A FUZZY LOGIC INFERENCE SYSTEM TO ASSESS FISHERY PRODUCTIVITY IN COASTAL FISHING GROUNDS.

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Abstract

Fuzzy logic provides a powerful tool to capture the uncertainties associated with human cognitive processes. In the present study, a methodology based on Mamdani-type fuzzy inference system (FIS) was applied to classify the Greek coastal fishing landings according to their fishery productivity during the period 1988-2005. However, five fuzzy sets to split the inputs and outputs have been considered suitable for the scope for this study. Eight common fish species have been selected to be the indicators for the classification of the fishing grounds and two hundred eighty nine inference rules (expressed in IF-THEN clauses) were developed. This fuzzy inference system has advantages in flexibility of input data, in the explicit representation of uncertainty and in the ease of incorporating new knowledge, so it can be used as a decision support tool in fishery management.

Keywords: Classification, Fishery Productivity, Fishing Landings, Fuzzy Inference Systems, Fuzzy Logic.

1. Introduction

Marine ecosystems and habitats are quickly deteriorating due to human activities. Since almost all anthropogenic activities ultimately affect the coastal waters, access properties and processes in this environment is the major issue in decision making and system management (Pereira and Ebecken, 2008). The most threatened systems are coastal areas (Hixon et al, 2001) because they are at the center of economic activities and have more than 60% of the world population. The management and control of coastal resources is a complex multidisciplinary task requiring the adequate approaches and techniques (Pereira et al, 2009) and in the form of plan of actions is urgently needed to reach preservation goals (Boesch, 2006).

One of the main fishes driving the changes in marine ecosystems is recognized to be the fisheries. Fishing is the most widespread exploitation activity of marine resources and can severely affect marine ecosystems both directly and indirectly (Jennings and Kaiser, 1998; Jackson et al., 2001). In an ecosystem approach to fisheries, management must draw an information of widely different types, and information addressing various scales (Jarre et al, 2008). Understanding productivity change is very important to fisheries management (Jin et al., 2002). Productivity measurement can provide useful information about fishing effort. The development and application of fishery production and productivity models can evaluate fishery areas performance and provide significant value in future policy guidance.

Mediterranean fishery is characterized by a multi-species composition, where many commercial species appear seasonally in the catches (Reina-Hervas and Serrano, 1987; Spanier et al., 1989; Stergiou et al., 1997). This characteristic creates difficulties in the definition and application of management measures (Kallianiotis et al., 2004). In Greece, where the total length of the coastline is over 15 000 km, fisheries production should play a very important role in the national economy (Stergiou and Pollard, 1994). The total Greek fisheries production has levelled off in contrast to a gradual rise in fishing effort (Stergiou and Petrakis, 1993). This suggests that many of fisheries resources may be fully exploited or overfished (Stergiou and Pollard, 1994) and the need of fishery management is therefore urgent.

Several statistical models (ARIMA, transfer function models, intervention analysis, decomposition and regression models and recently MAFA techniques) have been widely used for the analysis of fishery production data sets (Koutroumanidis et al., 2006). Furthermore, several methods based on multivariate procedures as Principal Component Analysis, Multiple Correspondence Analysis and Cluster Analysis have been applied for the grouping of various fishery areas according to their main characteristics (Sylaios et al., 2009). The major drawback of the above models and methods is that they should be considered as stochastic fluctuating around a 'fuzzy' value and not to follow strictly deterministic rules (May et al., 1978). Conventional hierarchical and fuzzy approaches can describe gradual changes between clusters and unclear boundaries. The main difference between conventional hierarchical approaches and fuzzy approaches is that in conventional hierarchical approaches well defines boundaries between clusters are determined, allocating each case (fishery area) into a single cluster, when fuzzy approaches such as fuzzy cluster analysis allow the determination of similarity of a case to all defines clusters (Sylaios et al., 2009).

The overall aim of the present study is to classify the Greek coastal fishing landings according to their fishery production status by using a Mamdani-type Fuzzy Inference System. Annual landing data of eight fish species during the period 1988-2005 were used for the classification of coastal fishing grounds, which have been recorded by the Hellenic National Statistical Service (HNSS). Although these official statistics are not considered as fully accurate and reliable (Stergiou et al., 1997), HNSS data could be used to identify patterns, groupings and trends of fishery areas production (Sylaios et al., 2009). The Fuzzy Inference System in the field of fishery classification is a useful tool to assess the impacts of fishing on fishery productivity, to provide a more transparent representation of the system under study and to recommend management policies.

Several authors have successfully applied similar fuzzy logic methods in the field of fishery. Fuzzy sets and rules have been constructed for implementation in impact assessment of fish farming on benthos (Silvert, 1997; Angel et al., 1998; Silvert, 2000) and fuzzy models were used to evaluate the vulnerability of marine fishes to fishing (Cheung et al., 2005). Similarly, Jarre et al. (2008) developed a fuzzy logic modern for Southern Benguela to monitor implementation of an ecosystem approach to fisheries (EAF) in the sardine fishery, while Sylaios et al. (2009) established three different fuzzy logic methods to group and rank coastal fishing grounds according to their fishery production status. Chiou et al. (2005) used a Fuzzy MCDM approach to evaluate sustainable fishing development strategies.

2. Materials and Methods

2.1 Fuzzy Logic

In fuzzy logic theory, originally developed by Zadeh (1965), a subject can belong to one or more fuzzy set(s) with a gradation of membership. The degree of membership is defined by fuzzy membership functions. The conventional characteristic mapping of a classical set (called crisp set) takes only two values: one, when an element belongs to the set; and zero, when it does not (Adriaenssens et al., 2004). The mathematical definition of a fuzzy set F is a membership function $\mu_F(x)$ that associates any value x of the variable X to a membership grade between 0 and 1 ($0 \leq \mu_F(x) \leq 1$). Fuzzy logic can be used for mapping inputs to appropriate outputs. Figure 1 shows an input-output map to the fishing grounds productivity status.

The sixteen Greek fishery landings, whose fishery production in all commercial species is recorded by the HNSS, are shown in Figure 2. If we consider that $S = \{s_1, s_2, \ldots, s_n\}$ is the number of the sixteen fishery areas and $X = \{x_1, x_2, \ldots, x_m\}$ is the number of the eight examined species recorded in each area then an 8×16 matrix is produced containing the fishery production of these eight species through the sixteen fishing grounds. The matrix is repeated for the eighteen years considered in this analysis. The equation (1) gives the fishery production in non-dimensionalised form of the i-th species in the j-th fishery area $x_i(s_j)$:

$$z(x_i(s_j)) = z_{ij} = \frac{x_i(s_j) - \min\{x_i(s_k)\}}{\max\{x_i(s_k)\} - \min\{x_i(s_k)\}} \quad (1)$$

where i = 1,2,..,m ; j = 1,2,…n ; k = 1, 2, …n. Finally the landings $x_i(s_j)$ transform into z_{ij}, where z_{ij} takes values from 0 to 1.

2.2 Fuzzy Inference System

Fuzzy Inference is the process of formulating the mapping from a given input to an output using fuzzy logic (Ocampo-Duque et al., 2006). The fuzzy inference process involves three important concepts: membership functions, fuzzy set operations and inference rules. In fuzzy inference systems the relation between the input variable(s) and the output variable(s) are represented by means of fuzzy IF-THEN rules of the following general form: if ‘antecedent proposition’ then ‘consequent proposition’. The antecedent proposition is typically composed of propositions on several input variables joined together by an aggregation operator. Given particular values of the input variables, the degree of fulfilment of a rule is obtained by aggregating the membership degrees of these input values into the respective fuzzy sets. The fuzzy output is determined by the degrees of fulfilment and the consequent parts of the rules. When variables are though to be differently important for the determination of the output, they can be differently weighted (Angel et al., 1998). The values of the different weights of the input variables was based on the mean annual market price of each fish species (expressed in euros per kilogram, averaged over the period that landings refer, 1988 to 2005). A fuzzy output can also be ‘defuzzified’ to produce quantifiable results with no references to fuzzy sets theory (Marchini et al., 2009).

2.3 Structure and functioning of the fuzzy inference system

We developed a fuzzy inference system which aimed to classify the fishery landings according to their fishery production status. The input variables include the species: (a) anchovy, (b) club mackerel, (c) pickerel, (d) European sardine, (e) horse mackerel, (f) common squid, (g) goatfish and (h) bogue (Figure 3). The outputs are expressed as five linguistic categories referring to the levels of the totally fishery production score:

(1) very low, (2) low, (3) medium, (4) high, (5) very high (Figure 4). Total fishery production score is expressed on an arbitrary scale from 0 to 1, with 1 being the highest fishery production score. Trapezoidal membership functions (maximum of 1) were used to represent the input and output fuzzy sets as shown in Figures 3 and 4. Table 1 shows the list of the a, b, c and d membership functions parameters.

The selection of the number of the membership functions of the input and output fuzzy sets has been done with the help of the results of the fuzzy k-Means Clustering procedure. Software FuzMe (Minasny and McBratney, 2002) was used for the fuzzy k-Means Clustering analysis. Table 2 presents the fishing production (in tons) corresponding to the fishing grounds cluster centers, for each fish species.

The optimum number of classes was established on the basis of minimizing the Fuzzy Performance Index (FPI) and the Modified Partition Entropy (MPE), (McBratney and Moore, 1985). In our study the number of classes was five. Two hundred eighty nine rules were enunciated. These rules developed based on the weighted factors of each variable. The form of the first 25 fuzzy inference rules and the weighted factors of each species are shown in Table 3. The successful application of a fuzzy inference system depends on an appropriated weight assignment to the variables involved in the rules. The fuzzy inference system was developed using the Fuzzy Logic Tool box operating under Matlab 7.0.

2.4 A simple example describing a Fuzzy Inference System (FIS)

The procedure of a FIS explained with the following example. We hypothesized that the fishery production of only two species (goatfish and European sardine) is sufficient to evaluate the fishing landings productivity by means of the established FIS, we choose 'low', 'medium', and 'high' fuzzy sets for inputs, and 'low', 'medium', 'high', and 'very high' fuzzy sets for the output. In fuzzy language, the above will defined:

> **Rule 1.** If Landings of goatfish is Low and Landings of European sardine is Low then Fishery Productivity is Low.

Similarly other rules can be enunciated. Obviously occurs that FIS robustness depends on the number and quality of fuzzy rules established. In this example we present three more rules:

> **Rule 2.** If Landings of goatfish is Medium and Landings of European sardine is Medium then Fishery Productivity is Medium.
>
> **Rule 3.** If Landings of goatfish is High and Landings of European sardine is High then Fishery Productivity is Very High.
>
> **Rule 4.** If Landings of goatfish is Medium and Landings of European sardine is High then Fishery Productivity is High.

The above FIS shown in Figure 5. In 1988 the fishery landing 3 produced 50.1 tons of goatfish and 284 tons of European sardine. Non-dimensionalization gives $z_{1,\ 3}$ = 0.0332 and $z_{2,\ 3}$ = 0.0545. After fuzzification, inference rules evaluation, aggregation and defuzzification, the result of fuzzy inference system score for fishery ground 3 is 0.0937, which corresponds to the 'low' production class.

3. Results and Discussion

By employing the fuzzy model and by constructing the Fuzzy Inference System mentioned above, the fishery productivity of the sixteen Greek fishing grounds is evaluated and the final results are shown in Figure 6. Figure 6 shows the FIS scores for each fishing ground through the studied period 1988-2005. None of the examined areas reached a score corresponding to the ‘Very High’ fishing production class. Fishery productivity for all the sixteen fishing grounds changes in time. Areas 4, 5, 6, 7, 9, 11, 16 were constantly in the ‘Very Low’ production class. Fishing grounds 3, 12, 15, and 18 presented a fluctuation in their Fuzzy Inference Systems (FIS) scores through time. The values of the areas 3, 12, 15, and 18 fluctuated between the ‘Very Low’ and the ‘Low’ production classes. Analytically, fishing area 3 and fishing area 15 presented a fluctuation in the time period 1988-1990 and they remained constantly in the ‘Very Low’ production class. Fishing ground 12 was constantly in the ‘Low’ production class except the period 1996-1998, where the values of the FIS scores were in the ‘Very Low’ production class. Fishing areas 12 and 15 presented an increased production in the low and middle-weighted species as anchovy, sardine, club mackerel and pickerel. Area 18 was constantly in the ‘Very Low’ production class except the period 1988-1993 and characterized by an increased production of middle-weighted species, such as horse mackerel, pickerel and bogue. Areas 8, 10, and 17 presented a fluctuated FIS score between three fishing production classes: the ‘Very Low’ production class, the ‘Low’ and the ‘Medium’ production class. The above areas presented an increased production in middle-weighted species as club mackerel, horse mackerel, pickerel, bogue and goatfish. The FIS score for fishing ground 13 fluctuated between the ‘Very Low’, ‘Low’, ‘Medium’, and ‘High’ fishery production classes. Fishing area 14 presented a fluctuation between ‘Low’, ‘Medium’, and ‘High’ fishery production classes. The fluctuations in fishery productivity of areas 13 and 14 seem associated with the production change in anchovy and club mackerel. Fishing ground 8 is characterized by ‘Low’ fishery productivity during years 1988-1989 and 1991-1992, but an increase in FIS score transferred the area to ‘Medium’ production class during the period 1992-1994 and 1995-1996. In years 1989-1990 and through the period 1998-2005, fishing area 8 belongs in ‘Very Low’ production class. During the period 1988-1991, area 10 presented an increase in fishery productivity from ‘Very Low’ production class to ‘Medium’ production class but in years 1992-1993, the FIS score decreases from ‘Medium’ to ‘Low’ fishery productivity. After the year 1995, fishing ground 10 was characterized by ‘Very Low’ fishery productivity. Fishing area 17 during the years 1988-1991 presented a decrease in FIS score from ‘Low’ production class to ‘Very Low’ production class. During the years 1992-1996 area 17 showed an abrupt increase in productivity due to the increase of pickerel, bogue, club mackerel and horse mackerel, which reached in their maximum annual values for the year 1994.

The Fuzzy Inference System that has been constructed in this study, gives the ability to the fishery managers to import the values of the fishery production (in tons) of the selected species for each fishery area, and to obtain a value, which corresponds to the fuzzy inference system score (FIS-score) of the fishing ground for the studied year. By enunciated high number of fuzzy inference rules in our fuzzy model, lower scores and higher variability was not observed in our results. Even after extensive testing it is difficult to determine how many rules are really required. The number of fuzzy rules increases exponentially with the number of variables (Marchini et al., 2009). If one of the rules is wrong, other rules that are correct are likely to fire as well and they may compensate for the error. The most important advantage of fuzzy logic systems is that fuzzy inference systems are flexible and can easily be updated with new knowledge. Fuzzy models allow to combine quantitative and qualitative data and to produce results that are more similar to the real world.

Conclusions

In this paper, we present a fuzzy method to assess the fishery productivity of coastal fishing grounds, based on their fishery production. Fuzzy logic allows using information that other methods cannot include and translates expert judgement expressed in linguistic terms into precise number, so the laws of fuzziness are scientifically sound. The most important advantage of the fuzzy methodology is that the inference system is built with words and the main feature of fuzzy models is that they tolerate the inclusion of qualitative variables together with quantitative ones. None equation is used to represent the inference model. The flexibility of the methodology based on fuzzy inference systems provides a simple framework for developing classification models. Fuzzy-logic based methods are appropriated to address uncertainty and subjectivity that define the criteria of different classes and fuzzy logic formalism is a suitable and alternative tool to be used in developing effective fishing management plans.

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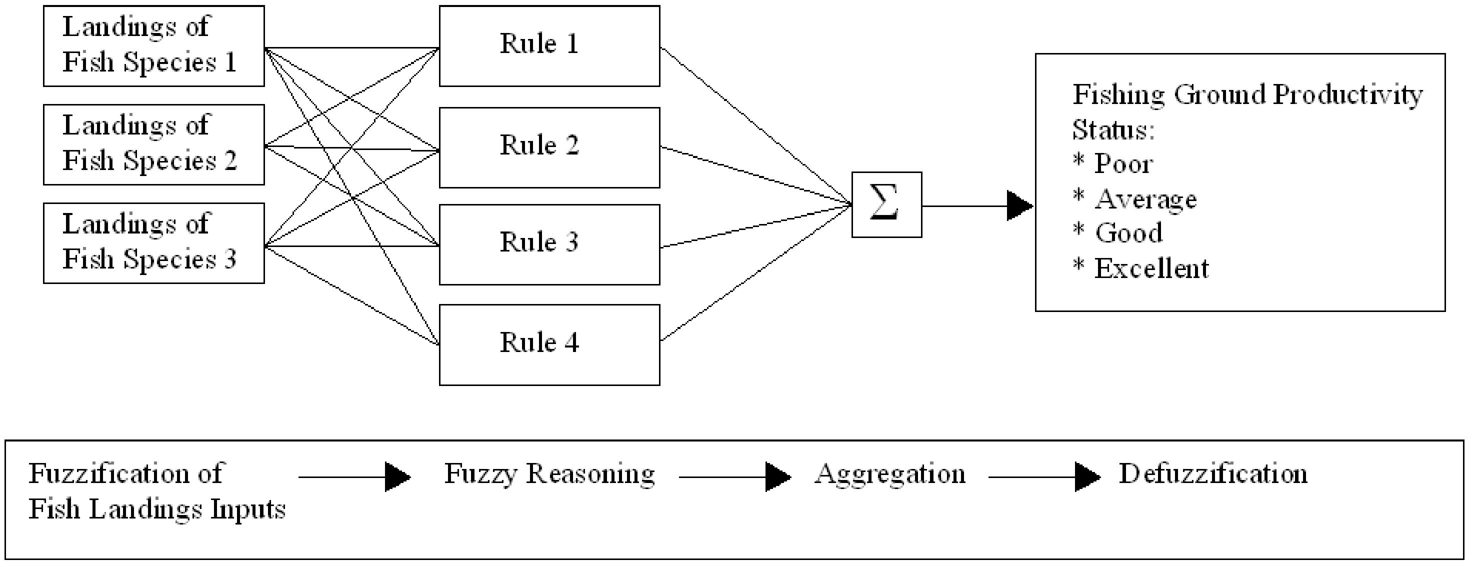


Figure 1. Description of the Fuzzy Inference System for evaluation of the fishing grounds productivity status.

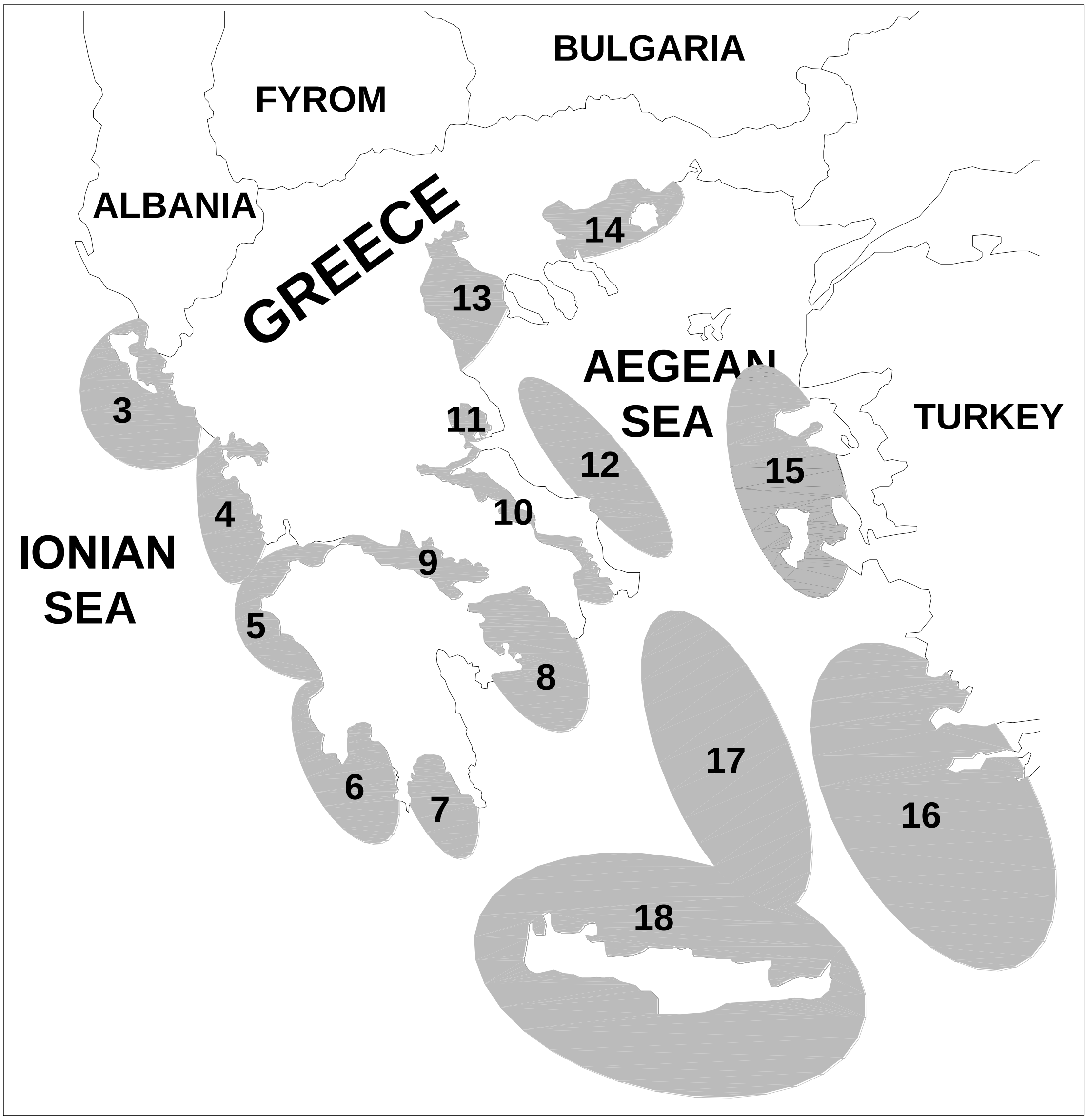


Figure 2. The Study Area.(3: Ipiros Coasts – Corfu; 4: Amvrakikos Gulf – Lefkada; 5: Patraikos Gulf – Kefalonia; 6: Kiparisiakos – Mesiniakos Gulfs; 7: Lakonikos Gulf; 8: Argolikos – Saronikos Gulfs; 9: Korinthiakos Gulf; 10: North and South Evoikos Gulfs; 11: Pagasitikos Gulf; 12: Sporades Islands; 13: Thermaikos Gulf; 14: Strymonikos and Kavala Gulfs; 15: Chios – Lesvos – Samos Islands; 16: Dodekanisa Islands; 17: Cyclades Islands; 18: Crete Island).

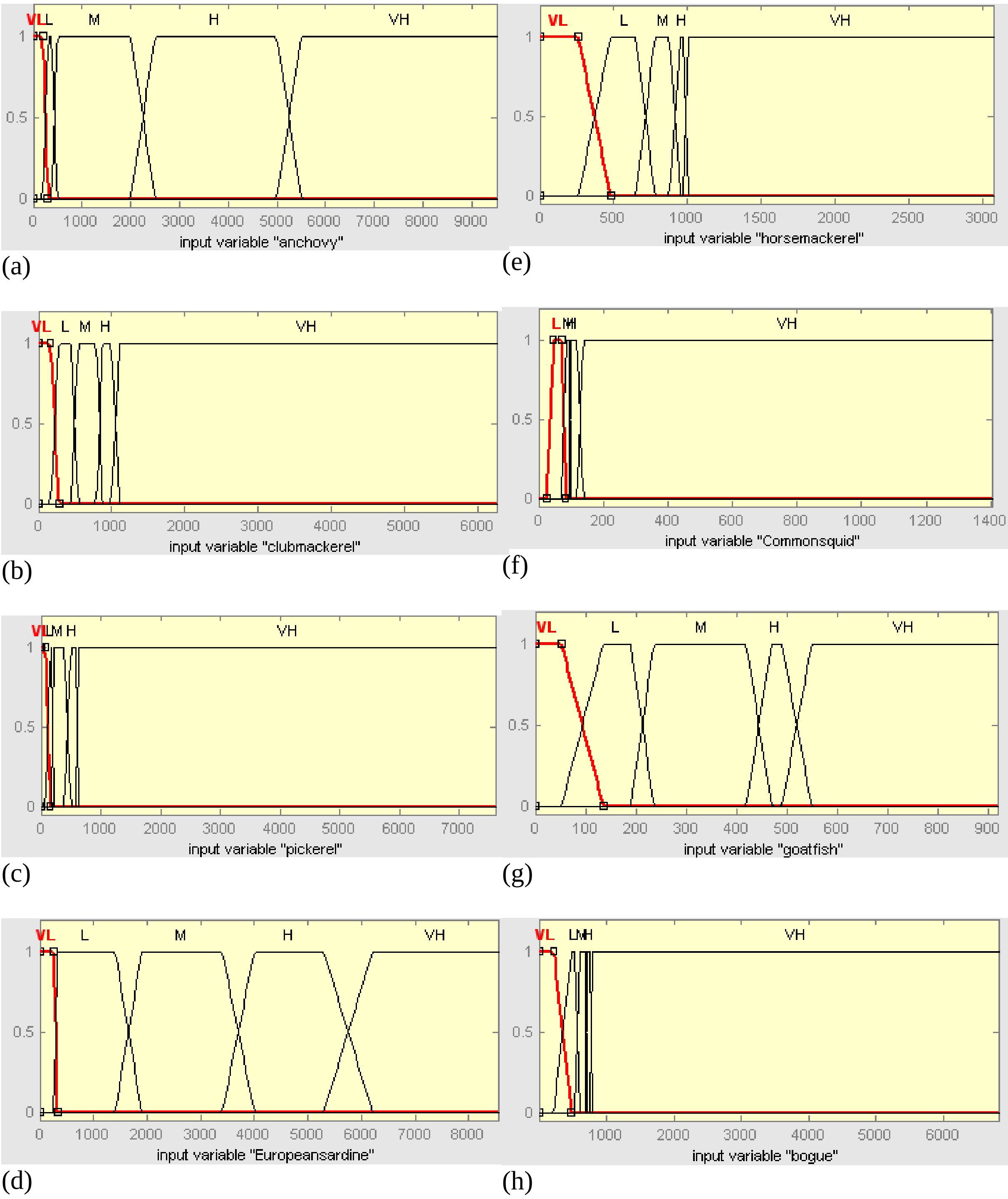


Figure 3. Fuzzy sets defining the input variables: (a) anchovy, (b) club mackerel, (c) pickerel, (d) European sardine, (e) horse mackerel, (f) common squid, (g) goatfish, (h) bogue. VL-very low, L-low, M-medium, H-high, VH-very high fishery production (in tons).

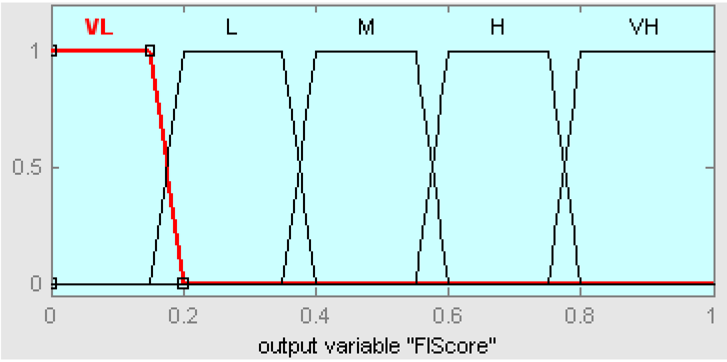


Figure 4. Output fuzzy sets for the total fishery productivity expressed by trapezoidal membership functions. Fishery productivity was scaled from 0 to 1.

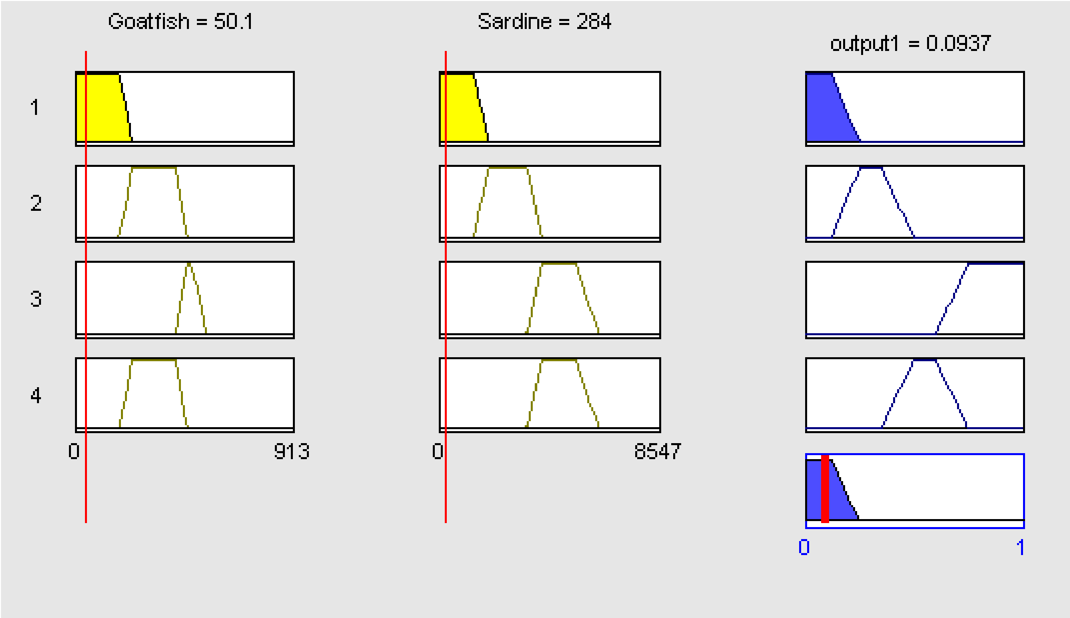
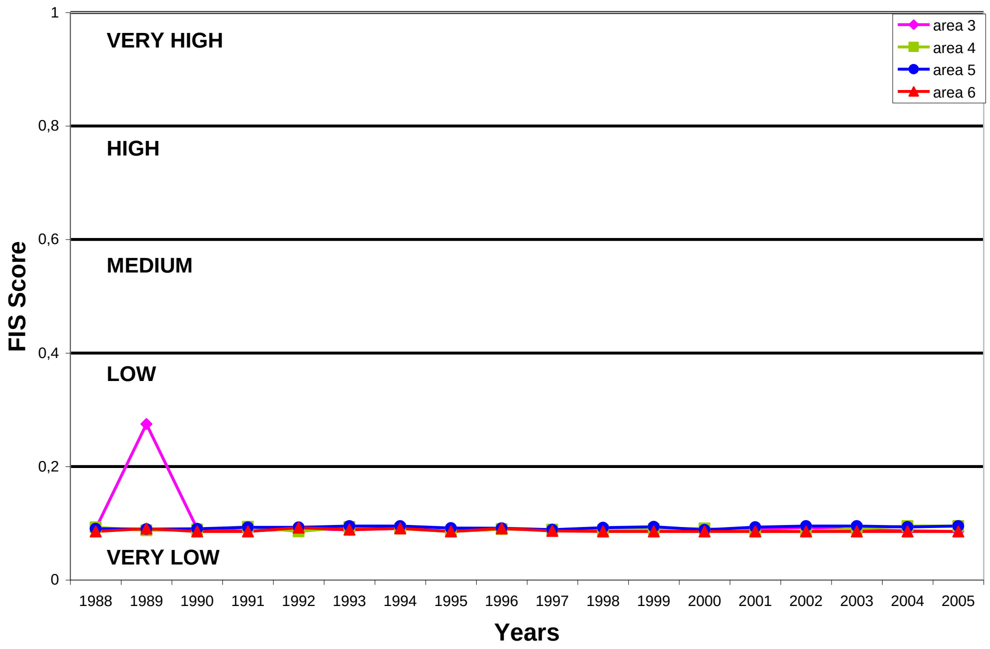
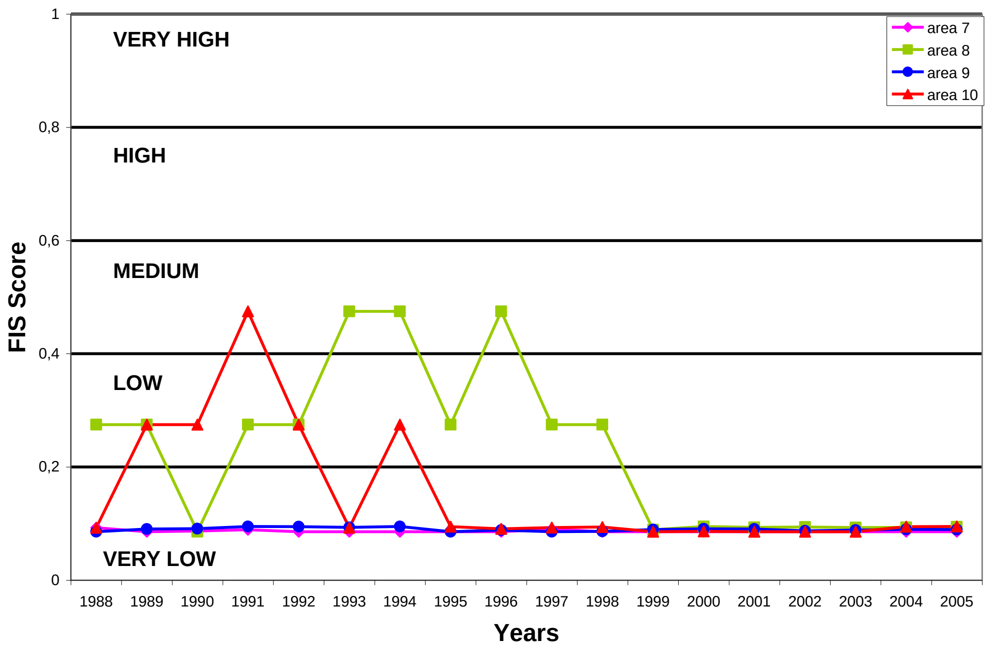


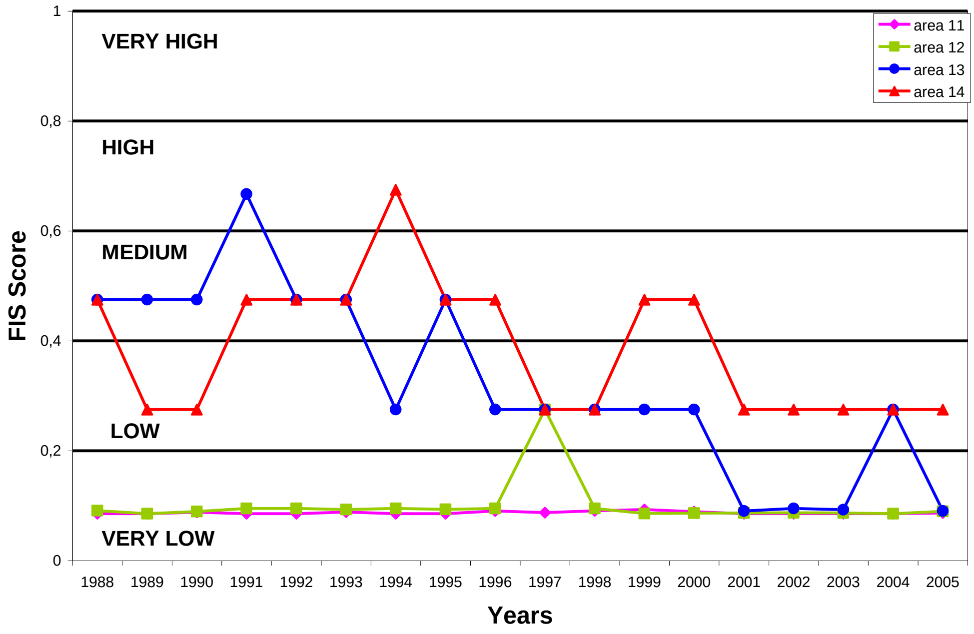
Figure 5. Fuzzy inference diagram for fishery productivity, considering to the landings of two fish species (goatfish and European sardine) and establishing four rules.



FIS Score
Years
VERY HIGH
HIGH
MEDIUM
LOW
VERY LOW
area 3
area 4
area 5
area 6
1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005
0 0,2 0,4 0,6 0,8 1



FIS Score
Years
VERY HIGH
HIGH
MEDIUM
LOW
VERY LOW
area 7
area 8
area 9
area 10
1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005
0 0,2 0,4 0,6 0,8 1



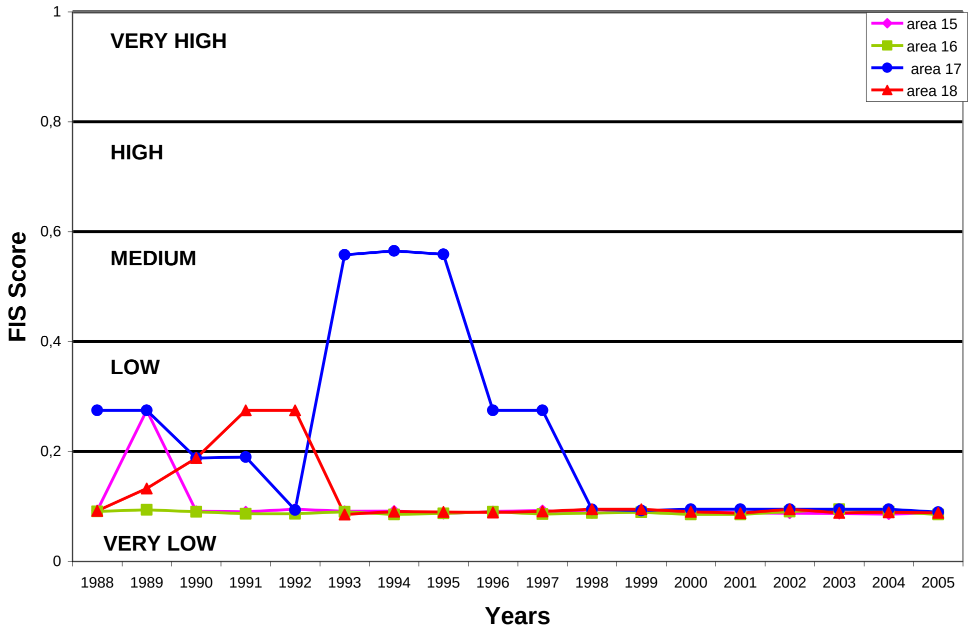


Figure 6. Temporal variability of the Fuzzy Inference System Model total scores for all Greek fishing areas.

Table 1. Parameters for membership functions used in the Fuzzy Inference System.

Indicator	' VeryLow '			' Low '				' Medium '				' High '				' VeryHigh '		
	a=b	c	d	a	b	c	d	a	b	c	d	a	b	c	d	a	b	c=d
Anchovy (*Engraulis encrasicholus*)	0	200	280	200	280	400	480	400	450	2000	2500	2000	2500	5000	5500	5000	5500	9509,09
Club mackerel (*Scober japonicus*)	0	160	280	160	280	450	535	450	535	790	870	790	850	990	1100	990	1100	6248
Pickerel (*Spicara smaris*)	0	80	150	80	150	185	200	185	200	400	480	400	480	600	630	600	1300	7602
European sardine (*Sardina pilchardus*)	0	250	520	480	820	1400	1900	1700	2500	3400	4000	3700	4300	5300	6200	5800	6100	8547
Horse mackerel (*Tranchurus sp.*)	0	260	480	410	500	730	780	730	780	880	950	880	910	980	1000	975	1100	3073
Common squid (*Loligo vulgaris*)	0	25	45	38	48	73	82	73	82	96	100	99	102	121	135	128	220	1403
Goatfish (*Mullus barbatus*)	0	52	136	125	165	190	236	220	285	420	470	460	470	490	500	490	530	919
Bogue (*Boops boops*)	1,4	220	480	440	490	540	600	580	590	690	700	680	690	762	765	740	1500	6814

Table 2. Fishery production (tons) representing the fishing grounds cluster centers for each species.

Clusters	Anchovy	Club mackerel	Pickerel	European Sardine	Horse mackerel	Common Squid	Goatfish	Bogue
A	1728,93	540,544	482,621	2010,51	815,355	86,7595	241,537	704,78
B	310,757	286,399	636,935	560,401	504,782	70,6132	149,384	768,439
C	7007,02	1173	203,805	4253,12	1035,02	136,166	615,302	602,574
D	136,217	61,6087	141,894	158,488	79,8969	18,5626	50,2304	153,242
E	4507,84	985,005	186,592	6669,5	967,556	115,4	501,427	524,088

Table 3. Fuzzy inference rules and weighted factors w_i of each species to assess fishery productivity. VL-Very Low, L-Low, M-Medium, H-High and VH-Very High.

Rule		**Conditions**									**Consequences**
		Anchovy **(w_1=0,05)**	Club mackerel **(w_2=0,10)**	Pickerel **(w_3=0,15)**	European Sardine **(w_4=0,05)**	Horse mackerel **(w_5=0,15)**	Common squid **(w_6=0,20)**	Goatfish **(w_7=0,15)**	Bogue **(w_8=0,15)**		Fishery Productivity
1	IF	VL	VL	VL	VL	VL	VL	VL	VL	THEN	VL
2	IF	VL	VL	M	L	VL	VL	VL	L	THEN	VL
3	IF	VL	VL	L	VL	VL	VL	L	VL	THEN	VL
4	IF	VL	VL	VL	VL	VL	VL	VL	VL	THEN	VL
5	IF	VL	VL	H	VL	VL	VL	L	VL	THEN	VL
6	IF	L	VL	VH	L	H	L	M	VH	THEN	L
7	IF	VL	VL	VL	VL	VL	VL	VL	VL	THEN	VL
8	IF	M	VL	M	L	M	L	L	L	THEN	VL
9	IF	VL	VL	VL	VL	VL	VL	VL	VL	THEN	VL
10	IF	M	VL	VL	L	VL	VL	VL	M	THEN	VL
11	IF	VH	L	L	M	VH	VH	H	L	THEN	M
12	IF	VH	M	M	M	VH	H	H	VH	THEN	M
13	IF	VL	VH	H	L	L	L	L	M	THEN	VL
14	IF	VL	L	VH	VL	VL	M	VL	L	THEN	VL
15	IF	VL	VL	VH	VL	H	M	VL	VH	THEN	L
16	IF	VL	VL	VH	VL	L	VL	L	VH	THEN	VL
17	IF	VL	VL	VL	L	VL	VH	VL	VL	THEN	L
18	IF	VL	VL	M	VL	VL	VL	VL	VL	THEN	VL
19	IF	VL	VL	M	VL	VL	VL	L	L	THEN	VL
20	IF	VL	VL	VL	VL	VL	VL	VL	VL	THEN	VL
21	IF	VL	VL	VH	VL	VL	VL	VL	VL	THEN	VL
22	IF	VL	VL	VH	VL	M	VL	M	VH	THEN	L
23	IF	VL	VL	VL	VL	VL	VL	VL	VL	THEN	VL
24	IF	M	VL	M	L	VH	H	L	H	THEN	L
25	IF	VL	VL	VL	VL	VL	VL	VL	VL	THEN	VL