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Incorporating qualitative indicators to support river managers; application of fuzzy sets

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Abstract:. In evaluation of river management strategies it is generally difficult to deal with the loosely structured and uncertain information at hand. Due to the increasing number of interests and objectives involved in river management it becomes more important to find a way to deal with such information. This paper explores to what extent fuzzy set theory can help in the modelling of relations between river management measures and their effects. The authors conclude that fuzzy logic can provide a valuable contribution because of the relative transparency of the method, the possibility to include qualitative knowledge and the incorporation of uncertainty. Particularly the latter requires further study before a broad application in river management is feasible.

Keywords: Fuzzy set theory, uncertainty, river management.

1. INTRODUCTION

Strategic river management involves a relatively long time horizon, and hence information which in general is loosely structured, aggregated and uncertain [Loucks, 1995]. There are various ways to deal with such information; in many cases it is processed in numerical models in combination with scenario analysis [Nieuwkamer, 1995; Hoekstra, 1998; De Kok et al., 2004]. For some aspects of the future which decision makers like to see explored, however, [Ministerie van Verkeer & Waterstaat, 2002], crisp mathematical relations are hard to define. In addition a tendency towards more stakeholder involvement can be observed over the past decade, and subjectivity in the policy process is more and more acknowledged [Pahl-Wostl, 2004]. Involvement of more stakeholders and more 'soft' criteria poses the decision makers for problems of ambiguity, uncertainty and indicators or relations which are difficult to include as ranking criteria because of their qualitative character. Nguyen [2005] and Nakamori & Swaragi [2000] a.o. suggest the application of fuzzy set theory as a way to deal with these issues. Others show that the application of fuzzy set theory may indeed provide added value to crisp modelling in decision support [van der Werf ten Bosch & Goossens, 1997; Clark & Richards, 2002; Nguyen, 2005]. We will now explore the advancement that can be made in dealing with uncertainty and ambiguity in the assessment of river strategies by applying fuzzy sets. We expect that the use of fuzzy sets will allow us to

1) deal with qualitative relations and indicators, and
2) easier process and represent uncertainty.

These expectations are tested with a relatively simple model based on the principles of fuzzy set theory. The research is applied to the Integrated Exploration Meuse (IEM) study, an ongoing study on the management of the Meuse River in the Netherlands [Ministerie van Verkeer & Waterstaat, 2002]. The Netherlands has only very slight differences in elevation level, is densely populated and its rivers are mostly typical lowland rivers. The small differences in elevation level and the presence of two major lowland rivers and a long coastline make a large part of the Netherlands prone to flooding. In combination with the high population density safety has hence become one of the major interests at stake. Safety is the first objective in our model; it is represented by the water level change (WLC). The water level change can be modelled deterministically. The advantage of involving it is that a lot of knowledge is

available, which will allow us to evaluate the reliability of model outcomes.

The high population density has lead to scarcity of space in the Meuse catchment. Many people are involved in the discussion about the effect of different measures on their all day environment. The second objective in our model is landscape quality (LQ), a subjective and qualitative indicator.

Two measures are applied to achieve these objectives; the construction of a side-channel and planting a lowland riparian forest. The first is represented by the side channel width (SCW), the second by the riparian forest density (RFD). These measures are often combined in view of landscape quality and ecology, but have a conflicting effect on safety because the forest increases the roughness and hence causes higher water levels. Although we acknowledge that the actual relations between particularly the RFD and the output indicators can be more complicated than this, we assume that this description is satisfactory for our purposes. In the fuzzy model we will define rules for possible combinations of these two measures (Figure 1).
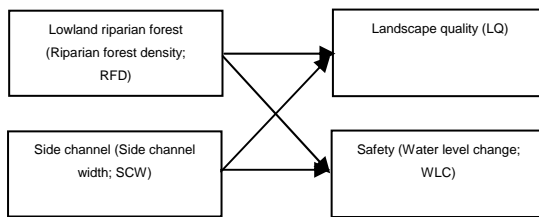
Figure 1: Conceptual model; measures and effects

It is not possible to formulate individual effects for SCW and RFD and combine them afterwards, because the combined effect is not simply the sum of the individual effects; the interaction has to be taken into account when formulating the rules. We assume the effects are defined for a high discharge condition, because the effect of the side channel will only be registered in case of high discharges.

2 METHOD

This section will first go into the description of our objectives in more detail. Then the applied implementation procedure is described. The Matlab ® Fuzzy Toolbox was used to implement the steps, and a Mamdani controller is applied [Mamdani and Assilian, 1975]. Finally the processing of uncertainty is described.

2.1 Evaluation criteria

We examine the usefulness of fuzzy set theory based on its ability I) to process qualitative information and II) to process and interpret uncertainties.

1. Processing of qualitative information
We define qualitative information as information described on a nominal or ordinal scale of measurement [Stevens, 1946]. A nominal scale of measurement refers to variables which can be categorized but not ranked. Variables measured at an ordinal scale level can be ranked, i.e. a higher number represents a higher value, but the intervals between the numbers do not necessarily have equal length. Quantitative variables can be measured on either an interval scale level, where the intervals are equal but the absolute zero is lacking, or a ratio scale level, where the intervals between the numbers are equal and there is an absolute zero. Relations between variables should at least be on an ordinal measurement level and nominal variables can only be modelled if some of their characteristics can be described on ordinal level or higher. Our simple model involves one ordinal and three ratio variables.

2. Processing and interpretation of uncertainties
According to Zadeh [2005] uncertainty is a characteristic of information. According to his description of a generalized theory of uncertainty (GTU) information can be represented as a generalized constraint. The uncertainties are defined in a very natural manner, through the process of mapping the possible values of a variable x to a certain membership function (MF) according to the concept of granularity [Zadeh, 1973]. In this way the uncertainty in the inputs is incorporated into the model. The rules represent relatively imprecise information about the relations between input and output. Yet their definition takes place in a very open structure, allowing for discussion between experts and simple modification. If we can find an interpretable representation of uncertainty in the fuzzy outcome, we can say the approach is successful.

2.2 Translation of variables into fuzzy membership functions

There are four variables to be implemented. The ranges of possible values for the variables are defined in Table 1. For our ordinal variable 'landscape quality' the range is defined between zero and one. Also for the lowland riparian forest density the range is defined between zero and one, but this could in practice be replaced by the number of bush per square meter.

Table 1: Variable ranges

Variable	Range
Side channel width	0 to 100 cm
Lowland riparian forest density	0 to 1 (-)
Water level change	-15 to 10 cm
Landscape quality, positive effect	0 to 1 (-)

For each of the input variables we have worked with three Gaussian membership functions (MF's), categorized by linguistic characterizations related to the width of the side channel and the density of the lowland riparian forest. For landscape quality we work with three MF's ranging between 0 and 1, representing a positive effect on landscape quality. We defined five MF's for water level because we have more knowledge about the expected water level changes in relation to the proposed measures. Note that no negative interpretation can be given to landscape quality.

2.3 Formulation of the conditional inference rules

The variables are related by conditional inference rules. These determine which input set relates to a certain output set. Because we have two output variables and two inputs with three MF's each, the maximum number of rules equals $2 \times 3^2 = 18$. In Tables 2 and 3 the rules are given for both output variables.

Table 2: Input effects on water level change (-- = strong decrease, - = decrease, 0 = neutral, + = increase, ++ = strong increase)

S.ch.width	Lowland rip. forest density		
	Low	Average	High
Narrow	-	+	++
Medium	-	0	+
Wide	--	--	+

Table 3: Input effects on landscape quality (S = small, A = average and L = large)

S.ch.width	Lowland rip. forest density		
	Low	Average	High
Narrow	A	L	L
Medium	S	A	L
Wide	S	A	L

The changes in water level are expressed in five categories. The effect on landscape quality can be small, average or large and is interpreted as a positive effect. According to our expert, the SCW has a negative relation to WLC; an increase in width means a decrease in water level. The RFD, which can be implemented in combination with the side channel, has the opposite effect. All relations are expected to be monotonous.

For LQ it is assumed that a side channel has a positive effect. The difference between a medium or a wide side channel in terms of landscape quality is considered negligible. The riparian forest is considered a desirable ecotope type, and increasing density is considered more desirable.

2.4 Application of the rules

Application of our fuzzy rules is preceded by the choice of fuzzy set operators. The AND- operator is chosen to be 'min'. OR rules are not used. The aggregation takes place by application of the 'max' operator and for defuzzification the centre of area (COA) is taken. The implication operator which provides the translation from antecedent to consequent is 'min'. This min method incurs a truncation on the consequent. The results of rule application are described in section three.

2.5 Processing of uncertainties

The uncertainties in the output of the model are processed by calculating the COA of the area left of the original COA and another one for the area right of the COA. The difference between these two then represents an uncertainty range in the model outcome. The advantage of this method is that it is close to the original fuzzy calculation; it gives a variance around the central outcome. Its practical value depends on the interpretation we gave to the uncertainty in the input.

3 RESULTS

Implementation of the fuzzy system described in the previous section gives the outcomes as shown in Figures 2-5. Figures 2 and 3 give an overview of the outcomes for all possible inputs, based on a COA defuzzification. Figures 4 and 5 give an overview of the uncertainty in these outcomes based on calculation of the centres of area left and right of the COA. The difference between the two is a yardstick to measure the uncertainty range in the outcomes.

In comparison to the LQ the WLC has a more smooth response surface. This is due to the larger number of MF's that were defined for the WLC and from the inference rules. Moreover we see (Figure 3) that the shape of the Gaussian MF's appears in the output surface, causing some interesting decreases and increases which we would not expect based on our assumption that all relations are monotonous. At some locations, e.g. in Figure 2 at SCW = 500m and the RFD ≈ 0.21,

the output surface shows sudden bumps. This unexpected model behaviour can be observed in cases in which different inputs are mapped to the same output set. This should be avoided, for example by switching to 'NOT' or 'OR' rules. In this simple case the problem can be handled, but in more complex models it is not possible to generate output surfaces and the problem may remain hidden and propagate through the model.

For landscape quality we see that the surface is not as smooth as for water level change, due to the fewer number of MF's of the first. This also results in higher (relative) uncertainties.

The study of five specific yet random cases provides additional information about the model behaviour and its relation to reality. The five cases are summarized in Table 4.

a) An SCW value in the set 'small' is combined with a RFD = 0.40, giving μ = 1 for MF 'medium'. μ represents the membership value. The optimal value of μ = 1 represents a minimum uncertainty regarding the question to which MF the RFD belongs.

b) SCW remains the same compared to case a), whereas the RFD is slightly increased. The μ

for MF 'medium' decreases and the RDF also becomes member to 'high density'. This means that an extra rule is involved and the COA will slightly move. In Table 4 we see that the uncertainty in water level change has increased, according to our expectation based on the decrease in μ for the RFD. For LQ however the uncertainty remains the same.

c) SCW is increased and is now 'wide' whereas μ = 1 for MF 'high' for the RFD. Again this means that uncertainty concerning the question to which MF the given RFD belongs is minimal. This does not apply to the SCW.

d) In comparison to case c) the membership values are now μ = 1 for both). Although the COA remains the same, meaning that there is a relatively low sensitivity of the WLC for a change in SCW,
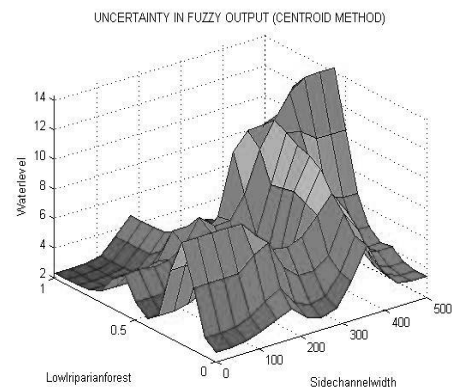
Table 4: Input and output values for case a-e

	Input		Output		Uncertainty	
	SCW (m)	RFD (-)	WLC (cm)	LQ (-)	WLC (cm)	LQ (-)
a	51	0.40	3.47	0.85	2.62	0.19
b	51	0.54	4.40	0.83	3.88	0.19
c	359	1	3.58	0.81	2.85	0.12
d	500	1	3.58	0.87	1.99	0.15
e	500	0.61	2.82	0.57	14.0	0.56

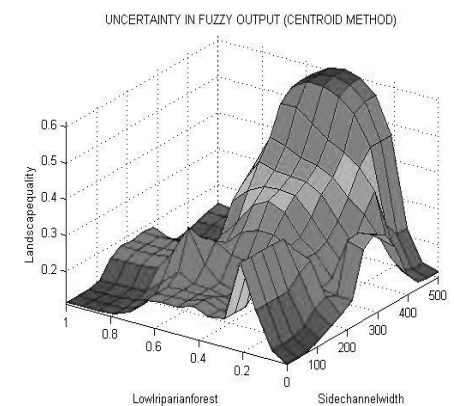**Figure 4:** Output for uncertainty in water level change (WLC)
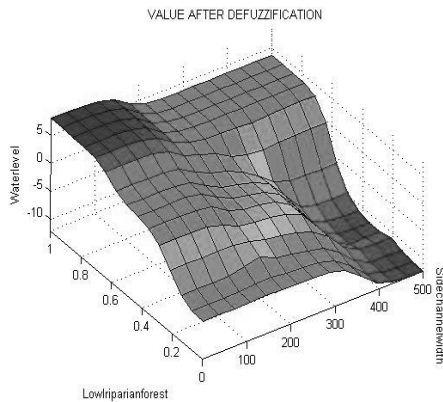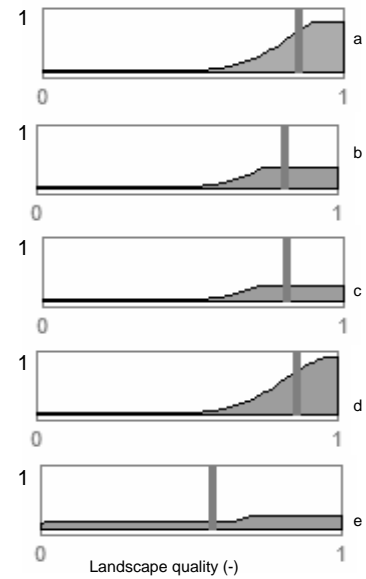

Figure 2: Output for water level change (WLC)
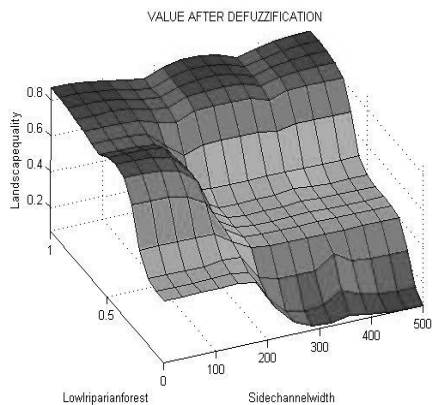
Figure 3: Output for landscape quality (LQ)

Figure 5: Output for uncertainty in landscape quality (LQ)
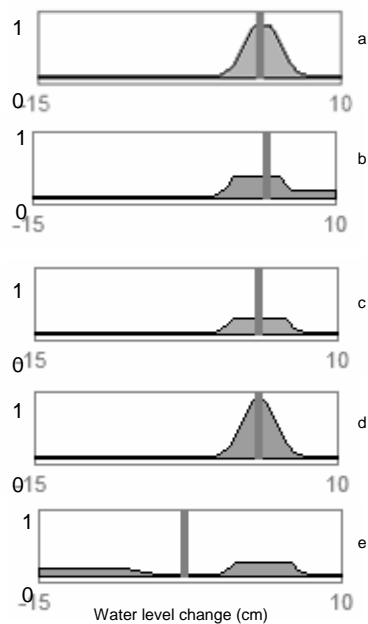
Figure 6: Membership for water level change for the five cases

Figure 7: Membership for landscape quality for the five cases

we expect a decrease in the uncertainty due to increased membership of SCW to its set. For the WLC this seems true, but the behaviour of LQ is in this sense unexpected.

e) When the value of the RFD is decreased in comparison to the previous case and becomes member of both 'high' and 'medium' RFD both the output value and uncertainty show a high sensitivity. In this final case it becomes clear what the consequences of the definition of opposite relations to the water level of SCW and RFD are; the possibilities for both outcomes give a μ on both extremes and a resulting COA in the middle. The corresponding uncertainty range is large, as could be expected based on our method.

Figures 6 and 7 depict the outcomes for water level change (WLC) and landscape quality (LQ) for the five cases.

4 CONCLUSIONS

In general the fuzzy approach seems promising for our research. The creation of MF's for the input and output requires some time and thought, but the establishment of the fuzzy rules was experienced as
an interesting and clarifying process. The relative transparency of the method supports discussion among experts. The outcomes of the simple fuzzy model give information about the actual output value based on COA, the sensitivity of these outcomes to changes in the input and the uncertainty in the outputs.

4.1 Processing qualitative information

The processing of qualitative variables and relations is easy once the range and number of MF's is agreed upon. The levels of measurement of the variables in this example were ratio (SCW, RFD and WLC) and ordinal (LQ). Notwithstanding the ability to reason with qualitative information, fuzzy set theory remains a normal mathematical procedure requiring numerical values within the model. In case of nominal variables, e.g. land use types, a translation would have to be made through quantifiable features of the different land use types before it is possible to apply fuzzy sets. Mapping of inputs to outputs based on qualitative knowledge is relatively easy. However, the inability to give a satisfactory representation of different inputs mapped to the same output consecutively is a model artefact which has to be avoided by using different operators.

4.2 Processing and interpreting uncertainty

The shape of the membership functions is linked to the uncertainty in the input. The horizontal spread of the surface under the MF output, as depicted in Figures 6 and 7, is a measure for the uncertainty in the outcomes. In case e we see that the definition of the rules has a large influence on the uncertainty in model outcome. For SCW = 'high' the step from 'average' RFD to 'high' RFD includes an implicit critical point; when considered

'average' the water level will decrease, but from this point onwards the water level will increase, even when the side channel is wide. In the output this critical point results in a high uncertainty. If the expert would be able to define an extra membership class between 'average' and 'high' RFD and link this to a neutral water level change the horizontal spread in case e would be smaller. In the spread of the fuzzy outcomes we see a representation of the uncertainty concerning the question which rules will fire, given the input. It is hence related to the overlap in the sets defined. It therefore represents *only* this type of uncertainty, and it does not represent information about the statistical likelihood with which a certain outcome may occur. The method allows for comparison between uncertainties in different outputs. Comparing cases c) and d) for example we see that although the outcome values remain the same, the uncertainty values change, and case d) would be preferred over case c) based on uncertainty.

4.3 Future research

The interpretation and calculation of uncertainty in our model leaves us with several questions. As we demonstrated in the cases some of the behavior does not respond to our expectations. Future research will aim at further studies of the relation between uncertainty in fuzzy modelling and reality, and will more general involve the interpretation of fuzzy sets in combination with uncertain data.

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