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No.10

THE NUMERIC WEIGHTING OF ENVIRONMENTAL INTERACTIONS

BY
JOHN H. ROSS

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FOREWORD

The difficulty in choosing between alternative courses of action is directly related to the amount of information pertaining to each alternative. This difficulty is especially acute in environmental problems, where facts and interrelationships usually have levels of importance that cannot be determined by the relatively simple economic rules generally employed by decision makers. The development of a body of techniques capable of establishing the importance of discrete environmental parameters is critical to the evolution of methodologies for the assessment of environmental alternatives.

This paper proposes a numeric method designed to aid decision makers in determining the importance of individual pieces of environmental information, and suggests a framework for the combination of these data into single quantitative measures of the environmental disruption of each of the alternatives examined. As such, the paper represents another step towards a theory of rational environmental use.



R.J. McCormack

Director General

Lands Directorate

AVANT-PROPOS

La difficulté à fixer son choix parmi toute une gamme de partis possibles est directement liée à la quantité d'information qui s'y rattache. Cette difficulté est particulièrement sérieuse dans le cas de l'environnement où les faits et les relations ont un degré d'importance qu'il est impossible de déterminer par les règles économiques relativement simples auxquelles les technocrates ont souvent recours. La mise au point d'un ensemble de techniques qui permettent d'établir l'importance de paramètres discrets est capitale pour l'évolution des méthodes d'évaluation des choix.

La présente étude propose une méthode numérique qui aidera les technocrates à déterminer l'importance d'éléments d'information isolés et suggère un cadre de travail pour la combinaison de ces données en mesures quantitatives simples des incidences environnementales de chacun des partis examinés. Cette étude représente ainsi une autre étape vers une théorie de l'utilisation rationnelle du milieu naturel.

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R.J. McCormack

Directeur général

Direction générale des terres

ABSTRACT

This paper sets forth a numeric methodology that uses the technique of non-metric multidimensional scaling to determine interval measures of the importance of environmental component interdependencies and then combines these to yield numeric indices of environmental impact.

The proposed methodology is applied to a real-world environmental impact assessment project. The results are found to be in very close agreement with those of a study group charged with performing the same task by conventional methods of impact assessment.

SOMMAIRE

La méthode numérique exposée dans cette étude fait appel à la technique de l'échelle non métrique multidimensionnelle pour déterminer les mesures par intervalle de l'importance de l'interaction des composants environnementaux; leur combinaison produit ensuite les indices numériques des incidences sur le milieu.

La méthode proposée est appliquée à un projet d'évaluation des incidences environnementales dans un milieu réel. Les résultats concordent étroitement avec ceux d'un groupe d'étude chargé d'effectuer les mêmes tâches d'évaluation au moyen de méthodes classiques.

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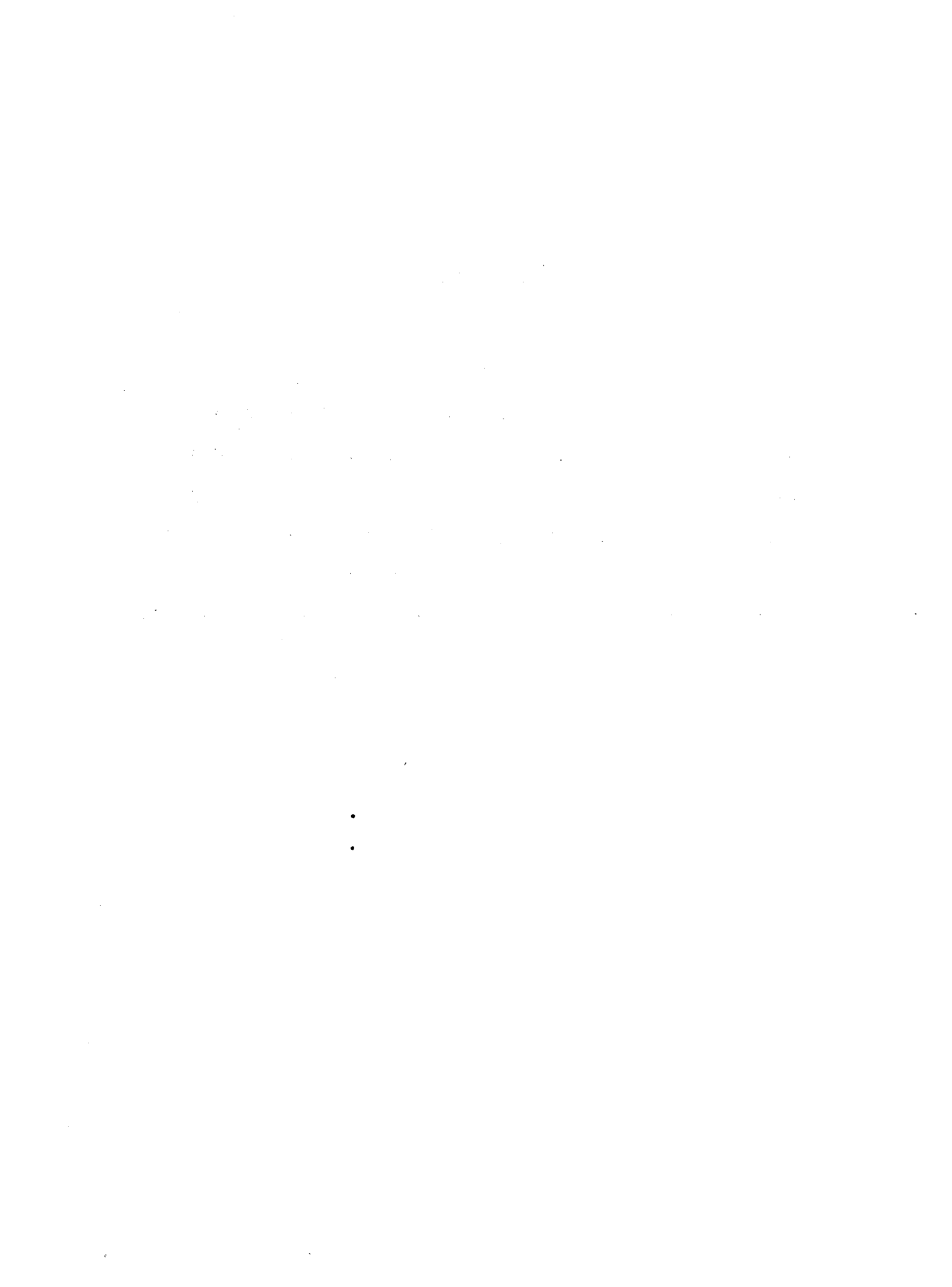
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PREAMBLE

Traditional approaches to the problem of assessing the environmental impact of alternative development options (see, for example, Leopold et. al., 1971) have not evolved rigorous methodologies for evaluating the myriad environmental parameters involved. The chief problems have been encountered in the identification of impacts beyond the first order, the derivation of importance weights for each impact and the design of a technique suitable for combining such weights to form single numeric indices of environmental impact. A previous paper (Ross, 1974 b) has dealt with the first of these problems. The purposes of this paper are to present a method for determining the importance of discrete environmental impacts, and to suggest a technique that may be used to combine these weights to form numeric impact indices.

In an earlier paper, the author has described a component dependency matrix, which identifies first order, or direct, interactions between discrete components of the environment (Ross, 1974 a, Appendix V, pp. 3-8). This matrix (Figure 1), in which a "1" in any cell denotes the dependency of the row component on the column component, is structured in such a way that second and higher orders of interaction may be extracted simply by powering the matrix. In the same paper, the author presents a set of environmental disruption matrices that record ordinal measures of the degree to which each of the environmental dependencies mentioned above would be disrupted by each of the proposed developments (Ross, 1974 a, Appendix V, pp. 9-11). In this latter matrix, (Figure 2) the measures of environmental disruption are expressed ordinally, that is, they cannot be added as interval measures could be. This is its chief weakness.

Figure 1
NANAIMO COMPONENT INTERACTION MATRIX

	CURRENTS	WIND	WATER TEMPERATURE	LIGHT	INTERTIDAL VEGETATION	UPLAND VEGETATION	BACTERIA	INSECTS	LARVAE	SHELL FISH	CRABS	OTHER CRUSTACEANS	PELAGIC FISH	BOTTOM FISH	WATERBIRDS	BIRDS OF PREY	SONG BIRDS	MARSH & SHORE BIRDS	UPLAND GAME BIRDS	AQUATIC & MARINE MAMMALS	UPLAND MAMMALS	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	
CURRENTS	1																					
WIND						1																
WATER TEMPERATURE	1	1		1																		
LIGHT																						
INTERTIDAL VEGETATION	1		1	1																		
UPLAND VEGETATION				1			1	1									1	1	1			1
BACTERIA			1		1	1		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
INSECTS	1	1	1		1	1	1															
LARVAE	1		1		1		1			1	1	1	1	1								
SHELL FISH	1		1		1		1															
CRABS			1		1				1	1		1	1	1								
OTHER CRUSTACEANS			1		1		1	1	1	1	1		1	1								
PELAGIC FISH			1					1	1													
BOTTOM FISH			1		1			1	1	1	1	1	1									
WATERBIRDS					1			1	1	1	1	1	1	1								
BIRDS OF PREY						1		1			1	1	1	1	1		1	1	1			1
SONG BIRDS						1		1		1		1	1	1								
MARSH & SHORE BIRDS						1		1		1	1	1	1	1								
UPLAND GAME BIRDS						1		1														
AQUATIC & MARINE MAMMALS										1	1	1	1	1								
UPLAND MAMMALS						1				1	1	1					1		1			

Note: A(1) in any cell indicates that the row component is dependent on the column component.

Figure 2
NANAIMO DISRUPTION MATRICES

	CURRENTS	WIND	WATER TEMPERATURE	LIGHT	INTERTIDAL VEGETATION	UPLAND VEGETATION	BACTERIA	INSECTS	LARVAE	SHELL FISH	CRABS	OTHER CRUSTACEANS	PELAGIC FISH	BOTTOM FISH	WATERBIRDS	BIRDS OF PREY	SONG BIRDS	MARSH & SHORE BIRDS	UPLAND GAME BIRDS	AQUATIC & MARINE MAMMALS	UPLAND MAMMALS	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	
CURRENTS	1	0 0 0																				
WIND	2				0 1 1																	
WATER TEMPERATURE	3	1 1 1	2 1 1	3 1 1																		
LIGHT	4																					
INTERTIDAL VEGETATION	5	3 2 1	1 1 1	3 3 3																		
UPLAND VEGETATION	6			0 3 3			0 1 1	0 1 1									0 1 1	0 1 1	0 1 1		0 1 1	
BACTERIA	7		1 1 1		2 2 2	0 2 2	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1	1 1 1
INSECTS	8	1 0 0	1 1 1	1 1 1	1 1 1	0 1 1	1 1 1															
LARVAE	9	2 2 2	2 2 2	3 3 3	2 2 2	2 2 2				2 2 2	2 2 2	2 2 2	2 2 2	2 2 2	2 2 2							
SHELL FISH	10	2 2 2	2 2 2	3 3 3	2 2 2	2 2 2																
CRABS	11		2 0 0	2 0 0	2 0 0			2 0 0	2 0 0	2 0 0	2 0 0	2 0 0	1 0 0	2 0 0								
OTHER CRUSTACEANS	12		2 2 2	2 2 2	2 2 2	1 1 1	1 1 1	2 1 1	2 2 2	1 0 0			1 1 1	1 1 1								
PELAGIC FISH	13		2 2 2				2 2 2	3 3 3														
BOTTOM FISH	14		2 2 2	2 2 2	2 2 2		2 2 2	3 3 3	1 0 1	1 0 1	3 3 3	1 2 2										
WATERBIRDS	15			3 1 1			1 0 0	2 0 1	3 1 0	3 0 1	3 1 0	2 1 1	2 1 1	2 1 0								
BIRDS OF PREY	16				0 3 3		0 1 1			1 0 0	1 0 0	1 1 1	1 0 1	2 1 1		0 2 2	0 1 0	0 1 1		0 2 2		
SONG BIRDS	17				0 3 3		1 3 3		1 0 1		2 1 1	1 1 1	1 1 1									
MARSH & SHORE BIRDS	18				0 2 2		0 1 0		1 0 1	1 0 1	2 2 2	1 1 1	3 3 3									
UPLAND GAME BIRDS	19				0 3 3		0 1 1															
AQUATIC & MARINE MAMMALS	20								1 1 1	2 0 0	2 2 2	2 2 2	2 2 2	2 2 2								
UPLAND MAMMALS	21				0 3 3				0 2 2	0 1 0	0 3 3					0 1 1		0 1 1				

ALTERNATIVE

1	3
2	4

DISRUPTION LEVEL

- ALTERNATIVE 1 = INNER HARBOUR
- ALTERNATIVE 2 = JACK POINT
- ALTERNATIVE 3 = DUKE POINT (A)
- ALTERNATIVE 4 = HARMAC SOUTH
- ALTERNATIVE 5 = DUKE POINT (B)

- 0 - NO NOTICEABLE DISRUPTION
- 1 - SLIGHT DISRUPTION
- 2 - APPRECIABLE DISRUPTION
- 3 - SEVERE DISRUPTION

The crux of the matter, obviously, is the development of a technique that would enable one to weight and summarize the information contained in the component interaction and environmental disruption matrices. Subsequent sections of this paper deal with a tentative methodology for weighting and summarizing environmental disruption, and present an application of the proposed techniques to a real-world problem of environmental assessment.

PART A -- METHODOLOGY

The body of theory from which the following techniques are taken can be mainly classified as psychometrics, a field that has long been concerned with the measurement of items generally held to be immeasurable. Although an attempt has been made to explain the necessary techniques in simple terms, some readers may experience considerable difficulty with a few of the underlying concepts. Those having problems are advised to refer to a general text on the topic (e.g. Moroney, 1968, Chapter 18) for further clarification.

The Evaluation of 'Intangibles'

Arranging objects or relationships in order of importance or quality, can be especially arduous if judgements are to be based on dimensions, or qualities, that are difficult to define and measure. One is often, for example, requested to prioritize a number of alternative courses of action, each composed of many separate elements. In such a case, hard quantitative decisions are seldom possible because one finds it difficult to say anything more precise than, "I prefer alternative A over alternative B because...".

Clearly, when there are a large number of alternatives to be considered, the task becomes onerous and, as a result, often haphazard.

A logical structure, termed the technique of paired-comparisons, has been developed to aid in the solution of the above-mentioned problem. When using this technique, an individual who has been requested to assess a number (N) of objects is presented with every possible combination of these objects, and asked to make judgements as to which of each pair is favoured. His decisions are recorded in a paired-comparison matrix. An entry (C_{ij}) of "1" in this matrix denotes that the row object i (row stimulus) was judged as being better, or more desirable, than the column stimulus j. Once all possible pairs have been compared, and the decisions recorded in the matrix, the ranking of stimuli can be readily ascertained by summing the rows of the matrix. The stimuli are ranked in order of these row sums. An example comparison matrix is presented as Figure 3.

Figure 3 -- Example Comparison Matrix

Stimulus	1	2	3	4	5	6	Row Sum
1	-	1	1	1	0	0	3
2	0	-	0	1	0	0	1
3	0	1	-	1	0	0	2
4	0	0	0	-	0	0	0
5	1	1	1	1	-	1	5
6	1	1	1	1	0	-	4

The correct ordering of the stimuli in this case is 5, 6, 1, 3, 2, and 4. When the paired-comparison matrix is permuted according to the ranking derived, a characteristic pattern appears in which the upper right portion of the matrix is observed to be composed of 1's, and the lower left portion of 0's (see Figure 4).

Figure 4 -- Permuted Example Comparison Matrix

Stimulus	5	6	1	3	2	4	Row Sum
5	-	1	1	1	1	1	5
6	0	-	1	1	1	1	4
1	0	0	-	1	1	1	3
3	0	0	0	-	1	1	2
2	0	0	0	0	-	1	1
4	0	0	0	0	0	-	0

In the foregoing example, the individual making the comparisons, hereafter termed the judge, has been perfectly consistent in his judgements. It reveals that he has a clear idea of the stimuli, and that he has a good decision rule to follow while making the individual paired comparisons. Such is often not the case. Inconsistent judgements are revealed by the presence of 1's below the diagonal in the permuted matrix. In Figure 5, for example, the preference of the judge for 4 over 5, 5 over 1, and 1 over 4 (generally denoted $4 > 5$, $5 > 1$, $1 > 4$, and termed an intransitive triad) is revealed. It is clearly a case of inconsistent judgement and may indicate an unclear understanding of the stimuli, or a confused or poor decision rule. It might also indicate that one attribute of stimulus 1 was so far superior to that of stimulus 4 that it became the sole determinant of the choice

made in that particular comparison. The paired-comparison technique permits and identifies inconsistencies that would be lost in more traditional ranking approaches.

Figure 5 -- Permuted Example Comparison Matrix
(Inconsistent)

Stimulus	5	6	1	3	2	4	Row Sum
5	-	1	1	1	1	0	4
6	0	-	1	1	1	1	4
1	0	0	-	1	1	1	3
3	0	0	0	-	1	1	2
2	0	0	0	0	-	1	1
4	1	0	0	0	0	-	1

The degree to which the judge has been consistent can be determined by calculating the coefficient of consistency (K) defined by Kendall (1962):

$$K = 1 - \frac{24d}{n^3 - n} \quad \text{if } n \text{ is an odd number}$$

or...
$$K = 1 - \frac{24d}{n^3 - 4n} \quad \text{if } n \text{ is an even number}$$

where n = the number of stimuli and,

where d = the number of intransitive triads observed

The value of K equals 1.0 when d takes a value of 0.0 (i.e., when there are no intransitive triads), and declines to 0.0, as d approaches the maximum number possible. The number of intransitive triads (d) can be

determined by inspecting each of the $n(n-1)(n-2)/6$ triads individually, but in general, it is best to compute its value from the equation:

$$d = \frac{T \text{ max} - T}{2}$$

where T = the sum of the squared deviations of the row sums from their theoretically expected values, and,

$$T \text{ max} = \text{the maximum possible } T = \frac{n^3 - n}{12}$$

The expected number of 1's in each row of the matrix, assuming that the judgements are made randomly, is $(n-1)/2$. We can now extend Figure 5 as shown in Figure 6.

Figure 6 -- The Calculation of T

Stimulus	Row Sum	Expected	Deviation	Deviation ²
5	4	2.5	1.5	2.25
6	4	2.5	1.5	2.25
1	3	2.5	.5	.25
3	2	2.5	.5	.25
2	1	2.5	1.5	2.25
4	1	2.5	1.5	2.25
				<hr/>
			$T =$	9.50

$$\text{Therefore } d = \frac{17.5 - 9.5}{2} = 4$$

$$K = 1 - \frac{96}{192} = .5$$

The interpretation of K is often difficult. Inspection of the permuted comparison matrix, Figure 3, reveals that only one "1" is out of place, yet the number of incorrect judgements this involves (4), is high enough to bring the coefficient of consistency well down. The statistical significance of K must be assessed by comparing d to its expected distribution. A table for this comparison developed for $n < 8$ reveals that $d = 4$ is significant only at the .792 level (Kendall, 1962, p. 192).

The chi square distribution, to which the distribution of d tends as n increases (Kendall, 1962), is used to determine the probability of finding as few as d intransitive triads in a matrix where $n > 7$. Chi square is found from the equation:

$$\chi^2 = \frac{8}{(n-4)} \left| \frac{1}{2} \left(\frac{n(n-1)(n-2)}{6} \right) - d + \frac{1}{2} \right| \pm v$$

where $v = \frac{n(n-1)(n-2)}{(n-4)^2}$

In this case, the probability of χ^2 is the probability that an equal, or higher value of d would be found at random, rather than the inverse - as is usually the case.

The single-judge paired-comparison matrix may be extended to a multi-judge situation by summing the comparison matrices of a number of single judges to yield a group comparison matrix C (Figure 7). In such a case, one could hardly expect the level of unanimity to be as perfect as with a single judge matrix. However, this very fact later permits us to convert the ranking into a metric scale, in which the stimuli are given real values rather than ranks.

Figure 7 -- Permuted Example Group Comparison Matrix (n = 100)

Stimulus	1	2	3	4	5	6	Row Sum
1	-	80	95	97	100	100	472
2	20	-	75	85	95	100	375
3	5	25	-	60	70	90	250
4	3	15	40	-	70	80	208
5	0	5	30	30	-	75	140
6	0	0	10	20	25	-	55

As in the single-judge case, we are concerned with the consistency of the paired comparisons in the matrix, and can use the same methodology to determine both the ranking of the stimuli and the coefficient of consistency. The fact that a number of judges have assessed the stimuli and have not been unanimous in their judgements leads us to calculate the probability of one stimulus being judged better than any other stimulus. This task is performed by calculating the P matrix (Figure 8) in which each entry P_{ij} is defined as:

$$P_{ij} = \frac{C_{ij}}{C_{ij} + C_{ji}}$$

Figure 8 -- Example Proportions Matrix

Stimulus	1	2	3	4	5	6
1	-	.80	.95	.97	1.00	1.00
2	.20	-	.75	.85	.95	1.00
3	.05	.25	-	.60	.70	.90
4	.03	.15	.40	-	.70	.80
5	0.00	.05	.30	.30	-	.75
6	0.00	0.00	.10	.20	.25	-

In this case, each entry P_{ij} designates the proportion of the judgements between row stimulus i and column stimulus j , that favoured i . This matrix, in turn, is transformed into a proximity matrix which indicates the spacing of the stimuli in an M dimensional preference space. In this paper, discussion is restricted to uni-dimensional space, but, the writer wishes to acknowledge the possible existence of preference spaces of many dimensions (hyperspaces).

Each entry in the proximity matrix P^1 (Figure 9) is defined as:

$$P^1_{ij} = |.5 - P_{ij}|$$

In this matrix each entry P^1_{ij} is interpreted as being a measure of the closeness of stimulus i and stimulus j . The smaller P^1_{ij} becomes, the closer the stimuli lie in preference space. In Figure 9, for example, stimuli 1 and 2 are .30 units apart while stimuli 2 and 3 are separated by .25 units. It is legitimate, therefore, to conclude that 2 and 3 are closer together than 1 and 2. Whether it is also valid to conclude that, for example, the distance 2, 1 is thrice as great as distance 4, 3 is debatable, and furthermore, the conclusion is unnecessary to the analysis, as Abler et. al., pp. 97-98 so succinctly demonstrate.

Figure 9 -- Example Proximity Matrix

Stimulus	1	2	3	4	5	6
1	-	.30	.45	.47	.50	.50
2	.30	-	.25	.35	.45	.50
3	.45	.25	-	.10	.20	.40
4	.47	.35	.10	-	.20	.30
5	.50	.45	.20	.20	-	.25
6	.50	.50	.40	.30	.25	-

If we consider the P^1 entries to be ordinal in nature (i.e., we treat .30 merely as being greater than .10) and examine each in turn, a great deal of metric information about the positions of the stimuli in preference space may be deduced by applying a technique known as non-metric Multidimensional Scaling. Although this technique is not described in detail here, a short discussion of the underlying theory is pertinent. Readers wishing to become familiar with the field of measurement by scaling, are referred to the text Mathematical Psychology by Coombs, Dawes and Tversky, 1970.

Let us first consider a hypothetical case in which four stimuli A-D have been compared. From these comparisons, the proximity matrix presented as Figure 10 has been prepared.

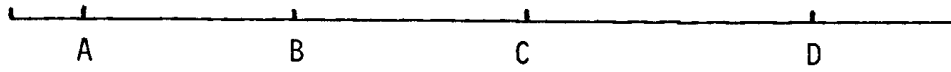
Figure 10 -- Proximity Matrix (Simple Case)

Stimulus	A	B	C	D
A	.00	.11	.23	.34
B	.11	.00	.15	.27
C	.23	.15	.00	.19
D	.34	.27	.10	.00

These proximities are then arranged in rank order: AB (smallest), BC, CD, AC, BD, AD (largest). There are many ways in which the four stimuli could be located in linear space in such a way that all these proximal relationships are satisfied (Figure 11a). It is clear that each of the stimuli may be moved without violating any proximity relationship, but it is also evident that the range of any such perturbation is quite limited (Figure 11b), and that the correlation between possible solutions will be high.

Figure 11 -- The Constraints of Proximal Rankings

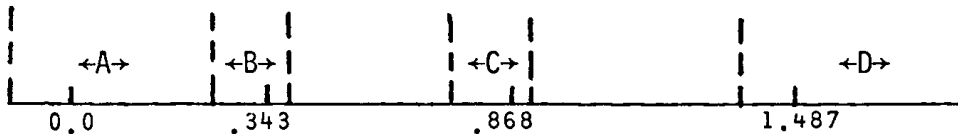
(a) Rank order to stimuli as deduced from the ranking of proximities (spacing consistent with the proximal constraints)



Proximal Constraints

$$AB < BC < CD < AC < BD < AD$$

(b) Ranges of stimuli consistent with these constraints



Logic:

A cannot move further to the left without violating AB < BC
" " " " " " right " " CD < AC

B cannot move further to the left without violating BC < CD
" " " " " " right " " AB < BC

C cannot move further to the left without violating AB < BC
" " " " " " right " " BC < CD

D cannot move further to the left without violating BC < CD
" " " " " " right " " CD < AC

Stimulus values as derived by non metric-multidimensional scaling (TORSCA-9):

$$A = 0.000$$

$$B = 0.343$$

$$C = 0.868$$

$$D = 1.487$$

In the four-stimuli example presented, the amount by which the stimuli can be perturbed is relatively large, but as the number of stimuli, and consequently the number of proximal relationships, increases,

the points are forced to satisfy more and more....(constraints, and) the spacing tightens up until any but very small perturbations of the points will usually violate one or more of the inequalities. (Shepard, 1966, pp. 288)

Thus it is shown that it is not necessary to assume that the individual entries in the proximity matrix (the P^1_{ij}) are metric in nature.

It is sometimes impossible to order a set of points in one dimension in such a way as to satisfy all the interpoint distance constraints. In such cases, one would have to introduce additional dimensions in order to satisfy all constraints or, if only a one-dimensional scale is desired to accept a solution that in some way minimizes the number of constraints broken.

The extent to which a matrix of proximities can be fitted to a metric scale determined by these methods is indicated by a 'stress coefficient', which expresses the degree to which the ordering of the interpoint proximities of the derived configuration agrees with those of the original proximity matrix.

In order to test the ability of the paired-comparison/multidimensional scaling technique to determine an underlying preference scale, the following simulation experiment was conducted.

Twenty objects were hypothesized, ranked, and each assigned a true preference score according to its rank. If people's perceptions of these objects were accurate, they would experience no difficulty in performing paired comparisons and all choices would be unanimous since the highest valued stimulus -object would always be favoured in the comparison.* If, however, people had only a rough idea of the value of a stimulus, some would perceive it as being higher than it really is, and some lower, and thus their choices would not be unanimous. In this experiment, the true values of the stimuli are altered by varying amounts in such a way that the average perturbed value of a stimulus is equal to its true value, but that the distribution of perturbed values about the true value is normal and can be described by a set standard deviation. This experiment results in comparisons between similarly valued stimuli (e.g., 15 and 16) sometimes being judged correctly and sometimes incorrectly. This situation closely models the real world where people are required to choose between pairs of alternatives, the true values of which are rather poorly defined.

In the simulation experiment, the number of hypothetical subjects performing the comparisons between the twenty stimuli was varied. One would expect that the reliability of the individual P_{ij} entries in the proportion matrix, - and consequently the proximities and the final scale derived - would increase as the number of subjects increased, the standard deviation of the distribution of the perceived values being held constant.

* This unanimity would permit us to rank the stimuli, but because all entries of the proximity matrix would have the same value (.50), we would not be able to order the proximities, and would be unable to determine a metric scale.

This was indeed the case; the results, presented in Figure 12, reveal that the recovery of the original scale of stimuli values was relatively good in spite of the high stress values. The recovered scale, it is obvious, becomes more accurate as sample size increases, and as the standard deviation, analogous to the degree of uncertainty, decreases.

The application of the paired-comparison/multidimensional scaling methodology to the component interactions identified by Ross (1974b, p. 19) resulted in the identification of ratio scale weights for each of the interactions he noted.

Figure 12 -- Scale Deduction, Varying Sample Size

<u>Sample Size</u>	<u>Standard Deviation</u>	<u>Stress</u>	<u>Correlation of Recovered Scale with Original Scale</u>
10	2.0	.422	.8875
20	2.0	.345	.9710
50	2.0	.295	.9963
100	2.0	.255	.9964
200	2.0	.252	.9959
500	2.0	.250	.9965
2	20.0	.480	.1241
5	20.0	.500	.2968
10	20.0	.461	.5873
20	20.0	.477	.6678
50	20.0	.355	.9898
100	20.0	.316	.9944
200	20.0	.218	.9943
500	20.0	.166	.9976

To accomplish this task, a paired-comparison matrix is constructed. The stimuli are the interdependencies. One next sets forth the criterion on which the judgements must be made, and directs a number of judges to complete the paired-comparison matrix. In the case of an environmental impact study, they are likely to be the study team although a sample of the well-informed public would be suitable. Figure 13 presents a hypothetical comparison matrix based on the interdependencies identified in Figure 1. The application of the foregoing methodology to this data produces weights for each of the interdependencies, and brings us one step closer to our goal.

Figure 13 -- Hypothetical Comparison Matrix Based on Figure 3

Stimulus	1,2	2,6	3,1	3,2	3,4
1,2	0	5	10	15	20
2,6	15	0	15	12	18
3,1	10	5	0	7	14
3,2	5	8	13	0	4
3,4	0	2	6	16	0

The foregoing discussion sets forth a methodology capable of determining the values of stimuli from the quantitatively much weaker information obtained by presenting paired comparisons to a number of subjects. It describes a simulation experiment in which this methodology was used to recover values from a set of simulated paired-comparison data; and it assesses the degree of relationship between the recovered values and the original values on which the comparisons are based.

The following sections of this paper present a method of combining the stimuli values with the ranked disruption measures discussed previously, a method of summarizing these data in order to permit alternatives to be selected, and a practical application of this methodology to the field of environmental impact prediction.

The Combination of Interdependency Weights and Disruption Rankings

Ross (1974b) formed a three-dimensional matrix D (Figure 2 above) in which two dimensions were the stimuli and the third was that of alternative courses of action. The entries in this matrix were ordinal estimates of the damage that would accrue to each interaction as a result of the choice of each alternative. In order to make use of the information contained in this matrix D , it was necessary to combine the individual D_{ijk} with the corresponding W_{ij} which express the importance of each interaction.

If the interdependency weights derived from the paired-comparison matrix are entered in their appropriate cells in a weighting matrix W , i.e., the weight derived for dependency ij is assigned to W_{ij} , it is evident that the same cells will be occupied as in each 'layer' of the three-dimensional disruption matrix D . If one now considers these data, with the objective of being able to summarize them, a decision can be made about the impact of each of the alternatives. It becomes evident that one may summarize by calculating the total disruption that would be caused by each alternative. This summarization is accomplished by combining for each alternative the rank of each disruption ij with the weight of the corresponding dependency ij . The question, of course, is how to proceed with this combination. It would not be valid to calculate these summary measures by summing the product of the rankings and the

corresponding weights (i.e. using the equation:

$$S_k = \sum_{i=j}^{NV} \sum_{j=i}^{NV} D_{ijk} * W_{ij} \text{ where } S_k = \text{the summary measure of } k\text{th alternative,}$$

$NV = \text{the number of variables in the interdependency Matrix } A,$
 $D = \text{the disruption matrix, and}$
 $W = \text{the weighting matrix)}$

because the rank data contained in D cannot be multiplied, since they denote order, not interval spacing.

One may, however, utilize this information in a paired-comparison way. Another comparison matrix (X) is constructed, this time between alternatives rather than variables, (Figure 14).

Figure 14 -- Hypothetical Alternative Comparison Matrix (X)

Alternative	1	2	3
1	0.0	X_{12}	X_{13}
2	X_{21}	0.0	X_{23}
3	X_{31}	X_{32}	0.0

One then inspects all the cells ij in the disruption matrix D and increment X_{k1} each time that alternative k is observed to be more disruptive than alternative 1. The amount X_{k1} is incremented is, in each case, equal to W_{ij} . Each entry in X is therefore defined as -

$$X_{k1} = \sum_{i=1}^{NV} \sum_{j=1}^{NV} W_{ij} d \text{ where } d = 1 \text{ if } D_{ijk} > D_{ij1}, 0 \text{ otherwise}$$

It should be noted that in cases where all the alternatives have been judged to be equally disruptive d is always zero, and no contribution to X is made. In this case, it would be unnecessary to calculate a weight for the interdependency, and it is best omitted from the paired-comparison matrix. Such omissions, it is evident, will greatly reduce the number of

comparisons that must be made by the subjects because the number of these increases as $N(N-1)/2$ (where N is the number of stimuli - in this case inter-dependencies).

This comparison matrix is then converted to the proportions matrix Y (Figure 15) by the formula:

$$Y_{ij} = \frac{X_{ij}}{X_{ij} + X_{ji}}$$

Figure 15 -- Hypothetical Alternative Proportions Matrix (Y)

Alternative	1	2	3	Z
1	0.00	Y_{12}	Y_{13}	Z_1
2	Y_{21}	0.00	Y_{23}	Z_2
3	Y_{31}	Y_{32}	0.00	Z_3

where $Z_i = \frac{NA}{\sum_{j=i} Y_{ij}} / (NA)$

Interpretation of these Y_{ij} is difficult because of the introduction of the dependency weights. However, each Y_{ij} may be considered to be a measure of the probability that Alternative i causes more disruption than Alternative j . From this matrix, we may calculate a single value for each alternative by finding the average of each row in the matrix, denoting it as Z . The value of Z_i , then represents a metric measure of the disruption which would result from the choice of Alternative i .

The foregoing sections of this paper have outlined a methodology for determining a numeric measure of environmental disruption. The following section presents a real-world application of the methodology.

PART B -- THE NANAIMO CASE

The foregoing sections of this paper have outlined a tentative methodology designed to estimate the magnitude of the environmental disruptions that may accrue to an environmental system as a result of the construction of alternative development projects. This section of the paper will present the application of the proposed methodology to the problem of selecting a location for a lumber transshipment facility on the east coast of Vancouver Island (Ross, 1974a).*

Interdependency Weighting

The sixty-nine first order interdependencies identified as having different disruption levels (Figure 1) were arranged in pairwise comparison form and presented individually to each member of the study team for judgement. For each ij comparison, they were directed to formulate the question: "In terms of its contribution to the production of biomass, is interdependency i more important than interdependency j?". If the answer was in the affirmative, a "1" was entered in the ijth cell. To reduce fatigue in completing the P/C matrix, only the upper triangular portion was completed. The lower part was filled in during the analysis by entering the complement of each response in the appropriate cell below the diagonal.

*Ross was faced with the task of assessing the environmental disruption that would be caused by the construction of a major facility at one of five alternative sites. These are not discussed here, but are listed in Appendix I, along with the definitions of environmental components identified.

Analysis of the resultant individual comparison matrices (permuted examples of which are presented as Figures 16-20) revealed that each of the five subjects was extremely consistent in his judgements, as evidenced by the coefficients of consistency K presented in Figure 21. It is of interest to note that although all individuals revealed a remarkably high degree of consistency, indicating that each had a very firm idea of the "true" ordering of the sixty-nine stimuli, by no stretch of the imagination could the agreement among individuals be considered high. The rank correlations between the individuals' rankings are presented as Figure 22.

Figure 21 -- Nanaimo Individual Consistency Measures

<u>Subject</u>	<u>Consistency (K)</u>	<u>Significance</u>
1	.89331	>.001
2	.85269	.001
3	.92539	.001
4	.83507	.001
5	.94563	.001

Figure 22 -- Individual Ranking Correlation Matrix

Subject	1	2	3	4	5	Consensus
1	1.000	- .050	.337*	.104	- .023	- .034
2	- .050	1.000	- .071	.031	.456*	.054
3	.337*	- .071	1.000	- .203	- .126	.015
4	.104	.031	- .203	1.000	.170	.148
5	- .023	.456*	- .126	.170	1.000	.004
Consensus	- .034	.054	.015	.148	.004	1.000

*Statistically significant at the .95 level

Inspection of the sixth column of Figure 22 reveals that the consensus ranking derived from the five individual paired-comparison matrices was only weakly related to any of the individual scales.

The permuted group-comparison matrix (Figure 23) reveals the composite ranking of the interdependencies. The matrix shows a reasonable degree of unanimity, and has a consistency of .252 which is over thirty-three standard deviations from the mean and therefore very significantly non-random.

The proximity matrix (Figure 24) was scaled using the TORSCA-9 Multidimensional Scaling Program, which deduced the weights to be assigned to each component interdependency. The configuration reached during the analysis had a stress of .414; 78% of the 52,394 distance constraints were satisfied.

Figure 25 -- Nanaimo Alternative P/C Analysis -- Weighted

Comparison Matrix

Alternative	1	2	3	4	5
1	-	3.186	6.703	12.593	12.517
2	9.829	-	6.159	14.250	12.686
3	9.614	0.308	-	11.861	8.723
4	8.747	0.000	0.000	-	.493
5	9.135	0.000	0.000	3.930	-

Proportions Matrix

Alternative	1	2	3	4	5	Z
1	-	.245	.411	.589	.578	.455
2	.755	-	.952	1.000	1.000	.927
3	.589	.048	-	1.000	1.000	.659
4	.411	.000	.000	-	.110	.106
5	.422	.000	.000	.890	-	.328

Combination of Weights and Disruptions

The interdependency weights and disruption matrix (Figure 2) were combined by the methods outlined above. The results of this combination are presented in Figure 25. From the two scales presented therein, one can see that the sites are ranked in the order 2, 3, 1, 5, 4. This ranking indicates that the Harmac South alternative would cause the least environmental disruption. The ordering of the alternatives according to their environmental disruption is, therefore:

- (a) Jack Point
- (b) Duke Point (a) (with barge channel)
- (c) Inner Harbour
- (d) Duke Point (b) (without barge channel), and
- (e) Harmac South.

In order to test the procedure by which the Z scale was calculated, a proximity matrix formed from the data of Figure 25 was submitted for multidimensional scaling. The resulting scales are presented in Figure 26. The product moment correlation between the two scales is .884, indicating a very close agreement between them.

In order to test the sensitivity of the analysis, the alternative P/C analysis was performed again. This time the interdependencies were assigned equal weights. The results of the check are shown in Figure 27, which indicates that the solution reached is quite stable. The product moment correlation between the weighted and unweighted Z scales is .955.

Figure 26 -- Scale Comparison (Weighted Scales)

<u>Alternative</u>	<u>Z Scale</u>	<u>MDS Scale</u>
1	.455	.766
2	.927	1.339
3	.659	1.339
4	.106	.280
5	.328	.106

Figure 27 -- Nanaimo Alternative P/C Analysis -- Equally Weighted

Comparison Matrix

Alternative	1	2	3	4	5
1	-	9	17	36	35
2	34	-	13	36	34
3	32	1	-	31	25
4	32	0	0	-	0
5	31	0	9	0	-

Proportions Matrix

Alternative	1	2	3	4	5	Z
1	-	.209	.347	.529	.530	.404
2	.791	-	.929	1.000	1.000	.930
3	.653	.071	-	1.000	1.000	.681
4	.471	.000	.000	-	.000	.118
5	.470	.000	.000	1.000	-	.368

Discussion

The close agreement between the ordering of alternatives derived by the foregoing quantitative analysis and that reached via non-analytical processes (Ross, 1974a, p. 58 ff) led to a number of pointed questions. The study group, in ranking the alternatives 1, 2, 3, 5, 4, was not restricted to the information contained in this numerical analysis. The group was free to draw - and probably could not have been prevented from drawing - on a wide variety of additional information which may or may not have had a direct bearing on the problem, but which undoubtedly influenced their "subjective" decisions - whether or not they were aware of it.

The most obvious of these bits of outside information is the question of uniqueness. This analysis has not considered the uniqueness of the particular environmental interactions per se, although, it might be expected that these would be taken care of in the paired-comparison weighting portion of the analysis. Ross' group, when confronted with this suggestion, replied that the lack of information concerning the magnitude of the interactions, as contrasted with their importance, militated against the reduction of the problem to a quantitative exercise. They were unanimous in stating that environmental uniqueness parameters had not been included, and were adamant in their view that uniqueness considerations had played no part in their paired-comparison decisions relating to the environmental interactions. When presented with the quantitative replication of their decision, they expressed agreement with the ranking on purely biological grounds, but stated that the study area's relative scarcity of the estuarine sub-environment and its relative plenitude of rocky beach

and wooded upland environments caused the former to have a much greater value.

The choice of the original environmental components, from which Ross' interaction and, subsequently, disruption matrices were prepared, is obviously critical to the whole process of investigating environmental disruption in this manner. It is evident that a careful selection of these components would allow an unscrupulous researcher to bias a study at will, especially if the analysis did not weight the interactions as a base for quantitative analysis.

Although, in this analysis, the judgements of all judges were given equal weight, it is obvious that this need not necessarily be so. One could easily make a case for the differential weighting of the judges' responses according to their experience with the environment under investigation. The problem would occur in assigning the weights for each. Any scheme adopted would be arbitrary, and therefore, difficult to defend.

Another problem in the application of the technique discussed above, lies in the sheer amount of work that the judges must perform. In this study, each of the five judges was required to make 2,346 individual paired comparisons! This was even more onerous than it seems, because of the complex nature of the stimuli being compared.

Finally, the question of testing the final scale derived from the analysis must be discussed. In most modelling attempts, the analyst has a well-defined answer to use as an objective. In this experiment, there was only a rank ordering of the alternatives, and this ordering was necessarily assumed to be correct. Under this assumption, the model

performed quite well, for both the equally and unequally weighted trials. Whether it would perform as well in a different situation is another question.

PART C -- SUMMARY

The foregoing sections of this paper have presented a proposed methodology for determining the importance weights of discrete environmental impacts and combining these weights into numeric impact indices, and have described an application of this methodology to a real-world environmental assessment problem. The task of this section is to summarize the technique and the application, and to suggest how it may be employed in future environmental impact assessment problems.

The technique outlined above proceeds from an environmental interaction matrix which identifies dependencies among components of the environmental system being studied. An environmental disruption matrix, prepared from the former, identifies the dependencies for which weights must be determined. These, in turn, are submitted in a paired-comparison format to a panel of judges. The resulting data are reduced to interval weights through the use of multidimensional scaling, and are then combined with the entries of the disruption matrix, again in a paired-comparison mode. The resulting proportions matrix is scaled to derive interval indices of disruption for each alternative course of action.

The foregoing techniques were applied to a problem concerning port development. The results were in close agreement with those of a study group charged with performing the same task by conventional methods of impact assessment.

The future uses of the methodology outlined above depend on the ability of the scientific community to refine methods for the measurement of still more subjective concepts such as uniqueness, and to establish firm quantitative relationships between environmental components. The chief drawback of the outlined methodology is the often large amount of work that is required to judge the importance of the environmental dependencies.

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