An intensified vegetation classification of the Dutch river forelands

Designing a new, automatic classification and change detection method
An intensified vegetation classification of the Dutch river forelands
Designing a new, automatic classification and change detection method

By
K.J. Alphenaar

In partial fulfilment of the requirements for the degree of

Master of Science
in Civil Engineering

at the Delft University of Technology

Supervisor: Dr. Ir. B.G.H. Gorte TU Delft
Thesis committee: Prof. dr. M. Menenti TU Delft
Ir. A. Vargas-Luna TU Delft
Committee advisor A. Knotters Rijkswaterstaat
Preface
This graduation project started at the company Witteveen+Bos with as preliminary task: 'Study what can be improved to the current vegetation monitoring and maintenance methods of the Dutch river forelands'. The first phase of my research was to specify the objective and main question of this project. After an extensive literature study, multiple meetings with my supervisor at Witteveen+Bos and my TU Delft supervisor Ben Gorte I formulated the main question for this research.

My approach and specific goal for this research, with the technical aspect of classifications of aerial photographs and satellite images, did not match well with the approach of my company supervisor and the associated division. I contacted Rijkswaterstaat, with whom I discussed my objective, and it matched to their approach to this subject. They were really interested to support my research, and even started a pilot about the same subject a couple of months before, which my project could complement. I decided to leave Witteveen+Bos and to continue at the TU Delft with the strong support of Rijkswaterstaat who supported me and provided the data that I needed. In particular I want to thank Andries Knotters, from Rijkswaterstaat who shared his thoughts on this subject with me and made me familiar with the ambitions and priorities of Rijkswaterstaat related to vegetation monitoring of the Dutch river forelands.

I also want to thank Ben Gorte for his enthusiasm for this project, the weekly discussions and the assistance he offered with the design of the classification and segmentation programs.

Kirstin Alphenaar, Den Haag 24-01-2016
Abstract
The current vegetation monitoring method of Rijkswaterstaat is a manual, time consuming and costly method and therefore only is performed once in six years. The vegetatielegger is a map, which shows the standard situation of the vegetation types that are allowed at any location in the river foreland area of the Netherlands. No rougher vegetation is allowed than displayed in the vegetatielegger. However, vegetation grows and new, rougher vegetation forms within those six years between monitoring cycles. So, to ensure the conservation of the situation as given in the vegetatielegger, a new, faster method had to be designed. This research designed and automatic post-classification change detection and tested it on a representative test site. The object-based classification used is a kNN-classifier and a region growing segmentation. The object-based approach ensures a classification that is well comparable to the polygons of the vegetatielegger. The classification is done with summer aerial photographs as well as with winter satellite images. The aerial photographs have a higher resolution than the satellite images, but in the winter satellite some vegetation classes are better distinguishable. The six classes that are classified are: water, built-up, forest, grass, tall herb vegetation and trees. Aerial photographs give a high overall accuracy for the classification; satellite images score better on tall herb classification accuracy. All generated results have a higher accuracy than the current classification method. The change detection is generated taking into account the Rijkswaterstaat rules for change in the forelands: only changes to a rougher vegetation type of more than 500m² are important. The satellite image classification generates more accurate change detections than the aerial photographs.
# Table of Contents

Preface                                                                                                                                                                                                 | I
Abstract                                                                                                                                                                                                 | II
List of figures and tables                                                                                                                                                                                                                             | V
Introduction                                                                                                                                                                                            | 1

**Part One: Current situation in the Dutch river forelands**      3
1. The Dutch river forelands                                                                                                                                                                                                                                    | 4
   1.1 Natural factors that affect the discharge capacity                                                                                                                                                           | 5
2. Current situation at Rijkswaterstaat                                                                                                                                                                                                                           | 7
   2.1 Monitoring                                                                                                                                                                                                                                                  | 7
   2.2 Maintenance                                                                                                                                                                                                                                                   | 12
   2.3 Vegetatielegger                                                                                                                                                                                                                                               | 14
3. Problem Statement                                                                                                                                                                                                                                                | 16

**Part Two: The necessity of changing and intensifying the vegetation monitoring situation**                                                                                                             17
4. Vegetation growth analysis                                                                                                                                                                                                                                       | 18
   4.1 Comparisons                                                                                                                                                                                                                                                  | 19
   4.2 Conclusion                                                                                                                                                                                                                                                   | 26
5. Ecotope Overlap Comparisons                                                                                                                                                                                                                                       | 27
   5.1 Preparations                                                                                                                                                                                                                                                  | 28
   5.2 Comparison                                                                                                                                                                                                                                                   | 29
   5.3 Conclusions                                                                                                                                                                                                                                                   | 32
6. Accuracy of the current vegetation monitoring                                                                                                                                                                                                                   | 34
   6.1 Field validation methods                                                                                                                                                                                                                                       | 34
   6.2 Results                                                                                                                                                                                                                                                       | 35

**Part Three: Designing a new method**                                                                                                                                                                37
7. Available data and desired results                                                                                                                                                                                                                              | 38
   7.1 Desired results                                                                                                                                                                                                                                               | 38
   7.2 Available data                                                                                                                                                                                                                                                 | 39
8. Chosen methods                                                                                                                                                                                                                                                   | 41
   8.1 Post classification change detection                                                                                                                                                                                                                          | 41
   8.2 Automatic classification                                                                                                                                                                                                                                       | 43
   8.3 Selecting the training data automatically; new iterative method of Delft University of Technology                                                                                               48
   8.4 Object-oriented classification                                                                                                                                                                                                                               | 50
9. Added data and vegetatielegger comparison                                                                                                                                                                                                                       | 55
   9.1 Added data                                                                                                                                                                                                                                                   | 55
   9.2 Comparison with the vegetatielegger                                                                                                                                                                                                                          | 56
   9.3 Quality check                                                                                                                                                                                                                                                 | 57
10. Results                                                                                                                                                                                                                                                          | 59
   10.1 Results and accuracies of the classifications                                                                                                                                                                                                                 | 59
   10.2 Results and accuracies of the change detections                                                                                                                                                                                                              | 68
   10.3 Summarizing all results                                                                                                                                                                                                                                       | 78

Conclusion                                                                                                                                                                                                                                                         | 79
Discussion                                                                                                                                                                                                                                                         | 81
   Limitations                                                                                                                                                                                                                                                       | 81
### Recommendations

- Bibliography 82

### Appendices

- Appendix A 2
- Appendix B 4
- Appendix C 7
  - *Height data generated from stereo aerial photographs versus AHN data* 7
- Appendix D 11
- Appendix E 12
  - *Intermediate results of aerial photograph classification, proportional training-data* 13
  - *Intermediate results of aerial photograph classification, equal training-data* 14
  - *Intermediate results of satellite image classification, proportional training-data* 15
  - *Intermediate results of satellite image classification, equal training-data* 16
List of figures and tables

Figure 1: Schematic figure of the river forelands. Low discharge situation, upper image, and high discharge situation, lower image. ................................................. 4

Figure 2: Left image: example of an ecotope map of Rijntakken-Oost near Rhenen, 2008. Right image vegetation interpretation before the overlay procedure of the same location......... 9

Figure 3: Different adjustments to the riverbed, dikes and floodplain to create extra water storage. Source: www.ruimtevoorderivier.nl ............................................................. 13

Figure 4: Vegetatielegger of the river Maas and a zoom-in picture of the test site used for this project .................................................................................................................. 15

Figure 5: The four locations where vegetation growth is studied ........................................ 19

Figure 6: Aerial photographs from grassland in the Blauwe Kamer. 6A is taken in 2010, 6B in 2012 .................................................................................................................. 20

Figure 7: Appearance of bushes or trees in the Blauwe kamer. 7A is the aerial photograph of 2010, 7B is taken in 2011 .................................................................................... 21

Figure 8: Vegetation growth in the Afferdense en Deestse Waarden. 8A shows the photo of 2010, 8B of 2012 ................................................................................................. 22

Figure 9: Time series of vegetation growth in the Afferdense en Deestse Waarden. 9A is from 2008; 9B from 2009; 9C from 2012; 9D from 2013 .............................................. 23

Figure 10: Vegetation growth at grassland in the Merwedelanden. Figure 10A is a photo of 2011, 10B, is from 2013 ................................................................................................. 24

Figure 11: Vegetation growth along the Maas. 11A is a photo from 2010; 11B is from 2012 .... 25

Figure 12: Overview of the ecotope mapping of the river Maas, 2004, and Rijntakken-Oost, 2005. In figure 12A the red square shows the overlap location, 12B zooms in to the overlap (in red) ........................................................................................................................... 27

Figure 13: Comparison of the two vegetation interpretations of the river Maas, 2004 and Rijntakken-Oost, 2005 ......................................................................................... 28

Figure 14: Aerial photograph showing the locations with classification differences (grassland or agricultural field marked with white spots) ........................................... 29

Figure 15: Aerial photographs with white spots that mark the interpretation differences between tall herbs and reed and other halophytes class .................................................. 30

Figure 16: In both figures, A and B, white spots mark the areas classified as built-up area in one interpretation and grassland in the other ......................................................... 31

Figure 17: Aerial photograph which shows with white spots a line of trees that is only mapped in the river Maas 2004 map .................................................................................. 32

Figure 18: Test area used for this project: the river forelands of the river Maas near Boxmeer. .. 40

Figure 19: Flow chart of the processes and generated results of this project ............................ 42

Figure 20: Test area with training samples. In this set the classes have a proportional amount of training-data ......................................................................................................... 47

Figure 21: Test area with training samples. For this test set all classes have an equal amount of training-data ..................................................................................................... 47

Figure 22: Difference between object-oriented classification (figure a) and "salt and pepper" result of the pixel based method (figure b). Source: Whiteside and Ahmand, 2005 ........ 51

Figure 23: The three segmentations used in this project. Figure A is the segmentation with the lowest threshold (26); Figure B is the middle segmentation with threshold 30; figure C is the image with the largest segments (threshold 34) .................................................. 53
Figure 24: Control data used to study the accuracy of the classifications ........................................ 58
Figure 25: Control data used to study the accuracy of the change detection ................................. 58
Figure 26: The classification of the segmentation of the aerial photograph. The training-data that
is used contains a proportional amount of training pixels for each class ................................. 60
Figure 27: The classification of the segmentation of the aerial photograph. The training-data that
is used contains an equal amount of training pixels for each class ........................................... 60
Figure 28: The classification of the segmentations of the satellite image. The training-data that
is used contains a proportional amount of training pixels for each class .................................. 63
Figure 29: The classification of the segmentations of the satellite image. The training-data that
is used contains an equal amount of training pixels for each class ........................................... 64
Figure 30: Classification result of the aerial photograph classification with auto-generated
training-data ................................................................................................................................. 66
Figure 31: Change detection map of the aerial photograph classification - vegetatielegger
comparison. The classification is done with the proportional training-data ......................... 69
Figure 32: Change direction map of the aerial photograph classification - vegetatielegger
comparison. The classification is done with the proportional training-data ......................... 69
Figure 33: Change detection map of the aerial photograph classification - vegetatielegger
comparison. The classification is done with the proportional training-data ......................... 70
Figure 34: Change direction map of the aerial photograph classification - vegetatielegger
comparison. The classification is done with the equal training-data ........................................ 70
Figure 35: Change detection map of the satellite image classification - vegetatielegger comparison.
The classification is done with the proportional training-data ............................................... 72
Figure 36: Change direction map of the satellite image classification - vegetatielegger
comparison. The classification is done with the proportional training-data ................................ 73
Figure 37: Change detection map of the satellite image classification - vegetatielegger
comparison. The classification is done with the equal training-data ........................................ 73
Figure 38: Change direction map of the satellite image classification - vegetatielegger
comparison. The classification is done with the equal training-data ........................................ 74
Figure 39: Change detection of the aerial photograph with auto-generated training-data ............. 76
Figure 40: Change direction map of the aerial photograph classification with auto-generated
training-data ................................................................................................................................. 77

Table 1: Time schedule Rijkswaterstaat from photo flight to ecotope map ...................................... 10
Table 2: Date of the aerial photographs used in the study ............................................................... 18
Table 3: Accuracy results for the ecotope map as estimated by Knotters et al., 2008 .................... 35
Table 4 Accuracy of the ecotope map on vegetatielegger level of detail ....................................... 36
Table 5: The checkmarks represent the changes that are allowed, the crosses show changes that
make the surface rougher and therefore are not allowed ......................................................... 38
Table 6: Available datasets for this project ..................................................................................... 39
Table 7: Complete list of bad and good changes in the river forelands .......................................... 57
Table 8: Error matrix of the aerial photograph classifications with proportional training-data ...... 61
Table 9: Error matrix of the aerial photograph classifications with equal training-data .............. 62
Table 10: Error matrix of the satellite image classification with proportional training-data .......... 65
Table 11: Error matrix of the satellite image classification with equal training-data .................... 65
Table 12: The error matrix for the aerial photograph classification with auto-generated training-data

Table 13: Change detection accuracy of the aerial photographs, proportional training-data

Table 14: Change detection accuracy of the aerial photographs, equal training-data

Table 15: Change detection accuracy for the satellite image, proportional training-data

Table 16: Change detection accuracy for the satellite images, equal training-data

Table 17: Accuracy of the change detection of the aerial photograph classification with auto-generated training-data

Table 18: Classification results of all four datasets summarized

Table 19: Change detection accuracies for all four datasets

Unless stated otherwise the figures and tables are generated with data from this research and created by the author.
Introduction

Water management is highly important for the Netherlands. A large part of the country is situated below sea level, and several large rivers find their way to the coast through the inlands of the Netherlands. The land constantly needs to be protected against floods originated from both the sea and the rivers. Large dike constructions protect the people against those floods. The river areas with forelands contain two different dikes: high outer dikes and lower summer dikes. The outer dikes are most important and keep the inhabited areas free from water. The land within the outer- and inner dikes flood every year and is called the Uiterwaarden: the Dutch river forelands. The River forelands are mainly composed by agricultural fields and some nature reserves. The agricultural fields can be used during the dry periods. During high river discharges the river forelands become part of the river stream and thus will be flooded. The forelands are therefore essential to cope with the large amount of water during high river discharges.

Vegetation in the Dutch river forelands is important. Crops are grown and natural areas add enormous value for the biodiversity. However, vegetation in the river forelands is not solely positive. Vegetation obstructs the water flow, and can cause dangerous high water levels, which even threaten the area behind the outer dike. Therefore the river forelands are monitored and maintained to ensure water safety: ensuring that the river will not reach over the outer dike. This research studies the current monitoring and maintenance methods and deals with improvements on the monitoring. Is it possible to make it faster, cheaper and/or more accurate than it is now? Therefore first an extensive literature study is done regarding the current methods of vegetation monitoring and maintenance in the river forelands. What is done now to ensure the flood protection and who is responsible? What are the problems with the current method, which can be improved? After the literature study, the vegetation monitoring is further investigated for the possibilities and the need to improve the current method. When it appears that an improvement is needed a new method will be designed and assessed on its results.

The main question that should be answered at the end of this report is:

*Is it in relation to the conservation of the situation as given in the Vegetatielegger and for flood prevention, needed to intensify the vegetation monitoring, and how can this intensification be achieved?*

The sub question in this research project is about the data that is needed to achieve an intensification of the vegetation monitoring. The current method uses only aerial photographs. When a new method needs to be designed there are no restrictions what data to use. Therefore the sub-question in this project is:

*Does a new, intensified, vegetation monitoring method require satellite data or is the available aerial photograph data sufficient?*

To answer the research questions this report is divided in three parts. Part one of this report is a literature study to the current situation of monitoring and maintenance in the Dutch river forelands. With this study the problems and points for improvement of the current method are pointed out. This leads to a detailed problem statement at the end of part one.

The information in part one is organized as follows: The first chapter explains what the river forelands are and which processes affect the water conveyance capacity: sedimentation and vegetation growth. The vegetation in the forelands needs to be monitored and maintained, for which the second chapter describes the methods
Rijkswaterstaat (the Dutch Directorate-General for Public Works and Water Management) uses. They are responsible for the flood protection in the river forelands. As result of the monitoring, Rijkswaterstaat makes an ecotope map every 6 years by manually interpreting aerial photographs, a costly and time consuming method. Maintenance projects as “Room for the River” need to enlarge the water discharge capacity to prevent floods. The vegetatielegger describes the standard situation of the vegetation types in the forelands. No rougher vegetation than stated in the vegetatielegger is allowed to be present.

Part two of this report studies the need for intensification of the monitoring method. Therefore a vegetation growth analysis is done and aerial photographs of several years are used to study vegetation growth. The result shows significant vegetation growth within just two years, which explains the need for an intensified monitoring. This part of the report also studies another disadvantage of the current method: the subjectivity of the manual classification method. Therefore two datasets that overlap are studied. The last chapter of part two of this report describes an Alterra study to the accuracy of the current classification. The Alterra study contains errors, but is usable to give insight in the accuracy of the current classification on the level of the vegetation types of the vegetatielegger. These results can be later in this project used to compare the accuracy of the current method with the accuracy of the new method.

The last part of this report, part three describes the new monitoring method that is designed. The first chapter discusses the desirable result and which dataset are available. The end result that Rijkswaterstaat wants is a change detection that compares the current situation with the standard situation visualized in the vegetatielegger. To achieve this result satellite data, aerial photographs and height data can be used. The next chapter explains the used methods along with the motivation for these methods. The change detection is created with a post-classification change detection method. The classification method is an object based classification that uses region based segmentation and kNN-classification. The classification is done with satellite images and aerial photographs to test the need for winter satellite images. For both the classification and the change detection the accuracy is tested. The last chapter describes the classification and change detection results as well as the accuracies of the results.

The report ends with a conclusion, which answers the main question, and a discussion.
Part One:  
Current situation in the Dutch river forelands

Part one of this report describes the current situation of monitoring and maintenance in the Dutch river forelands. The first chapter explains what the river forelands are and which processes affect the water discharge capacity: sedimentation and vegetation growth. The vegetation growth in the forelands needs to be monitored and maintained. The second chapter of part one describes the methods Rijkswaterstaat uses for monitoring and maintaining. An ecotope map is made every 6 years by manually interpreting aerial photographs, a costly and time consuming method. Projects as “Room for the River” need to enlarge the river conveyance capacity to ensure the water safety. The vegetatielegger is a map that shows the standard situation of the vegetation types that are allowed at any location in the river foreland area of the Netherlands. No rougher vegetation is allowed than displayed in the vegetatielegger. After studying the current situation part one ends with a detailed problem statement with the main question of this research:

Is it in relation to the conservation of the situation as given in the Vegetatielegger and for flood prevention, needed to intensify the vegetation monitoring, and how can this intensification be achieved?
1. The Dutch river forelands

The Dutch river forelands (in Dutch: “de uiterwaarden”) are areas that are located between the outer dike and the riverbed (figure 1). The foreland areas are essential to deal with the, periodically, high water levels. They will flood in times of high discharges so it will not cause harmful floods elsewhere. Before the rivers in the Netherlands were diked there were no river forelands. Floods at that time submerged large stretches of land. Since 1150 farmers started to construct dikes to protect their land. With these new dikes the river had less space and the water got higher with every flood. As a consequence people made the dikes higher and higher and around 1300 almost the whole river area of the Netherlands was diked. A flood since then only affects the space between the riverbed and the outer dike: the river forelands (Janssen, 2009).

![Figure 1: Schematic figure of the river forelands. Low discharge situation, upper image, and high discharge situation, lower image.](image)

The primary task of the river forelands is water storage in times of floods, but they are used in many other ways. The fertile land of the forelands is widely used as hay and grazing meadows and for growing crops that can handle wet conditions. Also, because of the high biodiversity and the characteristic landscapes, numerous locations in the forelands have become nature reserves.

The Dutch Directorate-General for Public Works and Water Management (Rijkswaterstaat) has the responsibility for flood protection and prevention along the river forelands and thus to ensure that the primary task of the river forelands is fulfilled. The capacity of these areas should be large enough to prevent harmful floods. For this, the river area undergoes a lot of anthropogenic modifications (later on more about these modifications in section 2.2). However, the conveyance capacity of the river is influenced by two natural developments as well: vegetation growth and sedimentation (Makaske and Maas, 2007).
1.1 Natural factors that affect the discharge capacity

Rijkswaterstaat is responsible for the flood prevention around the river forelands. Vegetation growth and sedimentation affect the discharge capacity of these lands, and therefore Rijkswaterstaat should know the processes and effects of both developments.

Vegetation

Forelands are vegetated areas, which are of great value for the people and the nature in the Netherlands. The river forelands provide habitat and sources of nutrients for numerous organisms. The forelands are locations where both terrestrial and aquatic ecosystems mix and are therefore highly bio diverse (Federal Emergency Management Agency (FEMA), 1986). The land is fertile and especially the higher parts are well suited for crowing crops. The lower, wetter parts are often used for grazing (Verhoeven and Setter, 2009) Agricultural fields cover a large part of the Dutch river forelands (Wolfert, 2001).

Although the vegetation is important for the river forelands, it can also have a harmful effect on the water level. Vegetation exerts resistance on the water flow, which causes higher water levels and thus an increase in flood risk. The resistance on the water flow varies according to the plant’s rigidity, its form and dimensions, the spatially heterogeneous distribution of the vegetation, the plant population per unit area and the degree of submergence (Lee et al., 2004). As these factors show, the resistance on the water flow differs per vegetation type. Other factors, which not involve vegetation but do influence the resistance on the water flow, are the Reynolds number, slope of the channel bottom, upstream and downstream limits, channel morphology and meteorological conditions (Lee et al., 2004).

Rigid, or non-flexible, tall and wide vegetation obstructs the water flow most (Darby, 1999). As is shown in the study of Darby, 1999, a change from non-flexible vegetation to flexible vegetation reduces flood risk. The change from flexible to non-flexible vegetation increases flood risk. Production grassland, which only contains short, flexible vegetation obstructs the water flow least. Without management as intensive mowing or harvesting, smooth grassland will get rougher due to vegetation succession (Makaske et al., 2011). Due to spontaneous succession grassland will turn successively into dry herbaceous vegetation, softwood shrubs and forest (Makaske et al., 2011). Shrubs and, to a lesser degree, the riparian forests are the vegetation types that exerts the most resistance on the water flow (Stolker et al., 1999). This shows that when the vegetation in the river forelands is not mowed, grazed or removed regularly the obstruction of the water flow increases and the flood risk will be higher.

Since the beginning of the 1990s ecosystem rehabilitation plans have been developed to allow more natural vegetation in the foreland areas (Makaske et al., 2011). The project “Room for the River” (described in section 2.2) restores the natural floodplain to increase the discharge capacity of the river and enlarges the natural areas of the river forelands. The increase of natural areas leads to vegetation succession. The effect is that more (rough) vegetation obstructs the water flow, which can counteract the engineering measures to improve the discharge capacity (Makaske et al., 2011). It is important to know the resistance the different vegetation types exert on the water flow. This makes it possible to calculate what vegetation is allowed where to minimize the obstruction of the river flow and to prevent floods. Especially with the increase of natural areas in the forelands the vegetation has to be monitored and maintained to prevent large obstructions of the water flow.
**Sedimentation**

The river forelands flood regularly and when overbank flow occurs, sediment may be transferred from the river channel to the floodplain (Asselman & Middelkoop, 1995). Under natural conditions, sedimentation and erosion processes due to channel migration interrupt vegetation succession and floodplains to fill up with sediment. In the regulated rivers of the Netherlands uncontrollable erosion and sedimentation cannot be allowed. Lowered floodplains show a rapid sedimentation and vegetation traps the sediment. As a consequence the conveyance capacity of the floodplain will be reduced over time (Baptist et al., 2004). Cyclic Floodplain Rejuvenation (CFR) is a floodplain management strategy that mimics the effects of channel migration by lowering floodplains, removal of forest, and (re)construction secondary channels. These measures, which should be applied recursively, increase the cross-sectional area of the floodplain and reduce the flood risk (Baptist et al., 2004).

Although both sedimentation and vegetation growth affect the river conveyance capacity, the timescale on which they have impact is different. The vegetation development, so the increasing resistance of plants on the water flow, has on a short scale (<30 years) much more impact than sedimentation (loss of flow area). On a large timescale sedimentation has an important impact on the repetition rate of CFR measures (Makaske and Maas, 2007). Due to the gradual sedimentation the lowering of the floodplains or digging a secondary channel should be done more and more frequently. The lack of intensive vegetation management negates the effects of the CFR measures, where intensive management prolongs the effect of CFR measures (Makaske and Maas, 2007).

Rijkswaterstaat has the responsibility to ensure the flood protection of the river areas in the Netherlands. Therefore the monitoring of the different vegetation types, so knowing the resistance they exceed on the water flow, in the river foreland area is an important task of Rijkswaterstaat. How the monitoring and maintenance of the river area currently is done by Rijkswaterstaat is explained in the next chapter.
2. Current situation at Rijkswaterstaat

Rijkswaterstaat is part of the Dutch Ministry of Infrastructure and the environment. They are responsible for the design, construction, management and maintenance of the main infrastructure facilities in the Netherlands. Important for this research is that this responsibility includes the main water systems of the Netherlands. The rivers in the Netherlands are wedged between high outer dikes. The areas behind these dikes are densely populated. The river foreland area has to be maintained by maintaining (and removing) the vegetation growing in these areas. Also the dikes should be checked and raised if needed. With more rainfall expected in the future maintaining the vegetation and raising the dikes is no longer sufficient to prevent floods such. Rijkswaterstaat therefore started the "Room for the River" project (Dutch: Ruimte voor de Rivier), which is explained later in this chapter.

First the monitoring by Rijkswaterstaat of the vegetation in the Dutch river forelands is explained; later the methods that Rijkswaterstaat uses to maintain the river forelands are explained.

2.1 Monitoring

Rijkswaterstaat needs to monitor the Dutch river forelands. There are two important parts that belong to the monitoring. The first part is to know for every location in the river forelands what type of vegetation grows at that place. For this, Rijkswaterstaat makes an ecotope map every six years.

Only knowing the vegetation types is not good enough, because the resistance the vegetation exerts on the water flow has to be known as well. The second part, therefore, is to study the resistance parameters for all the vegetation types present in the Dutch river forelands. The two parts of the monitoring, ecotope map and resistance of the vegetation on the water flow, are described in this section.

Ecotope map

Rijkswaterstaat monitors the vegetation in the river foreland areas. When is known what vegetation grows where, this information can be used as input for the river flow model WAQUA. WAQUA is a simulation system for water movement and water quality in two dimensions (Rijkswaterstaat, 2007a). The WAQUA program calculates the flow resistance that is caused by the vegetation and has as end result the inundation levels. Because of the model it is possible to check whether the vegetation present in the forelands cause (dangerously) high water levels or not. The input that WAQUA needs to calculate the flow resistance are four structure parameters: the height of the vegetation, the skin friction, the drag coefficient and the roughness of the riverbed (van Velzen et al., 2003).

For this monitoring Rijkswaterstaat creates an ecotope map. This ecotope map is not only created to determine the obstruction of the water flow by vegetation, but it is also used for making redesign and nature development plans and quality assessments. The ecotope map visualizes abiotic, biotic and anthropogenic aspects of the river foreland areas. It is a vegetation structure map complemented with information about landscape features, water depth and landscape management. For all the national fresh waters an ecotope map is made. Those that describe the river forelands are called Rijntakken-Oost and Maas. Rijkswaterstaat makes the ecotope maps once in the six years to meet the obligation of the monitoring law in the European Water Framework Directive (Houkes and Buiks, 2011). Currently there are three ecotope map cycles delivered, in 1998, in 2006 and in 2009. The third cycle was produced earlier to fit well to the new programme 'Stroomlijn' (described in section 2.2 'Stroomlijn') and to the European Water Framework Directive (Ecotopenatlas, n.d.).
Aerial photographs

As basis for an ecotope map aerial photographs are used. Rijkswaterstaat uses false or true colour aerial photographs with a scale of 1:10,000, which gives a ground resolution of 12 centimetres. Because the photographs have a mutual overlap of 60 percent, it is possible to interpret the photos three-dimensionally. The photos are taken in summer to assure a good position of the sun, low cloud cover and a low water level (Houkes and Buiks, 2011). The entire area is recorded at the same time to avoid differences in water level and phenological differences appear between two records. Aerial photographs are preferred over satellite images. They have a higher resolution and can be scheduled on a perfect day. The satellite images have a lower resolution, can only be taken when the satellite is in the right position and they do not map the whole area at once. Because the aerial photographs stereographic, accurate vegetation height data can be generated from those photos. Knowing the vegetation height is essential for a proper classification, so this is a great advantage of aerial photographs with respect to satellite images. Later, in the chapter on available data (chapter 7), the differences between aerial photographs and satellite images are explained more will be discussed in detail. Rijkswaterstaat outsources the interpretation of these aerial photographs to make a vegetation structure map. The interpretation is done manually with the help of an interpretation key (see Appendix A). The interpretation key describes what can be seen in the aerial photograph and by answering the statements with ‘true’ or ‘false’ the analyst classifies the image. Eventually the key leads you to one vegetation type per location. To optimize the comparisons of the interpretations between the different cycles the ‘Existing Boundary Method’ (Dutch: ‘Oude Grenzen Methode’) is used. This means that as starting point the boundaries and content of the different areas of the foregoing cycle are used. The boundaries will only be changed if the new photograph shows a difference of at least ten meters with the old boundary (Janssen and Gennip, 1998). When there is doubt about which vegetation type to choose, the content of the area is kept the same as with the last interpretation. The interpretation key and the ‘Existing Border Method’ make the interpretation less subjective, so it won’t differ that much when done by different people. However, like Houkes and Buiks wrote in the Ecotopenkartering Rijntakken-Oost, 2011, the interpretation is still manual and subjective work.

The vegetation map created with the manual interpretation must comply with a number of requirements. The different polygons in the interpretation map should have a minimum area of 400m². Line-shaped vegetation like hedges should have a minimum length of 20 meters. Areas smaller than 400m² are not included on the vegetation interpretation map. This means that small hedges and solitary trees are not mapped with the aerial photograph interpretation (Jansen and Backx, 1998). This minimum area is chosen for the convenience and speed of the interpreter. The ecotope map was not designed for using it to define the hydraulic roughness of the areas in the river forelands. That application was developed later when the 400m² rule already existed. Because some vegetation types can be of importance even when smaller than this minimum size, future vegetation interpretations will be done with minimum areas of 5 by 5 meters.

Overlay procedure

After the aerial photograph interpretation is finished the ‘Overlay-procedure’ adds flooding data, water depth data, morphodynamics and landscape management data to the vegetation structure map (Houkes and Buiks, 2011). The overlay-procedure is performed with an ecotope classification model, which is designed to classify the ecotopes automatically. The order in which the different datasets are added with this overlay-procedure is fixed and based on the quality of the datasets. The files with high
quality and resolution will be used first (Houkes and Buiks, 2011a). Because of this fixed order the procedure is standardized and repeatable.

The boundaries and classes of the vegetation structure map created with the aerial photograph interpretation should not change due to the overlay-procedure, but be supplemented with the information in the datasets that are added (see figure 2). This is because the structure map is regarded as the layer with the highest quality and the best-defined boundaries. When, with the overlay-procedure, a surface is formed that is too small it will be assigned to the neighbouring surface with the most similar class. The result is an ecotope map like seen in figure 2. As is seen in this figure most borders are kept the same for the ecotope map and the vegetation interpretation. For the ecotope map some areas are divided into smaller polygons due to the overlay procedure.

Figure 2: Left image: example of an ecotope map of Rijntakken-Oost near Rhenen, 2008. Right image vegetation interpretation before the overlay procedure of the same location.
Time schedule ecotope maps

Table 1 shows the time schedule of all the products that together form the ecotope map. For the maps of the third cycle two versions are made: one delivered in 2009 that used the old data (from the second cycle) for the overlay procedure, and one in 2011 that used new data. As is seen in the table it takes more than a year to deliver an ecotope map and then the result still has to be checked with the vegetatielegger.

Table 1: Time schedule Rijkswaterstaat from photo flight to ecotope map

<table>
<thead>
<tr>
<th></th>
<th>Maas 2nd cycle</th>
<th>Maas 3rd cycle</th>
<th>Rijntakken-Oost 2nd cycle</th>
<th>Rijntakken-Oost 3rd cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Photo flight</td>
<td>07-07-2004</td>
<td>26-09, 10-10 &amp; 20-10-2008</td>
<td>18-08, 29-08 &amp; 04-09-2005</td>
<td>20-05, 21-05, 08-06, 09-06 &amp; 24-06-2008</td>
</tr>
<tr>
<td>Photo interpretation</td>
<td>2005</td>
<td>2009</td>
<td>2006</td>
<td>2009</td>
</tr>
</tbody>
</table>

The resistance on the water flow by floodplain vegetation

The vegetation is mapped with the procedure described above, but the four structure parameters are not given in the ecotope map. The WAQUA model needs the four parameters as input to calculate the inundation levels: the height of the vegetation, the skin friction, a roughness coefficient and the roughness of the riverbed (van Velzen et al., 2003). To determine these four parameters for the different vegetation types present in the Dutch river foreland area van Velzen et al., 2003 wrote the manual: 'Stromingsweerstand vegetatie in uiterwaarden'. This manual is composed by RIZA commissioned by Rijkswaterstaat. The manual divides the vegetation present in the river foreland area into seven clusters:

- Pioneer vegetation
- Grasslands
- Tall herb vegetation
- Swamp vegetation
- Brushwood
- Forest
- Other

Those seven clusters contain in total 30 different vegetation types and the manual also gives the possibility of combining different vegetation types for mixture classes. Every vegetation type represents a composition of species that have a specific vegetation structure and hydraulic characteristics. A value for hydraulic roughness is given to each vegetation type as well as the four structure parameters. The manual uses three kinds of formulas to calculate the hydraulic roughness. One formula is for flooded vegetation, so it can be used if the water depth is the same or more than the vegetation height. One is for the situation where the water depth is less than the vegetation height. And the last one is for calculating the hydraulic roughness for combinations of vegetation types (van Velzen et al., 2003a). The representative values for hydraulic roughness and structure parameters that are given by the manual for each vegetation type is based on the
characteristics of the vegetation types during winter (January – March). Because the determination of the hydraulic roughness/structure parameters mostly is based on the ecotope map, the manual gives a translation table of ecotopes to vegetation types. In this way the wanted parameter can be assigned to a certain ecotope and no new vegetation type map has to be made. Unfortunately, in an ecotope several vegetation types are likely to be present. In practice however, a location will be dominated by one type that is representative for that ecotope. So, the translation table shows the different occurring types and the dominant vegetation types within a certain ecotope. With this ecotope map that is created once in six years the vegetation types and the associating values for the hydraulic roughness in the Dutch river forelands are known. Possible modifications of the vegetation within those six years are not monitored.
2.2 Maintenance

With the ecotope map and the manual that gives the hydraulic roughness for each vegetation type Rijkswaterstaat can calculate the effect of the vegetation in the Dutch river forelands. However, this does not explain yet how Rijkswaterstaat decides where to maintain the forelands by cutting down vegetation or increasing the area where the river can flow. This section explains what methods Rijkswaterstaat uses to maintain the Dutch river forelands.

Project: ‘Room for the River’

Room for the River restores the river’s natural floodplain in places where it is least harmful. In times of flood the river has more space at controlled areas and areas near the river that are densely populated will be protected. On the next page figure 3 shows the adjustments that are possible with the Room for the River project. The program includes lowering and broadening of the floodplain; creating river diversions and temporary water storage areas; lowering the inner dikes and reinforcing the outer dikes and deepening the river channel. All these adjustments generate more storage space for excess water. The project started in 2006 and must be finished in this year, 2015 (Met Andere Woorden, 2006). Besides a flood protection project the Room for the River project improves of the environmental quality as well. By restoring the natural river landscape the biodiversity will be restored as well (Ruimte voor de rivier, 2012). To ensure the protection against floods it is of great importance that the extra river discharge capacity obtained by the Room for the River projects is preserved. Because the projects lead to natural vegetation development besides the extra conveyance capacity, the newly formed areas often produce a hydraulically rougher surface than before. Natural, spontaneous vegetation is mostly higher, and thus rougher, than agricultural vegetation. The extra conveyance capacity created then will be offset by the vegetation succession (Querner and Makaske, 2012). The monitoring and maintenance of the vegetation in river forelands is needed to act in time on this vegetation development to preserve the enlarged conveyance capacity.

Stroomlijn

To ensure the protection against floods by maintaining the vegetation Rijkswaterstaat started in 2012 the program ‘Stroomlijn’. For this program Rijkswaterstaat studied the river flow in times of high river discharges to see at which location the water flows the fastest through the river forelands. These areas are called the flow path of the river. Rijkswaterstaat also studied which vegetation types obstruct the river flow the most. As explained earlier, vegetation types with high values for hydraulic roughness are types that obstruct the river flow severely. The program ‘Stroomlijn’ is set up to remove the rough vegetation that has developed since 1996 which is the given starting situation. Stroomlijn catches up with the maintenance and takes care that rough vegetation in the river flow path will be removed and that the flow path mostly is vegetated by grasslands or other low vegetation types. In practice this means that most forests, brushwoods, hedges, reed and tall herb vegetation that are growing in the river flow path are removed. The operations take into account that locations with high nature value are preserved if possible. The principle of Stroomlijn is: "river flow path must be smooth, unless…” This last part is included to make room for nature legislation and other interests and make sure that not all areas in the river flow path are changed into grasslands.

For the areas outside the river flow path the approach is the ‘stand still’ principle. In these areas the vegetation does not have to be removed, but is not allowed to get rougher than it is now. Sometimes an exception can be made as compensation for vegetation that is removed in the river flow path (Rijkswaterstaat 2012).
Figure 3: Different adjustments to the riverbed, dikes and floodplain to create extra water storage.
Source: www.ruimtevoorderivier.nl
2.3 Vegetatielegger

In the end of 2014 Rijkswaterstaat developed a new instrument to see which kind of vegetation is allowed at a certain location in the river forelands. This instrument is called the 'vegetatielegger' and it is a map that shows the standard situation of the vegetation types that are allowed at any location in the river foreland area of the Netherlands. There are no rougher vegetation types allowed at a location than displayed in the vegetatielegger. The state of the vegetation after the Stroomlijn project operations will be recorded in the vegetatielegger (Tweede Kamer (2012-2103)). The vegetatielegger shows what vegetation is allowed where with a level of detail of 5 meters. The spatial resolution of 5 meters corresponds with the ambitions to generate the new ecotope maps with a level of detail of 5 meters as well. In the vegetatielegger 4 vegetation types are mapped and 3 mixture classes:

- Grasslands and agricultural fields
- Reed and tall herb vegetation
- Forest
- Brushwood/shrubs
- Mix 1: minimal 80% grass and agricultural fields
- Mix 2: minimal 30% grass and agricultural fields and maximal 40% brushwood
- Mix 3: minimal 10% grass and agricultural fields and maximal 60% brushwood

Figure 4 shows the vegetatielegger of the river Maas together with the detailed picture of the test site that is used for this project. The test site contains all vegetation classes except for the mixture classes. Although the ecotope map does not include solitary trees and small hedges, the vegetatielegger does display them. These trees and hedges are used as landmarks in the vegetatielegger to make it easier for people (e.g. land owners and gardeners) to recognise the area and to determine their position in the field. Those solitary trees or small groups of trees (maximum 3 trees) are allowed at any location in the river foreland areas. In an area with a homogeneous vegetation type new vegetation is allowed to develop on condition that it is less than 500m² in case of a rougher vegetation type. When there is too much (rough) vegetation present in an area Rijkswaterstaat can decide to carry out the required maintenance (Rijkswaterstaat, 2014). The vegetatielegger is available online so landowners themselves can look up their land to see what vegetation is allowed where. When they see that there is growing too much vegetation on their land, they can contact Rijkswaterstaat for maintenance. However, the responsibility for the flood prevention in relation to vegetation growth is still at Rijkswaterstaat. Landowners are not obliged to contact Rijkswaterstaat about vegetation growth on their land. Rijkswaterstaat has to organize the needed maintenance.

For Rijkswaterstaat agricultural fields are low-risk areas because the farmers intensively farm, and thus maintain the area. Also grassland and agricultural fields have low values for hydraulic roughness. Monitoring is more important for the natural areas. These areas are less intensively maintained and an increase in (rough) vegetation is more likely to occur. Rijkswaterstaat is, as said before, responsible for the flood prevention and the accompanying maintenance. However, Rijkswaterstaat contracted landowners of large nature areas (like Staatsbosbeheer) to perform the maintenance themselves. Then the landowners are responsible for the maintenance and Rijkswaterstaat only has to monitor these areas.
The situation as mapped in the vegetatielegger is the leading principle. At any time the vegetation in the forelands should match this standard situation where no more than 500m² per homogeneous surface may change to a rougher vegetation type. In the current situation the ecotope map that is created once in six years will be compared to the vegetatielegger. Maintenance actions will follow if change compared to the vegetatielegger is detected.

Figure 4: Vegetatielegger of the river Maas and a zoom-in picture of the test site used for this project.
3. Problem Statement

As explained in chapter 2 about the current situation at Rijkswaterstaat, Rijkswaterstaat uses one observation method, the aerial photographs, as basis to make a map of the ecotopes in the river foreland area. This map is made once in every six years. Rijkswaterstaat does have aerial photographs of the entire country available each year that can be used for this map of ecotopes, but the process of making a vegetation map from these photographs is labour intensive and costly. So, despite the fact that the aerial photographs are available more often, the interpretation of these photos for the ecotope map is still done only once in six years. The way the interpretation of the aerial photographs is done is manually which makes the classification slow and subjective (Houkes and Buiks, 2011).

Because of the frequency of the ecotope map there is no information used that takes into account the influence of differences within those 6 years. For six years, the situation of the vegetation (and thus resistance the vegetation exerts on the river flow) of the river forelands is assumed constant. This might be a problem. The riverbed area can change and vegetation grows, especially in areas that have changed because of the 'Room for the River' project. It could be that there are important changes within those six years that are not taken into account with this method. Also, it is possible that, after six years, the new data shows changes but it is already too late to act in time on these changes. A large amount of vegetation growth in the river flow path can cause a flood risk for that area.

With the problem stated above the research question of this graduation project is:

*Is it in relation to the conservation of the situation as given in the Vegetatielegger and for flood prevention, needed to intensify the vegetation monitoring, and how can this intensification be achieved?*

The sub question in this research project is about the data that is needed to achieve an intensification of the vegetation monitoring. The current method uses only aerial photographs. When a new method needs to be designed there are no restrictions what data to use. Therefore the sub-question in this project is:

*Does a new, intensified, vegetation monitoring method require satellite data or is the available aerial photograph data sufficient?*

The first thing to study is if there is evidence found for vegetation growth within those six years. If this is the case, it is a proof that an intensification of the vegetation monitoring will be an improvement to ensure the flood protection. The next part examines and discusses the vegetation growth within six years. It also examines the accuracy and subjectivity of the current method to be able to compare the current method with a later designed new method.

As mentioned above, the current method of classifying the vegetation is too slow and expensive to perform more frequent. New developments for monitoring the vegetation growth in the river forelands are desirable as written by Rijkswaterstaat in Houkes and Buiks, 2011. The current method of classifying is manually interpreting the images. A method that can map changes in vegetation automatically will be cheaper, faster and less subjective. Part 3, designing a change detection method, will continue on this subject. This chapter will focus on how to design a change detection method and study the data that is needed for such a new method.
Part Two: The necessity of changing and intensifying the vegetation monitoring situation

The current method of the vegetation monitoring is time consuming and costly. Part two of this project tries to answer the first part of the research question: Is intensification needed to ensure the water safety in and around the Dutch river forelands? Therefore a vegetation growth analysis is done where aerial photographs of several years are used to study vegetation growth. The result shows significant vegetation growth within just two years, which explains the need for an intensified monitoring. This part of the report also studies another disadvantage of the current method: the subjectivity of the manual classification method. Therefore two datasets that overlap are studied.

The last chapter of part two of this report describes an Alterra study to the accuracy of the current classification. The Alterra study contains a lot of errors, but is usable to give insight in the accuracy of the current classification on the level of the vegetation types of the vegetatielegger. These results can be used later in this project to compare the accuracies of the current and the new method.
4. Vegetation growth analysis

The ecotope maps that are used to monitor the vegetation in the river forelands are made once in 6 years. The goal of this project is to study whether it is an improvement if the vegetation monitoring is done more frequently, like once every year, and how this can be achieved. To decide whether a higher frequency of vegetation monitoring can be an improvement on the current situation, vegetation growth within those six years will be studied in this chapter. When there is vegetation growth visible within six years a new, more frequent method will be an improvement on the current situation.

The aerial photographs for the ecotope maps are just like the maps available once in every 6 years. Those images are public because they are made under the commission of Rijkswaterstaat and therefore can be seen online or be requested at the Rijkswaterstaat data service. With aerial images available for every 6 years vegetation growth within those six years can’t be seen. Rijkswaterstaat, however, has aerial photographs of the entire Netherlands available for every year. These photographs are bought by Rijkswaterstaat from other companies and thus are non-public documents. These documents can’t be requested, but for this study the images could be studied at the Rijkswaterstaat office at Delft.

Aerial images from 2007 till 2013 were studied to see vegetation differences within six years. The time of the year the photographs were made are listed in table 2. The interpretation of images for the ecotope maps is done with a photogrammetric system and special glasses so the images can be seen in 3D. For this study, such visualisation was not possible, so the height of the vegetation could not be seen. Therefore, only the appearance of trees, bushes and the change from grassland to very rugged grassland are visible. These vegetation appearances are also the most important ones for this study with respect to the hydraulic roughness, so this limitation is not a problem. It might look strange to expect a tree to be formed within 2 years, but there are frequently occurring willow species that germinate quickly and grow up to 2 meters per year (Wolters et al., 2001).

The changes are studied by comparing aerial photographs from different years for locations at the river forelands. The focus was on the natural areas during this study. Natural areas are, more than agricultural areas, subject to changes that make the surface rougher. Changes in agricultural fields do exist, but those changes are mostly within the grass and agricultural field class, which will not make the surface rougher. Some cases of vegetation growth are found and shown and described in the next section.

<table>
<thead>
<tr>
<th>No.</th>
<th>Date of aerial photographs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>04-2007</td>
</tr>
<tr>
<td>2</td>
<td>End of 2008</td>
</tr>
<tr>
<td>3</td>
<td>25-01-2009</td>
</tr>
<tr>
<td>4</td>
<td>20-09-2010</td>
</tr>
<tr>
<td>5</td>
<td>01-11-2011</td>
</tr>
<tr>
<td>6</td>
<td>08-10-2012</td>
</tr>
<tr>
<td>7</td>
<td>10-2013</td>
</tr>
</tbody>
</table>
4.1 Comparisons
In this section the vegetation growth of four different locations is studied. The four locations are shown on the map in figure 5.

Blauwe Kamer
The ‘Blauwe Kamer’ is situated along the Lower Rhine between Wageningen and Rhenen. It was in former times an area where clay was extracted, but since 1991-1992 it is redesigned to be a nature reserve. The area floods regularly and because of this the vegetation is continuously changing (Klink et al, 1995). In the Blauwe Kamer two examples of vegetation growth are found and shown. The first one, figure 6, is a grassland area. From the aerial photograph is clearly visible that the land has become a rougher surface instead of a smooth grassland in two years. Figure 6A shows mostly grasslands with some solitary bushes and trees, where in figure 6B the grassland has become a rough surface. Probably the grassland that has a low hydraulic roughness has changed into a surface with a lot of tall herb vegetation that has a higher hydraulic roughness.
Figure 6: Aerial photographs from grassland in the Blauwe Kamer. 6A is taken in 2010, 6B in 2012
The second example of vegetation growth in the Blauwe Kamer is shown in figure 7. In one year bushes or trees have formed on a location that first only showed grassland. The distinction between bushes or trees can't be made without knowing the height of the vegetation. The differences between trees and bushes according to the interpretation key are determined by height differences, so the vegetation grown in this area can only be defined as ‘bushes or trees’.

Figure 7: Appearance of bushes or trees in the Blauwe kamer. 7A is the aerial photograph of 2010, 7B is taken in 2011
Afferdense en Deestse Waarden

South of the Blauwe Kamer, along the Waal, the Afferdense en Deestse Waarden are situated. At two locations vegetation growth is found. The first example (a location north of the town Afferden) is shown in figure 8. In 2010 at the marked spot in the lower right grassland is visible (figure 8A). The marked spot in the upper right shows grassland with small groups of trees or bushes. Two years later, seen in figure 8B, the small groups of trees or bushes have changed into a densely vegetated area. The increase in tall herb vegetation is clearly visible. The lower right area that only showed grassland in figure 8A shows in 2012 one large group of rough vegetation, which due to the visible shadows classified as bushes.

The images of the second example are shown in figure 9 and are from a location near the town Druten, which is west of the natural area. Figures 9A – 9D show a time series of in total five years. Three different areas are marked, which all show vegetation growth. The largest one, along the riverbed is interesting to study for the whole time span. In 2008 there is little vegetation visible along the riverbed and also the other two marked areas are not densely vegetated. In the next few years, up to 2012, the vegetation keeps growing and getting denser. The last image in the series shows the situation of October 2013. The vegetation at the area near the riverbed (now marked with a blue line) has been removed due to the Stroomlijn program and looks like the situation of 2008 again. The other two areas have been left untouched and still contain a large amount of rough vegetation. The blue area has been cleared from vegetation because vegetation at that location increases the flood risk. The program Stroomlijn only removes vegetation at locations where vegetation significantly obstructs the water flow during large discharges. As seen in these aerial photographs already in 2009 is visible that vegetation is growing. However, it takes another four years until the vegetation is removed.

Figure 8: Vegetation growth in the Afferdense en Deestse Waarden. 8A shows the photo of 2010, 8B of 2012
Figure 9: Time series of vegetation growth in the Afferdense en Deestse Waarden. 9A is from 2008; 9B from 2009; 9C from 2012; 9D from 2013.
**Merwedelanden**

The two images shown in figure 10 are situated just east of the Merwedelanden near Dordrecht. The sandy grassland of 2011, figure 10A, changed in two years in grassland with bushes or trees on it, figure 10B. The vegetation growth within the red square where grassland has changed into bushes and trees stands out most. However, in the entire image vegetation growth is visible. Most of the bare land seen in figure 10A is in figure 10B covered with grass.

*Figure 10: Vegetation growth at grassland in the Merwedelanden. Figure 10A is a photo of 2011, 10B, is from 2013*
North of ’s Hertogenbosch along the Maas the images of figure 10 were taken. At the two locations marked with red ovals vegetation growth within 2 years is visible. In 2010 only small groups of trees (or bushes) are visible. Most of the area is covered with grassland and solitary trees. Two years later, at the spots with the solitary trees and small groups of trees a large amount of new trees/bushes have formed.

Figure 11: Vegetation growth along the Maas. 11A is a photo from 2010; 11B is from 2012
4.2 Conclusion

The examples shown in the previous section demonstrate that vegetation in natural areas can grow significantly within one or two years. Vegetation growth within six years is proven to be present and, therefore, important to identify. When the vegetation is only mapped once in 6 years important changes can be missed or seen to late. This means that it is possible for (rough) vegetation to start growing on locations where it could increase the flood risk. With the current situation, vegetation that formed within two years after the last monitoring is identified and, if needed, removed at least four years after it is visible on aerial photographs. Another disadvantage of only monitor the vegetation once in six years are the cost of the vegetation removal. When there are more (tall) woody vegetation types present, the land can no longer be mowed and the costs of the removal will be higher (Rijkswaterstaat, 2007).

These areas are not (yet) affected by the 'Room for the River’ project. This project is likely to have a large positive effect on nature development. But, as this section proves, even without being affected by the 'Room for the River’ project vegetation in natural areas is changing continuously. The natural area Afferdense and Deestse Waarden, that is shown twice above with examples of vegetation growth, will be redesigned from 2014 till 2018. Making secondary channels and lowering the floodplain will increase the 'Room for the river’ in the area. The size of the natural area will increase as well, which will have a positive effect on natural development and thus on vegetation growth. The natural area Afferdense and Deestse Waarden is just one example of a nature area that will be redesigned. More and more locations will be redesigned and natural areas are restored and enlarged.

Even without areas being affected by the 'Room for the river’ project vegetation grows rapidly. Multiple locations show the development of rough vegetation types like bushes and trees within two years. This vegetation can enlarge the flood risk by obstructing the water flow and causing floods reach over the outer dike. The increase of natural areas due to the ‘room for the river’ project will encourage the vegetation growth even more and thus will cause more obstructing object when left untouched. More frequent monitoring and maintain the vegetation could avoid dangerous situations and will lower the cost of vegetation removal. With the current monitoring method, which is time consuming and costly, more frequent monitoring is not possible. A new, faster method is desired which will be an improvement on the current situation with respect to flood prevention and vegetation removal costs.
5. Ecotope Overlap Comparisons

The current monitoring method has, as described earlier, multiple disadvantages: It is time consuming, costly and subjective. The time consuming part of the current method is proven to be a concern for the flood prevention in the former chapter: an intensification of the vegetation monitoring is needed. The other disadvantage, the subjectivity of the current method, is studied in this chapter.

Two important precautions are already used in the current method to reduce the subjectivity of manual interpretation. These are an interpretation key and the use of the ‘old border method’, which is explained in section 2.1. However, it is still a manual interpretation, and the ecotope map made by different persons each time (Houkes and Buiks, 2011). This chapter will test the subjectivity of the old method by comparing two maps of the same year.

The ecotope maps of the second cycle for Rijntakken-Oost and Maas have a small overlap (see figure 12). For this location the subjectivity of the interpretation method can be studied by comparing both ecotope classifications for the same area. Both interpretations are done, independently from each other, by EFTAS, Munster. Unfortunately, both interpretations are not based on the same aerial photographs. Aerodata took the aerial photographs for the Maas ecotope map on July 7, 2004 (Willems et al., 2007). Hansa Luftbild GmbH took the photographs for the Rijntakken-Oost ecotope map on August 18, August 29 and September 4 of 2005 by (Houkes, 2008). Differences visible in the ecotope map can therefore also be due to the time gap of a year that is between the two aerial photographs and are not necessarily due to differences in interpretations.

Figure 12: Overview of the ecotope mapping of the river Maas, 2004, and Rijntakken-Oost, 2005. In figure 12A the red square shows the overlap location, 12B zooms in to the overlap (in red)
However, inspecting the aerial photographs of both areas brought to light that the photographs of Rijntakken-Oost are not covering the overlap area as shown in figure 12. The ecotope map of Rijntakken-Oost does cover this area, so it is not clear which images are used for the interpretation. Studying the riverbank line of both ecotope maps can give more information about the photos used. When the riverbank line for both ecotope maps is exactly the same, the assumption can be made that both maps are created with the same aerial photographs as basis. This is because the water levels vary often, so when the water level is exactly the same for the two interpretations they must be based on the same photographs.

5.1 Preparations
To compare the both maps some preparations have to be done. The overlay procedure for the ecotope map of the Maas 2004 was not done completely. The last step that should merge adjacent polygons that are assigned to the same ecotope was not done properly. Therefore this ecotope map included a lot of unnecessary polygons, which makes the map unclear. To solve this problem adjacent polygons with the same ecotope classification are merged with the Q-GIS geo-processing tool Dissolve. Next, to compare both interpretations the intersection is saved as a separate shape file.

The intersection file is corrected for differences between the two images that are not due to a different classification of the area. The corrections mean that different water classes as ‘shallow water’ and ‘river supporting water’ will be equal and production grassland will be the same as natural grassland. The vegetatielegger does not include different types of water or grassland, so the comparison of two classifications should list two types of grassland/water as equal classified.

The new map that is created is shown in figure 13. Red areas show polygons that are differently classified by the two classifications. Green areas are classified the same for both classifications. With the help of this figure the interpretation differences and the differences in the riverbed line between the Maas 2004 mapping and the Rijntakken-Oost 2005 can be studied.

Figure 13: Comparison of the two vegetation interpretations of the river Maas, 2004 and Rijntakken-Oost, 2005
### 5.2 Comparison

While comparing the two interpretations of the aerial photographs it is clear that the riverbank line is exactly the same for both interpretations. This means that both ecotope maps are based on the same aerial photographs. Differences as seen in figure 13 cannot be due to vegetation growth or other land uses, but can only be due to interpretation differences.

Most of the image is green, which means that for most locations the vegetation interpretation was the same for both years. There are some differences that are interesting to mention regarding interpretation differences.

#### Agricultural field and grasslands

The three large red spots seen in figure 13 are all assigned to agricultural field in the Maas 2004 interpretation and as grassland in the Rijntakken-Oost 2005 classification. The aerial photograph of this area is shown in figure 14. This figure shows that there are three large areas that are interpreted differently. The interpretation key is in these three cases not sufficient to prevent interpretation differences between agricultural field and grassland.

![Aerial photograph showing the locations with classification differences (grassland or agricultural field marked with white spots)](image)

**Figure 14:** Aerial photograph showing the locations with classification differences (grassland or agricultural field marked with white spots)
**Tall herbs and Reed and other halophytes**

Another difference in the interpretation is that for the reed and other halophytes class with the tall herbs class. Figure 15 shows three locations for which Rijntakken-Oost 2005 the area defines as Reed and other helophytes and Maas 2004 the areas assigns to the tall herbs class.

![Aerial photographs with white spots showing differences between tall herbs and reed and other halophytes class](image)

**Figure 15:** Aerial photographs with white spots that mark the interpretation differences between tall herbs and reed and other halophytes class

According to the interpretation key the difference between tall herbs and the reed and other halophytes is the presence of texture and species. The tall herb class is rich of texture and vegetation types where the reed and other halophytes class is low in texture and amount of plant species. Apparently these properties are sometimes hard to distinguish from an aerial photograph. As already described in Houkes and Buiks, 2011, reed and tall herb vegetation is difficult to distinguish on an aerial photograph that is mostly taken in summer. During the winter it is easier to keep the two classes apart. A possible solution to this problem is already written in Houkes and Buiks, 2011: from 2011 also aerial photographs taken in winter should be available. These could be used to distinguish reed and tall herb vegetation properly.
Grassland and built-up area
Most built-up areas are clearly defined. However, when the area is not packed with buildings and there is more open space the interpretation between the two maps is different (see figure 16A and 16B). The Maas 2004 maps the areas with some buildings and open space as built-up area where Rijntakken-Oost 2005 maps it as grassland. Maybe a mixed class is better in these cases.

Figure 16: In both figures, A and B, white spots mark the areas classified as built-up area in one interpretation and grassland in the other
Other differences
Besides the three categories of differences explained above that cover a relative large area there are some other differences that only cover a small area as well. Mostly the small differences are due to slight differences in the borders between the tow maps. Another difference is whether or not a line shaped object is mapped. For example figure 17 shows a line of trees that is only mapped for the Maas 2004 map.

![Aerial photograph which shows with white spots a line of trees that is only mapped in the river Maas 2004 map](image)

5.3 Conclusions
The two interpretations can be compared because there is an overlap between the ecotope maps of Maas 2004 and Rijntakken-Oost 2005. Based on the fact that the riverbed line is exactly the same for both maps the assumption is made that they both used the same aerial photograph, flown by Aerodata on July 7, 2004. After some preparation and visualising the overlap map in Q-GIS the differences between the two maps are studied. After compensating for the different designations of the riverbed and the difference in the distinction between the types of grasslands there are very few differences found. Two categories of differences found, the agricultural fields – grasslands and the reed and other helophytes – tall herb vegetation, have minor consequences for the value for hydraulic roughness. The vegetation types that are swapped have values for hydraulic roughness that are quite similar. In the vegetatielegger discussed in the former chapter those two vegetation types are even combined into one class. However, although the differences are not that important for the value of the hydraulic roughness, these differences show that the distinction between the classes are sometimes hard to make with this interpretation key. The differences with the grassland and built-up area classes show that it is possible that the interpretation key is not clear enough in when to classify something as built-up area. Maybe a percentage can be given that describes the minimum area with paved grounds and buildings within a polygon to classify it as built-up area.

The validity of these results is questionable. There is no answer found why the ecotope map of Rijntakken-Oost 2005 does contain the overlap area, but the aerial photographs do not. With the similar riverbed lines it is most likely that both the ecotope maps use
the same photographs as basis. Not only the riverbed lines are similar; most borders are exactly the same. Strangely some entire features like a line of trees (figure 17) is missed in one map while the other did map it. Andries Knotters of CIV (central information provision) from Rijkswaterstaat is contacted about these results and his conclusion, after studying both datasets, is that these are not typical examples and that it might not be the best example to study the subjectivity of the interpretation. According to Knotters both maps are too similar to be produced independently but the differences are unexplainable.
6. Accuracy of the current vegetation monitoring

Chapter 4 showed that intensification of the monitoring is needed to ensure flood protection in the Dutch river forelands. The current method is costly and time consuming, so in order to intensify the monitoring of the river forelands a new method should be designed. However, it is useful to know how accurate the current vegetation interpretation method is. In this way the accuracy of a newly designed method can be compared to the accuracy of the current method. In this chapter the reliability and accuracy of the current vegetation monitoring method are described. A new method should be just as reliable or even more reliable then the current method in order to have a satisfactory result.

This chapter describes the methods that Alterra (the research institute for the green living environment of Wageningen university) used to validate the ecotope classifications of the current Rijkswaterstaat method and gives the total accuracy for all the ecotope maps as calculated by Alterra. The Alterra research group worked with a validation on the level of the ecotopes while this study focuses on the level of detail of the classes of the vegetatielegger. Therefore this chapter also shows the results of the validation of Alterra on the level of detail of the vegetatielegger classes. This makes the calculated accuracy of the current method comparable to the accuracy of the new method that will be designed later in this project. The research of Alterra is documented by Knotters et al. (2008).

6.1 Field validation methods

To study the accuracy of the ecotope map a field study is done by Alterra by sampling multiple areas. The accuracy of the map is the percentage of the surface on the map that is in accordance with the field validation. The maps that are checked are all the ecotope maps of the second ecotope cycle. The check is done on ecotope level instead of vegetation structure level. This means that the class as defined after the overlay procedure is performed, described in the chapter ‘current situation at Rijkswaterstaat’, is validated in the field. In the validation study the assumption is made that the field study reflects reality, so errors made during the fieldwork are not taken into account. The research institute Alterra developed a new sampling method to study the accuracy of the ecotope map, which has a more statistically reliable result than the old method. Alterra performed, for both the old and the new method, the statistical analysis (Houkes et al, 2008).

Old sampling method

The old sampling method is used for the areas IJsselmeer, Volkerak-Zoommeer, Rijntakken and Maas (so everything except the Rijn-Maas estuary).

By applying targeting search a number of core areas of approximately 5 by 5 kilometres are selected that have a large variation of interpretation classes. Within a core area validation locations are selected with the help of the ecotope map. The validation locations together contain all the possible ecotopes, except for the water classes and built up area classes, which are not taken into account with the validation process (Houkes, 2008).

Targeting search has the advantage of reducing travelling time, but the reliability of the estimated map accuracy cannot be determined without assumptions. The core areas as well as the validation locations are not chosen randomly and accessibility of the location was considered to be a more important factor than the spatial distribution. Therefore, the assumption is made that vegetation on the easily accessible locations represent the vegetation of the whole area. The statistical reliability of this method used to estimate the map quality is sub-optimal by not using random sampling.
**New sampling method**
To improve the statistical reliability of the sampling method, Alterra designed a new method that doesn't need assumptions. This new method is used for the Rijn-Maas estuary ecotope map. Again, built up areas and water classes are excluded from this validation method.

The sampling method chosen is a two-stage stratified sampling method. In the first stage the area is divided into 8 geographic strata that contain the most important river branches. In each of these strata two core areas are randomly chosen. The second stage is taking a simple random sample in every chosen core area. The amount of sampling points in the areas is laid down in advance and is determined by the size of the area. An expected sampling size of 1000 is used (Knotters et al., 2008).

### 6.2 Results
As can be read in the Alterra rapport of Knotters et al. (2008), a statistical analysis for all the ecotope maps is done to estimate the accuracy of the maps and the standard error of this estimated accuracy. The overall accuracy of the ecotope maps is quite low. Between 27.8% and 47.8%, of the surface is classified as the same ecotope in the field as on the map (see table 3). Appendix B shows the accuracy results for every ecotope class as calculated by Alterra.

#### Table 3. Accuracy results for the ecotope map as estimated by Knotters et al., 2008

<table>
<thead>
<tr>
<th>Area</th>
<th>% of the surface mapped correctly (Standard error in brackets)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rijn-Maas estuary</td>
<td>47.8 (3.5)</td>
</tr>
<tr>
<td>IJsselmeer</td>
<td>27.8 (5.3)</td>
</tr>
<tr>
<td>Volkerak-Zoommeer</td>
<td>31.9 (8.0)</td>
</tr>
<tr>
<td>Rijntakken</td>
<td>37.8 (4.2)</td>
</tr>
<tr>
<td>Maas</td>
<td>39.6 (5.7)</td>
</tr>
</tbody>
</table>

### Sources of errors
The percentage of the surface that is mapped correctly is low. Some factors that lead to a certain ecotope classification are not visible while in the field (like flood duration), so cannot be validated with field observations. In the field validation ecotope classifications like the flood duration are used which will lead field classifications that are not realistic. As described in Houkes et al., 2008, there are more reasons why the overall accuracy of the ecotope maps is estimated this low by the Alterra report. While performing the field validation there are assumptions made that are different from the ones made while interpretation the aerial photographs. The distinction between bushes and trees that is used for the photograph interpretation is a height of 5 meters, while the field study used 7 meters. Also, the field study has not taken into account that the photograph interpretation only maps surfaces that are larger than 20 by 20 meters. Surfaces smaller than this are merged with a neighbouring area, so are not mapped individually. In the field study they are mapped individually, which can lead to different results. Another source of errors is the visibility of the hydrological zones within the field. Zones as riverbank, floodplain and flood free area are difficult to distinguish in the field. In some areas, like the IJsselmeer, not all zones are present. In the IJsselmeer area there are no floodplain zones, but this is not taken into account with the field study. The classified locations will then never be the same for the field study as for the ecotope map.

Apart from the assumptions made and the subjectivity of the classification a contributing factor to the errors is the difference of a year that is present between the photographs and the field validation. As shown in chapter 4 vegetation can grow
significantly within a year. The field observations are taken as the ‘true’ values, so observation mistakes can be another source of errors.

The results from the Alterra report describe the accuracy of the ecotope map on the level of detail of the ecotope classes. Together, the differences in assumptions made between the field study and the photograph interpretation and ecotope classification factors that are hard to distinguish in the field, show that this level of detail might be inappropriate. Better could be to estimate the map accuracy on the level of detail that is the same as the level of detail of the vegetatielegger: 4 different vegetation types that are distinguished. Because a new method that will be designed in this project also uses these 5 classes the accuracies of both methods can then be compared. While the field classifications are incorrect on the level of ecotopes, is the classification on the level of the 4 vegetation types most likely be correct and thus comparable. This is because grass, forest built-up area, tall herbs and bushes are easy to distinguish in the field. Therefore, in this chapter the results of the Alterra rapport of Knotters et al (2008) of the Maas area are interpreted on the vegetatielegger level of detail. Classification errors on the level of hydrological zones are not taken into account and there are no subdivisions made between different types of forest or grass. The accuracy of the ecotope map on vegetatielegger vegetation types level is much higher than the one on the level of ecotopes. The results of the Alterra report (appendix B) are used to compute the accuracy on the level of detail of the vegetatielegger types. Table 4 shows the accuracy of the current Rijkswaterstaat method for the region of the Maas on the level of the 4 different classes. The reason why Maas area is chosen to make the accuracy computations on the 4 classes is because the test area for the new method also is located in the Maas area. In this way both accuracies of the old and the new method can be compared. The accuracy of the water class and the built-up classes is not computed in the study of Alterra. Therefore, the accuracy of those classes therefore can’t be compared to the accuracy of the new method that will be designed later in this project.

Table 4 Accuracy of the ecotope map on vegetatielegger level of detail

<table>
<thead>
<tr>
<th>Class</th>
<th>Correctly classified (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>68%</td>
</tr>
<tr>
<td>Grass</td>
<td>86%</td>
</tr>
<tr>
<td>Tall Herbs</td>
<td>29%</td>
</tr>
<tr>
<td>Bushes</td>
<td>49%</td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td>67%</td>
</tr>
</tbody>
</table>
As the necessity of the intensification of the vegetation monitoring is proven in part 2 of this report, part 3 describes the new monitoring method that is designed. The first chapter discusses what result is really wanted and which dataset are available. The end result that Rijkswaterstaat wants is a change detection that compares the current situation with the standard situation visualized in the vegetatielegger. To achieve this result satellite data, aerial photographs and height data can be used. The second chapter of this part explains the methods that are used to get to the end result and why these methods are chosen. The new method uses a post-classification change detection method. The classification method is an object based classification that uses region based segmentation and kNN-classification. The classification is done with satellite images and aerial photographs to test the need for winter satellite images. For both the classification and the change detection the accuracy is tested. The last chapter describes the classification and change detection results and also the accuracies of the method are listed.
7. Available data and desired results

In order to intensify the monitoring of the vegetation of the river forelands a new method has to be designed. Before a new method can be designed the desired results should be clear. Also the available data has to be studied. This chapter first explains the desired results and later describes all the data that is available en used for further processing.

7.1 Desired results

In part 1 of this report the current method is explained. The current method is labour intensive (thus slow), costly and subjective. Because the monitoring of the vegetation has to be done more frequently a new method that is faster than the current one is needed. To completely outperform the current method, the new one has to be cheaper, more objective, more accurate and available within one year.

So, the features of the new vegetation monitoring must be: fast, cheap en objective. But, what should the data look like? Currently the ecotope map is the end result of each monitoring cycle. However, in the end of 2014, the vegetatielegger is developed. This new tool as explained earlier describes the standard situation in the river forelands and vegetation growth should not exceed this standard level. The desired end result now has become a comparison of the current state of the vegetation (the monitored vegetation) and the vegetatielegger. One not only needs to know what grows where, but should also know whether or not this exceeds the situation of the vegetatielegger. Therefore the wanted result is a change detection. Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). A new method should show at which locations the vegetation has changed and where the vegetation has to be maintained. Not all the vegetation changes are relevant, only the changes that make the surface rougher. Table 5 shows the relevant changes in red and the changes that are not of importance in green. A newly designed change detection should highlight the surfaces that have become rougher with respect to the vegetatielegger in a fast, cheap en objective way.

Table 5: The checkmarks represent the changes that are allowed, the crosses show changes that make the surface rougher and therefore are not allowed

<table>
<thead>
<tr>
<th>From</th>
<th>Grass &amp; agricultural field</th>
<th>Reed &amp; tall herb vegetation</th>
<th>Brushwood</th>
<th>Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grass &amp; agricultural field</td>
<td>✔️</td>
<td>❌</td>
<td>❌</td>
<td>❌</td>
</tr>
<tr>
<td>Reed &amp; tall herb vegetation</td>
<td>✔️</td>
<td>✔️</td>
<td>❌</td>
<td>❌</td>
</tr>
<tr>
<td>Brushwood</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>Forest</td>
<td>✔️</td>
<td>✔️</td>
<td>❌</td>
<td>✔️</td>
</tr>
</tbody>
</table>
7.2 Available data
Now that is known what end result is desired the available data has to be studied. Rijkswaterstaat orders aerial photographs of the entire Netherlands each year. These photographs are made with an overlap of 60 per cent and a spatial resolution of 0.25 meter. They record the visible wavelengths as well as the near-infrared wavelengths. Because the photographs are taken with overlap they are called stereo aerial photographs and it is possible to interpret the photographs tridimensional. Geo-ICT and Earth observation company NEO created a height dataset from the stereo photographs in combination with AHN2 data that has a spatial resolution of 0.75m and a height accuracy of around 1 meter. The aerial photographs (and thus the height data as well) that are used for this project are from the summer of 2014.

Besides aerial photographs also satellite images are available. The images are SPOT 6 images, made in the winter of 2014. The spatial resolution is 1.5 meters and it records the visible bands as well as the near infrared wavelength. More types of satellite images exist that mapped the test-site area, but the images used were available for Rijkswaterstaat. All the available dataset used in this project are listed in table 6.

Table 6: Available datasets for this project

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Date</th>
<th>Spatial Resolution</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerial photographs</td>
<td>Summer 2014</td>
<td>0.25 meter</td>
<td>4 bands</td>
</tr>
<tr>
<td>Satellite images</td>
<td>Winter 2014</td>
<td>1.50 meter</td>
<td>4 bands</td>
</tr>
<tr>
<td>Height data</td>
<td>Summer 2014</td>
<td>0.75 meter</td>
<td>Height accuracy 1-2 meters</td>
</tr>
<tr>
<td>Vegetatielegger</td>
<td>N/A</td>
<td>Shapefile: Objects from 5 meters visible</td>
<td>Maps 6 classes and 3 mixture classes</td>
</tr>
</tbody>
</table>

All these datasets are available for one chosen study area located along the Maas near Boxmeer (see figure 18). This area shows a characteristic hedgerow landscape, which is very interesting as study area because the rough hedges should be monitored carefully. It also contains all the land cover classes of the vegetatielegger (except for the mixture classes): forest, shrubs, grassland and agricultural fields, tall herb vegetation, water and built up area.

The classification with a test-site that contains mixture classes would not be different. No new vegetation class has to be classified in that case. Only an easy calculation after the classification is needed to tell if the area still satisfies the rules of the mixture class. As described above the desired product is a change detection that compares the current state of the vegetation with the standard situation as described in the vegetatielegger. The next chapters describe and explain the methods that are used to make an automatic change detection of the Dutch river forelands. The methods will be used to classify the test area and to compare the classification to the vegetatielegger. The results will be described in chapter 10.
Figure 18: Test area used for this project: the river forelands of the river Maas near Boxmeer.
8. Chosen methods
The final result that is wanted is a change detection method. The method used to get to the final result should be chosen with care. This chapter explains the chosen methods for this project. First, the change detection method is discussed, later the classification methods are described.

8.1 Post classification change detection
There are many different change detection techniques. During the search for a suitable change detection method one should keep in mind that the accuracies of change detection results depend on many factors. Some factors are (Lu et al., 2004):

- The quality and resolution of the data
- The results of the pre-processing of the images and other data (geometric registration, atmospheric corrections)
- The availability of ground truth data
- Change detection methods and algorithms used
- Analyst’s skills and experience
- Familiarity and knowledge of the study area
- Time and cost restrictions

Some techniques only provide change/non-change information while others can provide a complete matrix of change directions. For a change detection method for the river forelands it is important to know which vegetation type has changed and what type it has become. This means a complete matrix of change directions is needed. The importance of knowing the change direction is due to the fact that not all changes are relevant (as showed in table 5). Change detections methods that only show change/no change information are therefore neglected.

One of the change detection methods that generate a complete change detection matrix is post-classification change detection. Post-classification change detection methods are based on classified images. It requires two classified images that will be compared on a pixel basis (Jensen, 1995). This method has a lot of advantages. It reduces the external impact from atmospheric, sensor and environmental differences between the multi-temporal data (Lu et al., 2004). An agricultural field for example can look very different in different times of the year. However, the fields are recognisable as fields all year round. The pixel values can be different, but due to the classification it is still recognised as the same land cover type, and the two images are still comparable for change detection purposes. With all the possible phenological differences in the river forelands of the Netherlands, a post-classification change detection method is preferred. Also, the results of these methods are easy to understand and to visualise (Jensen, 1995).

There are some disadvantages with this method as well. Since every error in the individually classified images will be present in the final change detection map the classification has to be done with great care (Rutchey and Velcheck, 1994). The result is as accurate (defined as the percentage of correctly classified pixels) as the accuracy of the one classification multiplied with the accuracy of the other (Stow et al., 1980, as cited in Singh, 1989).

Modified post-classification change detection
In the case of designing a change detection method for the river forelands in the Netherlands the disadvantage of having the errors of the two classifications multiplied with each other can be circumvented by using the vegetatielegger. With a standard post-classification change detection two classified images are used. In the modified method used in this project only one classified image and the vegetatielegger are being used. The
vegetatielegger is the standard situation for the vegetation that is allowed in the forelands and the classified image will have the same classes as this map. Therefore, the classified image can be compared to the vegetatielegger to see if something has changed relative to the desired situation. Only changes that make the surface rougher are important and should be highlighted in the result.

The new vegetation monitoring method will use a post-classification change detection. The accuracy of the result is dependent on the accuracy of the classification of the image that will be compared to the vegetatielegger. Figure 19 shows the flow chart for all the processes that are used to get to the final change detection result. The section of this report where the process or results is described is listed at the right side of the chart. In total there are 5 different results. Three results are generated with aerial photographs: one with proportional training-data (AP1 in the flow chart); one with equal training-data (AP2) and one with auto-generated training-data (AP3). Two results are generated with satellite images: one with proportional training-data (SI1) and one with equal training-data (SI2).

![Figure 19: Flow chart of the processes and generated results of this project](image-url)
8.2 Automatic classification
Because the new method will use the post-classification change detection, a classification of the Dutch river forelands is needed. The classified image can be compared to the vegetatielegger, and then show the changes in the area as final result. For an automatic classification technique there are many possibilities. First: which dataset is used for the classification method? And second: which classification method is used? The datasets chosen and methods used will be described and explained in this chapter.

Satellite data or Aerial photographs
For automatic classification of river floodplains different datasets can be used: Both satellite images and aerial photographs are available. Often satellite remote sensing data has many advantages above aerial photographs. Satellite data has repeat coverage, is less costly and less time consuming than aerial photography for large geographic areas (Ozesmi and Bauer, 2002). With satellite images it is easy to derive images for multiple seasons where aerial photographs are often only taken in summer. The availability of winter and summer images is an advantage for some features. For example, tall herb vegetation can be easier recognized in winter than in summer. Also, with respect to the aerial photographs used with the current method, many satellite images capture image data at more frequencies (have more spectral bands). The amount of spectral bands present (at least 4 bands) for satellite images makes automatic classification feasible. The three bands present for most of the aerial photographs are not enough to automatically separate all the classes present in the river forelands. However, satellite imagery also has its limitations. Compared to aerial photography the spatial resolution is low, which makes it difficult to identify small objects. Fluctuating water levels and cloud cover make some of the satellite images unusable (Ozesmi and Bauer, 2002). Because of these limitations Rijkswaterstaat always has only used the aerial photographs for vegetation monitoring.

In the case of the available data of the Dutch river forelands for this project it stands out that the satellite data and the aerial photographs have the same number of spectral bands. And, because Rijkswaterstaat already orders aerial photographs of the entire Netherlands each year, the disadvantage of the costs of these pictures is also rejected. Now rises the question if, for this project, the use of satellite images still has some added value. Satellite data still has the advantage of having data available in the winter period. Also, satellite data is, because of their lower spatial resolution and thus their data size, easier to handle and faster in computations. The question which dataset is preferred for the classification of the river forelands is answered at the end of this report. The classification will be done with both datasets: with satellite data and with the aerial photograph data.

Supervised or unsupervised classification
Classification is a common technique to extract information from remote sensing image data. It converts spectral data into thematic maps (Gorte, 1998). There are many ways to classify satellite images or aerial photographs. Automatic classification methods can be divided into two groups: supervised and unsupervised classification. This paragraph describes the differences between supervised and unsupervised classification and explains why supervised classification methods are preferred for this project.

Supervised classification
In the supervised classification the image analyst guides the pixel categorisation process. So called training areas of all the wanted classes are needed, which are
representative sample sites of the known cover types. Those sites are identified by the analyst and the spectral attributes of each those sites is described. In this way there is a spectral signature generated for every wanted land cover class. Each unknown pixel in the image is then compared numerically to each signature and is assigned to the land cover class it most closely resembles.

In supervised classification useful categories are formed and their spectral seperability is checked later (Lillesand et al., 2008). With supervised classification the analyst has more control over the type of classes defined than with unsupervised classification. A disadvantage of supervised classification is that the chosen classes not necessarily are spectral separable. Also, the training data might not account for the variation in environmental conditions (Shadowing, illumination, health of vegetation) throughout the study area (Richards & Jia, 2006). The selection of high quality training data is time consuming and often difficult. Knowledge and substantial reference data of the study area is required (Lillesand et al., 2008).

Unsupervised classification
Unsupervised classification does not need training data. Different than the supervised approach, spectral separable classes are formed by the software and their informational utility is defined later. With this method all the image data is grouped in natural spectral clusters. The amount of clusters (and thus the amount of classes) can be specified beforehand by the analyst. The classes that are formed are spectral classes and the identity of a cluster is initially not known. The Analyst has to check the clusters after the classification by comparing the result with reference data to determine the identity of the clusters. There are multiple clustering algorithms that are used to determine the natural spectral groups (Lillesand et al., 2008). An advantage of unsupervised classification is that the area can be classified without prior knowledge of the study area. Also, this classification method is less time costly than supervised classification. A disadvantage however is that the analyst does not has much control over the grouping of pixels and their identities. The result may not necessarily correspond to the categories of interest (Richards & Jia, 2006).

For this project it is important that the image is classified into classes that are comparable to the vegetatielegger. The classes that should be defined are known, so a supervised classification is preferred. With this many datasets present for the test location (ecotope maps, a vegetatielegger and multiple satellite images and aerial photographs) there is substantial reference data to make a supervised classification possible.

There are numerous statistical methods to make the comparison between the training data pixels and the unknown pixel. The method used in this project is described below.

Parametric or Non-parametric method
There are multiple supervised classification methods that can be used to classify an image. Just like with choosing a change detection method, the "best" classification method depends on the nature of the input data and the desired output.

Most satellite image classification methods are parametric classification methods. These methods use algorithms that model the class probability density (the chance that a class pixel has a certain feature vector) by a multivariate normal distribution function. That means that parametric methods assume that the vectors that are obtained for each class during the training phase are normally distributed (Gorte, 1998; Jensen, 1995). The problem with parametric classification algorithms is that the normal distribution model is not always suitable (Gorte, 1998). Non-parametric classification algorithms do not make any explicit assumption about the form of the probability density and would be better in these cases.
Satellite images often show irregularly shaped class probability densities, which non-parametric classifiers are able to model and parametric classifiers not. Also some classes may consist of several land covers with different spectral signatures (think of agricultural field or built-up area) (Gorte, 1998). Those classes are difficult to describe with normal probability densities where a non-parametric classifier has no difficulties. Because the classification of the agricultural fields is highly important in case of the classification of the Dutch river forelands a non-parametric classification method is preferred.

However, one of the disadvantages of a non-parametric classifier is that to obtain accurate non-parametric probability density estimate, many training samples are required. This is because a non-parametric method not only has to estimate the parameters, but also has to estimate the shape of the distribution (Gorte, 1998). This disadvantage is not a problem for the classification of the Dutch river forelands, because this area is already mapped numerous times and the purpose of the classification is just to update the information. Also, there are multiple datasets (satellite, aerial photographs and height data) available for this area. This means that it is possible to select large amounts of accurate training data and thus that a non-parametric method can and will be used for this project.

**Non-parametric classifier: KNN**

There are numerous statistical methods to make the comparison between the training data pixels and the unknown pixel. As explained above a non-parametric method is preferred for this project and the non-parametric method that is used is the k-Nearest Neighbour method (kNN-classification).

k-Nearest neighbour method is a flexible and simple supervised classification technique, which only requires one parameter: the number of nearest neighbours, k. This classifier does not require pre-processing of the data or assumptions with respect to the distribution of the training data (Samaniego et al., 2008). The kNN-method selects the k training samples that are spectrally the nearest to the unknown pixel (Gorte, 1998). The number of k, so the number of neighbours that are found around the unknown pixel, has to be specified by the user. It is important that k does not exceed the number of training pixels of the smallest class or else no pure pixel of that class can be found (Gorte, 1998). However, as showed in Gorte, 1998, when many training pixels are available for each class, the results of the kNN-method are stable under different values for k. In this project is chosen to work with a number of k of 13. This means that in feature space the 13 training pixels that are closest to the unknown pixel are found. The unknown pixel is assigned to the class that is most common within the 13 neighbours on condition that the most common class has at least 7 training pixels among the nearest neighbours. If the most common class has less than 7 training pixels along the nearest neighbours the pixels is defined as ‘unknown’ to prevent that pixels that don’t spectrally belong to any of the classes are wrongly assigned to one of them.

Besides the number for k, also the number of training pixels has to be considered. As told before: a non-parametric classifier needs a large amount of training data. However, with the kNN-method not only a sufficient amount of training data is required, also the number of training data per class should be considered. If there are many more training samples of class A than for class B, also relatively many A pixels will be found near to the unknown pixel. In other words: The unknown pixel is more likely to be classified as class A, just because class A has more training pixels. Because of this two different approaches for choosing the amount of training data can be distinguished: Equal sampling and Proportional sampling. With equal sampling equal number of training pixels are defined for each class. With proportional sampling the number of training samples per class reflect the (expected) class proportions (Gorte, 1998). There will be more training...
samples created of a class that is expected to be very abundant than of a less abundant class.
In this project both types of sampling are used and the difference is studied to be able to study which sampling type works best for this situation. Therefore two different training sets are created: one with proportional training data (figure 20) and one with equal training data (figure 21). The classification classifies the image into five classes:

1. Water  
2. Built-up area  
3. Forest  
4. Grass and agricultural fields  
5. Reed and tall herb vegetation

The brushwood class is not separately classified, but is combined with the forest class. Later (see section 9.1) the forest and brushwood classes are separated using the height data.
Figure 20: Test area with training samples. In this set the classes have a proportional amount of training-data.

Figure 21: Test area with training samples. For this test set all classes have an equal amount of training-data.
8.3 Selecting the training data automatically; new iterative method of Delft University of Technology

Section 8.2 explains the classifier that is used and shows the two different types of training data sampling, the proportional sampling and equal sampling. Both sampling methods explained above use training data that is specified beforehand by the analyst. The automatic classification method is called an objective method, but the selection of the training data certainly is subjective. Parallel to this research, Ben Gorte from the Delft University of Technology designed a new method, which does not need training data that is specified by an analyst. It is a promising method, which can make the classification completely objective, but it is still in its infancy. Because the data used in this project is well suited for testing this new method, it is shortly described and tested in this report. When the results are satisfactory and as expected this method could be described and studied into more detail in a later study. This report summarizes the methods used in this new classification method and test it with the aerial photographs used in this project. In this section the method is shortly described, in the chapter 9 the results of all the method used, including this one, are described and compared.

Auto-generated Training-data

Unlike the other training-data sampling methods, the method used in this procedure does not need an analyst to specify the training-data. Not needing an analyst makes the training-data as well as the whole method completely objective. To generate training-data automatically, first an assumption has to be made. This assumption is that most of the vegetation in the area to be classified still is the same as described in the vegetatielegger and only minor and local changes have occurred. This assumption has to be made because the training-data are automatically selected from the polygons in the vegetatielegger. 10.000 Pixels for each class are randomly selected from pixels in the vegetatielegger while border pixels between two classes are excluded. The training-pixels selected are then searched in the aerial photographs to define the spectral signature for each class.

Pixel assignment with the help of polygon values

The classification method used for this training-dataset still is the k-NN classifier, but with a couple of modifications. A segmentation of the aerial photograph is used before assigning the pixels to a class. The segmentation method that is used is described in detail in section 8.4. The segmentation polygons are used to take into account the assumed homogeneity of the polygon while classify the individual pixels. The kNN method looks for the spectrally 13 closest training pixels for each unknown pixel. The method described in the former paragraph (that is used for the specified equal and proportional training-data) classifies an unknown pixel to the class that is most common within those 13 training pixels. The method used for the automatically generated training data is slightly different. Per segmentation polygon the unique training pixels used for the kNN classifier for each class are counted. The more training pixels of a certain class are used, the more likely is it that all of the pixels of that polygon belong to that class. The probability that a pixel belongs to class A, \( P(A|x) \), is calculated with:

\[
\frac{px(A)\text{polygon}}{px\text{polygon}} / \frac{px(A)|x}{px|x}
\]

Where \( px(A)\text{polygon} \) is the amount of training pixels of class A used in the polygon; \( px\text{polygon} \) is the total amount of training pixels used in the polygon; \( px(A)|x \) is the amount of training pixels of class A used in the pixel x and \( px|x \) is the total amount of training pixels used in pixel x, which is 13.

The pixel is assigned to class with the highest probability. The polygons of a segmentation of the aerial photograph are used because they are not influenced by the
situation as mapped in the vegetatielegger and only consider the ‘true’ situation as seen in the photographs.

**Iterative process**
Besides the pixel assignment with the help of the training pixels used in the polygon, the classification with automatically generated training pixels uses another modification. This modification is an iterative process that improves the estimation of the prior probability, \( P(C) \), of each class. The prior probability of each class is unknown and stated equal for all in the beginning. After each iteration the prior probability is changed according to the outcome of the computation (equation below). In total six iterations are performed and the result improves with each iteration.

\[
P(C|x) = \frac{P(x|C) \cdot P(C)}{P(x)}
\]

where \( P(C|x) \) is the probability that pixel \( x \) belongs to class \( C \); \( P(x|C) \) is the probability that class \( C \) has a feature vector \( x \) (class probability density); \( P(C) \) is the prior probability and \( P(x) \) is the probability that a pixel has feature vector \( x \).

This method results, just as the methods with the selected training data in a classification with 5 classes: water; built-up; forest; grass; and tall herb vegetation. All the different classifications generated are later used to make classifications of a segmentation (explained in next chapter) to make the results better comparable to the vegetatielegger.
8.4 Object-oriented classification

The change detection method and the classification method chosen for this project are described above, but for this project not only a classification is used as input for the change detection. Important for this project is that the result of the classification is well comparable to the smooth polygons of the vegetatielegger. Therefore besides the kNN-method a segmentation method is used to get an object-oriented classification. What this object-oriented classification means and what kind of segmentation used is described below.

Object-oriented classification targets the identification and classification of segments rather than pixels (Geneletti and Gorte, 2003). Segments are groups of adjacent pixels that describe an object on the terrain. In case of the river forelands it could be an agricultural field or a forest or a solitary tree for example. An object-oriented classification requires the identification of meaningful objects over the image and labelling them with class attributes. The identification of the objects is done by segmenting the image and the labelling of the objects is done by applying the, in this case, kNN-classification technique (Geneletti and Gorte, 2003). Object-oriented classification has several advantages over other classification methods. Most classification methods, just as the kNN method used for this project, are pixel based. Each pixel is individually classified to a certain class. The resulting thematic image will have a significant “salt and pepper” effect because slightly deviating pixels can be classified to a different class as their neighbours (figure 22). Only the arrangement of the pixels in feature space (which only describes the spectral values of the pixels) is taken into account and the arrangement in the real image is ignored. In contrast to solely pixel-based methods, object-oriented classifications incorporate both spectral information as well as spatial arrangements. This method comes closer to the way humans interpret the aerial photographs visually and will make the resulting thematic image more realistic and better comparable to the smooth vegetatielegger (Laliberte et al, 2004). This segmentation can be done with the same dataset as used for the classification, but as first described in Geneletti and Gorte, 2003 the segmentation part and the classification part of the object-based classification can also be performed on different datasets. This is a way to reduce the disadvantages of low-resolution satellite images and the summer aerial photographs but still use the advantages of both remote-sensing techniques. For the classification of the Dutch river forelands it is now possible to classify the multispectral winter satellite images pixels according to the spectral value of the pixels with the kNN-method, and to segment the high-resolution aerial photographs to define the objects in the area. In this way the use of different image data can improve the classification because the disadvantages of one method are replaced by the advantages of the other method. The winter satellite images cause the different features to be easy to distinguish and the high-resolution aerial photographs cause the shapes and sizes of the features to be more accurate and lower the "salt and pepper-effect".

For this project three different object-based classifications are tested:

1. Classification and the segmentation performed on the high-resolution aerial photographs
2. Classification performed on the winter satellite image and the segmentation performed on the summer aerial photographs.
3. Classification and segmentation on the aerial photographs with the use of automatically generated training-data

This approach provides the possibility to study the need for satellite images. Are winter satellite images really needed to make a good classification of the river forelands or are the summer aerial photographs sufficient? For Rijkswaterstaat this is an important
question because they already own the aerial photographs, but need to buy the satellite images. The third option mentioned can be used to test a completely objective classification method. The current method is called subjective due to the manual classification of the aerial photographs. The automatic classification of option one and two (training-data specified by the analyst) already are much more objective, but the training-data selection still is a subjective procedure. Option three only uses automatically generated training-data originating from the vegetatielegger and therefore is completely objective.

Figure 22: Difference between object-oriented classification (figure a) and "salt and pepper" result of the pixel based method (figure b). Source: Whiteside and Ahmand, 2005
**Segmentation method**

The object-oriented method explained above uses a classification, the kNN-classification and a segmentation method. Segmentation is the process of completely partitioning an image into non-overlapping segments in image space (Schiewe, 2002). The segmentation needs to subdivide the image into different parts that correspond to objects in the terrain. To do so a segmentation technique uses both spectral information and spatial information (Geneletti and Gorte, 2003).

There are three strategies for segmentation:

- Point-based segmentation
- Edge-based segmentation
- Region-based segmentation

Point-based approaches search for homogeneous elements within the scene by applying global threshold operations, which combine pixels that show a similar pixel value. Later the spatially connected objects that have the same pixel value are grouped into one segment (Schiewe, 2002). Because of the varying reflection values within the image, pixel-based segmentation is less suitable for the evaluation of remote sensing data (Schiewe, 2002).

Edge-based approaches describe segments by using edge-detection algorithms. An area that is completely surrounded by edges becomes a segment. This method results in two types of image pixels: the edge pixels and the segment pixels. The disadvantages of this method are that small segments can consist completely of edge pixels and in forest and other densely vegetated area the edge detection is strongly affected by noise, which leads to over segmentation (Schiewe, 2002; Gorte, 1998, Geneletti and Gorte, 2003).

Region-based approaches have two different start procedures. The split and merge procedure starts with the entire image and splits the image into squares until the square satisfies the homogeneity criteria. In remote sensing applications this homogeneity criterion usually uses spectral values of pixels, so looks at the spectral homogeneity. As last step the adjacent squares that together form a homogeneous segment are merged (Schiewe, 2002, Gorte, 1998).

The second start procedure for region-based segmentation is the region growing procedure. This start procedure starts with a randomly placed seed pixel. From this pixel it grows a segment as long as the homogeneity criteria are satisfied. When no more pixels can be added to the segment it starts with a new seed pixel. This process is repeated until the whole image is divided into segments (Geneletti and Gorte, 2003, Gorte, 1998). The disadvantage of the region-based method is that the result is depended on the random, choice for the seed pixels. This problem is called an order dependency problem (Geneletti and Gorte, 2003).

**Region-based segmentation**

The region-based segmentation that is used for this project is the segmentation method as used in the study of Geneletti and Gorte, 2003. The segmentation method is based on quadtree data structure and implemented with software of Gorte as described in Gorte, 1996.

This method is a hybrid between region growing and split and merge and does not show the order dependency problem. It starts like the normal region growing method by taking one pixel and merges adjacent pixels that fit within the homogeneity criterion. The homogeneity criterion (that uses the spectral value of the pixels) is specified by the user as a threshold $t$. The criterion that is used in this project is first described by Ben Gorte and is called the 'box volume criterion'. This criterion estimates the volume of the $m$-dimensional hyperbox that encloses the set of feature vectors of the pixels in a segment. This means that for the set of pixels for each band the difference between the
minimum and the maximum value is taken. The total product for all the \( m \) differences (1 difference for each spectral band) is computed. The result is that the smallest volume of the box that fits around all pixels of the segment is known. With every new pixel or segment that is added to the segment, the new volume of the box is calculated. The threshold \( t \) describes the maximum volume the box is allowed to have to still be one segment. This method is convenient, because not all pixels have to be inspected when a new pixel of segment is added. Only the pixels with the maximum spectral value within the segment are of importance for the computation. The order dependency problem is solved by performing several iterations, while slowly easing the homogeneity criteria.

As explained earlier the segmentation is performed on the high-resolution aerial photographs. For the segmentation the analyst has to define a threshold value beforehand. The choice for this threshold value is one of the ‘trial and error’ method. Visual inspecting the segmentation result after using different values for the threshold \( t \) led to the suitable threshold value for this specific case. A value between 26 and 34 gave the best results. When a larger value than 34 was used, many different agricultural fields were merged as one. A lower value than 26 resulted in too much small, noisy segments. The best threshold value lies between 26 and 34, but there was not one best value for the whole image. The water and most of the agricultural fields are quite homogenous and a threshold value of 26 already gives a good segmentation. However, bushes and trees are very heterogeneous and with a threshold value of 26 only really small segments are formed. These land cover types are better visualized with a segmentation performed with a larger threshold value, like 34. Because of the differences for the land cover types, this project uses three different segmentations simultaneously for the classification: One segmentation with a threshold of 26, one with a threshold of 30 and one with a threshold of 34 (see figure 23).

**Figure 23:** The three segmentations used in this project. Figure A is the segmentation with the lowest threshold (26); Figure B is the middle segmentation with threshold 30; figure C is the image with the largest segments (threshold 34)
**Classification of the segmentation**

After the segmentation is performed the segmentation is classified by using the result of the kNN-classification as reference. For this step the dominant class per segment (according to the kNN-classification) has to be known as well as the percentage of the segment covered by the dominant class. Another rule that is used for the classification is that the segments should have a minimum size to be accepted as segment (a segment of 1 pixel will always be 100% pure, but will not give the wanted segmented image as result).

As described above three different segmentations are used for the classification. The classification of the segmented image is done in a few steps, which are described below:

1. The classification starts by looking at the coarsest segmentation (i.e. the highest value for $t$): A segment belongs to a certain class if at least 75% of its pixels belong to that class and the segment is at least 64 pixels large.
2. When for the coarsest segmentation a segment is not 75% pure the algorithm looks at the middle segmentation. Again the segment has to be 75% pure and the minimum size of the segment is in this case 32 pixels.
3. If the middle segmentation does not lead to a 75% pure segment, the finest segmentation is analysed. For the finest segmentation the segments should, again, be 75% pure and have a minimum size of 16 pixels.
4. If non of the three segmentations lead to a 75% pure segment, or when the segments are smaller than the minimum defined size, the single pixels are directly classified as how they were classified in the kNN-classification.

After all these steps are performed the result is a classification of the segmented image. To improve this result is combined with the available height data, which is explained in the next chapter.
9. Added data and vegetatielegger comparison
A complete classification of a segmented image is now available and, almost, comparable with the vegetatielegger to get the final result: a change-detection. However, to compare the two images the classification should contain one class extra: the shrubs. The shrubs are separated from the trees by differences in height. Therefore the vegetation height data that is obtained with the stereo aerial photographs is added to the classification. Apart from the vegetation height data, also NDVI values are added to improve the result. The NDVI values help to prevent the overestimation of the water class. After the NDVI values and the vegetation height data is added the map can be compared to the vegetatielegger and a change detection can be made. When all the results are generated a quality check is done for both the classifications and the change detections.

9.1 Added data

Vegetation height
The vegetation height data is essential to make the final result well comparable to the vegetatielegger. The forest class now consists of both the forest and the brushwood vegetation. Using the vegetation height data allows to separate these classes: vegetation between 2 and 5 meters is classed as brushwood; vegetation higher than 5 meters is classified as forest. Also the height data is used to correct for some wrongly classified grass or forest pixels. For this the height data is considered 'true', which means that vegetation classified as grass, but with a height of 6 meters will automatically be changed to the class 'forest'. The height data cannot be used to check and correct the differences between 'grass' and 'reed and tall herbs' because the height data is not accurate enough to see a difference of 0.5 meters. Tall herbs are, according to Rijkswaterstaat, between 0.5 and 2 meters high. More accurate height datasets exist, but are not as up to date as the height data generated from the yearly aerial photographs. When the height data would be accurate enough to distinguish grass from tall herbs it would be a large improvement on the classification. AHN2 data (Algemeen Hoogtebestand Nederland) is a laser altimetry datasets that maps the height more accurate that the height data that is used in this project. AHN2 has a spatial resolution of 0.5 meters and can map height differences of 5 centimetres (van der Zon, 2013). Due to its higher resolution than the height data used, AHN2 should able to distinguish tall herb vegetation and thus classify vegetation between 0.5 and 2 meters. Unfortunately, AHN datasets are not as up to date as the yearly aerial photographs. AHN. Since 1996 only 3 complete datasets for the Netherlands are made available (van der Zon, 2013). Because of the low temporal resolution the AHN data is not used in this project, but the possibility of using the AHN data to separate grass vegetation and tall herb vegetation is studied. In appendix C different locations of tall herb vegetation are visualized and the two different height datasets (generated from aerial photographs and the AHN2 data) are compared. The comparisons in appendix C show that laser altimetry can map the height in the river foreland more accurate than the stereo aerial photographs. The large areas of tall herb are visible in the AHN2 data, and are not visible in the aerial photograph height data. Both datasets do not show minor patches of tall herb vegetation within a field of grass. Because the AHN data is not up to date, some tall herb vegetation can be missed simply because it is not there yet. Overall the AHN data contains much more detail as the aerial photograph height data and is able to visualize tall herb vegetation. Therefore, up to date laser altimetry data will be an improvement on the current aerial photograph height data. Tall herb vegetation could be classified more accurate with the use of high-resolution laser altimetry data.
**NDVI Values**

NDVI stands for ‘Normalized Difference Vegetation Index’, and is calculated by the formula:

\[
NDVI = \frac{NIR - RED}{NIR + RED}
\]

Where NIR stands for near infrared and RED means the visible red band (Lillesand et al., 2008). The NDVI value varies between -1 and 1, but values lower than zero usually don’t have ecological meaning. Water bodies that have low values for both the RED and the NIR have NDVI values of around zero (sometimes slightly negative). Living vegetation has NDVI values from 0.2 (for shrubs and grassland) up to 0.8 (for tropical rainforests) (Weier and Herring, 2005).

In this project the assumption is made that pixels with a NDVI value of 0.2 or higher could not be water pixels. Due to this assumption the overestimation of water in the satellite classification can be corrected.

### 9.2 Comparison with the vegetatielegger

The classified image can now be compared with the vegetatielegger of Rijkswaterstaat. Locations where the vegetation has become rougher should be highlighted. An important factor for this change detection is to keep in mind what result Rijkswaterstaat is looking for. Rijkswaterstaat uses a rule to state how much the vegetation may change before calling it change: This rule states that a maximum of 500m² per homogenous surface may change to a rougher vegetation type. The vegetatielegger consists of homogenous polygons and therefore in this project is stated that per polygon 500m² is allowed to get rougher before the change detection map should highlight the area. When the area is highlighted by the change detection it is a region of interest for Rijkswaterstaat to carry out further checks.

Two different change detection maps are delivered in this project. One map shows a standard change detection: It draws a distinction between locations that show more than 500m² with respect to the vegetatielegger, and the areas that changed less. In this map two types of change are visualized: area that has become less rough and area that has become rougher. The changes, which make the surface rougher, are shown in table 6. The changes that make the surface rougher as stated in (almost the same) table 5 on page 38 only describe the vegetation types. However, in the classification map also the classes “water” and “built-up” area are present. All changes from water to another class are assumed to be “bad” changes that make the surface rougher. All changes from and to the built-up class are assumed to be unimportant classes. The classification and change detection is not designed to look for changes in roads and other man-built structures. Those kinds of structures built in the river foreland area are included in the river models to test if they fulfil the flood prevention rules. Therefore, in this project, changes from and to the built-up class are assumed to be unimportant changes. Therefore table 7 also includes the water and built-up land covers. This simple change/no-change map gives a quick insight to the extend of the change in the whole area.

The second change detection map that is created is a map where only the harmful changes are highlighted and unimportant changes are not visualized. In this case the map shows the change direction: what was the original vegetation and which rougher vegetation has it become? This map shows in a glance what the high-risk vegetation types and areas are.
The goal of this project was to design a faster, more frequent and at least just as accurate method as the current method for vegetation monitoring. As explained in the former paragraphs this whole project results in two maps: a classified segmentation and a change detection that compares the classified segmentation with the vegetatielegger. To be able to compare the accuracy of the newly designed method with the accuracy of the current method two quality checks are included. The first quality check checks the accuracy of the classified segmentation with the help of ground truth data that has been created manually. The ground truth data (figure 24) does not overlap with the used training data to get valid results. With this data and the classification data a confusion matrix is created, which shows the producers and the users accuracy as well as the overall accuracy of the classification. The producers accuracy shows how well the control pixels are classified for each class; the users accuracy shows the probability that a pixel classified as a certain class really represents that category on the ground. The overall accuracy is computed by dividing the total number of correctly classified pixels by to total number of reference pixels (Lillesand et al., 2008).

Just like for the classification of the segmented image also an accuracy check is done on the change detection. Again ground truth data is manually created, which in this case shows areas where the vegetation has changed and areas where the vegetation cover did not (figure 25). This ground truth data is compared with the change detection and can have four different outcomes: correctly detected change; correctly detected no change; wrongly detected change and wrongly detected no change. All the differences between the vegetatielegger and the segmentation classification are included, so the change detection does not include the rule of Rijkswaterstaat yet and changes of less than 500 m² are included as well. The result, described in the result section of this report, will give a percentage of the occurring for each of the 4 different outcomes.

### Table 7: Complete list of bad and good changes in the river forelands

<table>
<thead>
<tr>
<th>From</th>
<th>Grass &amp; agricultural field</th>
<th>Reed &amp; tall herb vegetation</th>
<th>Brushwood</th>
<th>Forest</th>
<th>Water</th>
<th>Built-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grass &amp; agricultural field</td>
<td>✔</td>
<td>✖</td>
<td>✖</td>
<td>✖</td>
<td>✖</td>
<td>✖</td>
</tr>
<tr>
<td>Reed &amp; tall herb vegetation</td>
<td>✔</td>
<td>✔</td>
<td>✖</td>
<td>✖</td>
<td>✖</td>
<td>✖</td>
</tr>
<tr>
<td>Brushwood</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Forest</td>
<td>✔</td>
<td>✔</td>
<td>✖</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Water</td>
<td>✖</td>
<td>✖</td>
<td>✖</td>
<td>✖</td>
<td>✔</td>
<td>✖</td>
</tr>
<tr>
<td>Built-up</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
</tbody>
</table>
Figure 24: Control data used to study the accuracy of the classifications

Figure 25: Control data used to study the accuracy of the change detection
10. Results
In this chapter all the final results of the methods explained in the former section are presented and described. As explained in chapters 7 an automatic object-based classification is performed using the kNN-method and a region-based segmentation. The classification result is then compared to the vegetatielegger of Rijkswaterstaat to give the final result: a change detection. As explained in the former chapter different datasets (aerial photographs and satellite data) and different training data set (proportional set; equal set; and an automatically generated set) are used to make the classification. Therefore in this chapter five different results are shown for both the classification and the change detection:

- Aerial photographs and proportional training data results
- Aerial photographs and equal training data results
- Satellite images with proportional training data results
- Satellite images and equal training data results
- Aerial photograph, automatically generated training data

The results described here are the final classification results that already include the segmentation and the height data. The maps that visualize the results of every intermediate step are generated as well, but are shown and described in appendix E. The improvements on the classification because of the use of the segmentation and height data are described in the appendix E as well. This makes the main report more readable and clarifies what the main results are.

The first section, 10.1 includes all the results and accuracy’s of the segmentation classifications. First the aerial photograph classifications, then the classification results of the satellite images and finally the classifications with auto-generated training data are described. Section 10.2 will show the results and accuracy of the change detections in the same order as for the classification results.

Section 10.3 summarizes the most important results in two tables.

10.1 Results and accuracies of the classifications

Classification of the aerial photographs
The classification of the aerial photographs is the classification with the highest spatial resolution. More than with the satellite classification small objects in the area will be visible. In this project two different classifications of the aerial photograph are made: one made with proportional training data (figure 26) and one with equal training data (figure 27). For the reader who wants to compare the classification result to the aerial photograph: a large image of the photograph is printed in appendix D.

As is seen in the two figures the difference between both images is clearly visible. The classification created with equal training data classifies a large part of the area as reed and tall herb vegetation (brown in the image), where this class is less common in the image made with proportional training data. In both images the built-up area, forests and hedges in the landscape are classified equally and they are very similar to the truth-value as can be seen in appendix D. This result shows that a classification with proportional training data classifies already large areas as reed and tall herb vegetation, but a classification with proportional training data seen to contain a large overestimation of this vegetation type. The error matrices that are shown in the next paragraph should give an indication whether these classifications correctly assign large areas to the tall herb class, or if it is an overestimation at the expense of the grass class.
Figure 26: The classification of the segmentation of the aerial photograph. The training data that is used contains a proportional amount of training pixels for each class.

Figure 27: The classification of the segmentation of the aerial photograph. The training data that is used contains an equal amount of training pixels for each class.
Error matrix of the aerial photograph classification

The accuracy of the aerial photograph classifications of the test-site is tested with the help of control data as explained in paragraph 5.3. The resulting error matrices, one for the proportional training-data classification and one for the equal training-data classification, are shown below in table 8 and 9. The producer's accuracy shows how well the control pixels are classified for each class; the user's accuracy shows the probability that a pixel classified as a certain class really represents that category on the ground. As is seen in these error-matrices the classes water, built-up, and trees/bushes are very accurately classified in both classifications (95% or higher accuracy).

The proportional-data classification classifies the grass class very accurate as well. The tall herb class stands out as the class that is classified the least accurate. The producer's accuracy of 57.38% and the user's accuracy of 48.49% for the proportional dataset show that there was not only a overestimation of the tall herb class, but that still not all pixels that should be classified as tall herb are classified correctly. The confusion matrix tells that the grass and tall herb class are often confused in both directions; grass is classified as tall herb and tall herb is classified as grass. The overall accuracy of the proportional dataset classification is 96.01%.

Table 8: Error matrix of the aerial photograph classifications with proportional training-data

<table>
<thead>
<tr>
<th>Classification data</th>
<th>control data set (known cover types)</th>
<th>row total</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>129209</td>
<td>129209</td>
</tr>
<tr>
<td>built-up</td>
<td>25</td>
<td>9358</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>grass</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>tall herbs</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>column total</td>
<td>129234</td>
<td>412391</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>water</th>
<th>built-up</th>
<th>tree/bushes</th>
<th>grass</th>
<th>tall herbs</th>
<th>row total</th>
</tr>
</thead>
<tbody>
<tr>
<td>producer's accuracy (%)</td>
<td>99.98</td>
<td>95.83</td>
<td>99.86</td>
<td>94.03</td>
<td>57.38</td>
<td>96.01</td>
</tr>
<tr>
<td>user's accuracy (%)</td>
<td>100.00</td>
<td>99.73</td>
<td>99.75</td>
<td>95.59</td>
<td>48.49</td>
<td></td>
</tr>
</tbody>
</table>

The classification accuracy of the grass class for the equal training dataset is not as accurate as for the proportional dataset. The user's accuracy is still high (97.37%), but the producer's accuracy is much lower, namely 56%. In the equal training-data classification more pixels are classified as tall herb and the confusion matrix shows a large overestimation of this class: the user's accuracy is only 15.95%. The largest confusion is again between the grass class and the tall herb class. The low user's accuracy means that the probability that a pixel classified as tall herb vegetation really is tall herb vegetation is rather low. Because of the large overestimation of the tall herbs in the expense of the grass class, there is an underestimated of the grass class and thus a low producer's accuracy of this class. The producer's error of the tall herb vegetation is higher for the equal dataset than for the proportional dataset. This is because there are now so many pixels classified as tall herb vegetation that most of the tall herbs are indeed classified correctly. The overall accuracy of the classification with equal training data is due to the large overestimation of the tall herb class significantly lower: 83.06%.
Table 9: Error matrix of the aerial photograph classifications with equal training data

<table>
<thead>
<tr>
<th>Classification data</th>
<th>control data set (known cover types)</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>water</td>
<td>built-up</td>
<td>tree/bushes</td>
<td>grass</td>
<td>tall herbs</td>
<td>row total</td>
</tr>
<tr>
<td>water</td>
<td>129208</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>129208</td>
</tr>
<tr>
<td>built-up</td>
<td>28</td>
<td>9379</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>9407</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>0</td>
<td>235</td>
<td>102317</td>
<td>0</td>
<td>0</td>
<td>102552</td>
</tr>
<tr>
<td>grass</td>
<td>0</td>
<td>151</td>
<td>0</td>
<td>85988</td>
<td>2176</td>
<td>88315</td>
</tr>
<tr>
<td>tall herbs</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>147</td>
<td>66513</td>
<td>12651</td>
</tr>
<tr>
<td>column total</td>
<td>129236</td>
<td>9765</td>
<td>102464</td>
<td>152501</td>
<td>14827</td>
<td>408793</td>
</tr>
</tbody>
</table>

**producer's accuracy (%)**

<table>
<thead>
<tr>
<th>Category</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>99.98</td>
</tr>
<tr>
<td>built-up</td>
<td>96.05</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>99.86</td>
</tr>
<tr>
<td>grass</td>
<td>56.39</td>
</tr>
<tr>
<td>tall herbs</td>
<td>85.32</td>
</tr>
</tbody>
</table>

**user's accuracy (%)**

<table>
<thead>
<tr>
<th>Category</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>100.00</td>
</tr>
<tr>
<td>built-up</td>
<td>99.70</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>99.77</td>
</tr>
<tr>
<td>grass</td>
<td>97.37</td>
</tr>
<tr>
<td>tall herbs</td>
<td>15.95</td>
</tr>
</tbody>
</table>

**Overall Accuracy**

83.06
Classification of the satellite images

The satellite images have a lower spatial resolution than the aerial photographs that are used for this project. The results should show whether or not this spatial resolution is good enough for this application and if the results of these classifications are different or even better than the classification results of the aerial photographs. Just as for the aerial photographs there are two different classifications made: one with proportional training data (figure 28) and one with an equal set of training data (figure 29). First the classification results are shown, later the accuracies of the results are listed in the form of error matrices.

Although the spatial resolution of the satellite image is lower then the resolution of the aerial photograph, the satellite classification does classify small objects like solitary trees. The small narrow river in the upper middle-right of the image is not classified as water at all, where the aerial photograph classification does classifies a large part of this river as water. The forest, bushes and river seem to be similarly classified as for the aerial classification and is well comparable to the photograph printed in appendix xx. The built-up class is classified different. The classification with proportional training data shows a little overestimation of the built-up area already, which gets worse for the equal training data set. The error matrices should give insight in this overestimation. The satellite classification does not show as much tall herb vegetation as the aerial photograph classification. In figure 29 is seen that a little more area is classified as reed and tall herb vegetation than in figure 28 but not in such amounts as the overestimation seen in the aerial photograph classification (figure 27). Another difference between the satellite classification and the aerial classification is that the satellite classifications show much less unknown pixels.

Figure 28: The classification of the segmentations of the satellite image. The training-data that is used contains a proportional amount of training pixels for each class.
Figure 29: The classification of the segmentations of the satellite image. The training-data that is used contains a equal amount of training pixels for each class

**Error matrix of the satellite image classification**

Just as for the aerial photograph classification the accuracy of the classification of the satellite image is tested using a control data set. An error matrix is generated for both the proportional training-data classification (table 10) as well as the equal training-data classification (table 11).

The water and tree/bushes classes are classified very accurately with an accuracy of 96.85% or higher. Corresponding to the results described in the former paragraph the error-matrices show an overestimation of the built-up class at the expense of, mostly, the grass vegetation. For the proportional training-data classification the user's accuracy of the built-up class is 23.40%; for the equal training dataset this number is 30.86%. The tall herb vegetation is again overestimated, but to a lesser degree as for the aerial photograph classification: the probability that a tall herb classified pixel really is tall herb is now 52.66% instead of 48.49%. Even more important than the difference in the user's accuracy is the difference in the producer's accuracy. In the classification of the satellite image a large amount of the tall herb test data, namely 91.68%, is correctly classified as tall herb vegetation. This percentage is significantly higher than the 57.38% of the proportional training-data aerial photograph classification and even higher then the 85.32% of the equal training-data aerial photograph classification that largely overestimated the tall herb vegetation.

The satellite classification that uses equal training-data has overestimated the built-up class more extreme in the expense of mostly the grass and the tall herb classes. Due to this overestimation the producer’s accuracies of grass and tall herbs decreased. Besides the built-up overestimation the tall herb class is also overestimated. Overall the equal data classification has a slightly lower accuracy than the proportional classification (91.50% against 89.70%). The effects of these overestimations mostly visible in the producer's accuracy of the large grass class that dropped from 82.02% to 78.20%.

Legend

- Unknown
- Water
- Built-up
- Grass
- Tall Herbs
- Shrubs
Table 10: Error matrix of the satellite image classification with proportional training-data

<table>
<thead>
<tr>
<th>classification data</th>
<th>water</th>
<th>built-up</th>
<th>tree/bushes</th>
<th>grass</th>
<th>tall herbs</th>
<th>row total</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>128890</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>128890</td>
</tr>
<tr>
<td>built-up</td>
<td>4</td>
<td>5869</td>
<td>622</td>
<td>17257</td>
<td>1329</td>
<td>25081</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>0</td>
<td>3313</td>
<td>101695</td>
<td>0</td>
<td>0</td>
<td>105008</td>
</tr>
<tr>
<td>grass</td>
<td>0</td>
<td>111</td>
<td>0</td>
<td>134341</td>
<td>0</td>
<td>134452</td>
</tr>
<tr>
<td>tall herbs</td>
<td>346</td>
<td>472</td>
<td>147</td>
<td>12194</td>
<td>14639</td>
<td>27798</td>
</tr>
<tr>
<td>column total</td>
<td>129240</td>
<td>9765</td>
<td>102464</td>
<td>163792</td>
<td>15968</td>
<td>421229</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>producer's accuracy (%)</th>
<th>user's accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>99.73</td>
</tr>
<tr>
<td>built-up</td>
<td>60.10</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>99.25</td>
</tr>
<tr>
<td>grass</td>
<td>82.02</td>
</tr>
<tr>
<td>tall herbs</td>
<td>91.68</td>
</tr>
</tbody>
</table>

Overall Accuracy (%) 91.50

Table 11: Error matrix of the satellite image classification with equal training-data

<table>
<thead>
<tr>
<th>classification data</th>
<th>water</th>
<th>built-up</th>
<th>tree/bushes</th>
<th>grass</th>
<th>tall herbs</th>
<th>row total</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>128890</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>128890</td>
</tr>
<tr>
<td>built-up</td>
<td>4</td>
<td>7304</td>
<td>1237</td>
<td>11687</td>
<td>3436</td>
<td>23668</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>0</td>
<td>1796</td>
<td>101080</td>
<td>0</td>
<td>0</td>
<td>102876</td>
</tr>
<tr>
<td>grass</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>128247</td>
<td>0</td>
<td>128247</td>
</tr>
<tr>
<td>tall herbs</td>
<td>346</td>
<td>665</td>
<td>147</td>
<td>24069</td>
<td>12379</td>
<td>37606</td>
</tr>
<tr>
<td>column total</td>
<td>129240</td>
<td>9765</td>
<td>102464</td>
<td>164003</td>
<td>15815</td>
<td>421287</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>producer's accuracy (%)</th>
<th>user's accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>99.73</td>
</tr>
<tr>
<td>built-up</td>
<td>74.80</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>98.65</td>
</tr>
<tr>
<td>grass</td>
<td>78.20</td>
</tr>
<tr>
<td>tall herbs</td>
<td>78.27</td>
</tr>
</tbody>
</table>

Overall Accuracy (%) 89.70
Classification results of the auto-generated training-data classification

The last classification results described are the results of the classifications with automatically generated training-data. As explained in section 8.3 this method is a new classification method developed at the TU Delft by Ben Gorte. It is a completely objective method because the training data are automatically generated from the vegetatielegger of Rijkswaterstaat. The data used are the aerial photographs, so the small details should be visible in the classification results. First the classification results are described, later the accuracy of the classification is shown. Just as for the other classification results, the results shown here are the final classification results that already contain the segmentation classification and the added height data. The intermediate results can be seen in appendix E. The results are compared to the results of the segmentation classification of the aerial photographs with proportional training-data. This is because the same data is used for both methods.

Figure 30 shows the classified image, classified with the auto-generated training-data method. The result is quite similar to the classification results of the classification of the aerial photograph with proportional training data (figure 26). This classification slightly overestimated the tall-herb vegetation as will be visible in the error matrix described below. Apart from the tall herb classifications the whole image is well comparable to the true situation as seen in the aerial photograph (see appendix D).

![Figure 30: Classification result of the aerial photograph classification with auto-generated training-data](image-url)
**Error matrix of the aerial photograph classification with auto-generated training data**

Table 12 shows the error matrix of the segmentation classification of the aerial photograph that uses automatically generated training data. As described above, the results is similar to the classification of the aerial photograph with proportional training data. The overall accuracy of this auto-generated training data classification is slightly lower (94.14% versus 96.01%). The overestimation of the tall herb vegetation is clearly visible in the matrix with a user’s accuracy of this class of 39.45% which explains the lower overall accuracy. The largest confusion is between the grass and tall-herb class. The built-up user’s accuracy is lower than for this classification as for the proportional training-data classification. This is because in this classification some trees of bushes have been falsely classified as built-up. Remarkable is the producer’s accuracy of the tall herb vegetation. This accuracy is significantly higher than for the proportional training data classification: 84.01% versus 57.38%. The overall accuracy of this classification is higher than for both satellite image classifications.

Table 12: The error matrix for the aerial photograph classification with auto-generated training data

<table>
<thead>
<tr>
<th>Aerial photograph, Auto-generated training data, segmentation polygons</th>
<th>control data set (known cover types)</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>row total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>water</td>
<td>built-up</td>
<td>tree/bushes</td>
<td>grass</td>
<td>tall herbs</td>
<td></td>
</tr>
<tr>
<td>water</td>
<td>129208</td>
<td>323</td>
<td>136</td>
<td>2</td>
<td>1</td>
<td>129670</td>
</tr>
<tr>
<td>built-up</td>
<td>32</td>
<td>9387</td>
<td>918</td>
<td>0</td>
<td>39</td>
<td>10376</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>0</td>
<td>55</td>
<td>101281</td>
<td>0</td>
<td>0</td>
<td>101336</td>
</tr>
<tr>
<td>grass</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>143971</td>
<td>2529</td>
<td>146502</td>
</tr>
<tr>
<td>tall herbs</td>
<td>0</td>
<td>0</td>
<td>127</td>
<td>20589</td>
<td>13497</td>
<td>34213</td>
</tr>
<tr>
<td>column total</td>
<td>129240</td>
<td>9765</td>
<td>102464</td>
<td>164562</td>
<td>16066</td>
<td>422097</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>producer’s accuracy (%)</th>
<th>user’s accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>water</td>
<td>99.98</td>
<td>water</td>
</tr>
<tr>
<td>built-up</td>
<td>96.13</td>
<td>built-up</td>
</tr>
<tr>
<td>tree/bushes</td>
<td>98.85</td>
<td>tree/bushes</td>
</tr>
<tr>
<td>grass</td>
<td>87.49</td>
<td>grass</td>
</tr>
<tr>
<td>tall herbs</td>
<td>84.01</td>
<td>tall herbs</td>
</tr>
</tbody>
</table>

Overall Accuracy (%) 94.14
10.2 Results and accuracies of the change detections
The classification results are compared to the vegetatielegger, which will result in a change detection. A change detection is the final result wanted by Rijkswaterstaat. They want to see where the roughness of the vegetation exceeds the standard situation of the vegetatielegger. As explained in section 8.2 of this part two types of change detection maps are created: One that only shows change (good or bad) and no change differences and the other that shows the change direction of the areas that have become rougher. As explained earlier, differences in land cover are assumed to be change if more than 500 m² of a vegetatielegger polygon has a different land cover in the classification than in the vegetatielegger.

In total this section contains 2 change detections for each classification:

- 2 change detection maps from aerial photograph classification with proportional training data
- 2 change detection maps from aerial photograph classification with equal training data
- 2 change detection maps from satellite image classification with proportional training data
- 2 change detection maps from satellite image classification with equal training data
- 2 change detection maps from aerial photograph classification with auto-generated training data

First change detections are described, later the accuracy of the change detection is shown.

**Change detection of the aerial photograph classification**

In figure 31 and 32 the two change detections are shown that are made with the aerial photograph data with proportional training-data. As explained before, there was some overestimation of the tall herb class in the expense of the grass class. This overestimation is clearly visible in the change detection maps as large red spots namely in the right side of the image. The change detection map clearly shows some hedges that are present in the landscape but were not present in the vegetatielegger. In the change direction map this is seen as green and yellow in the image. For most of the hedges the edges of the hedge are shown as a change area as well. The hedge was in those cases already present in the vegetatielegger, but it is slightly wider in the classification. The borders between grass and hedges have been classified as tall herbs, which results in that all the contours of the hedges are visible in the change detection.

Figure 33 and figure 34 show the change detection and change direction made with the aerial photograph classification with an equal training-dataset. The large overestimation of the tall herb class as noticed in section 10.1 is clearly visible. A large part of the change direction map colours red due to a change from grass to tall herbs. The hedges that were not present in the vegetatielegger are still shown in green and yellow in the change direction map, but are hardly visible due to the overruling of the overestimation of the tall herb class.
Figure 31: Change detection map of the aerial photograph classification - vegetatielegger comparison. The classification is done with the proportional training-data.

Figure 32: Change direction map of the aerial photograph classification - vegetatielegger comparison. The classification is done with the proportional training-data.
Figure 33: Change detection map of the aerial photograph classification - vegetatielegger comparison. The classification is done with the proportional training-data.

Figure 34: Change direction map of the aerial photograph classification - vegetatielegger comparison. The classification is done with the equal training-data.
Accuracy of the change detection of the aerial photographs

The change detection results are compared to a test set for which change and non-change areas are known. The comparison gives four possible results:

- Correctly detected change
- Correctly detected no-change
- Falsely detected change
- Falsely detected no-change

The percentages of the four results are visualized below for the proportional training-data (table 13) and for the equal training-data (table 14). The percentage of correctly classified changed pixels is 90.68% for the proportional training-data and 95.87% for the equal training-data. The pixels that are changed are more accurately classified for the equal training data as for the proportional data. However, the percentage of correctly classified no-changed pixels is much lower for the equal training-data. This can be explained by the overestimation of the tall herb class. Because of this overestimation large areas in the image are classified as changed pixels. So, when a lot of pixels changed, the change pixels listed in the known dataset will likely be classified as change as well. However, pixels known as non-change pixels are also (wrongly) classified as change. This explains the high value for correctly classified change, but the low value for correctly classified non-change pixels in table 13. In table 12 the percentages for correctly classified change/no-change pixels are much more similar, so the proportional dataset is classified more accurate.

Table 13: Change detection accuracy of the aerial photographs, proportional training-data

<table>
<thead>
<tr>
<th>Classified Changes</th>
<th>No Change</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Change</td>
<td>89.82%</td>
<td>9.32%</td>
</tr>
<tr>
<td>Change</td>
<td>10.18%</td>
<td>90.68%</td>
</tr>
</tbody>
</table>

Table 14: Change detection accuracy of the aerial photographs, equal training-data

<table>
<thead>
<tr>
<th>Classified Changes</th>
<th>No Change</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Change</td>
<td>68.09%</td>
<td>4.13%</td>
</tr>
<tr>
<td>Change</td>
<td>31.91%</td>
<td>95.87%</td>
</tr>
</tbody>
</table>
**Change detection of the satellite image classification**

The change detection results for the satellite images with proportional training data are shown in figure 35 and figure 36. Most of the changes that are visible are due to the change from grass to tall herbs (red in figure 36). Also some new hedges are classified (visualized as green and yellow spots in figure 36). The large yellow areas seen in figure 35 are due to the overestimation of the built-up class. Changes from and to the built-up class are assumed to be unimportant so in figure 36, those spots are no longer visual.

Figure 37 and 38 show the two change detections of the satellite images with equal training-data. The largest difference between the two satellite classifications was the overestimation of the built-up class that was more severe for the equal training-data classification. The larger area classified as built-up is also seen in figure 37 as the large yellow spot at the lower right corner of the image. As said before changes from and to the built-up class are assumed to be unimportant, so figure 36 and figure 38 are quite similar. There is a little more area classified as change from grass to tall herb in the proportional dataset, but overall the images look similar.

![Figure 35: Change detection map of the satellite image classification- vegetatielegger comparison. The classification is done with the proportional training-data](image-url)
Figure 36: Change direction map of the satellite image classification - vegetatielegger comparison. The classification is done with the proportional training-data.

Figure 37: Change detection map of the satellite image classification - vegetatielegger comparison. The classification is done with the equal training-data.
**Accuracy of the change detection of the satellite images**

Like with the aerial photograph change detections there is also an accuracy check done for the satellite image change detections. The results are shown in table 15 and table 16. As was noticed in the figure 35-38 the two different satellite change detections (for proportional and equal training-data) look rather similar. This statement is confirmed by the two tables, table 15 and 16. The change detection of the proportional dataset is more accurate for the non-change detection, but the percentage of correctly classified change pixels is almost the same. The lower percentage of correctly classified non-change pixels seen in table 16 is most likely due to the overestimation of the built-up class. The percentages of correctly classified change/non-change pixels are higher for the satellite change detections than for the aerial photographs.
**Table 15:** Change detection accuracy for the satellite image, proportional training-data

<table>
<thead>
<tr>
<th>Classified Changes</th>
<th>No Change</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Change</td>
<td>89.76%</td>
<td>2.75%</td>
</tr>
<tr>
<td>Change</td>
<td>10.24%</td>
<td>97.25%</td>
</tr>
</tbody>
</table>

**Table 16:** Change detection accuracy for the satellite images, equal training-data

<table>
<thead>
<tr>
<th>Classified Changes</th>
<th>No Change</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Change</td>
<td>84.84%</td>
<td>2.74%</td>
</tr>
<tr>
<td>Change</td>
<td>15.16%</td>
<td>97.26%</td>
</tr>
</tbody>
</table>
**Change detection results of the aerial photograph classification with auto-generated training-data**

Figure 39 shows the change detection map where green means 'no change', yellow is 'irrelevant change' and red means 'bad change'. Bad change is where the vegetation has become rougher with respect to the situation as mapped in the vegetatielegger. The overestimation of the tall herb vegetation is clearly visible in the change detection by large red areas in the image. The smaller red lines describe hedges that had not been described by the vegetatielegger, but are present in the aerial photograph. Figure 40 shows the change direction map. In this map is seen that the red lines in image 39 are indeed trees and bushes that were mapped as grass in the vegetatielegger.

![Change detection of the aerial photograph with auto-generated training-data](image)
Accuracy of the change detection of aerial photographs with auto-generated training data

Table 17 shows the accuracy of the change detection. It shows the percentage of correctly detected change (90.89%) and the percentage of correctly detected non-change pixels (83.17%). The correctly detected change percentage is similar to the accuracy of the change detection for the aerial photograph classification with proportional training data. However, due to the overestimation of tall herb vegetation, the percentage of correctly detected non-change pixels is lower. A large area that has not changed is mapped as change from grass to tall herbs.

Table 17: Accuracy of the change detection of the aerial photograph classification with auto-generated training-data
10.3 Summarizing all results
Here all the results discussed in the former sections are summarized in two tables. Table 18 shows the classifications results for all four datasets studied in this project. The overall accuracy as well as the built-up and tall herb accuracies is shown. For the two classes, built-up and tall-herb, is chosen because their accuracies differ the most between different datasets. Also, the tall herb vegetation is an important class due to its higher roughness compared to grass and due to the fact that it is a difficult vegetation class to classify.

Table 19 shows the change detection accuracies for all four datasets used for this project. Both the accuracy of correctly detected change and corrected detected non-changed pixels are shown.

Table 18: Classification results of all four datasets summarized

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Overall Accuracy (%)</th>
<th>Built-up producer's &amp; user's accuracy (%)</th>
<th>Tall Herbs producer's &amp; user's accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerial photographs</td>
<td>96.01</td>
<td>95.83</td>
<td>57.38</td>
</tr>
<tr>
<td>Proportional training-data</td>
<td></td>
<td>99.73</td>
<td>48.49</td>
</tr>
<tr>
<td>Aerial photographs</td>
<td>83.06</td>
<td>96.05</td>
<td>85.32</td>
</tr>
<tr>
<td>Equal training-data</td>
<td></td>
<td>99.70</td>
<td>15.95</td>
</tr>
<tr>
<td>Satellite images</td>
<td>91.50</td>
<td>60.10</td>
<td>91.68</td>
</tr>
<tr>
<td>Proportional training-data</td>
<td></td>
<td>23.40</td>
<td>52.66</td>
</tr>
<tr>
<td>Satellite images</td>
<td>89.70</td>
<td>74.80</td>
<td>78.27</td>
</tr>
<tr>
<td>Equal training data</td>
<td></td>
<td>30.86</td>
<td>32.92</td>
</tr>
<tr>
<td>Aerial photographs</td>
<td>94.14</td>
<td>96.13</td>
<td>84.01</td>
</tr>
<tr>
<td>Auto-generated training-data</td>
<td></td>
<td>90.45</td>
<td>39.45</td>
</tr>
</tbody>
</table>

Table 19: Change detection accuracies for all four datasets

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Correctly detected change (%)</th>
<th>Correctly detected non-change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerial photographs</td>
<td>90.68</td>
<td>89.82</td>
</tr>
<tr>
<td>Proportional training-data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aerial photographs</td>
<td>95.87</td>
<td>68.09</td>
</tr>
<tr>
<td>Equal training-data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satellite images</td>
<td>97.25</td>
<td>89.76</td>
</tr>
<tr>
<td>Proportional training-data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satellite images</td>
<td>97.26</td>
<td>84.84</td>
</tr>
<tr>
<td>Equal training data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aerial photographs</td>
<td>90.89</td>
<td>83.17</td>
</tr>
<tr>
<td>Auto-generated training-data</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Conclusion

This research started with an extensive literature study to the current situation of monitoring and maintaining the vegetation in the Dutch river forelands. The current monitoring method turned out to be manual, time consuming and costly which was only executed once in 6 years. Therefore this project is focused on the monitoring method and this led to the main question of this research:

Is it in relation to the conservation of the situation as given in the Vegetatielegger and for flood prevention, needed to intensify the vegetation monitoring, and how can this intensification be achieved?

The current method only uses aerial photographs, but a new method is not restricted to these photos. Therefore the sub-question of this research is:

Does a new, intensified, vegetation monitoring method require satellite data or is the available aerial photograph data sufficient?

The study to vegetation growth in the Dutch river forelands answered the first part of the research question and proved that there was significant vegetation growth within six years. When vegetation is only mapped once in 6 years important changes can be missed, or seen too late, which can higher the flood risk. Also the cost of removing the vegetation will be higher when done in a later stadium. Monitoring the vegetation with a higher frequency, like once per year, will be an improvement on the current situation with respect to the prevention of floods.

An intensification of the vegetation monitoring is not possible with the current monitoring method. The method is too slow and costly. Therefore, a new method of vegetation monitoring has to be designed to conserve the standard situation as given in the vegetatielegger and thus to ensure the flood protection. The desired result is a change detection that compares the current situation to the standard vegetatielegger. To make a useful change detection, this study focused on significant changes that make the surface rougher. The vegetation list in order of roughness (from smooth to rough) that is used in this study is: grass, tall herb vegetation, trees and shrubs. Insignificantly small changes and changes to smoother vegetation types are not of interest of Rijkswaterstaat. Only changes of more than 500m² per homogeneous polygon of the vegetatielegger to a rougher vegetation type are highlighted as a change.

The post-classification change detection with an object oriented classification method (kNN-classification and region based segmentation) generated a result that was well comparable to the vegetatielegger and reduced the ‘salt and pepper’ effect. The classification is performed with both aerial photographs and satellite images to be able to answer the sub-question of this research. Three types of training data for the kNN-classifier are used: Proportional and equal training datasets for both the aerial photographs and satellite images that are specified by the analyst, and an automatically generated training-dataset that classifies the aerial photograph with a newly developed method from the TU Delft. The new method from the TU Delft has an important advantage over the other two methods tested: it is completely objective and faster to use. For all the tested methods the results can be generated within one year from taking aerial photographs/satellite images.

The results show that for both the aerial photograph classification as for the satellite
image classification the sampling method of proportional training-data gives the best results. The classifications that used equal training data experienced overestimation of the less common classes in the expense of common classes, which leads to lower overall accuracies. The classifications perform equally with respect to forest and water classification, but the satellite classification has a lower overall accuracy due to the overestimation of the built-up class. The tall herb class is classified much more accurate for the satellite images than for the aerial photographs.

The completely objective, new TU Delft method performs, with respect to overall accuracy and accuracy of the tall herb class, in between the two other tested methods. The overall accuracy is slightly lower than the aerial photograph classification with proportional training data, but the tall herb classification accuracy is significantly higher.

The change detection results are just as for the classification results most accurate with proportional training-data. The satellite image change detection is more accurate than the aerial photograph change detection. The methods with equal training data score lower on change detection accuracy because of the overestimation of tall herb and/or built-up area. The method with auto-generated training-data scores similar to the aerial photograph change detection results on correctly detected change, but scores lower on correctly detected non-change pixels. Just as for the equal training-data sets this is due to the overestimation or tall herb vegetation.

The post-classification change detection with an object oriented classification method is able to accurately monitor the vegetation in the Dutch river forelands. When just a high overall accuracy is wanted, the use of aerial photograph is preferred due to its high spatial resolution and Rijkswaterstaat does not need Satellite images in this case. If the tall herb class is an important class to classify accurately, satellite images are better suited and therefore having both datasets available (aerial photographs and satellite images) would be ideal. All methods tested outperform the current monitoring method in speed, objectify and accuracy.
Discussion
This research studied the current vegetation monitoring method in the Dutch river forelands. The study focussed on the necessity of intensifying the monitoring method and how this could be achieved. As expected, there is a significant amount of vegetation growth within 6 years where rougher vegetation types can form within 2 years. The rapid vegetation growth can be explained by the presence of natural areas and appearance of rapidly growing vegetation types such as willows. In this study the need for intensification of the monitoring method is proven for the first time in chapter. is in this study for the first time in the vegetation growth analysis. The limitations of the current method clarify the need of a completely new, automatic vegetation monitoring method to be able to ensure the flood protection. Both the vegetation growth and need for a new method are important findings for Rijkswaterstaat, who is responsible for the prevention of floods.

This research tested new automatic classifications on a small, but representative test site. The test site contains all vegetation classes, including much of the important, rough shrub vegetation in the form of hedges. The new methods that are studied in this project proved to be more accurate and faster than the current monitoring method. The new methods are able to check the vegetation once in a year or once in two years depending on the demands of Rijkswaterstaat. The need of satellite images for automatic classifications depends on the priorities of Rijkswaterstaat: when a high overall accuracy has the highest priority, satellite images do not have added value. But due to the fact satellite images can be taken in winter in contrast to the aerial photographs, the tall herb vegetation can be classified more accurately when including satellite images. Tall herb vegetation is spectrally better distinguishable in winter, so when tall herb classification is important, satellite images have an advantage.

Limitations
Accurate and up-to-date vegetation height data is essential for good automatic classifications of the river forelands. Without the height data no distinction between trees and shrubs can be made which are now important classes in the vegetatielegger. However, the added value of the distinction between shrubs and trees with only vegetation height data is questionable. The classification regulations of Rijkswaterstaat for shrubs and trees make it impossible to identify trees with undergrowth of shrubs. Also small, not so rough, trees are automatically classified as rough shrubs. A distinction that keeps into account the undergrowth would be better, but the undergrowth is not visible with satellite images or aerial photographs. The results of this project show that satellite images classify the tall herb vegetation more accurate, but have a lower overall accuracy. The lower overall accuracy probably is due to the low resolution and therefore there are a lot of border pixels. Border pixels (pixels that contain multiple classes and therefore are mixed) are more difficult to classify correctly. When the training data that is used contains border pixels, the result can easily be affected. Better would be to use satellite images with a higher spatial resolution. When Rijkswaterstaat wants tall herb vegetation to be classified accurate and have a high overall accuracy, high-resolution satellite images could be the solution. A change detection that shows the changes to a rougher vegetation type with respect to the vegetatielegger is the final result wanted by Rijkswaterstaat. The definition of change that is used in this project comes from Rijkswaterstaat: 'When more then 500m$^2$ of a homogeneous area changes to a rougher vegetation type it is considered as change'. A homogenous area is the same as a polygon of the vegetatielegger, so up to 500m$^2$ per vegetatielegger polygon is allowed to change to a rougher vegetation type. About this 'change rule' important remarks can be made. Polygons of the vegetatielegger are not all
of the same size. Some polygons are even smaller than 500m². This means that some areas can never change according to the Rijkswaterstaat rule. Also, 500m² change in a very large polygon is less severe than a couple of small polygons that all contain 500m² of changed vegetation. Maybe a combination of area and percentage of a polygon that has changed would be an more ideal definition of change.

**Recommendations**

As described in section 8.3 the research to a new method designed at the Delft University of technology by Ben Gorte ran parallel to this study. This method does not need an analyst to specify the training data beforehand, but the training-data is generated automatically. This saves time and is much more objective than the training-data used in this project. This method, that uses segmentation and iteration to make the classification as accurate as possible, is only briefly described and tested in this project but has already some promising results. The method performs in between the satellite and aerial photograph classifications with respect to total accuracy and accuracy of the tall herb classification. A more detailed study of this method is recommended to understand the full potential and to improve the results.

Tall herb vegetation is a difficult class to distinguish. There is a lot of spectral overlap between tall herb grass and even trees. Winter satellite images classify the tall herb vegetation more accurately than the summer aerial photographs. The use of high-resolution satellite images are recommended to increase the overall accuracy of the satellite classification. Besides the use of high-resolution satellite images, the use of a classification method that takes into account the texture of the image could improve the result. Where tall herb vegetation is not spectrally separable, the texture of the vegetation can help to distinguish different vegetation classes.

Automatically monitoring the vegetation in the Dutch river forelands with satellite images or aerial photographs (depending on the priorities of Rijkswaterstaat) is technically feasible. The results are more accurate than the manual classifications (as calculated by the Alterra report, Knoters et al, 2008), faster to generate and less expensive. The automatic classification is less subjective as the manual interpretation of the current method. The new method of the TU Delft that should be studied in further detail even completely removes the subjectivity of the classification method. When Rijkswaterstaat specifies the exact information requirements with respect to classification and change detections, automatic classification is no far-fetched dream but can be implemented in the very near future.
Bibliography

- Tweede Kamer 2012-2103, 31 710, nr. 27.

Websites
- Ruimtevoorbewaald.nl consulted on October 22, 2015 from www.ruimtevoorbewaald.nl/nl/beeldmateriaal/luchtfotos/>
Appendices
Appendix A

Figure 1: Interpretation key riverbank vegetation (Houkes and Buiks, 2011)
Figure 2: Interpretation key terrestrial vegetation (Houkes and Buiks, 2011)
Appendix B
This appendix contains the results of the accuracy assessment of the ecotope classifications as studied by Alterra (Knotters et al, 2008). These results are used to study the accuracy of the ecotope maps on vegetatielegger level (chapter 6). The meaning of the ecotope codes as used in their tables is explained below in table xx.

<table>
<thead>
<tr>
<th>Ecotope code</th>
<th>Ecotope</th>
</tr>
</thead>
<tbody>
<tr>
<td>H-Rest</td>
<td>Flood-free temporary bare</td>
</tr>
<tr>
<td>HA-1</td>
<td>Flood-free field</td>
</tr>
<tr>
<td>HA-2</td>
<td>Flood-free built-up</td>
</tr>
<tr>
<td>HB-1</td>
<td>Flood-free natural forest</td>
</tr>
<tr>
<td>HB-2</td>
<td>Flood free shrubs</td>
</tr>
<tr>
<td>HB-3</td>
<td>Flood-free production forest</td>
</tr>
<tr>
<td>HG-1</td>
<td>Flood-free natural grassland</td>
</tr>
<tr>
<td>HG-1-2</td>
<td>Flood-free natural/production grass land</td>
</tr>
<tr>
<td>HG-2</td>
<td>Flood-free production grassland</td>
</tr>
<tr>
<td>HR-1</td>
<td>Flood-free tall herb vegetation</td>
</tr>
<tr>
<td>IL.1</td>
<td>Fresh water sand</td>
</tr>
<tr>
<td>IV.8-9</td>
<td>Reed and swamp vegetation</td>
</tr>
<tr>
<td>IX.a</td>
<td>Field on embankment</td>
</tr>
<tr>
<td>O-UA-1</td>
<td>Foreland or embankment Field</td>
</tr>
<tr>
<td>O-UB-2</td>
<td>Foreland or embankment natural forest</td>
</tr>
<tr>
<td>O-UG-1</td>
<td>Foreland or embankment natural grass land</td>
</tr>
<tr>
<td>O-UG-2</td>
<td>Foreland or embankment production grass land</td>
</tr>
<tr>
<td>O-UR-1</td>
<td>Foreland or embankment tall herb vegetation</td>
</tr>
<tr>
<td>U-Rest</td>
<td>Foreland temporary bare</td>
</tr>
<tr>
<td>UA-1</td>
<td>Foreland field</td>
</tr>
<tr>
<td>UA-2</td>
<td>Built-up in foreland</td>
</tr>
<tr>
<td>UB-1</td>
<td>Natural forest in foreland</td>
</tr>
<tr>
<td>UB-2</td>
<td>Bushes in foreland</td>
</tr>
<tr>
<td>UB-3</td>
<td>Production forest in foreland</td>
</tr>
<tr>
<td>UG-1</td>
<td>Natural grassland in foreland</td>
</tr>
<tr>
<td>UG-1-2</td>
<td>Natural/Production grassland in foreland</td>
</tr>
<tr>
<td>UG-2</td>
<td>Production grassland in foreland</td>
</tr>
<tr>
<td>UR-1</td>
<td>Tall herb vegetation in foreland</td>
</tr>
<tr>
<td>V.1.2-2</td>
<td>Swam herb vegetation</td>
</tr>
<tr>
<td>VI.2-3</td>
<td>Bushes or pioneers softwood forest</td>
</tr>
<tr>
<td>VI.4</td>
<td>Softwood forest</td>
</tr>
<tr>
<td>VII.1</td>
<td>Marshy grass land</td>
</tr>
<tr>
<td>VII.3</td>
<td>Marshy production grass land</td>
</tr>
<tr>
<td></td>
<td>HA1</td>
</tr>
<tr>
<td>--------</td>
<td>-----</td>
</tr>
<tr>
<td>V1</td>
<td></td>
</tr>
<tr>
<td>V2</td>
<td></td>
</tr>
<tr>
<td>V3</td>
<td></td>
</tr>
<tr>
<td>V4</td>
<td></td>
</tr>
<tr>
<td>V5</td>
<td></td>
</tr>
<tr>
<td>V6</td>
<td></td>
</tr>
<tr>
<td>V7</td>
<td></td>
</tr>
<tr>
<td>V8</td>
<td></td>
</tr>
<tr>
<td>V9</td>
<td></td>
</tr>
<tr>
<td>V10</td>
<td></td>
</tr>
<tr>
<td>V11</td>
<td></td>
</tr>
<tr>
<td>V12</td>
<td></td>
</tr>
<tr>
<td>V13</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** The table contains numerical data which cannot be accurately read due to the image quality. The table headers and some data points are provided, but the full content is not legible.
Appendix C

Height data generated from stereo aerial photographs versus AHN data

The height data used for this project are generated from stereo aerial photographs. This dataset has its limitations with respect to spatial resolution and maps the height data with an accuracy of around 1 meter. This accuracy is not enough to use the height data to distinguish grass vegetation (< 0.5 meters) from tall herb vegetation (0.5 – 2 meters). This height data can be used to separate trees (+5 meters) from bushes (2 – 5 meters). Tall herb vegetation is a difficult class to separate spectrally. A more accurate height dataset can help to avoid misclassifications between grass and tall herbs.

The AHN (Algemeen Hoogtebestand Nederland) contains files with detailed and accurate height data for whole of the Netherlands. The AHN2 data is obtained with laser altimetry and has a spatial resolution of 0.5 meters and can map height differences of 5 centimetres. Therefore, the AHN is much more accurate than the height data that is used for this project. However, the AHN data is not up to date. It is a dataset that has currently 3 versions, where the first version originates in 1996. To map vegetation changes within one year, the height data should be up to date just as the aerial photographs of satellite images. Because of this the AHN data is not used, but only compared to the height data from the aerial photographs. In this way can be studied if the method, the laser altimetry, can distinguish the tall herb vegetation where the aerial photograph data cant.

Figure 1 shows the test area with three data types: the aerial photograph (false colour); the height data from the photographs; and the AHN2 data. As is seen in this figure the AHN data contains much more detail than the other height data. To study if tall herb vegetation is distinguishable with the AHN data four tall herb locations are visualized for the three datasets: aerial photographs, height data form the photographs; and AHN data (figures 2 – 5).

![Figure 1. Upper image: false colour aerial photograph of the test area; lower left image: height data from the aerial photographs that is used in this project; lower right image: AHN2 data](image-url)
**Location 1**
Figure 2 shows three images: the false colour aerial photograph, the height data generated with the aerial photographs and the AHN data. This location contains a clear tall-herb field in the middle of the image as seen in the aerial photograph. The tall herb field is less visible in the height images. The height data from the aerial photograph does not show the tall herb at all, where the AHN data shows a little height difference between the tall herbs and the surrounding grass fields. This field of tall herb would be recognizable with the AHN data, but is not with the aerial photograph height data. The use of up to date laser altimetry data would be a improvement for the classification of tall herb at this location.

![Figure 2](image.png)

**Location 2**
Figure 3 shows the second location where tall herbs are visible in the aerial photograph. The triangle shaped tall herb field in the middle of the image contains clearly tall herb vegetation. Just like at location 1, the tall herb is visible in the AHN data as small yellow spots, but is not for the aerial photograph height data. However, the field right of the triangle contains a few patches of rougher (tall herb) vegetation as well. These patches are not visible in both height datasets.

![Figure 3](image.png)
Figure 3. Location 2, a tall herb field in the middle and patches of rough vegetation visible in the field on the right side of the image. Upper image shows the false colour photo; lower left image shows the aerial photograph height data; lower right image is the AHN data.

Figure 4. Location 3, a tall herb field in the middle of the image. Upper image shows the false colour photo; lower left image shows the aerial photograph height data; lower right image is the AHN data.
**Location 3**

Figure 15 shows the third location of tall herb vegetation. The grassland closest to the river is not regularly mowed and contains rough vegetation. In the height data from the aerial photograph there is no difference seen between the lower and the upper grassland. In the AHN data higher ground is visible, but this is not in the same shape as the patches seen in the aerial photograph. Both datasets do not show the tall herb patches.

![Image](image_url)

Figure 5. Location 4, a tall herb field in the middle of the image. Upper image shows the false colour photo; lower left image shows the aerial photograph height data; lower right image is the AHN data

**Location 4**

In the upper right corner, between the road and the water, of figure 16 a patch of tall herb vegetation is visible. The height data from the aerial photograph does not show any detail, so the tall herb in not visible with this dataset. The AHN data does show the tall herb vegetation.
Appendix D
This appendix contains the large size image of the true-colour aerial photograph of the classified area.
Appendix E

In this appendix the intermediate results of the classification of the segmentation are shown and the improvements described. For every dataset used 3 results are visualized. The first result is the result of the kNN-classification; the second result is the classification of the segmented image; and the third result is the classification of the segmented image together with the height data and (for the satellite classification) NDVI data.

The results that are shown are from 5 different classifications:

- Aerial photograph data with proportional training-data
- Aerial photograph data with equal training-data
- Satellite image data with proportional training-data
- Satellite image data with equal training-data
- Aerial photograph data with auto-generated training-data

First, on the next page, the results of the aerial photographs are shown, later the satellite image classification results and the auto-training data results are described.
Intermediate results of aerial photograph classification, proportional training-data

This figure shows the result of the kNN-classification. There is no difference between trees and bushes and a lot of the grasslands contain a lot of isolated pixels that are classified wrongly as tall herb vegetation. Some of the isolated pixels are classified as ‘unknown’.

When the segmentation is classified the image already looks a lot smoother. Many of the isolated pixels are gone and there are less ‘unknown’ pixels. The edges between different classes are more defined and more comparable to the straight lines of the vegetation legger.

In the last step the height data is added to the classification of the segmentation. Now, assuming shrubs are between 2 and 5 meters high and trees are higher than 5 meters, trees and shrubs are separated. Pixels classified as forest, but with a height of zero meters are hanged into tall herb vegetation.
Intermediate results of aerial photograph classification, equal training-data

The result of the k-NN classification shows a lot of pixels classified as tall herb vegetation. What were isolated pixels in the proportional training-data classification are entire fields now.

The classification of the segmentation causes mixed fields to turn into the predominantly class entirely. Most grass (yellow) fields are after the segmentation completely classified as grass and a lot of tall herb fields are now entirely classified as such (brown). The segmentation does not solve the overestimation of tall herb when fields are predominantly classified as tall herb.

The height data separate bushes and trees, but does not solve the overestimation of the tall herbs. Tall herbs have, with the data used, the same height values as grass and cannot be corrected with the height data.
Intermediate results of satellite image classification, proportional training-data

The kNN-classification of the satellite image with proportional training data. The built-up class is overestimated as is the water class. The edges of the hedges are often classified as water. Later, with the NDVI data, this overestimation of water can be solved.

The classification of the segmentation solved a part of the overestimation of the built-up class. In the left side of the image grass fields are now completely classified as grass. Unfortunately, the fields in the lower right corner are still mixed with both the grass and the built-up class.

The height data that is added separates trees and bushes. The NDVI value of the pixels is used to correct the misclassified water pixels. Now, the water is no longer overestimated.
Intermediate results of satellite image classification, equal training-data

In the k-NN classification of the equal training-data the overestimation of the built-up class is more severe. Also, more pixels are classified as tall herb (which appears to be an overestimation as well, referring to the error matrix in the results section paragraph 6.2.2).

The classification of the segmentation causes the whole lower right corner to be classified as built-up area. The isolated pixels in the forest in the upper left corner are corrected and no longer visible. Grass fields in the left side of the image are now completely classified as grass instead of a mixture of grass and built-up area.

In the last step of the classification the height data and the NDVI values are added. The NDVI corrects for the wrongly classified water pixels. The height data separates the trees and the shrubs. With the data added it is not possible to correct for the overestimation of the built-up area and tall herbs class.
The kNN-classification results of the aerial photograph data with automatically generated training data. Small objects like solitary trees are classified, so the high spatial resolution is sufficient. There are multiple areas that contain wrongly classified tree and tall herb pixels. These fields clearly show the 'salt and pepper effect' that can be solved with segmentation of the image.

After the segmentation a lot of solitary wrongly classified pixels are corrected, but some large areas are still a little pixelated (like the tall herb area in the left side of the image). The segmentation could not be coarser, because some details already disappeared because of the segmentation. (On the right side a small patch of water is changed to grass area due to the segmentation). For the loss of a few hedges will be corrected with the height data.

With the added height data all the trees and bushes are accurately classified. The large areas of misclassified trees are changed to tall herb vegetation. There is no longer a overestimation of trees and only an overestimation of tall herb vegetation is still present.