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Detecting change in vague interpretations of landscapes

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ARTICLE INFO

Article history:
Received 16 October 2005
Received in revised form
11 January 2006
Accepted 31 January 2006

Keywords:
Land cover mapping
Fuzzy sets
Fuzzy logic
Change analysis

ABSTRACT

For a number of years researchers have advocated the use of fuzzy classifications in the study of land cover mapping from satellite imagery. Some studies have looked at the change of fuzzy spatial object, but none have considered the direct corollary of the so-called change detection matrix. In this paper we discuss populating the fuzzy change matrix, using fuzzy logic statements. Intersection is the principal operation, but it is argued that the Bounded Difference is the intersection operation for which the results make sense for determining loss and gain of a cover type. While the minimum operator works in actually populating the matrix. An alternative matrix can be generated using just the Bounded Difference. The detection of ecotones and the analysis of ecotone change are also discussed. It is suggested that the mappings derived express subtle variations in land cover types and change in those types as well as in ecotones, which may be related more conclusively to an ecological process than are Boolean mappings with associated linear boundaries.

1. Introduction

The model of fuzzy sets as an approach to describing poorly defined ecological classes has received much attention in recent years. Thus Roberts (1986, 1989), Dale (1988) and Moraczewski (1993a,b) have argued that the basic concept of a plant community or an ecological habitat is poorly defined. Therefore not only are such communities suitable for modelling with fuzzy sets (Zadeh, 1965), but advantages in insight and understanding might accrue through that modelling. Specifically if the occurrence of a particular frequency of a specific plant is considered important in defining a vegetation community, is it really true to say that if there is only just less than the threshold of occurrence of that species, the plant association and the ecology of the area are significantly different from those areas where it is only just over the threshold; if 40% oak defines oak woodland, is there really a difference between an area with 39% oak and one with 41% oak, especially if the other plants are in exactly the same proportions at the two locations? This fuzziness can describe the spatial extent and ecotonal transitions as much as the match to a category (Arnot et al., 2004).

The fuzzy model of spatial information has been advocated for a number of different ecology-related phenomena including soil information (Burrough, 1989; Burrough et al., 1992) climatic zones (McBratney and Moore, 1985), terrain classes (Burrough et al., 2000; Fisher et al., 2004; Schmidt and Hewitt, 2004), terrain–climate classes (Burrough et al., 2001), landscape ecology (Arnot et al., 2004) and land cover mapping derived from satellite remote sensing (Fisher, 1997; Foody, 1996; Robinson and Strahler, 1984). In essence a fuzzy interpretation of mapping of a geographical area replaces the traditional

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doi:10.1016/j.ecoinf.2006.02.002

Boolean area-class map (Mark and Csillag, 1989), which shows every pixel (location) as belonging to one and only one class, by a set of n maps where n is the number of classes identified. In each of the n maps, for every pixel or area a so-called membership value (μ_x) is recorded as a real number in the interval [0,1], where 1 represents a complete match between the characteristics of the location and those of the class, and 0 indicates a complete mis-match. Values between 0 and 1 show the degree of matching (Fisher, 2000; Robinson, 1988; Zadeh, 1965). Implicit in this form of analysis is the spatial extent of the spatial intergrade between classes (the ecotone; Fortin et al., 2000), and Arnot et al. (2004) have highlighted the problems of using any of the metrics suggested in landscape ecology when explicit models of spatial uncertainty are employed.

At the same time as fuzzy sets have been advocated for the classification of environmental information derived from satellite imagery, that same technology has been widely advocated as a comprehensive method for the systematic analysis of environmental change. This is particularly attractive due to the regular and frequent satellite passes. The corpus of work on change detection is large and summarised in a number of publication (Coppin et al., 2004; Jensen, 1981, 1996; Lunetta and Elvidge, 1999). A number of approaches to change detection have been suggested, but post-classification comparison of information from more than one date is one of the most widely applied and most intuitive (Jensen, 1981, 1996; Jensen et al., 1999; Coppin et al., 2004). Some studies have sought to extend fuzzy analysis into some of the derivative analyses from land cover mapping.

A few studies have examined the consequences and possibilities for change analysis when the landscape is conceptualised under uncertainty with fuzzy sets. Fisher and Pathirana (1993) examine how the fuzzy memberships can be manipulated to buffer the detection of change where change is known not to have occurred. Cheng and Molenaar (1999) and Tang et al. (2005) extracted objects from scenes classified by a fuzzy semantic import model (Robinson, 1988). They then discuss the manipulation of fuzzy characteristics of those objects. Metternicht (1999) used a direct approach to fuzzy change detection using as input the ratio of reflectances at the two dates, and deriving the possibility that change had occurred at any location. A similar approach is used by Blonda et al. (1991). Meanwhile, Gong (1993) used fuzzy set theory to combine principal component images derived from multitemporal imagery. On the other hand, Foody and Boyd (1999) and Foody (2001) used post-classification comparison of multitemporal images, but they saw the fuzzy set membership as a simple vector of belonging to a forest class. They used the arithmetic difference between fuzzy set memberships at different times to show the change in equatorial forests. Only Deer (1998) has examined the logic of change pixel-by-pixel in the output from a classification process.

In this paper, like Deer (1998), Foody and Boyd (1999) and Foody (2001), we explore a pixel-by-pixel post-classification comparison approach to fuzzy land covers. Unlike Foody and Boyd (1999), and Foody (2001) we examine change as a problem of logic and unlike Deer (1998) we do not accept the standard fuzzy logic expressions. We conceptualise the landscape as a set of fuzzy membership fields (after the field conceptualisation of spatial information; Burrough and McDonnell, 1998, p 20), one field for each cover type at each time, and for every pixel a fuzzy membership is estimated in each land cover field. We then extend the field model of spatial information to the analysis of fuzzy post-classification change detection using a logical analysis of the fuzzy set memberships applying fuzzy logic operators.

In Section 2, we examine the logic of change detection in general and specifically with respect to the suitability of fuzzy set operators for this purpose. Essential set theoretic models, both Boolean and Fuzzy, are developed, and operators proposed. In Section 3, a study area is introduced and the multitemporal classifications derived. Section 4 discusses the results of change detection in this case study, and Section 5 presents a conclusion.

2. The logic of change

2.1. Boolean change

A number of approaches to change detection have been used (Jensen, 1981; Coppin et al., 2004), but post-classification comparison is that where classifications at two different times are compared (and so comparable to the fuzzy model of change used here). The classic way that the remote sensing community has addressed environmental change where the landscape has been segmented into categories of one type or another at two different times has been through a change (detection) matrix (Table 1; Jensen, 1996; Jensen et al., 1999) similar to the error matrix used in accuracy assessment (Congalton and Green, 1999). Here the rows indicate the i categories at time T1 and the columns the j categories at T2; usually not only does $i=j$, but the sets of possible classes at T1 and T2 are identical. If the categories are not equivalent, then the more complex problem of mixed semantics makes analysis complex (Comber et al., 2004).

The cells in the change table show the areas which were category Ci at time T1, and category Cj at T2. If categories 1 to i correspond to categories 1 to j, then for each category, the area that has remained unchanged is given by the diagonal elements in the table; thus for category C1, the area unchanged is given by $LC_{1,1}$ (Table 1). The area of C1 which has become C2 is given by the element $LC_{1,2}$, and the area of C1 that has become Cn is given by Loss(C1).

Although not normally discussed (but see Deer, 1998), the total area of category C1 which is lost, Loss, is given by the sum of off-diagonal elements in the row C1 (Eq. (1)). On the other hand, the area which is gained, Gain, of land cover C1 is the sum of all off-diagonal elements in the column C1 (Eq. (2)); an area lost from one cover type is gained by another. Finally it should

Table 1 – The change table used widely in remote sensing.

		T2			
T1		C1	C2	..	Cj
	C1	$LC_{1,1}$	$LC_{1,2}$	..	$LC_{1,j}$
	C2	$LC_{2,1}$	$LC_{2,2}$	..	$LC_{2,j}$
	..	..	..	..	..
	Ci	$LC_{i,1}$	$LC_{i,2}$	..	$LC_{i,j}$