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An Illustrative Case Study of the Application of Uncertainty Concepts and Methods for Ecosystem Restoration

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OVERVIEW: The U.S. Army Corps of Engineers (USACE) is engaged in ecosystem restoration projects that are often characterized by varying degrees of risk and uncertainty. Though current policy requires that these issues be addressed,[1] they are often given insufficient attention. Failure to quantify risk and uncertainty can result in overly conservative or misinformed restoration management policies, excess project costs, and failure to achieve project goals. The purpose of this technical note is to demonstrate — using an illustrative case study – how risk and uncertainty tools and techniques can be applied to ecosystem restoration projects. A global sensitivity and uncertainty analysis approach is proposed for identifying the most important factors to consider in a restoration project. In addition, the magnitude of the restoration needed to achieve a positive outcome for the target ecosystem is quantified. This case study is provided as a complement to *Application of Risk Management Concepts and Methods for Ecosystem Restoration: Principles and Best Practice* (Suedel et al. 2012). That technical note reviews current USACE risk and uncertainty management in ecosystem restoration projects, provides an overview of the relevant risk management concepts, and discusses the applicability of these concepts and tools to restoration projects. This technical note presents a case study that addresses the sensitivity of restoration outputs to uncertainty in key drivers of environmental processes. In particular, the Snowy Plover — a resident shorebird of Florida — and its risk of decline and extinction due to potential sea-level rise (SLR) is assessed. Finally, the best management outcomes are evaluated for the Snowy Plover in light of the sensitivity and uncertainty analysis.

CASE STUDY: THE EFFECTS OF SEA LEVEL RISE ON THE SNOWY PLOVER

Background. Uncertainty in environmental processes — specifically, the effects of uncertain drivers (having values that are only approximately known) — on restoration outcomes is widely acknowledged but seldom analyzed or properly accounted for in project planning (Wheaton et al. 2008). In environmental management and restoration, ignoring uncertainty — or assuming it is insignificant — can result in larger, more frequent problems (Holling 1978; Wheaton et al. 2008). Moreover, in many restoration projects, only one outcome is considered, when, in fact, uncertainty may lead to multiple possible outcomes in the target ecosystem. Embracing

[1] ER 1105-2-100 stipulates that "Planners shall identify areas of risk and uncertainty in their analysis and describe them clearly, so that decisions can be made with knowledge of the degree of reliability of the estimated benefits and costs and of the effectiveness of alternative plans."

uncertainty within restoration planning and design, on the other hand, allows decision makers to evaluate multiple scenarios and to draw inferences as to likely outcomes or consequences, thereby increasing the chances of project success (Johnson and Brown 2001). Wheaton et al. (2008) argue that embracing uncertainty can lead to significant benefits, such as an exploration of potential options, a clear communication of uncertainties, and a more transparent decision-making process. A better understood and quantified risk and uncertainty analysis also has the potential to become a major factor in ecosystem restoration project ranking.

One source of uncertainty in restoration planning is the future effect of climate change. For example, potential changes in coastal habitats caused by climate change may cause a population decline of shoreline-dependent species. In particular, SLR associated with climate change can drastically affect wetlands and beaches, which are essential shorebird foraging and nesting areas. Habitat models are widely used to predict how climate change and other factors may affect future habitat distributions. Uncertainties of the parameters that represent both the variability of the environmental processes and the ignorance that we have of them may result in very different scenarios for the ecosystem. Here the case of the Snowy Plover (*Charadrius alexandrinus nivosus*), a resident shorebird of the Florida Gulf Coast, is presented.

Research involving the Snowy Plover is part of a long-term project funded by the Strategic Environmental Research and Development Program (SERDP) (Linkov et al. 2010; Aiello-Lammens et al. 2011; Convertino et al. 2011a-c). In Florida, the Snowy Plover is a state-threatened shorebird geographically distributed along the northern and western white sandy beaches of the Gulf Coast. The estuarine and ocean beaches of the Florida Gulf Coast contain quartzite alkaline minerals essential to Snowy Plover habitat. The lack of this mineralogical feature along the Atlantic coast of Florida constitutes one of the major constraints for Snowy Plover habitat along the Atlantic coastline. Plovers are especially vulnerable to potential SLR impacts as they breed primarily on open sandy beaches and are less adaptive to alternate nesting sites than most other beach-nesting birds (FWC 2011).

Snowy Plover nesting areas have been consistently documented on Santa Rosa Island, a 40-mile barrier island within Eglin Air Force Base (AFB), located about 50 miles East of Pensacola in the Florida Panhandle (Figure 1). Approximately 20 percent of the total Florida Snowy Plover population resides on Santa Rosa Island. At Eglin AFB, there were concerns about the effects of military training activities (e.g., amphibious landings) and future infrastructure projects (e.g., access road armoring, dune and shoreline re-nourishment, and the creation of seawalls and bulkheads) on the habitat of the already declining Santa Rosa Island Snowy Plover population.

One of the most significant causes of Snowy Plover population decline is habitat loss and degradation (Brown et al. 2001; Aiello-Lammens et al. 2011; Convertino et al. 2011a). As Snowy Plover habitat may be strongly impacted by SLR, any potential restoration and/or conservation intervention must address potential SLR impacts. To determine the effect of SLR on shoreline habitat, Chu-Agor et al. (2010) used a land-cover model to predict the variation of the coastal ecosystem classes —thus, of the Snowy Plover habitat — as a function of projected SLR of 2 m by

2100[1]. Moreover, Linkov et al. (2011) studied the changes in the land cover at the Eglin AFB, FL, for different SLR projections (0.2, 0.5, 1.0, 1.5, and 2.0 m) at the annual scale from 2010 to 2100. These changes in the land cover were calculated as a function of inundation (i.e., reduction in elevation due to SLR), erosion, over wash (effects of large storms), saturation (rising water table), and accretion/sedimentation. Aiello-Lammens et al. (2011) considered land-cover change over the entire state of Florida for three scenarios: no SLR, 1 m SLR, and 2 m SLR. All these predictions cover the conventional planning period for ecosystem restoration projects (50 years).

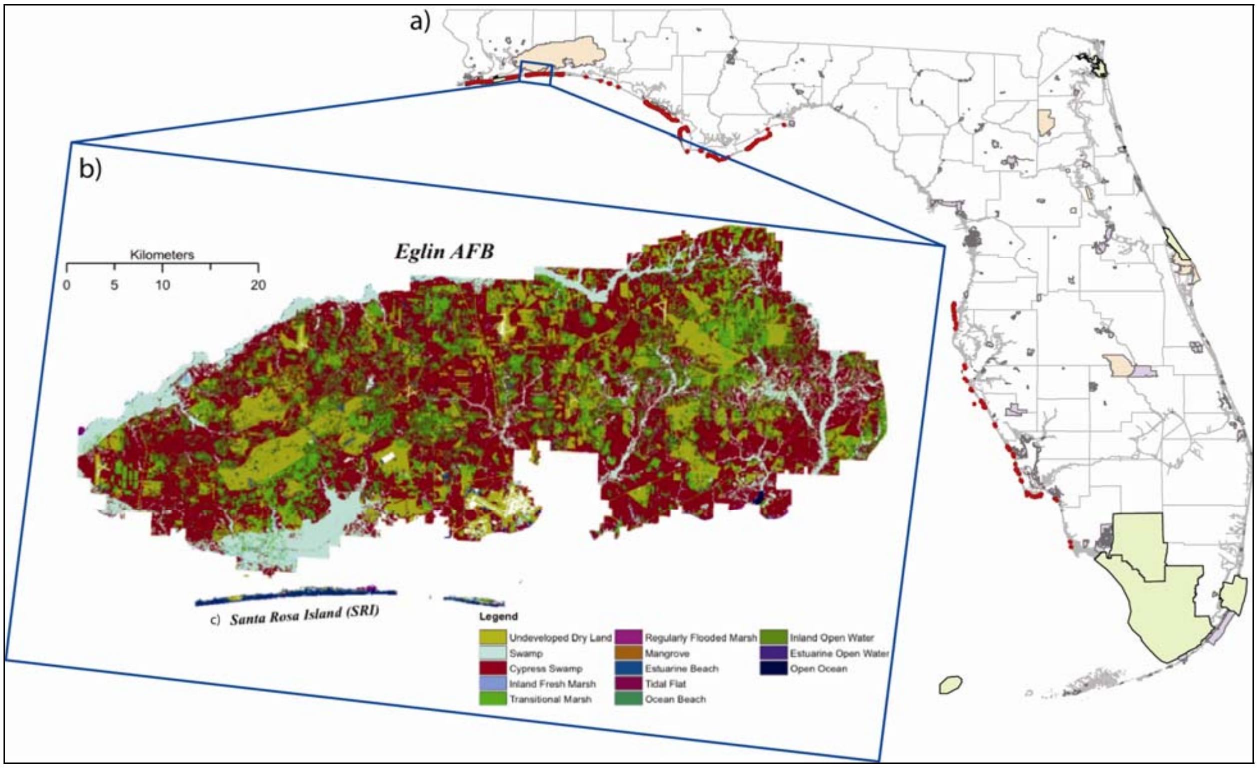

Figure 1. (a) State of Florida with military bases and state/national parks shaded red and green respectively; (b) Land-cover map for Eglin Air Force base in Florida, including (c) Santa Rosa Island, managed by Eglin AFB. Snowy Plover habitat includes the ocean and estuarine beach land cover categories.

This case-study demonstrates: (1) the impact of each input factor's uncertainty on the overall uncertainty of a land-cover model's output (the model evaluated the potential impacts of long-term SLR on the Snowy Plover population of the Florida Gulf Coast); and (2) the range of model inputs that produced a specific output meant to guide environmental management decisions. This was done by employing global sensitivity and uncertainty analysis (GSUA) using two generic methods, the qualitative screening Morris method and the quantitative variance-based Sobol method coupled with Monte Carlo filtering (MCF) (Saltelli et al. 2004; Chu-Agor et al. 2010; Muñoz-Carpena et al. 2010; Convertino et al. 2011b). The GSUA determines the model output uncertainty based on input parameter uncertainty, quantifies the impact of each factor on the outcomes, and — through

[1] In this example, only one SLR projection is utilized. EC 1165-2-211 provides the requirements for assessing SLR for USACE projects and stipulates that — in addition to an extrapolation of the historical rate — an intermediate and a high rate, that include future acceleration of SLR shall also be considered.

MCF — determines the range of inputs corresponding to the best restoration alternative based on the GSUA results. More specifically, GSUA is a sequential method. First the Morris method screens the input factors. Next, using the most important input factors, the Sobol method is applied. For the Sobol method, only the most important input factors and their associated uncertainties are used to determine the outputs of the model. As a final step, the MCF is performed. It's important to note that while commercial packages are available for performing GSUA (e.g., SIMLAB as described by Saltelli et al. 2004), emphasis herein is placed on the methods rather than the tools.

Global Sensitivity and Uncertainty Analysis is a powerful tool that can identify which restoration project alternatives should be selected for the model. While it is widely recognized that many models have gaps when applied in practice, GSUA does provide clear indications about the modality and intensity of the optimal restoration alternative for achieving the most positive outcome for the ecosystem, considering all the uncertainties that may arise. Consequently, GSUA can assist restoration managers who want to achieve the highest success rate possible, in terms of environmental restoration, thus minimizing the probability of project failure.

Sensitivity and Uncertainty Analysis

In general, uncertainty analysis (UA) determines the uncertainty in the model output that results from the combined uncertainties in the model inputs. Sensitivity analysis (SA), on the other hand, determines the individual contribution of uncertainty from each, respective input factor to the total uncertainty of a given output. Uncertainties in model inputs are represented by the range of values that the input factors can assume due to their natural variability, measurement errors, and climate change fluctuations. All possible value combinations for the input factors are synthesized using a GSUA method (e.g., the Morris or Sobol method) and the model output is then evaluated using these combinations. Following this, the distribution of the output values is produced using the MCF method. Thus, this technique allows one to explore all the possible states that the habitat may assume under future SLR scenarios. This is extremely important since from the information available, restorations have never explored all the possible uncertainties together and all the possible scenarios that may result from those uncertainties. In the following, first some of the habitat model results are reviewed; then the global sensitivity and uncertainty analysis for the salt marsh habitat type is shown; this habitat type correlates to the beach habitat of the Snowy Plover.

The results of the habitat model, SLAMM (Sea Level Affecting Marshes Model), predict that the overall physical Snowy Plover habitat in Eglin AFB would experience minimal losses (not exceeding 0.2% of its initial 2010 area) as a result of 2-m SLR from 2010 to 2100.[1] SLAMM is a land cover model that simulates the dominant processes involved in coastal wetland conversions and shoreline modifications during long-term sea level rise. Inundation (i.e., reduction in elevation due to sea level rise), erosion, overwash, saturation, and accretion are the primary processes included in SLAMM. The model can simulate 23 different wetland categories based on the National Wetland Inventory (Clough 2008). Each wetland type requires certain elevation boundaries and conditions (e.g., salinity, tidal ranges, etc.) in order to exist. SLAMM divides a spatial area into square cells of customized size and carries out the calculations for each cell, determining whether the cell is going to remain in the same category, or be converted to another.

[1] Note that in this example, a 90-year study period is utilized, whereas the typical planning horizon for ecosystem restoration projects is 50 years.

Conversion of a cell to another wetland type is generally governed by the minimum elevation of that cell. SLAMM is a simple model of land-cover evolution; therefore, other more sophisticated models may be used. The initial land-cover map for Eglin AFB is shown in Figure 1. The model predicts that the marshes of Santa Rosa Island (SRI), the land-cover category most impacted by SLR, could incur a maximum loss of 18% (30 ha) from 2010 to 2030, and beach habitat on SRI might incur a 1.7% (24 ha) loss by the end of the century. On the Eglin AFB coast, the regularly flooded marsh and the estuarine beach are the most vulnerable land cover categories, suffering the most significant losses between 2010 and 2100: 25%, and 11%, respectively. The tidal flat is predicted to experience a more dynamic inland migration compared to the rest of the categories (Chu-Agor et al. 2010; Linkov et al. 2011). Overall, Eglin AFB is more stable than other regions along the Gulf Coast of Florida (e.g., Tyndall AFB), incurring the least change in all land cover categories, except the tidal flat, from 2010 to 2100 as a result of 2-m SLR. These predictions show how many possible configurations the ecosystem may assume. The potential impacts of these habitat changes to the ecosystem and to humans can be assessed for future conservation and protection efforts, as shown in the next section.

A general schematic of the GSUA is shown in Figure 2. The uncertainty analysis demonstrates all the possible states of the output of interest, depending on the range in uncertainty of input variables. Figure 3 shows the results of the sensitivity analysis. On average, an increase in this salt-marsh area translates to an increase in the Snowy Plover beach habitat area (Chu-Agor et al. 2010). Salt-marsh areas are created by overwash events, and the model predicted a change of this habitat into tidal flats and estuarine/ocean beaches. The average elevation of salt-marsh habitats is higher than tidal flat habitats and estuarine/ocean beach habitats. In the habitat model, 27 parameters were initially considered as model inputs (Table 1). After sensitivity analysis, only 11 parameters (elevzone1, elevzone2, risetrend, tidalrange, tidalrangeinl, tiflaero, samaaccre, bramaaccre, tifreaccre, sedratebeach, and maxfrethres, in Table 1) were considered important for habitat change. For the salt-marsh habitat specifically, the sensitivity analysis further narrowed the inputs to two important parameters. Only the salt-marsh accretion and the trend in SLR were found to be driving the changes in this habitat type (Figure 3).

In the Morris analysis — or sensitivity analysis — for each input factor, two sensitivity measures can be calculated: (1) the mean elementary effect, μ, and (2) the standard deviation of the elementary effects, σ. The former estimates the overall effect (i.e., the importance) of the factor on a given output while the latter estimates the interactions. The most important parameters are those "Morris coordinates'' for which the mean elementary effect, and the standard deviation of the elementary effect (μ, σ) are not close to zero (Chu-Agor et al. 2010; Convertino et al. 2011b).

Risk Management Considerations

Performance of the sensitivity and uncertainty analysis results in the ability to identify both the important input factors that drive output uncertainty, and the ranges of these input factors that lead to each possible outcome (Saltelli et al. 2004). This is determined using MCF, where a set of constraints that targets the desired characteristics of the model realization (e.g., an acceptable range of outputs, or a threshold value as set by ecosystem managers or stakeholders) has to be defined. For the Snowy Plover, a favorable management mode was selected as the one producing a higher

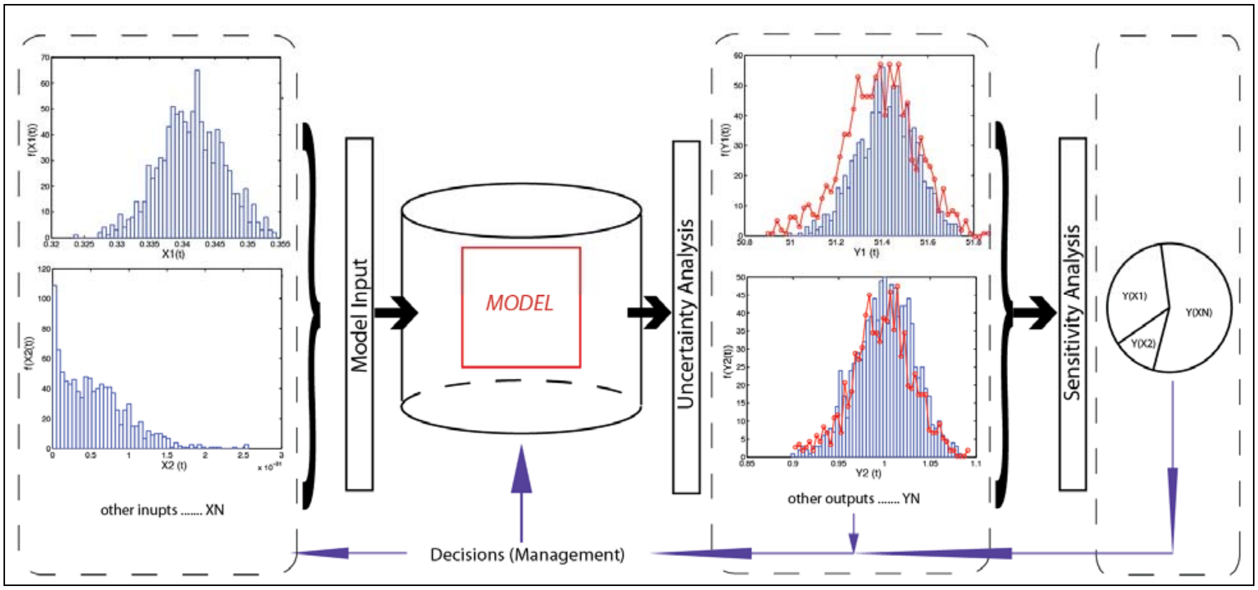

Figure 2. Overview of the model (SLAMM) sensitivity and uncertainty analysis. SLAMM inputs (X1, … XN) based on data (blue distribution, e.g., marsh erosion, and tidal flat erosion) or based on assumptions are considered uncertain and a range of possible values is assigned to each of them. The values are run through SLAMM which produces outputs (Y1, … YN) (red distributions, e.g., salt-marsh area) that may match the observed data or that constitute future predictions as a function of climate change. The uncertainty of the inputs produces outputs that can assume a range of possible values. The sensitivity analysis (Morris analysis) detects the relative impact that each uncertain input has on the model outputs; thus, YN(XN) (pie chart) is the part of the output YN produced by the input factor XN.

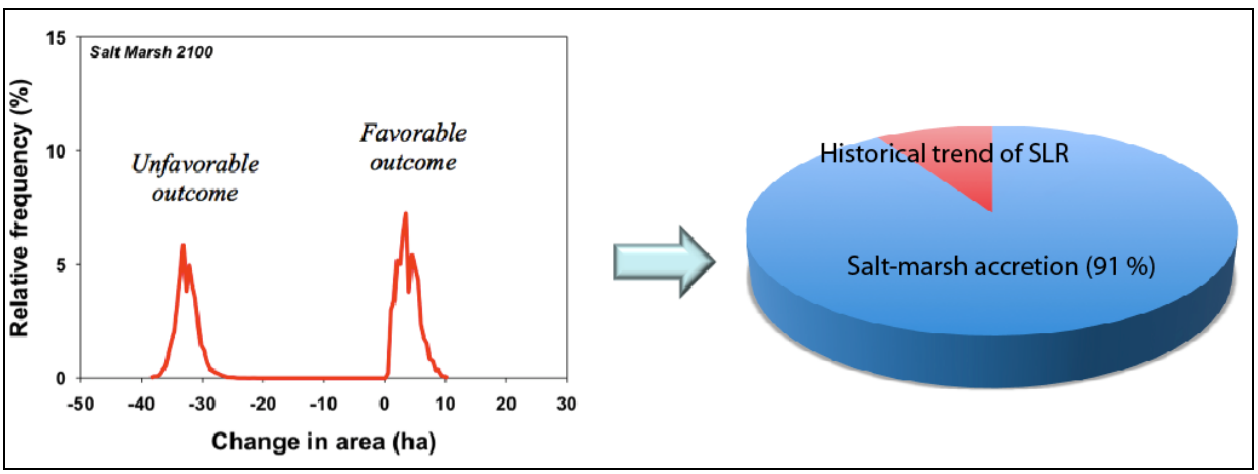

Figure 3. Sensitivity analysis shows which parameters are driving the outcomes. Here, the salt-marsh area is the outcome considered. In this case, salt marsh outcomes (left plot) — either favorable or unfavorable — are driven by two parameters, the historic trend of SLR and the salt-marsh accretion rate (right plot). The importance of the other parameters in forming the salt-marsh area is essentially equal to zero. This result is obtained using the Morris method. The accretion rate is the dominating factor with 91% of the outcome influence. Thus, the salt-marsh accretion is the parameter that restoration managers should focus on. The accretion of the salt marsh is, in fact, a parameter that can be directly controlled by coastal restoration alternatives such as renourishment.

Table 1. Input factors for SLAMM and assumed statistical distribution for the global and sensitivity analysis (from Chu-Agor et al. 2010).

No.	Input factors	Description	Units	Value	Distribution[b]
1	elevzone1	DEM vertical error (0-1 m)	m	0.2	U(-0.2, 0.2)
2	elevzone2	DEM vertical error (1-2 m)	m	0.2	U(-0.2, 0.2)
3	elevzone3	DEM vertical error (2-3 m)	m	0.2	U(-0.2, 0.2)
4	elevzone4	DEM vertical error (3-4 m)	m	0.2	U(-0.2, 0.2)
5	elevzone5	DEM vertical error (4-5 m)	m	0.2	U(-0.2, 0.2)
6	wetltype3	Wetland type (Swamp)	-	3	D (3, 5, 8)
7	wetltype5	Wetland type (Inland Fresh Marsh)	-	5	D (3, 5, 8)
8	wetltype8	Wetland type (Salt Marsh)	-	8	D (3, 5, 8)
9	risetrend	Historic trend of sea level rise	mm/yr	2.10	T(1.5, 2.1,2.4)
10	tidalrange	Tidal range at site (vertical)	m	0.35	U(0.35, 0.383)
11	tidalrangeinl	Tidal range inland	m	0.35	U(0.35, 0.383)
12	mhws	Mean high water spring	m	0.5235	U(0.464, 0.575)
13	marshero	Marsh erosion	horiz. m/yr	2.0[a]	U(1.6, 2.4)
14	swampero	Swamp erosion	horiz. m/yr	1.0[a]	U(0.8, 1.2)
15	tiflaero	Tidal flat erosion	horiz. m/yr	0.2[a]	U(0.16, 0.24)
16	samaaccre	Salt marsh vert. accretion	mm/yr	7.0-8.0	T(0.9, 3.2, 8)
17	bramaaccre	Brackish marsh vert. accretion	mm/yr	3.0-4.0[a]	U(3,4)
18	tifreaccre	Tidal fresh vert. accretion	mm/yr	4.0[a]	U(3.2, 4.8)
19	sedratebeach	Beach/tidal flat Sedimentation rate	mm/yr	3.9-8.6	T(0.01, 1.456, 5)
20	stormfrq	Frequency of large storms	yr/overwash	2	DU(1,2,3)
21	maxfethres	Max fetch threshold	km	9[a]	U(7.2,10.8)
22	maxwiow	Max width of overwash	m	500[a]	U(400,600)
23	owbeoc	Overwash beach to ocean	m	30[a]	U(24,36)
24	owdrbe	Overwash dryland to beach	m	30[a]	U(24,36)
25	owesbe	Overwash estuary to beach	m	60[a]	U(48,72)
26	owmarperlo	Overwash marsh percent loss	%	50[a]	U(40,60)
27	owmangperlo	Overwash mangrove percent loss	%	25[a]	U(20,30)

[a] Default values from SLAMM
[b] Assumed distributions and their parameters; U= uniform distribution (left boundary, right boundary), D: discrete distribution, T: triangular distribution (minimum, peak, maximum)

final Snowy Plover population than the other simulations, with a lower risk of species extinction (“favorable outcome’’ in Figure 3). This favorable outcome for the Snowy Plover is achieved by the salt-marsh habitat accretion that is one of the two forecasted outcomes for the coastal ecosystem when all the uncertainties are factored in together. The unfavorable outcome corresponds to a loss of salt-marsh area that translates into a decrease in abundance of the Snowy Plover.

Based on the results of the uncertainty analysis, MCF is performed for cases where management-favorable outputs could be defined (e.g., where some outcomes were clearly more desirable than others). In this study, the possible restoration alternatives include: (i) no action; (ii) minor salt marsh restoration; or (iii) major salt marsh restoration. Here, "salt marsh restoration'' means a creation of salt-marsh habitat by accretion. The classification into minor and major is determined by the range of values for the accretion rate determined by MCF. The higher the accretion parameter, the higher the expected salt-marsh increase. Due to the fact that it is very subjective to define *a priori* major and minor restoration, this technical note focuses on the extension of the salt marsh habitat, and how it can be achieved considering the drivers of the coastal processes. This technical note does not explore in detail, with incremental cost-benefit analysis methods, which restoration technology outperforms others. The goal is to quantify the salt marsh accretion rate that yields a positive outcome for the Snowy Plover population.

The output under consideration is the population of a threatened species, and the most favorable management decision — or the most "favorable outcome" — is the one giving rise to the largest final Snowy Plover population. This technical note predicted above that this corresponds to the greatest increase in salt-marsh habitat area; which, in turn, means the greatest increase in Snowy Plover habitat (Chu-Agor et al. 2010; Linkov et al. 2011).

The results of the MCF show that in order to potentially achieve the favorable outcome (an increase in the salt-marsh area), the accretion rate of the salt marsh must be in the range of 4 to 8 mm/year (Figure 4). In the context of the USACE, the optimal restoration of the salt marsh is thus expected to be a "major restoration'' of the salt marsh habitat that would lead to an accretion rate between 4 and 8 mm/yr. According to the MCF, the other options "no action" and "minor restoration'' would result in an unfavorable outcome (decrease in salt marsh area) for the Snowy Plover.

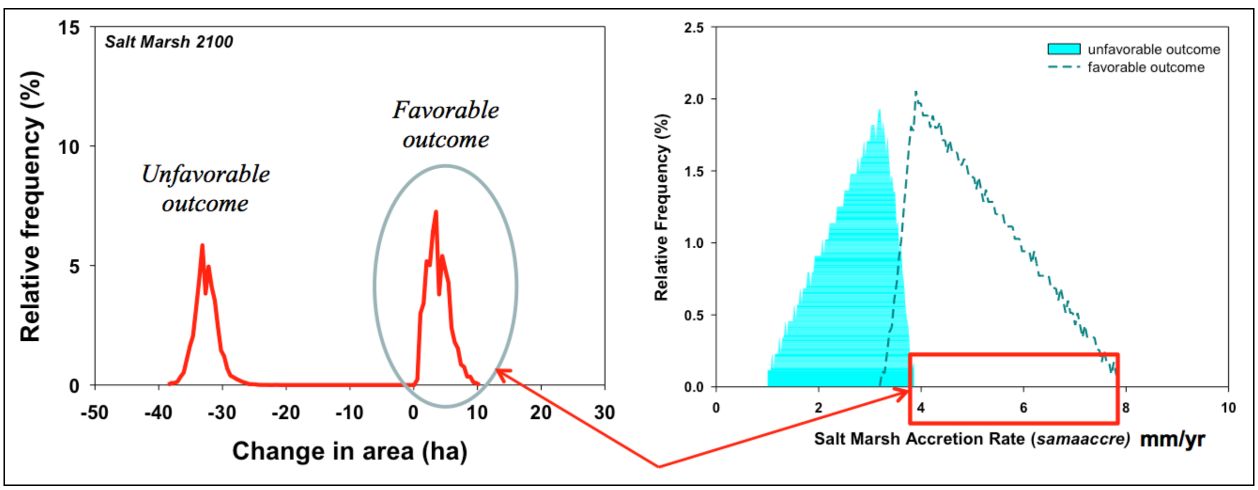

Figure 4. The MCF technique for assessing the range of values needing to be adopted in order to achieve a favorable outcome for the salt-marsh habitat. An accretion rate within the 4-8 mm/yr range (right plot) corresponds to a favorable outcome or increase in salt-marsh habitat (left plot). Thus, any type of restoration intervention that guarantees such accretion rates is going to be successful in terms of environmental benefits that are both an increased salt-marsh area and an increase in Snowy Plover abundance.

CONCLUSIONS: Global sensitivity and uncertainty analysis (GSUA) is a valuable tool that can aid project planning in a number of ways. It allows planners to harness uncertainty better by providing them with the range of possible outputs associated with an uncertain range of inputs, such as those resulting from SLR. GSUA also narrows restoration planners' focus by determining how much each factor contributes to the possible system outcomes. In this case, sensitivity analysis narrowed an initial 22 inputs to two important drivers for salt marsh habitat change. Finally, GSUA can guide restoration planning by determining the range of input values that will lead to each outcome. Informed by the results of the sensitivity analysis and MCF, planners can make decisions that better correspond to the most favorable outcomes. In this case, the sensitivity analysis led to the conclusion that the accretion rate is the dominant driver for change in habitat class, and the MCF led to the range of accretion rate values that would result in a favorable outcome. This information allows managers to focus their efforts on the most important factors for Snowy Plover vitality and provides them with a concrete objective (a 4 to 8 mm/yr accretion rate) that is most likely to lead to project success. Conducting a GSUA simplifies and directs projects, thus increasing both the efficiency and the likelihood of success. This case study demonstrates how GSUA can be applied to increase the efficiency and likelihood of success of ecosystem management projects by properly accounting for uncertainty.

Global sensitivity and uncertainty analysis allows ecosystem restoration planners to:

1) consider the uncertainty of the input parameters in order to explore all possible outcomes that an ecosystem may assume in the future under changes from external drivers such as SLR;
2) determine which inputs are driving ecosystem change. This can inform management decisions by revealing which aspects need to be considered in the restoration of the degraded ecosystem;
3) use modeling to evaluate the magnitude of the interventions required in order to reach the desired outcomes. For example, in this case study, a certain range of the salt-marsh accretion rate was found to be necessary for a favorable outcome; a higher or lower accretion rate may bring the system to an unfavorable outcome leading to Snowy Plover population decline or extirpation. Based on this information, the USACE restoration team should consider taking action to bring the accretion rate within the target range.

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