A FUZZY LOGIC EXPERT SYSTEM FOR ESTIMATING THE INTRINSIC EXTINCTION VULNERABILITIES OF SEAMOUNT FISHES TO FISHING

William W. L. Cheung, Tony J. Pitcher and Daniel Pauly
Fisheries Centre, The University of British Columbia. 2259 Lower Mall, Vancouver, B.C., V6T 1Z4, Canada
w.cheung@fisheries.ubc.ca; t.pitcher@fisheries.ubc.ca; d.pauly@fisheries.ubc.ca

ABSTRACT

Fishing has become a major conservation threat to marine fishes. Effective conservation of threatened species requires timely identification of vulnerable species. However, evaluation of extinction risk using conventional methods is difficult for the majority of fish species as the population data normally required by such methods are unavailable. This paper presents a fuzzy expert system that integrates life history and ecological characteristics of marine fishes to estimate vulnerability to fishing. We extract heuristic rules describing the known relationship between biological characteristics and vulnerability of marine fishes from published literature. The rules consist of the conclusions from one or more conditions connected by IF-THEN clauses. Input and output variables are defined by fuzzy sets which deals explicitly with the uncertainty associated with knowledge framed in qualitative terms. Conclusions inferred from input parameters are combined through fuzzy inference and defuzzification processes. Our fuzzy system provides vulnerability estimates that correlate with observed declines more closely than existing alternatives. The system has advantages in flexibility of input data requirements, in explicit representation of uncertainty and in high adaptability to new knowledge. This fuzzy expert system can be used as a decision support tool in fishery management and marine conservation planning.

INTRODUCTION

Increasing evidence indicates that marine species may be put under threat of local, and ultimately, global, extinction by the direct or indirect effects of fishing (Roberts and Hawkins, 1999; Reynolds et al., 2002; Dulvy et al., 2003). Commercially important species can be fished down to a vulnerable level because of their economic value, e.g. Chinese Bahaba (*Bahaba taipingensis*, Sciaenidae) (Sadovy and Cheung, 2003), Southern Bluefin tuna (*Thunnus maccoyii*, Scombridae) (Hayes, 1997). However, species with little or no commercial value are not safe from the threats of fishing. Non-targeted species may be threatened through bycatch (e.g. common skate, *Raja batis*, Rajiidae, Brander, 1981; barndoor skate, *Raja laevis*, Rajiidae, Casey and Myers, 1998). Moreover, fishing activities can create large disturbance and damages to benthic habitats (Jennings et al., 2001; Kaiser et al., 2002; 2003). Declines and extinctions can be associated with loss of essential habitat critical to complete the life cycle of the species (McDowall, 1992; Watling and Norse, 1998). Furthermore, experience from now extinct marine species suggests long delay in reporting marine extinction, also the ability to detect extinction is poor even on a local scale (Dulvy et al., 2003). Given the overexploited status of most fishery resources in the world (Pitcher, 2001a; Pauly et al., 2002; Hilborn et al., 2003), timely identification of species or populations that are vulnerable to extinction is urgently needed so that appropriate counter-measures can be formulated and implemented (Jennings et al., 1999a).

Owing to lack of data, conventional assessments of extinction vulnerability, which involve understanding of population dynamics, impose strong limitations to rapid assessment of marine fish species. Currently, the required population parameters can be estimated only for a small number of marine fishes, mainly commercially targeted species in developed countries. At the same time, quantitative data on fisheries and population status of exploited species are costly to collect (Reynolds et al., 2002; Dulvy et al., 2003). Moreover, the intrinsic rate of increase r, a population parameter that is key to conventional assessment, is particularly difficult to estimate reliably (Musick, 1999; Reynold et al., 2002; Dulvy et al., 2003).

LIFE HISTORY AND ECOLOGICAL CHARACTERISTICS AS A PROXY FOR EXTINCTION VULNERABILITY

Using life-history traits as 'rule-of-thumb' proxies to evaluate the intrinsic vulnerability of marine fishes to fishing has been suggested by Jennings et al. (1998, 1999a, 1999b) and Reynolds et al. (2002), given that responses of fish populations to exploitation are, at least in part, determined by life history characteristics (Adams, 1980; Roff, 1984; Kirkwood et al., 1994). Here, intrinsic vulnerability is defined as the relative extinction risk resulting from fishing, disregarding other factors, such as, e.g., pollution or coastal developments. Significant correlations have been empirically demonstrated between selected life history parameters and proxies for extinction vulnerabilities, e.g., historical population trends and recruits-per-spawner at low spawner abundance (Jennings et al., 1999a; 1999b; Denney et al., 2002). The American Fisheries Society (AFS) has adopted a scheme to identify the productivity (essentially the inverse of vulnerability) of fishes, incorporating life history characteristics such as intrinsic rate of population increase, longevity, age at first maturity, fecundity and the von Bertalanffy growth parameter K (Musick, 1999). The productivity estimates are then used to determine threshold population levels for extinction risk (Musick, 1999; Musick et al., 2000; Froese and Sampang, this vol.). Generally, species with larger body size (maximum body length or asymptotic length), higher longevity, higher age at maturity, and lower growth rate are suggested to have higher vulnerability to extinction (Smith et al., 1998; Jennings et al., 1999a; 1999b; Dulvy and Reynolds, 2002; Denney et al., 2002).

Certain ecological characteristics may also contribute to an increased vulnerability to fishing. Species forming large aggregations can be easily targeted by fishers and aggregative or shoaling behaviour often results in hyperstability of catch-per-unit-effort (CPUE), which masks the depletion of populations (Hilborn and Walters, 1992; Pitcher, 1995; 1997; Walters, 2003). Moreover, hyperstability of CPUE implies that economic incentives to fish can be sustained under low resource abundance (Hutchings, 1996) and as a result, bionomic equilibrium may not be reached until populations are depleted to a dangerously low level (Hilborn and Walters, 1992; Mackinson et al., 1997). In particular, species which form spatially and temporally predictable spawning aggregations are especially vulnerable. Depletion of these spawning aggregations may permanently prevent reproduction in these populations (Dulvy et al., 2003).

Assuming that specific life history and ecological traits can contribute concurrently to increasing vulnerability of marine fishes to exploitation, an indicator combing these traits should be useful in comparing vulnerability across species. Such indicator would be particularly useful for exploited fish assemblages where data are generally limited. For instance, knowledge on the biology and population dynamics of seamount fishes is generally limited (Froese and Sampang, this vol.) However, seamounts are being targeted by fishing (Watson and Morato, this vol.). Thus, an *a priori* understanding on the relative vulnerability of seamount-associated fishes would be useful when formulating conservation and management strategies. However, life history and ecological characteristics affect extinction vulnerability in complex, non-linear ways. Moreover, information for the majority of species is incomplete. Therefore, it is difficult to establish an index of extinction vulnerability from a wide range of life history and ecological characteristics using conventional parametric techniques such as linear regression.

FUZZY SET THEORY AND FUZZY LOGIC

We propose that the application of fuzzy set theory and fuzzy logic should be useful in deriving an index of extinction vulnerability that combines different life history and ecological characteristics. Fuzzy set theory was originally developed by Zadeh (1965) to represent how a domain can associate with a fuzzy set through a gradation of membership, instead of classifying them as either 'true' or 'false', as in conventional Boolean ('crisp') sets. At the same time, fuzzy logic also allows conclusions to be reached from premises with a gradation of truth. The memberships of a domain to one or more sets are defined by fuzzy membership functions (Figure 1).

The explicit use of vagueness in fuzzy sets is very useful for handling the uncertainty inherent to extinction vulnerability (Akcakaya et al., 2000). For example, we know that large fish tend to be associated with higher extinction vulnerability. However, it is difficult to provide a clear cut definition of what a 'large fish' is, i.e., to separate large and small body size, and thus high and low extinction vulnerability. Moreover, other characteristics may give the fish a low vulnerability, despite its size. On the other hand, fuzzy sets allow a fish to be defined as partly large and partly small, the parts being associated with a gradation of membership to each set, or category. They also allow a fish to be classified by multiple categories of vulnerability, with different degree of membership based on it different characteristics. Fuzzy logic been used in fisheries science (Saila, 1996), with applications ranging from stock-recruitment relationships (Mackinson et al., 1999; Chen, 2001), to predicting fish shoaling behaviour (Mackinson, 2000) and identifying sub-stocks of fish (Zhang, 1994). It has also been used to assist the IUCN Red List's species assessment (Akcakaya et al., 2000). Tinch (2000) also proposed the use of fuzzy logic to assess extinction risks of different Pacific salmon stocks.

A fuzzy knowledge-based (= 'expert') system, designed to mimic how expert solve problems, is based on heuristic rules that describe the available expert knowledge, here on how different life history and ecological characteristics can be combined to estimate extinction vulnerability. The heuristic rules summarizing the available expert knowledge take the IF-THEN form:

IF *A* THEN *B*

where *A* is the premise while *B* is the conclusion which may lead to an object, events or other rules (Kasabov, 1996). In this study, the knowledge base consists of the various known relationships linking extinction vulnerability with life history and ecological characteristics of fishes. Following the above example on fish's body length, the rules would be:

IF fish's maximum body length is *large* THEN extinction vulnerability is *high*

IF fish's maximum body length is *medium* THEN extinction vulnerability is *moderate*

where large and medium are fuzzy sets of maximum body length and high and moderate are fuzzy sets of extinction vulnerability.

In some cases, the IF statement includes two premises connected by 'AND' or 'OR' operators. The 'AND' or 'OR' operators are defined mathematically by the MIN-MAX rule (Zadeh, 1965). When two or more conditions are connected by 'AND' operator, the membership of the combined premise is the minimum of the membership of all the conditions. On the other hand, when the premise is composed of conditions connected by 'OR' operator, the maximum membership among all the conditions is taken (Zadeh, 1965).

The actions defined by the rules are fired when the membership on the premises exceed certain trigger values. The trigger values are subjective criteria which define the minimum required membership assumed for an expert to require for that particular rule to be fired. Conflicting rules are allowed to fire jointly. For example, if a particular fish species is both large and medium with different memberships exceeding the trigger values, then both rules will be fired.

In this paper, we aim to develop an index of the intrinsic vulnerability of marine fishes based on published relationships between life history and ecological characteristics and extinction vulnerability of marine fishes, using a fuzzy expert system approach. We also aimed to determine whether the newly developed index would correlate with empirical data. Individual species is treated as the unit of assessment here, but the methodology can be applied to individual population or sub-stock. We further compared the pros and cons of the fuzzy expert system with other approaches in terms of its practical applications.

METHODS

Structure of the fuzzy expert system

We developed a fuzzy expert system (hereafter called fuzzy system) which aimed to evaluate the extinction vulnerability of marine fishes based on easily-obtainable life history and ecological characteristics i.e., features available through FishBase (Froese and Pauly, 2003; http://www.fishbase.org). We defined four linguistic categories referring to the levels of intrinsic vulnerability: (1) very high vulnerability to extinction, (2) high vulnerability, (3) moderate vulnerability and (4) low vulnerability. The domain

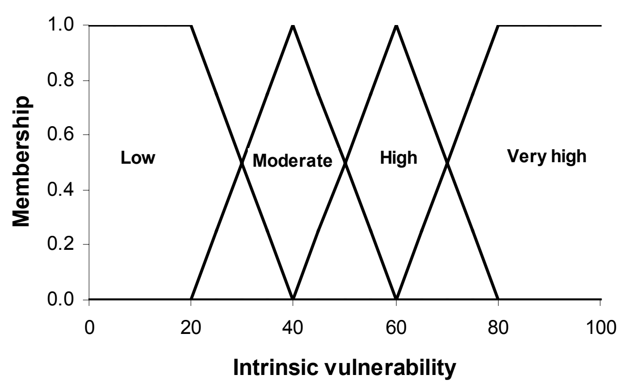


Figure 1. Output fuzzy sets for the intrinsic vulnerability of marine fishes. The "High" and "Very low" vulnerabilities are defined by trapezoid functions while the "Moderate" and "Low" vulnerabilities are defined by triangles. Intrinsic vulnerability was scaled arbitrary from 0 to 100. The dotted line present the supremums of the fuzzy sets (Degree of belief= membership).

for these fuzzy sets is an arbitrary 'intrinsic vulnerability' scale from 1 to 100, with 1 being the least vulnerable (Figure 1). Without prior knowledge on the best type of function to be used, we assumed the simplest form of fuzzy membership functions. Thus, trapezoids are used for 'Very high vulnerability' and 'Very low vulnerability' categories, and symmetric triangles for the other two categories (Figure 1). Thus, a species with an intrinsic vulnerability of 20 is 'low' with full membership, while a species with 70 would be both 'high' and 'very high,' with partial membership to each set.

We collated known relationships between life-history and ecological characteristics to intrinsic vulnerability from the published literature (Table 1), excluding those overwhelmingly disproved by empirical data. For example, high fecundity has been suggested to imply high productivity, and hence low vulnerability (Musick, 1999). However, empirical analyses do not support the inverse relationship between fecundity and vulnerability (see Sadovy, 2001). The published relationships were transformed into expert system (heuristic) rules. The rules are all in the IF-THEN format and relate the life history and ecological characteristics to the four vulnerability categories (Table 1).

We transformed the input biological attributes into linguistic categories defined by fuzzy sets (Figure 2), with trapezoid functions at the upper and lower limits, and triangular sets at intermediate position on the axis. We assumed the minimum membership in the premises (conditions) required to fire the rules (Alpha value) to be 0.2. Therefore, any premises with a membership below 0.2 would not trigger any rule to be fired. Without prior knowledge on the relative validity of each rule, we made an initial assumption of equal weighting with 0.5 confidence factor (CF) to all rules. The CF represents the uncertainty associated to the rule; thus, 0.5 means that we have only half certainty in the validity of the rule. That is:

$$Membership_{conclusion} = Membership_{premise} \bullet CF$$

We then tested the validity of the equal weighting assumption using a jackknife approach.

We obtained the membership to the fuzzy set of the final conclusion (four levels of intrinsic vulnerability) by combining the conclusions from each heuristic rule. Membership in the conclusion from each rule was combined using the knowledge accumulation method in Buchanan and Shortliffe (1984):

$$Membership_e = Membership_{e-1} + Membership_i \bullet (1 - Membership_{e-1})$$

where $Membership_e$ is the membership in the conclusion after accumulating memberships from *e* sets of rules, and $Membership_i$ is the membership of rule *i*. For instance, considering the following rules:

IF *A* THEN *E* (*membership* = 0.3)

IF *B* THEN *E* (*membership* = 0.4)

IF *C* THEN *E* (*membership* = 0.5)

$$Membership_2 = 0.3 + 0.4 \bullet (1 - 0.3) = 0.58$$

$$Membership_3 = 0.58 + 0.5 \bullet (1 - 0.58) = 0.79$$

Using this method, the order in which evidence appears has no effect on the final membership in the conclusion.

Operation of the fuzzy system

1. Determining fuzzy membership to input fuzzy sets (Fuzzifications)

We input the life history and ecological parameters into the fuzzy system. The input parameters were categorized into the different linguistic categories (e.g. large maximum size, low value of von Bertalanffy growth parameter *K*) with the corresponding membership based on the pre-defined fuzzy sets (Figure 2). Categories with membership exceeding the alpha values would trigger the firing of their corresponding rules. For example, for a fish species with maximum body length of 68 cm, the input parameters would correspond to "medium body size" and "large body size" with Membership of 70% and 30% respectively (Alpha value = 0.2) (Figure 3).

Table 1. Heuristic rules defined in the fuzzy system to assign relative vulnerabilities to fishes

Attribute	Rule	Conditions		Consequences		Supporting evidence[1]	Opposing evidence[2]
1	1	IF	Maximum length[3] is *very large*	THEN	Vulnerability is *very high*	8, 11, 13, 14, 15, 16, 17, 21, 24, 27, 28, 29	
1	2	IF	Maximum length[3] is *large*	THEN	Vulnerability is *high*		
1	3	IF	Maximum length[3] is *medium*	THEN	Vulnerability is *moderate*		
1	4	IF	Maximum length[3] is *small*	THEN	Vulnerability is *low*		
2	5	IF	Age at first maturity (t_m) is *very high*	THEN	Vulnerability is *very high*	1, 2, 3, 4, 5, 11, 14, 15, 19, 20, 24, 33	28
2	6	IF	Age at first maturity (t_m) is *high*	THEN	Vulnerability is *high*		
2	7	IF	Age at first maturity (t_m) is *medium*	THEN	Vulnerability is *moderate*		
2	8	IF	Age at first maturity (t_m) is *low*	THEN	Vulnerability is *low*		
3	9	IF	Maximum age (t_{max}) is very *high*	THEN	Vulnerability is *very high*	13, 19, 33	14
3	10	IF	Maximum age (t_{max}) is *high*	THEN	Vulnerability is *high*		
3	11	IF	Maximum age (t_{max}) is *medium*	THEN	Vulnerability is *moderate*		
3	12	IF	Maximum age (t_{max}) is *low*	THEN	Vulnerability is *low*		
4	13	IF	VBGF (*K*) is *very low* Natural mortality (*M*) is *very low*	OR THEN	 Vulnerability is *very high*[4]	5, 6, 13, 19, 28, 33	11
4	14	IF	VBGF *K* is *low* Natural mortality (*M*) is *low*	OR THEN	 Vulnerability is *high*[4]		
4	15	IF	VBGF K is *medium* Natural mortality (*M*) is *medium*	OR THEN	 Vulnerability is *medium*[4]		
4	16	IF	VBGF *K* is high Natural mortality (*M*) is *high*	OR THEN	 Vulnerability is *low*[4]		
5	17	IF	Geographic range is *restricted*[5]	THEN	Vulnerability is *high*	8, 19, 22	
5	18	IF	Geographic range is *very restricted*	THEN	Vulnerability is *very high*		
6	19	IF	Fecundity is *low*[6]	THEN	Vulnerability is *high*	1, 2, 3, 4, 5, 19, 20, 33	11, 14, 18, 23, 26, 28, 31
6	20	IF	Fecundity is *very low*	THEN	Vulnerability is *very high*		
7	20	IF	Spatial behaviour strength is *low*[7]	THEN	Vulnerability is *low*	7, 9, 10, 12, 25, 32	
7	21	IF	Spatial behaviour strength is *moderate*	THEN	Vulnerability is *moderate*		
7	22	IF	Spatial behaviour strength is *high*	THEN	Vulnerability is *high*		
7	23	IF	Spatial behaviour strength is *very high*	THEN	Vulnerability is *very high*		
8	24	IF	Spatial behaviour is related to feeding aggregation	THEN	Vulnerability resulted from spatial behaviour decreases	25	
8	25	IF	Spatial behaviour is related to spawning aggregation	THEN	Vulnerability resulted from spatial behaviour increases	30, 32	

[1] Peer-reviewed literature supporting the assertions of the specific rules;

[2] Peer-reviewed literature opposing the assertions of the specific rules;

[1, 2] References: 1. Holden (1973); 2. Holden (1974); 3. Holden (1977); 4. Brander (1981); 5. Hoening and Gruber (1990); 6. Pratt and Casey (1990); 7. Hilborn and Walters (1992); 8. Brown (1995); 9. Pitcher (1995); 10. Pitcher (1997); 11. Jennings et al. (1998); 12. Mackinson et al. (1999); 13. Russ and Alcala (1998); 14. Smith et al. (1998); 15. Walker and Hislop (1998); 16. Jennings et al. (1999a); 17. Jennings et al. (1999b); 18. Myers et al. (1999) ; 19. Musick (1999) ; 20. Stevens (1999) ; 21. Dulvy et al. (2000) ; 22. Hawkins et al. (2000); 23. Stevens et al. (2000); 24. Frisk et al. (2001); 25. Pitcher (2001b); 26. Sadovy (2001); 27. Dulvy and Reynolds (2002); 28. Denney et al. (2002); 29. Cardillo (2003); 30. Rowe and Hutchings (2003); 31. Sadovy and Cheung (2003); 32. Sadovy and Domeier (in press); 33. Rainer Froese (pers. comm.);

[3] Asymptotic length(L_∞), a VBGF parameter, was used preferentially. However, if this was not available, we used maximum length (L_{max}) instead;

[4] Growth of fish is represented by the von Bertalanffy growth function (VBGF) parameter *K*. Since natural mortality (*M*) and von Bertalanffy growth parameter *K* of fish are highly correlated (Pauly 1980), they were combined here, using an 'OR' operator;

[5] Geographic range is roughly estimated from the known distribution of fish in Exclusive Economic Zones (EEZs) and Food and Agriculture Organization (FAO) statistical areas. For instance, if a fish species is known to occur in China and in FAO statistical area 61, its geographic range is represented by the area of the EEZ of China that falls within FAO statistical area 61;

[6] Strong evidence is available suggesting that high fecundity does not reduce the extinction vulnerability of fishes. However, there is evidence suggesting that lower fecundity (less than 100) increases the vulnerability of fishes. Therefore, the rule relating low fecundity to increased extinction vulnerability is retained. Fecundity is expressed as the minimum number of eggs or pups produced per individual per year;

[7] Spatial behaviour expresses how groups of fish aggregate together at varying time and spatial scale. Spatial behaviour may be related to spawning, feeding, migration, or defense (schooling and shoaling). The strength of the spatial behaviour is defined by an arbitrary scale ranging from 1 to 100. The method used to assign strength of spatial behaviour onto this scale is described in Appendix 1.

2. Rule firing and fuzzy reasoning

All premises (antecedents) with membership exceeding the alpha values ($membership_{ant}$) triggered the fuzzy system to fire their corresponding rules in the inference engine. Following the example used in the fuzzification sessions, the rules:

IF fish maximum body size is *medium*, THEN intrinsic vulnerability is *moderate*

IF fish maximum body size is *large*, THEN Intrinsic vulnerability is *high*

would be fired. The membership associated to each conclusion of rules *i* (precedent) ($membership_{pred,i}$) was calculated by:

$$Membership_{pred,i} = Membership_{ant,i} \bullet CF_i$$

When several rules with the same conclusion were fired, the conclusions (precedents) and their memberships were stored in the inference engine which were then combined and accumulated using the method of Buchanan and Shortliffe (1984).

3. Defuzzification

'Defuzzification' refers to the reduction of a range of conclusions being reached with different memberships to a single point output. The conclusions stored in the inference engine were defuzzified based on the output fuzzy sets (Figure 1). Defuzzification was based on the centroid weighted-average method (Cox, 1999), i.e., the output intrinsic vulnerability factor was calculated from the average of the supremums of each output fuzzy membership function, weighted by the membership associated with each conclusion (Figure 1). In a triangular fuzzy membership function, the supremum is equivalent to the intrinsic vulnerability factor with the highest membership. For trapezoid membership functions, the supremum was assumed to be the mid-point between the two ends of the plateau. Confidence limits were estimated by using the smallest and largest intrinsic vulnerability factors that fall within the particularly fuzzy membership function at the specified membership level, instead of using the supremums. Therefore,

$$\textit{Intrinsic vulnerability} = \frac{1}{\sum_{i=1}^{4} Membership_i} \bullet \left(\sum_{i=1}^{4} Membership_i \bullet Sup_i \right)$$

$$\textit{Conf. Limits} = \frac{1}{\sum_{i=1}^{4} Membership_i} \bullet \left(\sum_{i=1}^{4} Membership_i \bullet f_i(\phi) \right)$$

where Sup_i is the supremums of conclusion fuzzy membership functions *i*, and $f(\phi)$ is the estimated upper or lower limit of the conclusion fuzzy membership functions at the specified membership (ϕ).

System evaluations

We examined the distribution of the fuzzy system output generated from ranges of realistic life history and ecological characteristics input. We extracted from FishBase a list of all marine fishes which, at the time of the query (February 2004), had full records of the life history and ecological characteristic: asymptotic or maximum length, von Bertalanffy growth parameter *K*, age at first maturity, longevity, fecundity and geographic range (N=159). Using the life history and ecological information available for these fishes, we calculated their intrinsic vulnerability based on the fuzzy system.

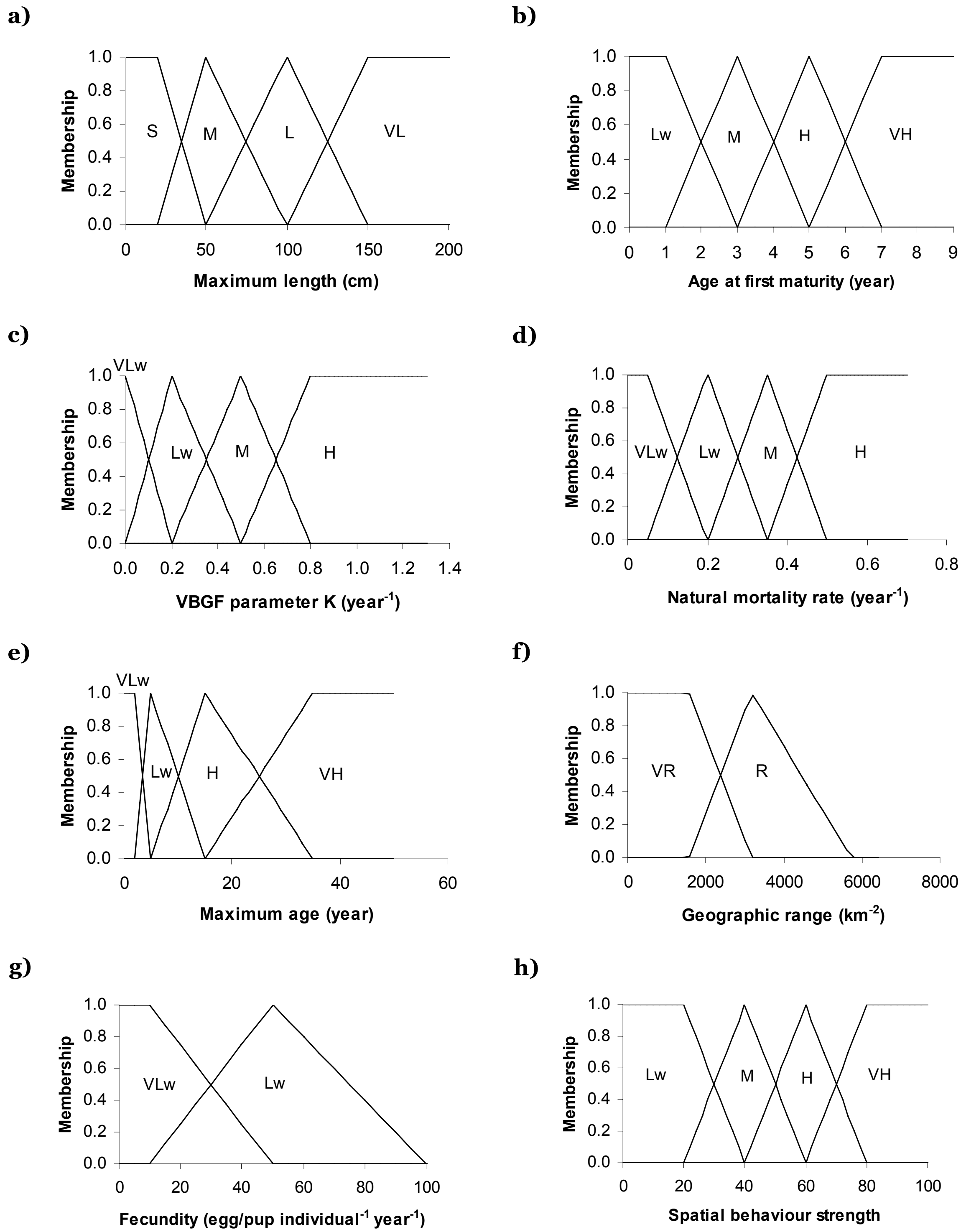


Figure 2. Fuzzy sets defining the input life history and ecological characteristics, with 'Degree of belief' = membership in a fuzzy membership function: (a) maximum body length, (b) age at first maturity (T_m), (c) von Bertalanffy growth parameter K, (d) natural mortality rate (M), (e) maximum age (T_{max}), (f) geographic range (km^2), (g) annual fecundity (egg or pup female^{-1} year^{-1}), (h) strength of aggregation behaviour (see appendix 1). VLw – very low, Lw – low, M –medium/moderate, H – high, VH – very high, L – large, VL – very large, R – restricted, VR – very restricted..

We evaluated the impacts of individual attributes and rules to the output of the system using a jackknife approach (Sokal and Rohlf, 1995) whereas the calculations of the intrinsic vulnerability are repeated, while excluding one of the rules each time. A pseudovalue, which presented the degree of deviation from the output estimated with full sets of rules (Sokal and Rohlf, 1995), was calculated for each species i when rule j was removed from the system:

$$Pseudovalue = nR_T - (n-1) \bullet R_{-j}$$

where n is the total number of rules (25) and R is the estimated output from the system with full set of rules (T) and rule j being removed. We repeated the sensitivity analysis by jackknifing attributes instead of individual rules.

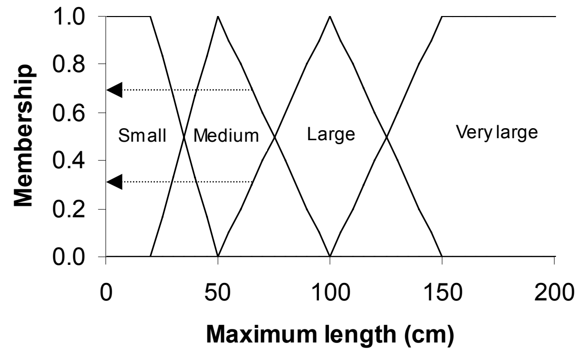


Figure 3. Example of a fuzzy membership function, used to classify fish lengths: small, medium, large and very large. The shapes and slopes of the FMF are pre-defined. For instance, a fish with a maximum length of 68 cm falls within the sets for medium and large, with degree of belief of 0.7 and 0.3 respectively. Degree of belief = membership.

Validity tests on vulnerability estimates

We examined the validity of the intrinsic vulnerability estimated from the fuzzy system using empirical data. We conducted three tests that used three independent sets of data in which historical abundance trends of the marine fish species or populations in the datasets were known. Species included in the data sets represent examples from wide longitudinal and habitat ranges. The three tests included:

1. 40 species of marine fishes in the IUCN Red List (Hilton-Taylor, 2000);
2. 24 species of demersal fishes in the northern North Sea (Jennings et al., 1999a); and
3. 13 species of reef fishes (Scaridae, Serranidae and Lutjanidae) in Fiji (species in Jennings et al., 1999b with at least 15% of their observed population trends explainable by fishing).

For each test, the intrinsic vulnerabilities estimated by the fuzzy system were regressed against the observed historical abundance trends of the corresponding species. Whenever the required biological parameters for the species were unavailable in the original data sets, we obtained the data for the same species from FishBase (Froese and Pauly, 2003). We used the goodness-of-fit of the linear regression (R^2) between the vulnerability estimates and the observed population trends as an indicator of the goodness of the representation of extinction vulnerability.

We repeated the tests using two other selected proxies of extinction vulnerability: (1) whichever life history parameters (maximum or asymptotic length, age at first maturity, longevity or von Bertalanffy growth parameter K) which provided the best fit (highest R^2); (2) Productivity categories evaluated using the AFS scheme (Musick, 1999). We compared the intrinsic vulnerability from the fuzzy system with these two proxies using two attributes: (1) predictive ability - represented by the goodness-of-fit with the empirical data, (2) data requirement – the amount and flexibility of data required in the calculation of the proxies. We also conducted an additional test to evaluate the correlation between intrinsic vulnerability from the fuzzy system with an independent resilience indicator. The 'resilience' indicator was estimated by quantitative criteria of biological characteristics of the species and expert judgments (Rainer Froese, FishBase coordinator, pers. comm.). We tested the correlation between the two indicators using a Spearman non-parametric test.

RESULTS

Based on the input life history and ecological parameters, the fuzzy system estimated the intrinsic vulnerability of the fishes in both continuous and ordinal scale with an associated membership on the outputs. For instance, using the biological parameters available from FishBase, we estimated that Baird's smooth-head (*Alepocephalus bairdii*, Alepocephalidae) has an intrinsic vulnerability of 71 (100 being the most vulnerable) with a confidence limit (ϕ=0.5) of 57 to 85. It was identified as being highly to very highly vulnerable, with a membership of 0.54 to 0.31, respectively on this statement.

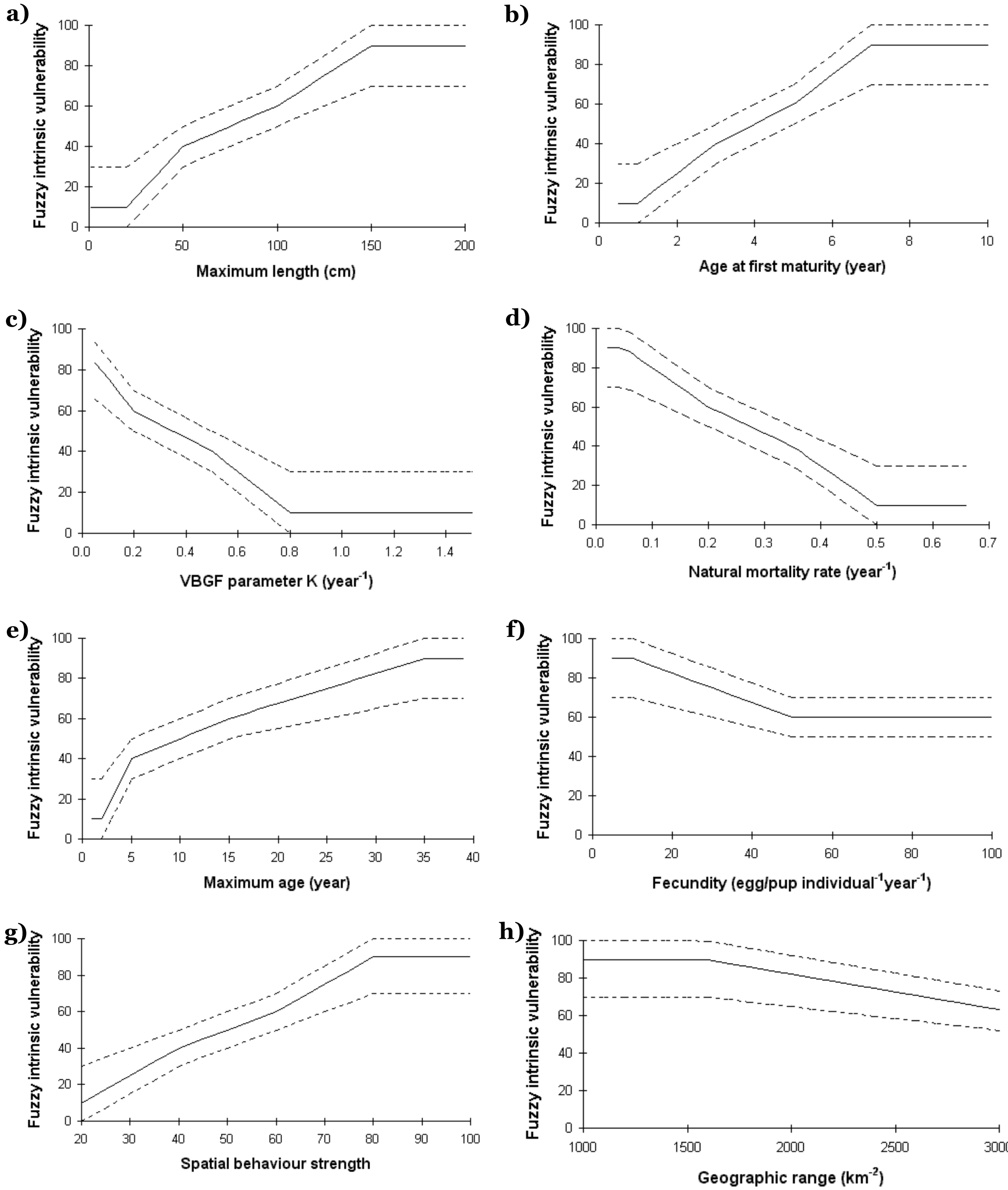


Figure 4. The output surface of the fuzzy system as we varied each individual input parameters: (a) maximum length (cm), (b) age at first maturity, (c) von Bertalanffy growth parameter *K* (year^{-1}), (d) natural mortality rate (year^{-1}), (e) maximum age (year), (f) fecundity (egg/pup individual^{-1}year^{-1}), (g) strength of aggregation behaviour (see Appendix 1), (h) geographic range (km^2). The dotted lines represent the confident limits based on an assumed acceptable degree of belief of 50%. We set the threshold level (Alpha value) to zero during system evaluation.

The response of the estimated intrinsic vulnerability to the input parameters is shown in Figure 4. In general, the intrinsic vulnerability estimated from the fuzzy system increases non-linearly with maximum length, age at first maturity, maximum age, and spatial behaviour strength. Conversely, vulnerability decreased with the increase in von Bertalanffy growth parameter *K* and natural mortality rate. Moreover, fecundity and geographic range, at low level, varies inversely with vulnerabilities.

Jackknifing showed that the deviations in the estimated intrinsic vulnerabilities were similar when individual attributes or rules have removed from the fuzzy system (Figure 5). Pseudovalues of individual rules were generally similar to the baseline, except for rules 6, 13, 17 and 20, which exerted slightly higher impacts on the outputs of the fuzzy system (high age at first maturity, very low von Bertalanffy growth parameter *K* or natural mortality rate, restricted geographic range and very low fecundity, respectively).

The intrinsic vulnerabilities estimated from the fuzzy system were significantly related to the population declines of marine fishes in the IUCN Red List with the highest goodness-of-fit relative to the two other vulnerability proxies (Figure 6). Musick's productivity and maximum length were significantly correlated to population declines (R^2=0.16: Spearman non-parametric test p-value=0.003, R^2=0.228: ANOVA p-value-0.002 respectively). However, intrinsic vulnerabilities performed best in explaining the variance in population trends (R^2=0.35: ANOVA p-value=0.0001).

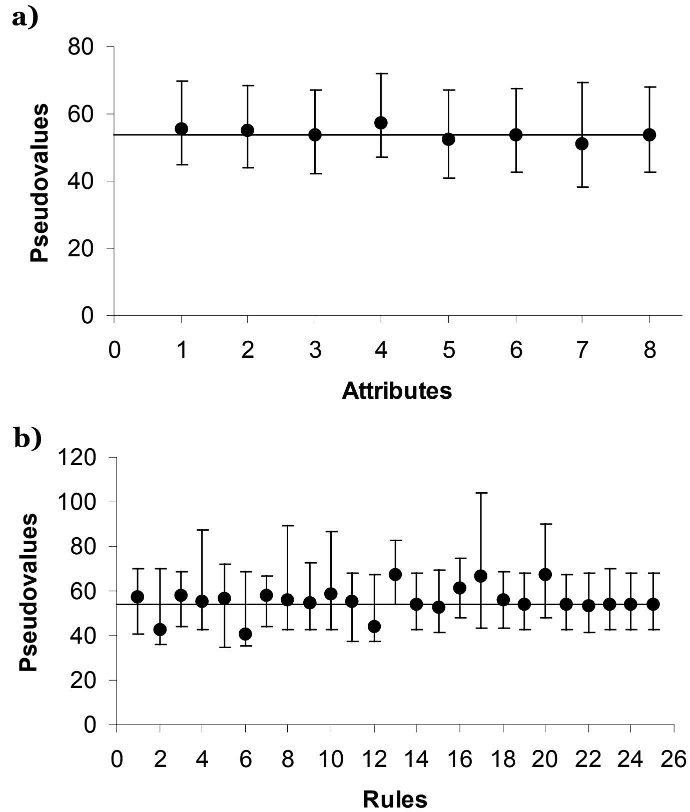
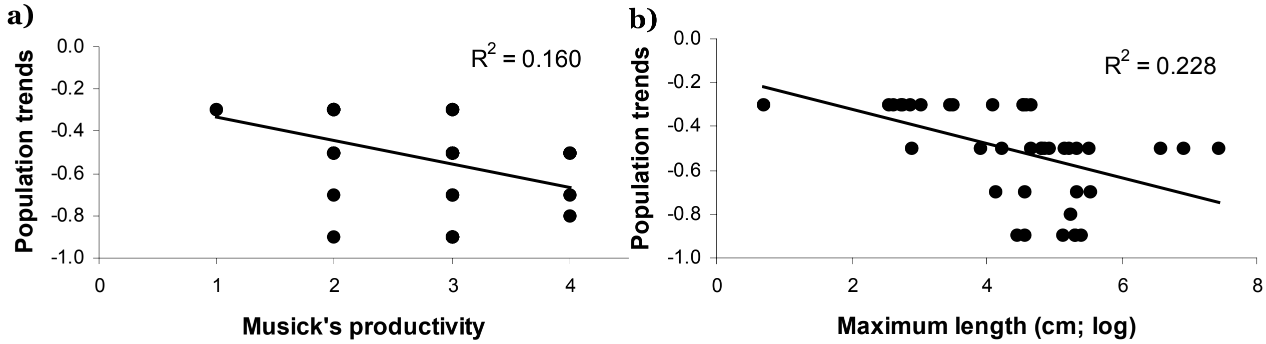


Figure 5. Sensitivity of the estimated intrinsic vulnerability to individual attributes and rules incorporated in the fuzzy system evaluated using the jackknife approach (Sokal and Rohlf, 1995). The black dots are the median of the pseudovalues of the 159 marine fishes from FishBase when individual (a) attributes and (b) rules were removed. The error bars are the 25% and 75% quartiles of the pseudovalues. The solid lines represent the baseline pseudovalues in which full sets of rules and attributes were included. Large deviation from the total averaged pseudovalues indicates that the estimated intrinsic vulnerabilities are sensitive to the individual attribute or rule.

The intrinsic vulnerabilities were also significantly related to the population trends of demersal species in the North Sea (Jennings et al., 1999a) with the highest goodness-of-fit (Figure 7). When we considered dragonet (*Callionymus lyra*) and spurdog (*Squalus acanthias*) as outliers, AFS productivity estimates (Musick's productivity; Musick, 1999) and individual life history parameters (age at first maturity) explained 34% and 28% of the variance respectively whereas our fuzzy system was able to explain over 36% of the variance. The relationship between the intrinsic vulnerability and the observed population trends was also significant when we included dragonet and spurdog in the analysis; however, its goodness-of-fit was higher than the other two vulnerability proxies by a smaller margin (Figure 7).

We did not obtain significant relationships between the three vulnerability proxies and the observed population trends of the Fiji reef fishes based on the information available from FishBase only (Figure 8). We could only estimate Musick's productivity for seven species as a result of lack of life history data. Based on these estimates, no significant correlation between Musick's productivity and the observed population trends could be obtained (Spearman non-parametric p-value=0.414). There was also no relationship between individual life history parameter (maximum length) and the fuzzy system intrinsic vulnerabilities with the observed population trends (ANOVA p-vaue=0.142 and 0.170 respectively).



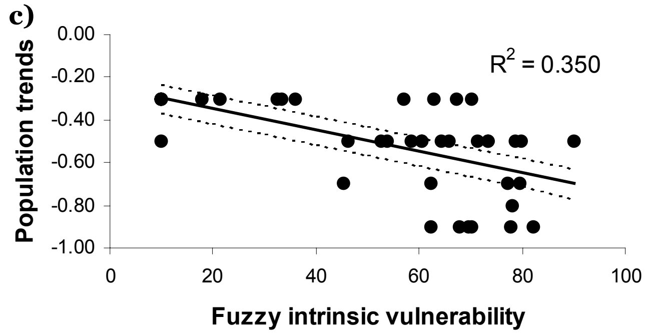
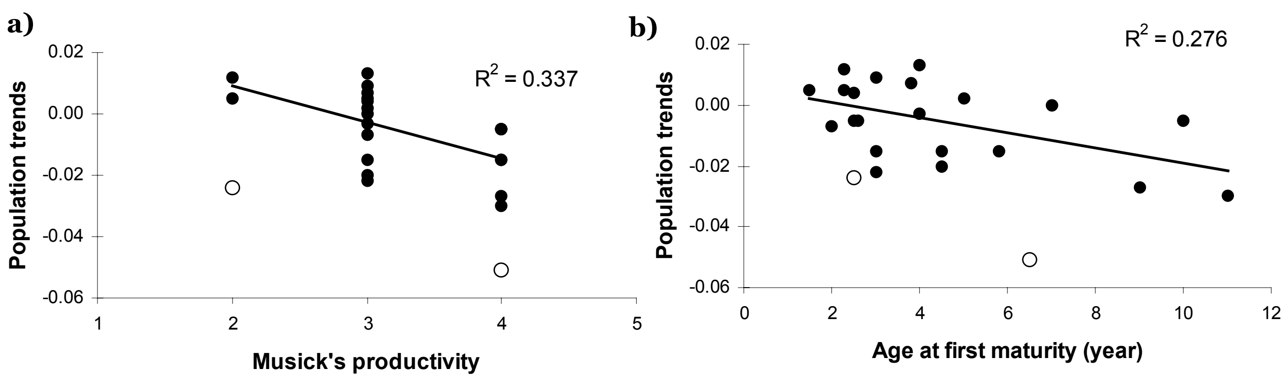


Figure 6. Linear regression (solid line) between the population trends of 40 species of marine fishes listed in the IUCN Red List (Critically Endangered, Endangered and Vulnerable) and (a) Musick's productivity (R^2 = 0.16, Spearman non-parametric test p-value= 0.003), (b) maximum length (log) (R^2=0.228, ANOVA P-value=0.002) and (c) fuzzy system intrinsic vulnerability (R^2=0.350, ANOVA P-value<0.0001). We only included species that were categorized by criteria A: reduction in population size (IUCN Species Survival Commission, 2001). Estimates of population trends were based on the IUCN categories and criteria (version 3.1). As such, the perceived population trends for different IUCN categories were assumed to be: Critically Endangered (A1) = -90%, Critically Endangered (A2-4) = -80%, Endangered (A1) = -70%, Endangered (A2-4) = -50%, Vulnerable (A1) = -50%, Vulnerable (A2-4) = -30%. The dotted lines represent the CF from the fuzzy system based on an assumed acceptable membership of 50%.



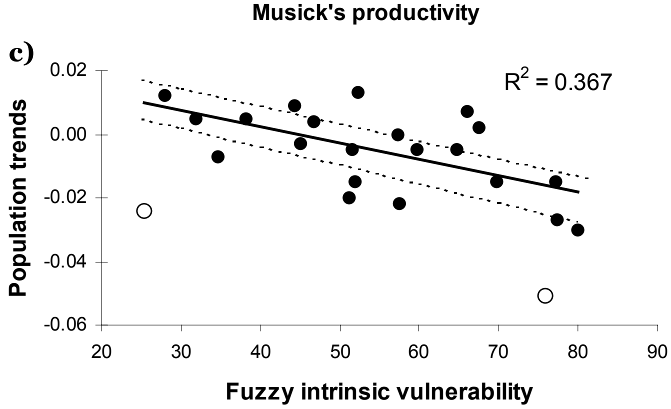


Figure 7. Regression (solid line) between the observed population trends of the 24 species of demersal fish in the North Sea and proxies of extinction vulnerability: (a) productivity from the AFS scheme (Musick, 1999) (R^2=0.337, Spearman non-parametric test p-value = 0.006), (b) age at first maturity (T_m) (R^2=0.276, ANOVA P-value = 0.014), (c) fuzzy system intrinsic vulnerability (R^2=0.367, ANOVA P-value=0.004). Musick's estimates expressed in ordinal scale: 1 = high, 2 = medium, 3 = low, 4 = very low. When we included dragonet (*Callionmyrus lyra*) and spurdog (*Squalus acanthias*) (open dots), the goodness-of-fits of the three proxies became: Musick's productivity (R^2=0.204, Spearman non-parametric p-value=0.019), T_m (R^2=0.207, ANOVA p-value=0.029) and fuzzy system intrinsic vulnerability (R^2=0.246, ANOVA p-value=0.016). The dotted lines represent the confidence limits estimated from the fuzzy system based on an assumed acceptable membership of 50%.

Significant relationship between the fuzzy system intrinsic vulnerabilities and the population trends of Fiji reef fishes exists when we supplemented information on occurrence of spawning aggregation available from the global database of the Society for the Conservation of Reef Fish Spawning Aggregation (SCRFA Global Database, 2004) (Figure 8d). The fuzzy system is able to explain about 34% of the variance in population trends (ANOVA p-value=0.03).

The fuzzy system intrinsic vulnerabilities were significantly correlated with the resilience categories assigned by R. Froese to the selected species ('Froese's resilience') (Figure 9). The two estimates were significantly correlated (Spearman non-parametric test p-value=<0.0001) and had the expected negative sign. We summarize the comparisons between different approaches to estimation of extinction vulnerability in Table 2.

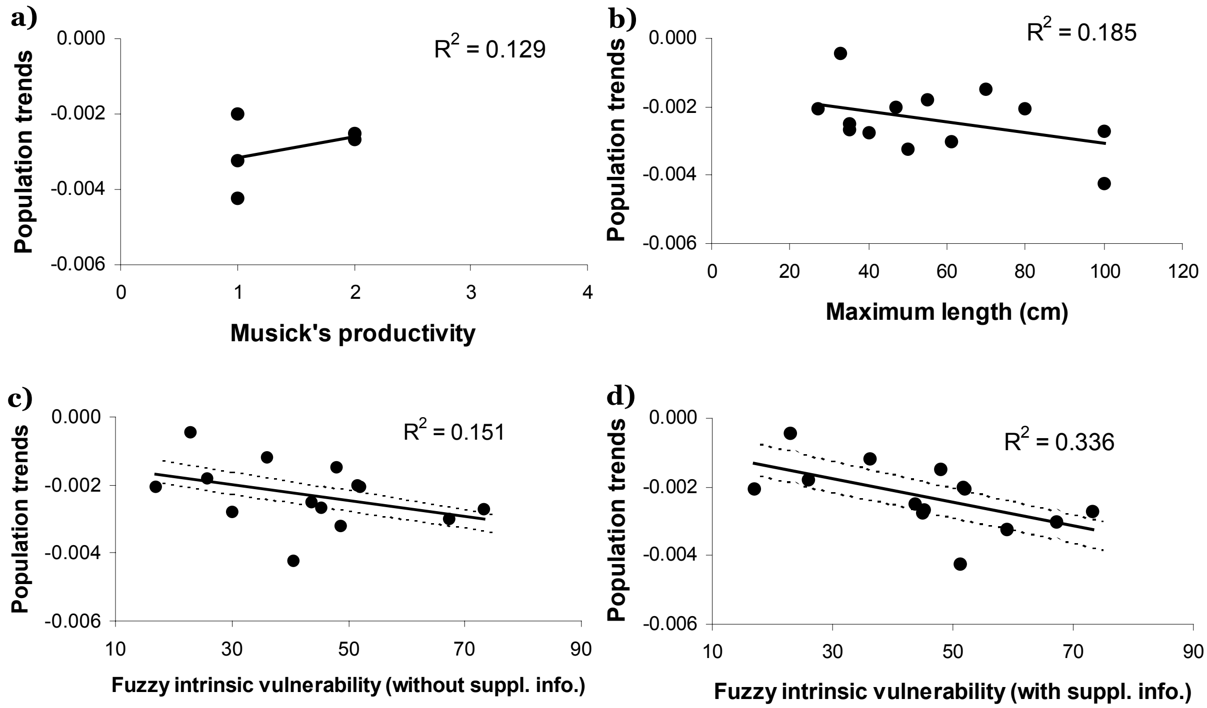


Figure 8. Linear regression (solid line) between the observed population trends of the 13 species of reef fish in Fiji and (a) Musick's productivity (Spearman non-parametric p-value=0.414), (b) maximum length (R^2=0.185, ANOVA P-value=0.142); (c) intrinsic vulnerability estimated by the fuzzy system based on information from FishBase only (R^2=0.151, ANOVA P-value=0.170). (d) intrinsic vulnerability estimated by the fuzzy system with supplementary information from SCRFA Global Database (2004) (R^2=0.336, ANOVA P-value=0.03).The dotted lines represent the confidence limits estimated from the fuzzy system based on an assumed acceptable membership of 50%.

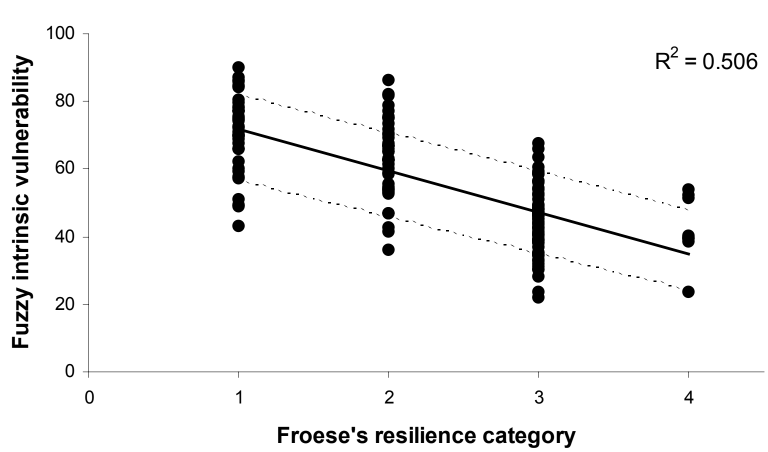


Figure 9. Comparisons between the fuzzy system intrinsic vulnerability and the resilience categories estimated in FishBase for the 159 species of marine fishes (Froese and Pauly, 2003). The resilience categories were assigned by quantitative life history criteria and subjective expert judgment (R. Froese pers. comm.), with 1 = very low, 2 = low, 3 = medium, 4 = high. The dotted lines represent the confident limits based on an assumed acceptable degree of belief to the output of 50%. The two indicators are significantly correlated (Spearman non-parametric test p-value<0.0001).

Table 2. Comparisons between approaches suggested to evaluate extinction vulnerability or resilience of marine fishes.

	Approaches			
Attributes	**American Fisheries Society Scheme**	**Individual life history parameters**	**FishBase Resilience Category**	**Fuzzy system intrinsic vulnerability**
Data requirement[1]	One or more of the followings: r, T_m, T_{max}, K *and fecundity*	One of the life history parameters (L_{max}, T_m)	Expert judgments with one or more of the followings: r, T_m, T_{max}, K *and fecundity*	One or more of the followings: L_{max}, T_{max}, T_m, *K, M, fecundity, spatial behaviour, geographic range*
Outputs	Four ordinal categories	Continuous scale of the selected life history parameters	Four ordinal categories	(a) Arbitrary scale from 1 to 100 (b) Upper and lower confident limits (c) Four ordinal categories With estimated degrees of belief associated to each category
Goodness-of-fit with observed population trends (R^2)[2]	Test 1 – 0.160 Test 2 – 0.337 Test 3 – 0.129*	Test 1 – 0.228 Test 2 – 0.276 Test 3 – 0.185	N/A	Test 1 – 0.350 Test 2 – 0.367 Test 3 – 0.151(0.336)[3]

[1] L_{max} – maximum length, T_{max} – maximum age, T_m – age at first maturity, K – von Bertalanffy growth parameter, M – natural mortality rate, r – intrinsic rate of population increase, *aggregation strength* – see Appendix 1.

[2] Test 1 – 23 species of demersal fishes in North Sea (Jennings et al., 1999a); Test 2 – 13 species of reef fishes in Fiji (Jennings et al., 1999b); Test 3 – 41 species of marine fishes listed as Critically Endangered, Endangered or Vulnerability in the IUCN Red List (Hilton-Taylor, 2000). N/A – not available.

[3] Values in parentheses represent the R^2 between the estimated vulnerabilities and the observed population trends when information from SCRFA Global Database (2004) was included.

* The direction of relationship between the Musick's productivity and the population trends was opposite to the expected direction.

DISCUSSION

The comparisons with empirical population abundance trends showed not only that a fuzzy system could be used to predict the intrinsic vulnerability of marine fishes, but also that its performance was superior to that of approaches proposed earlier. The population trends included in the analysis were confounded by factors other then fishing and differences in fishing intensities between species. Therefore, they could only be viewed as rough indicators of the vulnerability of the populations or the species to fishing. Thus, it was expected that the goodness-of-fit between intrinsic vulnerability and population trends would be low. However, the intrinsic vulnerabilities estimated from the fuzzy system still explained a considerable proportion of variance among species. Moreover, the proportions of variance explainable by the intrinsic vulnerability were higher than two suggested proxies of extinction vulnerability Furthermore, the fuzzy system could be applied to species from a wide range of geographic locations, habitats and ecosystem types, and for which different levels of knowledge is available.

Fuzzy system allows incorporation of information from a wide range of sources (Mackinson and Nøttestad, 1998) through which the predictive ability of the system may be increased especially when information is limited. For example, reef fish spawning aggregations are generally poorly documented in formal scientific literature. On the other hand, occurrence of reef fish spawning aggregations identified from both scientific and local knowledge (e.g. fishers interview) are systematically documented in the SCRFA Global Database (2004). Incorporation of such information into the fuzzy system greatly increased the goodness-of-fit between the estimated vulnerabilities and the empirical population trends. This also implies the importance of spawning aggregation behaviour in the assessment of vulnerability of reef fishes (Sadovy and Domeier, in press).

Small variations of pseudovalues of the rules and attributes suggested that varying the weighting of individual rules and attributes does not measurably affect the performance of the fuzzy system. Conventional expert systems require individual rules to be weighted according to subjective expert judgment (Cox, 1999) or availability of evidence supporting the particular rules or attributes (Mackinson, 2000). Since we defined the attributes and rules incorporated in the fuzzy system from published literature, expert weighting of individual rules was not possible. Moreover, the amount of literature describing a rule (which has been suggested as a weighting factor) does not necessarily reflect the importance of this rule. Moreover, the intrinsic vulnerability estimated from the fuzzy system barely affected by the weights on individual attributes or rules. This supports the equal weight approach adopted here.

The fuzzy system can provide estimates of intrinsic vulnerability for species with different data availability. Despite the availability of FishBase, biological characteristics remain unavailable for a large number of marine fishes (Johannes, 1998), especially in the tropics. As the system inputs are connected in parallel to the outputs, intrinsic vulnerability can still be estimated by the rules fired from the inputs where data are available. Moreover, results from the analysis showed that the estimated intrinsic vulnerability was generally insensitive to individual attributes or rules. Thus, the output of the fuzzy system should not be greatly affected by incomplete data. In addition, the vagueness on the output, partly dependent on the amount of available data, can be explicitly measured by the estimated membership to the output values.

Fuzzy expert systems enable the integration of local and scientific knowledge (Mackinson and Nøttestad, 1998) and can be used to help improve our understanding about the extinction vulnerability of marine species. The fuzzy system can adapt to new information from either quantitative studies or qualitative experts' knowledge. The fuzzy expert system presented here was constructed from the best available, current knowledge. We inevitably made assumptions when particular knowledge was absent. However, new rules can be easily incorporated into the system as they become available. The choice of fuzzy memberships and weighting on the rules can also be adjusted when new evidence or experts' opinions are available. Therefore, a fuzzy expert system can be particularly useful in facilitating workshop or focus group discussion on the assessment of extinction vulnerability of marine species (see Hudson and Mace, 1996). In this case, the discussions and opinions from the experts can act as the knowledge base. The knowledge engineer who maintains the expert system can use the knowledge base to revise and update the expert system (Mackinson and Nøttestad, 1998; Cox 1999).

The approach described here can facilitate the identification of vulnerable species onto which management and conservation efforts can be focused. Current monitoring and management efforts mainly focus on commercially important species. However, commercially important species may not necessarily be the most vulnerable species. Bycatch and other indirect fishing impact may threaten non-commercial species (Dulvy et al., 2003). The near extinctions of the common and barndoor skates, both low-value bycatch species in bottom trawl fisheries are clear examples. A large reduction in the abundance of pelagic shark in the Gulf of Mexico was unnoticed previously because of their relatively low value compared to the tunas, despite life history characteristics which made them highly vulnerable (Baum and Myers, 2004). This is particularly true for tropical fisheries where diverse species are caught and resources for monitoring and management are low (Silvestre and Pauly, 1997; Johannes, 1998; Johannes et al., 2000). The intrinsic vulnerability estimated from the fuzzy system could provide a priori indicator on the vulnerability of the species. As such, prioritization of species according to their potential extinction vulnerabilities can help to allocate limited research and monitoring resources, and develop more effective fishery management and conservation policies. Development of fishing technology that minimizes the bycatch of vulnerable species could also be encouraged (Stobutzki et al., 2001; Kennelly and Broadhurst, 2002).

Intrinsic vulnerability may combine with the other external factors in estimating the total vulnerability of the species. Here, we narrowly defined vulnerability of fish as the risk of extinction associated with the life history and ecological characteristics of a species. However, external factors such as fishing intensity, degradation of essential habitat and climate change contributes significantly to the extinction risk associated with each species (Dulvy et al., 2003). These external factors, together with intrinsic vulnerability, should be integrated in assessing overall extinction risk. In fact, these external factors can be represented at a higher hierarchical level in the fuzzy system. Rules describing the effects of these external factors, and their synergistic effect with the intrinsic vulnerability, can be incorporated into the fuzzy system through which outputs representing the total vulnerability of the species can be obtained. This may provide a decision support tool on local or global extinction risk assessment and categorization such as the IUCN Red List of the World Conservation Union or the species listing under the Canada's Species At Risk Act.

APPENDICES

The method that assigns strength of spatial behaviour was described:

1. Assignment of strength of spatial behaviour of fish onto a 1 to 100 arbitrary scale.

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