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Fuzzy Classification of Simulated Droughts and Floods of Water Bodies

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Abstract: In general, geomorphological landforms are viewed as Boolean objects. However, recent studies have shown that landforms are more suitable to be viewed as fuzzy objects, whereby a landform is defined as a region in the continuum of variation of the surface of the earth. In this study, the fuzzy classification of simulated droughts and floods of water bodies is performed. First, concepts of mathematical morphology are employed to generate simulated droughts and floods of water bodies. Fuzzy classification is then performed based on by the average of Boolean memberships of the water bodies over the levels of droughting and flooding. The proposed fuzzy classification method is useful for statistical analyses and determination of sample schemes.

Key words: Water bodies, mathematical morphology, simulated drought and floods, fuzzy classification

INTRODUCTION

In Boolean set theory, if an object belongs to a set, it is assigned an integer value of 1 as membership for that set. If the object does not belong to that set, it is assigned with a membership of 0. In fuzzy set theory, a core concept is defined and objects which exactly match that core concept are assigned with a class membership of 1. The membership is assigned a reducing real number for objects as they are increasingly dissimilar from that core concept, when the membership is assigned a value of 0 (Zadeh, 1965, 1975, 1978; Novak, 1989; Zimmermann, 1991; Klir and Yuan, 1995, 1996; Novak *et al*., 2000; Gottwald, 2001; Ross, 2004).

In general, geomorphological landforms are viewed as Boolean objects. However, recent studies have shown that landforms are more suitable to be viewed as fuzzy objects, whereby a landform is defined as a region in the continuum of variation of the surface of the earth (Gale, 1972; Robinson, 1988, 2003; Burrough and Heuvelink, 1992; Irvin *et al*., 1997; Fisher and Wood, 1998; Burrough *et al*., 2000, 2001; Cheng and Molenaar, 1999a,b; Fisher, 2000a,b; MacMillan *et al*., 2000, 2007; Dehn *et al*., 2001; Varzi, 2001; Mackay *et al*., 2003; Fisher *et al*., 2004; Schmidt and Hewitt, 2004; Carré and McBratney, 2005; Drăgut and Blaschke, 2006; Dinesh, 2007a,b). In general, three approaches have been employed to perform the fuzzy classification of various landforms. The first approach, known as the semantic import model, uses a priori knowledge, such as height, to assign a value of fuzzy membership to a landscape feature with a particular metric property (Dehn *et al*., 2001). Usery (1996) determined the fuzziness of Stone Mountain, Georgia, using the height above elevation as a membership function, with membership increasing with height. Cheng and Molenaar (1999a and b) used height to determine membership functions of separate elements of dynamic beach landforms. The second approach, known as the similarity relation model, uses surface derivatives, such as slope and curvature, as input to a multivariate fuzzy classification which yields the membership values (Irvin *et al*., 1997; Burrough *et al*., 2000, 2001; MacMillan *et al*., 2000, 2007; Schmidt and Hewitt, 2004; Carré and McBratney, 2005; Drăgut and Blaschke, 2006). In the third approach, fuzzy classification of landforms is performed based on landforms extracted over multiple scales of measurement. In Fisher *et al*. (2004) and Dinesh (2007a and b), the fuzzy classification of geomorphometric and physiographic features extracted from multiscale digital elevation models was performed based on by the average of Boolean memberships of the extracted features over the scales of measurement.

In this study, the fuzzy classification of simulated droughts and floods of water bodies is performed. First, concepts of mathematical morphology are employed to generate simulated droughts and floods of water bodies. Fuzzy classification is then performed based on by the average of Boolean memberships of the water bodies over the levels of droughting and flooding.

GENERATION OF SIMULATED DROUGHTS AND FLOODS OF WATER BODIES USING MATHEMATICAL MORPHOLOGY

Mathematical morphology is a branch of image processing that deals with the extraction of image components that are useful for representational and descriptional purposes. Mathematical morphology has a well developed mathematical structure that is based on set theoretic concepts. The effects of the basic morphological operations can be given simple and intuitive interpretations using geometric terms of shape, size and location. The fundamental morphological operators are discussed by Matheron (1975), Serra (1982) and Soille (2003). Morphological operators generally require two inputs; the input image A, which can be in binary or grayscale form and the kernel B, which is used to determine the precise effect of the operator.

Dilation sets the pixel values within the kernel to the maximum value of the pixel neighbourhood. Binary dilation fills the small holes inside particles and gulfs on the boundary of objects, enlarges the size of the particles and may connect neighbouring particles (Duchane and Lewis, 1996). The dilation operation is expressed as:

$$A \oplus B = \{a+b: a \in A,\ b \in B\} \tag{1}$$

Erosion sets the pixels values within the kernel to the minimum value of the kernel. Binary erosion removes isolated points and small particles, shrinks other particles, discards peaks on the boundaries of objects and disconnects some particles (Duchane and Lewis, 1996). Erosion is the dual operator of dilation:

$$A \ominus B = (A^c \oplus B)^c \tag{2}$$

where, A^c denotes the complement of A and B is symmetric with respect to reflection about the origin.

Droughting and flooding simulation was implemented by performing erosion and dilation, respectively, on the water bodies using square kernels (Dinesh, 2007c, d). However, the disadvantage of this approach is that the rate of change across the levels of drougthing and flooding is too larger for the purposes of fuzzy classification. An alternative approach is to perform droughting and flooding simulation using morphological opening and closing.

An opening is defined as erosion followed by a dilation using the same kernel for both operations. Opening tends to remove some of the foreground pixels from the edges of regions of foreground pixels. It preserves the foreground regions that have a similar shape to kernel, or that can completely contain the kernel, while discarding all other regions of foreground pixels (Fisher *et al.*, 1994). The opening operation is expressed as:

$$A^{\circ}B = (A \ominus B) \oplus B \tag{3}$$

A closing is defined a dilation followed by an erosion using the same kernel for both operations. Closing tends to enlarge the boundaries of foreground regions in an image and shrink background holes in such regions. It preserves the background regions that have a similar shape to the kernel, or that can completely contain the kernel, while eliminating all other regions of background pixels (Fisher *et al.*, 1994). The closing operation is expressed as:

$$A \bullet B = (A \oplus B) \ominus B \tag{4}$$

Droughting and flooding simulation is implemented by performing opening and closing, respectively, on water bodies using square kernels. Opening reduces the area of water bodies, mimicking droughting, while closing increases the area of water bodies, mimicking flooding. The level of droughting/flooding is indicated by the kernel size.

Gothavary River, which lies in central India, originates near Triambak in the Nasik district of Maharashtra and flows through the states of Madhya Pradesh, Karnataka, Orissa and Andhra Pradesh. Although its point of origin is just 80 km away from the Arabian Sea, it journeys 1,465 km to empty into the Bay of Bengal. Some of its tributaries include Indravati, Manjira, Bindusara and Sarbari. Some important urban centers on its banks include Nasik, Aurangabad, Nagpur, Nizamabad, Rajahmundry and Balaghat. The Gothavary River is often referred to as the Vriddh (Old) Ganga or the Dakshin (South) Ganga. The Gothavary River catchment has an area of 312, 870 km^2 and receives more than 85% of its annual rainfall during the monsoon season (June-September). Hence, the water resource in this river is largely due to monsoon rainfall and largely affected by monsoon extremities, resulting in floods during some years and droughts during others.

Figure 1 shows a number of water bodies of varying shape and sizes situated in a portion of the flood plain

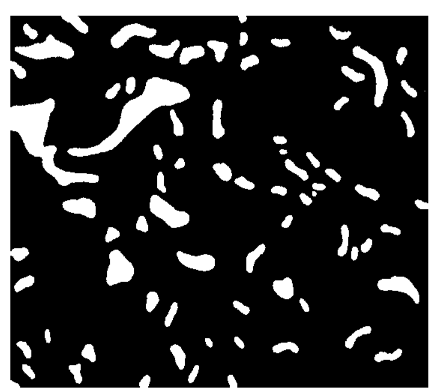

Fig. 1: Water bodies of varying shapes and sizes traced from IRS 1D remotely sensed data

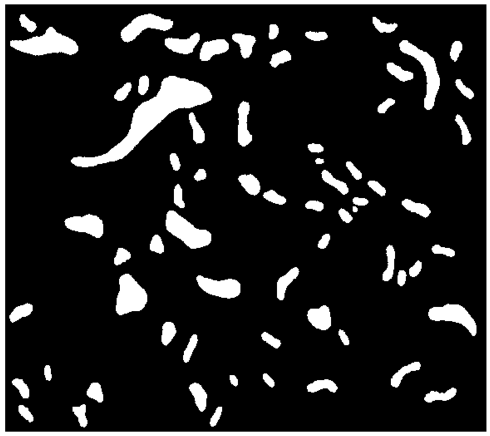

Fig. 2: The water bodies after the removal of incomplete water bodies

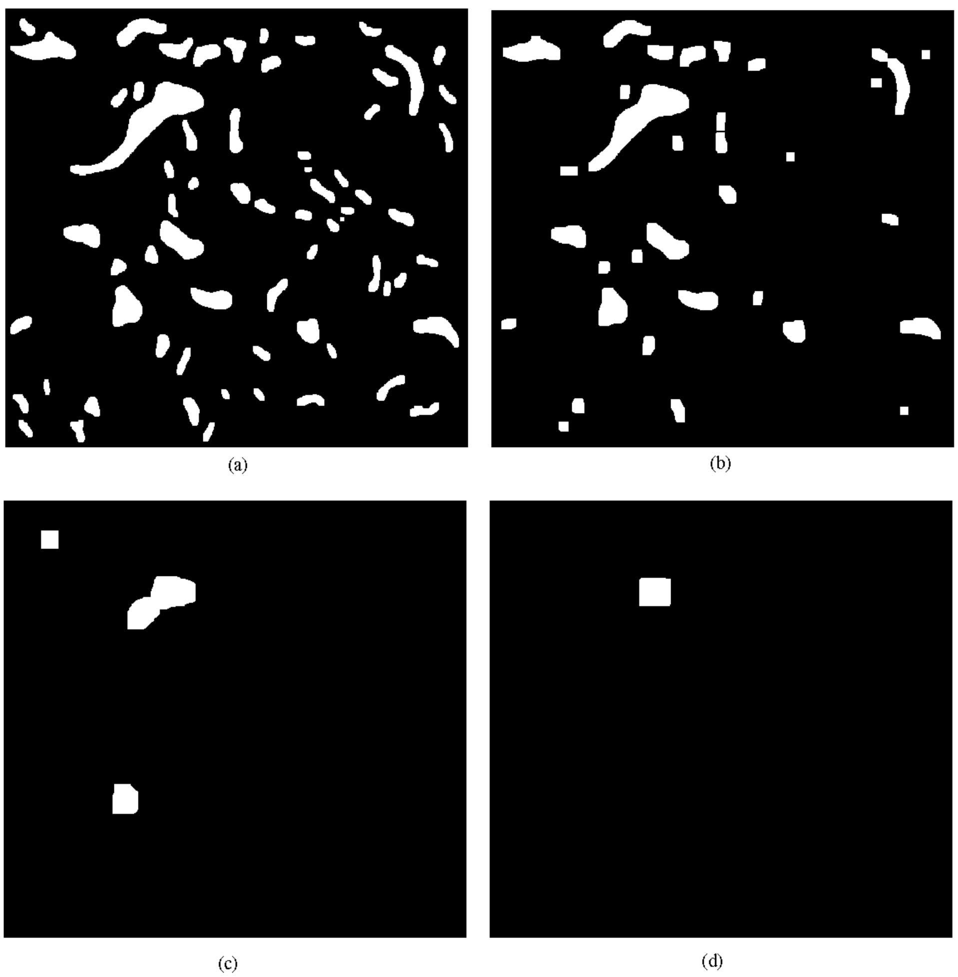

Fig. 3: The generated simulated droughts of the water bodies at droughting levels of: (a) 5 (b) 10 (c) 20 and (d) 30

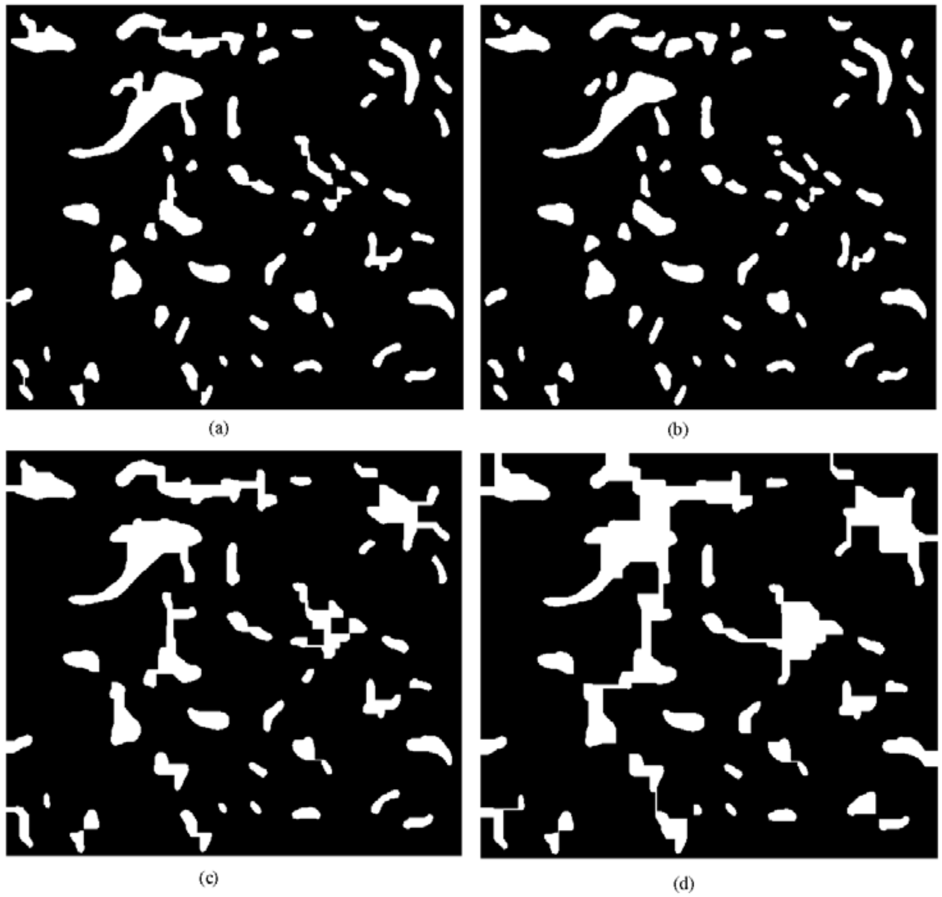

Fig. 4: The generated simulated floods of the water bodies at flooding levels of: (a) 5 (b) 10 (c) 20 and (d) 30

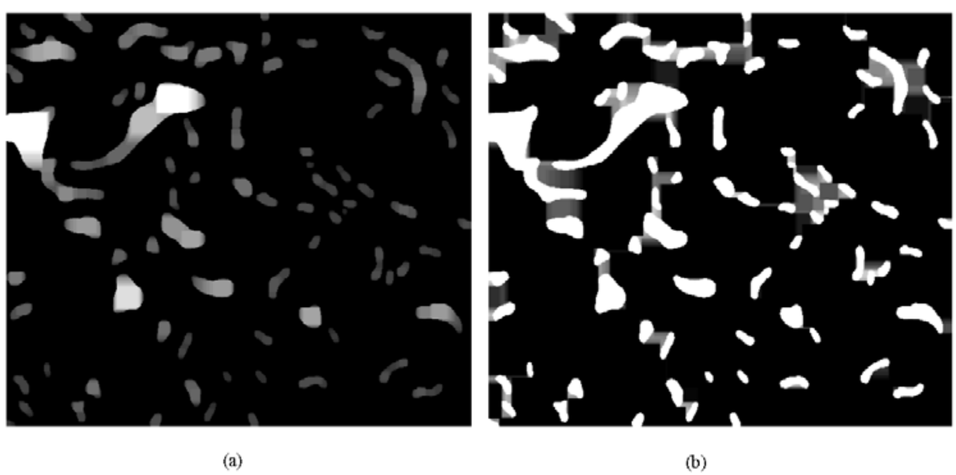

Fig. 5: Fuzzy memberships of the (a) simulated droughts (b) simulated floods. The membership values ranging from 0 to 1 are rescaled to the interval of 0 to 255 (the brightest pixel has the highest membership value)

Table 1: Areas of the generated simulated droughts and floods of the water bodies

	Area (pixels)	
Level	Drought	Flood
1	29078	29078
2	29028	29100
3	28948	29126
4	28819	29151
5	28543	29196
6	28090	29254
7	26786	29446
8	24680	29652
9	21530	29945
10	18189	30209
11	15937	30609
12	14044	30902
13	12048	31320
14	10279	31957
15	9122	32811
16	8348	33111
17	7769	33817
18	6795	34393
19	5301	35064
20	4130	35460
21	3549	37164
22	3318	37783
23	2415	38266
24	2323	38802
25	2227	39474
26	2127	40221
27	1347	41763
28	1320	43129
29	1264	44132
30	1206	45170

region of Gothavary River. The water bodies were traced from IRS 1D remotely sensed data. Due to the impracticalities of dealing with incomplete water bodies, these incomplete water bodies are removed and only the complete water bodies are considered (Fig. 2). Simulated droughts (Fig. 3) and floods (Fig. 4) of the water bodies for levels of 1-30 are computed. The areas of the generated simulated droughts and floods are shown in Table 1.

FUZZY CLASSIFICATION OF SIMULATED DROUGHTS AND FLOODS OF WATER BODIES

In order to perform the fuzzy classification of the generated simulated droughts and floods, it is first assumed that at any droughting/flooding level, the water bodies are Boolean objects. Hence, whereby a terrain can be divided into two classes: mountain (m_x= 1) and non-water bodies at location x. The main reason why simulated droughts and floods are more suitable to be considered as fuzzy objects is that the Boolean assignment of water bodies is not necessary stable under repeated observation at different levels of droughting/flooding. Thus, if $m_{x|l1}$ = 1 for a particular landscape, it does not mountain (m_x= 0), where m_x is the Boolean membership of

Table 2: Distribution of the pixels based on their fuzzy memberships

Fuzziness range	Drought	Flood
0.0-0.1	246272	232091
0.1-0.2	858	3655
0.2-0.3	9901	2310
0.3-0.4	4145	2100
0.4-0.5	4922	1953
0.5-0.6	2327	1791
0.6-0.7	3246	1111
0.7-0.8	1226	763
0.8-0.9	976	295
0.9-1.0	1347	29151

follow that either $m_{x|l2}$ = 1, or $m_{x|l3}$ = 1, where l_1, l_2 and l_3 indicate different levels of droughting/flooding.

The fuzzy membership of water bodies μ at location x can be given by the average of Boolean memberships of that feature over the levels of droughting/flooding:

$$\mu_x = \frac{\sum_{i=1}^{30} m_x \,|\, l_i}{30} \tag{5}$$

Figure 5 shows the fuzzy memberships of the generated simulated droughts and floods. The distribution of the pixels based on their fuzzy memberships is shown in Table 2.

CONCLUSION

In this study, the fuzzy classification of simulated droughts and floods of water bodies is performed. First, concepts of mathematical morphology were employed to generate simulated droughts and floods of water bodies. Fuzzy classification was then performed based on by the average of Boolean memberships of the water bodies over the levels of droughting and flooding. The proposed fuzzy classification method is useful for statistical analyses and determination of sample schemes.

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