Using Decision Analysis to Integrate Habitat and Community Values for Coastal Resilience Planning

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Received: 26 March 2021 / Revised: 28 May 2021 / Accepted: 2 June 2021 / Published online: 15 June 2021
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Abstract

Decision analysis is applied to habitat and community resilience planning in Maryland, USA. Sea level rise is causing wetland loss and increased flooding in coastal areas. A team at The Nature Conservancy analyzed a decision to identify high-value conservation planning units across Maryland's Lower Eastern Shore. The team selected two fundamental objectives: minimize habitat loss and minimize community flood impacts. Sub-objectives included habitat function, habitat migration potential, critical infrastructure, and social vulnerability. Spatial attributes were selected based on ecological knowledge about habitat and socio-economic knowledge about sustaining populations in flood-prone areas. Seven planning units were developed across the Lower Eastern Shore. Single-attribute value functions determined the overall value of each unit per attribute, whereas multi-attribute value functions determined the overall value of each unit for all fundamental objectives. Sensitivity analysis incorporated data adjustments based on different flood scenarios and unit sizes, and variation in attribute weights associated with the multi-attribute value function. The Pareto efficiency principle revealed tradeoffs between units for habitat protection and management and community engagement and adaptation. Results indicate that four units are Pareto efficient under different sensitivity iterations and they trade off value in the fundamental objectives, whereas one unit provides the highest combined habitat and community value. This research guided thinking about equity in decision making and targeting conservation actions at local scales. The approach and methods can be used to inform conservation decisions in other similar contexts.

Keywords Conservation · Equity · Structured decision making · Social vulnerability · Wetland

Introduction

Sea level rise is projected to cause significant impacts to coastal ecosystems and human communities (Hinkel et al. 2014). Higher tides and inundation can cause drowned wetlands if they are unable to accrete vertically and migrate horizontally (Borchert et al. 2017), and saltwater intrusion may cause stress and result in shifts in wetland condition (Tully et al. 2019). Wetlands are one of the most valued ecosystems in the world (Costanza et al. 2008) because they

dampen wave energy, absorb floodwaters, accrete sediment, improve water quality, and provide habitat for a host of plants and animals (Shepard et al. 2011). Flood inundation is expected to increase in communities, defined as people living in the same geographical area, because of sea level rise and wetland loss. These effects can exert disproportionate flood-related impacts to socially vulnerable populations (Arkema et al. 2013).

Coastal resilience refers to the abilities of coastal ecosystems and communities to resist or adapt to sea level rise and other climate-related impacts (Sutton-Grier et al. 2015). The resilience concept provides guidance for coastal management, policymaking, and funding (Beatley 2009; Barbier 2014). For instance, targeting tidal wetland protection and providing for wetland migration into adjacent uplands are important ecosystem-based adaptation responses (Borchert et al. 2017). Likewise, nature-based flood protection and policies for the movement of people and infrastructure outside of flood-prone

Communicated by Holly Greening

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areas are important community-based adaptation responses (Sutton-Grier et al. 2015; Siders et al. 2019).

The ecological and social aspects of adaptation are important components of coastal resilience, but there is no straightforward framework for combining these aspects for decision-making purposes (National Research Council 2012). Decision makers, including federal agency staff, state natural resource managers, and non-governmental conservation program managers, are challenged with identifying locations and conducting analyses that integrate ecosystem and community values into a resilience plan of action. To account for this limitation and enhance coastal resilience, landscape-level conservation planning (Pressey et al. 2007) provides a framework for decision makers to implement and monitor socio-ecological climate adaptations.

Conservation planning was initially conceptualized to ensure conservation activities like habitat protection aligned with desired biodiversity outcomes (Kiesecker et al. 2010). Advances in conservation planning include integrating human and social factors (Knight et al. 2010). Recent studies combine habitat and community values (e.g., Silver et al. 2019; Heiner et al. 2019), but research is needed on combining these values in group decision-making contexts and explicitly incorporating decision-maker preferences into a deliberate analysis. There are several reasons why this research is needed. First, different habitat and community values drive decisions, but these values are hard to identify and they often conflict with each other (Keeney 1992). Second, ecological models and community data are important, but they only provide a partial understanding of the values necessary to make informed decisions (Fischhoff and Davis 2014). Third, decision-maker preferences can lead to bias, especially when there is an abundance of possible data sources and different ways to integrate them (Kahneman 2013). As a result, the decision-making process often lacks transparency and accountability to the values, data, and preferences used in it (Gregory et al. 2012). Lastly, equity considerations in decision making are important, including but not limited to social equity. Equity is about being fair when considering the ethical implications of an analysis and its methodological assumptions. For this reason, equity considerations are context specific, and there is no unifying approach to incorporate the many dimensions of equity into conservation planning (Law et al. 2018). Planning approaches that can accommodate these research challenges can lead to better quality decisions and conservation outcomes.

Decision Analysis

This study applies decision analysis to coastal habitat and community resilience planning. In general, decision analysis is a way of thinking about complex decisions. The approach combines value-focused facilitation methods and scientific

inquiry to provide insights into the desirability of decision options. The outputs of a decision-analytic process are used by decision makers, including their designated team members and other interest groups, to inform a decision.

A set of five principles guide the many aspects of decision analysis. The principles include (Gregory et al. 2012): (i) defining problems or planning opportunities as decisions; (ii) clarifying desirable values as objectives with measurable attributes for assessing performance; (iii) developing alternative decision options; (iv) modeling the contribution of each option toward achieving the objectives; and (v) understanding tradeoffs between the options. Implementing these principles can yield a transparent audit trail that holds users accountable to their preferences and biases, as compared to other approaches to decision making (Keeney 1992; for examples of experimental studies, see Arvai et al. 2001; Hostmann et al. 2005).

Decision analysis has been used to advance quantitative and qualitative thinking about coastal management decisions, with case studies in waterfowl (Lyons et al. 2008), salt marsh (Neckles et al. 2015), and barrier island management (Dalyander et al. 2016). There is a lack of research and real-world case studies to learn about how decision analysis may be used under integrated planning contexts. This study focuses on opportunity mapping, with a case study in Maryland, USA. Opportunity mapping aims to understand the environmental, social, and economic factors that may lead to action and incorporate them into the identification of landscape areas where action is suitable for implementation (Knight et al. 2010). Many studies use opportunity mapping to identify high-priority conservation areas (e.g., Heiner et al. 2019; Gardon 2021). Applied studies using decision analysis are needed to demonstrate their relevance and validity at combining disparate values, data, and preferences for resilience planning purposes.

A team of eight staff at The Nature Conservancy—a global conservation organization—implemented the research on Maryland's Lower Eastern Shore, including facilitation support by the lead author. Expertise among team members included ecological, social, and spatial science as well as engagement and project management in Lower Eastern Shore communities. The team identified decision-relevant habitat and community objectives and attributes. Planning units were developed as conservation opportunities in important ecological and cultural heritage areas. The team compiled spatial data representing the value of each unit per attribute and modeled these values as a function of team preferences, referred to as single- and multi-attribute value functions. Data adjustments and preference elicitation incorporated variation and uncertainty into the single- and multi-attribute value functions. Lastly, tradeoffs between the units were evaluated to guide critical thinking about conservation opportunities in high-value units.

Methods

Decision Context

Maryland's Lower Eastern Shore (Fig. 1) includes the full extent of Dorchester, Wicomico, Somerset, and Worcester counties. This area contains 186,885 ha of wetlands, including 63,326 ha of tidal salt marsh and 23,275 ha of other intertidal habitats, such as tidal freshwater marshes and forested wetlands. The Lower Eastern Shore is highly vulnerable to sea level rise and storm-related impacts due to its low-lying topography and exposure to the Chesapeake Bay and Atlantic Ocean. Tide range and frequency of coastal inundation are increasing on the Lower Eastern Shore (Boesch et al. 2013), resulting in habitat loss. Blackwater National Wildlife Refuge has lost over 2000 ha of wetlands since it was established in 1938, and there is a high probability that sea levels will continue to increase across the Lower Eastern Shore between 0.24 and 0.49 m by 2100 (Boesch et al. 2018). This estimate

is over 1.6 times higher than some global average estimates (Sweet et al. 2017). Likewise, the Lower Eastern Shore contains some of the poorest and most vulnerable counties in Maryland (Maryland Department of Planning 2018). Sea level rise impacts are expected to cause significant residential, commercial, and other infrastructure damages (Markle 2015; Bass et al. 2018).

Key activities in The Nature Conservancy's conservation portfolio in coastal Maryland include wetland habitat protection, habitat management (e.g., restoration), and community-based adaptation activities such as living shorelines, dune restorations, and infrastructure relocation. The Nature Conservancy aims to implement these activities across the Lower Eastern Shore but is limited by time and resource constraints. Notably, the team assumes that broader conservation outcomes may be a function of targeted efforts in specific areas rather than equal efforts in all areas (Morrison 2014). Focusing engagement and demonstrations in priority areas will develop more tangible evidence of their effectiveness and leverage

Fig. 1 Planning units (1–7) and unit boundaries on Maryland's Lower Eastern Shore. Unit boundaries extended to 5-m elevation and a 1-km buffer

investment for broader change across the entire Lower Eastern Shore. In addition, there are equity aspects to prioritizing conservation work at the scale of the Lower Eastern Shore, such as how to develop and combine values into a recommended plan of action. These organizational planning contexts present a mapping decision opportunity: *Which coastal areas provide the highest value in terms of conservation opportunity?* Although the decision statement is broad in scope, The Nature Conservancy performed the analysis to organize tasks for future targeted conservation and engagement decisions. This decision frame will highlight future integrated decision contexts where the values and preferences of other conservation organizations and interest groups are key to successful conservation work across the Lower Eastern Shore.

Objectives and Attributes

Conservation-relevant values are often ascribed to places (Heiner et al. 2019) or ecological or social targets (Field and Elphick 2019). In decision analysis, context-dependent objectives distinguish the importance of such places or targets for a specific decision. An objectives hierarchy was developed to visualize and understand complexity in the team's values regarding the decision context (Fig. 2). Asking “why is it important” helps to distinguish fundamental objectives, or the essential reasons for interest in the decision (Keeney 1992). Asking “what aspects are important” or “what do you mean by that” helps to further subdivide fundamental objectives into lower-level objectives, sometimes referred to as sub-objectives (Fig. 2; Keeney 1992). It is important to characterize the relationships among objectives, especially organizing sub-objectives into distinct categories, to maintain a logical order of thinking.

The team selected two fundamental objectives: minimize habitat loss and minimize community flood impacts. Two habitat sub-objectives, improve habitat function and maximize migration potential, were selected because existing wetland condition and landward wetland migration are critical for climate adaptation (Borchert et al. 2017), and both are important for minimizing habitat loss in Maryland. They were further specified into sub-objectives regarding characteristics of habitat function (habitat type and extent, focal species, fragmentation) and migration potential (migration space, impervious surfaces, connectedness, developmental pressure; Fig. 2). One community sub-objective, minimize community exposure in flood-prone areas, was further specified into two sub-objectives, critical infrastructure and social vulnerability. These objectives were selected because community impacts from flood-related hazards can compromise critical health and safety assets, access to resources, and

Fig. 2 Objectives hierarchy for setting habitat and community objectives. Organizing objectives involves specifying their basic relationships using “why” and “what” inquiries (see text). Two fundamental objectives are minimize habitat loss and minimize community flood impacts on the left-hand side. The fundamental objectives can be further specified into sub-objectives on the right-hand side

the activities people do to achieve their livelihood goals (Zahran et al. 2008; Hinkel et al. 2014). These social factors vary for geospatial, demographic, and socioeconomic reasons, and the team wanted to direct conservation work toward communities that are disproportionately more vulnerable to flood effects.

The team developed attributes for the habitat function, migration potential, critical infrastructure, and social vulnerability sub-objectives with public spatial data and measures (Table 1). The best available scientific information informed the selection of attributes, including published reports and spatial data from regional federal, state, and non-governmental organizations, as well as key discussions with partners about the ecological and social aspects of habitat and community sub-objectives. Eight attributes represented habitat function (H1–H8). These attributes describe the type and extent of existing wetland habitat and also indirect suitability factors related to focal species and fragmentation. These factors include the type and magnitude of high quality and rare ecological communities and Maryland’s rare, threatened, or endangered animals (Maryland Natural Heritage Program 2016; Harrison 2016), roadway density (Forman and Alexander 1998), and connectedness, or the degree that habitat is conducive to animal movement and the flow of ecological processes (Anderson and Barnett 2017). The direction of preference for these attributes—maximize or minimize—vary based

Table 1 Attributes and measures for evaluating planning units

Sub-objective	Attribute label	Attribute ^a	Direction	Source ^a
Habitat function	H1 submerged aquatic vegetation	Amount of submerged aquatic vegetation in open water (hectares)	Maximize	Virginia Institute of Marine Sciences
	H2 salt marsh	Amount of salt marsh (hectares)	Maximize	National Wetlands Inventory
	H3 non-marsh tidal wetlands	Size and spatial distribution of non-marsh tidal wetlands (constructed score)	Maximize	National Wetlands Inventory
	H4 roadways	Roadways in current marsh (meters/hectare)	Minimize	Maryland State Highway Administration
	H5 wetland connectedness	Proportion of existing habitat hectares rated “above average” per total hectares of wetland connectedness (number)	Maximize	Anderson and Barnett (2017)
	H6 occurrences	Count of rare, threatened, and endangered species occurrences (number)	Maximize	Maryland Department of Natural Resources
	H7 natural communities	Count of rare natural communities (number)	Maximize	Maryland Department of Natural Resources
	H8 ecologically important lands	Amount of Tier 1–3 habitat (hectares)	Maximize	Maryland Department of Natural Resources
Habitat migration	H9 migration space	Unprotected migration space (constructed score)	Maximize	National Oceanic and Atmospheric Administration
	H10 migration space	Protected migration space (constructed score)	Maximize	National Oceanic and Atmospheric Administration
	H11 wetland adaptation areas	Amount of wetland adaptation area rated “medium and high priority” (hectares)	Maximize	Maryland Department of Natural Resources
	H12 zoning development	Amount of least-protective zoning (hectares)	Maximize	Maryland Department of Planning
	H13 impervious	Proportion of hectares of impervious surface per total hectares of migration space (number)	Minimize	Chesapeake Conservancy
	H14 wetland connectedness	Proportion of migration space rated “above average” per total hectares of migration space (number)	Maximize	Anderson & Barnett (2017)
Infrastructure ^b	C1 roadways	Roadways in flood zone (meters)	Maximize	Maryland State Highway Administration
	C2 water quality infrastructure	Count of wastewater treatment plants and concentrated animal feeding operations (number)	Maximize	Maryland Department of the Environment
	C3 population infrastructure	Count of fire stations, police stations, schools, energy (number)	Maximize	Multiple Maryland Agencies and Hitachi Powergrids Velocity Suite
	C4 developable area	Amount of developable zoning (hectares)	Maximize	Maryland Department of Planning
	C5 population	Count of residents (number)	Maximize	American Community Survey
	C6 housing units	Count of housing units (number)	Maximize	American Community Survey
Social vulnerability ^b	C7 child population	Count and percent of child residents (constructed score)	Maximize	American Community Survey
	C8 senior population	Count and percent of senior residents (constructed score)	Maximize	American Community Survey
	C9 income	Count and percent of households below poverty level (constructed score)	Maximize	American Community Survey
	C10 minority	Count and percent of minority residents (constructed score)	Maximize	American Community Survey
	C11 technology	Count and percent of households with no internet, no smartphone, and no computer (constructed score)	Maximize	American Community Survey
	C12 disability	Count and percent of households with at least one disabled person (constructed score)	Maximize	American Community Survey
	C13 single-parent households	Count and percent of households with a single parent (constructed score)	Maximize	American Community Survey

^aDetailed information on measures and data sources are available in the Supplementary Information (Table S1)

^bCommunity attributes were measured in flood-prone areas inside each planning unit, informed by three flood scenarios (see “Sensitivity Analysis”)

on the planning context. The team preferred to focus planning and prioritization in areas with higher habitat quality and less fragmentation (Table 1).

Six attributes represented habitat migration (H9–H14). These attributes describe the extent of future wetland habitat, including marsh migration space (NOAA 2017), Maryland's target wetland adaptation areas (Papiez 2012), and also indirect suitability factors that may influence the transition of upland areas into new habitat. These factors included future zoning development, roadway and other impervious surface density, and connectedness. Some of the habitat attributes incorporated temporal variation in the spatial data (e.g., H1 submerged aquatic vegetation), whereas others incorporated variation in sea level rise projections (e.g., H9–H10 migration space). Similar to habitat function, the direction of preference for habitat migration attributes varied and focused on maximizing migration potential and minimizing fragmenting features (Table 1).

Six attributes represented infrastructure in flood-prone areas (C1–C6), and seven attributes represented social vulnerability of populations in flood-prone areas (C7–C13). These attributes were developed from an initial list based on known critical infrastructure in flood-prone areas and well-established theoretical indicators of social vulnerability (Rufat et al. 2015). The refined list of attributes was based on available data, including US Census Bureau data (American Community Survey), and whether those data varied significantly across planning units. The community attributes were estimated inside flood-prone areas only in each unit using the GeoEnrichment service from Esri (Supplementary Information), informed by different flood scenarios (see “Sensitivity Analysis”). The team decided to maximize these attributes based on the planning context, that is, flood-prone areas with more people and infrastructure are preferable to flood-prone areas with less people and infrastructure (Table 1).

Costs were not included in this study for several reasons. First, the team assumed that time and funding conservation work is uniform across the analysis area. In other words, resource allocation feasibility is not a function of land area across the Lower Eastern Shore. Second, estimating costs would require more detail about implementation of conservation activities in one or more planning units, which is beyond the scope of the research. Third, valuation models in Maryland are based in part on wetland habitat size, connectivity, and presence of focal species (Campbell et al. 2020), which correspond to several attributes in this study (Table 1), and it is reasonable that the analysis provides a surrogate habitat valuation across the analysis area.

It is important to note the distinction between attributes in this study and other possible ecological and social indicators. In decision analysis, objectives and attributes indicate important aspects of specific decisions. This approach to gathering relevant data is very different than identifying all

possible causal factors to a management area or ecological system. In general, not all causal factors are important to distinguish the desirability of decision options (Keeney 1992). This aspect of decision analysis does not ignore causal factors or complex interrelationships between causal factors. Rather, causal factors are used for modeling and developing data that inform the consequences of objectives and attributes as important determinants to a decision. To illustrate, elevation and slope characteristics influence how wetlands may migrate (NOAA 2017). These causal factors are incorporated into a broader measure of the amount of space (hectares) that wetlands can move in the future, which was identified by the team as an important determinant to deciding where conservation activities will be most impactful (Table 1).

Planning Units

Ecological analyses often use watersheds to examine critical biophysical characteristics of an area. Based on the integrated context of this study, watersheds do not provide a meaningful basis of analysis to guide adaptation planning and community engagement at the scale of the Lower Eastern Shore. Rather, the team developed special planning units that maintained habitat-specific characteristics and were culturally meaningful to people who live in the area (Fig. 1). The upland boundaries included all land area up to five meters in elevation, buffered by one kilometer to smooth the upland boundary and create planning units without any “holes” or islands of land greater than 5 m. This boundary was set to account for current and projected flood-prone areas and wetland habitat. The units were separated by tributaries, distinguishing one bay and six peninsula communities that are culturally meaningful to people living on the Lower Eastern Shore. The units are locally referred to as Bishops Head (unit 1), Elliot's Island (unit 2), Nanticoke (unit 3), Deal Island (unit 4), Rumbley/Fairmount (unit 5), Crisfield (unit 6), and Coastal Bays (unit 7).

Single-Attribute Value Functions

A value function takes individual attribute measures and produces a single number representing the value or “worth” of each decision option. These numbers can be directly associated with the attribute measure if they are meaningful for decision making, but they can also represent an interpretation of the relationship between attributes and decision-maker preferences (von Winterfeldt and Edwards 1986). These numbers provided the basis for making an informed choice or prioritization of the planning units.

Single-attribute value functions were developed using natural measures, proxy measures, and constructed scores (Table 1; Keeney and Gregory 2005). Natural measures

are easily counted or measured and have an explicit interpretation, such as linear meters of roadways and counts of residents and housing units in flood-prone areas (attributes C1–C6; Table 1). Proxy measures are counted but do not explicitly measure the objective or attribute. An example is amount (hectares) of least-protective zoning in habitat migration space (attribute H12; Table 1), which represents the amount of migration space that is the most threatened with development. Constructed scores were developed for attributes where no natural measure exists or when several different factors must be considered. An example is potential migration space (attributes H9–H10; Table 1). The amount (hectares) of migration space varies based on different sea level rise projections, and the team's preferences for the projections differed. Therefore, the units were rated on a scale (from zero to one) for these attributes, reflecting the relative preference of each projection and the amount of migration space per projection (Table S10; Supplementary Information). This type of approach was also used to develop constructed scores for the social vulnerability attributes.

Detailed information on the single-attribute value functions are provided in the [Supplementary Information](#).

Multi-Attribute Value Functions

The single-attribute value functions were aggregated into a multi-attribute value function for all fundamental objectives. An additive multi-attribute value function was used because the objectives and attributes are distinct and do not interact with or act as multipliers on each other. The functional form of the multi-attribute value function takes each single-attribute value z_{ij} and transforms them to 0–1 values using a scaling function x_{ij} :

$$x_{ij} = \frac{z_{ij} - z_j^*}{z_j^{**} - z_j^*} \quad (1)$$

for all attributes j , planning units i , where z_j^* and z_j^{**} are the “worst” and “best” values for each attribute across units, respectively. Global scales were used on attributes with constructed scores, indicating team preferences for evaluating attributes in a way that puts *perceived* limits (e.g., zero to 100 scores) to the possible single-attribute values across units (Martin and Mazzotta 2018). Local scales were used on the other attributes, indicating team preferences for evaluating attributes in a way that puts a *fixed* interval value on the attributes, using their minimum and maximum measures, across units (Martin and Mazzotta 2018). The multi-attribute value function V_i aggregates the scaled values into an overall value per planning unit i :

$$V_i = \sum_{j=1}^{11} w_j x_{ij} \quad (2)$$

for all attributes j , units i , where w_j are cumulative attribute weights that sum to one. The multi-attribute value function was implemented per fundamental objective. Equations (1) and (2) were also used to interpret multiple data sources and preferences and develop constructed scores for some individual attributes (Tables S10 and S11; Supplementary Information).

Weights are scaling parameters that measure the contribution of each single-attribute value function to the desirability of the units (Dyer and Sarin 1979). Weights should be considered in the context of the attribute ranges to safeguard against bias (von Winterfeldt and Edwards 1986). This study used swing weighting, which is an elicitation technique to approximate relative attribute weights that sum to one. Swing weighting presented a thought experiment, where team members were asked to consider swings in the ranges between “worst case” and “best case” values across all attributes per sub-objective (Table 2). They then ranked the hypothetical swings in order of their importance, with 1 representing the most important, and assigned scores between 0 and 100 to the ranked swings (Table 2). They could enter the same score for multiple attributes and provide explanations for their reasoning. The array of scores assigned to the attribute swings was normalized into weights that sum to one per sub-objective.

Swing weights were elicited from five team members individually, with facilitation support by the lead author, who designed the analysis but did not provide a swing weighting. Three sets of infrastructure and social vulnerability weights were elicited based on different attribute measures per flood scenario (see “[Sensitivity Analysis](#)”). Recall that attributes were developed hierarchically per sub-objective. Therefore, *cumulative attribute weights* were calculated as the product of all attribute weights, informed by swing weighting, and their respective sub-objective weights, informed by sensitivity analysis. This approach to weighting attributes is not necessary if attributes are directly associated with fundamental objectives and not logically divided into a hierarchy of sub-objectives and corresponding attributes.

Sensitivity Analysis

Community attributes were measured in each planning unit under three flood scenarios, provided by the Eastern Shore Regional GIS Cooperative and Maryland State Highway Administration ([Supplementary Information](#)). The flood scenarios represent current nuisance tidal inundation (Nuisance2020), current mean higher high water 25-year storm

flood depth (Storm2015), and future mean higher high water 25-year storm flood depth (Storm2050). These flood scenarios were selected because they are relevant to local adaptation planning needs on the Lower Eastern Shore. The water quality infrastructure attribute (C2) was not measured in any units under the Nuisance2020 scenario, and it was not included in the swing weighting for that scenario.

Unit sizes differ significantly (Table S12; Supplementary Information), and we recognized that unit size may be a determinant in the amount of habitat function, habitat migration space, infrastructure, and social vulnerability in each unit. To test for this limitation, the habitat attribute data were divided by size of unit or size of migration space in a unit, whereas the community attributes were divided by size of flood-prone area in a unit. These proportional data were used in the sensitivity iterations of the multi-attribute value function to estimate overall values for the units per fundamental objective.

To calculate cumulative attribute weights per fundamental objective, sub-objective weights are multiplied by their attribute weights informed by swing weighting. Eliciting sub-objective weights in a hierarchical sense can lead to confusion (Martin 2021). Instead of assigning sub-objective weights deliberately, a sensitivity analysis informed whether variation in sub-objective weights influenced the results. For each fundamental objective, a higher proportion of weight was given to one of the two sub-objectives, between 55 and 90% in increments of 5%. To illustrate using the habitat fundamental objective, one sensitivity iteration for one team member involved assigning a weight of 55% to, say, the habitat function sub-objective, with the 55% apportioned among its eight attributes (each apportioned weight is $0.55/8 = 0.0688$). The apportioned weight is multiplied by the attribute swing weights assigned by that team member (e.g., Table 2, right-hand column). The remaining 45% of the total weight is then apportioned among the six habitat migration attributes and multiplied by the attribute swing weights of the same team member.

Eight sensitivity iterations simulated preferences for each pair of sub-objectives, multiplied by five team members' swing weights, totaling 80 sensitivity iterations per fundamental objective. Community data varied over three flood scenarios, meaning that 240 sensitivity iterations of the multi-attribute value function were calculated for the community fundamental objective. These sensitivity iterations were implemented using the source data and proportional data that accounted for unit size differences.

Pareto Efficiency

The economic concept of efficiency was used to evaluate tradeoffs between units. In this study, a decision option is efficient if no other option dominates it. Dominance refers to elimination of less desirable or inefficient options that are worse than others over all fundamental objectives. Pareto-efficient options trade off values between objectives. In short, efficiency means that there exists a single preferred or "optimal" option, whereas Pareto efficiency means that there are tradeoffs between options. To illustrate efficiency using the case study, one planning unit may have better overall values regarding both habitat and community objectives than another unit, and the inefficient unit may be eliminated from further planning. To illustrate Pareto efficiency using the case study, one unit may have a better overall value regarding habitat but a worse overall value regarding community, as compared to another unit. In this context, both units are desirable for different reasons and discussions can elucidate important tradeoffs and differences in possible planning strategies within each unit. Therefore, pursuing Pareto efficiency and deliberating tradeoffs can be a worthwhile process for conservation planning.

This study partitioned the units regarding their multi-attribute value functions per fundamental objective. The mean and ranges of all overall values of each unit, including values calculated in the sensitivity analyses, were plotted in two-dimensional coordinate space. Visualizing alternatives

Table 2 Example swing weighting table for habitat function attributes

Attribute label	Baseline ("worst")	Swing ("best")	Rank	Score	Weight
H1 submerged aquatic vegetation (hectares)	0	7,449	5	50	0.1
H2 salt marsh (hectares)	3,167	20,170	1	100	0.19
H3 non-marsh tidal wetlands (hectares; constructed score)	325; 0	7,396; 100	4	70	0.13
H4 roadways (meters per marsh hectare)	5	2	7	45	0.09
H5 wetland connectedness (percent)	69	99	2	90	0.17
H6 occurrences (number)	6	144	5	50	0.1
H7 natural communities (number)	0	62	8	30	0.06
H8 ecologically important lands (hectares)	11,057	50,633	3	85	0.16

Baseline and swing rounded to ones. Weight rounded to hundredths. This structure was used to assign swing weights to all attributes per sub-objective (Supplementary Information)

in coordinate space can be an effective way to distinguish dominance, identify efficient or Pareto-efficient units, and discuss tradeoffs.

Results

The decision analysis applied in this study identified four Pareto-efficient planning units for consideration as priority conservation areas. The preferences team members assigned to the attributes through swing weighting influenced the results.

Swing weights for the habitat function attributes show a more uniform distribution across team members as compared to the other attributes (Fig. 3a). Salt marsh (H2) was the most important habitat function attribute, in part because its range across planning units was very large (3167 to 20,170 ha; Table 2) and salt marsh represents one of the largest and most critical structural habitats on the Lower Eastern Shore (Bilkovic et al. 2018). Swing weights for the habitat migration attributes were highly variable as compared to the weights for the habitat function attributes (Fig. 3b). These weights indicate a larger difference in preferences across team members. Unprotected migration space (H9) was the most important habitat migration attribute, in part because the attribute describes the amount of opportunity for salt marsh to migrate. Social vulnerability weights were more uniform across flood scenarios (Fig. 3f–h), as compared to highly variable infrastructure weights (Fig. 3c–e). This result may be associated with the time and effort in assigning seven swing scores to attributes that did not vary significantly over the flood scenarios. Developable zoning in flood-prone areas (C4) and minority populations (C10) were the most important attributes regarding infrastructure and social vulnerability, respectively, based on preferences.

There was very little difference in weight distribution of infrastructure and social vulnerability attributes between the two storm scenarios, whereas there was a larger difference between the nuisance and storm scenario types. This trend in preference corresponds to the difference in attribute measures between the two scenario types. The nuisance scenario overlays areas of increased vertical tide ranges, whereas the storm scenarios overlay areas where current and future storm surge is pushing over land. Intuitively, amount of land area inundated in the nuisance scenario will result in less infrastructure and social vulnerability attributes than the storm scenarios. This result highlights the strength of the swing weighting approach, which accounts for range differences in the attributes.

Multi-attribute value functions for the planning units are presented over all sensitivity iterations per source and proportional data analysis (Fig. 4). Equation (2) was multiplied by 100 to display multi-attribute value functions on a zero to 100 scale. According to the mean values over all sensitivity

iterations, units 1, 6, and 7 are Pareto-efficient and units 2, 3, 4, and 5 are inefficient using the source data (Fig. 4a). To illustrate, unit 2 is dominated by unit 1 because unit 1 has higher habitat and community value. Unit 2 can be considered inefficient on this proposition alone, even though it has a better habitat value than unit 7. Unit 7 cannot be eliminated because it has a better community value than all other units; in other words, it is not dominated by any other unit over both fundamental objectives. In summary, units 1, 6, and 7 are Pareto-efficient because they trade off value over the fundamental objectives, whereas units 2, 3, 4, and 5 are dominated by at least one of the Pareto-efficient units.

Results of the source data analysis vary when taking the ranges of multi-attribute value functions into account. For instance, unit 1 is efficient in sensitivity iterations where a high proportion of weight is assigned to the habitat migration and infrastructure sub-objectives. Likewise, unit 6 is efficient in sensitivity iterations where high proportion of weight is assigned to the habitat function and infrastructure sub-objectives, as well as instances where a high proportion of weight is assigned to social vulnerability under the Nuisance2020 flood scenario. There were no sensitivity iterations where unit 7 was efficient, even though it has a very high social vulnerability value under the Storm2015 and Storm2050 flood scenarios.

Units 1, 2, 6, and 7 are Pareto-efficient and units 3, 4, and 5 are inefficient using the proportional data (Fig. 4b). Like the source data analysis, these results vary when taking the ranges of multi-attribute value function values into account, but there were no instances of efficiency in any sensitivity iteration. The main tradeoff in this context is between the habitat value of units 1 and 2 and the community value of units 6 and 7. Based on different team members' swing weights, both units 1 and 2 presented the highest overall habitat value in sensitivity iterations where a high proportion of weight was given to the habitat function and habitat migration sub-objectives. This result is inconsistent with results of the source data analysis, where unit 6 dominated unit 2 regarding habitat value in all sensitivity iterations. In summary, unit size was an important determinant of habitat value for unit 2.

Unit 7 presented the highest overall community value in sensitivity iterations where a high proportion of weight was given to either sub-objective, except for one team member's emphasis on infrastructure attributes under the Nuisance2020 flood scenario. This result is inconsistent with results of the source data analysis, where unit 6 dominated unit 7 in sensitivity iterations where a high proportion of weight was given to infrastructure under the Nuisance2020 flood scenario and social vulnerability under the Nuisance2020 flood scenario and sometimes under the Storm2015 and Storm2050 scenarios. In summary, unit size was an important determinant of community value for unit 7.

Fig. 3 Swing weight distributions from five team members for habitat function (a), habitat migration (b), infrastructure (c–e), and social vulnerability (f–h) attributes. Infrastructure and social vulnerability attributes were weighted under three flood scenarios: Nuisance2020,

Storm2015, and Storm2050. Boxes contain the 50% interquartile range, separated by the median line. Whiskers contain the 90% interquartile range with outlier points extending from the range

All data and metadata regarding the attributes, single-attribute value functions, and multi-attribute values functions are provided in the [Supplementary Information](#).

Discussion

Decision analysis brings clarity to a resilience planning process. According to team members, distinctions between planning units were easily justified by following a set of common-sense principles for eliciting values, collecting and analyzing data based on those values, and incorporating the team's preferences into the analysis. Based on the results, the habitat value of units 1 and 2, and in some instances unit 6, can be justified in comparison to the other units. Likewise, the community value of units 6 and 7 can be justified in comparison to the other units. These critical insights can be traced to the values, data, and preferences gathered in setting objectives, attributes, and value functions, respectively. As a result, team

members were comfortable with the results and in knowing how the results were derived. A structured survey was not included in the team evaluation to quantify the degree of comfort. Making sense of a complex decision problem is a critical foundation for any structured decision-making process because it can guard against bias (von Winterfeldt and Edwards 1986), organize thinking about objectives and data (Gregory et al. 2012), and reveal important values and preferences (von Winterfeldt 2013). A key advantage of using decision analysis was that it provided the team with a logical ordering of analysis, using decision-focused concepts, tools, and insights, to inform the important aspects of the planning context.

We illustrate how the results may inform The Nature Conservancy's conservation priorities on the Lower Eastern Shore. For example, units 1, 6, and 7 were identified as Pareto-efficient using the source data (Fig. 4a). These units are high priorities for developing on-the-ground conservation strategies in different planning contexts. Regarding

Fig. 4 Visualization of means (points) and ranges (lines) of community (x-axis) and habitat (y-axis) multi-attribute value functions under all sensitivity iterations. The same sensitivity iterations were implemented using source data (a) and proportional data (b) that accounted for planning unit size

habitat activities, further discussions will identify possible habitat protection (e.g., conservation easements) and management activities (e.g., sediment enhancement, invasive plant control) near Blackwater National Wildlife Refuge and two state-designated conservation planning areas in units 1 and 2 (see below). Focusing on these areas can guide planning and proposal writing for future partnerships and funding opportunities. Regarding community activities, further discussions will identify possible adaptation options to safeguard communities against sea level rise near several coastal communities in unit 7. The geographic narrowing accomplished through decision analysis reduces the amount of landscape area to focus conservation work and thinking for unit-specific activities.

Equity considerations are important when implementing decision analysis. In general, equity considerations address possible ethical implications of (i) how the decision is made, (ii) the values and preferences that are included in the decision analysis, as well as (iii) who is involved in the decision-making process (Law et al. 2018). We give examples of the first two considerations based on this study. One example regards the way decision options are evaluated on achieving multiple fundamental objectives. According to the results, a single unit does not maximize both habitat and community objectives. The ideal but non-existent option that maximizes both objectives would display in the upper right-hand corner (coordinate 100,100) of Fig. 4. However, we can ask which unit is “close enough” to the ideal option as a sufficiency condition for placing a fair and impartial emphasis on both fundamental objectives in comparison. This approach would be similar to placing equal weights on the fundamental objectives and calculating a single multi-attribute value function for the units, rather than individual multi-attribute values functions for each fundamental objective. The results provided evidence that unit 6 may be a satisfactory option to plan habitat and community conservation activities. Unit

6 is sufficiently close to achieving both fundamental objectives, depending on how closeness may be measured (Zeleny 1974), regardless of whether source data or proportional data are considered (Fig. 4). The results did not provide evidence that other units could provide the same balance of the two fundamental objectives.

This example demonstrates how clarifying a process-based decision rule (*sensu* Keeney 1984) can provide depth to conversations about conservation work, especially where multiple values are deliberated. The degree of emphasis placed on the fundamental objectives will be different for each decision context. The impartiality rule may be replaced by a partiality rule if there are inequities that can be ameliorated with more focused conservation work. In other words, decision makers may reasonably choose options from the lower-right or upper-left portions of Fig. 4, as illustrated above.

A second example regards the values included in setting objectives and attributes. The team recognized that the effects of climate change will exacerbate inequities across the Lower Eastern Shore (Islam and Winkel 2017). For this reason, they were very explicit about valuing vulnerable and underrepresented demographics to elevate their priority for community engagement and conservation work. The decision analysis and results provided a meaningful way to initiate planning strategies in units where the combined effect of geophysical impacts from sea level rise and limited socio-economic resilience may be the most severe. This selection contrasts with areas where the combined effects may be less severe.

The team will use these two examples of equity considerations to combine habitat and community work in unit 6. There is evidence that habitat migration and community adaptations can be conceptually linked on the Lower Eastern Shore (Van Dolah et al. 2020). Based on these findings, grant proposals for work within unit 6, in collaboration with the City of Crisfield and surrounding Somerset County, will

be prepared to demonstrate integrated resilience solutions that incorporate the values and preferences of local community members facing future impacts of sea level rise.

These examples of equity considerations are not exhaustive of all possible equity considerations, and the team recognized their privilege and lack of diversity in composition and community representation affected the values, data, and preferences that informed the decision analysis. As mentioned earlier, next steps will include focusing on specific priority units for habitat and community work. Each unit may have a different culture and set of values, preferences, and geophysical and socioeconomic factors, and there are potential ethical implications of these differences (Harris et al. 2021). It will be important to co-develop actionable partnerships and other unique decision contexts that incorporate the values and preferences of the people being impacted by or managing for sea level rise in priority units. Given that the purpose of decision analysis is to guide critical thinking and yield insights and recommendations for specific decisions, this methodology could be compatible with many different equity considerations in coastal resilience planning (Keeney 1984).

The principles and tools used in this study are transferable to other conservation decision contexts. Two examples are noteworthy. First, the team encountered a timely decision while conducting this research based on whether to pursue a conservation easement on a 1,214-hectare parcel in unit 1, comprised largely of salt marsh. The team used the objectives hierarchy (Fig. 2) and some preliminary attribute maps to guide thinking about whether to pursue the opportunity. This binary (yes or no) decision was quickly resolved by implementing the qualitative aspects of decision analysis alone. Second, and as a follow up to the case study, the team mapped 594 privately-owned undeveloped parcels in units 1 and 2 that intersect the Department of Defense's Readiness and Environmental Protection Integration Program boundary. The team used the objectives hierarchy, along with other parcel-specific factors, to guide thinking about which parcels to pursue habitat protection easements under the program's funding mechanism. This decision was resolved within a short amount of time by implementing the qualitative and quantitative aspects of decision analysis. These examples illustrate how decision analysis can be used in many ways and gives further strength to its transferability to many conservation decisions.

Conclusions

Decision makers need a thoughtful approach to integrate habitat and community aspects into resilience planning (Molino et al. 2020). This study used decision-analytic principles and tools to guide thinking into a specific decision

about where The Nature Conservancy could focus conservation and engagement strategies on Maryland's Lower Eastern Shore. It builds on previous work to combine human and social dimensions into opportunity mapping (Knight et al. 2010). The methods and results are not a prescription for on-the-ground action, nor do they guarantee consensus. Rather, they are used as insights into the desirability of decision options for different reasons, and they are used by decision makers, including their designated team members and other interest groups, to inform a decision.

We recognize that many different types of problems can alter the use of decision analysis (Gregory et al. 2012). In general, uncertainty, risk, and group and/or linked decision contexts make decision analysis more challenging. Replicating these methods under these contexts may require different assumptions and tools (Bower et al. 2018; Schwartz et al. 2018). The choice of methodological assumptions should depend on decision makers while considering those who may be impacted by a decision. This study provides evidence that decision makers can be comfortable justifying their decisions when methodological assumptions are based on decision-analytic principles, value-based data, and personal preferences. These aspects of resilience planning are rarely emphasized, and we and others (Martin and Mazzotta 2018) recognize a lack of transparency in this dimension in the literature. This study provides context to inform this knowledge gap.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s12237-021-00970-x>.

Acknowledgements The authors thank Aileen Craig, Pabodha Galgamuwe, Donna M. Bilkovic, and James E. Lyons for manuscript reviews.

Declarations

Conflict of Interest The authors declare no competing interests.

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