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# WORTHY: a new model for ecological ranking and evaluation

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**Abstract**
Ecological ranking and environmental decision making require that a set of “objects” (e.g., competing sites for species introduction, or alternative sites for the allocation of man-made features) are listed from the best to the worst one. The resulting ranking is then used to choose which actions to implement; worse and intermediate solutions are immediately excluded, while optimal and sub-optimal solutions are taken into account, discussed and then applied. In this paper, WORTHY is presented as a new model for ecological ranking and evaluation of competing alternatives based on a set of weighted criteria. I have developed WORTHY model with the goal of employing a TOPSIS-like algorithm for worthy solutions in situations of environmental and ecological conflict management. Compared to TOPSIS algorithm, WORTHY allows to: a) decide the type of normalization, b) build an user-defined decision function, c) perform what-if analysis and d) sensitivity analysis.

**Keywords** competing alternatives; decision making; sensitivity analysis; TOPSIS-like algorithm; user-defined decision function; what-if analysis.

## 1 Introduction

Ecological ranking and decion making is among the pivotal topics in ecology, both at a local and landscape scale (Ferrari et al., 2008). It has been widely applied to a variety of issues, like for instance sustainability at municipal level (e.g., Ferrarini et al., 2001; Clerici et al., 2004), optimization of tourist activities within protected areas (e.g., Ferrarini et al., 2008; Parolo et al., 2009), individuation of proper actions for habitats of conservation interest (e.g., Rossi et al., 2009), assessment of ecological risk at landscape level (e.g., Zurlini et al., 2001; Zurlini et al., 2004).

In environmental decision-making and ecological ranking, the main steps are the following:

a) setting up evaluation criteria for the topic under study;
b) generating alternatives to be judged;
c) evaluating alternatives in terms of criteria;
d) applying a decision method;
e) accepting one (or few) alternative(s) as the preferred one(s).

Numerous decision methods have been developed in the last decades (Ferrarini, 2011; Janssen, 1994, Saaty, 1980; Voogd, 1983; Zadeh, 1965). In this paper, I introduce a new decision model for ecological ranking and evaluation. It borrows some concepts from the TOPSIS algorithm (Hwang and Yoon, 1981), but it introduces major modifications, the most important being the chance for the user to build an *ad hoc* decision function.

## 2 TOPSIS Model

TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) method is described in Chen and Hwang (1992). It's based on an aggregating function representing closeness to the a reference point in a decision space. The basic principle is that the fittest alternative should have the shortest distance from the ideal (zenith) solution, and the farthest distance from the negative-ideal (nadir) solution.

The rationale for TOPSIS can be expressed in a series of steps.

a) obtain performance data for $n$ competing alternatives over $j$ criteria;

b) develop a set of importance weights $w_j$ for each criteria;

c) calculate the normalized decision matrix;

d) calculate the weighted normalized decision matrix;

e) identify the vector of the ideal (zenith) performances;

f) identify the vector of the negative-ideal (nadir) performances;

g) develop a distance measure of each criterion to both zenith ($D^+$) and nadir ($D^-$).; A number of distance metrics can be applied. Traditional TOPSIS applies the Euclidean norm (square root of the sum of squared distances) to ideal and nadir solutions. There is a variant where distances are measured in absolute value terms. Another commonly used metric is the Tchebychev metric;

h) for each alternative, calculate a ratio equal to the distance to the nadir divided by the sum of the distance to the nadir and the distance to the zenith, as follows:

$$T = \frac{D^-}{D^- + D^+} \tag{1}$$

i) rank alternatives by maximizing $T$.

## 3 WORTHY Model

Given $n$ alternatives $x_i$ ($i$=1...$n$), $m$ weighted criteria $c_j$ ($j$=1…$m$), $m$ weights $w_j$ ($j$=1…$m$), the algorithm behind WORTHY performs 6 steps on the decision matrix (Fig. 1).

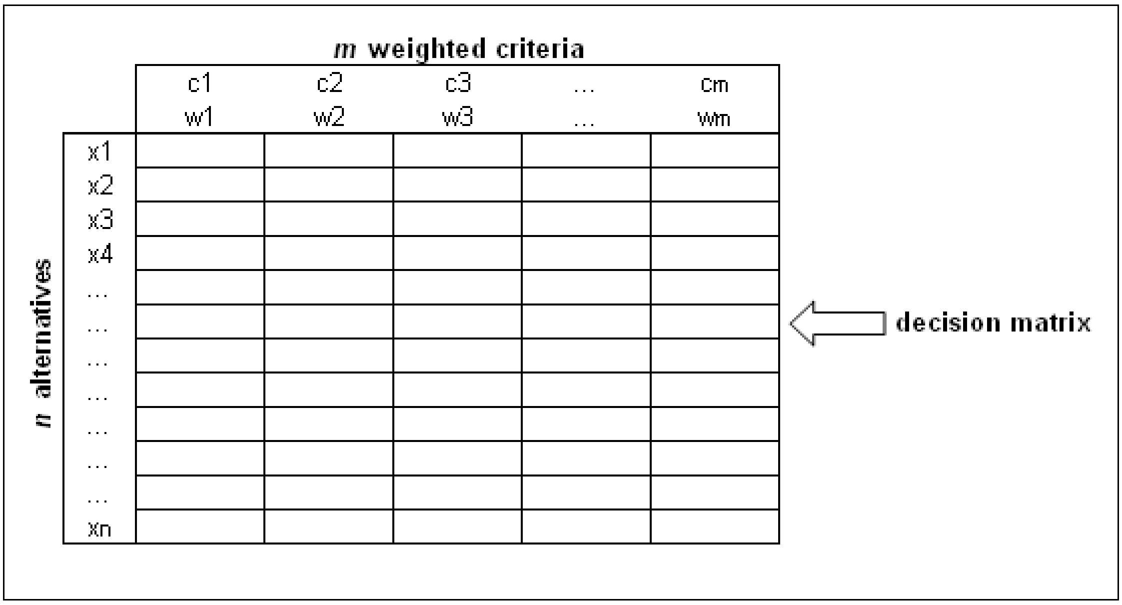


**Fig. 1** Structure of the decision matrix for a generic decision model.

**Step 1) data normalization**

WORTHY makes use of a different and simpler normalization phase with respect to TOPSIS. In this step, the *i-th* observation belonging to the *j-th* column (i.e. $x_{ij}$) is normalized in the [0-1] interval, as follows:

$$v_{ij} = \frac{x_{ij} - \min_j}{\max_j - \min_j} \qquad (2)$$

where $min_j$ and $max_j$ are the minimum and maximum values for the *j-th* criterion, respectively. This transformation is especially useful when criteria have different scales or units of measure, a very common situation in environmental sciences. Alternatively, WORTHY allows for a max-normalization in the form:

$$v_{ij} = \frac{x_{ij}}{\max_j} \qquad (3)$$

Both normalizations impose that the maximum value for criteria is equal to 1, but while equation (2) also imposes the minimum value to be equal to 0, equation (3) does not. This could seem of little importance, but in the former case (i.e. min-max normalization) the maximum possible distance from the zenith or nadir reference point is equal to:

$$D_{\max} = \sqrt{\sum_{i=1}^{m} w_j} \qquad (4)$$

Hence, in the special case of weights all equal to 1 (i.e., no weighted criteria), $D_{max}$ becomes:

$$D_{\max} = \sqrt{m} \qquad (5)$$

where $m$ is the number of criteria. When the maximum distance from zenith or nadir vectors are known, one can compare the resulting distance of each alternative to the maximum possible one. This is a great advantage from an interpretative viewpoint.

**Step 2) building the zenith vector $\vec{Z}$ and the nadir vector $\vec{N}$**

In this step, the two vectors of fittest and unfittest performances are built as follows.

$$\vec{Z} = \left\{ (\max v_{ij} \mid j \in J_1), (\min v_{ij} \mid j \in J_2) \right\} \qquad (6)$$

where $J_1$ is the set of benefit (the higher the better) criteria, while $J_2$ is the set of cost (the higher the worse) criteria. Instead, the nadir vector is built in the form:

$$\vec{N} = \left\{ (\min v_{ij} \mid j \in J_1), (\max v_{ij} \mid j \in J_2) \right\} \qquad (7)$$

In other words, $\vec{Z}$ is the vector which collects the highest values for columns of the decision matrix which represent benefit criteria, and the lowest ones for columns of cost criteria. Since matrix values have been normalized in the previous step, $\vec{Z}$ is made of $m$ binary values equal to 1 for benefit criteria and to 0 for cost ones. $\vec{N}$ is the opposite vector.

**Step 3) calculating the WORTHY score for each alternative**

In this step, for the *i-th* alternative a weighted Euclidean distance from $\vec{Z}$ is calculated as follows:

$$D^+ = \sqrt{\sum_j w_j (v_{ij} - v_{Zj})^2} \qquad (8)$$

where $v_{zj}$ is the *j-th* value of the zenith vector.

At the same time, distance from $\vec{N}$ is calculated as:

$$D^- = \sqrt{\sum_j w_j (v_{ij} - v_{Nj})^2} \quad (9)$$

where $v_{Nj}$ is the *j-th* value of the nadir vector.

At this point, TOPSIS makes use of equation (1) to calculate final scores for alternatives. It's clear that equation (1) is a 3D decision surface (Fig. 2) in the form:

$$Z = \frac{x}{x+y} \quad (10)$$

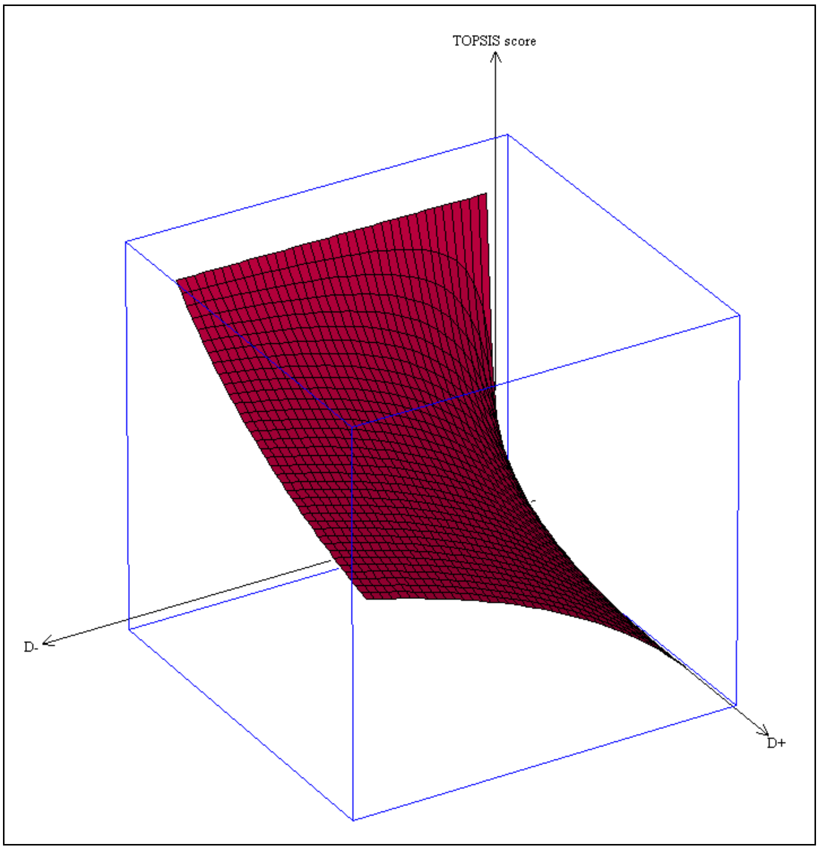


**Fig. 2** The decision curve employed by TOPSIS. $D^+$ is the distance from zenith vector, while $D^-$ is the distance from nadir one. Z-values represent the TOPSIS scores as a function of $D^+$ and $D^-$.

When both $D^+$ and $D^-$ are close to 0, the TOPSIS scores increase rapidly. WORTHY allows for better 3D decision surfaces. For instance the user may choose a 3D decision function like this:

$$Z = \frac{D^- + 1}{D^+ + 1} \quad (11)$$

that fixes the previous problem (Fig. 3).

With respect to equation (10), the latter decision surface grows slower as $D^-$ increases, and WORTHY scores are lower when both $D^+$ and $D^-$ are high (Fig. 3).

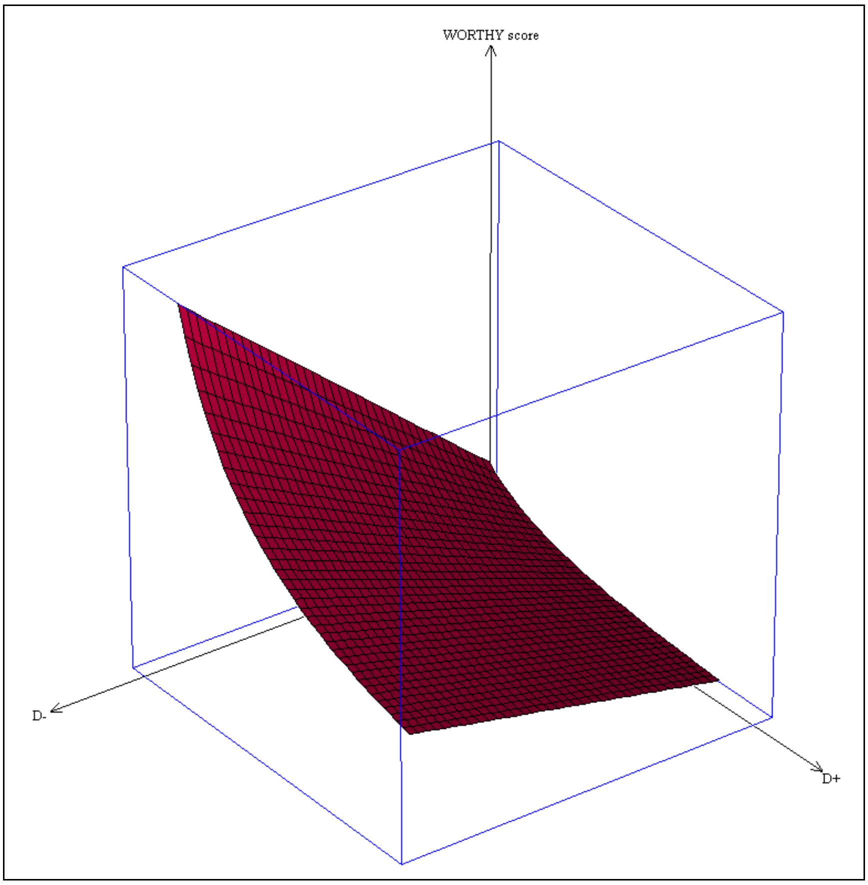


**Fig. 3** A possible decision surface employed by WORTHY. $D^+$ is the distance from the zenith vector, while $D^-$ is the distance from the nadir one. Z-values represent the WORTHY scores as a function of $D^+$ and $D^-$.

Another suitable decision surface could be:

$$Z = \frac{(D^-)^2}{D^+ + 1} \qquad (12)$$

that produces the 3D decision surface of Figure 4.

With respect to equation (11), the latter decision surface grows slower as $D^-$ increases, and Z scores are higher when both $D^+$ and $D^-$ are high (Fig. 4).

The choices represented by equations 11 and 12 are just a subset of WORTHY possible options. In fact, WORTHY allows the user to choose any possible decision function based on $D^+$ and $D^-$. This induces WORTHY to be very flexible and supervised by the user. This makes the user an active actor of the decisional flow, not only during the choice of alternatives, criteria and weights, but also throughout the computational phase.

**Step 4) rank order for each alternative**

In this step, alternatives are ranked from 1 to *n* beginning with the highest WORTHY score (the most desirable alternative), and ending with the lowest (unfittest alternative). WORTHY also accepts cut-off values from the user in order to group WORTHY scores into 3 categories: a) optimal, b) intermediate, c) insufficient.

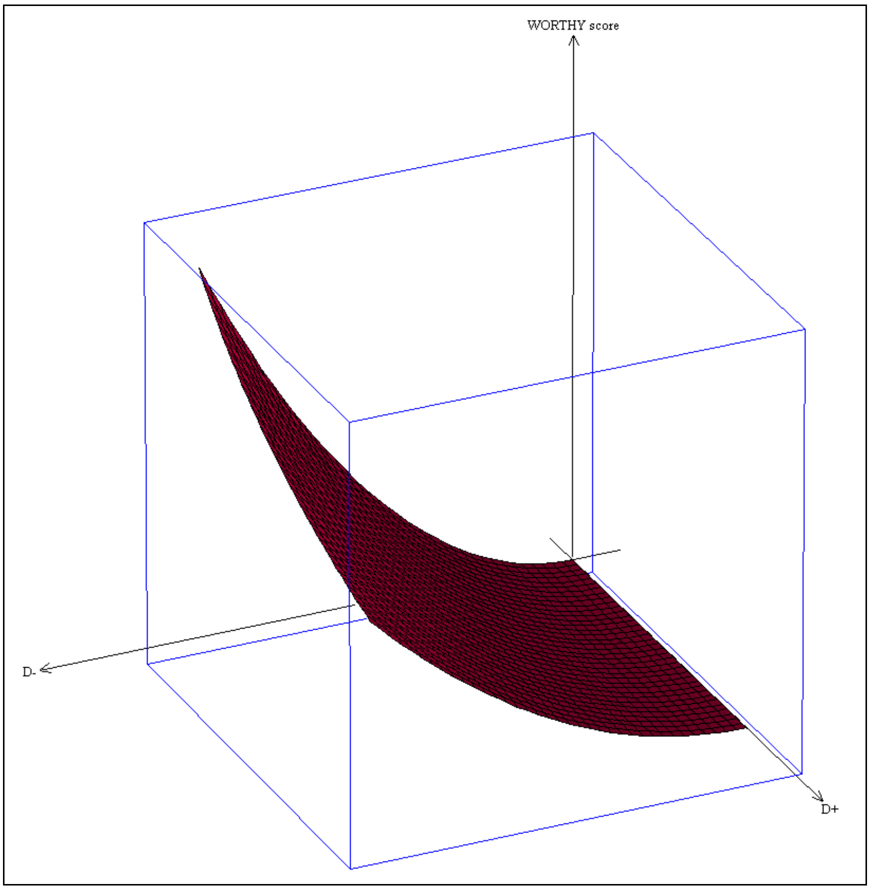


**Fig. 4** A further example of decision surface employed by WORTHY. $D^+$ is the distance from the zenith vector, while $D^-$ is the distance from the nadir one. Z-values represent the WORTHY scores as a function of $D^+$ and $D^-$.

**Step 5) what-if analysis on WORTHY scores**

In this step, WORTHY assesses what happens to the rank order if one criterion is excluded. Criteria are dropped one at a time (leave-one-out analysis), and steps from 1) to 4) are repeated in order to assess the contribution of each criterion to the rank order.

Given *j* criteria, this step is repeated *j* times, hence giving *j* different rank orders. The importance of each criterion is measured by WORTHY through Spearman's *rho* correlation coefficient between each partial rank order and the overall one. Spearman's *rho* correlation coefficient ranges from +1 to -1: a criterion is scarcely important if, after its exclusion, *rho* is close or equal to 1. On the contrary, a criterion gives a substantial contribute to the overall ranking when, after its exclusion, the *rho* value becomes negative.

**Step 6) sensitivity analysis on WORTHY scores**

A major concern in ecological evaluation is the need of justification for matrix data and weights. In this view, sensitivity analysis has the purpose to estimate the degree of uncertainty on WORTHY scores based on uncertainty on criteria weights $w_j$ and on $x_{ij}$ values.

WORTHY allows for sensitivity analysis in two ways: a) by randomly varying *t*-times (with *t* defined by the user) the criteria weights by an user-defined percentage (UDP; usually 1% or 5%), and then calculating the average WORTHY score for each alternative; b) by randomly varying *t*-times $x_{ij}$ values using UDP, and giving back the average score for each alternative.

## 4 Conclusions

Ecological ranking and evaluation are at the core of environmental decision making and conflict management. Proper models are required to do them in a rigorous way.

WORTHY has been proposed here as a new model for ecological ranking and decision making. It borrows some aspects from the TOPSIS decision model, but it presents four main differences: 1) a different and simpler normalization phase, 2) an user-defined 3D decision function, 3) what-if analysis, 4) sensitivity analysis. A software has been developed in order to implement WORTHY into OpenOffice Calc.

The main contribution of WORTHY is the use of an *ad-hoc* decision surface that requires the user to be a more involved actor of the decisional flow.

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