ENVIRONMENTAL ASSESSMENT

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Fuzzy Decision Analysis for Integrated Environmental Vulnerability Assessment of the Mid-Atlantic Region[1]

LIEM T. TRAN[2,*]
C. GREGORY KNIGHT[2,3]
ROBERT V. O'NEILL[4]
ELIZABETH R. SMITH[5]
KURT H. RIITTERS[6]
JAMES WICKHAM[5]
[2]Center for Integrated Regional Assessment
Pennsylvania State University
University Park, Pennsylvania
[3]Department of Geography
Pennsylvania State University
University Park, Pennsylvania
[4]Oak Ridge National Laboratory
Environmental Sciences Division
Oak Ridge, Tennessee
[5]US Environmental Protection Agency
Office of Research and Development
National Exposure Research Laboratory
Research Triangle Park, North Carolina
[6]US Department of Agriculture, Forest Service
Forest Health Monitoring Program
Research Triangle Park, North Carolina

ABSTRACT / A fuzzy decision analysis method for integrating ecological indicators was developed. This was a combination of a fuzzy ranking method and the analytic hierarchy process (AHP). The method was capable of ranking ecosystems in terms of environmental conditions and suggesting cumulative impacts across a large region. Using data on land cover, population, roads, streams, air pollution, and topography of the Mid-Atlantic region, we were able to point out areas that were in relatively poor condition and/or vulnerable to future deterioration. The method offered an easy and comprehensive way to combine the strengths of fuzzy set theory and the AHP for ecological assessment. Furthermore, the suggested method can serve as a building block for the evaluation of environmental policies.

Regional analysis of environmental condition and vulnerability (Boughton and others 1999) represents a significant assessment challenge (Jones and others 1997). New sources of information from satellite imagery (O'Neill and others 1997) and new principles developed in landscape ecology (O'Neill and others 1999) provide exciting opportunities. To take advantage of these opportunities, however, a number of technical problems need to be addressed (e.g., Riitters and others 1997, Wickham and others 1997).

One of the most important problems of regional vulnerability assessment involves integrating information from many different sources into an overall ranking of relative risk (Wickham and others 1999). At the smaller spatial scale of a watershed, focusing on specific end points (EPA 1998) or devising an index of overall environmental integrity (Ott 1978, Karr and others 1986, Karr 1991) may represent feasible approaches to integration, although these simple approaches have faced serious criticism (DeAngelis and others 1990, Suter 1993). The problem becomes even more complex at the regional scale where information may be available on terrestrial and aquatic ecosystems, land-use changes, and a variety of simultaneous stressors.

One of the critical problems of integrated assessment is dealing with uncertainty that arises from different sources, such as error in measurement and/or modeling, imprecision in knowledge of relationships between stressors and receptors, and even ambiguity in the meaning of risk. The set of measured and calculated values being integrated are complexly interrelated and cannot be considered as statistically independent. A careful approach to integrated assessment, founded on state space theory (Johnson 1988, Kersting 1988) or multivariate analysis (Boyle and others 1984, Smith and others 1989), seems to be required.

KEY WORDS: Vulnerability assessment; Fuzzy decision analysis; Ecological indicators

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*Author to whom correspondence should be addressed at: 2217 Earth & Engineering Sciences Building, University Park, Pennsylvania 16802, USA; *email*: LTT1@psu.edu

Table 1. Indicators of regional ecological conditions[a]

No.	Indicators	Abbreviations
1	Population density (1990)	POPDENS
2	Population change (1970–1990)	POPCHG
3	Human use index	UINDEX
4	Road density	RDDENS
5	Average atmospheric wet NO3 deposition (1987 and 1993)	NO3DEP
6	Average atmospheric wet SO4 deposition (1987 and 1993)	SO4DEP
7	Air pollution: ozone (1988 and 1989)	OZAVG
8	Percent of watershed streamlength with forest within 30 m	RIPFOR
9	Percent of watershed streamlength with agriculture land within 30 m	RIPCROP
10	Percent of watershed streamlength with roads within 30 m	STRD
11	Number of impoundments per 1000 km of stream	DAMS
12	Percent of watershed with cropland on slopes >3%	CROPSL
13	Percent of watershed with agricultural land on slopes >3%	AGSL
14	Estimated N load in streams	STNO3L
15	Estimated P load in streams	STPL
16	Soil loss (estimated from USLE)	PSOIL
17	Percent of watershed that is forested	FOR %
18	Forest fragmentation	FORFRAG
19	Forest edge habitat in 7-ha window	EDGE7
20	Forest edge habitat in 65-ha window	EDGE65
21	Forest edge habitat in 600-ha window	EDGE600
22	Forest interior habitat in 7-ha window	INT7
23	Forest interior habitat in 65-ha window	INT65
24	Forest interior habitat in 600-ha window	INT600
25	Proportion of watershed that supports forest interior habitat at three scales (22, 23, and 24)	INTALL
26	Largest forest patch (expressed as proportion of watershed area)	FORDIF

[a]Detailed information of the indicators can be found in the Landscape Atlas of Mid-Atlantic Region (Jones and others 1997).

This paper presents an initial approach to a fuzzy decision analysis model for ecological vulnerability assessment. The method was a combination of a fuzzy ranking method and the analytic hierarchy process (AHP). In addition, principal component analysis (PCA) was used as guidance for constructing the hierarchy in AHP. The method was capable of ranking of ecosystems in terms of environmental conditions and relative cumulative impacts across a large region.

Materials and Methods

Data

For this analysis we analyzed 26 of 33 indicators (Table 1) provided in the landscape atlas of the Mid-Atlantic region (Jones and others 1997) on a watershed-by-watershed basis, using US Geological Survey (USGS) 8-digit hydrologic unit maps (USGS 1982), for 123 watersheds in the Mid-Atlantic region (Figure 1). The other seven indicators were not included because of missing data.

Methods

Fuzzy Ranking. For ecological indicators, uncertainty is inherent. Hence there is a need to represent values of the indicators in parallel with their information on uncertainty. If the indicators are stand-alone, it is not a problem, as we can define an indicator as a duplex (value, uncertainty). However, it becomes problematic, both theoretically and practically, to use such duplexes in further complicated calculations, as in an integrated ecological assessment, using a conventional probabilistic approach. One of the main reasons is that the relationships among stressors and receptors are unclear and extremely complicated. Within that context, fuzzy set theory appears to be a good complimentary approach. With the fuzzy approach, the indicators' uncertainty can be associated with their values using the concept of fuzzy set [see Zadeh (1965, 1978), Dubois and Prade (1980), and Klir and Yuan (1995) for more details on fuzzy set]. Once the indicators are represented by fuzzy sets, there are several different fuzzy techniques that can be used to facilitate different calculations on those fuzzy indicators. Some of them are fuzzy arithmetic (Kaufmann and Gupta 1991), fuzzy rule-based modeling (Bárdossy and Duckstein 1995), or fuzzy ranking (Chen and Hwang 1992). Several environmental studies in that direction have been seen in the literature recently. For example, Silvert (1997, 2000) applied fuzzy logic to derive fuzzy indices of environmental conditions and to classify ecological im-

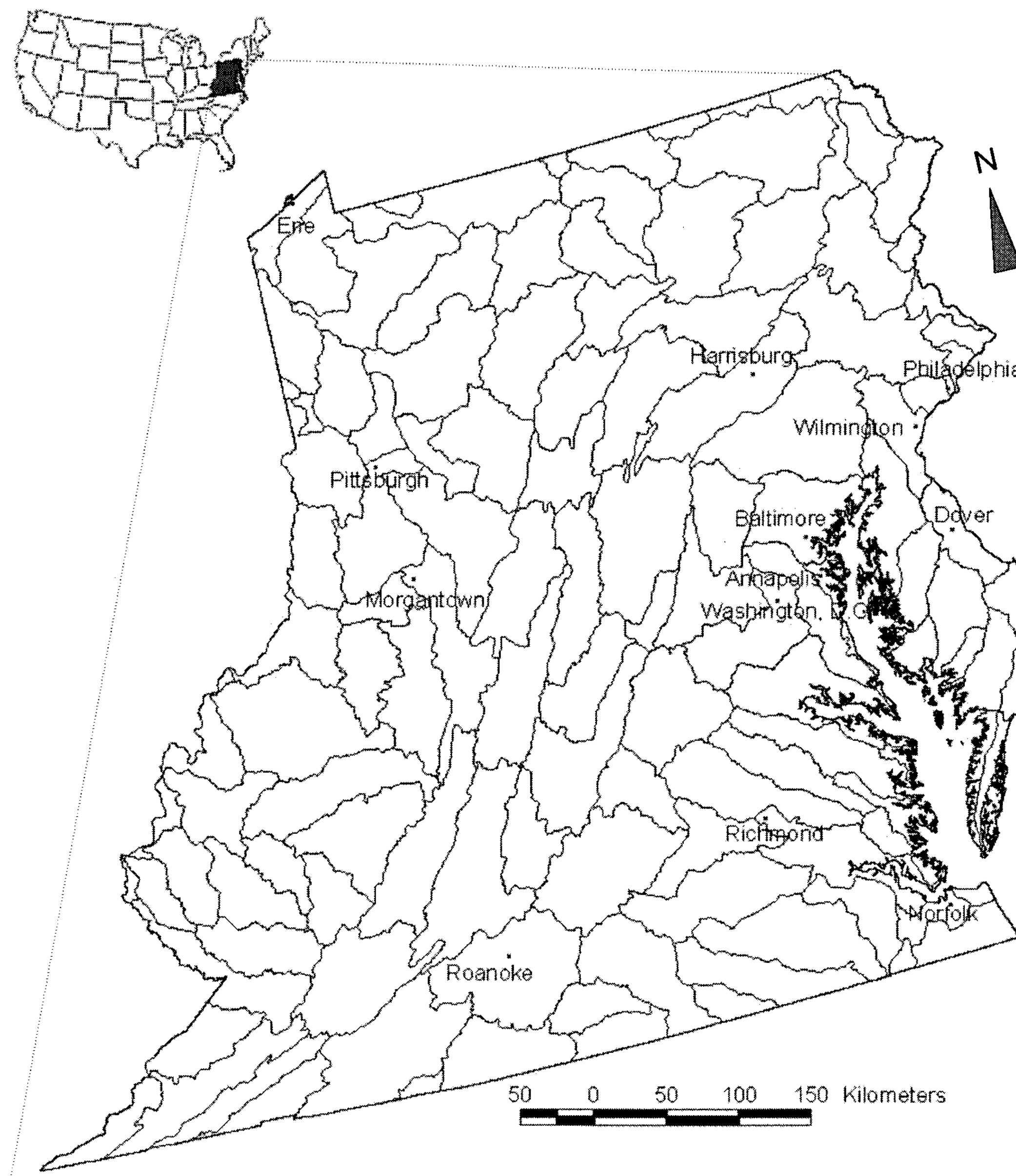

Figure 1. Watershed boundaries within the Mid-Atlantic region. Source: USGS, Hydrologic Unit Code Boundaries (HUC250), 1:250,000 scale.

pacts. However, the fuzzy approach in ecological assessment is still considered a relatively new avenue.

If data of an indicator for all of the watersheds under study are in the fuzzy set format, then fuzzy ranking can be used to derive a ranking for the watersheds with respect to that indicator. In this analysis we applied a fuzzy-ranking method that was recently developed by Tran and Duckstein (2002). It was shown that this method overcame several problems inherent to existing fuzzy ranking methods, namely, inconsistency with human intuition, indiscrimination, and difficulty of interpretation [see Tran and Duckstein (2002) for a detailed discussion]. In addition to ranking, the suggested method also can be used to reveal the distance from an ecological entity to some reference points. A brief description of the method and its functions to compute distances for some commonly-used fuzzy numbers are displayed in Appendix 1.

Principal component analysis (PCA). PCA, which was originally introduced by Pearson (1901) and independently by Hotelling (1933), is one of the oldest and most widely used statistical multivariate techniques.

The basic idea of the technique is to describe the variation of a set of multivariate data with a new set of uncorrelated variables, each of which is a linear combination of the original variables, using covariance (or correlation) matrix. PCA involves calculations of eigenvalues and their corresponding eigenvectors of the covariance (or correlation) matrix to derive the new variables in a decreasing order of importance in explaining variation of the original variables. Usually, if correlations among the original variables are large enough, the first few components will account for most of the variation in the original data. If that is the case, then they can be used to represent the data with little loss of information, thus providing a suitable way in reducing the dimensionality of the data.

PCA has been applied in a wide array of studies in environmental sciences, especially for determining sources of some substances (e.g., Rachdawong and Christensen 1997, Statherropoulos and others 1998, Topalián and others 1999, Yu and Chang 2000) and revealing the relationships among different indicators (e.g., Calais and others 1996, Yu and others 1998). PCA in this study was used as an exploratory tool to reveal key variables associated with different principal components (PCs). That information then was used to guide the construction of the hierarchy in AHP.

It should be mentioned that the data used for PCA in this study did not completely meet the assumption of multivariate normality. It is known that multivariate normality, which implies linear relationships among variables, is a condition required in PCA to meet the assumptions necessary for the use of the general linear model. However, it can be argued that PCA can be used as an exploratory tool and some inference may still be derived from nonnormal data. On the other hand, transformation of variables, which is a common remedy for outliers, failures of normality, linearity, and homoscedasticity, often causes increased difficulty in interpretation of the transformed variables. In addition, as outliers represent extreme ecological conditions—the focus of this study—their removal or transformation is not desirable. From that point of view, the data were analyzed without any transformation except normalization. This was considered reasonable as the PCA's general linear model was not utilized in other steps of the analysis and the aim of PCA in this study was to reveal the key variables associated with the PCs.

Analytic hierarchy process (AHP). AHP (Saaty 1980) has been considered the most widely used multicriteria decision-making method. One of the reasons for AHP's popularity is that it derives preference information from the decision-makers in a manner that they find easy to understand. AHP is a systematic procedure to construct and represent the elements of a problem in a hierarchy format. The basic rationale of AHP is organized by the breakdown of the problem into smaller constituent parts at different levels. Decision-makers are guided through a series of pairwise comparison judgments to reveal the relative impacts, or the priorities of elements (e.g., criteria, alternatives) in the hierarchy. These judgments, in turn, are transformed to ratio-scale numbers representing relative local and global weights of the elements at a certain level of the hierarchy. The hierarchy in AHP is often constructed from the top (goal from management standpoint, e.g., environmentally sound development), through intermediate levels (criteria on which subsequent levels depend, e.g., physical, chemical, biological, and socioeconomic criteria), to the lowest level (usually a set of alternatives, possible actions).

Since the original version of Saaty, there have been several variants of AHP seen in the decision-making science literature. For instance, Lootsma (1997, 1999) modified the scale and aggregation procedure in the original AHP to come up with the additive AHP and multiplicative AHP. The AHP's original version as well as its two variants developed by Lootsma have been altered to deal with fuzzy numbers [see Saaty (1977, 1978), Chen and Hwang (1992) for the original model, and Lootsma (1997, 1999) for the modified versions]. AHP has been applied widely in different environmental problems (e.g., Saaty 1986, Lewis and Levy 1989, Varis 1989), especially in resources allocation and planning (e.g., Ramanathan and Ganesh 1995, Mummolo 1996, Alphonce 1997).

Somewhat different from common AHP applications, absolute measurement rather than pairwise comparison was applied at the lowest level of the hierarchy in this analysis with the use of the fuzzy ranking method developed by Tran and Duckstein mentioned above. Its aim was to rate the watersheds on a single-indicator basis. As absolute measurement involves a measuring standard, the watersheds were rated against some reference points, namely some ideal and undesirable ecological states (conditions) of the indicator under study. In this analysis, we simply constructed the ideal and undesirable states for a particular indicator by using its minimum and maximum values derived from the indicator's data from all of the 123 watersheds. Then those single-indicator-based distances of a watershed were aggregated gradually from the bottom to the top the hierarchy to come up with an ultimate score for that watershed. Conceptually, the ultimate score of a watershed represents the distance of the watershed to an arbitrary ideal watershed that has the ideal states for all of the indicators. Next all of the ultimate scores were

Table 2. Eigenvalues of the correlation matrix

PCs	Eigenvalues	% of Variance	Cumulative %
1	12.322	47.393	47.393
2	3.715	14.288	61.682
3	2.281	8.775	70.456
4	1.696	6.522	76.978
5	1.493	5.744	82.722
6	1.021	3.928	86.651

used to derive a relative ranking for the 123 watersheds, which in turn can be used to identify and/or to prioritize the most vulnerable ecosystems in the study area.

Results

PCA

The PCA was performed on SPSS with varimax rotation as an attempt to minimize the number of variables that have high loadings on each factor, simplifying the interpretation of the factors (Everitt and Dunn 1992). The use of the correlation matrix instead of the covariance matrix in the PCA was to assign equal weights for all of the 26 indicators in the analysis in forming the principal components (Chatfield and Collins 1980).

Using 1.0 as the cutoff value for eigenvalues, the first six PCs accounted for 86.65% of the total variation (Table 2). Table 3 shows that the first principal component (PC1) had high loadings with 12 indicators (UINDEX, STRD, STNO3L, STPL, PSOIL, FOR %, FORFRAG, INT7, INT65, INT600, INTALL, and FORDIF). PC2 had high loadings with four indicators (POPDENS, EDGE7, EDGE65, and EDGE600). The four high-loading indicators in PC3 were RIPFOR, RIPCROP, CROPSL, and AGSL and the three high-loading indicators in PC4 were NO3DEP, SO4DEP, and OZAVG. PC5 had high loadings with two indicators (POPCHG and RDDENS), while PC6 had high loading with only one indicator (DAMS).

By looking at key indicators associated with a PC, an approximate label can be made for that particular PC. PC1 was roughly related to the amount and quality of upland habitat and ecological condition of streams. The presence of the human use index (UINDEX) in this group indicated that the quality of upland habitat and streams had a strong connection with the amount of urban and agricultural land-use. PC2 was identified as the amount of forest edge habitat. As population density (POPDENS) in the Mid-Atlantic landscape atlas was calculated based on differences in road density across the region (Jones and others 1997), its existence in this group was explainable: forest fragmentation was highly related to the distribution of road and population. PC3 had a clear connection to agricultural activities. PC4 was highly associated with the quality of air. PC5 was related to infrastructure and population change. PC6 was associated with number of impoundments. Among the six PCs, the interpretation of PC4 and PC6 was relatively straightforward while those of the others were somewhat more difficult. For example, both PC1 and PC2 had several forest-related indicators, which in turn were highly correlated. Furthermore, some of them had high loadings on both components (e.g., FORFRAG, EDGE7). These factors made the distinction among components more difficult. On the other hand, it should be mentioned that the identification of PCA components is arbitrary to a considerable extent. Other PC analyses with different operational options (e.g., using the covariance matrix instead of the correlation matrix, or using different rotation methods) can produce different sets of PCs and probably different sets of labels. Hence trying to attach to much meaning to components might be misleading.

AHP

A four-level hierarchy was constructed with its highest level for the ultimate scores of the 123 watersheds (Figure 2). The second level had six components, representing the six PCs (so-called PC-based criteria). The third level contained 26 indicators, each of which was associated with the PC where it had the highest loading. The lowest level (the fourth level) was for the 123 watersheds.

Normally in AHP, the next step after constructing the hierarchy is to carry out pairwise comparison judgments at different levels of the hierarchy to reveal the criteria's relative weights. This step, however, was skipped in this analysis, as our aim was to construct a baseline model with as few subjective judgments as possible. To create the baseline model, we assigned equal weights for the six PC-based criteria at the second level (i.e., equal local weights of 0.166), implying they were treated equally. In the same manner, weights at the third level for criteria associated with the same PC-based criterion were equally assigned. For example, equal local weights of 0.5 were assigned for indicators POPCHG and RDDENS that were associated with the PC5-based criterion.

On the other hand, when the model is used for an actual ecological assessment with actual decision-maker(s) and stakeholder(s) in later phases, pairwise comparisons will be carried out thoroughly, following the common procedure of AHP, to determine the criteria's relative weights at all levels in the hierarchy (except the lowest level). Therefore, those potential real-world ap-

Table 3. Eigenvectors (loadings) of the correlation matrix

Indicators	PC1	PC2	PC3	PC4	PC5	PC6
POPDENS	0.207	0.707	−0.139	0.090	0.448	−0.238
POPCHG	0.324	−0.083	−0.192	−0.284	−0.503	−0.275
UINDEX	0.813	0.502	0.219	0.051	0.043	0.053
RDDENS	0.215	0.061	0.107	0.028	0.764	−0.057
NO3DEP	0.078	0.102	0.173	0.948	0.074	0.037
SO4DEP	0.082	0.205	0.154	0.912	0.032	0.134
OZAVG	0.141	0.185	−0.132	−0.598	−0.085	0.528
RIPFOR	−0.288	−0.410	−0.789	−0.063	−0.026	−0.037
RIPCROP	0.289	0.152	0.864	0.034	−0.169	0.161
STRD	−0.602	0.359	0.445	0.019	0.148	−0.157
DAMS	0.045	0.170	−0.146	−0.104	−0.022	−0.845
CROPSL	0.072	−0.062	0.855	0.233	0.147	−0.021
AGSL	0.120	−0.066	0.899	0.164	0.193	0.048
STNO3L	0.856	0.387	0.126	0.075	−0.127	0.095
STPL	0.854	0.377	0.113	0.077	−0.136	0.087
PSOIL	0.812	0.184	0.364	0.009	−0.196	0.203
FOR %	−0.854	−0.483	−0.079	−0.029	0.011	−0.057
FORFRAG	0.740	0.551	0.088	0.068	0.244	−0.093
EDGE7	0.664	0.696	0.191	0.116	0.023	0.021
EDGE65	0.471	0.831	0.175	0.098	−0.042	0.029
EDGE600	0.316	0.869	0.074	0.065	0.010	−0.059
INT7	−0.921	−0.327	−0.095	−0.008	−0.125	0.045
INT65	−0.952	−0.171	−0.089	0.011	−0.153	0.096
INT600	−0.939	−0.017	−0.109	0.041	−0.168	0.142
INTALL	−0.928	−0.010	−0.109	0.059	−0.180	0.157
FORDIF	0.598	0.386	0.171	0.161	−0.171	0.197

plications probably will have different sets of weights and consequently have different sets of ranking, which in turn might not be the same as those in this baseline analysis. Those differences reflect divergence in public values, preferences, and priorities of different decision-makers and stakeholders.

Commonly in AHP, after local weights are determined, they are synthesized from the second level down to derive the global weights for all criteria. For example, the global weight of a criterion at the third level is computed by multiplying its local weight by the weight of its corresponding criterion in the second level. (Note that the local weight of a criterion at the second level is also its global weight as the weight of the single top-level goal is unity). For this baseline analysis, the global weights of the indicators associated with the six PC-based criteria from 1 to 6 were 0.014, 0.042, 0.042, 0.056, 0.083, and 0.167, respectively. Note that, although the global weights of the indicators associated with different PC-based criteria were different, the global weights of the six PC-based criteria were equal (0.166). Of course, as mentioned above, this is just one particular way of assigning weights for the baseline model. In real-world applications, different sets of weights can be derived from different decision-makers and stakeholders.

Although the global weights were synthesized to reveal the criteria's priorities, actually the local weights were used in this analysis to compute scores of the 123 watersheds at each criterion in the hierarchy. The aim of this use was to make the scores computed at all criteria in all levels of the hierarchy be on the same 0–1 scale, conceptually representing the distances from the watersheds to the ideal states of the corresponding criteria. For example, the score at the PC5-based criterion of a watershed computed with the local weights of POPCHG and RDDENS symbolizes the distance of that watershed to the ideal state of the PC5-based criterion (i.e., a combined ideal state of POPCHG and RDDENS). Note that the conversion between scores computed by local weights with those by global weights is trivial.

Fuzzy Ranking

First, all of the indicators were normalized and scale-reversed, if necessary, to have them all on the same 0–1 scale with 0 and 1 representing the ideal and undesirable reference points, respectively. Then, by applying the fuzzy distance measure described in Appendix 1, the distances from a watershed to the ideal points with respect to different indicators were calculated.

We intended to construct a triangle fuzzy number

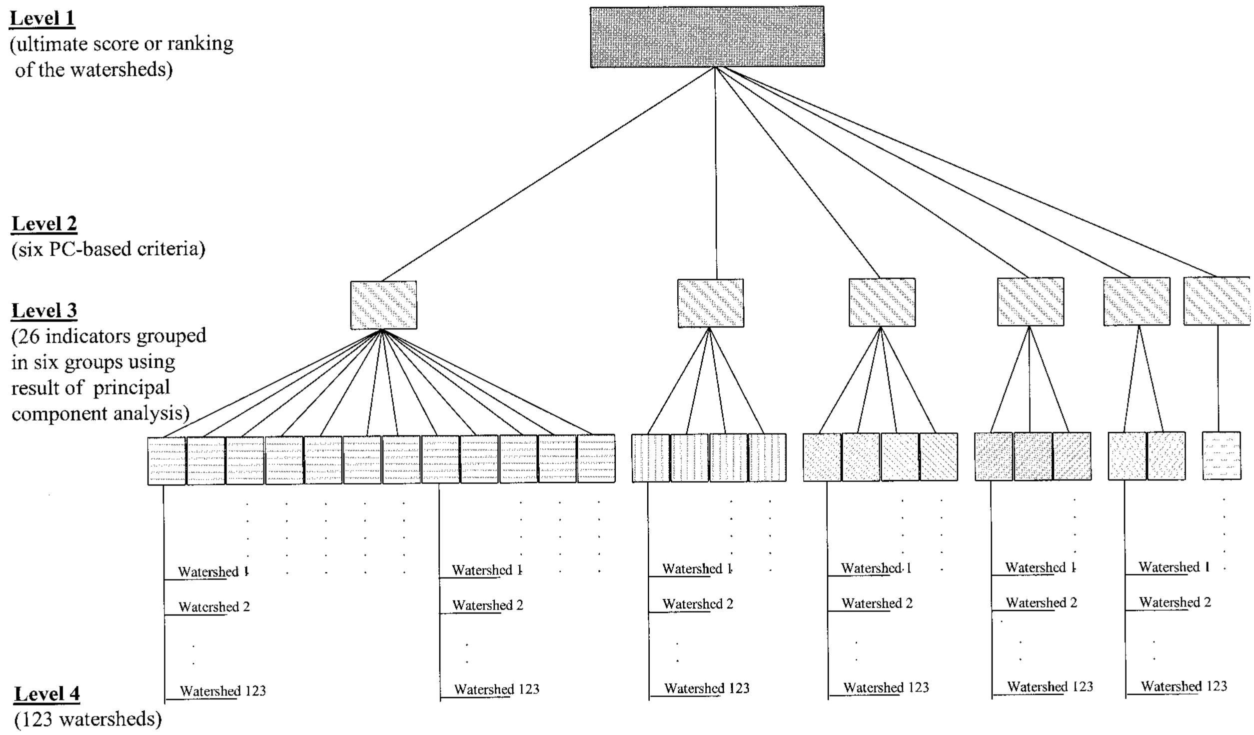

Figure 2. The four-level hierarchy of the AHP.

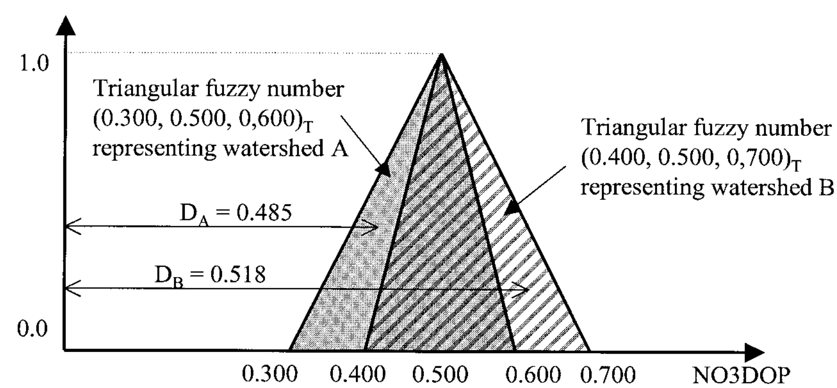

Figure 3. Illustration of using triangular fuzzy number and Tran and Duckstein's fuzzy distance measure for ecological indicators.

for an indicator in a watershed by using its value and its possible range (i.e., its minimum and maximum values) in that watershed. To illustrate, assume the minimum, average, and maximum values of NO3DOP in watershed A are 0.300, 0.500, and 0.600, respectively. Then NO3DOP in watershed A can be represented by the triangular fuzzy number $(0.300, 0.500, 0.600)_T$ [see Dubois and Prade (1980), Kaufman and Gupta (1991) for more details on fuzzy numbers]. In the same manner, a triangular fuzzy number $(0.400, 0.500, 0.700)_T$ can be used to represent NO3DOP in watershed B whose minimum, average, and maximum values of NO3DOP are 0.400, 0.500, and 0.700, respectively (Figure 3). Using equation A-9 (provided in Appendix Table A-1), the distances of watersheds A and B to the ideal state of NO3DOP (representing by the triangular fuzzy number $(0.0, 0.0, 0.0)_T$) are 0.485 and 0.518, respectively. Note that both watersheds A and B have the same average value of 0.500 but different minimum and maximum values, making their distances to the ideal state of NO3DOP different.

In fact, the information on uncertainty (e.g., minimum, maximum values, and/or objective/subjective error estimates) for the 26 indicators was not available when this analysis was carried out. Therefore, we could not construct the designed fuzzy numbers for all indicators in the 123 watersheds as illustrated in the example above. Alternatively, we created an arbitrary minimum (maximum) value for an indicator in a watershed by subtracting (adding) 0.050 to its average value and then constructed the triangular fuzzy numbers based on those arbitrary minimum and maximum values. Accordingly, we expect some slight differences between results of this analysis and those in future calculations, when the real information on uncertainty is used in the calculation.

Next the scores (or distances) computed at the lowest level were aggregated at other higher levels of the hierarchy. Scores at the third level were computed by two different methods: L_1 norm (sum of the scores) and L_2 norm (square root of sum of the squared scores) as follows:

$$L_1: \qquad D_{level\ j}^{criterion\ i} = \sum_{k=1}^{m} W_k \cdot D_{level\ j+1}^{criterion\ k} \tag{1}$$

$$L_2: \qquad D_{level\ j}^{criterion\ i} = \sqrt{\sum_{k=1}^{m} W_k \cdot (D_{level\ j+1}^{criterion\ k})^2} \tag{2}$$

where $D_{level\ j}^{criterion\ i}$ is the score at criterion i in the level j; W_k is the local weight of criterion k in the level $j + 1$; and m is the number of indicators (criteria) in the level $j + 1$ associated with criterion i. Scores at the second and first levels were computed by the L_1 norm only. The ultimate scores for the 123 watersheds and their rankings, derived from the two different methods (so-called AHP-L_1 and AHP-L_2), in turn were grouped into seven groups ranked from 1 (good condition) to 7 (bad condition) (Figures 4 and 5). Figure 6 represents ranges of the scores of the seven groups at the second level (i.e., the six PC-based criteria) and their ultimate scores at the top level of the hierarchy for the two models AHP-L_1 and AHP-L_2.

Discussion

Some spatial patterns were revealed from results of this analysis. In general, watersheds located near urban centers (e.g., Philadelphia, Washington, DC, Pittsburgh) had relatively high ultimate impact scores (i.e., bad condition). On the other hand, there were several adjacent watersheds in the southwestern part of the study area (i.e., West Virginia) that were in good condition in compared with the others in the region. However, there was no simple spatial transition from the bad watersheds to the good ones. With the exception of those in the rank-7 group (i.e., watersheds in relatively bad condition), the watersheds in other groups were not clearly spatially contiguous but rather intermingled throughout the study area. Some relatively good watersheds were located right next to some bad watersheds (e.g., those in the northeastern part of the study area, close to the Pittsburgh area). It is obvious that watersheds are not independent but rather interdependent in terms of ecological impacts. What happens in one watershed might have impacts on its neighboring watersheds to a certain extent. For example, a new transportation line is likely to cause some impacts (e.g., air pollution, changes in stream flow and sedimentation, etc.) not only on the watersheds that it goes through but also on some good watersheds nearby. Hence, even if there are no direct risks within their boundaries, good watersheds are not completely safe from degradation due to interrelated impacts among all of the watersheds. It suggests that an environmental policy or a land-use plan applied to either a small or large area in the region needs to be looked at from the local and regional points of view simultaneously.

Results of the two models, AHP-L_1 and AHP-L_2, were different due to the use of different norms (L_1 versus L_2) at the lowest level of the hierarchy. However these differences were considered insignificant. In 21 of 123 watersheds associated groups were different from one model to another. Furthermore, most of these discrepancies occurred in the groups of rank 2 to rank 6. There was only one difference in the rank-1 group and none in the rank-7 group between the two models, showing that the rank-1 and rank-7 groups were very stable from one model to another. In other words, the ecological states of the watersheds in these two groups were noticeably good (the rank-1 group) or bad (the rank-7 group) compared with watersheds in the other groups. This can be explained by the fact that most of the PC-based criteria scores of the watersheds in the rank-1 and rank-7 groups were quite distinct from those of the other groups (see Figure 6). In addition, the results of both AHP-L_1 and AHP-L_2 (i.e., the spatial pattern of good and bad watersheds in terms of ecological conditions) were quite similar to those from the cluster analysis in the landscape atlas of the Mid-Atlantic region (Jones and others 1997, Wickham and others 1999).

The two models in this analysis are not only able to provide relative ranking for the watersheds in the study area, they also can be used for policy-making analysis and planning evaluation. For example, if a decision-maker wants to see how a watershed can be improved if a certain amount of money is spent, these models can be used as a decision-support tool. To illustrate, assume

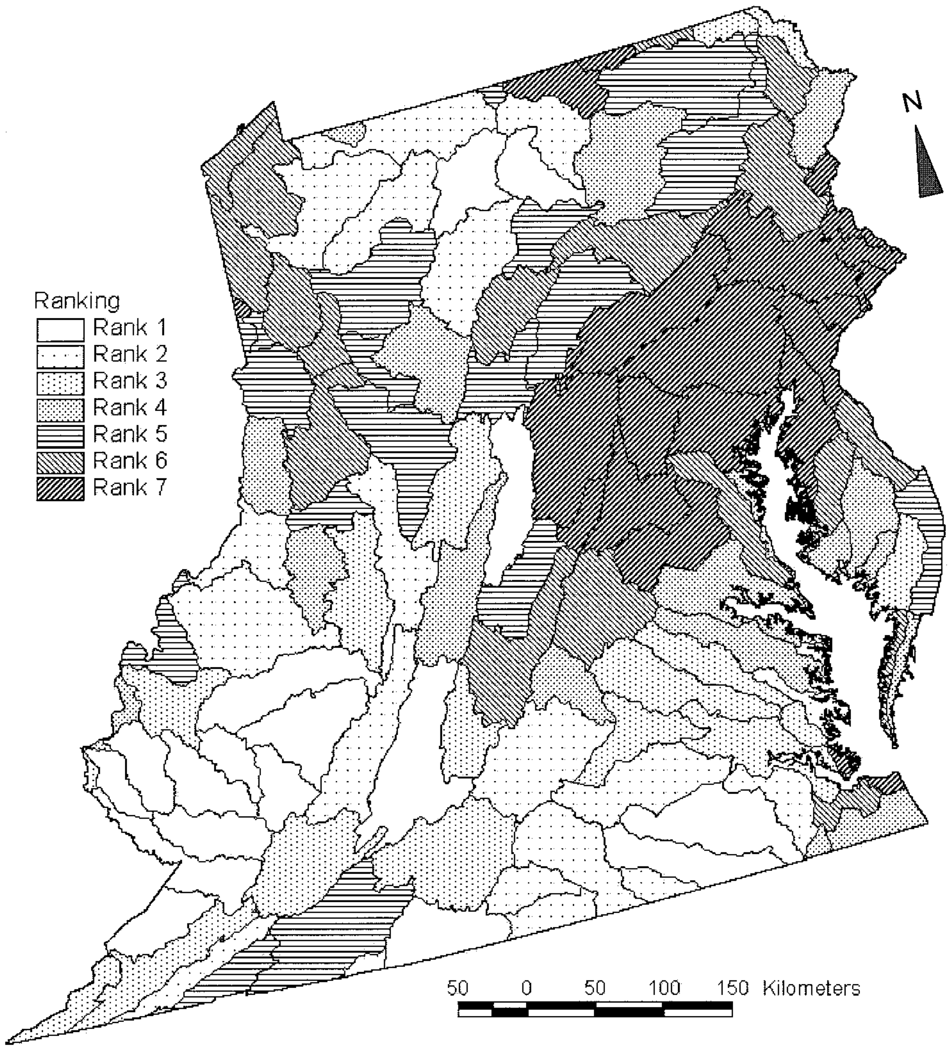

Figure 4. Ranking of watershed groups from AHP-L_1, ranging from 1 (for good condition) to 7 (for bad condition).

$5 million will be used to improve the forest cover along a stream for watershed 2050104 (Tioga). Assume that with that amount of money, RIPFOR, can be improved from the current value of 0.920 to 0.300, 0.400, and 0.500 on the best, average, and worst, respectively. Similarly, RIPAG can be improved from the current value of 0.862 to 0.200, 0.300, and 0.400 on the best, average, and worst, respectively. From such information, a triangular fuzzy number $(0.300, 0.400, 0.500)_T$ can be used to describe RIPFOR as a result of the conservation program. In the same way, the triangular fuzzy number $(0.200, 0.300, 0.400)_T$ can be used for RIPAG. Then the ranking of the watershed can be recalculated, applying the procedure described above. Results show that, with such a program, the integrated score of the watershed can be improved by 0.092 (from 0.599 to 0.507) and 0.075 (from 0.584 to 0.509) in the models AHP-L_1 and AHP-L_2, respectively. Such improvement will move this watershed from the rank-7 group (bad condition) to the next rank-6 group of the baseline model.

The issue of codependence was very sensitive in this analysis. Although the first PCs in the PCA comprised more variables and account for more variation of the variables (see Table 2), most of the variables in those PCs were highly correlated. In other words, several variables in one PC described more or less the same aspect of the ecosystem. As a consequence, it is likely that change in one variable will accompany changes in other variables in the same PC. Therefore, if larger weights are assigned for those first PCs at the second level in the hierarchy (for example, use the amount of variation explained by that PC as its weight), the result will be biased toward the ecological condition de-

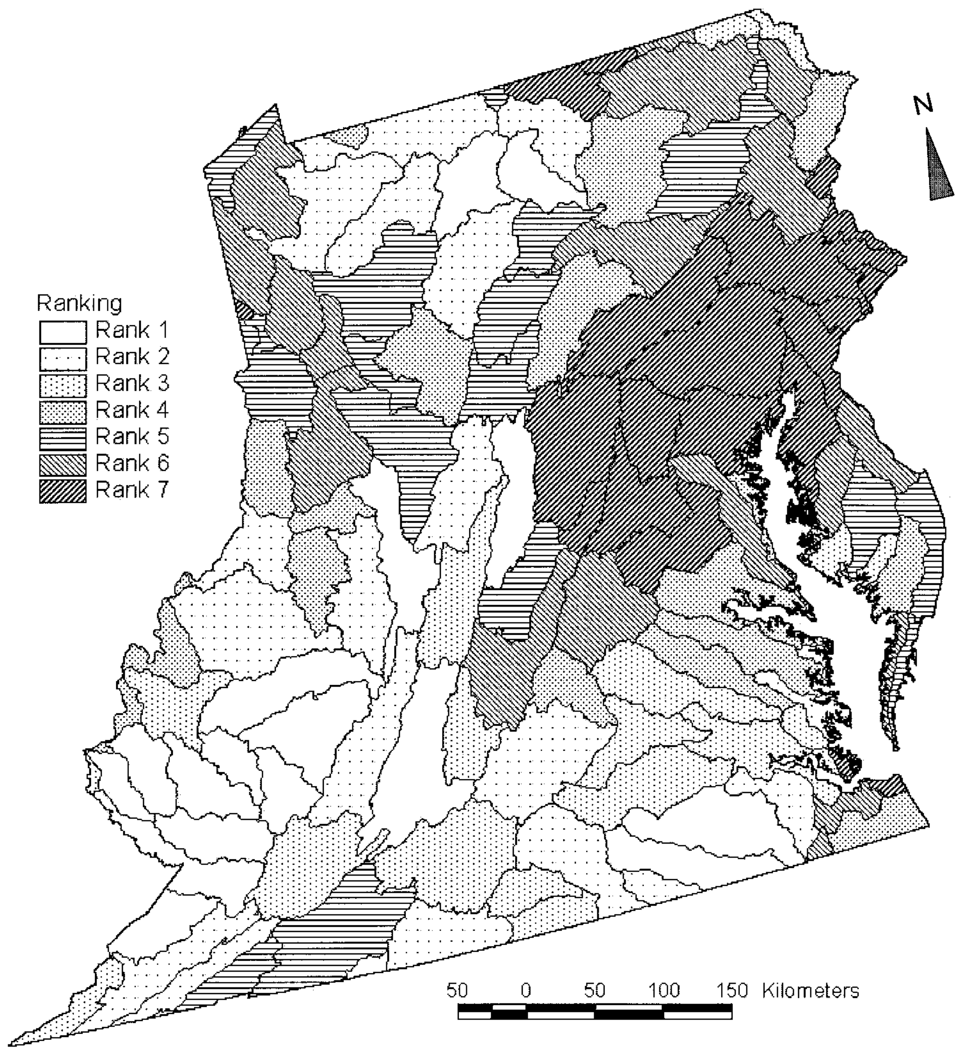

Figure 5. Ranking of watershed groups from AHP-L_2, ranging from 1 (for good condition) to 7 (for bad condition).

scribed by more variables (e.g., forest-related indicators). On the other hand, one might question why highly-correlated variables are not eliminated from the analysis. It can be argued that, although some variables are highly correlated, they still have their own signatures that are distinct from those of others to some extent. For example, both of the indicators EDGE7 and EDGE600—forest edge habitat in 7-ha and 600-ha windows, respectively—describe the condition of forest fragmentation. However they are derived at two different scales, representing the picture of forest edge habitat from two different angles. Hence picking one up while eliminating the other is not an easy decision to make. A better approach should be to use both of them but have some appropriate way to cope with the codependence problem.

Although the use of PCA in constructing the AHP hierarchy helped to deal with the problem of codependence of indicators to some extent, it did not solve the problem completely. The reason was, while some variables were highly correlated, there was no clear common ground among them. For example, PSOIL—soil loss estimated by the universal soil loss equation for agricultural land—showed strong correlations with several forest-related indicators in PC1 (e.g., FOR %, FORFRAG, INT7, INT65, INT600, INTALL, FORDIF). However, they characterized two different conditions of the ecosystem: conservation planning on agricultural land and forest conditions. Changes in conservation planning (e.g., reduce soil loss on existing agricultural land) are not necessarily associated with changes in forest conditions. Hence, by assigning equal weights for all six PC-based criteria, although the first couple of PCs had more vari-

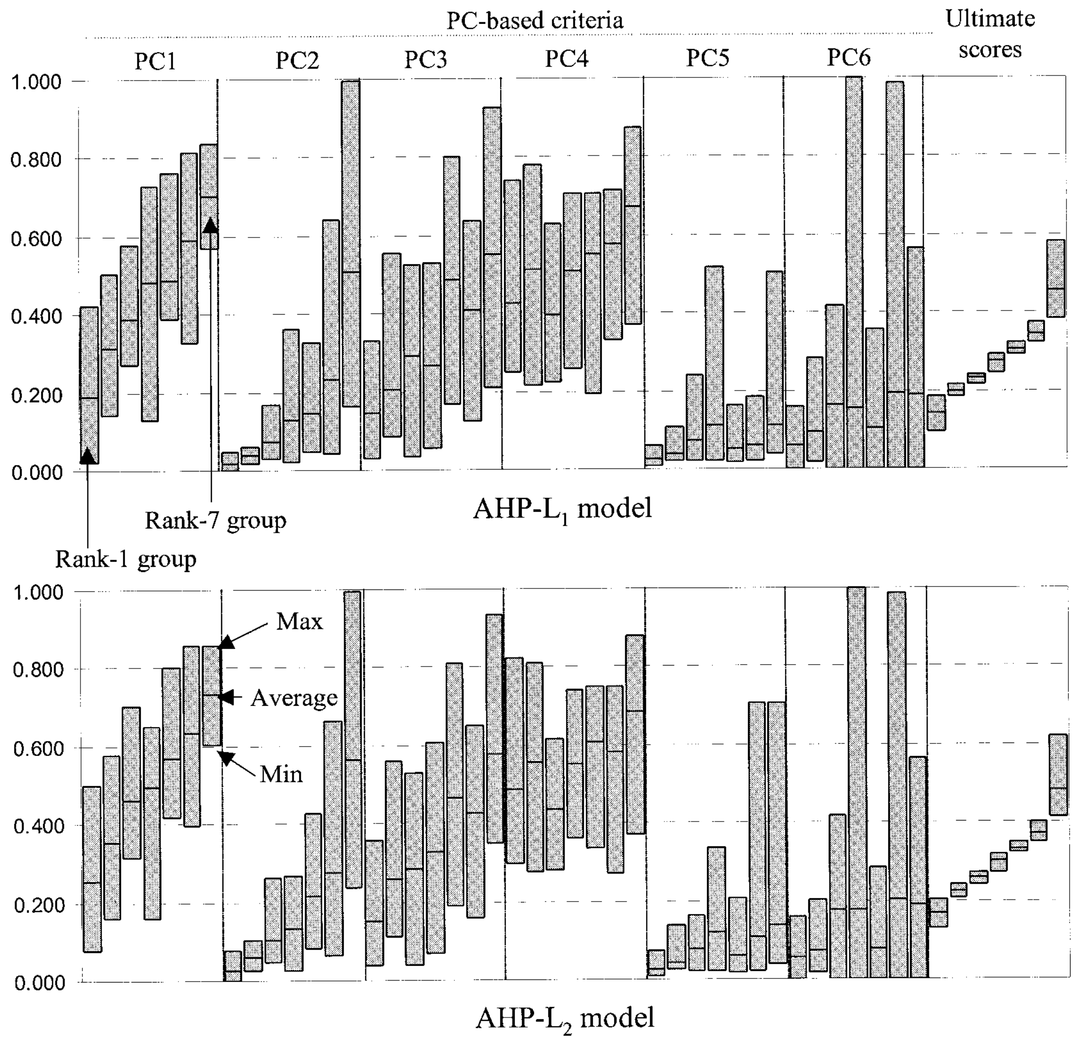

Figure 6. Ranges of the scores of the seven groups at the six PC-based criteria and their ultimate impact scores.

ables than the others, we somewhat undermined the contribution of PSOIL to the ultimate score of the watershed. This problem can be overcome by going beyond the correlation values and examining carefully the relationship among variables to assign more appropriate weights, instead of equal weights, at the second and third levels of the hierarchy. However, equal weights at the second and third levels of the hierarchy, as in this analysis, were considered reasonable for a baseline model, when insights of the relationships among variables have not been verified by other careful judgments or analyses.

In terms of methodology, the use of absolute measurement with fuzzy ranking in the AHP hierarchy made the calculation much simpler (i.e., no pairwise comparisons at the lowest level of the hierarchy, a task that is practically impossible with more than 100 watersheds to be compared). Furthermore, the model was relatively easy to understand in concept (e.g., the concepts of ideal/undesirable references are familiar to ecologists and decision-makers).

The use of AHP has shown several advantages. First of all, it helped to organize a complex problem into a well-structured hierarchy. Second, the model can be expanded in the future to include other social, cultural, and economic components (e.g., putting the hierarchy in this analysis into another larger hierarchy), moving from ecological assessment to social, economic, and environmental policy evaluation.

Conclusions

The key points of this analysis are summarized as follows:

- Fuzzy set with appropriate fuzzy ranking method provided a powerful and suitable way to represent ecological indicators. This feature is not only important for the integration of ecological indicators but also crucial for environmental policy evaluation in later phases.
- The use of multivariate statistical analysis in clustering the indicators in the AHP's hierarchy allowed the model to deal with codependence among the indicators to some extent.
- The AHP provided a productive framework in dealing with complexity (by means of a structured hierarchy) and in moving from ecological assessment to environmental policy evaluation.

In terms of scientific contribution, the developed method offered a quite creative and comprehensive way to combine fuzzy set theory and decision-making science for an ecological integrated assessment. The approach permitted a variety of environmental indicators and monitoring data to be integrated into an overall ranking of environmental condition across a region. This model can serve as the building block for the evaluation of environmental policies.

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Appendix 1: Tran and Duckstein's Fuzzy Ranking Method

The fuzzy ranking method developed by Tran and Duckstein is based on a distance measure for fuzzy numbers (FNs), which in turn is based on a distance measure for interval numbers (INs) as follows:

Distance measure for interval numbers. Let **F(R)** be the set of INs in **R**, and the distance between two INs A (a_1, a_2) and B (b_1, b_2) be defined as (Tran and Duckstein in press):

$$D^2(A,B) = \int_{-1/2}^{1/2}\int_{-1/2}^{1/2}\left\{\left[\left(\frac{a_1+a_2}{2}\right) + x(a_2-a_1)\right] - \left[\left(\frac{b_1+b_2}{2}\right) + y(b_2-b_1)\right]\right\}^2 dx\,dy \quad \text{(A-1)}$$

$$= \left[\left(\frac{a_1+a_2}{2}\right) - \left(\frac{b_1+b_2}{2}\right)\right]^2 + \frac{1}{3}\left[\left(\frac{a_2-a_1}{2}\right)^2 + \left(\frac{b_2-b_1}{2}\right)^2\right] \quad \text{(A-2)}$$

Distance measure for fuzzy numbers. To be able to deal with curvilinear membership functions, generalized left–right fuzzy numbers (GLRFN) of Dubois and Prade (1980) as described by Bárdossy and Duckstein (1995) are defined first. A fuzzy set $A = (a_1, a_2, a_3, a_4)$ is called a GLRFN if its membership function satisfy the following:

$$\mu(x) = \begin{cases} L\left(\dfrac{a_2-x}{a_2-a_1}\right) & \text{for} \quad a_1 \le x \le a_2 \\ 1 & \text{for} \quad a_2 \le x \le a_3 \\ R\left(\dfrac{x-a_3}{a_4-a_3}\right) & \text{for} \quad a_3 \le x \le a_4 \\ 0 & \text{else} \end{cases} \quad \text{(A-3)}$$

where L and R are strictly decreasing functions defined on [0, 1] and satisfying the conditions:

$$L(x) = R(x) = 1 \text{ if } x \le 0 \quad \text{and}$$

$$L(x) = R(x) = 0 \text{ if } x \ge 1$$

For $a_2 = a_3$, we have the classical definition of left–right fuzzy numbers (LRFN) of Dubois and Prade (1980). Trapezoidal fuzzy numbers (TrFN) are special cases of GLRFN with $L(x) = R(x) = 1 - x$. Triangular fuzzy numbers (TFN) are also special cases of GLRFN with $L(x) = R(x) = 1 - x$ and $a_2 = a_3$.
A GLRFN A is denoted as:

$$A = (a_1, a_2, a_3, a_4)_{L_A - R_A} \quad \text{(A-4)}$$

and an α-level interval of fuzzy number A as:

$$A(\alpha) = (A_L(\alpha), A_U(\alpha)) = (a_2 - (a_2 - a_1) L_A^{-1}(\alpha), a_3 + (a_4 - a_3) R_A^{-1}(\alpha)) \quad \text{(A-5)}$$

Let **F(R)** be the set of GLRFNs in **R**. Using the distance measure for interval numbers defined above, a distance between two GLRFNs A and B can be defined as:

$$D^2(A, B, f) = \left\langle \int_0^1 \left\{ \left[\left(\frac{A_L(\alpha) + A_U(\alpha)}{2} \right) - \left(\frac{B_L(\alpha) + B_U(\alpha)}{2} \right) \right]^2 + \frac{1}{3}\left[\left(\frac{A_U(\alpha) - A_L(\alpha)}{2} \right)^2 + \left(\frac{B_U(\alpha) - B_L(\alpha)}{2} \right)^2 \right] \right\} f(\alpha)\, d\alpha \right\rangle \Bigg/ \int_0^1 f(\alpha)\, d\alpha \quad \text{(A-6)}$$

Here f, which serves as a weighting function, is a continuous positive function defined on [0, 1]. The distance is a weighted sum (integral) of the distances between two intervals at all α levels from 0 to 1. It is reasonable to choose f as an increasing function, indicating greater weight assigned to the distance between two intervals at a higher α level. The equations to

Table A-1. Distance functions for some commonly used fuzzy numbers

Fuzzy numbers	$f(\alpha)$	$D_T^2\ (A, B, f)$
Trapezoidal fuzzy numbers $A = (a_1, a_2, a_3, a_4)_{\mathrm{Tr}}$ $B = (b_1, b_2, b_3, b_4)_{\mathrm{Tr}}$	α	$\left(\frac{a_2+a_3}{2}-\frac{b_2+b_3}{2}\right)^2+\frac{1}{3}\left(\frac{a_2+a_3}{2}-\frac{b_2+b_3}{2}\right)[(a_4-a_3)-(a_2-a_1)-(b_4-b_3)+(b_2-b_1)]+\frac{2}{3}\left(\frac{a_3-a_2}{2}\right)^2+\frac{1}{9}\left(\frac{a_3-a_2}{2}\right)[(a_4-a_3)+(a_2-a_1)]+\frac{2}{3}\left(\frac{b_3-b_2}{2}\right)^2+\frac{1}{9}\left(\frac{b_3-b_2}{2}\right)[(b_4-b_3)+(b_2-b_1)]+\frac{1}{18}[(a_4-a_3)^2+(a_2-a_1)^2+(b_4-b_3)^2+(b_2-b_1)^2]-\frac{1}{18}[(a_2-a_1)(a_4-a_3)+(b_2-b_1)(b_4-b_3)]+\frac{1}{12}[(a_4-a_3)(b_2-b_1)+(a_2-a_1)(b_4-b_3)-(a_4-a_3)(b_4-b_3)-(a_2-a_1)(b_2-b_1)]$ (A-7)
	1	$\left(\frac{a_2+a_3}{2}-\frac{b_2+b_3}{2}\right)^2+\frac{1}{2}\left(\frac{a_2+a_3}{2}-\frac{b_2+b_3}{2}\right)[(a_4-a_3)-(a_2-a_1)-(b_4-b_3)+(b_2-b_1)]+\frac{1}{3}\left(\frac{a_3-a_2}{2}\right)^2+\frac{1}{6}\left(\frac{a_3-a_2}{2}\right)[(a_4-a_3)+(a_2-a_1)]+\frac{1}{3}\left(\frac{b_3-b_2}{2}\right)^2+\frac{1}{6}\left(\frac{b_3-b_2}{2}\right)[(b_4-b_3)+(b_2-b_1)]+\frac{1}{9}[(a_4-a_3)^2+(a_2-a_1)^2+(b_4-b_3)^2+(b_2-b_1)^2]-\frac{1}{9}[(a_2-a_1)(a_4-a_3)+(b_2-b_1)(b_4-b_3)]+\frac{1}{6}[(a_4-a_3)(b_2-b_1)+(a_2-a_1)(b_4-b_3)-(a_4-a_3)(b_4-b_3)-(a_2-a_1)(b_2-b_1)]$ (A-8)
Triangular fuzzy numbers $A = (a_1, a_2, a_3)_{\mathrm{T}}$ $B = (b_1, b_2, b_3)_{\mathrm{T}}$	α	$(a_2-b_2)^2+\frac{1}{3}(a_2-b_2)[(a_3+a_1-2a_2)-(b_3+b_1-2b_2)]+\frac{1}{18}[(a_3-a_2)^2+(a_2-a_1)^2+(b_3-b_2)^2+(b_2-b_1)^2]-\frac{1}{18}[(a_2-a_1)(a_3-a_2)+(b_2-b_1)(b_3-b_2)]-\frac{1}{12}(2a_2-a_1-a_3)(2b_2-b_1-b_3)$ (A-9)
	1	$(a_2-b_2)^2+\frac{1}{2}(a_2-b_2)[(a_3+a_1-2a_2)-(b_3+b_1-2b_2)]+\frac{1}{9}[(a_3-a_2)^2+(a_2-a_1)^2+(b_3-b_2)^2+(b_2-b_1)^2]-\frac{1}{9}[(a_2-a_1)(a_3-a_2)+(b_2-b_1)(b_3-b_2)]-\frac{1}{6}(2a_2-a_1-a_3)\times(2b_2-b_1-b_3)$ (A-10)

compute distance for some of the commonly used fuzzy numbers with two different weighting functions [$f(\alpha) = 1$, representing equal weights for intervals at different α levels, and $f(\alpha) = \alpha$, indicating more weight given to intervals at higher α level] are presented in Table A-1.

Literature Cited

Alphonce, C. B. 1997. Application of the analytic hierarchy process in agriculture in developing countries. *Agricultural Systems* 53(1):97–112.

Bárdossy, A., and L. Duckstein. 1995. Fuzzy rule-based modeling with applications to geophysical, biological and engineering systems. CRC Press, Boca Raton, Florida, 232 pp.

Boughton, D. A., E. R. Smith, and R. V. O'Neill. 1999. Regional vulnerability: A conceptual framework. *Ecosystem Health* 5:312–322.

Boyle, T. P., J. Sebaugh, and E. Robinson-Wilson. 1984. A hierarchical approach to the measurement of changes in community induced by environmental stress. *Journal of Environmental Testing and Evaluation* 12:241–245.

Calais, M. D., R. G. Kerzee, J. Bing-Canar, E. K. Mensah, K. G. Croke, and R. S. Swger. 1996. An indicator of solid waste generation potential for Illinois using principal component analysis and geographic information system. *Journal of the Air and Waste Management Association* 46:414–419.

Chatfield, C., and A. J. Collins. 1980. Introduction to multivariate analysis. Chapman and Hall, London, 246 pp.

Chen, S.-J., and C.-L. Hwang. 1992. Fuzzy multiple attribute decision making. Springer-Verlag, Berlin, 536 pp.

Crawford, G., and C. Williams. 1985. A note on the analysis of subjective judgement matrices. *Journal of Mathematical Psychology* 29:387–405.

DeAngelis, D. L., L. W. Barnthouse, W. Van Winkle, and R. G. Otto. 1990. A critical appraisal of population approaches in assessing fish community health. *Journal of Great Lakes Research* 16:576–590.

Dubois, D., and H. Prade. 1980. Fuzzy sets and systems: Theory and applications. Academic Press, New York, 393 pp.

EPA. 1998. Guidelines for ecological risk Assessment. Risk assessment forum. EPA/630/R-95/002F. *Federal Register* 63(93):26846–26924.

Everitt, B. S., and G. Dunn. 1992. Applied multivariate data analysis. Oxford University Press, New York, 304 pp.

Hotelling, H. 1933. Analysis of a complex of statistical variables into principal components. *Journal of Educational Psychology* 24:417–41.

Johnson, A. R. 1988. Diagnostic variables as predictors of ecological risk. *Environmental Management* 12:515–523.

Jones, K. B., K. H. Riitters, J. D. Wickham, R. D. Tankersley, R. V. O'Neill, D. J. Chaloud, E. R. Smith, and A. C. Neale. 1997. An ecological assessment of the United States: Mid-Atlantic region: A landscape atlas. EPA/600/R-97/130. Office of Research and Development, Washington, DC, 105 pp.

Karr, J. R. 1991. Biological integrity: A long-neglected aspect of water resource management. *Ecological Applications* 1:66–84.

Karr, J. R., K. D. Fausch, P. L. Angermeier, P. R. Yant, and I. J. Schlosser. 1986. Assessing biological integrity in running waters: a method and its rationale. Special Publication 5, Illinois Natural History Survey, Champaign, Illinois.

Kaufman, A., and M. M. Gupta. 1991. Introduction to fuzzy arithmetic, theory and application. Van Nostrand Reinhold, New York, 351 pp.

Kersting, K. 1988. Normalized ecosystem strain in micro-ecosystems using different sets of state variables. *Verh. Int. Verein. Limnol.* 23:1641–1646.

Klir, G. J., and Yuan, B. 1995. Fuzzy sets and fuzzy logic: Theory and applications. Prentice Hall, Upper Saddle River, New Jersey, 574 pp.

Lewis, R., and D. E. Levy. 1989. Predicting a national acid rain policy. Pages 155–170 *in* B. L. Golden, E. A. Wasil, and P. T. Harker (eds.), Application of the analytic hierarchy process. Springer-Verlag, New York.

Lootsma, F. A. 1997. Fuzzy logic for planning and decision making. Kluwer Academic Publishers, Dordrecht, 195 pp.

Lootsmar, F. A. 1999. Multi-criteria decision analysis via ratio and difference judgement. Kluwer Academic Publishers, Dordrecht, 283 pp.

Mummolo, G. 1996. An analytic hierarchy process model for landfill site selection. *Journal of Environmental Systems* 24(4): 445–465.

O'Neill, R. V., C. T. Hunsaker, K. B. Jones, K. H. Riiters, J. D. Wickham, P. Schwarz, I. A. Goodman, B. Jackson, and W. S. Baillargeon. 1997. Monitoring environmental quality at the landscape scale. *Bioscience* 47:513–551.

O'Neill, R. V., K. H. Riitters, J. D. Wickham, and K. B. Jones. 1999. Landscape pattern metrics and regional assessment. *Ecosystem Health* 4:225–233.

Ott, W. R. 1978. Environmental indices—theory and practice. Ann Arbor Science, Ann Arbor, Michigan, 371 pp.

Pearson, K. 1901. On lines and planes of closest fit to systems of points in space. *Philosophical Magazine* 2:559–572.

Rachdawong, P., and E. R. Christensen. 1997. Determination of PCB sources by principal component method with non-negative constraints. *Environmental Science and Technology* 31:2686–2691.

Ramanathan, R., and L. S. Ganesh. 1995. Energy resource allocation incorporating qualitative and quantitative criteria: an integrated model using goal programming and AHP. *Socio-Economic Planning Sciences* 29(3):197–218.

Riitters, K. H., R. V. O'Neill, and K. B. Jones. 1997. Assessing habitat suitability at multiple scales: a landscape-level approach. *Biological Conservation* 1997:191–202.

Saaty, T. L. 1977. A scaling method for priorities in hierarchical structure. *Journal of Mathematical Psychology* 15:234–281.

Saaty, T. L. 1978. Exploring the interface between hierarchies, multiple objectives, and fuzzy sets. *Fuzzy Sets and Systems* 1(1):57–68.

Saaty, T. L. 1980. The analytic hierarchy process, planning, priority setting, and resource allocation. McGraw-Hill, New York, 287 pp.

Saaty, T. L. 1986. Absolute and relative measurement with the AHP: The most livable cities in the US. *Soci-Economic Planning Sciences* 20(6):327–331.

Silvert, W. 1997. Ecological impact classification with fuzzy sets. *Ecological Modelling* 96(1/3):1–10.

Silvert, W. 2000. Fuzzy indices of environmental conditions. *Ecological Modelling* 130(1/3):111–119.

Smith, E. P., K. W. Pontasch, and J. Cairns. 1989. Community similarity and the analysis of multispecies environmental data: A unified statistical approach. *Water Resources* 24:507–514.

Statherropoulos, M., N. Vassiliadis, and A. Pappa. 1998. Principal component and canonical correlation analysis for examining air pollution and meteorological data. *Atmospheric Environment* 32(6):1087–1095.

Suter, G. W. 1993. A critique of ecosystem health concepts and indices. *Environmental Toxicology and Chemistry* 12:1533–1539.

Topalián, M. L., P. M. Castañé, M. G. Rovedatti, and A. Salibián. 1999. Principal component analysis of dissolved heavy metals in water of the Reconquista River (Buenos Aires, Argentina). *Bulletin of Environmental Contamination and Toxicology* 63:484–490.

Tran, L., and L. Duckstein, L. 2002. Comparison of fuzzy numbers using a fuzzy distance measure. *Fuzzy Sets and Systems* (in press).

USGS. 1982. Codes for the identification of hydrologic units in the United States and the Caribbean outlying areas. USGS Circular 878-A. US Geological Survey, Reston, Virginia.

Varis, O. 1989. The Analysis of preferences in complex environmental judgments—A focus on the Analytic Hierarchy Process. *Journal of Environmental Management* 28(4):283–294.

Wickham, J. D., R. V. O'Neill, K. H. Riitters, T. G. Wade, and K. B. Jones. 1997. Sensitivity of selected landscape pattern metrics to land-cover misclassification and differences in land-cover composition. *Photogrammetric Engineering and Remote Sensing* 63:397–402.

Wickham, J. D., K. B. Jones, K. H. Riitters, R. V. O'Neill, R. D. Tankersley, E. R. Smith, A. C. Neale, and D. J. Chaloud. 1999. An integrated environmental assessment of the Mid-Atlantic Region. *Environmental Management* 24(4):553–560.

Yu, C.-C., J. T. Quinn, C. M. Dufournaud, J. J. Harrington, P. P. Rogers, and B. Lohani. 1998. Effective dimensionality of environmental indicators: a principal component analysis with boothstrap confidence intervals. *Journal of Environmental Management* 53:101–119.

Yu, T.-Y., and L.-F. Chang. 2000. Selection of the scenarios of ozone pollution at southern Taiwan area utilizing principal component analysis. *Atmospheric Environment* 34:4499–4509.

Zadeh, L. A. 1965. Fuzzy sets. *Information Control* 8:338–353.

Zadeh, L. A. 1978. Fuzzy sets as a basis for a theory of possibility. *Fuzzy Sets and Systems* 1:3–28.