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A pilot study for the drinking water extraction areas Haarlo and Vessem, The Netherlands.

K. Kuipers

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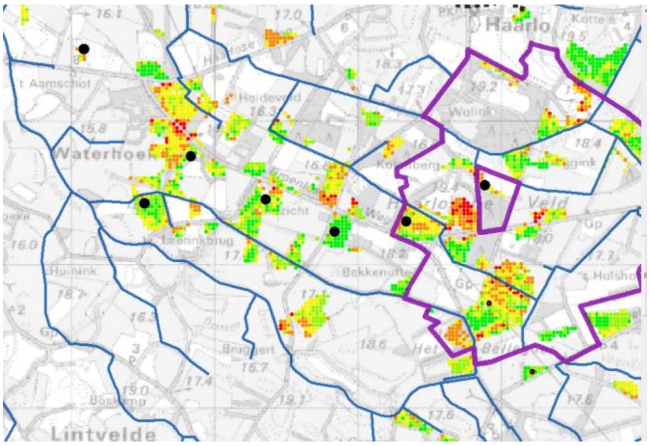

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Drought Damage Determination in Drinking Water Extraction Areas Using Remote Sensing Products

A pilot study for drinking water extraction areas Haarlo and Vessem, The Netherlands.

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Foreword

This master thesis is written for the Master Geo-Information Science at the Wageningen University. The programme focuses on geo-information science methods, technologies and applications within environmental and life sciences for a changing world. The research topic of this master thesis, using remote sensing data to determine drought damage to vegetation caused by drinking water extractions, lies within the scope of the master study. The goal of this study was to determine if the Normalized Difference Vegetation Index can contribute to determining the drought damage settlements which drinking water companies have to pay to farmers as compensation for the damage caused by extracting drinking water to the crops.

The opportunity to work on this project arose during my internship at the drinking water company Vitens. I was very enthusiastic about this topic because it combines Geo-Information Science with my bachelors in Soil, Water and Atmosphere. The perfect way to finalize my studies. It turned out that mitigating remote sensing and a specialized topic of hydrology was more challenging than expected beforehand. However, working on this project enabled me to learn a lot about both fields of expertise and the opportunities to implement one in the other.

I would like to thank my two main supervisors Wilco Klutman (from Arcadis) and Jan Clevers for granting me the opportunity to work on this project and for their supervision during the thesis. I thank Gerbert Roerink for supplying the NDVI data. Furthermore, I would like to thank Jons Jongema and Marcus Kuipers for providing me the perfect environment for writing the report. Last but not least I would like the thank Anouk Hakman for taking the time to correct a dyslectics writing.

Abstract

Drinking water companies lower the ground water level by extracting water. This reduces the soil moisture content in the root zone possibly resulting in drought stress for the vegetation. Drought stress results in a lower yield compared to crops which do not experience drought stress. Farmers are compensated by the water companies with drought damage settlements. The methods currently used to determine these settlements are not sufficient. Due to climate change the demand for alternative methods to estimate the drought damage settlements increases. This study investigated if the Normalized Difference Vegetation Index can contribute in determining the drought damage settlements.

The study areas chosen are the drinking water extractions Haarlo and Vessem. Haarlo is located in the East of the Netherlands and the main land use type is permanent grassland. Vessem is located in the south of the Netherlands with as main land use type temporary grassland. This latter study area also contains two fault lines. The main soil type in both study areas is Hn21 (veldpotzolgrond).

For both study areas quantile regressions, of the 0.9^{th} quantile, have been applied on the monthly maximum NDVI values for 2013 against the distance to the drinking water extraction. Only the pixels with the main land use type on Hn21 have been selected. The trends found for the area inside and outside the influence of the drinking water extractions have been compared. For Haarlo the quantile regression was also performed for the NDVI against the drawdown. The same regressions were done with sub-study areas based on cardinal direction, soil type and, for Vessem, the fault lines. The temporal analyses consisted of comparing the NDVI though time for a pixel every half kilometre, determining if the number of grass cuts increased with distance from the extraction and if the recovery time after a grass cut decreased with distance.

A positive relation between the monthly maximum NDVI and the distance to the drinking water extraction was found for five out of seven months for Haarlo. In this study using sub-study areas was more suited for Vessem due to the presence of fault lines. This shows that, for the most suitable method depending on the distribution of the soil types and hydrological properties within a study area, NDVI data can be used to show relationships with the drinking water extraction.The temporal analyses were limited by the number of high quality images. Future development will enable the acquisition of a higher number of high quality images, making the method for determining the number of grass cuts and recovery time feasible.

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Abbreviation List

AMIGO Actueel Model Instrument Gelderland Oost

BFAST Breaks For Additive Seasonal and Trend

DMC Disaster Monitoring Constellation

HANTS Harmonic Analysis of Numerical Time Series

Hn21 loam poor veldpotzolgrond

MODIS Moderate Resolution Imaging Spectroradiometer

MUST Model for Unsaturated flow above a Shallow water Table

NDII Normalized Difference Infrared Indices

NDVI Normalized Difference Vegination Index

NDWI Normalized Difference Water Index

NIR Near InfraRed

pZg23 loamy beekeerdgrond

SPOT Satellite Pour l'Observation de la Terre

TCGB Technische Commissie Grondwater Beheer

VCI Vegetation Condition Index

VIS VISible light

VWI Vegetation Water Index

zEZ23 humous topsoil

1. Introduction

1.1 Context and Background

ARCADIS and KWR are commissioned by Vitens and Brabant Water to investigate the opportunities for remote sensing data to back up drought damage settlements (Klutman, 2014). Vitens and Brabant Water are companies who extract groundwater for consumer usage (Kloosterman et al., 2011).

The extraction of water can reduce the ground water level (when extraction is more than the replenishment). This reduces the soil moisture content in the root zone with possible drought stress for the crops cultivated on those soils. Drought stress results in a lower yield compared to crops which do not experience drought stress (Hsiao & Acevedo, 1974). In order to prevent drought stress, farmers will have to invest in extra irrigation for those fields which are influenced by the water extraction. These extra expenses are compensated by the water companies (drought damage settlements).

The drought damage settlements are currently estimated with the use of HELP-2006 tables or TCGB-tables. The LAMOS model (Bakel, Waal, Haan, Spruyt, & Evers, 2007) calculates the moisture shortages for the HELP-2006 tables. The estimated yield loss related to the moisture shortage is based on practical insights and trial field research. The TCGB-tables use the MUST model (Bouwmans, 1990) to derive moisture shortage, which is used to ascertain the yield loss for grassland on sandy soil for an individual year, based on a combination of average higher groundwater level and average lowest groundwater level data.

The TCGB-method (Technische Commissie Grondwater Beheer) (Bouwmans, 1990) and HELP-method (Bakel et al., 2007), currently used to estimate the drought damage settlements, are not sufficient. They do not take into account the effect of climate change (Bakel & Eertwegh, 2011), the main reason being that the tables are based on non-reproducible calculations with weather data from 1950-1980.

Due to climate change the demand for alternative methods to estimate the drought damage settlements increases (Bartholomeus et al., 2013; Ruijtenberg, Bartholomeus, Kroes, Hack, & Van Bakel, 2012). Remote sensing offers a lot of products that can give insight in drought damage. This thesis will focus on the usability of the Normalized Difference Vegetation Index (NDVI) as a remote sensing product for the estimation of drought damage settlements.

1.2 Problem Definition

This section explains the problem in more depth and how other countries tackled similar problems. To conclude the scope of this research is defined.

1.2.1 Drought Assessment

Droughts are extreme climatic events which reoccur and cause a lot of damage to crops. Traditionally, drought monitoring has been based on weather station observations, which lack the continuous spatial coverage needed to characterize and monitor the detailed spatial pattern of drought conditions (Gu, Brown, Verdin, & Wardlow, 2007), (Thenkabail, Gamage, & Smakhtin, 2009).

Landscape parameters including land cover, soil permeability, available water capacity, soil texture, depth to water table, and slope can also be used to determine potential drought damage (Reed, 1993). Such methods are limited if the area of interest does not have all this information available. Moreover, it only determines potential drought damage. Meteorological influences are not accounted for.

1.2.2 Drought damage estimation in the Netherlands

The drought damage settlements in the Netherlands are estimated by Vitens and Brabant Water using the TCGB-method and HELP-method. The TCGB-method only accounts for grassland (Bouwmans, 1990). The HELP-method uses tables containing yield per crop type based on groundwater level and soil type (Bakel et al., 2007). Though the tables do not take weather conditions into account, the eventual methods to determine drought damage do compensate for a dry or a wet year. Nevertheless, climate is changing. The yearly average temperatures are higher compared to when the tables were made. More warmth results in an overall drier root zone and yield loss (Geertsema, Runhaar, Spek, Steingrover, & Witte, 2011).

Moreover, the rainfall nowadays is more extreme (Klein Tank & Lenderink, 2009). There is more rainfall in a short period of time giving the water less opportunity to infiltrate, which leads to an increased surface runoff (Geertsema et al., 2011). Drought damage estimation based only on ground water levels and soil type has its limitations; therefore, other systems are being developed to find climate proof relations between yield and hydrological conditions (Bartholomeus et al., 2013).

1.2.3 Remote Sensing and Drought Assessment

Satellite data with high quality is regularly available and can be used to detect and monitor a drought, whereas weather station observations lack the continuous spatial coverage. Multiple studies describe how remote sensing data can be used to monitor and assess drought damage.

Gu et al. (2007) show how different vegetation indexes based on moderate resolution imaging spectroradiometer (MODIS) data can be used to assess grassland droughts in the United States. Similar research has been done for Iran (Rahimzadeh Bajgiran, Shimizu, Hosoi, & Omasa, 2009).

In southern Africa, droughts are a big problem and because the meteorological data is often incomplete, they use satellite data for drought monitoring (Unganai & Kogan, 1998). Unganai and Kogan used vegetation indices and temperature indices to estimate the health and productivity of the vegetation. In India a satellite based drought assessment methodology was developed based on the relationship between the NDVI data and the agricultural performance (Krishna, Ravikumar, & Krishnaveni, 2009).

Even though the drought problems described above are of a different magnitude and scale compared to the Netherlands, remote sensing shows possibilities (Roerink & Mucher, 2012).

1.2.4 NDVI and Drought Assessment

Various drought researches use vegetation indexes as variable:

- Normalized difference vegetation index (NDVI) (Karnieli et al., 2010), (Krishna et al., 2009), (Reed, 1993), (Nemani & Running, 1989) and (Tucker, 1979).
- Normalized difference water index (NDWI) (Gu et al., 2007).
- Vegetation Condition Index (VCI) (Muthumanickam et al., 2011).
- Normalized Difference Infrared Indices (NDII6 and NDII7 using band 6 and 7 MODIS data, respectively) (Rahimzadeh Bajgiran et al., 2009).
- Vegetation Water Index (VWI) (Reich, 2012)(Rahimzadeh Bajgiran et al., 2009).

In this research, we focused on the NDVI because it is the most used vegetation insex in similar researches and the data was available via the Groenmonitor of Alterra (Roerink & Mucher, 2012). The NDVI is based on the theory that chlorophyll strongly absorbs visible light and reflects a lot of near-infrared (Tucker, 1979).

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)}$$

VIS is the spectral reflectance measurement acquired in the visible region of the spectrum (0.4 to 0.7 µm). NIR is the spectral reflectance measurement acquired in the near infrared region of the spectrum (0.7 to 1.1 µm) (Nemani & Running, 1989).

The NDVI values through time for agricultural grasslands show the occurrence of grass cuts (Roerink & Mucher, 2012). It would be interesting to relate amount of yield per grass cut to the drought damage caused by the drinking water extraction. Unfortunately, this data (yield per grass cut) was not available. Nevertheless, the number of grass cuts and the recovery can be determined from the NDVI time series. The recovery time is the number of days it takes for the NDVI to reach the next maximum NDVI after a grass cut.

1.2.5 Scope of this research

Determining drought damage is one thing, but this research went a step further. We were interested in the damage caused by ground water extraction for drinking water. This adds a layer of complexity. The methods used by Vitens and Brabant Water have their limitations. The goal of this study was to determine if the remote sensing product (NDVI) can contribute in determining the drought damage settlements. Remote sensing products show a lot of potential as a tool to support the drought damage settlements. It can help the water companies explain and clarify to the farmers how the settlements are computed.

1.3 Research Objectives, Questions and Hypothesis

The main objective of this research was to determine if the NDVI can be used as a tool to observe drought damage on vegetation as a result of groundwater extraction for drinking water.

Main research question: Is drought damage caused by ground water extraction perceptible with the NDVI?

The main research question was addressed by the following sub-questions:

1. Does the NDVI show a relationship with distance to the drinking water extraction?
2. Does the NDVI show correlation with the lowering of the water table?
3. Do the NDVI time series differ with distance to the drinking water extraction?
4. Does the number of grass cuts differ with distance to the drinking water extraction?
5. Does the recovery time after a grass cut differ with distance to the drinking water extraction?

Hypothesis:

When drought damage is caused by drinking water extractions, the expectation is that there will be lower NDVI values close to the extraction and higher values further away. A positive relation is expected between the NDVI and the distance to the drinking water extraction. When the drinking water extraction is the only cause, outside the influence of the extraction idealy no relation is expected between NDVI values and distance to the drinking water extraction. Nevertheless, relations found outside the influence of the drinking water extraction should be significantly smaller that the relations found within the influence of the extraction. A genuine difference is confirmed when the relation within is three times the relation outside the influence of the drinking water extraction (in consultation with J.P.M. Witte from KWR).

A high drawdown (lowering of the ground water table) results in no water in the root zone when the capillary rise from the water table won't reach the root zone. With insufficient water in the root zone, the plant will experience stress and a low NDVI is expected. Close to the extraction the drawdown is high compared to further away. A negative relation between NDVI and drawdown is expected.

Within a field no variation in NDVI is expected. Nevertheless, the pixels on the edges of the field might be influenced by adjacent roads, shadow from trees and ditches. It is also expected that all the pixels will show the grass cuts at the same moment of time.

Over time it is expected that the NDVI values will be consistently lower close to the drinking water extraction.

When drought damage occurs due to drinking water extraction, the number of grass cuts is expected to be less close to the drinking water extraction and more cuts are expected further away from the drinking water extraction. A positive relation between the number of grass cuts and distance to the extraction is expected inside the influence of the drinking water extraction. Outside of the influence of the drinking water extraction no relation between the number of grass cuts and distance to the extraction is expected.

The recovery time of the grass after a grass cut is expected to be longer close to the drinking water extraction than further away. The grass needs less time to recover from a grass cut further away from the extraction. A negative relation is expected between the recovery time and the distance to the drinking water extraction. Outside the influence of the drinking water extraction no relation between the recovery time and the distance to the drinking water extraction is expected.

1.4 Outline Report

This section describes the content of every chapter.

Chapter 1 is the introduction of the research and provides context and background information for this research. The problems are stated and relevant research is reviewed. The research objectives, questions and hypotheses are presented as is the outline of the report.

Chapter 2 describes the methodology used during this research. The study areas are introduced. An overview is given of the used data and the analyses are explained in depth.

Chapter 3 shows the results of the analyses per study area.

Chapter 5 discusses the results and draws conclusions by answering the research questions.

Chapter 6 gives recommendations for further research.

2. Methodology

This section describes the methods which are used within this research. First, the study area will be briefly described followed by a description of the data. Then, the research strategy will be described. This study is divided in a spatial and a temporal analysis.

During the spatial analysis, the following relations were studied:

- A relation between NDVI and distance to the drinking water extractions; within and outside of the influence of the drinking water extractions and in the chosen sub-study areas.
- A relation between the NDVI and the drawdown caused by the drinking water extractions; within and outside of the influence of the drinking water extractions and in the chosen sub-study areas.

The time series analyses consisted of:

- Comparing time series of pixels within a field
- Comparing time series of pixels with increasing distance from drinking water extraction
- Number of grass cuts
- Days needed for recovery after grass cut.

2.1 Study Area

This sub chapter describes the chosen study areas Haarlo and Vessem. Both these areas are located in the Netherlands as shown in Figure 1.

Figure 1. The Netherlands with the location of the study areas.

2.1.1 Haarlo

The drinking water extractions Haarlo and Eibergen are situated north of Groenlo in Gelderland close to the border with Germany.

Haarlo and Eibergen are situated in a draining area. Haarlo's surface level is approximately 17 meters above sea level. Eibergen's surface level is between 19 and 20 meters above sea level. Figure 2 shows both drinking water extractions. Around drinking water extraction Eibergen, water is infiltrated.

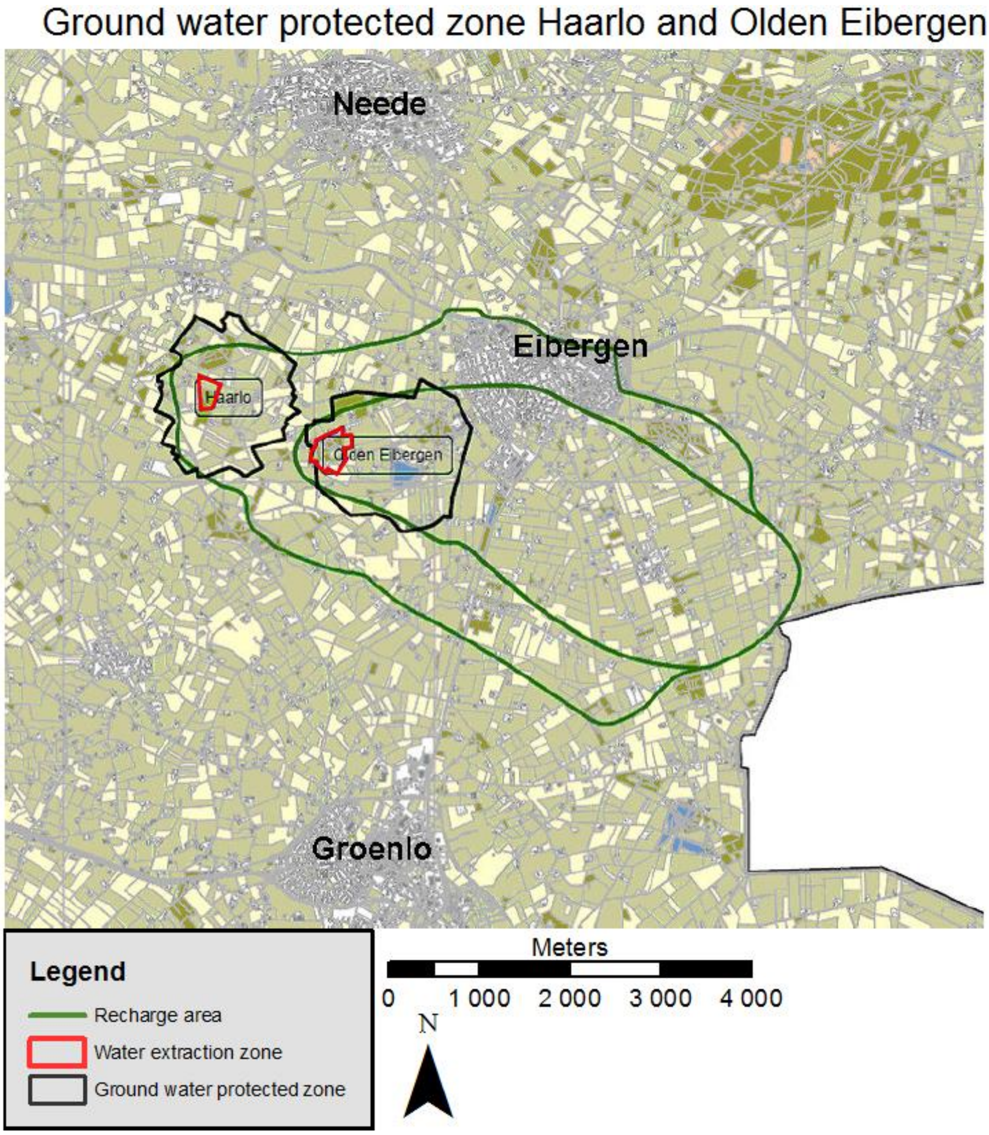

Figure 2. Study area Haarlo (source: Vitens). The drinking water extraction (red), the 25 years-zone (groundwater protected zone, black) and 100 years-zone (recharge area, green) of Haarlo (left) and Olden Eibergen (right).

The subsoil consists of a 25 m thick layer of sand, containing (from surface downward) the formation of Boxtel, Drente and Urk (Figure 3). The texture ranges from course to medium coarse sand on the location of the pumping filters. The filters are not closed by any non-permeable layers. Therefore, these drinking water extractions are phreatic. The filters are located at depths ranging from 0 to 10 meter below sea level.

Together, both drinking water extractions are allowed to pump up 2.8 million m^3 water per year.

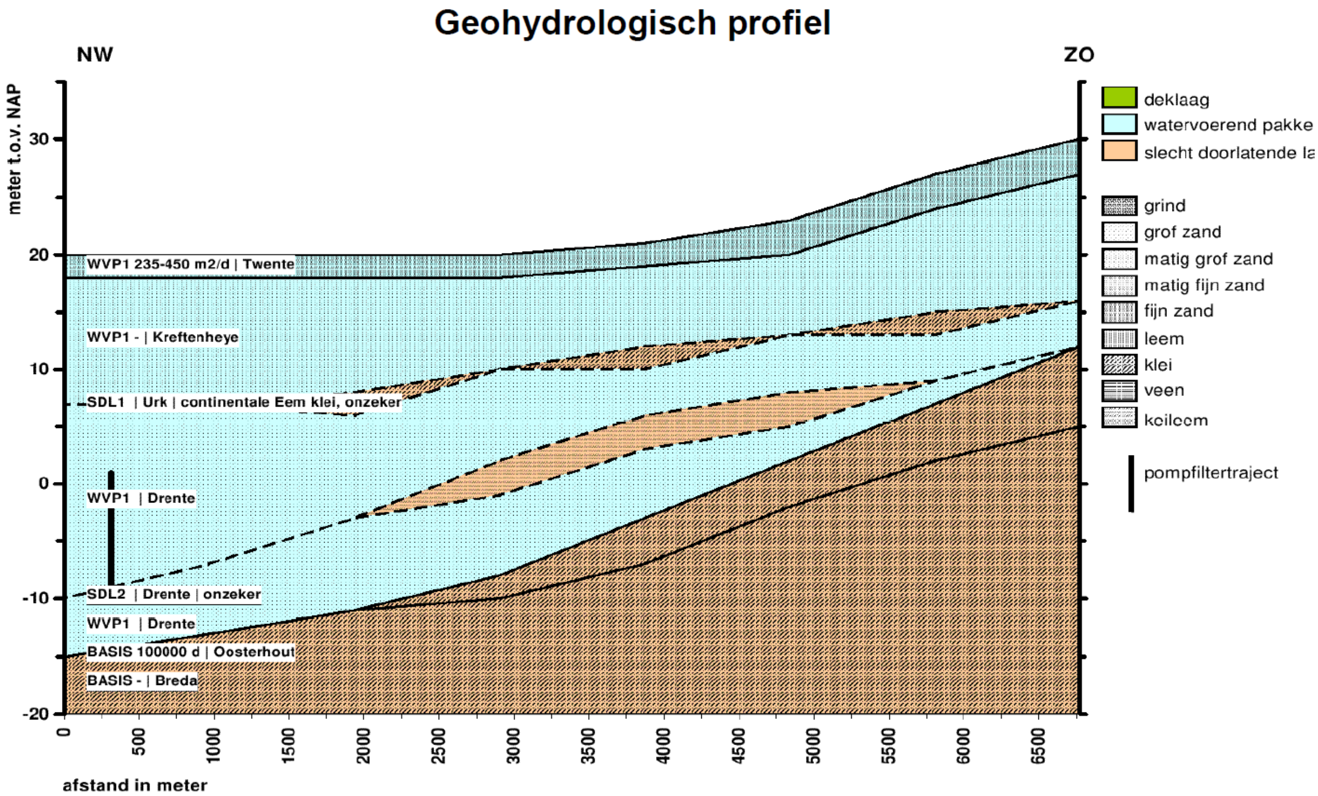

Figure 3. Geohydrological cross section Haarlo (source: Arcadis). Meters from sea level against distance in meters North-West to South-East. With from top to bottom: cover layer, aquifer, aquiclude, gravel, course sand, semi course sand, semi fine sand, fine sand, loam, clay, peat, boulder clay and the pumping filter depths.

The main soil type within the study area is Hn21 (35% of the study area is a loam poor veldpotzolgrond). With 20% the pZg23 soil is the next most apparent soil type in the study area (loamy beekeerdgrond) (Appendix 7.1).

The land cover type of this study area is mainly permanent grassland (52% of the total area) (Appendix 7.3). Maize and temporary grassland are with 24% and 16% cover, respectively, the next most apparent land cover types. The study areas consist of fields from 0.5 to 1 ha.

2.1.2 Vessem

The drinking water extraction Vessem is situated South-West of Eindhoven (Figure 4). The filters are located at depths ranging from 25 to 50 meters below surface level. The maximum capacity of the extractions is 120 m^3 per hour. In 2013 an extraction of 6.5 million m^3 water per year was allowed.

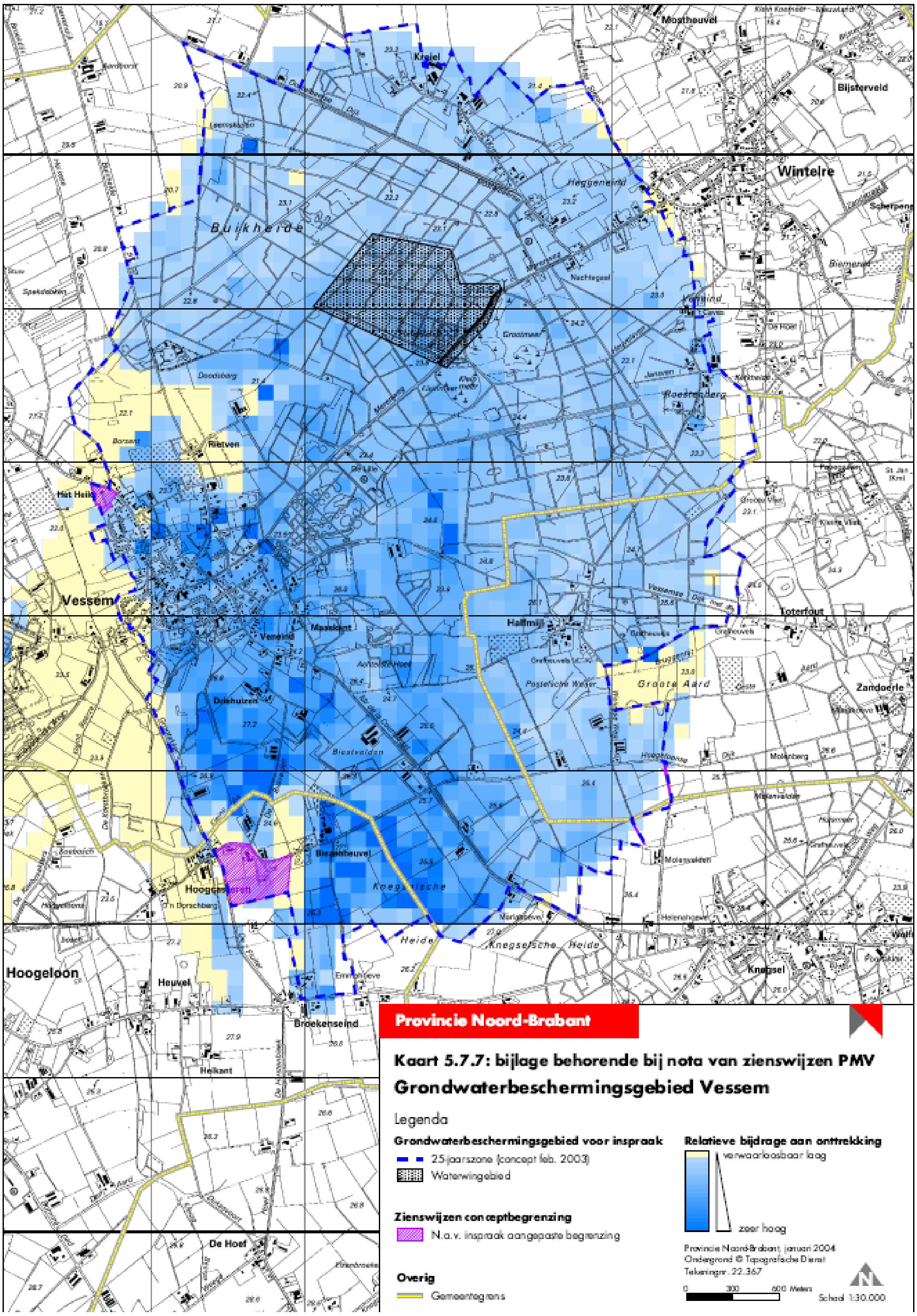

Figure 4. Study area Vessem (source: Brabant Water). Black dotted area is the water extraction zone. Blue dashed line indicates to border of the 25 years protected zone.

To the East and South-West of the drinking water extraction there are fault lines with a North-West to South-East orientation (Appendix 7.2). Figure 5 is a Regis cross section with North-South orientation. Figure 6 is the East-South cross section. Blue indicates the location of the filters. The layers are based on geo-hydrological properties. The fault lines can influence the flow of the groundwater. Smearing of the clay layer can result in a low permeability around the fault lines. In Figure 5 and Figure 6 the aquifers are coloured yellow and mostly contain sand. The impermeable layers are coloured grey and mainly contain clay.

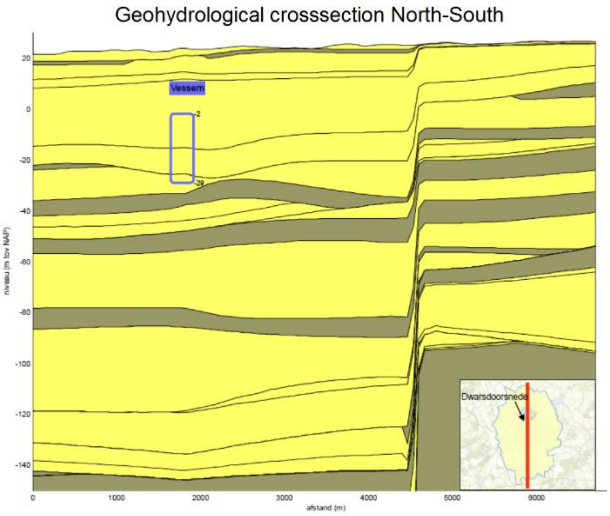

Figure 5. North-South cross section of the ground water protected zone with locations of the filters in blue (source: Brabant Water).

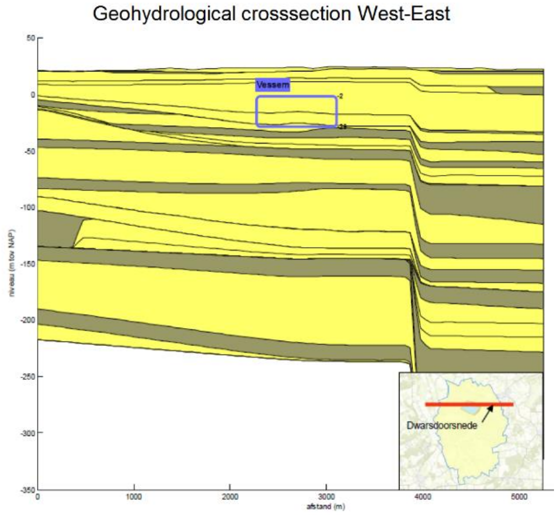

Figure 6. West-East cross section of the groundwater protected zone with locations of the filters in blue (source: Brabant Water).

The most abundant soil type in this area is loam poor veldpodzolgrond (25%). The study area consist for 23% of “high black” loamy enkeerdgronden with a humous topsoil (zEZ23) (Appendix 7.2).

The main land cover type close to the drinking water extraction is forest. The study area consists of maize (33%), temporary grassland (30%) and permanent grassland (7.7%) (Appendix 7.4). The study areas consist of fields from 0.5 to 1 ha.

2.2 Data

An overview of the data used during this research is given in Table 1.

Table 1. Overview of the data used during this research.

Data	Year	Source	Type	Cell size [m]
NDVI values*	2013	Groenmonitor	Raster	25 x 25
Soil type	2006	Geo-desk	Polygon	-
Crop assignments (Basis Registratie Percelen)	2013	Geo-desk	Polygon	-
Drawdown**	2013	Vitens	Raster	25 x 25
Water extraction zone	2013	Vitens, Brabant Water	Shape	-
Ground water protected zone	2013	Vitens, Brabant Water	Shape	-
Water	2013	Arcadis	Shape	-
Towns	2013	Arcadis	Shape	-

* The NDVI data has multiple images.

**only available for Haarlo

2.3 Pre-analyses

The extent of the study area was determined by the groundwater protected zones and fields, which are supposed not to be influenced by the water extraction. This resulted in the extents shown in appendix 7.1 and 7.2.

A 25 by 25 meter raster with for every pixel the distance to the drinking water extraction zone was created. The Euclidian distance to the shapes of the drinking water extraction zones were used.

The NDVI data was only delivered for this extent. The soil data was converted from polygon to raster with the same extent and cell size as the NDVI data. The Crop Assignment data was also cut to the extents and converted to a 25 by 25 raster. This crop raster was used as a mask to cut out all the NDVI images, the soil type, the distance to well and the drawdown.

2.4 Spatial Analyses

The NDVI data consisted of multiple images per month. Some images still included cloud effects. Also grass cuts influenced the NDVI significantly. Those low values can greatly influence the spatial analyses. To prevent this, the NDVI images were combined in a monthly maximum NDVI value resulting in seven images (March to September). A maximum NDVI during the growing season was also computed. The spatial analyses was done on these 8 images.

The spatial analysis consisted of regressions between distance to well and NDVI and of drawdown against NDVI. The expectation is that the NDVI increases with distance from the well. A regression of drawdown against NDVI is expected to result in a negative correlation. The more the reduction, the lower the NDVI. Beforehand, we know that there will be pixels influenced by multiple factors (e.g. irrigation, pixels including roads and shadow). These cases strongly influence a normal regression analysis. Quantile regression would be the preferred method for these analyses (Reich, 2012).

Naturally, not all the variables are measured and included in the statistical models. This may result in weak relations. Other parts of the response variable distribution (different quantiles) might show a stronger and a more useful predictive relationship. Quantile regression is a linear regression model used when conditional quantile functions are of interest. It provides a more complete view of possible causal relationships between variables. An advantage is that the quantile regression estimates are more robust against outliers. Unfortunately it does not account for unobserved heterogeneity and beforehand knowledge about the processes being studied is necessary in order to choose the correct quantile (Cade & Noon, 2003).

The .90 quantile will distil only the effect of the distance to the well, excluding the noise of other variables. For example, when looking at Figure 7, where the x1 axis would be the distance to the well and the y1 axis the NDVI, the .90 line would be the relationship between the NDVI and the distance where 90% of the NDVI is less than or equal to the specified function of the distance (Cade & Noon, 2003).

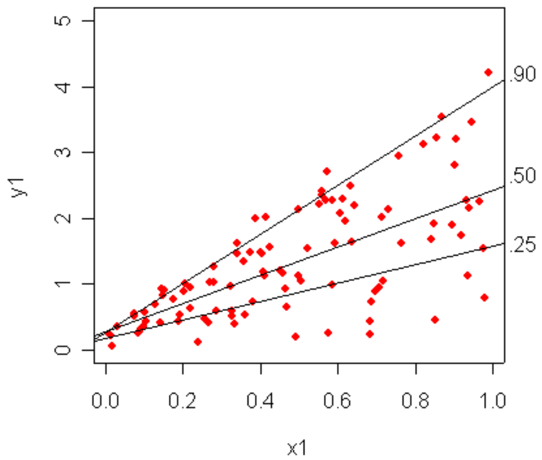

Figure 7. Example of quantile regression results of the 0.90, 0.50 and the 0.25 quantile regressions (Cade & Noon, 2003), *where x1 would be the distance to the extraction and y1 the NDVI values.*

The trend line will describe the following function:

(1) $$y1 = ax1 + b$$

In equation (1) "y1" is the NDVI and "x1" the distance to the drinking water extraction or the drawdown. The value for "a" is the slope of the line and indicates how strong the relation is. The bigger the value for "a" the stronger the influence. The intercept is given by "b".

Not all the pixel values were on the theoretical trend line. In order to determine if the trend line was significant (the value of the slope is high enough), the slope plus or minus the standard error should not include 0. If the slope plus or minus the standard error does include 0, the trend is non-existent. Next to trend line analyses, the summary statistics were also used for quantitative comparisons.

2.4.1 Within and outside of the influence of the drinking water extraction

Two zones were distinguished: (i) the zone where it is certain that the drinking water extraction has influence on the ground water level and, (ii) a zone outside the influence of the drinking water extraction. The pixels with a drawdown of more than 0.05 meters were assumed to be influenced by the groundwater extraction. Pixels with a drawdown of less than 0.02 meters were assumed to be outside of the influence of the groundwater extraction. The choice for 0.02 meters is strict to prevent possible noise in the drawdown data. Therefore, the pixels with a drawdown between 0.02 and 0.05 meters were not used in the analyses. For Haarlo, Vitens delivered the drawdown data calculated with the AMIGO groundwater model (Appendix 7.5). For Vessem, equation (2) of Depuit-Forchheimer (Fraanje, 1974) was used to calculate the distance at which the drawdown would be 0.05 meters and 0.02 meters. The result is illustrated in Appendix 7.6. Table 2 gives an overview of the values used to fill in the variables in equation (2) and determine the distances to the drinking water extraction where the drawdown is 0.05 meters and 0.02 meters.

(2)
$$Q = \frac{\pi k(H^2 - h^2)}{\ln\left(1.5\sqrt{kHt/\varepsilon}\right) - \ln(r)}$$

Table 2. Values used for the variables in equation (2) to determine the distance to the extraction with a certain drawdown and the result of the calculation.

Input		**Values used with** Δh=0.05	**Values used with** Δh 0.02	**Unit**
Withdrawal	Q	17808.22	17808.22	m3/d
Permeability	k	75	75	m/d
Thickness aquifer	H	40	40	m
Time	t	365	365	d
Effective pore volume	ε	0.3	0.3	-
Drawdown	Δh	0.05	0.02	m
Distance to well	**r**	**2710**	**2800**	**m**

Outside of the influence of the drinking water extraction no relations were expected between the distance to the drinking water extraction (or drawdown) and the NDVI. If a relation was found it could have been interpreted as noise or standard error. The relation found within the influence of the drinking water extraction had to be larger than the relation found outside the influence of the drinking water extraction. A genuine difference was confirmed when the relation within is three times the relation outside the influence of the drinking water extraction (in consultation with J.P.M. Witte from KWR).

The analyses for Haarlo were done for the pixels with as land use type permanent grassland and Hn21 as soil type (loam poor veldpotzolgrond). For Vessem the pixels with permanent grasslands and temporary grasslands (which also were grassland in 2012, Appendix 7.4) on an Hn21 soil were selected.

2.4.2 Sub-study areas

The sub-study areas of Haarlo were based on the cardinal directions and the soil types (Appendix 7.7). For Vessem the fault lines and soil types were the main reason for division (Appendix 7.8). The Southern sub-study area of Vessem does not contain any temporary or permanent grasslands on Hn21 soil and therefore has not been analysed.

2.5 Time series analyses

The time series analysis consisted of comparing time series of pixels within a field with increasing distance from drinking water extraction. The number of grass cuts has been determined and a linear regression was used to see if the number of cuts increases with distance to well. The same has been done for the recovery time after a grass cut.

2.5.1 Time series within a field

To see if there was a lot of variation in NDVI within a field, time series of multiple pixels within a field were compared. Per study area a field on grassland and Hn21 was selected. Within this field point 1 to 4 were chosen clockwise along the edge. The other points were placed within the field. Figure 8 and Figure 9 show the chosen pixels. The time series of those points were exported with iMOD (Deltaris, 2015) and visualized in Menianthys (Asmuth, 2013).

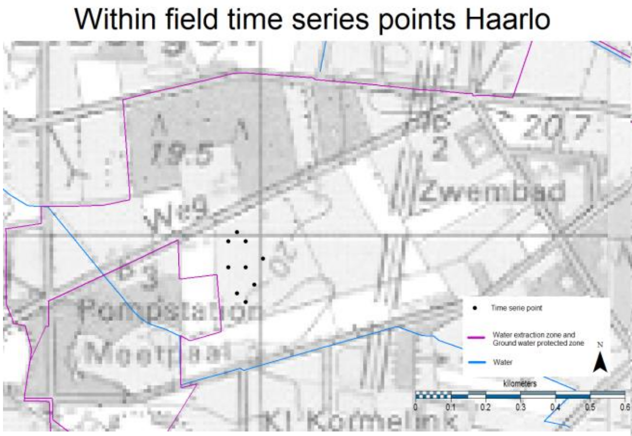

Figure 8. Chosen pixels to compare time series within a field near drinking water extraction Haarlo.

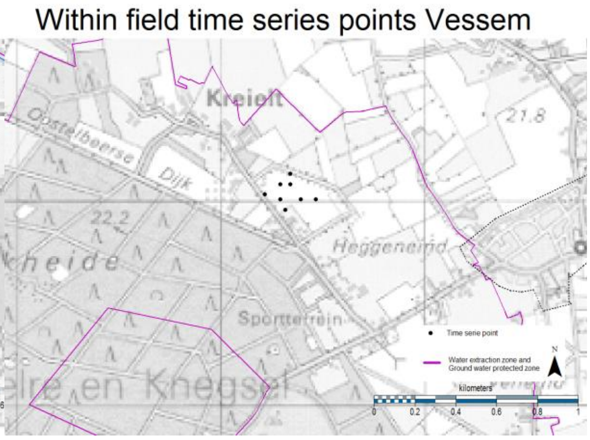

Figure 9. Chosen pixels to compare time series within a field near drinking water extraction Vessem.

2.5.2 Time series per half kilometre distance

In order to see if the time series differ with distance to the drinking water extraction, pixels have been chosen every 0.5 km from the drinking water extraction (where possible). The chosen pixels are as much as possible in the middle of a grassland on Hn21 following one of the four main cardinal directions. Figure 10 is an example of such a ray.

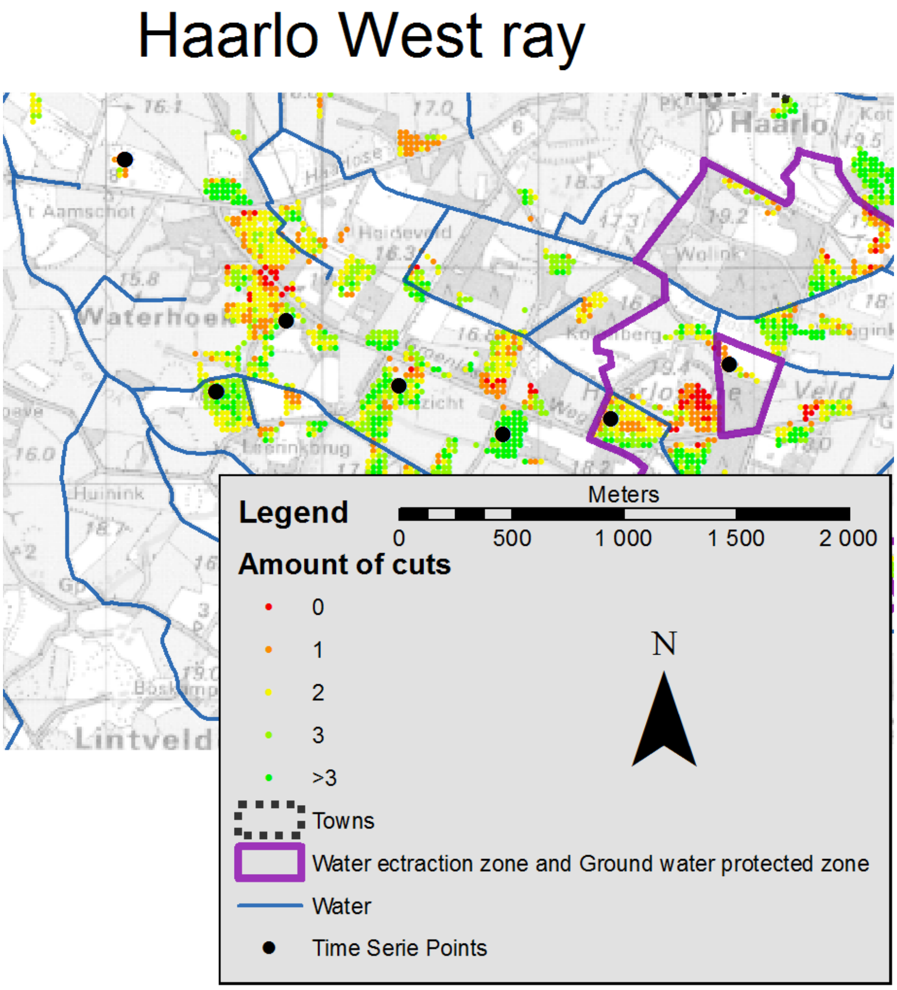

Figure 10. Chosen pixels for West ray near Haarlo.

2.5.3 Grass cuts

The number of grass cuts was based upon the assumption that when grass is mown the NDVI will decrease with a minimal value of 0.1. A decrease in value less than 0.1 can be caused by for example illness or meteorological disturbances. After a cut the grass recovers. Therefore the NDVI value increases. With equation (3) it can be approximated, per pixel, if the available date is a cut. The sum of this results in the number of grass cuts per pixel.

(3) $$\sum_{i=1}^{n-1} IF(AND((i_{+1} - i) > 0.1; i < i_{+1}; i <= i_{-1}); 1; 0)$$

A linear regression between the number of grass cuts and the distance to the drinking water extraction has been done to determine if there are more grass cuts further away from the drinking water extraction.

Figure 11 illustrates the spatial visualization of the number of grass cuts of a few fields in the Vessem study area with corresponding time series to check if equation (3) works properly.

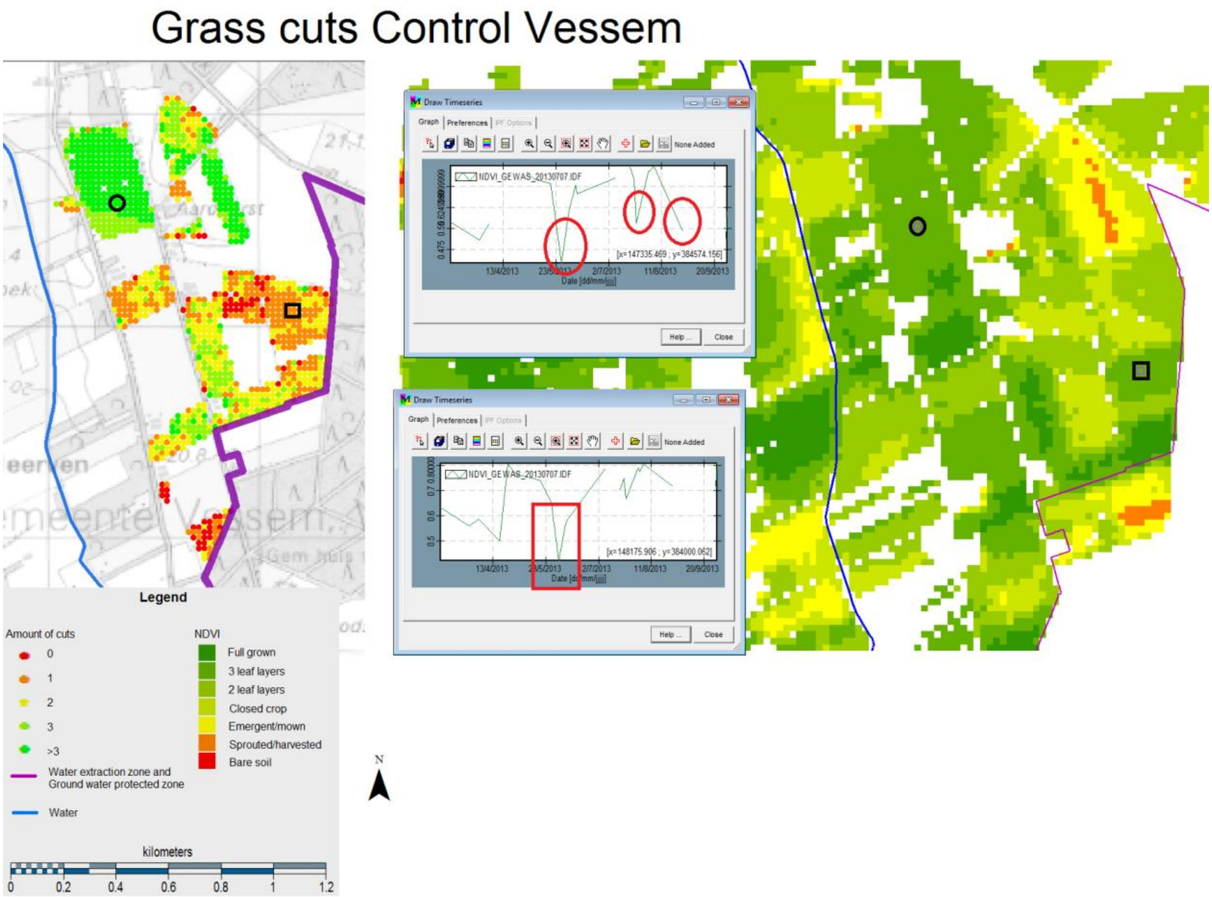

Figure 11. Number of grass cuts computed and checked with corresponding time series (study area Vessem).

Figure 11 also shows that at the edges of the field often less cuts are calculated. Here the NDVI did not decrease by 0.1. Shadow, roads and ditches can be the cause of this. The histograms (Figure 12 and Figure 13) show that the pixel count for an extreme number of cuts (0, 5, 6 and 7) is very low.

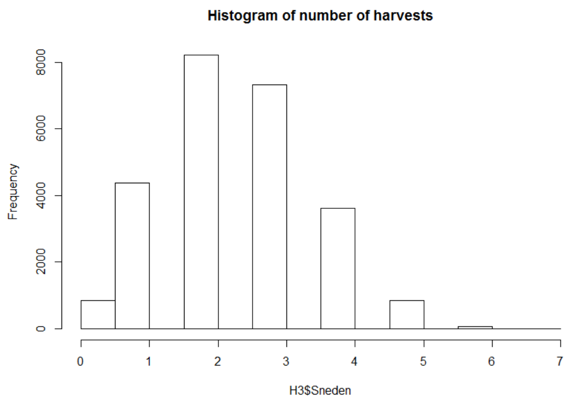

Figure 12. Number of pixels that show 0, 1, 2, 3, 4, 5 or 6 grass cuts in the Haarlo study area.

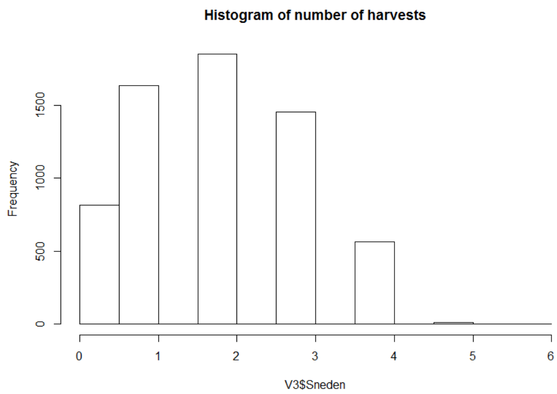

Figure 13. Number of pixels that show 0, 1, 2, 3, 4, 5 or 6 grass cuts in the Vessem study area.

2.5.4 Recovery time

The recovery time in days after a grass cut was determined by the difference in days from the day of cut till the next maximum with an NDVI above 0.65. The chosen grass cut is between the 23rd of May and the 11th of August of 2013. This has been done to ensure that the recovery time between a spring cut and a summer or autumn cut were not compared. A linear regression between the recovery time and the distance to the drinking water extraction was done to determine if the recovery time is shorter further away from the drinking water extraction.

Figure 14 illustrates the spatial visualization of the recovery time of a few fields in the Vessem study area with corresponding time series to check if the function works properly.

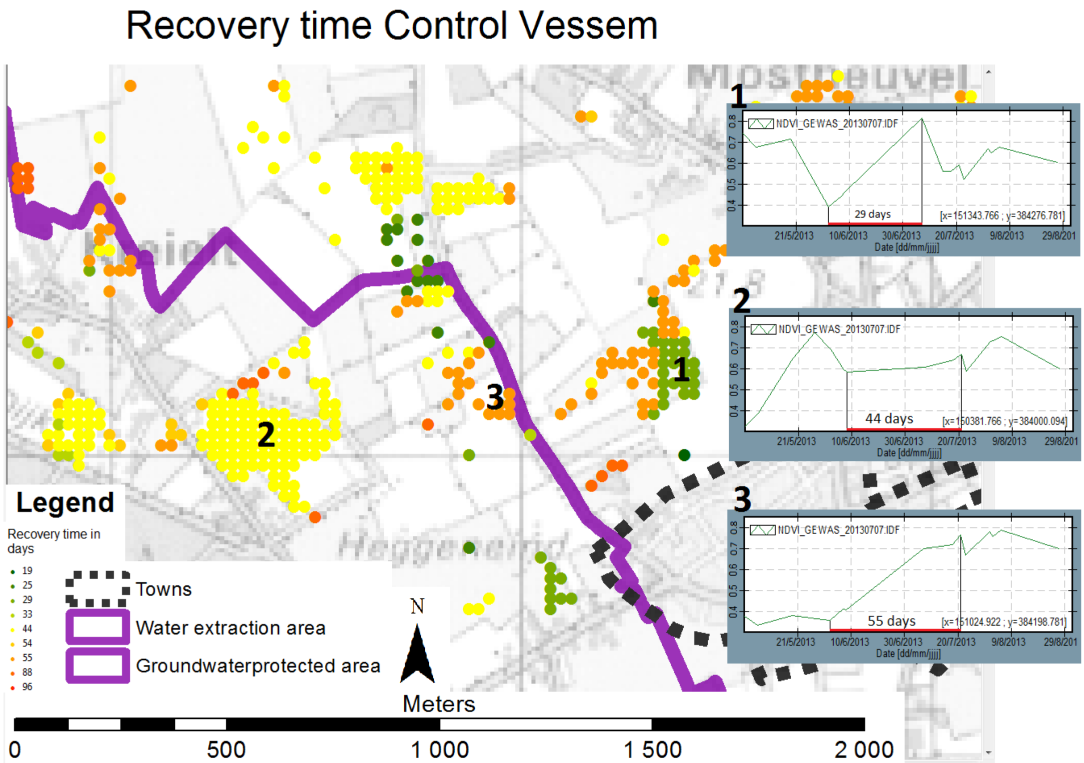

Figure 14. The recovery time of fields in the Vessem study area for 3 control points.

3. Results

Within this section the results for each study area are shown. The first three subparagraphs are the spatial analyses and subparagraph 4 to 7 are the results of the time series analyses.

3.1 Haarlo

3.1.1 Outside and inside the influence of the drinking water extraction

The results consist of 2 populations; H1 is the population of pixels within the influence of the drinking water extraction area and H0 is the population of pixels outside the influence of the drinking water extraction.

Table 3 shows the averaged NDVI values per month within and outside the drinking water extraction. The hypothesis is that the average NDVI is higher for H0 compared to H1. This is the case for all the months except June 2013. June 2013 was a very dry month (Homan, 2014), which causes the influence of the extraction to be negated.

Table 3. Average NDVI within (H1) and outside (H0) the influence of the drinking water extraction and the difference between H0 and H1 per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Averages	March	April	May	June	July	Aug	Sept	MAX
H1	0.572	0.697	0.725	0.675	0.776	0.725	0.755	0.799
H0	0.589	0.718	0.739	0.618	0.790	0.742	0.756	0.803
Difference	0.017	0.021	0.014	-0.058	0.015	0.017	0.001	0.005

The quantile regression expects a positive trend between the NDVI and the distance to the extraction for the H1 population and (ideally) no trend for the H0 population. March, April, May, June, September and the maximum NDVI confirm this for H1 (Table 4). For July and August the errors are bigger than the slope, rendering the trend non-existent. It can be concluded that for those months there is no relationship between the NDVI and the distance to the extraction.

April and May show a slope of 0.008 for H1: with every kilometre distance increase the NDVI increases with 0.008. With an area of influence of approximately 1.5 km, the NDVI can differ with 0.012 over this distance. An average NDVI in those months around 0.720 and NDVI of 0.708 is a significant difference (Figure 15, Table 4).

June on the other hand can have a difference in NDVI of 0.0435 over 1.5 kilometre (Figure 16**Error! Reference source not found.**).

Outside of the influence of the extraction only small relations were found most of which were significant (Table 4, H0). They are more significant than the relations found in H1 (the errors for the H0 are smaller than the errors found with H1) because there are more observations (pixels) in the H0 population (Appendix 7.5). In the ideal situation the slopes should be zero. Nevertheless, the found relations in H0 could be noise and they are more than three times smaller than the relation found in H1. Therefore, the hypothesis is confirmed; the relation found within the influence of the drinking water extraction is more than three times larger than the relation found outside the influence of the drinking water extraction.

Table 4. Slope and Error of the 0.9 quantile regression of NDVI against the distance to the extraction for the H1 and H0 population of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

NDVI, Distance									
	Month	March	April	May	June	July	Aug	Sept	MAX
H1	Slope	0.018	0.008	0.008	0.029	0.000	0.001	0.016	0.005
	Error	0.003	0.002	0.001	0.004	0.002	0.002	0.002	0.001
H0	Slope	-0.001	0.002	0.001	-0.003	0.001	-0.002	0.001	0.001
	Error	-0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000

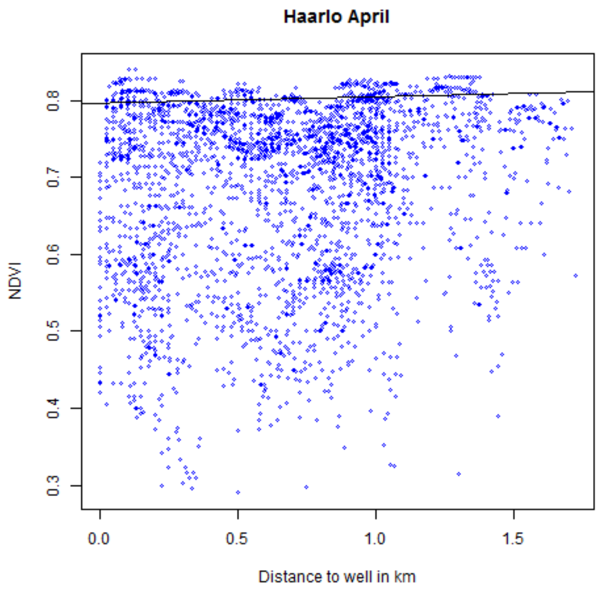

Figure 15. NDVI against Distance to extraction [km] for the H1 population of Haarlo in April with the 0.9 quantile regression trend line.

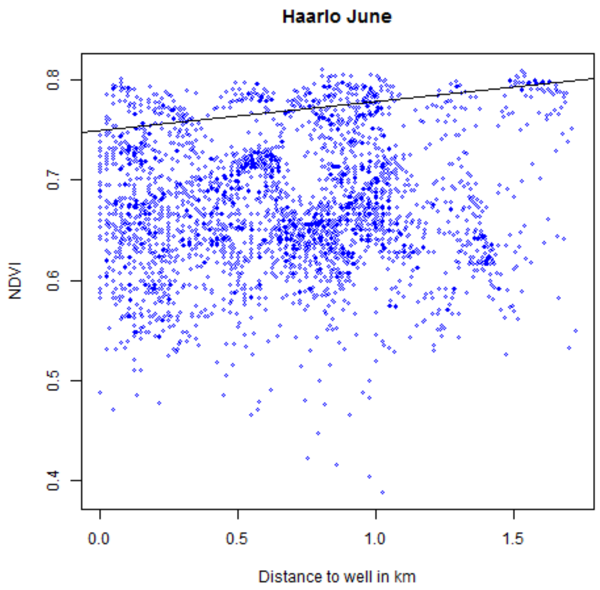

Figure 16. NDVI against Distance to extraction [km] for the H1 population of Haarlo in June with the 0.9 quantile regression trend line.

3.1.2 Drawdown

The more drawdown the more stress and therefore a lower NDVI value is expected. This shows as negative slopes from the quantile regression. This is the case for March, May, July, August, September and the maximum NDVI (Table 5). The errors are smaller than the slopes. April and June show a positive slope, but the errors are also bigger than the slope rendering the trend non-existent in those months. In July the NDVI decreased with 0.012 with every meter of drawdown (Figure 17). The ground water level can be approximately 1.5 meter lower due to the drawdown resulting in a NDVI 0.018 lower than with no drawdown in July.

Table 5. Slope and Error of the 0.9 quantile regression of NDVI against the drawdown for the H1 population of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

NDVI, Drawdown									
	Months	March	April	May	June	July	Aug	Sept	MAX
H1	Slope	-0.013	0.002	-0.009	0.003	-0.012	-0.006	-0.019	-0.007
	Error	0.002	0.003	0.001	0.003	0.003	0.003	0.002	0.001

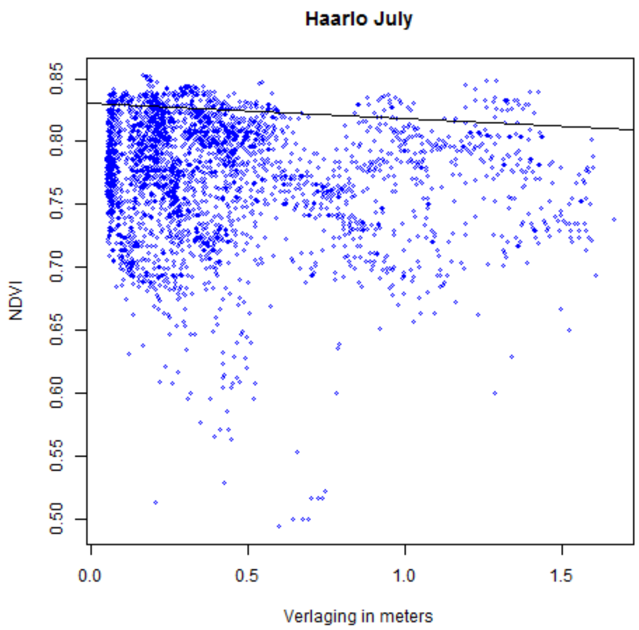

Figure 17. NDVI against Drawdown [m] for the H1 population of Haarlo in June with the 0.9 quantile regression trend line.

3.1.3 Sub-study areas

The North-East sub-study area of Haarlo shows smaller trends in relation with distance to the drinking water extraction than the relations found for H1 in chapter 3.1.1. Nevertheless, the trends are significant. The area covers 8 kilometres instead of 1.5, so a slope of 0.0029 in April can be a difference of NDVI between 0.718 and 0.6948. June is the only month is this sub-study area not following the hypothesis of the NDVI increasing with distance to the drinking water extraction (Figure 18).

Table 6. Slope and Error of the 0.9 quantile regression of NDVI against distance to extraction for the North-East sub-study area of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Distance	March	April	May	June	July	Aug	Sept	MAX
Slope	0.0008	0.0029	0.0014	-0.0110	0.0010	0.0014	0.0014	0.0010
Error	0.0003	0.0003	0.0001	0.0006	0.0002	0.0003	0.0003	0.0001

The NDVI against drawdown for the North-East sub-study area of Haarlo yields for the months April, May (Figure 19), July, August, September and the maximum NDVI expected results. The errors are smaller than the slopes. Only March and June do not follow the expected hypothesis.

Table 7. Slope and Error of the 0.9 quantile regression of NDVI against drawdown for the North-East sub-study area of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Drawdown	March	April	May	June	July	Aug	Sept	MAX
Slope	0.0000	-0.0087	-0.0100	0.0495	-0.0082	-0.0043	-0.0197	-0.0089
Error	0.0018	0.0028	0.0007	0.0017	0.0025	0.0027	0.0015	0.0008

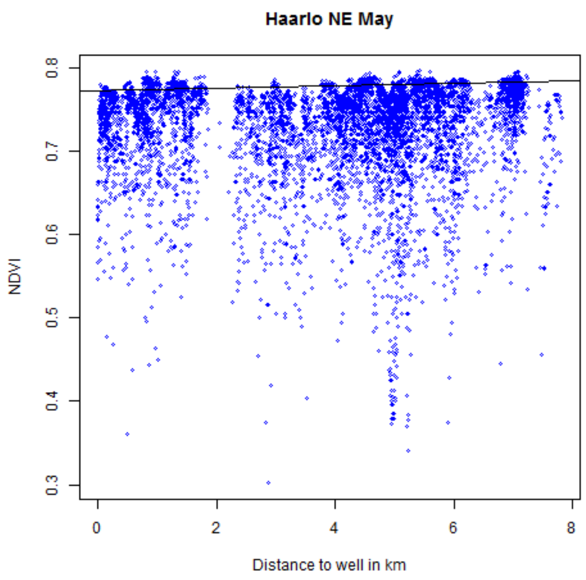

Figure 18. NDVI against Distance to extraction [km] for the North-East sub-study area of Haarlo in May with the 0.9 quantile regression trend line.

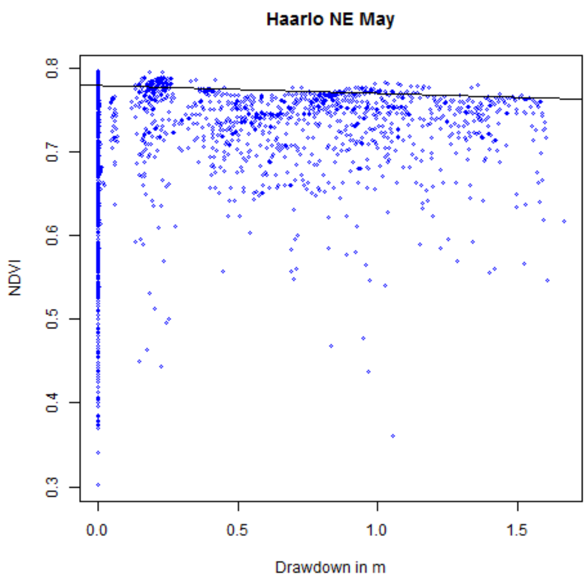

Figure 19. NDVI against Drawdown [m] for the North-East sub-study area of Haarlo in May with the 0.9 quantile regression trend line.

The South-East sub-study area only shows the expected positive relation between NDVI and Distance to extraction in April, July and the maximum NDVI over the growing season (Table 8). The NDVI against drawdown only shows an expected negative relation in June and July and the maximum NDVI during the growing season (Table 9). This sub-study area does not include the drinking water extraction itself and is in-between build-up area which makes the usefulness of analysing this subarea questionable (Appendix 7.7).

Table 8. Slope and Error of the 0.9 quantile regression of NDVI against distance to extraction for the South-East sub-study area of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Distance	March	April	May	June	July	Aug	Sept	MAX
Slope	-0.0055	0.0006	0.0000	-0.0028	0.0033	-0.0030	0.0000	0.0016
Error	0.0004	0.0003	0.0002	0.0015	0.0002	0.0004	0.0003	0.0002

Table 9. Slope and Error of the 0.9 quantile regression of NDVI against drawdown for the South-East sub-study area of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Drawdown	March	April	May	June	July	Aug	Sept	MAX
Slope	0.0229	0.0466	-0.0112	-0.1437	-0.1186	0.0814	0.0147	-0.0007
Error	0.0020	0.0077	0.0128	0.0107	0.0093	0.0047	0.0028	0.0058

The South-West sub-study area shows in May, July, August, September and the maximum NDVI over the growing season the expected positive trend between NDVI and distance to well with an error smaller than the slope (Table 10). The NDVI against drawdown shows an expected negative relation in May, July, August and the maximum NDVI during the growing season

(Table 11). This sub-study area does not include the drinking water extraction itself and is in-between build-up area which makes the usefulness of analysing this subarea questionable (Appendix 7.7).

Table 10. Slope and Error of the 0.9 quantile regression of NDVI against distance to extraction for the South-West sub-study area of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Distance	March	April	May	June	July	Aug	Sept	MAX
Slope	-0.0007	-0.0021	0.0009	-0.0105	0.0037	0.0010	0.0003	0.0026
Error	0.0007	0.0005	0.0005	0.0013	0.0004	0.0006	0.0006	0.0004

Table 11. Slope and Error of the 0.9 quantile regression of NDVI against drawdown for the South-West sub-study area of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Drawdown	March	April	May	June	July	Aug	Sept	MAX
Slope	0.0531	0.0410	-0.0155	0.2847	-0.0583	-0.1182	0.0036	-0.0312
Error	0.0042	0.0035	0.0081	0.0715	0.0060	0.0048	0.0029	0.0029

The North-West sub-study area shows in April, May, August, September and the maximum NDVI over the growing season the expected positive trend between NDVI and distance to well with an error smaller than the slope (Table 12). The NDVI against drawdown shows an expected negative relation in all the months except June (Table 13).

Table 12. Slope and Error of the 0.9 quantile regression of NDVI against distance to extraction for the North-West sub-study area of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Distance	March	April	May	June	July	Aug	Sept	MAX
Slope	-0.0008	0.0008	0.0028	-0.0102	-0.0028	0.0026	0.0011	0.0002
Error	0.0011	0.0009	0.0004	0.0017	0.0006	0.0010	0.0009	0.0005

Table 13. Slope and Error of the 0.9 quantile regression of NDVI against drawdown for the North-West sub-study area of Haarlo per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Drawdown	March	April	May	June	July	Aug	Sept	MAX
Slope	-0.0218	-0.0236	-0.0247	0.0343	-0.0097	-0.0286	-0.0115	-0.0101
Error	0.0077	0.0030	0.0050	0.0069	0.0037	0.0066	0.0057	0.0034

3.1.4 Time series within a field

As described in chapter 2.5.1 the first 4 points (NDVI1-NDVI4) are at the edges of a field (Figure 8). Line NDVI2 in Figure 20 shows a lower NDVI value compared to the others. This is probably due to the fact that a pixel at the edge of a field can be influenced by shadows of nearby trees, roads or water in ditches. Nevertheless, the grass cuts are for all the pixels at the same time and (except for NDVI2) the NDVI values are close to similar, which is expected within the same field.

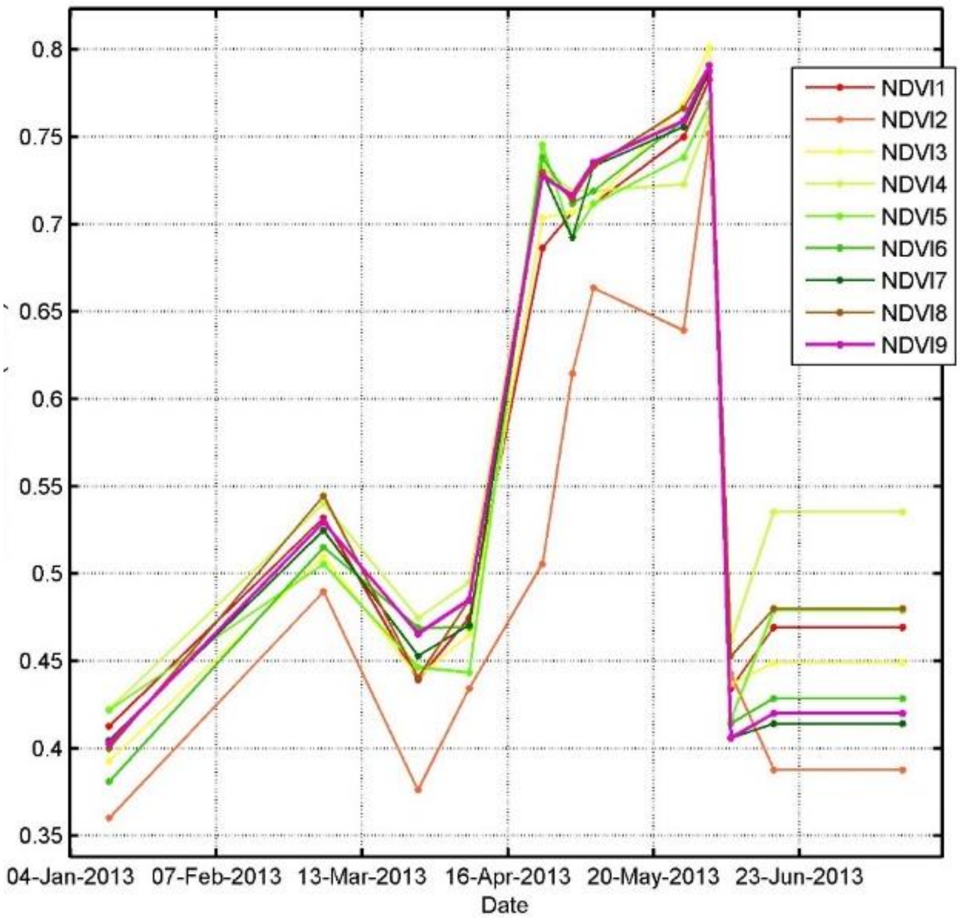

Figure 20. Time series within a permanent grassland on Hn21 in the study area of Haarlo. NDVI1, NDVI2, NDVI3 and NDVI4 are at the edges of a field NDVI5, NDVI6, NDVI7, NDVI8 and NDVI9 are inside the field.

3.1.5 Time series per half kilometre distance

The following section shows the chosen points with the resulting time series of the NDVI values. Haarlo has 3 directions; West, South and East.

The West ray is from the drinking water extraction towards the city of Borculo (Figure 21**Error! Reference source not found.**). The first point is within the drinking water extraction and has very low NDVI values (NDVI0_0, Figure 22) in comparison with the points at 0.5 to 2.5 kilometre distance (NDVI0_5 to NDVI2_5, Figure 22). The last point also has low NDVI values. This field is influenced by a build-up area close by.

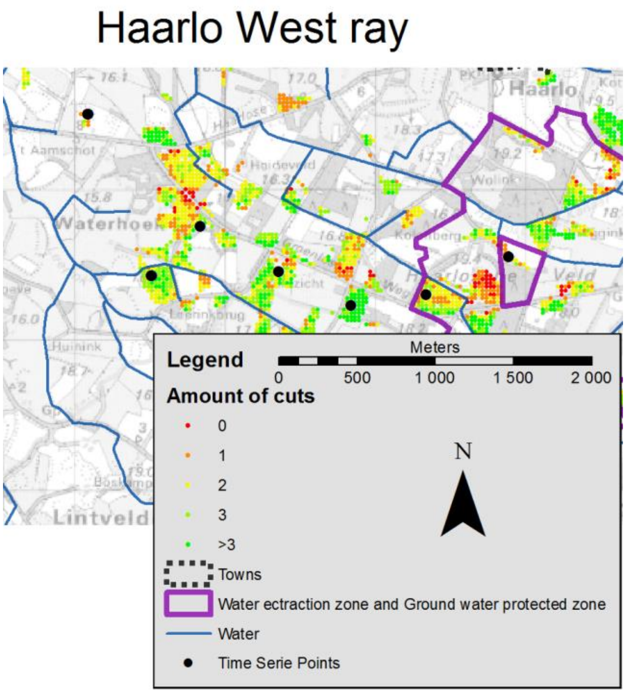

Figure 21. The chosen points of the West ray of Haarlo.

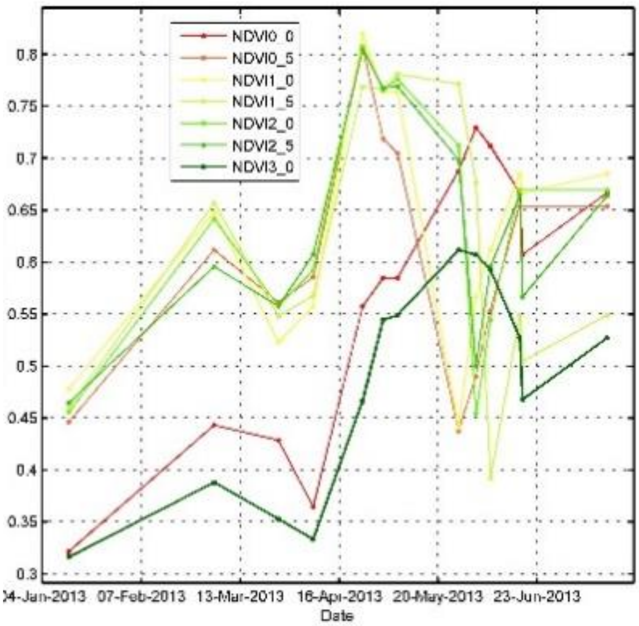

Figure 22. NDVI time series per point of the West ray of Haarlo with NDVI0_0, NDVI0_5, NDVI1_0, NDVI1_5, NDVI2_0, NDVI2_5 and NDVI3_0 at 0, 0.5, 1.0, 1.5, 2.0, 2,5 and 3.0 kilometre distance from the drinking water extraction, respectively.

The South ray (towards Beltrum) shares the same first point as the West ray (Figure 23). This point shows low NDVI values compared to the other points. In Figure 24 it can be observed that the fields at 0.5, 1 and 1.5 kilometre distance are mown later in the season than the fields at 2.0 and 2.5 kilometre distance. It can also been seen that the NDVI at 2.5 kilometre distance decreases drastically from 0.775 to 0.35 and it still manages to recover to a higher NDVI value than the fields at 0.5 and 1 kilometre distance.

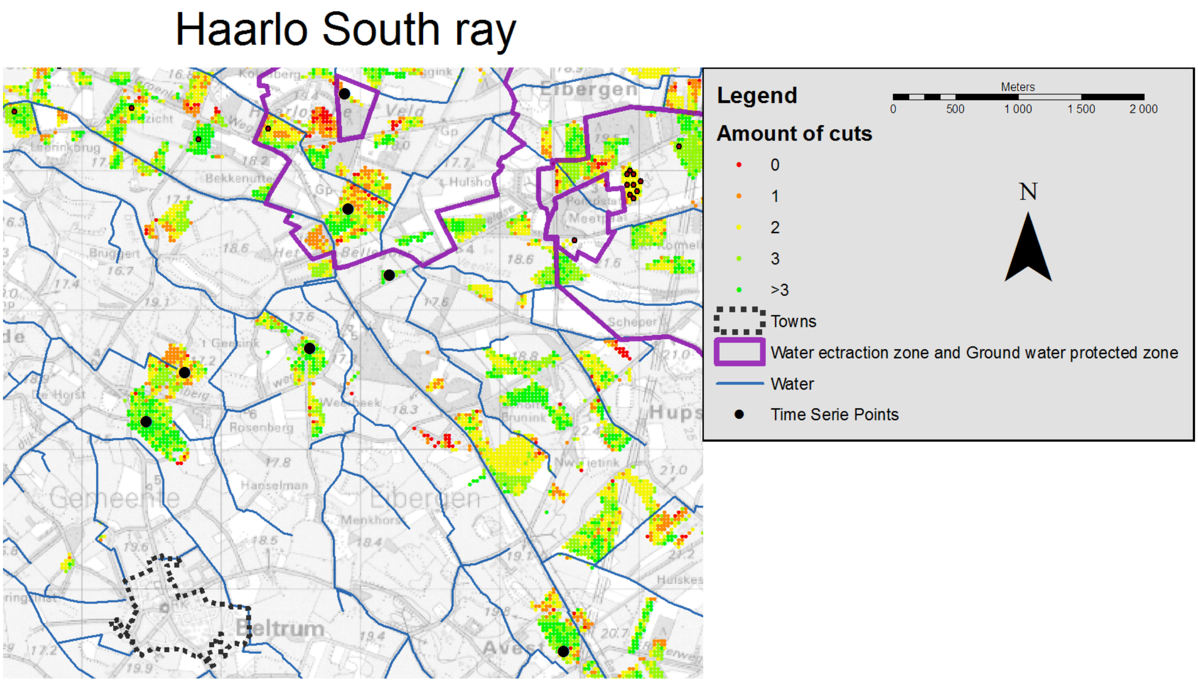

Figure 23. Chosen point of the South ray of Haarlo.

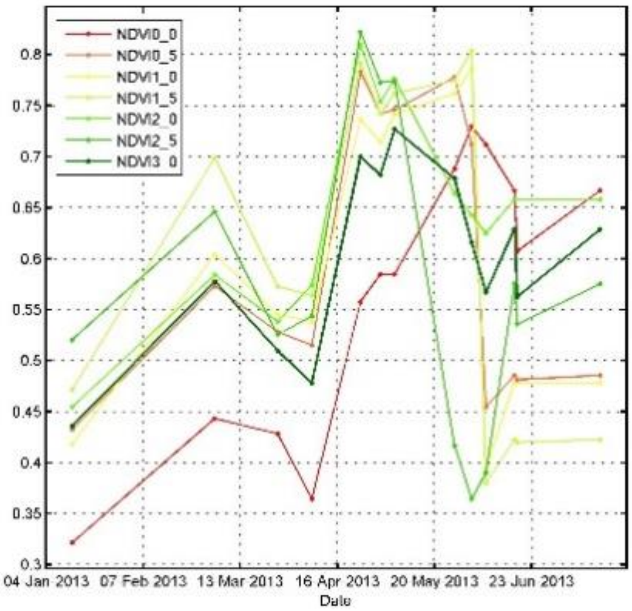

Figure 24. NDVI values through time per point of the South ray of Haarlo with NDVI0_0, NDVI0_5, NDVI1_0, NDVI1_5, NDVI2_0, NDVI2_5 and NDVI3_0 at 0, 0.5, 1.0, 1.5, 2.0, 2,5 and 3.0 kilometre distance from the drinking water extraction, respectively.

The first point of the East ray (towards Groenlo Eibergen, Figure 25) has a lot of trouble to get to the maximum NDVI (NDVI0_0, Figure 26). The field at 0.5 kilometre distance shows a less steep NDVI increase after winter and after the 2nd grass cut compared to the other points. It can also be seen that after the 2nd grass cut the fields at 3.0, 2.5 and 2.0 kilometre distance recover to a higher NDVI value than the fields at 0.0, 0.5, 1 and 1.5 kilometre distance (Figure 26). The field at 1.5 kilometre distance has a slow start but increases rapidly and recovers quickly after the dip in April.

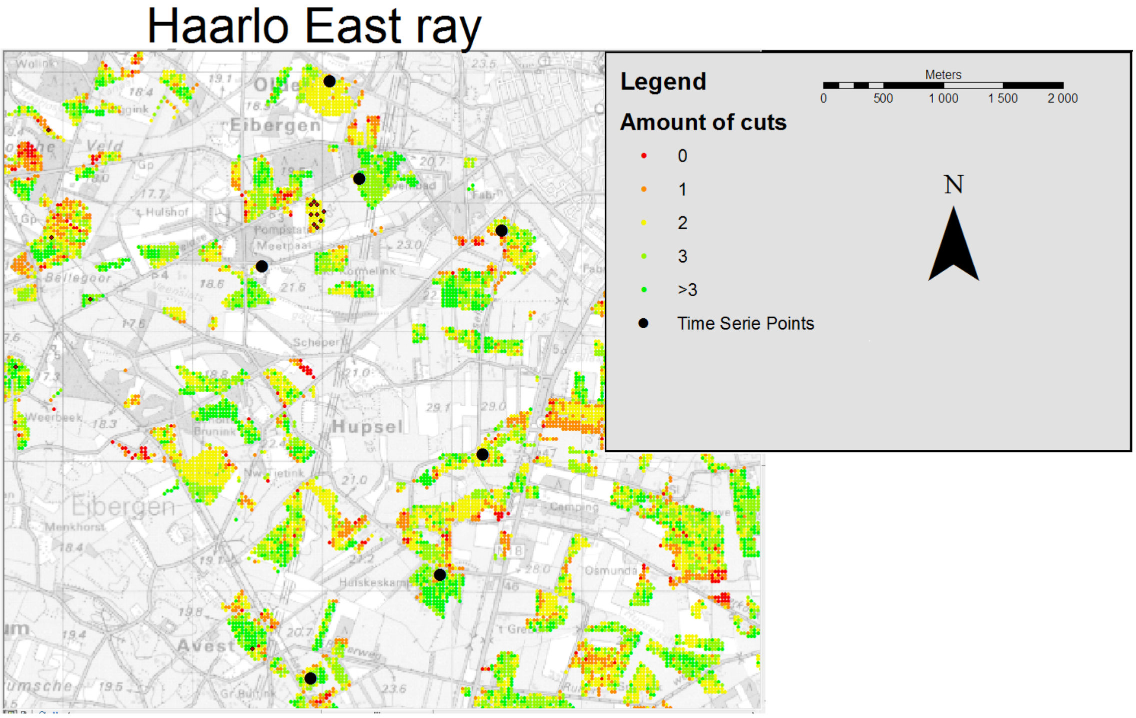

Figure 25. Chosen point of the East ray of Haarlo.

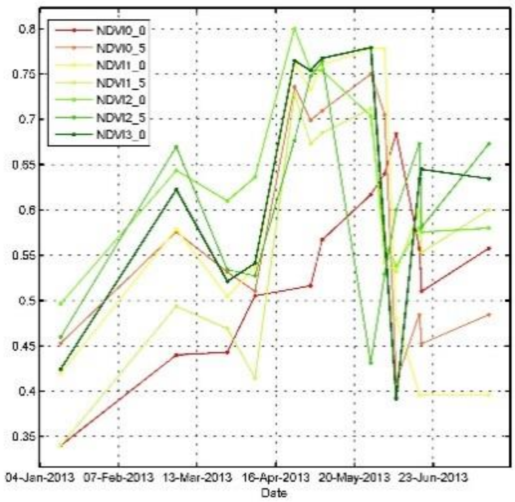

Figure 26. NDVI values through time per point of the East ray of Haarlo with NDVI0_0, NDVI0_5, NDVI1_0, NDVI1_5, NDVI2_0, NDVI2_5 and NDVI3_0 at 0, 0.5, 1.0, 1.5, 2.0, 2.5 and 3.0 kilometre distance from the drinking water extraction, respectively.

3.1.6 Grass cuts

The average number of grass cuts outside the influence of the drinking water extraction is 0.011 higher than the number of grass cuts inside the influence of the drinking water extraction (Table 14). This is a small difference.

Table 14. Average number of grass cuts within (H1) and outside (H0) the influence of the drinking water extraction and the difference between H0 and H1. Green indicated that the hypothesis is met.

	Grass cuts
H1	1.969
H0	1.958
Difference	0.011

Within the influence of the extraction (H1) we see a positive trend between the number of grass cuts and the distance (Table 15, Figure 27). Outside the influence (H0) no relation is expected but a small one is found. The slope of 0.02 is only a fraction from the relation found in the H1 population (0.472). Also the linear regression between the number of grass cuts and drawdown shows the expected trend. The more drawdown the less grass cuts are observed (Figure 28).

Table 15. Slope and Error of the linear relation between the number of grass cuts and the distance to the drinking water extraction for the H1 population, H0 population and drawdown. Green indicated that the hypothesis is met.

Grass cuts	H1	H0	Drawdown
Slope	0.472	0.020	-0.196
Error	0.047	0.005	0.052

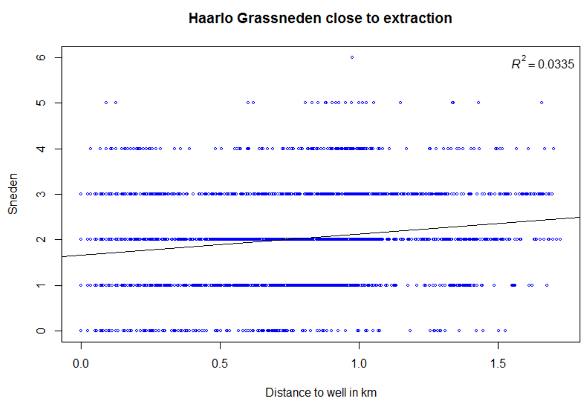

Figure 27. Number of grass cuts against distance to the extraction [km].

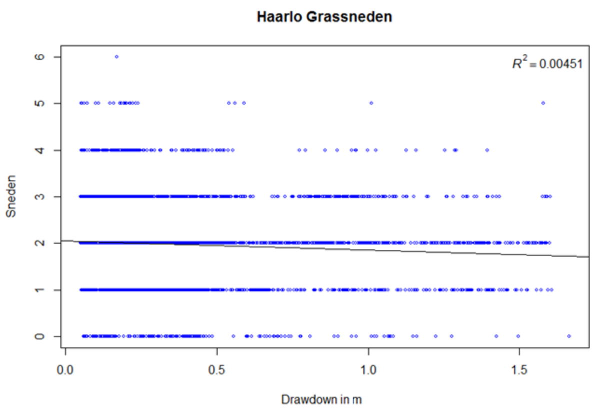

Figure 28. Number of grass cuts against drawdown [m].

3.1.7 Recovery time

The average number of days that the grass needs to recover after the cut between the 23rd of May and the 11th of August is shown in Table 16. Outside the influence of the drinking water extraction the recovery time is 0.469 days shorter than inside the influence of the extraction. This difference is not significant.

Table 16. Average recovery time in days within (H1) and outside (H0) the influence of the drinking water extraction and the difference between them. Green indicates that the hypothesis is met.

	Recovery time
H1	28.902
H0	28.432
Difference	-0.469

The slope of the linear regression between the recovery time and the distance to the extraction within the influence of the extraction shows that with every kilometre further from the extraction the recovery time decreases with 3 days (Table 17, Figure 29). This confirms the expectations. Outside the influence of the extraction (H0) a significantly smaller negative relation is found (-0.086) compared to the relation found in the H1 population (Table 17). The error is almost as big as the slope rendering the relation found in the H1 population nihil. Also the relation between the drawdown and recovery time confirms the hypothesis. With every meter drawdown the recovery time increases with 2.34 days (Table 17, Figure 30).

Table 17. Slope and Error of the linear relation between the recovery time after a grass cut and distance to the drinking water extraction for the H1 population, H0 population and drawdown. Green indicated that the hypothesis is met.

Recovery time	H1	H0	Drawdown
Slope	-3.046	-0.086	2.340
Error	0.771	0.079	0.825

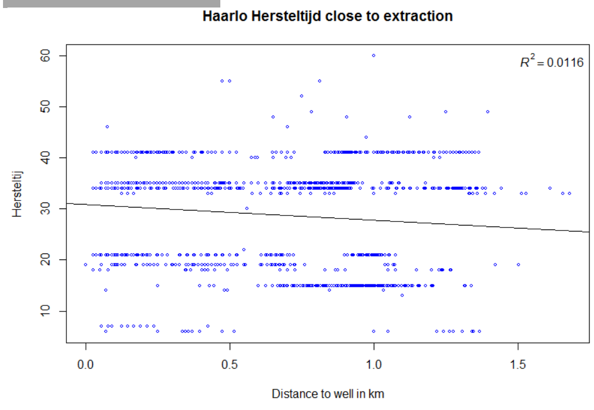

Figure 29. Recovery time [days] against distance to the extraction [km].

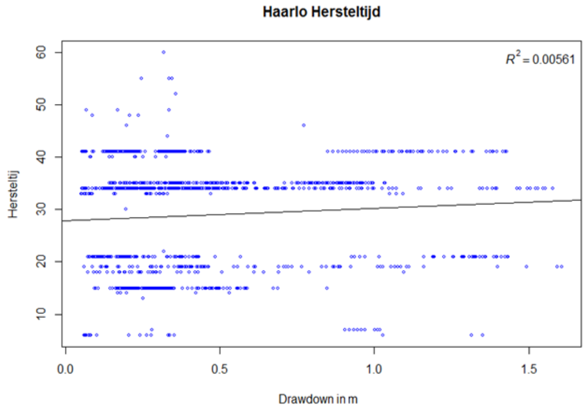

Figure 30. Recovery time [days] against drawdown [m].

3.2 Vessem

3.2.1 Outside and inside of the influence of the drinking water extraction

The results consist of 2 populations; V1 is the population of pixels within the influence of the drinking water extraction area and V0 is the population of pixels outside the influence of the drinking water extraction.

Table 18 shows an overview of the average NDVI values, for every month and the maximum NDVI during the growing season, inside (V1) and outside (V0) of the influence of the drinking water extraction. The hypothesis is that the NDVI values outside the influence of the extraction are higher than the NDVI values inside the influence of the extraction. Only in August this does not seem the case.

Table 18. Average NDVI within (V1) and outside (V0) the influence of the drinking water extraction and the difference between V0 and V1 per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Average	March	April	May	June	July	Aug	Sept	MAX
V1	0.530	0.637	0.695	0.611	0.742	0.731	0.696	0.779
V0	0.546	0.648	0.708	0.634	0.763	0.726	0.734	0.792
Difference	0.017	0.011	0.014	0.023	0.021	-0.005	0.038	0.013

The expected positive trend between NDVI and distance to the drinking water extraction was only found in August, September and the maximum NDVI during the growing season. Unfortunately, the trends found outside the influence of the extraction are comparably strong or stronger (bigger slopes) than the trends found inside the influence of the extractions. Therefore, the trends found in the V1 populations can be noise. So, for Vessem there are no months that show an increase in NDVI with distance inside the influence of the drinking water extraction. Only the maximum NDVI during the growing season shows a significant positive trend with distance to the extractions. This relation is probably pure chance.

Table 19. Slope and Error of the 0.9 quantile regression of NDVI against the distance to the extraction for the V1 and V0 population of Vessem per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

NDVI, Distance									
	Month	March	April	May	June	July	Aug	Sept	MAX
V1	Slope	-0.0069	-0.0021	0.0000	-0.0198	0.0000	0.0077	0.0104	0.0053
	Error	0.0024	0.0015	0.0009	0.0024	0.0011	0.0009	0.0043	0.0012
V0	Slope	-0.0148	0.0149	0.0095	0.0169	0.0094	0.0074	-0.0113	-0.0036
	Error	0.0021	0.0022	0.0013	0.0036	0.0009	0.0023	0.0025	0.0019

3.2.2 Sub-study areas

The North-East sub-study area of Vessem shows for the month March, June, July and August an expected positive trend between the NDVI values and the distance to the drinking water extractions, where the errors do not render the trend non-existent. In July the NDVI increases with 0.008 (Table 20) for every kilometre. Over 5 kilometres (Figure 31) this is the difference between an NDVI of 0.763 (Table 18) and 0.723.

Table 20. Slope and Error of the 0.9 quantile regression of NDVI against distance to extraction for the North-East sub-study area of Vessem per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Distance	March	April	May	June	July	Aug	Sept	MAX
Slope	0.008	0.001	-0.002	0.006	0.008	0.018	-0.006	-0.002
Error	0.002	0.001	0.001	0.004	0.001	0.001	0.001	0.001

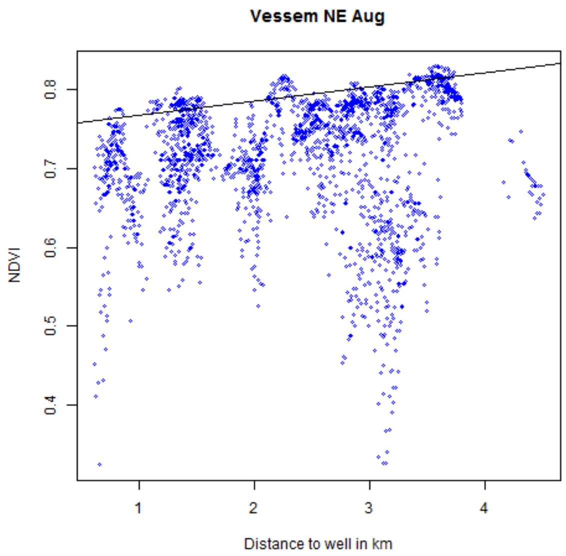

Figure 31. NDVI against Distance to extraction [km] for the North-East sub-study area of Vessem in August with the 0.9 quantile regression trend line.

The North-West sub-study area of Vessem shows for April, May, June, July, September and the maximum NDVI during the growing season a positive trend. Over a distance of 5 kilometre (June, Table 21) this can be the difference in a NDVI of 0.634 (Table 18) and 0.554 (Figure 32). This is considered a big difference.

Table 21. Slope and Error of the 0.9 quantile regression of NDVI against distance to extraction for the North-West sub-study area of Vessem per month. Green indicates that the hypothesis is met, red indicates that the hypothesis is not met.

Distance	March	April	May	June	July	Aug	Sept	MAX
Slope	-0.007	0.005	0.004	0.016	0.002	-0.001	0.023	0.007
Error	0.001	0.001	0.000	0.001	0.000	0.000	0.001	0.000

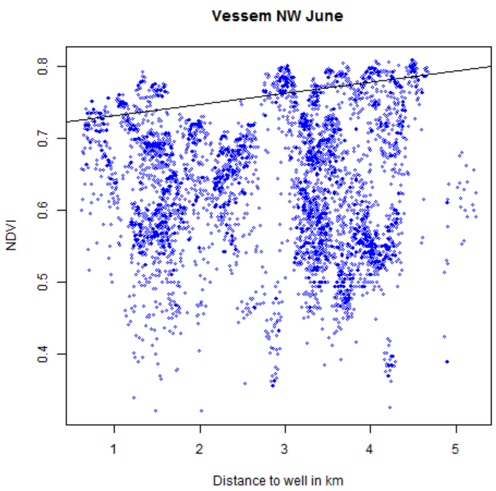

Figure 32. NDVI against Distance to extraction [km] for the North-West sub-study area of Vessem in June with the 0.9 quantile regression trend line.

The use of sub-study areas for Vessem based on the fault lines and soil type yield better results than making a distinction on drawdown.

3.2.3 Time series within a field

As described in chapter 2.5.1 the first 4 points (NDVI1-NDVI4) are at the edges of a field (Figure 8Figure 9). Figure 33 shows the time series with the points. NDVI1 and NDVI4 show a different trend in the beginning of the growing season from the other lines. Nevertheless, the grass cuts are for all the pixels at the same time and the NDVI values are close to similar to each other from May onward. Within a field there is not much variation in NDVI values.

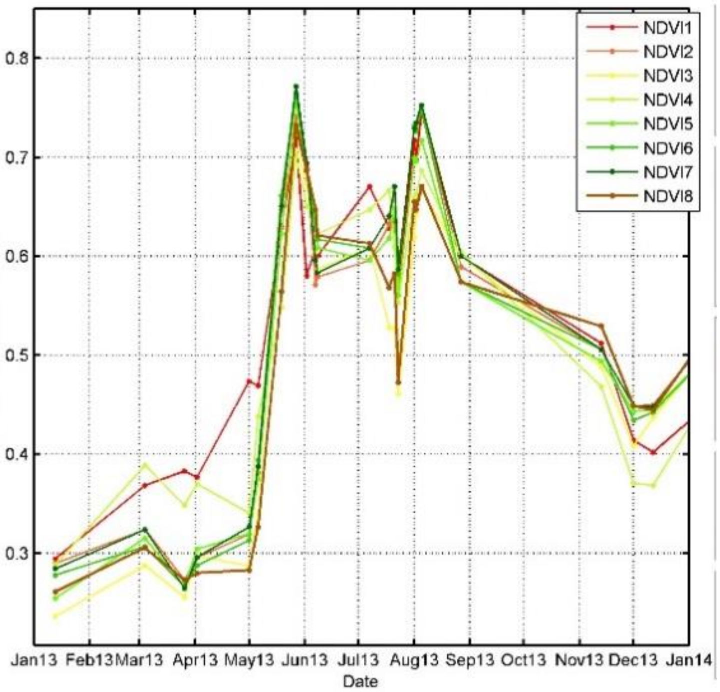

Figure 33. Time series within a grass field on Hn21 in the study area of Vessem. NDVI1, NDVI2, NDVI3 and NDVI4 are at the edges of a field NDVI5, NDVI6, NDVI7, NDVI8 and NDVI9 are inside the field.

3.2.4 Time series per half kilometre distance

This section shows the chosen points with the resulting time series of the NDVI values. Vessem has 3 rays; North-East, North-West and South.

The North-East ray starts at 0.5 kilometre because between 0 and 0.5 there is no grassland on Hn21, but only forest (Figure 34). The first field has a low NDVI throughout the year (Figure 35). The fields at 1.0, 1.5, 2.0 and 3.0 kilometre distance are all doing well. The field at 2.5 km has low NDVI values because it is close to a build-up area (Figure 34).

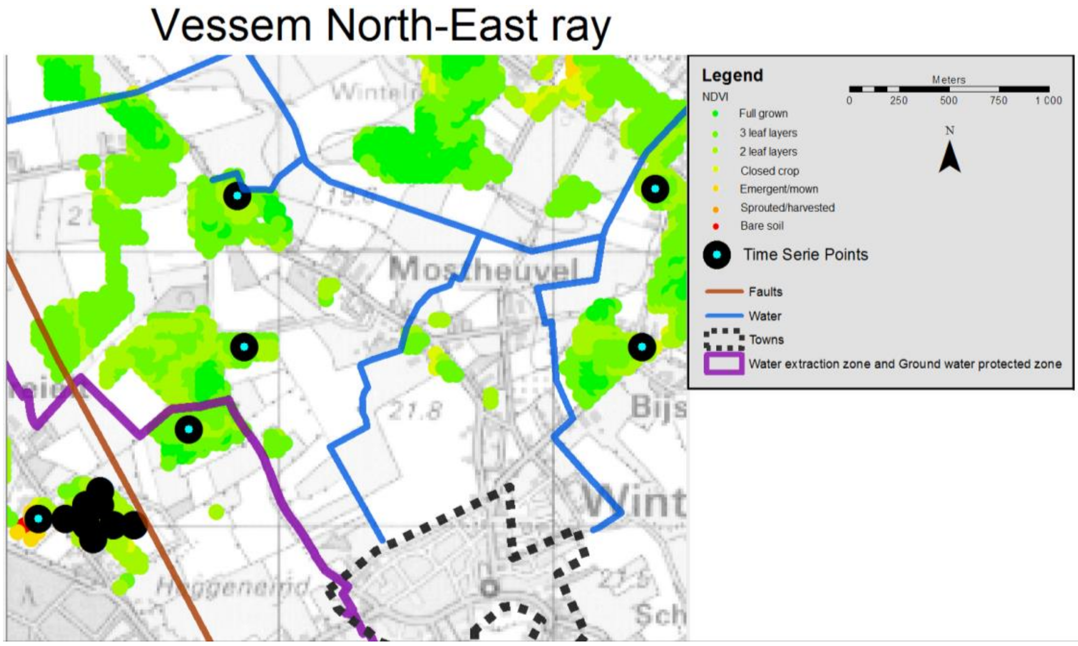

Figure 34. The chosen points of the North-East ray of Vessem.

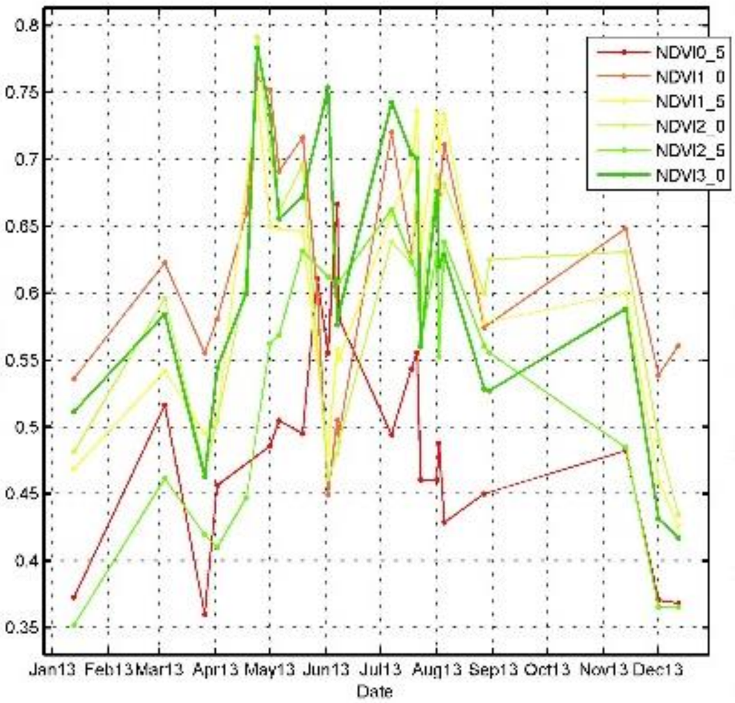

Figure 35. NDVI time series per point of the North-East ray of Vessem with NDVI0_5, NDVI1_0, NDVI1_5, NDVI2_0, NDVI2_5 and NDVI3_0 at 0.5, 1.0, 1.5, 2.0, 2,5 and 3.0 kilometre distance from the drinking water extraction, respectively.

The North-West ray of Vessem starts at 1 kilometre distance, because there is 1 kilometre of forest between the drinking water extraction and the first field in that direction. The NDVI values through time show hardly any deviation (Figure 37). It can be noted that the field at 1.5 kilometre distance has a very low start probably caused by management but this cannot be confirmed.

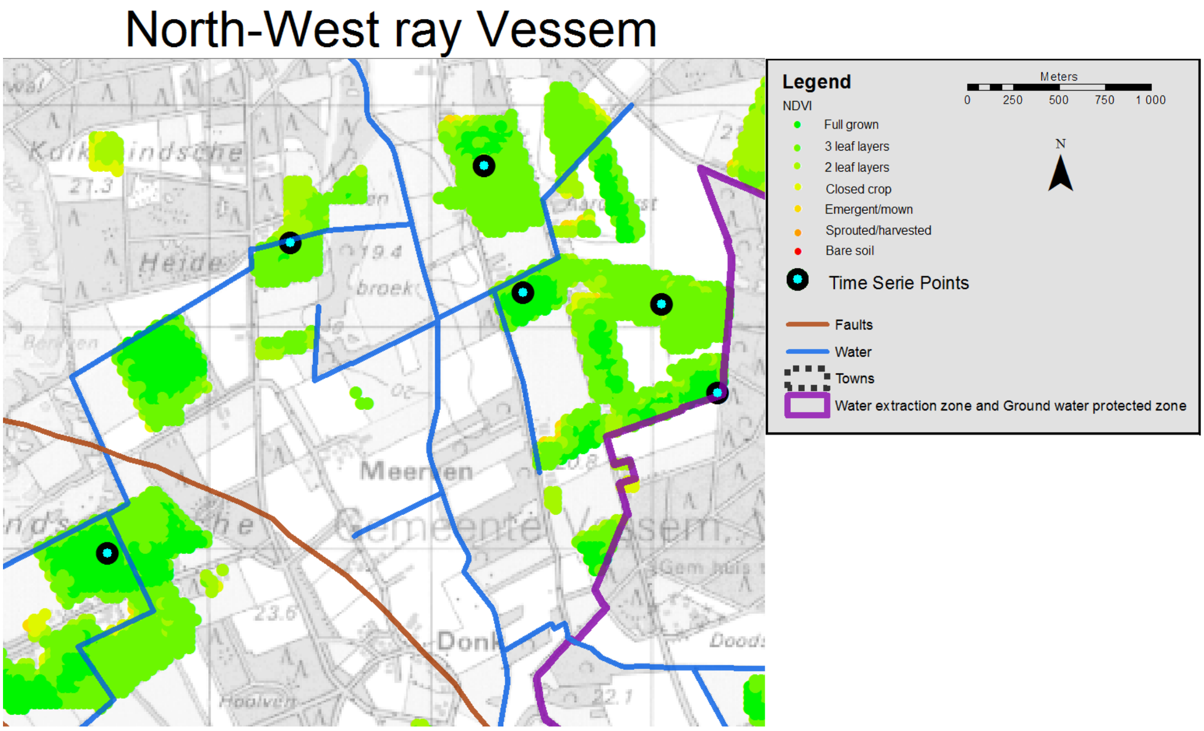

Figure 36. The chosen points of the North-West ray of Vessem.

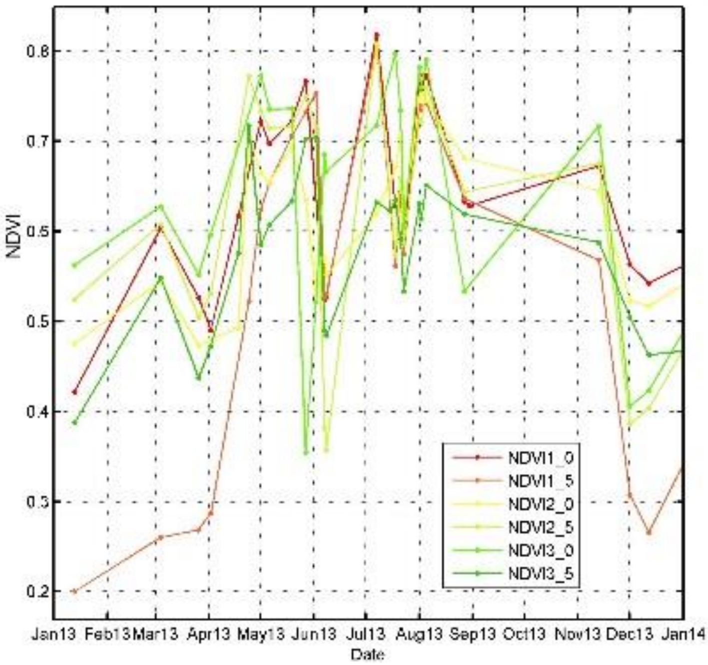

Figure 37. NDVI time series per point of the North-West ray of Vessem with NDVI1_5, NDVI2_0, NDVI2_5 and NDVI3_0 at 1.0, 1.5, 2.0, 2,5 and 3.0 kilometre distance from the drinking water extraction, respectively.

In the South of Vessem there are not many grasslands on Hn21 (Appendix 7.2). Nevertheless, a ray is made with 5 points (Figure 38). Just as with the previous ray there is not much deviation between the time series. The grass cuts are mostly regrown around the same time too. Only the last point NDVI4_0 has overall lower NDVI values (Figure 39).

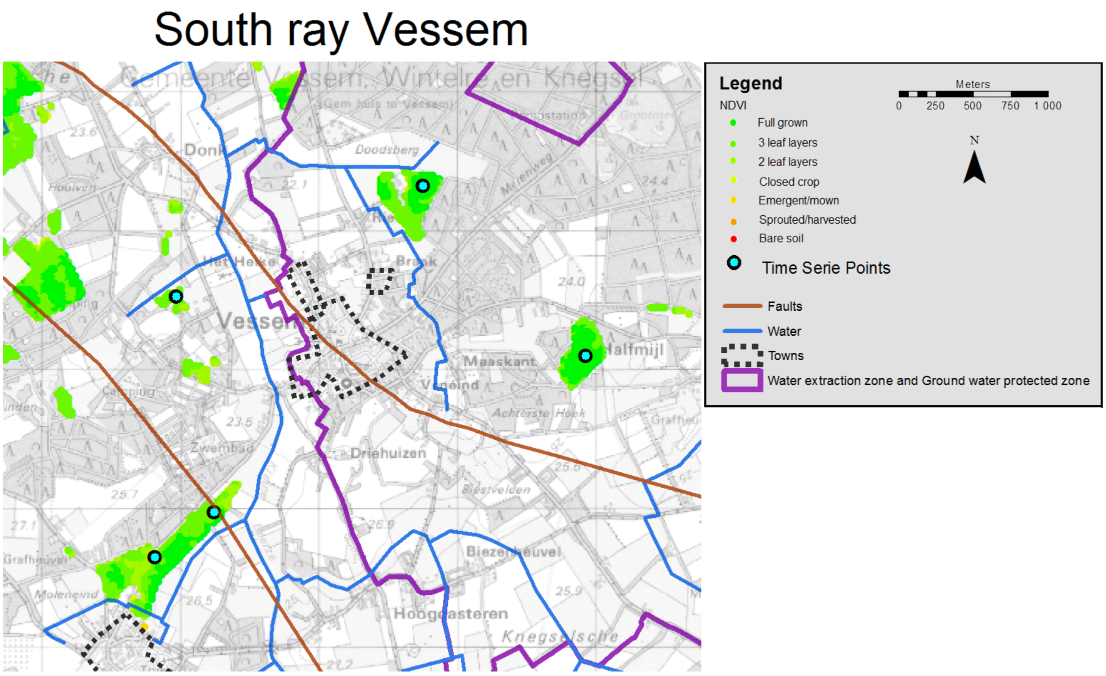

Figure 38. The chosen points of the South ray of Vessem.

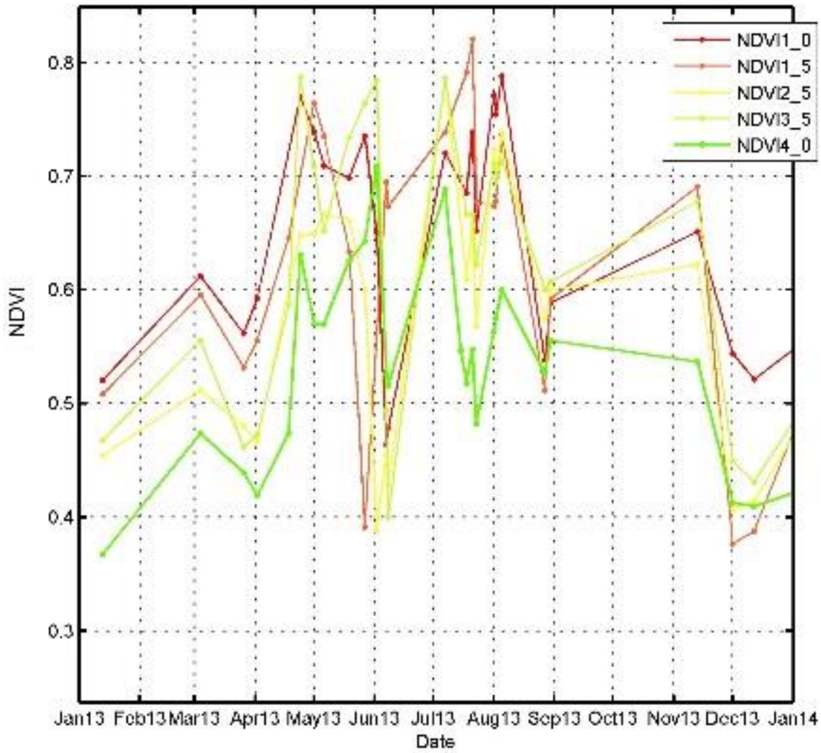

Figure 39. NDVI time series per point of the North-West ray of Vessem with NDVI1_5, NDVI2_0, NDVI2_5 and NDVI3_0 at 1.0, 1.5, 2.0, 2,5 and 3.0 kilometre distance from the drinking water extraction, respectively.

3.2.5 Grass cuts

The average number of grass cuts outside the influence of the drinking water extraction is 0.186 lower than the number of grass cuts inside the influence of the drinking water extraction (Table 22). This difference does not confirm the hypothesis nor is it a significant difference. There is no difference in number of grass cuts inside or outside the influence of the drinking water extraction of Vessem.

Table 22. Average number of grass cuts within (V1) and outside (V0) the influence of the drinking water extraction and the difference between V0 and V1. Green indicated that the hypothesis is met.

	Grass cuts
V1	1.995
V0	1.810
Difference	-0.186

Within the influence of the extraction (V1) we see a positive trend between the number of grass cuts and the distance (Table 23, Figure 40). Outside the influence (V0) no relation is expected, but a positive relation stronger than inside (V1) is found (Table 23, Figure 41). With every kilometre distance to the extraction the number of grass cuts increases with 0.688 (Table 23). There is a significant trend (the error does not make the trend zero), but it cannot be concluded that this trend is due to the drinking water extraction.

Table 23. Slope and Error of the linear relation between the number of grass cuts and V1 population, V0 population and drawdown. Red indicated that the hypothesis is not met.

Grass cuts	V1	V0
Slope	0.688	0.690
Error	0.039	0.040

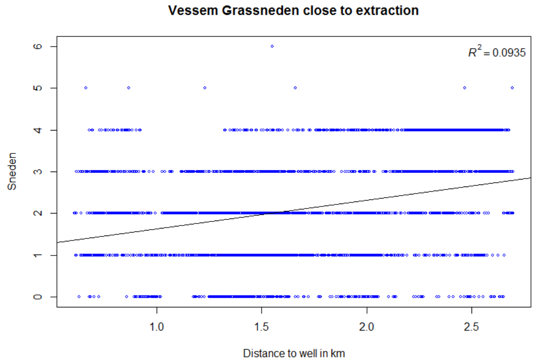

Figure 40. Number of grass cuts against distance to the extraction [km].

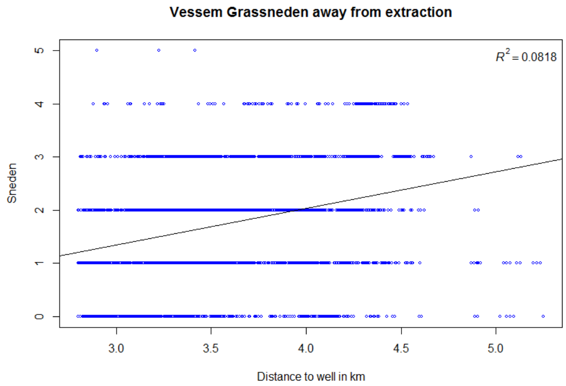

Figure 41. Number of grass cuts against drawdown [m].

3.2.6 Recovery time

The average number of days that the grass needs to recover after the cut between the 23rd of May and the 11th of August is shown in Table 24. Outside the influence of the drinking water extraction the recovery time is 0.79 days longer than inside the influence of the extraction. This is a too small difference which can be caused by chance.

Table 24. Average recovery time in days within (V1) and outside (V0) the influence of the drinking water extraction and the difference between them. Red indicates that the hypothesis is not met.

	Recovery time
V1	45.649
V0	44.859
Difference	-0.790

The slope of the linear regression between the recovery time and the distance to the extraction within the influence of the extraction shows that with every kilometre further from the extraction the recovery time decreases with 3 days (Table 25, Figure 42). Unfortunately the error renders the trend inside the influence of the drinking water extraction insignificant. Outside the influence of the extraction a *stronger* negative relation is found (Figure 43) compared to inside the influence of the drinking water extraction. There is a negative relation between the recovery time and the NDVI, but it cannot be concluded that the drinking water extraction is the main cause.

Table 25. Slope and Error of the linear relation between the recovery time after a grass cut and V1 population, V0 population and drawdown. Red indicated that the hypothesis is not met.

Recovery time	V1	V0
Slope	-3.098	-15.966
Error	3.104	8.029

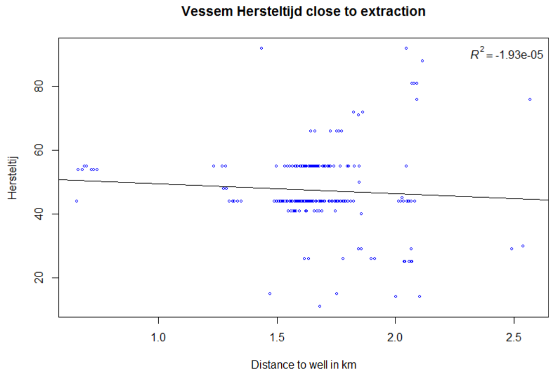

Figure 42. Recovery time [days] against distance to the extraction [km] within the influence of the extraction (V1).

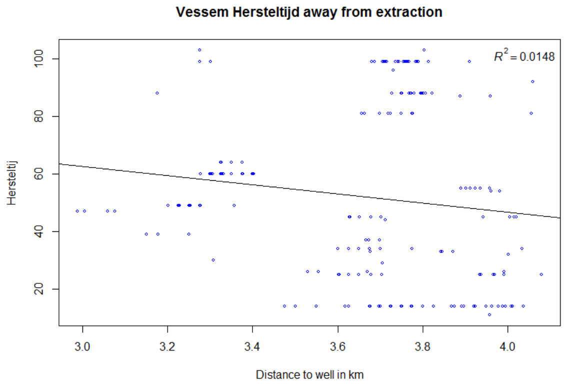

Figure 43. Recovery time [days] against distance to the extraction [km] outside the influence of the extraction (V0).

4. Discussion and Conclusion

The main objective of this research was to determine if the NDVI data can be used as a tool to observe drought damage on vegetation as a result of groundwater extraction for drinking water. Various methods have been used to test this.

This chapter will answer and discuss the sub questions in section 4.1 to 4.5 and section 4.6 will give the final conclusion.

4.1 Sub Question 1

Does the NDVI show a relationship with distance to the drinking water extraction?

Within the study area of Haarlo 5 out of 7 months and the maximum NDVI during the growing season show an increase in NDVI values with the distance to the drinking water extraction. The same goes for the North-West sub-study area of Vessem. The study area of Vessem differs from Haarlo in that Vessem has more variety in soil types and has fault lines running through the study area (appendix 7.1 and appendix 7.2). The hydrogeological properties of the fault lines have a significant impact on the groundwater flow in the study area of Vessem as described in section 2.1.2 (Bense & Van Balen, 2003). This explains why looking at a certain sub-study area of Vessem based on soil type and the fault lines yields better results than using the same methods for the more homogeneous study area Haarlo.

4.2 Sub Question 2

Does the NDVI show correlation with the lowering of the water table?

Within the study area of Haarlo 5 out of 7 months, as well as the maximum NDVI during the growing season, show a decrease in NDVI values with increasing drawdown. However, the months showing the expected relationship differ from the months in section 4.1. The relations between NDVI and drawdown are weaker than the relationships between NDVI and distance to the extraction (Table 4 and Table 5).

Drawdown of Vessem was not known. Therefore, the Depuit-Forchheimer approximation (equation (2) section 2.4.1) (Fraanje, 1974) was used to determine the area where the drinking water extraction was assumed to influence the water table. This is an assumption that was not validated. Especially the variety of soil types in this study area and the fault lines make the estimation questionable (Bense & Van Balen, 2003). The Depuit-Forchheimer approximation neglects vertical ground water flows (Anderson, 2005; Dam et al., 2010; Knight, 2005), and therefore underestimates the groundwater flow (Gallop, 2001; Grismer & Rashmawi, 1993) or, with the formula used in this study, underestimates the distance that the drinking water extraction has an influence. If the area influenced by the drinking water extraction in reality would be bigger, this would explain the ongoing trend in the area outside the influence of the extraction. This entails that the study area chosen might have been too small. Nevertheless, using sub-study areas based upon soil properties and the fault lines did show the expected trends. This shows that extended knowledge of the study area is needed in order to use the correct method to determine the relationship between NDVI and the distance to the drinking water extraction or drawdown.

4.3 Sub Question 3

Do the NDVI time series differ with distance to the drinking water extraction?

The Haarlo study area shows explainable NDVI differences through time with distance to the drinking water extraction. Within the time series of the Vessem rays, those differences are not apparent. Vessem does show a positive relation between distance and NDVI for most of the months in the North-West (Figure 32, Chapter 3.2.2), but looking at the NDVI though time with increasing distance to the well (Figure 35. NDVI time series per point of the North-East ray of

Vessem with NDVI0_5, NDVI1_0, NDVI1_5, NDVI2_0, NDVI2_5 and NDVI3_0 at 0.5, 1.0, 1.5, 2.0, 2,5 and 3.0 kilometre distance from the drinking water extraction, respectively.Figure 35, Chapter 3.2.4), there is hardly any difference between the time series to confirm the relationships found.

The fact that only a limited number of points are used for the analysis creates a bias. This selection bias is not corrected for and therefore can cause an incorrect representation of the whole population (Heckman, 1979).

Time series analyses were done by visual interpretation and not quantified. A set of t-tests can be used to test if the time series differ significantly from each other (Seize, 1977). Next to drinking water extraction, there are also other parameters influencing the NDVI through time (weather (Shisanya, 2011) and management of the farmer (Vrieling, de Beurs, & Brown, 2011) for example). A multivariate data analysis (e.g. principal component regression, multiple linear regression, partial least square regression) (Clevers et al., 2014) or Breaks For Additive Seasonal and Trend (BFAST) (Verbesselt, Hyndman, Zeileis, & Culvenor, 2010) could have been used to give more information about the influence of multiple parameters or seasonal change on the NDVI.

Another limitation in the research is the limited number of high quality NDVI images. The DCM satellite delivers around four images every week (Roerink and Mucher 2012), but because of atmospheric interferences the number of high quality images is limited (Clevers et al., 2014). In 2016, the Sentinel-2B satellite will be launched to support its twin launched on June 23rd 2015. These satellites are part of the “Copernicus wide-swath high-resolution multi-spectral land imaging mission”, which provides continuity and enhancement of the Landsat and SPOT-type missions (Eurockot, 2014). This will result in more images per week. Moreover, there are multiple techniques to extract only the high quality information, e.g. cloud screening and replacement (Gómez-Chova, Camps-Valls, Calpe-Maravilla, Guanter, & Moreno, 2007), Harmonic Analysis of Numerical Time Series (HANTS) (Roerink, Menenti, and Verhoef 2000) calculating statistical parameters or using the known land cover (Clevers et al., 2014). Data fusion of images with different resolution can also be used to fill gaps (Roy et al., 2008) and enable more high quality images.

4.4 Sub Question 4

Does the number of grass cuts differ with distance to the drinking water extraction?

For Haarlo the difference in number of grass cuts inside and outside of the influence of the drinking water extraction is not big, but the number of grass cuts does increase with distance to the extraction. Vessem does not show a different number of grass cuts inside or outside the influence of the extraction. However, with increasing distance from the extraction, the number of grass cuts increases questioning if the border between inside and outside the influence is estimated correctly or if the trend is due to the drinking water extraction.

The number of grass cuts shows variation within a field. This could be solved by assigning the median of the pixel values within a polygon to the polygons. No validation has been done, which makes it questionable if the method used, to determine the number of grass cuts, is correct. The farmers should be asked if the respective fields were indeed mown the computed number of times. No earlier studies have been found on this subject, only that high resolution NDVI data can aid decision-making of managed grazing systems (Flynn, 2006) and that colour-composites can be used to visualize which fields are mown at which moment (Roerink and Mucher 2012).

Moreover, the number of grass cuts might be the same with distance to the drinking water extraction, but the amount of biomass removed might differ. There might be less yield close to the extraction compared to further away. Unfortunately, this could not be tested within this study because there was no data on biomass available.

4.5 Sub Question 5

Does the recovery time after a grass cut differ with distance to the drinking water extraction?

For Haarlo there is no difference in recovery time after a grass cut inside or outside of the influence of the drinking water extraction. Nevertheless, the recovery time does decrease with distance to the extraction. Vessem does not show a difference in recovery time after a grass cut inside or outside of the influence of the drinking water extraction nor is the relation with distance significant. The determination of the recovery time after a grass cut is limited by the number of images available. When there are no images for 2 months after a cut, the recovery time will be at least 2 months for all the pixels making a severe overestimation. No validation of recovery time has been done making the results questionable. With the launch of the Sentinel-2B more images will be available and the method to determine the recovery time after a grass cut can be improved and validated.

4.6 Final Conclusion

Is drought damage caused by ground water extraction perceptible with the NDVI?

For Haarlo the monthly maximum NDVI shows a relationship with distance to the drinking water extraction and drawdown for five out of seven months. This only goes for Vessem when looking at the North-West sub-study area implying that extensive knowledge of the study area concerning soil types and hydrological properties is needed in order to determine the correct method for each study area to determine if the drinking water extraction influence the nearby fields. In this study using sub-study areas was more suited for Vessem due to the presence of fault lines. For Haarlo the whole area influenced by the drinking water extraction can be used because the soil type distribution is more homogeneous compared to Vessem. The time series analyses were limited by the number of high quality images. Nevertheless, future development will enable the acquisition of a higher number of high quality images, making the method for determining the number of grass cuts and recovery time feasible.

5. Recommendations

This chapter presents multiple recommendations, which should be taken into account in follow-up research.

Extensive knowledge of the study area is needed. Information about land use types, soil types and hydrogeological properties are necessary to determine the correct method that should be applied for the analyses. For a study area with a homogeneous distribution of soil types the whole area influenced by the drinking water can be used to establish relationships between the NDVI and the distance to the drinking water extraction. Whereas, when the study area has fault lines running through it the use of sub-study areas is more suited. In this study the analyses have been done on the most common soil and land use type in the area, but it might also be interesting to see if the hypothesis holds using other soil and land use types. Moreover, when one of the research objectives is to test the drawdown against the NDVI, a validated dataset of the drawdown is necessary.

There are multiple farmers within the study areas. There was no information available about how they managed their fields. Different kinds of management can be the main cause for the difference in NDVI. This, however, has not been tested within this study. Other studies (Gizachew & Suryabhagavan, 2014; Rahimzadeh Bajgiran et al., 2009; Shisanya, 2011; Vrieling et al., 2011) show that management has an influence on the NDVI. This should be taken into account in subsequent studies.

The time series analyses can be improved by quantifying if there is a statistical difference between them (by a student's t-test for example). A multivariate analyses is also recommended in order to determine how much certain parameters (like weather) influence the NDVI values and how much the NDVI is actually influenced by the extraction of drinking water.

An important limitation in this research is the number of high quality NDVI images. The launch of new satellites in combination with techniques to extract the high quality information will enable more usable NDVI images in the future.

Another recommendation is based on observations made in chapter 3.1.4 and 3.2.3. These sub-sections show that there is not much difference in NDVI over time within a field, with exception of drops in NDVI values around the edges. This indicates that the number of grass cuts can be visualized as one value for a whole field. Assigning the median of the pixel values to the polygon of the field will give a nice overview and tool in communication with the farmers to validate if the algorithm, that calculates the number of grass cuts, is correct.

For follow-up studies it is also interesting to look at the yield per grass cut. The number of grass cuts might be the same for different fields but a field closer to the drinking water extraction might show lower yields than the field further away. This is exactly the information the drinking water companies are interested in.

Other recommendations regard extending the analyses by also testing the hypothesised average NDVI instead of the maximum NDVI and other regression methods than the quantile regression.

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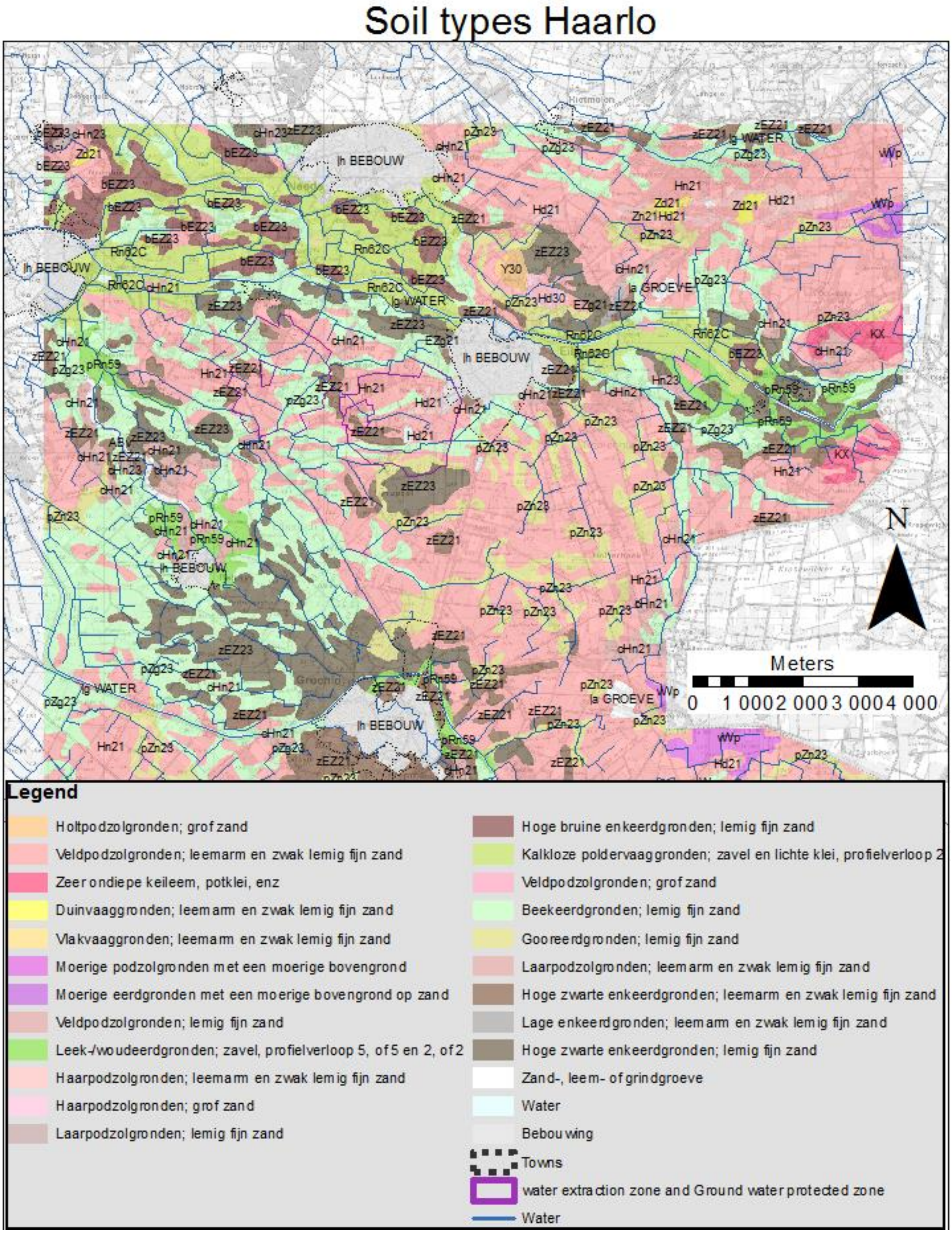
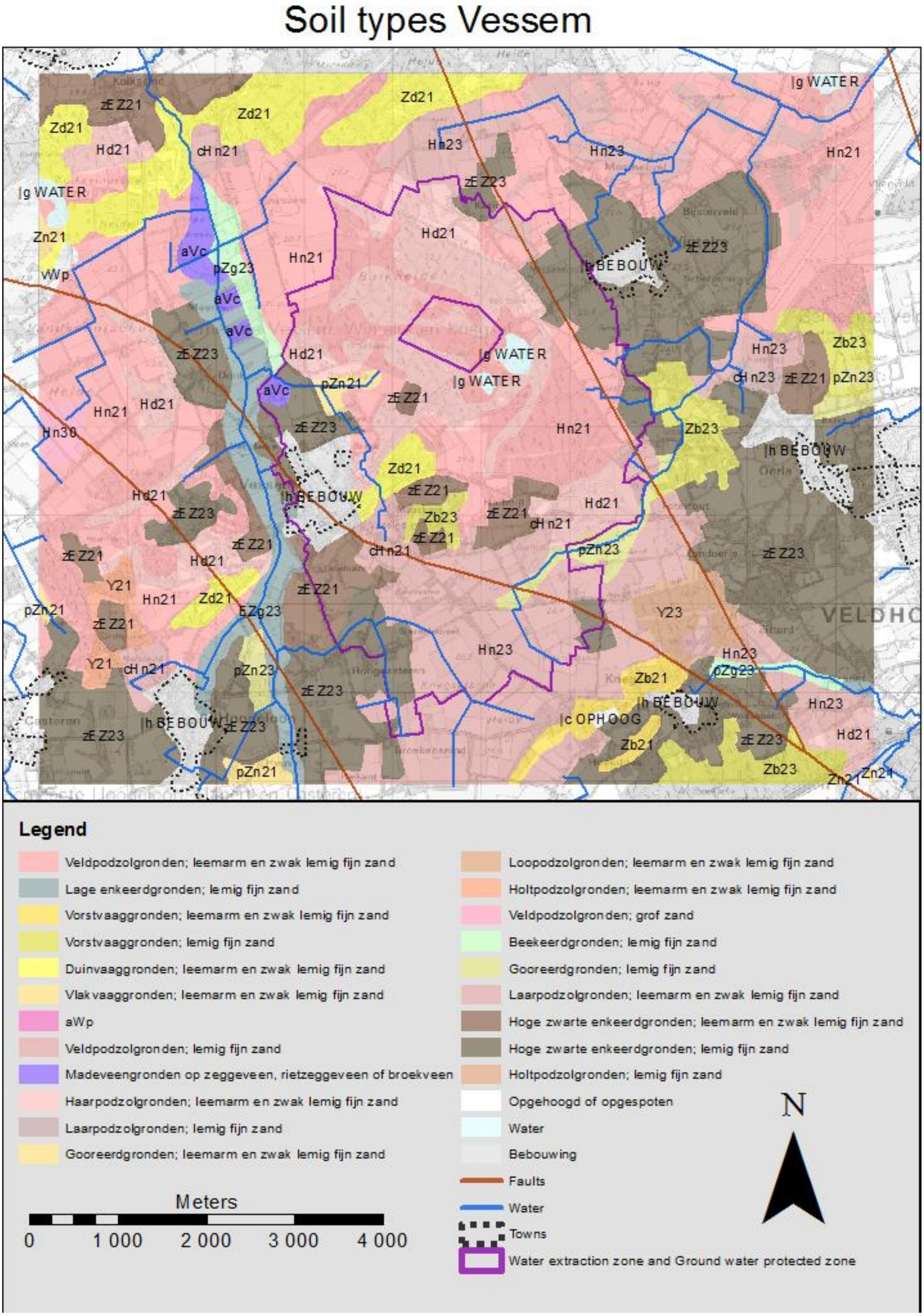
7. Appendices

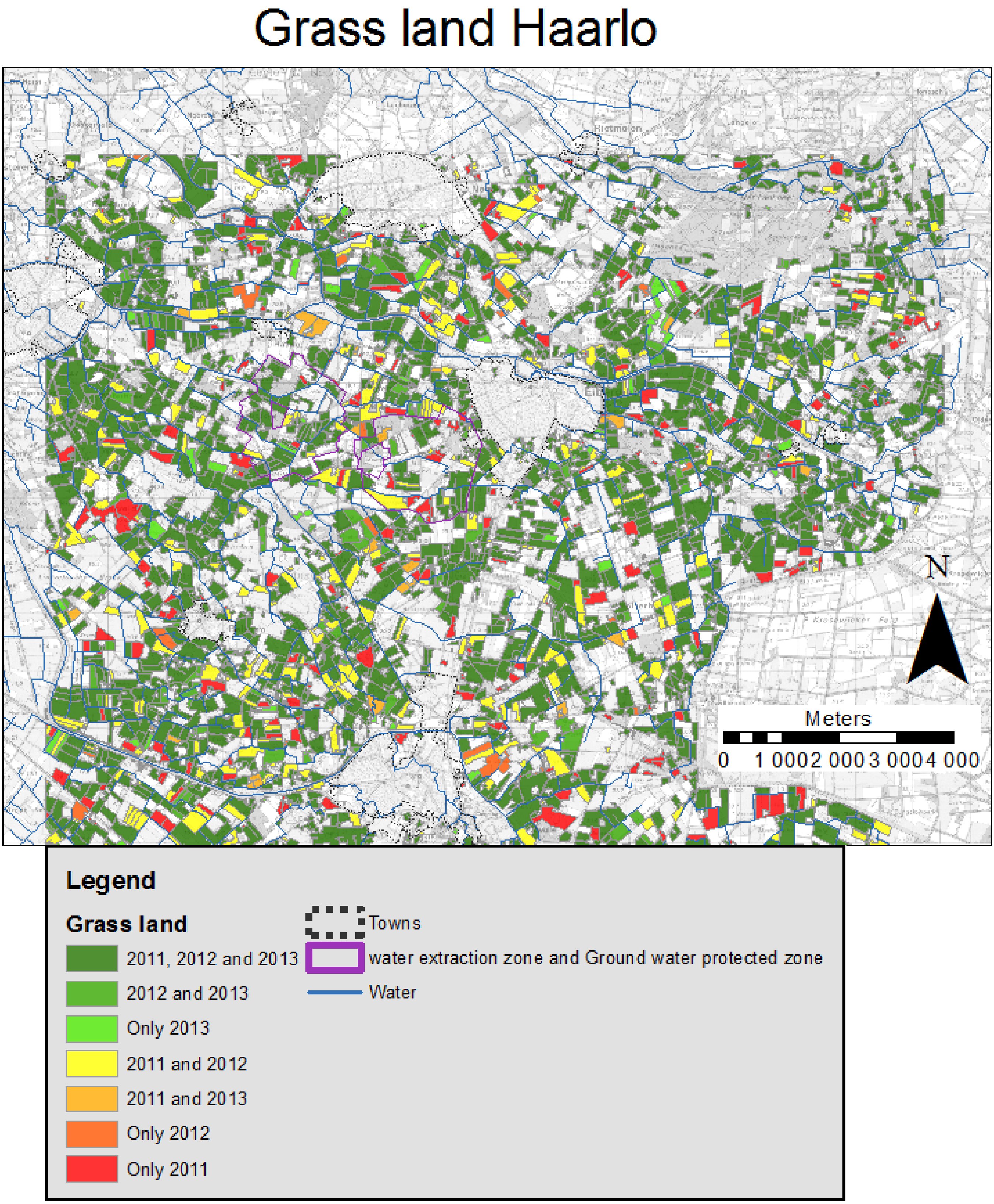
7.1 Soil types Haarlo



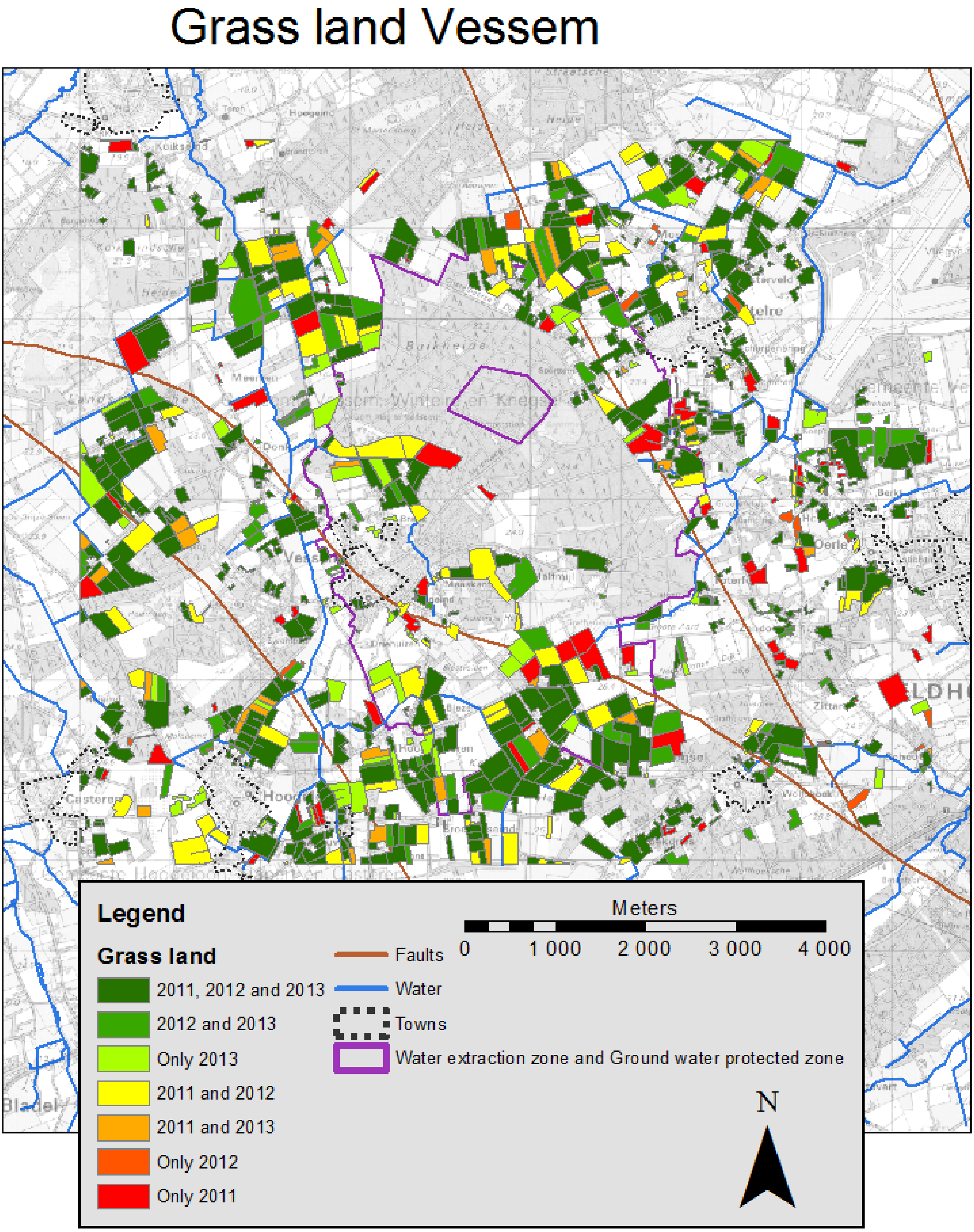
7.2 Soil types Vessem



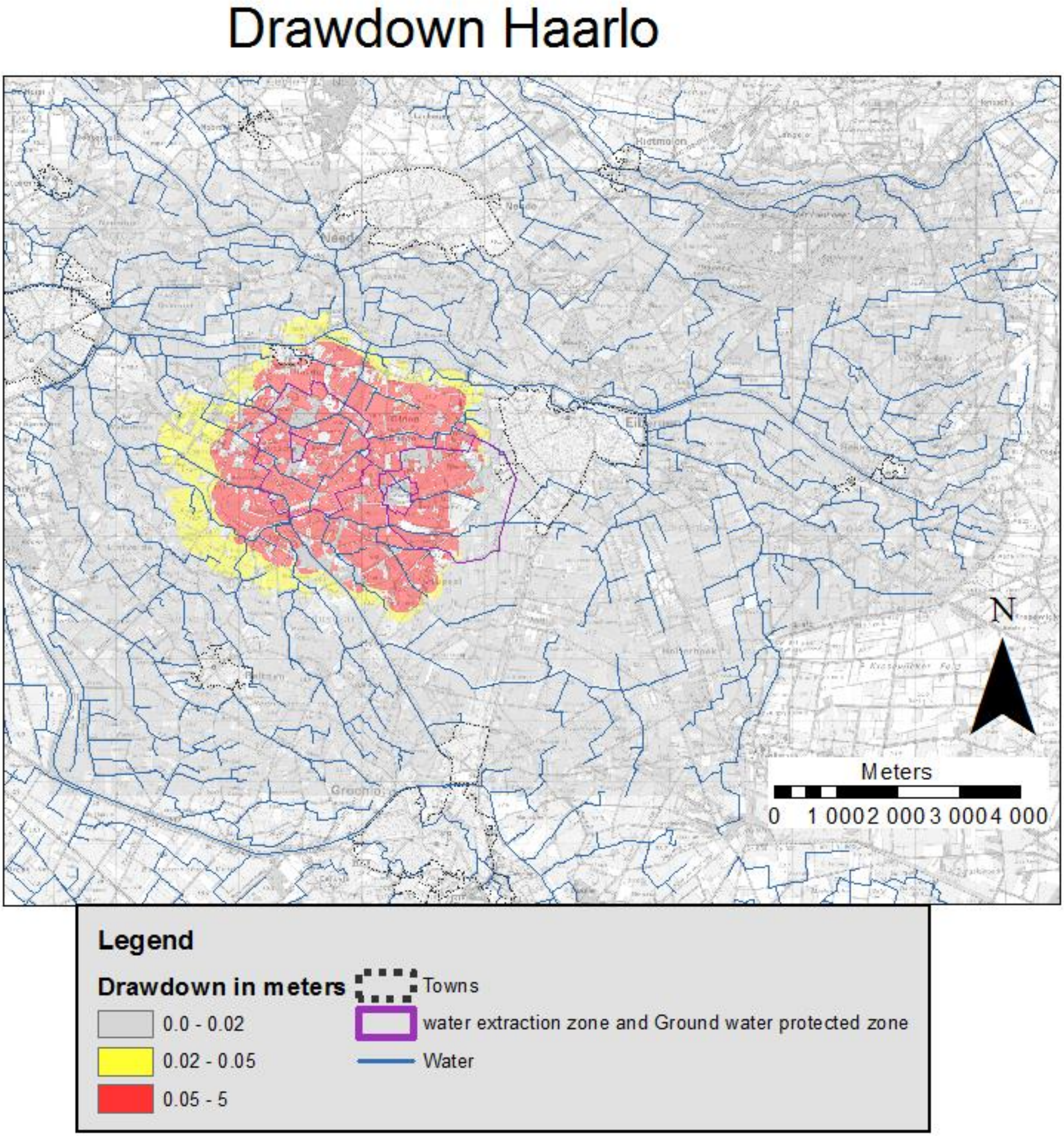
7.3 Grassland Haarlo



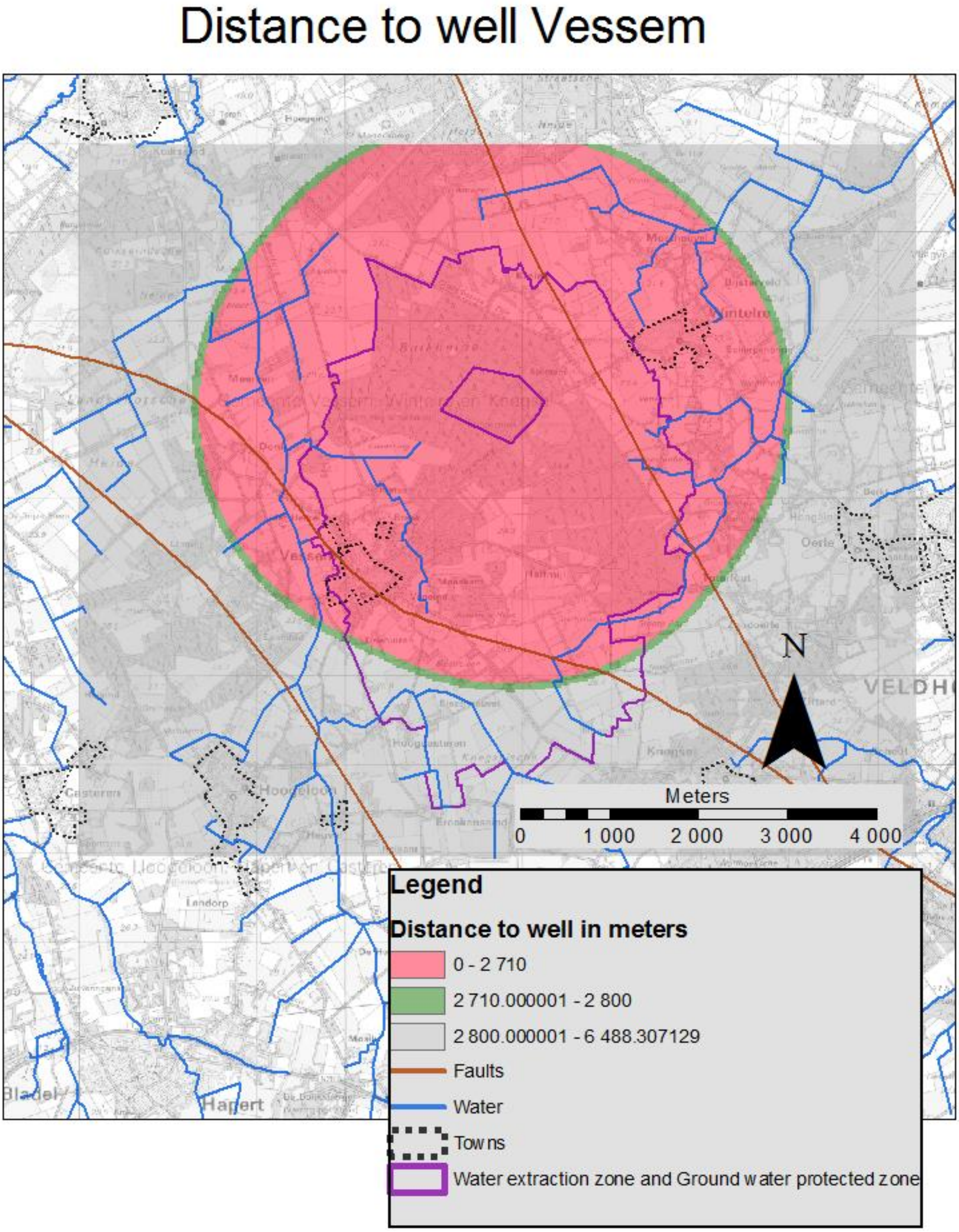
7.4 Grassland Vessem



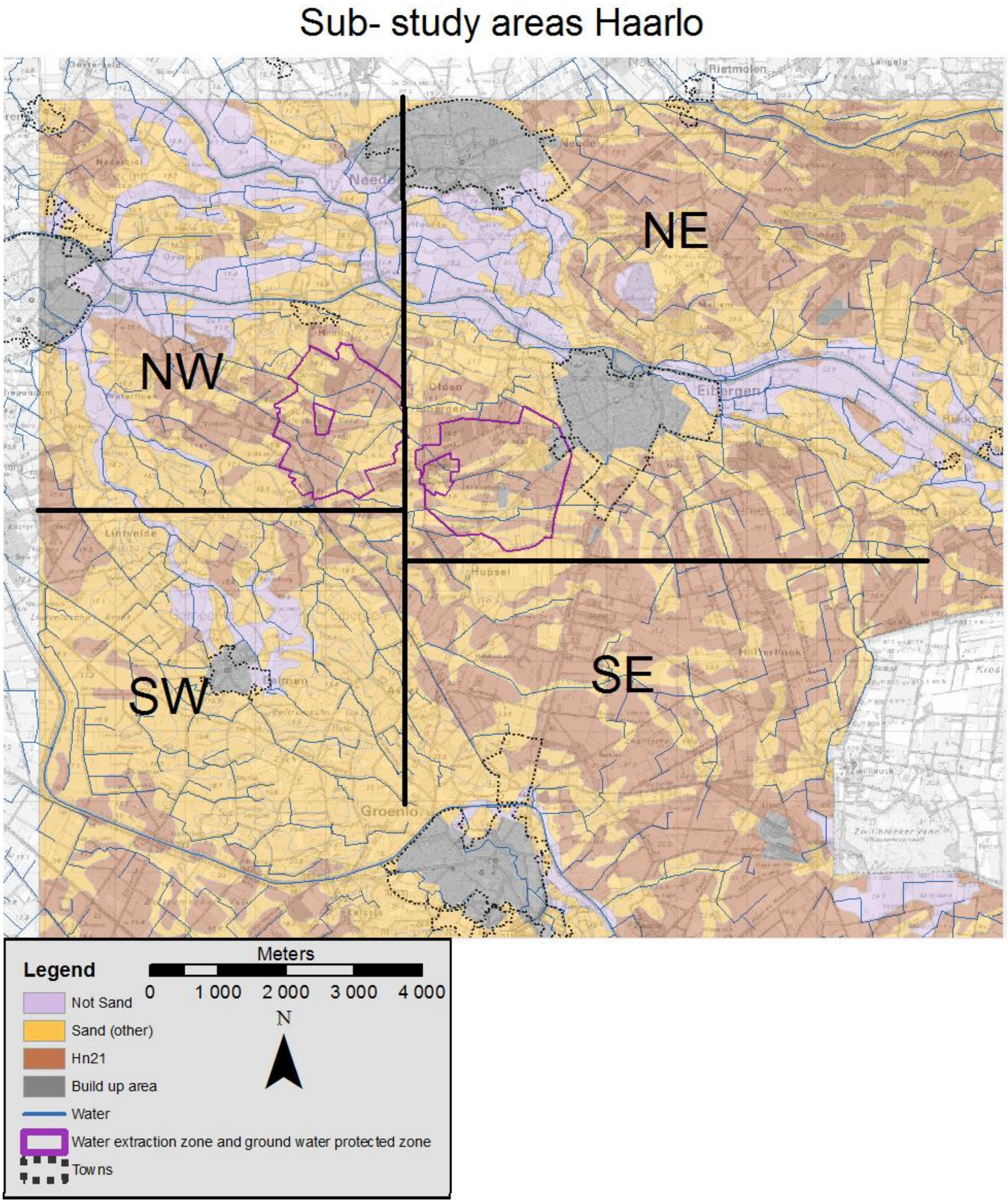
7.5 Drawdown Haarlo



7.6 Distance Vessem



7.7 Sub-study areas Haarlo



7.8 Sub-study areas Vessem