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METHODS

Modeling carrying capacity for national parks

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Abstract

Units of the National Park System are required to develop a general management plan that is consistent with visitor carrying capacities. Newer definitions of carrying capacities for protected areas, such as national parks and wilderness areas, are in terms of the acceptability of natural resource and human impacts as measured by selected biophysical resource and social conditions, rather than the number of visitors. Most methods for evaluating carrying capacity are non-quantitative and lack analytical rigor. Carrying capacity decisions are easier to justify when based on quantitative methods. This paper describes a carrying capacity modeling system that allows park managers to quantitatively determine whether the current state of a park's ecosystem is in compliance with established standards for carrying capacities and, in cases where it is not, to identify the management action having the greatest likelihood of bringing the ecosystem into compliance with those standards. The modeling system uses an ex post adaptive ecosystem management (AEM) model to determine whether the current state of an ecosystem complies with biophysical and social carrying capacities, and an ex ante multiple attribute scoring test of capacity (MASTEC) to identify the best management action for achieving compliance. The AEM model addresses potential errors that can occur when inferring an ecosystem's state from resource/social conditions. Errors occur when a manager decides that an ecosystem is in one state when in reality it is in another state. The consequences of such errors are greater when resource/social conditions are at the extremes. The AEM model minimizes the likelihood of such decision errors by using Bayes' rule to determine the state of an ecosystem. The MASTEC method allows a park manager to identify the best management action for bringing an incompliant ecosystem into compliance with carrying capacities. It integrates elements of two carrying capacity methods, Limits of Acceptable Change and Visitor Impact Management, and multiple attribute decision-making. The latter characterizes management actions in terms of their multiple biophysical and social attributes. The best management action maximizes the manager's expected utility function subject to stochastic carrying capacity constraints that require the probability that the value of an attribute exceeds its standard to be no less than a reliability level selected by the manager. Several factors limit the ability of national parks to implement the carrying capacity modeling system. Using a spatial decision support tool to implement the modeling system eases some of these limitations.

Keywords: Carrying capacities; National parks; Adaptive ecosystem management; Bayes' rule; Multiple attribute decision-making

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1. Introduction

According to the US National Park Service Organic Act of 1916 (16 U.S.C. §§1-18f), national parks must be managed so as to conserve the scenery, natural and historical objects, and wildlife therein, and to provide for public enjoyment and non-impairment of resources. The Organic Act's dual mandate of conservation and public use is a major challenge for national park managers, particularly in parks with high visitation. The National Parks and Recreation Act (P.L. 95-625) of 1978 requires the ecological integrity of units of the National Park System to be protected from internal and external threats (Keiter et al., 1999) and development of a general management plan for units that includes 'identification and implementation of commitments for visitor carrying capacities for all areas of the unit'. The latter requires park managers to define standards for carrying capacity, assess whether conditions in the park comply with those standards and take action in cases where standards are violated.

Carrying capacity is conventionally defined as the number of visitors an area can sustain without degrading natural resources and visitor experiences. Newer definitions of carrying capacity for protected areas, such as national parks and wilderness areas, center on the acceptability of natural resource and human impacts of visitation, and consider biophysical characteristics of a protected area (soils, topography and vegetation), social factors (location and mode of travel, season of use, group size, and behavior of visitors), and management policies (visitor use restrictions) to be more important determinants of carrying capacity than the number of visitors.

While significant progress has been made in evaluating carrying capacity, most current methods are non-quantitative and lack analytical rigor. Park management decisions based on quantitative methods would be less difficult to document and defend before the public (Peterson, 1996). This paper describes a carrying capacity modeling system that allows park managers to quantitatively determine whether the current state of a park's ecosystem is in compliance with established standards for biophysical and social carrying capacities and, in cases where it is not, to identify the management action having the greatest likelihood of bringing the ecosystem into compliance with those standards.

2. Evaluation methods

The carrying capacity modeling system proposed here consists of an ex post adaptive ecosystem management (AEM) model that determines whether the current state of an ecosystem is compliant with biophysical and social carrying capacities, and an ex ante multiple attribute scoring test of capacity (MASTEC) that identifies the best management action for bringing an incompliant ecosystem into compliance. The AEM model incorporates adaptive management and ecosystem management principles and is implemented using Bayes' rule. The MASTEC method utilizes a stochastic multiple attribute programming model.

2.1. AEM model

Principles of ecosystem management and adaptive management form the foundation for the AEM model. Ecosystem management (EM) represents a fundamental shift in the philosophy for managing natural resources that incorporates larger spatial scales, longer time periods and more variables than commodity-based resource management (Thomas, 1997) and strives for sustainable productivity of the whole ecosystem (Franklin, 1997; Schowalter et al., 1997). The goal of ecosystem management is to "manag(e) ecosystems so as to assure their sustainability" (Franklin, 1997). This goal is challenging because of uncertainties about how natural ecosystems respond to management actions. Uncertainties arise because ecosystems "are characterized by strong (usually non-linear) interactions between the parts, complex feedback loops that make it difficult to distinguish cause from effect, and significant time and space lags, discontinuities, thresholds, and limits" (Costanza et al., 1993).

Adaptive management is the dominant management philosophy for dealing with biophysical uncertainty in natural ecosystems (Holling, 1978;

Walters, 1996). The basic premise of adaptive management is that “if human understanding of nature is imperfect, then human interactions with nature (i.e. management actions) should be experimental” (Lee, 1995). Kohm and Franklin (1997) point out that “adaptive management is the only logical approach under the circumstances of uncertainty and the continued accumulation of knowledge”. Adaptive management treats management actions as experiments for acquiring information about ecological and social responses. Experimental results provide a basis for determining whether or not a particular management action results in an ecosystem state that supports the manager’s objectives related to carrying capacity. Adaptive management is not without problems. It is time consuming and expensive and is likely to give faulty results when relevant variables are either ignored or not held constant (Smith, 1997).

While AEM is well suited for evaluating the effectiveness of park management actions, the analytical framework for implementing AEM is poorly developed. Ellison (1996) points out that “Bayesian inference and decision theory provide a quantitative framework and intelligible language in which to analyze and express adaptive management procedures”. The AEM model proposed here uses Bayes’ rule to determine the extent to which the state of an ecosystem is compliant with carrying capacities.

Consider a unit of the National Park System that encompasses an ecosystem that is in one of four mutually exclusive states of compliance with carrying capacities, M_1, M_2, M_3 and M_4. The prior probabilities of states are $p(M_1)$, $p(M_2)$, $p(M_3)$ and $p(M_4)$ and their sum is one. M_1 is highly incompliant, M_2 is moderately incompliant, M_3 is moderately compliant and M_4 is highly compliant with biophysical and social carrying capacities. Suppose the park manager considers ecosystem states M_1 and M_2 not to be in compliance and states M_3 and M_4 to be in compliance with carrying capacities. An ecosystem’s current state of compliance is evaluated in terms of selected biophysical and social attributes chosen by the manager. Let the percent of native species present and habitat suitability for an endangered species be the biophysical attributes, and the level of congestion on backcountry hiking trails and the length of time visitors have to wait for public transportation in the park be the social attributes. Suppose the manager chooses the following resource/social conditions to determine an ecosystem’s state: (a) significant loss in native species, highly degraded habitat for endangered species, high congestion on trails and very long waiting times for public transportation denoted R_1; (b) moderate loss in native species, moderately degraded habitat for endangered species, moderate congestion on trails and long waiting times for public transportation denoted R_2; (c) most native species present, good habitat for endangered species, low congestion on trails and short waiting times for public transportation denoted R_3; and (d) widespread abundance of native species, excellent habitat for endangered species, no trail congestion and very short waiting times for public transportation denoted by R_4. In practice, several resource/social conditions could be used to determine the most likely state of an ecosystem. The resource manager needs to select the set of conditions that are most indicative of ecosystem state (presumably with the help of scientists) and describe those conditions in quantitative terms. For example, if significant loss in native species is selected as a resource condition (indicator of ecosystem state), then it could be defined as a situation in which 25% or more of the species in an ecosystem are non-native. This particular definition was used to evaluate range conditions (Prato, 2000).

Inferring an ecosystem’s state from resource/social conditions is subject to two types of errors. First, the park manager could decide that the ecosystem is not compliant with carrying capacities based on resource/social conditions when, in fact, it is. Second, the manager could decide that the ecosystem is compliant with carrying capacities when, in fact, it is not. The likelihood of such errors is minimal when resource/social conditions are at their extremes. In particular, both errors are minimal when the manager decides that the ecosystem is in state M_1 or M_2, neither of which is compliant, when the resource/social condition is R_1, or state M_3 or M_4, both of which are compliant with carrying capacities, when the resource/social condition is R_4.

The state of the ecosystem is less obvious and the likelihood of making an error is greater when the resource/social condition is R_2 or R_3. An error is made when the manager decides that the ecosystem is compliant (in state M_3 or M_4) when in fact it is not (actual state is M_1 or M_2). In this case, management action should be taken, but none is. This type of decision error not only creates a false sense of security regarding the ecosystem's compliance with carrying capacities, but also increases the risk that the ecosystem will diverge even farther from carrying capacities. Conversely, an error is made when the manager decides that the ecosystem is not compliant (in state M_1 or M_2) when in fact it is compliant (the actual state is M_3 or M_4). In this case, the manager is likely to implement a new management action when none is warranted. This type of error results in an inefficient use of human and financial resources.

The AEM model uses Bayes' rule to minimize errors regarding the state of an ecosystem. An outcome is defined as a combination of an ecosystem state (M_i) and a resource/social condition (R_q), written as ($M_i\ R_q$), where $i=1,\ldots,I$ and $q=1,\ldots,Q$. There are IQ possible outcomes denoted by the set $\{M_i\ R_q\}$. Since outcomes are mutually exclusive, the prior probability of resource/social condition R_q, is:

$$p(R_q) = p(M_1\ R_q) + \cdots + p(M_I\ R_q) \tag{1}$$

where $p(M_i\ R_q)$ is the joint probability of ($M_i\ R_q$). According to Bayes' rule, the probability that the ecosystem is in state M_i given the condition R_q, is:

$$p(M_i|R_q) = p(M_i\ R_q)/p(R_q) = [p(R_q|M_i)p(M_i)]/[\sum_{i=1}^{I} p(R_q|M_i)p(M_i)] \tag{2}$$

where $p(M_i|R_q)$ is the posterior probability, $p(R_q|M_i)$ is the likelihood function for R_q, $p(M_i)$ is the prior probability of M_i, and $\Sigma_{i=1}^{I} p(R_q|M_i)p(M_i)$ is the expected value of the likelihood function. In the example used here, $p(M_4|R_3)$ is the posterior probability that the ecosystem is highly compliant with carrying capacities given the condition R_3. The likelihood function is the probability of R_q given the ecosystem state M_i. When the likelihood function dominates the prior probabilities, the condition has a greater effect on the posterior probabilities than the prior probabilities (Box and Tiao, 1973). Section 3 gives a numerical example of the AEM model.

2.2. MASTEC method

If the AEM model indicates that the most likely state of the ecosystem is M_3 or M_4, then there is no need for the manager to take action until resource/social conditions change. However, if the most likely state of the ecosystem is M_1 or M_2, then the ecosystem is not compliant with carrying capacities. In this case, the manager should implement a management action designed to achieve a compliant ecosystem state. The MASTEC method is an ex ante procedure designed to help the manager select the best management action for achieving compliance with carrying capacities. It integrates elements of two carrying capacity methods: Limits of Acceptable Change and Visitor Impact Management. The Limits of Acceptable Change method establishes limits of change for key biophysical and socio-psychological processes (Hendee et al., 1990; McCool and Cole, 1997). It focuses on the impacts of use rather than how much use an area can tolerate. The Limits of Acceptable Change method requires a manager to identify where, and to what extent, changes in key biophysical and social processes are appropriate and acceptable, and to select a management action that is most likely to achieve conformance between observed conditions and established standards.

The Visitor Impact Management method identifies key indicators and standards for evaluating visitor impacts, compares those indicators to existing field conditions, and determines appropriate management actions for alleviating unacceptable impacts (Graefe et al., 1986). Impacts are defined in terms of natural, cultural and historical resources and visitor experiences. Indicators used in the Visitor Impact Management method are equivalent to the attributes of management actions used in the carrying capacity modeling system proposed here.

The MASTEC method implements the integrated Limits of Acceptable Change/Visitor Impact Method in a multiple attribute decision-making framework. The Limits of Acceptable Change/Visitor Impact Method was adapted from Marion et al. (1985) and applied in backcountry management planning in Shenandoah National Park in the state of Virginia. Multiple attribute decision-making has been used to formulate and make decisions related to: water resources management (Haimes and Hall, 1974), environmental management (Backus et al., 1982; Janssen, 1992), food security (Haettenschwiler, 1994), forest management (Kangas and Kuusipalo, 1993; Kangas, 1994; Penttinen, 1994), agricultural production (Xu et al., 1995), protection of natural areas (Gehlbach, 1975; Sargent and Brande, 1976; Smith and Theberge, 1986, 1987; Anselin et al., 1989), regional water quality analysis (Makowski et al., 1995), management of agroecosystems (Prato et al., 1996a), wildlife management (Prato et al., 1996b) and soil and water management (Prato, 1998). Multiple attribute decision-making is well suited for park management decision-making because it accounts for multiple attributes of alternative management actions, can be applied interactively with many participants using a computer-based decision support tool, and provides a quantitative basis for decisions (Schmoldt et al., 1994; Peterson et al., 1994).

A schematic of the MASTEC method is given in Fig. 1. The method uses multiple attribute decision theory to identify the best management action for bringing an ecosystem into compliance with carrying capacities. The best management action is the one that maximizes the manager's expected utility function, $E[U(\mathbf{z})]$, subject to carrying capacity and other constraints. $\mathbf{z} = \mathbf{a} + \mathbf{e}$, where $\mathbf{z}$ is a stochastic vector of attributes provided by a management action, $\mathbf{a}$ is the deterministic component of $\mathbf{z}$, which gives the expected amounts of all attributes provided by that management action, and $\mathbf{e}$ is the stochastic component of $\mathbf{z}$, where $E(\mathbf{e}) = 0$. The manager is assumed to maximize this utility function with respect to a given set of feasible management actions.

The best management action is the solution to the following chance-constrained mathematical programming problem:

$$\begin{aligned} &\text{maximize } E[U(\mathbf{z}^*)] \\ &= E[U(\mathbf{a}^* + \mathbf{e}^*)] \text{subject to: } \Pr\{b_j^* \geq b_j^{**}\} \geq 1 - \alpha_j \\ &\quad \text{for } j = 1,\ldots,J \Pr\{s_k^* \geq s_k^{**}\} \geq 1 - \beta_k \\ &\qquad \text{for } k = 1,\ldots,K \end{aligned} \tag{3}$$

A single asterisk (*) indicates normalized values. Attribute values are normalized in order to reduce bias in the ranking of management actions caused by differences in the measurement units for at-

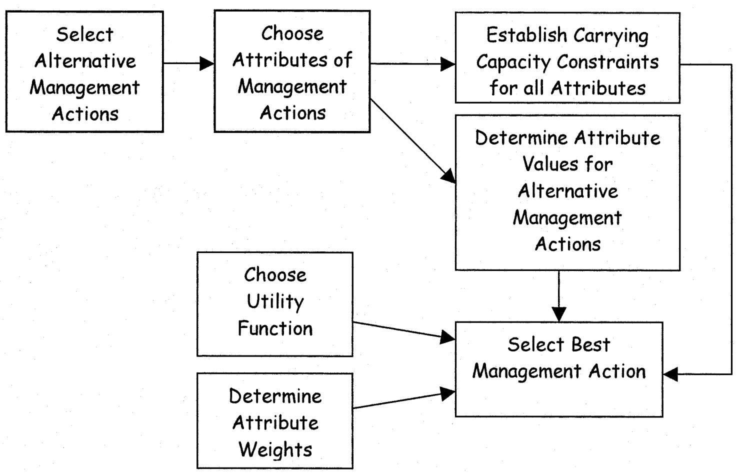

Fig. 1. Schematic of MASTEC method.

tributes and to convert attributes that are negatively related to utility (less of the attribute increases utility) to positive attributes (more of the attribute increases utility). A normalized attribute falls in the [0, 1] interval and has the property that more of it increases utility. Management actions are allowed to vary over space and time.

The two chance constraints ensure that the best management action results in biophysical attributes b_j^* that are at least as great as the biophysical standards b_j^{**} with reliability $1-\alpha_j$ for all J biophysical attributes and social attributes s_k^* that are at least as great as the social standards s_k^{**} with reliability $1-\beta_k$ for all K social attributes, where $0 \le \alpha_j \le 1$ and $0 \le \beta_k \le 1$. Standards b_j^{**} and s_k^{**} are established based on the limits of acceptable change for attributes. For example, if the manager chooses $\alpha_j = 0.05$, then b_j^* must equal or exceed b_j^{**} with probability 0.95 for all feasible management actions, which implies a high reliability of compliance. Managers should select low values for α_j and/or β_k when the consequences of violating carrying capacity standards are very adverse.

In order to solve Eq. (3), it is necessary to specify the form of the expected utility function, $E[U(\mathbf{z}^*)]$. The functional form should reflect the relationships among attributes and be consistent with the manager's risk attitudes. A common specification for inter-attribute relationships is that $E[U(\mathbf{z}^*)]$ is additive. In other words, $E[U(\mathbf{z}^*)] = E[U_1(z_1^*)] + \cdots + E[U_V(z_{J+K}^*)]$, which implies that the marginal utility of one attribute is independent of the amounts of all other attributes, i.e. $\partial U_i(z_i^*)/\partial z_{i'}^* = 0$ for all $i \neq i' = 1,\ldots,J+K$. Additive utility functions are popular because they are simple to apply and relevant to real world problems (Keeney and Raiffa, 1976; Yakowitz et al., 1993; Foltz et al., 1995; Tecle et al., 1995).

A manager's risk attitudes are determined by the risk aversion function $r(z_i^*) = -U''(z_i^*)/U'(z_i^*)$, where $U'(z_i^*)$ is the first derivative and $U''(z_i)$ is the second derivative of the expected utility function with respect to z_i (Keeney and Raiffa, 1976). A manager is risk neutral, risk averse or risk prone when $r(z_i^*)$ is zero, greater than zero or less than zero, respectively. Only risk neutral and risk averse attitudes are considered here.

If the utility function is additive and the manager is risk neutral, then the expected utility function is:

$$E[U(\mathbf{z}^*)] = \sum_{j=1}^{J} w_j b_{jv}^* + \sum_{k=1}^{K} w_k s_{kv}^* \tag{4}$$

where w_j is the weight for the jth biophysical attribute, w_k is the weight for kth social attribute, $0 \le w_j \le 1$, $0 \le w_k \le 1$ and $\Sigma_{j=1}^{J} w_j + \Sigma_{k=1}^{K} w_k = 1$. Attribute weights indicate the relative importance of attributes to the manager. Weights reflect the manager's preferences for attributes of management actions and are estimated using methods such as fixed-point scoring (Prato and Hajkowicz, 1999), paired comparisons (Saaty, 1987) and judgment analysis (Cooksey, 1996). A risk neutral utility function is more restrictive but easier to apply than a risk averse utility function (Prato, 1999b).

Risk aversion can be constant or variable. When the utility function is additive, expected utility is given by Eq. (5) if the manager has constant risk aversion and by Eq. (6) if the manager has variable risk aversion and the utility subfunctions, $U_i(z_i^*)$, are quadratic in z_i^*:

$$E[U(\mathbf{z}^*)] = \sum_{j=1}^{J} w_j[a_j - c_j\sigma_j^2] + \sum_{k=1}^{K} w_k[a_k - c_k\sigma_k^2] \tag{5}$$

$$E[U(\mathbf{z}^*)] = \sum_{j=1}^{J} w_j[U[a_j] - c_j\sigma_j^2] + \sum_{k=1}^{k} w_k[U[a_k] - c_k\sigma_k^2] \tag{6}$$

where a_j and a_k are expected values, σ_j^2 and σ_k^2 are variances, and c_j and c_k are positive scaling constants for the jth and kth attributes, respectively. Further details regarding specification of risk averse utility functions are given by Prato (1999b). Note that the risk averse utility functions given by Eqs. (5) and (6) have two additional parameters (σ^2 and c) for each attribute or a total of $2(J+K)$ more parameters than the risk neutral utility function given in Eq. (4).

The multiple attribute decision-making framework used to implement the MASTEC method has several advantages. Firstly, it allows complex information on the multiple impacts of management actions to be collapsed into a single number, which facilitates the comparison of alternative management actions. Secondly, it permits managers and/or stakeholders with different attribute weights and/or attribute values to evaluate, rank and select management actions. Thirdly, it allows managers to identify the best management action for complying with carrying capacities. Fourthly, it allows managers to determine how sensitive the choice of a best management action is to changes in attribute values and weights.

Mathematical optimization models, like the one given by Eq. (3), have been used to address a variety of natural management problems. Prato and Wu (1995) used a chance-constrained linear programming problem to determine the economically efficient farming systems for an agricultural watershed in north-central Missouri. Peterson et al. (1994) used mixed-integer programming to implement a multiple objective planning process for inventory and monitoring programs in Olympic National Park in the state of Washington. In order to solve chance-constrained linear programming problems, the statistical distributions of the attributes must be specified. Most applications assume normal distributions. If this assumption is not appropriate, then non-parametric methods should be used to obtain solutions. Prato and Wu (1995) and Prato (1999a) present a method of solving chance-constrained programming problems like Eq. (3).

In summary, the MASTEC method provides a rational comprehensive framework for determining the best management action for bringing an incompliant ecosystem into compliance with biophysical and social carrying capacities. Park managers can use MASTEC to evaluate and rank management actions for achieving compliant ecosystems and determine the sensitivity of the ranking to attribute weights and standards and reliability levels for achieving carrying capacity standards.

3. Application

The carrying capacity modeling system described above is well suited for evaluating compliance with carrying capacities and determining best management actions under the wide range of natural and cultural conditions that exist in the 379 units of the US National Park System. This section discusses various issues regarding implementation of the carrying capacity modeling system. Since the ex post AEM model and ex ante MASTEC method are used sequentially, the order of discussion is arbitrary. The AEM model and MASTEC method are discussed in that order.

The AEM model can be implemented using the following four-step procedure. First, an interdisciplinary panel composed of the park manager and technical experts select the possible ecosystem states and determine which ones are compliant with carrying capacities. Second, the panel assigns prior probabilities to ecosystem states based on their knowledge of the park. Third, the most likely current state of the ecosystem is decided based on the Bayesian posterior probabilities. Fourth, monitoring is conducted to determine whether or not the most likely state of the ecosystem is compliant with carrying capacities.

Calculation of posterior probabilities requires knowledge of the prior probabilities, $p(\mathrm{M}_1),\ldots,p(\mathrm{M}_I)$, and the likelihood functions, $p(\mathrm{R}_q|\mathrm{M}_i)$, for all ecosystem states. Bayes suggested setting prior probabilities equal to one another, i.e. $p(\mathrm{M}_1)=\cdots=p(\mathrm{M}_I)=1/I$. This assumption implies that the expert panel is completely ignorant regarding the likelihood of ecological states. Comments made by Ellison (1996) and Wolfson et al. (1996) suggest that ecologists are unlikely to be completely ignorant regarding possible ecological states. Mendenhall (1975) insists that prior probabilities should be determined based on best judgment. For example, if the park is located in a relatively pristine area and visitation rates are low, as is the case for park units in the state of Alaska, then it is reasonable to expect prior probabilities to be higher for compliant than incompliant ecosystem states. On the other hand, if the ecosystem is in a highly populated area and visitation rates are high, as is the case for park units in the eastern US, then it is reasonable to expect prior probabilities to be higher for non-compliant states than compliant ecosystem states. Likelihood functions are somewhat easier to specify than prior probabilities

Table 1
Posterior probabilities for four hypothetical ecosystem states when resource/social conditions are R_1 and R_3

State		R_1		R_3	
	$p(M_i)$[a]	$p(R_1 \mid M_i)$[b]	$p(M_i \mid R_1)$[c]	$p(R_3 \mid M_i)$	$p(M_i \mid R_3)$[d]
M_1[e]	0.4	0.5	0.63[g]	0.1	0.19
M_2[e]	0.3	0.3	0.28	0.2	0.29
M_3[f]	0.2	0.1	0.13	0.4	0.38[h]
M_4[f]	0.1	0.1	0.06	0.3	0.14

[a] Prior probabilities.
[b] Likelihood functions.
[c] $[p(R_1|M_i)p(M_i)]/[\Sigma_i p(R_1|M_i)p(M_i)]$.
[d] $[p(R_3|M_i)p(M_i)]/[\Sigma_i p(R_3|M_i)p(M_i)]$.
[e] States not in compliance with carrying capacities.
[f] States in compliance with carrying capacities.
[g] Maximum posterior probability for condition R_1.
[h] Maximum posterior probability for condition R_3.

because it is possible to estimate the probability that a resource/social condition occurs when the population (ecosystem) from which it comes is known. For example, if the percent of native plant species present in a particular ecosystem (z_m) is normally distributed, then the likelihood function for a sample drawn from that distribution is normally distributed with mean $\acute{z}_m$ and variance $s_m/(n_m)^{1/2}$, where $\acute{z}_m$ is the mean, s_m is the standard deviation and n_m is the sample size.

Table 1 illustrates how Bayes' rule is used to calculate posterior probabilities for four hypothetical ecosystem states when the current condition of the ecosystem is R_1 and R_3. The fourth column of the table shows that ecosystem state M_1 has the highest posterior probability (0.63) when the resource/social condition is R_1. Hence, the current ecosystem state does not appear to be in compliance with carrying capacities based on R_1.

In this case, the manager employs the ex ante MASTEC method to identify the management action that has the greatest likelihood of bringing the ecosystem into compliance. The best management action is determined by solving the chance-constrained programming problem given in Eq. (3). In order to solve this problem, the manager must: (a) indicate whether he/she is risk neutral or risk averse, which influences the form of the expected utility function; (b) select the attributes of management actions ($b_1,\ldots,b_J$, $s_1,\ldots,s_K$); (c) use expert opinion and/or simulation models to determine the values of the attributes for all feasible management actions; (d) specify carrying capacity standards for all attributes ($b_1^{**},\ldots,b_J^{**}$, $s_1^{**},\ldots,s_K^{**}$) and reliability levels for achieving standards ($\alpha_1,\ldots,\alpha_J$, $\beta_1,\ldots,\beta_K$); and (e) choose attribute weights. Carrying capacity standards could be determined based on resource and social surveys, and statutory requirements.

After the best management action is determined, it is then implemented. Suppose post-implementation monitoring of the ecosystem indicates that the resource/social condition is R_3. Posterior probabilities of the four ecosystem states conditional on resource/social condition R_3 are given in the sixth column of Table 1. Ecosystem state M_3 has the highest posterior probability when the resource/social condition is R_3 (0.38). Hence, the best management action appears to result in an ecosystem state that is compliant with carrying capacities. In this case, the manager should continue using the best management action as long as monitoring data indicate that the ecosystem is not deteriorating to state R_1 or R_2. Such deterioration is possible due to increases in park visitation, changes in park visitation patterns and the dynamic nature of ecosystems.

Use of the carrying capacity modeling system requires considerable information. Its implementation is simplified by incorporating the AEM model and MASTEC method into a spatial decision support tool. The latter is a knowledge-based system that integrates data, information and models for the purpose of identifying and evaluating solutions to complex problems involving spatially distributed information (Djokic, 1993). Developing a spatial decision support tool not only simplifies quantitative assessments of ecosystem compliance with carrying capacities, but also makes it easier for the public to participate in carrying capacity assessments. A well-designed spatial decision support tool: (a) makes it easier for park managers to acquire and process technical information and public comments pertinent to the establishment and implementation of carrying capacities; (b) allows the public to self-learn about the likely biophysical and social consequences of selecting different management actions; and (c) enhances the manager's and public's understanding of how different attribute weights, attribute standards and reliability levels for achieving standards influence the selection of the best management action (sensitivity analysis). In addition, by focusing attention on a well-reasoned analytical method for assessing compliance with carrying capacities, the spatial decision support tool is likely to reduce private and public conflicts regarding the implementation of management actions designed to bring an ecosystem into compliance with carrying capacities.

Several factors limit the ability of national parks to apply the carrying capacity modeling system proposed here. These include insufficient budgets and personnel, limited technical expertise, frequent changes in park management over time and the long timeframes required for AEM. While the spatial decision support tool described above eases some of these limitations, significant commitments of personnel and financial resources would be required. Several events have improved the ability of national parks to make such commitments. The Recreational Fee Demonstration Program allows 100 national park units to retain at least 80% of the gate receipts at the park units where they are collected (National Park Service, Undated a). A portion of those receipts can be used to establish and achieve compliance with carrying capacities. The Park Service increased its commitment to science-based resource management in the Natural Resource Challenge (National Park Service, Undated b). Three goals of the Natural Resource Challenge are particularly favorable toward implementing the carrying capacity modeling system: (a) greater reliance on scientific knowledge; (b) developing and employing techniques that protect the inherent qualities of national parks and restore natural systems; and (c) gaining knowledge through scientific research.

4. Conclusions

Units of the US National Park System must be managed to conserve their natural and cultural resources for the benefit of future generations, and allow public enjoyment by the current generation. This dual mandate and the legal requirement to identify and implement visitor carrying capacities for park units are a major challenge for park managers. Meeting this challenge requires defensible, quantitative procedures for assessing and complying with biophysical and social carrying capacities. While significant advancements have been made in evaluating carrying capacities, most current methods lack quantitative and analytical rigor and do not capitalize on the principles of multiple attribute decision-making and mathematical programming, and advancements in information management technologies and spatial decision support.

The carrying capacity modeling system proposed here determines whether the current state of an ecosystem is compliant with carrying capacities and, in cases where it is not, identifies the best management action for achieving compliance. The ex post AEM model allows a park manager to determine whether the current state of an ecosystem is in compliance with carrying capacities. It integrates principles of ecosystem management and adaptive management and uses Bayes' rule. The ex ante MASTEC method allows a park manager to identify the best management action for bringing an incompliant ecosystem into compliance with carrying capacities. It incorporates elements of the integrated Limits of Acceptable Change/Visitor Impact Method of assessing carrying capacities and uses multiple attribute decision-making and chance-constrained programming to determine the best management action.

Implementation of the carrying capacity modeling system requires considerable information. This feature alone would discourage its use by park managers. Incorporating the modeling system in a spatial decision support tool would significantly enhance user accessibility. The tool would facilitate public understanding and acceptance of the procedures used to achieve compliance with carrying capacities and make it easier for the public to comment on alternative management actions. Personnel and budgetary limitations would still need to be relaxed before national parks could use the modeling system to make carrying capacity decisions.

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