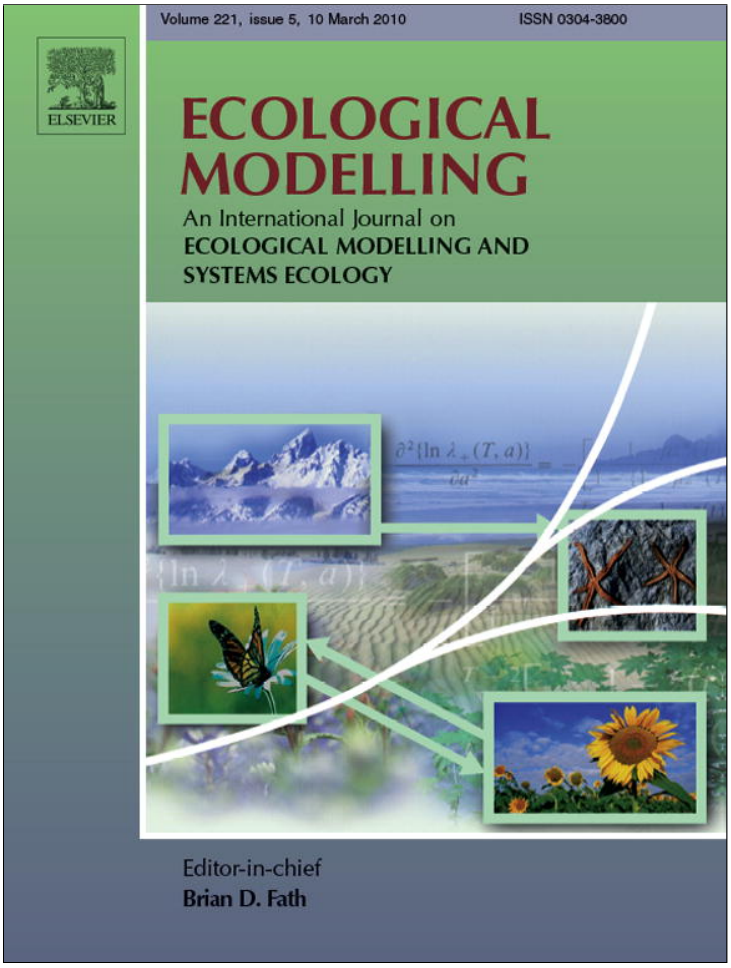
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Fuzzy experts on recreational vessels, a risk modelling approach for marine invasions

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ABSTRACT

Understanding risks from the human-mediated spread of non-indigenous species (NIS) is a critical component of marine biosecurity management programmes. Recreational boating is well-recognised as a NIS pathway, especially at a regional scale. Assessment of risks from this pathway is therefore desirable for coastal environments where recreational boating occurs. However, formal or quantitative risk assessment for the recreational vessel pathway is often hampered by lack of data, hence often relies on expert opinion. The use of expert opinion itself is sometimes limited by its inherent vagueness, which can be an important source of uncertainty that reduces the validity and applicability of the assessment. Fuzzy logic, specifically interval type-2 fuzzy logic, is able to model and propagate this type of uncertainty, and is a useful technique in risk assessment where expert opinion is relied upon. The present paper describes the implementation of a NIS fuzzy expert system (FES) for assessing the risk of invasion in marine environments via recreational vessels. The FES was based on expert opinion gathered through systematic elicitation exercises, designed to acknowledge important uncertainty sources (e.g., underspecificity and ambiguity). The FES, using interval type-2 fuzzy logic, calculated an invasion risk value (integrating NIS infection and detection probabilities) for a range of invasion scenarios. These scenarios were defined by all possible combinations of two vessel types (moored and trailered), five vessel components (hull, deck, internal spaces, anchor, fishing gear), two infection modes (fouling, water/sediment retention) and six frequently visited marine habitats (marina, mooring, farm, ramp, wharf, anchorage). Although invasion risk values determined using the FES approach was scenario-specific, general patterns were identified. Moored vessels consistently showed higher invasion risk values than trailered vessels. Invasion risk values were higher for anchorages, moorings and wharves. Similarly, hull-fouling was revealed as the highest infection risk mode after pooling results across all habitats. The NIS fuzzy expert system presented here appears as a valuable prioritising and decision-making tool for NIS research, prevention and control activities. Its easy implementation and wide applicability should encourage the development and application of this type of system as an integral part of biosecurity, and other environmental management plans.

1. Introduction

Biological invasion, defined as the entry, establishment and spread of non-indigenous species (NIS) into a new region, is recognised today (after habitat destruction) as the main threat to biodiversity (Vitousek et al., 1997). Although the effects of NIS in the environment depend on specific species–ecosystem interactions, there are examples throughout the world showing that biological invasions can cause significant impacts (frequently irreversible), which can have adverse economic consequences (Pimentel et al., 2000; Colautti et al., 2006). It is not surprising then, that the risks of NIS to marine, freshwater and terrestrial environments are currently one of the main concerns in environmental management (Deines et al., 2005).

Although interest in biological invasions amongst scientists has increased in recent decades, knowledge of invasion processes and pathways is still limited. This is especially true in the marine field, where research on bioinvasion pathways has focused on ballast water and fouling associated with commercial shipping (e.g. Carlton, 1985; Gollasch, 2002; Coutts and Taylor, 2004). To date however, at least 15 invasion pathways have been identified in the marine environment (Carlton, 1985; Hewitt et al., 2004), with aquaculture (Naylor et al., 2001; Locke et al., 2007; Minchin, 2007) and recreational boating (Johnson et al., 2001; Bax et al., 2002; Dijkstra et al., 2007; Floerl and Inglis, 2009) being among the most

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important. In fact, relatively recent research suggests that recreational boating (defined here as the movement of recreational vessels between different habitats such as marinas, wharves and boat ramps) could play an important (if not crucial) role in the spread of NIS, especially at regional scales (e.g., Johnson et al., 2001; Bax et al., 2002; Floerl et al., 2005; Ashton et al., 2006). Research has also identified that the likelihood of NIS entrapment, transport and release via recreational boating is subject to a large number of variables such as vessel component (e.g., deck, hull) (Hayes, 2002), user habits, species biology, and spatio-temporal characteristics of the environment (Floerl and Inglis, 2003; Acosta and Forrest, 2009).

Ecological risk assessment has been recognised as a useful methodology for identifying, prioritising and managing marine bioinvasion risks (Hayes, 1997; Hewitt and Hayes, 2003; Forrest et al., 2006a), which can assist scientists and managers to optimize the allocation of available (usually scarce) resources. Often however, due to a lack of research or the complexity of the system/process considered, the required information for the risk assessment is limited or unavailable. A normal practice to overcome this problem is the use of expert opinion. Expert opinion (also known as expert judgement) is commonly used as a data source and support for system analysis, alternative evaluation and decision-making processes in a wide range of fields such as nuclear power generation (e.g., Guimarães and Lapa, 2004; Ha and Seong, 2004; Evsukoff and Gentil, 2005), business and finances (Fildes, 2006; Chin et al., 2009; Wu et al., 2009), and occupational health (Azadeh et al., 2008), among many others. There are however, factors associated with expert opinion such as underspecificity and vagueness that can considerably increase the uncertainty present in such approaches (Burgman, 2005). In order to reduce this uncertainty and make expert data useful therefore, three main aspects need to be considered in the risk assessment process: (i) the knowledge of experts, (ii) the elicitation method, and (iii) when more than one expert is considered, the averaging technique (Moon and Kang, 1999). Fuzzy logic (Zadeh, 1965) is a technique that can accommodate these three considerations, hence provides a useful approach for dealing with risk-based processes that rely on expert opinion. Fuzzy logic is able to handle data imprecision and provides the additional ability to deal naturally with vagueness of language, a valuable advantage when data are represented through linguistic terms (e.g., likely, high). Fuzzy logic systems (FLS) are nowadays commonly used in fields where different levels of uncertainty are present such as modelling and control (Bezdek, 1993), signal processing (Castro et al., 2009), computer and communication networks (Cheong and Lai, 2009; Tajbakhsh et al., 2009; Fadaei and Salahshoor, 2008), diagnostic medicine (Schaefer et al., 2009; Toprak and Güler, 2008) and financial investing (Celikyilmaz et al., 2009; Plikynas et al., 2005). Most of these studies however, have applied traditional fuzzy sets (i.e., type-1 fuzzy sets, T1FS), and only recently have *interval* type-2 fuzzy sets (IT2FS) been recognised as a more suitable approach to modelling expert opinion and linguistic uncertainties (e.g., Wu and Mendel, 2007a; Wu and Tan, 2006; Mendel, 2001). Similarly, despite increasing interest in the benefits of fuzzy logic in ecology and environmental management fields (e.g. Cheong and Lai, 2009; Mouton et al., 2009; Li and Sun, 2008; Prato, 2007, 2005; Marchini and Marchini, 2006; Cheung et al., 2005; Regan and Colyvan, 2005), the potential of FLS to model and analyse biological invasions, or even to assist in the implementation of expert systems in this field, has not been explored.

This paper describes the design and implementation of a fuzzy expert system (FES) to assess the hypothetical infection risk of coastal marine habitats via the release of NIS from recreational vessels. The system used expert information generated through systematic elicitation exercises and integrated with fuzzy logic; specifically *interval* type-2 fuzzy logic (IT2FL, Mendel, 2001). This approach not only simplified expert data averaging, a frequently difficult and computer-demanding task, but also ensured that uncertainties associated with expert opinion were both modelled and propagated. The final product, the IT2FL expert system, appears as a valuable prioritising and decision-making tool for NIS research, prevention and control activities. Its easy implementation and wide applicability should encourage the development of this type of system as an integral part of biosecurity management plans.

2. Methods

2.1. Expert opinion and elicitation exercises

Expert data were generated through three elicitation exercises, which were based on questionnaires designed to: (i) assess the probability of coastal habitats becoming infected with NIS via recreational vessels, (ii) estimate the probability of detecting NIS in the coastal environment, and (iii) integrate these two probabilities to define single risk values for specific invasion scenarios. The first exercise, which was used to develop a conceptual model for marine invasions, included ten experts with experience in at least one of the following fields: marine biology, invasion biology, recreational boating or risk assessment. However, as high accuracy levels for expert estimates can be reached with between 3 and 6 people (Ashton, 1986; Ashton and Ashton, 1985), the second and third exercises (where experts had to give probability estimates) involved only five of the ten experts. This subgroup was selected for their particular knowledge on recreational boating and invasion biology. Experts were chosen from different governmental and non-governmental agencies, reducing the likelihood of their answers being correlated (Clemen and Winkler, 1999).

Five specific aspects were considered in this process to improve the accuracy of experts, and both reduce the uncertainty in the generated data and model it throughout the analysis. First, each questionnaire (including a cover letter explaining the aim of the exercise and the methodology to follow) was tested with groups of at least five people before being sent to the experts. Second, specific baseline information was included at the beginning of the exercises so all the experts had a common knowledge of the issues considered (Ayyub, 2001). Third, technical terms and words with unclear or potentially confusing meanings were clearly defined to prevent ambiguity (Burgman, 2005) and definitional disagreements (Clemen and Winkler, 1999). Similarly, in order to avoid underspecificity, a plausible and specific scenario was always given when experts had to estimate probabilities (Morgan and Henrion, 1990). Fourth, after giving an initial estimate, experts were required to think about one reason that could "make it wrong" (i.e., disconfirming information) and decide whether this would lead them to change their answer (Morgan and Henrion, 1990). Finally, and most importantly, experts had to indicate their assessments of probability and risk through simple and commonly used words (e.g., *likely*, *high*).

2.2. First exercise

One of the main sources of uncertainty when using expert opinion comes from differences in the way experts conceive the working of the process/system (Burgman, 2005). The main objective in the first exercise was therefore to produce a comprehensive conceptual model, accepted by all the experts as valid, for the invasion process via recreational vessels. For this, experts were provided with information on this pathway and its role in the marine invasion problem, and asked to analyse, modify and comment on an initial model created by the authors. An updated and more comprehensive model was then generated with their feedback. The

Table 1
List of variables considered when estimating the invasion risk.

Habitat	Vessel type	Vessel component	Infection mode
Anchorage	Moored	Hull	Fouling
Boat ramp	Trailered	Deck	Water/sediment retention
Mooring		Internal spaces	
Marine farm		Anchor	
Marina[a]		Fishing gear	
Wharf[a]			

[a] Invasion risk was estimated in the presence and absence of surveillance.

model described and analysed the infection process applying the *Fault–tree analysis* technique. This technique uses a top-bottom approach to define the occurrence of the top event (i.e., event of interest) as the consequence of previous events (Bedford and Cooke, 2001). In this particular case, the event of interest was the infection of a coastal marine environment by the release of a NIS from a recreational vessel. The model considered recreational vessels to have five distinct components (i.e., *Hull*, *Deck*, *Internal spaces*, *Anchor* and *Fishing gear*), that could become contaminated with NIS through two infection modes: (i) *fouling* (i.e., sessile and mobile organisms that use a surface as a habitat) and/or (ii) *water/sediment retention* (Hayes, 2002) (Table 1). Although the model represented the invasion process as a whole, each component was analysed separately, identifying the main variables and series of events that would lead to the release of NIS into the environment (see Acosta and Forrest, 2009, for details on this exercise and the final conceptual model).

2.3. Second exercise

A survey of vessel users conducted in Tasman Bay, New Zealand, in 2004 showed that recreational boats visit mainly six types of coastal habitats: (i) wharves/jetties, (ii) anchorages, (iii) mooring, (iv) boat ramps, (v) marinas, and (vi) marine farms (Acosta, unpubl. data). Hence, such localities are potential introduction points for NIS and stepping stones for further spread (Floerl and Inglis, 2009). The second elicitation exercise was therefore designed to assess the probability of these six coastal marine habitats becoming infected via movements of recreational vessels (Table 1).

The second exercise comprised three sections. The initial section presented the conceptual model created in the first exercise. It also provided baseline information on the characteristics of the marine structures and habitats considered. The next section required experts to use the conceptual model and information provided, as well as their personal knowledge, to assess the probability of the structures becoming infected with a NIS from an infected recreational vessel. Experts in general are recognised as having more difficulty assessing a complicated system/process as a whole than as a set of simpler/basic sub-systems (Morgan and Henrion, 1990). Because of this, and the fact that the potential of a vessel to release a NIS into a new environment depends not only on the species but also on the vessel component and infection mode considered (Hayes, 2002; Acosta and Forrest, 2009), experts had to assess the probability for each particular combination (i.e., system disaggregation). Experts were therefore asked to indicate the likelihood of infection for each infection scenario specified by 72 possible *habitat-vessel component-infection mode* combinations (e.g., marina-deck-fouling) (Table 1). Experts however, were only allowed to use one of the following four words when indicating their assessment: (i) *very unlikely*, (ii) *unlikely*, (iii) *likely*, or (iv) *very likely*.

The risk of infection posed by recreational vessels that spend most of the time (e.g. >80% of the year) in the water (i.e. moored vessels) is considerably higher than the risk of recreational vessels that are trailered and not kept in the water (Floerl et al., 2009). Hence, in order to consider this variable in the analysis, and obtain more realistic estimates, experts had to assess each vessel category separately (Table 1). Similarly, in order to increase accuracy and encourage experts to be consistent assessing a considerably long number of scenarios (72), after finishing their initial assessment experts had to analyse each scenario and answer (i.e., assigned probability) again, thinking about a reason that could make their estimate incorrect and decide whether it had to be updated (Morgan and Henrion, 1990). The final section of the exercise asked experts to consider the scenario where *"a man reaches into a bag of 100 golf balls and grabs one"*, and state the minimum and maximum number of blue balls that should be in the bag for them to consider the probability of the man randomly choosing a blue ball as: (i) *very unlikely*, (ii) *very unlikely-unlikely*, (iii) *unlikely*, (iv) *unlikely-likely*, (v) *likely*, (vi) *likely-very likely* or (vii) *very likely*. This gave an indication of the natural scale each expert associates with the words used, including information on their perception of the uncertainty of the terms.

2.4. Third exercise

Control and eradication programmes are more likely to be effective at an early stage of the invasion when the numbers of organisms are low and before the NIS has spread beyond the initial point of incursion (e.g., Wotton et al., 2004; Miller et al., 2004; Coutts and Forrest, 2007). Consequently, early NIS detection is expected to increase the likelihood of success in control and eradication programmes, which makes detection probability an essential variable in the assessment of NIS invasion risk management. Hence, the third elicitation exercise had four sections. The objective of the first two sections was to estimate the probability of detecting NIS in the marine environment, while the aim of the remaining sections was to combine the probabilities of infection and detection under a single risk value, and to assess the extent to which detection probabilities, and thus risk values, were altered by the presence or absence of active surveillance. The latter was considered for marinas and wharves only, partly for simplicity, but also because new NIS incursions are often detected on these two types of habitat, as a result of both active surveillance (e.g., the Mediterranean fanworm *Sabella spalanzanii* in New Zealand) and inadvertent discovery (e.g., the clubbed tunicate *Styela clava* in New Zealand; Davis and Davis, 2006).

The first section presented experts with a list of the main variables that could influence the likelihood of detecting the presence of NIS in the coastal environment. Each variable was clearly defined and explained with real examples and references. Experts were asked to agree or disagree on each variable, providing arguments for their decision. This induced them to analyse the detection process carefully, thus was expected to increase the validity and accuracy of their answer (Morgan and Henrion, 1990). In the second section, experts had to apply the same four words used in the second questionnaire (i.e. *very unlikely*, *unlikely*, *likely*, or *very likely*) to indicate the NIS detection probability at each habitat considered (Table 1). Experts were asked to consider wharves and marinas with and without active surveillance when assessing detection probability.

The third section required experts to classify the risk for each invasion scenario (i.e., *infection probability/detection probability* combination) as either: (i) *very low*, (ii) *low*, (iii) *medium* or (iv) *high*. For this, experts were presented with a simple example explaining the use of linguistic *if-then* rules and their construction procedure, so they could indicate their answers in a risk matrix following this methodology. Finally, experts were asked to scale between 0 and 10 the previously used risk words following the same procedure as the second exercise (see details of the second and third elicitation exercises in supplementary material).

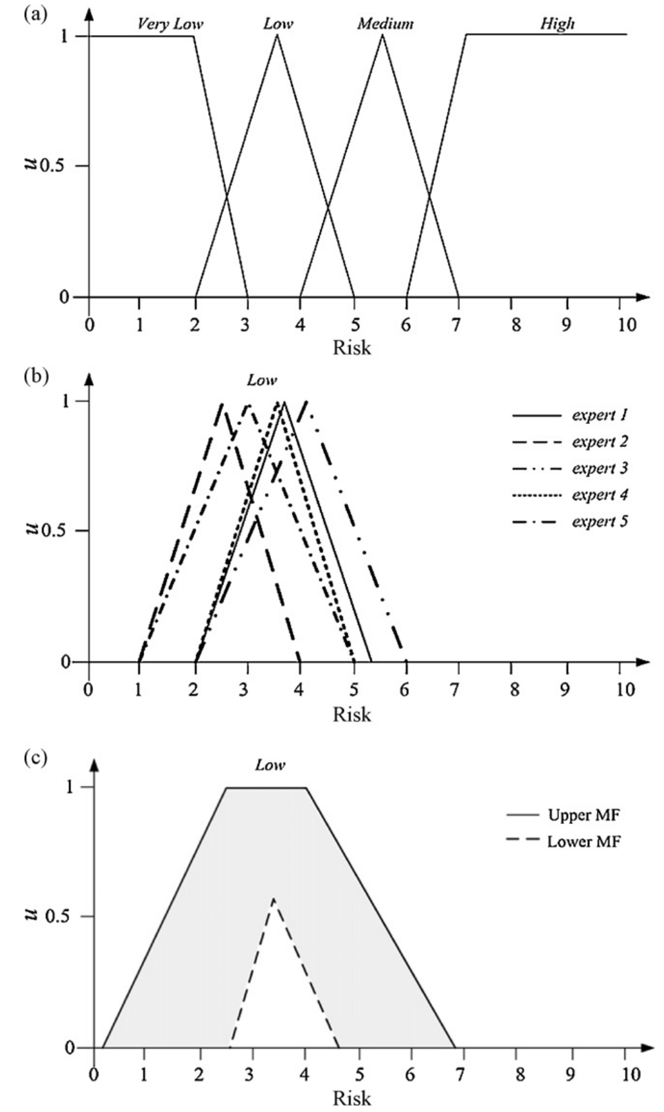

Fig. 1. Membership functions. (a) Four type-1 fuzzy sets used to describe the variable Risk. Each set is defined by its MF, which was created based on the answers of expert 1 in exercise 2. (b) MFs of the type-1 fuzzy set *Low* based on the value range given by each expert to this word. (c) MF of the interval type-2 fuzzy set *Low* created by using the Interval Approach method (Liu and Mendel, 2008) to integrate all the value ranges given by experts to this risk word. The FOU of the IT2FS is defined by the union of the upper MF and the lower MF (shaded area).

2.5. Fuzzy logic, interval type 2 fuzzy logic and fuzzy logic systems

The present study used fuzzy logic to integrate, under a single fuzzy expert system, the NIS infection, detection and risk data generated through the elicitation exercises. Fuzzy logic was first introduced by Zadeh (1965) as an alternative to binary logic, where elements can only "belong" or "not-belong" to a set. In fuzzy logic on the contrary, elements belong to a set (i.e., fuzzy set) but only to a certain degree defined by a continuous function between [0,1], called *membership function* (MF) (Fig. 1a and b). Fuzzy sets therefore, provide a more robust and realistic representation of linguistic terms and thus, reality. For example, people could be described as short or tall if their heights were less than or greater than 1.70 cm, respectively. Following this classification, a person who is 1.69 cm would be considered as short, and a person 1.71 cm would be considered tall. In reality however, the 1 cm above or below the 1.70 threshold would not make much difference when describing the height of either person, and both would be probably described as "sort of tall". Fuzzy logic overcomes this kind of problem by assigning degrees of belonging to each category; in this way, each person would belong to a certain degree to the group of "short people" and to a certain degree to the group of "tall people".

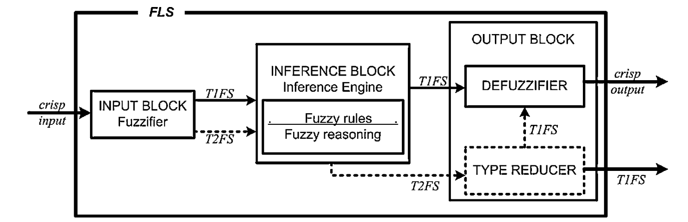

Fig. 2. Fuzzy logic systems. General architecture of a T1FLS (solid lines) and a T2FLS (dashed lines). The output block in the T2FLS also includes a Type-reducer, which reduces the resulting T2FS into a T1FS so it could be defuzzified later.

Membership functions were initially conceived to have only crisp values (i.e. type-1 fuzzy sets, T1FS). Zadeh (1975) however, introduced type-2 fuzzy sets (T2FS) characterised by a *fuzzy* MF, which means that the membership value (degree of membership) for each element of a T2FS is a T1FS instead of a crisp number. This fuzziness of the MF improves the ability of the set to both model and minimize the effect of numerical and linguistic uncertainties. It also avoids the problem of defining an exact MF when this is not a straightforward or valid procedure; as in modelling words (e.g., small, fast, high) (Mendel and Wu, 2010). Although having more design degrees of freedom (parameters) makes T2FS better than T1FS when modelling words, the computational complexity associated with this T2FS approach has usually discouraged people from using it (Mendel, 2007). However, Interval type-2 fuzzy sets (IT2FSs), a special case of T2FSs defined by Mendel (2001), assume the membership grade for every point of the secondary MF to be 1 (Fig. 1c). Although this reduces its complexity, the essence of the T2FS is preserved and its ability to represent uncertainty is maintained. IT2FSs are usually represented by the footprint of uncertainty (FOU), which is the bounded region defined between the upper MF and the lower MF; which are type-1 functions that represent the maximum and minimum membership grade of the set, respectively (Fig. 1c).

The main contribution of fuzzy logic and fuzzy sets has been providing a methodology for computing directly with words (Zadeh, 1996; Mendel and Wu, 2010), which at the same time has made fuzzy logic systems (FLS) possible. These are knowledge—or rule-based systems built in the form of inference ***if-then*** rules (Wang, 1997), which comprises three main parts: (i) an input block or fuzzifier, (ii) an inference block, and (iii) an output block or defuzzifier (Fig. 2). The fuzzifier turns crisp inputs into fuzzy inputs, which are then computed by the inference block to produce output sets based on the specified ***if-then*** rules. Finally, the defuzzifier transforms these sets into crisp outputs. As with fuzzy sets, there are three categories of FLS: (i) type-1 FLS (T1FLS), (ii) type-2 FLS (T2FLS) and (iii) *interval* type-2 FLS (IT2FLS). The main difference between them, as suggested by their names, is the type of fuzzy set each is based on. Also, while a T1FLS only uses crisp inference rules, T2FLS and IT2FLS use fuzzy inference rules. Consequently, although the structure of the systems is very similar, the output block of T2FLSs and IT2FLSs includes a type-reducer; an additional component preceding the defuzzifier that converts the type-2 set yielded by the fuzzy inference block into a type-1 set output. Then, as in T1FLSs, this output is passed onto the defuzzifier to obtain a crisp answer.

2.6. NIS fuzzy expert system implementation

In this study we used an IT2FLS designed with two inputs (i.e., infection and detection probabilities) and one output (i.e. invasion

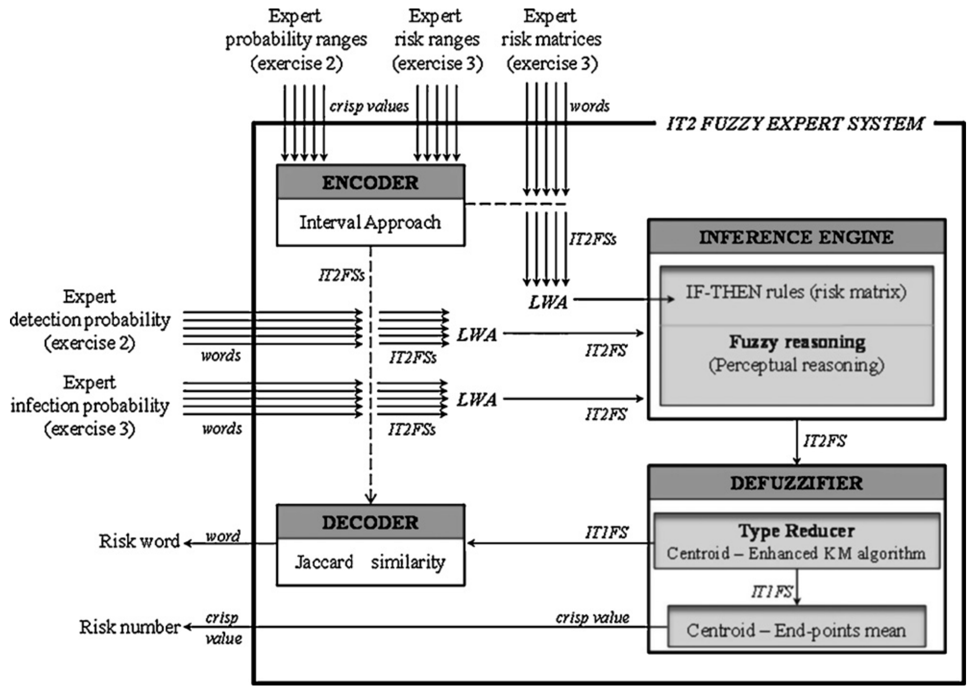

Fig. 3. Fuzzy logic expert system (FES). Architecture of the FES, which was designed as a Per-C. This FES combined the Interval Approach (Liu and Mendel, 2008), Linguistic weighted average (Wu and Mendel, 2007a) and Perceptual reasoning (Wu and Mendel, 2009a; Mendel and Wu, 2010) to encode probability and risk words, integrate expert answers and generate risk estimates. The Jaccard similarity measure (Wu and Mendel, 2009b) was also used by the system to decode the answers (i.e., present results in a linguistic format).

risk); all represented by IT2FSs (Fig. 3). However, as the responses of the experts were words, an encoder was required to process their answers before using them in the system. Similarly, in order to map the final crisp results of the IT2FS into meaningful risk words, a decoder was also integrated into the system (Fig. 3). An IT2FS like this one, for which inputs and outputs are perceptions (i.e. granulated terms, words), is called 'Perceptual computer' (Per-C) and is ideal for analysing expert opinion represented through linguistic terms (Mendel and Wu, 2010).

2.7. MFs, fuzzifier and encoder

Membership functions are the core of fuzzy logic, hence the way in which they are defined (shape, levels and values) determines the validity of the FS represented. Unfortunately, MFs are variable and situation-specific, and although techniques have been suggested to obtain partitions for fuzzy variables (e.g., de Soto and Recasens, 2001), no standard method or rules on how to define their functions is currently available. Some studies, for example, have used the Delphi approach (Dalkey and Helemer, 1963) to help experts to generate 'unanimous' MFs (e.g., Kaufmann and Gupta, 1988). It is possible to say therefore, that MFs are usually created by analysts *ad hoc*, with (Marchini and Marchini, 2006) or without (e.g., Raj and Kumar, 1999) input from experts.

The present study considered that by obliging experts to either agree on MFs or use previously defined functions, their answers would be less natural and intuitive and, more importantly, the uncertainty originating from different opinions on the meaning of the words would be ignored. Therefore, to minimise the interference of the analyst and maintain this uncertainty, experts were told to apply probability and risk words intuitively, and not until they had finished the assessments were they asked for a value range describing each term (see exercise 2). These ranges were integrated using the Interval Approach (Liu and Mendel, 2008) to define a representing IT2FS for each word, which achieved both fuzzification and encoding (Figs. 1, 3 and 4Figs. 1b, c, 3, 4). All answers (i.e.,

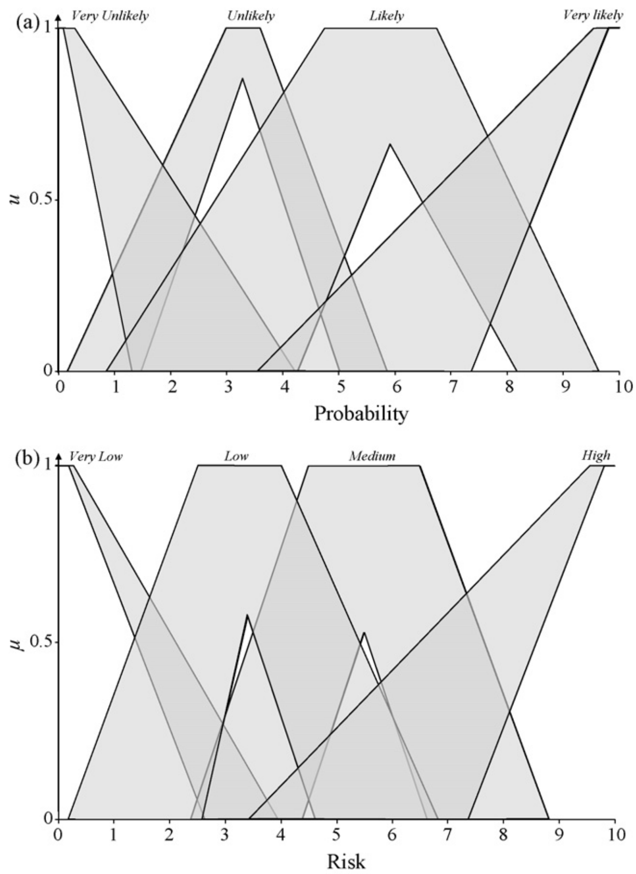

Fig. 4. Membership functions used in the study. Each MF was generated using the Interval Approach method (Liu and Mendel, 2008) to integrate the probability (exercise 2) and risk (exercise 3) value ranges given by the experts. (a) MFs of the four words used to describe infection and detection probabilities. (b) MFs of the four words used to describe risk.

Table 2
Risk matrix. *IF-THEN* fuzzy rules of the system integrated under a matrix, where row headings indicate infection probability ($\tilde{P}_{inf}$) and column headings detection probability ($\tilde{P}_{\text{det}}$) (antecedents). Cells indicate the resulting risk $\tilde{R}_i$ (consequents) for each combination of antecedents, which the IT2FS is resulting from the LWA of the responses of all the experts (see Section 4 from exercise 3). Consequents are also represented by their corresponding risk word after decoding $\tilde{R}_i$ using the Jaccard similarity measure.

$\tilde{P}_{inf}$	$\tilde{P}_{\text{det}}$			
	Very unlikely	Unlikely	Likely	Very likely
Very unlikely	$\tilde{R}_1$ = Low	$\tilde{R}_2$ = Low	$\tilde{R}_3$ = Very low	$\tilde{R}_4$ = Very low
Unlikely	$\tilde{R}_5$ = Low	$\tilde{R}_6$ = Low	$\tilde{R}_7$ = Very low	$\tilde{R}_8$ = Very low
Likely	$\tilde{R}_9$ = High	$\tilde{R}_{10}$ = Medium	$\tilde{R}_{11}$ = Medium	$\tilde{R}_{12}$ = Medium
Very likely	$\tilde{R}_{13}$ = High	$\tilde{R}_{14}$ = High	$\tilde{R}_{15}$ = Medium	$\tilde{R}_{16}$ = Medium

words) given by experts in exercises 2 and 3 on invasion probability, detection probability and risk, were then replaced by their representing IT2FSs. This not only made computation of different words possible, but also incorporated into the analysis the uncertainty arising from perception differences among experts about word meanings (Mendel, 2003).

2.8. IF-THEN rules, inference model and firing levels

IF-THEN fuzzy rules, also known as inference or firing rules, can be considered the essence of a FLS and thus responsible for its behaviour under different input scenarios. They are comprised of antecedents (*IF* part) and consequents (*THEN* part), and must cover every input possibility. The present system had 16 rules integrated under a risk matrix, which indicated the resulting risk value for each combination of four infection and four detection probabilities (Table 2). In this matrix the first rule for example reads as:

$$\textbf{\textit{IF}}\ \tilde{P}_{\text{inf}} = \textit{Very unlikely}\ \textbf{\textit{AND}}\ \tilde{P}_{\text{det}} = \textit{Very unlikely}\ \textbf{\textit{THEN}}\ \textit{Risk} = \tilde{R}_1 \quad (1)$$

where $\tilde{P}_{\text{inf}}$, $\tilde{P}_{\text{det}}$ and $\tilde{R}_1$ represents the infection probability, detection probability and resulting risk value of the rule, respectively. For each rule, the resulting risk value $\tilde{R}_i$ was calculated as the average of the risk assigned by experts to that particular $\tilde{P}_{\text{inf}} \leftrightarrow \tilde{P}_{\text{det}}$ combination (exercise 3) using the Linguistic Weighted Average (LWA, Wu and Mendel, 2007a). The LWA is defined as:

$$\tilde{R}_i = \frac{\sum_{j=1}^{n} w^j \tilde{R}_i^j}{\sum_{j=1}^{n} w^j} \quad (2)$$

where n is the number of experts, w^j is the weight for expert j, and $\tilde{R}_i^j$ represents the word chosen by expert j. However, as all experts were considered to be equally important in the system, their answers were equally weighted.

Although it is the fuzzy rules set of the FLS that maps inputs into outputs, the actual rule firing and combining process that leads to an answer is determined by the specific type of fuzzy reasoning used. The NIS fuzzy expert system applied the recently proposed Perceptual reasoning (PR) that characterises Per-C (Wu and Mendel, 2009a). In contrast to other reasoning models, including the commonly used Mandami model (Mandami, 1974), PR is the only one that generates a combined fired rule output with an FOU resembling the FOUs of the encoded IT2FSs (Wu and Mendel, 2009a; Mendel and Wu, 2010). Hence, with PR, not only the meaning of the answer but the entire process is more intuitive. The two required steps of PR are: (i) obtaining a firing level for each rule and, (ii) combining the IT2FS consequents of the fired rules using an LWA, where the weights are the firing levels from step one (Wu and Mendel, 2009a; Mendel and Wu, 2010). The firing level of the ith rule in the present system was calculated following Wu and Mendel (2009a) and Mendel and Wu (2010) as:

$$F_i = S_j(I_{\text{exp}}, \tilde{P}_{\text{inf}(i)}) * S_j(D_{\text{exp}}, \tilde{P}_{\text{det}(i)}) \quad (3)$$

where I_{exp} and D_{exp} are the actual IT2FSs (generated from exercises 2 and 3) used by the system as input values or entries (infection and detection, respectively) to produce the risk estimate (Fig. 4). Each system entry was calculated as the LWA of the responses obtained from all the experts for that particular infection or detection scenario. The terms $\tilde{P}_{\text{inf}(i)}$ and $\tilde{P}_{\text{det}(i)}$ are the IT2FS infection and detection antecedents of the rule (e.g., *unlikely*, *likely*) and * the minimum t-norm. S_j represents the Jaccard similarity measure (Wu and Mendel, 2009b) for IT2FSs, calculated as

$$S_j(\tilde{A}, \tilde{B}) = \frac{\sum_{i=1}^{N} \min(\mu_{\bar{A}}(x_i), \mu_{\bar{B}}(x_i)) + \sum_{i=1}^{N} \min(\mu_{\underline{A}}(x_i), \mu_{\underline{B}}(x_i))}{\sum_{i=1}^{N} \max(\mu_{\bar{A}}(x_i), \mu_{\bar{B}}(x_i)) + \sum_{i=1}^{N} \min(\mu_{\underline{A}}(x_i), \mu_{\underline{B}}(x_i))} \quad (4)$$

where N is the number of samples and $\mu_{\bar{A}}$, $\mu_{\bar{B}}$, $\mu_{\underline{A}}$ and $\mu_{\underline{B}}$ are the membership grades of x on the upper and lower MFs of $\tilde{A}$ and $\tilde{B}$, respectively. Once all firing levels (F_i) had been obtained, the output IT2FS of the PR ($\tilde{Y}$) was computed as (Wu and Mendel, 2009a; Mendel and Wu, 2010):

$$\tilde{Y} = \frac{\sum_{i=1}^{n} F_i \tilde{R}_i}{\sum_{i=1}^{n} F_i} \quad (5)$$

where n is the total number of rules and $\tilde{R}_i$ is the consequent of the ith rule.

2.9. Defuzzifier, decoder and output values

A main characteristic and advantage of Per-C is its capacity to present results in a linguistic format so users understand them readily (without any particular knowledge of the system). Similarly, the NIS fuzzy expert system defuzzified and decoded the results simultaneously using the Jaccard similarity measure to classify each $\tilde{Y}$ as one of the four risk words defined (Mendel and Wu, 2010). The output was therefore the word with the maximum Jaccard similarity with $\tilde{Y}$. This classification gave a general idea of the estimated risk and made broad comparisons possible. Having only four levels however, restricted the system from clearly ranking the large number of scenarios considered, and identifying those with the highest invasion risks. For this, the system also calculated the centroid of $\tilde{Y}$ which is defined by the characterizing left- and right-end points ([C_l,C_r]) and calculated as

$$C_l = \min_{\forall \mu_Y(y_i) \in [\mu_{\underline{Y}}(y_i), \mu_{\bar{Y}}(y_i)]} \frac{\sum_{i=1}^{N} y_i \mu_Y(y_i)}{\sum_{i=1}^{N} \mu_Y(y_i)} \quad (6)$$

$$C_r = \max_{\forall \mu_Y(y_i) \in [\mu_{\underline{Y}}(y_i), \mu_{\bar{Y}}(y_i)]} \frac{\sum_{i=1}^{N} y_i \mu_Y(y_i)}{\sum_{i=1}^{N} \mu_Y(y_i)} \quad (7)$$

where N is the number of samples, and $\mu_{\bar{Y}}(y_i)$ and $\mu_{\underline{Y}}(y_i)$ are the membership grades of y_i on the upper and lower MFs of $\tilde{Y}$, respectively. C_l and C_r were computed using the Enhanced Karnik-Mendel algorithm (Wu and Mendel, 2009c) producing an *interval* T1FS that could be later defuzzified into a crisp value (Figs. 3 and 5). As an *interval* T1FS is characterised entirely by its left- and right-end points (i.e., C_l and C_r), the defuzzification (i.e., centroid computation) is reduced to simply calculating the mean

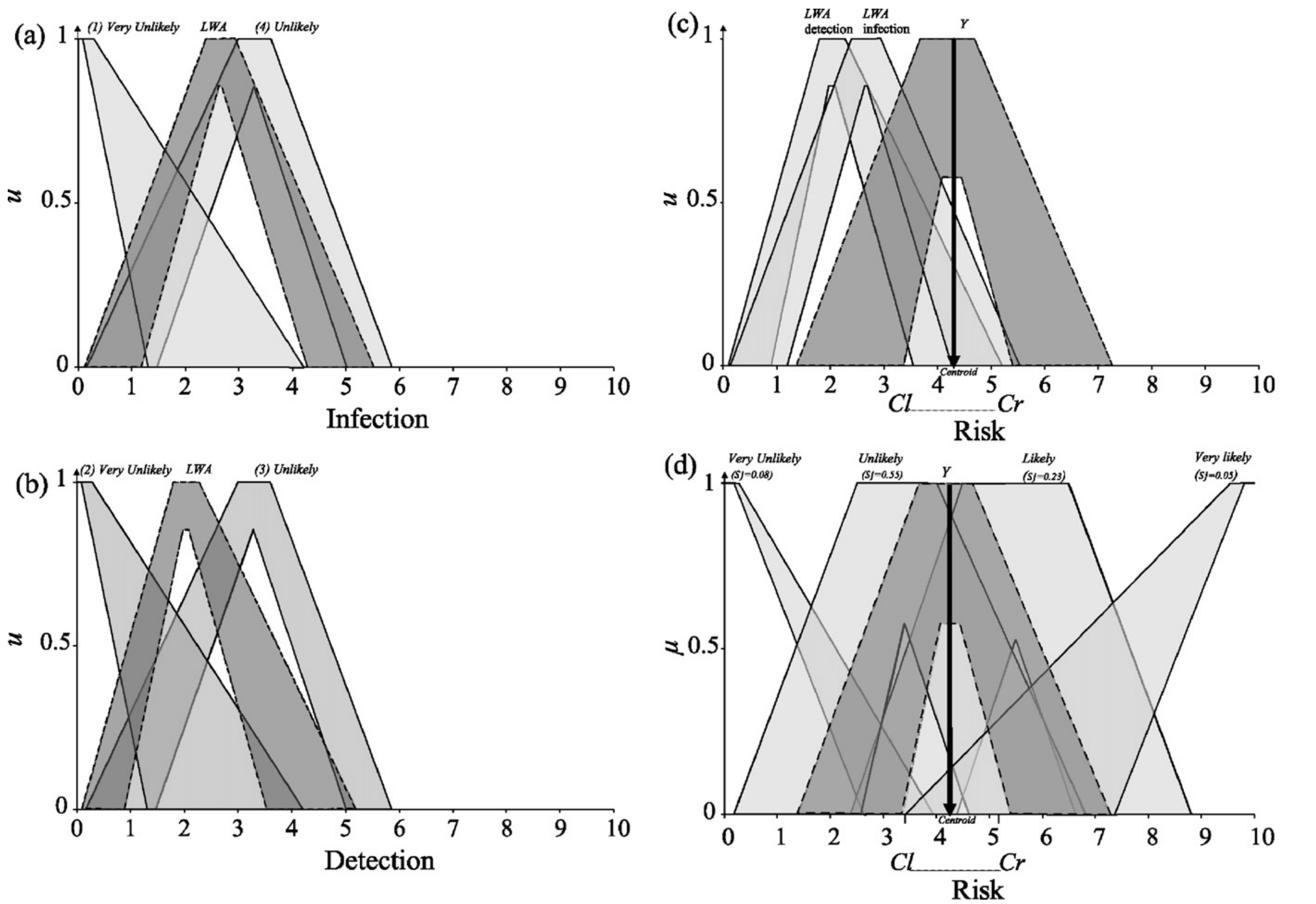

Fig. 5. Computation sequence followed by the FES to estimate the invasion risk of the invasion scenario *trailered–deck–fouling–anchorage*. (a) Integration of five expert infection assessments (1 *Very unlikely* and 4 *Unlikely*) into a single infection probability IT2FS using the Linguistic weighted average (LWA, Wu and Mendel, 2007a). (b) Integration of five expert detection assessments (2 *Very unlikely* and 3 *Unlikely*) into a single detection probability IT2FS using the LWA. (c) Computation of inputs (i.e., LWA *infection* and LWA *detection*) using the Per-C to estimate the invasion risk $\tilde{Y}$. (d) Comparison between the resulting $\tilde{Y}$ and each of the four risk IT2FS *very low*, *low*, *medium* and *high*, based on the Jaccard similarity index (S_j). This figure also shows the centroid of the IT2FS invasion risk, which was computed as the mean of the characterising end-points of the *interval* T1FS obtained using the Enhanced Karnik-Mendel algorithm (Wu and Mendel, 2008, 2009c). The uncertainty for this crisp value calculated as the spread of the centroid (i.e., $C_r - C_l$, the difference between the characterising left- and right-end point of the *interval* T1FS) is also represented in the figure by the dotted line.

of these end-points (Mendel, 2001). This crisp value therefore represented the actual risk estimated (r) for the invasion scenario considered (Figs. 3 and 5):

$$\frac{C_l + C_r}{2} = \text{crisp value} = r \tag{8}$$

Crisp values (i.e., defuzzified), were then used not only to compare the risk between scenarios but also to estimate and compare average risk values for habitats, vessel components and infection modes.

2.10. Variability measure

Several measures such as, cardinality, centroid, fuzziness and variance, have been proposed to estimate the uncertainties, or variability, associated with IT2FS (Wu and Mendel, 2007b). However, uncertainty, defined as the distance between the characterizing left- and right-end points (C_l and C_r) of the resulting *interval* T1FS has been identified as the best variability measure when dealing with expert opinion (Wu and Mendel, 2009b). The present study therefore, used uncertainty to estimate variability among IT2FSs. Similarly, standard deviation was the preferred option to represent variation among crisp (i.e., defuzzified) values.

2.11. Input values and FES operation

Once the NIS fuzzy expert system was implemented, the answers of the experts (already represented as IT2FSs) for each invasion and detection scenario were integrated using the LWA method (Wu and Mendel, 2007a). The resulting averaged IT2FSs were the infection and detection input values used by the system to assess the invasion risk for coastal habitats via different vessel types, vessel components and infection modes (Figs. 3 and 5). Each of these combinations of infection and detection probabilities fired a specific set of *if-then* rules, producing an IT2FS ($\tilde{Y}$) that represented the calculated risk. This IT2FS was then both defuzzified into a single crisp value and translated into a risk word. The uncertainty associated with this IT2FS was also calculated (Fig. 3). For example, the input used by the FES as the probability of infection ($\tilde{P}_{\text{inf}}$ in Eq. (1)) for the invasion scenario *trailered-deck-fouling-anchorage* was the IT2FS generated by the LWA of one '*Very unlikely*' (i.e., 1 expert considering this scenario *Very unlikely*) and four '*Unlikelies*' (i.e., 4 experts considering this scenario *Unlikely*) (Fig. 5a). Similarly, the input used by the FES as the probability of detection ($\tilde{P}_{\text{det}}$ in Eq. (1)) in the habitat *anchorage* was the IT2FS generated by the LWA of two '*Very Unlikelies*' (i.e., 2 experts considering the detection of the invasion in this habitat *Very likely*) and three '*Unlikelies*' (i.e., 3 experts considering the detection of the invasion in this habitat

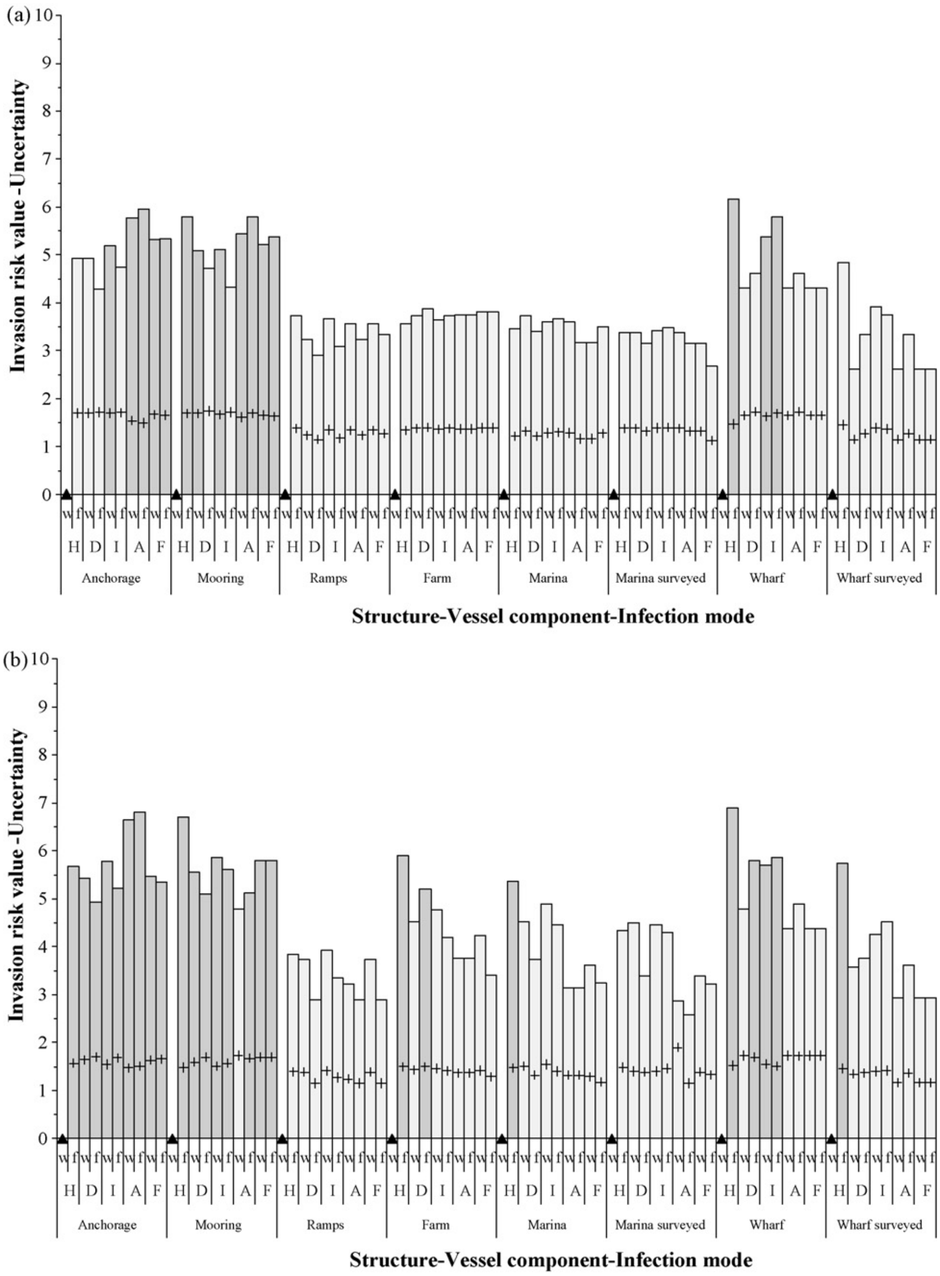

Fig. 6. Invasion risk values for six coastal habitats and associated uncertainties. Crisp values (i.e., defuzzified IT1FS) generated by the fuzzy expert system for each invasion scenario. Invasion scenarios for each habitat were defined by the *vessel type*, *vessel component*, *infection mode* and *habitat* considered. The variability of the generated invasion risk values was estimated using their associated uncertainty value (+), following Wu and Mendel (2009b). (a) Trailered vessels. (b) Moored vessels. H = *Hull*, D = *Deck*, I = *Internal spaces*, A = *Anchorage*, F = *Fishing gear*, w = *water/sediment retention*, and f = *fouling*. Dark grey bars and light grey bars indicate risk invasion values that the fuzzy expert system represents linguistically as *medium* and *low* risk, respectively. The symbol ▲ indicates that this infection mode is not considered for the *Hull* component.

Unlikely) (Fig. 5b). The resulting invasion risk ($\tilde{Y}$) for this particular combination of infection and detection inputs was also an IT2FS calculated using equation 5 (Fig. 5c). $\tilde{Y}$ was defuzzified (using the Karnik-Mendel algorithm to calculate Eqs. (6) and (7)) into the crisp value (r) = 4.3 (Eq. (8)). It was also decoded into the word *low*, as this was the risk word with the highest Jaccard similarity measure (S_j, Eq. (4)) (Fig. 5d). The uncertainty of $\tilde{Y}$ was then calculated as 1.7 (i.e., $C_r - C_l$).

3. Results

The NIS fuzzy expert system generated a crisp (i.e., defuzzified) single risk value between 0 and 10 (i.e., *very low risk–high risk*) for each invasion scenario. All values are initially displayed in single graphs for trailered and moored vessels (Fig. 6a and b), so that combinations of *habitat-vessel component–infection mode* for each vessel category that leads to the greatest invasion risk, or greatest uncertainty among experts, can be readily visualised.

Although results varied among invasion scenarios, a similar pattern was observed between moored vessels and trailered vessels (Figs. 6 and 7). In Fig. 7a, which shows the mean of the invasion risk values when grouped by habitat type, it is evident that the values in both vessel types were considerably lower for wharves with active surveillance compared with wharves without surveillance. In contrast, for marinas the difference in risk values with and without surveillance was not visually evident in

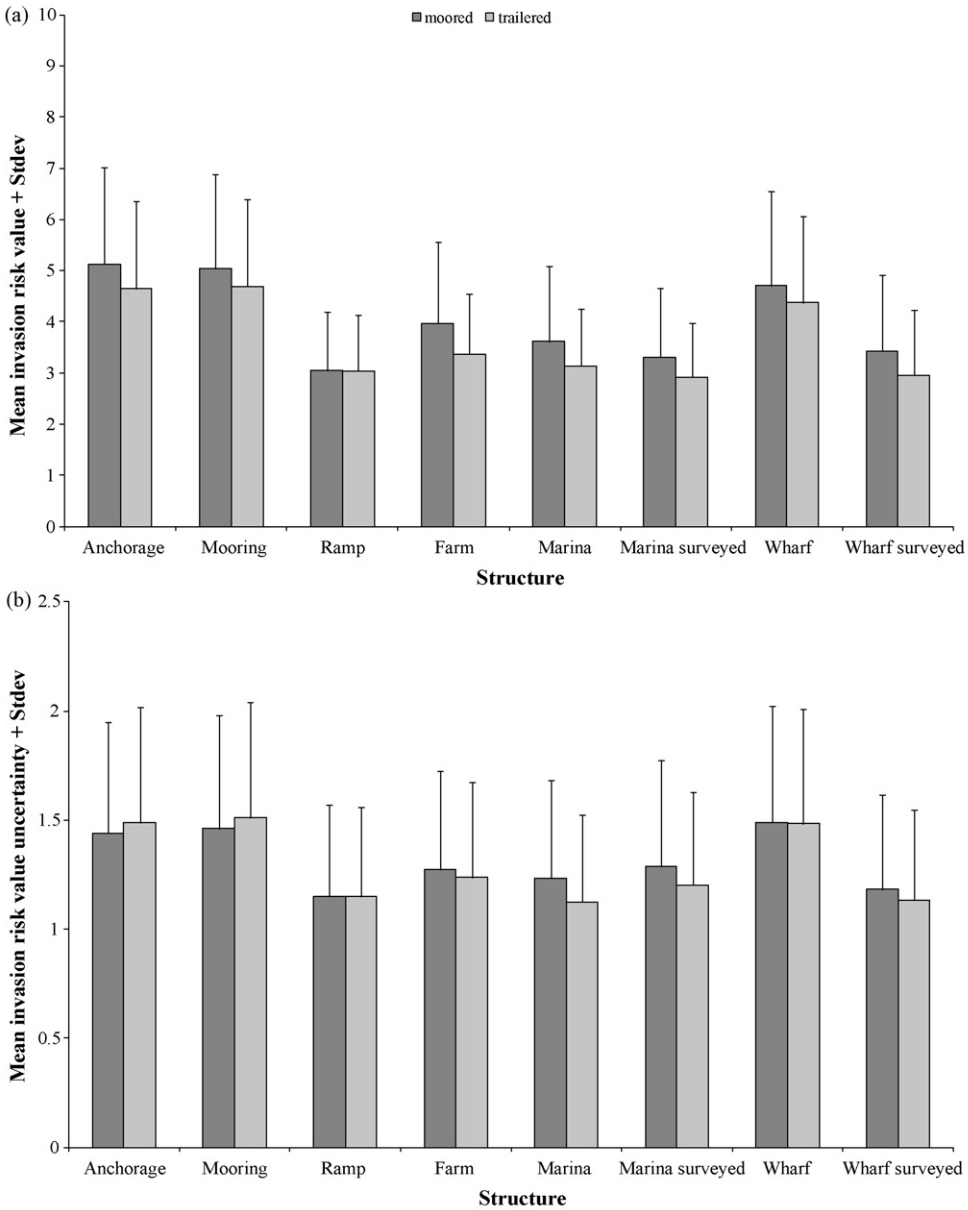

Fig. 7. Invasion risk value and associated uncertainty means for each habitat. (a) Invasion risk value mean. Mean calculated using the crisp representation (i.e., defuzzified value) of calculated invasion risk value $\tilde{Y}$ (i.e., defuzzified as the centroid of $\tilde{Y}$, Eq. (8)) for *vessel component-infection mode* scenarios grouped under the variable *habitat*. (b) Associated uncertainty means. Mean of associated uncertainties of calculated invasion risk values for *vessel component-infection mode* scenarios grouped under the variable *habitat*.

most of the infection scenarios (especially for trailered vessels), with only the risk from the scenario *hull-fouling* in moored vessels being reduced by surveillance (Figs 6 and 7a). Overall, surveillance for wharves and marinas led to experts ranking invasion risk values for these habitats among the lowest for all combinations of habitat-vessel component-infection mode (Figs. 6 and 7a). Invasion risk values for ramps were also consistently low compared with other habitats (Figs. 6 and 7a). Anchorages, moorings and wharves without surveillance displayed higher risk values, with scenarios *hull–fouling–wharf* (no surveillance) and *anchor–fouling-anchorage* having the highest values for both vessel types (Fig. 6). After pooling across habitats within each vessel component, *hull-fouling* was scored by experts as having the highest invasion risk (Fig. 8). Comparisons between fouling and water/sediment retention risks in both vessel types did not show clear differences, and only for wharves (both with and without surveillance) was the invasion risk for fouling comparatively higher (Fig. 9).

Despite similarities in patterns for each vessel type across different habitats, vessel components and infection modes, actual risk values were consistently higher in moored vessels (maximum = 6.90, minimum = 2.61) compared with trailered vessels (maximum = 6.16, minimum = 2.59) (Figs. 6 and 7a). In both vessel types however, decoding of risk values only generated the word either *medium* or *low* (Fig. 6), despite the NIS fuzzy expert system using a four-word risk classification format (i.e., *very low*, *low*, *medium* and *high*). The majority of these values were considered *low*, with only 33% of the scenarios for moored vessels and 21% of the scenarios for trailered vessels being classified as *medium*. The absence of *very low* and *high* (extreme values) in the results did not reflect experts not using these words in their answers. It was instead due to the "smothering" effect of variance from two sources. First, variability among the value ranges used by experts to represent each probability and risk term used. Large FOUs associated with these terms indicated that this was

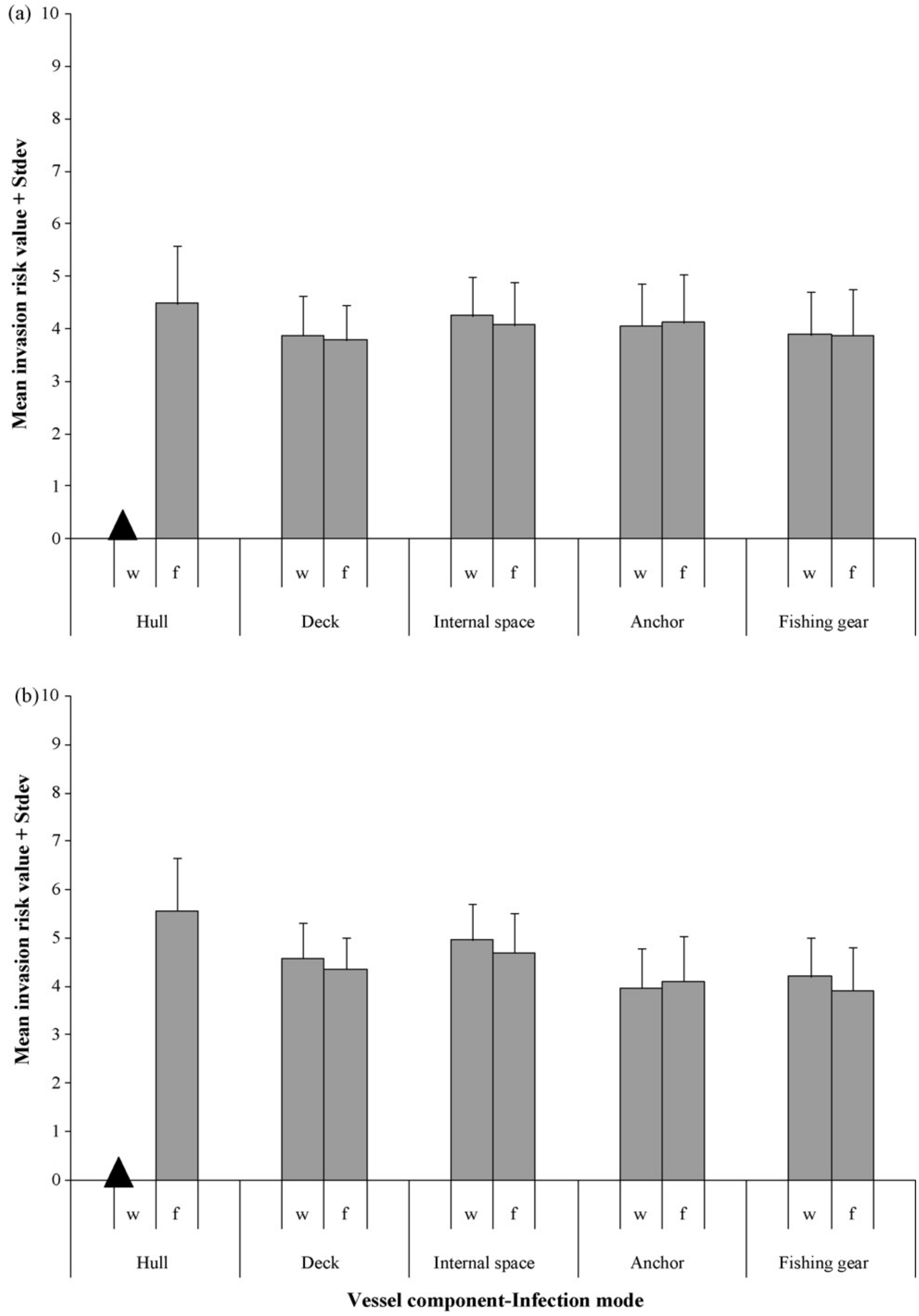

Fig. 8. Mean invasion risk value for vessel components. (a) Trailered vessels, (b) Moored vessels. Means calculated using the crisp representation (i.e., defuzzified value) of calculated invasion risk value $\tilde{Y}$ (i.e., defuzzified as the centroid of $\tilde{Y}$, Eq. (8)) for *habitat-infection mode* scenarios grouped under the variable *vessel component*. f = fouling, w = water/sediment retention. ▲ indicates that this infection mode is not considered for the *Hull* component.

an important source of variance (Fig. 4). Second, there was variance among expert assessments. As there was always at least one expert in disagreement, all the infection and detection assessments showed some level of variation; even those that generated the highest risk values (e.g., ***hull-fouling***, ***anchor-fouling***, ***anchorage***, ***wharf***). Similarly, although there was consensus on some of their consequents, most fuzzy rules had at least one expert in disagreement.

The uncertainty, measured as the spread of the centroids of the resulting IT2FS, had a pattern similar to that described for risk values. Although this general similarity is observed when pooling results by habitat type and comparing the means of the risk values (Fig. 7a) and the means of the associated uncertainties (Fig. 7b), observations of the uncertainty alone showed that higher risk values did not always correspond with higher uncertainty values. In both vessel types for example, although the scenarios *wharf–hull–fouling*, *anchorage–anchor–water/sediment retention* and *anchorage–anchor–water/sediment–fouling* showed the highest risk values among all scenarios, they had the lowest uncertainties among their respective habitats (Fig. 6). Similarly, while the invasion risk of *marina–anchor–water/sediment retention* in moored vessels was among the lowest, it had the highest uncertainty value, indicating the low level of agreement among experts on their assessment for this scenario.

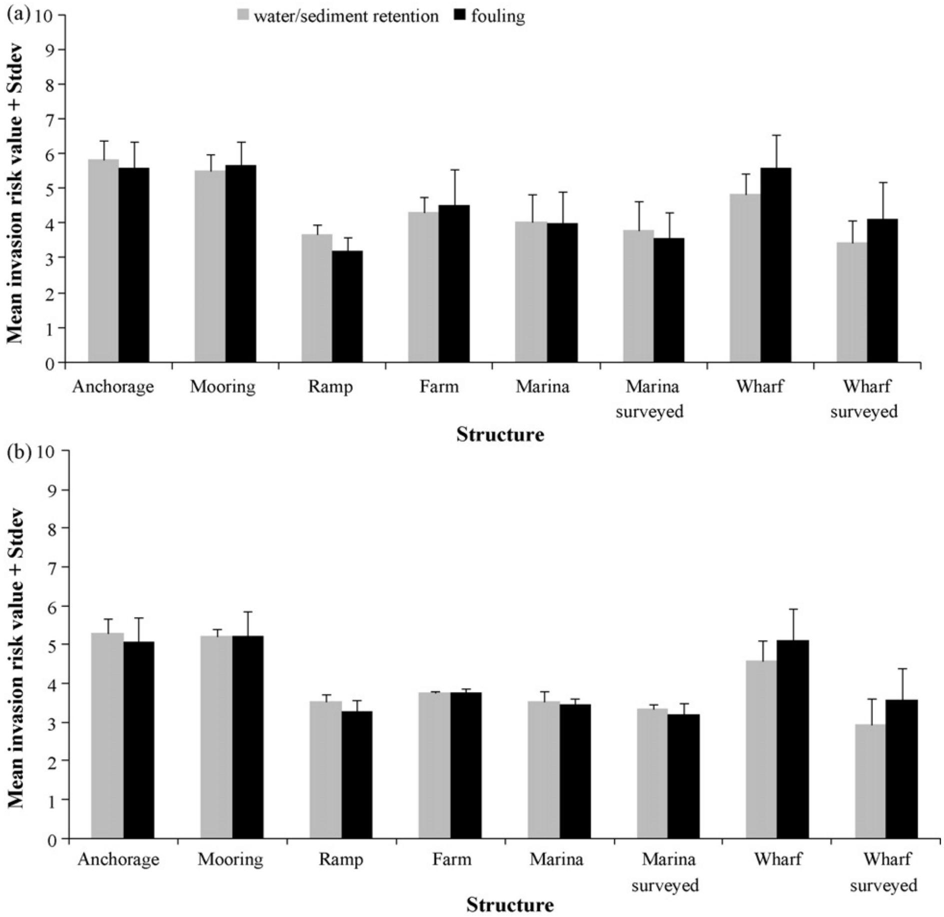

Fig. 9. Mean invasion risk value for infection modes. (a) Trailered vessels, (b) Moored vessels. Means calculated using the crisp representation (i.e., defuzzified value) of calculated invasion risk value $\tilde{Y}$ (i.e., defuzzified as the centroid of $\tilde{Y}$, Eq. (8)) for *habitat-vessel component* scenarios grouped under the variable *infection mode*.

4. Discussion

Expert opinion is considered in risk assessment a useful source of data but not a source of rational consensus (Cooke, 1991). The latter is related to the vagueness, ill-definition and imprecision present in most data representation and aggregation methods used in expert judgement analysis (Moon and Kang, 1999). However, if these factors are addressed by the elicitation process and averaging system, and the uncertainty associated with expert data is both acknowledged and represented, the lack of consensus among experts could be comparable (to a certain extent) to the normal variability present in quantitative data. In this sense, the elicitation process and NIS fuzzy expert system developed here followed a systematic approach that made this possible. Four aspects however, were considered essential for this approach. First, although uncertainty about the form of a model is harder to conceive than uncertainty about the value of a quantity, the first one is usually more important and more likely to affect the results of the analysis (Morgan and Henrion, 1990). Often however, in their effort to present quantitative analyses, researchers overlook and underestimate this uncertainty, generating incomplete and inaccurate models with systematic biases. The NIS fuzzy expert system therefore, involved experts in the creation of the conceptual model used for the assessment (exercise 1, Acosta and Forrest, 2009), which ensured that a more comprehensive invasion model was developed and that all experts analysed the problem from the same perspective.

Second, most people prefer expressing probabilities qualitatively rather than quantitatively, especially about situations and events that they have not previously considered (Morgan and Henrion, 1990). Hence, in order to make it easier for experts to indicate their answers, they had to express probability and risk assessments using words instead of numbers. However, as well as introducing vagueness associated with linguistic terms, this approach caused the additional uncertainty of different experts conceiving the same word differently. Furthermore, conventional averaging techniques are not able to deal directly with linguistic terms. For this reason, the use of fuzzy logic in general, and IT2FSs in particular, was essential for integrating linguistic uncertainty and computing with these terms. Finally, the development of the NIS fuzzy expert system as a Per–C made the entire process (elicitation, averaging and analysis) more natural and straightforward, eliminating the need to educate experts on complex fuzzy logic concepts (e.g., FOU).

Recreational boating is a complex marine NIS pathway that generates various invasion scenarios and risks, which must be modelled and assessed in order to design effective risk-based biosecurity management programmes. However, the limited knowledge of marine invasions and spatio-temporal variation that characterizes recreational boating makes risk-based management difficult, such that NIS management for this pathway is absent in many parts of the world. Furthermore, where this management is present, such as in California (Gonzalez and Johnson, 2007), South Australia (Ballantine, 2008) and Fiordland, New Zealand (MFE, 2004), it is typically voluntary. The NIS fuzzy expert system presented here was able to assess different invasion scenarios and estimate their corresponding invasion risk, which varied among habitats, vessel types, vessel components and infection modes. As indicated in Acosta and Forrest (2009), experts considered that the nature and extent of interaction between each vessel component and the environment varies depending on the habitat visited. The present FES reflected this assumption and assigned higher risk values to those infection scenarios where the interaction between the habitat and the component was potentially greater. For example, while recreational vessels are likely to repeatedly use their anchor the same day at different anchorages, this would be a rare event in other areas such as marinas and boat ramps. The NIS fuzzy expert system was therefore consistent with this information and ranked *marina–anchor* and *ramp–anchor* scenarios relatively low. Nonetheless, infection of such areas is possible, for example because vessel users may clean their anchors on return to port at the end of a day boating. By contrast, *anchorage–anchor* combinations were ranked among the highest risk values for both vessel types. These high values agree with evidence that suggests anchors could be an effective mechanism for the spread of some NIS (e.g., macroalgae); especially where conditions during vessel passage (e.g. high humidity in an anchor locker) enhance tolerance to desiccation (Sant et al., 1996; Schaffelke and Deane, 2005; Forrest and Blakemore, 2006). Similarly, despite the behaviour of the vessel user at each habitat being determined by specific variables such as exposure, weather, habitat usage rules, as well as the specific vessel type (e.g., racing, cruising), it is not uncommon for recreational vessel users to also conduct fishing, diving, and vessel repairing and cleaning when visiting anchorages. As a result, there is potentially a high interaction between the vessel (including all its components) and the anchorage environment, which would explain why all the invasion scenarios at anchorages were ranked among the highest risks by the NIS fuzzy expert system.

Hull fouling was highlighted as the most important spread mechanism for the recreational boating pathway. Although this would be consistent with the resurgence of interest in this mechanism in recent years (e.g., Floerl et al., 2005; Mineur et al., 2008), it is important to consider that experts (in general) often use the heuristic procedure of availability, which means that their assessment is driven by how easily they can either think of previous occurrences of an event or imagine an event occurring (Morgan and Henrion, 1990; Cooke, 1991). The recent attention focussed on hull fouling could therefore itself influence experts during the elicitation process and make them to both exacerbate the importance of this mechanism in the spread of NIS and underestimate others. Despite this, the system acknowledged the NIS invasion risk of the other components and highlighted the fact that depending on the marine habitat analysed their risk could be comparable to that from hull fouling. The NIS fuzzy expert system showed for example that, as with hull fouling risk, risks from components ***deck*** and ***internal spaces*** at wharves and moorings were considered to be high. This result could be explained by knowledge or expectation that skippers may clean vessel decks, inlets, outlets and bilges when using these habitats (e.g., after sailing or fishing trips).

Surveillance of coastal habitats affected the estimated risk value. Although this was not obvious when comparing surveyed and not surveyed marinas, a clear difference was observed between surveyed and not surveyed wharves. A determining factor in most (if not all) successful marine eradications has been detecting NIS incursions at relatively early stages when pest species have not reached pest densities (e.g., Wotton et al., 2004; Miller et al., 2004; Coutts and Forrest, 2007). Paradoxically, the effectiveness of NIS surveys (i.e., detection of target species) greatly depends on species density (Hayes et al., 2005). Detection would be therefore more likely at advanced stages of incursions when densities are usually higher. Despite this, as the presence of periodic surveys increases the probability of detecting NIS and thus, increases the likelihood of conducting effective eradication programs (Inglis et al., 2006), lower invasion risks are expected in areas with ongoing NIS surveillance programs.

It appears counter-intuitive that invasion risks overall varied only between *medium* and *low* for the different scenarios, but this reflected the smothering effect of averaging, combined with the variance in both expert assessments and expert numeric representation of the words used. This prevented input scenarios (e.g., infection = *Very likely* AND detection = *Very unlikely*), which certainly would lead the FES system to output the word *high* (Table 2). Although the lack of "*highs*" in the assessment could be seen as an underestimation of some of the risks, it is important to consider that *medium* is the second highest category used by the NIS fuzzy expert system to characterise invasion risks. Similarly, the final linguistic characterization of risk did not interfere with actual risk values; it was, on the contrary, the result of decoding these numbers. Therefore, even if linguistic characterization is impractical for risk ranking, the invasion risk values calculated by the NIS fuzzy expert system are still useful for comparing and thus prioritizing research and management within the recreational boating pathway.

4.1. Management implications

The results of the NIS fuzzy expert system have two important NIS management implications. First, they suggest that risk-based management of NIS spread via recreational vessels in coastal regions should ideally be scenario-specific, taking into account the vessel type, vessel component, infection mode and habitat visited. This type of approach would be most feasible and effective in situations where a target NIS and its spread mechanisms were fully identified. For example, for a species like the clubbed tunicate *Styela clava*, which transport is often associated with vessel fouling (Lützen, 1999; Davis and Davis, 2004; Minchin et al., 2006), the results of the NIS fuzzy expert system presented here suggest that management should be a priority for moored vessels and around wharves and moorings. On the other hand, when the objective is to prevent NIS introductions and spread in general, or if spread mechanisms are poorly understood, such specificity is not realistic and a broader approach may be more desirable, for example the application of generic rather than species-specific risk-based approaches to pathway management (Forrest et al., 2008).

In relation to habitats visited by vessels or likely to become infected with NIS, an application of the fuzzy expert system and associated risk values could be useful in setting management priorities (e.g., targeting surveillance or developing response tools for habitats with the highest invasion risk values). For habitats visited by recreational vessels, the present FES indicates that particular attention should be given to anchorages, wharves and moorings as the most likely points of incursion. Where high risk habitats were situated in localities having values of ecological or socio-economic importance, or could be used as stepping stones to such localities, a comparative analysis of values could be incorporated into the priority-setting process (e.g., Sinner et al., 2000; Forrest et al., 2006b).

In Tasman Bay, New Zealand, for example, there are several wharves, moorings, anchorages and marinas scattered around the coastline, including an international shipping port having a range of artificial structures on which high profile NIS have established (e.g., *Undaria pinnatifida*). Across the greater embayment, these habitats may equally be visited by recreational, fishing and aquaculture vessels (Acosta, unpubl. data), thus providing likely pathways for the human-mediated spread of NIS at a regional scale. Moreover, two of the most visited anchorages of this region are located within close proximity to a marine reserve, and adjacent to a National Park which is a tourism and conservation asset of national importance (Sinner et al., 2000). NIS infections at these habitats could have much wider ramifications (e.g. lead to a greater likelihood of secondary spread or adverse impacts) than infections in other areas where human-mediated or natural spread pathways are absent or limited, or where values are comparatively less. Prevention of spread to such habitats, or surveillance and early response to any pest species that are detected, should be a priority for any biosecurity management program in the region.

Another implication that arises from the present study in relation to NIS management is that hull fouling should not be considered the only important spread mechanism associated with recreational boating. Although the risk from the five vessel components considered in our studies varies with the habitat visited, the results indicate that other components in addition to hull fouling (i.e., deck, internal space, anchor, fishing gear) are also potentially effective NIS transport mechanisms. Hence, management of the recreational vessel pathway should consider all of these mechanisms and not be limited to hull fouling alone, as it typically the case in many regions around the world. Notwithstanding this view, a broader approach should not undertaken at the expense of reducing the attention given to hull fouling, especially at a time when a global ban on TBT-based antifouling paint (IMO, 2001) is likely to increase the number of organisms transported this way (Sonak et al., 2009).

5. Conclusions

Recreational boating encompasses a range of components that generate different invasion scenarios with different invasion risks associated. Lack of knowledge of the mechanisms of spread by recreational boating however, is often translated into NIS management plans that are not only limited but also restricted to consideration of hull fouling alone (e.g., Ashton et al., 2006). The invasion risk ranking presented here could be the basis for managing the potential of recreational boating to introduce and spread NIS to particular coastal areas, allowing time for more specific and quantitative data to be generated. It could also be used to define and support policies to ensure the management of this pathway in any coastal region where recreational boating is likely to be important in NIS spread, and to evaluate recreational vessel risks relative to other pathways. For this purpose, the NIS fuzzy expert system presented in this paper will need to be modified if more complex or specific invasion scenarios were to be simulated. Nonetheless, the general approach and associated risk ranking that we describe could be seen as an initial step for more in depth and thus, potentially more effective, risk-based approaches for managing NIS. This paper also highlights the particular benefits offered by IT2FLSs to deal with expert data, which has not previously been exploited in the biological invasions field. Finally, the elicitation methodology and model building approach (i.e., IT2FL-based) that we describe could be readily used as a framework for similar risk systems and analyses.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2009.11.025.

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