Monitoring of salt-marsh vegetation by sequential mapping
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3 Uncertainties in vegetation mapping and monitoring: general introduction

J.A.M. Janssen

3.1. Introduction

A vegetation map is a two-dimensional model of the real world phenomena vegetation, where the vegetation is represented by objects. It is part of a reasoning system of which the outputs are statements on the objects (figure 3.1). The objects are not simply ‘out there’ in the real world and it is not always clear how the objects in a model can be linked unambiguously to real world phenomena. Therefore, the statements on these objects have a certain measure of uncertainty (Molenaar 1994). In a reasoning system, uncertainty is defined as the difference between a certain statement on an object and the truth. Uncertainty on the objects results from uncertainties in source data and processing steps and real world variability.

For a user of geographical data it is necessary to separate between the data and the uncertainty in the data (Fenstermaker 1994). To separate between these it is necessary to know the real world variability as well as the uncertainties in the source data and processing steps.

![Vegetation mapping as part of a reasoning system](image)

Figure 3.1. Vegetation mapping as part of a reasoning system
In this chapter an inventory will be made of the uncertainties that occur in the used vegetation mapping methods (photo-interpretation and digital image processing) and in change analysis. Firstly, the terms that are used in the uncertainty analysis are defined (§3.2). The remaining part of the chapter provides an overview of uncertainties in photo-interpretation (§3.3), digital image processing (§3.4) and vegetation change analysis (§3.5). The uncertainties have been divided after the different attribute dimensions of geographical objects: spatial, thematic and temporal and after the different steps in the mapping methods. Chapters 4 to 6 aim at analyses of the uncertainties that contribute mainly to the uncertainties in the results of change analyses based upon sequential vegetation maps. In chapter 7 the interaction between the main uncertainties in a change analysis is discussed and an overall uncertainty model is constructed for change analysis with sequential maps.

3.2. Terminology

Many authors give an overview of uncertainties in models of geographical phenomena (a.o. Burrough 1986; Campbell 1987; Drummond 1987; Chrisman 1991; Lunetta et al. 1991; Lanter & Veregin 1992; Heuvelink 1993; Molenaar 1993; Janssen & van der Wel 1994; Burrough & McDonnell 1998; Skidmore 1999; Khorram et al. 1999; van der Wel 2000). The terminology and classification of uncertainties differ strongly among the various authors. Van der Wel (2000) attempted to bring about uniformity by discussing the various terms and taxonomies. This thesis follows his definitions of terms, except for ‘uncertainty’ which is considered synonymous to error (after Heuvelink 1993).

Uncertainty is used as a general term and is defined as the difference between reality and a representation of reality. It includes not only ‘mistakes’ or ‘faults’ but also the statistical concept of ‘variation’. Error is synonymous to uncertainty. Error propagation is defined as the way in which input errors accumulate and affect the end-result of a model (Burrough & McDonnell 1998).

Accuracy is a measure for the deviation between observation values and values excepted as being true (after Burrough 1986). To assess accuracy, a source of higher accuracy is needed as a representation of the true world (van der Wel 2000). Accuracy relates to discrepancy between two models, while uncertainty relates to discrepancy from the truth.

Precision is the exactness with which a value is expressed, whether the value be correct or incorrect (AGI 1991); it is a measure for the spread of results of repeated measurements.

Reliability is defined in a statistical way, as the repeatability and verifiability of measurements and processing results.

Resolution is equivalent to the detail level.

Quality is the fitness for use of data or a model. It is a relative concept, dependent on the pursued aims and the considered context and it is synonymous with suitability and applicability.
3.3. Vegetation mapping by photo-interpretation

3.3.1. The Landscape Guided Method

Vegetation maps have been made by visual interpretation of aerial photographs according to the Landscape Guided Method (LGM) as developed by Zonneveld at the ITC in Enschede (Zonneveld et al. 1979; Zonneveld 1979; 1988; 1994; 1995). At the Rijkswaterstaat Survey Department (RWS-MD) this method has been formalised in order to use it in an operational way for vegetation mapping (Kloosterman et al. 1987; Kloosterman 1991b; Janssen 1996).

The essence of the method is a stereoscopic interpretation of aerial photographs in which land units are distinguished and delineated in a hierarchical way (chorological classification). The content of a land unit is described in a legend unit by the proportion of photo-elements (the smallest spatial units that can be distinguished on an aerial photograph, but can not be mapped individually at the photo scale). A land unit can be either homogeneous (containing one photo-element) or consisting of a complex of elements that cannot be mapped separately. A field sampling is carried out in a stratified random way,

![Diagram](image_url)

*Figure 3.2. Mapping stages in which uncertainties arise in the Landscape Guided Method*
based on the distinguished photo-elements. At the sample points in the field vegetation relevés are made and the vegetation relevés are clustered into vegetation types (vegetation classification), according to the Braun-Blanquet method (Westhoff et al. 1995; Schaminée et al. 1995b). As a sample point represents both a photo-element (in the chorological classification) and a vegetation type (in the vegetation classification) it is used to establish the relation between the legend units and the vegetation types. Finally the map is digitised and stored in a geographical information system (GIS). The process stages are shown in figure 3.2. The method is described in detail in appendix 3.

3.3.2 The Photo Guided Method

The Photo Guided Method (PGM) is a variant of the Landscape Guided Method in which the photos are only used to derive boundaries of the land units. This photo-interpretation is carried out in a non-hierarchical way (Zonneveld et al. 1979). The field work is carried out in a photo guided way, meaning that the determination of land unit content is carried out in the field. For the translation from vegetation stands to vegetation types in general, a preliminary vegetation classification is used.

The PGM is generally used for surveys in which the complete area can be visited in the field. Besides, the PGM is the only suitable photo-interpretation method in areas with a dense homogeneous upper vegetation layer, which covers vegetation differences underneath (Zonneveld et al. 1979). For many surveys a combination of the LGM and the PGM is used, in which the latter method is used for those areas where a translation from photo-elements to vegetation types is difficult.

3.3.3. Uncertainties in photo-interpretation

The steps of the Landscape Guided Method in which uncertainties arise are shown in figure 3.2. An overview of the uncertainties in the LGM and in digital image processing is given in table 3.1.

In the image acquisition geometric and thematic uncertainties arise that are related to the spatial and spectral properties of the sensor system, the elevation, stability and movement of the platform and the atmospheric conditions and season of image acquisition. For the images in this thesis a photogrammetric quality check was handled, as described by Koppejan et al. (1999). By passing this check, these uncertainties are considered negligible. The image acquisition uncertainties that effect the geometric and thematic interpretation of the image are discussed in those stages.

The thematic units on a vegetation map are vegetation types. The vegetation typology depends on the field sampling and on the classification of vegetation samples. Both steps contain subjective steps and expert-input. This causes uncertainty on the results. These uncertainties are discussed in chapter 5. In the photo guided method the description of the content of chorological units is carried out in the field. This process requires more ecological knowledge and introduces subjective interpretations in the field, which induce uncertainty. The uncertainties in the photo-guided method are not discussed here in detail. The spatial land units are derived from photo-interpretation. In this step uncertainties occur due to subjectivity in the interpretation of boundaries. This chorological uncertainty is discussed in chapter 6. In the photo-interpretation thematic uncertainties arise from the
classification of photo-elements and the description of land units. These thematic photo-interpretation uncertainties are discussed in §6.2.

Chorological and thematic photo-interpretation uncertainties are closely related: the identification of a boundary involves the description of the land unit content and vice versa. Thematic uncertainties arise also in the translation from photo-elements to vegetation types. This ‘allocation uncertainty’ is discussed in §6.3.

Other sources of spatial uncertainties are geometric uncertainties during geo-referencing. These uncertainties arise due to the geometric imprecision and inaccuracy of the source data, which are a.o. related to the properties of the sensor system and the elevation, stability and movement of the remote sensing platform and relief in the field (Skidmore 1999). Imprecision or inaccuracy of co-ordinate measurements of ground control points (GCPs), inaccuracy in the allocation of the GCPs on the image and the number of GCPs used for geometric transformation also bring about uncertainties. Furthermore, geometric uncertainty is heightened by the algorithm used for geo-referencing and the interpretation of analogue images (from the acquisition of boundaries from aerial photographs by pen and from digitising of the boundaries).

Geometric accuracy may be expressed as a root-mean-square error (RMSE), which is the difference between the transformed GCPs and the original GCPs or the standard error (Skidmore 1999) or may be modelled as an epsilon band (a band that indicates the uncertainty range in the position of a line), according to Perkal (1966), Blakemore (1984) and Dunn et al. (1990). Alternatively, geometric uncertainty may be measured by intersect sampling (Skidmore & Turner 1992; Abeyta & Franklin 1998).

In general the geometric accuracy is relatively high in the mapping methods applied in this thesis. Generally a RMSE < 3 m is derived for maps based on aerial photographs at scale 1:5,000. The geometric uncertainties are of minor importance, compared to thematic uncertainties, so they will not be discussed here in further detail.
3.4. Vegetation mapping by digital image processing

3.4.1. Supervised, unsupervised and fuzzy classification

Digital remote sensing images are recorded in a raster format, resulting in an image of pixels (rectangular faces), which consist of measurements of electro-magnetic radiation (usually sunlight) intensity, which is reflected by the earth surface. The processing of digital images has been carried out in two different ways: supervised or unsupervised (figure 3.3). These methods differ in the way of allocation of thematic classes to pixels, which is called image classification.

In an unsupervised classification a fully automatic classification is carried out, based on the spectral features of all pixels. The only input is the number of classes to be distinguished. No training samples are used. The resulting classes in the image are allocated afterwards to thematic classes, using ancillary data.

For unsupervised classification the ISODATA algorithm in the software IMAGINE 8.3 (ERDAS 1997) has been used. This algorithm uses the minimum spectral distance between classes for clustering in an iterative way.

A supervised classification is based on a priori image sampling. The sites of known ground samples are located in the digital image as so-called areas-of-interest (AOIs), the training samples. The spectral and spatial signatures of these AOIs are used to classify all pixels of the image. To separate between different thematic classes the spectral values of AOIs must be relatively homogeneous and must differ from the spectral values of other classes. This may be judged by plotting the values (mean and standard deviation) in a two-dimensional representation of the values for all samples in two wave bands, called a feature space plot.

![Diagram](image)

**Figure 3.3.** Process stages in which uncertainties arise in digital image processing
For supervised classification the maximum likelihood algorithm in IMAGINE 8.3 (ERDAS 1997) has been used. This is a classifier, which calculates for each pixel the probability that it belongs to any class. The calculation is based on estimates of the probability density. A priori probabilities may be incorporated. Finally, the algorithm chooses the class with the largest probability. When estimating probability densities it is assumed that reflections are drawn from a normal (Gaussian) distribution (Gorte 1999). The maximum likelihood algorithm allocates one thematic class to each pixel. In this thesis besides a fuzzy algorithm has been used for this allocates more than one thematic class to each pixel.

Both supervised and unsupervised classification methods start with geometric correction (geo-referencing) of the original image, for which ground control points are used. This step involves resampling of the pixels. Other steps which may be applied are stratification (using ancillary data) and post-processing (for example with smoothing filters).

A fuzzy classification algorithm enables a pixel to possess multiple and partial class membership (Foody 1992a, 1996; Droesen 1999). A pixel is assigned to different classes and for each class a membership value (MV) is calculated, where the sum of MVs equals 1. The fuzzy classification enables more accurate characterising of mixed pixels and of gradual transitions between thematic classes. Besides, a fuzzy sets approach has the advantage of not making assumptions about the statistical distribution of the data.

For fuzzy classification a fuzzy algorithm may be used (Bezdek et al. 1984) or ‘soft’ outputs from other algorithms may be used, like the probability values from a maximum likelihood classifier or the results from a linear unmixing algorithm (Bastin 1997). In the optimal form, fuzziness is accommodated in the training, classification and validation stage of digital image processing (Foody 1999).

### 3.4.2. Uncertainties in digital image processing

In digital image processing, uncertainties occur during the different steps of figure 3.3. The steps of field sampling and vegetation classification are the same as for the Landscape Guided Method. These are discussed in chapter 5.

Thematic uncertainties in the source data arise due to the spatial and spectral resolution and accuracy of the sensor system, the elevation, stability and movement of the platform, atmospheric conditions and weather conditions. These thematic uncertainties in the source data change due to radiometric enhancement and resampling during geo-reference. All these uncertainties are considered of minor importance.

Geometric uncertainties are also of minor importance for the making of a single map. If sequential maps of the same area are compared on a pixel-by-pixel basis, the geometric accuracy must be within 0.5 pixel (Khorram et al. 1999). If the geometric inaccuracy is larger, spatial generalisation may be applied before carrying out a change analysis procedure. If the spatial patches in a classified image are much larger than the pixel size, a RMSE of more than 1 pixel may be acceptable. The digital images, used in this thesis, had a RMSE of less than 1 pixel. Sequential images were geo-referenced with a RMSE < 0.5 pixel. Therefore, geometric uncertainties in digital images are considered negligible.

In image classification, uncertainty arises due to spectral confusion between thematic classes and due to mixed pixels or mixels (pixels that in reality contain a mixture of different vegetation stands, but are allocated to one thematic class). The spectral confusion is influenced by the sampling strategy (spectral homogeneity of the samples, the number of samples of each class, the geometric accuracy of the sample locations, merging of individual samples of the same class), the classification algorithm and the properties of the
RS-image (the spatial, spectral and radiometric resolution) compared to the vegetation patterns in the field and the defined vegetation classes (Janssen et al. 1999a).

3.4.3. Accuracy assessment of image classification

Standards in accuracy analysis of image classification are the validation matrix (or accuracy, error or confusion matrix) and parameters derived from it (Congalton & Mead 1983; Dicks & Lo 1990; Congalton 1991; Lunetta et al. 1991; Janssen & van der Wel 1994). Parameters that can be derived from a validation matrix are producer’s accuracy (% of the classified pixels of a class that is allocated to that class correctly), user’s accuracy (% of the classified pixels of a class that indeed belongs to that class), errors of commission or type I error (100% - user’s accuracy), errors of omission or type II error (100% - producer’s accuracy) and overall accuracy (Congalton & Mead 1983; Congalton et al. 1983). An example of a validation matrix with derived parameters is given in table 3.2.

In the overall accuracy a certain number of correctly classified cases are expected to occur by chance (Goodchild 1994). Furthermore, the overall accuracy does not take into account the accuracy of different categorical classes. Cohen (1960) and Bishop et al. (1975) defined a different measure of agreement for nominal scales, called the Kappa coefficient. The ‘Kappa’ measures the relationship beyond chance agreement to expected disagreement. It uses all cells in the validation matrix, not just the diagonals. The Kappa can be estimated by:

\[
\kappa = \frac{N \sum_{i=1}^{r} X_{i} - \sum_{i=1}^{r} X_{i} X_{i}}{N^2 - \sum_{i=1}^{r} X_{i} X_{i}},
\]

where \( r \) is the number of rows and columns in the validation matrix, \( N \) is the total number of observations, \( X_{i} \) is the sum of the \( i \)th row, \( X_{i} \) is the sum of the \( i \)th column and \( X_{ij} \) is the count of observations at row \( i \) and column \( i \) (Bishop et al. 1975; Skidmore 1999). The Kappa coefficient provides a relative measure of the agreement between map data and ground truth compared to the agreement by chance. A value of 0 indicates that all agreement between map data and ground truth occurred by chance. A value of 1 indicates that there is perfect agreement between two data sets. Less than chance agreement leads to

<table>
<thead>
<tr>
<th>Classified</th>
<th>Producer’s accuracy</th>
<th>Omission error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference data</td>
<td>Totals</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>150</td>
<td>21</td>
</tr>
<tr>
<td>Crop</td>
<td>0</td>
<td>730</td>
</tr>
<tr>
<td>Range</td>
<td>33</td>
<td>121</td>
</tr>
<tr>
<td>Water</td>
<td>3</td>
<td>18</td>
</tr>
<tr>
<td>Forest</td>
<td>23</td>
<td>81</td>
</tr>
<tr>
<td>Barren</td>
<td>39</td>
<td>8</td>
</tr>
</tbody>
</table>

Table 3.2. Example of a validation matrix (data after Campbell 1987)
a negative value of $\kappa$ (Rosenfield & Fitzpatrick-Lins 1986). The degree of chance agreement may be overestimated in the calculation of the Kappa coefficient, because it is derived from the observed rows and columns values, which include actual as well as chance agreement (Foody 1992b).

A conditional Kappa may be calculated for individual classes (Rosenfield & Fitzpatrick-Lins 1986; Campbell 1987). The conditional Kappa can be estimated by:

$$\kappa = \frac{N X_{ii} - X_{ii} X_{ii}}{N X_{ii} - X_{ii} X_{ii}}$$

(Rosenfield & Fitzpatrick-Lins 1986)

If appropriate sampling is carried out, confidence limits can be determined and hypothesis testing can be carried out for the individual categories and the classification as a whole. A binomial distribution can be used to define confidence limits for an accuracy assessment (Hord & Brooner 1976; Thomas & Allcock 1984). If the sample size is large, and the percent correct cases are high, the binomial distribution may be approximated by a normal distribution (Thomas & Allcock 1984). Thomas & Allcock (1984) provide the formulas for determining confidence levels of the accuracy. Hudson & Ramm (1987) provide the formulas for calculating the variance of the Kappa coefficient, which can be used to calculate confidence limits.

With the confidence limits and the sample size, it can be tested, whether a minimum required accuracy is met or not, providing a determined risk (Janssen & van der Wel 1994). The larger the sample size, the greater the confidence one can have in assessments based on that sample. If a high mapping accuracy is obtained with a small sample size, there is a chance that no erroneous pixels are sampled. The probability of accepting a map while it is inaccurate, is called a type II error or producer’s risk. The probability of rejecting a correct map is called a type I error or consumer’s risk (Skidmore 1999).

A general disadvantage of the validation matrix is that it does not provide information on the distribution of the classification uncertainty. It is assumed that the validation matrix is representative for the entire classification (Congalton 1991). This problem and an alternative are discussed in chapter 7.

In general it is difficult to validate fuzzy classifications as conventional measures of classification accuracy are not appropriate (Foody 1995). For example no user’s and producer’s accuracy can be calculated with fuzzy maps and validation samples. A crisp classification of the fuzzy maps is needed to compare validation results to the accuracy measurements of the crisp classifications. An other approach for validation of fuzzy classifications is based on measures of entropy (Foody 1995, 1996), which is an uncertainty value for the assignment of a pixel to two or more alternative classes. Finally, fuzzy classifications may be validated by a measure of the closeness of the classification output to the ground data. This approach is used in this thesis.

### 3.5. Change analysis with sequential maps

#### 3.5.1. Change analysis methods

In a GIS different types of temporal analyses may be carried out with sequential vegetation maps (van der Wel 1995). Temporal analyses may be carried out with the basic data of the vegetation maps or with generalised or transformed data (for example data on species, environmental indication, total area, etc.) (see also Civco et al. 1986; de Jong et al. 1993;
Change analysis with digital RS-images may be divided into methods based on classification and methods based on radiometric change between acquisition dates (Johnson & Kasirschke 1998; Khorram et al. 1999). Two methods belonging to the second group are image differencing and principal component analysis. In the former method the digital numbers of the raw images are subtracted, resulting in a new map with the classes ‘changed’ and ‘non-changed’. In the latter method images of two years are combined and a principal component analysis of the multi-temporal image is applied. Of these two, image differencing was found to produce the most accurate change map for Eelgrass monitoring (Macleod & Congalton 1998). The change analysis procedure in this thesis belongs to the first group and is called post classification comparison (Macleod & Congalton 1998; Khorram et al. 1999).

In this thesis, changes in the area that is covered by a vegetation type are analysed over a period, based on comparison of final maps. The change analysis procedure starts with an overlay procedure of maps in a GIS. An overlay procedure with vector maps often leads to many new polygons or pixels, because of small errors in the geometry of boundaries or pixels that are supposed to lie in the same place (Burrough & McDonnell 1998) and because of differences in the chorology of the compared maps. A second step is the definition of the thematic units (vegetation types at a certain hierarchical level) for which analyses are carried out. Next, for all faces, calculations are carried out on the differences in area cover of a vegetation type in all years. The procedure is shown in figure 3.4. Resulting vegetation change maps based upon vector and raster maps are for example shown in figures 9.3 and 9.11.

3.5.2. Uncertainties in change analysis

In the change analysis procedure new uncertainties arise and uncertainties in the input maps are propagated (Lanter & Veregin 1992).
New uncertainties arise due to a difference in the spatial and thematic model of the compared maps. In an overlay operation, geometric and chorological differences lead to new spatial units, called ‘faces’. The thematic content of the faces is not exactly known. It depends on the relative area of the face compared to the area of the original polygon and on the homogeneity of the original polygon or pixel. This ‘overlay uncertainty’ is discussed in §7.2.

For the analysis of changes in the area covered by a vegetation type, the vegetation type has to be considered as the same in the compared maps. Differences in the vegetation typology of compared maps lead to uncertainty on the similarity of compared vegetation types; this is termed ‘type similarity uncertainty’. The similarity between vegetation types may be calculated in different ways, as is discussed in §4.3.

During the change analysis various uncertainties in the input maps interact. The interaction can be studied by error propagation methods, which need a statistical representation of the data (Heuvelink et al. 1989; Heuvelink et al. 1990). In chapter 7 analytical error propagation methods are used for analysis of the interaction of thematic uncertainties.

3.5.3. Accuracy assessment of change analysis

The accuracy of a change map may be assessed by constructing a change validation matrix (Macleod & Congalton 1998; Biging et al. 1998; Khorram et al. 1999). However, sampling for change detection validation is much more complex than sampling to assess the accuracy of a single map, as permanent validation plots are needed. A problem is that change polygons or pixels often cover only a small portion of the original image and this area may be poorly included in the permanent samples. In that case, the number of samples in the changed area may be too low for reliable validation.

In chapter 9, the information from permanent plots is used as a validation of changes detected from sequential maps. However, no change validation matrix has been constructed, as only a limited number of permanent plots were available.