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A fuzzy logic expert system to estimate intrinsic extinction vulnerabilities of marine fishes to fishing

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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 because 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 their intrinsic vulnerability to fishing. We extract heuristic rules (expressed in IF–THEN clauses) from published literature describing known relationships between biological characteristics and vulnerability. Input and output variables are defined by fuzzy sets which deal explicitly with the uncertainty associated with qualitative knowledge. Conclusions from different lines of evidence are combined through fuzzy inference and defuzzification processes. Our fuzzy system provides vulnerability estimates that correlate with observed declines more closely than previous methods, and has advantages in flexibility of input data requirements, in the explicit representation of uncertainty, and in the ease of incorporating new knowledge. This fuzzy expert system can be used as a decision support tool in fishery management and marine conservation planning.

Keywords: Fuzzy logic; Extinction vulnerability; Marine fish; Life history; Resilience

1. Introduction

Increasing evidence indicates that marine species may be placed under threat of local, and ultimately global, extinction by the direct or indirect effects of fishing (Pitcher, 1998; Roberts and Hawkins, 1999; Wolff, 2000; Reynolds et al., 2001; 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 also 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), or by fishing activities that create large disturbance and damages to benthic habitats (Jennings et al., 2001; Kaiser et al., 2002, 2003). Declines and extinctions can be associated with the loss of essential habitat critical to complete the life cycle of the species (McDowall, 1992; Watling and Norse, 1998). Given the overexploited status of most fishery resources in the world (Jackson et al., 2001; Pitcher, 2001a; Pauly et al., 2002; Hilborn et al., 2003), timely identification of species or populations that are vulnerable to local extinction (='extirpation') is urgently needed so that appropriate counter-measures can be formulated and implemented (Jennings et al., 1999a; Dulvy et al., 2004).

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Conventional assessments of extinction vulnerability involve an in-depth understanding of population dynamics (e.g. Matsuda et al., 2000), and so lack of data limits rapid assessment for marine fish species. Currently, the required population parameters are available only for a small number of marine fishes, mainly commercially targeted species in developed countries. Collecting the necessary quantitative data on the population status is costly (Reynolds et al., 2001; Dulvy et al., 2003). The problem is most apparent in tropical, developing country fisheries where species diversity is high but resources for monitoring are poor (Jennings and Polunin, 1996; Johannes, 1998). Moreover, the intrinsic rate of increase *r*, a key population parameter for conventional assessment, is particularly difficult to estimate reliably (Musick, 1999; Reynolds et al., 2001; Dulvy et al., 2003).

1.1. Life history and ecological characteristics as proxies for extinction vulnerability

Life history and ecological traits, which have evolved to ensure persistence in the face of biotic and abiotic variability, have been suggested as 'rule-of-thumb' proxies to evaluate the intrinsic vulnerability of marine fishes to fishing (Jennings et al., 1998, 1999a,b; Reynolds et al., 2001). Here, extinction risk is a combination of intrinsic vulnerability and exposure to some threatening factor. Intrinsic vulnerability to fishing is the inherent capacity to respond to fishing that relates to the fish's maximum rate of population growth and strength of density dependence. Responses of fish populations to exploitation are, at least in part, determined by life history and ecological characteristics (Adams, 1980; Roff, 1984; Kirkwood et al., 1994; Dulvy et al., 2003; Sadovy and Domeier, in press). Selected life history parameters and ecological characteristics are demonstrated to be correlated with intrinsic vulnerabilities (Jennings et al., 1999a,b; Denney et al., 2002; Rowe and Hutchings, 2003; Sadovy and Domeier, in press), some of which are suggested to be used as 'rules-of-thumb' to *triage* vulnerable species (Dulvy et al., 2004). However, while these rules-of-thumb are available, little effort is given to how these rules may be combined and applied to assess a large number of species.

Since life history and ecological traits contribute concurrently to fishing vulnerability, an indicator conflating them should be useful in comparing vulnerability across species. 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 techniques.

Rule-based systems that classify fishes into ordinal extinction vulnerability levels are available (Dulvy et al., 2004). These systems are based on population parameters and biological characteristics and generally employ classical logic, which classifies fish exclusively to categories of each biological characteristic. An example is the scheme adopted by the American Fisheries Society (AFS) that aims to identify the productivity (assumed the inverse of vulnerability) of fishes (Musick, 1999; hereafter called 'AFS's scheme'). AFS's scheme determines fish productivity level (high, medium, low, very low) from pre-defined categories of life history and population characters such as intrinsic rate of increase, longevity, age at first maturity, fecundity and the von Bertalanffy growth parameter, *K*. The productivity estimates are then used to assess threshold population levels for extinction (Musick, 1999; Musick et al., 2000).

Fuzzy set theory can be useful in deriving an index of extinction vulnerability. Vagueness exists in our knowledge of fish biological and ecological characteristics. Vagueness or uncertainty also exists when we infer vulnerability to fishing from a variety of intrinsic characteristics. For example, we know that large fish tend to be associated with higher extinction risk. However, it is difficult to provide a clear cut definition of what 'large fish' is, i.e., to separate large and small body size, and thus high and low extinction vulnerability. Moreover, other biological characteristics may confer low risk on a species despite large size. Such vagueness and uncertainty can be addressed in fuzzy set theory (or 'fuzzy logic').

In fuzzy set theory (or 'fuzzy logic'), originally developed by Zadeh (1965), a subject can belong to one or more fuzzy set(s) with a gradation of membership, instead of classifying membership as either 'true' or 'false' as in the classical logic system. The degree of membership is defined by fuzzy membership functions (e.g., Fig. 1). For instance, based on the fuzzy membership functions presented in Fig. 1(a), fish with a maximum length of 68 cm can be classified as medium and large size, with degree of membership of 0.7 and 0.3, respectively (maximum of 1). Fuzzy logic also allows conclusion(s) to be reached from premise(s) with a gradation of truth. Membership can be viewed as a representation of the 'possibility' of association with the particular set (instead of the 'probability' used in frequentist or Bayesian statistics) (Zadeh, 1995; Cox, 1999). Kandel et al. (1995), Laviolette et al. (1995), Zadeh (1995), and Regan and Colyvan (2000) provide discussion on the applications of fuzzy logic and probability theory.

An expert system is an artificial intelligence system which is designed to mimic how expert(s) solve problems. It is usually a computer program that uses heuristic rules to describe the available expert knowledge. Rules are expressed in the form:

IF *A* THEN *B*

where *A* is the premise while *B* is the conclusion (Kasabov, 1996). The actions defined by the rules are 'fired'

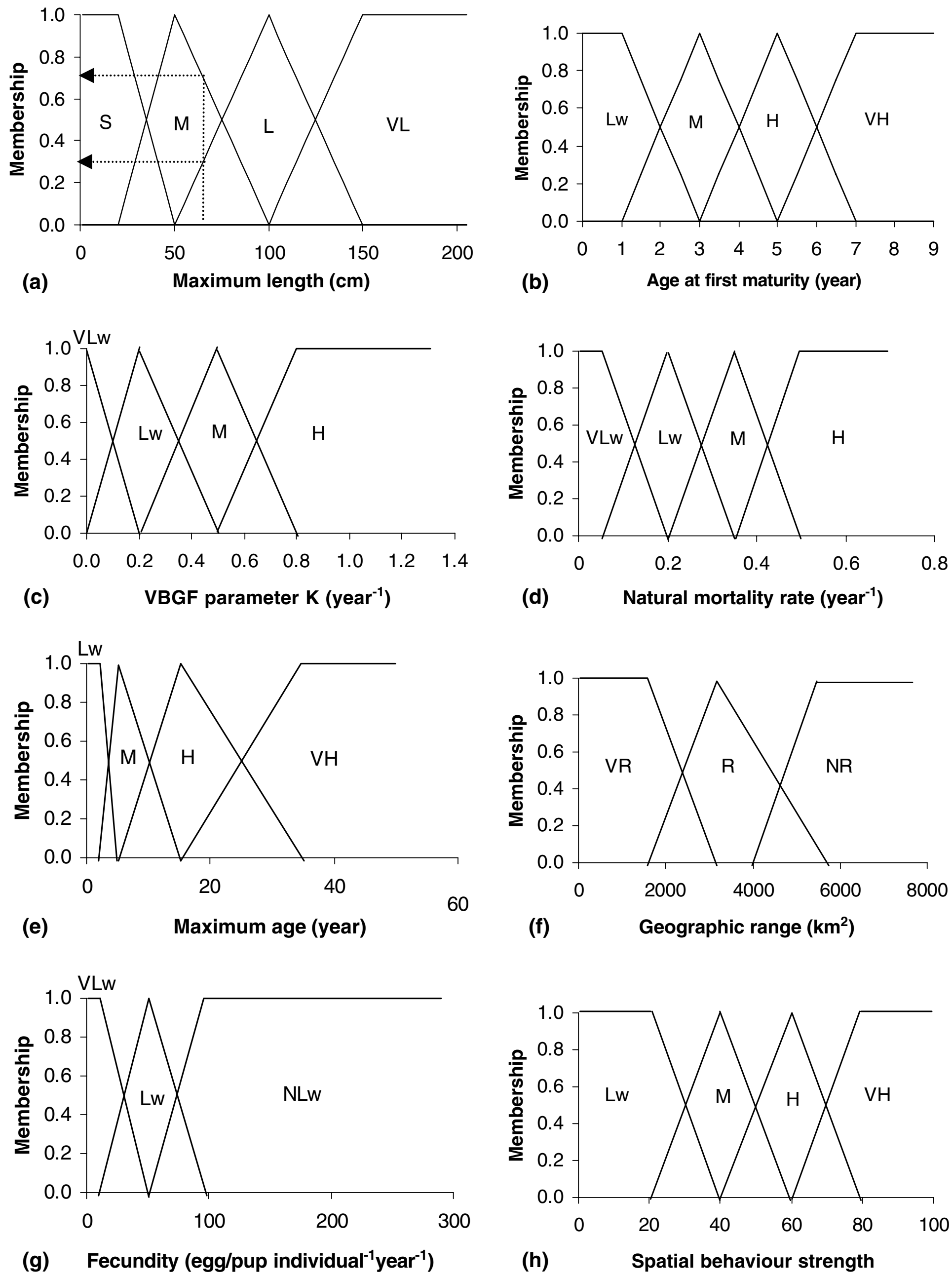

Fig. 1. Fuzzy sets defining the input life history and ecological characteristics: (a) maximum body length, (b) age at first maturity, (c) von Bertalanffy growth parameter K, (d) natural mortality rate, (e) maximum age, (f) geographic range, (g) annual fecundity, (h) strength of aggregation behaviour (see technical annex A.3.). VLw – very low, Lw – low, NLw – not low, M –medium/moderate, H – high, VH – very high, L – large, VL – very large, R – restricted, VR – very restricted, NRV – not restricted, S – small. A fish species with maximum body length of 68 cm corresponds to "medium body size" and "large body size" with membership of 0.7 and 0.3, respectively (threshold value = 0.2).

(=operated) when the degree of membership of the premises exceed certain threshold values. The threshold values define the minimum required membership of the premises that an expert would expect for that particular rule to be fired and are generally defined by subjective criteria. Conflicting rules are allowed to fire jointly.

In this paper, a fuzzy expert system is used 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. Individual species are treated as the unit of assessment here, but the methodology can be applied to individual populations or sub-stocks. The new index is validated by correlations with empirical data. The empirical data include the observed rate of population decline of fishes in the North Sea (Jennings et al., 1999a) and Fiji (Jennings et al., 1999b), and species listed in the IUCN list of threatened species (Hilton-Taylor, 2000). We evaluate the robustness of the system and its assumptions using various sensitivity analyses. We compare the pros and cons of the fuzzy expert system with other approaches in terms of its practical application. The technical details of fuzzy set theory and the fuzzy expert system are presented in the technical annex (Sections A.1 and A.2).

2. Methods

2.1. Structure and functioning of the fuzzy expert system

We developed a fuzzy expert system (hereafter called fuzzy system, developed using Microsoft Excel® and Visual Basic for Applications) 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). The input variables include maximum length, age at first maturity, longevity, von Bertalanffy growth parameter K, natural mortality rate, fecundity, strength of spatial behaviour, and geographic range (Fig. 1). The outputs are expressed as four linguistic categories referring to the levels of intrinsic vulnerability to extinction: (1) very high, (2) high, (3) moderate and (4) low (Fig. 2). Intrinsic vulnerability is also expressed on an arbitrary scale from 1 to 100, with 100 being the most vulnerable. Membership (maximum of 1) to each of the input and output linguistic category is defined by a fuzzy membership function (Figs. 1 and 2).

The fuzzy system includes sets of heuristic rules that allow the inferences of the intrinsic vulnerability based on the inputs. Essentially, fishes are classified into different linguistic categories of life history and ecology with associated degrees of membership based on the input fuzzy sets (Fig. 1). The inputs trigger the pre-specified rules that relate the different input linguistic categories

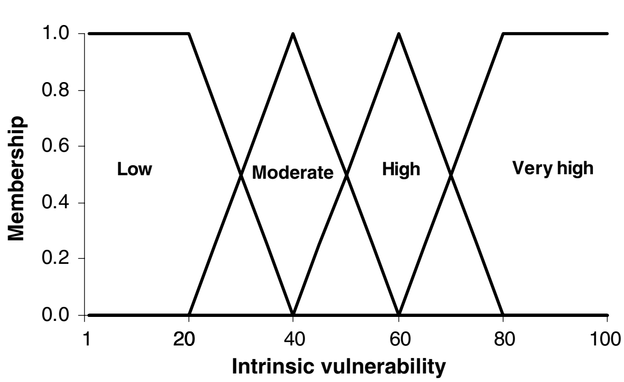

Fig. 2. Output fuzzy sets for the intrinsic vulnerability of marine fishes. The "Low" and "Very high" vulnerabilities are defined by trapezoid membership functions while the "Moderate" and "High" vulnerabilities are defined by triangle membership functions. Intrinsic vulnerability was scaled arbitrary from 1 to 100.

to intrinsic vulnerability. The heuristic rules were developed based on relationships described in published literature (Table 1), excluding those overwhelmingly disproved by empirical data. Each rule is weighted and we made an initial assumption of equal weighting with 0.5 for all rules. We assumed the minimum membership required to trigger the rules (threshold value) to be 0.2. This means that the system considers the premises to be totally false unless they have membership of 0.2 or more. Thus the system screens out premises that have very low degree of membership.

At the end, the system estimates the degree of membership to the four categories of intrinsic vulnerability for a fish taxon (Fig. 2), and provides a quantitative index of vulnerability. The system also provides lower and upper bounds of the vulnerability index (see Appendix A – technical annex for details on the development of the fuzzy sets and heuristic rules, and functioning of the fuzzy expert system).

2.2. 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 ($N = 159$). Using the life history and ecological information available for these fishes, we calculated their intrinsic vulnerability based on the fuzzy system.

We evaluated the impacts of individual attributes to the output of the system using a jackknife approach (Sokal and Rohlf, 1995) where the calculations of the intrinsic vulnerability are repeated, while excluding one or more attribute(s) each time. If the system outputs are greatly sensitive to the removal of individual attributes, the outputs may also be sensitive to the weighting factors on the attributes. Thus, through this test, we aimed to evaluate our assumption on weighting individual attributes equally. The degree of deviation (Dev), represented by the changes in the predicted intrinsic vulnerability, was calculated for each species when attribute j was removed from the system:

$$\mathrm{Dev} = R_{T-j} - R_T,$$

where R is the estimated output from the system with full set of attributes (T) and attributes j being removed. We repeated the analysis by randomly removing increasing number of attributes except maximum length, as maximum length was the most readily available parameter for marine fishes. We repeated the latter 50 times to obtain a distribution of the estimated deviations.

We tested the sensitivity of the system output to different threshold values. We systematically varied the threshold value of the fuzzy expert system and recorded

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

Attribute	Rule		Conditions		Consequences	Supporting evidence[a]	Opposing evidence[b]
1	1	IF	Maximum length[c] 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[c] is *large*	THEN	Vulnerability is *high*		
1	3	IF	Maximum length[c] is *medium*	THEN	Vulnerability is *moderate*		
1	4	IF	Maximum length[c] 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*	OR		5, 6, 13, 19, 28, 33	11
			Natural mortality (*M*) is *very low*	THEN	Vulnerability is *very high*[d]		
4	14	IF	VBGF *K* is *low*	OR			
			Natural mortality (*M*) is *low*	THEN	Vulnerability is *high*[d]		
4	15	IF	VBGF *K* is *medium*	OR			
			Natural mortality (*M*) is *medium*	THEN	Vulnerability is *medium*[d]		
4	16	IF	VBGF *K* is *high*	OR			
			Natural mortality (*M*) is *high*	THEN	Vulnerability is *low*[d]		
5	17	IF	Geographic range is *restricted*[e]	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*[f]	THEN	Vulnerability is *high*	1, 2, 3, 4, 5, 19, 20	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[g]	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	

[a,b] References: 1. Holden (1973), 2. Holden (1974), 3. Holden (1977), 4. Brander (1981), 5. Hoenig 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. (1997), 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).

[a] Literature supporting the assertions of the specific rules.

[b] Literature opposing the assertions of the specific rules.

[c] Asymptotic length was used preferentially. However, if asymptotic length was not available, we used maximum length as surrogate.

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

[e] Geographic range is crudely 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.

[f] Strong evidence suggests that high fecundity does not reduce the extinction vulnerability of fishes. However, evidence suggesting that lower fecundity (less than 100) increases vulnerability of fishes is valid. 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.

[g] Spatial behaviour was defined as groups of fish aggregating 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 that ranges from 0 to 100. The method that assigns strength of spatial behaviour onto the arbitrary scale is described in the technical annex A.3.

Table 2
The definitions of classical (Boolean) sets used to classify life history and ecological characteristics into different categories, and the rules that connected them to different level of intrinsic vulnerabilities

Life history characteristics	Categories of life history characteristics and their resulted vulnerability			
	Low	Moderate	High	Very high
Maximum length (cm)	$50 \geqslant L_{max}$	$50 < L_{max} \leqslant 100$	$100 < L_{max} \leqslant 150$	$150 < L_{max}$
Age at first maturity (year)	$2 \geqslant T_m$	$2 < T_m \leqslant 4$	$4 < T_m \leqslant 6$	$6 < T_m$
VBGF parameter K (year^{-1})	$0.8 < K$	$0.5 < K \leqslant 0.8$	$0.2 < K \leqslant 0.5$	$0.2 \geqslant K$
Natural mortality rate (year^{-1})	$0.5 < M$	$0.35 < M \leqslant 0.5$	$0.2 < M \leqslant 0.35$	$0.2 \geqslant M$
Maximum age (year)	$3 \geqslant T_{max}$	$3 < T_{max} \leqslant 10$	$10 < T_{max} \leqslant 30$	$30 < T_{max}$
Geographic range (km^2)	–	–	3170 < Range $\leqslant$ 5730	3170 $\geqslant$ Range
Fecundity (egg/pup individual^{-1} year^{-1})	–	–	50 < Fec $\leqslant$ 100	50 $\geqslant$ Fec
Spatial behaviour strength	40 $\geqslant$ SB	40 < SB $\leqslant$ 60	60 < SB $\leqslant$ 80	80 < SB

the output for the 159 marine fishes from FishBase. We examined the differences in the system output for different threshold values.

2.3. Validity tests on vulnerability estimates

We examined the validity of the intrinsic vulnerability estimated from the fuzzy system using empirical data with three tests that used three independent sets of data in which extinction risk or historical abundance trends of the marine taxa in the datasets were known. We used population decline as an indicator of extinction risk because it was readily available for a large number of marine fish species. A similar approach had been used in other comparative analysis between life history traits and vulnerability of marine fishes (e.g., Jennings et al., 1999a,b). Species included in the data sets represent examples from wide geographic and habitat ranges. The three datasets included:

(1) extinction risk categories of 40 species of marine fishes in the IUCN Red List of threatened species (Hilton-Taylor, 2000);
(2) population trends of 24 species of demersal fishes in the northern North Sea (Jennings et al., 1999a);
(3) population trends of 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).

We used the goodness-of-fit of the test statistics as an indicator for the accuracy of the extinction risk predicted from the explanatory variables. For dataset 1, since the independent variable (IUCN extinction risk categories) is ordinal, logistic regression was used (Agresti, 1996). For datasets 2 and 3, linear regression was used. 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 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) provided the best fit; (2) productivity categories evaluated using the AFS's scheme (see Musick, 1999 for details on the methodology). Since AFS's productivity (assumed inverse of vulnerability) is expressed in ordinal categories, we used a Chi-square test for dataset 1 (species from the IUCN Red List), and ANOVA for datasets 2 and 3 (species from Jennings et al., 1999a,b). 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 conducted an additional test to compare the performance of the expert system with classical logic. We constructed an expert system with attributes and rules that were exactly the same as the fuzzy system. However, classical (Boolean) sets were used instead of fuzzy sets (Table 2). Thus fish species were classified exclusively to a single category for each biological attribute. If the input parameters of a species resulted in multiple conclusions, the final conclusion would be the highest resulting vulnerability category (Musick, 1999). We evaluated the vulnerability of the species in the three test data sets using this system and compared the goodness-of-fit to the empirical data with other vulnerability proxies.

3. Results

Based on the input life history and ecological parameters, the fuzzy system estimated the intrinsic vulnerability with associated possibilities. For instance, using the biological parameters available from FishBase, we estimated that Atlantic cod (*Gadus morhua*, Gadidae) has an intrinsic vulnerability of 61 (100 being the most vul-

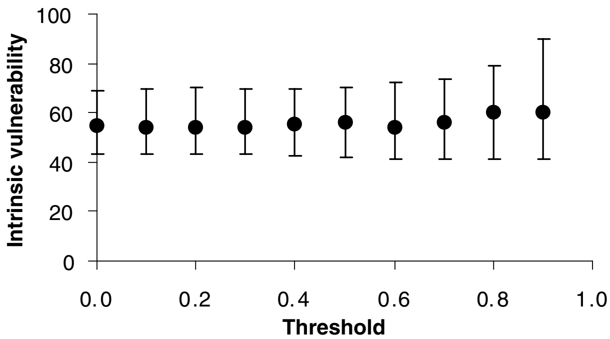

Fig. 3. Estimated intrinsic vulnerability from the fuzzy logic expert system for the 159 species of marine fishes when threshold value varied from 0 to 0.9. The dots represent the median, while the bars represent the 25% upper and lower quartiles.

nerable) with lower and upper bounds (membership = 0.5) of 48–72. It was identified as being highly to very highly vulnerable, with possibility of 0.78–0.63, respectively.

Sensitivity analysis showed that the estimated intrinsic vulnerabilities were insensitive to the pre-defined threshold value (Fig. 3). The estimated intrinsic vulnerabilities varied slightly as we increased the threshold value from 0 to 0.9. Variations in the estimated outputs increased when the threshold value increased to 0.6 and more.

Jackknifing showed that the deviations in the estimated intrinsic vulnerabilities were relatively small for the majority of species when individual attributes were removed from the fuzzy system (Fig. 4(a)). In most cases, upper and lower quartiles (75% and 25%, respectively) of the deviations in the predicted intrinsic vulnerability were small, within 5 (maximum of 100) relative to the baseline estimates (i.e., all attributes included). However, maximum deviations were up to 20–30 for some species. In some cases, deviations were particularly strong when attributes number four and seven were removed (maximum age and spatial behaviour strength, respectively). Removal of attributes three, five and six tended to result in unsymmetrical negative bias on the predicted vulnerability, while removal of attribute eight (nature of spatial aggregation) tended to result in positive bias.

Deviations of the output from the baseline increased when we randomly removed increasing number of attributes from the system (Fig. 4(b)). The median of deviated vulnerability ranged from about 1 (maximum deviation is about 18) when one attribute was randomly removed, to about 12 (maximum deviation is about 42) when only maximum length was used. Predicted vulnerability tended to be under-estimated when only maximum length was considered by the system.

The intrinsic vulnerabilities estimated from the fuzzy system were significantly related to the extinction risk

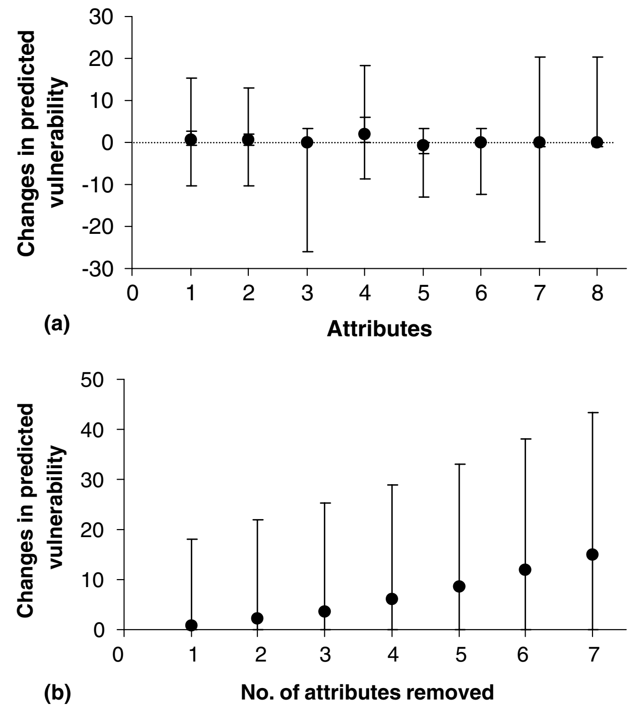

Fig. 4. Sensitivity of the estimated intrinsic vulnerability to individual attributes incorporated in the fuzzy system evaluated using the jackknife approach (Sokal and Rohlf, 1995). The black dots are the median of the deviations of the 159 marine fishes from FishBase when individual (a) attributes were removed and (b) increasing number of attributes were randomly included (absolute magnitude of changes). The bars are the 25% and 75% quartiles of the deviations (inner bars in Fig. 4(a)). The other bars in Fig. 4(a) are the maximum and minimum ranges of the deviations.

categories of marine fishes in the IUCN threatened species list with better goodness-of-fit than the two other vulnerability proxies (Fig. 5). Both AFS's scheme and maximum length could not significantly explain the differences in the IUCN categories of the tested species at 5% significant level (AFS's productivity: p value = 0.085, L_{max}: 0.0731), while the estimated intrinsic vulnerability could significantly explain them (intrinsic vulnerabilities: p value = 0.0253).

Intrinsic vulnerabilities were also significantly related to the population trends of demersal fishes in the North Sea (Jennings et al., 1999a) with higher goodness-of-fit (Fig. 6) than the other proxies. When we considered dragonet (*Callionymus lyra*) and spurdog (*Squalus acanthias*) as outliers, AFS's scheme and individual life history parameters (maximum length and age at first maturity) explained 34% and 28% of the variance, respectively, whereas our fuzzy system explained over 36% of the variance. The relationships remained 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 (Fig. 6).

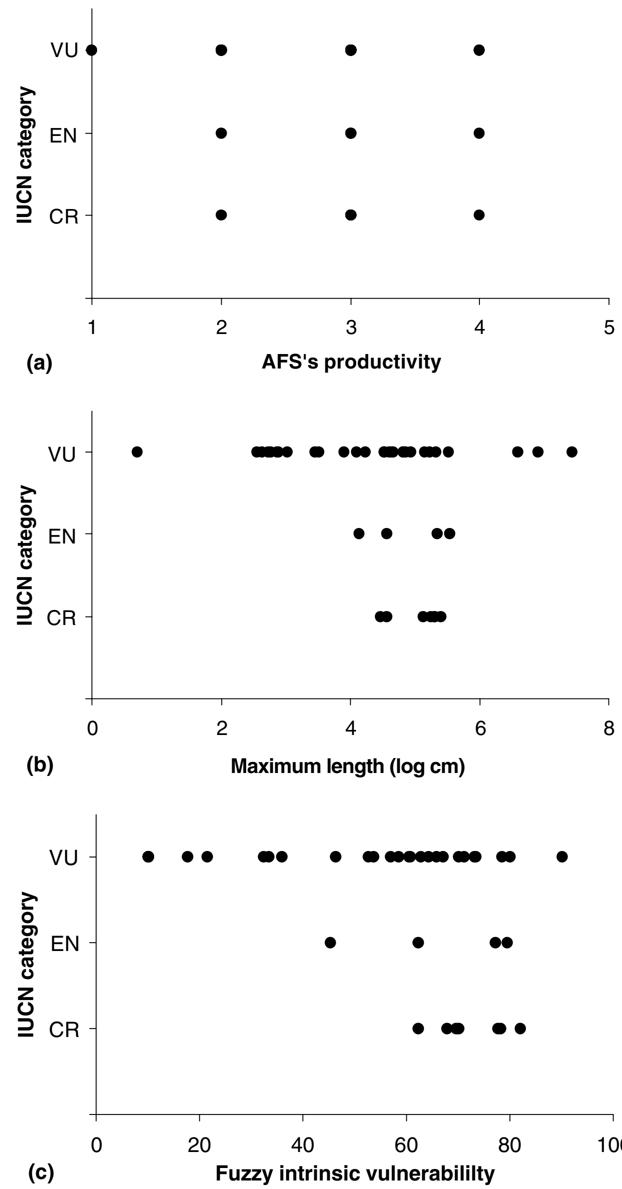

Fig. 5. Plot of population trends of 40 species of marine fishes listed in the IUCN list of threatened species (Critically Endangered, Endangered and Vulnerable) and (a) AFS's productivity – productivity categories estimated by the AFS scheme (Musick, 1999), (b) maximum length (log) and (c) fuzzy system intrinsic vulnerability. We only included species that were categorized by criteria A: reduction in population size (IUCN Species Survival Commission, 2001). CR – critically endangered, EN – endangered, VU – vulnerable.

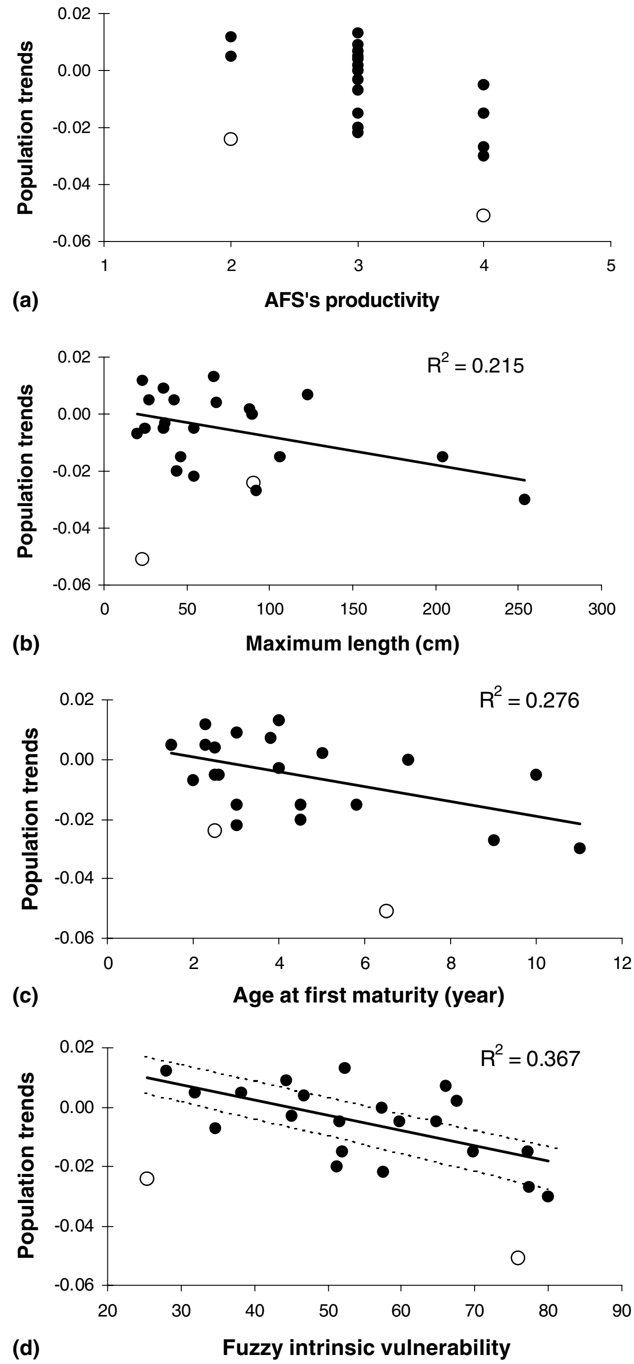

Fig. 6. Plot of the observed population trends of the 24 species of demersal fish in the North Sea and the proxies of extinction vulnerability: (a) AFS's productivity (ANOVA p value = 0.024), (b) maximum length (L_{max}) (ANOVA p value = 0.034), (c) age at first maturity (T_m) (ANOVA p value = 0.014), (d) fuzzy system intrinsic vulnerability (ANOVA p value = 0.004). AFS's productivity were 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) in the analysis, AFS's productivity was only marginally significant (R^2 = 0.272, ANOVA p value = 0.042), The goodness-of-fits of age at first maturity and the fuzzy system intrinsic vulnerability became: T_m (R^2 = 0.207, ANOVA p value = 0.029) and intrinsic vulnerability (R^2 = 0.246, ANOVA p value = 0.016). The dotted lines represent the upper and lower bounds estimated from the fuzzy system based on an assumed acceptable membership of 0.5.

We did not obtain significant relationships between the three vulnerability proxies and the observed population trends of the Fiji reef fishes based only on the information available from FishBase (Fig. 7). Lack of life history data meant that we could estimate AFS's productivity for only seven species, preventing us from statistically analyzing the data. There was also no relationship between individual life history parameters (enough data only available for maximum length) and the fuzzy system intrinsic vulnerabilities with the ob-

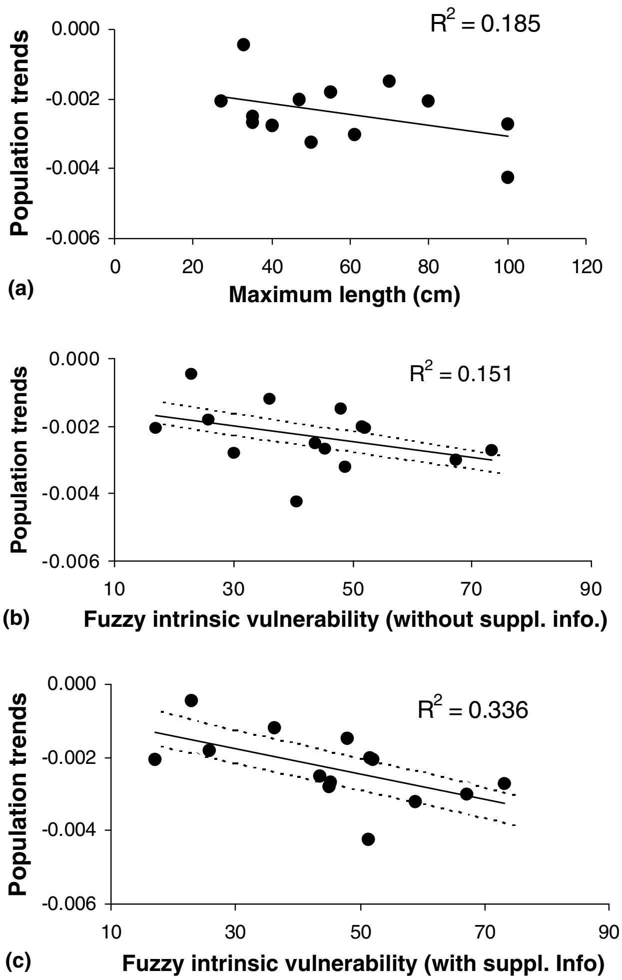

Fig. 7. Plots between the observed population trends of the 13 species of reef fish in Fiji (a) maximum length (ANOVA p value = 0.142); (b) intrinsic vulnerability estimated by the fuzzy system based on information from FishBase only (ANOVA p value = 0.170). (c) intrinsic vulnerability estimated by the fuzzy system with supplementary information from SCRFA Global Database (2004) (ANOVA p value = 0.03).The dotted lines represent the upper and lower bounds estimated from the fuzzy system based on an assumed acceptable membership of 0.5. The lack of the necessary life history data prevented us from analyzing the AFS's productivity.

served population trends (ANOVA p value = 0.142 and 0.170, respectively).

A significant relationship between the fuzzy system intrinsic vulnerabilities and the population trends of Fiji reef fishes exists when we employed supplemental 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) (Fig. 7(c)). The fuzzy system is then able to explain about 34% of the variance in population trends (ANOVA p value = 0.03).

When the fuzzy sets were replaced by classical sets (Table 2), the estimated intrinsic vulnerabilities did not correlate with the population trends in the three empirical datasets. The test statistics for the three tests were: marine fishes from the IUCN Red List – Likelihood ratio χ^2 p value = 0.206; demersal fishes in the North Sea – ANOVA p value = 0.313; reef fishes in Fiji – ANOVA p value = 0.133.

4. Discussion

Comparisons with empirical population abundance trends showed that a fuzzy system could be used to predict the intrinsic vulnerability of marine fishes. It is also a better predictor of rate of population decline than other proxies proposed earlier. The population trends included in the analysis were confounded by factors such as differences in fishing intensities between species. Therefore, they could only be viewed as rough indicators of the vulnerability to fishing. Thus, intrinsic vulnerability is expected to be able to explain only a fraction of the variance in population trends among species. However, the fuzzy system predicted intrinsic vulnerability still explained a considerable proportion of such variance. The proportions of variance explainable by the predicted intrinsic vulnerability were higher than two suggested proxies of extinction vulnerability. Furthermore, the tests suggest that the use of fuzzy logic in the expert system provides a better predictor of intrinsic vulnerability than a system employing classical logic. These support the validity of the fuzzy system. In addition, 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 are available.

We did not account for the number of required input parameters in the comparisons between different vulnerability proxies. The fuzzy system has more attributes than the other proxies. Also, the jackknife analysis suggested that deviations of the outputs increased when attributes were removed from the system. Therefore, its ability to predict vulnerability, and therefore its performance relative to other methods, may decrease when information becomes scarce.

On the other hand, the fuzzy system can provide estimates of intrinsic vulnerability for species with different data availability and can explicitly represent a degree of confidence in the output. In the fuzzy system, the conclusions (level of intrinsic vulnerability) can be reached by multiple inputs. Thus intrinsic vulnerability can still be estimated by the rules fired from the inputs where data are available. The jackknife analysis suggests that the estimated intrinsic vulnerability tends to converge when more attributes are included. Thus the deviation of the estimated output could be reduced by increased data availability and more rules linking the input attributes to intrinsic vulnerability. It is noted that when attributes only relate to either high or low vulnerability (fecundity, geographic range and type of spatial behaviour), their removals may result in unsymmetrical deviations in the predicted intrinsic vulnerability.

Although removals of attributes result in relatively small deviations of predicted vulnerabilities for the majority of the tested species, some species may have a suite of biological characteristics that render them sensitive to the weighting of particular attribute(s). For instance, by incorporating information on reef fish aggregation from SCRFA Global Database (2004), the fuzzy system greatly increased the goodness-of-fit between the estimated vulnerabilities and the empirical population trends of Fiji's reef fishes. Therefore, weighting of individual rules according to subjective expert judgment (Cox, 1999), or availability of evidence supporting the particular rules or attributes (Mackinson, 2000) may improve the performance of the system. However, since we defined the attributes and rules 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. Future studies may include systematically collating experts' opinions to decide the relative importance of different attributes and thus their weighting factors.

Fecundity may not be a significant attribute to be included in the fuzzy system. Ample evidence suggests that fecundity does not relate to the intrinsic vulnerability of fishes when other life history traits such as maximum length and age at maturity are accounted for (see Sadovy, 2001 for review on the topic). In particular, the notion that highly fecund fish are resilient to fishing has been disproved. Although, some literature suggests that low fecundity is a factor causing high intrinsic vulnerability, majority of them focus on limited group of species (elasmobranchs). On the other hand, we considered all available evidence to develop heuristic rules in the fuzzy system. Moreover, inclusion of rules that relate low fecundity to high vulnerability makes the system more conservative i.e., the system tends not to underestimate vulnerability. However, our results suggest that removal of fecundity as an attribute results in small deviations in the predicted intrinsic vulnerability. This appears to support the low importance of the relationship between low fecundity and high vulnerability. Thus fecundity may be excluded from future usage of the system, or should be given relatively smaller weights than the other attributes.

The fuzzy system can adapt to new information from both quantitative studies and qualitative experts' knowledge, and enables an integration of local and scientific knowledge (Mackinson and Nøttestad, 1998). Currently, some rules in the system are based on literature that does not represent species with full range of life history and ecological traits, and thus these rules were extrapolated from a smaller range of species. Thus the heuristic rules, fuzzy membership functions, and the values that defined them, can be modified based on expert knowledge or newly available information (Cox, 1999). The weighting on the rules can also be adjusted when new evidence or experts' opinions are obtained. Therefore, a fuzzy expert system can be particularly useful in facilitating workshop or focus group discussions 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 so that management and conservation efforts can be focused. Current monitoring and management efforts mainly concentrate on commercially important species, which, however, may not necessarily be the most vulnerable. Bycatch and other indirect fishing impacts 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 (Brander, 1981; Casey and Myers, 1998). A large reduction in the abundance of pelagic sharks 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 (Dulvy et al., 2004). For instance, Morato et al. (2004) applied the fuzzy system presented in this paper to evaluate the intrinsic vulnerability of more than 900 species of seamount-associated fishes and found that they had significantly higher vulnerability than non-seamount fishes. Therefore, this suggests serious conservation concerns on the increasing fishery exploitations of seamount assemblages.

In conclusion, we suggest that the fuzzy expert system approach described here is a useful tool to predict intrinsic vulnerability of marine fishes. It may also be easily extended and further improved. 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 local 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 contribute 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 threatened species of the World Conservation Union (Todd and Burgman, 1998; Regan et al., 2000) or the species listing under the Canada's Species At Risk Act.

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Appendix A. Technical annex

A.1. Development of the fuzzy expert system

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 instance, high fecundity had been suggested to be associated with low vulnerability. However, both theoretical and empirical studies lately do not support such relationship (see Table 1 for the list of evidence). Thus the rules relating high fecundity and low vulnerability are excluded from the system.

The published relationships were transformed into IF–THEN rules relating life history and ecological characteristics to the four vulnerability categories (Table 1). Firstly, we transformed the input biological attributes into linguistic categories, defined by fuzzy sets (Fig. 1), and based on an existing vulnerability categorization scheme (AFS's scheme, Musick, 1999). However, studies reported in Table 1 may not represent the full range of each trait for marine fishes. Thus we have to extrapolate the reported qualitative relationships between biology/ecology and vulnerability to fishes with wider range of traits. As prior knowledge about the choice of fuzzy membership functions for the input attributes was lacking, we employed the simplest forms: trapezoid membership functions at the upper and lower limits and triangular membership functions at intermediate positions on the axis. Other options include membership functions in sigmoid, gamma, and irregular shapes (Cox, 1999) which may be explored if their use are justified by experts.

Trapezoid and triangular membership functions can be defined by values of independent variables that give minimum (0) and maximum (1) memberships. These values are modified from AFS's scheme; maximum length, geographic range and spatial behaviour strength were not included and so, for consistency with other attributes, we classified each of them with linguistic categories (only two categories of geographic range are associated with rules). We defined the membership functions for maximum length and geographic range from the lower quartile, median, and upper quartile of each attribute from all marine fishes recorded in FishBase (over 15,000 species; Froese and Pauly, 2003). Membership functions of spatial behavior strength were defined by arbitrary values (see Section A.3.). For all the fuzzy membership functions, we assumed high degree of overlap between fuzzy sets. This assumption reflects our uncertainty on the exact relationship between the premises (the biological and ecological characteristics) and the conclusion (intrinsic vulnerability) (Kosko, 1993).

We defined four linguistic categories referring to the levels of intrinsic vulnerability: (1) very high vulnerability to local extinction, (2) high vulnerability, (3) moderate vulnerability and (4) low vulnerability. These linguistic categories were defined by fuzzy sets on an arbitrary 'intrinsic vulnerability' scale from 1 to 100. Without prior knowledge, we assumed the simplest forms of fuzzy membership function: trapezoid and triangular membership functions. A trapezoid membership function was used for the 'very high vulnerability' and the 'low vulnerability' categories, while symmetric triangular membership functions were used for the other two categories (Fig. 2).

We assumed the minimum membership in the premises (conditions) required to fire the rules (threshold value) to be 0.2. This means that we considered the premises to be totally false unless they had membership of 0.2 or more. Thus the system screens out premises that have very low degree of membership. We evaluated the sensitivity of the system outputs to different threshold values.

We made an initial assumption of equal weighting with 0.5 for all rules. The weighting factor represents the level of belief associated with the rule. Thus a weighting factor of 0.5 means we have 50% of belief to the validity of the rule. That is:

$$\text{Membership}_{\text{conclusion}} = \text{Membership}_{\text{premise}} \cdot \text{CF},$$

where CF represents the weighting factor. The conclusion of a particular rule can only have a maximum degree of membership of 0.5 to its fuzzy set. We tested the validity of the equal weighting assumption using a jackknife approach.

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

$$\text{Membership}_e = \text{Membership}_{e-1} + \text{Membership}_i \cdot (1 - \text{Membership}_{e-1})$$

where Membership_e is the degree of membership of the conclusion after combining the conclusions from e pieces of rules, and Membership_i is the degree of membership of the conclusion of rule i.

A.2. Operation of the fuzzy system

A.2.1. Fuzzification

Fuzzification is a process that determines the degree of membership to the fuzzy set based on the fuzzy membership function. 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 membership functions (Fig. 2). Categories with membership exceeding the threshold value would fire the 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 0.7 and 0.3, respectively (threshold value = 0.2) (Fig. 1).

A.2.2. Rule firing and fuzzy reasoning

All premises with membership exceeding the threshold values ($\text{Membership}_{\text{ant}}$) triggered the fuzzy system to fire their corresponding rules. 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 vul nerability is *high*

would be fired. When several rules with the same conclusion were fired, the conclusions were combined and accumulated using the method of Buchanan and Shortliffe (1984).

A.2.3. Defuzzification

Defuzzification refers to the reduction of a range of conclusions with different membership to a single point output. The conclusions reached from the rules were defuzzified based on the output fuzzy membership functions. Defuzzification was based on the centroid weighted-average method (Cox, 1999), i.e., the output intrinsic vulnerability factor was calculated from the average values with maximum membership of each output fuzzy membership function weighted by the membership associated with each conclusion. In a triangular membership function, the values with maximum membership refer to the intrinsic vulnerability factor with the highest membership (peak of the triangle). For trapezoid membership function, this was assumed to be the mid-point between the two ends of the plateau. The upper and lower bounds of the output were estimated by using the smallest and largest intrinsic vulnerability factors that fall within the particularly fuzzy sets at the specified membership level, instead of using the average values with maximum membership (Mackinson et al., 1999). They represent the range of intrinsic vulnerability that falls within the pre-specified membership of the conclusion fuzzy membership functions and thus are dependent on the base width of the conclusion fuzzy sets (Mackinson et al., 1999).

$$\text{Intrinsic vulnerability} = \frac{1}{\sum_{i=1}^{4} \text{Membership}_i} \cdot \left(\sum_{i=1}^{4} \text{Membership}_i \cdot \text{Sup}_i \right),$$

$$\text{Bounds}_{\text{U/L}} = \frac{1}{\sum_{i=1}^{4} \text{Membership}_i} \cdot \left(\sum_{i=1}^{4} \text{Membership}_i \cdot f_i(\text{ML}_{\text{U/L}}) \right),$$

where Sup_i is the average intrinsic vulnerability index with maximum membership from conclusion fuzzy membership functions i, and $f(\text{ML})$ is the estimated upper or lower bounds (U and L, respectively) of the conclusion fuzzy membership functions at the specified membership level (ML).

A.3. Assignment of strength of spatial behaviour of fish

We obtained qualitative descriptions on the spatial behaviour of the fish from FishBase. We looked for keywords that linguistically describe the spatial behaviour of fish (Table A.1). We assumed a baseline spatial behaviour strength of 1 for species forming groups or colonies, 40 for aggregations and shoals and 80 for schools (Pitcher, 2001b). The baseline spatial behaviour strength (B) was then adjusted by a multiplication factor

Table A.1
Keywords that linguistically describe the strength of spatial behaviour and their corresponding multiplication factors

Linguistic descriptions	Multiplication (A)
Usually solitary/pair	−40%
Occasionally/sometimes/alternately/ may/probably/loose/small	−40%
Sometimes solitary/pair	−20%
Presumably/apparently/	−20%
Frequently/often	20%
Commonly/usually/large/dense	40%

(A) based on their linguistic descriptions (Table A.1). That is:

$$S = B \cdot (1 + A_1 + A_2 + \cdots A_n),$$

where S is the total spatial behaviour strength (0–100) of the species. If S is above 100, it is rounded to 100. n is the number of linguistics terms included. Moreover, if spatial behaviour only occurs in either juvenile or adult stage, the total spatial strength was divided by two.

For example, *Callionymus limiceps* (Round-headed dragonet) is described as ''usually in small aggregations'' in FishBase. The baseline spatial behaviour strength for 'aggregation' is 40, the multiplication factors for 'usually' and 'small' are 40% and −40%, respectively. Therefore, the spatial behaviour strength is calculated as:

$$S = \frac{1}{1} \cdot (1 + 40\% - 40\%) \cdot 40 = 40.$$

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