 0.66 to 0.95) between January–April daily water depths at P33 and water levels at seven principal gages (NE2, NP201, EVER6, CP, P36, NP46, CR2) in ENP, each representing one of the landscape classifications shown in Figure 3. With this information we consider water levels at P33 a useful indicator of water depths throughout most of the ENP, particularly in the areas of Shark Slough where wading bird foraging is concentrated.

[12] Observations of foraging Great Egret and White Ibis in May of each year (1985–2006) are also displayed in Figure 3. High wading bird counts can be noted in those regions of ENP that show the highest correlation with P33 water levels. As a consequence, water levels at P33 may be useful to infer the suitability of hydrologic conditions for wading birds throughout the park.



**Figure 2.** Seasonal trends and variation (box plots) in monthly values of (a) water stage at P33, and foraging abundance of (b) Great Egret and (c) White Ibis from 1985 to 2006. Observations of wading birds in June, July, September, October, and November are not available.



**Figure 3.** (left) Great Egret and White Ibis foraging abundance in May 2006, community types, and correlation of water depths to P33 during the dry season. The colored contour map shows the correlation between grid-based water depths in ENP and P33 water levels during the period from January to April 2006. The black circles represent the number of birds in May 2006 and the size of the circle is proportional to the number of birds. (right) Outside of ENP and subject to different water management practices, resulting in depths with low correlations with P33 and few wading birds (not labeled). The small area of low correlation on the left-hand side indicates a tidal influence not present in other parts of the coverage.

### 3.2. Identifying Suitable Predictor Variables From the P33 Data

[13] Bird foraging patterns are affected by many different factors such as prey availability [Gawlik, 2002; Krebs and Cowie, 1976; Lima and Dill, 1990; Safina and Burger, 1985] and the threat of predation [Cristol and Switzer, 1999; Houtman and Dill, 1998; Lima and Dill, 1990]. Hydrologic conditions are also known to play a role [Powell, 1987]. Changes in the historical pattern of water level fluctuation are considered to be a significant factor that determines foraging patterns and the abundance of bird populations in ENP [Russell et al., 2002; Strong et al., 1997].

[14] It is important to recognize that hydrologic conditions may be related to other factors influencing wading bird foraging [Gawlik, 2002]. For example, the density and distribution of vegetation in ENP is a habitat factor related to hydrologic conditions that may affect foraging patterns. Marsh vegetation types and density in the Everglades are known to change with alterations to hydroperiod [Ross et al., 2003; Armentano et al., 2006; Saunders et al., 2006], and these changes in vegetation distribution/density may affect the habitat quality for foraging wading birds. The populations of wading birds in areas outside of ENP (e.g., the water conservation areas) and the migrations of birds to and from these areas may also be a determinant of the foraging patterns observed during the SRF. The impact of these migrations on the SRF observations is not well known and was not included in our model. Since little information on the impacts of factors such as vegetation types or migration on foraging patterns is available, we focus on hydrologic statistics of within-season variation in the P33 stage as potential predictors of foraging numbers for the two species of interest.

[15] Everglades wading birds nest in the December–May dry season, and successful foraging during this period can be considered a prerequisite for successful nesting [Russell et al., 2002; Frederick and Ogden, 2003]. Foraging success in the dry season is dependent on water depths being low enough to allow standing, and on appropriate surface water recession rates which concentrate prey in the low-lying areas [Kushlan, 1986; Frederick and Collopy, 1989; Gawlik, 2002]. Disruptions to the dry season recession caused by winter rainfall events or from managed water releases tend to reduce foraging success because of the resulting prey dispersal [Frederick and Ogden, 2003]. Too rapid recession rates or too low water levels in December may shorten the nesting season, although it is important to consider that the impacts of these and other hydrologic factors on foraging/nesting are often species-dependent [Frederick and Spalding, 1994]. For this initial analysis, the number of Great Egret and White Ibis in May at the end of the dry season are selected as the predictands reflecting aggregate hydrologic variables calculated from January to April. These two species were chosen because their white color makes them easy to identify in the SRF flights, and these data are therefore less subject to error. As in Russell et al. [2002], bird counts in May were chosen because late-dry season foraging numbers can be considered as an indicator of nesting initiated earlier in the season. Similar models could be developed using data collected during any dry season month and for other species of wading birds. Models which incorporate within-season variability in foraging and nesting patterns with changes in the regional and local-scale hydropatterns will improve understanding of the specific relationships between hydrology, foraging, and the success of individual colonies [Bancroft et al., 1994]. The objective of this paper represents a step in this direction by

demonstrating the development of a robust analytical framework capable of linking ecological outcomes to hydrologic indicators in a manner that is useful to managers and restoration planners.

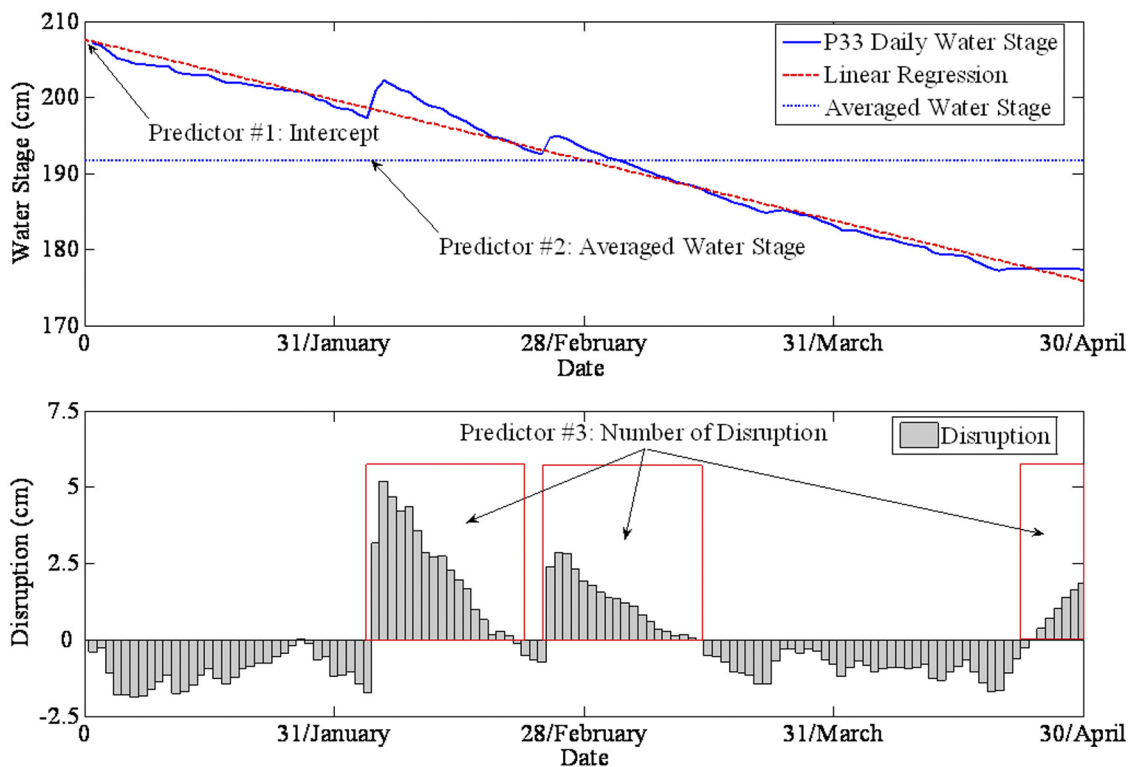
[16] Now we consider the seasonal statistics of the daily water levels recorded at P33 that may be useful predictors of the May bird count. The approach followed is generally similar to that used by *Russell et al.* [2002], except that the predictors are derived from actual daily water level data from a single location, P33, instead of using the gridded qualitative aerial observations of water level at a monthly scale.

[17] The procedure used to develop seasonal water stage statistics as predictors from the daily water stage data at P33 is illustrated in Figure 4. First, consider a linear decline of stage with time during the middle of the dry season (January–April) representing the seasonal recession of the water table. For this recession, a linear regression of stage versus time into the season provides the intercept as an estimate of the mean of initial water level, and the slope as an estimate of the recession rate. Once this recession behavior is estimated, a disruption can be defined as a positive residual from the linear regression line. For each season, we can then compute the number of disruptions, a standard deviation of disruption, a maximum consecutive disruption, the initial water stage, and average water stage at P33 as potential predictors.

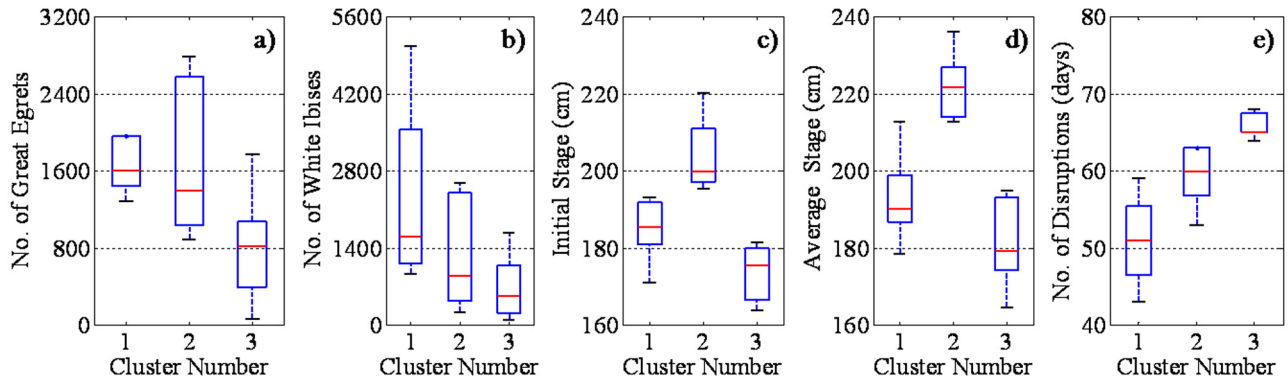
[18] An exploratory data analysis was pursued first. A *k*-means [*Spath*, 1985] cluster analysis was applied to the standardized time series of the three predictors and

population counts for each bird species. The intention was to see how these attributes group together. Box plots of the number of birds and the predictors for the three clusters identified are shown in Figure 5. The first cluster corresponds to a medium water stage and relatively low disruption. The median bird populations are the highest for this cluster. The White Ibis population has a high variation for this cluster, but is still generally higher than for the other clusters. Cluster 2 has the highest water levels and a medium level of disruption. It maps to a middle category of median bird population, but with a high variation in the Great Egret bird count. The third cluster corresponds to the lowest water levels and the highest disruption frequency and maps on to the lowest bird counts for both species. The nonlinearity of the relationship between the predictors and the predictand is illustrated by this analysis.

[19] A smooth surface fit using a cross-validated thin-plate smoothing spline [*Wahba*, 1990] of the birds as a function of initial water stage and disruption, and as a function of initial and average stage are shown in Figure 6. These pairwise relationships are nonlinear, suggesting that a nonlinear model in all three predictors may be appropriate. The correlations across the three predictors and the two predictands, and partial correlations for each prediction for the period 1985–2006 are provided in Table 1. On the basis of these partial correlations it is apparent that while the predictors are correlated with each other, they still contribute useful additional predictive information. Bird counts initially increase with average or initial water level, but



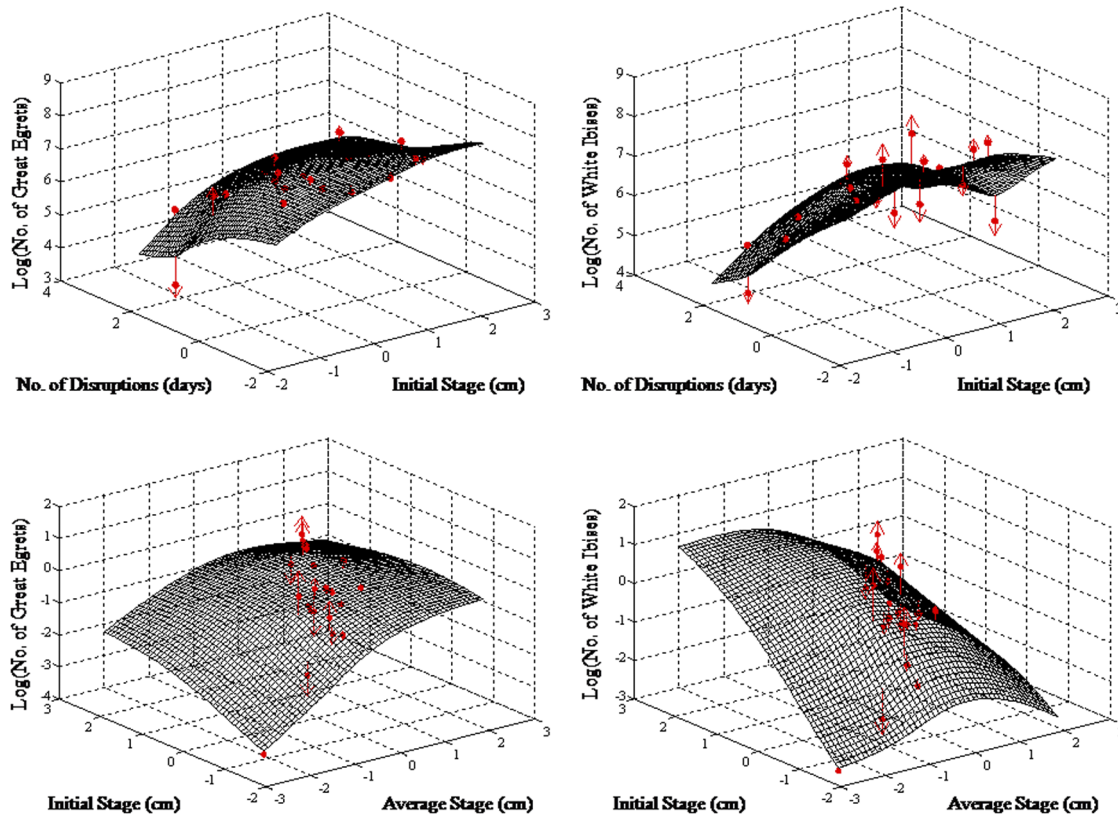
**Figure 4.** Three predictors derived from water stage at the P33 station. The first is the initial water stage (IWS) at the beginning of the dry season, the second is the average water stage (AWS), and the final predictor is the number of disruptions (DIS) to the recession rate as the dry season progresses.



**Figure 5.** Box plots of the number of a) Great Egrets, b) White Ibis, c) initial water stage (IWS), d) average water stage (AWS), and e) disruption (DIS) given three clusters.

decrease or level out for a high stage. This agrees with prior research [Russell *et al.*, 2002] that a quadratic relationship between the predictand and these predictors may be useful. A stepwise regression procedure in a generalized linear modeling (GLM) framework (considering log transformed bird counts, a Poisson distribution for bird counts, and quadratic terms including cross-products across predictors) was next considered to refine the model choice. In the

GLM framework, one can consider either a Gaussian or non-Gaussian distribution for the predictand while using a maximum likelihood calculation for parameter estimates. This setting approximates the conditions assumed in a hierarchical Bayesian approach. The initial GLM/stepwise model selection resulted in a nonlinear combination of log transform data that included the initial stage, the average stage, and the disruption frequency depending on which



**Figure 6.** Smooth surface fit using a cross-validated thin-plate smoothing spline [Wahba, 1990] of (left) Great Egret and (right) White Ibis foraging numbers as a function of initial water stage and disruption illustrates the nonlinearity of the relationship. Note the generally linear relationship between the logarithm of bird counts with the number of days with disruptions, and the more complex relationship with stage.

**Table 1.** Correlation Coefficients for the Three Predictors Initial Water Stage (IWS), Average Water Stage (AWS), and Number of Disruptions (DIS) and the Two Predictands (Great Egret and White Ibis Foraging Populations), Including Partial Correlations<sup>a</sup>

Bird, IWS AWS,DIS	-0.13	0.04
Bird, AWS IWS,DIS	0.17	-0.14
Bird, DIS IWS,AWS	<b>0.83</b>	<b>0.86</b>
Bird, IWS AWS	<b>0.83</b>	<b>0.87</b>
Bird, IWS DIS	0.12	-0.21
Bird, AWS IWS	<b>0.83</b>	<b>0.87</b>
Bird, AWS DIS	0.03	-0.16
Bird, DIS IWS	0.12	-0.21
Bird, DIS AWS	0.03	-0.16

<sup>a</sup>IWS is initial water stage, AWS is averaged water stage and DIS is number of disruptions at P33 from January to April. Values in bold are significant at the 95% level.

bird population was being predicted. Differences between candidate models in terms of the likelihood criteria were small and the instability of choice across models reflects the small data set and correlated predictors. Models with the Poisson assumption as to the bird count distribution typically tended to perform much better than those with the log(bird) predictand in terms of the likelihood criteria and in terms of cross-validated prediction. However, these models typically admitted nearly the full quadratic model (with cross products) formed across the three predictors. Thus, using the Poisson formulation, but accounting for predictor correlation in a Bayesian framework while seeking a reduced model was indicated. Detailed results of these initial screening models are not presented here. The Bayesian model that was formulated using the initial analyses considers noninformative priors and explicitly considers the uncertainty in estimating the covariance matrix across predictors [Gilks and Roberts 1995; Gelman et al. 2004; Gelman, 2005]. This model is presented in section 4.

#### 4. A Predictive Model for Foraging Birds Populations

[20] A hierarchical Bayesian model is developed for the seasonal prediction of populations of Great Egret and White Ibis using the selected hydrologic variables, specifically the initial water stage, the average water stage, and the number of disruptions. The model considers that the population of each bird species follows a Poisson distribution with time varying mean  $\lambda_j(t)$  equal to the expected number of birds for species  $j$ . A generalized linear model for the mean  $\lambda_j(t)$  for bird species  $j$  in terms of each predictor is then formulated as follows:

$$Z_{jt} \sim \text{Poisson}(\lambda_j[t]). \quad (1)$$

$$\begin{aligned} \log(\lambda_j[t]) = & \beta_{1j} + \beta_{2j} \cdot \text{AWS}(t) + \beta_{3j} \cdot \text{IWS}(t) + \beta_{4j} \cdot \text{DIS}(t) \\ & + \beta_{5j} \cdot \text{AWS}(t) \cdot \text{IWS}(t), \end{aligned} \quad (2)$$

where  $Z_{jt}$  represents the bird count for species  $j$  for season  $t$ , with mean rate  $\lambda_j(t)$ . IWS is the initial water stage, AWS is the averaged-water stage, and DIS is the number of disruptions at P33 from January to April. The specific

predictors retained in equation (2) were obtained from pre-screening and forward/backward and backward/forward stepwise selection considering linear and quadratic terms in each predictor as well as cross products. Both cross-validated performance and parsimony in model selection were the key factors in selecting the final set of predictors in the candidate model. In equation (2), the log transform is introduced to ensure that predicted bird counts are non-negative. We consider the model parameters to have the following prior distribution:

$$\begin{pmatrix} \beta_{1j} \\ \beta_{2j} \\ \beta_{3j} \\ \beta_{4j} \\ \beta_{5j} \end{pmatrix} \sim N \left( \begin{pmatrix} \mu_{\beta_1} \\ \mu_{\beta_2} \\ \mu_{\beta_3} \\ \mu_{\beta_4} \\ \mu_{\beta_5} \end{pmatrix}, \Sigma \right) \quad (3)$$

[21] Here uncertainty in parameter estimation is considered explicitly, through this multivariate distribution, and inference is made on both the mean values of the parameters,  $\mu_{\beta}$ , and  $\Sigma$  the covariance matrix of these parameters.

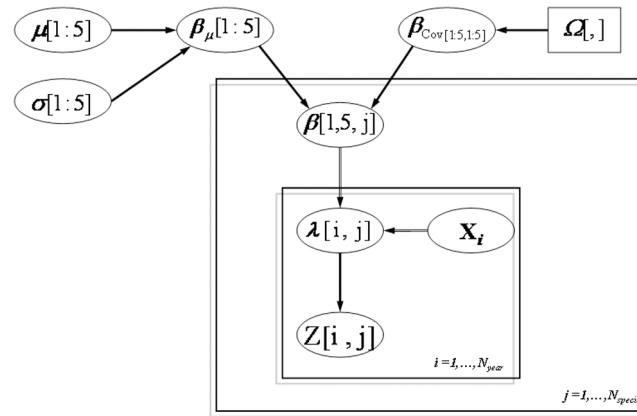
[22] Following Gelman [2005], a conjugate prior distribution with hyperparameters ( $\Omega$ ,  $\nu$ , and  $\hat{\mu}_{\beta}$ ) estimated from the data is employed to describe the uncertainty in estimating the parameters of the prior distribution:

$$\Sigma \sim \text{Inv - Wishart}(\Omega, \nu), \quad (4)$$

$$\begin{pmatrix} \mu_{\beta_1} \\ \mu_{\beta_2} \\ \mu_{\beta_3} \\ \mu_{\beta_4} \\ \mu_{\beta_5} \end{pmatrix} \Bigg| \Sigma \sim N \left( \begin{pmatrix} \hat{\mu}_{\beta_1} \\ \hat{\mu}_{\beta_2} \\ \hat{\mu}_{\beta_3} \\ \hat{\mu}_{\beta_4} \\ \hat{\mu}_{\beta_5} \end{pmatrix}, \hat{\Sigma} \right), \quad (5)$$

where  $\Omega$  and  $\nu$  are the inverse scale matrix and the degrees of freedom of the inverse Wishart distribution, respectively.

[23] Each of the parameters and the hyperparameters, is considered as a random variable with an associated probability distribution. A schematic of the model is presented in Figure 7. We note that the correlation of the observed abundance between the two bird species is 0.85, and hence it may be useful to consider pooling these data in a regression conditioned on the same predictors. The hierarchical Bayesian model used here provides an objective way to choose the degree of pooling. First, we define the predictand  $Z_{jt}$  as the foraging bird population for species  $j$  standardized by dividing its raw data by its corresponding mean annual bird population. Next, we consider that the regression coefficients for each bird species for each predictor that comes from a common distribution with a common mean and variance. If this variance is small, then effectively we have a pooled regression. Conversely, if this variance is large, then independent regressions for the two species result. If the number of bird species introduced into the model increases, then this procedure would still apply and would lead to a better estimate of the mean and variance of the common regression coefficient.



**Figure 7.** The  $\mu$ -hierarchical Bayesian regression model, where  $\mu$  indicates the location parameter (mean) and  $\sigma$  indicates scale parameter (variance).

[24] The joint posterior distribution of the complete set of parameters  $\Phi$  can be derived by combining prior distributions and the likelihood functions:

$$p(\Phi|Z) \propto \prod_{j=1}^2 \prod_{i=1}^N \text{Poisson}(Z_j[i] | \beta_{1,j} + \beta_{2,j} \cdot x_1[i] + \beta_{3,j} \cdot x_2[i] + \beta_{4,j} \cdot x_3[i] + \beta_{5,j} \cdot x_1[i] \cdot x_2[i])$$

$$N \left( \begin{matrix} \beta_{1,j} \\ \beta_{2,j} \\ \beta_{3,j} \\ \beta_{4,j} \\ \beta_{5,j} \end{matrix} \middle| \begin{matrix} \mu_{\beta_1} \\ \mu_{\beta_2} \\ \mu_{\beta_3}, \Sigma \end{matrix} \right) \cdot \left( \begin{matrix} \mu_{\beta_1} \\ \mu_{\beta_2} \\ \mu_{\beta_3} \\ \mu_{\beta_4} \\ \mu_{\beta_5} \end{matrix} \middle| \begin{matrix} \hat{\mu}_{\beta_1} \\ \hat{\mu}_{\beta_2} \\ \hat{\mu}_{\beta_3}, \hat{\Sigma} \end{matrix} \right) \cdot \text{Inv - Wishart}(\Sigma | \Omega, \nu).$$

(6)

[25] The hierarchical regression model is estimated in a Bayesian framework. Noninformative priors are assumed for each of the hyperparameters (e.g.,  $\mu_\beta$ ,  $\Omega$ ,  $\nu$ ) and their optimal values are selected through a maximization of the posterior likelihood of observing the data. A Markov chain Monte Carlo (MCMC) procedure is used. In particular, the Gibbs sampling approach to MCMC [Gilks et al., 1995] was used. We chose to run three chains simultaneously searching for optimal parameters. The evolution of each

chain was monitored to check for convergence to a common value. Selection of the hyper-priors and the appropriateness of the prior distributions and the model structure were judged by the deviance information criterion (DIC) [Berg et al., 2004]. All computations were performed in MATLAB using WinBUGS [Spiegelhalter et al., 2003]. To assess convergence for each parameter the Gelman and Rubin [1992] “shrink factor” was computed. This factor compares the variation in the sampled parameter values within and between chains, and it describes how much the increase in the number of iterations improves the estimates. Gelman and Rubin [1992] suggest running Gibbs sampler chains until the estimated shrink factors are less than  $\sim 1.2$  for all parameters. WinBUGS produces scale reduction factors that are very close to 1 for the fixed effects. Values  $\sim 1$  were obtained after 20,000 iterations.

[26] Table 2 summarizes key results for each regression coefficient. The posterior mean, standard deviation, and 95% credible interval are derived using MCMC as noted above. If the posterior distribution is centered about a value of zero, and is relatively tight, then one can be quite certain that the associated coefficient is essentially zero, and the predictor does not belong. On the other hand, if the variance of the posterior is large, and the predictor is correlated (as indicated in the covariance matrix) with another, then it is possible that it is useful to retain the predictor since its sign may change in a simulation in association

**Table 2.** Hierarchical Model Parameters for Wading Bird Populations and Associated Uncertainty Bounds

Node	Description	Mean	SD	2.50%	Median	97.50%
<i>Great Egret Population Model</i>						
$\beta_1$	Intercept	0.096	0.272	-0.451	0.105	0.604
$\beta_2$	Averaged W.S	-0.157	0.549	-1.252	-0.152	0.932
$\beta_3$	Initial W.S	0.605	0.481	-0.368	0.600	1.574
$\beta_4$	Number of Disruption	-0.220	0.241	-0.684	-0.228	0.265
$\beta_5$	Averaged W.S * Initial W.S	-0.518	0.327	-1.219	-0.492	0.035
<i>White Ibis Population Model</i>						
$\beta_1$	Intercept	0.104	0.287	-0.475	0.113	0.641
$\beta_2$	Averaged W.S	-0.466	0.574	-1.624	-0.456	0.649
$\beta_3$	Initial W.S	0.727	0.492	-0.235	0.719	1.737
$\beta_4$	Number of Disruption	-0.409	0.243	-0.891	-0.407	0.069
$\beta_5$	Averaged W.S * Initial W.S	-0.680	0.387	-1.541	-0.641	-0.051



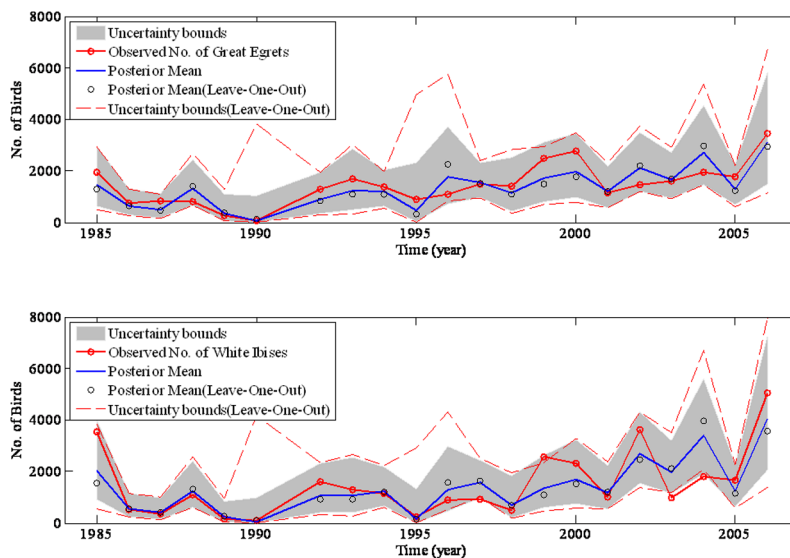
with the sign ascribed to the coefficient of the correlated predictor. Traditional analysts often look for a *t*-test to accept or reject a predictor. However, such a procedure is not always supported by other criteria such as the maximum likelihood performance of the traditional model. In the hierarchical Bayesian framework, the analyst seeks to present the posterior probability distribution of the predictand, rather than just the mean value, and in this context, retaining “weak” predictors is not quite the same as the “overfitting” that results in the traditional case where the performance, with respect to the mean value, and a subjective (threshold) hypothesis test for retaining a predictor is used. In the Hierarchical Bayesian Model (HBM), the variance associated with retaining an additional predictor is represented in the posterior distribution.

[27] The HBM presented here considers a multistage prediction problem and provides an effective means for propagating both the model and parameter uncertainties through all the stages simultaneously. In a Bayesian framework, the entire process is linked into one model, and the causal structure can be readily explored in terms of these conditional distributions. Propagation of uncertainty is considerably more complex in a traditional setting where the uncertainty must be estimated separately for each individual regression. Another advantage of our method stems from the manner in which HBM provides clear criteria for pooling across multiple predictands. Traditional regression typically provides for only two choices, either pooling across all predictands or performing independent regressions for each predictand/predictor combination. HBM allows a consistent way to perform this estimation across all the multiple predictands with appropriate shrinkage. This in turn may lead to a reduction in the uncertainty of estimation, but not necessarily a change in the mean prediction. That is, if there is no opportunity of pooling across the

different response variables, the HBM will give results comparable to those from individual regressions. The reader is referred to *Raftery* [1995], *Wikle* [2003], *Elsner and Jagger* [2004], *Clark* [2005], and *Kwon et al.* [2008] for additional information on HBM applications.

[28] Recall that the predictors considered are mutually correlated. Consequently, one needs to consider an aggregate performance measure for choosing an appropriate model, rather than the deletion of individual coefficients using only the posterior probability density of that parameter. The performance of the selected candidate models was compared using the DIC as calculated in WinBUGS [*Spiegelhalter et al.*, 2003]. The lower the DIC value, the better the model fits the data. The model presented in equation (2), with the associated results for parameters was the best one based on this criteria. Recall that in the Bayesian formulation, we solved for the coefficients for both bird populations simultaneously, and hence this set of parameters is in some sense best for both, rather than for an individual species.

[29] The time series of observed wading birds and the values predicted at ENP in May, using a hierarchical Bayesian model for 1985–2006 are shown in Figure 8. The posterior mean and the 2.5%–97.5% posterior uncertainty bounds are provided. In addition, the results of a hierarchical Bayesian model fit under a leave-one-out cross-validation setting are also shown. In this setting, the entire MCMC model fitting procedure is repeated dropping the observation to be predicted from the fitting set while using the predictors selected in the final model. However, the model selection procedure is not repeated each time. From Figure 8, the performance under cross validation is seen to be generally consistent (with slightly higher variance as expected in general, but more so in the years 1990, 1995, and 1996) with the full sample performance. Model predictive ability is quantitatively assessed to judge the degree to



**Figure 8.** Posterior mean Bayesian model predictions (blue lines) and observed bird counts at ENP in May using AWS, IWS, and DIS values at P33 as predictors for 1985–2006 (red lines, open red circles). The shaded area represents the 2.5% and the 97.5% uncertainty bounds for the posterior distribution for each year. Dashed lines represent the 2.5% and 97.5% uncertainty bounds on the posterior mean values (open black circles) generated by a sequential leave-one-out procedure.

which the model simulation matches the actual observations. One can utilize different statistics of efficiency to measure the goodness of fit or prediction skill. While the likelihood measure scored against the posterior probability density of  $Z_{jt}$  would be the appropriate measure, to facilitate comparison for traditional analysts we present selected measures that traditional analysts use. *Legates and McCabe* [1999] have critically reviewed many of the principal statistics of efficiency. *Nash and Sutcliffe* [1970] defined the coefficient of efficiency (CoE) which ranges from minus infinity (poor model) to 1.0 (perfect model). The CoE has been widely used to evaluate the performance of prediction models [e.g., *Wilcox et al.*, 1990]. For more details regarding goodness of fit measures, see *Legates and McCabe* [1999] and *Willmott et al.* [1985]. The definitions of these performance statistics are summarized in Table 3 and the performance of the model for the period from 1985 to 2006, according to these measures, is shown in Table 4. The Great Egret and White Ibis posterior means predicted by the model have a correlation of  $\sim 0.8$  with the observed series, with a CoE 0.7 over cross validation. Analysis of residuals (observed–posterior mean) for the model for Great Egret and White Ibis supported the assumption of zero mean, independent, and identically normally distributed errors. The Jarque-Bera test for goodness of fit to a normal distribution [*Judge et al.*, 1988] and the Shapiro-Wilk parametric hypothesis test of composite normality [*Royston*, 1995] were performed, and the hypothesis that error has a normal distribution is not rejected at the 5% and 10% level.

[30] The model developed above is now applied for retrospective prediction of wading bird foraging numbers for the period 1952–1984 for which daily P33 stage data is available but bird data are not. The results are illustrated in Figure 9. Note the wide variation in the width of the posterior distribution indicating years in which the predicted bird counts may be more or less precise. The long-term trends for the P33 average water stage, disruption, and rainfall are indicated by Lowess [*Cleveland*, 1979] smooth lines superimposed on graphs of time series in Figure 10. The concurrent decadal to multidecadal variability in the relevant time series is shown. An interesting feature is the increase in the foraging bird population post-1995, even though the seasonally averaged rainfall and P33 stage do not show any marked trends. We note, however, that the disruption time series reveals a decreasing trend over the same time period, reinforcing the earlier assessment that both the stage and the disruption frequency are important indicators for foraging conditions. The trends in foraging

**Table 3.** Regression Model Performance Measures<sup>a</sup>

Statistics	Formula
Correlation coefficient	$r = \frac{\sum_{t=1}^N (O_t - \bar{O})(P_t - \bar{P}_t)}{\left(\sum_{t=1}^N [O_t - \bar{O}]^2\right)^{0.5} \left(\sum_{t=1}^N [P_t - \bar{P}]^2\right)^{0.5}}$
Coefficient of efficiency	$\text{CoE} = 1 - \frac{\sum_{t=1}^N (O_t - P_t)^2}{\sum_{t=1}^N (O_t - \bar{O})^2}$
Normalized bias	$\text{Bias} = N^{-1} \sum_{t=1}^N (O_t - P_t) / O$

<sup>a</sup> $N$  is the sample size,  $P$  is the model-simulated data, and  $O$  is the observed data.

**Table 4.** Model Performance for Wading Bird Foraging Predictions Using Traditional Criteria

Predictors	$R$	CoE	Normalized Bias
Great Egret	0.83	0.66	1.82%
White Ibis	0.83	0.67	–5.45%

numbers in the period before systematic observations are available are consistent with our expectations from the nonlinear model. The period from 1962 to 1970 is marked by relatively low water levels and higher disruption frequency, and translates into lower bird counts. On the other hand, the higher bird counts around 1960 and 1980 again correspond to average to higher water levels with a lower disruption frequency. These results rely on the assumption that the relationship between P33 and water levels in the other areas of the ENP where wading birds are known to forage remained relatively constant over the complete period of record. Some changes in water management regulation schedules and policies have occurred during this time period. However, the central location of P33 in Shark Slough gives confidence that it has consistently reflected the general hydrologic condition of the areas where wading birds tend to forage. Our goal in presenting these results is to set the stage for a comparative evaluation of different release policies from the control structures that translate into different AWS, IWS, and DIS values at P33 and therefore, different numbers of foraging bird populations.

## 5. Modeling Water Levels at P33

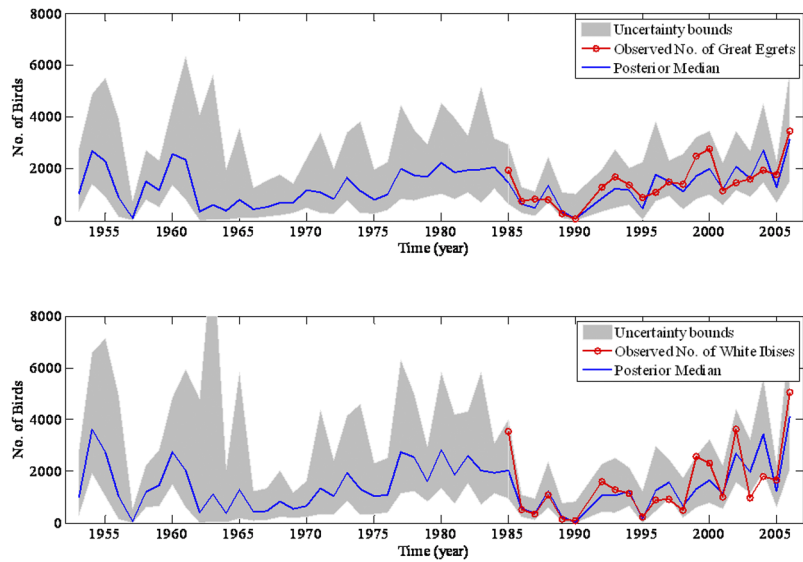
[31] A Bayesian approach is developed to relate observed water levels at P33 to a combination of hydrologic predictors representing the water budget parameters at the site. The model considers that over time period  $t$  the water level at P33,  $Z(t)$ , is normally distributed with a time-varying mean  $\mu(t)$  and a constant variance  $\sigma$ . The water level is measured with respect to a fixed land surface datum, and can be positive or negative relative to that datum. A model of the mean  $\mu(t)$  in terms of each predictor is then formulated as follows:

$$Z(t) \sim N(\mu[t], \sigma), \quad (7)$$

$$\begin{aligned} \mu(t) = & \beta_1 + \beta_2 \cdot P_{33}(t-1) + \beta_3 \cdot \delta_R(t)(t-1) + \beta_4 \cdot \delta_R(t)(t-1)^2 \\ & + \beta_5 \cdot \delta_I(t)(t-1) + \beta_6 \cdot \delta_I(t)(t-1)^2, \end{aligned} \quad (8)$$

$$\delta_R = \begin{cases} 0 & R \leq 0 \\ 1 & R > 0 \end{cases}, \quad \delta_I = \begin{cases} 0 & I \leq 0 \\ 1 & I > 0 \end{cases}, \quad (9)$$

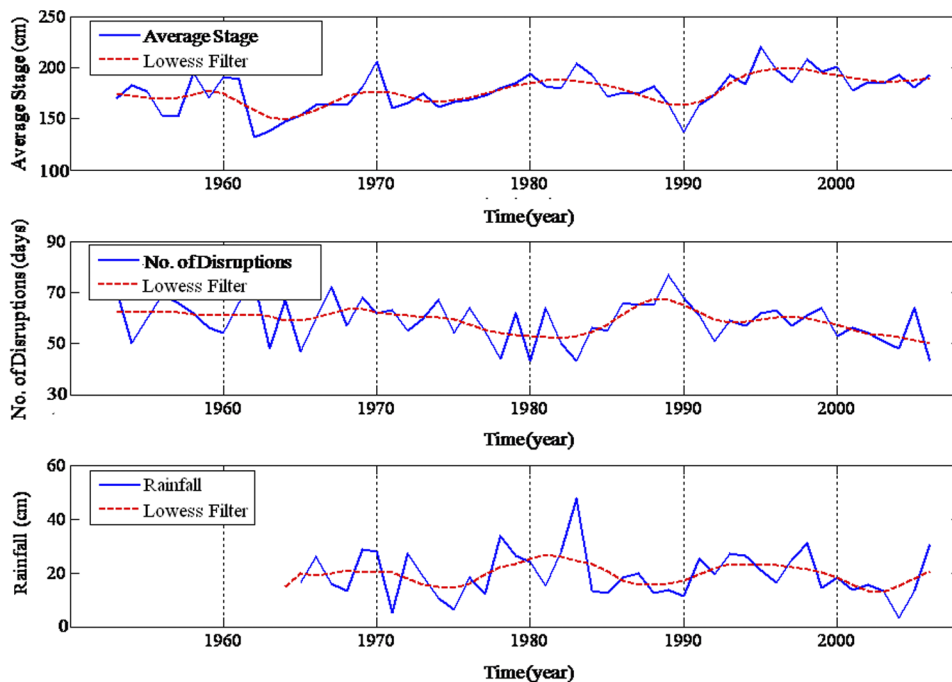
where  $P_{33}$  is daily average water stage,  $R$  is total daily rainfall, and  $I$  is the daily average rate of surface water inflow through upstream control structures into ENP. A delta function is employed to differentiate the zero and the nonzero case for  $R$  and  $I$ . The form of the equation in this case reflects the univariate relationships between the hydrologic parameters known to occur at this site; namely, that the mean water levels increase with  $I$  and  $R$ , and that the water stage is highly autocorrelated. The factors leading to



**Figure 9.** A retrospective analysis of wading bird foraging numbers. Model predictions (solid lines) and observed birds (open circles) at ENP in May, using hierarchical Bayesian regression (equation (2)) and AWS, IWS, and DIS derived from 1952 to 2006 water levels at P33. The late 1950s and early 1960s were marked by significant hydrologic manipulations in the regional water management system.

observed nonlinear relationships between rainfall, water levels, and structural discharges in the ENP are discussed by *He et al.* [2010]. Noninformative priors were selected and a three chain Gibbs sampling approach to MCMC [*Gilks et al.*, 1995] was employed to solve for the parameters in MATLAB using WinBUGS [*Spiegelhalter et al.*, 2003]. A [*Gelman and Rubin*, 1992] “shrink factor” criteria of 1 in the MCMC was used to establish the parameter

values (Table 5) and their variation within and between chains. The model coefficient of variation, the coefficient of efficiency, and the bias show very high fidelity with observed values during separate calibration (1978–1987) and verification (1988–2006) periods. The output of the model is a posterior probability density function for daily P33 stage, conditional on rainfall and releases. Thus, as part of a Monte Carlo simulation, given a proposed release



**Figure 10.** (top) The long-term trends for P33 annual average water stage, (middle) number of disruptions, and (bottom) rainfall are indicated by Lowess [*Cleveland*, 1979] smooth lines superimposed on graphs of time series. The concurrent decadal to multidecadal variability in the relevant time series is shown.

**Table 5.** Model Performance Measures, Parameters, and Associated Uncertainty Bounds for Daily Predictions of P33 Water Levels on the Basis of Hydrologic Parameters

Measure	Cal. 30%	Ver. 70%	Node	Description	Mean	SD	2.50%	Median	97.5%
$r$	0.981	0.989	$\beta_1$	Intercept	6.151	0.906	4.823	5.908	7.761
			$\beta_2$	P33 $_{t-1}$	0.913	0.012	0.892	0.916	0.931
CoE	0.963	0.978	$\beta_3$	Rainfall $_{t-1}$	0.440	0.078	0.289	0.440	0.596
			$\beta_4$	Rainfall $_{t-1}^2$	-0.017	0.013	-0.043	-0.017	-0.008
Bias (m)	-0.001	-0.057	$\beta_5$	Inflow $_{t-1}$	0.398	0.083	0.245	0.396	0.561
			$\beta_6$	Inflow $_{t-1}^2$	-0.007	0.033	-0.069	-0.007	0.058

strategy and a synthetic (from a prediction or stochastic model) or historical record of rainfall, one can sample from the posterior distribution of daily P33 stage to identify the seasonal predictors for the bird model. This approach was taken to investigate the role of managed structural releases in regulating bird populations in the ENP under varying levels of rainfall.

## 6. Impacts of Alternative Water Management Policies on Water Levels and Foraging Populations

[32] The impacts of water release policies was investigated by linking predictions of seasonal P33 water levels (and the corresponding AWS, IWS, and DIS) on the basis of different inflow scenarios to the Bayesian model of foraging bird populations. In this scheme, posterior distributions of P33 water levels were first calculated using equations (7) and (8) with calibrated parameter values, and with variable inflow volumes corresponding to different management scenarios for the period 1986–2000. The hydrologic predictors used in equation (2) were then derived from the P33 values expected under each scenario and used to generate probability distributions of the numbers of foraging birds for each year of the simulation. The results are presented as a time series of predicted mean values with the 2.5% and 97.5% confidence intervals for each posterior distribution. The following management scenarios are considered:

[33] 1. The “baseline” case represents P33 and foraging population predictions using measured rainfall and inflows discharging into ENP.

[34] 2. Three alternative inflow management scenarios were then tested and are ordered here on basis of the total amount of water delivered to ENP. Rainfall amounts do not vary across scenarios; they refer to observed values for the period. The first scenario, “no inflow,” assumes zero releases from the surface water control structures located across the northern boundary of the park. The second scenario, “rainfall plan” regulates inflows to ENP as a function of rainfall in the northern contributing basins according to a formula derived by the South Florida Water Management District [Neidrauer and Cooper, 1989; Light and Dineen, 1994]. The final scenario, the combined structural and operational plan (CSOP) scenario is a management scheme accompanying a large-scale restoration project designed to increase and alter the timing of ENP inflows.

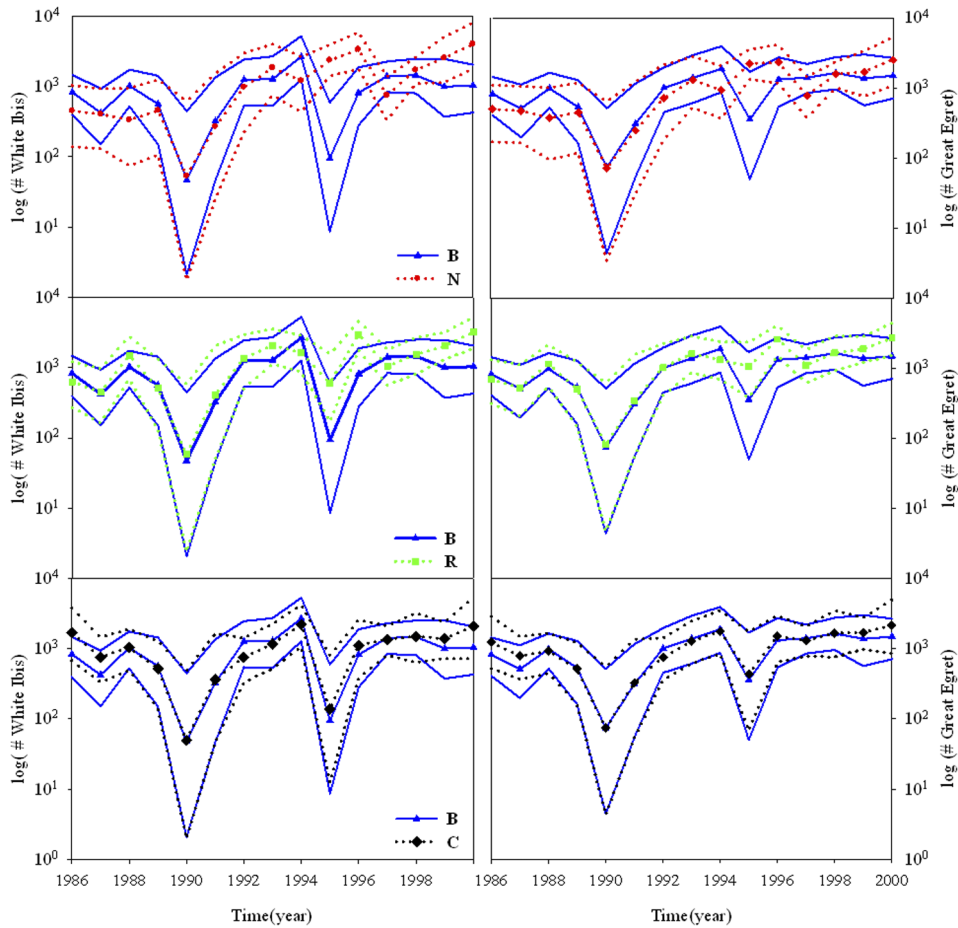
[35] Inflows into ENP under the CSOP scenario were derived from the South Florida water management model (SFWMM, available at [http://www.evergladesplan.org/pm/recover/system\\_wide\\_modeling.aspx](http://www.evergladesplan.org/pm/recover/system_wide_modeling.aspx)), a regional-scale hydrology model for south Florida. For January–April of each

year, the AWS, IWS, and DIS were calculated and used to generate probability density functions for wading bird populations generated in each scenario according to equation (2). The period 1986–1990 is characterized by low to below-average rainfall and relatively low numbers of foraging birds in all of the scenarios. The period from 1991 to 2000 is characterized by average to above-average rainfall, and relatively higher water levels and greater numbers of foraging birds.

[36] In the Bayesian framework, the posterior distributions of bird populations in these scenarios, which overlap, indicate no significant differences in the predictions. For most years in the scenario comparisons, only minor differences in the predicted probability distributions of bird counts were shown (Figure 11). The wide uncertainty intervals in these predictions arise primarily from the uncertainty in the relationship between the hydrologic parameters (AWS, IWS, and DIS) and bird populations. The uncertainty in water level predictions at P33 as a function of inflows and rainfall were small in comparison.

[37] The largest differences in scenario outcomes occurred during the very high rainfall years of 1995 and 1996. During these years, those plans that delivered the least amount of water to the ENP through the control structures (no inflow and rainfall plan) produced the largest numbers of both White Ibis and Great Egrets relative to the baseline values. The relatively low DIS values in these scenarios during 1995 contributed to the predictions of greater bird populations (Table 6). The no inflow scenario in 1995 was also characterized by AWS and IWS values that were closer to their annual mean (i.e., standardized values close to zero) compared to the other scenarios. As a result, the AWS and IWS cross product (a negative term in equation (2)) was also relatively closer to zero in this scenario, resulting in higher bird predictions. The overall differences in the numbers of foraging birds in the no inflow compared to the baseline scenarios can be interpreted as an estimate of the ecological impact of structural discharges on the quality of foraging habitat in the ENP over the 1986–2000 period. Since more birds are consistently predicted during wet years under the reduced inflow scenarios, this suggests high rainfall alone is capable of maintaining AWS and IWS within optimal ranges for wading birds during wet periods without the addition of managed structural releases.

[38] A negative correlation between water levels and DIS was observed in all of the scenarios. The reason behind this is twofold. First, water levels are positively related to rainfall amounts, and recession rates in this system generally increase with water levels. As recession rates increase, the duration over which any temporary rainfall-driven increase in water level deviates from a linear recession is



**Figure 11.** Posterior distributions of foraging Great Egret and White Ibis populations under baseline (B) conditions and three different management scenarios: no inflows (N), the rainfall plan (R), and the CSOP (C). Lines for each scenario represent the mean number of birds and the 2.5% and 97.5% uncertainty bounds of each posterior distribution calculated on AWS, IWS, and DIS for each year of the simulation.

**Table 6.** Summary of Predicted Hydrologic Variables and Great Egret and White Ibis Foraging Populations for a Year With Low (1988), High (1995), and Average Rainfall (2000) for the Current Management Scheme (Baseline), and Three Alternative Management Scenarios<sup>a</sup>

	AWS	IWS	DIS	White Ibis			Great Egret		
				2.5%	Avg.	97.5%	2.5%	Avg.	97.5%
<i>1988</i>									
Baseline	-0.57	-0.62	0.19	521	1020	1737	519	983	1645
No inflow	-1.20	-1.28	0.77	74	334	946	94	374	1005
Rainfall plan	-0.61	-0.69	-0.86	682	1483	2768	547	1159	2161
CSOP	-0.62	-0.79	-0.28	488	1023	1857	445	924	1643
<i>1995</i>									
Baseline	2.04	1.74	2.06	9	94	591	50	358	1702
No inflow	0.15	0.49	-0.28	1405	2362	3947	1332	2223	3553
Rainfall plan	1.45	1.22	0.19	172	598	1562	380	1063	2351
CSOP	2.06	1.75	1.13	13	137	793	68	434	1736
<i>2000</i>									
Baseline	1.03	1.26	0.19	426	1032	2051	849	1404	2195
No inflow	-0.27	-0.12	-2.04	1794	4030	8126	374	784	1434
Rainfall plan	0.50	0.69	-1.45	1863	3183	5178	618	1101	1831
CSOP	1.16	1.34	-1.92	715	2070	5220	782	1300	2043

<sup>a</sup>The management scenarios representing no inflows, the rainfall plan, and the combined structure and operations (CSOP) restoration plan.

reduced, and the calculated DIS values decline. Second, during wet years, the frequency of rain events is relatively higher and the impact of any one rain event on water levels (and on the recession rate) also decreases. The combination of these two factors leads to an overall negative relationship between rainfall amounts and DIS. Intermittent managed inflows also influence DIS values and raise average water levels.

[39] During years with low rainfall, those plans that delivered relatively more water to the ENP generally produced larger numbers of foraging birds. For example, in 1988, very few birds were predicted for the no inflow scenario due to very low AWS and IWS values. The DIS value for this scenario in 1988 was also relatively high, contributing to the low bird predictions. For years with very low rainfall amounts (e.g., 1990), no significant differences in predicted birds were shown among the scenarios. Inflow amounts in all of the scenarios were close to zero during this year.

[40] Relatively large differences in bird predictions were also observed during 2000, a year with near average January–April rainfall amounts. During this year, more birds were predicted in the no inflow, rainfall plan, and the CSOP scenarios compared to the baseline predictions due largely to the differences in DIS values. Again, the no inflow and rainfall plans produced the lowest DIS and the most birds. IWS values for the baseline and CSOP scenarios were above average in this year due primarily to the high rainfall amounts in the latter half of 1999. This condition also contributed to the high AWS exhibited in these scenarios in the 2000 January–April dry season. Hydrologic conditions in the months prior to the start of the dry season recession thus contribute to the performance of these scenarios.

[41] The results of the scenario analyses point to the potential impacts of managed inflows on foraging conditions in ENP. During low rainfall periods, managed releases are necessary to maintain favorable water levels. However, during high rainfall periods these releases may contribute to maintaining water levels above optimal values. Over the entire 1986–2000 period, the largest average numbers of foraging birds of both species were predicted under the no inflow and the rainfall plan scenarios. However, this is largely because the majority of the period is characterized by high rainfall conditions when the scenarios, which restrict inflows, performed relatively well. We suggest it is therefore important to consider the relative performance of these scenarios in a larger context determined by longer-term rainfall amounts and timing. Optimizing foraging conditions for wading bird species over longer time periods is likely to require adaptive release schedules which incorporate real-time information on water levels, rainfall, and climatic drivers [e.g., Kwon *et al.*, 2006]. Of the four analyzed here, the management scenario most closely tied to climatic conditions is the rainfall plan, and while it did not produce the highest numbers of Great Egret or White Ibis during either the low or high rainfall periods, this scenario did produce the highest median number of foraging birds when the species were combined over the full period of record (2450 birds  $\text{yr}^{-1}$ ). Similar climate-based approaches to managing inflows into ENP could further improve habitat quality for foraging birds. However, the

variability that is inherent in the observed numbers of birds in relation to hydrologic conditions and which is captured in the Bayesian model lowers the confidence in our conclusions regarding the relative performance of the scenarios during most years. The large overlap in posterior distributions in these scenarios also suggest that the variability in wading bird foraging populations is driven primarily by rainfall, and that these populations may be relatively insensitive to the water level fluctuations driven by structure releases. It is recommended that additional analyses be conducted using population data from other species to investigate the broader ecological outcomes of rainfall-driven management plans. Also, the analysis opens the possibility of developing specific optimization schemes for operation, conditional on pre-season hydrologic conditions and forecasted rainfall scenarios that can maximize the probability of achieving target bird populations. Such an approach would require the convolution of the uncertainty distribution of the forecast, which could be achieved with a daily stochastic weather generator conditioned on that season's anticipated conditions, and with the two steps of posterior distributions evaluated in the models described here.

## 7. Summary and Conclusions

[42] Water depths and their fluctuation in the dry season are known to have an impact on wading bird habitat suitability in ENP. The Bayesian approach presented here incorporates basic hydrologic parameters (AWS, IWS, and DIS) at P33 to estimate the seasonal foraging populations of wading birds. Since water depth patterns throughout ENP are highly correlated, measurements at a single, centrally located gauge can reasonably be used to infer the suitability of foraging conditions across large areas of the park. This finding is relevant for water resource managers concerned with optimizing hydrologic conditions for wildlife but for which real-time data over large areas are often unavailable. The results also suggest that with knowledge of water depths in Shark Slough at the beginning of the dry season and some predictive information on expected rainfall patterns, structural discharges may be regulated to improve the probability of specific ecological outcomes. For instance, information on the initial water level, together with probabilistic climate forecasts, and a proposed water release policy, could be used to estimate both the probability distributions of the average water level in the upcoming season, and the disruption frequency. Future work will focus on developing models that map observed and forecast daily rainfall, current stage, and water release from control structures into future stage at P33. Daily rainfall simulations are under development that represent low frequency variation using wavelet autoregressive models [Kwon *et al.*, 2007] which may then be used as part of an adaptive policy to guide intraseasonal releases such that hydrologic conditions evolve toward improved end-of-season outcomes. It is noted that this type of feedback generally has not been utilized over the past several decades and this has contributed to the large fluctuations observed in wading bird foraging populations. Wading bird populations remain low in ENP relative to estimates from historic (i.e., pre-drainage) periods and low relative to other areas in the greater Everglades ecosystem. Our analyses of alternative structural release

policies for ENP that have been applied in the past (the baseline scenario) or are proposed for the future (CSOP) indicate that dynamic water release schedules, which are linked explicitly and primarily to rainfall amounts over the long term, resulted in high average numbers of wading birds across the widest range of conditions. However, during years with low rainfall, the management schemes, which released relatively greater amounts of water into ENP, tended to result in better foraging conditions than the more conservative schemes. These plans performed relatively poorly during years with high rainfall and already high water levels, suggesting that water release schedules should also be conditioned on downstream water levels to maximize desired ecological outcomes.

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