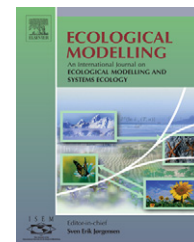


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Short communication

Are landscapes as crisp as we may think?

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ABSTRACT

Geographic information is traditionally represented by a one-entity–one-class method, assuming that each geographical entity in the map can be unambiguously assigned to a single thematic class. Also, thematic map classes are assumed to be exhaustive and mutually exclusive. By contrast, fuzzy classifications overcome the traditional limitations on the mutually exclusive nature of map classes assigning varying levels of class membership for individual map entities. The aim of this paper is to show that the substitution of fuzzy set theory for classical set theory is an essential improvement for representing geographic information using hierarchical classification schemes.

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1. Introduction

Recent interests in conservation and in environmental change have led to a renewal of efforts for developing robust methods of land surface characterisation (Goodchild, 1994). In this view, thematic maps are increasingly being used in landscape planning and management (Kepner et al., 2000; Butler et al., 2004; Romero-Calcerrada and Perry, 2004; Acosta et al., 2005; Rocchini et al., 2006). Typically, thematic maps are derived both from the classification of remotely sensed images and from GIS technology which produces new thematic maps through the analysis of existing maps and data (Gopal and Woodcock, 1994). In most cases, such maps are represented by x geographical entities (being X a universe of entities, see Goodchild, 1994) which convey information putting emphasis on a single attribute of interest, like soil type, land cover, land use, vegetation type, etc., displayed as thematic layers

(Burrough, 1986; Gopal and Woodcock, 1994) such that they are represented by:

$$\{z(x)|s(x)\}_{x=1,\dots,n} \quad (1)$$

where $z(x)$ is the property for the x th entity related to its $s(x)$ spatial component (Goodchild et al., 1999; Goodchild, 2004). In such cases, polygons or pixels represent the basic map entities in vector and raster format, respectively.

The information conveyed by the map is going to depend on the adopted classification scheme. There is no ideal classification, and it is unlikely that one could ever be developed. There is, in fact, no logical reason to expect that one thematic map should be universally adequate (Duda et al., 2001). Each classification is made to suit the needs of a particular category of users, and few users will be satisfied with a classification scheme that does not meet most of their needs.

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This expressive limitation in labelling thematic map entities has inevitably led to unsatisfactory extraction of information, especially if the same map is used in many applications with varying information needs (Woodcock et al., 1996). In addition, for environmental management purposes, it must be possible to reproduce the information derived by a given classification scheme at different scales to be useful at various decision-making levels. This requirement was recognized by a number of researchers and institutions in proposing hierarchical classification schemes within agreed research agenda (see Stoms and Estes, 1993; Bossard et al., 2000; Di Gregorio and Jansen, 2000; Bartholomé and Belward, 2005).

The idea that landscapes are hierarchically structured is useful for understanding different processes and landscape functions that occur at different spatial scales and require different levels of geographic information (Turner et al., 1989; Schröder and Seppelt, 2006). For instance, ecological processes that occur at the local level differ from those that occur at the regional or continental scale, such as biochemical cycles or species migrations (O'Neill et al., 1996; Locantore et al., 2004). Therefore, fine-scale information that shapes landscape structure at the lowest hierarchical level becomes irrelevant at higher levels of landscape aggregation.

Hierarchical classifications are usually crisp; that is, when map entities are linked to map categories, information is traditionally represented by a one-entity–one-class method, dividing the gradual variability of the earth's surface into a finite number of non-overlapping classes. Therefore, thematic classifications in which each entity in the map has to be assigned unambiguously to a single class are considered exhaustive and mutually exclusive (Foody, 1996a,b; Woodcock et al., 1996).

However, individual entities may contain more than one thematic map class. For example, in classical land cover maps, a polygon or a pixel can be described by only one land cover category, such as forest or pasture, or as a mixture class (e.g., pastures with isolated trees). Notice however that in traditional land cover mapping, the crisp membership restriction applies equally to a mixed class as to a unique class. That is, the class can only be mixed or non-mixed, with Boolean membership in the integer set $\{0, 1\}$ and the degree to which it is mixed cannot be differentiated.

One can imagine that defining land cover classes with sufficient accuracy, and choosing an adequate scale of representation, will remove the presence of mixed polygons or pixels. Nonetheless, due to the intrinsic structure of most terrestrial landscapes, which are at the same time both spatially continuous and hierarchically organized (Woodcock and Strahler, 1987) no matter how accurately map classes are defined, the uncertainty associated to class mixtures will be never completely eliminated (Costa Fonte and Lodwick, 2004; Shanmugam et al., 2006).

To improve the traditional methods of representing geographical information, an alternative solution consists in substituting the traditional crisp classifiers with fuzzy classifiers that explicitly allow for partial and multiple class membership of classified entities.

The purpose of this paper is to show how the substitution of fuzzy set theory for classical set theory leads to a much

more flexible tool for representing geographic information by hierarchical classification schemes focusing on multiscale approaching of land cover classification. It is worth remembering that fuzzy set based approaches have been used in ecology dating back to 1980s (see as an example, Feoli and Zuccarello, 1988; Roberts, 1986, 1996). Nevertheless, as far as we know no studies have dealt with fuzzy hierarchical classification issues.

2. Fuzzy representation of hierarchical classifications

From a cognitive viewpoint, uncertainty is a consequence of the fundamental imprecision proper of natural languages. Two main types of uncertainty are now recognized that require appropriate mathematical formalizations. These uncertainty types are: vagueness (or fuzziness) that results from the lack of sharpness of relevant distinctions, and ambiguity that is associated with any situation in which it is unclear which of several alternatives should be considered as the authentic one. More specifically, ambiguity emerges from the lack of certain distinctions characterizing an object (non-specificity), from conflicting distinctions (discord), or from both of these (Klir and Wierman, 1999). For a thorough overview of uncertainty measures dealing with both basic aspects of uncertainty, fuzziness and ambiguity, the reader is referred to Klir and Wierman (1999).

Whereas ambiguity has been extensively studied within the context of evidence theory (Shafer, 1976), the concept of fuzzy sets was first introduced by Zadeh (1965) for dealing with vagueness in complex systems, and represents a generalization of crisp sets to situations where the class memberships of single elements cannot be sharply defined.

The principle behind fuzzy set theory is that the situation of one class being exactly right and all other classes being equally and exactly wrong often does not exist. Conversely, there is a gradual change from membership to non-membership (Gopal and Woodcock, 1994).

Let X be a universe of entities, whose generic elements are denoted by x : $X = \{x\}$. According to classical set theory, membership in the set $A \subset X$ can be defined as a Boolean function χ_A from X to $\{0, 1\}$ (the integer set of 0 and 1) such that:

$$\chi_A(x) = \begin{cases} 1, & \text{for } x \in A \\ 0, & \text{for } x \notin A \end{cases} \quad (2)$$

This Boolean membership function gives rise to the conventional crisp representation of geographic information. Nonetheless, this one-entity–one-class method contrasts with the observation that all landscape variation does not fit unambiguously in single map categories.

Expanding on classical set theory, a fuzzy set can be defined as follows (Klir and Wierman, 1999): let X be a set as described in the previous section; a fuzzy set $B \subset X$ is defined by a new membership function μ_B , which associates for each $x \in X$ a membership level in the range $[0, 1]$ (the real range between 0 and 1). In this sense, the membership function μ_B expresses the possibility that a given entity (i.e. a polygon or a pixel) belongs to thematic map class B (see Zadeh, 1978). Accordingly, different classes can overlap to different degrees

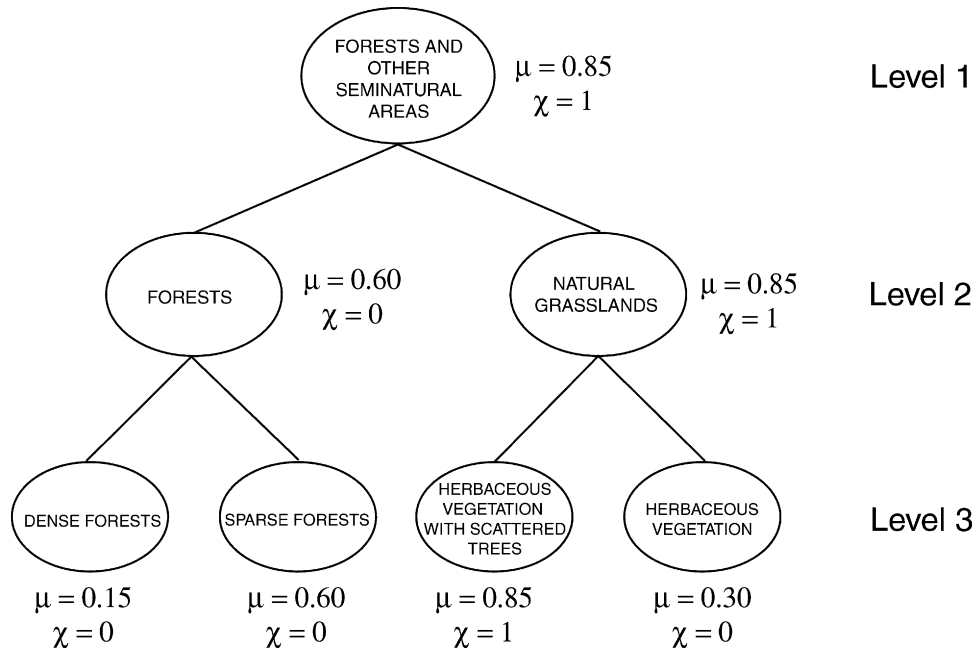


Fig. 1 – Fuzzy classification scheme based on three hierarchical levels. The fuzzy membership degrees μ represent the strength of association of a hypothetical entity (e.g., a polygon or a pixel) with all thematic map classes. For comparison, the Boolean membership function χ that is obtained by ‘hardening’ the fuzzy membership degrees μ are also represented.

overcoming the traditional restriction on the mutually exclusive nature of map classes.

Like traditional crisp sets, two or more fuzzy sets can be aggregated by the fuzzy union operator:

$$(A \cup B)(x) = [\max A(x), B(x)] \tag{3}$$

In the framework of fuzzy classifiers, the fuzzy union operator of Eq. (3) introduces a great amount of flexibility into hierarchical classifications. The following example from land cover mapping helps illustrating the problem.

3. Worked example

Given a hierarchical classification composed of n hierarchical levels (see Fig. 1; in this case $n=3$), imagine an entity (e.g., a polygon or a pixel) that is associated to the lowest hierarchical level with the following fuzzy membership degrees: $\mu_{\text{dense forests}} = 0.15$, $\mu_{\text{sparse forests}} = 0.60$, $\mu_{\text{herbaceous vegetation with scattered trees}} = 0.85$ and $\mu_{\text{herbaceous vegetation}} = 0.30$.

The fuzzy union operator described in Eq. (3) allows to associate a fuzzy membership level to any thematic map class at any hierarchical level in a straightforward manner. For instance, the degree of compatibility of the above entity to the thematic map classes (in this hypothetical classification) at the second hierarchical level are: $\mu_{\text{forests}} = 0.60$ and $\mu_{\text{natural grasslands}} = 0.85$. This example gives an idea of the intrinsic uncertainty rising from the univocal association of a mixed polygon or pixel to a single thematic class, as required by crisp classifications.

Relaxing the mutual exclusive nature of thematic map entities, fuzzy classifiers allow to remodel pre-defined hierarchical classifications according to the requirements of different users.

As an example, a forester may be interested in preserving the information associated to the classes ‘dense forests’ and ‘sparse forests’, and in aggregating all remaining thematic map classes at a higher hierarchical level. By contrast, a restoration ecologist, involved in the management of livestock grazing, might be interested in keeping both classes ‘herbaceous vegetation’ and ‘herbaceous vegetation with scattered trees’ separate, while all remaining thematic map classes may be aggregated at a higher hierarchical level.

This flexibility is not allowed by traditional one-entity–one-class methods. Also, the classification uncertainty related to the association of a given entity to a given crisp thematic map class would be definitely lost (Tapia et al., 2005), though handling and representing uncertainty is a critical issue for modelling geographic information (Goodchild, 1994; Wright et al., 1997).

4. Conclusions

Many studies on the effects of scale-dependence in landscape analysis are aimed at understanding the effect of arbitrarily grouped spatial phenomena on pattern-process relationships (e.g., Burnett and Blaschke, 2003). In this view, fuzzy set theory has been extensively used in landscape ecology to represent uncertainty in the spatial perception of the environment (Wang and Hall, 1996; Foody, 2000; Tang et al., 2005; Tapia et al., 2005).

Using the fuzzy union operator, we can associate information related to data uncertainty to thematic map classes at different hierarchical levels. This is in good agreement with the concept of 'ecological continuum' (Palmer et al., 2002) that relates observed spatial patterns to gradually varying ecological processes (Foody, 1996a,b). In turn, as stressed by Wu and David (2002), ecological processes possess a high degree of complexity, due to the large number of different components, non-linear interactions, scale multiplicity and spatial heterogeneity that control them (see Ricotta and Anand, 2006). Therefore, when dealing with ecological systems, a proper perception of the underlying pattern-process relationships is structurally, functionally and operationally dependent on the scale at which the interpretation is carried out (Stohlgren et al., 1997; Saura, 2002; Fassnacht et al., 2006). For all these reasons, the idea that a map entity may partially belong to a class and simultaneously belong to more than one class represents an essential improvement for representing geographic information bridging the gap between the gradual variability of the real world and the lack of flexibility of crisp GIS data models. We hope this short paper will serve to awake an appropriate and innovative use of fuzzy set theory for representing geographical information for ecological modelling.

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