Chapter 4
Fuzzy Approach for Integrated Coastal Zone Management

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Integrated Coastal Zone Management (ICZM) is "a dynamic, multi-disciplinary and iterative process to promote sustainable management of coastal zones" (ICZM 2008). It covers the full cycle of information collection, planning, decision making, management and monitoring of the implementation. Uncertainties, however, exist in almost all the activities in this cycle. This chapter presents the isle of Ameland as the case study area where uncertainties in ICZM can be identified, which provides a direct impression of the problems to be solved. The indeterminate nature of coastal zones and landscape units and associated uncertainties are discussed. This is followed by a discussion of formal fuzzy spatial object models, serving as the basis for representating fuzzy coastal landscape units. It then discusses the dynamic processes and their interactions of these landscape units that can be derived from the temporal series data. A further discussion on the change in area and volume of beach is given. The final Section concludes with the major findings and suggestions for further research.

4.1 Introduction

Coastal zones are the primary interface for the exchange of natural and man-made materials between territorial and coastal ecosystems. Such areas are important for living, fishery, agriculture, and tourism, etc. The growing concentration of population and socio-economic activities puts increasing pressure on coastal ecological systems, which at same time are threatened by inundation, coastal erosion, increased flooding, and loss of freshwater reserves and arable land, particular due to rising sea-levels. To sustain development and to minimize loss from possible natural disasters

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in these areas, ongoing developments and their consequences have to be guided and monitord.

Integrated Coastal Zone Management (ICZM) is “a dynamic, multi-disciplinary and iterative process to promote sustainable management of coastal zones” (ICZM 2008). ICZM aims to balance between economic development, coastal area prevention, and public access. It covers the full cycle of information collection, planning, decision making, management and monitoring of the implementation. Uncertainties, however, exist in almost all the activities in this cycle. During information collection, sampling and measurement usually contain erros, whereas during planning and decision making, the definition of objects and critiria are usually uncertain. The concept of “beach”, for example, commonly refers to the sandy area that separates the sea from the land. Definition of the boundary of a beach is difficult, because of tidal changes, ambiguous transition zones and different concepts in using it.

In this study we distinguish two types of uncertainty in the ICZM: data uncertainty and uncertainty in object/criteria definition. Data uncertainty means that the true value of a measurement is unknown. We are unsure of what exactly we are observing or measuring. It usually includes sampling and measurement errors. Because of its random nature, probability theory can be applied to handle this type of uncertainty. Uncertainty in the object and criteria definition refers to unsure knowledge such as how to define beach precisely. Mathematically, probability density function and membership functions are in the essence of “probability” and “fuzziness,” respectively (Chang 2005). Applications have emerged in environmental risk analyses based on probability theory and fuzzy sets theory, respectively (Chang 2005). Combination of the two would exhibit a synergistic effect in systems analysis, e.g. for illustrating interactive sources of uncertainty (Cheng et al. 1997).

Since Zadeh (1965) proposed fuzzy sets theory, its applications have flourished, varying from solving the inherent problem of uncertainty in natural resources assessment to accommodating vagueness and complexities of modeling environmental systems (see also Robinson 2003). This chapter discusses uncertainties of fuzziness involved in integrated coastal zone management. The fuzzy approach is still unmature, especially for coastal zone studies, although data uncertainties have been extensively studied.

The chapter is organized into seven sections. After the introduction, we present the isle of Ameland as the case study area where uncertainties in ICZM can be identified. This provides a direct impression of the problems to be solved. The indeterminate nature of coastal zones and landscape units and associated uncertainties are discussed in Sect. 4.3. This is followed by a discussion of formal fuzzy spatial object models in Sect. 4.4, serving as the basis for representating fuzzy coastal landscape units. Section 4.5 discusses the dynamic processes and their interactions that can be derived from the temporal series data. A further discussion on the change in area and volume of beach is given in Sect. 4.6. The final Section concludes with the major findings and with suggestions for further research.

4.2 The Case – Changing Beach of Ameland

4.2.1 General Description of the Case Study Area

Ameland, one of the six Dutch barrier islands, is situated north of the coast of the Netherlands (Fig. 4.1). Length in the East–West direction is approximately 24 km, and varies in the North–South from 1.5 to 4 km. It consists of three dune complexes: the Hollum-Ballum complex in the west, the Nes-Buren complex in the center, and the Oerderduinen complex in the east. These three dune complexes were originally separated from by tidal inlets, but they are connected today by sand dikes, as such forming one island (Van Zuidam et al. 1994, 1998). The test area is the right window in Fig. 4.1 and it occupies 54×60 grids in the 60-m DEM.

Processes influencing landscape units of Ameland can be divided into two types: erosion in the middle and southern parts of the western end due to shifting inlets by marine current and sedimentation in the northwest. To predict future development, we have to understand the various processes, their interaction and their effect on the development of the island. The results of the geomorphological processes can be measured qualitatively and quantitatively. Qualitative results can be identified by the erosion or accumulation of the landscapes, whereas quantitative results emerge from estimating (or calculating) volume changes. Such information is important for optimizing costly coastal defense works, e.g. beach nourishment or replantation of vegetation. This study mainly focuses on sediment transport at the land–sea interface as a result of erosion and sedimentation. To do so, the morphodynamically most active area in the northwest section of the island (the area in the small rectangle in the northwest) was selected as the test site.

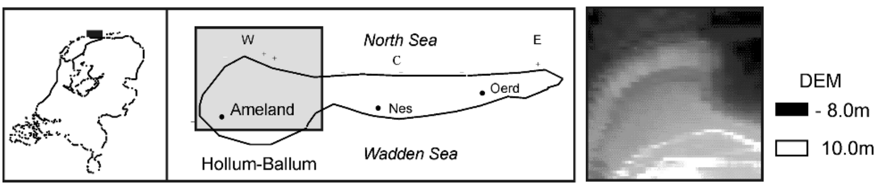


Fig. 4.1 Test site – Ameland, The Netherlands (after Cheng and Molenaar 1999b)

4.2.2 Definitation of the Geomorpholical Lansacpe Units

Traditionally, the effect of erosion and accretion is estimated using annual measurements in the form of coastal profile. Erosion and accumulation are identified by comparing the same profile for two different time horizons. Changes in volume of sand sediments are calculated. From these calculations, inferences of the changes in profiles over the years can be obtained. Some geomorphologists, however, try to analyze the development trend of the landscape units. To do so, the geomorphologic processes, particularly the erosion and accumulation of sediments, should 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 by field observations.

The landscape units – foreshore, beach and foredune – have specific characteristics in terms of altitude, slope, roughness, size, material, composition of mineral elements, compaction, humidity, and vegetation/land cover, etc. The definitions of these landscape units usually differ from surveyor to surveyor, from case to case and from time to time. Among other ways, the landscape units may be defined based upon altitude of terrain surface according to different water lines. Van 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 (VHT) and above the HT is beach, and the area above the VHT and below the foot of dune is foredune. Others, however, consider that the foreshore is the area above the closure depth (Ruessink and Kroon 1994) and beneath the low-water line (De Graaff 1977), that beach is the area above the low-water line and beneath dune foot (Reineck and Singh 1980), and that the foredune is the first row of dunes inland from dune foot. 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 1965–1984 and in year 1989, and used −8 m to represent the closure depth in the years 1985–1988 and 1990–1993. De Ruig and Louisse (1991) used −6 m to represent it in all these years. Therefore, there is no invariable and fixed definition of the landscape units. Figure 4.2 illustrates one set of definitions of the landscape units.

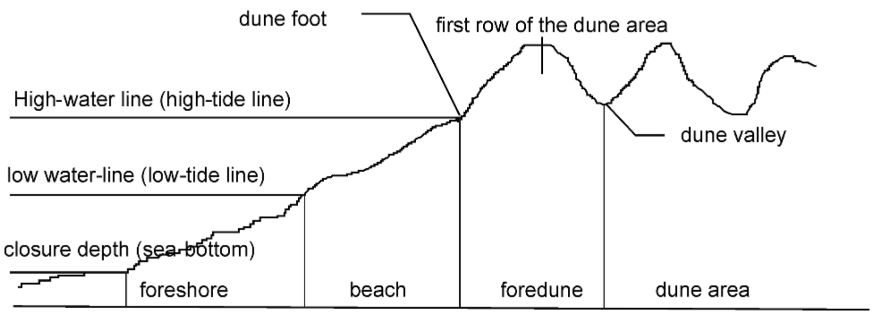


Fig. 4.2 Landscape units are defined by the closure depth, low water line and dune foot (Cheng and Molenaar 1999b)

4.2.3 Data

Since the mid – 1800s, the location of the foot of dune, the high-water line and low-water line along the Dutch coast have been measured each year. These measurements are carried out along defined sections, each demarcated by beach posts. These posts are encountered on the beach along the entire North Sea coast, with distances of 200–250 m between each of them. Since 1963, the coastal profile has been measured every year in each section. This includes that the heights/depths are determined up to a distance of about 800 m to seaward of the posts, and up to some 200 m landwards of the first line of dunes. Once every three years the profiles are extended up to 2–3 km to seaward (Van Heuvel and Hillen 1994). The inaccuracy of the height/depth measurements is between 0.1 m and 0.2 m and the inaccuracy in the horizontal position is up to 10 m.

The annual coastal measurements are interpolated along the profile with 10–20 m intervals. They are further interpolated into a height raster of $(60\,\mathrm{m} \times 60\,\mathrm{m})$ grids to obtain a complete coverage of the test site (as shown in Fig. 4.1). The accuracy of the heigh on grid is 0.2 m (Van Heuvel and Hillen 1994).

4.2.4 Summary

To summarize, there are several issues in the study of the change of coastal landscape units in Ameland: (i) the definition of the landscape units are highly subjective; (ii) the definition of the landscape units changes with time; and (iii) the measurements of the profiles of coastal zones contains errors, so does the DEM derived from them.

The first and second points are the uncertainties associated with the definitions of landscape units, we will discuss in detail in the following sections. The third point, however, is the uncertainty associated with the data (observation), which we will not discuss further. The reason is that research on uncertainties has been well documented in this aspect (Fisher 2003, Zhang and Goodchild, 2002). Data uncertainties, however, affect the classification accuracy when the data are applied for further analysis (Cheng et al. 1997). A vast body of research is included in this heading, looking at both positional and thematic accuracy and the consequences of error (Leung et al. 2004, Heuvelink et al. 2006a,b) based upon probability theories. Such research is usually under the assumption that the spatial objects can be defined precisely and identified crisply.

4.3 Indeterminate Nature and Associated Uncertainties of Coastal Landscape Units

Definitions of coastal landscape units are variant. This inherently results from the indeterminate nature of natural objects. These natural phenomena are distributed continuously in space, leading to a transitional boundary between these objects. When we delineate them from remotely sensed images, the boundary may even be drawn in a subjective way, i.e. different from one person to another (Lowell et al. 2000). Also spatial objects as such may be heterogeneous or may be mixed with each other. The mixture of trees and grass or of several types of trees is common in forests (Brown 1998, Foody 1999). Further, most geographical entities are dynamic and change with time. It is hard to measure them accurately since they change after the measurement. With geographical entities, taking more observations in the boundary zone does not necessarily resolve the "boundary" but reveals new details of variation in that zone (Burrough 1996). Therefore the "boundary" of dynamic entities is not fixed such as the coastline. Furthermore, definition of geographical entities is also scale- and context-dependent. Increasing the level of resolution often results in identification of new areas or classes, particularly in the border areas of the higher aggregation level (Burrough 1996). The measured lengths of coasts and frontiers depend on the scales at which they are measured (Mandelbrot 1983). What is a beach, and what are the boundaries of the beach, are both scale- and context-dependent.

The *continuity, heterogeneity, dynamics* and *scale-dependence* cause uncertainties when we model and represent natural phenomena as spatial objects (Fisher 2000, Cheng 2002).

Due to the continuity and heterogeneity of natural phenomena, the central or core concept of classes of a phenomenon of study (vegetation and vegetation class) can be clearly and explicitly described and defined in categorical terms, but the boundary conditions between one core class and another are problematic (Fisher 2003, Robinson 2003). This is vagueness in class definition.

Ambiguity is usually resulted from the scale issues in geographical analysis. It arises when we have very well defined conceptualizations of categories in which we are interested, but categorization process has multiple equally valid correct outcomes at different scales which are, however, contradictory.

Discord is when one investigator uses one classification scheme, and a second uses a non-overlapping classification. For example, Ahlqvist et al. (2000, 2003) examined contradictory classifications of vegetation of the same area resulted from remote sensing imagery and from wetness of soils. Furthermore, the core concept of spatial objects might change with time; dynamics of reality will also cause discord.

Therefore, when we model coastal landscapes, these units are intuitively uncertain. There are vagueness, ambiguity and discord in the definition. Many ways of handling uncertain spatial data due to indeterminate categories have been proposed. For examples, fuzzy set theory has been applied to handle the vagueness in class definition; rough set theory has been adopted to model the ambiguity due to scale change and the discord in classification. Each of these theories has been largely developed independently of the others, but with the same goal of addressing the problems inherent in uncertainty. Among others, fuzzy set theory is far more popular and successful. In the next section, we will apply fuzzy approach to model the coastal landscape units.

4.4 Fuzzy Modeling and Representation of Coastal Landscape Units

4.4.1 Fuzzy Landscape Classification/Definition

Following Sect. 4.2.2 landscape units should be clearly identified, in order to understand the erosion and accumulation of geomorpholical process. Due to their inderterminate nature, however, it is difficult to have a crip definition to classify the foreshore, beach and foredune areas. Hereby we adopt a fuzzy approach to define them.

Fuzzy sets are sets or classes that for various reasons cannot, or do not, have sharply defined boundaries (Zadeh 1965), e.g. the "class of all real numbers which are much greater than 1", or "the class of beautiful women", or "the class of tall men". If Z denotes a space of objects, then the fuzzy set A in Z is the set of ordered pairs

$$A = \{z, MF_A(z)\} \ z \in Z$$

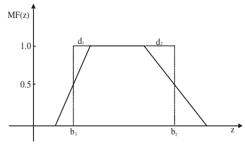
where the membership function $MF_A(z)$ represents the "grade of membership of z in A" and $z \in Z$ means that z is contained in Z. Usually $MF_A(z)$ is a number in the range [0, 1], with 0 representing non-membership and 1 representing full membership of the set.

Usually there are two ways to define the fuzzy membership function, either on the basis of expert knowledge or by using methods of numerical taxonomy. The semantic import model (SIM) is used when users have a more or less clear idea to group the data in a qualitative way, i.e. the central concept of the class is clear, but for various reasons the exact boundary can only be approximated. The fuzzy membership function is defined by adapting a crisp classification, e.g. extending the crisp boundaries into a transition zone. Therefore, fuzzy sets can be characterized by the boundaries ($b1$ and $b2$) plus the transition zones ($d1$ and $d2$). For mathematical description, the fuzzy membership function can be a linear, a curved, or an S-shaped function (Robinson 2003). For example, Burrough (1989) used this approach for soil evaluation. A symmetric membership function was chosen to distinguish "deep" soil from "shallow" and from "very deep" soils. Other application of *SIM* in GISs can be widely found in literature, such as the definition of sharpness of boundaries in Wang and Hall (1996), an air pollution danger zone around a city in Usery (1996).

Opposite to the subjective approach of *SIM*, the fuzzy c-means (FCM) approach tends to be an objective approach. It is analogous to cluster analysis and numerical taxonomy in that the value of the membership function is computed from a set of attribute data. In such a way, an individual sample may have memberships of multi-classes. *FCM* is usually used in image classification (Bezdek et al. 1984, Chi and Yan 1995). Furthermore, other objective methods are applied to derive fuzzy membership values, such as self-organizing maps (Chi et al. 1995), fuzzy supervised classification (Mannan et al. 1998) and neural network (Sun and Jang 1993).

Table 4.1 Fuzzy definition for coastal landscape units (after Cheng and Molenaar 1999b)

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



Note: 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.

Here we took the *SIM* approach and defined the coastal landscape units by modifying the crisp definition in Fig. 4.2. The transition zones between these landscape units are defined as in Table 4.1. $b1$ and $b2$ represent the boundaries of the landscape units; $d1$ and $d2$ represent the half width of the transition zones. For example, if a region belongs to the foreshore then the height value of the region should be between -6.0 m and -1.1 m. As most experts take -6 m to be the closure depth, we could consider -6 m to be the boundary between foreshore and deep sea, but sometimes others take -8 m 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 $d1$ 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. In order to reveal the vagueness of definitions for the landscape units, we adopt a trapezoidal membership function to represent the fuzzy semantics.

We classify the grid cells of the case study area (Fig. 4.1) into classes of landscape units. As shown in Fig. 4.3(a) (b) and (c), each pixel has three membership values to three classes of landscape units.

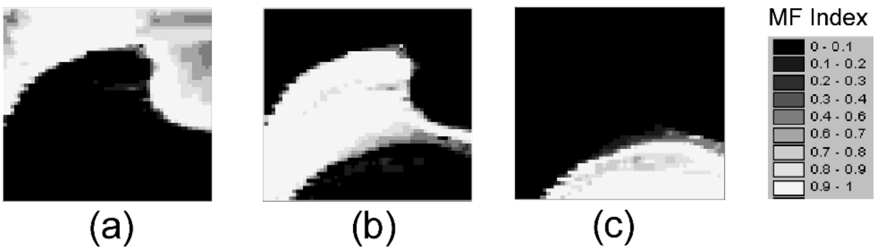


Fig. 4.3 Fuzzy classification results of Ameland (Cheng 1999): (**a**) Membership value of belonging to foreshore; (**b**) Membership value of belong to beach; and (**c**) Membership value of belonging to foredune (*darker* means lower membership)

4.4.2 Fuzzy Spatial Representation of Coastal Landscape Units

Figure 4.3 shows that the uncertainties in the specification of the spatial extent of objects are in this case due to fuzzy thematic classification of the raster cells. Although the uncertain classification is primarily considered to be thematic, it will lead to the geometry vagueness. For example, during image classification the certainty that a pixel belongs to a thematic class might be expressed through a likelihood function, which is evaluated in the classification process (Lillesand and Kiefer 1994). Image segments can then be formed of contiguous sets of pixels falling under the same class. If these segments represent the spatial extent of objects then the uncertainty of the geometry of these objects is due to the fact that the value of the likelihood function varies per pixel (Canters 1997, Wickham et al. 1997). Therefore, the thematic uncertainty is transferred to geometric uncertainty after segmentation (Molenaar 1998, Cheng and Molenaar 1999a). This section discusses how to represent coastal landscape units as fuzzy spatial objects.

The estimation of the spatial extent of objects from these fuzzy classifications is related to the interpretation of fuzziness of the objects and their topological relationship, as is their representation. In general, four views are applied to represent the fuzzy objects (Cheng 2002):

- ***Fuzzy – fuzzy area***: This representation is intuitively coming from the fuzzy classification result. Spatial objects can be extracted from these classification results with image segments consisting of contiguous sets of pixels, or grid cells, belonging to one class. The objects of one class can then be represented as a layer of the raster, so that layers of objects will be formed, each consisting of fuzzy regions (Molenaar 1998). If each region represents the spatial extent of an object, the object is called a fuzzy-fuzzy object (FF-Object), where the first "fuzzy" means that its spatial extent is fuzzy and the second "fuzzy" means that its thematic interior is fuzzy, because it contains cells that have been assigned to the thematic class of the region with a certainty less than 1 (see Fig. 4.4a). The representation of FF-objects is apparently similar to the fully-fuzzy area concept proposed by Foody (1999). The fully-fuzzy area is, however, still a direct representation of the fuzzy classification result. This means that thematic data is represented per cell (or pixel). The information has not been aggregated to an

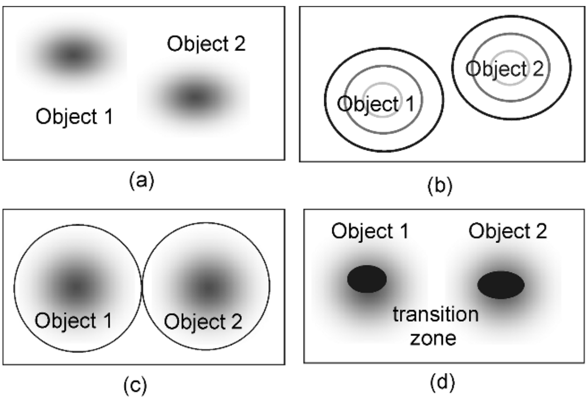


Fig. 4.4 Four ways to represent fuzzy objects (Cheng 2002): (**a**) Fuzzy-fuzzy areas; (**b**) α-cut boundaries; (**c**) Conditional boundaries; and (**d**) Core-transition zones

object level so that the uncertainty of the spatial extent of objects does not play a role in the analysis.

- ***α-cut boundary***: If we define a threshold value α, for the classification for each layer of the fuzzy-fuzzy areas, an α-cut boundary will be formed (Fig. 4.4b). In this case, the segments of each layer will have α-cut boundaries.
- ***Conditional boundary***: In other applications, area objects are defined as being spatially disjoint in space (in single context), i.e. they do not overlap such that each grid cell belongs in principle to one object. If the objects form a spatial partition then each cell should belong to exactly one object, as in the case study of coastal zone, where foreshore, beach and foredune are considered to be spatially disjoint objects. Although the boundary between beach and foredune cannot be located very crisply, the conceptual model suggests that a specific location should either belong to beach or foredune, but not to both. In this case it is necessary to combine the objects of different layers into one layer and to form a complete spatial partition of the area, which can be further differentiated into two classes of objects. One case is that a boundary has to be set to define explicitly the spatial extent of any object by assigning each grid cell to exactly one object. In such cases criteria (conditions) have to be applied to assign a cell to a specific class. After segmentation, the spatial extents of objects are identified and the boundaries between them are apparent automatically (Fig. 4.4c). These boundaries are called conditional-boundaries since they are based upon conditions (or criteria, Cheng et al. 2001).
- ***Core-transition zone***: Another case is that a clear boundary cannot be defined, but that there are transition zones between the objects. In the transition zones, no decision is made about which object the grid cells might belong to. Similarly, certain criteria are applied to assign the cell to the core of the objects or to the transition zones (Fig. 4.4d).

To differentiate between the last two situations, we call objects with conditional boundaries as crisp-fuzzy objects (CF-Object, see Fig. 4.4c), which means that the conditional boundaries between objects are crisp but the interiors of the objects are fuzzy. We call objects with core-transition zones as fuzzy-crisp objects (FC-Object, see Fig. 4.4d), where fuzzy means that their spatial extents (transition zones) are fuzzy and crisp means that their interiors (cores) are certain. Therefore, we call the objects based upon fuzzy-fuzzy areas and α-cut boundaries as FF-objects and αF-objects, respectively. The conventional objects with crisp boundary and crisp interiors are called CC-objects (see also Table 4.2).

Table 4.2 Different views of objects and their characteristics (Cheng 2002)

Type*	Boundary	Interior	Transition
CC	Crisp	Crisp	/
FF	Fuzzy	Fuzzy	Fuzzy
αF	Crisp(α)	Fuzzy	Fuzzy
CF	Crisp(c)	Fuzzy	/
FC	/	Crisp(c)	Fuzzy

*Refer to Fig. 4.4 for the definition of each type of fuzzy object representation.

How to derive the fuzzy spatial objects from fuzzy classification please refer to Cheng et al. (2001) for details. The next subsection shows the results of Ameland case under different fuzzy spatial object models.

4.4.3 Modeling Results of Ameland

Here we present the spatial representation of the landscape units under four fuzzy object models:

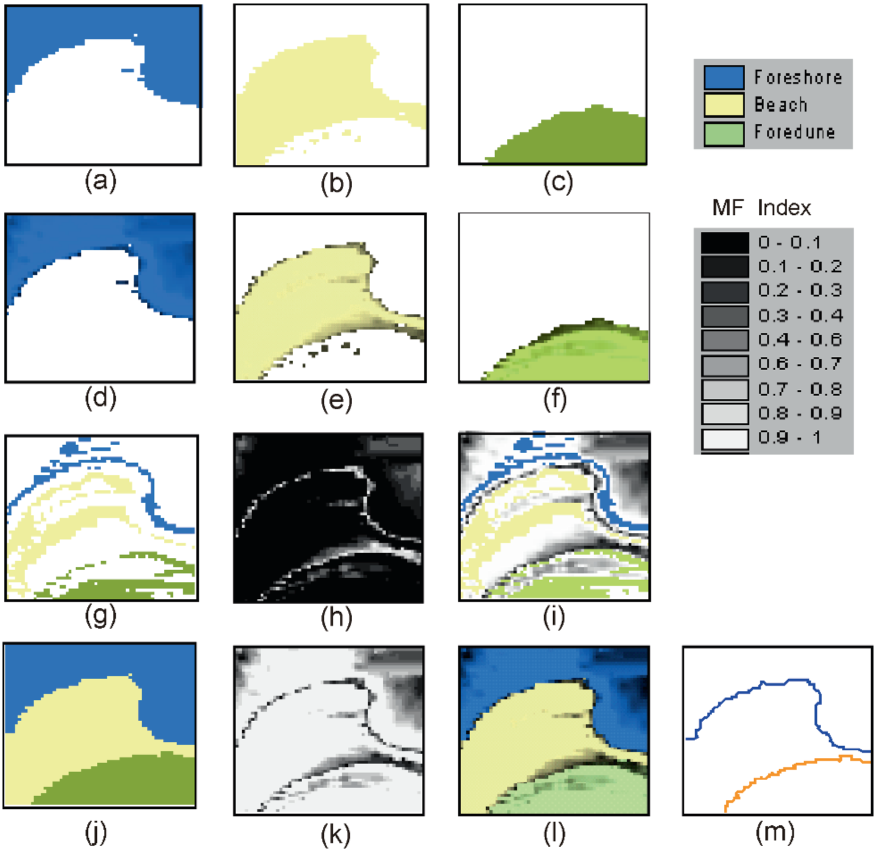


Fig. 4.5 Fuzzy modeling results of Ameland (Cheng 1999). Results from the FF-objected modeling are represented by (**a**): FF-objects belong to foreshore*; (**b**): FF-objects belong to beach*; (**c**): FF-objects belong to foredune*; (**d**): (**a**) FF-objects belong to foreshore with fuzziness; (**e**): FF-objects belong to beach with fuzziness; and (**f**): FF-objects belong to foredune with fuzziness. Results from the FC-object modeling are represented by (**g**): Cores of FC-objects; (**h**): Transition zones of FC-objects; and (**i**) FC-objects with fuzziness. Results from the CF-Object modeling are shown in (**j**): CF-object model; (**k**): Certainty of cells belonging to objects; (**l**): Objects with uncertainty; and (**m**): Conditional boundaries between regions. Note that the threshold value (*) used was 0.2 and darker means greater uncertainty

- ***Modeling by fuzzy-fuzzy object model***: The modeling results by FF-object model are shown in Fig. 4.5(a–f). The edges of the outmost grid cells of each object are the conditional boundaries, with a threshold of 0.2. Figure 4.5(a–c) each represents a layer with objects of one type. When these layers are overlaid, it is clear that these regions overlap. The fuzzy spatial extent of the objects is shown in Fig. 4.5(d–f).
- ***Modeling by fuzzy-crisp object model***: Figure 4.5(g–i) represents the core of the FC-objects. Figure 4.5g represents the cells with values approximately equal to 1, which represent transition zones among FC-objects. By combining Fig. 4.5(g,h), FC-objects are shown in Fig. 4.5i.
- ***Modeling by crisp-fuzzy object model***: The modeling results of the CF-object model are shown in Fig. 4.5(j–m). Figure 4.5j shows the spatial extent of CF-objects. Figure 4.5k represents the uncertainty of cells belonging to the objects. The transition boundaries among objects (belonging to three classes) are shown in Fig. 4.5l.

4.5 Dynamic Process of Fuzzy Coastal Landscape Units

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 by linking the lifeline the regions at different epochs to form lifelines of the objects (Cheng 1999). This section, however, proposes a method for analyzing the relationships of regions and for identifying objects and their processes automatically.

This can be realized based on the assumption that natural phenomena are changing gradually, especially the change of coastal zone can be regarded as a gradual continuous process (Galton 1997), so the objects are considered to be rather stable. 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 $t_{\text{n}+1}$. The one that has maximum overlap will be identified as the successor (Cheng and Molenaar 1999b).

4.5.1 Linkage Between Epochs

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

Assuming that $Size(P(i,j)) = 1$, then $\mu_s(i,j) \cdot \mathrm{Size}(P(i,j)) = \mu_s(i,j)$. Further, let $\mathrm{Size}(S) = \sum_{(i,j)} \mu_s(i,j)$ be the integral of the membership function associated to the region S, over the spatial domain. Then $\mathrm{Size}(S \cap S') = \sum_{(i,j)} \mu_{s \cap S'}(i,j)$ 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 and R_2 the set of regions at epoch T_{i+1}. Further, 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 (Molenaar 1998)

$$ROverl(S'|S) = \frac{Size(S \cap S')}{Size(S)} \tag{4.1}$$

$$ROverl(S|S') = \frac{Size(S \cap S')}{Size(S')} \tag{4.2}$$

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 (Cheng and Molenaar 1999b)

$$\mathrm{Similarity}(S,S') = \frac{Size(S \cap S')}{\sqrt{Size(S) \cdot Size(S')}} \tag{4.3}$$

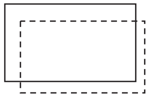
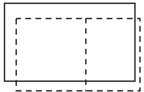
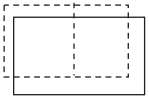
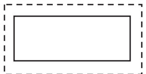
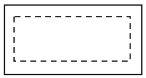
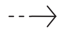
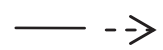
4.5.2 State Transitions

Using these indicators, object state transitions can be identified between two epochs. Seven fundamental cases are shown in Table 4.3. The combinations of indicator functions behave differently for these seven cases. State transitions can be identified by the following process:

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 $Roverl(S' \mid S)$, $Roverl(S' \mid S)$, $Similarity(S' \mid S)$
      >evaluate $shift(S;S')$, $expand(S;S')$, $shrink(S;S')$
    >evaluate $split(S;\ldots S',\ldots)$, $appear(S')$
>evaluate $merge(\ldots,S,\ldots,S')$, $disappear(S)$

Evaluation is done by identifying the type of state transition between S and S' based upon the indicators according to the situations indicated in Table 4.1. For

Table 4.3 Identification and presentation of state transition (Cheng1999)

Regions at T_1	Regions at T_2	Overlay	Indicators			State Transition	Symbol
			Rovelap(S_b|S_a) Similarity Rovelap(S_c|S_a)	/Rovelap(S_a|S_c)	Rovelap(S_a|S_b)		
			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)	
		–	– –	– –	– –	appear(S_b)	
	–	–	– –	– –	– –	disappear(S_a)	

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 process implies that two or more regions $S \in R_1$ merge into one region $S' \in R_2$. Here we illustrate how the indicators could be used to detect the state transitions. Threshold vales have been chosen intuitively based on expert knowledge. Further research is required to establish threshold values for these indicators.

The fuzzy sizes of these regions and the fuzzy overlap of regions of successive years are shown in Table 4.4. The indicators of Sect. 4.5.1 can now be evaluated; with these we can link the regions (as shown in Table 4.4) 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 too.

Table 4.4 Fuzzy overlaps and links between fuzzy regions (Cheng and Molenaar 1999b)

Year	Region	Area	Overlap with regions in next year				Class Type
1989/1990			4	5	6	7	
	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
1990/1991			8	9	10		
	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	64.3		Foredune
	7	28.0	0.0	0.0	26.3		Beach
1991/1992			11	12	13	14	
	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
1992/1993			15	16	17	18	
	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

4.5.3 Lifelines of Dynamic Objects

The procedure of the previous section 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

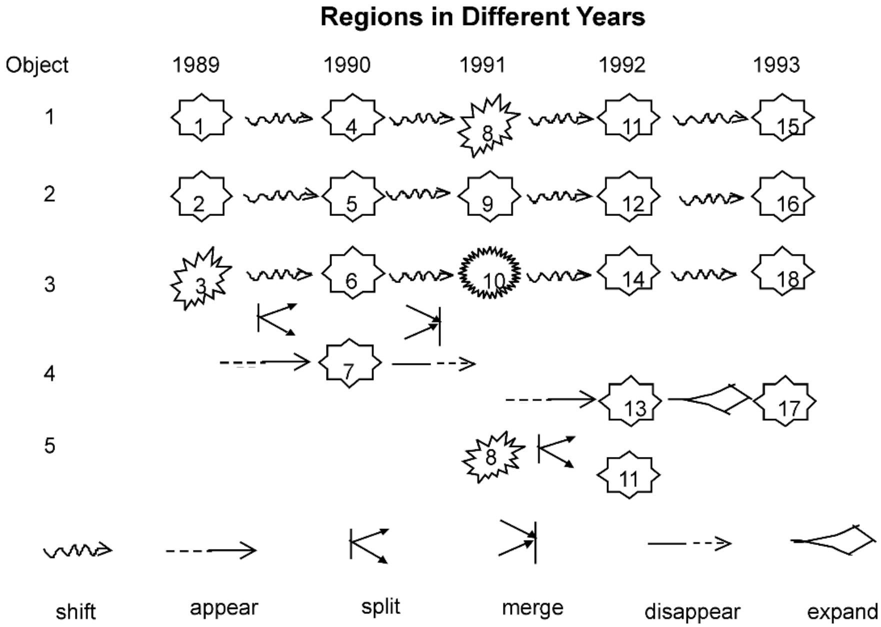


Fig. 4.6 Identified fuzzy objects and processes (Cheng 1999)

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 (See Fig. 4.6). The objects are finally identified and are represented in Fig. 4.7a.

Recently Guilbert and Lin (2007) used snake algorithm to detect the change of cloud for weather forecasting, which is quite similar to the method proposed here. It implies that the method proposed is also applicable for crisp objects.

4.6 Change in Area and Volume of Beach

4.6.1 Change of Shape and its Uncertainty

By comparing the spatial extents of an object in two successive years we can derive the change of shape. This can be done through a simple spatial overlay operation. The uncertainty of change can be derived from the classic intersection of the uncertainty of the grid cells belonging to the object's extent for each year (Molenaar 1998, Cheng 2002)

$$\mu^{p}_{S_a;S_b} = MIN(\mu(P,S_a)_{t_1}, \mu(P,S_b)_{t_2})\ (a \neq b) \tag{4.4}$$

where $\mu^{p}{}_{S_a;S_b}$ is the uncertainty of the change of a grid cell P which belongs to Object O_a at t_1 and Object O_b at t_2; S_a is the spatial extent of O_a at t_1, S_b is the

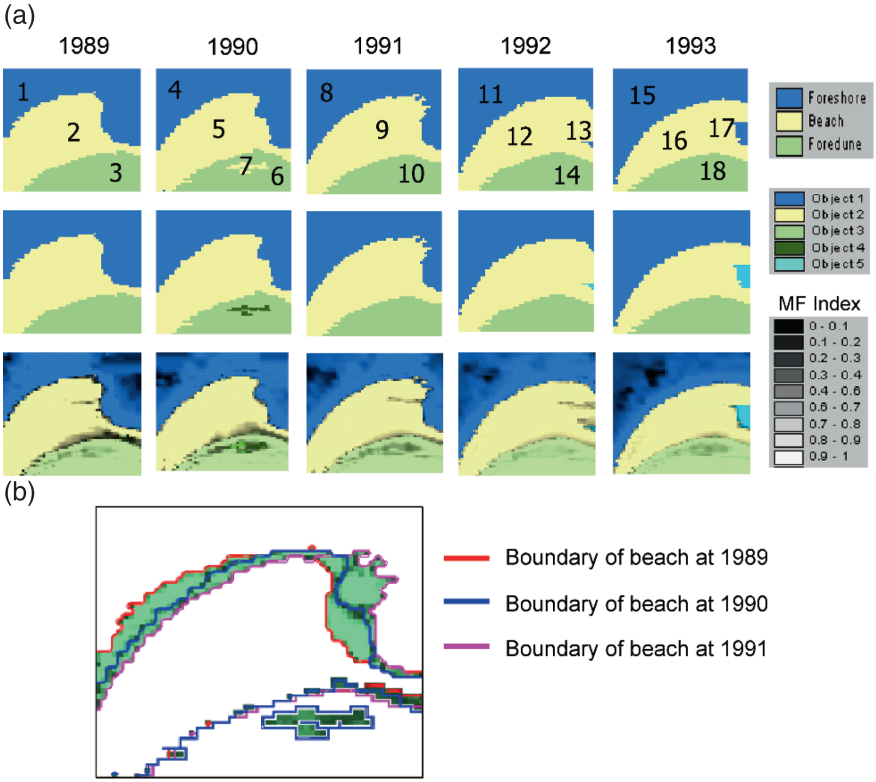


Fig. 4.7 (**a**) Dynamics of fuzzy objects (after Cheng 1999) (the *top three rows*): the *top row* for identified fuzzy-crisp regions, the *second row* for fuzzy objects without showing uncertainties, and the *third row* for fuzzy objects showing uncertainties; (**b**) Change of beach during 1989–1991 (Cheng 2002) (the *bottom row*)

spatial extent of Object O_b at t_2; $\mu(P,S_a)_{t_1}$ represents the uncertainty of P belonging to S_a at time t_1; $\mu(P,S_a)_{t_2}$ represents the uncertainty of P belonging to S_b at time t_2.

For example, a grid cell belonged to foreshore (Object O_a) in year 1989 with certainty value $\mu(P,S_a)_{t_1} = 0.65$. It belonged to beach (Object O_b) in year 1990 with certainty value $\mu(P,S_b)_{t_2} = 0.78$. Therefore, the uncertainty of change of this cell according to Eq. (4.4) is then,

$$\mu^{P}{}_{S_a;S_b} = MIN(0.65, 0.78) = 0.65.$$

The changes of extent of these landscape units of 1989–1990 and 1990–1991 are presented in Fig. 4.7b. It can be seen that the foreshore and beach were very active, but the foredune was quite stable. The changes of the foreshore and the beach were normally opposite to each other. It was also found that the certainties of change of the cells close to the center of the changed area were higher than those close to the edge of the changed area. This is due to the fact that the cells closer to the edge of the changed area are closer to one of the edges of the two objects, which are less certain than the cells closer to the centers of the objects.

Based upon this analysis, the developing trends of these landscape units can be analyzed qualitatively. Moreover, based upon this result, the changes of the landscape units can be calculated at different certainty levels. The changes of foreshore and beach (1989–1990) at different certainty levels are reported in Table 4.5. The number of cells falls with the increasing level of certainty. It implies that only definite changes from foreshore to beach (accumulation) fare in 25 pixels and beach to foreshore (erosion) are in a different 25 cells.

Based upon the change map of Fig. 4.7b, a series of change maps for different α-cuts (certainty levels) was derived in Fig. 4.8.

Table 4.5 Changes between foreshore and beach at different certainty levels (Cheng 2002)

Certainty level $\geq$	1.0	0.9	0.8	0.7	0.6	0.5
Foreshore to beach*	25	58	67	75	87	94
Beach to foreshore*	25	77	92	102	110	121

*Number of grid cells.

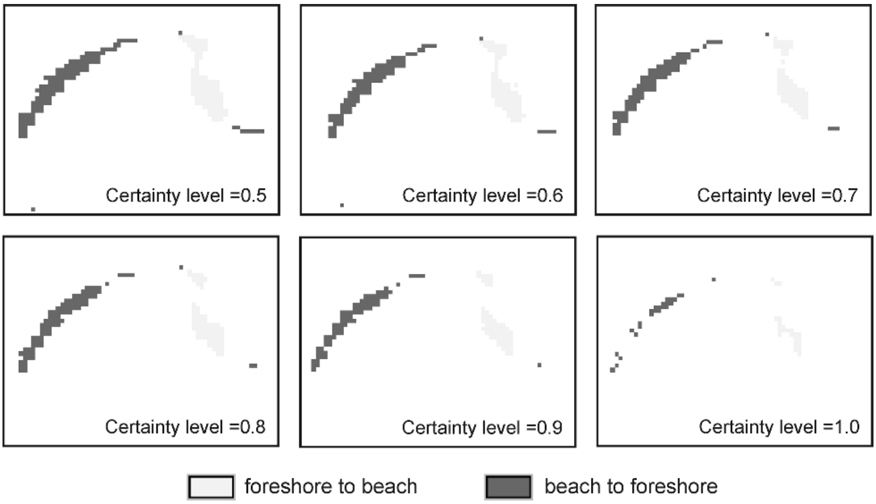


Fig. 4.8 Change between foreshore and beach at different certainty level (1989–1990) (Cheng 2002)

4.6.2 Changes of Area and Volume

In the crisp object model, the area of an object O is

$$Area(O) = \sum_{P \in 0} Size(P) \tag{4.5}$$

The area of a fuzzy object O is then defined as (Molenaar 1998)

$$FArea(O) = \sum_{P \in S} \mu(P,S) * Size(P) \tag{4.6}$$

where S is the fuzzy spatial extent of O, $\mu(P,S)$ is the uncertainty that grid cell P belongs to S, and in our case $Size(P) = 60 \times 60\ (\mathrm{m}^2)$.

Calculating the volume of a fuzzy object is similar to calculating its area. In both case uncertainties of the grid cells belonging to the objects have to be taken into account.

$$FVolume(S) = \sum_{P \in S} \mu(P,S) * Size(P) * h_P \tag{4.7}$$

where h_p is the height of the grid cell with respect to a reference level and it is -20 m in our case, since some points on the test area are lower than sea level, e.g., -16 m. Other symbols refer to Eq. (4.4).

The area and volume of the landscape units are presented in Fig. 4.9, which shows that the fuzzy area of the whole region is not constant. This is because the certainties of the spatial extents of the landscape units varied from year to year. The total volume of sediment in the test field is decreasing which indicates general erosion. This information can be used to guide the coastal defense works such as beach nourishment that needs high investments.

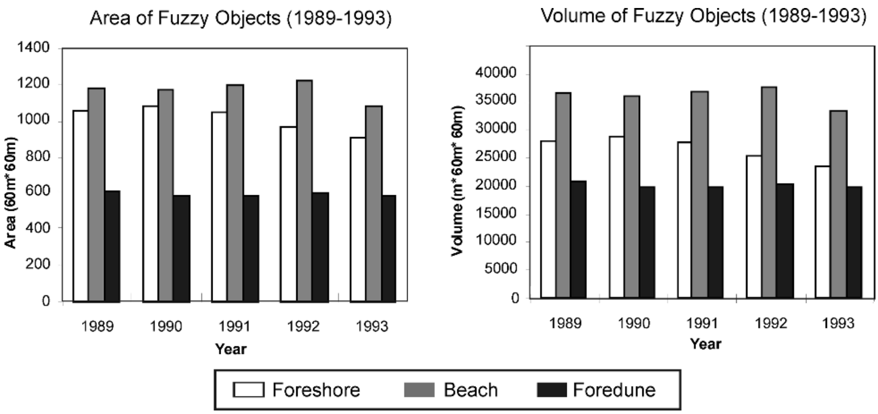


Fig. 4.9 Dynamic changes of area and volume of fuzzy objects (after Cheng 2002)

4.6.3 Discussion

4.6.3.1 Two Ways of Calculating Change of Beach

Two ways were proposed to calculate the change of beach area. In the first approach the changes are based upon the areas of beach in the consecutive years. The cells of the whole area of beach, including the unchanged part, are considered for the calculation. Therefore, in this case, the calculation is related to cells in the changed areas and to their certainties of belonging to the areas. It is also related to the change of certainty in the unchanged area (Cheng 2002). In the second approach, only cells in the changed area are considered for the calculation. In this case study, the calculation is related to the certainties of the cells in the changed areas, which are related to both the certainties the cells belonging to foreshore, beach and foredune in two years.

The first approach has been based on the changes of the certainties of cells belonging to beach in two consecutive years, while the second approach has been based only on the areas of the change. Which method should be chosen for fuzzy objects depends on the specific case. It is important to understand and analyze the uncertainty behind the calculations in order to provide accurate information to decision makers. In the first case the area is predefined, the uncertainty is related to the whole area. The change of area also considers the uncertainty of the whole area. In the second case, uncertainty is considered only for the changed area which implies a specification of the type of change. Therefore, when we want to measure the change related to a landscape unit, the first approach should be taken. When we want to measure the change as an interaction between two landscape units, the second approach should be taken. Generally Fig. 4.7b provides a more accurate and efficient way of representing the change, since the maps in Fig. 4.8 could be derived from it (Cheng 2002).

4.6.3.2 Fuzzy and Crisp Approaches

In order to estimate the consequence of the uncertainties in object definition and field observation data, we derive crisp objects by using crisp object definition and without considering the uncertainty of object identification. The spatial extents of crisp objects are similar to fuzzy objects. However, the area and volume of crisp objects are different, they are larger (please refer to Cheng (2002) for details). The differences between these imply the influences of uncertainties. The foreshore area has the most obvious difference because its fuzzy definition has a wider transition zones (2.0 m) than beach (0.5 m) and foredune (0.5 m). The change of beach derived from crisp approach is similar to the result derived from fuzzy approach 1 since they apply similar approach i.e. consider the whole area of beach for calculation (Cheng 2002).

4.6.3.3 Prediction of Changes

To model and predict changes of coastal landscape units, we analyzed the stationarity of change over a period of 7 years (1989–1995) by both crisp and fuzzy approaches. This study extends previous work on fuzzy Markov chains by Dilo (2006, Chap. 7). For the fuzzy approach, the changes of objects under the *CF* model have been discussed above (as shown in Fig. 4.9). We also analyzed the interactive changes between Foreshore, Beach, Foredune and undecisive areaes for the αF model (Table 4.2) with α at 0.25, 0.5, 0.75 and 1, respectively.

1. The results of the CF model are similar to those for α is at 0.25 or 0.5, but they are quite different from the results for α is at 0.75 or 1. These results clearly confirm the fuzzy nature of these coastal landscape units and that a crisp or a slightly fuzzified approach does not give very realistic results.
2. We further see that the average interactive changes for α at 0.25, 0.5 are the same as those for the *CF* model:

   - the average percentages of the beach area changing into respectively foreshore, foredune, undecisive areas are 9.8%, 1.2%, 0%, and
   - the average percentages of respectively forshore, foredune and undecisive areas changing into beach are 4.8%, 2.8% and 0%.

This indicates the whole case study area has been eroded over this period of seven years since there is a dominant change from beach to foreshore and from foredune to beach. This is also shown in our results, only 89% of the beach area remains beach in the consecutive years.

3. In most years, at almost all levels of α, undecisive areas change into foreshore, whereas only a small part changes to beach for $\alpha > 0.5$. This implies that the foreshore area is fuzzy indeed, with low membership values. Those areas might have height < -6.0 m, indicating erosion in the area, which is mainly changing into foreshore. That also indicates a general erosion of this coastal area, with a dominant change from beach to foreshore.

4.6.3.4 Other Approaches

Fuzzy area estimation is also discussed in Woodcock and Gopal (2000), but their analysis is based upon fuzzy classes, not fuzzy objects. Although they also intended to estimate the area of a class as a function of levels of fuzzy membership, they calculated the area of a class meeting certain criteria, i.e. membership levels. The class proportions have to be calculated for each class at different membership levels. In our case, the membership function per cell belonging to an object (the spatial extent) is considered in the calculation of the area of the fuzzy object. We cannot tell which method is better, but the method proposed here is quite simple and straightforward. However, the author agrees with Woodcock and Gopal (2000, p. 171) to that to determine areas meeting various conditions, questions of the sum equaling unity are irrelevant. Since the problem of area estimate is viewed from fuzzy set theory, this assumption of unity for the sums of the areas of map categories also becomes irrelevant. It also applies to the fuzzy areas that change with time.

4.7 Conclusion

This chapter presents a systematic discussion of fuzzy approach for integrated coastal zone management. It discussed the indeterminate nature of coastal landscape units and how they are represented as fuzzy spatial objects in GIS. Furthermore, the identification of dynamic process and the change of these fuzzy objects and uncertainties are investigated. An example of the dynamic changes of sediments along the Dutch coast is applied to illustrate the methodology. The method is also applicable in monitoring geographical entities such as natural vegetation units or land use areas.

By comparing the results mapped by the crisp object model and the fuzzy object model, it was revealed that uncertainties in object definition and in field measurements have obvious influences on change detection of geometric attributes of geographical entities. It is important to study these influences to provide accurate information to decision makers. The changes of uncertainty for an object imply its potential change in future. Exploring these changes is essential for the prediction of the potential development of geographical entities; this will be the future direction of this research. Moreover, this chapter only discussed the situation that fuzzy classification is due to multiple criteria of object definition and errors in the measurement. How to handle other situations, such as the definition of objects changing with time, will be another topic for future research (Van de Vlag and Stein 2006). Furthermore, the uncertainties resulted from multi-scale definitions needs further investigation and further reading can be found at (Cheng et al. 2004, Fisher et al. 2007).

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