CHAPTER

10

Fuzzy Adaptive Management of Coupled Natural and Human Systems

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10.1 INTRODUCTION

Coupled natural and human systems are systems for which natural and human elements interact (Liu et al., 2007). Three kinds of rules can be used to make management decisions for coupled systems: crisp, stochastic, and fuzzy (Prato, 2009). Crisp decision rules assume that a manager can make unambiguous assessments regarding the state of a coupled system based on measured or forecasted values for system attributes. An example of a crisp decision rule is that the system is strongly sustainable if $X_i \geq X_i^*$ for positive attributes and $X_j \leq X_j^*$ for negative attributes, where X_i and X_j are measured values and X_i^* and X_j^* are threshold values of attributes, respectively. Crisp decision rules do not account for sampling and measurement errors in attribute data and stochastic variability in attributes both of which can result in decision errors regarding the state of a coupled system. Stochastic decision rules account for stochastic variability in system attributes, and thereby reduce the likelihood of decision errors. An example of a stochastic decision rule is that a coupled system is strongly sustainable if $p\{X_i \geq X_i^*\} \geq \alpha_i$ for positive attributes and $p\{X_j \leq X_j^*\} \geq \beta_j$ for negative attributes of the system, where p stands for probability, $0 \leq \alpha_i \leq 1$, and $0 \leq \beta_j \leq 1$. Most stochastic decision rules require managers to specify probability distributions for system attributes, which is not possible when there is uncertainty about changes over time in those attributes. Fuzzy decision rules allow for sampling and measurement errors in the data used to estimate attributes and stochastic variability in system responses to drivers and do not require managers to specify probability distributions for system drivers or attributes.

Managing coupled systems for climate change and human impacts is challenging as evidenced by remarks by Ann Rodman of the Yellowstone Resources Center. She described the challenge of managing Yellowstone National Park—a coupled system—with respect to climate change as follows: "Knowing this [warming of climate systems] is true does not necessarily help us understand how these changes are affecting Yellowstone National Park and the surrounding area. … It is even harder to go out on a limb and say how complex natural systems, with all their fuzzy feedback mechanisms, might react to a changing climate" (Rodman, 2015). Rodman's statement is apropos to all coupled systems, not just Yellowstone National Park. In general, managers of coupled systems and scientists whose research informs management decisions for coupled systems face the daunting task of understanding how coupled systems are likely to respond to management actions and uncertain future changes in climate and human use. Examples of management actions for alleviating potential adverse impacts of climate change on coupled systems include assisted migration, preserving genetic diversity for foundation species, and conserving nature's stage (Carswell, 2015).

Fuzzy decision rules are based on fuzzy logic, which is a mathematical way of representing the imprecise or approximate nature of decision-making under uncertainty (Zadeh, 1965; Bellman and Zadeh, 1970; Bass and Kwakernaak, 1977; Barrett and Pattanaik, 1989; Klir and Yuan, 1995; Carlsson and Fuller, 1996; Phillis and Andriantiatsaholiniaina, 2001; Andriantiatsaholiniaina et al., 2004; Prato, 2007). Fuzzy logic is well suited to formulating decision rules for managing coupled systems when there is uncertainty about future changes in system driver(s) (e.g., Chen, 2003; Adriaenssens, 2004; Svoray, 2004; Prato, 2009, 2012). Most fuzzy logic-based decision rules involve the use of complex mathematical operations (e.g., Prato, 2005, 2009) that are difficult for managers of coupled systems to understand and apply. In contrast, the fuzzy logic-based decision rules proposed here can be understood by coupled system managers.

This paper describes a fuzzy logic-based, adaptive management (FLAM) model for adapting coupled systems to future climate change when there is uncertainty about the extent of that change and the efficacy of management actions in achieving desired outcomes. The FLAM model provides three kinds of results: (1) the preferred management action for each climate change scenario and time period determined by applying the fuzzy Technique for Order Preference by Similarity of Ideal Solution (fuzzy TOPSIS) to a manager's ratings of the estimated attributes of system responses to climate change and management actions (or attributes for short) and the relative importance of those attributes; (2) the preferred management action for each time period determined by applying the minimax regret criterion to the first result; and (3) the best strategy for adapting management actions to future climate change across time periods determined based on the second result.

10.2 METHODS

This section describes a FLAM model for managing the backcountry of Cascadia National Park (CNP), a hypothetical coupled system. A hypothetical coupled system is used because the FLAM model has not been applied to a real coupled system. In addition, using a hypothetical coupled system makes the description of the model less abstract.

10.2.1 FLAM Model for CNP

CNP's backcountry contains environmentally sensitive alpine and subalpine areas that are vulnerable to natural resource degradation and loss of biodiversity from human use and climate change. In recent years, the demand for backcountry camping permits has increased. For that reason, park managers want to determine preferred management actions over time for increasing the number of backcountry campsites while minimizing degradation of backcountry areas from increased human use and climate change. Increasing the number of backcountry campsites would allow CNP managers to issue more backcountry camping permits thereby increasing the number of backcountry campers.

An overview of the FLAM model for CNP is illustrated in Fig. 10.1. The model assumes that, in each of four, five-year time periods, a different climate change scenario can occur, a different management action can be implemented, and different system responses can result. The hypothetical FLAM model for CNP contains four climate change scenarios (C_1, C_2, C_3, and C_4), four management actions (A_1, A_2, A_3, and A_4), and four system responses to climate change and management actions (R_1, R_2, R_3, and R_4). Climate change scenarios are equivalent to the Intergovernmental Panel on Climate Change's (IPCC's) four representative concentration pathways (RCPs), namely RCP2.6, RCP4.5, RCP6, and RCP8.5 (IPCC, 2014). The number associated with each RCP (e.g., 2.6) refers to radiative forcing in the tropopause measured in watts per square meter of the Earth's surface. The higher the radiative forcing, the greater the climate change.

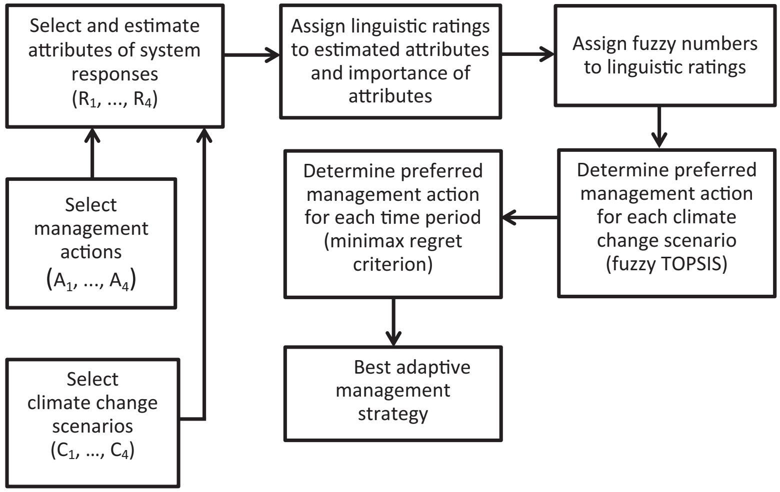

FIGURE 10.1 Diagram of FLAM model for CNP.

The four management actions correspond to four percentage increases in the number of backcountry campsites chosen by CNP managers: 0% increase for A_1; 5% increase for A_2; 10% increase for A_3; and 15% increase for A_4. System responses are discussed in the next section.

Preferred management actions for the CNP are determined taking into account two kinds of uncertainty. First, there is uncertainty about future climate change, which implies the probabilities of the climate change scenarios are unknown in all time periods. Climate change uncertainty is realistic because the IPCC's Fifth Assessment Report does not assign probabilities to the RCPs.

Second, there is uncertainty about system responses to climate change scenarios and management actions, which implies the probabilities of R1 through R4 are unknown. Consequently, risk-based decision frameworks that require knowledge of the probabilities of different responses to system drivers cannot be used to determine the preferred management actions and best adaptive management strategy for CNP. Examples of such frameworks include maximizing the expected value of responses and Bayesian belief networks, both of which require knowledge of the $p(R_j)$s, and Monte Carlo simulation that requires knowledge of the probability distributions for climate variables (i.e., precipitation and temperature) for each climate change scenario. The FLAM model does not require knowledge of $p(C_i)$s and $p(R_j)$s, or the probability distributions for climate variables.

10.2.2 Attributes

Coupled systems are typically managed for multiple attributes. Consequently, the FLAM model evaluates system responses to climate change and management actions in terms of multiple attributes. Other studies have used multiple attributes to characterize system responses. For example, Mackinson (2000) developed an adaptive fuzzy expert system for predicting structure, dynamics, and distribution (responses) of herring shoals. Responses were evaluated in terms of 26 attributes. Prato (2005) developed a FLAM model for determining whether or not management of an ecosystem is strongly sustainable based on three attributes: regional income, biodiversity, and water quality.

The FLAM model for CNP evaluates system responses in terms of four attributes: two attributes for backcountry campers' satisfaction and two attributes for resource protection. Camper satisfaction attributes are the percent of backcountry camping permittees that believe: (1) the number of parties encountered on backcountry trails is excessive (PT); and the number of backcountry campsites is sufficient (PC). Conservation attributes are the percent of backcountry areas with favorable habitat for threatened and endangered species (PF) and the percent of backcountry trails with unacceptable soil erosion rates (SE).

10.2.3 Adaptive Management

Adaptive management (AM) has been proposed and/or used to adapt management actions over time in response to changes in system drivers (Holling, 1978; Walters, 1996; Parma, 1998; Prato, 2007). AM is a form of integrated learning that acknowledges and accounts for the surprising and unpredictable nature of system responses due to uncertainty about the temporal changes in drivers. Kohm and Franklin state that "adaptive management is the only logical approach under the circumstances of uncertainty" (Kohm and Franklin, 1997). Baron et al. (2009) assert that AM is the best way to manage natural protected areas for future climate change and variability.

Adaptive management can be active or passive. There are different opinions about the distinction between active and passive AM (Bormann et al., 1996; Schreiber et al., 2004). Based on Walters (1996), Williams (2011) defines active AM as an approach that evaluates management alternatives for reducing uncertainty about ecological processes and how those processes are influenced by management actions, and passive AM as an approach that focuses on resource management objectives with less emphasis on learning about the efficacy of management actions on ecological processes. Nyberg (1998) and Prato (2012) define active AM as a management approach that designs and conducts experiments to test hypotheses about the efficacy of management alternatives and adapts management alternatives over time when warranted based on test results, and passive AM as a management approach that does not involve experiments and hypothesis testing. For the results of active AM to be statistically reliable, the experiments must incorporate replicated, randomized, and independent treatments and controls; the latter refer to management actions.

For the hypothetical coupled system, active AM experiments are conducted on the four management actions to generate experimental data on the attributes of system responses to those actions and climate change. Experiments are based on the following experimental design. The backcountry region of CNP is divided into several biophysical zones having dissimilar biophysical characteristics. Each biophysical zone is divided into several areas that serve as experimental units. At the beginning of the first time period, the four management actions are randomly assigned to the areas within each zone, such that the number of areas treated with the same management action (i.e., number of replications per zone) is approximately the same.

A_1	A_4	A_3	A_2	A_4
A_1	A_2	A_4	A_3	A_1
A_4	A_3	A_1	A_2	A_4
A_2	A_1	A_3	A_2	A_3

FIGURE 10.2 Example of random allocation of management actions to areas of a biophysical zone.

Fig. 10.2 illustrates a random allocation of management actions to areas within a single zone. For simplicity, the figure illustrates a square zone containing square areas. In reality, zones and areas are not square. At the end of each time period, backcountry satisfaction attributes are measured for each zone using data obtained from backcountry camping surveys and conservation attributes are measured using field surveys. If the backcountry area of CNP is divided into m biophysical zones and each zone has five replications of management actions, then there are 5m data points per attribute per time period for each management action.

10.2.4 Estimating Attributes

The FLAM model estimates the attributes using one of two methods. First, the attributes of responses to experimental combinations of climate change scenarios and management actions (i.e., combinations for which experiments have been performed) are estimated using the experimental data. For example, if climate change scenario C_2 occurs during the first time period, then the attributes under C_2 are estimated using the experimental data for the four management actions under C_2. Valid experimental data are available for estimating attributes when the experiments have replicated, randomized, and independent treatments and controls (i.e., management actions). Second, the attributes of responses to nonexperimental combinations of climate change scenarios and management actions (i.e., combinations for which experimental data are not available) are estimated using expert judgment (Linstone and Turoff, 2002) and/or simulation models. For example, it would be necessary to use the second method to estimate the attributes of responses under C_1, C_3, and C_4 if climate change scenario C_2 occurs during the first time period. The combined effect of climate change and management actions on PF can be estimated using habitat suitability models (e.g., Store and Jokimäki, 2003) and on SE can be estimated using the Variable Cross-Sectional Area method (Olive and Marion, 2009).

10.2.5 Determining Preferred Management Actions

A preferred management action is determined at the beginning of each time period using a two-step procedure. In the first step, fuzzy TOPSIS is used to rank the four management actions for each climate change scenario. The preferred management action for each climate change scenario is the top-ranked action for that scenario. In the second step, the preferred management action for each time period is determined by applying the minimax regret criterion to maximum loss indices for the preferred management actions identified in the first step. This section explains both steps.

10.2.5.1 Determining Preferred Management Action for Climate Change Scenarios

The preferred management action for each climate change scenario within time periods is determined by applying fuzzy TOPSIS to the estimated attributes of responses for each combination of management action and climate change scenario. For example, at the beginning of the first time period, fuzzy TOPSIS is applied to the estimated attributes of responses to C_1 and A_1, C_1 and A_2, C_1 and A_3, and C_1 and A_4 to determine which of the four management actions is preferred under C_1. This procedure is repeated to determine the preferred management actions under C_2, C_3, and C_4.

As an example, consider using fuzzy TOPSIS to calculate the distances of the estimated attributes of responses to C_1 and A_1, C_1 and A_2, C_1 and A_3, and C_1 and A_4 from the fuzzy positive-ideal solution (d_i^+) and the fuzzy negative-ideal solution (d_i^-) for the attributes and the closeness coefficient (E_i) for each attribute. These metrics are calculated as follows:

$$d_i^+ = \sum_j d\left(w_j r_{ij}, v_j^+\right) \tag{10.1}$$

$$d_i^- = \sum_j d\left(w_j r_{ij}, v_j^-\right) \tag{10.2}$$

$$E_i = d_i^- / \left(d_i^+ + d_i^-\right) \quad (0 \leq E_i \leq 1) \tag{10.3}$$

where:

$i = C_1$ and A_1, C_1 and A_2, C_1 and A_3, and C_1 and A_4;
$j =$ PT, PC, PF, and SE;
$w_j =$ normalized triangular fuzzy number corresponding to the linguistic variable chosen by managers to rate the relative importance of attribute j;
$r_{ij} =$ normalized triangular fuzzy number corresponding to the linguistic variable chosen by managers to rate the estimated effect of C_1 and A_i on attribute j;
$d(w_j r_{ij}, v_j^+) =$ vertex distance between the weighted normalized fuzzy effect of management action i and climate change scenario C_1 on attribute j and the positive-ideal solution for attribute j; and
$d(w_j r_{ij}, v_j^-) =$ vertex distance between the weighted normalized fuzzy effect of management action i and climate change scenario C_1 on attribute j and the negative-ideal solution for attribute j.

Various linguistic variables can be used to rate the estimated attributes and their relative importance. An example of linguistic variables and corresponding triangular fuzzy numbers is given in Table 10.1. Each triangular fuzzy number (a, b, c) defines a triangular probability distribution like the one illustrated in Fig. 10.3. The triangular probability distribution for a random variable x is $T(a, b, c) = [2(x - a)/(c - a)(b - a)]$ for $a \leq x \leq b$ and $T(a, b, c) = [2(c - x)/(c - a)(c - b)]$ for $b < x \leq c$, where a is the minimum value, b is the modal

TABLE 10.1 Linguistic Rating Scale for Estimated Attributes and Relative Importance of Attributes, and Corresponding Triangular Fuzzy Numbers

Linguistic Rating	Triangular Fuzzy Number[a]
Very low	(0.05, 0.05, 1)[b]
Low	(0.05, 1, 3)
Moderate	(3, 5, 7)
High	(7, 9, 10)
Very high	(9, 10, 10)

[a]*Adapted from Chen (2000) and Prato (2012).*
[b]*The first number is the minimum value, the second number is the mode, and the third number is the maximum value for a triangular probability distribution.*

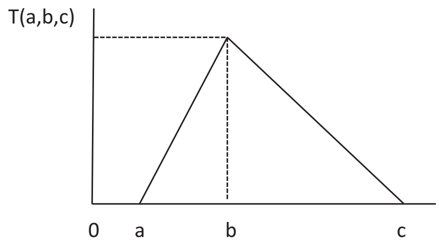

FIGURE 10.3 Triangular probability distribution.

value, and c is the maximum value of x. Fuzzy numbers can be defined based on other probability distributions besides the triangular.

The vertex distance between two triangular fuzzy numbers $z_1 = (e_1, e_2, e_3)$ and $z_2 = (k_1, k_2, k_3)$ is $d(z_1, z_2) = \{0.33[(e_1 - k_1)^2 + (e_2 - k_2)^2 + (e_3 - k_3)^2]\}^{0.5}$, where, for Eqs. (10.1) and (10.2), $z_1 = w_j r_{ij}$ and $z_2 = v_j^+$ or v_j^-.

A positive attribute is one for which more of the attribute is desirable and a negative attribute is one for which less of the attribute is desirable from the viewpoint of the decision maker. For CNP managers, PC and PF are positive attributes and PT and SE are negative attributes. The fuzzy positive- and negative-ideal solutions for the four attributes are:

$$v_j^+ = (1,1,1) \text{ for } j = \text{PC and PF};$$

$$v_j^- = (0,0,0) \text{ for } j = \text{PC and PF};$$

$$v_j^+ = (0,0,0) \text{ for } j = \text{PT and SE; and}$$

$$v_j^- = (1,1,1) \text{ for } j = \text{PT and SE}.$$

E_i approaches 0 (or 1) as the triangular fuzzy numbers for the attributes of the response to C_1 and A_i move farther away from (or closer to) the fuzzy positive-ideal solution and closer to (or farther away from) the attributes for the fuzzy negative-ideal solution for attributes. Because the desirability of a response decreases (or increases) as the closeness coefficient for the attributes of that response approaches zero (or one), the four responses to C_1 and A_1, C_1 and A_2, C_1 and A_3, and C_1 and A_4 are ranked based on the values of the closeness coefficients. The rank order for these four responses implies a rank order for the four management actions. For example, if the rank order of the responses indicate C_1 and A_3 is preferred to C_1 and A_2 is preferred to C_1 and A_1 is preferred to C_1 and A_4, then the rank order of management actions under C_1 is A_3 is preferred to A_2 is preferred to A_1 is preferred to A_4. Therefore, A_3 is the preferred management action under C_1. This ranking procedure is repeated for responses involving C_2, C_3, and C_4 and each of the four management actions to determine the preferred management actions under each of those climate change scenarios. Suppose the preferred management actions under C_2, C_3, and C_4 for the first time period are A_4 under C_2 and C_3, and A_2 under C_4.

10.2.5.2 Example of Preferred Management Action for a Climate Change Scenario

This section uses a numerical example to illustrate how fuzzy TOPSIS is used to determine the preferred management action for one climate change scenario in one time period, namely climate change scenario C_1 in the first time period. Applying fuzzy TOPSIS involves several steps. In the first step, the manager must linguistically rate the estimated attributes of responses to combinations of C_1 and each of the four management actions and the relative of importance of the attributes. For the hypothetical example, the CNP managers determine the linguistic ratings shown in Table 10.2. If there is a management team for CNP and the team collectively rates the estimated attributes of responses and the relative of importance of attributes, then the triangular fuzzy numbers corresponding to the collective linguistic ratings are used. If managers on the team independently rate the estimated attributes of responses and the relative of importance of attributes, then the triangular fuzzy numbers corresponding to the linguistic ratings made by individual members of the team are averaged to obtain collective fuzzy numbers. If there are multiple estimated values of an attribute for the same management action, climate change scenario, and time period, then the triangular

TABLE 10.2 Linguistic Ratings of the Estimated Values and Relative Importance of the Four Attributes of Responses Under Climate Change Scenario C_1 in the First Time Period

Management Action	PT	PC	SE	PF
A_1	Very low	Very low	Very low	Very high
A_2	Low	Moderate	Moderate	High
A_3	Moderate	High	High	Moderate
A_4	High	Very high	High	Low
Importance	Moderate	Moderate	High	Very high

fuzzy numbers corresponding to the linguistic ratings for the multiple estimated values are averaged.

In the second step, the fuzzy effects matrix (see Table 10.3) is created by assigning the triangular fuzzy numbers in Table 10.1 to the corresponding linguistic ratings in Table 10.2. In the third step, the normalized fuzzy effects matrix is formed (see Table 10.4). Each element of the normalized fuzzy effects matrix is formed by applying the following formula to the corresponding element of the fuzzy effects matrix:

$$\text{Positive attributes}: r_{ij} = \left(a_{ij}\big/c_j^{+}, b_{ij}\big/c_j^{+}, c_{ij}\big/c_j^{+}\right) \text{ where } c_j^{+} = \max_i c_{ij}\,(j = \text{PC, PF}); \text{and}$$

$$\text{Nagative attributes}: r_{ij} = \left(a_j^{-}\big/c_{ij}, a_j^{-}\big/b_{ij}, a_j^{-}\big/a_{ij}\right) \text{ where } a_j^{-} = \min_i a_{ij}\,(j = \text{PT, SF}).$$

In the fourth step, the weighted normalized fuzzy effects matrix is determined (see Table 10.5) by multiplying the normalized weight for an attribute and the corresponding normalized fuzzy effect for that attribute. For example, the weighted normalized fuzzy effect of A_1 on PT is $w_{PT} \times r_{A1PT}$, where w_{PT} is the triangular fuzzy number for the relative importance of PT and r_{A1PT} is the normalized fuzzy number for the effect of A_1 on PT. The numerical weighted normalized fuzzy effect of A_1 on PT is $w_{PT} \times r_{A1PT} = (0.3, 0.5, 0.7)(0.05, 1, 1) = (0.015, 0.5, 0.7)$. Other weighted normalized fuzzy effects are calculated in a similar manner.

TABLE 10.3 Fuzzy Effects Matrix for Climate Change Scenario C_1 and Four Management Actions in the First Time Period and Fuzzy Numbers for Relative Importance of Attributes

Management Action	PT	PC	SE	PF
A_1	(0.05, 0.05, 1)	(0.05, 0.05, 1)	(0.05, 0.05, 1)	(9, 10, 10)
A_2	(0.05, 1, 3)	(3, 5, 7)	(3, 5, 7)	(7, 9, 10)
A_3	(3, 5, 7)	(7, 9, 10)	(7, 9, 10)	(3, 5, 7)
A_4	(7, 9, 10)	(9, 10, 10)	(7, 9, 10)	(0.05, 1, 3)
Importance	(3, 5, 7)	(3, 5, 7)	(7, 9, 10)	(9, 10, 10)

TABLE 10.4 Normalized Fuzzy Effects Matrix for Climate Change Scenario C_1 and Four Management Actions in the First Time Period

Management Action	PT	PC	SE	PF
A_1	(0.05, 1, 1)	(0.9, 1, 1)	(0.05, 1, 1)	(0.005, 0.005, 0.11)
A_2	(0.017, 0.05, 1)	(0.7, 0.8, 0.9)	(0.007, 0.01, 0.017)	(0.33, 0.55, 0.77)
A_3	(0.007, 0.01, 0.017)	(0.3, 0.5, 0.7)	(0.005, 0.006, 1)	(0.77, 0.88, 1)
A_4	(0.005, 0.006, 0.007)	(0.005, 0.1, 0.3)	(0.005, 0.005, 0.005)	(0.77, 0.88, 1)

TABLE 10.5 Weighted Normalized Fuzzy Effects Matrix for Climate Change Scenario C_1 and Four Management Actions in the First Time Period

Management Action	PT	PC	SE	PF
A_1	(0.015, 0.5, 0.7)	(0.81, 1, 1)	(0.015, 0.5, 0.7)	(0.004, 0.004, 0.1)
A_2	(0.005, 0.025, 0.7)	(0.63, 0.8, 0.9)	(0.002, 0.005, 0.012)	(0.23, 0.44, 0.7)
A_3	(0.002, 0.005, 0.012)	(0.27, 0.5, 0.7)	(0.002, 0.003, 0.7)	(0.54, 0.71, 0.9)
A_4	(0.002, 0.003, 0.005)	(0.004, 0.1, 0.3)	(0.001, 0.002, 0.003)	(0.54, 0.71, 0.9)

10.2.5.3 Determining Preferred Management Actions for Time Periods

The preferred management action for a time period is determined by applying the minimax regret criterion to the preferred management actions for the climate change scenarios for that time period. With the minimax regret criterion, the preferred management action for a time period is the one that minimizes the maximum loss index (MLI) over the four preferred management actions under C_1, C_2, C_3, and C_4 for that time period. The MLI for the preferred management action for a climate change scenario is a weighted average of the expected maximum losses in the attributes that would occur if that action was implemented. Expected maximum loss for a single attribute with the preferred management action for a climate change scenario is the estimated value of that attribute with that action and no future climate change minus the estimated value of that attribute with that action and the climate change scenario for which that action is preferred. Losses in individual attributes without and with climate change are estimated using biophysical simulation models, visitor surveys, and/or mental models. Construction of the MLI requires managers to assign weights to the four attributes, such that the weights sum to one.

The MLIs for the preferred management actions for each climate change scenario in the first time period are given in Table 10.6. A_3 is the preferred management action for the first time period because it has the lowest MLI across the four climate change scenarios. Therefore, A_3 is implemented at the beginning of the first time period.

The preferred management actions for the second, third, and fourth time periods are determined using a similar procedure to the one used for the first time period with two major differences. First, the attributes for the second, third, and fourth time periods are measured using a combination of experimental data (provided active AM is implemented at the

TABLE 10.6 MLIs for Preferred Management Actions Under Four Climate Change Scenarios in the First Time Period

Climate change scenario	C_1	C_2	C_3	C_4
Preferred management action	A_3	A_4	A_4	A_2
MLI	45	58	65	72

beginning of the first time period) and nonexperimental data. Second, if active AM is implemented, then there are multiple observations on the attributes of responses to C_{it} and A_1, C_{it} and A_2, C_{it} and A_3, and C_{it} and A_4, where C_{it} is the climate change scenario that occurred during time period t for $t \geq 2$. In this case, distances from the fuzzy positive-ideal solution (d_i^+) and fuzzy negative-ideal solution (d_i^-) for those attributes and the closeness coefficient (E_i) for each management action are estimated for each observation and the average value of E_i over the multiple observations is used to rank management actions.

10.2.5.4 Determining Best Adaptive Management Strategy

The previous section describes how the minimax regret criterion is used to determine that A_3 is the preferred management action for the first time period. Suppose the minimax regret criterion indicates that the preferred management actions for the second through fourth time periods are A_3 in the second time period, A_2 in the third time period, and A_1 in the fourth time period. Based on these results, the best AM strategy for CNP is to implement A_3 at the beginning of the first time period and continue using it through the end of the second time period, implement A_2 at the beginning of the third time period, and implement A_1 at the beginning of the fourth time period. This strategy assumes it is feasible to change management actions across time periods. If that is not the case, then the best strategy would have to be altered to accommodate any limitations on altering management actions across time periods for CNP.

10.3 DISCUSSION

This section discusses the steps a coupled system manager would have to take in order to implement the FLAM model. Those steps include: (1) selecting the length and number of time periods for evaluating management actions; (2) picking future climate change scenarios; (3) choosing management actions; (4) selecting the multiple attributes of system responses; (5) if active AM is used, designing and conducting AM experiments in each time period to determine how experimental combinations of climate change scenarios and management actions influence the attributes; (6) using expert judgment, surveys, and/or simulation models to estimate how nonexperimental combinations of climate change scenarios and management actions influence the attributes; (7) using fuzzy TOPSIS to determine the preferred management action for each climate change scenario within time periods; (8) applying the minimax regret criterion to determine the preferred management action for each time period; and (9) determining the best AM strategy.

The time periods should span a sufficiently enough long period of time to allow climate change and management actions to fully influence the attributes. The slower the responses to climate change and management actions, the longer the time periods should be.

The most commonly used climate change scenarios are the ones developed by the IPCC (see Section 10.2.1). The IPCC scenarios project changes in climate through 2100. The FLAM model requires climate projections for a portion of or the entire area of a coupled system. Such projections can be developed using the high-resolution (800-m), bias-corrected, ensemble climate projections for monthly average maximum temperature, minimum temperature, and precipitation developed by NASA Earth Exchange (NEX)

(Thrasher et al., 2013). Such projections should be sufficient to evaluate the responses of a coupled system to climate change. The choice of management actions and attributes depends to a large extent on the mission of the agency managing the coupled system and the management challenges facing that system. For example, the hypothetical CNP is a national park. National parks in the United States are managed by the National Park Service whose goal is "… to conserve the scenery and natural and historic objects and the wildlife therein and to provide for the enjoyment of the same by such manner and by such means as will leave them unimpaired for the enjoyment of future generation" (National Park Service Organic Act of 1914). For the hypothetical CNP, the four management actions and the two camper satisfaction attributes address enhancing visitor enjoyment by increasing the number of backcountry campsites, and the two conservation attributes address conserving scenery, natural objects, and wildlife.

Designing and conducting AM experiments requires applying the principles of experimental design, a well-established branch of statistics. In some cases, it may not be feasible for managers to conduct AM experiments due to technical and/or financial reasons. For example, from a technical viewpoint, if the management actions pertain to alleviating adverse impacts of climate change on grizzly bears, it is unlikely that the treatments (i.e., management actions) applied to biophysical zones will be independent because the home range for grizzly bears is likely to exceed the size of a biophysical zone. From a financial viewpoint, managers may not be able to afford long-term AM experiments due to limited operating budgets.

Using expert judgment, such as the Delphi method, surveys, and/or simulation models, to estimate how nonexperimental combinations of climate change scenarios and management actions influence the attributes is likely to be the most difficult step in implementing the FLAM model. While these estimation methods are commonly used by researchers, they are not typically used by coupled system managers. Managers can overcome this potential limitation by enlisting the assistance of technical experts that are knowledgeable about the application of these methods.

Applying fuzzy TOPSIS requires the coupled system manager to assign linguistic ratings to the estimated values and relative importance of the attributes, such as the ones shown in Table 10.2 and perform the fuzzy mathematical operations needed to generate Tables 10.2–10.5. The hypothetical CNP generates numerous estimated attributes, which means that managers would have to do a large number of linguistic ratings of estimated attributes. The number of linguistic ratings can be substantially reduced by developing a look-up table that indicates which linguistic variables the manager assigns to different percentage ranges of the estimated attributes. An example of a look-up table for an attribute is 0–15% is very low, 16–45% is low, 46–65% is moderate, 66–84% is high, and greater than 85% is very high. A look-up table is not be needed to rate the relative importance of the attributes because it only requires one rating per attribute. If the linguistic ratings vary across time periods, then it would be necessary to develop separate look-up tables for each time period.

The fuzzy mathematical operations required to generate Tables 10.3–10.5 can be performed using a spreadsheet developed by the author. That spreadsheet requires the user to create a table, like Table 10.1, that assigns numerical codes (e.g., 1 through 5) to the five linguistic ratings/triangular fuzzy numbers, and develop a matrix for each climate change scenario that contains the corresponding codes for all combinations of management actions and attributes and the relative importance of the attributes. The spreadsheet automatically generates Tables 10.3–10.5 based on those codes.

Using the minimax regret criterion is relatively straightforward once the MLIs have been calculated (i.e., Table 10.6). Defining the MLI requires the manager to estimate the attributes without future climate change for each time period, which can be done using biophysical simulation models, visitor surveys, and/or mental models, and assign weights to the attributes.

Determining the best AM strategy is straightforward once the preferred management actions have been determined for all time periods.

10.4 CONCLUSIONS

This chapter describes a FLAM model for adaptively managing a hypothetical coupled system when the manager is uncertain about the extent of future changes in system drivers and system responses to both climate change and management actions. The FLAM model demonstrates two advantages of fuzzy decision rules. First, the fuzzy decision rule used in the FLAM model allows for sampling and measurement errors in attribute data and stochastic variability in attributes. Second, the decision rules used in the model do not require managers to specify probability distributions for system attributes. This feature is particularly advantageous when climate change is one of the drivers of system attributes because probability distributions for climate change scenarios have not been specified.

In general, the FLAM model can be applied to any coupled system. The mathematical operations required by most fuzzy logic-based decision rules are complex. In contrast, the mathematical operations required to implement the FLAM model have been programmed into a spreadsheet that is relatively easy to use. However, other elements of the model, notably using expert judgment, surveys, and/or simulation models to estimate how nonexperimental combinations of climate change scenarios and management actions influence the attributes, are more challenging to apply. For that reason, managers who want to use the FLAM model would most likely have to enlist the assistance of individuals who are familiar with applying those elements.

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