GeoInformatica 3:4, 337–355 (1999)

Diachronic Analysis of Fuzzy Objects

TAO CHENG
Joint Laboratory of Geoinformation Science, Chinese University of Hong Kong, Shatin, N.T., Hong Kong
E-mail: tcheng@cuhk.edu.hk

MARTIEN MOLENAAR
International Institute for Aerospace Survey and Earth Sciences – ITC, P.O. Box 6, 7500 AA Enschede, The Netherlands
E-mail: molenaar@itc.nl

Abstract

This paper presents a method to monitor the behavior of fuzzy spatial objects through time. The method consists of two steps. Firstly the spatial extents of objects are determined at several sequential epochs. The method explains the case where objects are not crisply defined, so that the identified spatial extents will be fuzzy. Secondly, to detect dynamic changes in fuzzy objects, a method was proposed to identify objects and their state transitions from fuzzy spatial extents (regions) at different epochs. Similarity indicators of fuzzy regions were calculated based upon overlap between regions at consecutive epochs. Different combinations of indicator values imply different relationships between regions. Regions that are very similar represent the consecutive states of one object. By linking the regions, the historic lifelines of objects are built automatically. Then the relationship between regions became the relationship or interactions between objects, which were expressed in terms of processes, such as shift, merge or split. This approach will be illustrated by means of a coastal monitoring study of a barrier island in The Netherlands.

Keywords: dynamics, fuzzy objects, processes, fuzzy spatial extent

1. Introduction

Many environmental studies measure, model and predict the dynamics of natural phenomena. This requires that changes of natural phenomena are detected, represented, analyzed and modeled. Most natural spatial phenomena are not crisply delineated, but are bounded by fuzzy transitions or transition zones. For example, the boundary between the grassland and woodland may be gradual through a transition zone rather than a crisp boundary. Therefore, their spatial extent appears to be fuzzy and should be represented in a way that is intermediate between field representations of geographic phenomena and the traditional crisp representation of area objects [1]–[3]. It seems that neither the present continuous field model nor the object model [2], [8], [14], [17] satisfactorily describes the behavior of such natural phenomena. A more general concept is needed to encapsulate both object-oriented and field-oriented characteristics of these phenomena. Therefore, we will develop a concept of objects with a fuzzy spatial extent to represent them, i.e., for these objects only conditional boundaries can be defined, and the interiors of these objects have field properties, representing their gradual and continuous distribution characteristics [4], [6].

Moreover, these natural spatial objects are dynamic, i.e., they change from time to time. The literature to date, however, hardly discusses the dynamics of these phenomena (particularly spatial changes) in a generic way. In fact, these dynamics are the basis for designing a proper data model to represent and to predict them. Similarly, little research has been reported on the dynamic behavior of objects with indeterminate boundaries. It is more difficult to model temporal changes of fuzzy objects. Therefore, this paper will explain a method to monitor the behavior of natural phenomena that have a fuzzy spatial extent.

This paper is structured as follows: The next section briefly introduces a general procedure to identify the dynamics of natural phenomena from field observation data. As in the procedure object definitions generally tend to be vague and errors occur in field measurements, the third section discusses the effect of these uncertainties on the identification of the spatial extent of fuzzy objects. The fourth section proposes an approach to identify fuzzy object dynamics. Section five delineates the practical usefulness of the advocated methods for a coastal geomorphologic study. The final section summarizes the major findings so far and gives suggestions for more research.

2. Procedure to identify objects and their dynamics

Many natural phenomena have a field character that may change with time. To monitor such phenomena they should be observed over a sequence of epochs, but the sampling per epoch is necessarily sparse. In general, a seven-step procedure can be followed to identify objects and their dynamics from field data sampled at different epochs:

1. **sampling** thematic values at specific points at particular epochs, i.e., observing values at sample points.
2. **interpolating** thematic values. A suitable interpolation algorithm will be selected to estimate the thematic values for the complete raster covering the observed area.
3. **classifying** all pixels into pre-defined classes. Each pixel is assigned to one class of the natural phenomenon types of interest.
4. **clustering** the classified pixels into regions. Each contiguous set of pixels of a same type will form a region that represents the spatial extent of a particular natural phenomenon.
5. **merging** regions which are smaller than a pre-defined minimum mapping unit, and the regions of unknown class type into other regions by some merging criteria. Traditional merging methods, such as ''window filtering'', ''nibbling'', ''dropping the longest shared boundary'', and ''maximum area merging'' can be used to remove these small regions [18].
6. **identifying** objects represented by regions, i.e., to identify the actual objects represented by the regions after merging. Because of the dynamics of the natural phenomena, the regions extracted at different times are instances (states) of a

phenomenon in reality (represented as an object) at a particular time. A process is required to link these regions to form a complete description of the phenomena along time horizons. We call this process identification of dynamic objects.

7. **detecting** changes of these objects. Compare boundary, area and volume of each object at different times, and calculate the changes of them between different epochs.

Steps 1 to 5 are repeated for each epoch to generate time series data. Step 6 will identify the geometric states of objects represented by these regions. Step 7 will detect the change of natural phenomena based upon data at two epochs. Step 6 will be the main concern of this paper and will be discussed in detail in Section 4.

Figure 1 illustrates the procedure from Step 2 to Step 6 for a coastal area where height observations have been made at two epochs. The steps represented in this figure start with the interpolated grid cells after Step 2. In Step 3 the grid cells are classified into three elevation classes: ''S'' (foreshore) ranging from -6 m thru -1.1 m, ''B'' (Beach) ranging from -1.1 m thru 2 m and ''D'' (Foredune) ranging from 2 m thru 23 m. The segmentation of Step 4 identifies three regions. In Step 5, Region 3 has been merged into Region 2 at T_1 and Region 6 into Region 5 at T_2. By analyzing the relationships of the four regions (1,2, 4 and 5) at two epochs, we can see that Region 1 is very similar to 4. In fact, they represent spatial extents of an object (''S'') in reality at two epochs. Regions 2 and 5 are spatial extents of another object (''B''). So finally two objects —''S'' (foreshore area) and ''B'' (beach area) are identified in Step 6. Their changes can be detected by comparing the regions and the thematic data of the two rasters.

3. Identification of the fuzzy spatial extents of objects

The discussion in the previous section did not consider uncertainty in the procedure of identification. The definition of natural phenomena is, however, usually fuzzy (i.e., no

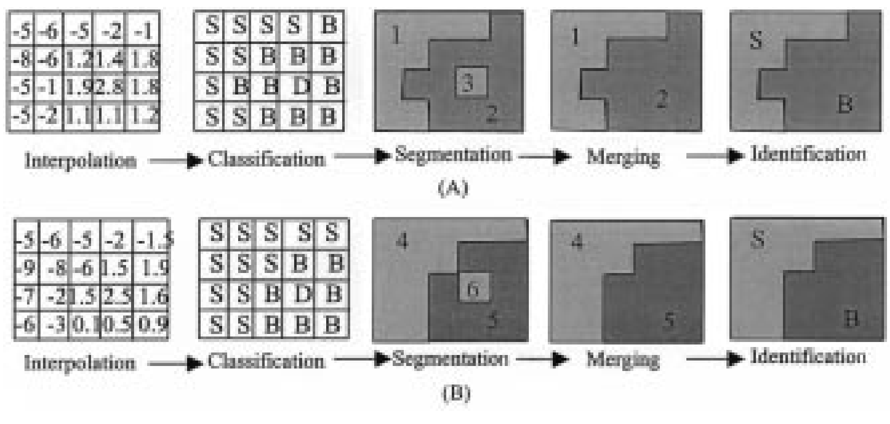


Figure 1. Procedure of object identification.

crisp class boundaries) and the field data are stochastic. These two kinds of uncertainties can be dealt with by fuzzy classification and probabilistic approaches. Their combined effect on the classification of raster cells was discussed in [5]. Here we will resume some of the concepts for deriving the fuzzy spatial extent of objects based upon uncertain classification results.

Due to the vagueness of object class definitions and the errors in field sampling points, each grid cell $P(i, j)$ will be assigned a membership function value vector $[\mu_1(i,j), \mu_2(i,j), \ldots, \mu_n(i,j)]^T (0 \leq \mu_k(i,j) \leq 1, k = 1, \ldots, N)$ in Step 3 of Section 2. Here $\mu_k(i,j)$ represents the membership function value of grid cell $P(i, j)$ belonging to class C_k, N is the total number of the classes. For each class C_k regions can be identified consisting of cells with $\mu_k(i,j) > 0$ [6]. Each region can then be interpreted as the fuzzy extent of a spatial object belonging to a class C_k. If the classes are assumed to be spatially exclusive then each grid cell belongs to at most one class, and consequently to only one object; if the objects form a spatial partition then each grid cell belongs to exactly one object. In other applications, fuzzy spatial overlaps among objects are permitted, i.e., the objects have fuzzy transition zones that may overlap [1], [24]. In the transition zones, the pixels might belong to multiple objects. The fuzzy topologic relationships of spatial objects are discussed in [7], [11] and [25]. However, here we will not discuss this issue, as in our case the landscape units form spatial partitions. So each grid cell is supposed to belong to exactly one class and one object, which can be determined by criteria such as we will define. In this case only conditional boundaries can be formed after assigning the grid cells to objects [6], [7].

Let $d_k[i,j]$ represent the decision function assigning $P(i, j)$ to class C_k, which can de defined as:

$$\text{If } \forall l, \mu_k(i,j) \geq \mu_l(i,j) \quad \text{then } d_k(i,j) = \mu_k(i,j), \quad \text{otherwise, } d_k(i,j) = 0, \tag{1}$$

where $k = 1, \ldots, N; l = 1, \ldots, N; k \neq l; N$ is the total number of the classes.

If there are several k such that μ_k is maximum (hence equals), another criterion is needed to discriminate between them, i.e., an additional evidence is required to come to a selection of a unique class for the grid cell.

When all grid cells have been assigned to classes, one or more regions S can be formed per class C_k with the following two rules,

Let $P(i,j) \in S$ where S is a region of class C_k and let $\mu_s(i,j) \equiv d_k(i,j) \neq 0$

Let $P(m,n)$ be a pixel adjacent to $P(i,j)$ (8-connectd)

$$\text{If } d_k(m, n) \neq 0 \quad \text{then } P(m, n) \in S \text{ and we note } \mu_s(m,n) = \mu_k(m,n) \text{ the membership function of } P(m,n) \text{ to } S \quad \text{else } \mu_s(m,n) = 0. \tag{2}$$

Therefore, the membership of $P(i,j)$ to S of C_k is a ''maximum likelihood'' based on μ_k, i.e.,

$$\mu_s(i,j) = d_k(i,j) \equiv \mu_k(i,j). \tag{3}$$

4. Identification of fuzzy object dynamics

When fuzzy regions are extracted from field observation data, a further step is needed to identify the objects that are represented by these regions. Conventionally, this step is based on interpretation by domain experts or by a field check. Afterwards, changes in objects are detected by comparing their states at different epochs. The experts then analyze the processes the objects have undergone. For example, as shown in figure 2, three states of objects were obtained from observation data. The historic lifeline can be constructed by linking the regions appearing in consecutive states. Region 1 is linked with Region 4, and 4 with 7, representing the lifeline of Object 1; Region 2 is linked with Region 5, representing the lifeline of Object 2; Region 3 with Region 6, representing the lifeline of Object 3; Region 5 with 8 and Region 6 with 8, representing the lifeline of Object 4. This procedure is usually done by domain experts. Afterwards, the processes the objects involved in such as shift, are also analyzed. The temporal relationships between objects are also derived, e.g., Object 2 and Object 3 have merged into a new Object 4. This section, however, proposes a method for analyzing the relationships of regions and for identifying objects and their processes automatically.

4.1. Assumption

The procedure in Section 3 identifies the regions that represent the spatial extents of objects at each epoch. The regions at different epochs should be linked to form lifelines of the objects. This can be realized based on the assumption that natural phenomena are changing gradually, especially the change of coastal zone in the case of Section 5 can be regarded as a gradual continuous process [13], so the objects are considered to be rather stable. The approach developed in this paper will be designed for such cases. This implies that if two regions are the spatial extents at two subsequent epochs of one and the same object, their overlap should be larger than their overlaps with the region of any other object. Under this assumption we can find the successor of a region at epoch t_n by calculating its spatial overlaps with all the regions that appeared at epoch t_{n+1}. The one that has maximum overlap will be identified as the successor.

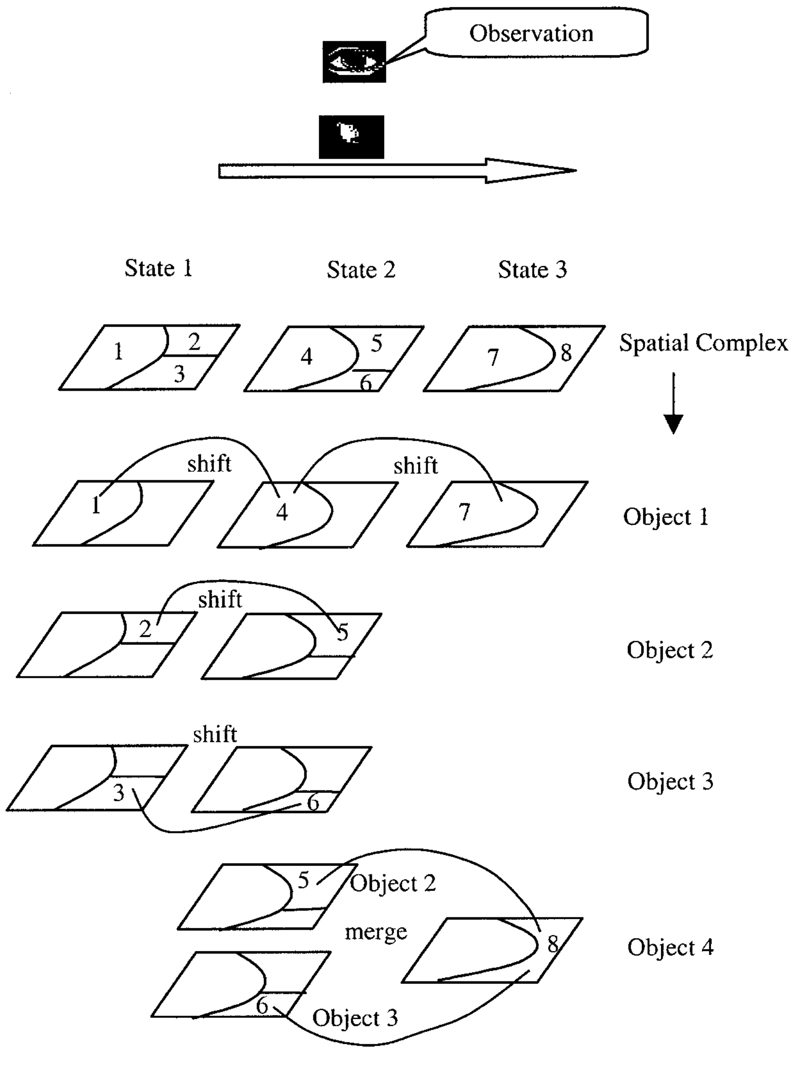


Figure 2. States and process of objects are monitored through time series data ([4], p.73).

4.2. Similarity indicators

If μ_s denotes the membership of a grid cell belonging to the region S, and $\mu_{s'}$ to the region S', then $\mu_{s \cap s'} = \mathrm{Min}(\mu_s, \mu_{s'})$ denotes the membership to the overlap between S and S'.

Assume $Size(P(i,j)) = 1$, then $\mu_s(i,j) \cdot Size(P(i,j)) = \mu_s(i,j)$. Let $Size(S) = \sum_{(i,j)} \mu_s(i,j)$ be the integral of the membership function associated to the region S, over the spatial domain. Then $Size(S \cap S') = \sum_{(i,j)} \mu_{s \cap S'}(i,j)$ is the integral of the membership function associated to the overlap between S and S'.

Based upon the spatial overlap between regions, we can match the regions that are spatially related. Let R_1 be the set of regions at epoch T_i, let R_2 be the set of regions at epoch T_{i+1} and let $S \in R_1$ and $S' \in R_2$. The following indicators can be used to evaluate the types of relationship between regions at two epochs.

The relative fuzzy overlap between two regions can be defined as

$$ROverl\ (S'|S) = \frac{Size(S \cap S')}{Size(S)} \tag{4}$$

$$ROverl\ (S|S') = \frac{Size(S \cap S')}{Size(S')} \tag{5}$$

where $ROverl(S|S')$ represents the ratio of the overlap to the size of S (relative fuzzy overlap to S); $ROverl(S'|S)$ is the ratio of the overlap to the size of S' (relative fuzzy overlap to S').

The similarity of two fuzzy regions can be defined as

$$Similarity(S, S') = \frac{Size(S \cap S')}{\sqrt{Size(S) \cdot Size(S')}}. \tag{6}$$

4.3. State transitions

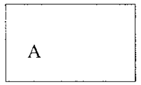
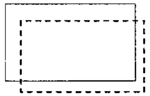
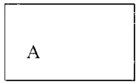
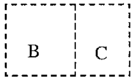
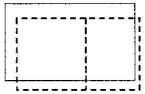
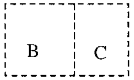
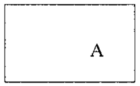
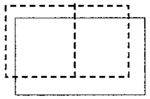
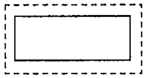
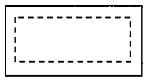
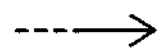
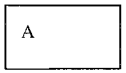
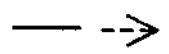
Using these indicators, object state transitions can be identified between two epochs. Seven fundamental cases are shown in table 1. The combinations of indicator functions behave differently for these seven cases.

State transitions can be identified by the following procedure.

For all $S' \in R_2$ compute Size (S')
For all $S \in R_1$ do
    > compute Size (S)
    For all $S' \in R_2$
        > compute $Size(S \cap S')$
        > compute $Roverl(S'|S)$, $Roverl(S|S')$, $Similarity(S, S')$
        > evaluate $shift(S; S')$, $expand(S; S')$, $shrink(S; S')$
    > evaluate $split(S;\ldots S', \ldots)$, $appear(S')$
> evaluate $merge(\ldots, S, \ldots; S')$, $disappear(S)$

The evaluation is made by identifying the type of state transition between S and S' based upon the indicators according to the situations indicated in table 1. For example, the split process implies that one region $S' \in R_1$ splits in two or more regions $S' \in R_2$ and the merge

Table 1. Identification and presentation of state transitions.

Regions at T_1	Regions at T_2	Overlay	Indicators: Rovel $(S_b\|SS_a)$ Rovel $(S_c\|SS_a)$	Indicators: Rovel $(S_a\|SS_b)$ Rovel $(S_a\|SS_c)$	Indicators: Similarity	State Transition	Symbol
			Large	Large	High	shift(S_a;S_b)	
			Small Small	Large Large	Low Low	split(S_a;S_b,S_c)	
			Small Small	Large Large	Low Low	merge(S_b,S_c; S_a)	
			Large	Small	Low	expand(S_a;S_b)	
			Small	Large	Low	shrink(S_a;S_b)	
		0	/	0	/	appear(S_b)	
	/	0	0	/	/	disappear(S_a)	

process implies that two or more regions $S' \in R_1$ merge into one region $S' \in R_2$. Threshold values have been chosen intuitively based on expert knowledge. Further research is required to establish threshold values for these indicators.

4.4. Dynamic objects

The procedure of the previous subsection identified possible dynamic relationships between regions at two different epochs. Regions thus related can be linked to form lifelines of objects that may have ''shifted'', ''expanded'' or ''shrunk'' between two successive epochs. The regions that appeared at a specific moment represent a new object, and regions that disappeared at some moment represent disappearing objects. Furthermore, ''merging'' and ''splitting'' objects can be identified. The procedure to identify the dynamic objects will be illustrated by the case study of Section 5.

5. Case study

5.1. Study area and the problem

The coastal zone of Ameland, one of the six Dutch barrier islands was chosen as our test area. It is situated north of the coast of Friesland, the Netherlands on the southern margins of the North Sea (figure 3). At certain locations in the middle and southern parts of the western end of the island, severe erosion of beaches occurs (due to shifting inlets caused by the marine current), while at other places in the northwest accretion or accumulation occurs. To be able to predict future development, it is necessary to understand various

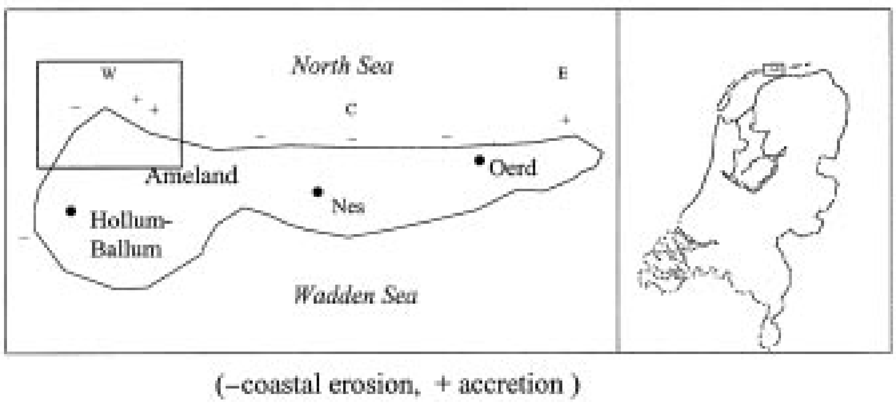


Figure 3. Test area — Ameland.

processes, their interaction and their effect on the development. Such information is quite important for optimizing coastal defense works, e.g., beach nourishment or planting of grass, which both require high investments [12].

The geomorphologic process, particularly the erosion and accumulation can be distinguished through interpretation of changes in the landscape units, i.e., the foreshore, beach and foredune areas. Therefore, to monitor these geomorphologic processes it is necessary to identify these landscape units and trace their changes.

These landscape units have specific characteristics in terms of altitude, slope, roughness, size, material compaction, humidity and vegetation/land cover [22]. The definition of the landscape units are not crisp so that their identifications usually differ from surveyor to surveyor, from case to case and from time to time. One method is to define the landscape units based upon altitude of terrain surface according to different water lines. Heuvel and Hillen (1994) considered that the area beneath the high-tide line (HT) and above the low-tide line (LT) is foreshore; the area beneath the very high-tide line (VHT) and above the HT is beach, and the area above the VHT and below the dune foot is foredune [15]. Others, however, consider that foreshore is the area above the closure depth [23] and below the low water line [9]; beach is the area above the low water line and up to the dune foot [22]; foredune is the area above the dune foot up to the dune (see figure 4). Furthermore, the values for these water lines are not fixed. Ruessink and Kroon (1994) used -6 m to represent the closure depth in the years 1965 to 1984 and in the year 1989, and used -8 m to represent the closure depth in the years 1985 to 1988 and 1990 to 1993 [23]. Ruig and Louisse (1991) used -6 m to represent it in all these years [10]. Therefore there is no invariable and fixed definition of the landscape units. Figure 4 illustrates one set of definitions of the landscape units.

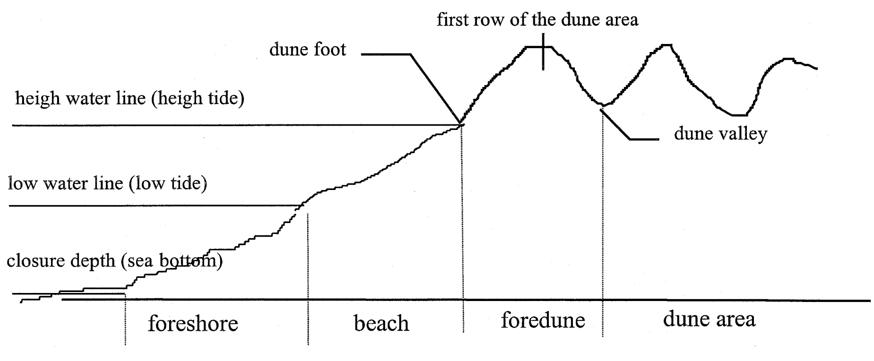


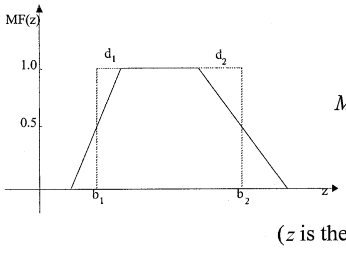
Figure 4. The landscape units are defined by the height of the depth of closure depth (-6 m), low water line (-1.1 m) and dune foot ($+2$ m).

5.2. *Fuzzy definition of the landscape units*

The transition zones between these landscape units are defined as in table 2. b_1 and b_2 represent the boundaries of the landscape units; d_1 and d_2 represent the half width of the transition zones. E.g., if a region belongs to the foreshore then the height value of the region should be between -6.0 m to -1.1 m. As most experts take -6 m to be the closure depth [9], [10], we could consider -6 m to be the boundary between foreshore and deep sea, but sometimes others take -8 m [23] to be the closure depth. We use -8 m to be the outmost boundary of the foreshore. Thus the transition zone between foreshore and deep sea has a height range of about 4 m and d_1 has a value of 2 m (half width). The height range of transition zone from foreshore to beach is 0.5 m, from beach to dune 0.5 m, and from foredune to dune 3 m [5]. In order to reveal the vagueness of definitions for the landscape units, we adopt a trapezoidal membership function to represent the fuzzy semantics (see figure 5, [5]).

5.3. *Data and preprocessing*

The Dutch coasts have been surveyed each year since 1963 [15]. These surveys are carried out along defined coastal profiles perpendicular to the coastal shoreline with a distance of 200 to 250 meters between them. The height/depth are determined up to a distance of about 800 m seaward from the posts, and up to some 200 m landward from the first line of dunes (figure 6). These data have been linearly interpolated to generate a full height raster with a spacing of 60 m in x and y directions between the grid pixels. Tests have shown that these interpolated data have a height accuracy of ($\sigma = 0.15$ m) [16]. All grid cells are classified into these pre-defined fuzzy classes of height intervals related to ''foreshore'', ''beach'' and ''foredune'' (equation 7, figure 5). The uncertainties of cells belonging to the three classes can be derived from the combination of fuzzy class definition and the errors of the interpolated elevation data [5]. The effect of the fuzzy class definitions appeared to dominate the effect of height inaccuracy. Therefore this approach is not very sensitive for the actual interpolation method applied in this case. The classified raster is then segmented in regions belonging to different height intervals. These regions represent the foreshore, beach or foredune. Lastly, we take the ''maximum area merging'' approach



$$MF(z) = \begin{cases} 0 & (z < b_1 - d_1) \\ \dfrac{1}{2d_1}(z + d_1 - b_1) & (b_1 - d_1 \le z \le b_1 + d_1) \\ 1 & (b_1 + d_1 \le z \le b_2 - d_2) \\ -\dfrac{1}{2d_2}(z - d_2 - b_2) & (b_2 - d_2 < z < b_2 + d_2) \\ 0 & (z > b_2 + d_2) \end{cases} \quad (7)$$

(z is the height value of the grid; b_1, b_2, d_1, d_2 refer to table 2.)

Figure 5. Fuzzy classification function.

Table 2. Fuzzy definition for coastal landscape units.

ClassId	Landscape Unit	b_1 (m)	b_2 (m)	d_1 (m)	d_2 (m)
1	Foreshore	− 6.0	− 1.1	2.0	0.5
2	Beach	− 1.1	2.0	0.5	0.5
3	Foredune	2.0	25.0	0.5	3.0

Notes. b_1 and b_2 represent the boundaries of the landscape units; d_1 and d_2 represent the half width of the transition zone.

to merge regions which are smaller than a certain threshold and regions of unknown type into the largest adjacent region. The fuzzy regions created after merging are illustrated by figure 7, where the numbers in the figure are the identifiers of the regions used in table 3.

5.4. *Diachronic analysis of the landscape units*

The fuzzy sizes of these regions and the fuzzy overlap of regions of successive years are shown in table 3. The indicators of Section 4.2 can now be evaluated; with these we can link the regions (as shown in table 3) which indicate that the linked regions are most likely the representations of the spatial extent of an object in successive years. For example, Region 1 has been linked with 4, 4 with 8, 8 with 11; Region 3 has been linked with Region 6, 6 with 10, 10 with 14. We also found that there is a new region in 1990 (region 7). By checking the overlap of this region with the regions at 1989 and 1991, we found it has overlap with Region 3 and 10; these regions are linked by a line also.

For example, the spatial overlap of Region 1 in 1989 (S_1) and Region 4 in 1990 (S_4) is 937.531 ($Soverl(S_1 \cap S_4)$), and here $Size(S_1) = 1108.1$, $Size(S_4) = 1138.7$. So

$$Rovel\ (S_1|S_4) = 937.5/1138.7 = 0.823$$

$$Rovel\ (S_4|S_1) = 937.5/1108.1 = 0.846$$

$$Similarity\ (S_1, S_4) = 0.835$$

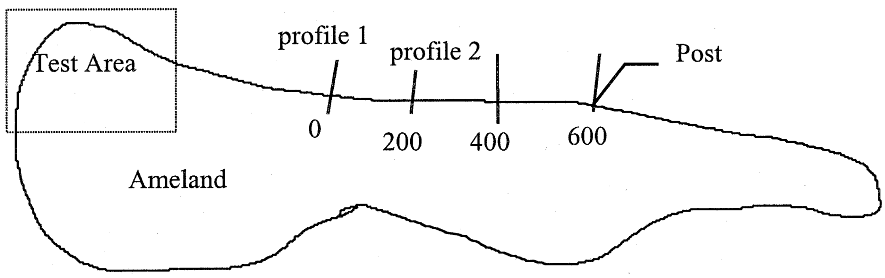


Figure 6. Schematic view of profiles measured along the coastline of Ameland.

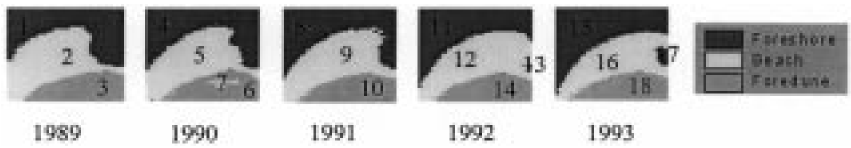


Figure 7. Classified regions.

Therefore, these two regions are very similar to each other and can be considered as instances of the same object (here we call it Object 1) at two epochs. As there are differences between the boundaries of these two regions, we considered that Object 1 shifted from Region 1 in 1989 to Region 4 in 1990.

A similar conclusion is valid for Region 3 in 1989 (S_3) and Region 6 in 1990 (S_6). The similarity between them is as follows,

$$ROvel\ (S_3|S_6) = 572.5/644.3 = 0.819$$

$$ROvel\ (S_6|S_3) = 572.5/586.8 = 0.976$$

$$Similarity\ (S_3, S_6) = 0.894$$

Therefore, also these two regions are instances of the same object (Object 3) at two epochs.

We also calculated the similarities between Region 3 (S_3) and Region 7 (S_7),

$$ROvel\ (S_7|S_3) = 27.5/644.3 = 0.043$$

$$ROvel\ (S_3|S_7) = 27.5/28.0 = 0.982$$

$$Similarity\ (S_3, S_7) = 0.205$$

Table 3. Fuzzy overlaps and links among fuzzy regions.

Year	Region	Area	Overlap with Regions in Next Year				Class Type
1989	1	1108.1	937.5	81.8	0.0	0.0	Foreshore
	2	1246.8	106.3	1104.8	9.2	0.0	Beach
	3	644.3	0.0	12.7	572.5	27.5	Foredune
1990	4	1138.7	975.0	76.0	0.0		Foreshore
	5	1229.7	76.0	1129.5	2.6		Beach
	6	586.8	0.0	0.0	564.3		Foredune
	7	28.0	0.0	0.0	26.3		Beach
1991	8	1101.3	862.7	116.9	6.4	0.0	Foreshore
	9	1260.1	87.3	1146.6	0.0	0.5	Beach
	10	609.8	0.0	3.3	0.0	605.7	Foredune
1992	11	1004.9	751.5	6.8	0.0	0.0	Foreshore
	12	1288.7	119.3	1101.1	38.9	2.8	Beach
	13	6.4	0.0	1.6	4.6	0.0	Foreshore
	14	625.7	0.0	2.7	0.0	604.4	Foredune

We can conclude that these two regions are not similar to each other, but Region 7 is more or less contained in Region 3. It can be identified as a new object appearing in 1990, and is split from Object 3 (Region 3 represents its spatial extent in 1989). By analyzing the overlap between regions of 1990 and 1991, we found that Region 7 disappeared in 1991, it was merged into Object 3 (Region 10 in 1991). Using the above approach, the objects and the processes involved in object developments are identified as illustrated by figure 8. The icons represent the regions (states) of objects at different times. The symbols represent the types of state transition. It can be seen from the figure that Object 4 split off from Object 3 between 1989 and 1990; it is merged again into Object 3 between 1990 and 1991; Object 5 split off from Object 1 between 1991 and 1992.

Figure 9A presents the identified objects, whereas figure 9B presents them as fuzzy objects with uncertainty of their spatial extent; this figure shows that the uncertainty of the assignment of grid cells to region changes from year to year with the spatial extent of the objects.

5.5. *Discussion*

This case study has examined the identification of fuzzy objects of three object types. These types have been defined so that the objects always form a spatial partition of the

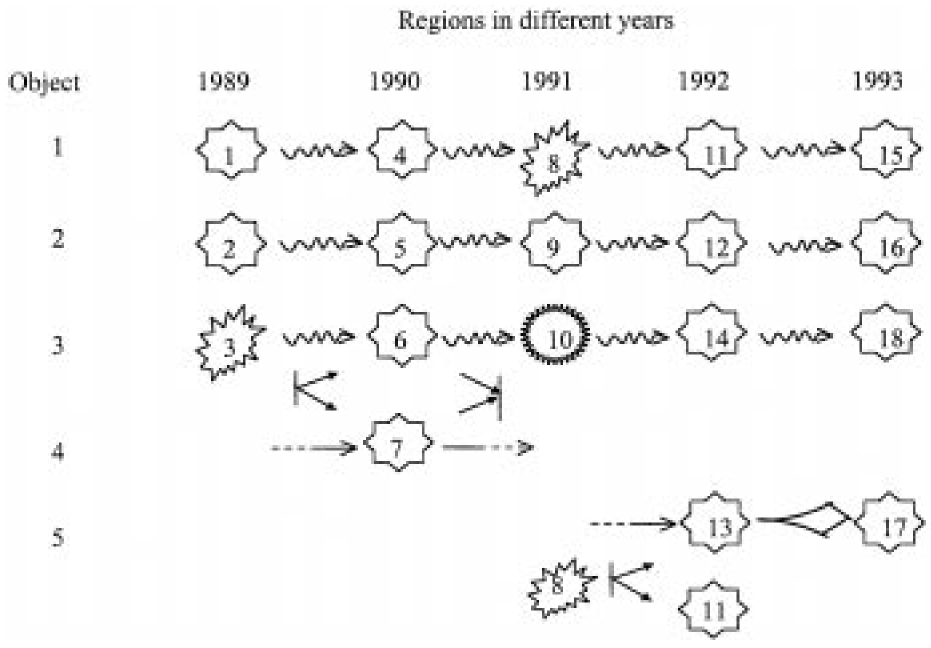


Figure 8. Identified fuzzy objects and processes.

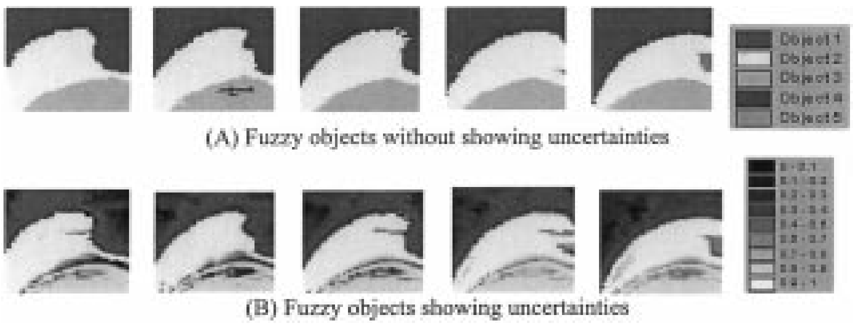


Figure 9. Dynamics of fuzzy objects.

mapped region. The dynamics of such a spatial complex can be determined by comparison of the states of the complex at successive epochs.

The processing time for the evaluation of indicators to identify the state transition of objects will increase with the number of regions appearing at each epoch. A two-step approach can be used, however, to improve the efficiency. The first step compares the spatial overlaps of regions per object type. If region S' at epoch T_{l+1} is of the same type as region S at epoch T_i and if they have a maximal similarity, then S' can be considered as the successor of S. In this step most of the regions can be identified as spatial extents of objects at different epochs. There may be regions, however, (e.g., Region 7 in our case study) which might have no spatial overlaps with regions of the same type at previous and/or later epochs. In this case, a further step should be taken.

We can compare the spatial overlap of this region with the regions belonging to other object types and check whether the region has been misclassified. Region 7 has originally been classified as beach area. Checking its spatial relationship with regions in other years, however, showed that it is only related to regions belonging to foredune and, therefore, it will also be assigned to the foredune instead of beach. In fact, it was a low part of the foredune region (dune valley). Therefore, by using the temporal and topological information of the objects, the misclassification of regions can be corrected. This is an advantage of the proposed approach, i.e., to adjust the classification results.

6. Conclusions

This paper presents a method to identify the spatial extents of objects from field data sampled at different times. State transitions of objects were detected by comparing the extent of each object at two subsequent years. The methodology has been demonstrated by an example from a coastal geomorphological study of Ameland, The Netherlands. We expect that it will also be applicable to modeling natural environments and physical processes in other fields. This method is based upon two principles:

1. Objects are fuzzy. The concept of objects with fuzzy spatial extents is proposed to encapsulate both object-oriented and field-oriented characteristics of natural phenomena. The fact that the spatial extents of the objects are fuzzy implies that its geometry can not be represented by a boundary polygon. The fuzzy spatial extent of an object can be represented as a contiguous set of raster elements or pixels with a $\mu_{s_l}(i,j) > 0$. When pixels are to be assigned to one object with an extent S_k exclusively then we will find that $\mu_{s_k}(i,j) > \mu_{s_l}(i,j)(l \neq k)$. This means that objects are represented as fuzzy fields.
2. Objects are dynamic. Their dynamics are revealed through the spatial extents at different epochs. The state transition of an object from one year to the next can be inferred from the two states. Several fuzzy measures have been proposed to express how two subsequent states of an object are related. The different value combinations of these measures are indicators for the type of state transition each object has gone through. The lifelines can then be expressed as a sequence of its states of each object. The process of the object evolution can be expressed by the sequence of states and the related state transitions.

It is revealed in our experiment that the uncertainties in the field observation data and in the definition of object classes have obvious influences on the identification of the spatial extent of objects at different epochs. Therefore, the geometric uncertainty of objects is due to the uncertainties of their thematic aspects. It means that the existential, extensional, and geometric aspects of objects all have a degree of uncertainty and they are related to each other [19], [20].

A new generation of spatio-temporal data models should be developed to represent this dynamic fuzzy object concept. We demonstrated the approach in a raster format, but the basic ideas can also be realized in other geometric models such as the vector model, or as cell complexes [8], [17], [21]. The new spatio-temporal data model should support analyzing and querying of the objects, including their spatial extent, their state transition processes, the thematic values they have, the time range of their existence and their dynamic behavior during a certain period, etc. In order to support physical environmental modeling, such a spatio-temporal data model should also support the analysis from other perspectives, be it time-based or location-based. A prototype of such spatio-temporal data model has been developed by the authors [4].

Acknowledgments

The authors wish to thank Marieke Eleveld for preparing the height data for the case. We also thank Lucas Janssen, Robert A. Van Zuidam and Wolfgang Kainz for the stimulating discussions we had about several issues of this paper. Comments and suggestions from anonymous reviewers are gratefully acknowledged.

The research has been funded by the International Institute for Aerospace Survey and Earth Sciences (ITC). The Survey Department of the Directorate-General for Public Works and Water Management of the Dutch Ministry of Transport, Public Works and Water Management kindly made the data for the Ameland case available.

References

1. P.A. Burrough. ''Natural Objects with Indeterminate Boundaries,'' in P.A. Burrough, and A. U. Frank (eds.), Geographic Objects with Indeterminate Boundaries, Taylor & Francis: London, 3–28, 1996.
2. P.A. Burrough and A.U. Frank. ''Concepts and Paradigms in Spatial Information: Are Current Geographic Information System Truly Generic?,'' *Int. J. Geographical Information Systems*, Vol. 9–2:101–116, 1995.
3. P.A. Burrough and A.U. Frank. Geographic Objects with Indeterminate Boundaries, Taylor & Francis: London, 1996.
4. T. Cheng. A Process-Oriented Data Model for Fuzzy Spatial Objects, Ph.D. Thesis, Wageningen/ITC, 1999.
5. T. Cheng, M. Molenaar, and T. Bouloucos. ''Identification of Fuzzy Objects from Field Observation Data,'' In S.C. Hirtle, and Frank, A.U., (eds.), Spatial Information Theory: A Theoretical Basis for GIS, (Lecture Notes in Computer Sciences, Vol. 1329), Spring-Verlag: Berlin, 241–259, 1997.
6. T. Cheng and M. Molenaar. ''Objects with Fuzzy Spatial Extent,'' *Photogrammetric Engineering & Remote Sensing*, Vol. 65(7):797–801, 1999.
7. T. Cheng, M. Molenaar, and T. Bouloucos. ''Fuzzy Object Models and their Application,'' *Proceedings of International Conference of Spatial Information Science, Technology and its Applications*, (SIST'98), 13–16, Wuhan, pp. 408–416, 1998.
8. H. Couclelis. ''People Manipulate Objects (but cultivate fields): Beyond the Raster-Vector Debate,'' in A.U. Frank, I. Campari, and U. Formentini (eds.), Theories and methods of spatio-temporal reasoning in geographic space (Lecture Notes in computer Sciences), Springer-Verlag: Berlin, Vol. 639:65–77, 1992.
9. L.W.S. De Graaff. ''Het Strand: De Relatie Tussen Processen, Materialen en Vormen, en Een Proeve van Terminologie-Gebruik,'' *Koninklijl Nederlands Aardrijkskundig Genootschap Geografisch Tijdschrift, Nieuwereeks*, Vol. XI-1:47–67, 1977.
10. J.H.M. De Ruig and C.J. Louisse. ''Sand Budget Trends and Changes Along the Holland Coast,'' *Journal of Coastal Research*, Vol. 7–4:1013–1026, 1991.
11. J. Dijkmeijer and S. De Hoop. ''Topologic Relationships between Fuzzy Area Objects,'' in M.J. Kraak and M. Molenaar (eds.), Advences in GIS Researches II, Proceedings of 7th Spatial Data Handling, London: Taylor & Francis, 377–394, 1996.
12. M.A. Eleveld, Cheng T., and R.A. van Zuidam. ''Towards a Decision Support System for Coastal Zone Management by Applying Morphodynamic Modeling with Remote Sensing Data Input in a 4-D GIS Environment,'' *Proceedings of Third Thematic Conference of Remote Sensing for Marine and Coastal Environments, Technology And Applications*, Seattle, USA, Vol. 1:256–265, 1995.
13. A. Galton. ''Continuous Change in Spatial Regions,'' in S.C. Hirtle, and Frank, A.U., (eds.), *Spatial Information Theory: A Theoretical Basis for GIS*, (Lecture Notes in Computer Sciences, Vol. 1329), Spring-Verlag: Berlin, 1–13, 1997.
14. M.F. Goodchild. ''The State of GIS for Environmental Problem-Solving,'' in M.F. Goodchild, B.O. Parks, and L.T. Steyaert (eds.), Environmental Modeling with GIS. Oxford University Press: New York, 8–15, 1993.
15. Van der T. Heuvel and R. Hillen. Coastline Management, internal publication of the Ministry of Transport, Public Works and Water Management, Directorate-General for Public Works and Water Management, The Netherlands, 1994.
16. E.J. Huising, R.W.L. Jordans, F.M. Spruijt, E.M.J. Vaessen, R.J. Wicherson, J.F. Zomerdijk, and M. van Persie. 1996, Framework Digital Elevation Models Dutch Coast—Various Techniques for Topographic Measurement Tested on a common Site, The Netherlands Remote Sensing Board (BCRS) Programme Bureau, Rijkswaterstaat Survey Department, Delft, 63 p.
17. K.K. Kemp. ''Environmental Modeling with GIS: a Strategy for Dealing with Spatial Continutity,'' in *Proceedings, GIS/LIS'92 Annual Conference and Exposition*, San Jose, California, Vol. 1:397–406, 1992.

18. Z. Ma and S. Zhao. ''Using an Object and Rule-Based Merging Algorithm to Eliminate Small Regions Less Than Minimum Mapping Unit,'' *Geographic Information Sciences*, Vol. 1–2:110–117, 1995.
19. M. Molenaar. ''A Syntax for the Representation of Fuzzy Spatial Objects,'' in M. Molenaar, and S. de Hoop (eds.), Advanced Geographic Data Modeling. Netherlands Geodetic Commission, Delft: New Series, Nr. Vol. 40:155–169, 1994.
20. M. Molenaar. ''The Extensional Uncertainty of Spatial Objects,'' In M. J. Kraak and M. Molenaar (eds.), Advances in GIS Researches II, Proceedings of 7th Spatial Data Handling, Taylor & Francis: London, p. 571–583.
21. M. Molenaar, An Introduction to the Theory of Spatial Object Modeling for GIS. Taylor & Francis: London, 229 pp, 1998.
22. H.E. Reineck and I.B. Singh. Depositional Sedimentary Environments (2nd edition), Springer Verlag: Berlin, 1980.
23. B.G. Ruessink and A. Kroon. ''The Behavior of a Multiple Bar System in the Nearshore Zone of Terschelling, The Netherlands: 1965–1993,'' *International Journal of Marine Geology, Geochemistry and Geophysics*, Vol. 121:187–197, 1994.
24. E.L. Usery. ''A Conceptual Framework and Fuzzy Set Implementation for Geographic Feature,'' in P. A. Burrough, and A. U. Frank (eds.), Geographic Objects with Indeterminate Boundaries. Taylor & Francis: London, 71–85, 1996.
25. F.B. Zhan. ''Approximation of Topological Relationship between Fuzzy Regions Satisfying a Linguistically Described Query,'' in S.C. Hirtle, and A.U. Frank (eds.), Spatial Information Theory: A Theoretical Basis for GIS (Lecture Notes in Computer Sciences, Vol. 1329). Spring-Verlag: Berlin, 509–510, 1997.

Tao Cheng received her Bachelor of Science degree (1989) in Surveying Engineering and her Master of Science degree (1992) in Photogrammetry and Remote Sensing from Wuhan Technical University of Surveying and Mapping (WTUSM), P. R. China. She was a researcher and lecturer at the Research Center for GIS of WTUSM from 1992 to 1994. She started her Ph.D. research project at the Inetrnational Institute fro Aerospace Survey and Earth Sciences (ITC) in 1995 and obtains her Ph.D. title on May 18, 1999, in GoeInformation Sciences from Wageningen Agricultural University, The Netherlands. She joined Chinese University of Hong Kong in June 1999.

Tao Cheng has been involved in various scientific research projects covering topics in intelligent GISs and image processing. Her current research interests span uncertainty in geographic information, spatio-temporal data models, and the integration of GIS, remote sensing and decision support systems for coastal environmental monitoring and management. She is the author and co-author of a number of scientific articles.

Martien Molenaar has a Doctors degree (Ph.D. level) in Geodesy of Delft Technical University. From 1973 until 1983 he was a senior lecturer in Photogrammetry at the International Institute for Aerospace Survey and Earth Science (ITC). From 1983 until 1996 he was a full professor in GIS and Remote Sensing at Wageningen Agricultural University. In 1996 he returned to the ITC as a full professor in Geoinformatics and Spatial Data Acquisition. He wrote more than 100 scientific publications (among which one book) about geodesy, photogrammetry, spatial modeling, remote sensing and GIS. At present he is also active a Chairman of the Scientific Program Committee for the XIXth ISPRS Congress in Amsterdam, July-2000.