Coastal Protection and Restoration Authority

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2017 Coastal Master Plan

Attachment C3-24: Integrated Compartment Model Uncertainty Analysis

Report: Version I

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Coastal Protection and Restoration Authority

This document was prepared in support of the 2017 Coastal Master Plan being prepared by the Coastal Protection and Restoration Authority (CPRA). CPRA was established by the Louisiana Legislature in response to Hurricanes Katrina and Rita through Act 8 of the First Extraordinary Session of 2005. Act 8 of the First Extraordinary Session of 2005 expanded the membership, duties, and responsibilities of CPRA and charged the new authority to develop and implement a comprehensive coastal protection plan, consisting of a master plan (revised every five years) and annual plans. CPRA's mandate is to develop, implement, and enforce a comprehensive coastal protection and restoration master plan.

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Executive Summary

In long-term coastal planning efforts, especially one as critical as the Louisiana Coastal Master Plan, it is important to consider the effects of uncertainties on predicted outcomes. To build upon the 2012 Coastal Master Plan modeling effort, the approach proposed herein provides a framework to perform the uncertainty analysis (UA).

A coast wide Integrated Compartment Model (ICM) has been developed as a landscape model for use in the 2017 Coastal Master Plan. It includes hydrology, water quality, morphology, vegetation, barrier islands, and habitat suitability indices. In the modeling effort of the 2017 Coastal Master Plan, two primary sources of uncertainties were investigated. First is the uncertainty in the environmental drivers, namely, eustatic sea level rise, subsidence, precipitation, and evapotranspiration. This uncertainty was addressed through an environmental scenario approach, where the modeled landscape response was evaluated across different combinations of values for these environmental drivers (Appendix C – Chapter 2). The second source of uncertainty investigated is associated with the calculations of critical model variables and how they influence key model output. This component of the UA is the focus of this report. The main objective of this analysis is to quantify the magnitude of the uncertainty in key model output driven by uncertainties in critical model variables. Land area was identified as the key model output for the analysis. The analysis performed here is applied to the validated future without action (FWOA) ICM model simulation, also referred to here as the base case.

The uncertainty analysis approach utilized in this report was based on applying perturbations to model variables that are directly linked to the calculations of land area. The model variables examined include water level, salinity, wetland types, suspended mineral sediment concentration, and organic accretion. The magnitudes of the perturbations were estimated based on the calibration errors, and were then applied annually and for the duration of the 50-year simulations.

The perturbations were initially applied individually to identify which model variables had significant impacts on land area. The individual perturbations showed that water level and organic accretion have the most influence on land area. Salinity, while having an influence on the wetland type, did not have significant impact on land area. Land area was also not impacted significantly by total suspended sediment. Perturbations to predicted areas of different wetland types were not included here as they were controlled by the prevailing hydrologic conditions. As such, the uncertainty in land area, as determined by wetland type, was determined indirectly via perturbations to hydrologic conditions, and as such uncertainties due to vegetation type were removed from further consideration.

The uncertainty range resulting from linearly adding the uncertainty of the individual perturbations was compared to the outcome of a set of 16 experiments designed to examine the interdependency among the uncertainty of the model variables. The comparison showed that the uncertainty range resulting from the 16 experiment composite set was wider than the linearly added uncertainty bracket. This outcome demonstrates that interdependency among the model variables is important. The results of the composite experiments show that water level, organic accretion, and their interdependence are the most influential on coast wide land area.

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List of Abbreviations

BD	Bulk Density
CPRA	Coastal Protection and Restoration Authority
FWOA	Future Without Action
ICM	Integrated Compartment Model
MAE	Mean Absolute Error
OM	Organic Matter
RMSE	Root Mean Square Error
TSS	Total Suspended Solids
UA	Uncertainty Analysis

1.0 Introduction

1.1 Rationale and Background

Understanding and quantifying uncertainties associated with numerical model predictions is important for planning activities such as Louisiana's Coastal Master Plan. An uncertainty analysis (UA) was conducted for the 2012 Coastal Master Plan landscape modeling effort (Habib & Reed, 2013), but the results were not available in time to be used in the decision making (plan formulation) process. A new landscape modeling approach has been developed for use in the 2017 Coastal Master Plan. The Integrated Compartment Model (ICM) is a coast wide landscape model capable of generating 50 year simulations. It is comprised of the following subroutines: hydrology and water quality, morphology, vegetation, barrier islands, and habitat suitability indices. An overview of the ICM components is found in Appendix C – Chapter 3.

Two primary sources of uncertainties were investigated for the ICM. First, is the uncertainty in the environmental drivers that govern the overall model dynamics. This was addressed through identifying plausible values for environmental drivers that are combined into a number of scenarios that then allow examination of the landscape response to variations in the drivers (Appendix C – Chapter 2). The environmental drivers evaluated include eustatic sea level rise, subsidence, precipitation, and evapotranspiration. The second source of uncertainty is associated with the values of variables calculated by the numerical models. This component of the UA is the focus of this report. A goal of this analysis is to understand the magnitude of the uncertainty in the output of the ICM due to uncertainties in specific model variables. The basic structure of the ICM is described in Appendix C – Chapter 3. As information is passed from one ICM subroutine to another, the effects of uncertainties on model outputs may increase; for example, as information passes from the hydrology subroutine to the morphology subroutine and eventually to the vegetation and habitat suitability index subroutines, uncertainty may increase. Conversely, uncertainties could be dampened or reduced due to temporal or spatial integration calculations (e.g., use of two-week mean salinity in the morphology subroutine based on daily outputs from the hydrology subroutine). The dual sources of uncertainty (environmental scenarios versus model parameters) are assumed independent of one another; however, the relative sensitivity of the ICM to these two sources is not. For example, as relative sea level rises substantially in later decades under a high scenario, the model prediction of land area will likely be much more sensitive to sea level rise rates than a temporally static model error in mean water level predictions; the uncertainty due to model error is inversely proportional to environmental scenario "severity." Therefore, the low scenario for future environmental conditions (e.g., low sea level rise, low rates of subsidence, and a relatively wet future) was chosen for this analysis of model parameter uncertainties. In other words, it is assumed for this analysis that the uncertainty in land area with respect to model error will be greatest under a least "severe" future environment.

1.2 Terminology

Below is a brief definition of three terms that are used in this document. The definitions provided here are to ensure clarity of what each term refers to herein:

- Parameters: This term refers to model coefficients such as roughness, diffusion, bulk density, etc.

- Variables: This term refers to "state variables" such as water level, salinity, and anything the model actually "calculates."
- Drivers: This term refers to external boundary conditions that "drive" the model (e.g., eustatic sea level rise, subsidence, precipitation, evapotranspiration, etc.).

2.0 Approach

2.1 Overview of 2012 Coastal Master Plan Uncertainty Analysis

The 2012 Coastal Master Plan effort included an UA (Habib & Reed, 2013). The 2012 UA focused on parametric-related uncertainties, which are due to imperfect knowledge about the parameters and relationships used within the models. Due to the large number of individual models used in the 2012 Coastal Master Plan, a practical approach was followed where a reduced set of model parameters (34) was identified as being most uncertain. A stratified sampling experiment was designed from pre-defined simple probability distributions of the selected parameters. Two phases of the UA were conducted. The first phase (project-level) focused on examining the impacts of parameter uncertainties on model predictions and comparing such uncertainties to the predicted impacts of individual projects. The second phase (alternative-level) focused on comparing model uncertainties in predicting the future without action (FWOA) conditions versus a draft version of the master plan.

Questions asked in the 2012 UA:

- How uncertain are the models in predicting changes in key ecosystem metrics?
- Does the uncertainty vary spatially across the coast and temporally into future years?
- How do parameter-induced uncertainties compare with those due to other large-scale environmental (external) drivers? The 2012 effort included a comparison of land-area predictions with two FWOA environmental scenarios (moderate and less optimistic), which reflected uncertainties due to large-scale external drivers such as subsidence, eustatic sea level rise, precipitation, etc.
- How can the uncertainty analysis inform decisions?

Lessons learned from the 2012 UA:

- The model-induced uncertainties did not greatly affect the total coast wide predicted land gains provided by the master plan over the next 50 years, although uncertainties of model predictions did grow as the predictions extended into the future years. The degree and significance of such growth varied from one region to another.
- Projected changes in ecosystem outcomes, such as oyster and brown shrimp habitat suitability indices, included greater levels of uncertainties when compared to land area. In general, model uncertainty in predicting these types of outcomes varied substantially across the coast.
- A comparable magnitude was found of the two types of uncertainties (external and parameter-related), which indicates the importance of both types in determining coast wide outcomes as well as regional patterns.

2.2 Uncertainty Analysis Approach for the Integrated Compartment Model

The ICM includes a number of subroutines (e.g., hydrology, vegetation, and barrier Islands) that have been independently calibrated. Specific model variables are calculated in one subroutine then are passed to other subroutines to perform other calculations. For example, salinity is calculated in the hydrology subroutine, and then it is passed to the vegetation subroutine where it is used to determine the establishment of various vegetation species. Ultimately, output from these calculations will be used to inform the development of the 2017 Coastal Master Plan.

The UA process starts with identifying key model variables during the ICM calibration process (Attachment C3-23 – ICM Calibration, Validation and Performance Assessment) as those that influence important model output. The uncertainty range for these key model variables is calculated using statistical tools to assess the model performance during the calibration process. The statistical tools include Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). In the UA, a set of numerical experiments was designed to explore how uncertainties in the model variables, calculated during calibration, influence specific model output variables. This approach was recommended by the Predictive Models Technical Advisory Committee.

Although the ICM produces a large number of outputs that are used in plan formulation for the 2017 Coastal Master Plan, this analysis focuses on land area, as it is a key decision driver in selecting projects for inclusion within the plan. Thus, the focus of this UA is on how the uncertainties identified during calibration collectively influence the calculation of land area.

Land area is both a key decision driver during plan formulation and an important metric in reporting the master plan's effects over 50 years. In addition, different projects interact in the landscape in a complex manner to influence the amount of land maintained, created, or lost. Accordingly, such analysis can be conducted in phases collectively addressing three questions:

1. How does parametric uncertainty influence model predictions of land area (both spatial distribution as well as temporal evolution) for FWOA?
2. Is land area produced by large-scale restoration projects (sediment diversions or marsh creation) more/less uncertain than land area predicted under FWOA?
3. What is the level of confidence in the predictions of land area produced by the draft/final master plan?

The design of each phase builds on what has been learned regarding the role of parametric uncertainty in previous phases. This report focuses on the first phase (addressing question 1 above). The outcome of the first phase can be used in the experimental design of subsequent phases of this analysis.

The UA is guided by the calibration analysis for each of the subroutines that substantially influence the calculation of land area. Given that the barrier island calibration has been based on a visual fit of island profiles and shoreline position, and thus has not produced a quantified calibration error, the effect barrier islands on total land area is not considered herein.

The following key model variables influence land area and have quantified calibration error:

- **Annual water level**: Provided by the hydrology subroutine to the morphology subroutine and used in marsh collapse threshold calculation for non-fresh vegetation wetland types.
- **Standard deviation of annual water level**: Provided by the hydrology subroutine to the vegetation subroutine and used to determine vegetation species distribution and thus vegetation wetland type.
- **Two-week salinity**: Provided by the hydrology subroutine to the morphology subroutine and used in marsh collapse threshold for fresh vegetation wetland type.
- **Annual mean salinity**: Provided by the hydrology subroutine to the vegetation subroutine and used to determine vegetation species distribution and thus vegetation wetland type.
- **Total suspended solids (TSS):** Used to calculate mineral sediment depositional rates in the hydrology subroutine, which are then used in the morphology subroutine to calculate accretion.
- **Wetland type – fresh marsh**: Wetland type provided by the vegetation subroutine to the morphology subroutine where it is used to apply marsh collapse threshold and to determine organic components of accretion.
- **Wetland type – intermediate marsh:** Wetland type provided by the vegetation subroutine to the morphology subroutine where it is used to apply marsh collapse threshold and to determine organic components of accretion.
- **Wetland type – brackish marsh**: Wetland type provided by the vegetation subroutine to the morphology subroutine where it is used to apply marsh collapse threshold and to determine organic components of accretion.
- **Wetland type – saline marsh:** Wetland type provided by the vegetation subroutine to the morphology subroutine where it is used to apply marsh collapse threshold and to determine organic components of accretion.
- **Organic loading component of annual accretion:** Calculated within the morphology subroutine based on wetland type and used to determine elevation and thus land loss/maintenance.

For the first five variables listed above, a calibration error was determined based on the calibrated hydrology subroutine. In the development of the vegetation subroutine, the calibration error was determined based on the percent of 500 m x 500 m cells that had a positive match (against observations) for species and the percent of cells that had a correct negative match. For this UA, a calibration error was estimated using the same data sets but for the percent of cells where the wetland type, not the species, was a correct match. The UA for the tenth variable listed above, the organic loading component of the annual accretion, was not based on the calibration error; rather, the UA for vertical accretion was based on uncertainty of organic matter (OM) and bulk density (BD) input data. This was derived from the range of data used to regionally estimate OM and BD based on wetland type.

3.0 Methodology

The UA was conducted on version 1 of the calibrated ICM, and the input variable values for the initial condition were not changed (Appendix C3-23 – ICM Calibration and Validation). All UA model runs used the same scenario values for the environmental drivers. The low scenario (S01) was selected as it resulted in less land loss than the other scenarios tested (Appendix C - Chapter 2); this enabled the response of land area to the UA to be better identified.

A perturbation term, ε, derived from the calibration error was introduced to the targeted model variable after it is calculated within the associated subroutine but prior to use by the next subroutine. Only one model variable was perturbed per simulation, and the perturbation value was maintained throughout the 50-year simulation. Figure 1 illustrates how the perturbations were applied.

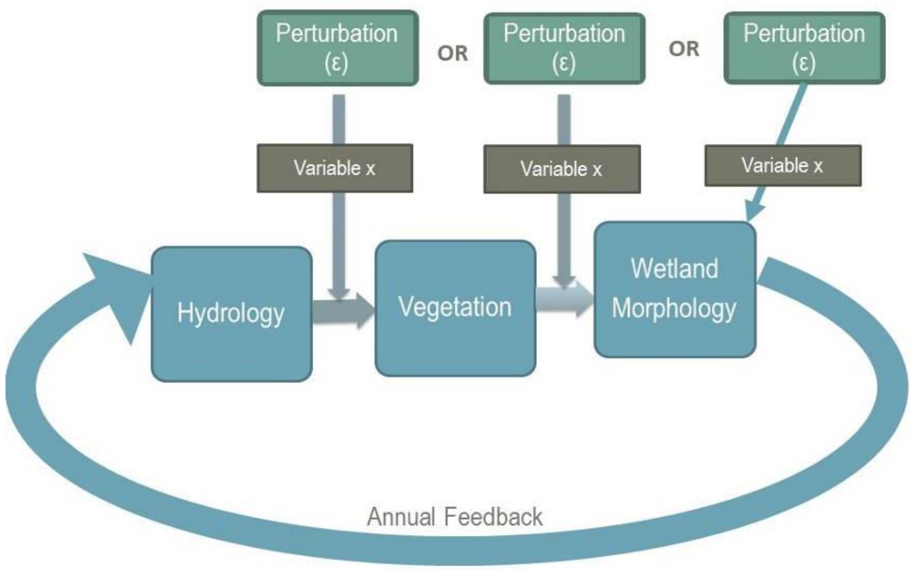

Figure 1: Conceptual Diagram for Phase 1 Parametric Uncertainty Approach (U01 – U20).

There are considerations that should be observed regarding the perturbation values used in the analysis:

- Perturbation values do not result in a non-physical or unnatural value for the variable under examination (e.g., negative salinity). If this occurred, adjustments were made to ensure a spread of values within the acceptable range was tested;
- For variables that were calibrated in a spatially variable manner, the perturbation values were also varied spatially. For example, the perturbation applied to salinity in a fresh environment was of different magnitude compared to saline areas; and
- Perturbations are constant in time. The magnitude of the perturbation was not adjusted from year to year during a 50-year simulation. Little is known about how the error would change with time, and as such, any temporal adjustment would be difficult to justify.

The next section provides the perturbation values used to perform the UA experiments. For example, for the UA experiment where the annual water level is perturbed, at the end of year 1, the annual water level for each cell is perturbed by the specific amount (e.g., the +75 percentile). The increased water level values are then used in year 1 of the morphology subroutine to calculate whether the marsh collapse threshold has been exceeded. The values are also used in the vegetation model to determine which species are present, and thus which wetland type is dominant. This increase may or may not result in greater land loss in year 1. The landscape topography and bathymetry is updated accordingly and used as input for the hydrology calculations for year 2. The year 2 annual water level is calculated based on the model dynamics and year 2 boundary conditions. When the annual water level is passed to the morphology subroutine, it is perturbed again by the same magnitude. By applying the perturbation term 'between subroutines' as shown in Figure 1, the effects of the uncertainty in water level are included in the land calculation without altering the basic hydrology of the model. This approach focuses on the uncertainty of the targeted model variables and how it influences the key model output while sustaining the integrity of the model calibration since the perturbations are introduced after the targeted model variable is calculated in the relevant subroutine.

3.1 Estimating the Perturbation Terms for Water Level, Salinity, and Total Suspended Solids

For annual water level, standard deviation of annual water level, two-week salinity, and TSS a distribution of points around the mean was derived based on the statistical analysis performed during the calibration process. The two-week salinity comparison is a more stringent assessment on model performance than annual mean salinity (see Section 4.0). Therefore, all salinity perturbations throughout this analysis were based solely upon the two-week error values. The mean is the variable value used in the calibrated model, but a probability distribution of the error around the mean is not fully known; therefore, a normal distribution was assumed and used to calculate the +/- 25th and +/- 75th percentiles for both the RMSE and the MAE. The UA considered the composite uncertainty of multiple variables (the list of 10 variables provided above in Section 2.2). This led to the decision to select the 25th and 75th percentiles instead of a wider range (e.g., 5th and 95th percentiles). If a wider range is considered, the likelihood of occurrence of the 5th or 95th percentile of all model variables simultaneously is quite low. The 25th and 75th percentiles present a more likely space of occurrence.

The difference between the RMSE and MAE and whether one statistical tool is favorable over the other in terms of average model performance has been argued in literature (e.g., Willmott & Matsuura, 2005; Chai & Draxler, 2014). Although it is beyond the scope of this document to contribute to this debate, the MAE assigns a linear score where all individual differences are weighted equally in the average, while the RMSE gives a relatively high weight to large errors.

For this analysis, the MAE was used to estimate the perturbation values for all variables, with the exception of TSS, which had a much wider spread in error magnitudes. Furthermore, to account for the wide range in TSS values, the error was also adjusted as a percentage, rather than as a simple magnitude. This allowed for regions of the model with higher TSS concentrations to be perturbed by a value on the same order of magnitude as the predicted values. A similar approach was used for the salinity perturbations, but rather than a percent error term, the salinity observations were bracketed into four regimes, ranging from fresh to saline, so that the error in fresh areas would not unduly result in a lower magnitude of perturbation in the saline regions.

A set of experiments was designed (described in detail in Section 4 below), and the error terms used in the perturbations are summarized in Table 1.

Table 1: Error Terms from the Hydrology Subroutine Calibration Period used to Perturb the Integrated Compartment Model (see Appendix C-23 ICM Calibration and Validation for error terms and discussion).

Parameter	Units	Number of Observations	Mean Model Error		75th Percentile Perturbation
			Root Mean Square Error	Absolute Mean Error	
Annual Water Level	m	204	-	0.07	0.1
Annual Water Level Variability	m	204	-	0.018	0.03
Annual TSS	mg/L	146	25	-	70%
Two-week Salinity 0-1	ppt	55	-	0.2	0.3
Two-week Salinity 1-5	ppt	51	-	0.8	1.2
Two-week Salinity 5-20	ppt	74	-	1.6	1.9
Two-week Salinity 20-35	ppt	4	-	2.8	3.7

3.2 Estimating the Perturbation Terms of Wetland Types

During calibration of the vegetation subroutine, a percent correct match value for each year of the calibration period was determined for each wetland type. That percent is based on all the cells across the coast for which calibration data are available. These data could, theoretically, be used to perturb the model prediction of coverage area for each wetland type. One perturbation value could be chosen for each wetland type and at the end of each model year, the vegetation subroutine could adjust the cover of all species present that are classified as the perturbed wetland type (e.g., all species that are within the brackish wetland type) by the chosen perturbation value in each grid cell. While such an approach would be analogous to the perturbations made to the other model subroutines, the resulting vegetation coverages would not be consistent with the hydrodynamic conditions, resulting in the vegetation coverage simply reverting to the previously calculated vegetation coverage.

For example, consider the case where saline marsh coverage is to be perturbed in the negative direction, meaning decreasing their presence while the non-saline species would have their coverage increased. The model would convert saline marsh areas to non-saline types; however, during the next model year, the hydrodynamic conditions (e.g., salinity and water level variability) would still result in conditions in which the model would predict saline marsh was present. The vegetation model is a niche model that allows for the immediate establishment and growth of appropriate species for the current conditions (if they are within the dispersal distance); therefore, the perturbed output would simply revert to the vegetation type preferred by the model during the next model year.

The initial intent of this analysis was to determine the uncertainty associated with each model subroutine. However, the perturbation of the vegetation output would not be sustained unless the hydrodynamic model outputs are concurrently perturbed. In essence, perturbing the hydrodynamic model is sufficient to provide an idea about the impact and variability to the vegetation output. Specifically, the two primary drivers of the vegetation model, salinity, and water level variability were already included in this analysis. As will be shown in a later section, the perturbations of these two variables do not have a particularly large impact on the modeled coast wide land area, but they do result in different vegetation patterns. This provides an indirect approach to assess the impact of uncertain vegetation coverage on predicted land loss in the model. Therefore, the vegetation model output was not perturbed as part of this analysis.

3.3 Estimating the Perturbation Terms for Organic Loading

The accretion calculation within the morphology subroutine is derived from two sources: 1) the inorganic sediment load predicted by the hydrology subroutine, and 2) the OM and BD values assigned to each marsh type (this is spatially varied across the coast). As discussed above, the uncertainty in the mineral depositional rates was perturbed based on the hydrology subroutine's TSS calibration statistics. The uncertainty in the organic component is not easily quantified from the measured Cesium cores used in the calibration of the subroutine. Therefore, in the UA, the organic portion of the accretion calculation was perturbed based on the variability of the measured OM and BD data used as model input. The organic accretion is directly proportional to the OM and BD values used; therefore, an analysis of the variability in these data results in a quantifiable range in the organic component of the vertical accretion rates.

The underlying dataset used to derive the OM and BD input data included not only mean values, but also standard deviations. The 25^{th} and 75^{th} percentiles of OM and BD input values were used to examine the uncertainty of the organic component of accretion calculations. The low BD values were paired with the high OM values to result in the maximum increase in vertical accretion calculations, and vice versa for the maximum decrease in accretion. The underlying dataset was summarized by basin and marsh type, which is the format that the model applies these organic loading rates, and therefore perturbation values vary spatially.

4.0 Experimental Design and Results

In the first set of experiments, only one variable was perturbed at a time. Table 2 shows the list of experiments performed. The first four experiments focused on perturbing the two-week salinity. Four perturbations were considered corresponding to the +/- 25^{th} and +/- 75^{th} percentiles of the MAE distribution around the mean. Change in coastal land loss, across the entire model domain, as compared against the "baseline" FWOA model run is described below. Figures 2 and 3 show a very small change in total land area associated with the +/- 25^{th} perturbations (runs U01 and U02). Based on the outcome of the first four experiments, only the +/- 75^{th} percentiles of the MAE distribution were considered for the remainder of the variables. Also based on the outcome of these four experiments, a separate perturbation for the annual salinity was not performed; instead, the two-week salinity perturbation was used and applied to all salinity output (used in both the vegetation and morphology subroutines). If a separate annual perturbation was calculated, it would have been smaller than the two-week perturbation that was already tested. Clearly that would have resulted in less deviation from the "baseline" model run than what has been observed from the two-week salinity perturbations shown through the first four experiments. In addition to the first four experiments, eight experiments (two perturbations for each of the four remaining variables) were performed. The perturbation values are summarized in Table 2.

In all 12 experiments, one variable was perturbed at a time. The response of the model to these perturbations was analyzed through the total land area (across the entire coast) and land area in each ecoregion (spatial units identified within the ICM). The analysis also shows the behavior of the model response over 50 years, as the model output could potentially diverge from the "baseline" model run over time.

Table 2: Experimental Runs – Variables and Individual Perturbations.

Model Run	**Perturbed Variable**	**Perturbation Magnitude**
U01	Two-week salinity	+ 25th percentile
U02	Two-week salinity	- 25th percentile
U03	Two-week salinity	+ 75th percentile
U04	Two-week salinity	- 75th percentile
U05	Annual water level (m)	+ 75th percentile
U06	Annual water level (m)	- 75th percentile
U07	Annual water level variability (m)	+ 75th percentile
U08	Annual water level variability (m)	- 75th percentile
U09	Annual TSS (mg/l)	+ 75th percentile
U10	Annual TSS (mg/l)	- 75th percentile
U11	Organic sediment	More accretion (increased OM and decreased BD)
U12	Organic sediment	Less accretion (decreased OM and increased BD)

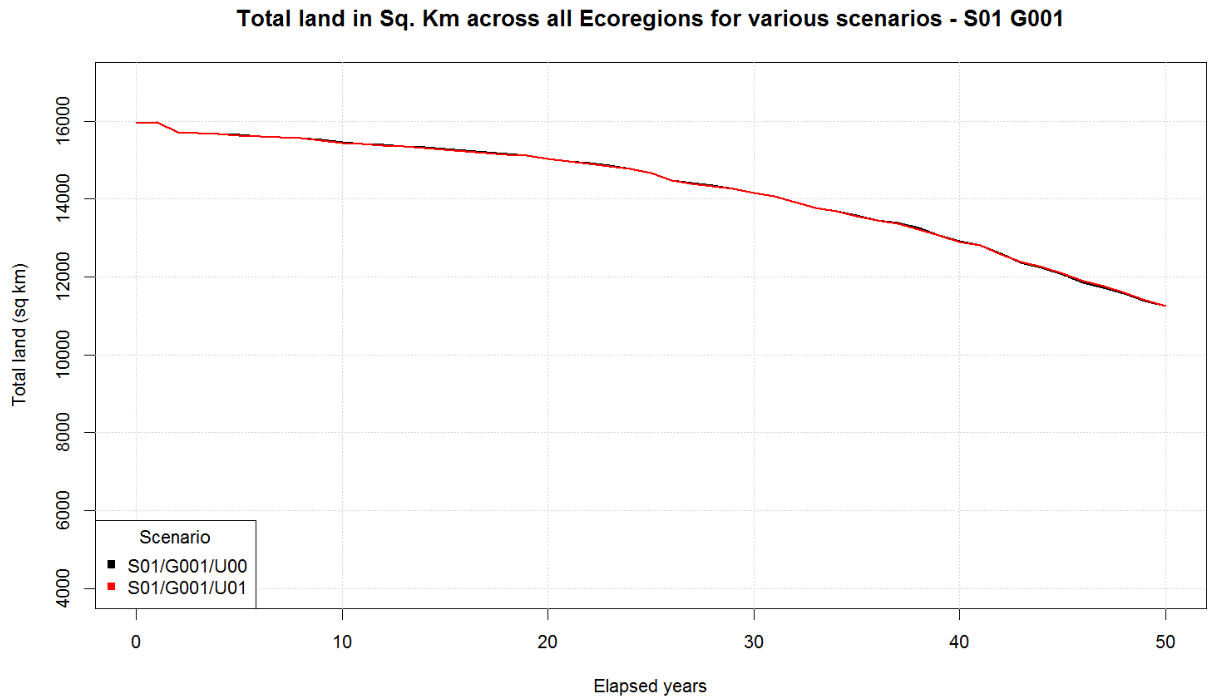

Figure 2: Total Land Change over Time for U01. Salinity perturbed by +25th percentile run (red line) as compared to the baseline model run (FWOA - black line).

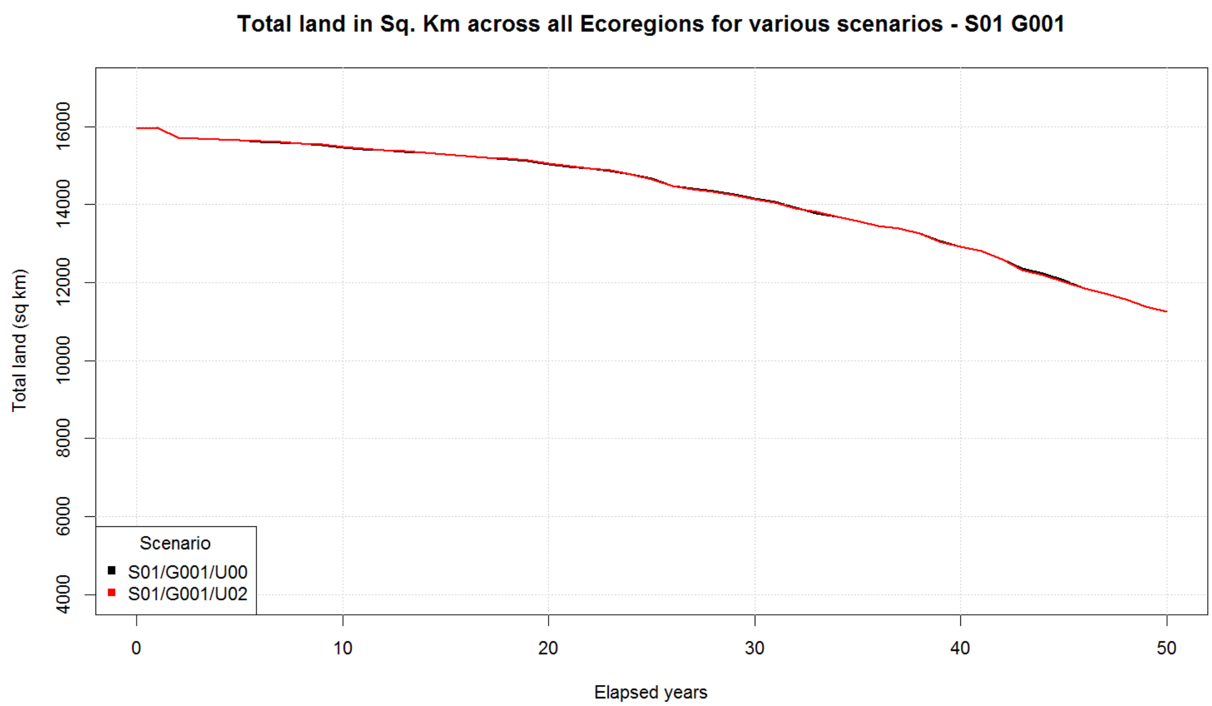

Figure 3: Total Land Change over Time for U02. Salinity perturbed by -25th percentile (red line), as compared to the "baseline" model run (FWOA - black line).

4.1 Salinity Analysis

The salinity perturbations show a number of complex patterns. In the earlier years of the model run, an increase in salinity values (U03, Figure 4) resulted in slightly more land loss than the baseline model run, whereas a decrease in salinity (U04, Figure 5) resulted in a slight decrease in land loss in earlier years. By the end of the 50-year simulation, however, the decreased salinity (U04) run resulted in more land loss than the baseline model run. The increased salinity run (U03) made up for the earlier losses and resulted in approximately the same amount of land loss by year 50 as the baseline model run. These more complex interactions are explained by the dual mechanisms in which salinity is used in the ICM land change algorithms. First, the long-term salinity values are used within the vegetation subroutine to determine what type of marsh is present. Second, the short-term, maximum two-week salinity is used within the morphology subroutine to collapse fresh wetlands that experience a salinity spike. Over time, an increase in the long-term mean salinity values results in the vegetation type converting from species on the fresher end of the spectrum to the more saline-tolerant species. These intermediate, brackish, and salt marsh species are therefore not subjected to the salt-spike collapse thresholds imposed by the morphology subroutine. If, however, the salinity values are decreased, the fresh wetlands remain fresh and are more exposed to salt-spike collapse thresholds during later years as the sea level rises, and the model domain becomes increasingly hydraulically connected.

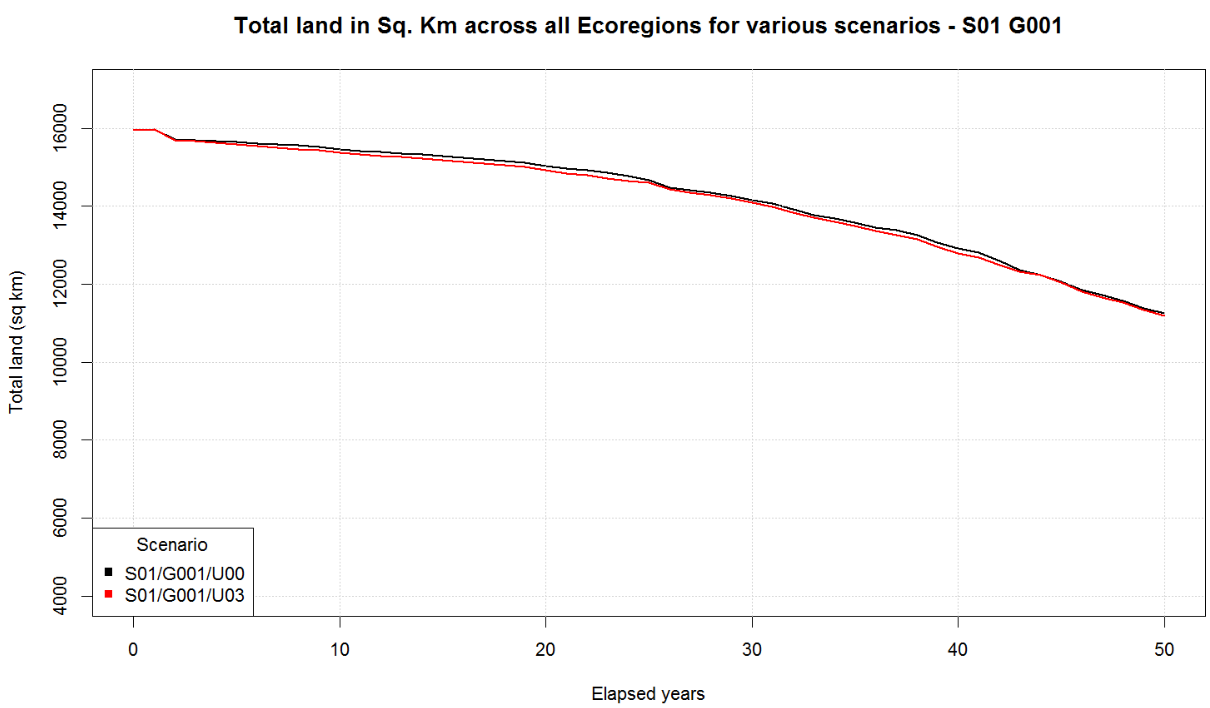

Figure 4: Total Land Change over Time for U03. Salinity perturbed by +75th percentile (red line), as compared the baseline model run (FWOA - black line).

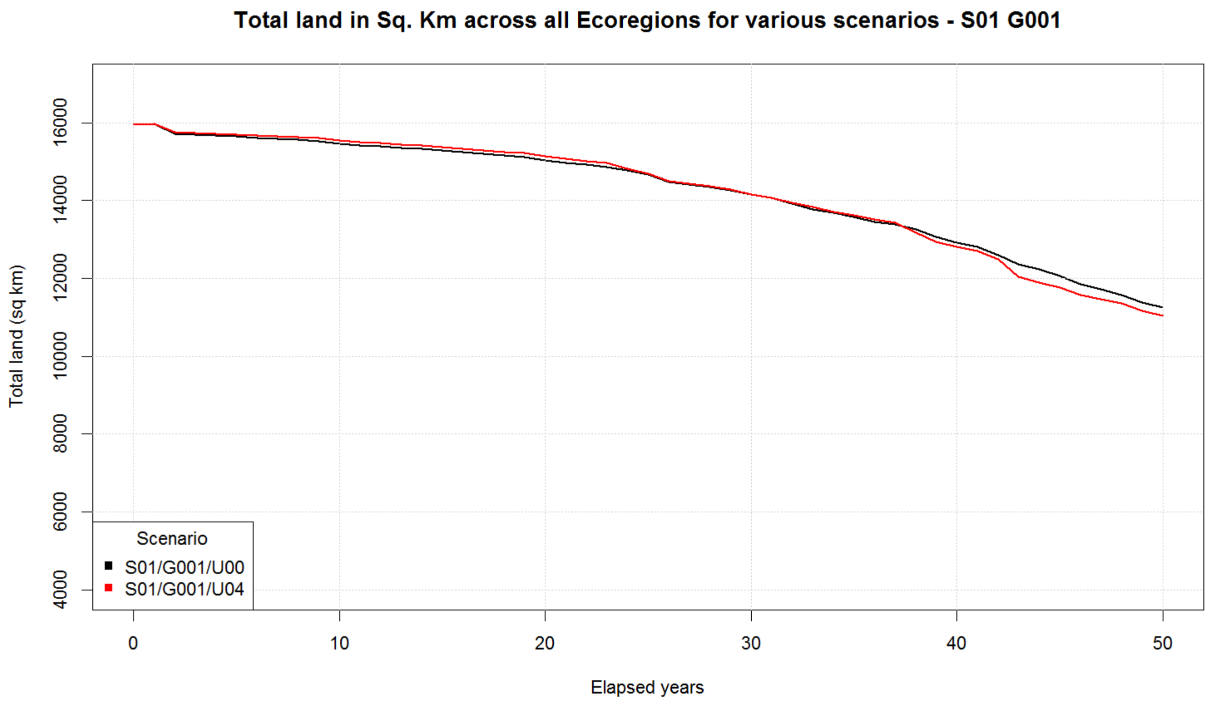

Figure 5: Total Land Change over Time for U04. Salinity perturbed by -75th percentile (red line), as compared to the baseline model run (FWOA - black line).

4.2 Water Level Analysis

The mean water level perturbations, U05 and U06, resulted in the largest divergence from the baseline model run (Figures 6 and 7). The coast wide land loss divergence followed an intuitive response given that inundation is a key land loss mechanism in the ICM. The +75th percentile perturbation (U05), which perturbed the water level estimates upward, resulted in more land loss over time, whereas the lowering of the water level estimates using the -75th percentile perturbation (U06) maintained more land over the 50 year simulation. These results are consistent with those from the future scenarios analysis that indicate that coastal land area, as predicted by the ICM, is sensitive to varying rates of sea level rise (Appendix C – Chapter 2).

Increasing water level variability (run U07) resulted in slightly more land loss over time, but decreasing this parameter (run U08) did not have a large impact on the coast wide land loss calculations (Figures 8 and 9). The relatively minimal impact of these perturbations, on land area, is likely due to the small magnitude of the water level variability error term (+/- 0.03 meters at 75th percentile). This variable is only used within the vegetation subroutine and is on the same order of magnitude as the resolution of the vegetation subroutine input data. The probability of establishment and mortality of the individual vegetation species is provided in increments of 0.04 meters of water level variability. Therefore, perturbing the model output by the 75th percentile of the error is resulting in a very small adjustment to the establishment/mortality probabilities within the vegetation subroutine. These perturbations impacted the relative extent of specific vegetation types by the end of the model run (Figure 10 – vegetation at year 50); however, the magnitude of these changes in cover type did not substantially impact the coast wide area of land loss. While these perturbations did have some impact on vegetation type, and subsequently the collapse mechanisms driving land loss, the magnitude of these impacts were overwhelmed, at the coast wide scale, by other drivers of land loss throughout the 50 year simulation. In other words, the change in water level variability may change the vegetation type in the model, but the relatively minor differences in collapse mechanism between vegetation types was overwhelmed by the relative sea level rise throughout the model run.

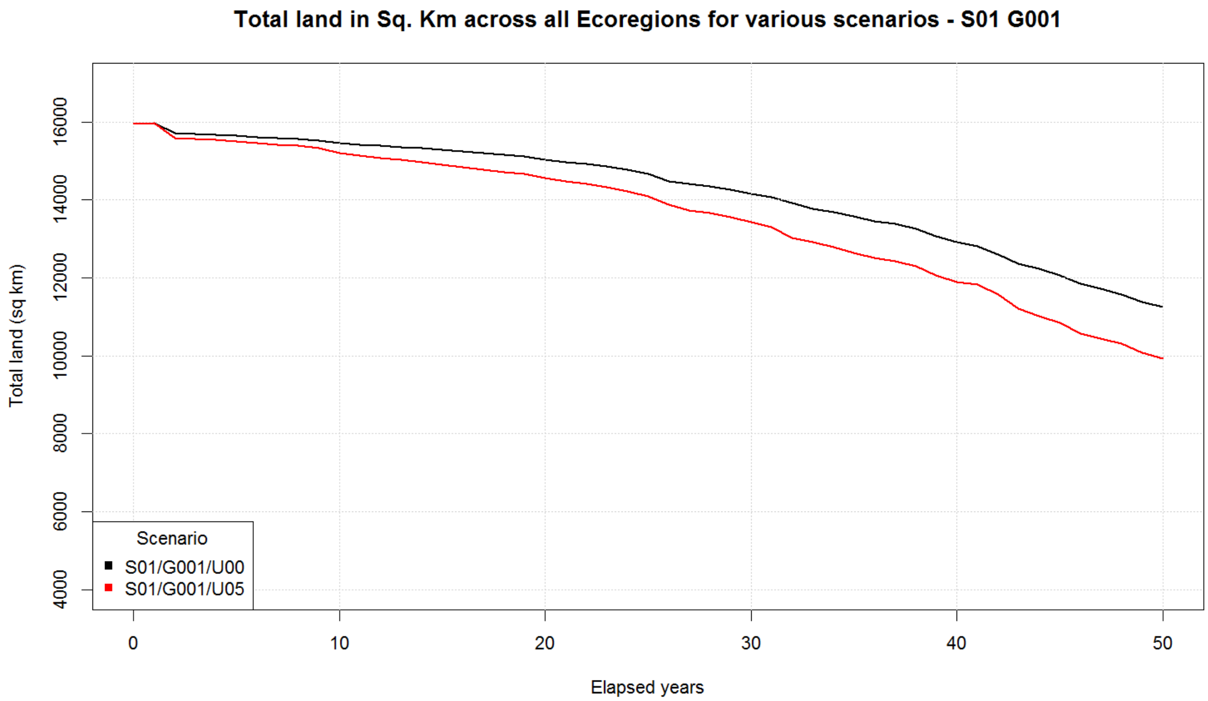

Figure 6: Total Land Change over Time for U05. Annual water level perturbed by +75th percentile (red line), as compared to the baseline model run (FWOA - black line).

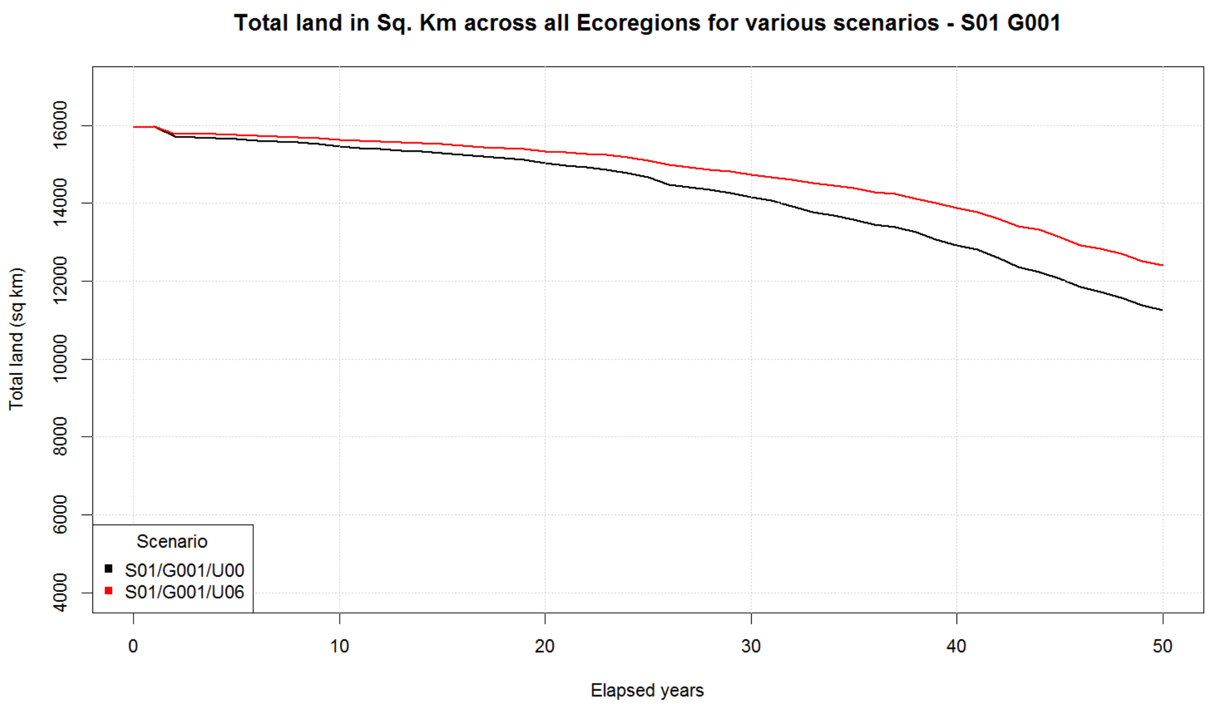

Figure 7: Total Land Change over Time for U06. Annual water level perturbed by -75th percentile (red line), as compared to the baseline model run (FWOA - black line).

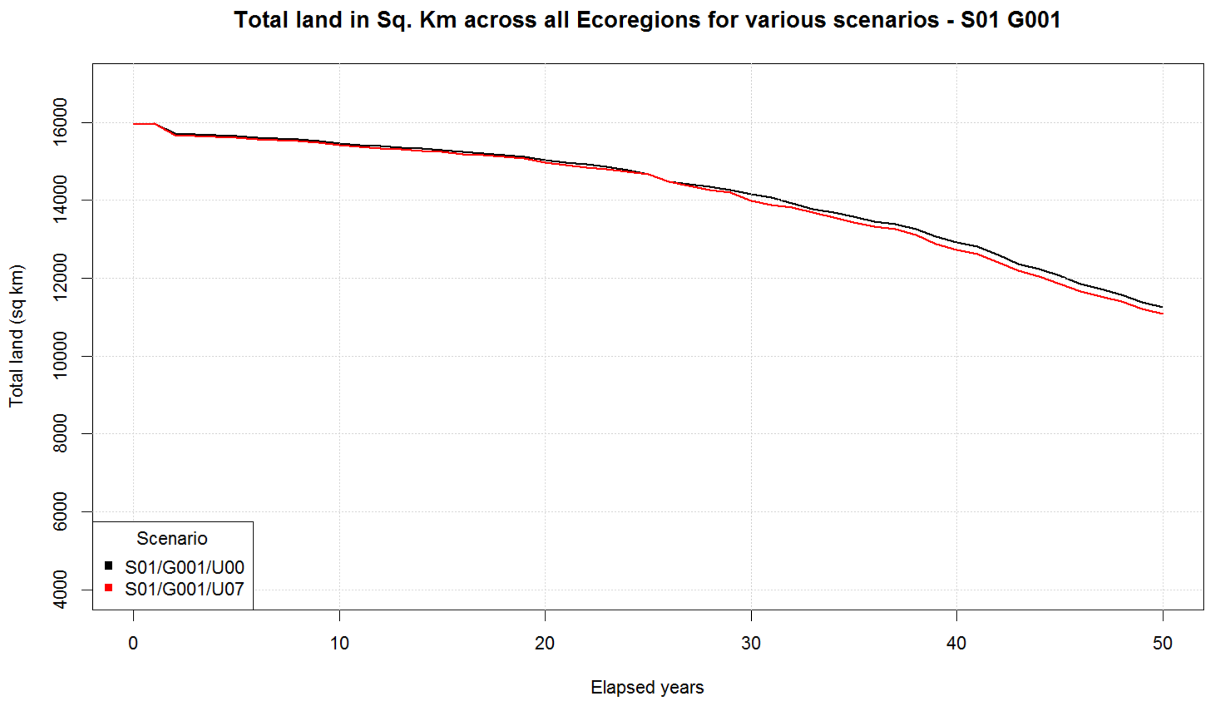

Figure 8: Total Land Change over Time for U07 – annual water level variability perturbed by +75th percentile (red line), as compared to the baseline model run (FWOA - black line).

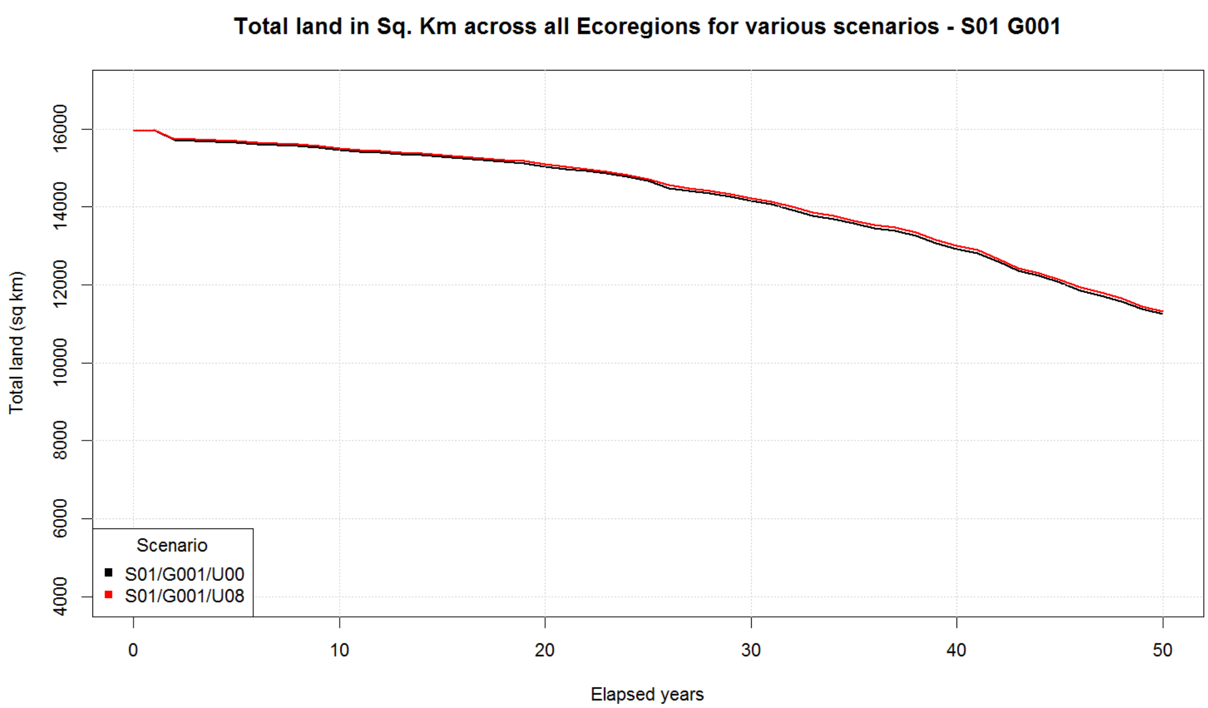

Figure 9: Total Land Change over Time for U08. Annual water level variability perturbed by -75th percentile (red line), as compared to the baseline model run (FWOA - black line).

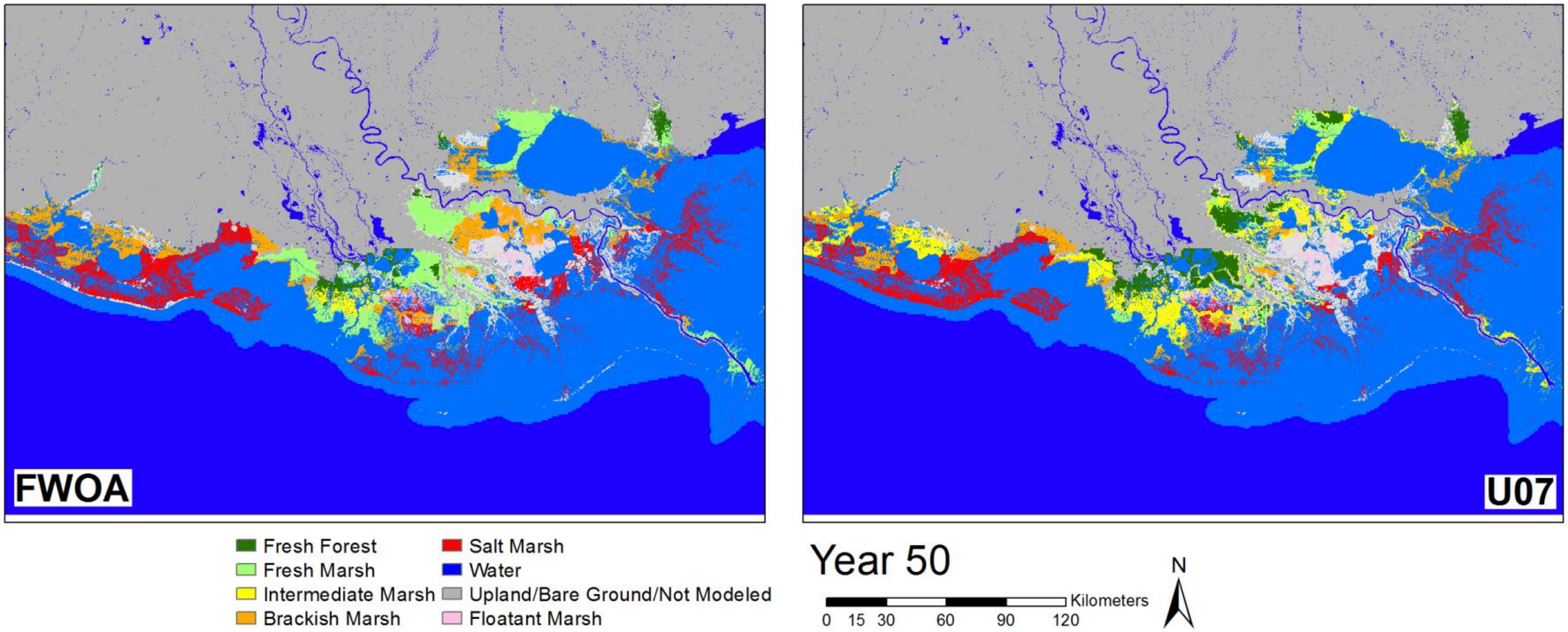

Figure 10: Relative Abundance of Vegetation Types over the 50 Year Simulation; U07 (+75th percentile of annual water level variability).

4.3 Total Suspended Solids Analysis

The coast wide land loss predictions appeared to be insensitive to perturbations to the annual inorganic TSS concentration that was perturbed in runs U09 and U10 (Figures 11 and 12). This can be explained by a number of factors. First, the TSS perturbation value (38 mg/L) was determined from the calibration error of a fairly small dataset. Both the observed and modeled TSS data varied by as much as an order of magnitude and it is likely that the model area that would be most sensitive to a change in land area due to TSS perturbations would be the areas of the largest TSS concentrations. These areas are on the extremes of the TSS distribution and are therefore likely insensitive to just a +/- 75th percentile perturbation. Second, land gain in the model domain and in the real landscape, (e.g., Wax Lake Delta) is occurring where there is a steady sediment supply from outside the system. The entrainment of estuarine bed sediments is not a large driver of land gain in coastal Louisiana (Burkett et al., 2007). Therefore, the inflow TSS boundary conditions are likely a much more sensitive parameter than the calculated TSS values from the deposition/resuspension routines in the hydrology subroutine. Third, the areas in the FWOA model run that experience land gain are limited. Overall, the impact of the TSS perturbations at the coast wide or ecoregion scales originates primarily from specific locations with definitive external sediment loading (e.g., Wax Lake Delta, West Bay, Big Mar, etc.) and ultimately did not result in significant response to the perturbations. It should be noted that the TSS perturbations might be important for certain project types such as large sediment diversions.

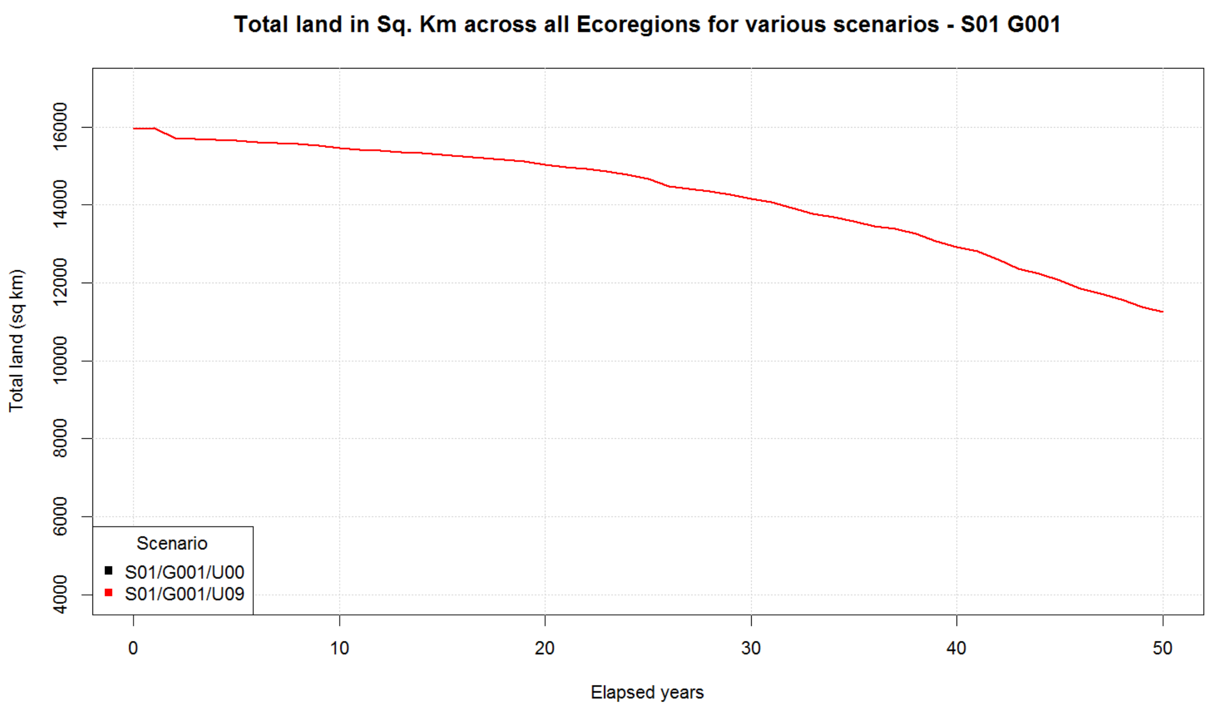

Figure 11: Total Land Change over Time for U09. Annual inorganic TSS perturbed by +75th percentile (red line), as compared to the baseline model run (FWOA - black line).

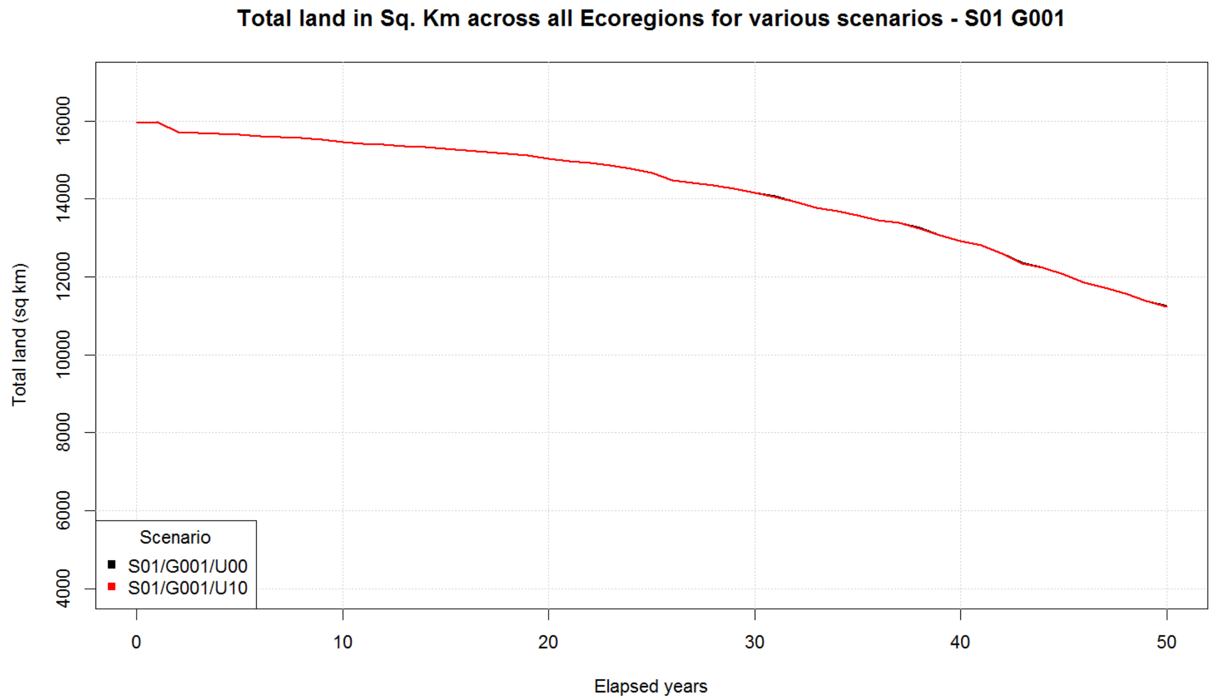

Figure 12: Total Land Change over Time for U10. Annual inorganic TSS perturbed by -75th percentile (red line), as compared to the baseline model run (FWOA - black line).

4.4 Organic Sediment Analysis

Perturbing the organic accretion, as determined by OM input and BD values, resulted in an intuitive model response. Higher accretion due to high OM and low BD (run U11) resulted in a substantial increase in coast wide land area at year 50, as compared to the baseline model run (Figure 13). Conversely, run U12, which modeled lower accretion rates, resulted in a decrease in land area at year 50 (Figure 14). The impact of these perturbations on coast wide land area at year 50 is similar in magnitude to the mean water level perturbations (runs U05 and U06). However, the organic sediment perturbations are asymmetric around the baseline run. This asymmetry could be explained by areas of collapsed land in the baseline run that are close to but slightly above the collapse threshold in the baseline run. Once an area has collapsed, it will not be influenced by a decrease OM/BD; it simply remains collapsed. However, an increase to the OM/BD would sustain an area that was just on the threshold of collapsing/not collapsing, hence the asymmetry in the results.

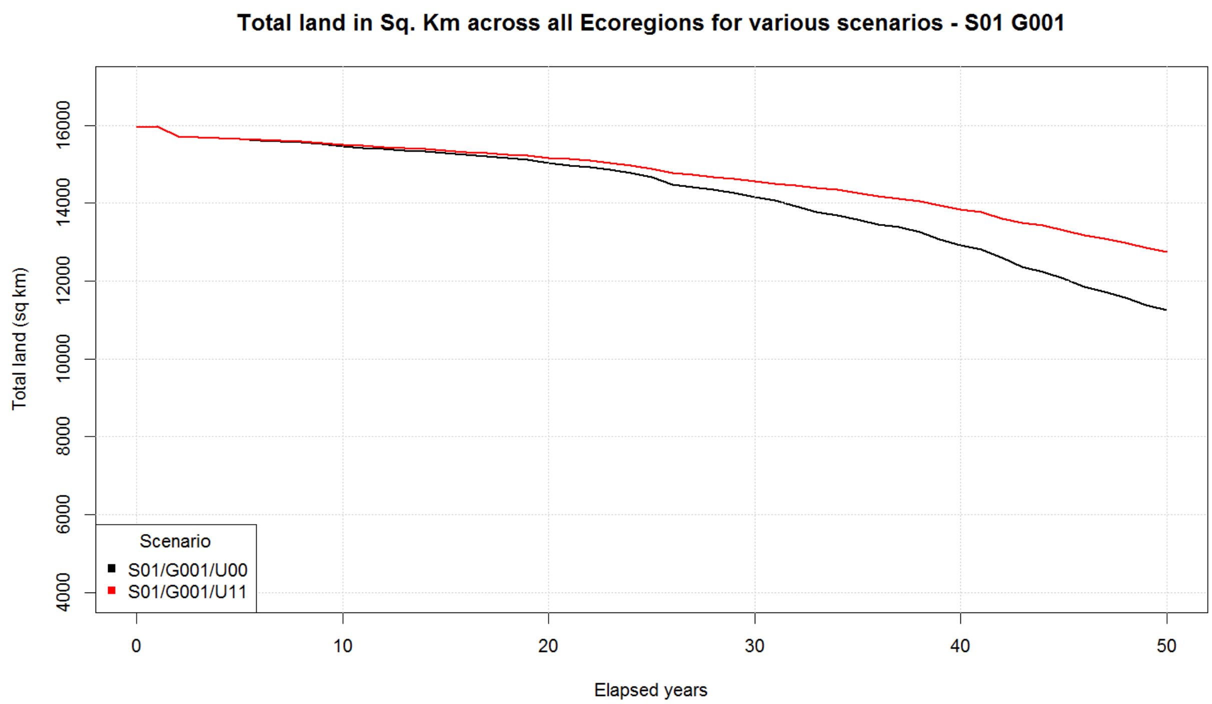

Figure 13: Total Land Change over Time for U11 – Organic sediment perturbed to increase accretion by increasing organic matter content and reducing bulk density values (red line), as compared to the baseline model run (FWOA - black line).

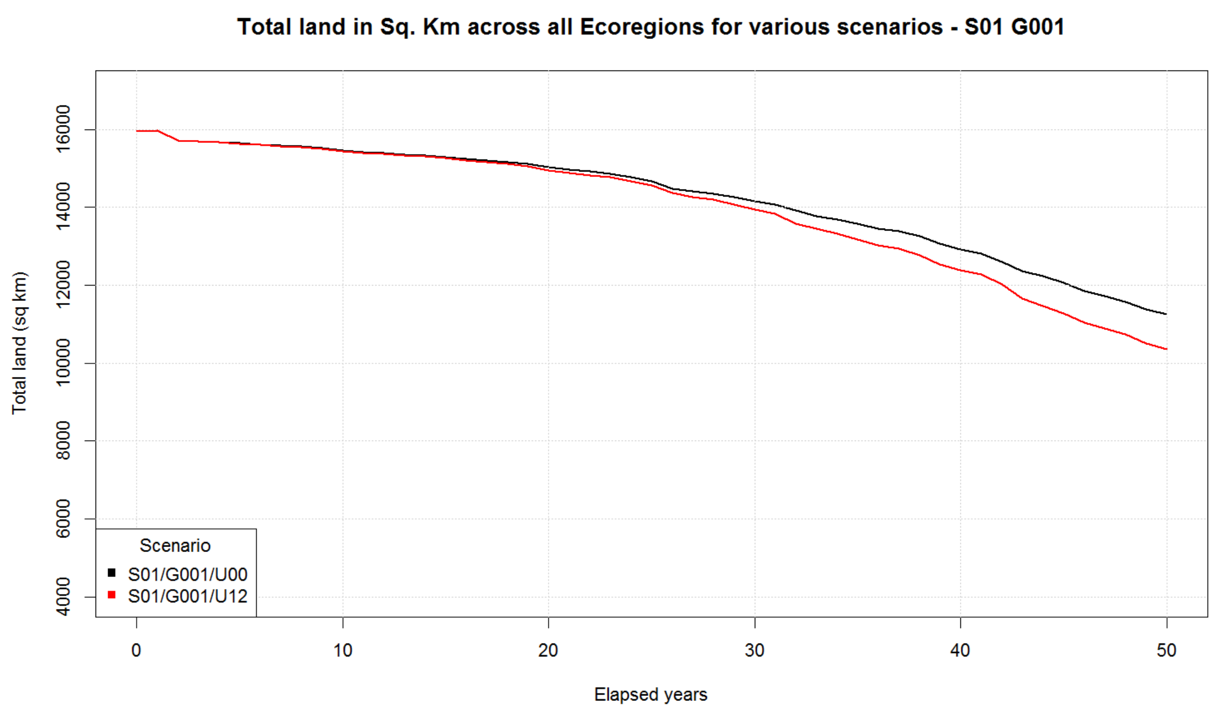

Figure 14: Total Land Change over Time for U12. Organic sediment perturbed to decrease accretion by decreasing organic matter content and increasing bulk density values (red line), as compared to the baseline model run (FWOA - black line).

4.5 Composite Experiments

The initial set of experiments examined the individual perturbations of each variable. To explore the interdependence among these variables, a simulation was performed in which all the variables were perturbed at once. All the variables were concurrently perturbed using the +/- 75th percentile perturbations. Two "composite" simulations, U21 and U22, were designed such that they would produce the largest and smallest land area coast wide. For this to be accomplished, the sign of the perturbation for each variable was selected based on the response of the initial adjustments of the 12 non-vegetation simulations (U03-U12). For example, all the experiments that individually resulted in more land area than the baseline (U00) model run were combined and used simultaneously in experiment U21. Similarly, all experiments that individually resulted in less coast wide land area than the baseline model run were combined in experiment U22. The exact combinations of values for these runs are provided in Table 3.

The results from these two composite runs, U21 and U22 (Figure 15), can be used to bracket the uncertainty in land area over time as compared to the baseline case of FWOA under the low future environmental scenario (S01).

Table 3: Composite Experimental Runs.

Model Run	Composite Perturbation	Perturbation Variable	Perturbation Value
U21	Composite perturbations - low (minimum land coast wide at year 50)	Salinity	Same as U04
		Mean Water Level	Same as U05
		Water Level Variability	Same as U07
		Annual TSS	Same as U10
		Organic sediment	Same as U12
U22	Composite perturbations - high (maximum land coast wide at year 50)	Salinity	Same as U03
		Mean Water Level	Same as U06
		Water Level Variability	Same as U08
		Annual TSS	Same as U09
		Organic sediment	Same as U11

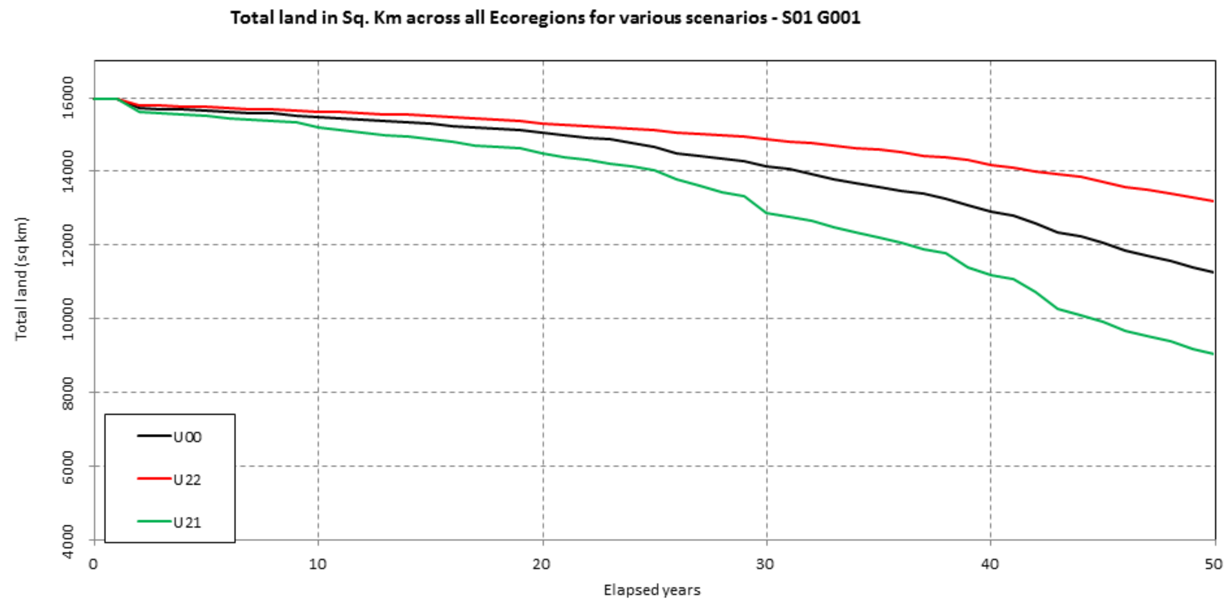

Figure 15: Total Land Change over Time for U21 (green line) and U22 (red line). The composite uncertainty runs provide the upper and lower limits on model uncertainty, as compared to the baseline model run (FWOA - black line).

5.0 Spatial Analysis of Uncertainty

Figures 2 through 15 show the magnitude of uncertainty in land area over time, but they do not indicate the spatial distribution of uncertainties. To examine where the ICM was more (or less) certain in predicting land gain or loss over time, the results of the 12 individual perturbations discussed earlier (see Table 2) were combined into a spatial dataset that determined how often an individual land/water pixel (30 m x 30 m) was classified as land or as water at year 50. This was then compared against the year 50 classification from the baseline FWOA run (U00) to determine a relative certainty around the year 50 prediction of land or water at each 30 m pixel (Figure 16). The green regions in Figure 16 represent pixels that were classified as water during FWOA at year 50, but were more likely to be predicted as land in the perturbation runs (U3-U11). The darker the green, the more often it was classified as water, indicating a higher level of uncertainty that the FWOA prediction of water would, in fact, be water. Contrarily, the red regions in Figure 16 represent pixels that were predicted to be land at year 50 in FWOA U00, but were more often predicted to be water during the perturbation runs (U3-U11). Again, the darker the shade of red, the higher the uncertainty around the FWOA prediction that a given land pixel at year 50 would in fact be land. Regions that are gray (land) or blue (water) in Figure 16 indicate pixels that, regardless of the perturbation applied, are consistently predicted to be the same classification at year 50 as the FWOA baseline run. These gray and blue regions, taken together, represent the area within the model domain that is consistently predicted as either land or water during all individual perturbation simulations conducted for this analysis.

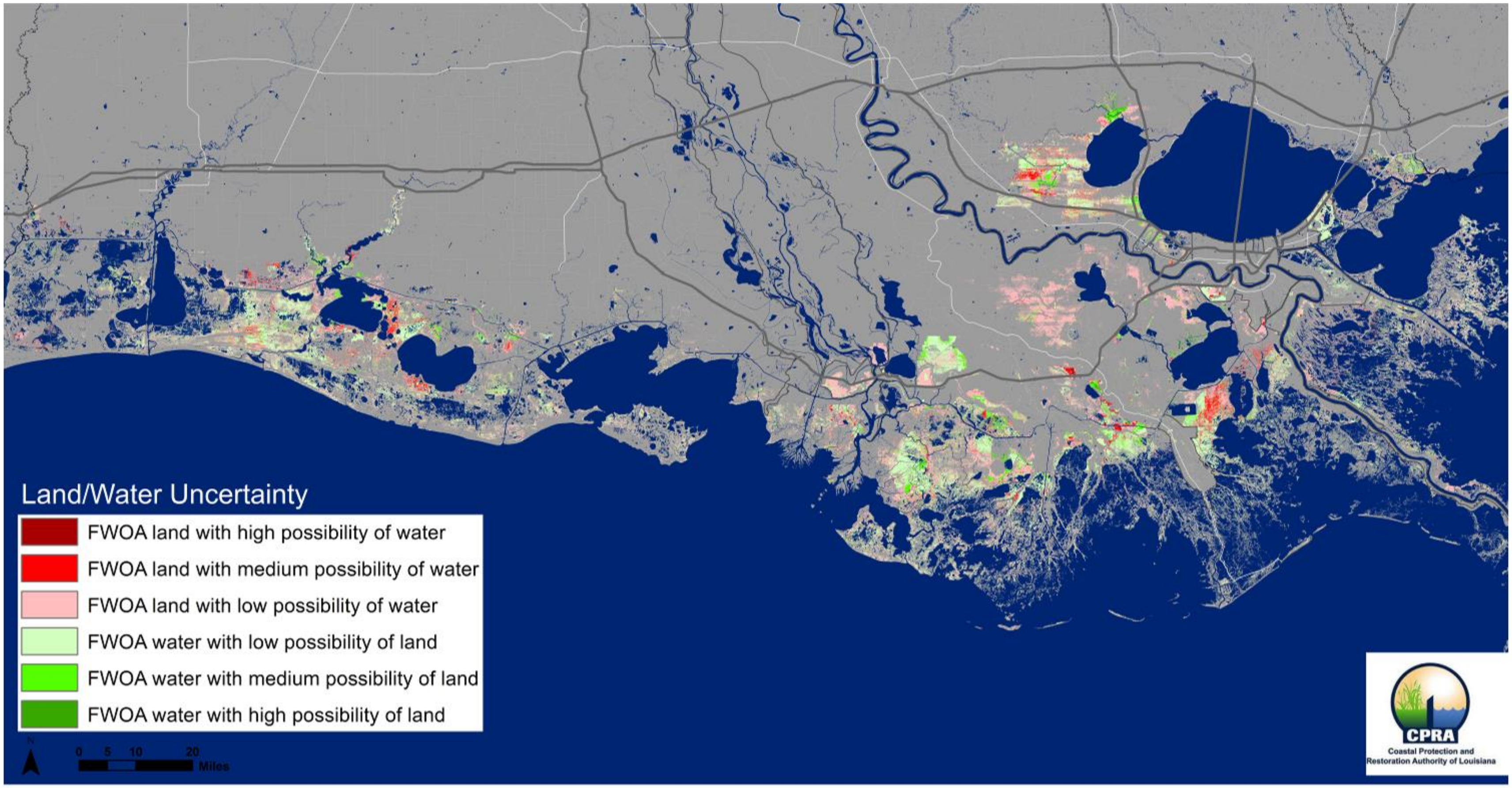

Figure 16: Land/Water Prediction Uncertainty – All Individual Perturbations at Year 50.

The regions where the perturbed runs consistently result in a year 50 land/water value different than the FWOA U00 case (dark green and dark red) indicate that there are many land/water pixels that are consistently impacted by perturbations. These are the pixels that are close to a collapse threshold in the baseline run (U00). Once perturbed, it is quite likely for these pixels to result in a different outcome at year 50, regardless of the perturbation applied. The regions that are seldom different from the baseline (light green and light red), on the other hand, indicate pixels that respond to one (or two) very specific perturbations only. Based upon the magnitude of impact from the individual runs, it is likely that these pixels of lower uncertainty are 'activated' into losing or sustaining land when the mean water level or the organic accretion perturbations are applied. Physically, these are the only two perturbed variables that will directly influence the elevation, and could result in these changes.

A composite run in which the mean water level and the organic accretion are perturbed in opposite directions (e.g., lower mean water level, higher organic accretion, and vice versa), will potentially have a synergistic effect on land pixels that are lost or sustained. Figure 17 shows that this synergistic effect does indeed take place when the variables are perturbed simultaneously. The purple regions in Figure 17 are pixels that are land at year 50 from the composite run, U22, that were water in all individual runs as well as the FWOA baseline.

Some of the land/water pixels that did not change from their baseline condition during the individual perturbations did respond to the composite runs of U21 and U22. Thus, a complete set of composite perturbations needed to be analyzed to determine if U21 and U22 bracket the uncertainty in coastal land area over time.

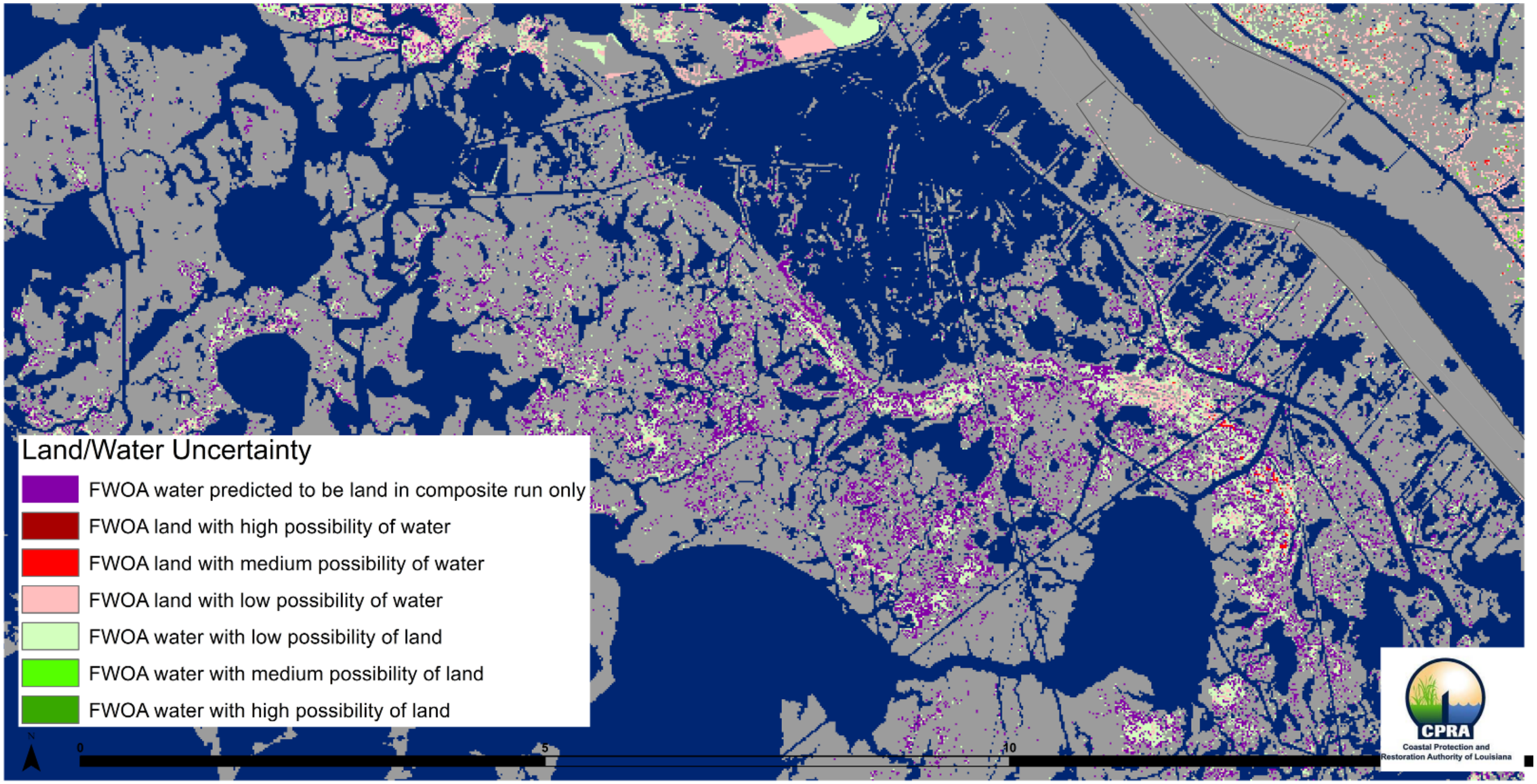

Figure 17: Land/Water Prediction Uncertainty – All Individual Perturbations and Composite Run U22 (near Myrtle Grove, year 50).

From the individual perturbation runs (U09 and U10), it was determined that errors in suspended inorganic sediments (TSS) did not result in any appreciable change in coast wide land area over time. Removing TSS from further analysis allowed for 16 additional simulations that would test model uncertainty as a function of all possible permutations of two perturbed values for mean water level, salinity, water level variability, and organic accretion. These 16 permutations (Table 4) were analyzed, allowing for a thorough determination of uncertainty in the FWOA land/water predictions and the relative sensitivity to the different perturbation permutations.

Table 4: Experimental Runs – Composite Perturbations – All Permutations.

Model Run	**Salinity**	**Mean Water Level**	**Water Level Variability**	**Organic Sediment**
U25	+75 percentile	+75 percentile	+75 percentile	+OM/-BD
U26	+75 percentile	+75 percentile	+75 percentile	-OM/+BD
U27	+75 percentile	+75 percentile	-75 percentile	+OM/-BD
U28	+75 percentile	+75 percentile	-75 percentile	-OM/+BD
U29	+75 percentile	-75 percentile	+75 percentile	+OM/-BD
U30	+75 percentile	-75 percentile	+75 percentile	-OM/+BD
U31	+75 percentile	-75 percentile	-75 percentile	+OM/-BD
U32	+75 percentile	-75 percentile	-75 percentile	-OM/+BD
U33	-75 percentile	+75 percentile	+75 percentile	+OM/-BD
U34	-75 percentile	+75 percentile	+75 percentile	-OM/+BD
U35	-75 percentile	+75 percentile	-75 percentile	+OM/-BD
U36	-75 percentile	+75 percentile	-75 percentile	-OM/+BD
U37	-75 percentile	-75 percentile	+75 percentile	+OM/-BD
U38	-75 percentile	-75 percentile	+75 percentile	-OM/+BD
U39	-75 percentile	-75 percentile	-75 percentile	+OM/-BD
U40	-75 percentile	-75 percentile	-75 percentile	-OM/+BD

After completion of these 16 permutations, the output from U31 was compared to U22. The only difference between these two composite perturbation runs was the inclusion of TSS perturbation in U22; all other perturbed variables were identical between U22 and U31. As Figure 18 shows, there was some impact at very small scales (e.g., near Davis Pond); however, on a coast wide basis, the inclusion of TSS perturbations was determined to be unnecessary in assessing overall model uncertainty. At a coast wide scale, there was only negligible differences between these two composite perturbations.

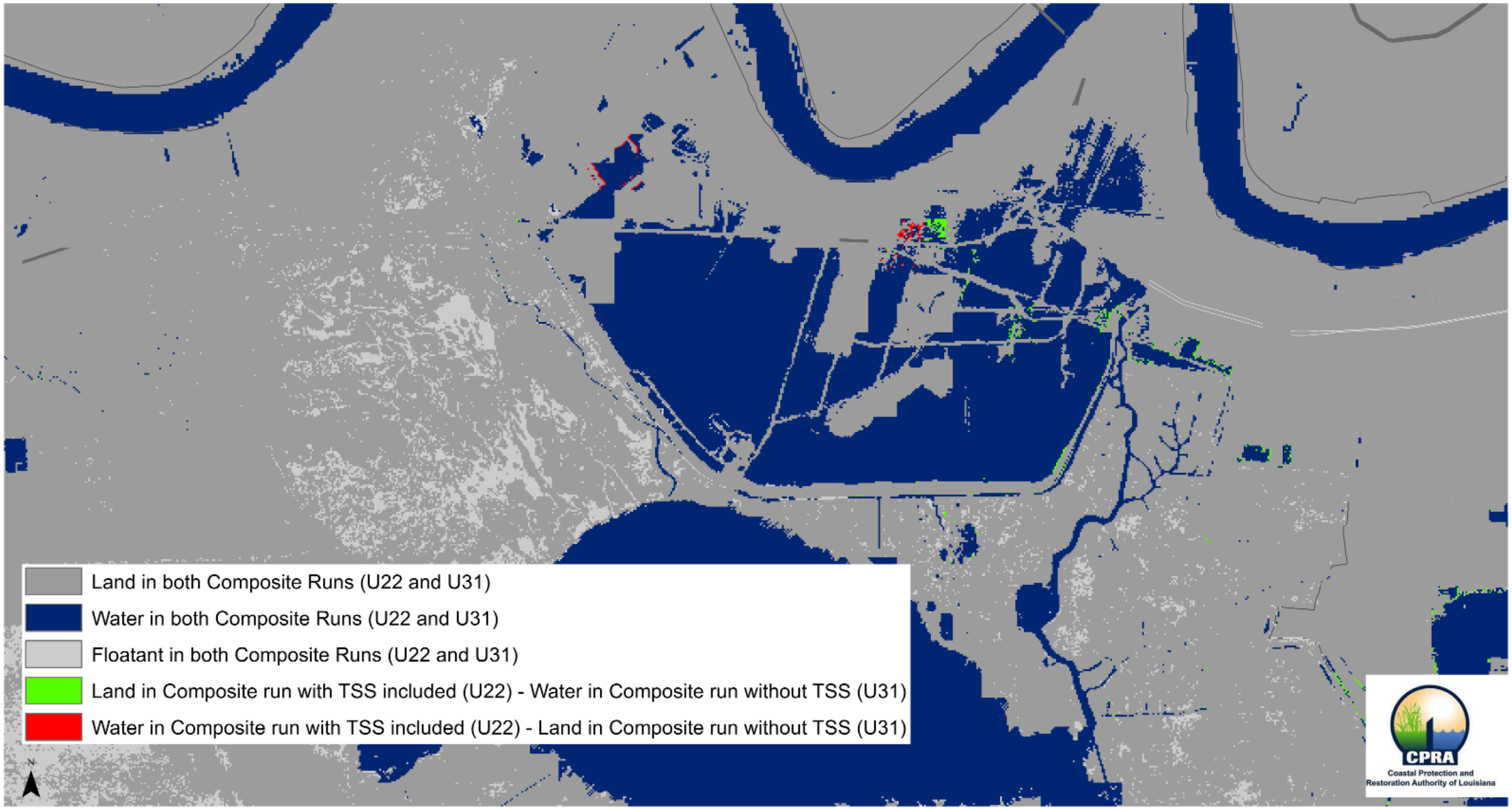

Figure 18: Land/Water Prediction Uncertainty – Composite Perturbations with (U22) and without TSS Perturbed TSS (U31); near Davis Pond, year 50.

As predicted by analyzing the pixels affected by the composite run U22, but none of the individual perturbations (Figure 17), the range in land area change over time is highly sensitive to perturbations to mean water level and organic accretion. In Figure 19, the four runs that result in the highest land area over time (U29, U31, U37, and U39), all included a decrease in mean water level and an increase in organic accretion. The salinity and water level variability perturbations appear to drive a difference in vegetation cover and do have some impact on the land area over time. If the mean water level and organic accretion perturbation counteract one another, the salinity and water level variability perturbations do appear to have some impact on the final land area. However, regardless of the exact combination, all of these runs appear to result in slightly more land at year 50 than the baseline U00 run.

If the mean water level is increased at the same time as the organic accretion is decreased (U26, U28, U34, and U35), it does not appear as if the exact combination of salinity and water level variability makes much of an impact. The final land area in the last decade of the model run is remarkably consistent, indicating more loss coast wide than the U00 FWOA baseline run.

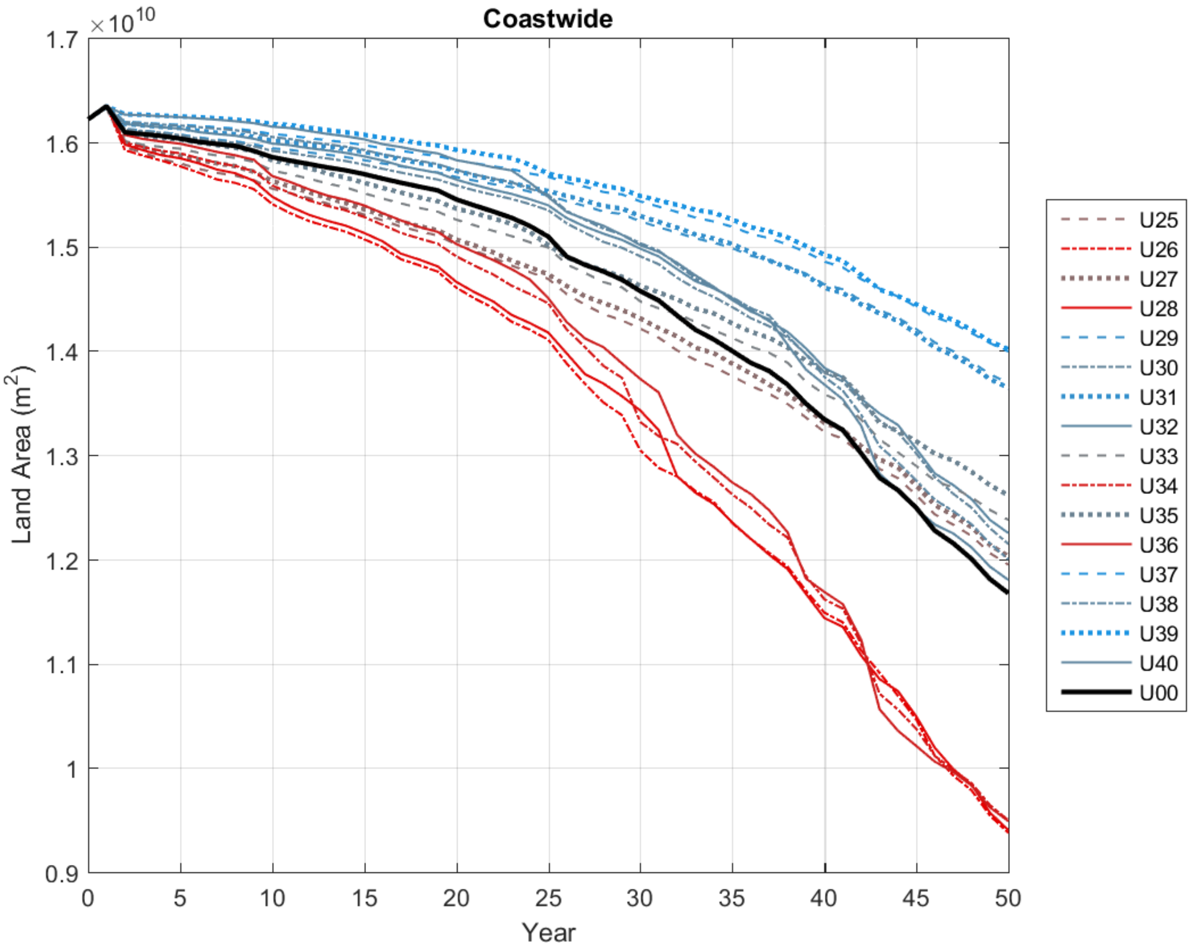

Figure 19: Baseline FWOA Land Area over Time (U00, black line) Compared against All 16 Permutations of Composite Uncertainty Perturbations.

6.0 Proposed Approach for Alternatives and/or Master Plan Analysis

In addition to the temporal and spatial assessment of overall parametric uncertainty, the outputs from the FWOA analysis provided in this report helped to identify the key model variables with significant impact on land area and to examine sensitivity to change of the perturbation terms for each variable. This examination can be used to design a more streamlined and/or more detailed UA for application to several large projects that reflect different aspects of system dynamics on land area change (e.g., sediment diversions, extensive marsh creation), depending upon the time and resources available.

Based on the results presented in this report, it appears that the interdependency among the model variables is important (Figure 19) and should be considered while designing UA runs for restoration projects. To analyze and quantify the uncertainty of a single project, full alternative, or the master plan, it is recommended to use 16 perturbation runs similar to those presented in Table 4 and Figure 19. These 16 runs can be performed concurrently and thus can be completed within three weeks (two weeks for the simulations, and one week for processing the results). The results could then be analyzed at the coast wide or ecoregion scales.

7.0 Summary and Conclusions

This uncertainty analysis was based on applying perturbations to model variables that are directly linked to the calculations of land area. These model variables included water level, water level variability, salinity, TSS concentration, and organic accretion. The perturbations were applied to each of these variables before they were used in subsequent model subroutines. These perturbations were consistently applied through the 50-year simulations, and the magnitude of the perturbation of each variable was estimated based on the calibration errors. Perturbing wetland types were not examined here as they were controlled by the prevailing hydrologic conditions, and as such were removed from further consideration.

A set of experiments were designed to examine the perturbation of individual variables. The individual perturbations showed that water level and organic accretion have the most influence on land area. Salinity showed an influence on the wetland type but not on land area, while TSS showed minor influence on land area.

Additional composite experiments were performed to examine simple addition of uncertainties originating from individual perturbations. Further, and to fully examine the interdependency among the model variables, a set of 16 experiments was performed. These experiments provided a bracket of uncertainty around the FWOA baseline run. The results show that water level and organic accretion are the most influential on the coast wide land area.

To examine the uncertainty in the calculations of land area in simulations containing individual restoration projects, groups of projects, and/or the final master plan projects, it is recommended to perform these 16 composite experiments. These runs can be performed concurrently and are expected to produce informative uncertainty brackets.

8.0 References

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