MONITORING VEGETATION STRUCTURE IN FLOODPLAINS FOR FLOOD RISK ESTIMATION

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ABSTRACT:

Floodplains are among the most valuable ecosystems of the world. In the Netherlands they have a double function, serving both safety and nature, recreational purposes. Safety standards for flood protection of this densely populated country are the highest world-wide, protecting against events expected to occur with an annual probability of 1/10,000. Rivers in the Netherlands are all embanked by dikes to protect the low-lying polders from flooding. Along the main river channels, embanked floodplains carry excess water during high-water periods. Objects within these embanked floodplains, whether natural or man-made, increase the hydraulic roughness and hamper the water flow, causing flood waters to increase. In 2006, the Dutch government adopted the Spatial Planning Key Decision *Room for the River*, aiming at reducing flood-water levels, together with restoring riverine ecosystems. To account for changes in floodplain vegetation over time, the government requires five-yearly updates of vegetation maps, to monitor hydraulic roughness patterns and ecological quality of the floodplain.

We developed a monitoring method which combines object-based analysis of CIR photos with knowledge on vegetation-succession paths. We selected the nature reserve De Blauwe Kamer, in the floodplain of the river Neder-Rijn as a pilot study. In 1992 an open connection was created here between the main river channel and the floodplain, accompanied by creating relief differences in this formerly agricultural area, to increase landscape dynamics.

Image interpretation of natural vegetation is generally hampered by spectral overlap between vegetation types. Within our monitoring method we combine two improvements to reduce this effect and increase classification accuracies. Object-based interpretation is the first step, because it deals with shape and internal variation of vegetation types, thus reducing spectral confusion. Next, we introduce succession rules based on succession paths observed in the reserve and similar areas. Knowing the vegetation stage at t=0, possible stages at t=1 can be deduced, reducing the number of possible classes. Together with the number of classes, spectral overlap will scale down.

1. INTRODUCTION

1.1 Floodplains: nature and safety

Floodplains have a high biodiversity and are among the most threatened habitats on Earth (Tockner and Stanford, 2002). Their transitional position between river channels and the hinterland provides the ecosystems with strong gradients, resulting in high biodiversity. At the same time, the floodplains should protect the hinterland against flooding by storing the flood pulse during high water. Consequently, management of floodplains is facing two contradictory goals: 1) facilitating the development of natural vegetation and providing recreational space and 2) adapting room for peak discharge during high water. Aiming at just the first goal would result in a forested floodplain with vegetation patches of different development stages steered by the river dynamics. This would be a visually attractive landscape. Aiming at just the second goal would provide a floodplain with only low vegetation, so no obstacles would slow down the river. This would provide unsightly scenery.

The Dutch government maintains the highest safety levels against flooding world-wide, with flooding risks being smaller than one per 10.000 years. However, to meet these safety levels, while at the same time conserving the historic fluviatile landscape, they adapted the Spatial Planning Support Decision 'Room for the River' (V&W 1996). This combines natural river development with safety guarantees, e.g. by creating areas which can be inundated during high water. The anticipated result of this decision is a visually attractive landscape meeting the safety requirements set by the government.

To guarantee safety levels, flood-risk models must be run every five years. This requires spatially explicit data on vegetation to derive hydraulic roughness parameters (Straatsma and Baptist, 2008). Despite the wide availability of data, tools and knowledge, and the strict legislation and regulations in the Netherlands, there is still no adequate concept for large-scale monitoring of natural areas.

Earth observation is the proper tool to map changes in vegetation characteristics, as it provides spatially continuous data with high resolution. However, some problems are associated with change detection with remote sensing as well (Addink, 2001). Given the geometric accuracy of the images, pixels are easily compared with their neighbours. Besides, spectral differences, particularly in brightness, impede direct comparison between images. Finally, spectral confusion between classes hampers post-classification change detection.
Object-oriented image analysis considers groups of pixels rather than individual pixels (Benz et al., 2004; Navulur, 2007). This provides many more variables to include in the analysis, like shape and neighbour characteristics, and furthermore do the

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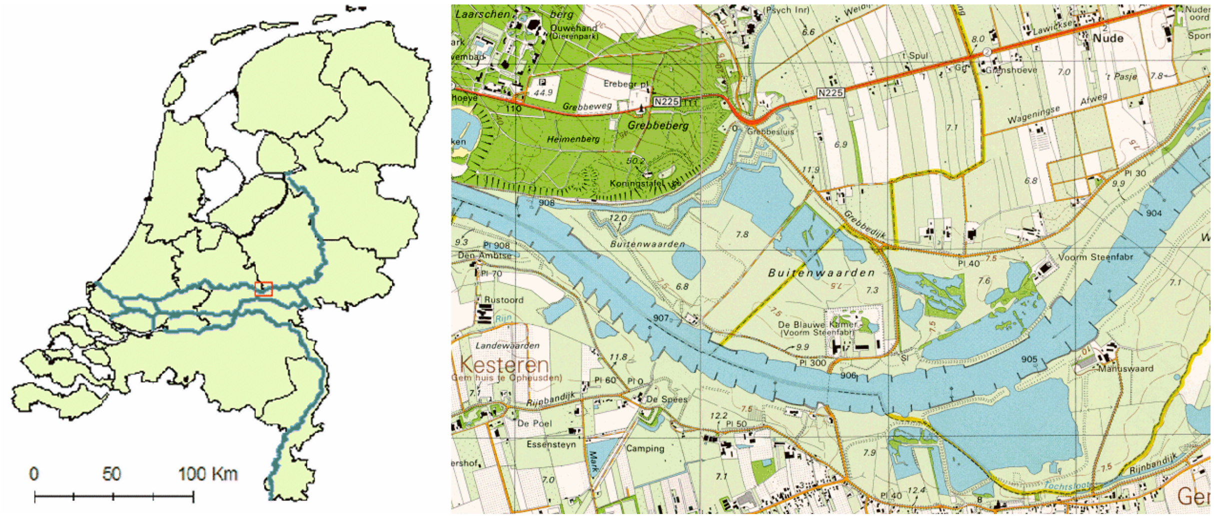

Figure 1. Left: Location of De Blauwe Kamer in the Netherlands. Blue lines indicate the major rivers. Right: The floodplain north of the river belongs to the nature reserve. Situation in 1990 before modifying the area and inducing more natural dynamics.

spatial objects of the analysis better represent natural objects at the Earth's surface (Fisher, 1996). The concept of the Modifiable Area Unit Problem (MAUP) is directly linked to object definition. MAUP states that the same analysis will provide different results when performed with different tessellations (Openshaw, 1964). This is true for object-size and for object-shape variations.

Object-based classification produces more accurate results, because the studied objects do better represent vegetation patches at the surface (Addink et al., 2007) and because spectral confusion between classes is reduced (Quartel et al., 2006). The feasibility of object-based change detection or monitoring has only limited extensively been explored (e.g. Addink et al., 2006; Hall and Hay, 2003), although it seems to overcome a number of the limitations of pixel-based change detection and thus to provide a more powerful change detection method.

At the same time, vegetation processes are not random. Given a starting situation, vegetation can only show a limited number of states after a certain time. Natural succession, grazing, and flooding will all have their effect, but still the outcome will be related to the starting situation and will not be random.

We aimed at developing a monitoring system where knowledge on natural vegetation development is integrated in object-oriented change detection. By knowing the status of vegetation at a certain moment one can predict the possible stages the system may have reached after a given number of years. This knowledge can then be used to reduce the effect of spectral overlap between classes and thus to improve classification of vegetation. To provide useful input for the flood-risk models we focused on vegetation structure.

1.2 Study Area

In this study we selected the nature reserve 'De Blauwe Kamer' along the river Nederrijn, a tributary of the Rhine (figure 1). This formerly agricultural area was transformed into a nature reserve with dynamic river processes in 1992. The summer dike, the lower of the two dikes and closest to the main channel, was opened to enable direct interaction between the entire floodplain and the main river channel also during low discharge. Besides, new water bodies were created in the floodplain. Management consists of grazing by horses and sheep.

This area was not transformed in the framework of the Room for the River initiative, but changes were already invoked in 1992 to instigate increase of natural values. The effects of the increased river dynamics were closely followed and both vegetation maps and high-resolution photos are available for the area. Therefore, this area is ideal to develop and evaluate a monitoring system.

2. DATA AND PREPROCESSING

1.3.1 Aerial photos

Analogue color-infrared photographs of the area are available for 1994 (Koppejan and Melman, 1995). For 2000 we had positives of aerial photographs (Koppejan, 2000). All were scanned such that the pixel size was 25cm. Using a digital elevation model they were orthorectified and mosaicked into two large images using histogram matching (figure 2). Whenever possible, cutlines would coincide with roads or parcel boundaries. Both images were radiometrically normalised, i.e. their mean value was set to 125 and the standard deviation to 60. This accounted for all variance present in the photos and allowed comparison over time.

1.3.2 Vegetation structure

Vegetation maps of the area are available for 1994. For 2000 an ecotope map is available. The legends of these maps do not show vegetation structure, which is needed to calculate hydraulic roughness. The legends were therefore translated based on the keys provided by Van Velzen et al. (2003). They defined vegetation structure at two levels: clusters and types, where several types together exclusively belong to one cluster. In 'De Blauwe Kamer' 7 structure clusters and 16 structure types were found in 1994 (table 1). In 2000 a 17^{th} structure type had evolved. The areal extent of this class was only 0.05% of the total area, and was hence not taken into account.

From these vegetation structure maps, succession paths were created for both structure clusters and types. The two maps were overlaid and intersected, creating polygons with attributes showing vegetation structure for 1994 and for 2000. Because of possible edge effects, all intersected polygons smaller than $2m^2$ were neglected in further interpretation. For each structure class in 1994, the transition probability was calculated from the relative area occupied by the respective classes in 2000.

Figure 2. Mosaics of the CIR photos of 1994 (top) and CIR positives of 2000 (bottom)

Structure cluster	Number of Structure types
Pioneer	1
Grass	3
Herbaceous	1
Swamp	5
Shrubs	2
Forest	2
Other	2

Table 1. Vegetation structure classes (based on Van Velzen et al., 2003)

3. METHODS

The photos were first segmented, then classified and finally combined with the succession paths to obtain their final structure class (figure 3). This procedure was followed for both the structure clusters and for the structure types.

1.4.1 Segmentation

The photos were segmented using only spectral information. Weight for the near-infrared band was twice the weight for the visible bands. The internal heterogeneity of the objects was set such that many objects would fall into one map unit of the vegetation maps. This way the geometric representation of the classes was likely to be more precise.

1.4.2 Classification

For each segment the following attributes were selected: mean and standard deviation for bands Green, Red and NIR, and Brightness. To limit the necessary fieldwork in the final monitoring system as much as possible, the 1994 data was used to train the 2000 photos. A training set was created by using the vegetation map of 1994. From each class 30 randomly located objects were selected to comprise the training set. With these training sets (on structure clusters and types), the photo mosaic of 2000 was classified using quadratic discriminant analysis (QDA; often referred to as maximum likelihood classification within remote sensing studies). This produced posterior probability values of belonging to a certain class for each object.

1.4.3 Integrating succession paths

Based on the vegetation structure in 1994, the probabilities for the different structure classes in 2000 are determined. These values are multiplied with the posterior probabilities from the QDA analysis. The posterior classification probabilities and the succession path probabilities are weighed equally. The class showing the highest value after multiplication is assigned to an object as the vegetation structure class of 2000.

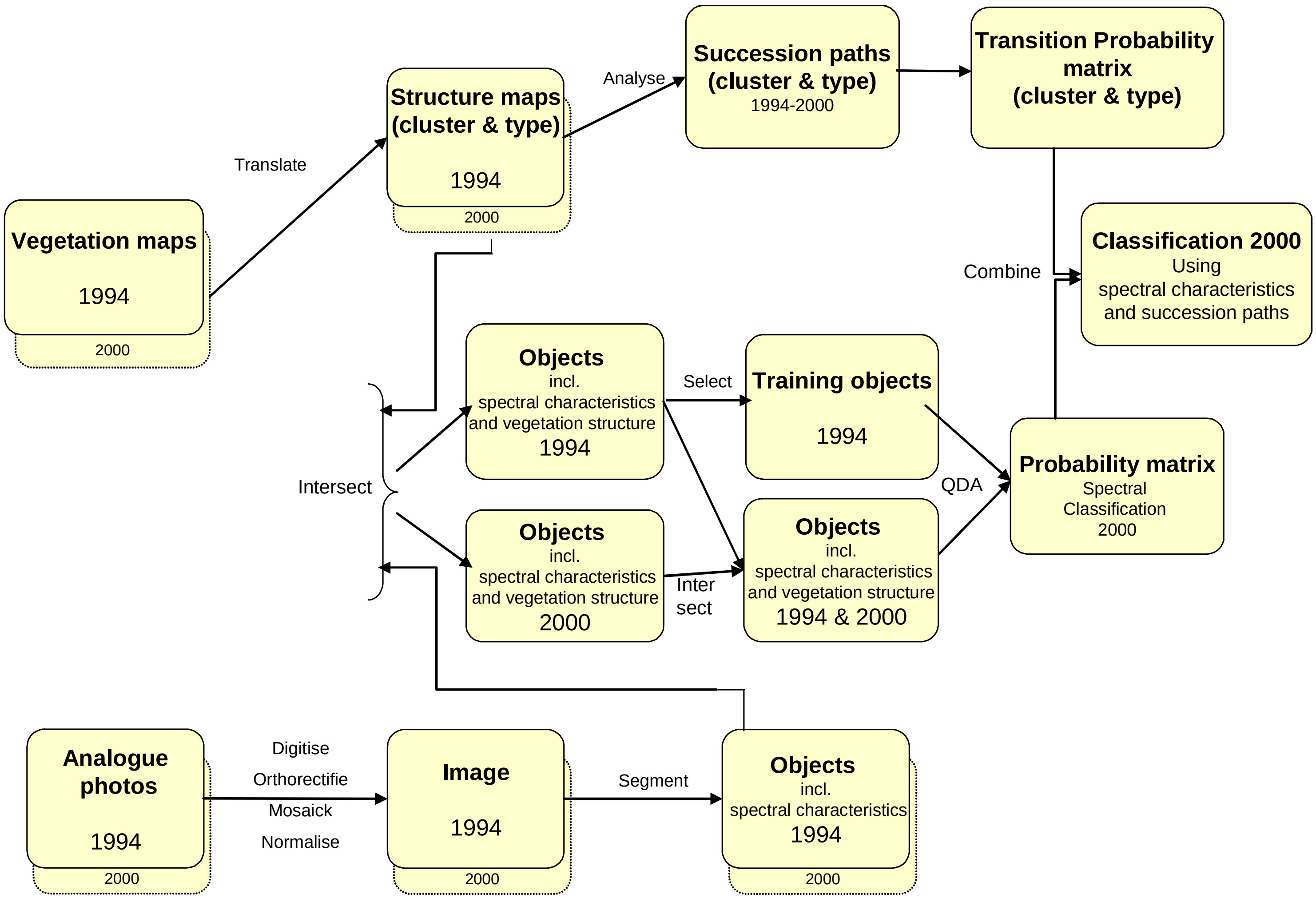

Figure 3. Flow diagram of the classification process

4. RESULTS

4.1 Succession paths

At the structure cluster level 49 different succession paths are theoretically possible. We found 45, indicating that vegetation does not necessarily follow the expected path. Beforehand, we considered some transitions unlikely, like 'other' (containing buildings, roads and water) changing into vegetation classes 'grass' or 'herbaceous'. But since the area was modified only in 1992, revegetation was still in full swing between 1994 and 2000. For instance, a road that was still clearly visible in the 1994 image, was overgrown in 2000.

At the structure type level 256 paths would be possible. Here we found 142. When analysing at type level, the succession paths can have a stronger effect than at the cluster level.

4.2 Spectral classification

The image of 2000 was classified based on training objects extracted from the 1994 image, both on cluster and on type level (table 1). The quadratic discriminant analysis provided posterior probability values for each class for each object. Accuracy values were very low, which did not come as a surprise given the limited spectral information and the strong spectral confusion within vegetation. At the structure type level, overall accuracy for the objects was 12%, while at the cluster it level it was 33%.

4.3 Classification integrating succession paths

The posterior probability values that were obtained with the QDA, were multiplied with the transition probabilities derived from the succession path analysis. The object was assigned to the class with the highest outcome (table 2).

The accuracy increased significantly by including the succession paths. Overall accuracy at the type level increased to 38% of all objects, while at the cluster level it reached 56%.

Structure cluster	Accuracy
Pioneer	44%
Grass	69%
Herbaceous	49%
Swamp	35%
Shrubs	25%
Forest	34%
Other	65%
Overall	**56%**

Table 2. Classification accuracy at cluster level (expressed in percentage objects)

5. DISCUSSION

The aim of this study was to improve vegetation structure classification in order to allow reliable flood risk modelling. We combined object-based image analysis with knowledge on natural processes summarized by succession paths. Our study area De Blauwe Kamer was transformed from an intensively used agricultural area into an area where natural processes prevail. The inner-dikes were partly removed to allow interaction between the river and the floodplain during low discharges as well. Furthermore, new water bodies were created and elevation variation was increased.

Distinction between vegetation classes often suffers from spectral confusion. To reduce this effect we combined the spectral classification with transitions described by succession paths.

Classification was performed at two levels, structure clusters and structure types. Accuracy values without knowledge from the succession paths were 33% and 12%, respectively. By including the succession paths these values improved strongly and reached 56% (+70%) and 38% (+216%), respectively. The added value of the succession paths is obvious.

These values still leave considerable room for improvements. However, it should be noted that part of the error can be ascribed to uncertainties in the vegetation maps. The minimum size of the mapping unit was considerably larger than individual pixels and the smallest objects. Particularly in situations where contrasting classes intermingle, like an old house being overgrown with nettles and blackberries, this will cause errors.

A first step we intend to take to improve the accuracy is to make a selection of the posterior probabilities (entirely based on observations of the real situation) before combining them with the succession paths (predictions of the new situation). This way, more weight will be put on observations than on predictions.

A second step will be to use training data from the year of observation. We used 1994 data to train the 2000 image in order to limit field work as much as possible. However, observations of the real situation might improve classification accuracy significantly.

To extrapolate the method to other floodplains in the Netherlands, the succession paths should probably be adapted. A nation-wide scheme for transitions between structure classes is unlikely to offer the same beneficial results as a scheme for a specific floodplain. As we derived transition probabilities from area percentages, vegetation types with a larger extent will dominate the succession scheme.

Although the effect of object-based image analysis has not been tested separately, we believe that it contributes to the accuracy. A problem with classifying vegetation is the internal variation, which is often characteristic. When using objects, this is not so much a problem, but rather a valuable addition to the classification.

6. CONCLUSIONS

The aim of the larger study is to develop a monitoring system of vegetation structure, which can provide data to calculate and simulate flood risks. Such simulations require maps of hydraulic roughness of the floodplains. Within this paper we presented the first results we obtained for object-based monitoring of the nature reserve De Blauwe Kamer. We had images that we classified using object-oriented image analysis combined with succession paths. The coarsest classification level, with structure clusters, reached an accuracy value of 56%.

Improvements will be added to produce data that are sufficiently reliable to run safety checks with flood risk models.

Although not perfect, the first results seem to promise a much faster mapping method than the conventional visual interpretation.

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