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Original Articles

Toward objective assessment of the conservation status of (the Natura 2000) forest habitat types: A comparison of a qualitative and a quantitative modeling approach

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ABSTRACT

To halt the loss of biodiversity in natural habitats, the EU passed the Habitats Directive and established the Natura 2000 network. The network captured forest habitats and habitat types, whose conservation status must be reported under Article 17 of the Directive. Hence, the harmonization of habitat assessment methods and reporting formats are a critical issue. So far, the EU Commission and Member States have managed to design and issue reporting guidelines. However, as many of these reports are largely based on expert opinions, they tend to be biased and incomparable. To make conservation status assessments and reporting more consistent, this study evaluated a set of indicators with two decision support models. The DEX model operated with linguistic statements derived from numerical values, while the fuzzy model utilized numeric input. Both models were tested with data from Slovenia's three largest forest habitat types (FHT), namely 9110 – *Luzulo-Fagetum* beech forests, 91K0 – Illyrian *Fagus sylvatica* forests (*Aremonio-Fagion*) and 91L0 – Illyrian oak-hornbeam forests (*Erythronio-Carpinion*), provided by the Forest and Forest Ecosystem Condition Survey. The DEX model produced uniform results and defined the conservation status of all three FHTs as least favorable. Conversely, the fuzzy model produced three different conservation status grades for the FHTs: a favorable conservation status for the 91K0 FHT, least favorable for the 9110 FHT and unfavorable for the 91L0 FHT. Its results were logical and in accord with the existing assessments. The study showed that both models could be used for the evaluation of FHT traits. However, because of its larger sensitivity, the fuzzy model allowed detecting subtle differences among the indicator values due to the use of continuous numerical data and more sophisticated mathematical procedures.

1. Introduction

The notion of conservation status of natural habitats was introduced into the European concept of nature conservation by the Habitats Directive (Directive; OJEC, 1992). The Directive defines the conservation status as "the sum of the influences acting on a natural habitat and its typical species that may affect its long-term natural distribution, structure and functions, as well as the long-term survival of its typical species within the territory" (OJEC, 1992). The Directive also defines the conservation status of a natural habitat as favorable if i) the natural range and areas it covers within that range are stable or increasing, ii) its specific structure and functions that are necessary for its long-term maintenance exist and are likely to continue to exist for the foreseeable future and iii) the conservation status of its typical species is also favorable. As the Directive does not specifically address any land cover entity, the notion of natural habitats refers to forest habitat types (FHTs), their subtypes (Kovač et al., 2016) and the habitats of their typical plant and animal species, whenever dealing with the Natura 2000 forestlands.

The concept of conservation status has been criticized for some time due to its many deficiencies. While the recently proposed sets of indicators and assessment methods (Cantarello and Newton, 2008; Kovač et al., 2016), which still need to be fulfilled and tested, certainly represent a step toward greater objectivity, the vaguely defined conditions of the favorable conservation status of FHTs continue to be questioned (Mehtälä and Vuorisalo, 2007).

Developing habitat conservation status assessment methods has progressed slowly as well. Their main objective is to evaluate available data and express them in the form of three conditions of the conservation status (first paragraph; i, ii, iii) with simple numerical values (e.g. 1, 2, 3) or with statements such as "favorable", "least favorable" and "unfavorable". Until recently, only decision support models based

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Table 1
Indicators used for conservation status model construction (FHT = forest habitat type; DW = deadwood; dbh = diameter at breast height; ID = the number of the indicator in the study of Kovač et al. (2016)).

Criteria group	Name	Meaning (definition)	Unit	ID
Spatial	Core	Mean core (i.e. forest belt) diameter	m	2
Spatial	ForA	Mean forest patch size within a sample frame of 1 km^2	ha	–
Spatial	NofFHT	Number of different FHTs within a sample frame of 1 km^2 (density)	–	6
Spatial	PSFHT	Mean FHT patch size within a sample frame of 1 km^2	ha	7
Structural	Species composition	Share (%) of dominant species (spruce, beech, fir and sessile oak, hornbeam)	%	8
Structural	Development phase	Share (%) of young growth and pole stand combined; dbh $<$ 30 cm	%	9
Structural	Vol	Standing volume of timber wood (sawlogs; dbh $>$ 29.99 cm)	$m^3 ha^{-1}$	11a
Structural	Dwtotal	Amount of total deadwood volume	$m^3 ha^{-1}$	12
Structural	DW ≥ 30	Amount of standing and downed coarse woody debris	$m^3 ha^{-1}$	12a + 12b
Viability	Recruitment	Share of dominant and co-dominant tree species with dbh $<$ 10 cm	%	14
Viability	Damaged	Share of (more than 25% defoliated) trees	%	15

on simple calculations, linear sums and weighted summations have been presented (Hernando et al., 2010; Šmelko and Fabrika, 2007; Velázquez et al., 2010). All use diverse criteria (syn. indicators) whose data are obtained in many ways such as expert opinion, field inventorying, mapping and remote sensing.

A certain number of evaluation methods also have been developed by national agencies (Ellmauer and Essl, 2005; Müller-Kroehling et al., 2004). Pursuant to recommendations (Evans and Arvela, 2011; Salafsky et al., 2008), these methods commonly require data about FHTs' areas, ranges, structures and prospects for long term survival. However, because their indicators are defined ambiguously, as well as the data are often based on expert opinion, these methods generally produce biased and incomparable results at all spatial scales (i.e. sites, biogeographic domains and nations).

Many more evaluation models are developed for the needs of different environmental sectors. They are based on multiple-criteria decision making and artificial intelligence techniques such as neural networks, machine learning, and fuzzy sets. A well-recognized and widely used model type is multiple-criteria decision analysis (MCDA) (Zopounidis and Doumpos, 2002). Its models are commonly used to address multiple and possibly conflicting quantitative and qualitative criteria. The main approaches are multi-attribute utility theory (MAUT), outranking methods (PROMETHEE, ELECTREE) and analytic hierarchy process (AHP) (Ananda and Herath, 2009; Diaz-Balteiro and Romero, 2008; Herva and Roca, 2013; Huang et al., 2011; Kangas and Kangas, 2005).

Uncertainty, imprecision, vagueness and subjectivity of indicators are common in environmental studies. Usually they are expressed by linguistic terms and/or by fuzzy numbers, originating in the concept of fuzzy sets (Zadeh, 1965). Analysts have integrated uncertainty into i) qualitative multi-attribute models (Bohanec et al., 2012), to assess the impacts of urbanization on natural habitats (Scolozzi and Geneletti, 2012) and mountain lodge management in the Alps (Stubelj Ars and Bohanec, 2010), ii) fuzzy analytic hierarchy process (AHP) for urban land-use planning (Mosadeghi et al., 2015), iii) forest fire risk modelling (Kant Sharma et al., 2012) and iv) environmental impact assessment studies (Kaya and Kahraman, 2011).

A special fuzzy model family represent fuzzy inference systems (FIS) which combine fuzzy logic with inference rules. These models have evolved from artificial intelligence and knowledge-based systems and can process non-linear information that reflects human experiences, knowledge and thoughts (Gharibi et al., 2012). Similar to the earlier introduced models, these also produce outcomes in the form of numeric ranges (an arbitrary numeric range or the range between 0 and 1) that can be transformed into linguistic variables which are understood by non-specialists (Silvert, 2000). Such models are currently being used to evaluate environmental properties and quality (Peche and Rodríguez, 2012), water quality and management (Carbajal-Hernández et al., 2012b; Che Osmi et al., 2016; Gharibi et al., 2012; Lermontov et al., 2009; Mahapatra et al., 2011; Ocampo-Duque et al., 2006; Yan et al., 2010), forest conditions (Ochoa-Gaona et al., 2010), habitat quality (Mocq et al., 2013), decision support in ecosystem management (Adriaenssens et al., 2004) and exploration of population ecology (Kampichler et al., 2000).

Despite their contribution to better decision making, the models differ significantly. Models, such as DEX, combining the features of qualitative multiple-criteria and rule-based expert systems (Bohanec and Rajkovic, 1990), commonly operate solely with linguistic statements defined by experts. Because of this simplicity they may produce less precise results, yet, they are more easily evaluated and understood by end-users. Conversely, FIS models, integrating multi-criteria decision models and fuzzy sets, are likely more accurate due to the concrete (measured) data input and expert judgments, but are more demanding in view of mathematical knowledge and general understanding.

In this study, we compared the adequacy of the DEX and fuzzy models for assessing the conservation status of FHTs and subtypes. With the comparison, we aimed to show that the fuzzy model is more sensitive in detecting differences between FHT status. Additionally, we juxtaposed both models with the models currently in use. Finally, we discussed the state of the art in the Natura 2000 forest habitat type reporting in the view of international processes and argued for greater objectivity.

2. Methods and material

2.1. Criteria, data and methods

Models and criteria (syn. indicators) were tested with data of Slovenia's three largest FHTs, namely 9110 – *Luzulo-Fagetum* beech forests, 91K0 – Illyrian *Fagus sylvatica* forests (*Aremonio-Fagion*) and 91L0 – Illyrian oak-hornbeam forests (*Erythronio-Carpinion*) (Kutnar et al., 2011). These FHTs, native to many countries across Europe (European Commission, 2007), represent 22.6%, 48.0% and 7.2% of national forestlands, respectively. All three FHTs are subject to reporting.

Apart from the Forest patch area indicator (ForA; Table 1), the remaining habitat evaluation indicators were taken from the study of Kovač et al. (2016). We used 10 of 18 indicators from the spatial, structural and viability groups (Table 1). The ForA indicator was computed solely for this study. Its computation was performed in the same manner as for the Patch size indicator (PSFHT; Table 1). The indicators were selected subjectively. Regardless, we accounted for representativeness of all three components of the conservation status, likely correlations (e.g. weighted mean patch size, median patch size; see Kovač et al., 2016) and the relevancy of the indicators for biodiversity (e.g. total area, type of regeneration; Kovač et al., 2016).

The 2012 Forest and Forest Ecosystem Condition Survey database (GIS/SFI, 2013) was used for computing the indicator estimates such as means, variances and percentiles. The data set consisted of 614 sample units; 166 of them belonged to the 9110 – *Luzulo-Fagetum* beech forests,