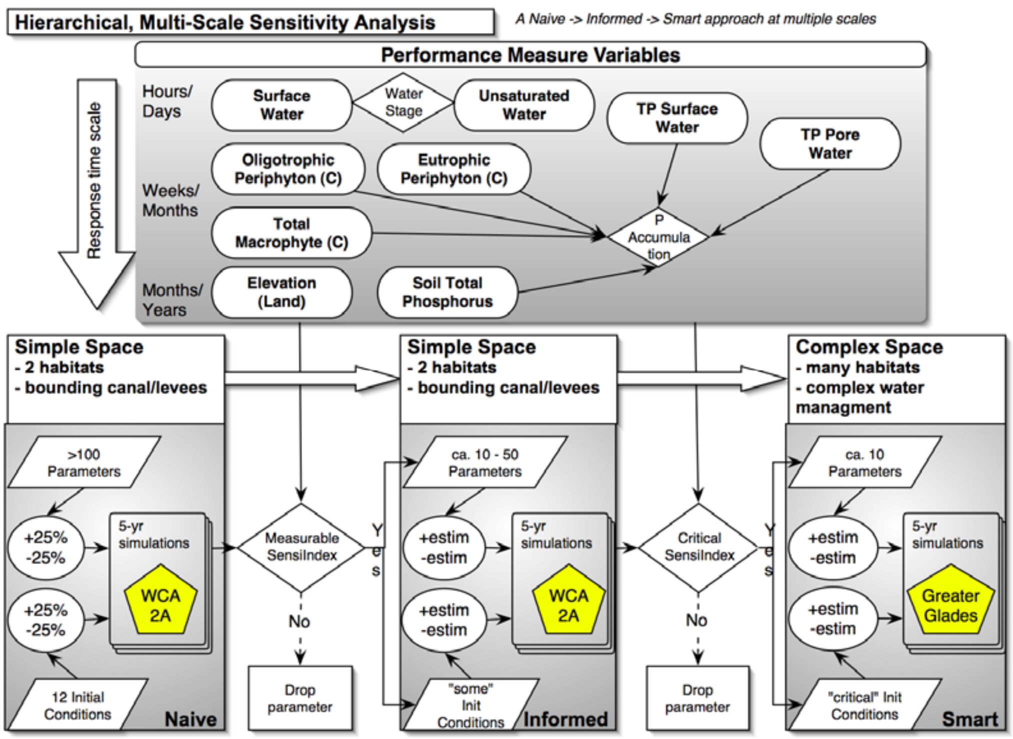
Documentation of the Everglades Landscape Model: ELM v2.5

Chapter 7: Uncertainty



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Chapter 7: Uncertainty

7.1 Overview

As we noted in the Introduction, Goals & Objectives Chapter, models are simple abstractions of reality, and may be used to guide our thinking. Towards this end, it is vital that modelers and model users acknowledge and understand the uncertainties inherent in any model. The topic of "Uncertainty" is broad, and a thorough treatment of it is well-beyond the scope of this documentation. Instead, we refer the reader to the report of the "Comprehensive Everglades Restoration Plan's Model Uncertainty Workshop" held in January 2002 (Lall et al. 2002).

In the Uncertainty Workshop technical report, Lall et al. (2002) specifically recommended that the Everglades Landscape Model (ELM) developers repeat the methods of prior sensitivity analyses on the current ELM version. In this chapter, we report on those results, and discuss their implications relative to model complexity.

Hydrology and water quality are primary drivers of the Everglades ecology, and are likewise an important component of the ELM ecological dynamics. Beyond the analysis of model sensitivity to parameter choices, we quantify the statistical expectations of the water quality performance metrics, which are highly dependent on the forces that drive the "boundaries" of the model. Another important concern in water quality modeling is that of "numerical dispersion", which is explicitly simulated in ELM (see Model Structure Chapter), and discussed here relative to model and data uncertainty.

Finally, we touch upon another common topic in modeling: what is validation, and can modelers truly validate the model output? The basic answer is "No". However, these model abstractions of reality have served useful purposes in better understanding system dynamics, and will continue to be important tools in aiding our decision-making process for uncertain topics such as understanding and restoring the Everglades.

7.2 Data uncertainty

Uncertainty in the data used to parameterize a model, to "drive" a model, and to compare to model output (i.e., calibrate), is a major source of uncertainty in simulation modeling. This topic of data uncertainty in modeling is a broad one, and the reader is referred to the recent synthesis of uncertainty in Everglades modeling (Lall et al. 2002). For this documentation Chapter, we present some important, specific considerations of the data uncertainty in water quality boundary conditions that drive much of the model dynamics.

7.2.1 Boundary inflows

As with any model, ELM simulations depend heavily on the forcing functions that drive the model. The major forcing functions are rainfall, potential evapotranspiration, inflows/outflows at water control structures, and other data described in the Data Chapter. Much of the effort in building a model application is the collection and synthesis of data to accurately represent these processes.

7.2.1.1 Nutrient sampling frequency

Water control structures that input water and constituents into the model domain were usually located along the model domain boundary (see Data Chapter). For water control structures at domain inflows, the intended historical sampling frequencies for water quality parameters ranged from one week to one month. However, at numerous of these locations, the time period between two consecutive samples often exceeded three months. Furthermore, at some stations (e.g., ACME1DS, with relatively minor inflow volumes) there were no observations of surface water TP concentration for the entire calibration period (1981-95). As described in the Data Chapter, missing values of flow and concentrations were filled in using several techniques, with linear interpolation between successive point samples. The use of linear interpolation between sampling events introduces additional error in prescribing model boundary conditions. This additional error propagates throughout the model domain and impacts any model's ability to replicate observed field conditions. Considering all available water quality sampling stations used in domain inflows, the mean TP sampling frequency for the period of record - *when data were available* - was 16 days.

7.2.1.2 Model performance expectations

The goodness of fit of these interpolated daily TP concentrations from the unknown true daily TP concentrations depends on how well the measured TP concentrations were linearly autocorrelated at each site. Ideally, we should use statistical validation to evaluate uncertainty introduced by the interpolation, by splitting the entire dataset into two subsets, and then calculate the uncertainty between measured and interpolated data from the first subset and measured data from the second data set. This was not an option because TP concentrations were infrequently sampled at numerous stations. However, we can still use autocorrelation and cross-validation to assess the relative uncertainty introduced by linear interpolation. For example, the autocorrelation assesses how much correlation is present between successive measurements (assuming equi-spaced intervals between sampling events). Given N measurements, Y_i at time X_i, the lag k autocorrelation function is defined as:

$$r_k = \frac{\sum_{i=1}^{N-k} (Y_i - \bar{Y})(Y_{i+k} - \bar{Y})}{\sum_{i=1}^{N-k} (Y_i - \bar{Y})^2}$$

This autocorrelation function is a correlation coefficient between two values (i.e., Y_i and Y_{i+k}) of the same variable at times X_i and X_{i+k}. The first autocorrelation coefficient (lag 1) equals 1.0 if the data are not random and totally autocorrelated. If the data set has no autocorrelation and is totally random, the resulting coefficient would equal zero. Interpolated daily TP concentrations from a non-autocorrelated (e.g., random) data set will not correlate with the unknown true TP concentrations on dates not sampled.

Cross-validation removes each data point, one at a time, and interpolates the associated total phosphorus value with the rest of the data points. The interpolated and the actual measured values (at the locations of each omitted data point) are then compared.

The calculated statistics from autocorrelation and cross-validation are presented in Table 7.2.1 for all stations that have inflows into the model domain; i.e., those that are important drivers of surface water quality. These statistics can be used as diagnostics to indicate the relative degree of uncertainty in model input data for total phosphorus loadings, and to help set appropriate expectations for model predictions using available input data. For TP concentrations used in ELM for domain inflow loads, the autocorrelation coefficients ranged from 0.04 to 0.56, with a mean of 0.32. The correlation coefficients from cross-validation are even lower, ranging from 0.001 to 0.45, with a mean of 0.20. Therefore, for any model that uses these input data, it is reasonable to expect that the goodness of fit between observed TP concentrations and model-predicted daily values would not likely exceed the statistics calculated from autocorrelation and cross-validation of input data: the expectation of any model should not exceed a mean $R^2 = 0.20$ and maximum $R^2 \leq 0.45$.

While the cross-validation analysis indicates that the interpolated daily TP concentrations (using the best, state-approved method available) may not well-resemble the dynamic of the true unknown TP concentrations, but the biases estimated from cross-validation are all within the range of 1 ppb (ug L^{-1}). This suggests that the interpolated daily TP concentrations can be used in developing unbiased estimates of the true (unknown) long term mean TP concentrations. Thus, for models that simulate TP dynamics from interpolated daily TP concentrations, calibration of simulated TP concentrations should seek to compare the aggregated mean of TP concentrations over a prolonged period, rather than point to point comparisons based on instantaneous observations of water column concentrations. Given these temporal constraints imposed by the input forcing data, measures of temporally-aggregated statistical bias and root mean square error of model predictions can be used to demonstrate the degree to which the model captures the long term eutrophication in locations distributed across space.

7.2.2 Tables: data uncertainty

Table 7.2.1. Results of autocorrelation and cross-validation of input data for TP concentrations at water control structures that have inflows into the model domain. The text explains the methods used in the analyses; Bias and RMSE are in units of ug/L (ppb) of TP concentration.

Station	Sample Date		Number of Days Sampled	Mean Sample Frequency (Day)	Cross Validation				Autocorrelation function (lag 1)
	Start	End			**Bias**	**R^2**	**RMSE**	**EFF**	
ACME1DS	2/5/1997	12/18/2000	48	29	0.7	0.04	59	0.20	0.18
ENR012	12/16/1993	12/28/2000	393	7	0.1	0.09	34	0.29	0.22
G200	7/26/1989	12/27/2000	285	15	-0.7	0.26	42	0.49	0.31
G310	6/1/2000	12/28/2000	30	7	0.3	0.45	14	0.66	0.52
G94D	2/5/1997	12/18/2000	54	26	0.3	0.001	67	-0.03	0.04
L28I	1/3/1979	10/16/2000	277	29	1.0	0.29	51	0.54	0.40
L3BRS	10/30/1984	12/27/2000	217	27	0.2	0.45	65	0.66	0.56
S140	1/3/1979	12/28/2000	431	19	0.4	0.36	57	0.59	0.46
S150	1/2/1979	12/26/2000	359	22	0.9	0.04	57	0.21	0.18
S175	5/2/1995	12/20/2000	150	14	0.0	0.10	3	0.31	0.26
S18C	10/5/1983	12/20/2000	368	17	0.0	0.02	7	0.13	0.10
S332	10/5/1983	12/20/2000	454	14	0.1	0.27	6	0.51	0.44
S332D	6/16/1999	12/28/2000	94	6	0.0	0.21	4	0.44	0.37
S5A	1/2/1979	12/28/2000	682	12	1.3	0.27	76	0.51	0.41
S6	1/2/1979	12/28/2000	729	11	-0.4	0.22	73	0.45	0.34
S7	1/2/1979	12/26/2000	674	12	1.3	0.14	66	0.37	0.30
S8	1/2/1979	12/27/2000	782	10	1.3	0.33	81	0.57	0.48
S9	1/3/1979	12/26/2000	518	15	0.0	0.07	15	0.25	0.18
Mean			364	16	**0.4**	**0.20**	**43**	**0.40**	0.32
Min			30	6	**-0.7**	**0.001**	**3**	**-0.03**	0.04
Max			782	29	**1.3**	**0.45**	**81**	**0.66**	0.56
STD DEV			243	8	0.6	0.14	28	0.19	0.15

7.3 Model sensitivity analyses

7.3.1 Sensitivity analysis overview

Simulation models are potentially powerful tools for ecological research and management, but their inherent uncertainties need to be properly evaluated for effective model utility. A wide number of efforts using procedures of varying rigor have been undertaken to evaluate model performance for different objectives. For process based models which employ numerous parameters in their equations, the accuracy of the parameter estimates can be a critical component of the model development. Parameter estimation is a significant concern in determining the degree of certainty of the model output for use in understanding the system dynamics and making any useful predictions or forecasting.

The ELM was developed in a hierarchical fashion, with a unit model at the ecosystem level that is coupled to spatial model drivers to flux water and constituents through canal vectors and raster cells in a landscape whose pattern may vary over time. The unit model is replicated in each grid cell of the landscape and incorporates the fundamental hydrologic and ecological processes that dictate much of the model behavior. With numerous parameters that are input to the model, the user needs to understand the relative influence of parameter variations on the model results. The parameters range from rate coefficients to nutrient stoichiometric ratios and initial conditions (see Data Chapter). Some parameters are known with relatively high accuracy, while others are less understood and are the subject of ongoing research. To understand how parameter uncertainties may affect the ELM dynamics and its interpretation, we performed the first of a suite of sensitivity analyses on the updated version of ELM.

While the ELM has very fast run times[1] for a model of its spatial and computational complexity, there is nevertheless a need to simplify the problem in order to undertake the hundreds of runs that are required to fully evaluate the model sensitivity. The approach is an extension of our sensitivity analyses (Fitz et al. 1995) on an early development version of ELM. Indeed, repeating our prior methods on the current version of ELM was a specific recommendation by Lall et al. (2002), who detailed the technical considerations of uncertainty in Everglades modeling for the Comprehensive Everglades Restoration Plan (CERP). We continue to approach the task of evaluating the model sensitivity and communicating those results in a stepwise, hierarchical fashion in keeping with the model structure (described in the Model Structure Chapter).

The conceptual model that underlies our method is shown in Figure 7.3.1. We consider several phases to fully evaluate model sensitivity to the parameters (including those that modify initial conditions): “Naive”, “Informed”, and “Smart”.

Naive: In the “Naive” phase, we evaluate parameter perturbations to an implementation of the model that is as simple as possible/desirable, assuming no *a priori* knowledge of

[1] The regional ELM application (10,364 1km2 grid cells) takes slightly more than 3 minutes of real-time per year of simulation time (on a 2.66 GHz Intel-based laptop).

the model or data. Each of the (entire set of) input parameters is adjusted by the same fixed percentage (one at a time), and the relative response of the Performance Measures are evaluated. Any parameter that has an observable effect on the Performance Measures is identified as a potentially important parameter.

Informed: Subsequently, the "Informed" phase is more knowledge-based, wherein *a priori* knowledge of parameter values is considered. For this phase, the subset of potentially important parameters that were identified in the Naive phase are more fully evaluated. Instead of using arbitrary values, we make sensitivity runs using realistic ranges of parameter values, in order to more accurately quantify the relative uncertainty of model outcomes based upon available data. This "Informed" phase is conducted on the same, simple model implementation that was used previously. As a result of the Informed phase, we identify the set of parameters that have significant (ecologically-meaningful) effects on the Performance Measure outputs; these parameters are (likely to be) a subset of those identified in the first "Naive" phase.

Smart: Finally, the "Smart" phase uses the ecologically significant parameters identified in the Informed phase, but extends the evaluation into the full complexity of the regional model implementation, with the regional-Everglades water management infrastructure and heterogeneity of habitats. Results of this phase may be used to better characterize the relative uncertainty of Performance Measures in model applications.

The primary considerations are 1) the *response time scales* of the model output Performance Measures, 2) the *spatial complexity* of the simulation, and 3) the *a priori knowledge of the parameter sensitivity*. We initiated the analyses using a relatively simple spatial implementation of ELM, and assume that we know nothing of the relative importance of any parameter. The objective of the sensitivity analysis is to develop an advanced understanding of the model parameters that are most influential on the model Performance Measure(s) output of interest. We seek to determine which parameters are most "important", on which we should focus our efforts in data acquisition and synthesis. Alternatively, evaluation of the sensitivity results may indicate the need to better refine future model algorithms. Regardless of the outcome for developers, the users of the model Performance Measures should be able to better understand and interpret results if we successfully summarize and communicate the results of the sensitivity analyses.

7.3.1.1 Response time scales

The most fundamental component of a sensitivity analysis is that of the objective function: what is the output that is of interest, and how is its response to perturbation (parameter change) measured? The goals of ELM (Introduction and Objectives Chapter) involve the understanding and assessment of the principal ecological dynamics that collectively determine the landscape or habitat characteristics. Ecosystems, and their depiction in ELM, encompass a rather wide range of time scales of response (Figure 7.3.1). Most hydrologic and surface water Performance Measures respond at scales on the order of hours to days. The biological responses of periphyton and macrophyte communities generally exhibit dynamic change at scales ranging from weeks to months. Integrators of these Performances Measures are the soil dynamic responses (and habitat succession), whose dynamic changes are generally considered over multiple seasons or years. An evaluation of the response of these Performance Measures to model perturbations necessarily needs to consider not only the magnitude of the change, but also its relationship to the variability within the appropriate response time scale.

For the current set of sensitivity analyses, we focused on the shorter time scales of hydrology and of water quality in surface and soil pore waters, which relate to the Performance Measures we support for ELM v2.5. At different locations along hydro-ecological gradients, the inherent variability of both of these hydrologic and water quality Performance Measures is large at relatively short time scales. Very small changes in water depths and phosphorus concentrations are of interest in this analysis, while these dynamic attributes can easily span an order of magnitude of change at the spatial and temporal scales under consideration.

7.3.1.2 Spatial complexity

In our early sensitivity analyses (Fitz et al. 1995), we were able to isolate the "unit" model from its spatial framework for the first step in sensitivity analyses. Because of subsequent changes to the model, we no longer can easily implement a non-spatial implementation of ELM that is identical to the algorithms and input forcing data within the spatial implementation. However, the ELM is easily "scalable", and thus we implemented a small subregional spatial version of ELM, with a total of only 449 active grid cells (vs. more than 10,000 in the regional implementation). This subregional implementation encompassed the hydrologic basin of Water Conservation Area 2A (WCA-2A) at a 1 km^2 grid scale. This basin contains no internal canals or levees other than those along its boundaries. Moreover, this implementation considered only the two habitat types of sawgrass and cattail, without the myriad of other habitats found in other portions of the greater Everglades (Figure 7.3.1).

An important characteristic of Water Conservation Area 2A is the extreme eutrophication (and lesser hydrologic) gradient that extends along a ~10 km transect downstream of major water control structure (point) inflows in the northeast quadrant. In order to evaluate the model sensitivity along this gradient, we considered seven Indicator Regions spanning its length. Within each Indicator Region, the Performance Measure outputs characterize the ecological (including hydrologic and water quality) responses to changing conditions – such as those associated with parameter perturbations. The aggregated whole-system (i.e., basin) response is part of this spatially explicit evaluation.

For the current set of sensitivity analyses, we did not consider the regional ELM. The latter implementation is the final component of the full sensitivity analysis suite, wherein we will consider the model sensitivity to the complex water management network and broader habitat mosaic (Figure 7.3.1).

7.3.1.3 A priori knowledge of parameters

Our approach was to initially assume that all parameters are important, i.e., that we have no *a priori* knowledge of the relative importance or sensitivity of any of the parameters. In this "Naive" phase of the analysis (Figure 7.3.1), we considered all parameters that are input to (and used by) the model from the parameter databases (see the Data Chapter for parameter descriptions). In each sensitivity simulation, a single parameter was modified by a fixed percentage from its nominal value (i.e., that used in current calibration). All other parameters were held at their nominal values. An index of sensitivity of the targeted Performance Measure was evaluated to determine if the parameter has any potential, large or small, to effect the model outcome at different spatial locations. The goal of the Naive phase was to “weed out” the parameters that have virtually no effect on the Performance Measure(s). This is an important component of the sensitivity analysis, as the foundation of the ELM is a generalized model of ecosystem dynamics, the General Ecosystem Model (Fitz et al. 1996). Partly due to this generality, there are parameters that may not have an effect on the Everglades landscape implementation. Moreover, some parameters may be somewhat important to macrophyte growth or habitat succession, but not affect hydrology or surface water quality to a measurable extent.

The Naive phase of the analysis serves to identify the subset of the total parameter set that has some non-trivial effect on dynamics of the targeted Performance Measures. This phase has the potential to be highly informative to both users who want to become familiar with the model, and to developers who need some further guidance in which “coarse” adjustments of parameters may be useful in refining model performance. Because it significantly reduces the number of parameters under consideration, this component of the sensitivity analysis can be valuable for that purpose alone. Moreover, the results from the Naive parameter-value perturbations can be used to ascertain the relative contributions of each parameter to model uncertainty, albeit potentially limited due to the naive choice of parameter changes (irrespective of the range that they may be known to take from field observations/experiments).

In further phases, that were not completed for these sensitivity analyses, we use more realistic ranges of parameter values, as opposed to arbitrary increments. Results from these phases provide more informed recommendations on the priorities for further data acquisition and synthesis, while also providing more quantitative evidence of the relative uncertainties associated with parameterization of the model.

7.3.2 Model configuration

The model was configured to simulate historical conditions inclusive of the years 1981 – 1985. The domain was that of the subregional ELM application in Water Conservation Area 2A, employing a 1 km^2 grid mesh encompassing all of that Water Conservation Area. The Indicator Regions used in model post-processing are shown in Figure 7.3.2. The vector topology of the canal/levee network and the point locations of water control structures were constant during the simulation period. Habitat succession was “turned off”, while still having dynamic feedbacks associated with macrophyte growth/mortality within a constant habitat type. Dynamic boundary conditions included data on rainfall, potential evapotranspiration, managed water control structure flows with associated constituent concentrations, and stage (along the borders of the domain).

Full descriptions of the requisite data and the functionality of the source code is provided in Data and the Model Structure Chapters, respectively. The Data Chapter includes the full documentation of the parameters, including definitions and units. The User’s Guide Chapter describes the simple steps to invoke the automated suite of model sensitivity runs, with each run acquiring the appropriate (low, nominal, or high) value of the parameter from one of the three parameter files generated by both the HabParms and GlobalParms databases. In the case of the database containing habitat-specific parameters (that may have unique values for each habitat), the parameter change was maintained at

25% for each parameter in each habitat, with two habitats (sawgrass habitat #2 and cattail habitat #11) simulated in this implementation. Each simulation was run for the 5-year period, and summarized for analysis by the mean daily value of each Performance Measure during entire simulation period. For one invocation of a suite (e.g., hundreds) of sensitivity runs, a single output file summarizes all of the Performance Measures for all of the runs.

7.3.3 Results

7.3.3.1 Hydrology

Table 7.3.1 lists all of the parameters that were evaluated, indicating whether a non-trivial (≥ 1%) hydrologic Performance Measure response was obtained for the ±25% parameter change. Depending on the Indicator Region's location along the gradient, changes to approximately 10 to 20 parameters[2] showed at least a 1% change to the 5-year mean surface water depth Performance Measure, relative to the NOMINAL parameter set (Table 7.3.1). Figure 7.3.3 shows the magnitude of the Performance Measure response for the twenty most-sensitive parameters, indicating that a many of these "top-20" consistently had relatively low effects across the spatial gradient.

7.3.3.2 Surface water nutrients

Table 7.3.2 lists all of the parameters that were evaluated, indicating whether a non-trivial (≥ 1%) surface water quality Performance Measure response was obtained for the ±25% parameter change. Depending on the Indicator Region's location along the gradient, changes to approximately 10 to 25 parameters[3] showed at least a 1% change to the 5-year mean surface water phosphorus concentration Performance Measure, relative to the NOMINAL parameter set (Table 7.3.2). Figure 7.3.4 shows the magnitude of the Performance Measure response for the twenty most-sensitive parameters, indicating that a many of these "top-20" consistently had relatively low effects across the spatial gradient. Note that the lowest value output by the model is 0.001 mg TP•L^{-1} (1 ppb), which is well under the detection limit of field sampling.

7.3.3.3 Soil nutrients

Table 7.3.3 lists all of the parameters that were evaluated, indicating whether a non-trivial (≥ 1%) soil pore water quality Performance Measure response was obtained for the ±25% parameter change. Depending on the Indicator Region's location along the gradient, changes to approximately 30 to 60 parameters[4] showed at least a 1% change to the 5-year mean soil pore water phosphorus concentration Performance Measure, relative to the NOMINAL parameter set (Table 7.3.3). Figure 7.3.5 shows the magnitude of the Performance Measure response for the twenty most-sensitive parameters, indicating that even though a relatively large number of parameter changes produced a non-negligible

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[2] Note that the total count summary shown on the final row of each Table usually includes Performance Measure threshold responses to both high and low values of a particular parameter.

[3] Note that the total count summary shown on the final row of each Table usually includes Performance Measure threshold responses to both high and low values of a particular parameter.

[4] Note that the total count summary shown on the final row of each Table usually includes Performance Measure threshold responses to both high and low values of a particular parameter.

response, perhaps only the "top-10" of this group had potentially significant effects across the spatial gradient.

7.3.4 Discussion

In this "Naive" phase of a three-part analysis, the sensitivity of the hydrologic and water quality Performance Measures varied spatially, and some parameters had relatively specific effects on specific Performance Measures, as expected. The parameter requirements increased, along with the sensitivity of the model to those parameters, as we considered physical hydrology, then surface water quality, and finally soil pore water quality. Each of these ecological dynamics are critical to understanding the system, and they respectively increase in process complexity due to their increased integration of more complete ecosystem properties.

Of particular interest in this analysis is the prioritization of data needs: from this initial perspective, which parameters were most "important", and thus should be focused on in better parameterizing the model? Table 7.3.4 summarizes the answer at this point. The results in the table include the parameters which appeared in the "top 20" of any Performance Measure, and show which of the parameters had effects across more than one Performance Measure. While the associated "State of our knowledge" of the data behind each parameter varies in quality, all are supported by existing studies or supportable by aggregations of our understanding of Everglades ecosystem dynamics. This is not meant to imply that the data are constrained to anything close to an "ideal" state of knowledge. It does represent a useful perspective of our current understanding, and where we should put our resources to "do better".

For the next phase of the full sensitivity analysis, we will further evaluate the model-influence of the subset of parameters that were identified here as potentially (or certainly) important. In this next "Informed" Phase, we will assign parameter values within a realistic range that is supported by observations, scaled/aggregated as best as possible using either quantitative methods or science-based inference if necessary. In advancing in this straightforward process, we will better constrain the input data to match our true knowledge of the system, and use the results to communicate a better understanding of the model performance.

The ELM has a "large" number of parameters due to its objectives of simulating integrated ecosystem dynamics across a spatially distributed, heterogeneous landscape. Furthermore, an early and fundamental objective of the modeling project was that of generality: a) the ecological dynamics were designed to be applicable across ecosystems in other regions, and b) code and parameters were generated to allow flexibility in implementation and analysis. These latter attributes of the ELM modeling system increase the "apparent" parameter complexity: a naive, simple count of the number of parameters contained in databases is not reflective of the number that are used in critical algorithm calculations, and thus represent critical data needs. As indicated in the results of this Naive phase of the ELM sensitivity analysis, the actual complexity induced by parameterization (i.e., data) needs is reasonable, and reflective of the basic properties of the integrated ecosystems - meaning that it is generally supported by available data and ongoing research. An important part of our future work is continued synthesis of research data, including the collaboration in design of field and lab experiments to help better understand these basic ecosystem properties within the Everglades landscape.

7.3.5 Tables: sensitivity analyses

Four tables follow on the next 7 pages.

Table 7.3.1. Hydrology. Naive case: +/-25% change in parameter. Compared to the 5-yr mean of the NOMINAL run output, if a simulation with a changed parameter resulted in at least a 1% change in the surface water depth Performance Measure in an Indicator Region (IR), the (ParmChangeRun - NominalRun) difference (meters) is shown for that simulation & IR. Parameters are grouped by ecological module (as found in databases).

	SfWat_9	SfWat_8	SfWat_7	SfWat_6	SfWat_5	SfWat_4	SfWat_3	SfWat_2	SfWat_0
NOMINAL	0.22	0.217	0.19	0.196	0.191	0.199	0.207	0.191	0.191
GP_SOLOMEGA_LO									
GP_SOLOMEGA_HI									
GP_ALTIT_LO									
GP_ALTIT_HI									
GP_LATDEG_LO									
GP_LATDEG_HI									
GP_mannDepthPow_LO	-0.003	-0.005	-0.009	-0.013	-0.016	-0.018	-0.023	-0.003	-0.003
GP_mannDepthPow_HI	0.007	0.009	0.015	0.019	0.021	0.021	0.026	0.007	0.007
GP_mannHeadPow_LO			-0.004	-0.007	-0.010	-0.012	-0.016	-0.002	-0.002
GP_mannHeadPow_HI	0.004	0.005	0.009	0.013	0.015	0.016	0.019	0.004	0.004
GP_calibGWat_LO	0.021	0.020	0.016	0.013	0.011	0.010	0.006	0.016	0.016
GP_calibGWat_HI	-0.014	-0.013	-0.010	-0.008	-0.007	-0.007	-0.003	-0.010	-0.010
GP_IDW_pow_LO									
GP_IDW_pow_HI									
GP_calibET_LO	0.223	0.216	0.193	0.177	0.162	0.151	0.119	0.192	0.192
GP_calibET_HI	-0.077	-0.071	-0.055	-0.048	-0.043	-0.042	-0.034	-0.065	-0.065
GP_HYD_IC_SFWAT_ADD_LO									
GP_HYD_IC_SFWAT_ADD_HI									
GP_HYD_IC_UNSAT_ADD_LO									
GP_HYD_IC_UNSAT_ADD_HI									
GP_HYD_ICUNSATMOIST_LO									
GP_HYD_ICUNSATMOIST_HI									
GP_DetentZ_LO									
GP_DetentZ_HI									
GP_MinCheck_LO									
GP_MinCheck_HI									
GP_dispLenRef_LO									
GP_dispLenRef_HI									
GP_dispParm_LO									
GP_dispParm_HI									
GP_SLRise_LO									
GP_SLRise_HI									
GP_ALG_IC_MULT_LO									
GP_ALG_IC_MULT_HI									
GP_alg_uptake_coef_LO									
GP_alg_uptake_coef_HI									
GP_ALG_SHADE_FACTOR_LO									
GP_ALG_SHADE_FACTOR_HI									
GP_algMortDepth_LO									
GP_algMortDepth_HI									
GP_ALG_RC_MORT_DRY_LO									
GP_ALG_RC_MORT_DRY_HI									
GP_ALG_RC_MORT_LO						0.002			
GP_ALG_RC_MORT_HI						-0.002			
GP_ALG_RC_PROD_LO									
GP_ALG_RC_PROD_HI									
GP_ALG_RC_RESP_LO									
GP_ALG_RC_RESP_HI									
GP_alg_R_accel_LO						0.003			
GP_alg_R_accel_HI						-0.003			
GP_AlgComp_LO									
GP_AlgComp_HI									
GP_ALG_REF_MULT_LO									
GP_ALG_REF_MULT_HI									
GP_NC_ALG_KS_P_LO									
GP_NC_ALG_KS_P_HI									
GP_alg_alkP_min_LO									
GP_alg_alkP_min_HI									
GP_C_ALG_KS_P_LO									
GP_C_ALG_KS_P_HI									
GP_ALG_TEMP_OPT_LO									
GP_ALG_TEMP_OPT_HI						0.002	0.003		
GP_C_ALG_threshTP_LO					-0.003	-0.005	-0.003		
GP_C_ALG_threshTP_HI						0.004			
GP_ALG_C_TO_OM_LO						-0.004	-0.003		
GP_ALG_C_TO_OM_HI						0.002			
GP_alg_light_ext_coef_LO									
GP_alg_light_ext_coef_HI									
GP_ALG_LIGHT_SAT_LO									
GP_ALG_LIGHT_SAT_HI									
GP_ALG_PC_LO									
GP_ALG_PC_HI									
GP_DOM_RCDECOMP_LO									
GP_DOM_RCDECOMP_HI									
GP_DOM_DECOMPRED_LO									
GP_DOM_DECOMPRED_HI									
GP_calibDecomp_LO									
GP_calibDecomp_HI									
GP_DOM_decomp_coef_LO						0.004	0.007		
GP_DOM_decomp_coef_HI									
GP_DOM_DECOMP_POPT_LO						0.002	0.005		
GP_DOM_DECOMP_POPT_HI									
GP_sorbToTP_LO									
GP_sorbToTP_HI									
GP_IC_BATHY_MULT_LO									
GP_IC_BATHY_MULT_HI									
GP_IC_TPtoSOIL_MULT_LO									
GP_IC_TPtoSOIL_MULT_HI									
GP_IC_DOM_BD_MULT_LO					-0.002	-0.005	-0.003		
GP_IC_DOM_BD_MULT_HI						0.002			
GP_IC_BulkD_MULT_LO									
GP_IC_BulkD_MULT_HI									
GP_IC_ELEV_MULT_LO	0.011	0.015	0.020	0.018	0.018	0.014	0.014	0.007	0.007
GP_IC_ELEV_MULT_HI	-0.014	-0.018	-0.020	-0.017	-0.017	-0.014	-0.012	-0.007	-0.007
GP_MAC_IC_MULT_LO	0.004	0.004	0.003	0.003	0.002			0.004	0.004
GP_MAC_IC_MULT_HI	-0.004	-0.003	-0.002					-0.003	-0.003
GP_MAC_REFUG_MULT_LO									
GP_MAC_REFUG_MULT_HI									
GP_mac_uptake_coef_LO							0.003		
GP_mac_uptake_coef_HI								0.002	0.002
GP_mann_height_coef_LO			-0.003	-0.004	-0.005	-0.006	-0.008		
GP_mann_height_coef_HI		0.003	0.005	0.006	0.006	0.007	0.007		
GP_Floc_BD_LO									
GP_Floc_BD_HI									
GP_FlocMax_LO									
GP_FlocMax_HI									
GP_TP_P_OM_LO									
GP_TP_P_OM_HI									
GP_Floc_rcSoil_LO									

GP_Floc_rcSoil_HI									
GP_TP_DIFFCOEF_LO									
GP_TP_DIFFCOEF_HI									
GP_TP_K_INTER_LO									
GP_TP_K_INTER_HI									
GP_TP_K_SLOPE_LO									
GP_TP_K_SLOPE_HI									
GP_WQMthresh_LO									
GP_WQMthresh_HI									
GP_PO4toTP_LO						0.003			
GP_PO4toTP_HI					-0.002				
GP_TP_IN_RAIN_LO									
GP_TP_IN_RAIN_HI									
GP_PO4toTPint_LO									
GP_PO4toTPint_HI									
GP_TP_ICSFWAT_LO									
GP_TP_ICSFWAT_HI									
GP_TP_ICSEDWAT_LO									
GP_TP_ICSEDWAT_HI									
GP_TPpart_thresh_LO									
GP_TPpart_thresh_HI									
GP_TP_DIFFDEPTH_LO									
GP_TP_DIFFDEPTH_HI									
GP_settlVel_LO									
GP_settlVel_HI									
HP_ALG_MAX_LO						0.002			
HP_ALG_MAX_HI						-0.002			
HP_DOM_MAXDEPTH_LO									
HP_DOM_MAXDEPTH_HI									
HP_DOM_AEROBTHIN_LO									
HP_DOM_AEROBTHIN_HI									
HP_TP_CONC_GRAD_LO									
HP_TP_CONC_GRAD_HI									
HP_SALT_ICSEDWAT_LO									
HP_SALT_ICSEDWAT_HI									
HP_SALT_ICSFWAT_LO									
HP_SALT_ICSFWAT_HI									
HP_PHBIO_MAX_LO									
HP_PHBIO_MAX_HI									
HP_NPHBIO_MAX_LO									
HP_NPHBIO_MAX_HI									
HP_MAC_MAXHT_LO			-0.003	-0.004	-0.005	-0.006	-0.008		
HP_MAC_MAXHT_HI		0.003	0.005	0.006	0.006	0.007	0.007		
HP_NPHBIO_ROOTDEPTH_LO	0.003	0.004	0.003	0.003	0.002	0.002		0.003	0.003
HP_NPHBIO_ROOTDEPTH_HI	-0.004	-0.004	-0.003	-0.002	-0.003	-0.003		-0.003	-0.003
HP_MAC_MAXROUGH_LO				-0.002	-0.003	-0.004	-0.005		
HP_MAC_MAXROUGH_HI				0.002	0.002	0.003	0.004		
HP_MAC_MINROUGH_LO	-0.005	-0.004	-0.004	-0.005	-0.005	-0.005	-0.004	-0.002	-0.002
HP_MAC_MINROUGH_HI	0.004	0.004	0.005	0.006	0.005	0.005	0.005	0.002	0.002
HP_MAC_MAXLAI_LO	0.006	0.006	0.006	0.005	0.004	0.004	0.003	0.006	0.006
HP_MAC_MAXLAI_HI	-0.006	-0.005	-0.004	-0.004	-0.004	-0.003		-0.005	-0.005
HP_MAC_MAXCANOPCOND_LO									
HP_MAC_MAXCANOPCOND_HI									
HP_MAC_CANOPDECOUP_LO									
HP_MAC_CANOPDECOUP_HI									
HP_MAC_TEMPOPT_LO									
HP_MAC_TEMPOPT_HI									
HP_MAC_LIGHTSAT_LO									
HP_MAC_LIGHTSAT_HI									
HP_MAC_KSP_LO									
HP_MAC_KSP_HI									
HP_PHBIO_RCNPP_LO									
HP_PHBIO_RCNPP_HI									
HP_PHBIO_RCMORT_LO						0.002	0.003		
HP_PHBIO_RCMORT_HI						-0.002			
HP_MAC_WAT_TOLER_LO									
HP_MAC_WAT_TOLER_HI									
HP_MAC_SALIN_THRESH_LO									
HP_MAC_SALIN_THRESH_HI									
HP_PHBIO_IC_CTOOM_LO									
HP_PHBIO_IC_CTOOM_HI									
HP_NPHBIO_IC_CTOOM_LO									
HP_NPHBIO_IC_CTOOM_HI									
HP_PHBIO_IC_PC_LO									
HP_PHBIO_IC_PC_HI									
HP_NPHBIO_IC_PC_LO									
HP_NPHBIO_IC_PC_HI									
HP_MAC_TRANSLOC_RC_LO									
HP_MAC_TRANSLOC_RC_HI									
HP_HYD_RCINFILT_LO									
HP_HYD_RCINFILT_HI									
HP_HYD_SPEC_YIELD_LO	0.018	0.017	0.013	0.011	0.009	0.009	0.004	0.014	0.014
HP_HYD_SPEC_YIELD_HI	-0.016	-0.015	-0.012	-0.009	-0.008	-0.008	-0.004	-0.013	-0.013
HP_HYD_POROSITY_LO	0.006	0.006	0.005	0.005	0.004	0.003	0.003	0.005	0.005
HP_HYD_POROSITY_HI	-0.006	-0.006	-0.005	-0.004	-0.004	-0.004	-0.003	-0.005	-0.005
HP_FLOC_IC_LO									
HP_FLOC_IC_HI									
HP_FLOC_IC_CTOOM_LO									
HP_FLOC_IC_CTOOM_HI									
HP_FLOC_IC_PC_LO									
HP_FLOC_IC_PC_HI									
HP_SfDepthLo_LO									
HP_SfDepthLo_HI									
HP_SfDepthHi_LO									
HP_SfDepthHi_HI									
HP_SfDepthInt_LO									
HP_SfDepthInt_HI									
HP_PhosLo_LO									
HP_PhosLo_HI									
HP_PhosHi_LO									
HP_PhosHi_HI									
HP_PhosInt_LO									
HP_PhosInt_HI									
HP_FireInt_LO									
HP_FireInt_HI									
Count:	21	23	26	27	30	44	31	23	23

Table 7.3.2. Surface water TP. Naive case: +/-25% change in parameter. Compared to the 5-yr mean of the NOMINAL run output, if a simulation with a changed parameter resulted in at least a 1% change in the surface water TP concentration Performance Measure in an Indicator Region (IR), the (ParmChangeRun - NominalRun) difference (mg/L) is shown for that simulation & IR. Parameters are grouped by ecological module (as found in databases).

	TPsf_9	TPsf_8	TPsf_7	TPsf_6	TPsf_5	TPsf_4	TPsf_3	TPsf_2	TPsf_0
NOMINAL	0.005	0.007	0.009	0.012	0.014	0.019	0.019	0.008	0.008
GP_SOLOMEGA_LO									
GP_SOLOMEGA_HI									
GP_ALTIT_LO									
GP_ALTIT_HI									
GP_LATDEG_LO									
GP_LATDEG_HI									
GP_mannDepthPow_LO	0.001								
GP_mannDepthPow_HI				-0.001				-0.001	-0.001
GP_mannHeadPow_LO	0.001								
GP_mannHeadPow_HI									
GP_calibGWat_LO									
GP_calibGWat_HI									
GP_IDW_pow_LO									
GP_IDW_pow_HI									
GP_calibET_LO		-0.001	-0.001		0.001				
GP_calibET_HI				-0.001				-0.001	-0.001
GP_HYD_IC_SFWAT_ADD_LO									
GP_HYD_IC_SFWAT_ADD_HI									
GP_HYD_IC_UNSAT_ADD_LO									
GP_HYD_IC_UNSAT_ADD_HI									
GP_HYD_ICUNSATMOIST_LO									
GP_HYD_ICUNSATMOIST_HI									
GP_DetentZ_LO									
GP_DetentZ_HI									
GP_MinCheck_LO									
GP_MinCheck_HI									
GP_dispLenRef_LO						0.001	0.001		
GP_dispLenRef_HI	0.001						-0.001		
GP_dispParm_LO	0.001						-0.001		
GP_dispParm_HI						0.001	0.001		
GP_SLRise_LO									
GP_SLRise_HI									
GP_ALG_IC_MULT_LO									
GP_ALG_IC_MULT_HI									
GP_alg_uptake_coef_LO	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002
GP_alg_uptake_coef_HI	0.002	0.001	0.002	0.001	0.002	0.002	0.002	0.001	0.001
GP_ALG_SHADE_FACTOR_LO									
GP_ALG_SHADE_FACTOR_HI									
GP_algMortDepth_LO									
GP_algMortDepth_HI									
GP_ALG_RC_MORT_DRY_LO									
GP_ALG_RC_MORT_DRY_HI									
GP_ALG_RC_MORT_LO	0.001		0.001		0.001	0.001	0.001		
GP_ALG_RC_MORT_HI				-0.001		-0.001		-0.001	-0.001
GP_ALG_RC_PROD_LO	0.001				0.001	0.001	0.001		
GP_ALG_RC_PROD_HI									
GP_ALG_RC_RESP_LO									
GP_ALG_RC_RESP_HI									
GP_alg_R_accel_LO	0.001		0.001		0.001	0.002	0.001		
GP_alg_R_accel_HI				-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
GP_AlgComp_LO					0.001	0.001	0.001		
GP_AlgComp_HI									
GP_ALG_REF_MULT_LO									
GP_ALG_REF_MULT_HI									
GP_NC_ALG_KS_P_LO									
GP_NC_ALG_KS_P_HI									
GP_alg_alkP_min_LO					0.001				
GP_alg_alkP_min_HI									
GP_C_ALG_KS_P_LO			-0.001	-0.001		-0.001	-0.001	-0.001	-0.001
GP_C_ALG_KS_P_HI	0.001		0.001		0.001	0.001	0.001		
GP_ALG_TEMP_OPT_LO				-0.001				-0.001	-0.001
GP_ALG_TEMP_OPT_HI	0.001				0.001	0.001	0.002		
GP_C_ALG_threshTP_LO			-0.001	-0.001	-0.001	-0.002	-0.002	-0.001	-0.001
GP_C_ALG_threshTP_HI	0.001		0.001		0.002	0.002	0.002		
GP_ALG_C_TO_OM_LO									
GP_ALG_C_TO_OM_HI									
GP_alg_light_ext_coef_LO									
GP_alg_light_ext_coef_HI									
GP_ALG_LIGHT_SAT_LO									
GP_ALG_LIGHT_SAT_HI									
GP_ALG_PC_LO	0.001	0.001	0.001	0.001	0.002	0.002	0.001		
GP_ALG_PC_HI		-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
GP_DOM_RCDECOMP_LO				-0.001		-0.001	-0.001		
GP_DOM_RCDECOMP_HI	0.001				0.001	0.002	0.003		
GP_DOM_DECOMPRED_LO									
GP_DOM_DECOMPRED_HI					0.001				
GP_calibDecomp_LO				-0.001		-0.001	-0.001		
GP_calibDecomp_HI	0.001				0.001	0.002	0.003		
GP_DOM_decomp_coef_LO	0.001	0.001	0.001	0.001	0.003	0.006	0.007	0.001	0.001
GP_DOM_decomp_coef_HI				-0.001	-0.001	-0.001	-0.002	-0.001	-0.001
GP_DOM_DECOMP_POPT_LO	0.001				0.001	0.004	0.006		
GP_DOM_DECOMP_POPT_HI									
GP_sorbToTP_LO									
GP_sorbToTP_HI									
GP_IC_BATHY_MULT_LO									
GP_IC_BATHY_MULT_HI									
GP_IC_TPtoSOIL_MULT_LO				-0.001			-0.001		
GP_IC_TPtoSOIL_MULT_HI	0.001				0.001	0.001	0.001		
GP_IC_DOM_BD_MULT_LO									
GP_IC_DOM_BD_MULT_HI									
GP_IC_BulkD_MULT_LO				-0.001					
GP_IC_BulkD_MULT_HI	0.001				0.001		0.001		
GP_IC_ELEV_MULT_LO									
GP_IC_ELEV_MULT_HI	0.001								
GP_MAC_IC_MULT_LO	0.001				0.001				
GP_MAC_IC_MULT_HI									
GP_MAC_REFUG_MULT_LO									
GP_MAC_REFUG_MULT_HI									
GP_mac_uptake_coef_LO				-0.001	-0.001	-0.001	-0.002	-0.001	-0.001
GP_mac_uptake_coef_HI	0.001		0.001		0.001	0.002	0.003		
GP_mann_height_coef_LO					0.001				
GP_mann_height_coef_HI									
GP_Floc_BD_LO									
GP_Floc_BD_HI									
GP_FlocMax_LO									
GP_FlocMax_HI									
GP_TP_P_OM_LO									

GP_TP_P_OM_HI									
GP_Floc_rcSoil_LO					0.001	0.001	0.001		
GP_Floc_rcSoil_HI									
GP_TP_DIFFCOEF_LO									
GP_TP_DIFFCOEF_HI					0.001				
GP_TP_K_INTER_LO					0.001	0.001	0.001		
GP_TP_K_INTER_HI									
GP_TP_K_SLOPE_LO									
GP_TP_K_SLOPE_HI									
GP_WQMthresh_LO									
GP_WQMthresh_HI									
GP_PO4toTP_LO	-0.001	-0.001	-0.001	-0.002	-0.001	-0.002	-0.002	-0.001	-0.001
GP_PO4toTP_HI	0.002	0.002	0.002	0.001	0.002	0.002	0.002	0.001	0.001
GP_TP_IN_RAIN_LO				-0.001				-0.001	-0.001
GP_TP_IN_RAIN_HI	0.001	0.001	0.001		0.001	0.001	0.001		
GP_PO4toTPint_LO	0.001				0.001	0.001			
GP_PO4toTPint_HI				-0.001					
GP_TP_ICSFWAT_LO									
GP_TP_ICSFWAT_HI									
GP_TP_ICSEDWAT_LO									
GP_TP_ICSEDWAT_HI									
GP_TPpart_thresh_LO	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
GP_TPpart_thresh_HI	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001
GP_TP_DIFFDEPTH_LO					0.001				
GP_TP_DIFFDEPTH_HI									
GP_settlVel_LO	0.001	0.001	0.001		0.001	0.001	0.001		
GP_settlVel_HI				-0.001				-0.001	-0.001
HP_ALG_MAX_LO	0.001	0.001	0.001	0.001	0.002	0.002	0.002	0.001	0.001
HP_ALG_MAX_HI		-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
HP_DOM_MAXDEPTH_LO						0.001			
HP_DOM_MAXDEPTH_HI									
HP_DOM_AEROBTHIN_LO									
HP_DOM_AEROBTHIN_HI	0.001				0.001	0.001	0.001		
HP_TP_CONC_GRAD_LO									
HP_TP_CONC_GRAD_HI									
HP_SALT_ICSEDWAT_LO									
HP_SALT_ICSEDWAT_HI									
HP_SALT_ICSFWAT_LO									
HP_SALT_ICSFWAT_HI									
HP_PHBIO_MAX_LO	0.001				0.001	0.001	0.001		
HP_PHBIO_MAX_HI				-0.001			-0.001		
HP_NPHBIO_MAX_LO									
HP_NPHBIO_MAX_HI									
HP_MAC_MAXHT_LO	0.001				0.001				
HP_MAC_MAXHT_HI									
HP_NPHBIO_ROOTDEPTH_LO									
HP_NPHBIO_ROOTDEPTH_HI									
HP_MAC_MAXROUGH_LO					0.001				
HP_MAC_MAXROUGH_HI									
HP_MAC_MINROUGH_LO									
HP_MAC_MINROUGH_HI									
HP_MAC_MAXLAI_LO	0.001				0.001				
HP_MAC_MAXLAI_HI									
HP_MAC_MAXCANOPCOND_LO									
HP_MAC_MAXCANOPCOND_HI									
HP_MAC_CANOPDECOUP_LO									
HP_MAC_CANOPDECOUP_HI									
HP_MAC_TEMPOPT_LO				-0.001	-0.001	-0.001	-0.002	-0.001	-0.001
HP_MAC_TEMPOPT_HI	0.001				0.001	0.001	0.002		
HP_MAC_LIGHTSAT_LO									
HP_MAC_LIGHTSAT_HI									
HP_MAC_KSP_LO									
HP_MAC_KSP_HI						0.001	0.001		
HP_PHBIO_RCNPP_LO	0.001				0.001	0.001	0.001		
HP_PHBIO_RCNPP_HI				-0.001			-0.001		
HP_PHBIO_RCMORT_LO									
HP_PHBIO_RCMORT_HI					0.001				
HP_MAC_WAT_TOLER_LO									
HP_MAC_WAT_TOLER_HI									
HP_MAC_SALIN_THRESH_LO									
HP_MAC_SALIN_THRESH_HI									
HP_PHBIO_IC_CTOOM_LO									
HP_PHBIO_IC_CTOOM_HI									
HP_NPHBIO_IC_CTOOM_LO									
HP_NPHBIO_IC_CTOOM_HI									
HP_PHBIO_IC_PC_LO	0.001				0.001	0.001	0.001		
HP_PHBIO_IC_PC_HI									
HP_NPHBIO_IC_PC_LO									
HP_NPHBIO_IC_PC_HI									
HP_MAC_TRANSLOC_RC_LO									
HP_MAC_TRANSLOC_RC_HI									
HP_HYD_RCINFILT_LO									
HP_HYD_RCINFILT_HI									
HP_HYD_SPEC_YIELD_LO									
HP_HYD_SPEC_YIELD_HI									
HP_HYD_POROSITY_LO									
HP_HYD_POROSITY_HI									
HP_FLOC_IC_LO									
HP_FLOC_IC_HI									
HP_FLOC_IC_CTOOM_LO									
HP_FLOC_IC_CTOOM_HI									
HP_FLOC_IC_PC_LO									
HP_FLOC_IC_PC_HI									
HP_SfDepthLo_LO									
HP_SfDepthLo_HI									
HP_SfDepthHi_LO									
HP_SfDepthHi_HI									
HP_SfDepthInt_LO									
HP_SfDepthInt_HI									
HP_PhosLo_LO									
HP_PhosLo_HI									
HP_PhosHi_LO									
HP_PhosHi_HI									
HP_PhosInt_LO									
HP_PhosInt_HI									
HP_FireInt_LO									
HP_FireInt_HI									
Count:	37	14	21	30	50	46	49	22	22

Table 7.3.3. Soils. Naive case: +/-25% change in parameter. Compared to the 5-yr mean of the NOMINAL run output, if a simulation with a changed parameter resulted in at least a 1% change in the soil porewater TP concentration Performance Measure in an Indicator Region (IR), the (ParmChangeRun - NominalRun) (mg/L) difference is shown for that simulation & IR. Parameters are grouped by ecological module (as found in databases).

	TPpore_9	TPpore_8	TPpore_7	TPpore_6	TPpore_5	TPpore_4	TPpore_3	TPpore_2	TPpore_0
NOMINAL	0.002	0.003	0.005	0.011	0.021	0.060	0.059	0.011	0.011
GP_SOLOMEGA_LO									
GP_SOLOMEGA_HI									
GP_ALTIT_LO									
GP_ALTIT_HI									
GP_LATDEG_LO									
GP_LATDEG_HI									
GP_mannDepthPow_LO		-0.001				-0.002	-0.001		
GP_mannDepthPow_HI	-0.001				-0.001		0.002		
GP_mannHeadPow_LO			0.001			0.001			
GP_mannHeadPow_HI		-0.001				-0.002	0.001		
GP_calibGWat_LO		-0.001				-0.005	-0.003	-0.001	-0.001
GP_calibGWat_HI						0.004	0.004	0.001	0.001
GP_IDW_pow_LO									
GP_IDW_pow_HI									
GP_calibET_LO	-0.001	-0.001	-0.001	-0.001	-0.002	-0.009	-0.002	-0.001	-0.001
GP_calibET_HI		0.001	0.002	0.002	0.002	0.006	0.005	0.002	0.002
GP_HYD_IC_SFWAT_ADD_LO									
GP_HYD_IC_SFWAT_ADD_HI									
GP_HYD_IC_UNSAT_ADD_LO									
GP_HYD_IC_UNSAT_ADD_HI									
GP_HYD_ICUNSATMOIST_LO									
GP_HYD_ICUNSATMOIST_HI									
GP_DetentZ_LO						-0.001			
GP_DetentZ_HI									
GP_MinCheck_LO									
GP_MinCheck_HI									
GP_dispLenRef_LO	-0.001	-0.001				0.003	0.006		
GP_dispLenRef_HI			0.001			-0.003	-0.004		
GP_dispParm_LO			0.001			-0.003	-0.004		
GP_dispParm_HI	-0.001	-0.001				0.003	0.006		
GP_SLRise_LO									
GP_SLRise_HI									
GP_ALG_IC_MULT_LO									
GP_ALG_IC_MULT_HI						-0.001			
GP_alg_uptake_coef_LO	-0.001	-0.001	-0.001	-0.001	-0.001	-0.003	-0.002	-0.001	-0.001
GP_alg_uptake_coef_HI			0.001	0.001	0.001	0.002	0.002	0.001	0.001
GP_ALG_SHADE_FACTOR_LO									
GP_ALG_SHADE_FACTOR_HI							0.001		
GP_algMortDepth_LO									
GP_algMortDepth_HI									
GP_ALG_RC_MORT_DRY_LO									
GP_ALG_RC_MORT_DRY_HI						-0.001			
GP_ALG_RC_MORT_LO			0.001	0.001	0.001	0.003	0.003	0.001	0.001
GP_ALG_RC_MORT_HI	-0.001	-0.001			-0.001	-0.002	-0.001		
GP_ALG_RC_PROD_LO			0.001	0.001	0.001	0.001	0.003		
GP_ALG_RC_PROD_HI		-0.001			-0.001	-0.001	-0.001		
GP_ALG_RC_RESP_LO									
GP_ALG_RC_RESP_HI						-0.001			
GP_alg_R_accel_LO			0.001	0.001	0.002	0.004	0.004	0.001	0.001
GP_alg_R_accel_HI	-0.001	-0.001		-0.001	-0.002	-0.004	-0.003		
GP_AlgComp_LO						0.001	0.004		
GP_AlgComp_HI						-0.001			
GP_ALG_REF_MULT_LO						-0.001			
GP_ALG_REF_MULT_HI									
GP_NC_ALG_KS_P_LO							0.002		
GP_NC_ALG_KS_P_HI						-0.001			
GP_alg_alkP_min_LO							0.001		
GP_alg_alkP_min_HI						-0.001			
GP_C_ALG_KS_P_LO	-0.001	-0.001		-0.001	-0.001	-0.001			
GP_C_ALG_KS_P_HI			0.001	0.001		-0.001			
GP_ALG_TEMP_OPT_LO	-0.001	-0.001			-0.001	-0.001	-0.001		
GP_ALG_TEMP_OPT_HI			0.001	0.001	0.002	0.003	0.005	0.001	0.001
GP_C_ALG_threshTP_LO	-0.001	-0.001		-0.001	-0.003	-0.007	-0.005	-0.001	-0.001
GP_C_ALG_threshTP_HI			0.001	0.001	0.002	0.004	0.005	0.001	0.001
GP_ALG_C_TO_OM_LO		-0.001			-0.002	-0.006	-0.006	-0.001	-0.001
GP_ALG_C_TO_OM_HI			0.001	0.001	0.001	0.004	0.006	0.001	0.001
GP_alg_light_ext_coef_LO									
GP_alg_light_ext_coef_HI									
GP_ALG_LIGHT_SAT_LO									
GP_ALG_LIGHT_SAT_HI									
GP_ALG_PC_LO			0.001	0.001	0.001	-0.001	-0.001		
GP_ALG_PC_HI	-0.001	-0.001		-0.001	-0.001		0.002		
GP_DOM_RCDECOMP_LO	-0.001	-0.001	-0.002	-0.004	-0.007	-0.016	-0.017	-0.003	-0.003
GP_DOM_RCDECOMP_HI	0.001	0.001	0.003	0.005	0.008	0.029	0.04	0.005	0.005
GP_DOM_DECOMPRED_LO	-0.001	-0.001	-0.001	-0.001	-0.002	-0.004	-0.004	-0.001	-0.001
GP_DOM_DECOMPRED_HI			0.001	0.002	0.002	0.004	0.005	0.001	0.001
GP_calibDecomp_LO	-0.001	-0.001	-0.002	-0.004	-0.007	-0.016	-0.017	-0.003	-0.003
GP_calibDecomp_HI	0.001	0.001	0.003	0.005	0.008	0.029	0.04	0.005	0.005
GP_DOM_decomp_coef_LO	0.009	0.011	0.017	0.025	0.039	0.107	0.115	0.022	0.022
GP_DOM_decomp_coef_HI	-0.001	-0.002	-0.003	-0.007	-0.013	-0.028	-0.029	-0.005	-0.005
GP_DOM_DECOMP_POPT_LO			0.001	0.001	0.003	0.062	0.1	0.006	0.006
GP_DOM_DECOMP_POPT_HI					-0.001	-0.007	-0.008	-0.001	-0.001
GP_sorbToTP_LO	-0.001	-0.001	-0.001	-0.002	-0.003	-0.004	-0.003	-0.001	-0.001
GP_sorbToTP_HI		0.001	0.002	0.003	0.003	0.003	0.004	0.002	0.002
GP_IC_BATHY_MULT_LO									
GP_IC_BATHY_MULT_HI									
GP_IC_TPtoSOIL_MULT_LO	-0.001	-0.002	-0.002	-0.004	-0.006	-0.01	-0.01	-0.003	-0.003
GP_IC_TPtoSOIL_MULT_HI	0.002	0.002	0.004	0.005	0.007	0.012	0.013	0.004	0.004
GP_IC_DOM_BD_MULT_LO			0.001	0.002	0.003	0.006	0.006	0.001	0.001
GP_IC_DOM_BD_MULT_HI	-0.001	-0.001	-0.001	-0.002	-0.004	-0.01	-0.009	-0.002	-0.002
GP_IC_BulkD_MULT_LO	-0.001	-0.002	-0.002	-0.004	-0.006	-0.009	-0.008	-0.003	-0.003
GP_IC_BulkD_MULT_HI	0.001	0.002	0.003	0.004	0.004	0.003	0.004	0.003	0.003
GP_IC_ELEV_MULT_LO	-0.001	-0.001			-0.001	-0.002			
GP_IC_ELEV_MULT_HI			0.001			0.002			
GP_MAC_IC_MULT_LO		0.001	0.002	0.002	0.002	0.002	0.003	0.002	0.002
GP_MAC_IC_MULT_HI	-0.001	-0.001		-0.001	-0.001	-0.001		-0.001	-0.001
GP_MAC_REFUG_MULT_LO									
GP_MAC_REFUG_MULT_HI									
GP_mac_uptake_coef_LO	-0.001	-0.002	-0.004	-0.009	-0.018	-0.036	-0.036	-0.007	-0.007
GP_mac_uptake_coef_HI	0.009	0.01	0.012	0.015	0.018	0.035	0.043	0.013	0.013
GP_mann_height_coef_LO		-0.001				-0.002			
GP_mann_height_coef_HI			0.001			0.001	0.001		
GP_Floc_BD_LO	-0.001	-0.001			-0.002	-0.005	-0.005	-0.001	-0.001
GP_Floc_BD_HI			0.001	0.001	0.001	0.004	0.006	0.001	0.001
GP_FlocMax_LO	-0.001	-0.001			-0.002	-0.005	-0.005	-0.001	-0.001
GP_FlocMax_HI			0.001	0.001	0.001	0.004	0.006	0.001	0.001
GP_TP_P_OM_LO						-0.001			
GP_TP_P_OM_HI							0.001		
GP_Floc_rcSoil_LO			0.001	0.001	0.002	0.006	0.008	0.001	0.001

GP_Floc_rcSoil_HI	-0.001	-0.001			-0.001	-0.004	-0.004		
GP_TP_DIFFCOEF_LO						0.002	0.004		
GP_TP_DIFFCOEF_HI					-0.001	-0.003	-0.002		
GP_TP_K_INTER_LO			0.002	0.004	0.007	0.021	0.024	0.004	0.004
GP_TP_K_INTER_HI	-0.001	-0.001	-0.001	-0.002	-0.005	-0.013	-0.012	-0.002	-0.002
GP_TP_K_SLOPE_LO						-0.002	-0.001		
GP_TP_K_SLOPE_HI						0.001	0.002		
GP_WQMthresh_LO									
GP_WQMthresh_HI									
GP_PO4toTP_LO	-0.001	-0.001		0.001	0.001	0.001	0.004		
GP_PO4toTP_HI			0.001		0.001		-0.003		
GP_TP_IN_RAIN_LO	-0.001	-0.001		-0.001	-0.001	-0.002	-0.001	-0.001	-0.001
GP_TP_IN_RAIN_HI			0.001	0.001	0.001	0.001	0.001	0.001	0.001
GP_PO4toTPint_LO							0.001		
GP_PO4toTPint_HI	-0.001	-0.001				-0.001			
GP_TP_ICSFWAT_LO									
GP_TP_ICSFWAT_HI									
GP_TP_ICSEDWAT_LO	-0.001	-0.001			-0.001	-0.001	-0.001		
GP_TP_ICSEDWAT_HI						0.001	0.002		
GP_TPpart_thresh_LO	-0.001	-0.001			-0.001		0.002		
GP_TPpart_thresh_HI			0.001	0.001			-0.001		
GP_TP_DIFFDEPTH_LO					-0.001	-0.004	-0.003		
GP_TP_DIFFDEPTH_HI						0.002	0.003		
GP_settlVel_LO			0.001			-0.002	-0.002		
GP_settlVel_HI	-0.001	-0.001				0.001	0.003		
HP_ALG_MAX_LO			0.001	0.002	0.003	0.005	0.005	0.001	0.001
HP_ALG_MAX_HI	-0.001	-0.001		-0.001	-0.002	-0.004	-0.003	-0.001	-0.001
HP_DOM_MAXDEPTH_LO	-0.001	-0.001	-0.001	-0.002	-0.002	0.003	0.002	-0.001	-0.001
HP_DOM_MAXDEPTH_HI	0.001	0.001	0.002	0.002	0.001	-0.003	-0.002	0.001	0.001
HP_DOM_AEROBTHIN_LO	-0.001	-0.001			-0.001	-0.002	-0.001		
HP_DOM_AEROBTHIN_HI			0.001				0.001		
HP_TP_CONC_GRAD_LO						0.004	0.005	0.001	0.001
HP_TP_CONC_GRAD_HI	-0.001	-0.001			-0.001	-0.004	-0.003		
HP_SALT_ICSEDWAT_LO									
HP_SALT_ICSEDWAT_HI									
HP_SALT_ICSFWAT_LO									
HP_SALT_ICSFWAT_HI									
HP_PHBIO_MAX_LO	0.003	0.004	0.006	0.007	0.008	0.017	0.023	0.006	0.006
HP_PHBIO_MAX_HI	-0.001	-0.002	-0.003	-0.005	-0.007	-0.013	-0.013	-0.003	-0.003
HP_NPHBIO_MAX_LO	-0.001	-0.001					0.001		
HP_NPHBIO_MAX_HI						-0.001			
HP_MAC_MAXHT_LO	-0.001	-0.001			-0.001	-0.003	-0.001		
HP_MAC_MAXHT_HI			0.001	0.001		0.002	0.002		
HP_NPHBIO_ROOTDEPTH_LO			0.001				0.001		
HP_NPHBIO_ROOTDEPTH_HI	-0.001	-0.001				-0.001			
HP_MAC_MAXROUGH_LO						-0.001			
HP_MAC_MAXROUGH_HI							0.001		
HP_MAC_MINROUGH_LO						-0.001			
HP_MAC_MINROUGH_HI							0.001		
HP_MAC_MAXLAI_LO	-0.001	-0.001	-0.001	-0.001	-0.002	-0.004	-0.002	-0.001	-0.001
HP_MAC_MAXLAI_HI			0.001	0.001	0.001	0.002	0.003	0.001	0.001
HP_MAC_MAXCANOPCOND_LO									
HP_MAC_MAXCANOPCOND_HI									
HP_MAC_CANOPDECOUP_LO									
HP_MAC_CANOPDECOUP_HI									
HP_MAC_TEMPOPT_LO	-0.001	-0.002	-0.004	-0.008	-0.016	-0.033	-0.033	-0.006	-0.006
HP_MAC_TEMPOPT_HI	0.004	0.005	0.007	0.008	0.01	0.024	0.031	0.007	0.007
HP_MAC_LIGHTSAT_LO									
HP_MAC_LIGHTSAT_HI									
HP_MAC_KSP_LO		-0.001			-0.002	-0.008	-0.009	-0.001	-0.001
HP_MAC_KSP_HI				0.001	0.001	0.007	0.012	0.001	0.001
HP_PHBIO_RCNPP_LO	0.003	0.004	0.005	0.007	0.008	0.017	0.023	0.006	0.006
HP_PHBIO_RCNPP_HI	-0.001	-0.002	-0.002	-0.005	-0.007	-0.013	-0.013	-0.003	-0.003
HP_PHBIO_RCMORT_LO	-0.001	-0.001			-0.001		0.001		
HP_PHBIO_RCMORT_HI			0.001	0.001					
HP_MAC_WAT_TOLER_LO			0.001	0.002	0.001	0.001		0.001	0.001
HP_MAC_WAT_TOLER_HI	-0.001	-0.001			-0.001	-0.001			
HP_MAC_SALIN_THRESH_LO									
HP_MAC_SALIN_THRESH_HI									
HP_PHBIO_IC_CTOOM_LO					-0.001	-0.002	-0.001		
HP_PHBIO_IC_CTOOM_HI							0.001		
HP_NPHBIO_IC_CTOOM_LO						-0.001			
HP_NPHBIO_IC_CTOOM_HI							0.001		
HP_PHBIO_IC_PC_LO	0.003	0.004	0.005	0.007	0.008	0.015	0.021	0.006	0.006
HP_PHBIO_IC_PC_HI	-0.001	-0.002	-0.002	-0.005	-0.007	-0.012	-0.012	-0.003	-0.003
HP_NPHBIO_IC_PC_LO						-0.001			
HP_NPHBIO_IC_PC_HI									
HP_MAC_TRANSLOC_RC_LO						-0.001			
HP_MAC_TRANSLOC_RC_HI									
HP_HYD_RCINFILT_LO									
HP_HYD_RCINFILT_HI									
HP_HYD_SPEC_YIELD_LO				0.001		-0.003			
HP_HYD_SPEC_YIELD_HI	-0.001	-0.001			-0.001	0.001	0.001		
HP_HYD_POROSITY_LO	-0.001	-0.001		-0.001	-0.001	-0.004	-0.002	-0.001	-0.001
HP_HYD_POROSITY_HI	-0.001		0.001	0.001	0.001	0.002	0.003	0.001	0.001
HP_FLOC_IC_LO									
HP_FLOC_IC_HI									
HP_FLOC_IC_CTOOM_LO									
HP_FLOC_IC_CTOOM_HI									
HP_FLOC_IC_PC_LO									
HP_FLOC_IC_PC_HI									
HP_SfDepthLo_LO									
HP_SfDepthLo_HI									
HP_SfDepthHi_LO									
HP_SfDepthHi_HI									
HP_SfDepthInt_LO									
HP_SfDepthInt_HI									
HP_PhosLo_LO									
HP_PhosLo_HI									
HP_PhosHi_LO									
HP_PhosHi_HI									
HP_PhosInt_LO									
HP_PhosInt_HI									
HP_FireInt_LO									
HP_FireInt_HI									
Count:	60	68	65	67	85	121	112	64	64

Table 7.3.4. Most 'important' parameters for different ecological process modules as understood from the Naive case. Note that the Naive case does not employ "realistic" changes to parameters, nor does it consider the broader spatial characteristics of the entire greater Everglades. A larger number of parameters than shown in this table are evaluated in the "Informed" phase of the NIS multi-scale sensitivity analysis.

"Yes" = affects performance in potentially significant manner at various spatial locations/scales

"Potential" = in "top 20", w/ observable affect on performance at various spatial locations/scales

Parameter	Hydrology	Surface water quality	Soil water quality	State of knowledge
GP_calibET	**yes**	**potential**	**yes**	Evapotranspiration rates known to Level II - III
GP_calibGWat	**yes**		**potential**	Subsurface groundwater flows known to Level I - II
HP_HYD_SPEC_YIELD	yes			Horizontal and vertical distributions of surficial storage = Level I - III
GP_IC_ELEV_MULT	yes			Land surface elevations known to Level III, some Level II
HP_MAC_MAXLAI	yes			Maximum LAI is Level II - III, but actual LAI is Level I - II
HP_HYD_POROSITY	yes			Horizontal and vertical distributions of surficial storage = Level I - III
GP_MAC_IC_MULT	**yes**		**potential**	Initial macrophyte biomass known to Level I - III
HP_NPHBIO_ROOTDEPTH	yes			Depth of principal root mass known to Level II
HP_MAC_MINROUGH	yes			Minimum Manning's N known to Level I -II, actual roughness is closer to Level I
GP_PO4toTP		yes		Ratio of bio-available to total phosphorus Level II, model value is Level I
HP_ALG_MAX	**potential**	**yes**		Maximum periphyton biomass is Level II - III, actual biomass is Level I - II
GP_TPpart_thresh		yes		Settling physics Level III, actual particulate and microbial dynamics Level I
GP_DOM_DECOMP_POPT	**potential**	**yes**	**yes**	Laboratory constants known to Level III, scaled constants Level II
GP_DOM_RCDECOMP		**yes**	**yes**	Laboratory constants known to Level III, scaled constants Level II
GP_C_ALG_threshTP	**potential**	**yes**	**potential**	Laboratory and field experiments for periphyton TP threshold are Level III
GP_ALG_TEMP_OPT		yes		Periphyton temperature optimimum known to Level III, correlated to Level I - II growth rate
GP_alg_R_accel	**potential**	**yes**		Biochemical cause for periphyton loss at high TP unknown; proxy here is calibrated
GP_ALG_RC_MORT		yes		Maximum specific mortality rate known to Level II; field rates known to I - III
GP_ALG_PC		yes		Phosphorus:Carbon periphyton ratio known to Level II
GP_C_ALG_KS_P		**yes**	**potential**	Laboratory constants known to Level III, scaled constants Level II
HP_MAC_TEMPOPT		**potential**	**yes**	Macrophyte temperature optimimum known to Level III, correlated to Level I - II growth rate
HP_PHBIO_MAX			yes	Maximum macrophyte biomass is Level II - III, actual biomass is Level I - II
HP_PHBIO_RCNPP		**potential**	**yes**	Maximum rate of macrophyte net primary production known to Level II, actual is level I - III
HP_PHBIO_IC_PC			yes	Phosphorus:Carbon macrophytes ratio known to Level II
GP_TP_K_INTER			yes	Laboratory constants known to Level III, scaled constants Level II
GP_IC_TPtoSOIL_MULT			yes	Initial soil TP concentration known to level II - III
GP_IC_BulkD_MULT	**potential**		**yes**	Initial (constant) soil bulk density known to level II - III

7.3.6 Figures: sensitivity analyses

Five figures follow on the next five pages.

Figure 7.3.1. Conceptual model of approach to sensitivity analysis of complex system simulations.

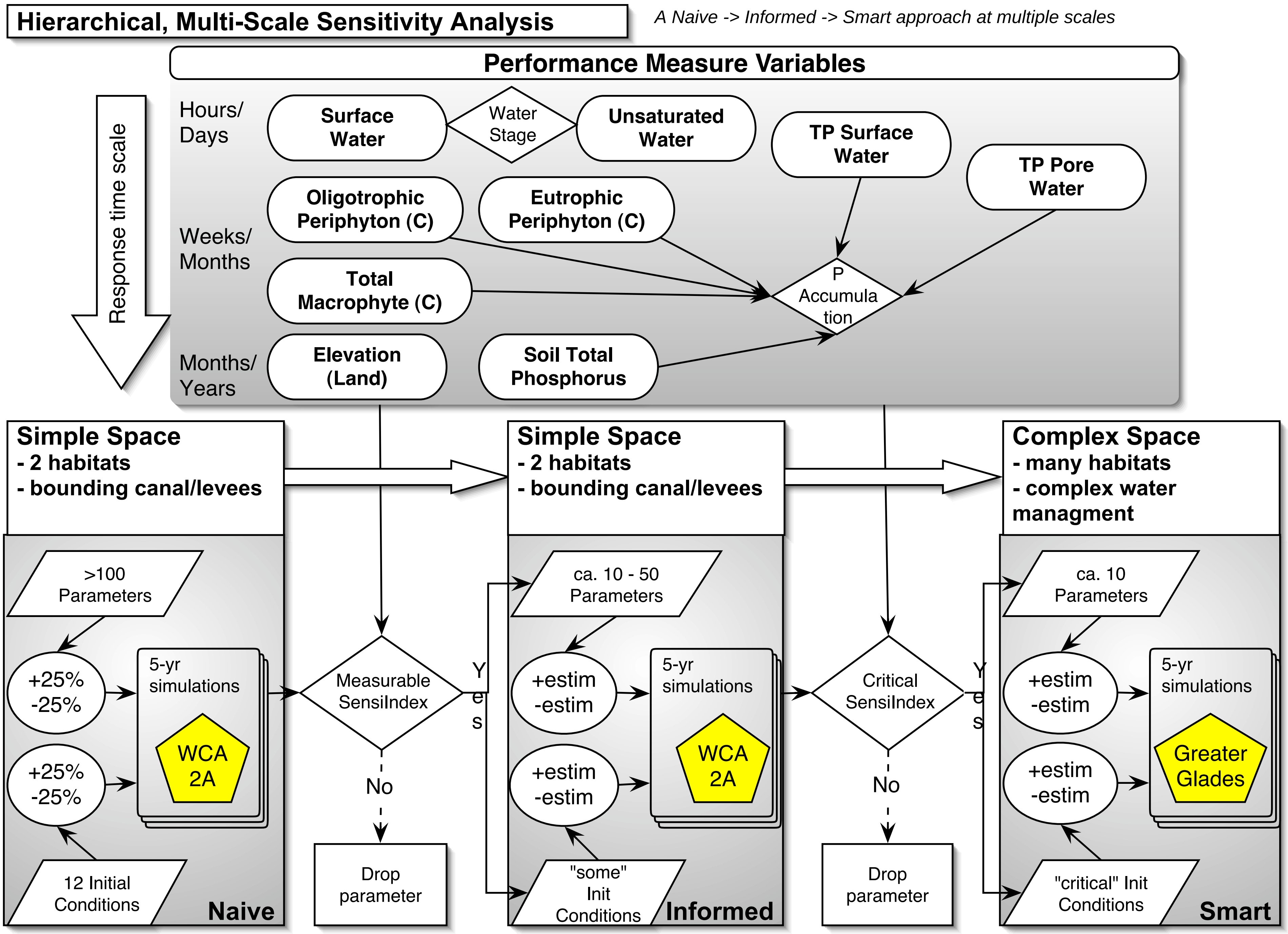


Fig.7.3.2.Basin/Indicator-Region configuration of model used in sensitivity analysis.

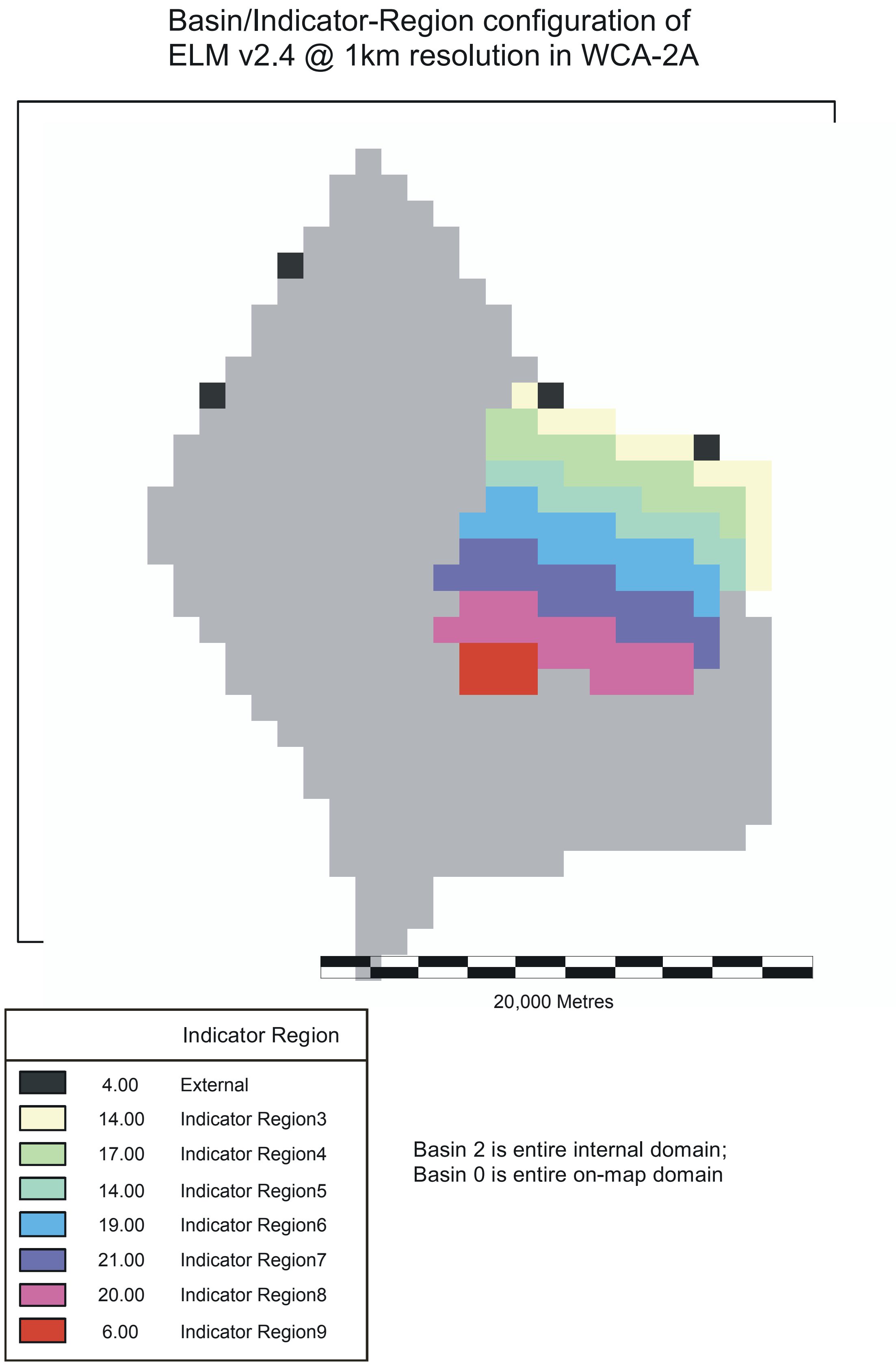


Figure 7.3.3a. Hydrology Naive case: +/- 25% change in parameter. Lowest (most negative) output differences of Performance Measure compared to the 5-yr mean of the NOMINAL run output. The twenty most-sensitive parameters are shown. See Figure 1 for definition & locations of the Indicator Regions 3 - 9 that are referred to in the legend (Basin 0 is entire domain).

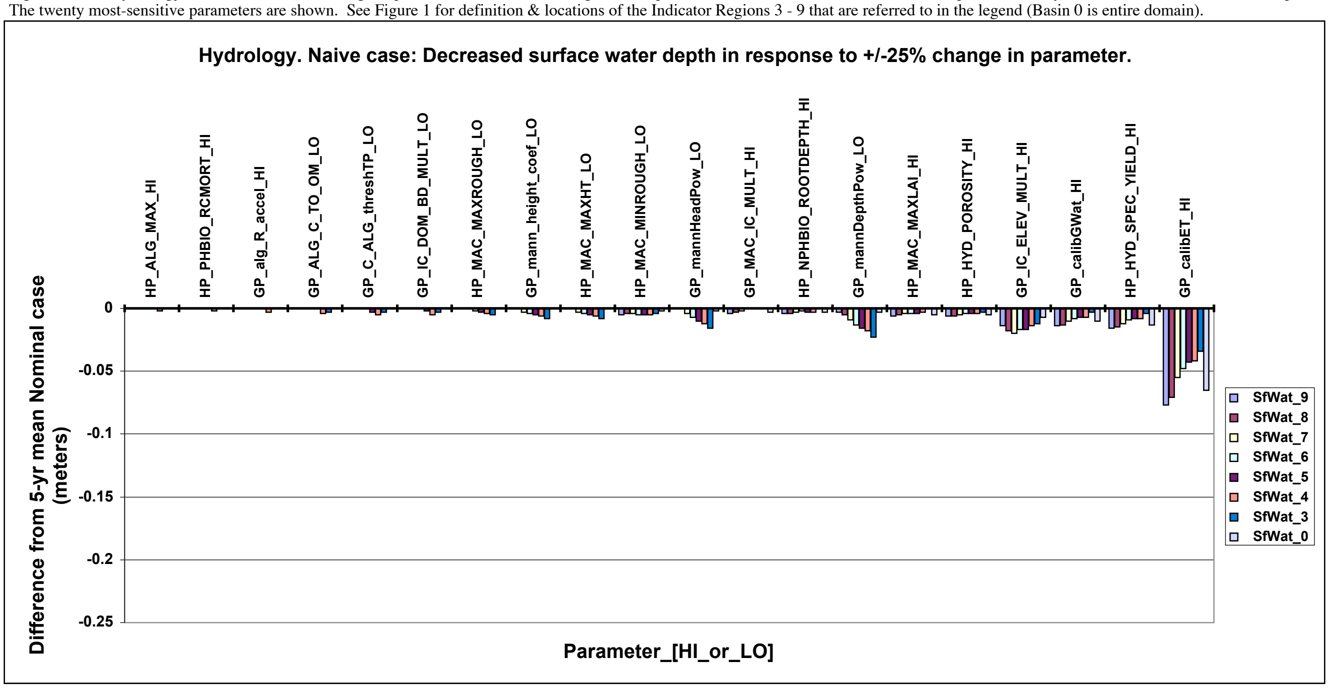


Figure 6.3.3b. Hydrology Naive case: +/- 25% change in parameter. Highest (most positive) output differences of Performance Measure compared to the 5-yr mean of the NOMINAL run output. The twenty most-sensitive parameters are shown. See Figure 1 for definition & locations of the Indicator Regions 3 - 9 that are referred to in the legend (Basin 0 is entire domain).

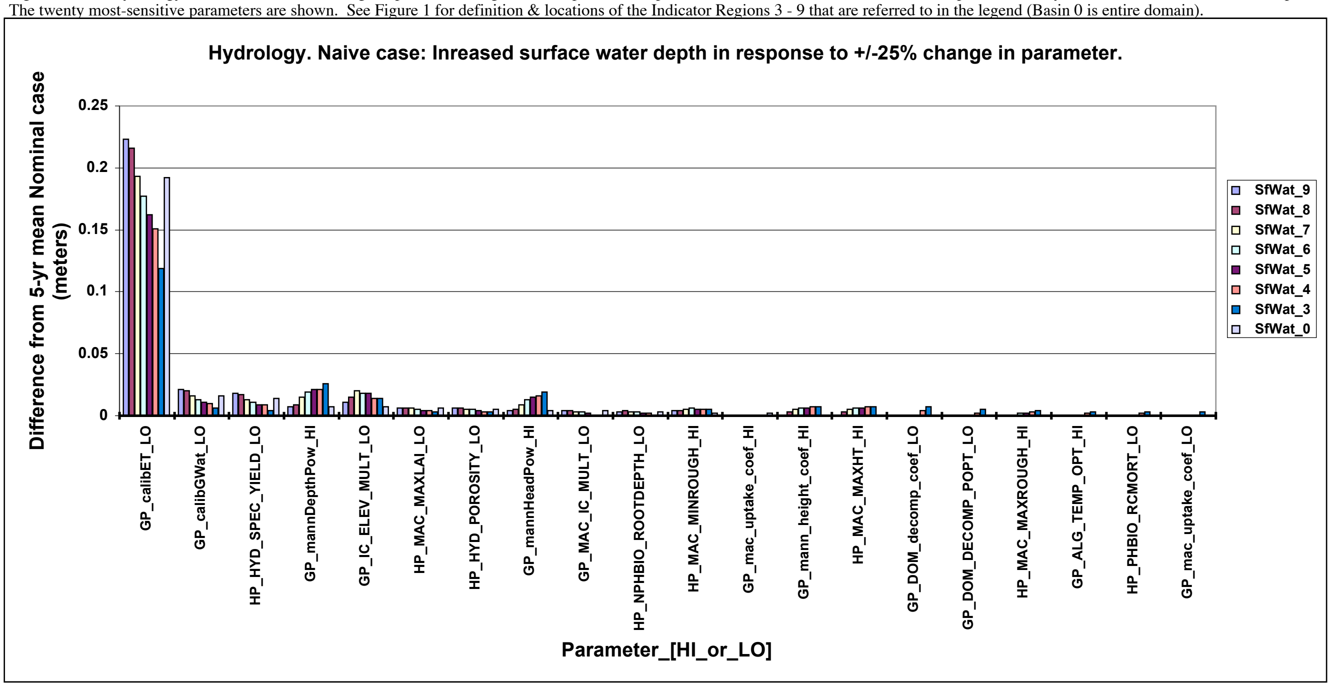


Figure 7.3.4a. Surface water TP Naive case: +/- 25% change in parameter. Lowest (most negative) output differences of Performance Measure compared to the 5-yr mean of the NOMINAL run output. The twenty most-sensitive parameters are shown. See Figure 1 for definition & locations of the Indicator Regions 3 - 9 that are referred to in the legend (Basin 0 is entire domain).

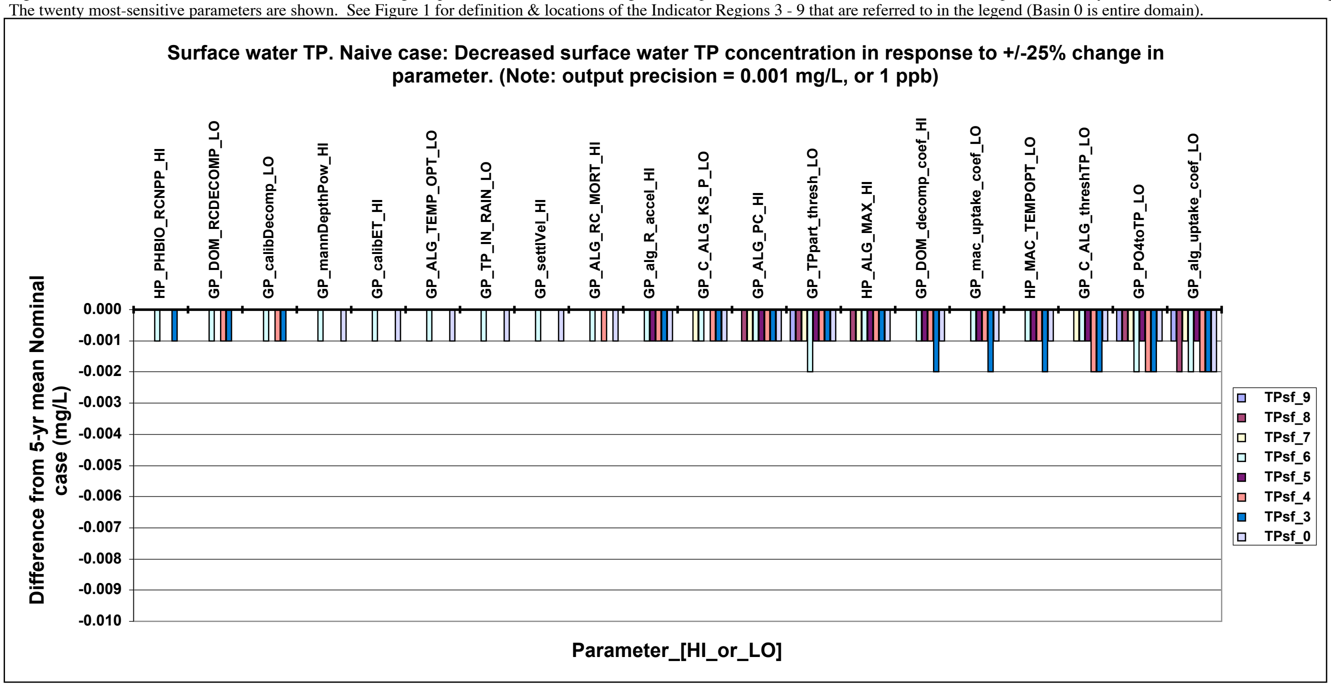


Figure 6.3.4b. Surface water TP Naive case: +/- 25% change in parameter. Highest (most positive) output differences of Performance Measure compared to the 5-yr mean of the NOMINAL run output. The twenty most-sensitive parameters are shown. See Figure 1 for definition & locations of the Indicator Regions 3 - 9 that are referred to in the legend (Basin 0 is entire domain).

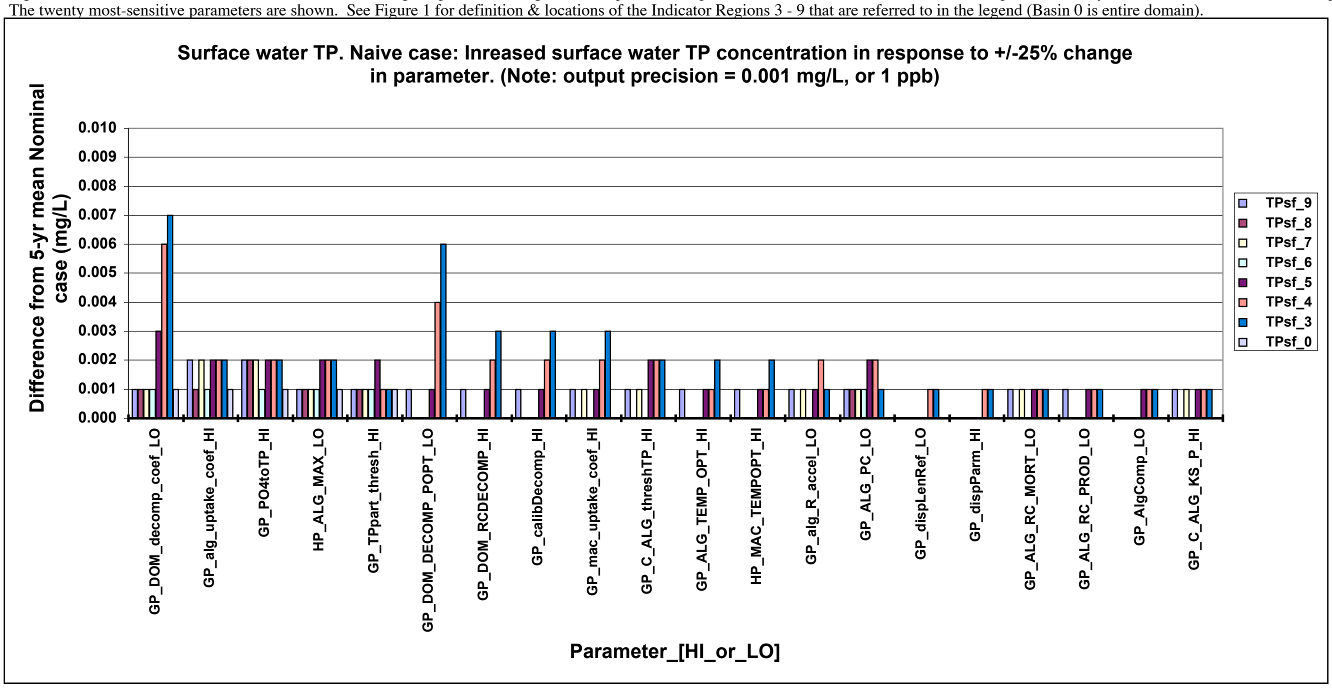


Figure 7.3.5a. Soils Naive case: +/- 25% change in parameter. Lowest (most negative) output differences of Performance Measure compared to the 5-yr mean of the NOMINAL run output. The twenty most-sensitive parameters are shown. See Figure 1 for definition & locations of the Indicator Regions 3 - 9 that are referred to in the legend (Basin 0 is entire domain).

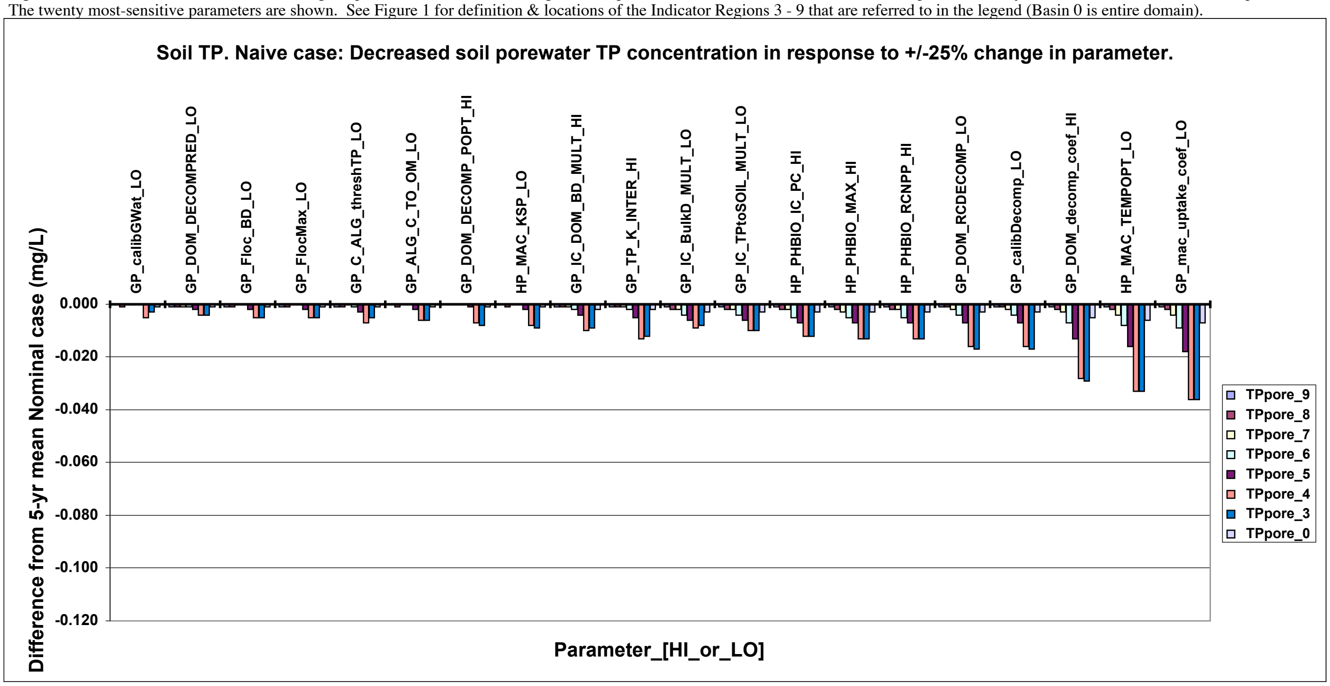
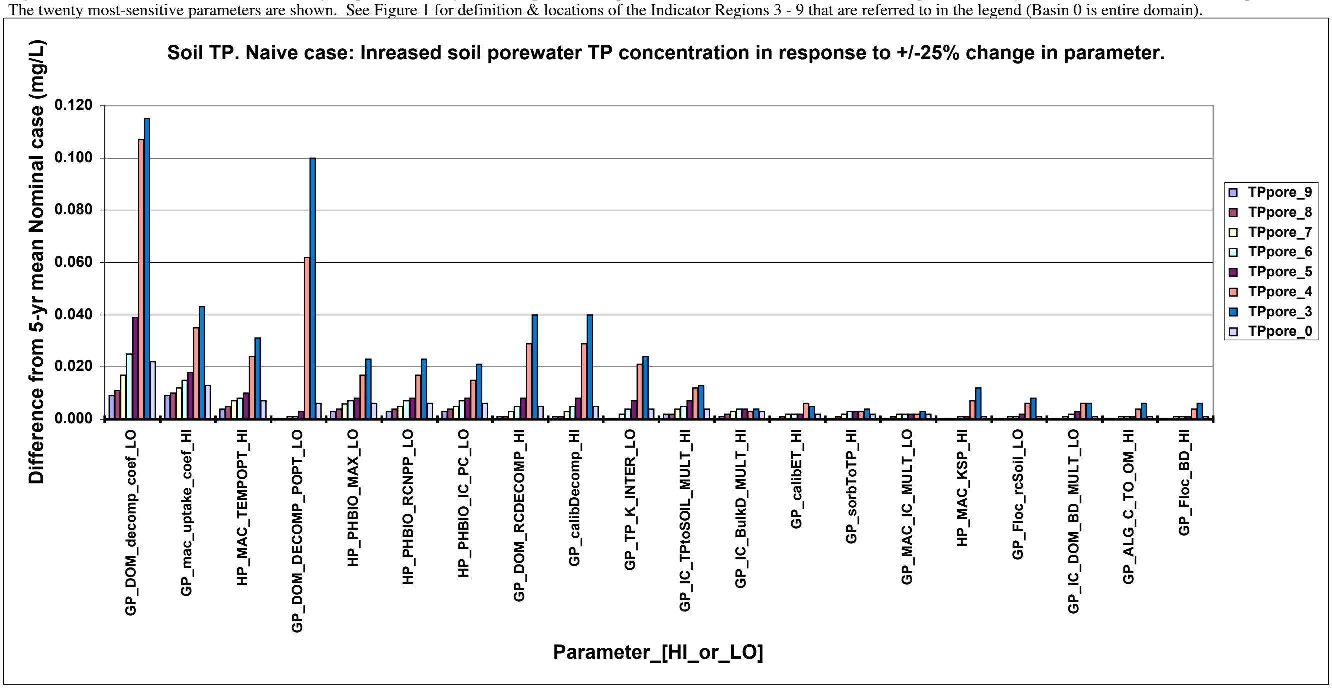


Figure 6.3.5b. Soils Naive case: +/- 25% change in parameter. Highest (most positive) output differences of Performance Measure compared to the 5-yr mean of the NOMINAL run output. The twenty most-sensitive parameters are shown. See Figure 1 for definition & locations of the Indicator Regions 3 - 9 that are referred to in the legend (Basin 0 is entire domain).



7.4 Model complexity

7.4.1 Parameters and complexity[5]

Because the ELM is a spatially distributed model of the fundamental ecosystem properties of a regional system, it necessarily uses a relatively large number of parameters to define rates, initial conditions, and various other system attributes. The parameters are not “hard-coded” into the model source code, but organized within user-friendly databases. The regional nature of this model encompasses a wide range of physical and biological characteristics. For example, a single parameter that is spatially distributed can take on a wide range of values – the important parameter of hydraulic conductivity varies over several orders of magnitude across the greater Everglades domain (see Data Chapter). To accurately communicate the data requirements of the model, the parameters should be classified according to their spatial distributions, according to their importance in influencing model results, and according to the degree to which they can be supported by available research.

Their spatial distribution is a fundamental component of these data. There are no more than approximately 40 individual parameters that are important to model results and that impose data acquisition needs. Some of these parameters are distributed in some spatial context. The spatial distributions involve those that are spatially-constant, those that are distributed among specific habitat types across the landscape, and parameters that are distributed among individual grid cells across the landscape.

While there are decades of monitoring and research activities in the greater Everglades, the past 5-10 years has dramatically increased our knowledge of system properties. Some of the parameters in use in the current ELM v2.5 have not been updated from ELM v2.1, and we anticipate that the next version of ELM (v3.0) will advance our synthesis of this base of knowledge of the Everglades.

7.4.1.1 Global parameters

As described in the Data Chapter, global parameters are those that apply uniformly throughout the spatial domain of the model. Of the 70 global parameters, 30 are unused or not intended to be modified except in model sensitivity experiments. The sensitivity analysis of this Chapter shows that a total of 23 of the 70 global parameters have the potential to affect, to at least a very small but observable extent, the hydrologic and water quality Performance Measures being considered[6]. Six of those 23 potentially- important parameters have significant effects on multiple Performance Measures.

7.4.1.2 Habitat-specific parameters

As described in the Data Chapter, habitat-specific parameters are those that apply only to the specified habitat type within spatial domain of the model. Of the 40 habitat-specific

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[5] Some of the text discussion here is also found in the Model Parameters section of the Data Chapter.

[6] Those performance measures are water depth, and TP concentration in surface and in pore water.

parameters, 5 are unused in this version of the model. The sensitivity analysis of this Chapter shows that a total of 13 of the 40 habitat-specific parameters have the potential to affect, to at least a very small but observable extent, the hydrologic and water quality Performance Measures being considered[7]. Of those 13 "important" parameters, one (1) has significant effects on multiple Performance Measures.

While each of the 40 habitat-specific parameters may have unique values for each of 28 habitats considered in the model (i.e., 1120 potentially unique values), such unique-by-each-habitat distributions do not exist for any of the parameters. The actual number of unique parameter values in the entire matrix is less than 140, with the most complex distribution of a single parameter across habitats having unique values for less than half of the habitats. When considering only the 13 "important" parameters, the actual number of unique values is 64, across all 28 habitats. Finally, only half (14) of the total number of habitats comprise >90% of the region of the ELM domain. Thus, in general, *there is, in total, on the order of several dozen unique-by-habitat values that may be important to quantify for model application*.

Of those parameters that we do assign unique values, basic field observations are used to support the parameter values. Generally, habitat-distributions of parameters are limited to differences among broadly defined ecosystem types involving *sedge, forest, savannah, and scrub* type habitats. Within an ecosystem type, any (usually limited) variation employs simple field-supported modifications of parameters according to the following: 1) slight modifications of maximum macrophyte biomass and related parameters along a gradient (e.g., the 3 cattail habitats of high, medium, and low density), 2) replication of data from one habitat type to values for a similar habitat, differing in one or two primary attributes (e.g., from a simplistic perspective, *Juncus* and *Cladium* could differ primarily in salt tolerance, with some limited structural parameter differences), and 3) specific field research and monitoring data that supports the use of distinctions among the attributes of different habitats.

Instead of supporting a parameter database that includes such a large number (28) of habitat types for 40 parameters (in a 2D array of parameters), we could obtain the same or similar model results in the current water-quality oriented version by simply not including all of the fundamental habitat types. This is attractive in terms of reducing the apparent complexity of the ELM via a smaller 2D array of parameters, but would do little to decrease the actual complexity in terms of the data that currently populates the 2D array of parameters. As discussed, the large majority of parameter values are the same for multiple habitat types, and thus the numerical complexity of such a large array is never realized. Moreover, a reduction of the number of habitat types would require increased maintenance of spatial and parameter databases, as future model updates include increased levels of differentiation among ecological dynamics of soils, periphyton, macrophytes, and habitat succession. Whereas we can currently simply improve the parameter values as data become available, the alternative is to incrementally modify both the habitat type map and the number of records supported in the database. The bottom line: from a model development and refinement perspective, it is attractive to

[7] Ibid.

maintain the two-dozen habitat types currently defined as the minimum (that only begins) to represent the regional heterogeneity across the greater Everglades.

We have taken a *simple approach that generally assumes a high degree of similarity among most habitats, while providing a database mechanism to recognize differences in attributes where they are important,* either currently or in the future. Regardless of the database implementation of habitat-specific parameters, that assumption of broadly-based habitat-similarity will remain until increased knowledge supports more refined distinctions in the heterogeneity of the greater Everglades.

The ELM “history-matching” performance was documented (see Model Performance Chapter) by a variety of analyses of an historical simulation that used single-estimates of parameters. We recognize that it can be beneficial to express the relative performance uncertainty of the model by employing distributions of uncertain parameter estimates. We plan on future refinements that will explore methods of expressing the model results in probabilistic outcomes under a range of parameter estimates.

7.5 Model numerical dispersion

There are a variety of mechanisms that result in water movement and transport of dissolved/suspended matter in hydrologic systems, and they can be conceptualized in two basic forms: *advection* and *diffusion*. *Advection* results from a unidirectional flow, such as water coursing down a river. This action of an advected water mass does not change the concentration of a mass of a solute within the water parcel, and thus does not affect the gradient of the solute within the system as the water parcel moves downstream. *Diffusion* can generally be considered to be the movement of mass due to random water motion or mixing (Chapra 1997). Molecular diffusion results from the random movement of water molecules, while turbulent diffusion is a similar type of random movement that occurs at much larger scales such as eddies. The effect is to distribute mass of solutes in the system, smoothing the gradient of concentration. The process of dispersion is closely related to diffusion in that dispersion also results in the lateral spread of the mass or concentration of the solute in the system. One may consider dispersion to be a special class of diffusion, at least with respect to the results of the processes. Dispersion, however, is the result of velocity differences across space, as opposed to random motion of water. It may be apparent that the spatial and temporal scale of observing, or modeling, the system is a critical characteristic that must be considered when exploring the contributions of these flux processes.

In dynamic modeling of flowing, spatially distributed (e.g., gridded) systems, the numerical solution technique has an effect on the accuracy of the model prediction. Use of an explicit, finite difference technique (such as used in ELM), is known to result in numerical errors that have the effect of dispersing the concentration of a solute in the system (Chapra 1997), (many others). Note that numerical dispersion (errors) can be assumed to have the same effect on solute gradients that real diffusion/dispersion in the observed system.

This numerical dispersion (error) is very sensitive to scale: numerical dispersion is increased by increasing the size of the model grid, and/or by increasing the number of temporal iterations per unit of time (i.e., decreasing the model time step, *dt*).

Additionally, this spatio-temporal relationship is a non-linear function of the modeled system's water velocity. Figure 7.5.1 demonstrates this relationship for scales that are pertinent to the ELM, which uses a 2 hour time step when implemented with a 1 km square grid. There are two important points to note. 1) The Everglades operates at velocities that are likely well under 5 cm•sec^{-1}, with measured velocities (Lee and Carter 1999, Ball and Schaffranek 2000, Schaffranek and Ball 2000, DBEnvironmental 2002, Noe et al. in press) in northern and southern regions of the Everglades generally less than 1-2 cm•sec^{-1}, (though Ball and Schaffranek (2000) measured a peak of 4.7 cm•sec^{-1} downstream of outflows from the L-31W canal apparently due to a pump test of the S-332D structure and releases due to tropical storm Harvey (Schaffranek and Ball 2000). 2) At the 3000 m model grid scale (slightly smaller than that of the 2 mile SFWMM), numerical dispersion is very high at all velocities.

While these numerical diffusion estimates are useful to understand the magnitude of the *potential* effect on ELM results, we (previously) implemented the model (ELM v2.1) at three different spatial scales in order to evaluate the *actual* effect on ELM results (Fitz et al. 2002). Using model implementations at 100, 500, and 1000 m grid scales in Water Conservation Area 2A, we showed that the highest numerical dispersion, at a 1000 m grid scale length, is of the same order of magnitude as dispersion estimates for a wetland system such as this. DBEnvironmental (2002) provided estimates of various hydraulic parameters that were obtainable from tracer dye studies in the Cell 4 wetlands of STA-1W. One of the estimated parameters they provided was the dispersion number D_n, which is a function of the dispersion coefficient D(m^2•d^{-1}), the nominal water velocity u (m•d^{-1}), and the pathlength of flow l (m) as follows:

$$D = D_n \bullet u \bullet L$$

They reported D_n ranging from 1.25 – 2.75 (dimensionless) from the Cell 4 dye study. Using a mean measured velocity for (for a different period but similar hydraulic conditions) of 0.54 cm•sec^{-1}, a path length of about 3000 m, a dispersion coefficient D would be roughly 1.5 – 4 million m^2•d^{-1}. While these somewhat incomplete data could possibly represent an overestimate of dispersion, it was clear that the numerical dispersion in the regional 1km^2 ELM (ca. 200,000 m^2•d^{-1} for a similar velocity) did not introduce significant bias to predictions of gradient dynamics, as the actual dispersion is at least the same order of magnitude as numerical dispersion in the 1km^2 ELM applications.

Because of this uncertainty in the magnitude of dispersion, we expanded (from ELM v2.1) the model's purely advective equations of flow, including a dispersion component. The ELM v2.5 Anti-Numerical Dispersion (AND, see Model Structure Chapter) algorithm is based simply on the well-known equation describing the behavior of the explicit solution technique. The AND was expanded to include the true dispersion estimates based on the equation (Wool et al. in press):

$$\frac{dM_{i,k}}{dt} = \frac{E_{i,j}(t) \bullet A_{i,j}}{L_{i,j}} \left(C_{j,k} - C_{i,k}\right)$$

where:

$M_{i,k}$ = mass of nutrient "k" in cell "i", g

$C_{i,k}$, $C_{j,k}$ = concentration of nutrient "k" in cells "i" and "j", g/m^3 (mg/L)

$E_{i,j}$ = dispersion coefficient (time function) for exchange "i,j", m^2/day

$A_{i,j}$ = interfacial area shared by cells "i,j", m^2

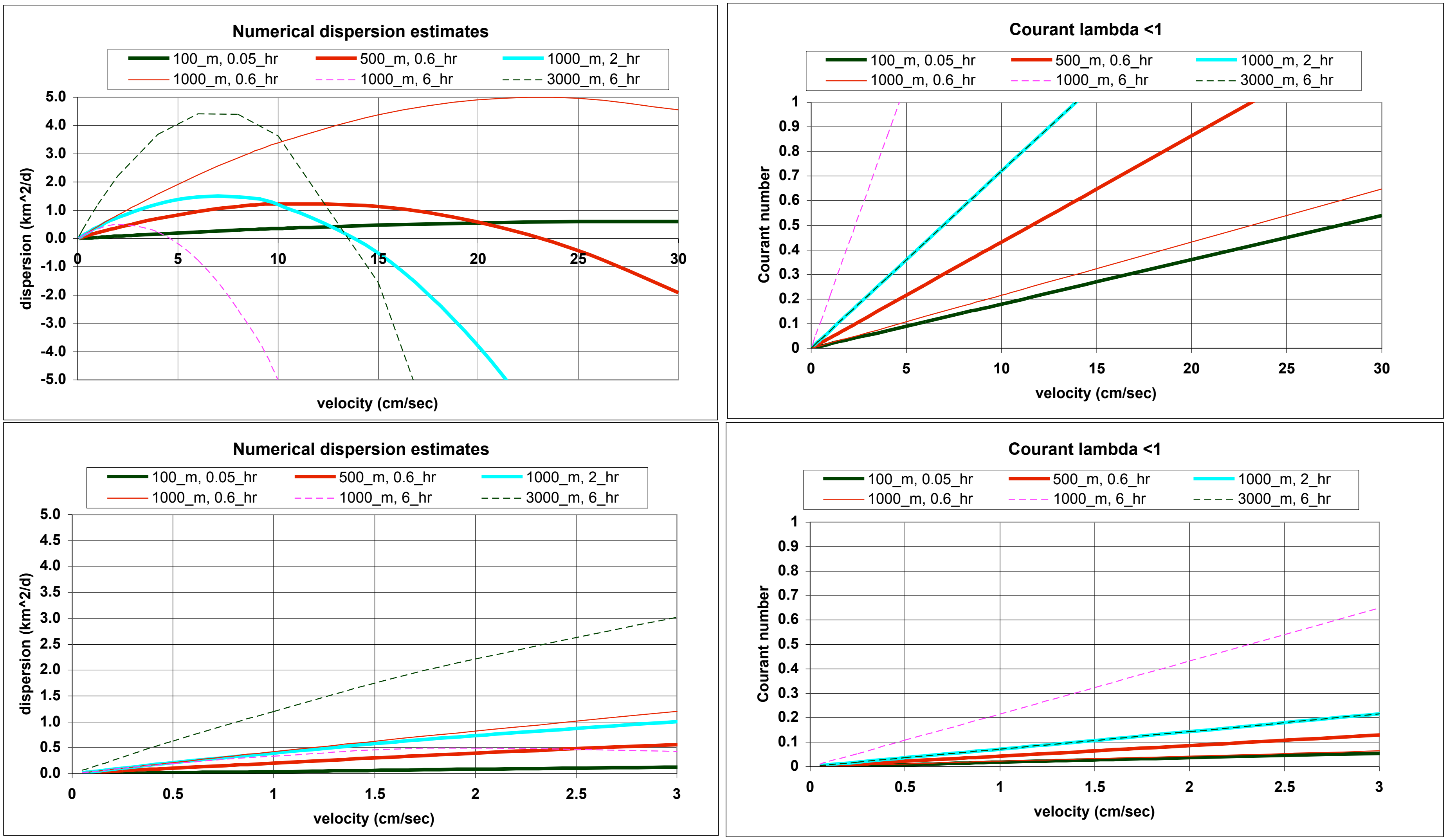
$L_{i,j}$ = mixing length between cells "i,j", m

With this simple algorithm, the degree of (numerical) dispersion in ELM can be maintained independent of model grid scales (using the length scale parameter), and the velocity-varying actual dispersion can be proscribed with the dispersion coefficient. However, this remains a relatively coarse “calibration knob”, as significantly more field-based evaluations are necessary to better estimate the true magnitude of dispersion under Everglades conditions.

7.5.1 Figures: dispersion

One Figure follows this page.

Figure 7.5.1. Calculated numerical dispersion and Courant lambda of finite difference models at different time steps and different (regular) grid scales. Courant numbers >1.0 have a tendency towards instability in the hydrologic flux solutions.



7.6 Model "validation"

It is uncertain that a classical "validation" process is required to demonstrate the utility of models. Validation is no longer considered the most credible way to evaluate model performance (Kleindorfer et al. 1998). "Verification and validation of numerical models of natural systems is impossible" (Oreskes et al. 1994). Logically, aka (Popper 1959), this appears to be true. Others (Konidow and Bredehoeft 1992, Beven 1993, Rastetter 1996) agree. However, it does not appear necessary to "validate" models. To build confidence in the models' utility, one needs to demonstrate that it performs in a manner consistent with objectives. A major utility of process-based models such as ELM is in synthesis of accumulated knowledge. Through this synthesis, we gain understanding of the system. And develop a self-consistent synthesis of the complex interactions in the bio-physical-chemical landscape (Rastetter 1996). With increasing knowledge of the system, and increasing confidence in the model performance for particular objectives, we can think about making projections of potential ecological (or hydrological) responses to external change. But models of complex systems – whether they are simple black-boxed numerical interpretations such as the DMSTA[8], or complex numerical interpretations such as ELM, SFWMM, ATLSS[9] models, Global Climate Models, – are not going to be "accurate" predictors of the future. These models still can be credible tools for evaluating potential scenarios of change. A credible, if imperfect, model is far better than reductionist "best guesses" when embarking on complex system changes – such as the restoring the Everglades, or ameliorating CO_2 increases in the atmosphere.

Very important for achieving credibility of a model is the demonstration of sufficiently high levels of performance under a wide range of conditions (external and internal). The longer the time scale over which observations are available for comparison, relative to the predictive time scales of the model, the more credible the model. The (previous version) ELM v2.1 simulated the historical period from 1979 – 1995, encompassing a wide range of drought and flooding conditions, with widely varying phosphorus inputs (ELM_Team 2002). As part of the update to ELM v2.5, we acquired new 1996-2000 data that can be used to "validate[10]" ELM (see Model Performance Chapter); however, we primarily offer those analyses as further demonstrations of the credibility of this model as a potential forecasting tool. In the Model Performance Chapter, we presented an evaluation of the performance of ELM under the new and extended forcing data, demonstrating that the model was validated in the "classical" sense. However, even though such an update indicated consistent -or better - levels of model performance in both periods of time, the process in itself did not sufficiently dictate "trust" in the model reliability. Most valuable for enhancing any model credibility would be the introduction of some suite of external inputs that are very different from those observed in prior years that have been used. However, the additional years appended onto the ELM simulation period did not appear to have any such dramatic change in external forcings, i.e. that extended beyond that of the past variability. In actuality, this '96-'00 extension to ELM v2.5 was merely a part

[8] Dynamic Model of STAs, http://wwwalker.net/dmsta/index.htm

[9] Across Trophic Level System Simulation, http://atlss.org

[10] sensu the traditional or classical use of the term

of the process of refining a model: an extended synthesis of new data, and enhancing the model performance relative to objectives.

An important part of a model evaluation is how effective the code logic is, and how effectively it is parameterized to meet the performance goals. In past comments on ELM, a reviewer pointed out that there could be other combinations of parameters that could provide a good model fit for TP concentration in the surface water. Indeed, any model with a few parameters or more can possibly have more than one combination of parameters to achieve a same/similar statistical fit of the model to observed data for one particular target variable. Fine tuned parameter sets for model calibrations are never unique (Spear 1997). It is likely that another combination of parameters could be found that will result in comparable performance of ELM predictions of TP concentration in the water column. However, in our testing of the model performance to different parameters, we explicitly evaluate more than just a single target variable to ensure that other components of this complex, interactive system remain within targeted boundaries. Thus, it is important to evaluate whether the proper mechanisms are responsible for model predictions.

Recently there has been significant discourse on what is truly meant by “model validation”, and the means by which to communicate the level of trust in the application of a particular model. Model validations include both conceptual validity and operational validation (Rykiel 1996, Parker et al. 2002). Conceptual validation checks if the theories, hypothesis, assumptions, system structures and processes underlying the model are sound and justifiable. Operational validation tests how well the model mimics the system. It does not, however, guarantee that the mechanisms contained in the model are scientifically complete and correct (Rykiel 1996). To re-iterate, we argue that it is impossible to validate models because the natural system is open and constantly evolving (Oreskes et al. 1994, Rastetter 1996, Oreskes 1998, Haag and Kaupenjohann 2001). As previously indicated, a simple dictum is operative: Models can only be falsified; they cannot be validated (sensu Popper 1959).

Despite this discourse on the logic associated with traditional validation, we have previously shown the ELM to be validated in this traditional sense (Model Performance Chapter). However, after a single parameter or equation is modified (in order to expand Performance Measures beyond water quality, or to improve water quality performance), the model will no longer be “validated” in the strict sense of unchanged models tested against ever-increasing extents of boundary conditions. Instead, we need to evaluate how consistently the model performs under an increasing range of conditions; adding 6 months, one year, or five years to a model’s Period of Record does not necessarily enhance credibility. Most important to enhanced model credibility is a demonstration of consistent, unbiased performance under very new boundary condition forcings (such as the 1994-95 high water years, or 1990 drought and associated changes in flows and loads).

Models are used to provide synthesis, reveal system properties, and outline system behavioral possibilities (Joegensen et al 1995; Rastetter, 1996; Haag and Kaupenjohann, 2001). It is the communication with model stakeholders that is essential to effect model validation and conformance with its intended purpose and performance criteria (Korfmacher 1995, Kleindorfer et al. 1998, Parker et al. 2002). ELM will be constantly updated and evolve, but it will not be "validated" under all conditions. Nor will other models.

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