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Marine litter prediction by artificial intelligence

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Abstract

Artificial intelligence techniques of neural network and fuzzy systems were applied as alternative methods to determine beach litter grading, based on litter surveys of the Antalya coastline (the Turkish Riviera). Litter measurements were categorized and assessed by artificial intelligence techniques, which lead to a new litter categorization system. The constructed neural network satisfactorily predicted the grading of the Antalya beaches and litter categories based on the number of litter items in the general litter category. It has been concluded that, neural networks could be used for high-speed predictions of litter items and beach grading, when the characteristics of the main litter category was determined by field studies. This can save on field effort when fast and reliable estimations of litter categories are required for management or research studies of beaches—especially those concerned with health and safety, and it has economic implications. The main advantages in using fuzzy systems are that they consider linguistic adjectival definitions, e.g. many/few, etc. As a result, additional information inherent in linguistic comments/refinements and judgments made during field studies can be incorporated in grading systems.

Keywords: Marine litter prediction; Neural network; Fuzzy systems; Beach grading; Artificial intelligence; Turkey

1. Introduction

Litter in the marine environment leads to numerous problems, which adversely affects coastal development sectors. Marine litter is defined as "solid materials of human origin that are discarded at sea or reach the sea through waterways or domestic or industrial outfall" (Williams et al., 2000). Because of beach litter, possible adverse effects can occur for human health and wild life on beaches. Prevention at source is one of the most important strategies in enabling litter pollution reduction, but for this aim to be achieved strong links between measurement and management need to be realized (Earll et al., 2000; Tudor and Williams, 2001; Balas et al., 2001; Tudor et al., 2002). Due to the high variability of beach characteristics and sources of beach litter, there is yet no widely accepted approach or standardized methodology to litter pollution. Some are

- Individual items of beach marine debris are counted and classified or recorded as presence or absence (Rees and Pond, 1996).
- The whole beach is surveyed from splash zone to waters edge (Dubsky, 1995).
- Transects—used to represent a sub section of a beach, may be used of varying width. The optimum transect width is one which provides a reliable sample width (Williams et al., 2000).
- Transect line quadrates or randomly dispersed quadrates (Dixon and Hawksley, 1980).
- Strand line counts (Williams and Simmons, 1997).
- The EA/NALG (2000) approach—see later.
- Sourcing the litter (Williams et al., 2003).
- Postal surveys (Dixon, 1992).

In addition, various indices, both qualitative and quantitative, have been used in order to assess litter (Williams et al., 2000). In this paper, artificial intelligence techniques such as neural network and fuzzy systems are applied as alternative methods for the

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determination of beach litter grading by using litter survey results obtained from the Antalya coastline, which is known as the Turkish Riviera.

Artificial intelligence consists of different techniques such as neural networks and fuzzy logic, utilized to solve complex problems based on human intelligence (Pham and Pham, 1999). Neural networks and fuzzy systems represent two methodologies that deal with uncertainty arising from system complexity. An artificial neural network (neuronet) is a non-linear computing system consisting of a large number of interconnected processing units (neurons), which simulates human brain learning. In recent years, neuronets have been successfully used for analysis of coastal environments, such as for time series processing (Deo and Kumar, 2000), tidal level forecasting (Tsai and Lee, 1999), pattern classification (Deo and Naidu, 1999; Balas, 2001), wave data assessment (Tsai et al., 1999) and structural failure predictions (Mase et al., 1995).

Fuzzy systems are the collection of "if-then" rules defining the fuzzy relations of fuzzy variables in the systems by utilizing fuzzy logic or fuzzy set theory (Zadeh, 1997; Zadeh, 1999). Fuzzy systems make effectively use of "additional information" such as knowledge and experience of humans, i.e. it is *different from* standard modeling approaches. It simulates management ability regarding complex tasks under significant uncertainties. Fuzzy systems can be used in modeling, analyzing, predicting and/or controlling of complex system behaviors associated with inherent non-linearity, when adequate knowledge and reliable methods of measuring system variables are not available (Moshgbar et al., 1995).

Available methodologies of beach litter grading cannot predict the number of litter items and categories based on previous measurements of litter data. Therefore, these are litter assessment methods rather than a prediction model. Furthermore, available methods require the tasks of counting, classification, surveying and evaluation carried out at various beaches. Field campaigns generally necessitate well-trained measurement teams and extensive disbursements over long time. The litter prediction model developed in this study provides the prediction of litter categories based on artificial intelligence. Therefore, this model will save time—only one category is measured, so it is easier for the field worker, and provides fast and reliable estimations of litter categories—a necessity for successful beach management. The constructed neural network satisfactorily predicted the beach gradings and litter categories, based on the number of litter in general litter category for beaches in Antaya. As a result, future predictions of litter items and categories can be performed by this model, which will lead to better management scheme concerning the health, safety and economic implications of beaches.

The artificial neural network was chosen as the prediction model for litter grading, since it is a non-linear robust prediction method that can satisfactorily handle the randomness and uncertainty inherent in data sets and complex natural systems. Neuronets exhibit the characteristics of "biological" networks to simulate the human brain learning and they have been successfully used nowadays for the prediction of environmental processes.

In addition, a fuzzy system was developed to obtain the classification of the beaches, since uncertainty is generally inherent in beach work due to the high variability of beach characteristics and the sources of litter categories. This resulted in effective utilization of "the judgment and knowledge of beach users" in the evaluation of beach gradings. Frequently, linguistic descriptions, such as "very good", "above average" have been used to grade a beach, "many/few items" etc. have been used for litter counts. Available methods cannot include qualitative knowledge of human to this extent.

In summary, artificial neural networks can demonstrate the learning and adaptation capabilities of biological neural systems by predicting litter grades from new data sets considering the change in environmental conditions. Therefore, they are flexible and robust non-linear prediction models. On the other hand, fuzzy systems can effectively utilize the uncertainties inherent in human knowledge, but they do not have the capability of learning. Therefore, neural networks have more "generalization ability" (functional approximation capability) than the fuzzy systems in using a database. However if the database is limited and contains qualitative information, fuzzy systems can be alternatively used as litter assessment models. The advantage of fuzzy systems is that, they can handle human based information such as experience and judgment, and can consider qualitative data described by language.

2. Artificial neural networks

Artificial neural networks (neuronets) are based on a simplified modeling of the human brain's biological functions. Therefore, they are very effective in computational systems where complex real world problems are modeled (Svozil et al., 1997). The analogy between the artificial neuron and the biological neuron is that connections between neurons represent axons and dendrites, connection weights stand for synapses, and the threshold approximates the activity in the soma as illustrated in Fig. 1, where y_j is the output of the jth neuron, x_i is the ith input signal, w_i is the connection weight from the ith input neuron to jth neuron, t_j is the threshold or bias value of the jth neuron and $f(x)$ is the nonlinear function modeling the system response. Neural networks can be classified according to their activa-

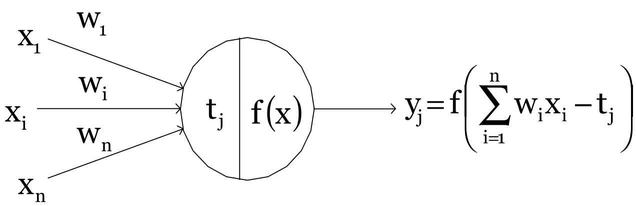

Fig. 1. Artificial neuron.

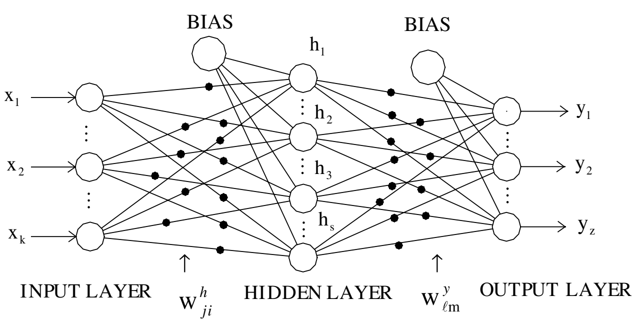

Fig. 2. Multi-layer feed-forward neural network.

tion phase as feed forward or recurrent, and according to learning phase as supervised or unsupervised.

A multi-layer feed-forward neural network (MFF) has a layered structure as given in Fig. 2. Hidden layers exist between the input (first) and the output (last) layer. Each layer has neurons that receive input from a layer below and send their output to units in a layer above. Activation of a hidden unit is a function of the weighted input and the threshold. A multi-layer feed-forward neural network is trained by a supervised learning algorithm with a set of chosen examples called a training data set and then tested via a data set.

In the supervised learning algorithm, weight and bias factors were determined by minimizing the convergence criteria, i.e. the performance index defined as:

$$\nabla J(\mathbf{w}) = \frac{1}{zN}\sum_{n=1}^{N}\nabla E(\mathbf{w}, n) \tag{1}$$

The weight and bias updates are proportional to the performance index ($\nabla\mathbf{J}$) by

$$\nabla E(\mathbf{w}, n) = \left[\frac{\partial E}{\partial w_{11}^{h}}\cdots\frac{\partial E}{\partial w_{ji}^{h}}\,\frac{\partial E}{\partial w_{11}^{y}}\cdots\frac{\partial E}{\partial w_{\ell m}^{y}}\right] \tag{2}$$

where N is the number of input and output vectors, n is the epoch number, z is the number of neurons at the output layer, $\nabla\mathbf{E}(\mathbf{w}, n)$ is the gradient vector of total instantaneous errors that have components associated with the weights of the hidden and output layers $\mathbf{W}^{\mathrm{h}}$ and $\mathbf{W}^{\mathrm{y}}$, respectively.

$$\mathbf{W}^{\mathrm{h}} = [w_{11}^{\mathrm{h}}\ldots w_{1i}^{\mathrm{h}}\ldots w_{ji}^{\mathrm{h}}] \quad j = 1,\ldots,s,\ \ i = 1,\ldots,k \tag{3}$$

$$\mathbf{W}^{\mathrm{y}} = [w_{11}^{\mathrm{y}}\ldots w_{1m}^{\mathrm{y}}\ldots w_{\ell m}^{\mathrm{y}}] \quad \ell = 1,\ldots,z,\ \ m = 1,\ldots,s \tag{4}$$

In the error minimization of the conjugate gradient (CG) learning algorithm, subsequent weight factors were calculated in the steepest descent direction ($\mathbf{P}_0 = -\mathbf{g}_0$) as follows

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \eta_k\mathbf{P}_k \tag{5}$$

$$\mathbf{P}_k = -\mathbf{g}_k + \beta_k\mathbf{P}_{k-1} \tag{6}$$

$$\beta_k = \frac{\mathbf{g}_k\mathbf{g}_k^T}{\mathbf{g}_{k-1}\mathbf{g}_{k-1}^{\mathrm{T}}} \tag{7}$$

where $\mathbf{w}(k+1)$ is the value of the weight vector at the iteration step $(k+1)$, η_k is the step size adjusted at kth iteration, β_k is the scalar Fletcher–Reeves factor (De Gersem and Hameyer, 2001).

3. Fuzzy systems

Fuzzy systems or fuzzy rule based systems are formal representations of informal linguistic descriptions by means of **if-then** rules or fuzzy rule base. A fuzzy rule base represents the relationship between two or more fuzzy variables in the general form of "**if**" antecedent proposition; "**then**" consequent proposition or a set of consequences that can be inferred. In the linguistic fuzzy system the antecedent and consequent propositions are always fuzzy propositions. For example, a fuzzy rule base consists of: *if* x is A_i *then* y is B_i $i = 1, 2, 3, \ldots, N$, where, x and y are linguistic variables or antecedent (input) and consequent (output) fuzzy variables, respectively; A_i and B_i are antecedent and consequent linguistic terms or primary values of the fuzzy variables. The values of the primary values A_i and B_i are fuzzy sets given by membership functions. A number between 0 and 1 indicates the degree of membership to a set. For example a membership function maps every element of the universe discourse X to an interval $[0, 1]$ and this mapping can be written as $\mu_A(x) : X \to [0, 1]$. Fuzzy logic differs from binary logic in the way that the membership function in binary logic suddenly jumps from 0 to 1, while the membership function in fuzzy logic smoothly varies between the values of 0 and 1. The main advantage of fuzzy sets for solving real world problems is the ability to capture non-linear relationship between inputs (antecedents) and outputs (consequents) without oversimplification. In order to use the fuzzy systems, an algorithm or fuzzy inference mechanism can be generally applied to compute the output value for the given input values, as conceptual units of fuzzy rule base.

Fuzzification is to transform the input fuzzy sets (the input information) into an appropriate form to be handled by the fuzzy rule based system. In the fuzzy rule based system, logical relationship between the fuzzy input and output sets are revealed and quantified. The fuzzy rule base consists of conditional statements that describe the dependence of one or more linguistic variable on another. The analytical form of an if/then rule is the fuzzy relation called the implication relation, which can be defined

$$R_i(x,y) = \int_{(x,y)} \mu_{R_i}(x,y)/(x,y) \tag{8}$$

where $\mu_{R_i}(x,y)$ is the membership function of the implication relation. There are different forms of implication relations reported in the literature (Czogala and Leski, 2001). Implication relations are obtained through different fuzzy implication operators, for example the Larsen implication operator (Ambalal, 2002) can be defined as follows

$$\mu_{R_i}(x,y) = \mu_{A_i}(x) \cdot \mu_{B_i}(y) \tag{9}$$

Fuzzy rules are connected by an aggregation operator of either union ($\vee$) or intersection ($\wedge$) depending on the implication operator. Results obtained from the fuzzy rule based system are retransformed from internal fuzzy quantities (consequent) into numerical quantities or crisp outputs (y') by the defuzzification methods. The center of gravity method is the most commonly used defuzzification method and is given as

$$y' = \frac{\int \tilde{\mu}_y(y) y \,\mathrm{d}y}{\int \tilde{\mu}_y(y)\,\mathrm{d}y} \tag{10}$$

4. A case study on beaches in Antalya, Turkey

In the first stage, litter categorization for the Antalya coast was obtained using artificial neural networks trained by litter measurement data obtained at Antalya beaches. In the second stage, these measurements were assessed by fuzzy systems and an alternative litter categorization system developed.

Field litter studies were conducted on some of the most attractive tourist beaches of the Turkish Riviera (Antalya) coast, namely Cirali, Konyaalti, Kemer, Side and Belek. For a 100 m stretch of beach located on the normal access points (Fig. 3), all litter items were enumerated and placed in their respective EA/NALG (2002) categories/grades. Litter amounts collected ranged from 18 to 743 items/100 m stretch of beach. Seven categories were determined for the assessment of litter, namely, sewage related litter and debris; potentially harmful litter items; gross litter; general litter; accumulations of litter; oil pollution and occurrence of faeces of non-human origin (EA/NALG, 2002). Litter items were graded from the best (grade A) to worst case (grade D) as shown in Table 1. Field measurements indicated that the main beach litter item (the most abundant in terms of quantity) was the general litter category. The number of litter items in other categories was low and oil pollution was not observed (Table 2).

The amount of litter in the other categories was in correlation with the general litter category and as numbers in the general litter category were amplified an increase in other litter items was commonly observed. For example, from Table 2, when numbers in the general litter category were taken at their minimum value of 13, there was no litter item in other categories, except sewage related debris (five items). When the number of items in the gross litter category was taken at its maximum value (10—category C), the number of litter items occurring in 'general litter' was 473 (category B). As the number of sewage related debris was taken to its maximum value of 9 (category C), 'general litter' items were measured as 103 (category B). When harmful litter items were measured at its maximum value of 31 (category D), the number of 'general litter' items observed was 529 (category C). For the number of faeces taken at a maximum value of 14 (category C), 'general litter' items were measured as 239 (category B).

Therefore, this relationship between general litter (when the number of litter items in the general litter category can be measured or identified) and other litter categories, was used for the construction of neural networks in order to predict the number of litter items in other categories and the beach grade. Input to the neural network is the number of litter items in the general litter category. The neural network predicts the classification of the beaches (A–D) for other litter categories given in Table 1.

For the neural network training stage, a single hidden layer consisting of 40 neurons was utilized. The CG learning algorithm was applied and the minimum mean square errors of computations (MSE) was defined as the performance index for the training stage. The uni-bipolar sigmoid and linear functions were allocated as activation functions of hidden and output layers, respectively. The initial value of the step size was taken as $\eta = 0.01$ and the number of iteration steps was selected as 1000. The minimum mean square errors of computations at the end of iterations were calculated as 0.0928. Input and output values of the neural network were normalized between 0 and 1 by using the maximum and minimum values of the ranges. Grading of litter categories (A–D) which are the output values of the neural network, were coded as numerical values of 1, 2, 3 and 4, respectively.

Testing stage results of the trained neural network are given in Fig. 4 for Antalya beaches. In this figure, the predicted litter categories of the trained neural network are compared with ones obtained from the measurements in their numerically coded form. The neural network predicted, with a high correlation of $R = 0.91$, the classification of litter items for the remaining six categories, (sewage related litter and debris; potentially harmful litter items; gross litter; general litter; accumulations of litter; oil pollution and occurrence of faeces of

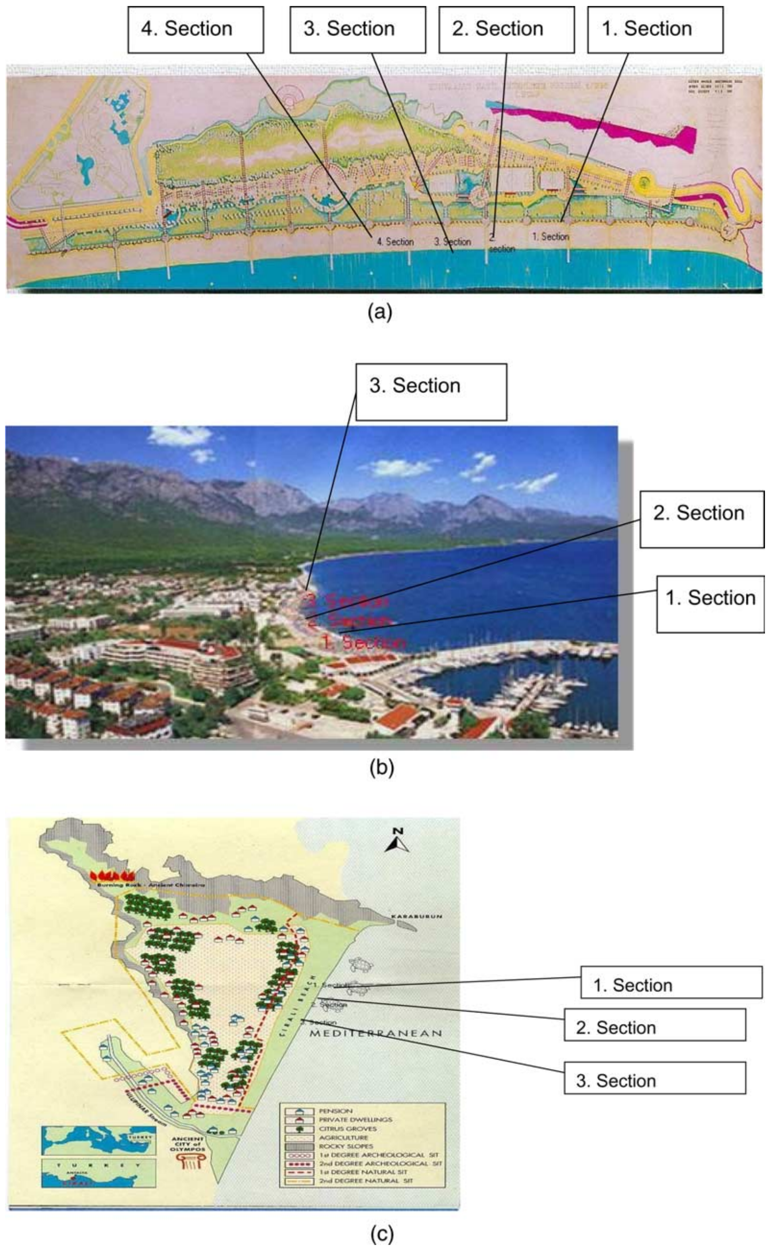

Fig. 3. Survey sections of: (a) Konyaalti; (b) Kemer and (c) Belek beaches.

Table 1
Categories for grading a beach (EA/NALG, 2000)

Category		Type	A	B	C	D
1	Sewage related debris	General	0	1–5	6–14	>15
		Cotton buds	0–9	10–49	50–99	>100
2	Gross litter		0	1–5	6–14	>15
3	General litter		0–49	50–499	500–999	>1000
4	Harmful litter	Broken glass	0	1–5	6–24	>25
5	Accumulations	Number	0	1–4	5–9	>10
6	Oil		Absent	Trace	Noticeable	Objectionable
7	Faeces		0	1–5	6–24	>25

non-human origin), as given for the overall measurement data obtained for the Cirali, Konyaalti, Kemer, Side and Belek beaches (Tables 1 and 2). The number of data points in this figure is $n = 210$. Non-parametric

Table 2
Range of litter items at Antalya beaches

Litter categories	Maximum	Minimum
General litter	733	13
Gross litter	10	0
Sewage related debris	9	0
Harmful litter	31	0
Accumulations	6	0
Faeces	14	0

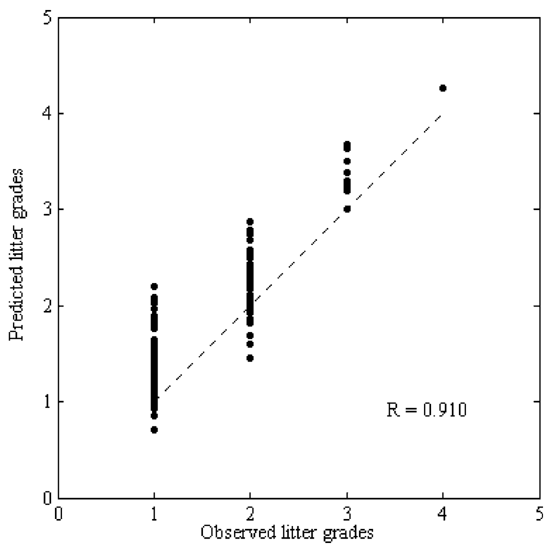

Fig. 4. Measured and predicted litter grades of the trained neural network for Antalya beaches.

Spearman rank correlation coefficients were used to describe the relation between the predicted and measured litter categories. The overall predictions of litter categories from general litter items can be considered as satisfactory, due to the high correlation coefficient between prediction and measurement for the overall data of the surveyed site. These predictions were converted to their original alphabetical litter categories in Fig. 5, for which the final grading can be obtained for Antalya beaches. In Fig. 4, the neural network predictions of litter categories are non-integer numerical values. In Fig. 5 they are converted to the alphabetical grades (A–D) of EA/NALG (2000). Taking the worst grade of the predictions of litter categories for each of the predictions obtained from the neural network, the correlation coefficient between prediction and measurement was increased to $R = 0.965$, although the correlations are carried out on different data set sizes (Fig. 6). Here the worst grade denotes the grade that involved the largest number of litter items for a specific category, as given in Table 1. Therefore, the constructed neural network satisfactorily predicted the grading of the beaches and litter categories based on the number of litter items in the general litter category. The main source of litter on

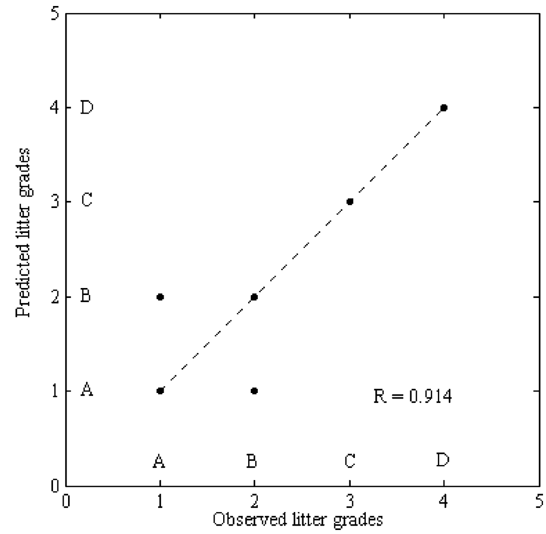

Fig. 5. Predicted litter grades for Antalya beaches using the grading system of EA/NALG (2000).

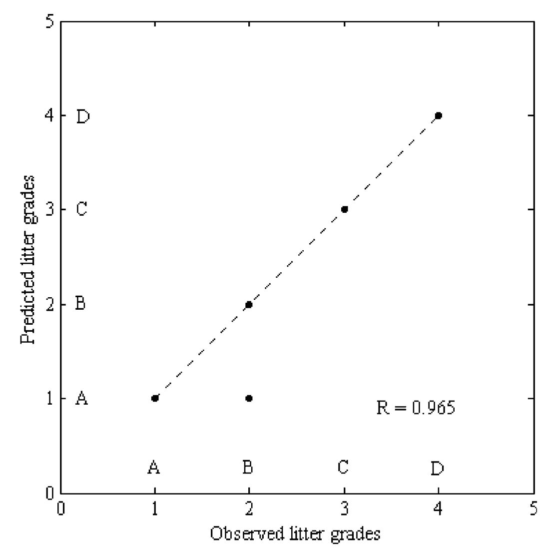

Fig. 6. Grades of litter categories by taking the worst grade for each of the predictions obtained from the neural network.

these beaches was ‘‘beach users’’. A similar study in the UK yielded, in addition, sewage related debris, river, shipping, fishing sources (Williams et al., 2000). For Antalya beaches, the trained neural network can be used for a fast estimation of the number and grading of litter categories, if the number of litter items in the main litter category is determined by field studies.

In the second stage of this study, a fuzzy system of artificial intelligence was developed, which had input parameters of general litter and sewage related debris, and an output parameter of the grading of litter categories. In this study, the uncertainty inherent in litter data that has not a standardized assessment methodology, was appraised by using the fuzzy system. In the

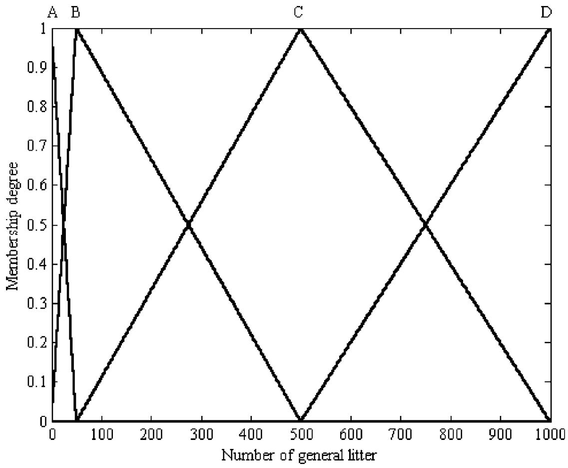

Fig. 7. Fuzzy input sets and the membership functions of the grading system for the category of general litter.

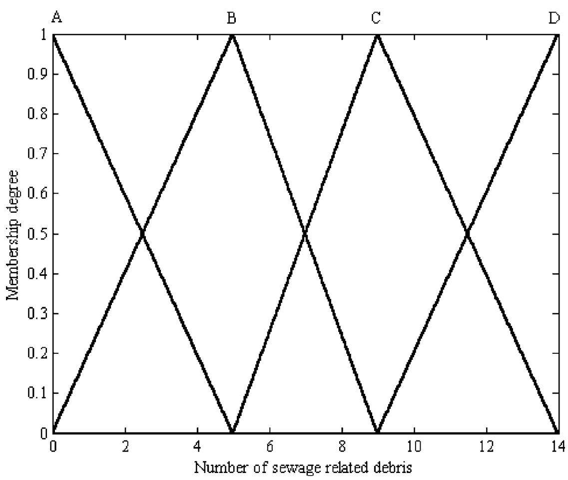

Fig. 8. Fuzzy input sets and the membership functions of the grading system for the category of sewage related debris.

fuzzification process of the system inputs, which were the number of general litter and sewage related debris items, the grading criteria and approach of EA/NALG (2000) was utilized. The fuzzy input sets and membership functions of these variables were obtained for the grading of A–D, from the best to worst case depending on the number of litter items measured on beaches as shown in Figs. 7 and 8. Fuzzy output sets for the grading of litter categories (A: excellent, B: good, C: average and D: worst) were coded as 1, 2, 3 and 4, respectively, as given in Fig. 9. The fuzzy rule based system was established by the Cartesian product (product space) of fuzzy input sets, which resulted in the logical base of 16 fuzzy rules.

An example for the fuzzy rules is the conditional statement in Fortran computer coded program developed for this study, describing the following dependence of linguistic variables:

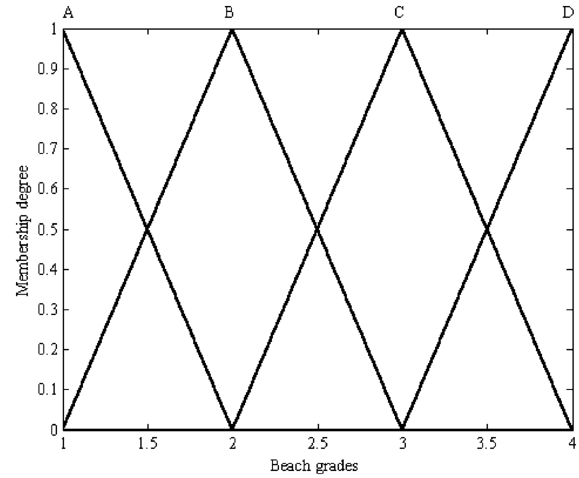

Fig. 9. Fuzzy output sets and the membership functions for the grading of litter categories.

- If the beach category for general litter is excellent and the beach category for the sewage related debris is good; then the grading of that beach is considered as good.

Other pollution categories were also considered in the analysis, since fuzzy systems can handle additional refined linguistic definitions of beach grades. The linguistic definitions of beach users, were aggregated with information obtained by field teams researching public perception, in which attitudes of the public on beach usage and grading were determined from questionnaires distributed to 381 beach users (Balas et al., 2003).

The fuzzy sets of grades given in Figs. 7 and 8 were slightly modified to assess the uncertainties inherent in other litter categories by including supplementary adjectives of “very good (B^+), to some extend good (B^-), above average (C^+), below average (C^-) and bad (D^+)”, i.e. the maximum number of litter items, greater than a certain limiting value in related categories will decrease a half grade in the input fuzzy subset of rules. Therefore, potentially harmful litter, gross litter and accumulations of litter exceeding their limits given in Table 1, will decrease the grading definition in fuzzy rules for general litter, a half grade. Similar interactions for the general litter definitions of rules are available, if there is a trace of oil pollution on the beach. Likewise, the occurrence of faeces of non-human origin affects the rules in the input fuzzy set for sewage related debris. At the testing stage, the litter measurements of the field study were compared with the predictions of the fuzzy system, as illustrated in Fig. 10. The fuzzy system satisfactorily predicted the grading of the beaches and litter categories, since the correlation coefficient between predictions and measurements was high ($R = 0.822$). Predictions were performed for an average central processing unit (CPU) time of 57 s within a standard mean error of $\varepsilon = 1\%$ by using a portable computer having an AMD K6-2^+ (3-D) processor.

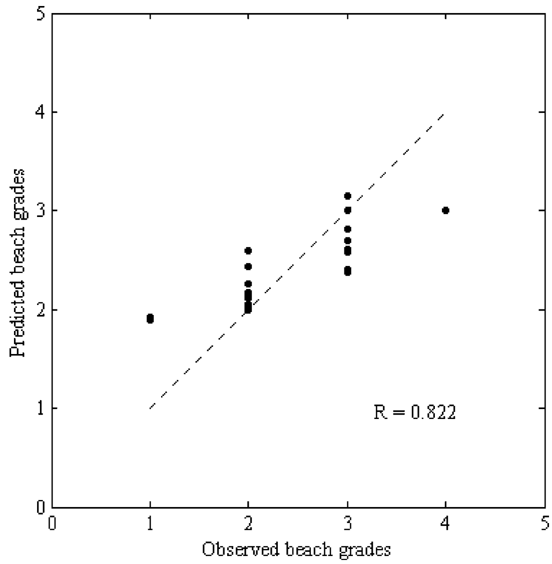

Fig. 10. Comparison of beach grades of the field study with the predicted grades of fuzzy system.

The main advantage in using fuzzy systems was that they could consider the linguistic definitions/notes of beach users and field study teams during measurements. Therefore, they make effective use of "additional information" such as the knowledge and experience of team members. As a result, additional information inherent in the linguistic comments/refinements and judgment of study teams and beach users could be included in the grading system. Specific issues related to beach characteristics, litter assessment methodology and definition of oil pollution, which could not be included in standard procedures and/or could be easily lost in mathematical expressions/evaluations, were incorporated by using this artificial intelligence system. Simply by noting the number of litter items in the general litter category for any beach, the EA/NALG (2000) beach grading system can be obtained and/or refined.

As a result, litter measurements were categorized and assessed by artificial intelligence techniques, and it was concluded that they were practical and fast methods in handling available litter data obtained by such field studies.

5. Conclusions

An alternative categorization system of beaches, to the EA/NALG (2000), was obtained. EA/NALG (2000) litter categories for Antalya beaches, Turkey (Cirali, Konyaalti, Kemer and Belek) were satisfactorily predicted from field studies using artificial neural networks and fuzzy logic systems.

Available methodologies of beach litter grading cannot predict the number of litter items and categories based on previous measurements of litter data. Therefore, they are only litter assessment methods rather than a prediction model. The litter prediction model developed in this study provided the prediction of litter categories based on artificial intelligence. Therefore, this model will save on field effort when fast and reliable estimations of litter categories are required for management purposes. The developed model, which would lead to better management schemes concerning beach health, can perform future predictions of litter items, categories and safety and it also has economic implications.

In addition, a fuzzy system was developed to obtain a beach classification, since uncertainty is generally inherent in marine environment litter management due to the high variability of beach characteristics and sources of litter categories. Litter measurement techniques, excess of litter sources and variability in the coastal characteristics of beaches, were observed as the main uncertainties inherent in the assessment and prediction of litter data for Antalya beaches. The model resulted in effective utilization of the "judgment and knowledge of beach users" by adding linguistic adjectival descriptions, such as "very good", "above average" "few items, many items", etc. Available methods cannot include qualitative knowledge to this extent. Therefore, artificial intelligence techniques, which take into account uncertainties inherent in litter data, could be considered as robust alternatives for assessment of EA/NALG (2000) results and prediction of litter data.

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