Linking land and sea through an ecological-economic model of coral reef recreation

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Highlights:

- Model integrates social values to simulate coastal management outcomes
- Coastal recreation benefits and management priorities vary spatially
- Land-sea management provides best strategy overall and at most local beach sites
- Some beaches require unique strategies to maximize benefit
- Snorkelers prefer sites with better visibility, fish abundance, and diversity

Abstract

Coastal zones are popular recreational areas that substantially contribute to social welfare. Managers can use information about specific environmental features that people treasure, and how these might change under different management scenarios, to spatially target actions to areas of high current or potential value. We explored how snorkelers' experience would be affected by separate and combined land and marine management actions in West Maui, Hawaiʻi, using a Bayesian Belief Network (BBN) and a spatially explicit ecosystem services model. The BBN simulates recreational attractiveness by combining snorkeler preferences for coastal features with expert opinions on ecological dynamics, snorkeler behavior, and management actions. A choice experiment with snorkelers elucidated their preferences for sites with better ecological and water-quality conditions. Linking the economic elicitation to the spatially explicit BBN to evaluate land-sea management scenarios provides specific guidance on where and how to act in West Maui to maximize ecosystem service returns. Improving coastal water quality through sediment runoff and cesspool effluent reductions, and enhancing coral reef ecosystem conditions, positively affected overall snorkeling attractiveness across the study area, but with differential results at specific sites. The highest improvements were attained through joint land-sea management, driven by strong efforts to increase fish abundance and reduced sediment, however, the effects of management at individual beaches varied.

Keywords: Bayesian Belief Network; Recreational ecosystem service; Management scenario evaluation; Land-sea interactions; Hawai‘i

1 Introduction

The opportunity for recreation is an important coastal ecosystem service, particularly in places where coral reefs support thriving tourism and leisure sectors (Brander et al., 2007; Moberg and Folke, 1999; Spalding et al., 2017). This predominantly non-consumptive service sustains residents living near coral reefs and fuels a multi-billion-dollar global tourism industry (Pendleton, 1994; Spalding et al., 2017). People directly enjoy reefs when SCUBA diving, snorkeling, and fishing, while activities such as swimming, sunbathing, beachcombing, and surfing at the coast may also be reef-dependent. Particular characteristics of coral reef ecosystems, like complex structure and diverse fauna, directly impact snorkeling, diving, fishing, and even surfing user experiences (Brander et al., 2007; Principe et al., 2012). Globally, a series of studies have documented abiotic, biotic, and social features of reefs that make them valuable to people for recreation (Beharry-Borg and Scarpa, 2010; Cooper et al., 2009; Inglis et al., 1999; Pendleton, 1995) including conditions of the reef and fish, presence of charismatic megafauna, water clarity, pollution, and crowding. While visitation, visitor spending, and associated economic impacts may be easier to measure, the recreational attractiveness of reefs may be more difficult to directly measure (Principe et al., 2012).

Human impacts directly affect the attributes that make reefs most valuable for recreation. Anthropogenic stressors, both global and local, can cause widespread coral mortality that leads to rapid and hard-to-reverse shifts away from coral dominated systems (Hughes et al., 2007; Nyström et al., 2008), with cascading effects on fish abundance and diversity (Pratchett et al., 2008). Specifically, corals are threatened by extreme sea temperature anomalies that cause coral bleaching, where corals expel their algal symbionts, and if temperatures stay high for too long, this can lead to widespread mortality (Brown and Roughgarden, 1997; Hoegh-Guldberg, 1999). Pollution can smother corals (in the case of sediment), exacerbate coral disease (in the case of pathogens from sewage), cause algal outbreaks (in the case of nutrients), have sublethal effects that alter reef genetics, and kill coral outright (in the case of toxins, including sunscreen) (Anthony et al., 2015). Further, unsustainable levels of fish harvest can unbalance the system (Jackson et al., 2001), leading to cascading effects on important ecological processes such as herbivory (Hughes et al., 2010; Mumby and Steneck, 2008). Given the multiple and potentially synergistic and cumulative effects of stressors on reef ecosystems (Ban et al., 2014; Darling and Coté, 2008), research is needed to guide management actions aimed at understanding the boundaries for success, and the tradeoffs that exist among multiple stressors for preventing declines and enhancing recovery that leads to delivery of reef-based recreational ecosystem services (Jouffray et al., 2019; Weijerman et al., 2018).

A detailed understanding of recreationalists' preferences for coral reef conditions can help managers focus their efforts to preserve or enhance reefs so they can deliver valued ecosystem services. The recreational value of coral reefs has been widely researched in the ecological-economics literature, but, apart from a handful of exceptions where spatial methods were used (Ghermandi and Nunes, 2013; Ruiz-Frau et al., 2013; Spalding et al., 2017; van Riper et al., 2012), studies have predominantly used environmental valuation methods that are point-in-time estimates with no spatial component. Furthermore, these approaches rarely link values to specific attributes in ways that enable simulation of threats and management scenarios (one exception is van Beukering and Cesar (2004). Recreational valuation studies have historically relied on methods like contingent valuation, where respondents were asked to state their willingness to pay for certain beach attributes (Ahmed et al., 2007; Loomis and Santiago, 2013; Petrosillo et al., 2007), choice experiments, where respondents were asked to make hypothetical trade-offs amongst attributes (Beharry-Borg and Scarpa, 2010; Nunes et al., 2015; Schuhmann et al., 2013), or travel cost, where respondents' actual recreational behavior was used to model willingness to pay (Ahmed et al., 2007; Ariza et al., 2012; Carr and Mendelsohn, 2003; Loomis and Santiago, 2013; Zhang et al., 2015). For a review of valuation studies in islands see Oleson et al. (2018). Despite this effort, most coral reef valuation studies have not been contextualized in a manner that enables place-based management scenario analysis.

Massive efforts are dedicated to coastal management globally. Are these efforts targeting the conditions and places most valuable to society? Are they addressing stressors in ways that can support continued delivery of ecosystem services? The aim of this study is to develop an applied valuation methodology that provides specific and useful management guidance to coastal managers. Information on the perceived value of specific areas for recreation - and how these might change under different scenarios - could help communities to ensure persistence of important values and services. Specifically, we assess the benefits to recreationalists and recreation-dependent communities of potential land and marine management strategies so that managers can prioritize which actions to take, and where these actions will yield the greatest benefits. To be relevant, our approach needs to include features of the nearshore environment that land and marine management could directly or indirectly affect, as well as physical and social features that influence the value of a site, such as access and crowding. It has to be ecologically sound, based on the best scientific understanding of coral reef dynamics, while also being grounded on the user experience. Our methodology rests on a Bayesian Belief Network (BBN) to integrate multiple types of information, including expert judgment about ecological dynamics, management, and snorkeler behavior, and snorkelers' stated preferences elicited through a choice experiment. While BBNs have been used in studies of coral ecology (Franco et al., 2016; Graham et al., 2008), this is the first study to use BBNs to assess ecosystem services in coral reef systems. An ecosystem services approach is relatable to decision makers, visitors, and residents as it ties ecological conditions to human preferences and wellbeing outcomes (Tallis and Polasky, 2009; Wainger and Mazzotta, 2011; Wainger and Boyd, 2009). The novel ecological-economic method we developed has the advantages of being able to model and provide spatially nuanced and policy-grounded information for conservation and resource management planning. In our spatially explicit case study we identify areas where management returns are highest, as well as specific management measures that would have the largest pay-off for popular beaches on the northwest part of the island of Maui, Hawaiʻi, USA.

The rest of the paper is organized as follows. In a models and methods section, we describe the site, then step through our approach, which integrates different methods and datasets, and builds scenarios. We detail the survey instrument, choice experiment, Bayesian Belief Network modeling, and scenario modeling. In each of these sub-sections we detail the method and the results, as the results are then used as inputs to the subsequent sub-section (i.e. the choice experiment results inform the BBN, which underpin the scenarios). Our discussion section focuses on the management implications, modeling innovations, and study limitations.

2 Models and Methods

2.1 Site characteristics

Over 167,000 people are residents of Maui island, in the state of Hawaiʻi, USA (U.S. Census Bureau, 2017). Nearly three million (2.7 million) tourists visited Maui in 2017, spending $4.68 billion (Hawaii Tourism Authority, 2016). Our case-study focuses on West Maui (Figure 1). West Maui's coasts are a popular recreation destination for tourists and residents, many of whom are attracted to the calm, clear waters and historically high-quality coral reefs. World-famous beaches in the West Maui region serve as launching spots for recreation. Today, land previously farmed as sugar or pineapple plantations for over a century is kept as fallow or being converted for residential use, while resort development continues along the coast.

Unfortunately, West Maui’s coral reefs have declined in the past fifteen years as a result of fishing and pollution from land (Sparks et al., 2015).

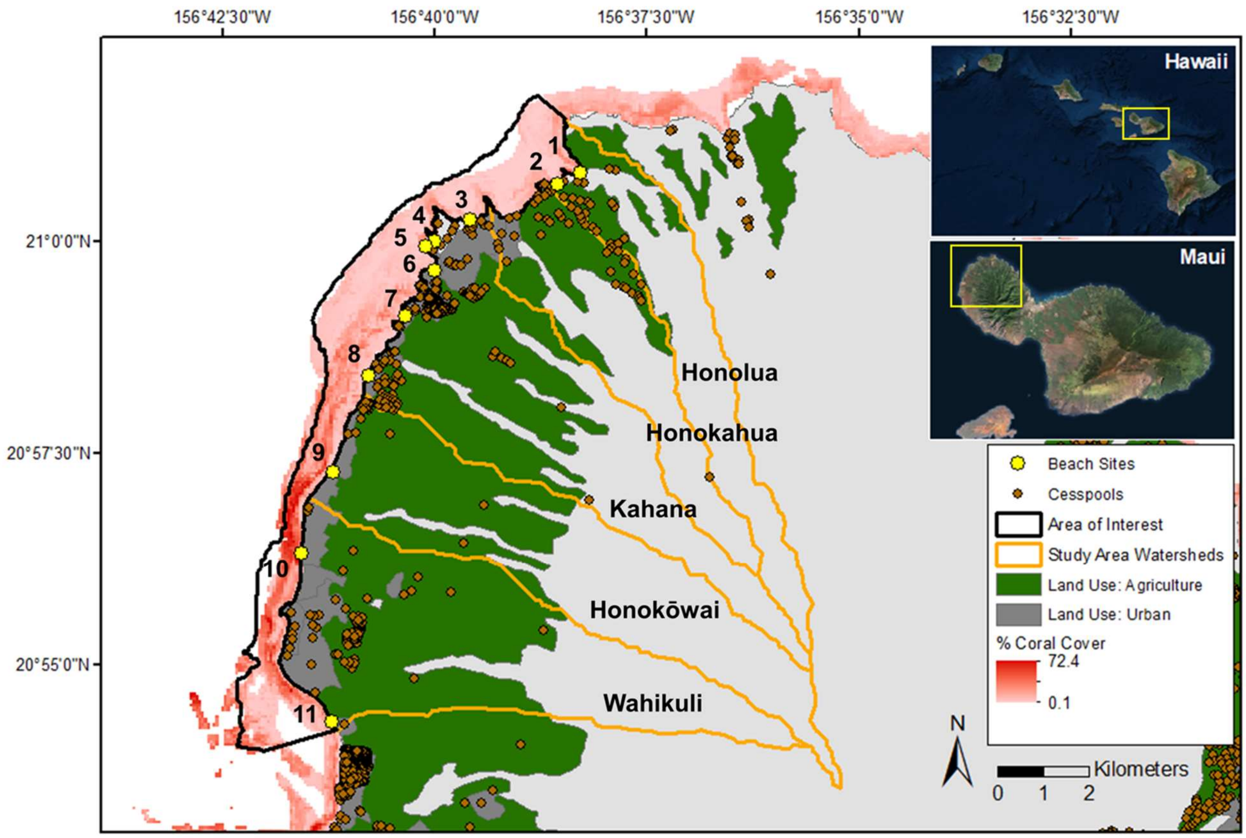

Figure 1 Map of study site with beaches, land use, cesspools, and coral reef cover depicted. Watershed boundary and land use from (State of Hawai‘i Office of Planning, 2019)) and predicted coral cover from (Weijerman et al., 2018).

2.2 Survey instrument

We used a tablet-based survey to collect responses from 290 recreational snorkelers in West Maui between August and September 2015. We intercepted resident and tourist snorkelers at beaches and in resort areas (Figure 1), distributing our sampling effort across five watersheds running north to south (Honolua (5% of respondents), Honokahua (8%), Kahana (22%), Honokōwai (8%), and Wahikuli (57%) based on visitation, which we estimated using a crowding model based on social media photo uploads (Wood, Guerry et al. 2013). The survey instrument, approved by University of Hawai‘i’s Institutional Review Board (2016-31181), was tested on beach goers on a nearby island. The survey included questions related to demographics, knowledge, values, experience, and preferences for attributes of snorkeling sites. We focused on snorkelers, as snorkeling is a common activity for both residents and tourists, and snorkelers tend to be aware of environmental conditions. The design enabled us to explore possible differences between residents and tourists. The survey instrument is included as supplementary information (SI_S1).

Full descriptive statistics are provided in Table SI_T1. Just over half (53%) of the respondents were female. Eighty-one were permanent Maui residents, twenty were seasonal residents, and 180 were visitors. The median respondent age was 45, higher than the median in the county (37), the median annual household income was $87,500, also higher than the average in Maui County ($72,762), and the sample was more educated than average (26.3% of 167,000 residents have a college degree vs. 60% in the sample) (U.S. Census Bureau, 2017). While Maui residents are ethnically diverse, the sample was skewed towards Caucasians (65% vs. 35% in Maui (U.S. Census Bureau, 2017)), likely reflecting both the tourists and the demographic who snorkels at the beaches surveyed. Most respondents reported additional snorkeling experience in locations other than Maui (240), and 40 said they had experience snorkeling on Maui. Ten noted they had no snorkeling experience and were planning on going. Snorkelers with experience had a median of 20 events. Nearly a third of all respondents (92) were also SCUBA divers.

2.3 Choice experiment

Following examples such as Schuhmann et al. (2013), we used a discrete choice experiment to determine snorkeler preferences for environmental attributes that may be affected by management and/or climate change. Snorkelers were asked to choose among three different beaches characterized by different travel costs and attributes. These attributes represent a subset of those important for snorkeler satisfaction that were cited during interviews with experts and local snorkelers, and reported in the literature (Beharry-Borg and Scarpa, 2010; Loomis and Santiago, 2013; Peng and Oleson, 2017). Due to known cognitive limitations when evaluating trade-offs in choice experiments (Johnston et al., 2017), we restricted the number of environmental attributes included in our choice experiment to: water quality, visibility, fish abundance and diversity, coral cover, and chance of seeing sea turtles, as well as price, which represents both transportation costs to access the beach and the opportunity value of time (Fezzi et al., 2014). We set three levels for each environmental attribute (Table 1), while travel cost had six levels. The levels of all attributes were depicted in photos (Figure SI_F1). Each respondent faced 10 choice tasks. We validated these levels by asking respondents about their perceptions of snorkeling on Maui.

A complete factorial design for our choice experiments includes all possible combinations of attributes and levels and would use 4,374 choice tasks (3*3*3*3*3*3*6 =4,374). From the total possible combinations, 100 choice tasks with two alternative combinations of attributes and one fixed status quo were generated in a series of ten different choice set versions (ten choice tasks per version) in SSI Web 10.0 Sawtooth Software. Snorkelers were asked to decide between a baseline site that represented the lowest conditions at zero cost (considered the opt-out), and two alternative sites with improved conditions.

Table 1 Attributes and levels for choice experiment

Attribute	**Low (Base condition)**	**Moderate**	**High**	**Citation/Justification**

Bacterial warning	12 days/year	6 days/year	0 days/year	(Hawai‘i Department of Health, 2019) and DOH experts
Visibility	15 feet	30 feet	60 feet	NOAA experts
Coral cover	<15%	26%	>45%	(Sparks et al., 2015)
Fish abundance	$75/125m^2$	$115/125m^2$	$150/125m^2$	(Friedlander et al., 2005; Williams et al., 2008)
Fish diversity	8 species	17 species	28 species	
Turtle sighting	P(sighting) = 0%	<50%	>50%	NOAA experts
Price	\$0, \$10, \$50, \$100, \$175, \$250			Estimate of cost for extra time and transportation

DOH = Department of Health

NOAA = National Oceanic and Atmospheric Administration

We analyzed the choice experiment data by specifying a random utility model (RUM), following the method established by McFadden (1974). Under this framework, the utility that respondent *j* receives from visiting option *i* can be written as:

$$(1)\ U_{ij} = \sum_{k=1}^{5} \theta_{ki} + \gamma cost_i + \beta SQ_i + \varepsilon_{ij}, \qquad (1)$$

Where ϑ_{ki} indicates the part of utility for each of the five attributes (*k*) characterizing option *i*, $cost_i$ is the cost of access, γ is the marginal utility of money, SQ_i is a dummy variable indicating whether the option is the status quo, *β* is the parameter allowing for “status-quo bias,” and ε_{ij} is the random component encompassing the unobserved (to the researcher) part of the utility that person *i* associates to option *j*. The ϑ coefficients illustrate the relative importance of attributes and their levels, and the willingness of respondents to trade one attribute level for another. To allow for maximum modelling flexibility, we model each attribute via dummy variables, with the worst level for each attribute selected as the baseline (for example, for the attribute “bacterial warnings” the baseline level is 12 days per year).

Again following (McFadden 1974), by assuming the random error ε_{ij} to be identically and independently distributed as a type I extreme value (i.e., Gumbel), and indicating with V_{ij} the observed portion of the utility (i.e., $V_{ij} = U_{ij} - \varepsilon_{ij}$), we can write the probability of choosing alternative *i* as:

$$P_{ij} = \frac{exp\ (V_{ij})}{\sum_{h=1}^{3}\ \ exp\ (V_{ih})} \qquad (2)$$

This conditional logit specification includes all the parameters in (1) and can be estimated via maximum likelihood.

Results of the choice experiment

We used the results of the choice experiment (below) to construct/parameterize the BBN model described below. Results of the choice experiment are summarized in Table 2. All attribute coefficients are significant. Interviewed snorkelers preferred sites with better ecological and water quality conditions, especially high and moderate visibility (coefficients 0.747 and 0.615), followed by high coral cover (0.497), high chance of sighting turtles (0.469), high bacteriological quality (0.465), and finally high fish diversity (0.379) and abundance (0.344). In many cases, most of the value to snorkelers lay in improving conditions to the moderate level from the base level; any additional improvement to the high level was less valued. This diminishing return is particularly strong in the visibility characteristic, suggesting that people were happy with being able to see 30 feet (+0.615) but the additional gains from visibility up to 60 feet were less valued

(+0.132). In contrast, fish diversity and abundance showed roughly linear preferences from base conditions through moderate to high. Notably, there were few differences amongst groups. Residents had similar preferences as tourists and seasonal residents, with one exception (residents prioritized visibility more), although the low sample size of residents prevents comparison of many of the attributes (Table SI_T2).

Table 2 Choice experiment results. Z-value is the number of standard deviations from the mean value.

Attribute	Estimate	Std. error	z-value	
Bacteria: 0 days	0.465	0.066	7.046	***
Bacteria: 6 days	0.243	0.063	3.834	***
Visibility: 30 feet (9.14 m)	0.615	0.063	9.707	***
Visibility: 60 feet (18.29 m)	0.747	0.065	11.378	***
Coral cover: high	0.497	0.065	7.628	***
Coral cover: medium	0.304	0.061	4.962	***
Fish number: high	0.344	0.062	5.478	***
Fish number: medium	0.149	0.065	2.27	*
Fish diversity: high	0.379	0.065	5.849	***
Fish diversity: medium	0.144	0.063	2.282	*
Turtles: high	0.469	0.064	7.369	***
Turtles: low	0.234	0.066	3.543	***
Cost	-0.006	0.000	-19.164	***
Status quo	-0.658	0.112	-5.868	***
pseudo R^2	0.27			
Log likelihood	-2281.83			

Notes: parameters need to be interpreted as differences with the baseline category, which is omitted from the model. For example, for bacteria the baseline category is 12 days in which bathing is unsafe because of potential contamination, for visibility it is 15 feet. All attributes are in Table 1.

2.4 Bayesian Belief Network

A BBN graphs the causal structure of variables in an inference or modeling problem, and uses conditional probability distributions to define relationships between variables (Aguilera et al., 2011; Ames et al., 2005). Combining diverse sources of information within a BBN is particularly important when one cannot include all attributes characterizing choices within a stated preference exercise, for well-known issues of cognitive burden (Johnston et al., 2017). BBNs have been used *inter alia* to model ecosystem services (Dee et al., 2017; Landuyt et al., 2013); and as a tool for planning (Gonzalez-Redin et al., 2016); pollution impact assessment (Spence and Jordan, 2013); guiding adaptive management (Nyberg et al., 2006); and assessing ecological water quality (Forio et al., 2015).

Our BBN model estimates spatially explicit relative snorkeling attractiveness in the West Maui study area by integrating attributes of ecological, water, and social quality such as coral cover, fish richness, pollution, depth, and accessibility. The model’s area of interest (AOI) consisted of West Maui shoreline from Honolua Bay to south of Black Rock Point, extending to 30m depth (Figure 1). The model variables, structure, and strength of relationships between variables were informed by a literature review, experts (Kuhnert et al., 2010), and the choice experiment described in the section above. Past valuation studies were useful in identifying important attributes for beach users, particularly divers and snorkelers (Grafeld et al., 2016; Parsons and Thur, 2008; Pendleton, 1994; Schuhmann et al., 2013; Wielgus et al., 2002).

Ultimately, the BBN had 11 attribute parent nodes that interact, as illustrated by the arrows, in order to determine snorkeling attractiveness (“Snorkeling Quality” in Figure 2). Each of these parent nodes have spatial data associated with them (Table 3) (SI, Figure SI_F2A-K). The current status of each attribute (i.e., prior probabilities) in West Maui is represented by the colored bars within the parent nodes; these represent the average status across the entire AOI and are divided into bins (Table 3, Figure 2). Parent nodes are aggregated into four intermediate nodes (social quality, water quality, visibility, and ecological quality) that determine snorkeling quality. The grouping of parent nodes into intermediate nodes simplifies the conditional probabilities of the BBN model and thus reduces the cognitive load required to determine the relationships. The selection of parent nodes and arrangement of intermediate nodes constitutes the causal structure of the model. We tested a number of model structures via interviews with 15 experts, including marine scientists with two Division of Aquatic Resources staff (DAR, the state agency charged with coral reef management), a lifeguard working in the area, ten avid snorkelers, and two snorkel tour operators.

Table 3 Attributes in the Bayesian Belief Network (BBN)

Attributes	**Data source**	**Measurement & Bins in BBN**	**Data resolution**
Access	(Hawai‘i Mapping Research Group, 2016; Wedding et al., 2018)	1-4 (classification)	10m
Exposure	(Wedding et al., 2018)	<5,300, >5,300 (wave energy, J*s/m)	500m
Crowding	(Wood et al., 2013)	<3, 3-6, >6 (Photograph user days)	60m
Cesspool discharge	data from (Barnes et al., 2019) using methods from (Wedding et al., 2018)	0-0.004, 0.004-0.008, >0.008 (kg N/m2)	500m

Sediment dispersion	updated, using methods from Wedding et al., (2018)	0-3, 3-10, >10 (ton/ha)	30m
Bathymetry	(Hawai‘i Mapping Research Group, 2016)	0-10, >10 (m depth)	5m
Coral cover	(Weijerman et al., 2018)	<20, 20-35, >35 (% cover)	60m
Fish abundance	(Weijerman et al., 2018)	<0.76, 0.76-1.06, >1.06 (count/m^2)	60m
Fish species richness	(Weijerman et al., 2018)	<8, 8-17, >17 (count/grid cell)	60m
Habitat diversity	(Friedlander and Kendall, 2006)	<0.37, 0.37-0.74, >0.74 (ranking)	60m
Turtle chance as a function of habitat	(National Centers for Coastal Ocean Science, 2007)	0-0.35, 0.35-0.99, 0.99-1 (% likelihood of viewing)	50m

Note: Probability of spotting turtles calculated as a function of habitat. High probability - coral dominated hard bottom habitat; Medium probability - algal dominated habitat (including macroalgae, turf, and crustose coralline algae (CCA)), both hard and soft bottom; Low probability - everything else - primarily uncolonized soft bottom or unknown/unclassified.

The next step was to set the relative importance of each variable via conditional probability tables. The conditional probability distribution defines the relative importance of each parent node. For instance, the intermediate node “water quality” is determined based on the value of two parent nodes, cesspool discharge and sediment dispersion. The water quality outcome is determined by specifying the likelihood that water quality is high, moderate, or low, given levels of cesspool discharge and sediment dispersion (the values of each column always sum to 1). An example conditional probability table for the water quality node is presented in Table 4. The thickness of the arrows in Figure 2, which illustrate each variable’s relative importance to the outcome, denoting average Euclidian influence, are based on the conditional probabilities (Koiter, 2006). Water quality is a relatively simple intermediate node, with only two determinants; as the relationships become more complicated, the number of columns in the tables expand very rapidly.

Table 4 Water quality (intermediate node) conditional probability table given parent nodes Cesspool discharge and Sediment dispersion.

Water Quality									
Cesspool Discharge	High			Moderate			Low		
Sediment Dispersion	High	Moderate	Low	High	Moderate	Low	High	Moderate	Low
High	0	0	0.1	0	0.2	0.3	0.4	0.8	0.9
Moderate	0.05	0.1	0.1	0.6	0.6	0.6	0.4	0.2	0.1
Low	0.95	0.9	0.8	0.4	0.2	0.1	0.2	0	0

We populated the conditional probability tables based on our data from the choice experiment and additional survey questions, as well as through consultation with coral reef managers and experts. The choice experiment focused on a limited number of the variables (six) in the BBN to elicit their relative importance for snorkelers in West Maui. For instance, from the choice experiment results we understand that snorkelers in West Maui highly valued improved visibility, more than reductions in the probability of bacteriological water quality below recreational water standards. Features of social quality (like access and crowding) were assessed in the survey. Interviews with experts elicited the relative importance of the other variables. Conditional probability tables for all variables are in Table SI_T4a and strength of influence in Table SI_T4b.

The model's output is a score (from 0 to 100) of the quality or attractiveness of each grid cell for recreational snorkelers. A score of 100 indicates a very high-quality snorkeling site within the study area, and 0 very poor. This score range is specific to the AOI and normalized to the range of outcomes and scenarios in this analysis. The score is binned into five levels (0-20 very low;

21-40 low; 41-60 moderate; 61-80 high; and 81-100 very high). To explore assumptions of the model, we ran various hypothetical scenarios to see if the results were consistent with expectations. For instance, we set the value of model inputs that the choice experiment or experts told us were highly important (e.g., turtle-sighting likelihood, fish species richness, or visibility) to the highest possible values and evaluated the model's sensitivity to changes in these inputs, as opposed to those deemed to be less important (e.g., crowding or habitat diversity). We generated results for the entire study area, as well as for subsetted areas within the highly and moderately accessible areas surrounding popular beaches. We ran models for current conditions and a set of management scenarios (described below) at 50 m resolution using the Artificial Intelligence for Ecosystem Services (ARIES) modeling platform (Villa et al., 2014).

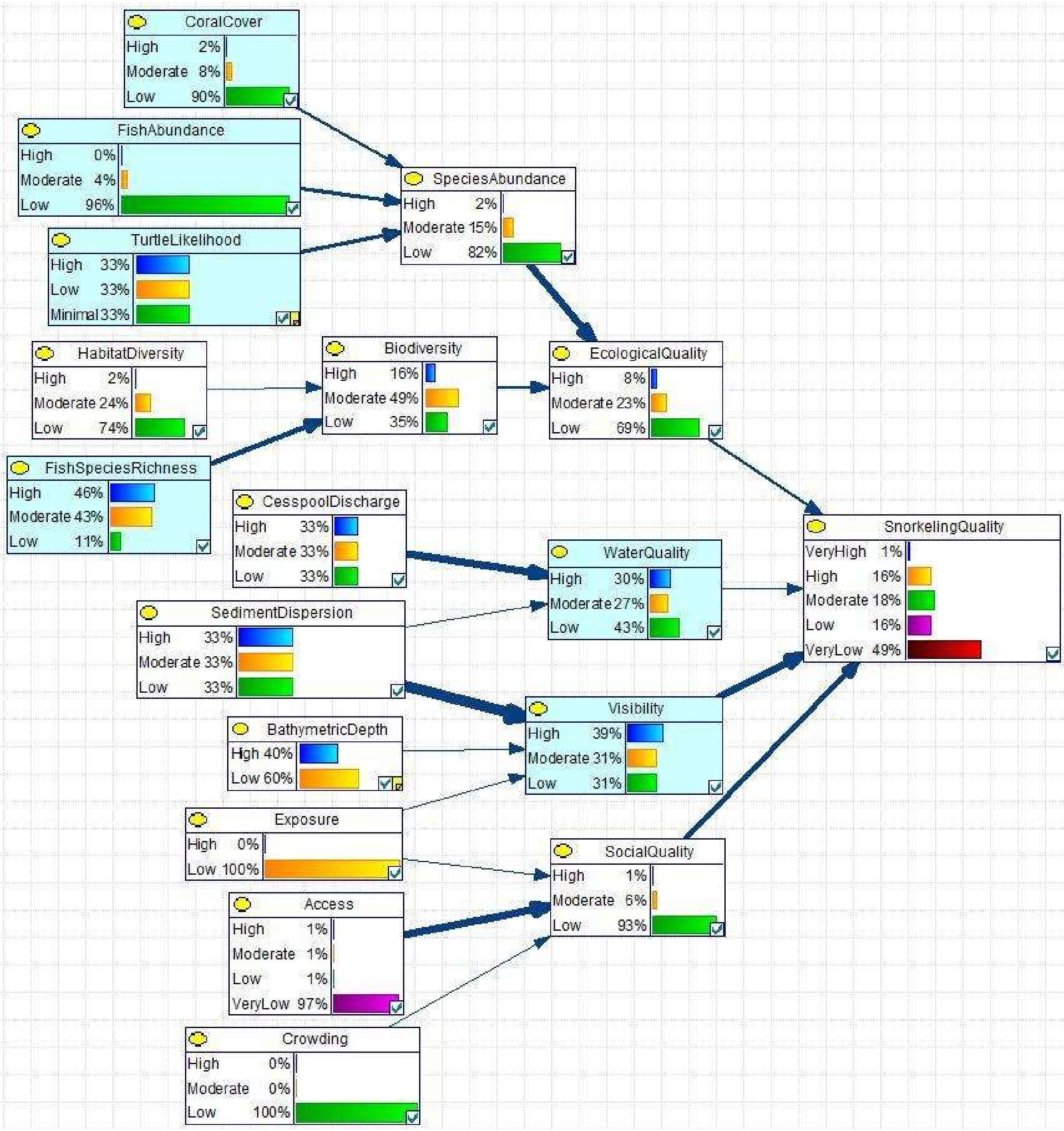

Figure 2 Bayesian Belief Network describing a site's snorkeling quality. Nodes shaded in light blue indicate variables included in the choice experiment. Arrow thickness denotes average Euclidian influence per the conditional probability tables (strength of influence for each relationship is included in SI Table SI_T4b). The most influential relationship (Sediment Dispersion on Visibility) is about 10 times the value of the weakest relationship (Crowding on Social Quality). The colored bars indicate current conditions across all pixels in the AOI in Figure 1. Note that this means that most pixels are far away from the coast or near a rocky shoreline, causing the access to be very low for most of them.

3 Scenario modeling

A primary objective of this paper is to determine what management actions would be most effective and where their implementation would have the strongest effects. Therefore, we modeled a number of land and marine management scenarios. Land management options target sediment and effluent reduction from cesspools. Marine-based management included reducing fishing, and the effect of changes in coral cover and associated fish abundance and richness. Target levels for these reductions were based on the goals stated in official watershed management plans (Group 70, 2015a, 2015b; Sustainable Resources Group International, 2012a, 2012b) and telephone, email, and in-person interviews with the watershed management coordinator, environmental consultants who prepared the watershed management plans, the State aquatic resource manager, and a Federal coral reef ecologist familiar with the area. We used four different levels for each scenario to represent increasing levels of investment in each type of management.

Land-based management

In the watersheds upstream of West Maui’s coral reefs, former agricultural lands currently remain fallow and access roads unfixed, stream banks continue to erode, and no cesspools are upgraded (Oleson et al., 2017; Stock et al., 2016; Whittier and El-Kadi, 2014). Land-based management scenarios represent realistic and aspirational levels of local pollution abatement. We modeled the following individually and in combination: reduce sediment input by 10%, 15%, 20%, and 25%; reduce cesspool input by 10%, 25%, 50%, and 100%. Notably, we did not adjust input layers for known cesspool upgrades, and we ignored discharge from the Kahekili wastewater treatment plant.

Marine-based management

We also constructed a second set of management scenarios based on improvements to coral reef benthic habitat and associated changes in coral reef fish communities. Local coral reef experts agreed that increasing coral cover by 5%, 10%, 15%, and 20% above current levels were reasonable aspirations in this area, particularly given historical coral cover levels and improvements in managed areas (Williams et al., 2016). To estimate how fish biomass would change under different marine management scenarios, we draw upon a previously published hierarchical, linear Bayesian model of how multiple biophysical and human population drivers influence fish biomass throughout the main Hawaiian Islands (Gorospe et al., 2018). Data from the same study show that increases in coral cover would also result in increases in reef complexity (Figure SI_F3). Therefore, although reef complexity was not a component of our snorkeler choice experiments, we use both coral cover and complexity to estimate changes in reef fish biomass. Finally, applying a linear model to data from West Maui fish surveys, we translate modeled fish biomass into the more snorkeler-relevant metrics of fish abundance (Figure SI_F4A) and fish species richness (Figure SI_F4B). Overall, this allowed us to derive a complete picture of how the reef attributes in the BBN (coral cover, fish abundance, and fish species richness) collectively changed (Table 5). All data for the above analyses came from fish and benthic surveys conducted by the NOAA Pacific Islands Fisheries Science Center's Ecosystem Science Division in 2012, 2013, and 2015 (Pacific Islands Fisheries Science Center, 2019).

Table 5 Model-predicted fish biomass, abundance, and species richness based on hypothetical, absolute increases in percent coral cover achievable with management. Using field data from throughout the main Hawaiian Islands, a hierarchical, linear Bayesian model (Gorospe et al. 2018) was used to predict fish biomass based on increases in coral cover and associated increases in reef complexity. Modeled fish abundance and richness outcomes are presented for different levels of absolute coral cover change over baseline, where the baseline is the current mean for *the Maui-Lahaina area. When coral reef cover increases over the baseline, the model predicts coral reef complexity increase (Figure SI_3), fish biomass, fish abundance, and fish richness. For instance, moving from baseline coral cover and complexity to a scenario where coral cover increases to baseline+5%, fish biomass would increase from 5.89g/m^2 to 7.10g/m^2, fish abundance from 0.028 fish/m^2 to 0.039 fish/m^2 (scenario is 139% of baseline), and fish richness from 6.13 to 6.97 species (scenario is 114% of baseline).*

Coral Cover	Model-linked Fish Biomass	Fish Abundance		Fish Richness	
(% absolute change over baseline at a site)	(g/m^2)	(# fish/m^2)	(% of baseline)	(# species)	(% of baseline)
Baseline	5.89	0.028	NA	6.13	NA
+5	7.10	0.039	139%	6.97	114%
+10	8.33	0.050	178%	7.83	128%
+15	9.63	0.062	220%	8.74	143%
+20	10.97	0.074	263%	9.68	158%

Combined marine-land management

As a third set of management scenarios, we combined all management outcomes into a single scenario, where both land-based pollution was reduced and benthic habitat and fish communities were rehabilitated at increasing levels.

Scenario results

Baseline snorkeling attractiveness was estimated using the BBN under current conditions and is mapped in Figure 3. Popular snorkeling destinations such as Ka‘anapali Beach have high snorkeling attractiveness, as expected, due to low exposure, sediment, and cesspool effluent, and good ecological quality. But not all popular beaches score high. For instance Honolua Bay has a lower than expected score, explained by high sediment, exposure, and crowding, which reduce its attractiveness, despite low cesspool discharge, high fish richness and abundance, and high probability of viewing turtles.

Using the BBN to estimate the effects of 20 management scenarios on recreation for the entire AOI and a subsetted area of high and moderate accessibility, we found that improving local water quality through controlling sediment and cesspool effluent and enhancing coral reef conditions (i.e., coral cover, fish abundance, fish diversity as "combined marine") positively affected snorkeling attractiveness across our study AOI (Figure 4; Table SI_T5). Reducing sediment alone had stronger effects on overall attractiveness than cesspool-related pollution reductions. Increasing fish abundance had the strongest effects on snorkeling quality of all ocean-related actions, while combined marine management (coral, fish abundance, and fish richness improvements) resulted in slightly larger quality improvements than combined land management (sediment and cesspool pollution reduction). Results of coral reef restoration scenarios cannot be evaluated independently, as fish abundance and richness estimates are directly tied to coral cover improvements, though we present the 12 decomposed results in Figure 4 to illustrate the relative benefits. The greatest improvements across the entire AOI and the accessible areas came from combining both land- and marine-based management.

Results of land-based scenarios suggest that sediment reductions have the most value to people, more so than cesspool effluent reductions. Reducing sediment by 25% - the highest-level erosion reduction scenario - improved the recreational value more than completely removing cesspools (7.1% vs. 4.3% improvement in the snorkeling attractiveness score for the highly and moderately accessible areas). A coordinated effort to control both sediment and cesspool effluent at the highest levels can improve the value by 11.4% in accessible areas.

Increasing coral cover to baseline plus 20%, fish abundance to 263% of baseline, and richness by 158% of baseline in a combined strategy would increase snorkeling quality by 15.7% in accessible areas. Combining all land and marine-based management activities at the highest levels resulted in a 27.7% improvement in snorkeling quality in more accessible areas, 15.7% from marine management and 11.5% from land management.

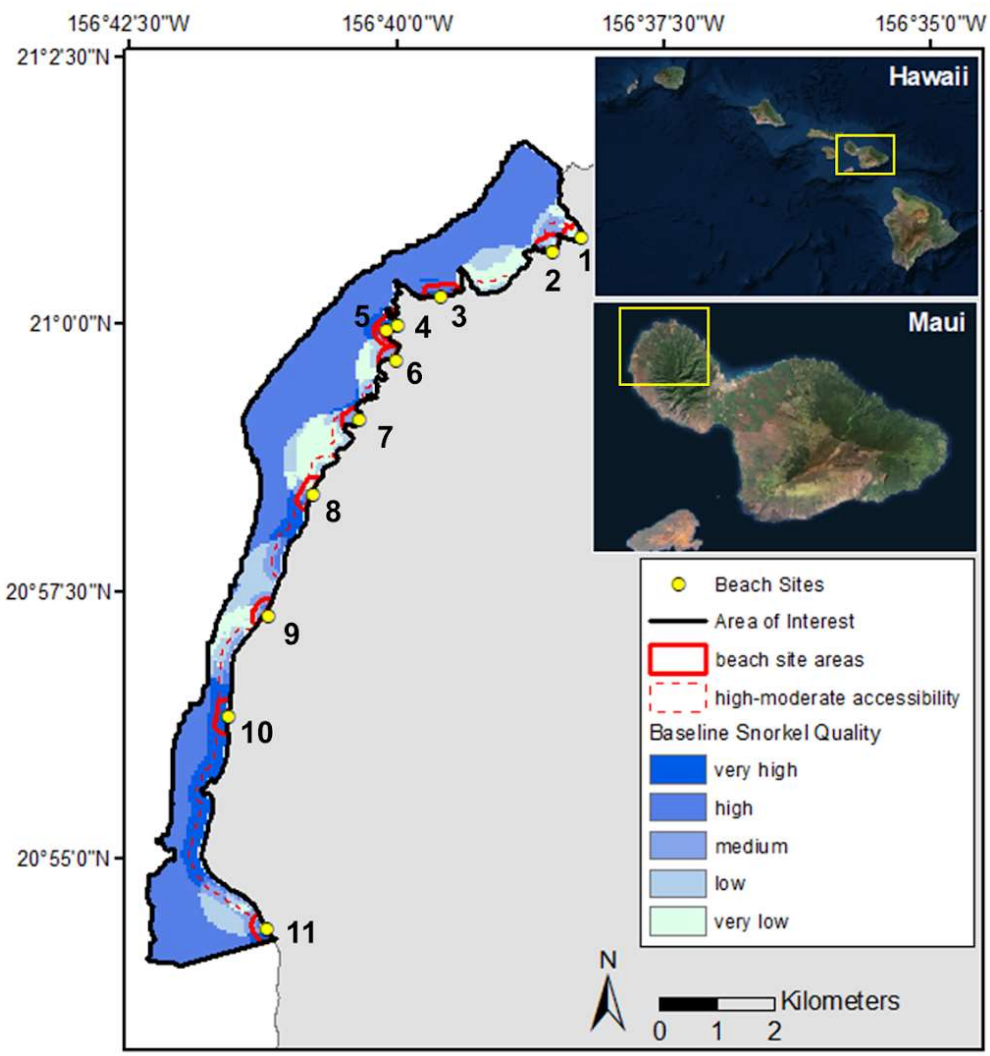

Figure 3 Baseline snorkeling quality at current conditions (initial data inputs), binned as 0-20 very low; 21-40 low; 41-60 moderate; 61-80 high; and 81—100 very high. Area of interest (AOI), high-moderate access area, and beach site areas depicted. Beach sites indicated by yellow dots and numbers (see beach names in Table 6).

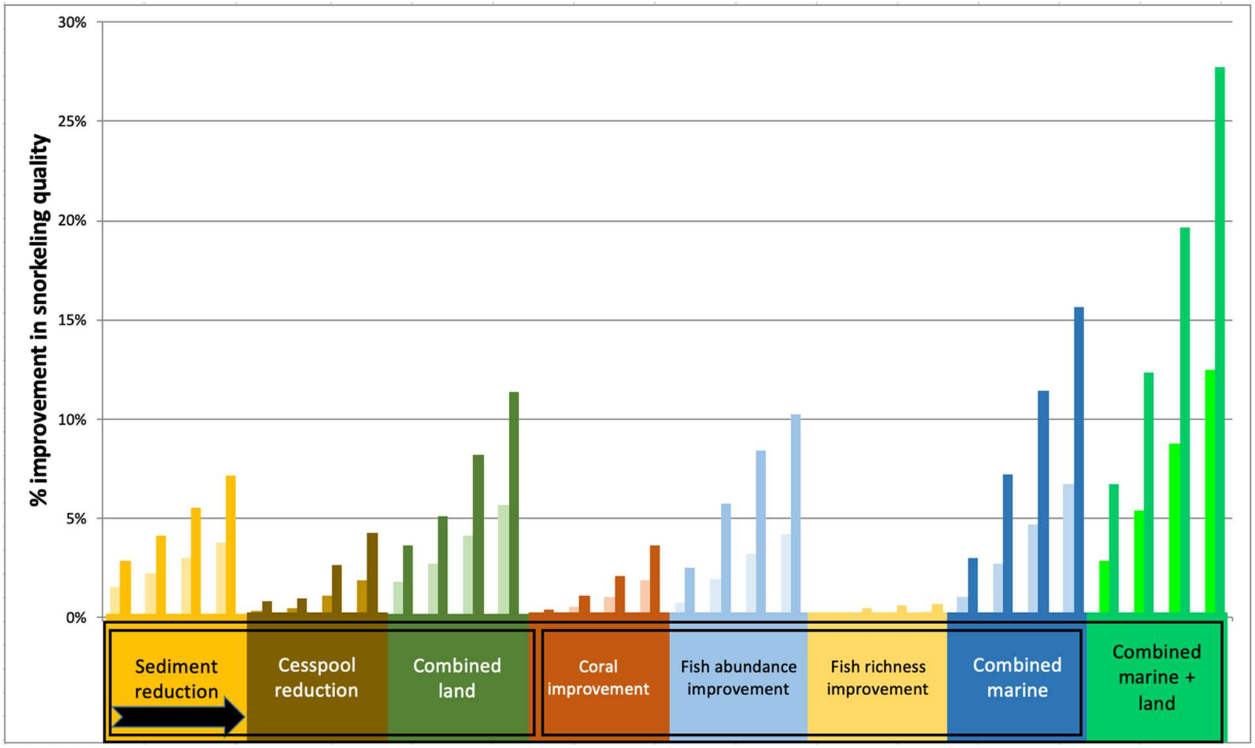

Figure 4 Improvement in snorkeling quality by management action/combination. Results show improvements across the entire area of interest (AOI) in lighter shading, and nearshore areas with high to moderate accessibility in darker shading. The sequence of four sets of bars for each management action shows progressively greater improvements for that activity, as described in the methods and Supplemental Information.

Zooming in on popular local beaches illustrates how site-specific conditions determine the effects of management outcomes within the most accessible areas around those beaches. While results across the entire AOI and the most accessible areas suggest that reducing sediment is more impactful than cesspool-related action (Figure 4), this is not always true when we look at the area around popular beaches individually (Figure 3). The current recreation value of each beach area, along with results for five of the management scenarios with the largest improvements in outcomes are summarized in Table 6 for the high-access areas within 300m around eleven key beaches (see Table SI_T6 for details and Figure SI_F5A-FF for maps). In some beaches, reducing cesspool effluent has more value than reducing sediment, and in others, land management has no effect on recreation. As expected from the overall results, marine management has the highest outcomes for the majority of examined beaches, higher even than both land management actions together.

Table 6 Snorkeling attractiveness score in highly accessible areas around each beach (listed in order north to south) under baseline conditions, and relative improvements due to high-impact management scenarios: 1. reduce sediment by 25%; 2. eliminate cesspools; 3. do both ["Land"]; 4. improve coral cover to baseline + 20%, fish abundance to 263% of baseline, and fish species richness to 158% of baseline ["Marine"]; and 5. do both "Land" and "Marine" simultaneously ["Combined"]).

Map	Beach	Baseline snorkeling attractiveness score	Snorkeling attractiveness score improvement due to management scenario				
			Sediment	Cesspool	Land	Marine	Combined
1	Honolua Bay	25.5	1.1	0.0	1.1	7.2	8.3
2	Mokulēʻia Beach	32.5	0.0	0.0	0.0	3.7	3.7
3	Oneloa Bay	66.2	3.3	0.0	3.3	11.3	14.9
4	Hanakaʻōʻō Beach	75.4	3.1	4.2	6.4	5.1	10.8
5	Kapalua Beach	65.4	6.6	0.0	6.6	13.9	20.7
6	Nāpili Bay	36.3	6.9	5.0	10.9	4.3	14.9
7	Keonenui	36.9	6.8	11.1	17.6	16.2	33.3
8	Kahana Beach	39.7	3.7	0.0	3.7	6.3	9.1
9	Honokōwai Beach Park	34.6	0.0	1.3	1.3	7.4	8.8
10	Kāʻanapali Beach	78.8	6.0	3.7	9.7	10.9	20.8
11	Wahikuli State Wayside Park	57.0	0.0	10.3	10.3	14.9	26.5

4 Discussion

Management implications

State agencies charged with protecting the environment often focus on ecological outcomes, but the ecosystem services approach used here translates ecological conditions into terms more relatable to decision makers, visitors, and residents by tying them to human wellbeing and preferences (Tallis and Polasky, 2009; Wainger and Mazzotta, 2011; Wainger and Boyd, 2009). In an era of increasingly scarce management resources and compounding threats, it is all the more important to ensure that management has net benefits. Hawai‘i’s economy and the Hawaiian lifestyle are tightly linked to ocean recreation, and people have positive willingness to pay for improvements to coastal amenities (Peng and Oleson, 2017; Penn et al., 2016, 2014). Our results underscore and add to the current trend globally to integrate science and management across the land-marine interface to address stressors to the ocean more holistically (Alvarez-Romero et al., 2011; Halpern et al., 2009; Pressey et al., 2007; Tallis et al., 2008; Toft et al., 2013) and efficiently (Klein et al., 2010). We introduce the human dimension to this trend: the benefits of integrated management also apply to maximizing returns to society through recreational ecosystem services.

Our approach identifies and prioritizes the many opportunities to conserve, improve, and restore recreation quality along West Maui’s coast, including which actions yield the greatest improvements in snorkeling attractiveness and where these benefits will occur. Combined efforts to address land and marine problems achieve the best outcomes overall and for most beaches (Figure 4, Table 6). This aligns with recent studies in Hawai‘i that have shown that addressing just one or the other (i.e., either land- or marine-based) stressors leads to sub-optimal ecological outcomes, and may even threaten ecological regime shifts (Jouffray et al., 2019; Weijerman et al., 2018). Focusing on particular beaches adds specificity to our management recommendations, highlighting the crucial need for tools to be applied at an appropriate scale. Guided by the broader scale analysis, management recommendations for West Maui as a whole are different than those coming from the local scale analysis. For instance, at some of the beaches, controlling effluent from cesspools would be more impactful than mitigating sediment (Table 6). Fortunately, recent evidence suggests that many of cesspools in West Maui were upgraded by homeowners over the ensuing years since the data were collected (Barnes et al., 2019), but the importance of effluent for recreational quality, and the link between wastewater and coral degradation (Wear and Thurber, 2015), raises the need for future analysis to also consider the effects of various wastewater treatment plants along the coast.

While the best results will generally come from integrated management, it is notable that marine management had higher payoffs overall than land management (Figure 4), driven by strong preferences for improvements in the various marine attributes, but mainly the modeled improvements in fish abundance (Table 2). The fact that fish abundance can greatly improve the delivery of recreational ecosystem services may help coastal managers, who face challenges managing for coral cover, given bleaching and other hard-to-mitigate threats, while the tools to manage fishes can be easier to implement. Further, in many places, the jurisdiction of a resource management agency may not cover both land and sea, as in the case of Hawai‘i, where the Division of Aquatic Resources has jurisdiction over fisheries but not watershed and land management, which is the responsibility of other divisions within the Department of Land and Natural Resources, as well as other government departments, and water quality is the purview of the Department of Health.

The benefits of the various management actions should ideally be weighed against their costs to determine whether action is justified, and which are the most cost-effective. These benefits may extend well beyond the recreational benefits measured here, and a full cost-benefit analysis would need to consider all costs and benefits (De Groot et al., 2013). Our results show positive preferences for improving ecosystem services, and given the scale of recreational users in Hawai‘i, willingness to pay is likely more than sufficient to justify taking action, but we do not attempt to estimate the magnitude of social benefit. Different management actions will have variable costs, and implementing the most cost effective (i.e., most benefit per cost) actions first will generate the greatest economic return on investment. Cesspool upgrades in the area could costs millions of dollars, while sediment reduction efforts could entail tens of millions of dollars of land restoration and infrastructure investments (Group 70, 2015a, 2015b; Sustainable Resources Group International, 2012b, 2012a). Fisheries management could have high enforcement expenses and opportunity costs for fishers and related businesses. Importantly, these costs could differ depending upon the watershed in question. Spatially explicit cost estimates to couple with the ecosystem services benefits modeled here would help decision-makers prioritize the most cost-effective actions (Naidoo et al., 2006).

Modeling innovations and limitations

Our efforts contribute to an ongoing research program to evaluate ecosystem services spatially through time using big data techniques and artificial intelligence to inform management (Villa et al., 2014). An increasing number of tools use BBNs in ecosystem services modeling, including plug-ins to GIS (Landuyt et al., 2015) and stand-alone modeling platforms like ARIES, used here (Villa et al., 2014). Our innovation of linking an economic elicitation method to inform the BBN provides additional rigor to the model structure and parameterization. Specifically, we embedded the results of a choice experiment along with an expert elicitation into the BBN’s structure and conditional probability tables. This enabled us to model how recreational attractiveness changes with improvements in specific, interrelated conditions. We grounded our management scenarios by eliciting reasonable outcomes for sediment and cesspool reduction and coral reef restoration from land and reef managers, and building an ecological model, based on a Hawaiian archipelago-wide dataset, to evaluate how fish conditions would change given improvements in coral cover.

The approach has some limitations. Preferences elicited from the choice experiment helped inform the conditional probabilities in the BBN. There was a design flaw that forced answers in the choice experiment, which affected the absolute, but not relative, value of the various attributes. For this reason, we do not report willingness to pay results. Our survey sample likely underrepresented residents and younger snorkelers, although no demographics exist compare. If managers are interested in examining how different management scenarios would affect different groups (e.g., tourists vs. residents; younger vs. older), then a broader survey could be conducted to build conditional probabilities (and perhaps alternate BBN structures) for these groups. Within a BBN's structure, intermediate nodes can temper or enhance the strength of influence of any given parent node on a subsequent node. For instance, in the choice experiment, snorkelers preferred fish abundance and fish species richness about the same, but in the end, fish abundance had much greater effect on overall snorkeler quality. Examining the arrows in Figure 2 that represent the strength of influence (also Table SI_4b, fish species richness has a strong influence on the biodiversity intermediate node, but the biodiversity node's smaller contribution to the ecological quality diminishes the contribution of fish species richness to the overall snorkeling quality. Intermediate nodes are important for keeping conditional probability tables tractable, but they can have side effects of amplifying or diminishing the importance of other variables. The aim is that the combined structure and conditional probabilities are a faithful representation of the system; validation is important for ensuring this (Marcot et al., 2006). While we used expert opinion and our own intuition to validate and test assumptions of the model based on the chosen conditional probabilities, new capabilities within ARIES for BBN structural learning algorithms would be a useful, additional step (Willcock et al., 2018).

5 Conclusion

Natural resource managers need to know how potential management strategies are likely to impact people's wellbeing. Ecological-economic models such as the one developed here can help managers choose what actions to take where, based on the outcome's societal value. For recreational ecosystem services, the use of a BBN to combine survey-based data of the relative value of important environmental and socioeconomic features with expert opinion and spatial modeling to enable scenario analysis can provide a new path forward for integrating social and natural science with management. Such integrated modeling of coupled nature-human systems can benefit the management of recreational resources, particularly in settings with complex combinations of stressors and human uses, such as recreation and management at the land-sea interface.

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