REVIEW ARTICLE

Prioritizing Wetland Restoration Sites: A Review and Application to a Large-Scale Coastal Restoration Program

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ABSTRACT

Wetland restoration has emerged as an important tool for counteracting and restoring lost ecological services resulting from urban and agricultural development. Over the last 20 years, Geographic Information Systems (GIS) modeling has also become a powerful mechanism for prioritizing potential wetland restoration sites across a variety of geographic scales. Although numerous studies have created GIS-based models for a variety of uses, no one has comprehensively analyzed and compared models to determine best practices and inform future site selection efforts. We performed a comprehensive literature review of GIS-based wetland prioritization models. We found no congruency between stated objectives, specific variables and metrics, and respective weighting and scoring systems. We then performed a case study, applying these findings to explore potential improvements to the spatial decision support system (SDSS) used by the Mississippi Coastal Improvement Program (MsCIP; USA), a large-scale coastal restoration project aimed at improving the resiliency and reducing flood risk after significant damage from Hurricane Katrina (2005). This case study draws on several state-of-the-art practices in the literature to retroactively study potential improvements in the SDSS's flexibility and accuracy in identifying potential wetland restoration sites. Our findings suggest improvements for wetland restoration prioritization models (including consistent variable use and ground-truthing) that could better direct future federal initiatives, as well as a wide range of domestic and international wetland restoration programs.

Keywords: coastal resilience, spatial decision support systems, wetland mitigation, wetland site selection.

Restoration Recap

- Geographic Information Systems (GIS) modeling is a powerful mechanism for prioritizing potential wetland restoration sites across a variety of geographic scales.
- We performed a comprehensive literature review of GIS-based wetland prioritization models.
- We found a lack of consensus across models in variables used to prioritize site selection.
- We applied our findings to gauge future improvements in federal targeting of wetland restoration.
- As a case study, we studied the Mississippi Coastal Improvement Program (MsCIP)'s spatial decision support system to determine potential improvements in flexibility and accuracy in identifying potential wetland restoration sites.
- Our findings suggest improvements for wetland restoration prioritization models, including using consistent variables and ground-truthing.

Healthy, well-functioning wetlands produce a variety of ecosystem functions and services, including increased flood prevention, improved water quality, wildlife preservation, and soil amelioration, among many others (Mitsch and Gosselink 2000). Wetland benefits are not strictly ecological, as water-retention and pollutant filtration services can decrease water treatment costs in municipal infrastructure systems (Strager et al. 2010). Additionally, the emergence of wetland mitigation banking (NRC 2001), a policy tool aimed at restoring lost ecological services resulting from

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harmful development, has added an economic impetus for wetland restoration and enhancement (Strager et al. 2010).

While various policies have been developed to direct the location and form of wetland restoration efforts, recent evidence has begun to call into question the effectiveness and success rate of these projects (Holland and Kentula 1992, Kentula et al. 1992, Pfeifer and Kaiser 1995, Cole and Shafer 2002, Reiss et al. 2009). Research suggests that restored wetlands often fail to meet expressed performance goals or function effectively as healthy environmental systems (Russell et al. 1997, Brown and Veneman 2001, Williams 2002). Reasons for these failures are varied, but many times can be largely attributed to technical error (construction or mechanical), problematic hydrology, lack of financial resources, and/or poor site selection (Williams 2002). Failure to recognize wetlands as part of larger natural landscapes also contributes to unsuccessful mitigation (NRC 2001).

Rather than viewing them as a collection of isolated restoration sites, studies have begun to show that a 'watershed approach' (originating from Davenport et al. 1996) to wetland site selection and restoration can have a far greater impact on wetland health, function, and overall performance than simply replacing damaged or destroyed wetlands onsite (White and Fennessy 2005, Kramer and Carpendo 2009). The watershed approach has been concisely defined by ELI and TNC (2014) as ". . . an analytical process for making decisions about the location and type of compensatory mitigation projects that should be carried out." In the absence of watershed plans, agencies instead rely on as deep a pool of watershed information as possible during decision-making processes (ELI and TNC 2014). As adopted by 2008 regulations, the approach's increased reliance on planning, watershed information, and site context is aimed directly at improving both the quantity and quality of compensatory wetlands created under the auspices of the U.S. Clean Water Act (USACE and EPA 2008).

Geographic Information Systems (GIS) analysis has emerged as a powerful mechanism to incorporate a variety of watershed and site-level data (following the 'watershed approach') into the wetland site selection process. Easily applied over a range of geographic scales and with input data flexibility, GIS-based wetland prioritization models hold great potential, as long as the organization using the model possesses the technical knowledge to run the software and has the necessary data inputs (Drummond and French 2008). Unfortunately, GIS-based wetland restoration prioritization models have struggled with the most basic, critical question of any site selection model: what attributes define a wetland and its ability to be restored to produce ecosystem functions?

Here we attempt to provide some clarity and organization to the literature on GIS-based wetland prioritization models. Through a comprehensive literature review, we categorize these models based on their stated objective, the variables used for site selection, and the specific weighting mechanisms (and theoretical reasoning behind weighting) used (if any) to rank and prioritize the sites for restoration. Aggregating this information provides researchers and practitioners with a comprehensive and detailed listing of the major works within a growing body of literature and research on GIS-based wetland restoration site prioritization modeling.

Expanding on this work, we then evaluate the spatial decision support system (SDSS) used to guide the Mississippi Coastal Improvements Program (MsCIP 2009), a comprehensive effort to increase coastal resiliency in the three Mississippi coastal counties following damage from Hurricane Katrina (2005). Ecological restoration is a key component of this plan, with the SDSS model responsible for wetland site selection and prioritization. Informed by the findings of the literature review, we aim to refine and improve the functioning and performance of the SDSS. The potential use by the U.S. Army Corps of Engineers (USACE) and other groups in future domestic and international projects make MsCIP an excellent case study for creating a more robust and extensible model.

Literature Review of GIS-Based Wetland Mitigation and Restoration Models

In performing a review of wetland restoration site prioritization projects, our objective was to examine and analyze GIS-based wetland mitigation and restoration models across a wide range of journal databases. In particular, we were interested in congruencies between the models with regards to their stated objectives (which may be very different across applications), the individual variables or metrics utilized, and their respective weighting and scoring systems.

Literature Review Process

With the explicit aim of identifying only GIS-based models that prioritized wetland mitigation and or restoration sites for all years, we initiated searches in three major online research databases during the Fall of 2012: Google Scholar, Sciencedirect, and Springerlink. These databases were specifically selected because of their comprehensive coverage of environmental management and ecological and environmental planning journals; publications believed to be most likely to contain studies of wetland restoration and mitigation spatial modeling. We used two related, but unique keyword searches: "GIS-based, wetland mitigation prioritization" and "GIS-based, wetland restoration prioritization". Together, these queries produced n = 2,353 potential research articles.

A number of principles guided the process of identifying relevant research studies within this initial search set. First, given the explicit interest in remote, GIS-based wetland prioritization models, we excluded studies from our review that relied exclusively on physical observations or on-site data collection (studies that were not, in fact, GIS-based prioritization models; this accounted for the vast majority [~ 99%] of articles initially identified). Once we collected all pertinent studies from the six searches (two search terms in three databases), the references of each individual article were consulted to locate any critical missing literature (a 'bootstrap' process). In total, the initial set of articles was filtered to identify all GIS-based wetland prioritization models available (n = 27), which were published between 1994 and 2013 in a wide-range of scholarly journals.

In assessing and analyzing the individual studies, we focused on three specific factors. First, we attempted to determine the explicit objective of the model. While all of the studies focused on wetland prioritization, many organized and ranked their identified wetlands based on one or more performance criteria (e.g., flood risk reduction or habitat provision). Second, we compiled and classified individual variables and indicators utilized in each model (we should note that our sample size did not facilitate analysis of temporal trends in variables and indicators over the 20–year time period of studies we reviewed). Finally, we located the internal weights or relative values assigned to each variable and the rationale used to justify them.

Model Objectives

Of the 27 studies, 22 explicitly aimed to provide a GIS-based model that prioritized wetlands (Table 1). More than half of the studies (15) provided additional objectives beyond general wetland prioritization (Supplementary Table S1). Locating and ranking wetlands that: 1) preserved/restored wildlife habitats: 2) improved water quality; and 3) increased flood attenuation were the three most popular additional objectives. Rather than solely focus on only one performance objective, eight of these 15 studies selected one or more, with two attempting to prioritize wetlands based on all three. Two of the models also had 'variable objectives,' which could be defined and rearranged based on the specific aims of the user. Mentioned, but less popular, objectives included prioritizing wetlands in order to produce ecosystem services (e.g., Kramer and Carpendo 2009) and identifying convertible farmland (Huang et al. 2010). The exact ecosystem services sought was often somewhat scattered, and included concepts such as "connectivity to existing conservation lands" and "maintenance of high water quality streams for biodiversity (Kramer and Carpendo 2009, Pg. 3)".

Model Variables

Each GIS-based wetland prioritization model identified and selected specific variables deemed essential to achieving the goals and aims of each study. Through multi-criteria decision analysis, variables were quantified and then mathematically arranged to either identify suitable restoration sites and/or provide a suitability score allowing for comparative ranking between locations. Equations often included both binary variables that filtered site locations through multiplication and weighted variables that were summed together to determine final site suitability. Below is an example of a simple equation from Ausseil (2007) illustrating suitability scoring (typically structured as a linear combination) for a number of variables/criteria, where n is the number of criteria, w_i is the weight associated with the variable, and V_i is the variable.

$$\text{Score}=\sum_{i=1}^{n} \mathrm{w}_i \mathrm{V}_i$$

From our 27 selected studies, we identified a total of 78 individual model variables covering a wide-range of environmental media including hydrology, geomorphology, surrounding built environment, and habitat connectivity (see the entire set in Table S1). Our analysis suggested that the stated objectives of each specific model helped to shape and direct variable selection; for example, studies which were explicitly interested in wildlife habitat preservation were more likely to include variables such as habitat core-area ratio and/or proximity to other protected wildlife preserves, instead of hydrologic connectivity or soil saturation index.

The most popular variable throughout all of the studies was the presence of hydric soils; 17 out of the 27 studies (62.9%) included this variable in their model. The second most popular variable (44.4%) could be termed 'hydrologic connectivity'. Although each of the 12 studies that included this variable varied in their specific approach, all 12 attempted to quantify sites' proximity and/or relationship to adjacent hydrology. Following hydrologic connectivity were land use (37%), land cover 33.3%), wetland connectivity (29.6%), and "classified as wetlands" (29.6%). Surprisingly, no single variable was consistent throughout all 27 models. Furthermore, 42 out of the 78 total variables (53%) were completely unique and used in only one model. This lack of consensus highlights the current fractured and subjective landscape of GIS-based wetland prioritization models.

Model Weighting

All of the models reviewed utilized some form of multi-criteria or multiple attribute decision analysis (MCDA) (Malczewski 1999; Prato 1999). MCDA facilitates collaborative decision-making and ". . . allows integration of preferences for attributes with objective measures" of a variety of variables (Strager et al. 2010, Pg. 7). We found inconsistent variable weighting throughout all of the models analyzed. Eight models assigned no secondary weights to their variables; that is, each variable had equal power to influence the model and no adjustments were made for the range or variance of measurements. That is, weights were dictated

Table 1. Stated study objectives of wetland restoration prioritization literature reviewed (n = 27 studies).

Study	Wetland Prioritization	Wildlife Habitat	Water Quality	Water Storage	Maximize Ecosystem Services	Convertible Farmland	User Defined Objectives	Undefined
Ausseil et al. 2007	X							
Berman et al. 2002	X							
Brophy 2005	X	X	X					
Brown and Strayner 1994		X	X	X				
Cedfeldt et al. 2000	X	X	X	X				
Copeland et al. 2010	X							
Huang et al. 2010	X					X		
Kauffman-Axelrod and Steinberg 2010	X							
Kramer and Carpendo 2009	X				X			
Lin and Kleiss 2007	X	X	X					
Liu et al. 2006	X							
McAllister et al. 2000	X			X			X	
McCauley and Jenkins 2005								X
Moreno-Mateos et al. 2012	X	X	X					
Newbold 2005	X		X					
Ouyang 2011	X							
Palmeri and Trepel 2002	X						X	
Richardson and Gatti 1999	X		X					
Russell et al. 1997	X	X		X				
Schleupner 2010								X
Schleupner and Schneider 2013								X
Strager et al. 2010	X							
Tang et al. 2012	X							
Van Lonkhuyzen et al. 2004	X							
Vellidis et al. 2003	X		X				X	
White and Fennessy 2005	X		X					
Williams 2002								X

by the arbitrary choice of measurement units for each variable. Nine models used a two-tier weighting system focused on first defining physical suitability, and then determining potential performance opportunities (e.g., Brown and Strayner 1994). Within this framework, specific variables were selected to function as binary criteria that quickly narrow down and define a site. These variables were usually focused on physical parameters that were seen as particularly useful to define wetland properties or features (White and Fennessy 2005).

After the wetlands in the area of interest or study are determined, additional variables were used, depending on the objectives of the model, to determine site suitability and wetland performance or function based on what White and Fennessy (2005) refer to as 'neighborhood parameters'. Depending on the specific model, these secondary variables could either be weighted evenly or assigned specific influence. Ten of the final 19 models that used weights applied variable weighting, assigning different strengths to each criterion based on its importance in determining the model's respective objective(s).

If varying weights were placed on model variables, we attempted to determine the specific rationale used to justify the distribution of influence in the model. Six of the 19 models that had variable weighting failed to provide any sort of justification or rationale for why they chose their respective weighting system. Of the remaining 13 models, 11 cited professional or expert-based judgment as the rationale behind their weight distribution, with two models weighting based on their own literature reviews (Kramer and Carpendo 2009, Richardson and Gatti 1999).

In summary, much like our exploration of model variables, it was difficult to discern any clear patterns or trends in models' variable weighting, as we observed a nearly even distribution between even (un-weighted), two-tier, and variable weighted models. Once again, this underlines the lack of consensus and cohesion between GIS-based wetland prioritization models, including models with very similar objectives.

Model Calibration

We found little to no ground-truthing, model calibration, and/or model validation across any of the studies reviewed. Donigian (2002, Pg. 44) defines model 'calibration' as ". . . an iterative procedure of parameter evaluation and refinement, as a result of comparing simulated and observed values of interest". We can contrast this with model 'validation,' which acts as a further check on the accuracy of model variables and weights through assessments of model accuracy in scenarios and environments separate from the calibration process (Donigian 2002, Refsgaard 1997). Calibration and validation are critical steps in the model building process as they verify and determine a model's accuracy and effectiveness (Donigian 2002, Long and Freese 2014, Train 2003, Refsgaard 1997).

Of the 27 models reviewed, not a single one of the models calibrated their weights and variables as a result of on-site field observations or ground-truthing efforts to verify model validity. No models engaged in the typical model calibration practice of reserving some data for post-calibration model validation, which would test if the model calibration based on ground-truthed data were correct (i.e., do model weights apply across the entire dataset?). While the function of weights is typically to indicate the relative importance that a decision-maker places on each biophysical factor (as specified through theory and data), field observations can be used to validate the biophysical aspects of the model (e.g., do hydric soils occur where GIS data indicate that they occur?). Although four models performed on-site field observations (Brophy 2005, Strager, et al. 2010, Williams 2002, Lin and Kleiss 2007) and three models (Moreno-Mateos et al. 2012, Cedfeldt et al. 2000, Palmeri and Trepel 2002) performed some type of independent validation, none performed any type of iterative calibration of specific variable weights (to improve the resulting model) as a result of their findings.

Our review of the literature on GIS-based methods for prioritizing wetland restoration did not identify many systematic features of previous studies. In particular, we were struck by the largely ad hoc nature of the literature, whereby measured variables and their weights are chosen almost entirely based on professional judgment. It is clear that there has been little to no systematic assessment of the functional relationships between the attributes of potential restoration sites and the various ecosystem service flows that these sites might enhance if restored.

Mississippi Coastal Improvements Program (MsCIP) Case Study

Based on the findings of our comprehensive literature review, and in an effort to apply that research to improve the functioning and efficiency of GIS-based wetland suitability and prioritization models, we chose to examine the spatial decision support system (SDSS) created by Lin and Kleiss (2007), which was a key technical tool in creating the Mississippi Coastal Improvement Program (MsCIP) Comprehensive Plan (MsCIP 2009) and one of the 27 studies in our literature review.

The MsCIP's SDSS model was chosen primarily for three reasons. First, with the extensive federal funding that MsCIP is allocated to receive, the SDSS has guided one of the most significant and well-financed wetland restoration programs in the United States. Second, MsCIP is slated to identify, prioritize, and drive an enormous amount of ecological restoration (i.e., it will be influential in the region). Finally, if the SDSS is used in a similar manner in the future, any improvements to its accuracy could have a very influential impact on wetland restoration efforts elsewhere on the Gulf Coast, and in future uses of the SDSS or similar models in other domestic or international applications.

In this case study, we: 1) review background information on the MsCIP; 2) examine the SDSS in detail, including its specific objectives, variables, and weighting mechanisms; and 3) review and experiment with additions and improvements to the SDSS model supported by the literature.

MsCIP Background

In the wake of the catastrophic destruction caused by Hurricane Katrina, USACE was directed by the US Congress to ". . . conduct an analysis and design for comprehensive improvements or modifications to existing improvements in the coastal area of Mississippi in the interest of hurricane and storm damage reduction, prevention of saltwater intrusion, preservation of fish and wildlife, prevention of erosion, and other related water resources purposes (MsCIP 2009, Pg. S–1)". The result of this inquiry was the creation of the MsCIP comprehensive plan, which is comprised of 12 major elements to address hurricane and storm damage reduction, saltwater intrusion, shoreline erosion, and fish and wildlife preservation.

To accomplish these goals, the plan calls for numerous activities, including a High Hazard Area Risk Reduction Program (HARP) involving land acquisition of approximately 2,000 tracts in areas at the highest risk of being damaged by storm surge, flood proofing, levee construction, and major ecosystem restoration projects. Special authority from Congress allowed cost effectiveness to be used in lieu of the typical 'national economic development benefits' typically needed to justify projects. In addition, MsCIP was also not required to follow an incremental benefit-cost analysis.

The financial backing for the MsCIP program is substantial; MsCIP is a 30–40 year program executed during three separate phases, with the initial phase estimated to cost over $1.01 billion USD (MsCIP 2009). Projects under MsCIP were selected to be compatible with the State Coastal Restoration Plan, and are expected to eventually

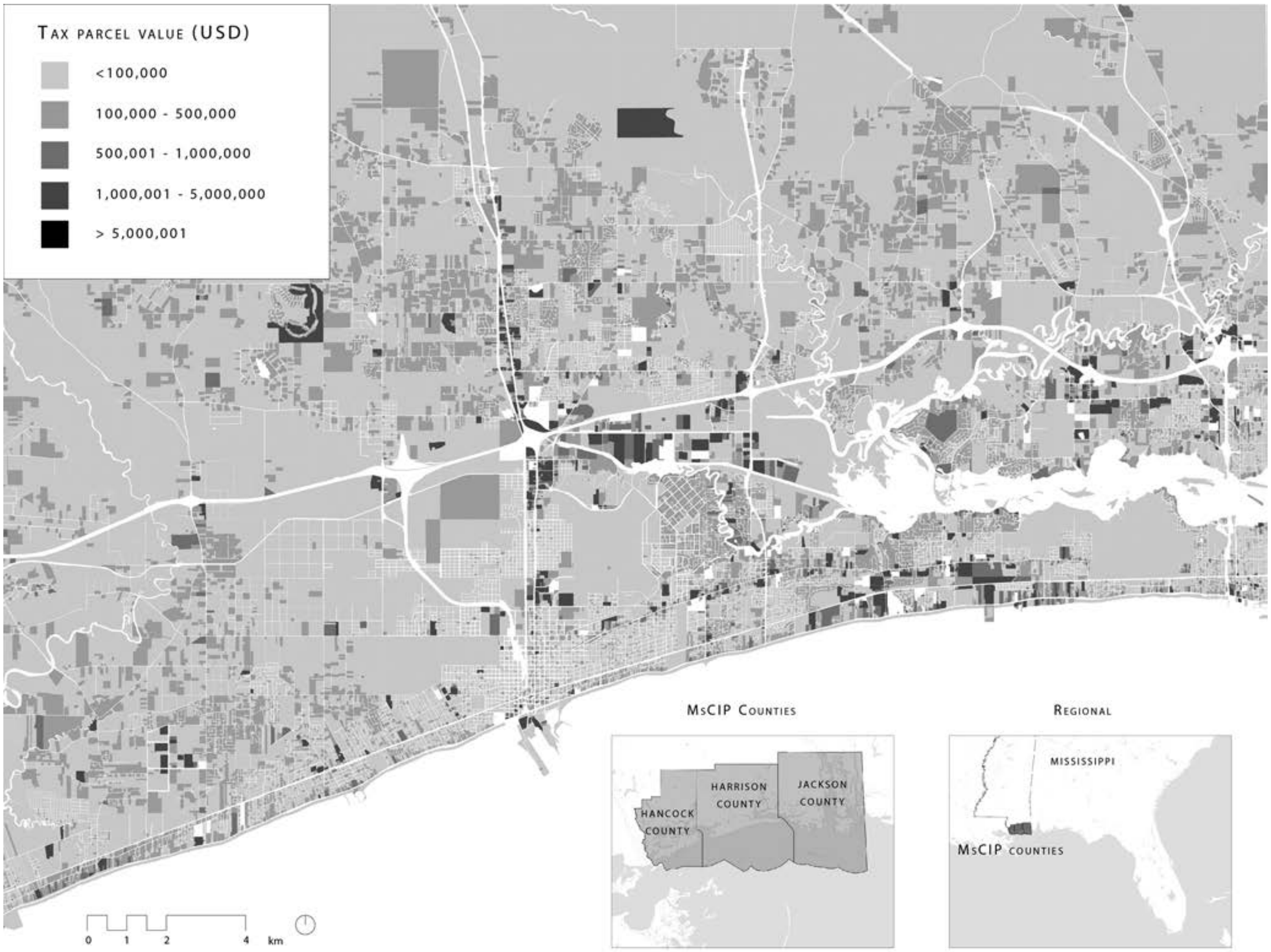

Figure 1. Jackson, Hancock, and Harrison County, MS parcel and land value data (2012 USD).

restore of over 3,000 acres of coastal forest and wetlands and nearly 30 miles of beach and dune restoration. MsCIP encompasses the three Mississippi coastal counties of Hancock, Harrison, and Jackson, and is explicitly tasked with identifying cost-effective programs that actively improve coastal 'resiliency' through extensive ecological restoration and hazard mitigation programs (MsCIP 2009; Figure 1). 'Resilience' has been promoted as a concept to guide the management of social-ecological systems (Schluter and Pahl-Wostl 2007), and can broad be defined as the ability of a system to cope with disturbance and adapt under stress to maintain structure and function (for more in-depth definitions, see Holling 1973, Holling 2009). MsCIP operationalizes this concept by identifying solutions to hurricane and storm damage, saltwater intrusion, and related water resource problems in coastal Mississippi. These solutions are intended to "render the region more resilient and less susceptible to damages resulting from future coastal storm events" (MsCIP 2009, Pg. 1–3).

MsCIP Spatial Decision Support System (SDSS)

Wetland restoration and enhancement were critical to the wider MsCIP aims of ecological restoration and flood mitigation (MsCIP 2009). Developed by Lin and Kleiss (2007), the SDSS was created to rapidly identify and prioritize possible wetland restoration areas across the extensive geographic area impacted by Hurricane Katrina. Additionally, the SDSS evaluates potential sites within a larger watershed and landscape context, allowing for a more comprehensive evaluation of the broader ecological system.

The stated objective of the SDSS is to locate suitable wetlands sites that ". . . provide quality wildlife habitat and storm and flooding protection (Lin and Kleiss 2007, Pg. 2)". The SDSS operates within a two-tier framework, first identifying potential restoration sites through binary weighting of several variables. Next, these potential restoration sites are analyzed based on four performance metrics, the results of which rank potential sites for wetland restoration on: 1) flood risk reduction; 2) wetland 'restorability'; 3) provision of wildlife habitat; and 4) 'Other,' which we will refer to as 'infrastructure connectivity'.

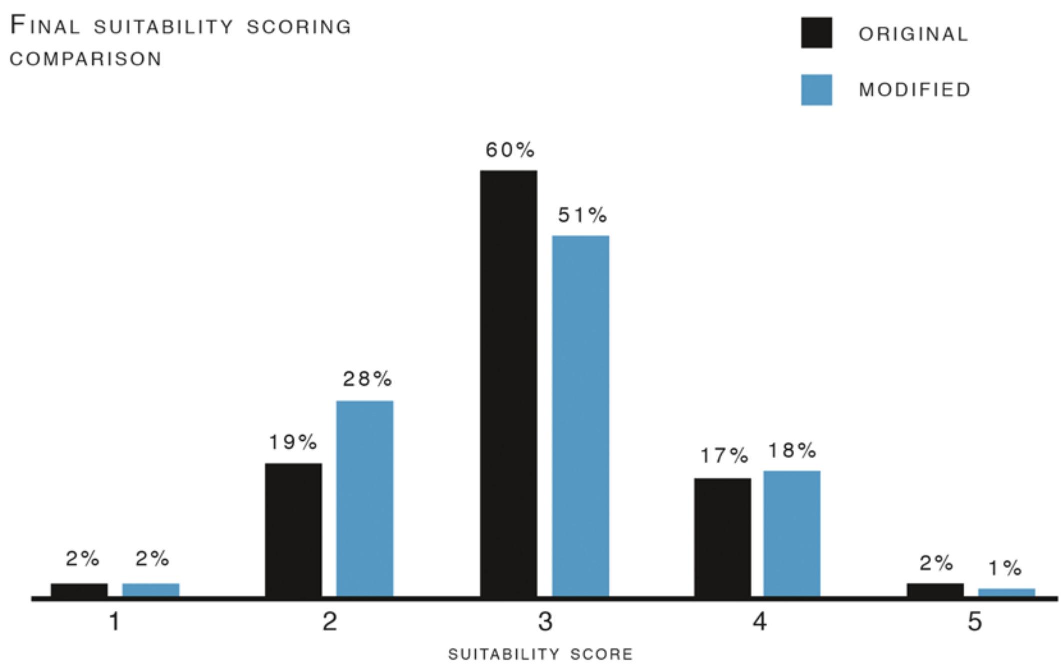

Figure 2. Comparison of potential restoration sites in original and modified MsCIP spatial decision support system (SDSS).

Identifying Potential Restoration Sites

A key assumption of the SDSS is that it is only intended to locate and restore wetlands on privately held, previously developed land. In order to create a study area based on this condition, three variables were used: *storm damaged areas*; *100–year floodplains*; and *non-natural land cover*. Use of these variables was justified by noting that land damaged by Hurricane Katrina and within the 100-year floodplain would be significantly cheaper to acquire by MsCIP.

Non-natural land cover was determined by selecting the following categories from the Mississippi Department of Marine Resources (MDMR) 2001 land cover data (based on the resolution of the MDMR, the SDSS employs raster datasets at a 10 m resolution): high/medium density urban (including residential, commercial, and industrial), cropland/pasture/grassland, upland sand/barren, wet sand/barren, wet cutover land, and upland cutover land. Any raster cell that fell within the binary parameters detailed above was identified as a potential restoration area. Finally, any potential areas smaller than one contiguous acre were removed. In total, 1,086 total potential restoration sites were located covering 7,892 acres (Lin and Kleiss 2007; see Figure 2).

Assessing Wetland Function and Prioritization

With the study area determined, the SDSS uses four performance metrics to determine wetland suitability and prioritization: flood risk reduction, wetland 'restorability,' provision of wildlife habitat, and infrastructure connectivity. The wetland restorability metric included variables aimed at measuring ". . . the suitability of an area to be a functioning and sustainable wetland (Lin and Kleiss 2007, Pg. 6)". Variables aimed at measuring the suitability of wetlands for storm and flood mitigation and quality wildlife habitats were included in the storm surge/flood protection and habitat metrics, respectively. The fourth metric, infrastructure connectivity, included three unique variables, two of which measured whether potential restoration locations overlap with potential future MDMR restoration projects. The final variable concerned Katrina storm damage, and was used as a measure of the government's ability to purchase privately owned property ('property buy-out potential'; Lin and Kleiss 2007). A complete listing of the variables that comprise each metric, as well as their respective scaled scores, is located in Table 2.

Specific scoring distributions varied between variables; the habitat metric drew on grouping and distribution information (excluding core-area ratio measurements) from O'Hara et al.'s (2000) SDSS for the Yazoo Backwater area in Mississippi. Contrasting this, for flooding, the SDSS drew on a '*wetness index*,' articulated as a measure of ". . . potential saturation in an area as compared to its surrounding landscape . . ." (Lin and Kleiss 2007, Pg. 6). The *wetness index* and *core area ratios* were divided according to equal distribution across the range of values. This approach has the effect of placing equal weight on each percentile of each variable's distribution. Unfortunately, this still does not measure the marginal effect of each variable on the benefits or costs of restoration. For the remaining multi-categorical variables, scores were distributed uniformly across the range. For true/false variables, true conditions were given

Table 2. Original MsCIP SDSS metric design (Lin and Kleiss 2007), variable list, and scaled score distribution.

Function	Variable	Raw Value	Scale Score
Provision Of Wildlife Habitat	Core Area Ratio	0–0.07	0
		0.07–0.15	5
		> 0.15	10
	Block Size (acres)	1–10	0
		10–320	5
		> 320	10
	Distance to Roads (m)	0–50	0
		50–500	3
		> 500	5
	Distance to Open Water (m)	0–150	5
		150–300	3
		300–750	1
	Distance to Protected Areas (m)	0–150	5
		150–300	3
		300–750	0
Wetland Restorablilty	Hydric Soils	1	20
		0	0
	Wetness Index	–10.6–1.44	0
		1.44–13.5	5
		13.5–25.6	10
	Distance to Seed Source (m)	0–60	10
		60–120	5
		> 120	0
Flood Risk Reduction	Depressions	1	15
		0	0
	Storm Surge Capacity	5	1
		4	3
		3	5
		2	8
		1	10
	Stream Buffer	1	15
		0	0
Infrastructure Connectivity	MDMR Restoration Sites	1	3
		0	0
	Damage Level	1	3
		3	1
	Proposed Coastal Reserves	6	0
		1	3
		0	0

Table 3. Original MsCIP SDSS final restoration prioritization scoring distribution for Hancock, Harrison, and Jackson Counties, MS (total sites and acres).

Classified Value	Provision of Wildlife Habitat		Wetland 'Restorability'		Flood Risk Reduction		All Functions	
	# of Sites	Total Acres	# of Sites	Total Acres	# of Sites	Total Acres	# of Sites	Total Acres
1	101	255	66	396	26	93	48	156
2	452	1,633	248	1,596	531	3,933	243	1,520
3	314	3,608	178	2,703	402	3,405	556	4,702
4	152	1,970	405	2,665	78	325	204	1,355
5	67	425	189	532	49	135	35	159

positive values, with false receiving negative scores (Lin and Kleiss 2007). Variable weighting was informed by the professional judgments of the authors, augmented by consultations with MDMR and U.S. Fish and Wildlife Service personnel (Lin and Kleiss 2007). As we have discovered in our literature review, this is an important limitation of both this model and the GIS-based restoration prioritization approach, generally.

The total for each of the four performance metrics were calculated by adding up the scores for each respective variable. The total scores for the fourth metric, infrastructure connectivity, were added to the total sum for each of the three remaining metrics; the SDSS provided no rationale for why the fourth metric was represented in this manner within the model, or why those variables could not be contained more traditionally within the other metrics (Lin and Kleiss 2007). To reach a final suitability score, the metric scores for each raster cell (flood risk reduction, wetland 'restorability,' and provision of wildlife habitat) were averaged together with equal weighting. To account for uneven maximum metric scores, *wetland restorability* and *storm/flood protection* were scaled accordingly (multiplied by 0.898). No specific justification was provided for the equal metric weighting structure (Lin and Kleiss 2007). Final average scores were reclassified through equal distribution onto a scale of one to five, with five being the most suitable, with the highest restoration performance potential, and one being the lowest. The SDSS's final prioritization of restoration sites is shown in Table 3.

As we saw in the literature review within this area, a major question surrounds the weighting technique when applying professional judgments. Ideally, each indicator variable should be related to either the benefits or costs of restoration. For example, we want to determine: how much does a one unit change in each indicator variable increase the quality of the restoration site—i.e., reduce flooding risk, improve habitat, and enhance water quality? Likewise, how much does a one-unit change in each variable increase or decrease the cost of its acquisition and restoration?

Leveraging the Literature to Improve MsCIP's SDSS

As discussed earlier, the MsCIP SDSS model was chosen for this case study based on its potential to function as an extensible framework for similar prioritization models for wetland restoration in the future. However, on-site field observations of sites recommended by the SDSS determined that the model was not particularly accurate; efforts to ground-truth sites scored as high-priority restoration locations by the model's remote sensing data found several to be either low quality or un-restorable (e.g., require expensive buyouts of already-developed land). The incongruence between model results and actual realties on the ground indicate the need for some improvements (16 sites of 1086 identified were visited; 1.5%).

Unfortunately, due to intense time constraints, no attempt was made recalibrate variable weighting based on ground-truthing, nor was any model validation performed (e.g., using calibration data from one county to estimate locations of high priority sites in other counties). Without well-designed ground-truthing efforts (i.e., random samples of sites rated at varying degrees of priority, in different locations throughout the study region), it is difficult to conclusively improve the outcomes associated with the SDSS. However, informed by our literature review, we can identify and integrate some of the best practices observed in other models into the SDSS, thereby demonstrating ways to improve the reliability and performance of similar models in the future.

Step 1: New wetland identification process (population of possible restoration sites)

To do this, we first comprehensively re-tooled the way the SDSS initially identifies potential restoration sites (using the same 10 m raster cell resolution as the original MsCIP SDSS). In addition to the three variables included in the original model, we added a fourth binary variable: the *presence of hydric soil*. Including the *presence of hydric soil* as a binary variable, rather than as a piece of a larger performance metric, improves the model in a number of ways. We added a *presence of hydric soil* into the model because it was included in a strong majority of models analyzed in our literature review (see Table S1). For the nine models that employed binary variables to create possible restoration sites, six of them used the *presence of hydric soils* as an initial screener. Additionally, the professional community has identified the *presence of hydric soils* as a key indicator of either historic wetlands and/or the necessary hydrology essential for successful wetland function and vitality (Williams 2002, Mitsch and Gosselink 2000, Richardson and Gatti 1999). This improves the SDSS dramatically from a theoretical perspective; instead of selecting and evaluating sites that may lack the necessary soil composition to support wetland systems, locations that have no hydric soils are now completely precluded from even being evaluated as potential restoration sites (this binary treatment also helps to handle the notoriously coarse resolution of hydric soil maps).

Step 2: Reforming the filtering process for government land purchase

After augmenting the binary conditions that the SDSS used to populate possible restoration areas, we modified the performance metrics used to rank the sites. As discussed earlier, although flood risk reduction and provision of wildlife habitat are the major goals of the model, the SDSS uses two additional metrics, 'wetland restorability' and 'infrastructure connectivity' as further filters for restoration site rankings. The key variable in the 'restorability' metric, the *presence of hydric soil*, is now represented much more strongly in Step 1 of the model's construction. Much of the rationale behind the original SDSS points to the need for cost-effective programs, making clear that land acquisition costs are an important part of locating potential wetland restoration sites.

Therefore, the 'restorability' metric was replaced with a *land value* variable (not included in the original SDSS) drawn from the total assessed value of the tax parcels within the three MsCIP counties (data were obtained from the Jackson and Hancock GIS/Mapping Departments and the Harrison County Online Mapping and GIS Services Division). While we acknowledge that parcel assessed tax value is not a perfect measure of land costs, its inclusion does facilitate land value data to influence and direct the model. While this change in the SDSS does not ensure a proper cost-effectiveness analysis (i.e., ranking sites based on biophysical restoration benefits to cost ratio), it is a move in the right direction. We should note that the land parcel value raster dataset covering Jackson, Harrison, and Hancock counties was not complete. The files were acquired from the respective counties' GIS departments and contain a number of omissions and/or land parcels with "no data". Land data that had no assessed value was not included in the final suitability analysis.

We also removed the 'infrastructure connectivity' metric for two reasons (see variables originally included in this metric in Table 2). First, the metric relied on future, hypothetical MDMR restoration projects, which, at the time, had yet to be implemented. While the literature typically includes a variety of connectivity measures, few studies have attempted to add future project connectivity given increased uncertainty that this variable adds into the model. Given that these variables are not based on currently existing conditions, and are instead centered on potential MDMR restoration projects, we removed them from our revised SDSS model. Second, the *storm damage* variable was included to approximate land that offered ". . . a better opportunity for buy-outs (Lin and Kleiss 2007, Pg. 15)". Our previous inclusion of a robust land cost metric more directly models potential areas for government land purchases ('buy-outs') than storm damage zones.

Step 3: Creating a stronger focus on habitat provision and flood risk reduction

Next, we substantially altered the two primary performance metrics: wildlife habitat provision and flood risk reduction. Starting with wildlife habitat provision, we kept three out of the five original variables intact, including *core-area ratio*, *distance to roads*, and *distance to protected areas*.

We removed *distance to open water* from the model and replaced it with a new metric aimed at assessing *wetland connectivity* based on the proximity of potential restoration sites to wetlands identified in the National Wetland Inventory (NWI) (Tiner 1997). We did this through a "Near" Analysis in ArcGIS 10.0 on NWI classified wetlands to locate closest potential restoration sites. Looking at the literature review on this topic, we can inform our revisions to the MsCIP SDSS through inclusion of existing classified wetlands as a connectivity measure. We hypothesized that this could improve the model's performance given that the original SDSS lacked any sort of variable that connected the proximity of potential restoration sites to currently existing wetlands. This is a measure that is strongly advocated for throughout many previous studies that we analyzed due to the presence of existing wetland hydrologic regimes and improved habitat connectivity (Brophy 2005, Brown and Strayner 1994, Kauffman-Axelrod 2010, Liu et al. 2006, Richardson and Gatti 1999, Strager et al. 2010, Schleupner and Schneider 2013).

Next, we removed minimum site size restrictions because the presence of a variable measuring *core area ratio* captured a more sophisticated measure of this factor. Evidence suggests that *core area ratio* is far more important than a simple area measurement in determining sustainable wildlife habitats (Collinge 1996, BenDor et al. 2009). However, it is important to note that core-area ratio measures may not apply as well for long, linear systems like rivers.

We augmented the storm/flood protection metric more extensively than the habitat metric keeping only two of the variables, including the indicator of *topographic depressions* and *storm surge/flood protection*. Almost half of the models analyzed in our literature review used some measure of hydrologic connectivity when assessing wetland mitigation suitability and performance potential. To incorporate hydrologic connectivity, we first altered the *stream buffer* variable to focus on *proximity to first-order streams*, as those wetlands have the greatest impact on desynchronization of stream flow prior to reaching watershed outfall points (Cedfeldt et al. 2000). In addition, we re-introduced an original SDSS variable (previously in the habitat provision metric), *wetland block size*, which is a simple calculation of the area of contiguous potential restoration sites, and is a key variable in determining successful wetland hydrologic function, including flood attenuation, water storage, and water quality (Cedfeldt et al. 2000, Huang et al. 2010, Ausseil et al. 2007, Brophy et al. 2005, Liu et al. 2006).

Step 4: Modified scoring and weighting system

We modified the SDSS scoring and weighting system to improve the reliability and performance of the model. In order to make baseline comparisons between the two models, we kept the scoring framework (the categories or 'bins' associated with the range of data for each variable) from the original SDSS largely intact. Variable scoring distribution and classification followed the original SDSS method of equitable distribution across the score range. However, we want to note several issues in this, or any previous, discussion of variable weighting and inclusion. While normalizing scores—as was done in the original MsCIP SDSS—to make each variable evenly weighted (e.g., re-scaling variables such that each increment along the scale is equally important) carries a broad type of face validity, there is nothing in the current range of these variables that tells how important a given unit change in each of them is to the general public, or to the decision makers who must choose on their behalf.

The majority of the multi-categorical variables were equally weighted, with each individual variable broken down into three quintiles. Each variable was given a score of five, ten, or fifteen points, with five representing the lowest performing and fifteen the highest (see Table 4). The *'storm surge capacity'* variable's distribution was left intact from the original SDSS. This layer projects the landward extent of storm surge resulting from category 1–5 hurricanes, with the highest scores going to sites with the greatest threat and frequency of flooding (Lin and Kleiss 2007). The *land value* variable was also unique and did not follow a quintile distribution; due to the wide variation in this variable's values, we estimated reasonable classification values. Finally, for binary (true/false) variables, true conditions were given positive scores, with false receiving a zero.

Instead of the equal weighting system used in the original SDSS, we gave variable weights to variables in each of the three performance metrics (flood risk reduction, wildlife habitat provision, and land costs). Like the original SDSS, to account for the uneven potential point total between the flood risk reduction metric (55 points) and the land value and wildlife habitat metrics (each 60 points), the two higher scoring metrics were scaled accordingly (multiplied by 0.9166). Recognizing the imperfections in our land value estimate, while also acknowledging that the MsCIP makes very clear that cost-benefit analysis should not drive decision-making, the land value metric is weighted at 20%. Provision of wildlife habitat and flood risk reduction was each allocated 40%. Given that the SDSS makes no clear indication as to favoring wildlife habitat protection over flood storage attenuation, it only seems appropriate to weight those two metrics evenly. To determine the final suitability scores, the data were broken down on a scale of one to five, with five being the most suitable and one being the least, using quintile classification.

Results

There are several significant differences between our model results and those produced by the original MsCIP SDSS. First, our model identified fewer potential restoration locations. While the original SDSS located 1,086 total sites covering 7,892 acres (Lin and Kleiss 2007), the modified version, limited by the inclusion of a *hydric soils* binary variable, produced 807 sites encompassing 4,715 acres, a 40%reduction in total acreage (see Figure 2 and Table 5). In terms of final prioritization scoring, the two models differed substantially (tested using chi-square goodness of fit test; $\chi^2 = 109.6$ for number of sites identified and $\chi^2 = 3363.2$ for acreage; both $p < 0.001$). While the classified values for the two models were quite similar (see Figure 3), there was a significant difference between the statistical distributions of final scores (1–5) assigned to potential restoration sites. This substantive difference suggests that our model may be more discerning and conservative in its ranking of average to below-average restoration sites, a potentially substantial upgrade to the original SDSS model as on-site field observations revealed inaccuracies in the model's results.

Sensitivity Modeling

As mentioned previously, variable weighting was inconsistent throughout the 27 studies consulted in our literature review of GIS-based wetland prioritization models. In order to assess the sensitivity of our own results to various weighting equations, we explored four alternative scenarios, each of which significantly altered the specific weights attached to the three performance metrics. The original and baseline modified SDSS model weights provision of wildlife habitat and flood risk reduction each at 40% and the land value metric at 20% (Figure 4A and 5B). We found that across the board, when changes were made to metric weighting, these had significant impacts on the distribution of suitability scores across our potential restoration sties.

Table 4. Modified SDSS metric design, variable list, and scaled score distribution. Units for block size have changed from acres to m².

	Variable	Raw Value	Scale Score
Provision of Wildlife Habitat	Core Area Ratio	0–0.000002	5
		0.000002–0.000081	10
		> 0.000081	15
	Wetland Connectivity (m)	0–109.40	15
		109.40–265.69	10
		> 265.69	5
	Distance to Protected Areas (m)	0–1,147.37	15
		1,147.38–2,847.18	10
		> 2,847.18	5
	Distance to Roads (m)	0–9.779	5
		9.78–41.56	10
		> 41.56	15
Land Value	Assessed Taxable Value (2006)	0–500,000	60
		500,001–1,000,000	54
		1,000,001–2,000,000	48
		2,000,001–4,000,000	42
		4,000,001–8,000,000	36
		8,000,001–16,000,000	30
		16,000,001–32,000,000	24
		32,000,001–64,000,000	18
		64,000,001–128,000,000	12
		>128,000,000	6
Flood Risk Reduction	Depressions	1	15
		0	0
	Block Size (m2)	3,131.97–25,908.85	5
		25,908.96–159,316.28	10
		> 159,316.28	15
	Storm Surge Capacity	5	1
		4	3
		3	5
		2	8
		1	10
	Hydrologic Connectivity (m)	0.09–112.38	15
		112.39–232.33	10
		> 232.34	5

The first scenario assumed equal weighting across the three metrics (Figure 4C). Compared to our model, there was an increase of 32% in sites receiving a suitability score of four or above, when all three of our metrics received equal weighting. The greatest decrease in suitability scoring was in sites receiving a two or below, which dropped 29% overall (see Figure 4G).

Next, we reversed the weighting between the metrics, first giving provision of wildlife habitat a 20% weight (Figure 4D; flood risk reduction and land value metrics

Table 5. Final restoration priority score distribution of modified MsCIP SDSS for Hancock, Harrison, and Jackson Counties.

Classified Value	# of Sites	Total Acres
1	26	57
2	282	766
3	415	1,424
4	111	489
5	12	41

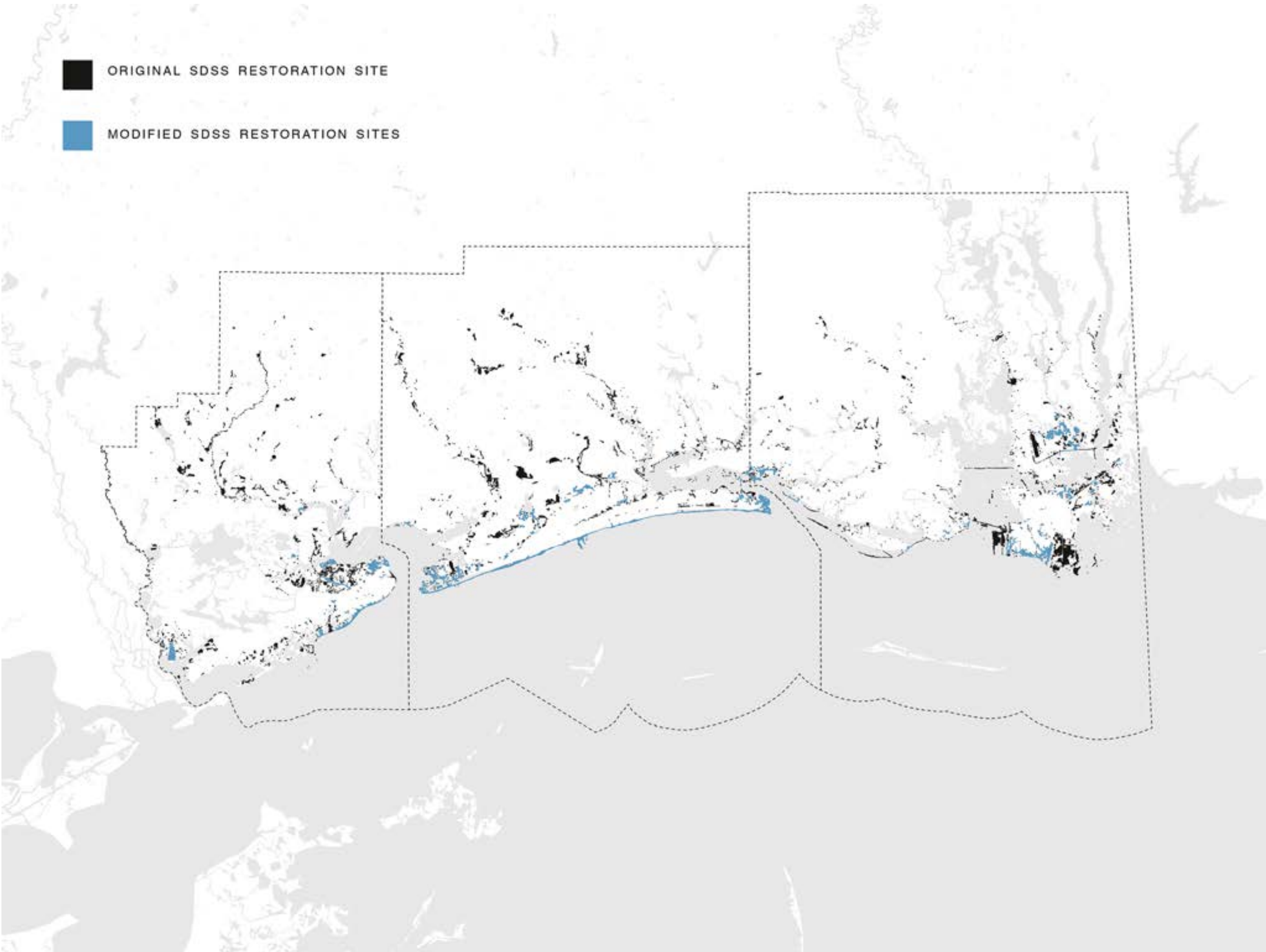

Figure 3. Comparison of final priority score distribution between modified and original MsCIP SDSS.

each received 40%) and then assigning a 20% weight to flood risk reduction (Figure 4E; provision of wildlife habitat and land value each received 40%). Compared to our modified SDSS model, both weighting iterations produced distinct results. There was again a sharp increase in suitability scoring for values four and above in both scenarios (47% and 54%, respectively). Once again, similarly to the equal weighting scenario, there was a severe decline in the number of low scoring (two or below) sites, with both augmented models seeing a decline of 29% (see Figure 4G).

Finally, we removed the newly created land value criterion entirely, distributing equal weighting across the two remaining metrics (Figure 4F). The results were distinctly different from the previous scenarios, with a more equal distribution of scoring than either of the three sensitivity models and our own modified SDSS. Forty percent of the total sites received a suitability score of two or below, with 27% receiving 4 or above (Figure 4G).

The results of our sensitivity analysis underscore the critical importance of variable weighting in multi-criteria or multiple attribute decisions analysis. Even relatively minor alterations in variable weighting can result in significant changes in final results. Given the context of GIS-based wetland prioritization models, where no pattern or coherent method to variable weighting exists in the literature (even within models that shared similar objectives), there exists a clear need for a more standardized, uniform approach. The results of our sensitivity model stress the need for greater ground-truthing and some form of iterative calibration of variable weighting.

Discussion

Our literature review revealed that across the existing 27 models, there were few similarities in models' stated objectives, specific variables, or respective weighting/scoring systems. Given the wide disparity of variables, and weighting mechanisms underlying GIS-based wetland prioritization models (even in models with similar objectives), it is clear that there is an acute lack of consensus within the literature. Each model presents its own unique rationale for defining identification variables, performance criteria, and the comparative value of specific indicators. Moreover, while

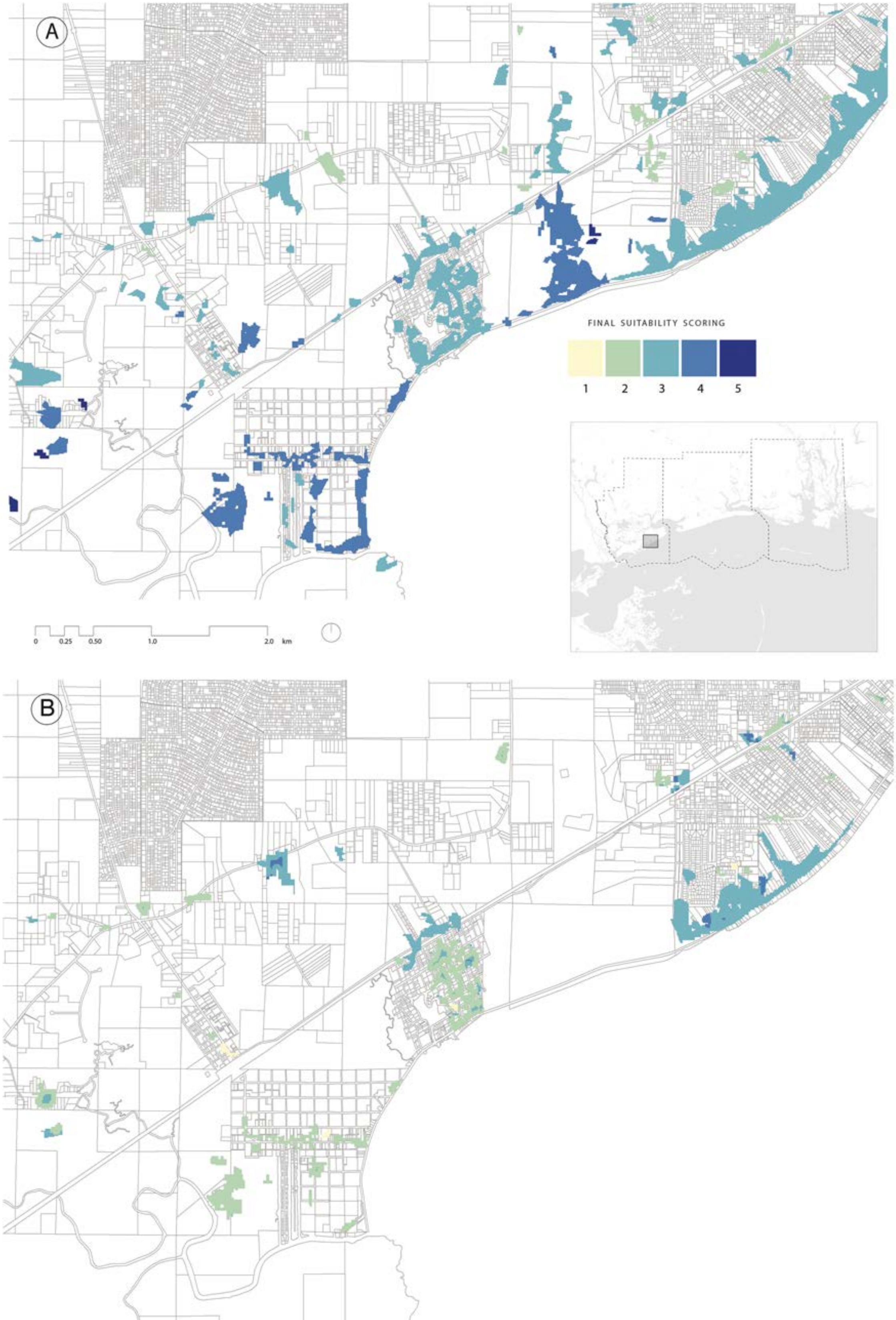

Figure 4. Sensitivity Analysis of changes to SDSS. Panel A: Final restoration suitability scores for original SDSS model (Lin and Kleiss 2007). Panel B: Baseline suitability scores for modified SDSS model.

continued

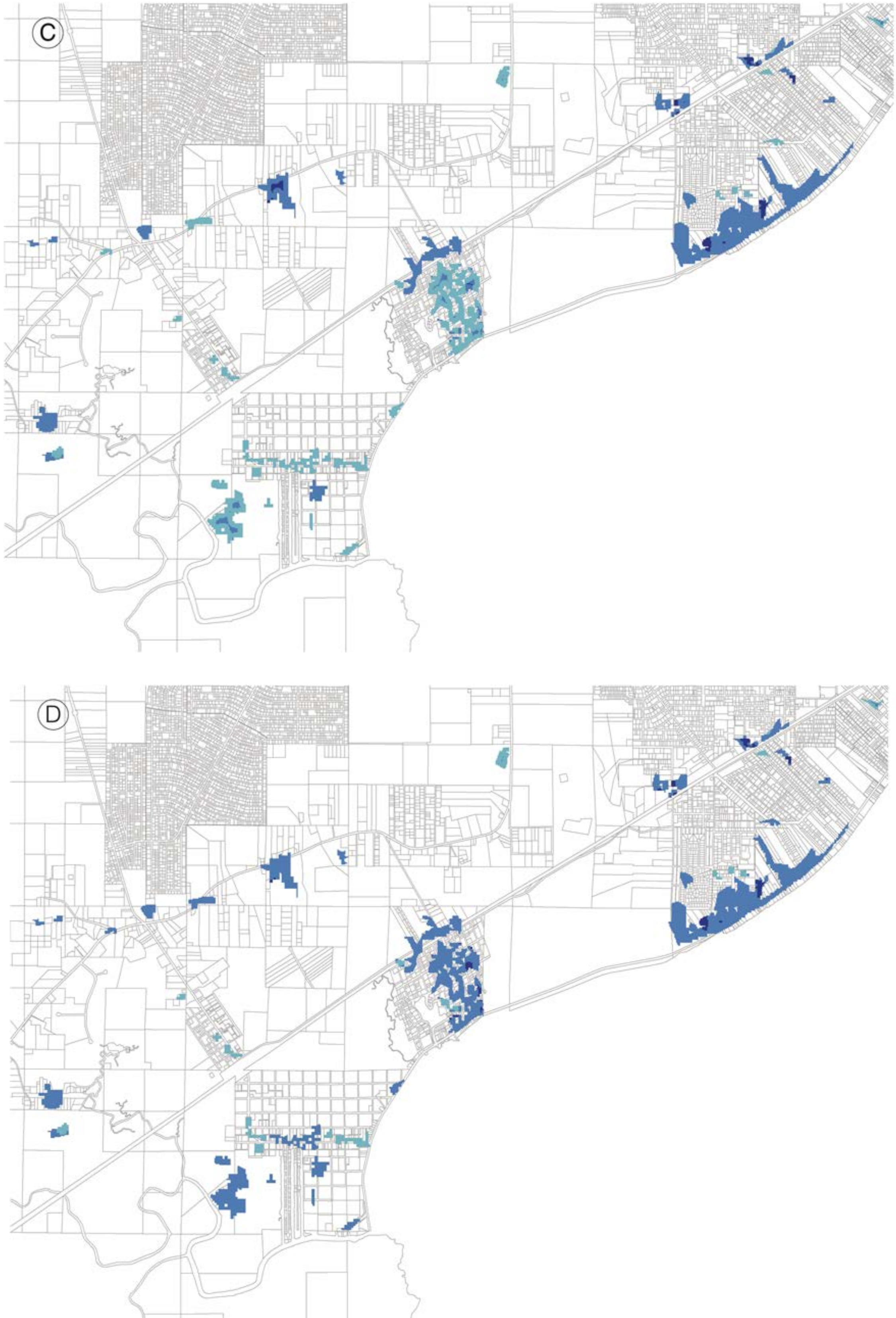

Figure 4. ***(continued)*** **Panel C: Equal weighting of three performance metrics. Panel D: Lower wildlife metric weight.**

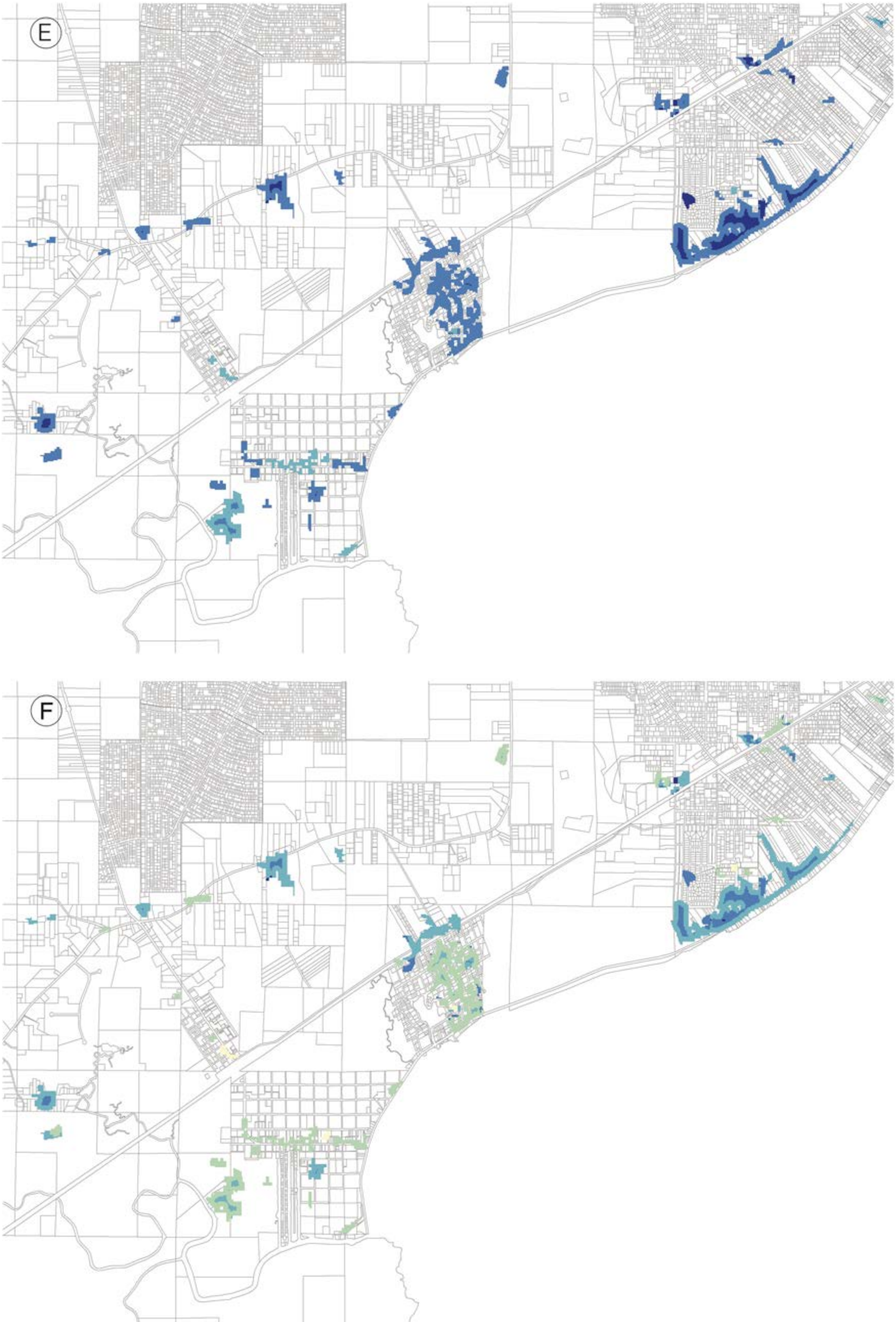

Figure 4. ***(continued)*** **Panel E: Lower flood storage metric weight. Panel F: Land value metric removed from performance metrics.**

continued

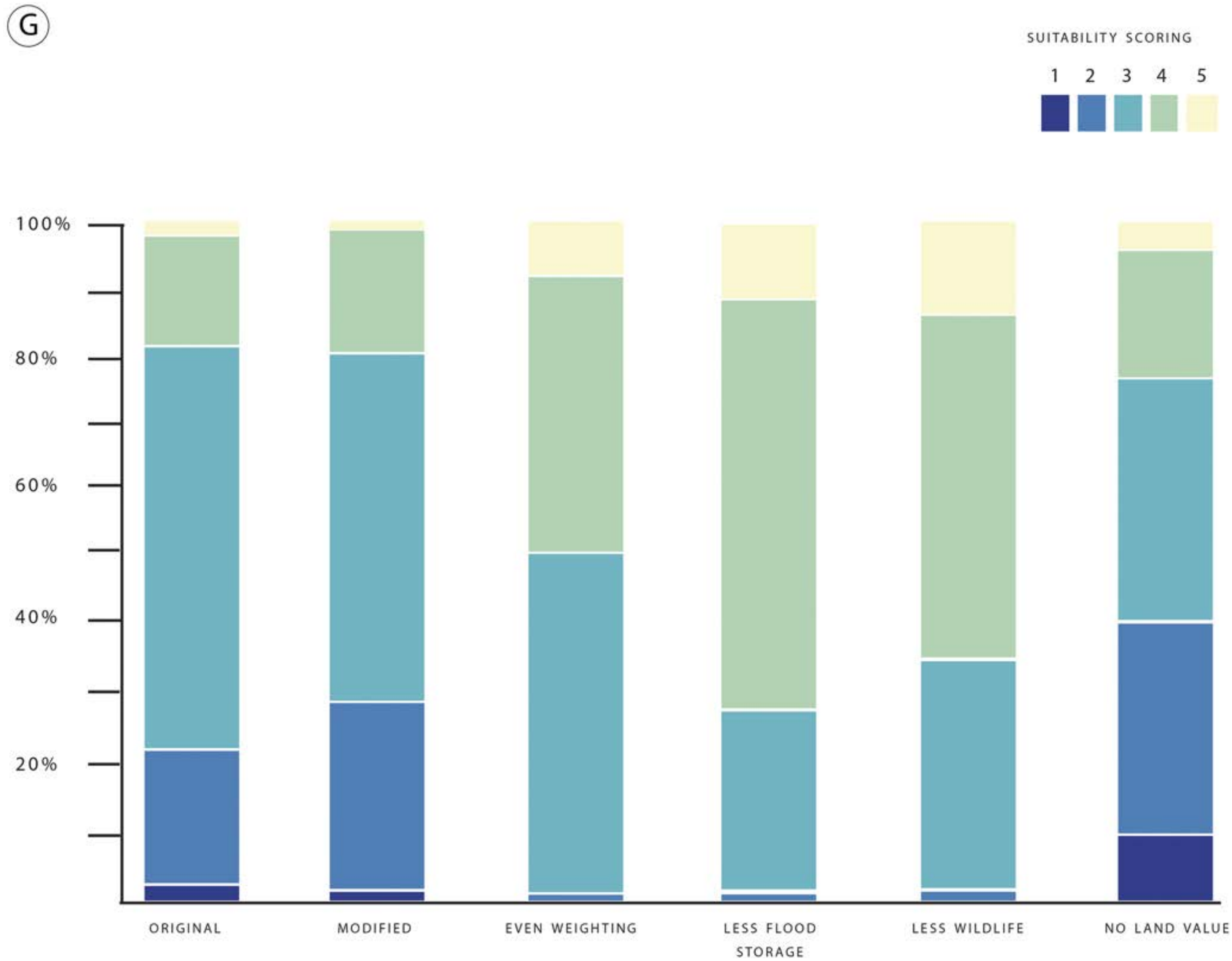

Figure 4. ***(continued)*** **Panel G: Final suitability score distribution among sensitivity analyses.**

most of the studies that employ GIS-based techniques may claim that they employ the watershed approach, most fail to employ the approach as it was originally conceived, whereby information on spatial relationships between wetlands (and uplands), watershed position, and inferred interactions based on flow of water, sediment, and materials are used to affect the ultimate ratings of restoration potential. Instead, many use static GIS overlays to develop rankings for specific locations instead of employing a more comprehensive watershed analysis.

While the aim of our literature review has not been to present any sort of definitive resolution to the ongoing debate over wetland prioritization, our hope is that by compiling and aggregating relevant studies, researchers will be able to access and review the emerging literature more quickly and effectively and thus improve their own work. There is an extensive literature on ecosystem valuation and ecosystem service quantification that could inform the estimation of weights in prioritization models (Barkman et al. 2008). Taking a rigorous stance, weights should be chosen based on an explicit theory about the relative importance of each factor used in a prioritization model (Vrana et al. 2012). Specifically, drawing from general theories about land suitability analysis, scores and weights should be based on functional relationships between attributes of potential sites to provide ecosystem services and the relative importance that the public places on those services (Malczewski 1999). The weakness of the literature in this area becomes even more apparent given the widespread lack of any meaningful sensitivity analysis around changes to the weights assigned to various factors in models. The benchmark (default) weights and the ranges over which they are varied seem completely ad hoc, with no grounding in any functional relationships between site attributes and ecosystem service flows or the values people place on those flows.

Guided by the results of the literature review, our modified SDSS attempted to improve the reliability and performance of the critical tool in the MsCIP plan for determining future restoration sites and guiding public investments. While the model is still un-informed by widespread field calibration and validation (including local knowledge about the quality of potential restoration sites), a major substantive improvement is that the modifications make the SDSS more discerning and conservative while ranking average to below-average restoration sites. However, our results point to substantial opportunity for creating a more flexible and accurate SDSS for use in other USACE-funded restoration programs, or other large-scale programs in domestic or international contexts. Future efforts will need to implement stronger field calibration and validation of models, as well as test the sensitivity of weighting schemas as a way of alleviating some of the uncertainty over weighting and scoring systems that is seen widely in the literature.

Integration with other ecosystem services models (e.g., INVEST—Nelson et al. 2009; ARIES—Nelson and Daily 2010) would greatly strengthen the SDSS, and aid the USACE and other organizations in achieving future high performing, successful wetland restoration efforts. While we feel that the modified SDSS achieves both these aims, the land value metric could be substantially improved with a more robust and complete dataset. County assessed tax value is an excellent starting point for introducing a financial variable into the SDSS, though it is not a perfect substitute for data on market-driven land values (i.e., sales data). A more in-depth strategy could involve an economic approach whereby weights are applied in proportion to the sum of stakeholders' willingness to pay for additional ecosystem services. Additionally, from a political point of view, it is quite important to establish a strong communication strategy with surrounding landowners and stakeholders. This strategy should use the results from SDSS tools as a first pass understanding where wetland restoration will be most effective and where it will likely be accepted by the public (and those who influence decisions about restoration investments).

Although the modified SDSS is likely an improvement on the original, this could only be verified through on-site ground-truthing. Unfortunately, the limited amount of ground-truthing and model validation across the reviewed literature, and the complete absence of any iterative calibration of variable weighting, remains perhaps the most serious problem with the current way that wetland restoration prioritization models are constructed. Calibrating the model based using randomly sampled ground-truth data and ordinal or multinomial logistic regression modeling (Train 2003; Long and Freese 2014) would create a better system for variable weighting, improving accuracy and effectiveness of our modified SDSS. Finally, model validation would provide further verification of the applicability of our new GIS-based wetland suitability and prioritization model to geographies outside of the MsCIP counties (e.g., other gulf coast counties).

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