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A tool to design fuzzy decision trees for sustainability assessment

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ABSTRACT

Assessment of sustainability is a multicriteria problem that addresses several criteria belonging to various themes structured in sustainability dimensions. There is the need for a relevant aggregation method in addition to the disaggregated indicators. To face this challenge, we developed a new aggregation method, CONTRA, which is based on a decision tree using fuzzy sets. We attempted to combine the advantages of previous tools like DEXi and FisPro that ensure simplicity, flexibility and transparency while limiting subjectivity in the design of decision trees. The results of two examples of implementation in the agricultural sector and a sensitivity test highlight the functionalities of the tool and its discrimination potential. The possibility offered by the tool to correct predetermined decision rules makes it possible to cope with compensation between input variables, an important issue in aggregation. The next step will be the finalisation of the Excel prototype in a user-friendly software.

Software availability

Name of software or dataset: CONTRA_v1.0_eng
Developer: Christian Bockstaller, INRA UMR1132 LAE, 28 rue de Herrlisheim, BP 20507, 68021 Colmar Cedex, France
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Year first available: 2016
Hardware required: standard PC for Windows 10
Software required: Microsoft Excel 2013
Availability and cost: available free of charge for testing after signing an agreement to provide the software
Programme language: Excel functions
Programme size: 4852 Ko

1. Introduction

Since the Rio conference in 1992, sustainability has become a central issue of many policy agendas, research programmes, and the design of innovative solutions in different economic sectors. Though its ability to federate, this concept has failed to meet a consensus on its implementation until now (Robinson, 2004) and to prove its validity (Bell and Morse, 2001), leading Lacousmes (2005) to speak about a "driving illusion". However, an agreement has emerged about the need to develop assessment methods based on sustainability indicators as a prerequisite to implementation. This need has entailed a growing number of indicators and assessment methods as reviewed by Singh et al. (2012), what has been described by Riley (2001) as an "indicator explosion". In any case, assessment of sustainability is by nature a multicriteria problem that addresses several criteria belonging to various themes generally structured in sustainability dimensions, i.e., the economic, environmental and social tripod (de Olde et al., 2016).

This rapid development of a multicriteria assessment method of sustainability over the last 30 years was supported by different approaches that draw on diverse fields of research (Cinelli et al.,

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2014; Gasparatos and Scolobig, 2012; Singh et al., 2012; Sadok et al., 2008). Referring to the typology of Sadok et al. (2008), we can distinguish three groups of methods. Among them, the first group of composite indicators has become very popular over the past 25 years (Nardo et al., 2005; Castoldi and Bechini, 2010; Schoenaker et al., 2015). A part of the composite indicators are based on the multi-attribute utility theory (e.g., Foltz et al., 1995). Their strength lies in their communicative power by yielding a single indicator that synthesizes different dimensions, components, etc., facilitating a conclusion on a level of sustainability or a comparison between different systems. However, they are subject to a great deal of criticism due to their subjective nature (Bondarchik et al., 2016) since they are heavily dependent on normalisation (Pollesch and Dale, 2016), weighting (Becker et al., 2017) and, in general, on the aggregation method. All of these weakness lead to a low reliability in many cases (Luzzati and Gucciardi, 2015). The second group that draws on operational research includes outranking methods, sometimes referred to as multicriteria assessment methods in the strict sense of the word (Gasparatos and Scolobig, 2012). Developed as an alternative to composite indicators, they aim to rank, sort or select from among a range of options or systems through pairwise comparisons. Several examples of implementation have been given for agricultural systems (e.g., Arondel and Girardin, 2000; Mazzetto and Bonera, 2003). In spite of their interest in limiting theoretical flaws linked to their aggregation into a single value, outranking methods rely on pairwise comparisons that remain relative (Hayashi, 1998), that have difficulties mixing quantitative and qualitative information (Sadok et al., 2008) and that cannot cope with a large number of indicators. Like Sadok et al. (2008), we focus here on a third group that can be considered as a compromise between the previous ones. They consist of mixed methods structured in the form of decision trees that rely on linguistic “if then” rules. The ability of mixed methods to cope with qualitative as well as quantitative heterogeneous information and their relative transparency, at least semantic through linguistic rules that are easy to understand for non-specialists (Babuška and Verbruggen, 2003; Phillis and Andriantiatsaholiniaina, 2001), makes them very attractive. However the design of the rules, often derived from expert knowledge, is not immune to subjectivity when no learning procedure using a dataset is implemented (Liu et al., 2013). To mitigate subjectivity, some other authors developed the SIRIS method that relies on a transparent fixed ranking method based on a set of given decision rules and penalties (Guerbet and Jouany, 2002; Vaillant et al., 1995).

Combining decision trees with fuzzy logic makes it possible to mitigate shortcomings in decision trees linked to the linguistic “if then” rules when they are Boolean, i.e., consisting of two alternatives, yes/no. Fuzzy logic introduces fuzzy subsets to deal with the whole set of intermediate cases. Thus, decision trees based on fuzzy logic (referred to later in this article as fuzzy decision trees) make it possible to account for the uncertainty in the outputs by avoiding the effect of the knife-edge limits of a given class and by increasing their sensitivity (Enea and Salemi, 2001; Prato, 2005; Silvert, 2000). All these combined advantages of decision trees and fuzzy logic have led to a growing number of environmental or sustainability assessment methods based on this approach (Cornelissen et al., 2001; Ferraro, 2009; Fragoulis et al., 2009; Lindahl and Bockstaller, 2012; Phillis and Andriantiatsaholiniaina, 2001; Prato, 2005; Sami et al., 2014; Sattler et al., 2010; van der Werf and Zimmer, 1998).

The availability of user-friendly software facilitates the implementation of any method used, as illustrated in several comparison studies (Bockstaller et al., 2009; Cinelli et al., 2014). To our knowledge, two published tools to support decision tree design are available in the form of user-friendly software for the sustainability assessment of agricultural systems by non-programmers: the DEXi tool (Bohanec et al., 2008) for decision trees based on Boolean rules and applied to the assessment of cropping systems (Pelzer et al., 2012; Sadok et al., 2009), and FisPro (Guillaume and Charnomordic, 2011, 2012) for fuzzy decision trees used, e.g., in the study of Coulon-Leroy et al. (2014). As reported by Craheix et al. (2015), three qualities, simplicity, flexibility, and transparency, favour the potential use and dissemination of any tool. DEXi satisfies the two former ones but suffers from a lack of transparency as observed in a preliminary test (data not shown). Another weak point of decision trees designed with the help of DEXi is the lack of sensitivity in distinguishing systems or options due to their qualitative rules (categorising situations in a small number of classes). Conversely, FisPro offers a broad range of possibilities to design fuzzy decision trees through expert knowledge or inference from a dataset. The drawbacks to the large flexibility offered by FisPro are the complexity and some lack of transparency for the non-specialist starting to use the tool. For instance, it is not evident for the user to understand the consequences of all the parameterisation choices he has to make on the final aggregated result. We propose a new tool here, CONTRA (the French acronym for ‘design of transparent decision trees’), which attempts to combine the advantages of DEXi and FisPro in order to ensure the simplicity, flexibility, transparency and sensitivity of the tool. In addition, we tried to limit subjectivity in the design of decision rules like in the SIRIS method by fixing the aggregation rules. This article aims to successively present the theoretical principles behind the tool, the structure of the tool, two examples of applications to highlight the application potential and, finally, a sensitivity test.

2. Material and method

2.1. Fuzzy decision tree

As shown in Fig. 1, decision trees are based on functions in the form of “if then” linguistic rules that link input variables (Xi) to an output variable (Y), which is expressed in the form of a “conclusion value”. Input variables can be raw variables that are aggregated based on scientific knowledge like in the pesticide risk I-Phy indicator (Lindahl and Bockstaller, 2012) to assess an effect on an output variable (groundwater quality). In this case, the decision tree replaces a quantitative simulation model. Decision trees can also be designed to aggregate different indicators that assess themes or dimensions of sustainability in a composite way, like in Phillis and Andriantiatsaholiniaina (2001). Input variables have to be expressed on a qualitative or an ordinal scale consisting of a small number of classes (e.g., “low”, “medium” “high”) or scores (1, 2, 3) so that a finite set of rules can be defined. The output variable is expressed on a scale that can be increasing (from worst to best situation), accounting for a performance, or decreasing (from best to worst situation), expressing an impact or risk with respect to sustainability.

When the input variable is originally expressed on a cardinal scale, it has to first be transformed onto a qualitative or ordinal scale. This is generally done by defining thresholds to limit the qualitative or ordinal classes. However, two input values close to the threshold value delimiting two different classes, one slightly below and the second slightly above, will yield two different output values although they are very close to each other, due to the fact they do not belong to the same class. Fuzzy logic formalism makes it possible to avoid such a knife-edge effect (or threshold effect) due to class limits by considering a fuzzy zone around the threshold value that delimits one class from another. In that fuzzy zone, the situation thus partially belongs to both classes. This induces small different output values instead of clearly different ones when input