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ORIGINAL ARTICLE

Using fuzzy set theory to address the uncertainty of susceptibility to drought

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Abstract This paper presents the technical aspects of a new methodology for assessing the susceptibility of society to drought. The methodology consists of a combination of inference modelling and fuzzy logic applications. Four steps are followed: (1) model input variables are selected—these variables reflect the main factors influencing susceptibility in a social group, population or region, (2) fuzzification—the uncertainties of the input variables are made explicit by representing them as 'fuzzy membership functions', (3) inference modelling—the input variables are used to construct a model made up of linguistic rules, and (4) defuzzification—results from the model in linguistic form are translated into numerical form, also through the use of fuzzy membership functions. The disadvantages and advantages of this methodology became apparent when it was applied to the assessment of susceptibility from three disciplinary perspectives: Disadvantages include the difficulty in validating results and the subjectivity involved with specifying fuzzy membership functions and the rules of the inference model. Advantages of the methodology are its transparency, because all model assumptions have to be made explicit in the form of inference rules; its flexibility, in that informal and expert knowledge can be incorporated through 'fuzzy membership functions' and through the rules in the inference model; and its versatility, since numerical data can be converted to linguistic statements and vice versa through the procedures of 'fuzzification' and 'defuzzification'.

Keywords Susceptibility to drought · Vulnerability to climate extremes · Fuzzy set applications · Climate change impacts

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Introduction

Climate change science and policy have kindled interest in understanding the extent and underlying causes of society's vulnerability to climate, especially to extreme climate events such as droughts and floods. But a weak point of vulnerability research has been the vagueness of many of the key concepts used in this research and this vagueness hampers the quantification of vulnerability. This problem has been addressed in the study 'Security Diagrams' (Alcamo et al. 2005) by using fuzzy set theory for the first time to quantify susceptibility to drought. Here we define susceptibility as the capability of an individual, community, or state to resist and/or recover from crises brought about by environmental stress (Alcamo et al. 2008). The new approach, consisting of inference modelling combined with fuzzy logic applications, is laid out in a set of two papers. In Alcamo et al. (2008) the authors present an overview of the approach and give results of its application to three disciplines and three case study regions. In the current paper we describe the technical details of the approach. We first review the basic ideas of fuzzy set theory and its previous applications. We then explain key technical aspects of its application to the problem of assessing susceptibility. Finally, we review some of the advantages and disadvantages of this methodology.

In selecting an approach to quantify susceptibility it is important to keep in mind the special characteristics of this concept: (1) It is vague and cannot be measured directly or precisely, but must be estimated through indicators; (2) The influence of various factors on susceptibility cannot be precisely articulated (e.g. susceptibility is obviously lower with higher incomes, but how does susceptibility change with different income levels?), and it is likely that many factors interact; (3) The relationship between influence factors and susceptibility is often non-linear (e.g. at some high income level, susceptibility is very low, and as income further increases it is unlikely that susceptibility proportionately declines). Considering these uncertainties, we surmise that the quantification of susceptibility must take into account the inexactness of the concept and of its influencing factors.

The type of uncertainty encountered here can be called ‘fuzzy uncertainty’. In comparison to ‘probabilistic’ uncertainty which ‘relates to events that have a well-defined, unambiguous meaning’ (Cornelissen et al. 2001, p. 174), non-probabilistic or fuzzy uncertainty deals with ambiguities that often rely on qualitative knowledge. Put another way, fuzzy set theory deals more with uncertainty stemming from vague definitions (Kangas ad Kangas 2004) than from lack of knowledge about something which can be precisely defined or measured (Phillis and Andriantiatsaholiniaina 2001).

There are several factors that make it difficult to derive mathematical models of susceptibility including the lack of standard numerical criteria for defining susceptibility and the absence of ‘sharp’ borders between susceptibility and non-susceptibility. An advantage of applying fuzzy set theory, therefore, is that it makes it possible to derive inference models that use ‘natural language’ to embody this uncertainty. As Levy and Yoon (1995) put it, fuzzy logic ‘supports incorporating natural language of human discourse into decision framework and handling inconsistent information from competing sources, contradictory observations, emotional arguments…’ We will show how fuzzy logic can be used to define the criteria for susceptibility in linguistic terms and how this permits the use of a blend of quantitative and qualitative indicators. Comparing indicators in this way makes it possible to compare estimates of susceptibility to drought from different disciplinary perspectives. Indeed, an important factor contributing to the fuzziness of the susceptibility concept is the fact that different disciplines (economics, political science, environmental psychology) hold different views about the nature of susceptibility (Alcamo et al. 2008). We later show how applying fuzzy set theory can help to make these differences transparent and comparable.

Another characteristic of fuzzy set theory making it relevant to the assessment of susceptibility is its ability to model human decision-making in an intuitive and transparent manner without using rigorous mathematical models (Lindström 1998; Phillis and Andriantiatsaholiniaina 2001). This transparency could increase the acceptance of modelling results by decision makers.

Review of applications of fuzzy logic

Since the 1960s, fuzzy logic has been advanced as a formal means to handle the inexactness of a wide range of problems, in industrial control, military operations, economics, engineering, medicine, reliability analysis, and pattern recognition and classification’ (Levy and Yoon 1995). As new interdisciplinary areas are developed, and as the need for research results accessible to decision makers increases, the applications of fuzzy logic become increasingly relevant. For example, fuzzy applications in environmental research are useful for clarifying the meaning and importance of various ill-defined indicators (Wu et al. 1996; Silvert 2000) and for analyzing sustainability issues related to government policies and business strategies (Callens and Tyteca 1999; Cornelissen et al. 2001). It is also useful for sorting out complex operational issues in the field of market analysis (Levy and Yoon 1995; Lindström 1998).

Up to now fuzzy set theory has not been applied to the evaluation of the susceptibility of society to drought. But it has been applied in other areas of environmental research, for instance by Roberts (1996), Wu et al. (1996), Silvert (2000), Mackay ans Robinson (2000) and Kangas and Kangas (2004). Silvert (2000) used fuzzy logic to develop indices of benthic conditions in an Israeli fish farm, with the aim to bridge the gap between scientific measurements and social objectives, as well as to provide a means for translating different types of information into common language. Mays et al. (1997) used fuzzy logic to express the vagueness and imprecision of interpreting soil surveys.

Despite the wide range of methodologies already available for economic analysis, a number of authors have applied fuzzy set theory to understanding the market environment (Levy and Yoon 1995; Dompere 1997; Lindström 1998; Mosmans et al. 2002). For example, Levy and Yoon (1995) used fuzzy logic for modelling the global market entry problem, particularly the assessment of risk to countries. According to these authors, fuzzy set theory is a useful tool for confronting a wide range of issues concerning the global market entry problem (e.g. complexity of interactive influences, inaccuracy of measures, uncertainty of environmental forces, and subjectivity of the decision-making process). Another example is that Lindström (1998) used a non-linear fuzzy logic procedure to empirically investigate the links between real interest rates and aggregate investments in Sweden. By using fuzzy logic he avoids the need for rigid mathematical modelling and the approach is well suited for complex situations difficult to describe analytically.

The literature on fuzzy applications to sustainability science includes Callens and Tyteca (1999), Cassel-Gintz and Petschel-Held (2000), Phillis and Andriantiatsaholiniaina (2001) and Andriantiatsaholiniaina, et al. (2004). The latter studies are particularly relevant to this paper because they use fuzzy logic to combine different concepts (e.g. economic and ecological) in an evaluation of the sustainability of economies. They use fuzzy logic to consolidate fragmented and qualitative information which, they argue, are needed for policy-making.

A fuzzy methodology to assess the susceptibility to drought

Overview

To begin with, the application of fuzzy logic to assessing susceptibility to drought has to address a set of key questions:

(1) Which indicators can be used to quantify and measure susceptibility? (2) How can these indicators be interpreted (e.g. What is are indicator values for 'high susceptibility' or 'low susceptibility') (3) How can the complex relationships between different factors for susceptibility be described and quantitatively modelled? (4) How can a single numerical index be computed for comparing susceptibility between regions or social groups? These four questions lead to a four-step methodology, namely, (1) selection of input variables, (2) fuzzification, (3) inference modelling and (4) defuzzification (e.g. Bothe 1998, Aliev et al. 2000). The following paragraphs describe the application of these four steps to assessing the susceptibility of three case study regions to drought (Andhra Pradesh, India; Volgograd and Saratov, Russia; and Algarve and Alentejo, Portugal.) In addition, the methodology was applied to three disciplinary perspectives—economics, political science, environmental psychology.

The details of the disciplinary applications are given in Acosta-Michlik et al. (2008), Krömker et al. (2008), and Tänzler and Carius (2008). An overview of results from the case study regions and disciplinary perspectives is given by Alcamo et al. (2008).

Selection of indicators

Different disciplines identify different sets of factors influencing susceptibility of a population to drought. For instance, from a socio-economics perspective, an important factor is the economic performance of a region, e.g. as indicated by GDP per capita. From the viewpoint of political science, a key factor is the degree of institutional corruption. By comparison, environmental psychology and behavioural science focus on factors of individual perception and appraisal of crises. As a first step in our methodology, researchers responsible for disciplinary models analysed the scholarly literature to identify the most important factors affecting susceptibility and their interactions. Then a base set of indicators to represent these influence factors was developed. The next step was to relate these indicators together in a conceptual model based on a current theory or construct from their discipline. Experts from these regions were also consulted before the final conceptual model was decided upon. The models and indicators were selected as general as possible so as to be applicable to a wide range of case study regions.

The next step was to investigate the availability of data for the selected indicators. Because of lack of data, some indicators were replaced by equally relevant variables having more abundant data. It became clear that comparative regional vulnerability studies are in many ways data-limited, especially by the lack of time-series data. The indicator set used in our study contains variables covering different disciplinary views towards susceptibility, while the data describing these indicators were gathered either from surveys in the case study regions or from various sources of regional statistics.

Fuzzification

One of the advantages of applying fuzzy logic to the estimation of susceptibility is that it allows for a flexible numerical interpretation of linguistic statements such as 'high' or 'low'. Moreover, these statements can be more finely differentiated depending on the situation by adding modifiers such as 'very', 'rather', or 'a bit'. For example, an income of US$ 80,000 per year might be considered a 'high income' in Europe but a 'very high income' in a developing country. The ability of fuzzy logic to translate numerical data into linguistic statements becomes particularly important later in this paper when we develop a model with inference rules such as *'if income is very high, susceptibility is low'*.

Another important property of fuzzy logic is that linguistic statements need not have the sharp thresholds they have under binary logic (left side, Fig. 1). Rather, they can have more realistic 'fuzzy' boundaries (right side, Fig. 1).

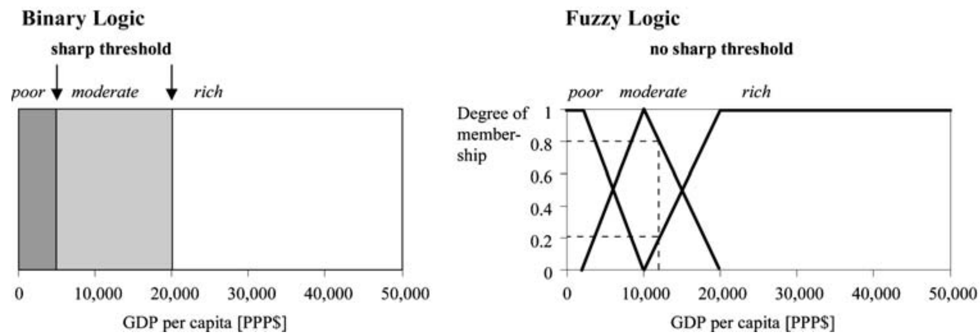

Fig. 1 Translation of numerical data on income into linguistic categories using binary and fuzzy logic

Whereas the boundary between 'moderate' and 'high' is infinitely small under binary logic (left side, Fig. 1), it can be overlapping and fuzzy under fuzzy logic (right side, Fig. 1).

The translation from numerical data to linguistic categories, called 'fuzzification', is accomplished through membership functions which define the degree of membership of each indicator in each category. The right side of Fig. 1 shows the fuzzification of the indicator 'income'. In this diagram different levels of income are translated with the help of three different membership functions, one each for the income categories *'poor'*, *'moderate'* and *'rich'*. We see from the right side of Fig. 1 that an income of US$12,000 per capita per annum has a membership of 0.8 in the category 'moderate',a membership of 0.2 in the category 'rich', and a membership of 0.0 in the category 'poor'. Hence, an income of US$ 12,000 would be translated as *'rather moderate'* or *'a bit rich'*, or *'certainly not poor'*. If the linguistic categories had traditional sharp boundaries, as shown on the left side of Fig. 1, agreement on translating numerical values could be much more difficult. For instance, in this diagram, an income of US$19,900 is called 'moderate' whereas a slightly higher income of US$20,100 is called 'rich'. Under fuzzy logic, referring to the right side of Fig. 1, an income of US$19,900 is 'nearly certainly rich' (membership value for 'rich' = 0.99) whereas an income of US$20,100 has almost the same definition (membership value for 'rich' = 1.0). Hence, through fuzzification, the translation of numerical values becomes at once more realistic and more transparent. (Assuming there is agreement on the membership functions.)

One of the many decisions that need to be taken in applying fuzzy logic is to decide on the shape of the membership functions. For our applications we chose triangles and trapezoids, as shown in Fig. 1. The advantage of these simple forms is that they can be defined without too many parameters. However, where it is apparent that results are sensitive to the shapes of the membership functions, bell-shaped curves can improve the precision of results (Koprinkova and Kova 1999; Koprinkova 2000). In our inference models, however, the computed susceptibility was found to be relatively insensitive to the shape of the membership functions. For example, for the model of susceptibility from the environmental psychology perspective (see Krömker et al. 2008) we compared results using sine functions, triangles and trapezoids and found small differences in the computed susceptibility index.

A typical criticism of fuzzy logic is that membership functions are taken to be subjective. In reality, however, they are not defined in an entirely subjective manner. For example, in our analysis we define membership functions based on a combination of existing knowledge in the literature and expert knowledge. Lienenkamp (1999) and others have also sought to define functions more objectively by using a statistical distribution of observed population data. However, Lienekamp's approach is not the final answer to the problem of subjective membership functions because if observed data sets are used, the question arises, how general and transferable are these data sets to other situations?

We now turn to the issue of the type of data used to construct membership functions. Above we saw a typical example of how statistical data or expert knowledge can used to make these functions. It is also possible, however, to use interview/survey data. In our applications of fuzzy logic to the susceptibility problem we found that the procedure for using interview data was similar, but not identical, to using statistical data. Figure 2 shows as an

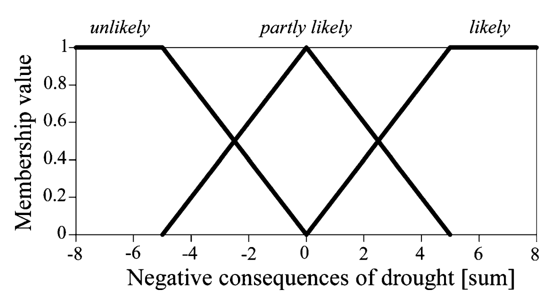

Fig. 2 Fuzzification diagram of indicator 'Negative consequences in case of drought'

example from the inference model built from the environmental psychology perspective (Krömker et al. 2008). In this case questionnaire data were used to derive membership functions for different categories of the indicator 'Negative consequences in case of drought'. The interviewed persons were asked to appraise eight classes of possible negative consequences of drought, including 'We would not have enough drinking water', 'We would be forced to leave our home', and 'We would become ill more often'. They were asked to rate each of the 8 consequences according to: 1 = 'likely', 0 = 'partly likely and partly unlikely', −1 = 'unlikely'. Then the sum of the different consequences were used to define the membership functions, as shown in Fig. 2. If the sum of the appraisal of all 8 classes added up to between 5 and 8, we interpreted this to mean that the interviewed person judged the sum of all 8 negative consequences to be 'likely' (membership value for 'likely' = 1.0). Accordingly, when the sum of the appraisal added up to between −8 and −5, this was considered to be 'unlikely' (membership value for 'unlikely' = 1.0). Sums from −5 to 0, and from 0 to 5, respectively, were deemed to be 'partly likely' with a membership of 1.0 at a sum of 0. The shapes of the membership functions given in Fig. 2 were selected because we observed that interviewees hesitated to choose extremes and tended towards selecting moderate values. Thus, values of −5 and 5 were judged to be high numbers.

Inference modelling with fuzzy logic

The heart of our approach for quantifying susceptibility is the construction of an inference model. This model consists of a rule system made up of linguistic statements, in turn made up of variables described by fuzzy logic. The rule system defines the relationship between a given combination of indicators. A rule is needed for all variables and all their categories (e.g. 'high' or 'low'). For example, if a fuzzy system consists of two variables 'A' and 'B', each having two categories (e.g. 'low' and 'high'), then four rules are needed to describe the resulting variable C:

rule 1: If A is low and B is low, then C is low
rule 2: If A is high and B is high, then C is high
rule 3: If A is low and B is high, then C is medium
rule 4: If A is high and B is low, then C is medium

As explained in 'Fuzzification', fuzzy set theory allows a single numerical value to have a 'degree of membership' in both categories 'low' or 'high'. From this it follows that more than one rule can be applicable to a particular combination of indicator values. For example, if variable A has a membership of 0.7 for 'low' and 0.3 for 'high', and variable B a membership of 0.4 for 'low' and 0.6 for 'high', then all four rules of the simple inference system come into play. Since these rules use *and*-conditions, the mathematically appropriate set operation is an intersection, computed as the minimum of the two membership values. Thus, the degrees of certainty μ of the variable C for the four rules of the inference system are given as:

rule 1: $\mu C(\text{low}) = \min\{0.7, 0.4\} = 0.4$
rule 2: $\mu C(\text{high}) = \min\{0.3, 0.6\} = 0.3$
rule 3: $\mu C(\text{medium}) = \min\{0.7, 0.6\} = 0.6$
rule 4: $\mu C(\text{medium}) = \min\{0.3, 0.4\} = 0.3$

(The final result is computed in the defuzzification step, described below).

Since the selection of each rule depends on the judgement of the model builder, it is important to justify all rule statements. It follows that the rule system is only as good as the theoretical understanding of the processes and connections behind it.

Since complex inference systems have a large number of variables and categories, the number of needed rules will also be very large and it can become very difficult to assign values for all of the variables. Therefore, it is important to simplify where possible. For example, two or three indicators can generally be aggregated into an index (in a fuzzy sub-system) and then several indices can be consolidated into a final resulting variable.

In our approach we developed an individual inference model for each of three disciplinary perspectives—economics, political science, environmental psychology. These models were based on theories or constructs from the respective disciplines as described in Acosta-Michlik et al. (2008), Tänzler and Carius (2008), and Krömker et al. (2008). To enhance the comparability of the models and their results we implemented the models using the same procedure (Fig. 3). The models were developed by first aggregating the set of indicators to so-called 'sub-dimensions', then aggregating the sub-dimensions to 'main dimensions' and finally the main dimensions to the final result for 'susceptibility to drought'. We began with three categories for the fuzzification of input indicators, and then increased this number as needed. We only used *and*-conditions and the minimum operator for the fuzzy intersection operation. It is possible, in principle, to use of other linguistic operators such as 'or' and 'not', but we found that consistent use of the *and*-operator was more transparent, easier to understand and was sufficient for representing all combinations of the model variables. One advantage of this procedure was that it produced numerical results not only for the final output variable 'susceptibility', but also for its intermediate dimensions. Examining these intermediate numerical results made it easier to understand the main factors influencing susceptibility.

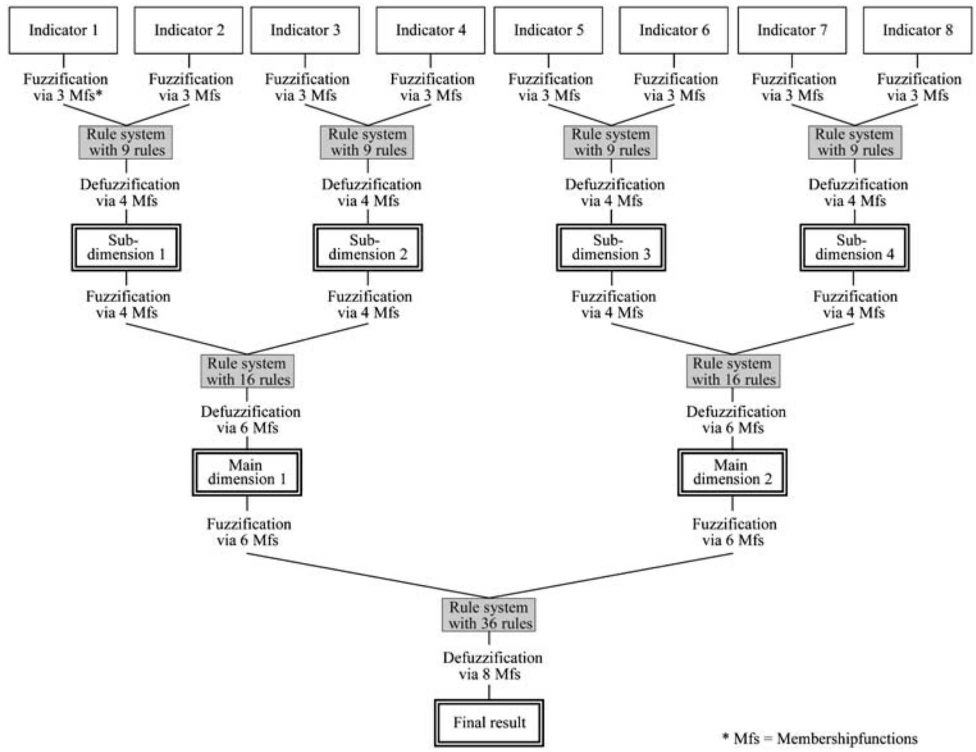

Fig. 3 Schematic fuzzy system with a three-step design

Defuzzification

Because the inference model is based on fuzzy logic, the outputs of the model are 'fuzzy estimates', that is, degrees of certainty of different possible outcomes. Hence, 'defuzzification' is required to combine the results of each rule into one unique quantitative result. Out of several options available for this step, we selected one of the most widely used approaches, namely the 'centre of gravity' method. This method requires a defuzzification diagram with membership functions for every category of the output variable. In this case the degree of certainty of each variable is represented by the area it covers of the corresponding membership function (Fig. 4).

To obtain a final estimate of susceptibility, the centre of gravity of the joined areas of all output variables are calculated and projected onto the abscissa. Figure 4 illustrates this procedure. Continuing with the example above, we have a rule system composed of two variables *A* and *B* and four rules describing the resulting variable *C*. Recall that we found that the degrees of certainty of the 4 rules were $\mu C(\text{low}) = 0.4$; $\mu C(\text{high}) = 0.3$; $\mu C(\text{medium}) = 0.6$; $\mu C(\text{medium}) = 0.3$. These results are shown on the respective membership functions in Fig. 4. The final value of the output variable, according to the centre of gravity of the joined area projected onto the abscissa, is approximately 0.45. This implies a category of 'medium' for the output variable.

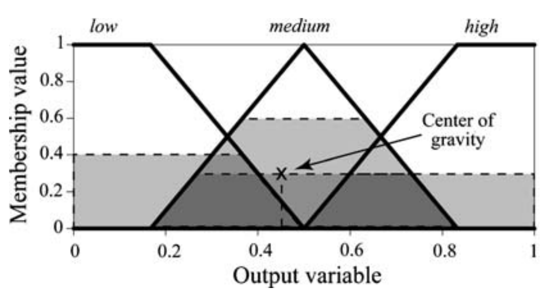

Fig. 4 Defuzzification example

Two methodological difficulties arise from using the centre of gravity approach:

– Since it is an 'average' approach, results of the analysis tend to cluster towards the middle of the defuzzification diagram and variance is smoothed. A large *'medium'* category has an especially strong smoothing effect, especially when an odd number of membership functions are used. Therefore, where possible we used an even number of membership functions (4, 6 or 8).
– Since the centre of gravity method is based on the computation of areas, the centre of an area usually cannot reach the extremes of the membership functions, i.e. it never tends to take values of 0 or 1. One way to compensate for this outcome is to use several narrower membership functions rather than a few wider ones. For example, in our analysis we used 8 relatively narrow membership functions in the final step of the rule

system and this limited the achievable minimum and maximum values of the output variable to 0.065 and 0.935, respectively.

Another important issue in defuzzification is to decide whether or not to weight the output from the different rules, and if so, how to do this weighting. Following the above procedure we have, in effect, weighted the output of the rules according to their uncertainty. The larger the uncertainty of the rule, the larger the area it has under the curve, and the more weight it is given in determining the overall centre of gravity of the curve. Other defuzzification methods, such as the 'mean of maximum' or 'largest of maximum', assign weights differently. A 'weighted centre of gravity' approach, such as that proposed by Bender and Simonovic (2000), could improve the weighting of rules because it distinguishes '… between fuzzy sets which may have the same centroid, but greatly differ in their degree of fuzziness' (Bender and Simonovic 2000).

Discussion and conclusions

In applying our methodology to three case study regions and three disciplinary perspectives some of the advantages and disadvantages of the approach became apparent.

Advantages

- It enhances the transparency of model assumptions. Since all the rules in an inference model must be explicitly specified, this means that all key cause-effect relationships in the model are relatively transparent to an outside observer.
- It provides a tool for qualitative interpretation of numerical data. Through the fuzzy membership functions, numerical data can be qualitatively interpreted. This translation into linguistic terms is based on literature and expert knowledge and facilitates the use of linguistic, qualitative inference models for quantification. Documenting the parameters and sources of information for the membership functions makes the procedure more transparent.
- It enables the use of qualitative knowledge. Expert knowledge can be used not only for defining membership functions, but also as a source of model input. This is particularly important because expert knowledge is often a main source of input to vulnerability assessments.
- It produces quantitative results through qualitative modelling. Since much of the information available to vulnerability assessments is qualitative rather than quantitative, the inference modelling approach outlined here is particularly appropriate because it relies on specifying inference rules which embody qualitative knowledge. Through fuzzy logic these rules are then converted to quantitative information. Moreover the inference rules can be used to express non-linear relationships between influence factors and susceptibility.
- It provides a method for comparing interdisciplinary concepts and enhancing understanding between disciplines. A central aim of our research was to compare three different disciplinary perspectives on susceptibility. This comparison was made possible by applying a consistent and harmonized methodology for deriving different disciplinary models. Moreover, experts from the different disciplines had to translate theories or constructs from their disciplines into transparent rules. The consistency and transparency of this methodology makes it possible (or at least easier) for researchers from one discipline to understand the models and insights of the other disciplines. The inference modelling approach produced not only comparable quantitative results, but also provided insight into the influence factors that were considered most important by the different disciplines examined.

Disadvantages

On the other hand the inference modelling and fuzzy logic approach has limitations that should be made clear:

- It is not an appropriate method for developing new fundamental knowledge. As compared to statistical analyses of new data sets, for example, the methodology presented in this paper is not a tool for developing new fundamental knowledge, but rather a user of this knowledge to provide new insights into susceptibility to drought. Nevertheless, as we have seen, existing theories from various disciplines can be further investigated through the formulation of inference rules and derivation of fuzzy membership functions.
- It generates results difficult to validate. In comparison to statistical approaches, an inference model can be built without quantitative empirical data. Nevertheless it produces output, the level of susceptibility, that in principle can be tested. The problem is that there are no independent data sets of measured susceptibility since there is no universally accepted definition (nor metrics) of this concept. In companion papers (Alcamo et al. 2008; Tänzler et al. 2008) we show how the concept of 'water stress', which is closely related to susceptibility, can be tested against a data set of observed drought occurrences. Perhaps this type of data set, or something similar, can be used in future research to test susceptibility estimates.

– Some aspects of the methodology are subjective. A serious limitation of the inference modelling and fuzzy logic approach is the subjectivity of defining membership functions and designing the rule system. Since parameters of the membership functions usually cannot be derived entirely from the literature and/or expert knowledge, they must be based at least partly on the judgment of the model developer. Furthermore, it is difficult to objectively decide on the most appropriate form of the membership functions.

To sum up, in evaluating the approach presented in this paper it is important to take into account the current impulse to quantify susceptibility to drought, from both the scientific- and policy-standpoints. Scientists need to quantify susceptibility so that differences between disciplinary perspectives can be better identified and so that changes in susceptibility can be monitored and estimated over time. From the policy perspective, quantification is needed for comparing the relative susceptibility of one region against another. This and other information from quantitative assessments of susceptibility can help to identify policies for reducing susceptibility and increasing coping capacity against drought and other climate extremes.

While the methodology presented in this paper has its drawbacks, it nevertheless takes into account that susceptibility to drought is not only an urgent concept but also a very imprecise one. Likewise, it recognizes that much of the knowledge about susceptibility is informal and expert-based, rather than numerical and well-established, and it provides a flexible vehicle for incorporating this knowledge. Finally, we should remember that the principal aim of vulnerability research is to reduce vulnerability, and achieving this goal does not require exact knowledge; but it does require information that is transparent, well justified and plausible in order to develop coping strategies and convince decision makers about these strategies. The methodology presented in this paper can contribute to this effort.

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