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SETTING RELIABILITY BOUNDS ON HABITAT SUITABILITY INDICES

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Abstract. We expressed quantitative and qualitative uncertainties in suitability index functions as triangular distributions and used the mechanics of fuzzy numbers to solve for the distribution of uncertainty around the habitat suitability indices derived from them. We applied this approach to a habitat model for the Florida Scrub-Jay. The results demonstrate that priorities and decisions associated with management and assessment of ecological systems may be influenced by an explicit consideration of the reliability of the indices.

Key words: Florida Scrub-Jay; fuzzy numbers; habitat suitability; HSI; uncertainty.

INTRODUCTION

The United States Fish and Wildlife Service (USFWS 1980) proposed that habitat evaluation procedures be used to quantify the value of land as habitat for a species. The procedures are based on calculation of a habitat suitability index (HSI) which is multiplied by the total area of available habitat to give the total value of a habitat patch, known as the habitat unit (HU). Habitat units are used to compare the relative value of different areas at a point in time and the relative value of the same area at future points in time (USFWS 1980). They were intended for applications involving estimation of the impacts of management alternatives, and the identification of steps that may be taken to compensate unavoidable habitat losses due to a proposed action. They have been applied to numerous habitat evaluation studies for single species (Van Horne and Wiens 1991, Gray et al. 1996, Rand and Newman 1998) and have been recommended for use in environmental monitoring and impact assessments (Rand and Newman 1998). Extensions to multiple-species models have been suggested (O'Neil and Schamberger 1983, Van Horne and Wiens 1991). HSIs have become an important tool for ecological assessment and conservation planning, particularly in North America (Gray et al. 1996).

The procedures stipulate that a documented habitat model be developed to represent the relationships between a species and its environment (USFWS 1980). The HSI for a given species and area of land represents a conceptual model that relates each measurable variable of the environment to the suitability of a site for the species, scaled from 0 (for unsuitable habitat) to 1 (for optimum conditions). Each variable is represented by a single suitability index (SI). The SIs are linked by additive, multiplicative, or logical functions that reflect relationships among the variables (USFWS 1981). For example, if the value of land as habitat depends on the presence of all variables, such that they do not compensate for one another, then the geometric mean of their values may represent site suitability best. If the environmental variables are compensatory (such as the presence of several food types, each of which is equally valuable), then an arithmetic mean or a logical conjunction (i.e., ''and/or'') may be more appropriate. Indices may be weighted. The functions relating environmental variables to suitability may take any form.

USFWS (1981) suggested that the ideal SI model has a direct linear relationship with carrying capacity, reflected in population density or biomass per unit area, a perspective reiterated by Rand and Newman (1998). Van Horne (1983) pointed out that density and demographic success are not necessarily closely related. Individuals of a species may not congregate in the most suitable locations because of behavior, intraspecific competitive exclusion, or dispersal dynamics. As a result of such processes, population sinks may have high population densities, but they may be of relatively limited value in contributing to the likelihood of persistence of a species. In concept, habitat suitability models should reflect the dynamics of a population such that areas of relatively high suitability support populations with relatively high fecundities and survivorships. Breininger et al. (1995, 1998) linked habitat suitability for Florida Scrub-Jays to fecundity and survival as well as to population abundance.

HSIs are calculated using best estimates, single numbers that ignore any uncertainty in the calculations. The reliability of habitat units is directly dependent on a ''well defined and accurate HSI'' (USFWS 1980:102). In an effort to standardize the way in which HSIs are developed, the USFWS produced a manual of methods (USFWS 1981; see Ellis et al. 1979). The USFWS (1981) suggested that acceptable levels of reliability for model output should be defined by whether outputs appear reasonable to an evaluation team or species au-

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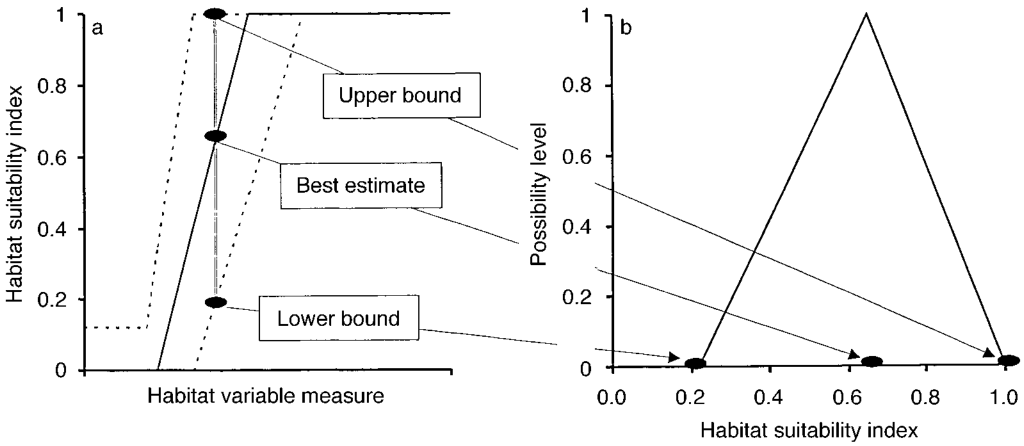

FIG. 1. A hypothetical example of bounds on a suitability index function, and the relationship between those bounds and a triangular distribution that may be used to represent and propagate uncertainty (after Van Horne and Wiens 1991). In this example, (b) represents an arbitrary vertical slice from (a), shown as a double vertical line on (a). It is a value that may be used subsequently to calculate HSI values. The continuous line between the two dashed lines in (a) is the best guess about the functional relationship between the variable and habitat suitability. The dashed boundary lines represent plausible limits within which we are reasonably certain the true functional relationship lies.

thority, or whether they rank sites in a manner similar to a species authority, are correlated with carrying capacity, or predict carrying capacity with a specified degree of statistical precision.

The USFWS (1980) described statistical errors that result from SI estimation including temporal variability, spatial variability, and systematic and random measurement errors. Unfortunately, in most, if not all, applications, there is no direct empirical evidence for the functional relationships between habitat suitability and the variables thought to determine demographic success. In most cases, HSI models are constructed from expert opinion. USFWS (1981) notes that such opinions can be highly variable and may not be comparable. The necessity to use expert opinion was emphasized by the development of explicit techniques for acquiring subjective habitat suitability information from experts (Crance 1987).

Management decisions based on untested models are unreliable (Cole and Smith 1983). Van Horne and Wiens (1991) recognized the need to account for uncertainty in habitat suitability models when they suggested constructing SI graphs to portray the mean (expected) relationship, as well as some form of outer limits on the response thresholds and function (Fig. 1). They suggested that the resulting distribution could be transformed into a probability distribution and used to provide values for a Monte Carlo simulation of the distribution of final HSI values. Bender et al. (1996) took measured variation around mean estimates of model variables to represent sampling error and natural variation. They used Monte Carlo simulation and bootstrapping to generate confidence intervals around HSI values.

The triangular distribution is only one of many plausible distributions (Seiler and Alvarez 1996). For example, Bender et al. (1996) assumed variables in their model were independent (correlations = 0) and variation was drawn from normal distributions. The uncertainty in Fig. 1 may be decomposed into shape uncertainty, which arises when the kind of distribution representing variation is unknown, and parameter uncertainty, which arises when the values of the moments of the distribution are uncertain. In the majority of cases, correlations among the stochastic variables are unknown, or are only partially known (for example, the relationship between two variables may be positive but otherwise unknown). The bounds in Fig. 1 must account for structural uncertainty, in which the form of the function relating the variable to habitat suitability is uncertain. Things are further complicated by circumstances in which there are no measurements, and the SI is based on subjective knowledge. The distribution in Fig. 1b and any subsequent operations performed with it should capture all of these elements of uncertainty.

The purpose of this paper is to discuss alternative approaches to dealing with uncertainty in setting reliability bounds on HSI calculations, to describe a method that may be used for a broad class of uncertainty, and to outline an example application to the Florida Scrub-Jay habitat model.

APPROACHES TO DEALING WITH UNCERTAINTY IN HSIs

The consequences of uncertainty may be examined using Monte Carlo simulation in which each variable of the HSI is varied, one at time. This approach may be used to evaluate natural (spatial and temporal) variation and measurement error. A full evaluation of uncertainty would consider alternative statistical distributions, functions linking variables to SI values, for each SI, as well as interactions among the SIs (Frey and Rhodes 1996). The sometimes arbitrary and unexplained structure of the equation that combines SI values into the HSI value for a patch adds an additional component of structural uncertainty. HSI models include variables that may be correlated, and the strength of the correlation may change from place to place in the landscape. A full range of dependencies among variables should be explored. For shape and parameter uncertainty, input distributions may be selected that are consistent with the state of current knowledge (Lee and Wright 1994). One may explore interactions between assumptions by varying variables to their bounds two at a time, then three at a time and so on, with and without different kinds of dependencies. There is a large number of combinations, even in simple models. In a Monte Carlo simulation, the limits of this exercise will result from the most pessimistic assumptions possible (for the lower bound) and the most optimistic assumptions possible (for the upper bound). Yet even this exercise will underestimate the full spectrum of uncertainty. Exploring all possibilities using Monte Carlo simulation is exceedingly difficult, if not impossible (Ferson 1996*a*).

Probability bounds (Ferson 1996*b*, Ferson et al., *in press*) can accommodate any level of knowledge about statistical uncertainty, and propagate the bounds on these uncertainties faithfully through a chain of calculations. These methods are particularly appropriate when representing shape, parameter, and structural uncertainty in the model. The extremes of model uncertainty make plain the extreme possibilities that are within the bounds of possibility, given the current state of our knowledge, depending on the assumptions one makes about the values of the variables, dependencies, model structure and the shapes of distributions. However, these methods may not be appropriate for calculations with HSIs.

The construction of HSIs is affected by an additional kind of uncertainty that is not amenable to conventional probability arithmetic, probability-bounds analysis, or Monte Carlo simulation because it is inherently subjective. Both the construction of SIs and the evaluation of the adequacy of HSIs usually are based on subjective judgement and vague concepts. For example, the development of an index depends on a definition of suitability, and often the definition is not provided. Instead, the term is vague. USFWS suggested it should reflect carrying capacity but this attribute is not measurable at a point in the landscape. For example, Lancia et al. (1982) constructed SIs for bobcats (*Lynx rufus*) without defining suitability, and subsequently validated the model against the frequency of radio locations in different map cells, implying that frequency of use reflected suitability.

A further instance of uncertainty is that the functions for SIs may only be relevant at a particular spatial scale, but the scales used in most studies are decided arbitrarily. For example, species may respond to very small scale features such as microclimatic conditions, or they may integrate the environment over very large scales, such as when species defend very large territories. Usually, the scale at which SIs are constructed is determined by the scale of available information. Rarely is it the subject of an explicit rationalization. Similarly, there is rarely any explicit treatment provided for the issue of extrapolating indices developed from data collected within small sample quadrats to much larger landscape scales.

Vague definitions are created when environmental variables are specified in inexact terms or when the definitions allow borderline cases. For example, Lancia et al. (1982), O'Neil and Schamberger (1983), Wakeley (1988), Van Horne and Wiens (1991), and Breininger et al. (1998) reported HSIs that used the term ''percentage cover'' without explaining how it was measured. The term is open to different interpretations because there is no single standard method for estimating vegetation cover. In addition, the time horizon over which the variables were interpreted was not specified. Thus, cover might be measured today, or averaged over the last 12 mo, or over the last decade. Similarly, Lancia et al. (1982) defined four categories of den site availability: abundant, moderate, scarce, and none. These terms are inherently vague. Such inexact definitions are commonplace in HSIs. Wakeley (1988) recommended a general procedure of reducing continuous habitat variables to a few classes (e.g., zero, low, and high) based on arbitrary thresholds to improve the efficiency of estimation of variables in the field, at a cost of reduced precision and greater subjectivity.

It might be possible to reduce or eliminate variation in estimation of SIs by making definitions more exact, but only at some cost of loss of generality. Vague but inclusive definitions may be replaced by somewhat arbitrary numerical thresholds. The consequence of subjective uncertainties is that different people will produce different results when confronted with the same data. It would be impossible to create a sensible set of definitions that would apply identically in all circumstances. We must conclude that some components of subjective uncertainty are unavoidable. Statistical measurement errors and biases, natural variability, and structural uncertainty are confounded with subjective uncertainties in HSI calculations.

A concept is vague if it permits borderline cases, where there is no clear demarcation of a concept and its complement (Zadeh 1965, 1978, Kaufman and Gupta 1991). Fuzzy numbers are convex (unimodal) distributions that reach possibility level 1 for at least one value of a variable. The simplest general examples are triangular fuzzy numbers. They are characterized by three quantities: two endpoints with possibility values of 0, and an intermediate point with possibility value 1. The function may be specified by connecting either endpoint to the intermediate point by a straight line.

Fuzzy numbers can be combined via the operations of addition, multiplication, and so forth to form new fuzzy numbers. The operations do not assume independence of the variables involved in the calculations.

The triangular distribution in Fig. 1b may be thought of as a fuzzy number that encapsulates uncertainty in the relationship between the value of an environmental variable, and the level of suitability the values represent. The value of the variable at possibility level 1 is the best guess, the point estimate in cases where uncertainty is ignored. Fuzzy numbers allow an interval at possibility level 1, so we could specify a range of ''best estimates'' depending on the source of uncertainty and quality of data. At possibility level 0, the interval represents our estimate of the variable when we are conservative about the uncertainty of the value, such that we are sure the true value lies somewhere within the interval. The *y*-axis of the fuzzy number represents the level of certainty, the level of reliability, between the interval and the dependent concept (habitat suitability). The term ''possibility level'' (Fig. 1) refers to the possibility that a given HSI value will be the true value. We imply we are certain that the true value lies somewhere within the interval defined by Fig. 1 at possibility level 0. The point or interval at possibility level 1 is our best guess. Fig. 1 represents the degree of agreement between the value of the variable (say, cover) and the concept of habitat suitability. The construction of a fuzzy number such as that in Fig. 1b is a subjective process. The best estimate is assigned a value of 1. That is, we are as certain as we can be that this value of the variable is consistent with the concept of suitable habitat.

Although fuzzy numbers were developed to deal with vagueness, they have been employed to handle uncertainty that arises due to measurement error and natural variation (Ferson et al. 1998). Plausible bounds around this value are determined by the precision of the equipment, spatial and temporal variation, the sampling methods at our disposal, the reliability of expert judgement, the uncertainty resulting from structural alternatives in the HSI model, the subjective interpretation of habitat suitability, and so on. Numbers that are further away from the best estimate are assigned lesser reliability values. Whatever way we choose to interpret uncertainty, the result is a fuzzy number that can be combined with other fuzzy numbers (and point estimates) via arithmetic operations to result in an estimate of an uncertain quantity. This is the strategy we employ to incorporate uncertainty into the calculation of habitat suitability indices.

Fuzzy Bounds for HSIs: an Example From Florida Scrub-Jays

A common application of HSIs is to perform compensation analysis in which impacts of a proposal on a species' habitat are calculated, and offsets to losses are explored. Rand and Newman (1998) described the possibility of trading habitat in one location for habitat for the same species at another location (in-kind offset), as well as the notion of trading habitat of one species with that of another species. In either case, it is important to know the relative value of parcels of land so that any trade is transparent. In this context, knowledge of the reliability of an HSI becomes important, particularly when dealing with threatened species.

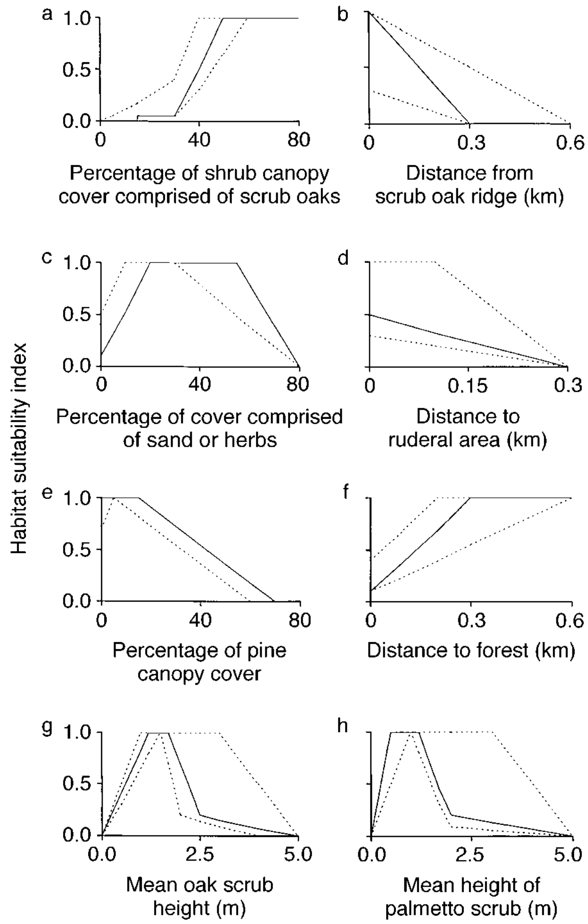

FIG. 2. A habitat suitability model for the Florida Scrub-Jay. The bounds represent plausible limits relating environmental variables to habitat suitability, encompassing both vagueness and measurement uncertainty. Details of the model are provided in Breininger et al. (1998).

An HSI model for the Florida Scrub-Jay was developed for identifying suitable habitat and ranking patches according to their relative suitability (Breininger 1992). Field validation of this model has demonstrated that the ranks of habitat patches are positively correlated with both Florida Scrub-Jay demographic success and density measurements (Duncan et al. 1995, Breininger et al. 1998).

The tests of the model provided new insights into the relationship of the species with its habitat. These observations were the basis for some modifications of the model (Fig. 2). The HSI model is a geometric mean of four habitat variables, reduced from a potential eight variables by maximum and minimum operations (Breininger et al. 1998). They include scrub oak cover (*Quercus* spp.) or proximity to dense oak cover, open space cover or proximity to open space, tree cover or proximity to forest, and mean shrub height. Habitat variables and Florida Scrub-Jay densities were derived from a study of bird-habitat relationships in which circular plots of 40 m radius were used (Breininger et al. 1991); this is the limit for reliable detection of the species, and considerably smaller than the size of a territory. Open space is defined as open sandy areas or ruderal grass <15 cm tall. All scrub is assumed suitable if it has ≥15% scrub oak cover or occurs within 300 m of oak scrub, and has <65% tree canopy. The geometric mean assumes that there is no compensatory relationship among the variables and that unsuitable conditions for one variable can make the habitat unsuitable for scrub-jays, even if the other variables are optimal.

Florida Scrub-Jays prefer to spend most of their time in focal patches of oak scrub that have been burned within 3–15 yr (Woolfenden and Fitzpatrick 1984, Breininger et al. 1995, *in press*). The model represented by Fig. 2 assumes that Florida Scrub-Jays use the habitat matrix surrounding the above patches and that the height of the vegetation in optimal habitat is low, allowing Florida Scrub-Jays to see predators and territorial intruders. The model assumes that oak scrub increases HSI of adjacent scrub that has few oaks; ruderal grass increases HSI of adjacent scrub with few natural openings; and forests decrease HSI of adjacent scrub. The values of variables were derived for each of the polygons from a digitized map of scrub-jay habitat that represented patches >20 m^2 derived from 1:2200-scale color infrared, aerial photographs (for details, see Breininger et al. 1995, 1998, Duncan et al. 1995, Duncan and Breininger 1998).

Occupied habitat is assumed to have a suitability greater than zero, even if it is always a population sink (mortality exceeds reproductive success) because it allows for overall larger population sizes and buffers Florida Scrub-Jays living in more suitable habitat. For example, Florida Scrub-Jays surrounded by other territories benefit from the species' sentinel system for detection of predators.

The bounds on each of the SI functions represent upper and lower plausible extremes, accounting for variation in ecological relationships in space and time, the ranges of variables reported in different empirical studies, their different spatial scales, the beliefs of authorities, and the ambiguity in definition of terms. Many of the descriptions of relationships between habitat variables and scrub-jay occupancy or demography have not been quantified (Breininger et al. 1998) so most of the uncertainty includes at least some subjective judgement. In addition, many of the terms and concepts are vague. For example, despite the intention to base habitat suitability on demographic success, model construction relied heavily on scrub-jay density which is not always correlated with demography (Breininger et al. 1998, *in press*). At least some uncertainty arises because validation of earlier models was attempted in only a few landscapes, providing information for a limited range of conditions (Duncan et al. 1995, Breininger et al. 1998).

Parts of the SI curves do not have bounds. For example, biologists consider it certain that habitat with canopy made up of >60% scrub oak is optimal (Fig. 2a). Florida Scrub-Jays are characterized as occurring only in scrub oak vegetation (Woolfenden and Fitzpatrick 1984, 1991, 1996). However, other parts of this curve are uncertain because habitat often is not dominated by scrub oaks (Breininger et al. 1991, 1995, 1998). Even in optimal habitat, Florida Scrub-Jay territories are large (e.g., 10 ha) and include some palmetto scrub that has few or no scrub oaks (Woolfenden and Fitzpatrick 1984, Breininger et al. 1995, 1998).

Different estimates of ideal proportions of open space within scrub-jay habitat have been reported. Nest sites occur commonly along openings where scrub-jays forage and cache acorns for winter (Woolfenden and Fitzpatrick 1984, 1991). The highest bird densities have occurred where open space comprised 20–55% percent of the area (Breininger 1992). However, Cox (1984) suggested that an optimal range of open space is 10–30% cover. Some subjective judgement was also involved because it seemed plausible that recently burned areas without open space (one year since fire) and of otherwise optimal habitat might have moderately high habitat suitability (see Fig. 2c).

The functions relating habitat suitability to percent open space, distance from ruderal grass, distance to forest, and percent pine canopy cover (Figs. 2c–f) are based in part on the effects of predation (Woolfenden and Fitzpatrick 1984, McGowan and Woolfenden 1989, Breininger 1992, Breininger et al. 1996). Scrub-jays are vulnerable to predation by hawks, particularly Cooper's hawks, along the Atlantic coast, and they have a well-developed sentinel system. However, these relationships have not been quantified or tested experimentally, and the bounds encapsulate a range of observations and expert opinions.

Figs. 2g and h relate habitat suitability to shrub height, and the form of the functions is derived from a mixture of quantitative field information and ecological judgement. Optimal oak scrub is sometimes described being 1–3 m tall (Cox 1984, Woolfenden and Fitzpatrick 1996). Scrub shorter than 1 m may not provide enough acorns or cover for nest sites or to escape predators (DeGange et al. 1989). However, Florida Scrub-Jays have only been described to have reproductive success that equals or exceeds mortality in vegetation 50–150 cm tall at an inland location and 70–170 cm tall at a coastal location (Breininger et al., *in press*). Vegetation that dominates palmetto scrub is more flammable and has a much shorter fire-return interval than oak scrub (Abrahamson and Hartnett 1990, Myers 1990). Natural fires occurred within the landscape frequently, but were often extinguished when they reached the oak scrub, because of the low flammability of scrub oaks (Webber 1935). These frequent fires might be important for sustaining open space (Breininger et al., *in press*). Therefore, optimal landscapes are likely to have palmetto scrub that is short, allowing for frequent burns into the edges of oak scrub and good visibility for predator detection.

Results

We applied the methods to a scenario in which options were explored for siting a facility that requires ~0.5 ha within scrub-jay habitat. RAMAS/RiskCalc (Ferson et al. 1998) was used to perform the operations. We used fuzzy number operations to calculate the HSI for eight separate patches, each of which could support the facility. Fig. 3 illustrates the habitat values and associated uncertainties for one of these patches (Patch 2). Each part of Fig. 3 corresponds to a vertical slice through the corresponding part of Fig. 2, representing the estimate of the relevant variable and its associated uncertainty for Patch 2. Two of the numbers are scalars with no uncertainty around them (e.g., Fig. 3f). They are represented as vertical lines.

The sequence of operations that makes up the habitat suitability index for the species is illustrated in Fig. 4. The maximum and minimum operations ensure that the resulting fuzzy number is always greater than (for the maximum) or less than (for the minimum) either of the arguments. This is easiest to see in Fig. 4c where the right hand bound is a consequence of the minimum operation involving a fuzzy number and a scalar. The product of the four SIs produces another fuzzy number that is skewed and curved, but which satisfies the definition of a fuzzy number, that is, it is convex and scaled between 0 and 1. The fourth root of this number results in the HSI for Patch 2.

The best estimate and the bounds for the eight fuzzy numbers that represent the HSIs for the eight patches are represented in Fig. 5. The value for Patch 2 is the same as that resulting from the operations illustrated in Fig. 4. If we were to rank the candidate patches from most valuable to least valuable on the basis of point estimates (the peak of each of the fuzzy numbers), the order would be as shown in Fig. 5 (Patch 1 is least valuable, and Patch 8 is most valuable). The distributions around the point estimates in Fig. 5 encapsulate the uncertainty surrounding each set of calculations, carried through the operations prescribed by the model. The bounds may be used to interpret the reliability and the range of possibilities for each HSI calculation.

Discussion

Attitude to risk and the context of the decision problem may change the way in which sites are ranked.

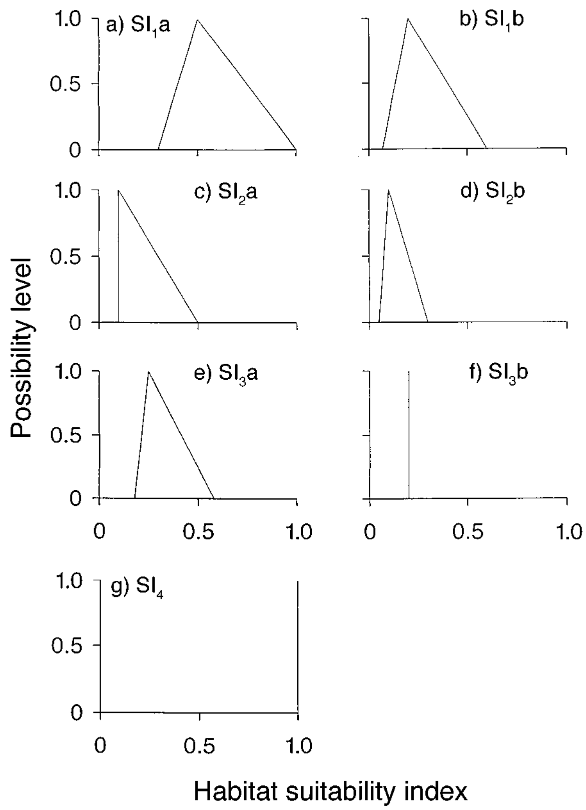

FIG. 3. SI values for Patch 2 of the analysis, for each of the habitat variables. The triangular distributions are derived from the relationships outlined in Fig. 2, following the protocol defined in Fig. 1. The labels "a" and "b" for each SI$_i$, represent the alternative states for each variable in the function relating the SI values to the HSI function. Details are provided in the legend of Fig. 4, and in Breininger et al. (1998). (a) SI for percentage canopy cover composed of scrub oak for Patch 2, (b) SI for distance (km) from scrub oak ridge, (c) SI for percentage ground cover composed of sand and herbs, (d) SI for distance (km) from ruderal area, (e) SI for percentage pine canopy cover, (f) SI for distance (km) to forest, (g) SI for scrub oak height (m). A figure for palmetto scrub height is not provided because canopy cover at Patch 2 is >30% (see legend of Fig. 4).

Consider the case in which we are asked to protect one site. We may decide to look for the most valuable location. In this case, Patch 8 is clearly and almost certainly the best, although it is possible that Patches 3, 6, and 7 have higher habitat suitability. In this circumstance, we may also decide to rank the sites on the basis of the lower bounds of the fuzzy numbers. This strategy is useful when the consequences of being wrong are catastrophic. The advantage of selecting the site with the largest lower bound is that the value of the site is at least as large. In decision theory, it is known as minimizing maximum regret (Morgan and Henrion 1990). In our example, Patch 8 has the largest lower bound. Thus, it is the best choice from the perspective of expected value, and from the perspective of avoiding unacceptable risks. This is a much more

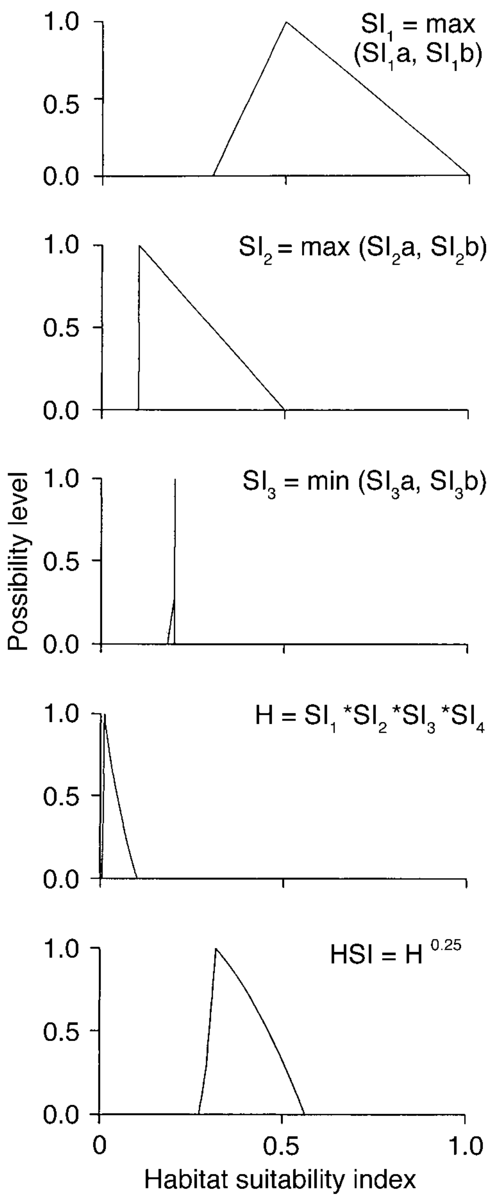

FIG. 4. An example of the sequence of calculations for the habitat suitability index of Florida Scrub-Jays outlined in Fig. 2, applied to Patch 2. The indices are combined as follows:

$$SI_1 = \max(SI_1a,\ SI_1b)$$

$$SI_2 = \max(SI_2a,\ SI_2b)$$

$$SI_3 = \min(SI_3a,\ SI_3b)$$

$$SI_4 = SI_4a \quad \text{if scrub oak cover} > 30\%, \quad \text{else } SI_4 = SI_4b$$

$$HSI = \sqrt[4]{\prod_{i=1}^{4} SI_i}.$$

robust basis for making a decision than is an interpretation of expected values in ignorance of uncertainty.

A different decision-making problem arises when we are asked to identify a site, the loss of which would cause the least impact on the species. As above, a sensible strategy is to rank on the basis of the best estimates, and select the lowest value (Patch 1). We may, however, consider that it is more important to be certain of not losing high quality habitat. To achieve this, we could rank the sites on the basis of the upper bounds of the HSIs, and then choose the site with the lowest upper bound. From this perspective, Patches 1 and 2 are much more even in value. Using this strategy, we can be sure that the value of the habitat that is lost is not greater than the value indicated.

Often, in constructing HSIs for a species, we are more certain about the extremes of a variable than we are about intermediate values. For example, in several of the SIs in Fig. 2, values close to either end of the SI curves are either definitely 0 or definitely 1. When an intermediate value of an HSI is calculated, it may be derived from several intermediate, and uncertain, SI values. Or it may be derived from several extreme, and relatively certain, SI values (some high and some low). If the situation demands that we be risk averse, a patch of intermediate value that is known with relative certainty will be more valuable than a patch of the same expected value that is relatively uncertain. In the example, Patch 5 has lower expected suitability than Patch 7, but the interval bounding the extremes is much smaller. If we were to choose between them, Patch 5 may be a better option, if the consequences of a mistake are important.

When fuzzy numbers are skewed, opportunities may exist for improved decision making. It may be considered worthwhile to protect a patch that has a slightly lower HSI if the set of possibilities includes some large values. In these circumstances, one would set a slight decrease in the expected suitability against the prospect that the quality of the patch may turn out to be better than expected. In the scrub-jay example, Patch 3 has an expected value of 0.42, and Patch 4 has an expected value of 0.45. The reliability bounds around Patch 3 are skewed. The lower bounds for both patches are roughly the same. Patch 3 might be considered a more valuable option than Patch 4, despite the lower expected value and the smaller lower bound, because there is a possibility that its suitability exceeds 0.8. At best, the suitability of Patch 4 might be slightly higher than 0.6.

The treatment of uncertainty in this study has not included the arbitrary structure of the equation that combines SI values into the HSI value for a patch. But the general approach outlined here could incorporate this kind of uncertainty. The distributions resulting from any number of different alternative equations for combining SI values for a patch could be combined with logical OR statements (Ferson et al. 1998).

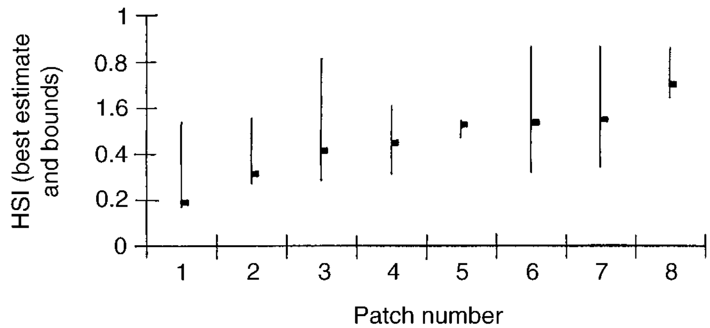

FIG. 5. Best estimates and bounds for the HSIs for each of eight patches of habitat.

The management of ecological systems demands that we make choices about the relative ecological value of land. The strategy developed here for incorporating uncertainty will be useful for such applications as compensation analysis involving trading patches of equivalent total habitat value (Rand and Newman 1998). It will also have applications in areas such as reserve design where choices are made between patches based on values derived from vague concepts and uncertain information (Pressey et al. 1993).

For optimal decisions about habitat, the product of patch size and the best estimate of habitat suitability is not, by itself, sufficient. In the process of comparing the values of different patches of habitat, the value of a patch should be conditioned by attitude to risk and the context of the decision problem. The rank of the value of a patch should be determined in part by the relative reliability of the HSI estimate for that patch. Fuzzy numbers provide a means of capturing uncertainty in circumstances in which data are scarce and concepts are vague, and of propagating this uncertainty through calculations for habitat suitability. General application of this strategy could improve substantially the quality of ecological decision making.

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