Generating Uncertain Fuzzy Logic Rules from Surveys

Capturing Subjective Relationships between Variables from Human Experts

Christian Wagner, Amir Pourabdollah
School of Computer Science
University of Nottingham
Nottingham, UK
christian.wagner, amir.pourabdollah
@nottingham.ac.uk

Michael Smith
Department of Parks and Wildlife
Western Australian Government
Perth, Australia
michael.smith@dpaw.wa.gov.au

Ken Wallace
School of Agricultural and Resource Economics
University of Western Australia
Perth, Australia
ken.wallace@uwa.edu.au

***Abstract*—One of the biggest challenges in the design of Fuzzy Logic Systems (FLSs) is the construction of their rule base. While fuzzy sets capture aspects of a system's variables and associates them with linguistic labels, it is the rules which capture the logical relationships of these labels and underlying fuzzy sets. Further, while fuzzy systems are credited for dealing well with uncertainty in system inputs and outputs, comparatively little research has focused on the capture of uncertainty in their actual inference rules. This paper focusses on the challenge of capturing the knowledge of multiple human experts on the relationships of linguistic labels in a given problem domain. Specifically, it proposes a novel survey-centric methodology which enables the capture of individual, subjective input from domain (not fuzzy logic) experts with minimal prior training and provides mechanisms to aggregate the resulting survey-data into a working and interpretable fuzzy system. The rule base of the resulting system incorporates weights to capture intra- and inter-expert uncertainty during rule specification. The paper follows a practical style to facilitate reproduction of the proposed methodology by peers. Results and initial evaluation based on real world case studies in the context of environmental conservation in Western Australia are provided.**

Keywords-rules, survey, fuzzy, human, expert, uncertain rules.

I. Introduction

Since their introduction in 1965 by Zadeh [14], Fuzzy Sets (FSs) and specifically Fuzzy Logic Systems (FLSs) have proved highly valuable in applications from time series prediction to control. Also, since their (in particular Mamdani fuzzy logic controllers [8]) application, a particular challenge of FLSs has been the identification of the crucial rules that provide the connection between a system's antecedents and consequents which in turn captures the logical relationship of a system's inputs and outputs.

Substantial bodies of work have addressed the challenge of creating a rule base from a knowledge extraction (rule-mining) or an optimization point of view. In [13], the structure of the rule base within a FLS is explored and a powerful method for automatic rule-extraction method for existing input-output datasets was presented. The authors show its application in time series prediction and control applications. In the same year, [6] introduced the concept of a distributed representation of fuzzy rules, capturing the possibility of "superimposing" fuzzy rules and showing its potential in a pattern classification context. A large number of other approaches to rule generation exist, including [2], [3], [5], [7], many of which employ hybrid techniques for rule elicitation such as through the use of evolutionary computing strategies, e.g., [2] and [5]. Several of the methods have also continuously been refined, for example in [1], further developments to the Wang-Mendel rule elicitation approach [13] are proposed.

While the above rule generation approaches have been highly successful in a number of applications, they do not specifically address the capture of rules from non-fuzzy-logic-experts. While the latter is often cited as a common approach for rule generation, in practice however, it is usually based on the interaction of a FLS designer with domain experts – after which the designer proceeds to generate the rule base.

Beyond the actual generation of rules, it is interesting to note that a number of rule generation approaches (and indeed other approaches of FLSs), incl. [2], [6] and [13] have employed rule-weights to capture additional information regarding the importance of given rules within the rule base and thus enable better FLS performance. More generally, it is clear that the weighting of rules commonly takes the role of "fine-tuning" of FLS performance in a given context.

This paper focusses on the challenge of generating rule bases from multiple application domain (not fuzzy logic) experts. In particular, it presents an approach on *1)* how to capture the required information, without the experts needing to be familiar with fuzzy logic or even rule based systems, and, *2)* how to address the problem of rule uncertainty (by a given expert) and conflicting rules (among experts).

The motivation for this paper is the application of FLSs in multi-disciplinary applications where their potential for dealing with uncertain data while maintaining high interpretability are often essential. In particular, we highlight the deployment and evaluation of the proposed approach in the context of a data-driven environmental management application for wetland conservation in Western Australia.

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The paper provides two main contributions. First, it introduces and provides complete detail for a methodology for capturing rules from multiple experts based on a structured survey which does not require prior knowledge about rule based systems or other computer science aspects. A practical style for the presentation of the methodology is adopted to enable and encourage the replication of the methodology by peers in order to motivate debate and refinement of the method.

Second, the paper details an initial path to capturing and processing uncertain rules, in this case, with the uncertainty in the rules arising from both inter-expert uncertainty, i.e., different experts providing different rules, and intra-expert uncertainty, i.e. individual experts expressing the viability of multiple conflicting rules.

The structure of the paper proceeds as follows. Section II elaborates on the motivation and context of the proposed approach, clarifying the type of applications it has been designed for. Section III presents the proposed rule elicitation framework, followed by a real world case study in Section IV. Section V finally provides a discussion and conclusions.

II. Motivation

The proposed framework for fuzzy logic rule elicitation has been designed for multi-disciplinary applications where domain experts possess crucial knowledge on the relationships between aspects/variables of the system which is to be modelled using an FLS. However, no familiarity with FLSs or even more generally, modelling and computer science is expected. Target audiences thus can include experts from domains such as medicine, biology, conservation management, but also stakeholders in a given context, such as residents in a city development context – who may be experts in the sense that they possess essential insight into a given modelling context.

Further, the framework focusses specifically on contexts where a pool of experts are available and where it is deemed important to capture a rich view of the relationships in the given problem domain, i.e. a standard survey context. As individual experts may differ in their opinion (i.e. potential for opposing "rules") and beyond this, may be more or less certain on given relationships, the framework is designed to explicitly address cross-expert discord (inter-expert) and individual expert (intra-expert) uncertainty.

Finally, specific emphasis has been given to providing a high degree of interpretability in the resulting framework outputs in order to enable experts to review and evaluate the outputs. Thus, a graphical representation combining simple tabular rule representation and a heat-map style shading is introduced.

In the following sections, we present the individual steps of the framework, from the survey design and relationship-data capture from experts, to the survey transcription and finally, the generation of fuzzy rules.

III. The Survey-centred Framework

The proposed framework is based on the design of a questionnaire which captures experts' perceptions on the relationships of variables in a simple, efficient, yet comprehensive way.

In order to illustrate the individual steps in this section, we will employ a simple toy example: consider that we are interested in the tipping behavior of customers in a restaurant based on the quality of the food. We model the food-quality and the level of tip using seven labels (i.e. seven fuzzy sets). We are now interested in capturing the relationship of increasing food-quality to the level of tip that would be given by different diners.

In the following subsections, we show how a questionnaire is designed for the proposed framework, referring to the tipping-example as illustration throughout.

A. Survey-based capture of variable relationships

Each survey is structured as a questionnaire where each of N experts is presented with a set of M matrices capturing the relationship between two variables which will respectively form the antecedent and the consequent of a rule. An example of a matrix "skeleton" is provided in Figure 1.

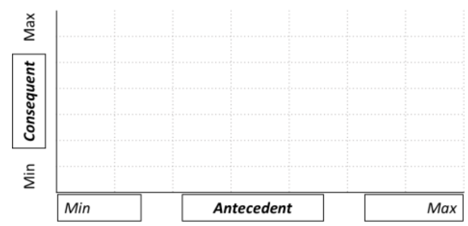

Figure 1. Example of a matrix "skeleton" which is used to capture the relationship between two variables. Note that, Antecedent, Consequent, as well as the numeric values for Min and Max (on both axes) are replaced by the variable names by the experimenter during the survey design.

1) Survey Preparation.

In order to prepare a survey for a given application, the following steps are required:

- All 2-tuple relationships between antecedent and consequent variables are identified for the given application. In our example, we only have a one-part antecedent (Food Quality) and one consequent (Level of Tip) variable. Note - it is possible to address multi-part antecedents (e.g., connected by AND in the rules), see Section V for a discussion of this.
- For each relationship, one matrix is created, where the Antecedent label (e.g., Food Quality) is used on the x-axis and the consequent (e.g., the tipping level) is used on the y-axes. The number of rows (I) and columns (J) in the matrix is established based on the desired number of linguistic labels (i.e. fuzzy sets) to be employed to qualify each variable. For example, in Figure 2, we use r=c=5 labels (e.g., Very Low, Low, OK, High, Very High) for both variables. Note that this matrix structure underlying a FLS's rule base has a long tradition (e.g., [6],[13]) but has not been leveraged as the basis for a survey-questionnaire.
- For both axes, the *min* and *max* levels are established and specified. In our example, Food Quality is rated as a value between 0 and 10, while Tipping Level is a value between 0 and 30 (%). See Figure 2 for an illustration.

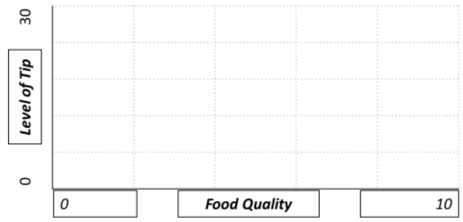

Figure 2. Example Rule Capture Matrix for the Tipping Problem

2) *Survey Administation*

After the survey has been produced (either on paper or digitally), human experts are given explanations on how to complete the matrices. In particular, they are instructed to put one cross per column in the row which captures the relationship between the given quantity of the variable on the x-axis (the antecedent) and the variable on the y-axis (the consequent). Effectively, for each column, participants are thus requested to answer the question "For a given amount of *X*, how much Y do you consider appropriate?". An example of a filled-in matrix for the Tipping Problem is shown in Figure 3.

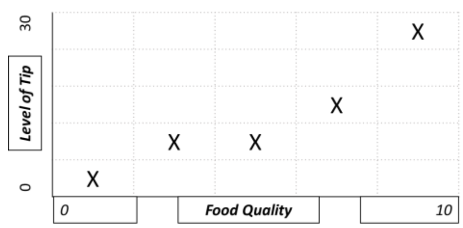

Figure 3. Example filled-in matrix for the Tipping Problem

In the applied work conducted by the authors so far using the proposed technique, explanations are given in a workshop context. However, it is similarly possible to provide written instructions with examples to participants.

Optionally, participants are also requested to use circles to indicate potential relationships which they consider possible, but less likely or less of a good match than those relationships which they indicated with crosses. In each column, multiple circles are allowed, but all circles need to be adjacent either to a cross or to another circle. This step is designed to enable participants to express their uncertainty on given relationships. An example is given in Figure 4.

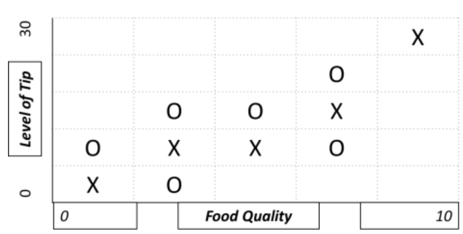

Figure 4. Example filled-in matrix including both best estimates (crosses) and possible relationships (circles).

After all participants have completed the survey, all *N* matrices for a given relationship are grouped before being numerically translated as explained in the following Section.

B. *From Survey to Digital Data*

After the survey has been completed by all N participants, the survey data for each of the M matrices/relationships is aggregated into two summary matrices, M_{Best} and M_{Poss}, capturing the best estimates (crosses), and the possible relationships (circles), respectively. In order to generate both summary matrices, the crosses, (respectively circles) in each field across all *M* participant-matrices are counted, providing an overall view of the strength of the given relationships. Figure 5 provides an example based on *N=3* participants.

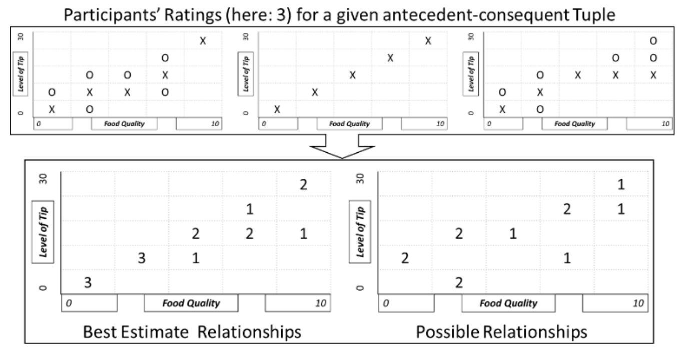

Figure 5. Generating summary matrices for best estimate and possible relationships. Note that for the best estimate matrix on the left, each "X" in the participant ratings is counted and the sum is added to the summary matrix. The same process is repeated with the "O" for the possible relationship matrix.

C. *From data to uncertain (weighted) fuzzy logic rules*

As noted, each matrix captures the relationships between an antecedent and a consequent variable over *J* columns and *I* rows respectively (five for both variables in Figure 5). Consider associating each column and row with linguistic labels as is common for fuzzy sets, i.e., for the antecedent, a possible option is to name the columns from Very Low, Low, …, Very High from left to right. An example for both antecedent and consequent is given in Figure 6.

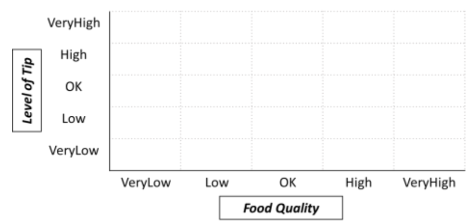

Figure 6 Matrix with example linguistic labels

In order to create rules, we consider each of the possible column/row combinations, resulting in simple rules in the format of: "IF FoodQuality IS VeryLow THEN LevelofTip IS VeryLow", "IF FoodQuality IS VeryLow THEN LevelofTip IS Low", etc. A total of $I * J$ rules can thus be generated. As noted previously, more complex rules are possible as discussed in Section V.

Clearly, it would be meaningless to generate a rule base which contained all possible rules as already noted for example in [6] and [13]. In our case, in order to focus only on rules arising from the participating experts, only rules with a non-zero weight are generated, where the weight arises from the participant's survey ratings. More formally, consider R rules, where $R_{i,j}$ refers to the rule generated for row i and column j. The weight $W_{R_{i,j}}$, or more simply $W_{i,j}$ of rule $R_{i,j}$ is given by:

$$W_{i,j} = \frac{M_{Best_{i,j}} \times \omega_{Best} + M_{Poss_{i,j}} \times \omega_{Poss}}{\omega_{Best} + \omega_{Poss}}, \quad (1)$$

,where $\omega_{Best} \in [0,1]$ is the weight for best estimate relationships and $\omega_{Poss} \in [0,1]$ is the weight for possible relationships. Note that the weights reflect how much emphasis is to be given to the best estimates and the possible relationships and are commonly specified based on the specific application context. As noted, the rule base of the resulting system comprises all rules, where $W_{i,j} > 0$.

D. *Executing a rule base with uncertain (weighted) rules.*

When performing inference with the resulting fuzzy logic system, the firing strength of a given rule $f'_{i,j}$, is modified from the standard firing strength $f_{i,j}$ resulting from the implication operation of the antecedents as follows:

$$f'_{i,j} = f_{i,j} * W_{i,j} \ , \quad (2)$$

where $*$ is any t-Norm, commonly multiplication.

Note that the overall structure of the resulting FLS is identical to standard type-1 FLSs. Figure 7 summarizes the structure, highlighting the two components which have been adapted. Specifically, the Rule Base is highlighted, as in the proposed system, each rule is associated with a weight; and the Inference Engine is highlighted as the firing strength computation for each rule within the FLS has been adapted based on (2).

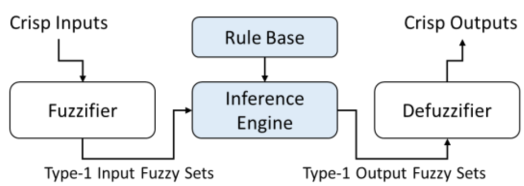

Figure 7. Structure of the type-1 FLS. Shaded components of the FLS are adjusted from standard FLS to capture uncertain (weighted) rules.

IV. Real World Case Study

The described framework was deployed and subsequently evaluated in the context of ongoing research projects on data-driven environmental planning and policy design in Western Australia. Environmental management is highly challenging, both because quantitative data on the natural environment (e.g., species diversity) is often highly uncertain, but also, as the relationship between given elements (e.g., fauna and flora species) within an ecosystem, and human priorities are often unclear. The latter is compounded as the 'users' of a management area are often diverse. A typical conservation management area (such as a national park) may need to meet the expectations of the general public and natural resource experts (scientists, managers, conservation groups) while also having to meet specific management objectives such as legislative stipulations (i.e., conservation of threatened species or habitats). All of these stakeholders possess an array of motivations and interests that ultimately lead to expectations which can be framed as (desired) human values such as Aesthetics, Adequate Resources, Meaningful Occupation, Health, etc. [12] [12].

In values-driven planning frameworks such as [12], decisions relating to the management of system elements (e.g., a given bird species such as swans for example) focus on the important element properties (e.g., size or intactness of the swan population). While management can affect elements' properties (e.g., we can affect the size of the population), it is vital to understand *how* changes in a property (antecedent) affect the different human values expected by stakeholders (the consequent). For example, how does a change in the size of the swan population affect the aesthetic pleasure that different stakeholders perceive?

In [9], we introduced a data-driven management framework which operationalizes [12]. While in [9], the rules within the underlying FLS were specified by fuzzy logic experts (with domain expert input), the framework proposed in this paper enables the incorporation of insight directly from a number of domain experts.

A. *Problem Summary*

Given a link between element properties and the delivery of important human values (e.g., [4]), it is important for managers and decision makers to quantify said links and any associated uncertainty. By understanding how a change in an important property will affect the way stakeholders rate the values associated with an element, managers can better focus their management activities towards controlling properties to better deliver priority values to stakeholders. However, in most natural resource domains there is little to no quantitative information to link the many properties that must be managed to the many values that must be delivered. However, important information about these links is typically available via expert opinion. Mining the opinions of experts (and associated uncertainty) provides an opportunity for natural resource managers to develop more targeted and effective management for the delivery of human values.

B. *Case Study: Lake Bryde Catchment, Western Australia*

As part of the value-driven conservation planning, *N=8* experts were surveyed in an interactive workshop in 2014. The rule-generation framework presented in Section III was employed specifically to elicit the potential of specific element-properties to deliver a key set of human values as their amount varies. The set of human values identified as of highest priority and thus explored included: Recreation, Knowledge & Heritage and Future Options. The element-properties considered were: Richness (or total number of species), Visibility, Size, Rarity, Loss, and Charisma.

As the presentation of all the results would go beyond the scope of this paper, we will present a subset of the resulting combinations, namely, a detailed, step-by-step example for property-value relationships (Richness-Future Options) followed by summary results (focusing on the weights) for all the property-value relationships for the human value Recreation.

Figure 8 shows the matrix employed to capture the relationship between the human value Future Options and varying levels of the property (Species) Richness.

After all N=8 experts had completed the questionnaire, the data from the respective matrices (Figure 8) was captured as described in Section III.b. Figure 9 shows the complete step-by-step data capture, including both summary matrices for best estimate and possible relationships as well as the resulting aggregated rule weights. Note that the weighting of $\omega_{Best} = 1$ and $\omega_{Poss} = 0.5$ was employed as it was considered appropriate by domain experts.

Note that we do not provide a complete listing of the rule set because of space considerations. It is trivially generated from Figure 9 using the process outlines in Section III.C. We used seven labels, i.e. extremely low, very low, low, medium, high, very high, extremely high, resulting in rules in the format, counting from the lower left in the matrix with i=j=0:

- $R_{0,0}$: IF Richness is ExtremelyLow THEN FutureOptions is ExtremelyLow; $W_{0,0} = 3.7$
- $R_{1,0}$: IF Richness is ExtremelyLow THEN FutureOptions is VeryLow; $W_{1,0} = 2$
- etc.

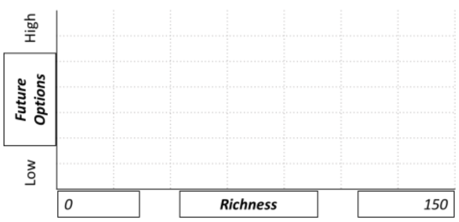

Figure 8. Survey matrix as employed to capture the relationship between the property "Richness" and the human value "Future Options". Note that the property endpoints [0,150] were established by the experts prior to the survey.

Certain Ratings

Future Options							
Ex. High	0.0	0.0	0.0	2.0	2.0	4.0	
	0.0	0.0	2.0	0.0	2.0	4.0	0.0
	0.0	2.0	1.0	2.0	4.0	0.0	0.0
	1.0	1.0	1.0	4.0	0.0	0.0	0.0
	2.0	1.0	3.0	0.0	0.0	0.0	0.0
	1.0	3.0	1.0	0.0	0.0	0.0	0.0
Ex. Low	4.0	1.0	0.0	0.0	0.0	0.0	0.0

Uncertain Ratings

Future Options							
Ex. High	0.0	1.0	2.0	0.0	2.0	2.0	0.0
	1.0	2.0	1.0	4.0	3.0	2.0	2.0
	2.0	1.0	3.0	3.0	2.0	3.0	1.0
	2.0	3.0		2.0	4.0	0.0	0.0
	2.0	4.0	4.0	3.0	0.0	0.0	0.0
	4.0	3.0	2.0	1.0	0.0	0.0	0.0
Ex. Low	3.0	2.0	1.0	0.0	0.0	0.0	0.0

Merged Ratings (combining certain and uncertain, using weights below)

Future Options							
Ex. High	0.0	0.3	0.7	1.3	2.0	3.3	4.7
	0.3	0.7	1.7	1.3	2.3	3.3	0.7
	0.7	1.7	1.7	2.3	3.3	1.0	0.3
	1.3	1.7	2.3	3.3	1.3	0.0	0.0
	2.0	2.0	3.3	1.0	0.0	0.0	0.0
	2.0	3.0	1.3	0.3	0.0	0.0	0.0
Ex. Low	3.7	1.3	0.3	0.0	0.0	0.0	0.0

0 Richness (number of species) 150

Figure 9. Summary matrices for Best Estimate and Possible Relationships between varying quantities of Species Richness and the human value Future Options. Note that N=8 experts filled in the survey. The shading has been applied to provide an easier visualisation of the data, highlighting the uncertainty. The resulting weights are based on $\omega_{Best} = 1$ and $\omega_{Poss} = 0.5$.

Considering the weights in Figure 9, it is visible that the experts as a group consider the value of Future Options to be roughly linearly increasing with increasing Species Richness. The output of the corresponding FLS generated as detailed in Section III (using evenly distributed triangular fuzzy sets for both variables) is plotted in Figure 10. As is expected, the FLS output increases quasi linearly as the Species Richness increases. Note that the "steps" in the FLS output in Figure 10 are the direct result of the discretization and use of simple FSs.

While various techniques could be employed to smooth the output, from using different FSs, to more detailed surveys and post-survey smoothing (e.g., using rule interpolation), interaction with stakeholders thus far has shown that domain experts value the transparency of the resulting FLS outputs, i.e. they can "tell" that the FLS output arises from the survey data that was collected.

Finally, note that while the quasi-linear relationship in this case can make it seem overly straightforward to capture such relationships, the actual relationships are frequently substantially more complex, both in terms of the captured intra- and inter-expert uncertainty as well as in terms of the non-linear nature of value delivery based on changes in a given property. Further, as can be seen in Figure 9, while overall linear, there is considerable and non-symmetric uncertainty in the relationship which has been captured in the rule weights.

Figure 11 provides an example for all properties employed in relation to the human value Recreation. Note the difference in resulting weight matrices for the property Richness for the different values in Figure 9 and Figure 11.

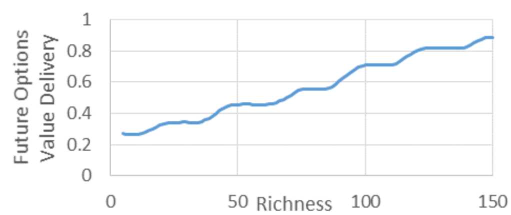

Figure 10. FLS output for the relationship of Future Options for varying levels of Species Richness

Recreation							
Ex. High	0.3	0.3	0.7	0.7	2.3	3.3	4.3
	0.3	1.0	1.3	2.3	1.7	2.3	1.3
	0.7	1.0	2.3	2.3	2.0	2.0	1.0
	0.7	2.3	2.7	2.7	2.3	1.3	0.7
	2.0	2.0	2.7	2.0	1.3	0.7	1.0
	2.3	2.3	1.7	1.7	0.7	0.3	0.3
Ex. Low	3.7	2.0	1.0	0.0	0.0	0.0	0.3

0 Richness (number of species) 150

Recreation							
Ex. High	0.3	0.0	0.0	0.0	0.7	1.7	3.0
	0.3	0.0	0.0	0.3	1.7	3.0	2.0
	0.3	0.0	0.3	2.0	2.7	1.7	1.3
	1.0	0.7	2.0	3.0	1.7	1.3	1.3
	1.3	2.7	3.3	1.7	1.3	1.0	0.3
	2.0	3.0	2.0	1.3	0.7	0.0	0.0
Ex. Low	2.7	1.3	0.3	0.3	0.0	0.0	0.0

0 Visibility (%) 100

Recreation							
Ex. High	0.0	0.0	0.0	0.7	1.3	2.7	4.0
	0.3	0.3	1.3	2.3	2.7	2.7	2.0
	0.7	1.7	2.7	3.7	3.7	1.3	0.7
	1.3	3.0	3.3	2.7	1.3	0.7	0.7
	2.0	3.7	2.7	1.7	0.7	0.7	0.7
	3.3	2.3	2.0	1.0	0.7	0.7	0.7
Ex. Low	3.0	1.0	0.3	0.3	0.3	0.3	0.3

0 Size (ha) 10,000

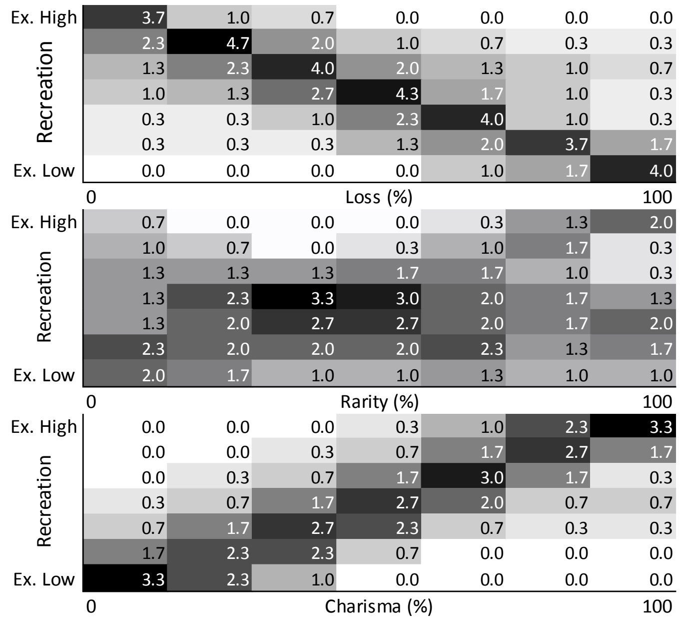

Figure 11. Relationships captured for the delivery of the human value "Recreation" (the consequent), based on a number of element-properties (the antecedents).

The rules resulting from the overall expert elicitation exercise are employed in the overall data-driven environmental framework described in [9]. Expert evaluation of the rules and the resulting system outputs has been very positive, highlighting in particular the capture of relationship uncertainty, rule-based interpretability and simple visualization of rule bases (as in Figure 11) as strong aspects of the approach. By exploiting the link between properties and human values through the generation of a set of verbal rules that capture these relationships and their uncertainty, the framework enables the creation of FLSs which provide a unique approach to deliver informed management and in turn, human values.

V. Conclusions

Rules are at the core of FLSs. Inter-disciplinary collaboration highlights increasing numbers of applications where the properties of FLSs, such as their ability to deal with uncertainty and their high interpretability, are highly valuable. In many of these applications, such as in the environmental management context described in this paper, there is a need for capturing the relationship between variables, i.e. the rules of the FLS, from human experts. Moreover, functionality is needed to capture the complexity, discord and potential uncertainty in those relationships and thus rules.

This paper has proposed a survey-based methodology to capture uncertain rules directly from domain (not FLS) experts. We have provided a step-by-step illustration of how the methodology is applied, together with real world examples from an environmental management application in Australia.

In this paper, we have only introduced the basic framework. Current limitations include the lack of both in-depth analysis of appropriate weighting for best estimate and possible relationships as well as a more satisfying mathematical approach to capturing the uncertainty in the relationships. While functional, the current weighting of a potentially very large number of rules may be better addressed by introducing appropriately parameterized inference operators (t-norms). We will consider this body of work in the future.

Finally, it may be perceived that a major potential shortcoming of the proposed approach is the use of only a single antecedent component. While currently most rules rely on such single-component antecedents and more complex system outputs are accumulated by aggregating individual FLS outputs, the framework is capable of addressing multiple component antecedents, as for example in rules of the form: "IF Rarity is x AND Charisma is y AND… THEN …". To capture such relationships, experts are given questionnaires which specify fixed amounts of all antecedent components except one (which is varied), resulting in questions such as: "For a Rarity of x and Charisma y, show how varying amounts of Loss affect the human value Recreation". The main challenge in the above is the significantly increased amount of expert-time required to fill in a potentially very large number of questionnaires. In future work, we are seeking to explore this option as part of an online crowd-sourcing approach.

References

[1] J. Casillas, O. Cordón, F. Herrera, "Improving the Wang and Mendel's fuzzy rule learning method by inducing cooperation among rules", Proc. of the 8th Inf. Proc. and Management of Uncertainty in Knowledge-Based Systems Conf., Madrid, Spain, pp. 1682-1688, 2000.

[2] S-M. Chen, C-M. Huang, "Generating weighted fuzzy rules from relational database s2ystems for estimating values using genetic algorithms,"IEEE Trans. Fuzzy Syst., vol. 4, no. 4, pp. 495-506, 2003.

[3] Y-C. Chen A, L-H. Wang B and S-M. Chen C, "Generating Weighted Fuzzy Rules from Training Data for Dealing with the Iris Data Classification Problem," Int. J. Appl. Sci. Eng., vol. 4, pp. 41-52, 2006.

[4] M. Garcia-Llorente et al., "Can ecosystem properties be fully translated into service values?," Ecological Applications, vol. 21, no. 8, pp. 3083-3103, 2011.

[5] F. Herrera, M. Lozano and J. L. Verdegay, "Generating Fuzzy Rules from Examples using Genetic Algorithms," Fuzzy Logic and Soft Computing, World Scientific, pp. 11-20, 1995.

[6] H. Ishibuchi, K. Nozaki and H. Tanaka, "Distributed representation of fuzzy rules and its application to pattern classification," Fuzzy Sets and Systems, vol. 52, pp. 21-32, 1992.

[7] H. Ishibuschi and T. Yamamoto, "Rule weight specification in fuzzy rule-based classification systems," IEEE Trans. Fuzzy Syst., vol. 13, pp. 428-435, 2005.

[8] E. H. Mamdani, "Application of fuzzy algorithms for control of simple dynamic plant," Proc. of the Inst. of Elec. Eng., vol.121, no.12, pp.1585-1588, 1974.

[9] A. Pourabdollah, C. Wagner, S. Miller, M. Smith, and K. Wallace, "Towards data-driven environmental planning and policy design-leveraging fuzzy logic to operationalize a planning framework," in Proc. of the 2014 Int. Conf. on Fuzzy Systems, pp. 2230–2237, Beijing, China.

[10] C. Wagner and H. Hagras, "A genetic algorithm based architecture for evolving type-2 fuzzy controllers for real world autonomous mobile robots," Proceedings of the IEEE International Conference of Fuzzy Systems, London, UK, July 2007, pp. 193-198.

[11] K. J. Wallace, "Classification of ecosystem services: problems and solutions," Biological conservation, vol. 139, pp. 235-246, 2007.

[12] K. J. Wallace, "Values: Drivers for planning biodiversity management." Environmental Science and Policy, vol. 17, pp. 1-11, 2012.

[13] L-X. Wang, J.M. Mendel, "Generating fuzzy rules by learning from examples," IEEE Trans, Systems, Man and Cybernetics., vol.22, no.6, pp.1414-1427, 1992.

[14] L.A. Zadeh, "Fuzzy Sets," Information and Control, vol. 8, no. 3, pp. 338-353, 1965.