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ADVANCED METHODS FOR ANALYSIS OF MULTI-TEMPORAL SENSOR DATA TO SUPPORT PRECISION AGRICULTURE

Eskender Beza

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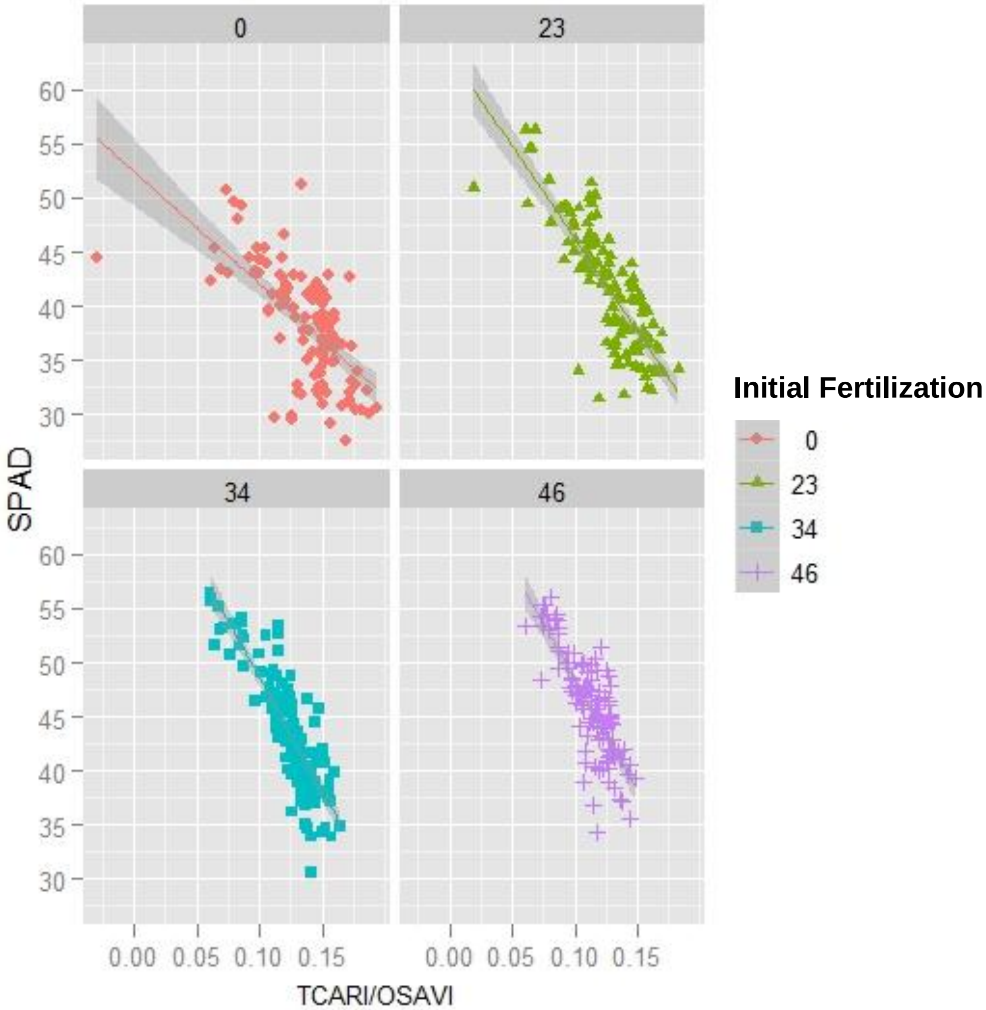

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Advanced methods for analysis of multi-temporal sensor data to support precision agriculture

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Foreword

During this thesis work I have learned a lot. When I started the research I did not have experience of developing a proposal and doing a research independently. At the beginning I really did not know where to start and I had some difficulties to understand the overall objectives of the research. Later by having detail discussions with my supervisors and by reading literatures the overall objectives of the research became clear. To address the overall objectives and specific research questions of the study I have used different methods. In the process, I have studied about the stastical software package R and used it for the analysis of the research work. It gave me a great opportunity to know more about the R stastical package. I also have learned about the different stastical models and time series analysis methods. Overall I have learned a lot from this thesis work and enjoyed working on the research. I am also very happy with the final results of the research.

Acknowledgments

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Lastly, I offer my regards and blessings to all of my MGI friends who supported me in any respect during the completion of the thesis work.

Abstract

As nitrogen is the main nutrient which has a major effect on the plant growth and final yield, it plays a major role in the overall performance of the crop. A mismatch between the requirement of the plant and the supply of nitrogen can potentially influence the growth of the plant and also has a negative effect on the environment. To prevent this, timely assessment of the nitrogen status of the crop is very crucial. The main objectives of this study were (1) to investigate the potential application of time-series analysis methods for the analysis of multi-temporal sensor data of agricultural crops and (2) to assess which vegetation indices are able to estimate the nitrogen status of potato crop. A detailed time-series of sensor data for an experimental potato field in the South of the Netherlands was used. The starting point of the research was the investigation of the relationship between the crop physical and biochemical parameters (e.g. N-SPAD, N-Plant Sap and LAI) which were acquired using ground based close sensing and remote sensing methods. The relationships between well-known vegetation indices (e.g. REP, NDRE, TCARI/OSAVI) with chlorophyll content from SPAD measurements for determining the nitrogen status of a crop were investigated. The results showed that the combined ratio vegetation index TCARI/OSAVI has the strongest relationship with the nitrogen indicator chlorophyll from SPAD with R^2 of 0.61 and RMSE of 3.7. The time series data of the TCARI/OSAVI was later used as an input for time series similarity measures. The most commonly used time series similarity measures which are mainly based on distance measures (Minkowski distance and Root Mean Square Distance) and correlation measures were evaluated. Time series similarity methods which are based on distance measures gave better result compared to the time series similarity methods based on correlation measures. The results showed that time series similarity methods which are based on distance measures are potentially capable of controlling the nitrogen status of a plot based on the nitrogen status of a reference plot which has optimal nitrogen content. Once the similarity based on distance between a specific plot and a reference plot was performed, the concept of Stastical Process Control (SPC) charts was used to determine the threshold values. The output from the SPC charts showed the crop status of a specific plot reference to the plot with optimal nitrogen content. The output can also be used as an operational control list by the modern farmer to check the status of a specific plot immediately after a sensor measurement has been taken.

Keywords: nitrogen, time series similarity measures, remote sensing, close sensing and stastical process control (SPC) charts.

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Abbreviations

CS:	Cropscan
GS:	GreenSeeker
MJ:	Mijnakker
LAI:	Leaf Area Index
NDVI:	Normalized Difference Vegetation Index
WDVI:	Weighted Difference Vegetation Index
REP:	Red-edge position
RVI:	Ration Vegetation Index
NDRE:	Normalized Difference Red Edge Index
TCARI:	Transformed Chlorophyll Absorption in Reflectance Index
OSAVI:	Optimized Soil-Adjusted Vegetation Index
CI:	Chlorophyll Index
SPC:	Stastical process control
RMSD:	Root Mean Square Distance

1. Introduction

1.1 Context and background

The increasing population number and higher consumption of food items has put a high pressure on the production of agricultural products and on ecosystems (Liu, Pattey et al. 2010). Producing enough yields, while at the same time protecting the environment from pollution as a result of excess supply of fertilizers and pesticides is a major challenge for the agricultural sector. These challenges induce the farmers and professionals to think critically and be innovative of new agricultural practices which can help the farmers to produce the required amount of yield while maintaining the safety of the environment. Among the different practices, precision agriculture is one of them and currently it is being implemented in the agricultural sector so that the question of enough productivity while maintaining the safety of the environment is achieved.

Precision agriculture also called precision farming is a management strategy that uses information technologies to derive data from multiple data sources to be used on decisions related to crop production and performance (National Research Council, 1997). The main objective of precision agriculture is to increase the productivity, optimize the profitability, and protect the environment (Haboudane, Miller et al. 2002). It involves doing the right things correctly both spatially and temporally. It helps to optimize fertilizer use to meet crops fertilizer requirement temporally and spatially while protecting the environment and maintaining farm profitability (Chen, Haboudane et al. 2010). The main objective of the farmers is to increase income by maximising the production from the plot of land under cultivation and minimise the associated extra fertilization and pesticide costs during the production. It is also the issue of the society to minimise the excess application of fertilizers and pesticides which have higher contribution to the pollution of the environment. In order to harmonise these requirements of the farmers and the society, precision agriculture plays the major role.

In order to increase the productivity and harvest sufficient yield at the end of the growing season, timely assessment of crop growth conditions and an early follow up on every stage of the crop growth is very crucial (Liu, Pattey et al. 2010). Among the different factors, nitrogen is generally the most important and also the major limiting factor for crop growth and productivity (Haboudane, Miller et al. 2002; Samborski, Tremblay et al. 2009). For this reason, timely assessment of crop nitrogen status is very critical in optimising yield and quality (Wu, Wang et al. 2007). Different methods have been developed and implemented for timely assessment of crop nitrogen status over the growing season (Goffart, Olivier et al. 2008). The most commonly used methods for assessing the crop nitrogen status are: the petiole sap nitrate concentration test (Carlson, Cabrera et al. 1990); leaf chlorophyll concentration measurements using hand-held chlorophyll meter (Gianquinto, Sambo et al. 2003); measurement of crop light reflectance using ground based near-sensing methods (Samborski, Tremblay et al. 2009) and using remote sensing methods (Wu, Wang et al. 2007). Besides measuring the nitrogen status of the crop, both near-sensing and remote sensing data and techniques have already proven to be relevant to many requirements of crop inventory and monitoring (Haboudane, Miller et al. 2002). Different studies and experiments have shown that the use of near and remote sensing data plays a major role in following crop status and monitoring, such as crop status and condition (Clevers, Büker et al. 1994), and crop disease and micronutrient deficiency (Adams, Norvell et al. 2000). Moreover, crop canopy growth-status indicators like green leaf area index (LAI), crop cover fraction, canopy water content, leaf chlorophyll and nitrogen content have been effectively estimated quantitatively using optical remote sensing(Haboudane, Miller et al. 2002; Champagne, Staenz et al. 2003; Haboudane, Miller et al. 2004).

1.2 Problem definition

Remote sensing images are capable of providing spatial information of features and phenomena on earth both at the global and local scale (Bala and Islam 2009). They have the potential of not only to identify the types of crops, but also provide information on the spatial variability of crop performance (Bala and Islam 2009).The various physical and biochemical parameters of crops, e.g., leaf area, ground cover, biomass, leaf chlorophyll content, residue cover can be sensed using near and remote sensing techniques (Hatfield and Prueger 2010). Especially remote sensing techniques have the ability to provide repeated measures from a field without destructive sampling of the crop, which can provide valuable information for precision agriculture (Hatfield and Prueger 2010).The repeated and consistent measurements result in the availability of time series data for a longer period of time. The availability of time series data for longer periods from different sensors helps the modern farmer to get up-to-date data on how a parcel performs over the growing season.

Spectral vegetation indices (VIs) derived from spectral reflectance have been shown to be useful for indirectly obtaining crop information such as photosynthetic efficiency, productivity potential, leaf chlorophyll content and N concentration (Thenkabail, Smith et al. 2000).

Recent studies by Delegido, Alonso et al. (2010) and Chen, Haboudane et al. (2010) have demonstrated the usefulness of optical indices from remote sensing in the assessment of vegetation biophysical and biochemical variables. In order to investigate the physical and biochemical parameters of a crop, a vegetation index which shows the characteristics of each of the parameters need to be derived from the acquired remotely and nearly sensed data. However, the main challenge is to evaluate the seasonal patterns of the VIs and determine which VIs are the most robust for detecting the chlorophyll content and the nitrogen status of the crop within a field over the growing season.

Among the different application areas, of particular significance in precision agriculture is the chlorophyll content of the leaf, which is an indicator of photosynthetic activity, which is related to the nitrogen concentration in green vegetation and serves as a measure of the crop response to nitrogen application (Haboudane, Miller et al. 2002). Chlorophyll gives an indirect estimation of the nutrient status as considerable leaf N is incorporated in chlorophyll (Filella et al., 1995; Moran et al., 2000). Nitrogen being the main nutrient which has a major effect on the plant growth and final yield, it plays the major role in the overall performance of the crop. A mismatch between the requirement of the plant and the supply of nitrogen can potentially influence the growth of the plant and also has a negative effect on the environment (Tremblay, Wang et al. 2009). It also will have larger contribution for the economic loss of the farmer. Excess supply of nitrogen will lead to leaching of the nitrogen into the ground water in the form of NO_3–N (Carpenter et al. 1998). It is therefore advisable to supply the required amount of nitrogen optimally both spatially and temporally.

As a result of the advanced technologies of today, currently it is possible to get information from different sources. For the determination of the optimal amount of the required nitrogen fertilization, information from global navigation satellite systems, remote sensing and near-sensing instruments on tractors and in wireless sensor networks can be used. Although these data sources are rich with up-to-date data, they still have some drawbacks, for example remote sensing data can frequently experience poor signal to noise ratio, late data delivery because of the requirement of additional data processing and depending on the type of the sensor it might have coarse resolutions (Kooistra, Bergsma et al. 2009). On the other hand in-situ sensors have an advantage of providing high spatial and temporal resolution data (Thessler, Kooistra et al. 2011) but lack the synoptic character of remote sensing data sources To overcome the drawbacks of one of the data sources and to use the strength of the other data sources, and to provide timely information, combining the data from the different data sources will have a better advantage than using one of the data sources (Teillet, Chichagov et al. 2007). Although there is sufficient data from the different sensors, still there is a gap and lack of scientific knowledge and models to get the best out of these available data sets and make use by site-specific management activities (Thessler, Kooistra et al. 2011).

Sensors for monitoring crop conditions are becoming more abundant on the farm (Inman, Khosla et al. 2005) and this creates an opportunity for the farmer to monitor essential vegetation parameters over time. Also the availability of several optical space-borne sensors with different temporal and spatial resolutions allows regular monitoring of the different temporal properties of ecosystems dynamic as they provide multi-temporal measurements of the land surface (Lhermitte, Verbesselt et al. 2011). The repetitive measurements from the different sensors results in the availability of time series data. Because of the huge potential of time series data for monitoring the status of an object on the Earth's surface over time, different methods for analysing the available time series data have been developed and used to detect changes in different ecosystems (Lu, Mausel et al. 2004). The relevance of time series analysis of multi-temporal remote sensing images or derived vegetation indices as a tool for monitoring the dynamicity of an ecosystem have already been proven (Lhermitte, Verbesselt et al. 2011). For example, the method Breaks For Additive Seasonal and trend (BFAST) has been implemented and tested for detecting timing of the phenological changes for a forested area in the South-east of Australia (Verbesselt, Hyndman et al. 2010). It was found that the method is capable of detecting the timing of the phenological changes within the time series data. The ability of BFAST for detecting changes in the trend component of a time series data is also tested and has already been proven (Verbesselt, Hyndman et al. 2010).

The available time series analysis techniques use different algorithms and change detection methods to detect the occurrence of change within the time series data. One of the key components in time series analysis is the function used to measure the similarity between two time series being compared (Liao 2005).As a result of this, time series similarity measure play an important role in the methods which are used for the analysis of multi-temporal time series data (Lhermitte, Verbesselt et al. 2011). The most commonly used similarity measures for time series data are: distance measures which are derived from Minkowski distance (Jain et al. 1999), correlation measures, mainly Person's correlation (Liao 2005), principal component analysis (Jolliffe 2005) and Fourier transforms (Canisius, Turral et al. 2007). The different time series similarity measures have been applied for different purposes. For example, Lambin and Ehrlich (1997) used time series similarity measures, particularly the distance measure approach, to detect land-cover changes in Sub-Saharan Africa based on remotely sensed surface temperature and vegetation indices at the continental scale. Lhermitte et al. (2010) also uses the spatial context and time series similarity measures approach (mainly distance and cross-correlation measures) to select control pixels and compute a per pixel regeneration index. The potential application of these time series similarity measures approach for analysing multi-temporal sensor agricultural crops data might have an additional contribution for timely assessment of crop characteristics which can be used by the modern farmer to make timely decision for applying the required management activities. However, the potential of time series similarity measures for detecting changes of a pixel (plot) based on time series data of a reference pixel (plot) with optimum nitrogen amount, is not yet fully explored for its applicability in agricultural practices like precision agriculture.

As mentioned earlier, precision agriculture has the objective of applying nitrogen and pesticides with the amount needed and when it is needed. In order to achieve these objectives, the modern farmers are in need of a system which can analyse the available multi-temporal sensor data and provide them a concrete result which can help them to apply nitrogen optimally both spatially and temporally.

1.3 Research objectives and research questions

The main objectives of this study are to investigate the potential application of time-series analysis methods for the analysis of multi-temporal sensor data of agricultural crops and to assess temporally based spectral vegetation indices which are able to determine the nitrogen status of the crop within the field. For this study, time-series data from different sensors and from field measurements for a potato field in the South of the Netherlands will be used. The study starts by identifying the relationship between the crop parameters and sensing measurements. The potential temporal based spectral vegetation indices will be derived from the spectral measurements of the crop over the growing season. The capability of the vegetation indices (VIs) and robustness for detecting nitrogen status of the crop over the growing season will be assessed based on the time-series data of the VI's. The final part of the study focuses on how the time-series of the VIs from plots (pixels) where the nitrogen treatment levels over the growing season are optimal, will be used as a reference to monitor the nitrogen status of the plots (pixels) with suboptimal nitrogen level.

The following research questions will be addressed in order to meet the objectives of this study:

1. How can the relationship between the field observations of the crop parameters and sensing measurements at one moment in the growing season be quantified?
2. Which vegetation indices are capable of detecting the nitrogen status of the potato crop over the growing season?
3. How can changes in the crop status or abnormal changes be detected using weekly near-sensing time series data?
4. Which temporal detail is required for detecting abnormal changes in the analysis of multi-temporal sensor data for agricultural crops?

1.4 Outline of the report

In the second chapter of this report a comprehensive literature review on the main topics of the research are presented: methods which are available for determining the nitrogen status of the crop, sensors available for both near and remote sensing, commonly used vegetation indices for precision agriculture and time series similarity measures. Chapter three comprises information about the study area and data, and the methodology that is followed for this thesis research. In chapter four the results are presented. In chapter five these results are discussed with respect to the research objectives and research questions, and in the light of the theoretical framework, using scientific literature. Chapter six contains the conclusions and recommendations for further research on the topic.

2. Literature review

In this part of the report a comprehensive literature review on the main topics of the research are presented. The main topics which are covered in this part of the report are: methods which are available for determining the nitrogen status of the crop (Section 2.1), sensors available for both near and remote sensing (Section 2.2), commonly used vegetation indices for precision agriculture (Section 2.3) and time series similarity measures (Section 2.4).

2.1 Overview of methods used for detecting crop N status in precision agriculture

Nitrogen (N) is the nutrient that often limits crop production in many crop types and because of this reason timely assessment of the N status is very crucial for adequate yield production and to obtain high quality crops (Samborski, Tremblay et al. 2009). For this timely assessment of crop N status, different types of methods are currently available and are being used. Crop N status can be operated at plant tissue, leaf, plant and canopy scales. The most commonly used methods to determine the N status of crop based on plant tissue measurements are Petiole Sap Nitrate Concentration (PSNC) test and wet chemistry analysis of total N (Goffart, Olivier et al. 2008). The methods based on plant tissue measurements need invasive sampling of plant parts (Wang, Chen et al. 2009). The other method to determine the N status of the crop is based on measurements taken at the leaf scales (Gianquinto, Goffart et al. 2004). The most commonly used methods based on measurements taken at the leaf scales are handheld chlorophyll meters (Goffart, Olivier et al. 2008). Commercially available handheld chlorophyll meters are the Minolta SPAD and the Dualex chlorophyll meter. However, in this report the focus will be on the Minolta SPAD chlorophyll meter.

2.1.1 Petiole Sap Nitrate Concentration (PSNC)

Among the available methods to determine the N status of the crop, the petiole sap nitrate concentration test method is the most commonly used one. It is based on the measurement of leaf petiole sap nitrate concentration (Wang, Chen et al. 2009). A petiole is the stalk attaching the leaf blade to the stem. After the petioles are sampled in the field, handled and stored, the sap is extracted following the standard procedures (Goffart, Olivier et al. 2000). Commercially two types of instruments are available for quick measurement of PSNC (Goffart, Olivier et al. 2008). The first type of instrument makes use of a Nitrate Specific Electrode (NSE) (reference) while the second type is a combination of nitrate test strips together with a handheld reflectrometer (Wang, Chen et al. 2009). The PSNC values obtained from the first type of instrument i.e. from NSE shows high correlation with the PSNC values made from dry petiole nitrate concentration values when both are taken from the same sample materials (Westcott, Rosen et al. 1993). Goffart et al. 2008 has reported that the PSNC test has shown to be very sensitive and responsive to different rates of N fertilization. A single application of different rates of N makes a seasonal trends of PSNC values (Zhang, Smeal et al. 1996). Mackerron et al. 1995 identified that part of the applied N could also be stored in other parts of the plant, for example it can be stored as in the form of nitrate in stems and lower leaves. This shows that this method has a limitation to be used solely as a method to determine the N status of the crop (Goffart, Olivier et al. 2008).

The capacity of the PSNC method to determine the N status of the crop over the growing season largely depends on some additional factors other than N (Goffart, Olivier et al. 2008). During periods of rain, N availability from the soil will peak resulting in increased values for the PSNC test which might have an influence on the usage and accuracy of the method during the whole growing season (MacKerron, Young et al. 1995). In order to minimise this variation of the PSNC values, it is advisable not to take measurements during extreme conditions i.e. during very wet or dry conditions. Also depending on the type of potato cultivar, the PSNC test has different values over the growing season and this enforces to have cultivar-specific N fertilization recommendations (Vitosh and Silva 1994).

Although the PSNC test is the quickest test method among the invasive methods to assess the N status of the crop, it is time consuming method compared to the non-invasive methods using a chlorophyll meter or using a near sensing or remote sensing method (Goffart, Olivier et al. 2008). Its labour and time intensive nature of the method makes it less applicable for large area farms and also for areas where labour is expensive. However, the cost of the equipment and materials used for the nitrate test based on strips-test are relatively cheaper than the cost of the materials for the other methods which are also based on plant tissue analysis i.e. for the methods which are based on Kjeldahl digestion, Dumas combustion or NIR spectroscopy analysis (Goffart, Olivier et al. 2008).

2.1.2 Chlorophyll meters

The other commonly used methods to determine the N status of the crop are based on measurements taken at the leaf scale. The most common ones based on measurements taken at the leaf scale are chlorophyll meters. The two similar chlorophyll meters which are commercially available and used are the SPAD-502 meter (Konica Minolta, Tokyo, Japan; from here on referred to as "SPAD") and the Hydro N-tester or HNt (Yara, Oslo, Norway) chlorophyll meter (Goffart, Olivier et al. 2008). Since SPAD-502 has been used for the analysis in this study, emphasis is given on the SPAD-502 chlorophyll meter. Chlorophyll being an indirect measurement of the N status of a crop, leaf chlorophyll meters have been used with various crops as an indirect indicator of crop N status (Gianquinto, Sambo et al. 2003). Because of this reason, accurate assessment and measurement of the chlorophyll content of the leaf helps for timely assessment and determination of the crop N status (Olfs, Blankenau et al. 2005). Accurate determination of the crop N status using chlorophyll meters depends on crop types and has been affected by many factors including differences in variety (Hoel 2002), growth stages (Ramesh, Chandrasekaran et al. 2002), nutrient deficiencies other than N (Turner 1991), environmental conditions (Schepers, Francis et al. 1992) and measurement positions on the leaves (Chapman 1997).

In general, the principle of the SPAD chlorophyll meter is based on the measurements of transmittance in two wavelengths (650 nm in the red and 940 nm in the near-infrared) of the electromagnetic spectrum (Goffart, Olivier et al. 2008). The first wavelength matches with the peak absorbance area of chlorophyll where absorbance is unaffected by carotenoids while the second wavelength is a reference wavelength where the absorbance of chlorophyll is extremely low (Gianquinto, Goffart et al. 2004). The SPAD values are calculated during measurements based on the transmitted light. The light transmitted by a leaf is converted into electrical signals, amplified and converted into digital signals (Gianquinto, Goffart et al. 2004). The values obtained with the chlorophyll meters are unit less and they express relative chlorophyll content instead of absolute chlorophyll content per unit leaf area, or concentration per gram of leaf tissue (Richardson, Duigan et al. 2002). The way the values of results of the measurements displayed on the devices are different. In the case of SPAD the measurement values are from 0 to 60 and for the case of HNt, the values are from 0 to 800. The SPAD device takes individual measurements and the values are averaged later on and this gives the opportunity to measure as many leaves as needed.

The two devices have been used to estimate the amount of chlorophyll present in the crop leaves of different crop types. A significant linear relationship between the SPAD measurements and the chlorophyll available in the leaf of the potato crop has been reported by (Vos and Bom 1993). The chlorophyll meters indicate the current plant N status, but neither can predict its future one, nor indicates how much N fertilizer should be applied (Samborski, Tremblay et al. 2009). However, the chlorophyll meter has the ability to detect the onset of N stress in many cases before it is visible to the human eye and can be used to correct the deficiency before it has an effect on the final yield (Shapiro 2006). SPAD or HNt values and their time-course are also largely dependent on other many external factors besides N. Some of the sources of variation of their values are because of environment conditions, variety type and crop management (Gianquinto, Goffart et al. 2004). Comparing to the PSNC method, chlorophyll based methods appear to be less sensitive with leaf position, as the values from the PSNC method dramatically increase with depth into the canopy (MacKerron, Young et al. 1995). Due to the reasons mentioned, it is difficult for precision agriculture to rely only on chlorophyll meter based methods. On the other hand, determining the chlorophyll content of the leaves using chlorophyll meters are easy to operate as the procedure of operating the devices does not require a qualified operator (Goffart et al. 2000) and this makes the usability of these devices relatively easy and as a result they can be operated by less skilled farmers.

2.2 Overview of close sensing, ground based and image based remote sensing sensors used for detecting crop N status in precision agriculture

The other way to determine the N status of the crop is based on measurements taken at the plant or canopy scale. Most of the methods under this category are non-invasive and rely on measurements of light reflected above the canopy (Goffart, Olivier et al. 2008). The methods are based on remote sensing methodology i.e. based on spectral canopy reflectance and can be operated at different spatial scales: close sensing, ground based and image based remote sensing (i.e. air-born or space born remote sensing) (Zhang, Smeal et al. 1996). Even though there is a difference on where the sensors are placed, they all share the same property i.e. all of them aim to estimate canopy structure parameters, mainly LAI (leaf Area Index) based on calculated indices (like NDVI). This is based on the knowledge that plant N, leaf chlorophyll and LAI estimated from the calculated indices are strongly related variables (MacKerron, Young et al. 1995).

2.2.1 Close sensing

Another way of indirectly determining the N status of a crop is by using ground-based platforms which are mainly equipped with active spectral sensors. These types of active sensors operate while being mounted on tractor or sprayers and can be used to collect the required crop reflectance data during normal agricultural activities.

Close sensing methods have the same methodology like the ground and image based remote sensing methods. However, close sensing methods are more applicable to overcome the limitations of space-borne sensors which are mainly caused by clouds (Goffart, Olivier et al. 2008). The close sensing methods operate at field scale and use ground-based platforms which are equipped with active spectral sensors (Samborski, Tremblay et al. 2009). The difference between passive and active sensors is; active sensors generate their own emitted electromagnetic rays in the required wavebands whereas passive sensors do not emit their own light and require an external source (Erdle, Mistele et al. 2011). The presence of these active spectral sensors on close sensing methods allows the canopy reflectance to be measured independently of incident sunlight and this makes measurements possible 24 h a day (Tremblay, Wang et al. 2009). The measured crop reflectance using the close sensing methods is used to calculate specific vegetation indices which are used to assess crop N status (Goffart., Olivier. et al. 2011).

Depending on where the sensors are placed, close sensing methods are categorised as handheld systems and tractor-mounted systems (Samborski, Tremblay et al. 2009). For the sake of this paper only the tractor-mounted systems will be discussed. The most commonly available tractor-mounted systems are: Yara N-sensor, GreenSeeker, and Crop Circle.

The Yara N-sensor (Yara International ASA, Oslo Norway) is a multispectral scanner which is mounted on the roof of a tractor (Tremblay, Wang et al. 2009). The sensor has two diode array spectrometers in which the first one is used to analyse crop light reflectance collected by four lenses with an oblique view of the crop (two on each side of the vehicle) while the second is used to measure the ambient light for permanent correction of the reflectance signal to ensure stable measurements with changing irradiance conditions (Tremblay, Wang et al. 2009). Due to the presence of the lenses on both sides of the vehicle, there is an option of separate measurement on the left or right side of the tractor (Samborski, Tremblay et al. 2009). By using the Yara sensor, approximately 25% of the total area is scanned at a 24-m working width (Samborski, Tremblay et al. 2009). The sensor determines the N status of the crop by measuring crop reflectance characteristics at selected wavebands in the region from 450 to 900 nm and it calculates NDVI or other vegetation indices used by algorithms to calculate optimal N application rates, which are then transmitted to a spreader equipped with a rate controller (Tremblay, Wang et al. 2009) (Li, Miao et al. 2009). Unlike the GreenSeeker the Yara-sensor can also record spectral information in the wavebands other than the red and infrared and this makes it possible to calculate other vegetation indices other than NDVI (Tremblay, Wang et al. 2009).

The other type of close sensing device is the Crop Circle (Holland Scientific, Lincoln, NE). It measures canopy reflectance at two narrow wavebands i.e. at 590 nm (Green) and 880 nm (NIR) (Solari, Shanahan et al. 2008). The measured crop reflectance is used to calculate a number of classic vegetation indices as well as basic reflectance information from crop canopies. It is a light sensor similar to GreenSeeker but it has different optical and electronics design and this results to have a different operational characteristics than the GreenSeeker sensor (Samborski, Tremblay et al. 2009).

GreenSeeker (N Tech Industries Inc., Ukiah, Canada) (Figure 1) is the other most commonly used ground-based close sensing sensor (Goffart, Olivier et al. 2008). It emits light at 660 nm (Red) and 780 nm (NIR) and the emitted light at these wavelengths allow Red and NIR crop reflectance to be assessed (Pena-Yewtukhiw, Schwab et al. 2008). The area reflectance for one waveband is not exactly the same as the area recorded by the companion waveband and as a result the crop area from which subsequent calculations of NDVI are made is not the same (Erdle, Mistele et al. 2011). This might result in greater variability of sensor readings during higher speeds of the tractor (Samborski, Tremblay et al. 2009). The embedded software in the sensor calculates the reflectance in the red and near infrared, and then computes the Normalized difference vegetation index NDVI using equation (1) (Inman, Khosla et al. 2005). Based on the values of the calculated NDVI, it adjusts the fertilizer rate according to the crop's requirements (Inman, Khosla et al. 2005). The reason why the GreenSeeker active sensor utilizes the NDVI is because this vegetation index, as well as other normalized indices are relatively sensitive to changes in reflectance; it is also insensitive to changes in sensor height due to vibration caused from being mounted and driven through the field (Inman, Khosla et al. 2005).

$$NDVI = (R - NIR) / (R + NIR) \qquad \textbf{(1)}$$

Before starting fertilizer application using the GreenSeeker, the absolute fertilizer level on the field needs to be fixed (on-field calibration). For this purpose, the concept of N-rich strip is most commonly used (Samborski, Tremblay et al. 2009). This approach will allow obtaining an absolute fertilizer level and the sensor will be calibrated based on this N-rich strip. Based on the readings from the N-rich strip, the sensor determines the amount of the required additional N fertilizer using the algorithms developed for different crop types (Napieralski and Nalepa 2010). Its variable rate application of the required N on the field makes GreenSeeker to be used for the concept of precision agriculture and currently it is being used by many farmers who implements the concept of precision agriculture (Shanahan, Kitchen et al. 2008).

Figure 2: Example of GreenSeeker sensor head mounted on spraying boom (left), and operating device for GreenSeeker sensor in tractor cabin (right).

2.2.2 Ground based remote sensing

The other method to determine the N status of the crop based on measurements taken at the plant or canopy level is using ground based remote sensing methods. Ground based remote sensing methods are based on the spectral characteristics of the aboveground canopy which is related to leaf pigment content (Goffart, Olivier et al. 2008). Since these methods take measurements at the plant or canopy scale, they represent an integrated measure of N contents over the total crop canopy depth, which gives direct values for crop N status (Jongschaap and Booij 2004). The measured crop reflectance at different wavelength bands allows the calculation of vegetation indices that can be related to and used for crop N status (Zhang, Smeal et al. 1996). Among the different devices used for ground based remote sensing methods, CropScan is one of them. The CropScan device (Figure 2) (CropScan Inc., Rochester, USA) is a multi-spectral radiometer used to measure incident and reflected light radiation of the canopy at several wavelength bands (Booij R 2004). It uses passive sensors that measure the reflected part of visible or near infra-red electromagnetic radiations which are emitted from the incident sun light and depending on the height of the radiometer above the canopy, the area which will be sampled in one scan can vary from 1 to 2 m2 (Goffart, Olivier et al. 2008). Depending on the type of the model, the device has different number of bands. The CropScan which was used for collecting the potato crop reflectance of this research has 16 bands. The availability of these bands enables the calculation and test of several VI's. The VIs' which are derived from the CropScan crop reflectance data and used for the analysis of this research are presented in the vegetation indices part of this report. The CropScan instrument is more a research instrument and not operationally used in precision agriculture practice.

Figure 2: Example of potato crop reflectance measurement using CropScan at different heights above the crop canopy.

2.2.3 Image based remote sensing

The other commonly used method for assessment of N status of the crop is using remote sensing (RS) methods. The air-born and space-born remote sensing methods are working with the same principle as the ground-based remote sensing methods. Both the methods are mainly depending on the acquisition of aerial and satellite images at the field or regional scale (Goffart, Olivier et al. 2008). Due to higher geographical resolution compared to ground-based near sensing methods, it allows to consider large areas within the same view, and to obtain temporal information that is detailed and spatially distributed over the whole field area (Moran, Inoue et al. 1997). Comparing to other methods, remote sensing techniques, particularly the use of satellite imagery, offer a great potential for frequent chlorophyll estimation both at the regional and local scales (Haboudane, Miller et al. 2002). Besides the large area coverage, remote sensing methods represent an integrated measure of N contents over total canopy depth, which gives direct values for crop N status while PSNC and chlorophyll based methods mainly measure the N content on the top young leaves (Jongschaap and Booij 2004). In precision agriculture these frequent and large area coverage advantages of the remote sensing method allows the farmer to assess and monitor crop chlorophyll status and spatial distribution (Haboudane, Tremblay et al. 2008). Although there is a huge potential of using remote sensing methods to access the N status of the crop, there are still many limitations to be considered in the use of remote sensing methods. These are: relatively higher costs (due to high costs of commercial satellite images) than for ground-based tools to acquire the information and weather conditions especially clouds interference in the visible and near infra-red wavelengths (Goffart, Olivier et al. 2008).

2.3 Vegetation Indices

Remote sensing data and techniques have already proven to be used as a relevant tool for crop inventory and monitoring purposes (Haboudane, Miller et al. 2002). Among the different issues, determining the crop status and condition (Clevers, Büker et al. 1994) and assessing micronutrient deficiency (Adams, Norvell et al. 2000) are some of the important issues in which remote sensing applications have been used. Besides, crop parameters, such as leaf area index(LAI), leaf chlorophyll content, leaf water content, and canopy cover have been successfully measured using remote sensing technology, especially using spectral vegetation indices (VIs) (Moran, Clarke et al. 1994; Rondeaux, Steven et al. 1996; Haboudane, Miller et al. 2004).

Because of the advancement of remote sensing methods in assessing the crop status, narrow band or hyperspectral sensors have been introduced and are being used to measure the crop reflectance in a very wide range (Hatfield and Prueger 2010). The measured crop reflectance data is then used to derive vegetation indices which are developed by combining the various wavebands. The purpose of the developed VIs is to improve the vegetation signal while minimising the solar irradiance and soil background effects (Huete, Didan et al. 2002). Depending on which wavebands are used to derive the vegetation indices, the usage of the VIs to assess the crop status is also different. Some vegetation indices are designed to relate to biomass (NDVI, WDVI), while others are very sensitive to the amount of chlorophyll or nitrogen in the leaf (REP, TCARI/OSAVI) and this implies that for monitoring various crop parameters different vegetation indices are needed (Kooistra 2011). The traditional and most commonly used vegetation indices like normalized difference vegetation index (NDVI) tend to saturate under high canopy coverage (Li, Miao et al. 2009) and to overcome this problem vegetation indices derived from the RED-edge position have become very promising (Cho and Skidmore 2006). The position of the inflexion point in the red edge region (680 to 780 nm) of the spectral reflectance signature is termed as the RED-edge position (Li, Miao et al. 2009). The Red edge position, as the inflection point of the strong red absorption to near infrared reflectance, includes the information of both crop N and growth status and as a result of this, vegetation indices which are derived from this region has always been considered important in relationships with biochemical or biophysical parameters of a crop and they are also good for the assessment of crop N status (Cho and Skidmore 2006).

For the purpose of this research, by considering the linkage between N and chlorophyll in green leaves, spectral indices recommended to determine the chlorophyll content of the leaf were derived from the CropScan spectral reflectance measurement.

Table 1: Overview of Vegetation indices evaluated for this thesis research.

Index	Name	Formula	Developed By
NDVI	Normalized Difference Vegetation Index	$(R_{NIR}-R_{RED})/(R_{NIR}+R_{RED})$	(Rouse, Haas et al. 1974)
RVI	Ratio Vegetation Index	R_{NIR}/R_{RED}	(Jordan 1969)
WDVI	Weighted Difference vegetation Index	$R_{NIR}-C*R_{RED}$ C = 2 (soil factor)	(Clevers 1989)
REP	Red edge position	700+40(Rre-R700)/(R740-R700) Rre: (R670+R780)/2	(Guyot, Baret.; et al. 1988)
TCARI	Transformed chlorophyll absorption in reflectance index	3((R700-R670)-0.2(R700-R550)(R700/R670))	(Haboudane, Miller et al. 2002)
OSAVI	Optimized Soil-Adjusted Vegetation Index	1.16x(R800-R670)/(R800+R670+0.16)	(Rondeaux, Steven et al. 1996)
TCARI/ OSAVI	Combined Index: TCARI with Optimized Soil-Adjusted Vegetation Index	TCARI/OSAVI	(Haboudane, Miller et al. 2002)
NDRE	Normalized Difference Red Edge Index	(R780-R720)/(R780+R720)	(Eitel et al. 2010)
$CI_{red\ edge}$	Chlorophyll Index	(R780/R550) - 1	(Clevers et al. 2011)

2.4 Time series similarity methods

The availability of both close sensing and remote sensors create an opportunity to measure and record the performance of crops over time. One of the major advantages of remote sensing methods is the ability to provide repeated measures from a field without destructive sampling of the crop which in turn can provide important temporal information for precision agriculture (Hatfield and Prueger 2010). For this purpose vegetation indices derived from the temporal data were used to study the essential vegetation parameters such as leaf area index (Herrmann, Pimstein et al. 2011) and crop chlorophyll content (Haboudane, Miller et al. 2002). These time series data about the performance of the crop can be used as an essential tool for the timely management of the crop by the farmer. In order to analyse these time series data, different methods have been developed and tested for different land ecosystems (Coppin, Jonckheere et al. 2004). The available time series analysis techniques use different algorithms and change detection methods to detect the occurrence of change within the time series data. Among the different methods used by these methods, time series similarity measures are one of the methods (Lhermitte, Verbesselt et al. 2011). Because of the generalised use, there is no fixed definition of time series similarity measures (Liao 2005). Time series similarity measures have been used for different purposes. The first approach or purpose in which time series similarity measures have been used is, for example they have been used as a complete measure to derive stastical inferences about the relationship between time series of different data sets (Tippett, DelSole et al. 2008). In this first approach, different methods have been applied in remote sensing studies to determine the relationship between time series of remote sensing data and bio and geophysical parameters (Lhermitte, Verbesselt et al. 2011). The types of methods which use this approach of time series similarity measures range from singular vector decomposition (SVD) and canonical correlation analysis (CCA) to the commonly used methods based on regression and correlation analysis (Herrmann, Pimstein et al. 2011). The second approach or purpose where time series similarity measures have been used is, as a relative criterion to numerically characterize the relationship between time series data and provide a decision criteria for the methods to cluster or discriminate based on the similarity or dissimilarity of the time series data (Lhermitte, Verbesselt et al. 2011). In this second approach, time series similarity methods have been used for several classification methods. The other situation where time series similarity measures have been used is for change detection approaches. In such approaches, time series similarity measures are used to discriminate changes within one time series, for example the change in vegetation growth between different years (Vanacker, Linderman et al. 2005).

Different time series similarity measures do exist. The nature of the data to be analysed and type of ecosystem to be characterised determine which similarity measures is most appropriate (Lhermitte, Verbesselt et al. 2011). Depending on the type of data used for the time series similarity, time series similarity measures are grouped into three categories. The first category is when the similarity is performed based on the original time series data. The second category is when the similarity is performed on the data extracted indirectly with transformation from the original time series data. The third category is when the similarity is performed on the data extracted indirectly with metrics derived from the original time series data (Lhermitte, Verbesselt et al. 2011). Since in the analysis of this research time series similarity measures based on the original time series data approach have been used, similarity measures which performs the similarity based on the original time series data have been described. The most commonly used time series similarity measures based on the original time series data are: distance and correlation measures (Herrmann, Pimstein et al. 2011). The most commonly used distance measures are derived from the Minkowski distance (Tippett, DelSole et al. 2008). It is a generalization of both the Euclidian distance (D_E) and the Manhattan distance (D_{Man}).

As Lhermitte (2011) described, the Minkowski distance between two individual time series fp (t) and fq (t) collected at time t for pixels p and q respectively is given by:

$$D_{Mink} = \left(\sum_{t=1}^{N} |f_t^p - f_t^q|^r \right)^{\frac{1}{r}} \qquad (1)$$

Where f_t^p is the fp (t) time series value at moment **t** and f_t^q is the fq (t) time series value at moment **t**. **N** is the number of samples in the time series and r is a user defined integer. Depending on the value of **r**, the Minkowski distance measure either the Euclidean distance (D_E) or the Manhattan distance (D_{Man}). When r = 1 it defines the Manhattan distance (D_{Man}), whereas when r = 2 it defines the Euclidean distance (D_E).

Geometrically the Euclidian distance between two points is the shortest possible distance between the two points (Herrmann, Pimstein et al. 2011). Besides its simplicity to calculate and interpret (Lhermitte, Verbesselt et al. 2011), the Euclidean distance measure is invariant under orthogonal transformations of the variables (rotating the points does not change the distance between the points) (Herrmann, Pimstein et al. 2011). However, the Euclidean distance measure is also more sensitive to outlier values like noise due to its non-linear character (Tippett, DelSole et al. 2008). Because of these reasons it has been applied to provide the similarity measure that is evaluated in several clustering algorithms (Lhermitte, Verbesselt et al. 2011). The other advantage of using the Minkowski distance is that it does not take into account the time interval between measurements which allows it to be applied to unequally spaced observations (Vanacker, Linderman et al. 2005). This makes it applicable to be used in datasets where data have been acquired with irregular sampling intervals, which is the case of this research.

The other similarity measure based on distance measures is the Root Mean Square Distance (RMSD). As Lhermitte, et al. (2010) described the RMSE is defined as:

$$RMSD = \sqrt{\frac{\sum_{t=0}^{N-1} (f_t^p - f_t^q)^2}{N^2}}.$$

Where f_t^p and f_t^q are the time series values at moment **t**. **N** is the length of the time series. (2)

Lhermitte, et al. (2010) explained as the RMSD is accountable by calculating only the distance between corresponding observations that are not missing. This means the RMSD can be used in datasets with missing values. The RMSD calculates the inter-point straight line distance in a multi-temporal space (Lhermitte, Verbesselt et al. 2010). As Lhermitte, et al. (2010) suggested the RMSD robustness for missing values; it makes it also applicable to be used in this research.

The other commonly used time series similarity measure using the original time series data is the correlation measure. It measures the correlation between the points in the time series data based on the Pearson's correlation coefficient (D_{cc}) (Liao 2005). The correlation between two time series is calculated using the formula:

$$D_{CC} = \frac{\sum_{t=0}^{N-1}\left[\left(f_t^p - \bar{f}^p\right) * \left(f_{t-s}^q - \bar{f}^q\right)\right]}{\sqrt{\sum_{t=0}^{N-1}\left(f_t^p - \bar{f}^p\right)^2} * \sqrt{\sum_{t=0}^{N-1}\left(f_{t-s}^q - \bar{f}^q\right)^2}} \tag{3}$$

Where f_t^p and f_t^q are the time series values at moment **t**, f^p and f^q are the means of the corresponding time series, **S** is the lag between both time series, and **N** is the length of the time series. Depending on the value of the D_{cc}, it is possible to determine the relationship between the two time series. D_{cc} is 1 when there is an increasing linear relationship and it is -1 when there is a decreasing liner relationship between the two time series (Lhermitte, Verbesselt et al. 2011). The D_{cc} time series similarity measure is often used in remote sensing time series similarity measures (Geerken, Batikha et al. 2005). Different people have used it for different purposes, for example (Wang, Chen et al. 2009) used it in an NDVI time series data for identifying inter-annual land cover changes.

As it has been mentioned above, time series similarity measures which are applied on the original time series data have been applied for detecting changes and also for classification purposes. However these time series similarity measures are not yet tested and applied to detect changes on the N status of the crop using a vegetation index which is capable to determine the N status of the crop over the growing season. In this research the potential applicability of these methods for detecting the N status of the potato crop over the growing season have been tested and the results are presented in the results section of this report.

3. Materials and methods

3.1 Study Area

The study area is located in the southern part of the Netherlands near the village of Reusel in the province of Noord-Brabant. It is an agricultural parcel which had a potato crop during the 2011 growing season. For the purpose of this study, twelve experimental 30*30m plots were prepared and supplied with different levels of N fertilization. There were four levels of organic fertilization (0, 23, 34 and 46 kg of N h^{-1}) before planting the potato crop and three types of treatments during the whole growing season of the crop (Table 2). The first type of treatment “CL” is a NO treatment during the whole growing season. Plots A, C, E and G were under this treatment group and these plots received 23, 0, 34 and 46 kg of organic N h^{-1} respectively before planting. However, these plots did not receive any additional treatment over the whole growing season. Plots B, D, F and H were under the second type of treatment “TTW”, and these plots received 23, 0, 34 and 46 kg of organic N h^{-1} respectively before planting. During the growing season, additional N was applied on these plots based on different sensor measurements. Plots I, J, K, and L were under the third type of treatment “MB”, and these plots received 46, 34, 0 and 23 kg of organic N h^{-1} respectively before planting. During the growing season additional N was applied on these plots at a specific point in the growing season when the crop vegetation closes its canopy and it was applied based on Weighted Difference Vegetation Index (WDVI) values. Overview of the experimental plots with four levels of N fertilization and three types of treatments is presented in Figure 3.

Table 2: N fertilization levels and treatments applied for the twelve experimental plots

N fertilization levels (kg h^{-1})		CL	TTW	MB
0	0	C	D	K
23	1	A	B	L
34	1.5	E	F	J
46	2	G	H	I

3.2 Data

During the growing season of the potato crop, data were acquired using different acquisition methods. To monitor the N status, measurements of important biophysical and biochemical parameters and corresponding canopy spectra were conducted. Within each block, georeferenced plots were established on representative sections of each block. For the field measurements, each of the plots was divided into two; left side and right side from the tractor path and four rows per plot (i.e. two rows on each side) were selected. The coordinates of the experimental plots were taken using GPS and the exact locations of the plots within the parcel were drawn using ArcGIS software.

Figure 3: Overview of the study area

Table 3: Amount of initial, additional and total N fertilization in kg per hectare applied to specific plots over the growing season partly based on recommendations from sensor readings.

Plot	Initial organic N kg/h	Treatment type	Fertilization During the growing season								
			May 18		June 21		July 7		July 20		
			Advised	Applied	Advised	Applied	Advised	Advised	Advised	Applied	Total
A	23	CL									165
B	23	TTW			15	13.5			15	13.5	192
C	0	CL									38
D	0	TTW			50	54			50	54	146
E	34	CL									229
F	34	TTW									229
G	46	CL									292
H	46	TTW									292
I	46	MB					49	54			346
J	46	MB					28	27			256
K	0	MB		54			0	54			146
L	23	MB	48	54			59	54			321

3.2.1 Crop biophysical and biochemical variables

Crop biophysical and biochemical parameters were measured on selected rows of the experimental plots. The crop parameters which were measured over the growing season were; Leaf Area Index (LAI) using the Plant Canopy Analyzer (LAI-2000) and leaf chlorophyll content using handheld chlorophyll meter (SPAD-502).

At each weekly measurement, six SPAD leaf chlorophyll readings per row (24 readings per plot) were taken by clamping the instrument on randomly selected leaves from the top of the plant. Each reading per plant was the averaged result of three leaf chlorophyll readings (18 readings per row).

The LAI was measured on the same day as the SPAD readings. Six LAI values per row (24 values per plot) were taken using the LAI-2000. Each reading per row was averaged result of six LAI readings. The measurement set-up of the LAI-2000 was, for every row one measurement at the start of the line above the canopy was taken, then six measurements at a regular distance below the canopy were taken, and at the end of the line one more measurement above the canopy was taken. This means that, the measured LAI was used as a mean over the line of 30 m. In short, each reading per row included two above-canopy readings and one below canopy reading. In total, thirteen weekly measurements starting from May 30 until August 29 were taken both for the SPAD and LAI measurements over the growing season (Table 4).

The other measurement method which was used as proxy for the N concentration was Petiole Plant Sap. It was taken following the standard procedures. The Plant Sap measurements were taken on a weekly basis and values were averaged per plot. In total, eleven weekly Petiole Plant Sap measurements starting from May 16 until July 27 were taken for all the plots over the growing season (Table 4).

For identifying relationships between leaf chlorophyll content from SPAD measurement with Plant Sap, values from SPAD measurement were averaged per plot. But for the rest of the analysis, crop parameter values from SPAD and LAI-2000 collected at row levels were used as these give more information on the variability within plots. The measurement dates of SPAD and Plant Sap were different and because of this reason, measurements which were acquired on few days interval were considered for identifying the relationship (Table 5).

3.2.2 Close sensing measurements

Canopy reflectance of the potato crop was acquired for the whole parcel with the GreenSeeker close sensing sensor, which emits light at 660 nm (Red) and 780 nm (NIR). The emitted light at these wavelengths allow Red and NIR crop reflectance to be assessed. Six sensors mounted on the tractor spraying beam behind the tractor were used to acquire the crop reflectance. The data acquisitions were performed on a weekly basis when other farm management activities (e.g., fungicide application) were being performed. The Normalized Vegetation Index (NDVI), which was found as an output from the GreenSeeker and the Ratio Vegetation Index (RVI) which was calculated using the standard formula as presented in Table 1 were used. Besides, the Weighted Difference Vegetation Index (WDVI) values were calculated following the standard formula. When calculating WDVI from GreenSeeker data, weekly reflectance measurements of bare soil for each plot from the Cropscan measurements were used.

The weekly measurement from the GreenSeeker sensor gave NDVI, RVI and WDVI values for the whole parcel. However, only those values which belong to the specific experimental plots were used for the analysis. The image of the whole parcel was overlaid by each plot’s shape file to get values of the NDVI, RVI and WDVI which belong to each of the plots. The weekly values of these indices for each plot were averaged and recorded per plot. In total, five weekly measurements for the whole parcel were taken over the growing season (Table 4).

3.2.3 Ground based remote sensing measurements

At each weekly measurement date, six canopy reflectance readings per row (24 readings per plot) were taken with the Cropscan instrument. The instrument has 16-bands and it measures simultaneously the reflected and incoming radiation in narrow spectral bands (Clevers and Kooistra 2011). Detail specifications about the instrument are described in the literature by Clevers and Kooistra (2011). Each reading in the rows was the averaged reflectance of two canopy reflectance readings. In total, eleven weekly measurements for all the plots were taken over the growing season (Table 4).

Reflectance measurements of bare soil were also taken at each measurement date for each plot using the same equipment. Each bare soil measurement in the plots was the averaged reflectance of two bare soil measurements. The soil reflectance measurements were used to calculate the Weighted Difference Vegetation Index (WDVI).

Besides the WDVI, the vegetation indices (VI's) which were derived from the Cropscan measurements were: RED-edge position (REP), Transformed Chlorophyll Absorption in Reflectance Index (TCARI), Optimized soil-adjusted vegetation index (OSAVI), the ration between TCARI and OSAVI (TCARI/OSAVI), Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge Index (NDRE). The VI's were derived following the standard formulas provided by specific papers as presented in Table 1.

For identifying the relationship between the Vegetation indices derived from the Cropscan measurements with SPAD measurements, the averaged readings of the canopy reflectance per rows were used. However, for the relationship between the vegetation indices derived from the Cropscan measurements with Plant Sap measurements, the averaged readings per plot were used.

3.2.4 Image based remote sensing measurements

The remote sensing data were provided by Mijnakker (www.mijnakker.nl). The original images were acquired using the DMC sensor and had a spatial resolution of 30*30 m. However, the images which were provided by Mijnakker for this research were resampled to a 10*10 m spatial resolution. The available Mijnakker remote sensing data are the NDVI, LAI, and N content on top of the leaf. The data were acquired on a weekly basis and were provided both as a shape file and raster file. Since the numbers of dates included in the shape files were more, the images provided as a shape file were used. For each of the products (NDVI, LAI, and N top of the leaf) eight image acquisitions were performed over the growing season (Table 4).

The weekly remote sensing measurements gave the NDVI, LAI and N top of the leaf values for the whole parcel. However, only those values which belong to the specific experimental plots were used for the analysis. To get those values which belong to each of the plots, an overlay operation was done. The weekly values of NDVI, LAI and N top of the leaf for each plot were averaged and recorded per plot and these values were used during the analysis.

From Table 4 we can see that the measurement dates from different sources were different and only those dates close to each other were selected for identifying the relationship. In other words the relationship between crops parameters from different sources were not identified based on measurements which were acquired on the same date. There were some day's differences on the acquisition dates by different methods. The dates considered for all the relationships are presented in Table 5.

Table 4: Dates when Petiole Sap samples, SPAD, LAI, close sensing, ground and image based remote sensing measurements were acquired in the 2011 growing season of the potato crop

Petiole Sap	SPAD	LAI	Cropscan	GreenSeeker	Mijnakker		
					NDVI	LAI	N top of leaf
May 16	May 30	May 30	May 30	May 2	April 2	April 2	April 2
May 23	June 6	June 6	June 6	May 12	April 11	April 11	April 11
May 30	June 13	June 13	June 13	May 19	April 18	April 18	April 18
June 7	June 20	June 20	June 20	May 26	May 3	May 3	May 3
June 14	June 27	June 27	June 27	June 11	May 25	May 25	May 25
June 21	July 4	July 4	July 11		May 30	May 30	May 30
June 27	July 11	July 11	July 18		June 2	June 2	June 2
July 5	July 18	July 18	July 25		June 24	June 24	June 24
July 12	July 25	July 25	-		Sept. 1	Sept. 1	Sept. 1
July 20	August 1	August 1	August 1				
July 27	August 17	August 17	-				
	August 22	August 22	August 22				
	August 29	August 29	August 29				

Table 5: Dates considered for determining relationships between different crop parameters

SPAD	May 30	June 6	June 13	June 20	June 27	July 4	July 11	July 18	July 25
Plant Sap	May 30	June 7	June 14	June 21	June 27	July 5	July 12	July 20	July 27

MJ LAI	May 30	June 2	June 24	August 16
LAI_2000	May 30	June 6	June 27	August 17

GS NDVI	May 2	May 26
MJ NDVI	May 3	May 25

MJ N top of leaf	May 30	June 24
Plant Sap	May 30	June 27

MJ N top of leaf	June 2	June 24	August 16
SPAD	June 6	June 27	August 17

MJ NDVI	May 30	June 2	June 24	September 1
CS NDVI	May 30	June 6	June 26	August 29

GS NDVI	May 26	June 11
CS NDVI	May 30	June 13

GS WDVI	May 26	June 11
CS WDVI	May 30	June 13

GS RVI	May 26	June 11
CS RVI	May 30	June 13

3.3 Methodology

3.3.1 Overview

The overall flow of the thesis research is presented in the flowchart (Figure 4). It describes the complete methodology that was followed during the thesis research to address the research questions which are described in the research objectives section of this report (Section 1.3). The research was divided into two phases. The first phase mainly focused on identifying the relationship between different crop biophysical and biochemical parameters which were acquired using different acquisition methods. For example, identifying the relationship between nitrogen measured using Plant Sap measurements with the nitrogen (chlorophyll) which was acquired using the SPAD instrument. As part of the first phase, the relationships between the same vegetation indices which were derived from the crop reflectance data of different sensors were also identified. For example, identifying the relationship between the NDVI derived from the GreenSeeker sensor with the NDVI derived from the Cropscan sensor. The last part of the first phase mainly focused on identifying the relationship between crop biochemical parameters with vegetation indices which were derived from the ground based remote sensing measurements (Cropscan). In the last part, the main focus was on identifying the most potential and robust vegetation index (VI) which was capable of estimating the N status of the potato crop over the growing season. The first phase is explained in detail in section 3.3.3.

The second phase of the research mainly focused on investigating the potential application of time-series similarity methods for the analysis of multi-temporal sensor data of potato crop. It started by selecting the most robust VI based on the relation identified on the last part of the first phase. Next, the time series profile of the identified VI was prepared. Based on the characteristics of the identified VI data, the most appropriate and commonly used time series similarity measures were selected. In order to perform the similarity between two time series, a reference time series has to be determined in which the time series of the other object will be compared with. For the case of this research, plot F was selected as the reference plot. It was selected based on the analysis done by one of the agricultural advisory companies involved in the experiment. The analysis result of the company revealed as plot F was the most optimal plot (both in amount and quality of the potato yield) with respect to fertilizer application.

The core part of the second phase of the research focused on performing time series similarity measures by using time series data of the selected potential VI. The selected appropriate time series similarity measures were used to compare the similarity between the reference plots F with the rest of the experimental plots using the time series data of the identified potential VI. The last part of the second phase of this research focused on determining the threshold value of the difference between the two time series. The detailed description of the second phase of the research is explained in section 3.3.4.

In short, the research started by identifying the relationship between crop parameters which were acquired using different acquisition methods. The capability of vegetation indices (VIs) and robustness for detecting N status of the potato crop over the growing season was assessed. After identifying the most robust VI which was capable of identifying the N status of potato crop over the growing season, a temporal profile of the identified VI for all plots was prepared. The temporal profile of the VI was used as an input for the time series similarity measure methods. Finally time series similarity measures between the reference plot and other plots were performed. In order to determine threshold values using results from similarity measures between two time series, a method based on control charts concept was tested and its operational applicability is discussed.

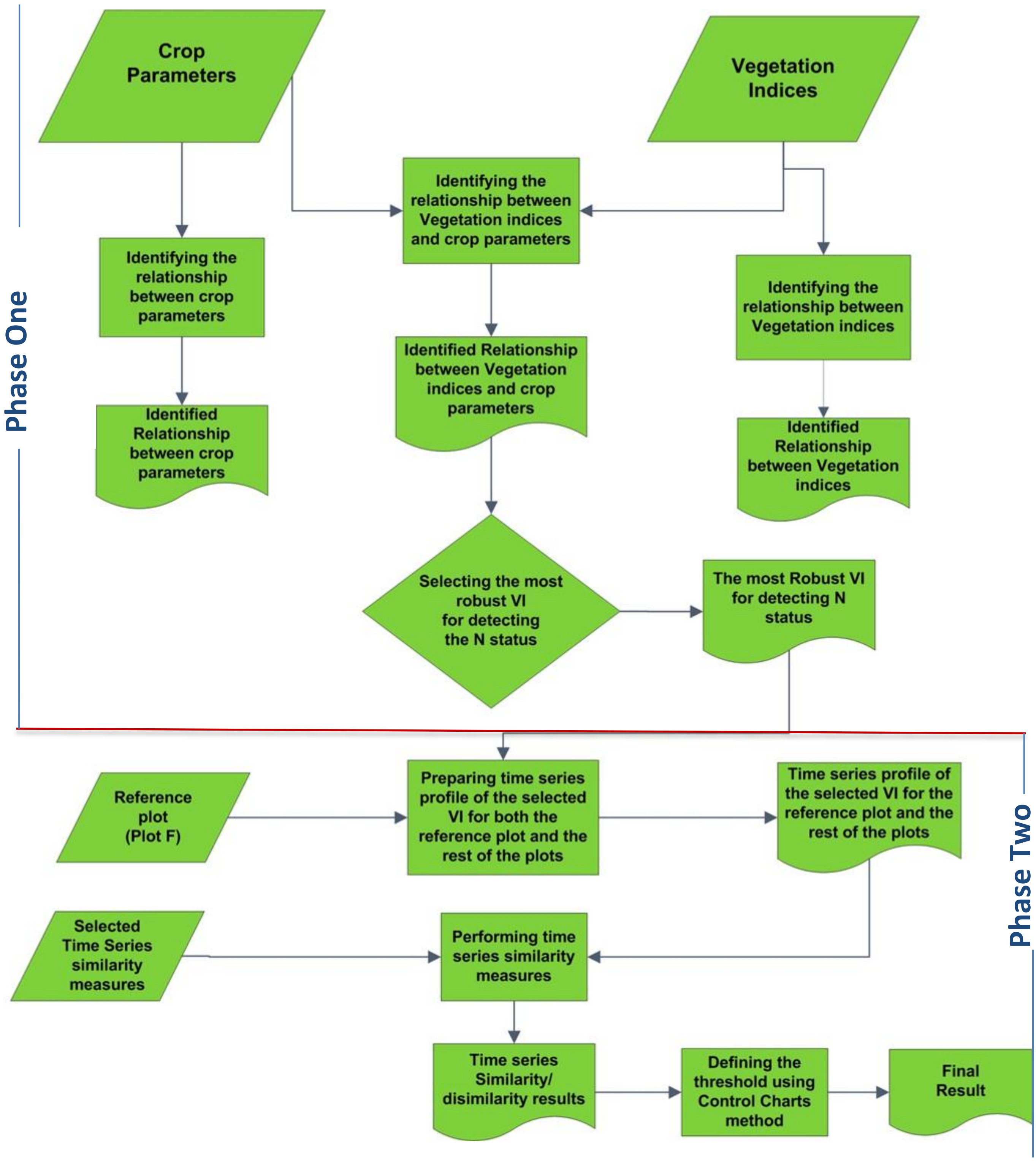


Figure 4: Overall flowchart showing the general overview of the methodology followed for this thesis research

3.3.2 Pre-processing

Transformation

The Geographic coordinates of the original GreenSeeker data were undefined. Using ArcGIS define projection tool, the geographic coordinate system was defined to WGS1984. After defining the geographic coordinate system, the resulted dataset was projected to the Rijksdriehoekstelsel (RD new) using the geographic transformation option Amersfoort-To-WGS-1984-4.

The datasets which were provided by Mijnakker had already the WGS1984 geographic coordinate system assigned to it. These datasets were projected to Rijksdriehoekstelsel (RD new) using the geographic transformation option Amersfoort-To-WGS-1984-4.

In order to check the accuracy of the transformation, both top 10 NL topographic data and aerial photograph of the study area were used. The projected datasets from Mijnakker and GreenSeeker sensors were used to check the accuracy and the result showed that the re-projection worked very well.

Clipping and preparing time series

In order to check if a plot was representing a block, comparisons between plots and blocks were done. A block is a small part of the large study area which has received the same amount of initial fertilization and treatment over the growing season whereas a plot is a 30*30 m area inside a block which has received the same amount of initial fertilization and treatment like the block where it belongs. The comparisons between blocks and plots were done using datasets from the GreenSeeker Sensor and from Mijnaker product (NDVI, LAI and N top of the leaf) images. The datasets from these sensors were selected because measurements which cover the complete area of the parcel were only available from these sensors. In order to get the values which fall in a specific plot or block, the individual plot and block boundaries were clipped out from the large study area. By using these clipped boundaries (shape files), the time series datasets from the two sensors were clipped by using an overlay operation. The values which belong to either the blocks or the plots were recorded for further analysis of the comparison between blocks and plots. The mean and standard deviation of the measurement points were calculated and used for the comparison between the two.

3.3.3 Data analysis

3.3.3.1 Relationships between crop biophysical and biochemical parameters

To examine the relationship between the different crop biophysical and biochemical parameters, a regression model was performed using the open-source stastical software package, R 2.13.2 (R Development Core Team, 2011). Since the crop parameters measurement dates of the different methods were different, measurements which were acquired in some day's difference were considered for the analysis. Goodness of fit of the regression model to the data was evaluated based on the commonly used model diagnostic plots. The strength of the relationship between the different crop biophysical and biochemical parameters was evaluated by means of the coefficient of determination (R^2).

To identify the relationship between the nitrogen content from the Plant Sap and the chlorophyll content from the SPAD chlorophyll meter, the calculated mean values both for the SPAD and Plant Sap per plots were used. As it is shown on Table 4, the data acquisition by the SPAD chlorophyll meter and Plant Sap were performed on different dates. In order to identify the relationship between the two, first measurements which were acquired by the two methods in a small day's difference were selected. After selecting the measurement values on those dates, the regression model was fitted by using the SPAD reading values as an explanatory variable and the Plant Sap values as a response variable.

In order to investigate the effects of temporal, spatial and different fertilization level on the relationship between SPAD and Plant Sap values, the model was refitted using these variables (location, time and fertilization level) as an additional explanatory variables. A stepwise regression analysis was conducted to identify which of the explanatory variables have a significant contribution for the relationship. The identified relationships between the two, using the univariate and multivariate regression model are presented in the results section of this report.

The relationships between LAI from the Plant Canopy Analyzer (LAI-2000) and LAI from Mijnakker (LAI_MJ) were also identified using the same methodology. Before fitting the model, LAI values from the Mijnakker LAI for each of the plots were clipped out. The LAI values from both sources were averaged per plot. The Univariate regression model was fitted using the LAI-2000 as an explanatory variable and LAI_MJ as a response variable.

The relationships between chlorophyll content from SPAD readings and N top of leaf from Mijnakker (MJ_N) were also identified using the same methodology.

3.3.3.2 Relationships between similar vegetation indices from different sensors

The common VI's from different sensors were calculated using the crop reflectance data acquired using the specific sensor and the possible relationship was identified. The NDVI was the common VI available from GreenSeeker, Cropscan and Mijnakker sensors. The measurement dates which were relatively close to all sensors were selected and averaged NDVI values for each of the plots were prepared. A regression model was fitted on NDVI values of the selected dates.

The WDVI and RVI were the other vegetation indices which were common for the Cropscan and GreenSeeker sensors. The relationship between WDVI from Cropscan and GreenSeeker was also identified by fitting regression models. During this process, measurements taken with small day's difference were selected and used to fit the regression model. The relationship between RVI from Cropscan and GreenSeeker was also identified using the same methodology.

3.3.3.3 Relationships between vegetation indices and crop chlorophyll content

To investigate the most robust vegetation index which can detect the N status of the potato crop over the growing season, the possible relationship between vegetation indices with the chlorophyll content from SPAD measurements was investigated. A range of well-known chlorophyll indices which are more applicable to the context of precision agriculture based on recommendations from (Haboudane, Miller et al. 2002) and (Clevers and Kooistra 2011) were calculated using the standard formulas as presented in Table 1. Regression models were fitted to determine the best fit function between the chlorophyll indices derived from Cropscan measurement and chlorophyll content from SPAD measurements.

The Goodness of fit of the models to the data were appraised based on the most commonly used model diagnostic plots as recommended by (Crawley 2007). Diagnostic of the model was done to make sure that the two most important assumptions i.e. constancy of variance and normality of the error were satisfied before doing the regression model. The plots used for model diagnosis were; a plot of residuals against fitted values, a scale-location plot of residuals against fitted values, a normal QQ plot and a plot of Cook's distances versus row labels. The detailed description about each of the plots is presented on section 4.1 (Fig.9). The results of these four diagnostic plots were used to determine which regression model can be used to fit the data very well. After checking the goodness of fit of the model to the data the next step was selecting the most robust VI based on the R^2 and RMSE values. Among the indices, the one with the highest R^2 and lowest

Root Mean Square Error (RMSE) was considered as the most robust VI for estimating the N status of the potato crop over the growing season.

3.3.4 Time series similarity measures

To investigate if different treatments applied on the plots over the growing season result in a significantly different temporal profile, the similarity between the time profiles from different plots was monitored. It was performed using the most commonly used time series similarity measures. For the purpose of this report similarity measures are represented by the letter D. The Ds' were selected based on the recommendation by (Lhermitte, Verbesselt et al. 2011). Since the D measures were performed using original time series data of the identified potential VI, D measures which work on original time series data were selected. The selected D measures were distance measures and measures based on correlation measures. From the distance measures, the most commonly used distance measures in classification or change detection approaches (Lhermitte, Verbesselt et al. 2011) were selected: namely Euclidean distance (D_E) and Manhattan distance (D_{Man}) measures. Both the Euclidean and Manhattan distance measures are derived from Minkowski distance(Tippett, DelSole et al. 2008). As Lhermitte (2011) described, the Minkowski distance between two individual time series collected in time **t** for pixels (plots) **p** and **q** respectively, is given by:

$$D_{Mink} = \left(\sum_{t=1}^{N} |f_t^p - f_t^q|^r \right)^{\frac{1}{r}} \quad \textbf{(1)}$$

Where f_t^p is the **fp (t)** time series value at moment ***t*** and f_t^q is the **fq (t)** time series value at moment ***t***. **N** is the number of samples in the time series and ***r*** is a user defined integer. When r = 1 equation (1) defines the Manhattan distance (D_{Man}) and when r=2 the equation defines the Euclidean distance (D_E).

By using equation (1) both the Euclidean distance and Manhattan distances between the reference plot (plot F) and the rest of the plots were calculated. For each of the plots, the values of the selected VI at a specific time were used to measure the distance difference between the two time series. For example, first date measurement of the VI from both the reference plot and other plots (e.g. plot A) were used to measure the difference between the two time series on the first iteration. For the second iteration, measurements from second date together with the first date measurement were used to calculate the difference. The distance differences between the two time series over the growing season were calculated by considering the VI values at each date of measurement. To summarize, the distance difference between the two plots at moment **t** was done by considering all the measurements at moment **t** and before moment **t** except for the case of the first date measurement. For the first date only the first date measurement values were used to calculate the distance difference.

The other similarity measure used was the Root Mean Square Distance measure (RMSD). It is defined by the formula:

$$RMSD = \sqrt{\frac{\sum_{t=0}^{N-1} (f_t^p - f_t^q)^2}{N^2}}. \qquad 2)$$

Where f_t^p and f_t^q are the time series values at moment **t. N** is the length of the time series.

Like the Minkowski distance measures, RMSD measures the distance between two points. However, it measures the distance between corresponding observations that are not missing. In such a way the RMSD quantify the straight line inter distance between points in a multi temporal space (Lhermitte, Verbesselt et al. 2010). Low values in RMSD means there is high temporal similarity between the points under similarity comparison. The RMSD between the reference plot F and the rest of the plots was calculated using equation (2). The procedures followed were the same as the Euclidean and Manhattan distance measures.

The other similarity measure considered for this study was based on correlation measures. The best known correlation measure between two time series is the Pearson's correlation coefficient (D_{cc}) (Liao 2005). It is a measure of the degree of linear relationship between the two time series and is defined by using the formula:

$$D_{CC} = \frac{\sum_{t=0}^{N-1}\left[\left(f_t^p - \bar{f}^p\right) * \left(f_{t-s}^q - \bar{f}^q\right)\right]}{\sqrt{\sum_{t=0}^{N-1}\left(f_t^p - \bar{f}^p\right)^2} * \sqrt{\sum_{t=0}^{N-1}\left(f_{t-s}^q - \bar{f}^q\right)^2}} \qquad (3)$$

Where f_t^p and f_t^q are the time series values at moment **t**, f^p and f^q are the means of the corresponding time series, **s** is the lag between both time series, and **N** is the length of the time series.

As Lhermitte, 2011 described, when the D_{cc} is computed for S = 0, it estimates the time series similarity without time shift and this is the concept used in this study. The correlations between the two time series were calculated by using equation (3). For each of the plots, the values of the selected VI at a specific time were used to measure the correlation between the two time series For example, the first date measurement of the VI from both the reference plot and other plot (e.g. plot B) were used to determine the correlation of the two time series on the first iteration. For the second iteration, measurements from second date together with the first date measurement were used to calculate the correlation. During the process, the correlation coefficient was recorded as the value for that specific moment of the growing season. The correlation between the two time series over the growing season were calculated by considering the VI measurement values at each date of measurement. To summarize, the correlation of the two plots at moment **t** was done by considering all the measurements at moment **t** and before moment **t** and the values were recorded for each specific measurement date except for the case of the first date measurement. For the first date only the first date measurement values were used to calculate the correlation.

3.3.5 Determining threshold values using quality control charts

After calculating the distance difference and correlation between the two time series over the growing season, the next step was determining threshold values at each specific moment of the growing season. The reason why we need to define the threshold values was to check if it is always close to zero for the case of distance measures and close to 1 in the case of correlation measures. When two time series are similar, the distance between the two is 0 (Herrmann, Pimstein et al. 2011) and when there is an increasing linear relationship between the two time series, the correlation coefficient is close to 1 (Lhermitte, Verbesselt et al. 2011). By using these ideas, the objective is to keep the distance difference between the two time series close to zero or the correlation measures close to 1. Monitoring the distance or correlation differences will help the modern farmer to control the N status of the plot under measurement during a specific moment in the growing season. After determining the distance or correlation between the two time series at a specific moment of the growing stage, the next most important thing is to check if the calculated value is within the acceptable threshold range or not. To determine threshold values, the concept of quality control charts was applied. Detail description about the concept of quality control charts is presented in the next section of this report.

Concept of quality control charts

This concept of quality control charts is adapted from Moameni and Zinck, (1997) who used the concept of quality control charts for soil quality assessment. The concept of stastical quality control has originated from industrial activities (Massart, Vandeginste et al. 1997). The main reason for conducting a stastical process control is to find observations which exhibit a pattern significantly different from those of other observations. Once those observations with unique behavior are found, a study is conducted to investigate the cause of that deviation from the normal behavior (Moameni and Zinck 1997). During the process of the investigation using statistical quality control, the first step is flowcharting the process monitored (Moameni and Zinck 1997). The construction of control charts is based upon stastical principles (Massart, Vandeginste et al. 1997). The centerline in Figure 3 could represent an estimate of the mean (μ), standard deviation (σX) or other statistical data (Mohammadi and Roohi 2002). The curve to the left of the vertical axis should be viewed relative to the upper and lower control limits. There is a very small area under the curve below the lower control limit (LCL) and also above the upper control limit (UCL) (Moameni and Zinck 1997). Areas under a curve for a continuous distribution represent probabilities (Massart, Vandeginste et al. 1997). Since a process or a property is out of statistical control when a value is outside the control limits, quality control requires that the probability for such an event to occur be small (Moameni and Zinck 1997). If the objective is to control the process or property mean, μ, and the limits are given as μ±3σX , the total probability outside the limits would be 0.0027 (0.00135 on each side) (Mohammadi and Roohi 2002). In the case of normal distribution and known σX, the chance would be 27 in 10,000 of observing a value for the sample mean, X, outside the limits when the population mean is μ. It is, however, unlikely that the distribution will be exactly normal or that μ and σX will be known (Moameni and Zinck 1997). Therefore, 3-sigma limits are more appropriate than probability limits, since the exact probabilities are unknown (Moameni and Zinck 1997). As already mentioned, there are several possible alternatives for constructing statistical quality control charts. The quality control charts can be made either based on the mean, standard deviation or range of the data (Massart, Vandeginste et al. 1997). In this thesis research statistical quality control based on the mean (X chart) was selected and used.

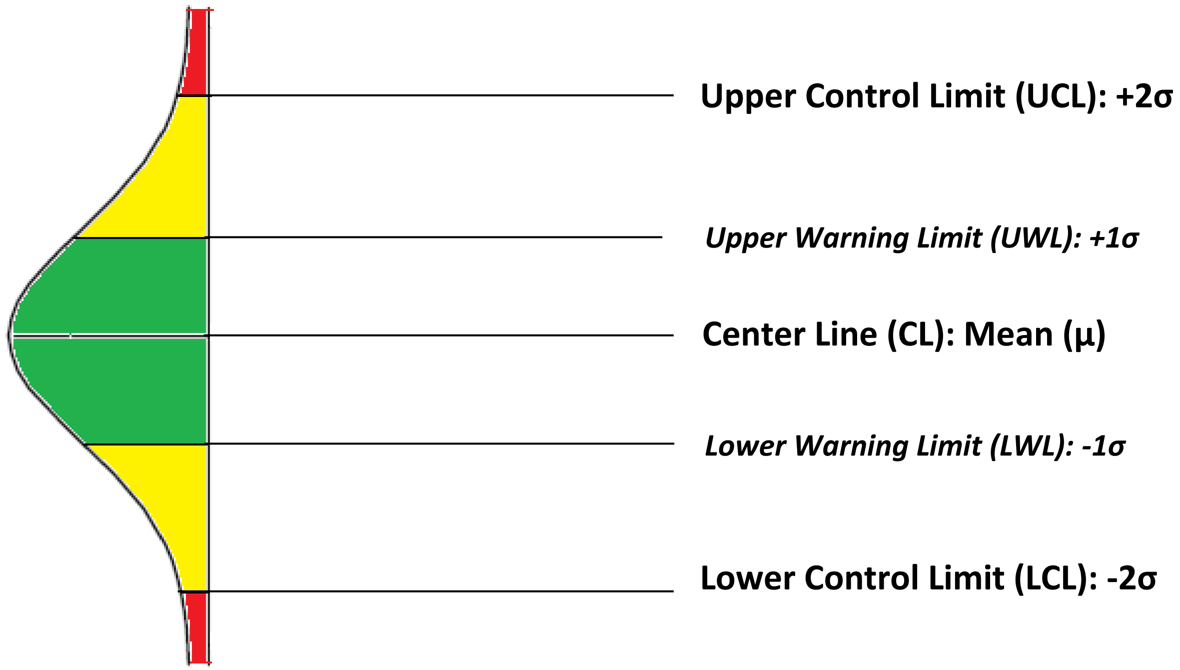


Figure 3: Basic form of a control chart after (Ryan 1989). The green area shows values which are 1 S.D from the mean, the yellow area shows 2 S.D from the mean and the red area shows 3 S.D from the mean. S.D means standard deviation (σ).

By adapting the concept of the quality control charts and using values from distance similarity measures, the qcc quality control package from R stastical software package was used to check the status of each of the plots at each specific time of the growing season. The status of a specific plot at a specific measurement date was checked by using different values of sigma (Standard deviation). When a plot is within ± 1σ from the mean, a green label is assigned to the plot. When a plot is within ± 2σ i.e. when it is within the warning limits, a yellow label is assigned to the plot. When it is beyond ± 2σ range i.e. when it is above the upper control limits; it is out of control and a red label is assigned to the plot.

The time series similarity data from the first two dates of measurements i.e. from May 30 and June 6 were used as a calibration datasets and the UCL and LCL were calculated using the data from these two dates. The status of a specific plot on the rest of the dates was assessed based on the calibration data. The data from these two dates were selected because there was no data from previous growing seasons and during these periods of the current growing season, the distance difference between the reference plot and the rest of the plots were relatively closer on these dates than on the other dates.

4. Results

4.1 Relationship between Plant Sap and SPAD

Figure 5 shows the relationship between Plant Sap and SPAD based on the amount of initial organic N fertilizer applied on the different experimental plots. For the plots with an initial fertilization of 0 kg of organic N h^{-1} both SPAD and Plant Sap measurements have the smallest relationship values throughout the growing season. The relationship between the two as determined from the coefficient of simple determination (R^2 = 0.1772) is very week. For the plots with an initial fertilization of 23 kg of organic N h^{-1} the measurements for both SPAD and Plant Sap increases directly as the measurement of one increases. The relationship between the two (R^2 = 0.7881, p < 3.259e-09) is strong compared to the other initial fertilization levels. For plots with an initial fertilization of 34 kg of organic N h^{-1}, the relationship between the two is still weak, it is with an R^2 of 0.3006. The relationship between the two is worse for the plots with an initial fertilization of 46 kg of organic N h^{-1}. The R^2 is 0.000755. For plots with 46 kg h^{-1}, Plant Sap values are saturated while values of SPAD were increasing and this makes the relationship between the two to be worse compared to other initial fertilization levels. The relationship based on the initial fertilization amounts revealed as there is no relationship between the two at low and high N levels. The relationship is even worse for high initial N fertilization level.

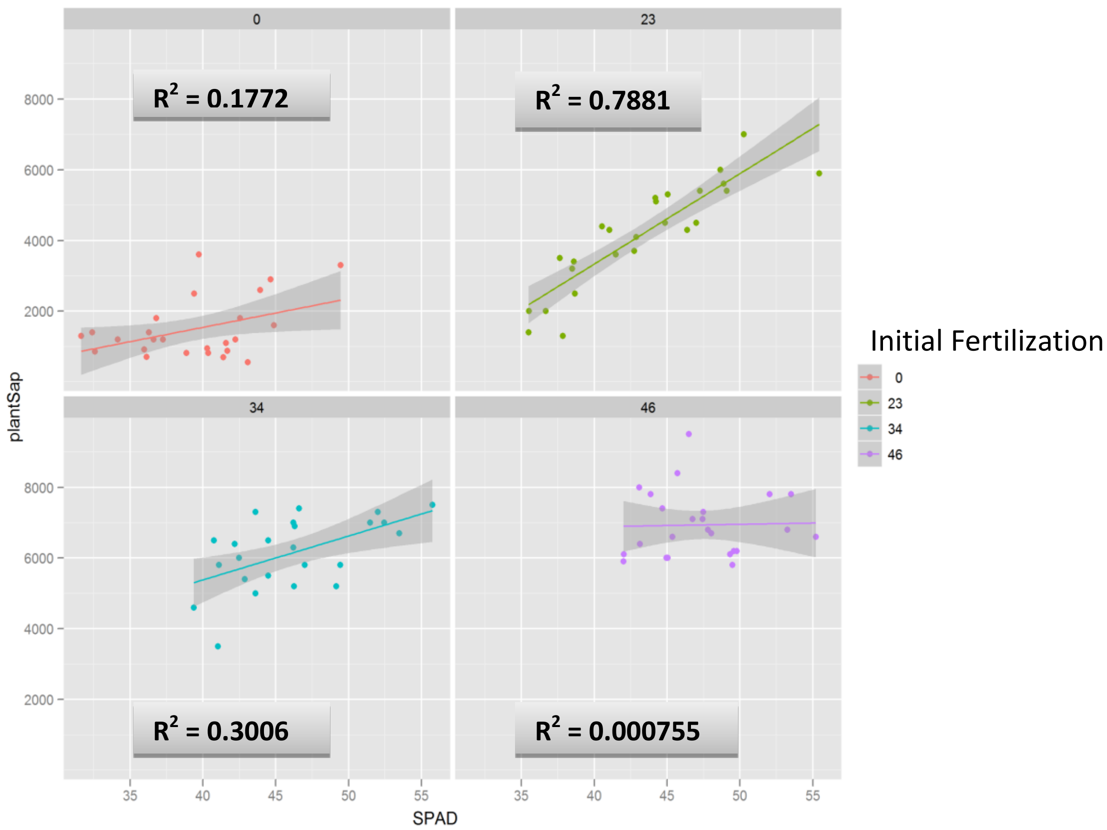


Figure 5: Relationship between Plant Sap and SPAD based on the amount of initial fertilizer applied

Figure 6 shows the relationship between SPAD and Plant Sap based on the specific dates when the measurements were taken. In general the relationship between the two is significant ($p < 0.05$) in all the dates which are considered for determining the relationship. Early in the growing season both SPAD and Plant Sap measurements have the highest values whereas late in the growing season both have the smallest values. The relationship between the two is significantly strong during the second date of measurement i.e. June 6. The overall relationship as it can be seen from Table 6 is very significant over the whole growing season.

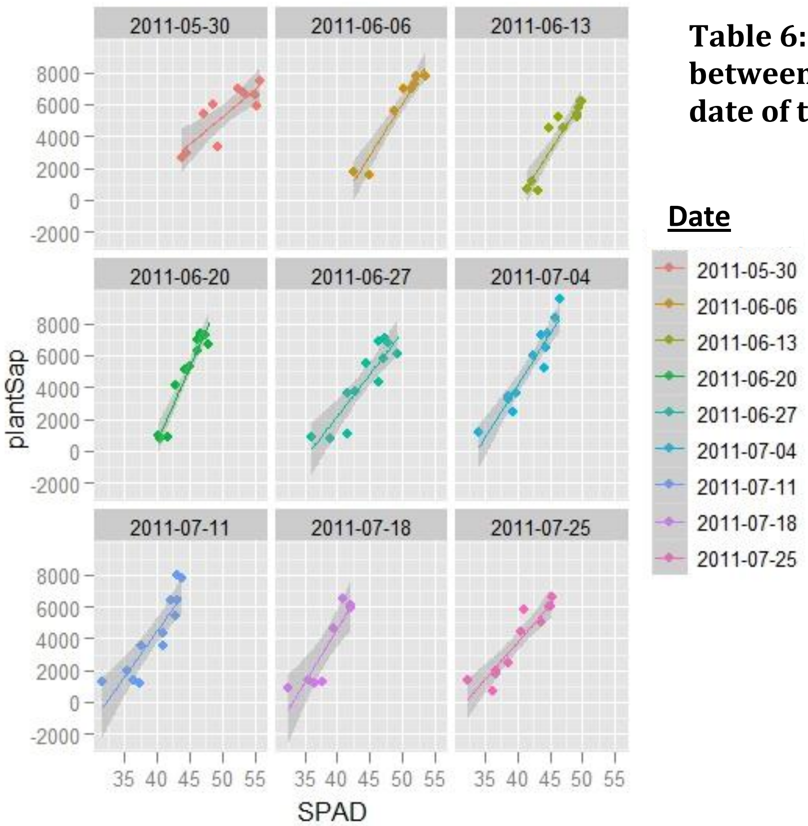


Figure 6: Relationship between SPAD and Plant Sap based on the specific dates of measurements.

Table 6: R^2 and *p* values for the relationship between Plant Sap and SPAD at each specific date of the growing season

Date	R^2	*P* value
May 30	0.7044	1.234e-03
June 6	**0.9418**	**6.29e-05**
June 13	0.8798	6.523e-06
June 20	0.9273	5.15e-07
June 27	0.8064	7.308e-05
July 4	0.8925	3.702e-06
July 11	0.7861	1.215e-04
July 18	0.8096	2.332e-03
July 25	0.8654	3.298e-05

Figure 7 shows the relationship between SPAD and Plant Sap based on the types of treatments applied on the experimental plots. The relationship is relatively stronger for the plots which have a “CL” treatments type with R^2 of 0.6511 ($P < 0.05$) and it is weak for plots which have the “MB” type of treatment. From Table 3 one can see that plots which have “MB” type of treatment also have high levels of total N fertilization over the growing season.

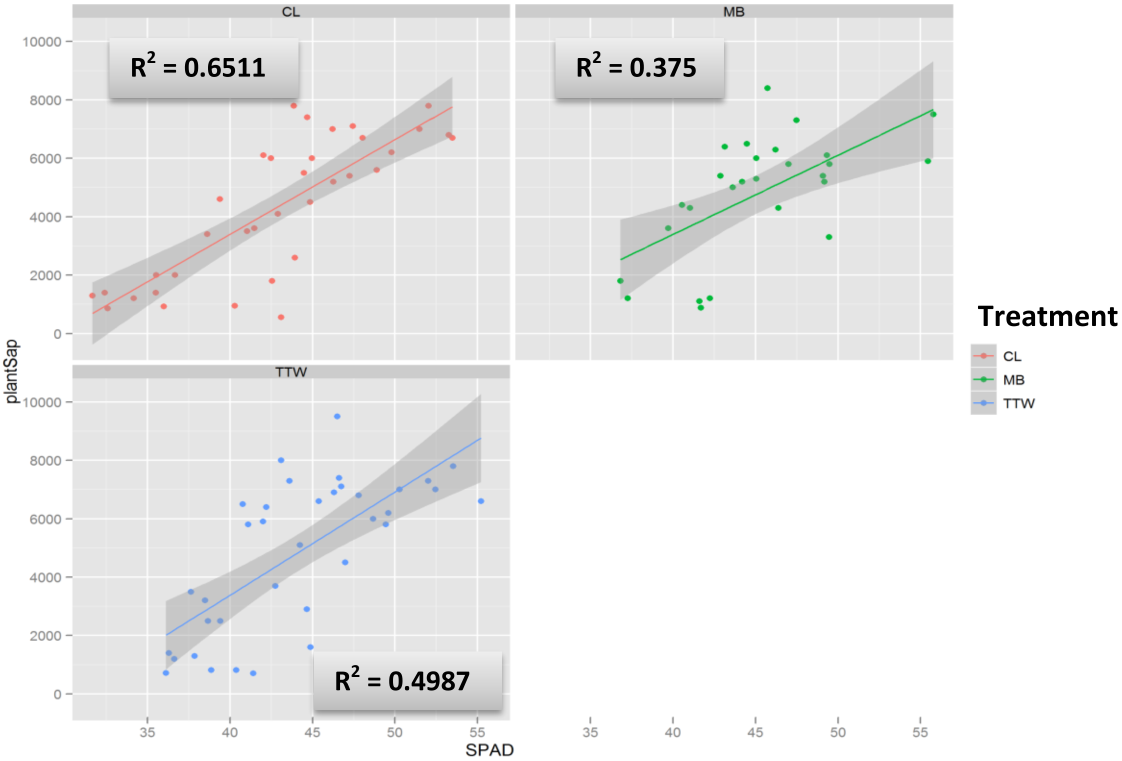


Figure 7: Relationship between SPAD and Plant Sap based on treatment types

Figure 8 shows the relationship between Plant Sap and SPAD values when all the data are bulked. It shows as there is a moderate significant (p < 2.2e-16) relationship between the chlorophyll content from SPAD and nitrate concentration from Plant Sap measurements. The coefficient of determination (R^2) is 0.5256.

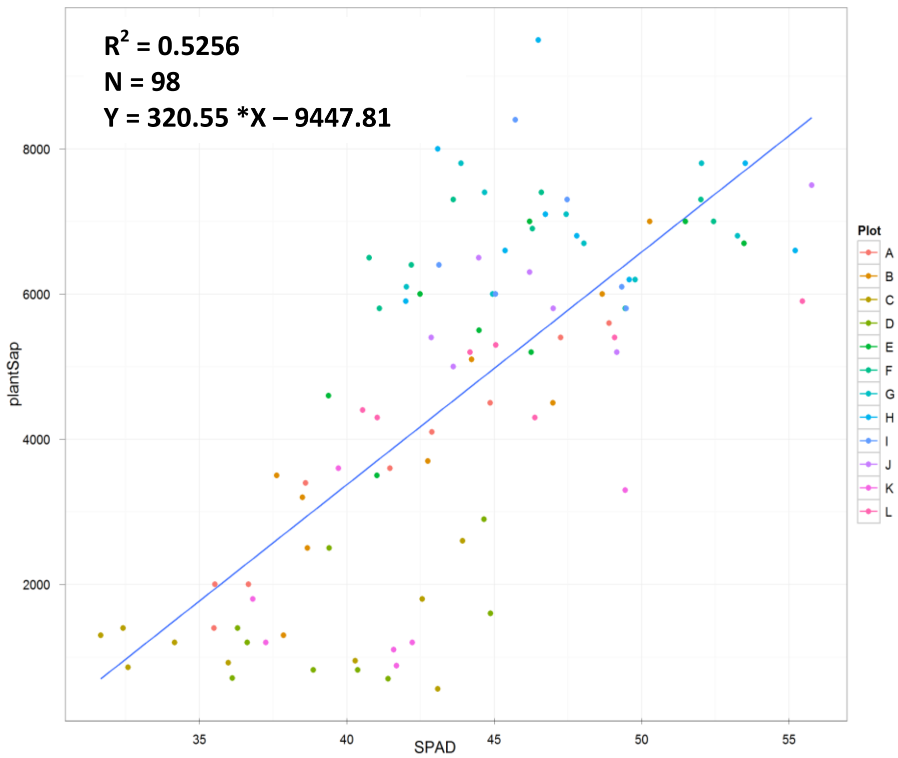


Figure 8: Relationship between SPAD and Plant Sap when all measurements are bulked together.

In order to investigate the effects of temporal, spatial and different fertilization levels on the relationship between SPAD and Plant Sap values, the model was refitted using these variables (location, time and fertilization level) as an additional explanatory variables. The automatic model simplification function ''step'' was used to identify the most significant explanatory variables. The result of the stepwise regression analysis shows as the R^2 improves. The R^2 is 0.8673 ($p < 2.2e-16$) after fitting the multivariate regression model. The variables SPAD and total fertilization level are found the significant explanatory variables ($p < 0.05$). This means, the relationship between SPAD and Plant Sap is well explained by considering the total fertilization applied to the plots over the growing season.

Figure 9 shows the studied model diagnostic plots when the regression model was used to determine the relationship between two variables. These diagnostic plots are used to check the goodness of fit of the model to the data. The top left graph called "**Residuals vs. Fitted values**". It is used to check if the variance is constant for the whole fitted values. It is clearly visible as the variance doesn't have any pattern over the fitted values. The top right graph called "**Normal Q-Q**" and it tells if the errors are normally distributed. It is a straight line and it shows as the errors are normally distributed. The bottom left graph is called "**Scale-Location Graph**", it tells if there is a problem, such as variance increasing with the mean, then the points would be distributed inside a triangular shape with the scattering of the residuals increases as the fitted values increase. In this case, the scatter of the residuals doesn't increase when the fitted values increase. The bottom right graph called "**Residuals VS Leverage**". The point of this graph is to highlight those y values that have the highest effect on the parameter estimates and check for outliers based on the Cook's distance. As a rule of thumb, points with Cook's Distance greater than 1 should get an attention. In this case, since the Cook's Distance is less than 1 for all the points, it shows as there are no influential outliers. The values of R^2 and the model diagnostic plots show as the goodness of fit of the model to determine the relationship between SPAD and Plant Sap is improved by considering total fertilization level as an additional explanatory variable.

Figures 10 shows concentration of nitrate in the Plant Sap recovered from the petioles of the uppermost fully grown potato leaves as a function of time (at each measurement date) for all the experimental plots and Figure 11 shows chlorophyll content of the uppermost fully grown potato leaves, measured with the SPAD chlorophyll meter (SPAD values) as a function of time (at each measurement date) for all the experimental plots.

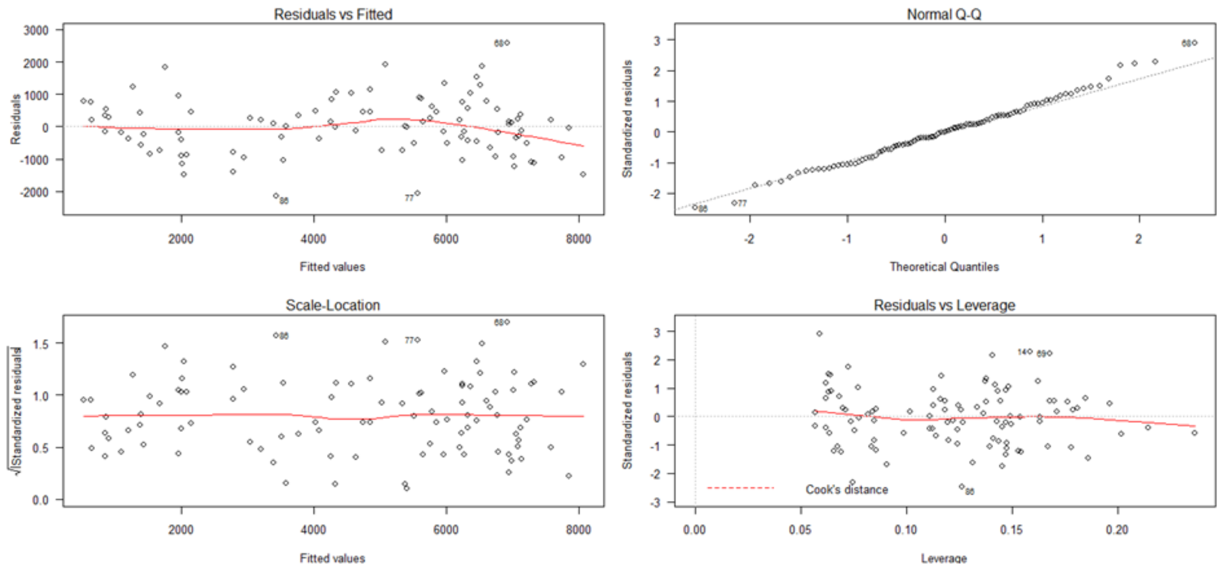


Figure 9: Model diagnostic plots to determine the goodness of fit of the model to the data.

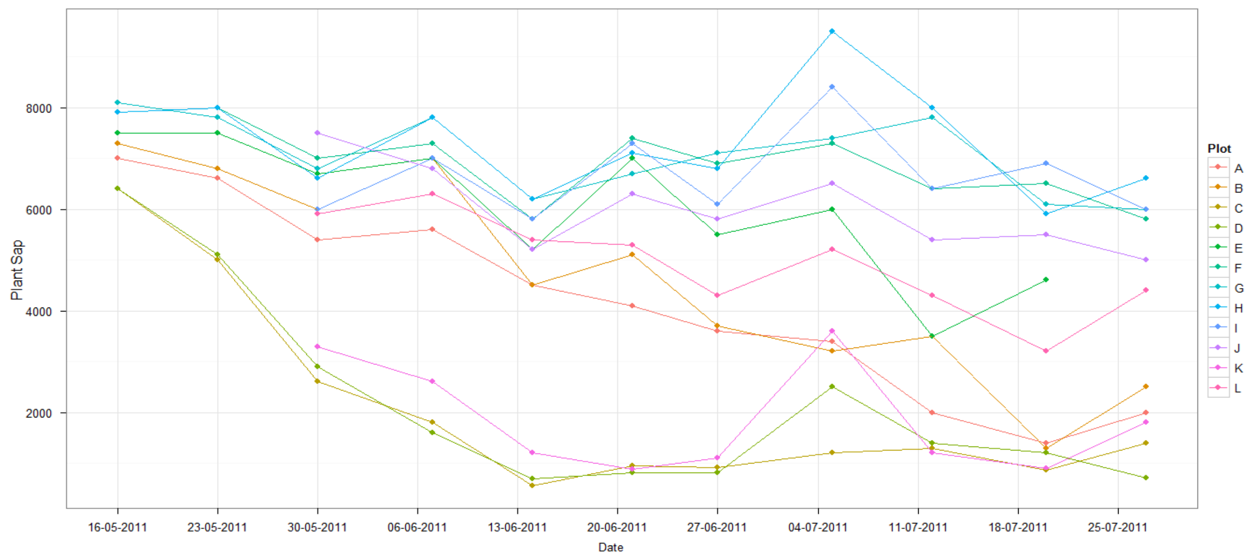


Figure 10: Concentration of nitrate in the Plant Sap recovered from the petioles of the uppermost fully grown potato leaves as a function of time (at each measurement date) for all the experimental plots.

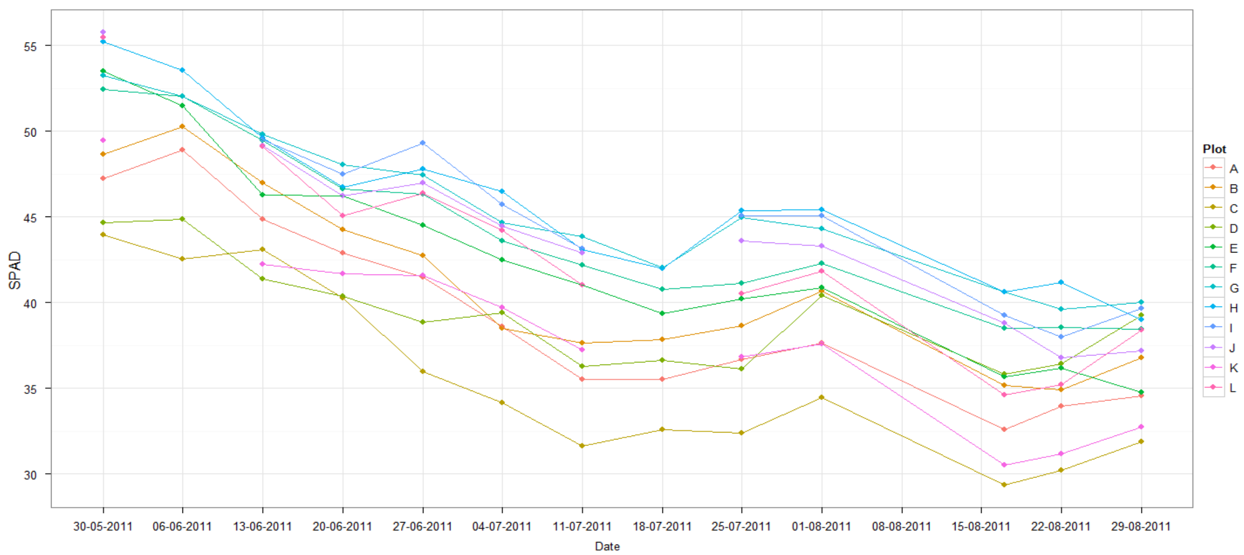


Figure 11: Chlorophyll content of the uppermost fully grown potato leaves, measured with the SPAD chlorophyll meter (SPAD values) as a function of time (at each measurement date) for all the experimental plots.

4.2 Relationship between LAI_2000 and LAI Mijnakker

Leaf Area Index (LAI) was defined by Watson (1947) as the total one-sided area of leaf tissue per unit ground surface. LAI values are dimensionless and typically range from 0, for bare soil to more than 7 for dense vegetation canopies. LAI is measured using both direct and indirect methods. Direct methods are extremely labor intensive and are mainly done by taking samples after destructing the plant. Indirect methods include usage of remote sensing and ground based optical instruments.

Figure 12 shows the relationship between LAI acquired using a Plant Canopy Analyzer (LAI-2000) and LAI derived from Mijnakker remote sensing images. As expected, LAI-2000 measurements have higher LAI values than Mijnakker. The LAI values range from 1.5 to 7.5 for the case of LAI-2000 and it is from 0.1 to 4.5 for the case of Mijnakker. It clearly shows there is a relationship between the two on the selected dates. Both methods have a smaller value late in the growing season. The readings from LAI-2000 have larger values compared to readings from Mijnakker LAI. The reason for this is the pixel size of the Mijnakker images is significantly bigger than that of the view of the LAI-2000 and this might create an opportunity for soil reflectance to be also considered during deriving LAI values from Mijnakker remote sensing images. The LAI values from both measurements are relatively smaller early in the growing season. For example during May 30 and June 6 the values are smaller than June 27. The reason for this is, early in the growing season the crop has a small vegetative cover and structure than in the middle of the growing season. However, during August 17, values from both measurements are smaller and this might be because since the crop was almost at its end of the growing season, most of the leaves were falling and the crop was losing its vertical structure. During early in the growing season the R^2 is 0.8067 and it is 0.6058 late in the growing season. The overall relationship between the two during the whole growing season as determined by the R^2 is 0.6888 (p = 3.054e-16).

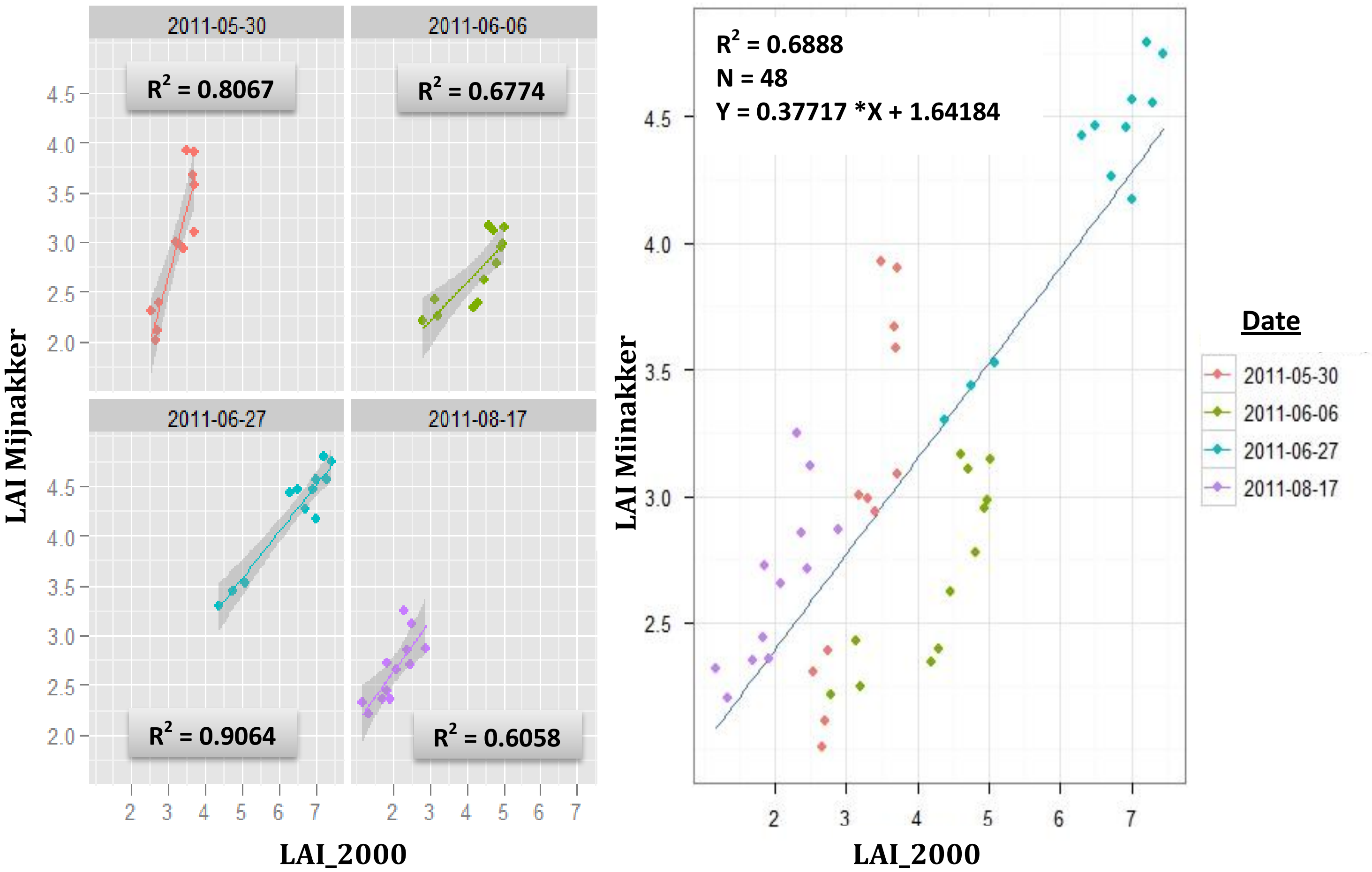


Figure 12: Relationship between LAI from LAI_2000 and LAI Mijnakker on specific dates (left) and when the data are bulked together (right).

4.3 Relationship between Mijnakker N top of the leaf and SPAD/PlantSap

The relationship between Mijnakker N top of the leaf and SPAD chlorophyll content values is presented on Appendix IV. It clearly shows there is a relationship between the chlorophyll, which is a surrogate for N from the SPAD meter and the N derived from top of the leaf. Even though there is no a supportive document which describes how the Mijnakker N top of the leaf is derived from crop reflectance data, its relationship with SPAD readings is better than the relationship between SPAD and Plant Sap (Figure 8). Early in the growing season, SPAD measurements have highest values whereas Mijnakker N from top of the leaf has smaller values. The reason for this is SPAD measures chlorophyll content at leaf level and there is no any other external factor which might influence the readings but in the case of N derived from remote sensing images, other extraneous effects related to canopy structure, illumination conditions and back ground soil reflectance contributes a significant amount (Haboudane, Tremblay et al. 2008). Especially early in the growing season since the crop canopy doesn't cover the whole surface, the soil reflectance has a major contribution for the lowest values from Mijnakker. This causes the difference between the two during early in the growing season.

Although there is a difference on the values of the readings, the relationship between the two is strong early in the growing season than late in the growing season. The overall relationship between the two over the growing season as determined using the simple determination coefficient (R^2) is 0.6744. The relationship between Plant Sap and N top of the leaf from Mijnakker is very weak compared to the relationship between SPAD and N top of the leaf. The R^2 is 0.00884.

4.4 Relationship between vegetation indices from different sensors

Figure 13 shows the relationship between NDVI from Mijnakker and NDVI from Cropscan measurements. As expected, Cropscan measurements have higher NDVI values than Mijnakker. The NDVI values range from 0.7 to 0.9 for the case of Cropscan and it is from 0.4 to 0.75 for the case of Mijnakker. As it can be seen from the graph on the left (Figure 13), the relationship between the two early in the growing season is relatively weaker than in the middle of the growing season. The reason for this is the potato crops were at their early growing stages in May 30 and June 6, and more soil surface exposure than June 27. Bare soils usually generate very small positive NDVI, which is much lower than the NDVI of the potato crop; that could be the reason for lower NDVI values from remote sensing image (Mijnakker) than ground measurement (Cropscan) on May 30 and June. The additional soil reflectance is mainly caused by the pixel size of Mijnakker; which is 10 m. This means, besides the reflectance of the crop, background reflectance from soil surface also plays greater role in the total reflectance of the remote sensing (Mijnakker). During early in the growing season reflectance of the soil between the potato crop and also from the path might have contributed for the background reflectance. For the plots which are on the border of the parcel, reflectance from water ditches and from other objects on the edges of the plots could also be the reason for the background reflectance effect. The overall relationship between the two is significant with R^2 of 0.7659 (p = 4.164e-16).

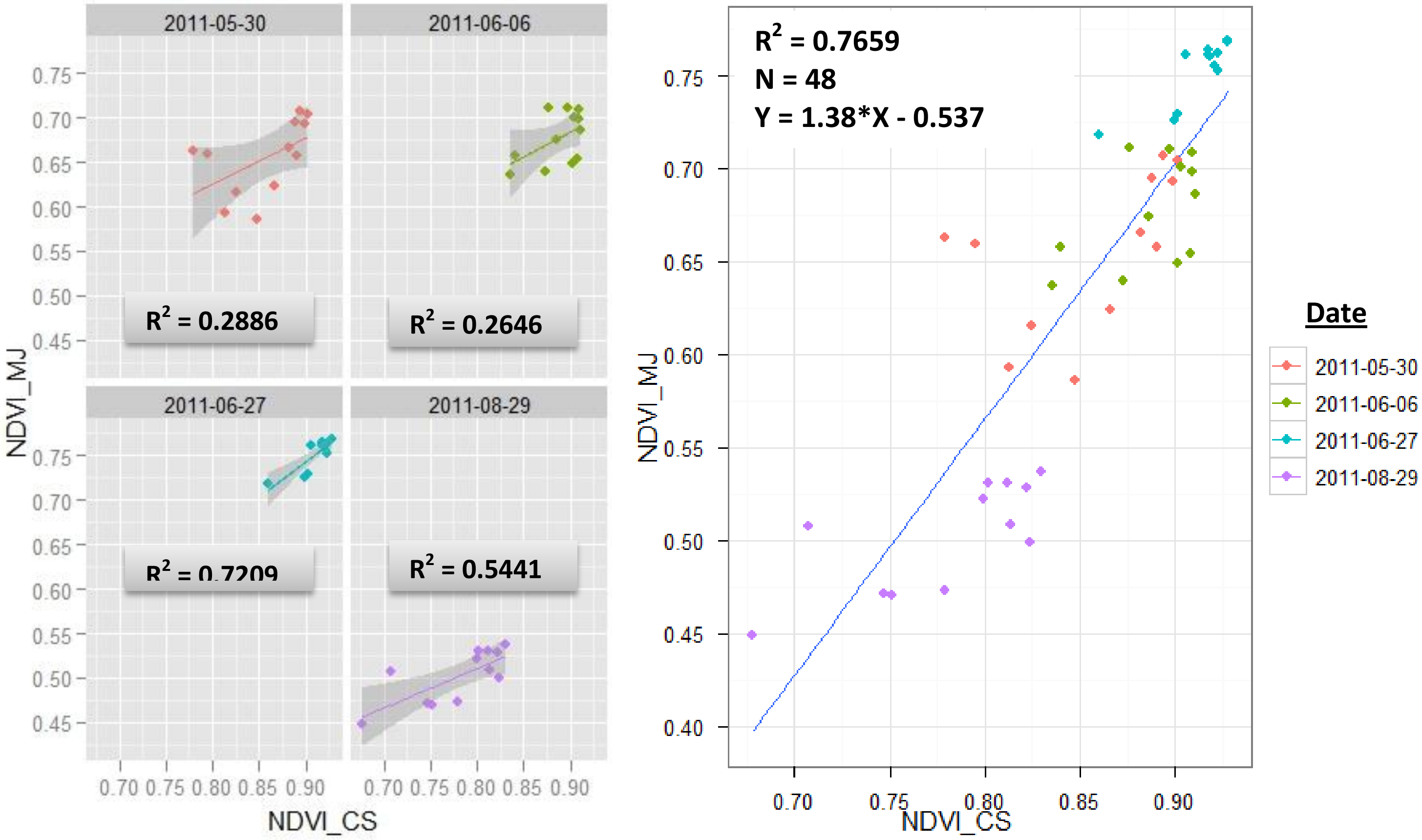


Figure 13: Relationship between NDVI from Mijnakker and Cropscan values on specific dates (left) and when the data are bulked together (right). Where MJ means Mijnakker and CS means Cropscan.

Figure 14 shows the relationship between NDVI from Mijnakker and GreenSeeker. The NDVI value ranges from 0.3 to 0.8 for the case of GreenSeeker and it is 0.2 to 0.55 for Mijnakker. As expected, GreenSeeker measurements have higher NDVI values than Mijnakker. The relationship is determined by considering only two dates of measurements; May 3 and 25. The relationship between the two on the specific dates is weak especially on May 25. The relationship between the two when the data from the two dates is fitted to the regression model, results a significant ($p <$ 2.2e-16) strong relationship (R^2 = 0.9831). However, the relationship is based on only two point clouds and it doesn't tell as there is a strong relationship between the two over the growing season. The growth of the plants during this time is explaining the variation of the NDVI from the two sensors. The NDVI was small during early in the growing season and higher in the middle of the growing season. Even though the R^2 tells as the relation between the two is strong based on the two dates, the model diagnostic plots for the goodness of fit of the model show as the variance is not constant over the fitted values and this indicates performing the relationship analysis using only the two dates data is not enough to show the strong relationship between the NDVI from the two sensors. It only tells as there is a strong relationship only on the selected dates.

The variation in the values of the NDVI could be because of the pixel size difference between the two sensors. Like the Cropscan measurements, the effect of background soil reflectance is minimized when the NDVI was calculated from the GreenSeeker sensor whereas in the case of the NDVI from Mijnakker the size of the pixel allows background soil reflectance to contribute for the small NDVI values.

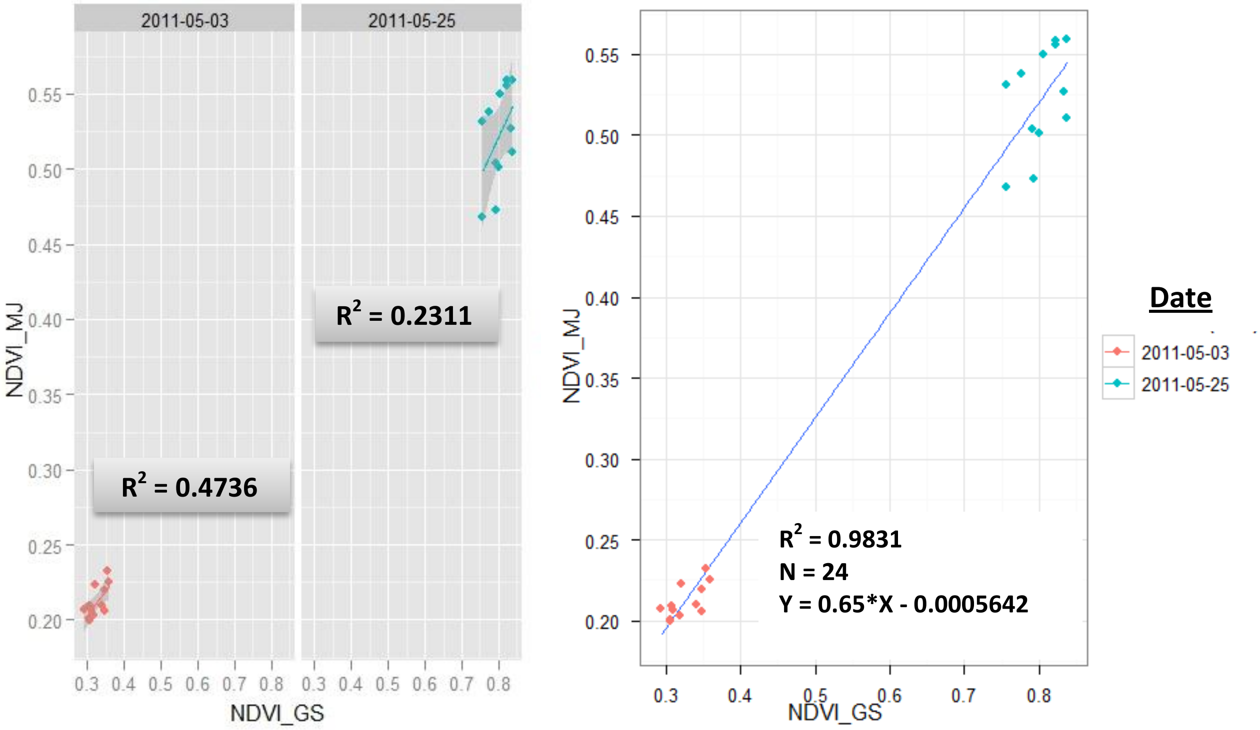


Figure 14: Relationship between NDVI from Mijnakker and GreenSeeker values on specific dates (left) and when the data is bulked together (right). Where MJ means Mijnakker and GS means GreenSeeker.

The relationship between RVI from GreenSeeker and Cropscan is presented on Appendix V. The RVI value ranges from 7.5 to 12 for the case of GreenSeeker and it is 8 to 22 for Cropscan. Cropscan measurements have higher RVI values than GreenSeeker. The relationship is determined using data only from two dates of measurements. The overall relationship between the two as explained by the R^2 is not very strong. Even though both sensors have the same pixel size (0.6m), the difference between the dates of acquisition might be the reason for this variation. The measurements using GreenSeeker were acquired on May 26 and June 11, while the measurements using Cropscan were acquired on May 30 and June 13. There is a difference of four and two days between the first date and second dates respectively. Depending on the type of management applied, there might be a difference on the crop growth within four days interval and this might contribute for the weak RVI relationship between the two sensors. Besides, reflectance values from NIR and RED used to calculate RVI values could have also contributed for the weak relationship. The NIR and RED reflectance values used to derive the RVI from GreenSeeker are averaged results from the six sensors mounted on the tractor spray beam, while in the case of Cropscan only a single NIR (780 nm) and RED (670 nm) reflectance values were used to derive the RVI. The overall relationship between the RVI from GreenSeeker and Cropscan is significant (p = 1.846e-05) with R^2 of 0.5732.

The relationship between WDVI from GreenSeeker and Cropscan is presented on Appendix VI. Early in the growing season the WDVI from both sensors have smaller values whereas in the middle of the growing season the WDVI values from both the Cropscan and GreenSeeker are different. The Cropscan has higher WDVI values in the middle of the growing season while GreenSeeker has smaller WDVI values. This variation of the WDVI in the middle of the growing season has made the overall relationship (R^2 = 0.2971) to be weak.

4.5 Relationship between vegetation indices and crop chlorophyll content

One of the objectives of this study was to identify the most robust vegetation index which is capable of detecting the N status of the potato crop over the whole growing season. To identify this vegetation index, chlorophyll indices calculated from Cropscan crop reflectance data were plotted and regressed against chlorophyll content measured using SPAD instrument (Figure 15). From the figure we can see that indices NDRE, REP and $CI_{red\ edge}$ have a linear relationship with the chlorophyll content from SPAD measurements, i.e. their value increase when the chlorophyll content from SPAD increases. On the other hand, TCARI and TCARI\OSAVI have a nonlinear relationship with the chlorophyll content from SPAD measurements, i.e. they decrease when the chlorophyll content from SPAD measurement increases. The scatter around the regression line on the REP, NDRE, $CI_{red\ edge}$ and TCARI indices is larger than that of the TCARI/OSAVI. The other important information revealed in Figure 15 is the strength of the relationships between chlorophyll indices and chlorophyll content from SPAD measurements. The ratio index TCARI/OSAVI has the strongest relationship with the chlorophyll content from SPAD with R^2 of 0.6131 and RMSE of 3.713936. The $CI_{red\ edge}$ index which is based on the NIR and red-edge band (Gitelson, Gritz † et al. 2003) has the second strong relationship with the chlorophyll content with R^2 0f 0.5969 and RMSE of 3.79077. The REP and NDRE also have a moderate relationship with chlorophyll content with R^2 of 0.5831 and 0.4999 and RMSE of 3.863501 and 4.222285 respectively.

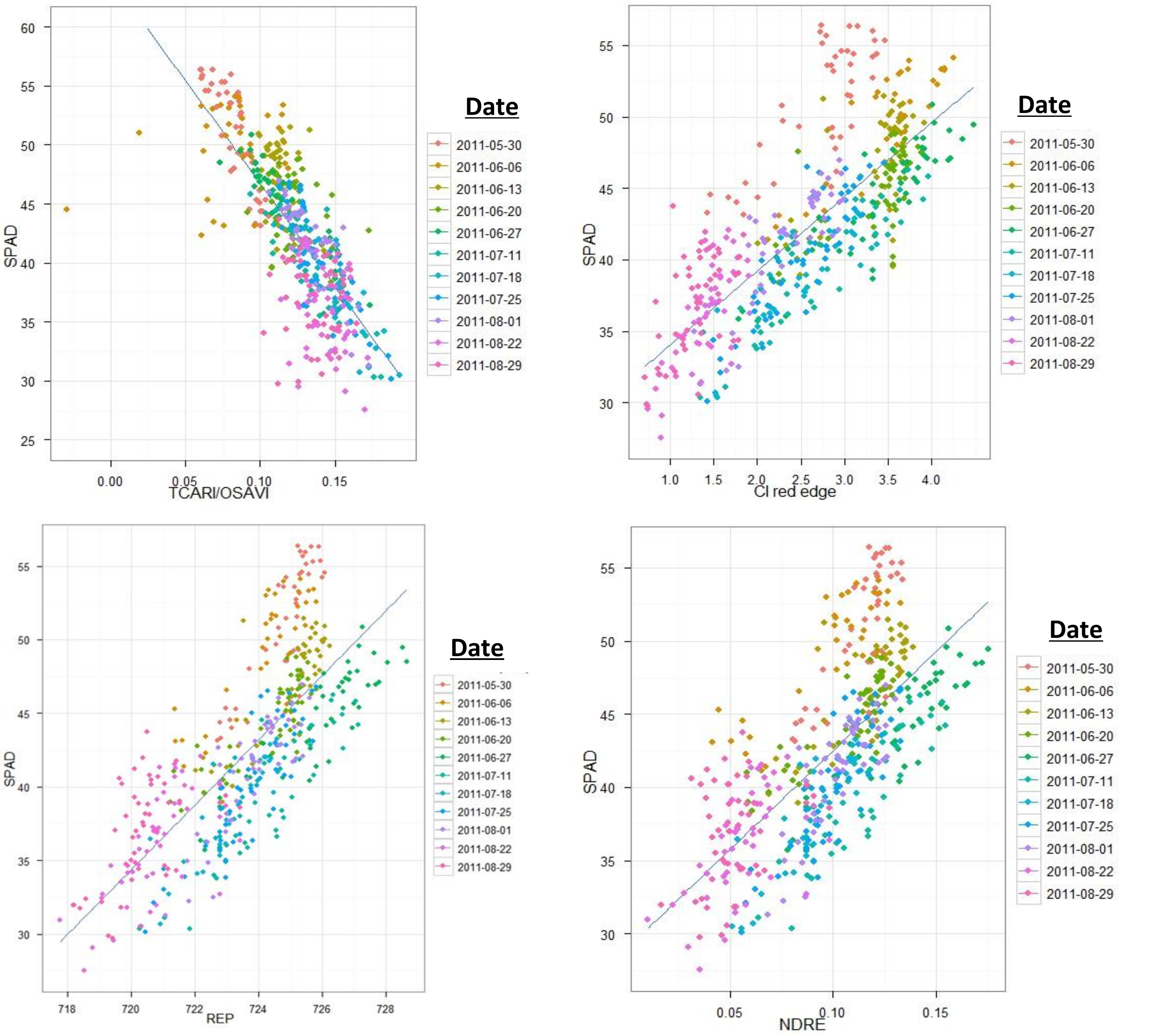


Figure 15: Relationship between chlorophyll indices and potato biophysical variable (Chlorophyll) obtained from Cropscan crop reflectance data and from SPAD measurements. Top left (TCARI/OSAVI), top right (CI $_{\text{red edge}}$), bottom right (REP) and bottom left (NDRE)

Table 7: Summary of R^2, RMSE and p-values between a chlorophyll index and chlorophyll content from SPAD measurements using all the observations.

Vegetation Index	R^2	RMSE	*P*- value
REP	0.5813	3.863501	< 2.2e-16
NDRE	0.4999	4.222285	< 2.2e-16
TCARI	0.1645	5.457425	< 2.2e-16
TCARI/OSAVI	0.6131	3.713936	< 2.2e-16
CI$_{\text{red edge}}$	0.5969	3.79077	< 2.2e-16

To address the issue of time, location, treatment types and fertilization levels on the relationship between chlorophyll indices and chlorophyll content from SPAD measurements, the relationship is determined by considering these variables.

4.5.1 Relationship between chlorophyll indices and SPAD chlorophyll content at a specific time of the growing season

The result of the relationship between chlorophyll indices and chlorophyll content at a specific moment of the growing season of the potato crop also revealed that the relationship between TCARI/OSAVI and chlorophyll content from SPAD measurements is significantly strong in the middle of the growing season, i.e. from June 27 until August 1 (Table 8). The relationship is relatively weak during the first three measurements of June (June 6, 13 and 20) and also during the last two acquisition dates (August 22 and August 29). In the case of the index $CI_{red\ edge}$ the relationship with chlorophyll content is strong over the growing season except on August 29 in which it is weak. Also for vegetation indices REP and NDRE the relationship is strong for all the acquisition dates except for the last two dates (August 22 and 29). For the vegetation index TCARI the relationship is relatively weak over the growing season especially during June and August. From Table 8 one can see that the strongest relationship with chlorophyll content when time is considered is still found with the index TCARI/OSAVI. The most striking observation which can also be made from Table 8 is; the relationship between all the chlorophyll indices and chlorophyll content from SPAD measurements is strong on June 27.

Table 8: Relationships between a chlorophyll index and chlorophyll content from SPAD measurements at a specific time of the growing season.

Date	TCARI/OSAVI	$CI_{red\ edge}$	REP	NDRE	TCARI
		Coefficient of determination (R^2)			
May 30	0.7371	0.588	0.6848	0.6046	0.2716
June 6	0.0004403	0.7404	0.7318	0.7058	0.01539
June 13	0.1572	0.4107	0.6746	0.6644	0.00169
June 20	0.124	0.4694	0.7253	0.7471	0.0068
June 27	0.8575	0.7967	0.8357	0.8253	0.6913
July 11	0.7457	0.7253	0.766	0.737	0.3899
July 18	0.7291	0.7044	0.734	0.7034	0.3139
July 25	0.7052	0.7962	0.7583	0.7258	0.3122
August 1	0.6168	0.7149	0.7235	0.6642	0.1649
August 22	0.1332	0.5692	0.4445	0.3457	0.0604
August 29	0.006871	0.2961	0.2319	0.08362	0.09868

4.5.2 Relationship between chlorophyll indices and SPAD chlorophyll content based on location

The relationship between chlorophyll indices and chlorophyll content from SPAD measurements based on location of the plots also revealed that the vegetation index TCARI/OSAVI has the strongest relationship with chlorophyll content. The significant relationship is found on plot J whereas the weakest relationship is found on plot C. For the index CI $_{red\ edge}$ the relationship with chlorophyll content is strong on plot A and it is weak on plot D. The indices REP and NDRE have their strongest relationship on plot I and their relationship is weak on plot D (Table 9). This result shows as the relationship between chlorophyll index and chlorophyll content can also be influenced by other environmental variables related with location like soil texture, soil water content etc. The reason for this is these variables might not be the same throughout the plots and also has their own contribution to the availability of N to the plant.

Table 9: Relationships between a chlorophyll index and chlorophyll content from SPAD measurements by considering the location of the experimental plots.

Plot	TCARI/OSAVI	CI $_{red\ edge}$	REP	NDRE	TCARI
		Coefficient of determination (R^2)			
A	0.6851	0.7004	0.5925	0.545	0.09959
B	0.6298	0.6265	0.5622	0.4503	0.2408
C	0.3875	0.6119	0.5566	0.2727	0.06407
D	0.4446	0.07602	0.01957	0.1816	0.4493
E	0.6897	0.547	0.4405	0.359	0.2057
F	0.6363	0.5763	0.5291	0.4934	0.2082
G	0.6281	0.5874	0.4468	0.3923	0.1151
H	0.6759	0.5525	0.4593	0.4209	0.3101
I	0.5161	0.671	0.6586	0.6326	0.00685
J	0.8963	0.3931	0.5353	0.470	0.5738
K	0.5665	0.5327	0.6191	0.5468	0.01304
L	0.6691	0.4401	0.5242	0.4703	0.1795

4.5.3 Relationship between chlorophyll indices and SPAD chlorophyll content based on treatment types

The objective was to see the relationship between chlorophyll indices and chlorophyll content by considering the different treatment types. We can see from Table 10 and Figure 16 that the relationship between TCARI/OSAVI, REP and NDRE with chlorophyll content from SPAD is strong for those plots which have a treatment type of MB. For the case of the index TCARI the relationship is strong for plots with treatment type TTW. The index CI $_{red\ edge}$ has the strongest relationship on the plots with the treatment type CL. Like all other cases the relationship is still strong with the vegetation index TCARI/OSAVI with an R^2 of 0.6976.

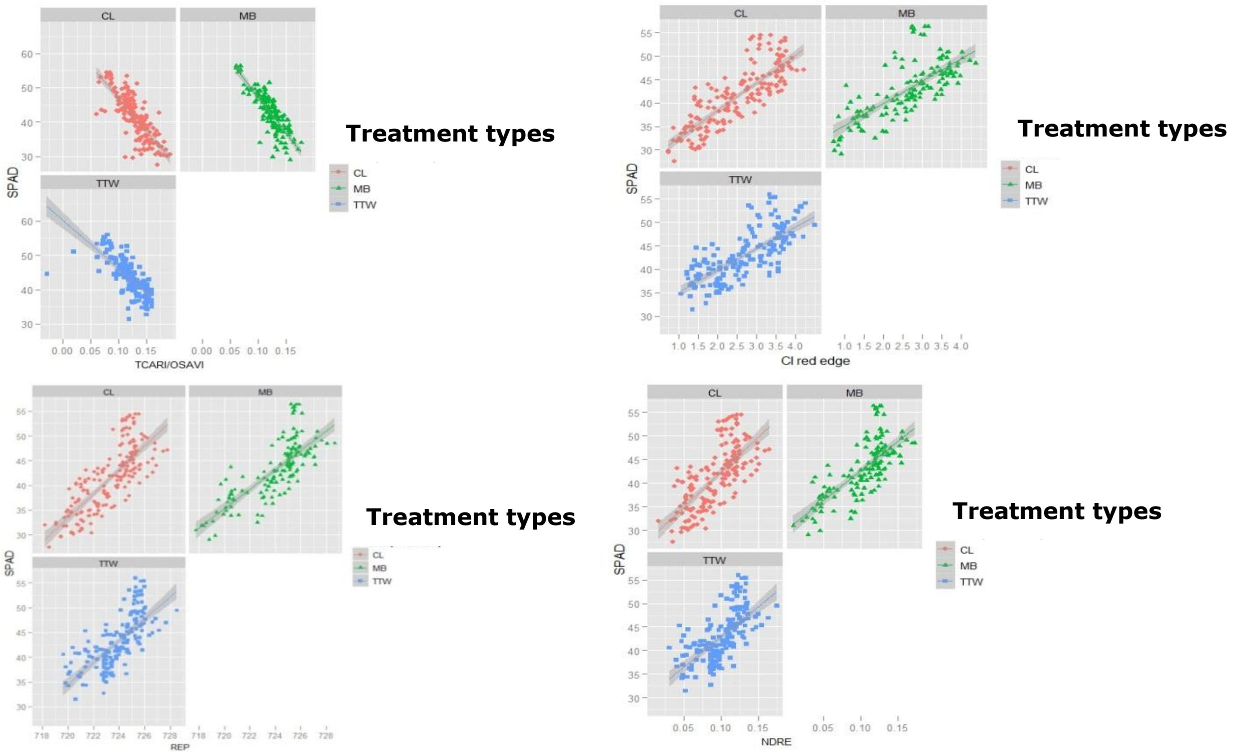


Figure 16: Relationship between SPAD and TCARI/OSAVI (top left), CI $_{red\ edge}$ (top right), REP (bottom left) and NDRE (bottom right) for the different treatment types.

Table 10: Relationship between chlorophyll indices and chlorophyll content from SPAD measurements by considering the different treatment types applied on the plots.

Treatment type	TCARI/OSAVI	CI $_{red\ edge}$	REP	NDRE	TCARI
		Coefficient of determination (R^2)			
CL	0.6262	0.6844	0.6064	0.5101	0.1166
MB	0.6976	0.5377	0.6107	0.5522	0.1176
TTW	0.5438	0.5445	0.5076	0.4189	0.2698

4.5.4 Relationship between chlorophyll indices and SPAD chlorophyll content based on initial fertilization levels

The other factor which was considered while determining the relationship between vegetation indices and chlorophyll content from SPAD measurements was initial fertilization levels applied on the plots before planting the potato crop. One can see from Table 11 and Figure 17 that for vegetation indices TCARI/OSAVI and TCARI the relationship with chlorophyll is strong on the plots which have an initial fertilization of 34 kg N h^{-1}. For these indices the relationship is weak on the plots which have an initial fertilization of 0 kg N h^{-1}. For the index CI $_{red\ edge}$ the relationship with chlorophyll content is strong on plots which have an initial fertilization of 46 kg N h^{-1} and it is weak on the plots with 0 kg N h^{-1}. The indices REP and NDRE have the strongest relationship on plots which have an initial fertilization of 23 kg N h^{-1}. REP has relatively weak relationship with chlorophyll on plots which has 46 kg N h^{-1} whereas NDRE has weak relationship on the plots which has an initial fertilization of 0 kg N h^{-1}.

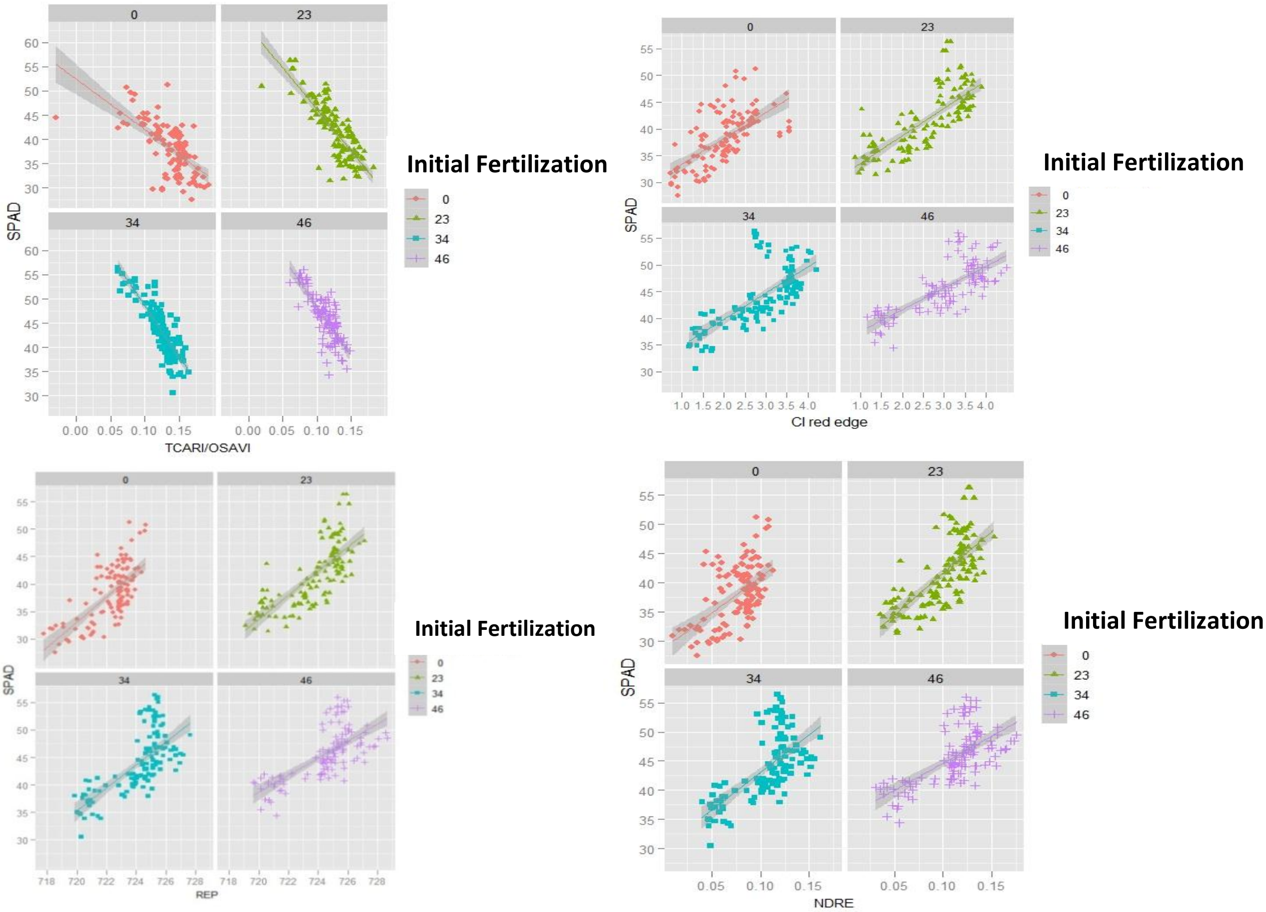


Figure 17: Relationship between SPAD and TCARI/OSAVI (top left), CI $_{red\ edge}$ (top right), REP (bottom left) and NDRE (bottom right) for the different initial fertilization amounts.

Table 11: Relationship between chlorophyll indices and chlorophyll content from SPAD measurements by considering the initial fertilization applied on the plots.

Initial N Fertilization (Kg h^{-1})	TCARI/OSAVI	CI $_{red\ edge}$	REP	NDRE	TCARI
		Coefficient of determination (R^2)			
0	0.4119	0.4102	0.4836	0.2887	0.0843
23	0.6667	0.5767	0.5725	0.4993	0.2042
34	0.7398	0.4995	0.4969	0.4343	0.3135
46	0.624	0.5836	0.4795	0.4396	0.1324

4.5.5 Relationship between chlorophyll indices and SPAD chlorophyll content based on total fertilization levels

During the growing season, the plots have received different amount of N (Table 3). To investigate the effect of total fertilization on the relationship between chlorophyll indices and chlorophyll content from SPAD readings, the regression model was fitted by grouping plots which has received same amount of N fertilization over the growing season. The result of the regression model revealed that vegetation indices TCARI/OSAVI and TCARI have a strong relationship with the chlorophyll content on plots which has received total N fertilization of 256 kg N h^{-1} and the relation was weak on the plots which have received only 38 kg N h^{-1}. On the other hand, indices REP and NDRE have the strongest relationship with chlorophyll content on the plots which have received a total of 346 kg N h^{-1}. In general compared with other indices, TCARI/OSAVI yielded relatively good relationships with potato chlorophyll content when the relationship is determined by considering time, location, treatment types, and different fertilization levels. The R^2 value of the regression model for TCARI/OSAVI is 0.6131.

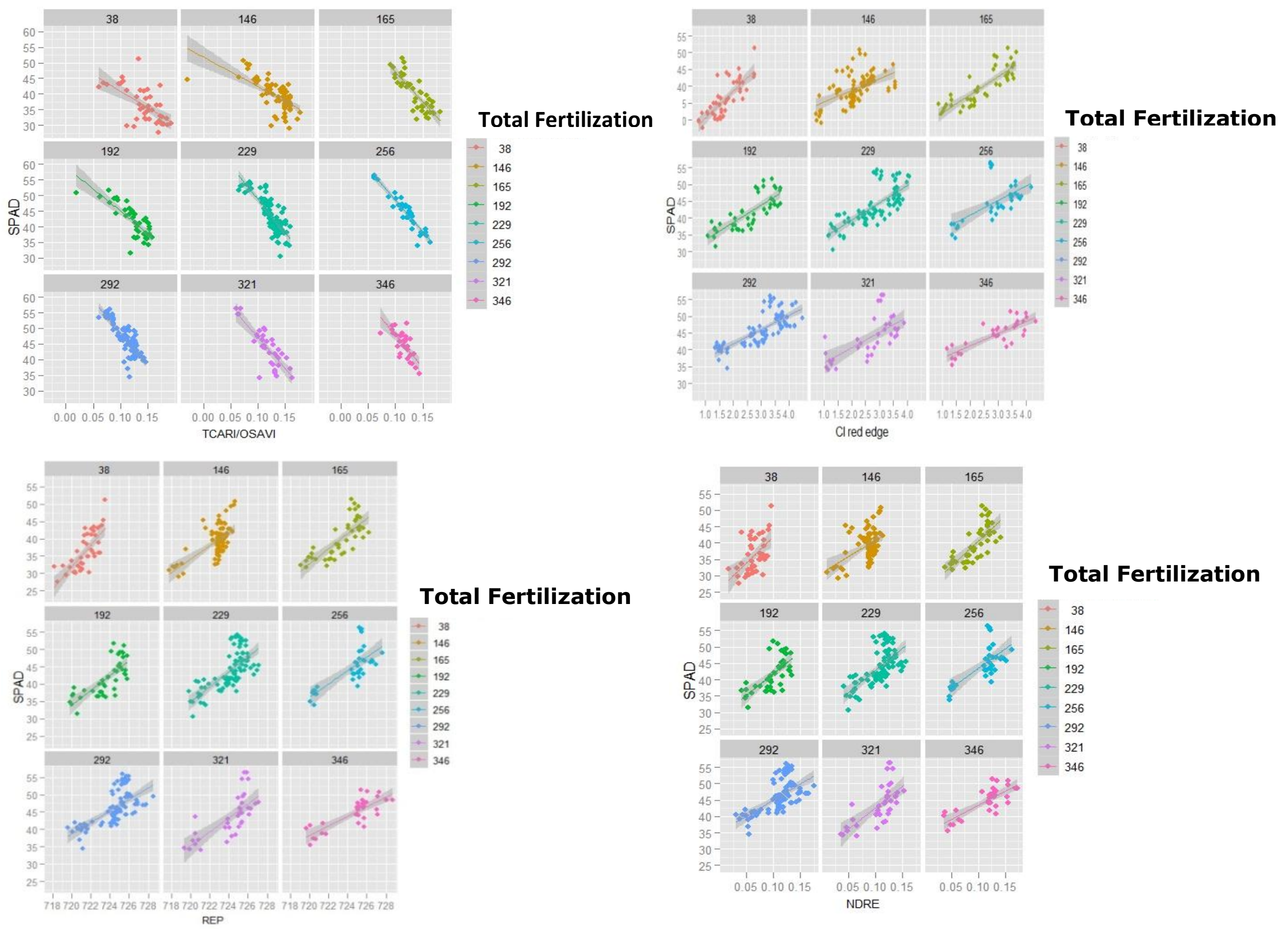


Figure 18: Relationship between SPAD and TCARI/OSAVI (top left), CI $_{\text{red edge}}$ (top right), REP (bottom left) and NDRE (bottom right) for the different total fertilization amounts.

4.6 Time series similarity measures

The other main core objective of this thesis research was to investigate the potential applicability of time series similarity methods to detect the change in the N status of the potato crop over the growing season. Time series similarity measures were used to check if differences between treatments also resulted in a significantly different temporal profile.

Figure 19 shows the result of time series similarity measure performed using the Euclidean distance (D_E) measure. We can see that the distance difference between the reference plot F and the other plots during early in the growing season are significantly small. However, during the temporal development of the crop we can see that some of the plots are deviating away from the reference plot F. A clear distance difference between the TCARI/OSAVI values can be observed between Plots B and D from plot F (reference plot) starting from the second date (June 6) of acquisition. During the second date of measurement we can see that there are three groups which are grouped together. The first group consists of plots E, F and G. The second group consists of plots B and D and the third group consists of the rest of the plots. This indicates that depending on the amount of applied N and management activities some of the plots are already having different N status than the reference plot. During the third measurement (June 13) and after that we can see that plot C is deviating away from the group where it was during the second measurement and continued to be far away from the reference plot . Immediately after the fourth measurement i.e. after June 20 we can see that plots B and D have a sudden increase in distance. Comparison with fertilization application dates and amount of additional N applied from the farmer data (Table 3) shows that, these plots have received some amount of additional fertilization based on different sensor measurements. However, the amount advised and received were different. On June 21 plot B received additional 13.5 kg of N^{-1} while the advice was 15 kg of N^{-1} and plot D received 54 kg of N^{-1} while the advice was 50 kg of N^{-1}. This difference could be the reason for the steep increase of the distance difference between these two plots and the reference plot immediately after June 20 measurement. For plots B and D the same effect can also be seen after July 20 when both plots received an amount which was different from the recommended. The graph also revealed that after June 27 the distance difference TCARI/OSAVI values from plots C and D are becoming more significant and continued until the end of the growing season.

It is clearly visible from the figure that after the fifth measurement i.e. after June 27, the plots which are more similar and closer to the reference plot have also started being apart from the reference plot, especially plot H.

In general, depending on the type of management activities and amount of N applied over the growing season, the N level of the potato crop on the different plots varies and this makes the plots to behave differently over the growing season. Plots which have similar or closer amount of N with the reference plot are mostly near to the reference plot and this can easily be monitored after each measurement dates.

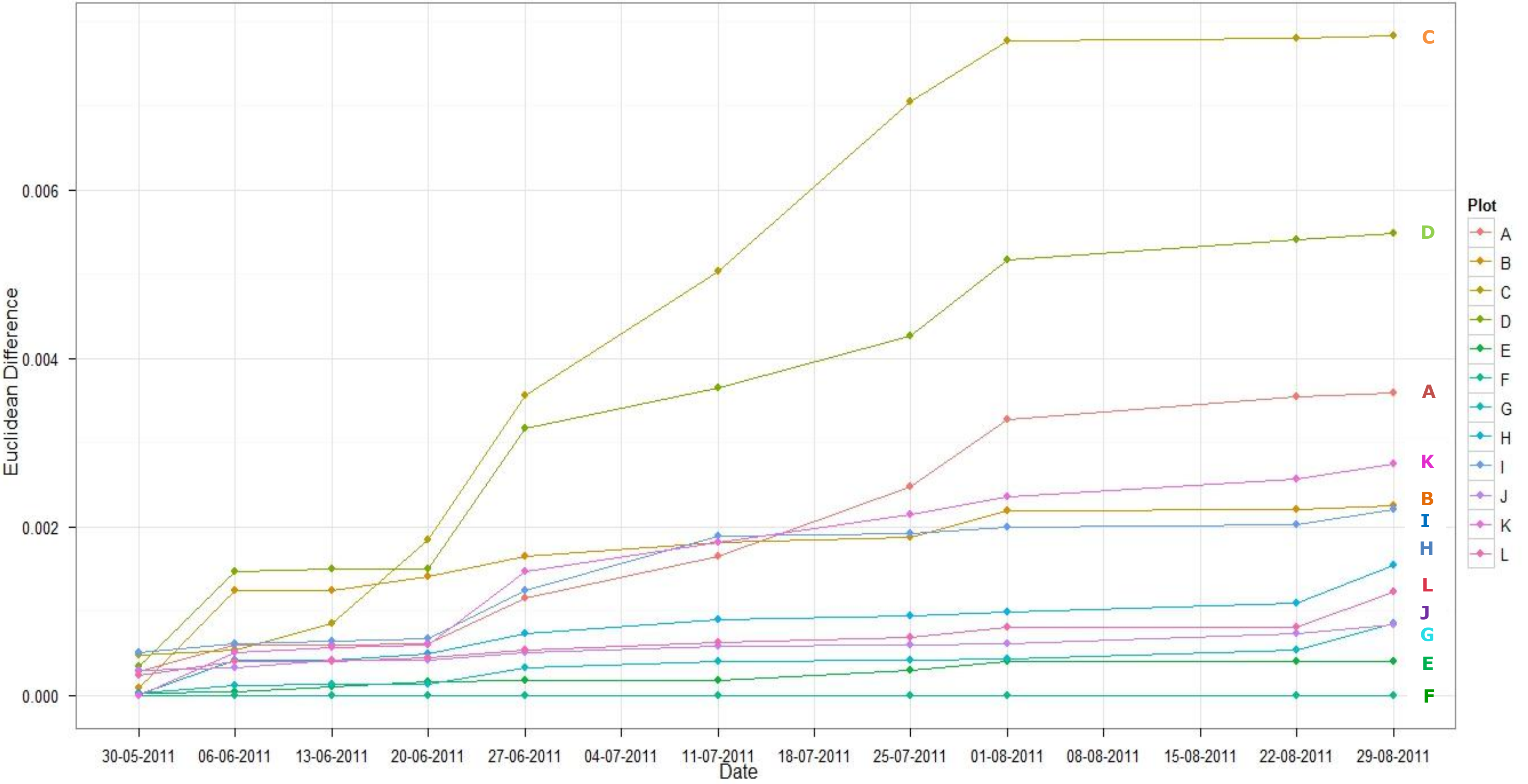


Figure 19: Time series similarity measure using Euclidean distance measure. The similarity is performed using Plot F as a reference plot and compared with the rest of the plots. The Y-axis represents the Euclidean distance difference between the reference plot F TCARI/OSAVI value and the rest of the plots at each specific moment of the growing season. The X-axis represents the weekly dates when the data were collected.

Figure 20 shows the result of time series similarity measure performed using the Manhattan distance (D_{Man}) measure. In the case of Manhattan distance measure, the distance difference between the TCARI/OSAVI values between the reference plot and the rest of the plots is more significant starting early in the growing season. Even the plots which are closer to the reference plot when the Euclidean distance measure was used are now deviating away from the reference plot starting early in the growing season. Like the Euclidean distance measure, immediately after the fourth measurement i.e. after June 20 we can see that plots B and D have a sudden increase in distance. This sudden increase in distance is because of the reason explained for the case of Euclidean distance measure. The order of the plots in terms of the distance difference between the plots and the reference plot is the same in both distance similarity measure cases except for plot B and I in which the order changed on the last few days of the growing season.

Figure 21 show the result of time series similarity measure performed using Root Mean Square Distance (RMSD) measure. The result shows that the RMSD is also able to detect the change in the temporal profile of the different plots which is the result of the difference in the treatment types. The RMSD account for missing values by calculating only the distance between corresponding observations that are not missing (Lhermitte, Verbesselt et al. 2010) and because of this reason the RMSD quantify the straight-line inter-point distance in a multi-temporal space, in which low values reflect high temporal similarity (Lhermitte, Verbesselt et al. 2010). Like the Manhattan distance measure, the result of RMSD measure also shows the clear distance difference between the reference plot and the rest of the plots starting early in the growing season. The first measurement was taken on May 30, in which most of the plots have already received more than 50% of the total applied N fertilization before this date and it is expected as there has to be a difference in the N status of the different plots. This difference is clearly visible starting from the first date of measurement when both the Manhattan and RMSD measures are used for the time series similarity. The order of the plots in terms of distance difference from the reference plot is the same for all the three distance similarity measures.

The result of the similarity measure performed using the correlation measures is presented on Appendix IX. The correlation coefficient between the reference plot and the rest of the plots was determined by considering the measurement values of the VI on the specific dates. The result clearly shows as most of the plots have a strong correlation with the reference plot F. A correlation value of 1 means there is an increase linear relationship and -1 is in case of a decreasing linear relationship. From the figure it is clearly visible that plots B, C and D have a decreasing linear relationship with the reference plot early in the growing season and later the relationship is improved. Starting from the fourth measurement i.e. June 20, the value of the correlation coefficient is between 0.5 and 1 for all the plots. The separation of the plots from the reference plot over the growing season seems very similar throughout the growing season. Immediately after June 27 we can see a sudden decrease of relationship between the reference plots and plot I. This might be because of the amount of additional N applied on plot I. From the farmer data (Table 3), it is evident that the advice from sensor readings was 49 kg N^{-1} but the farmer applied 54 Kg N^{-1} and the additional 5 kg might be the reason for the sudden decrease of the relationship between the two plots.

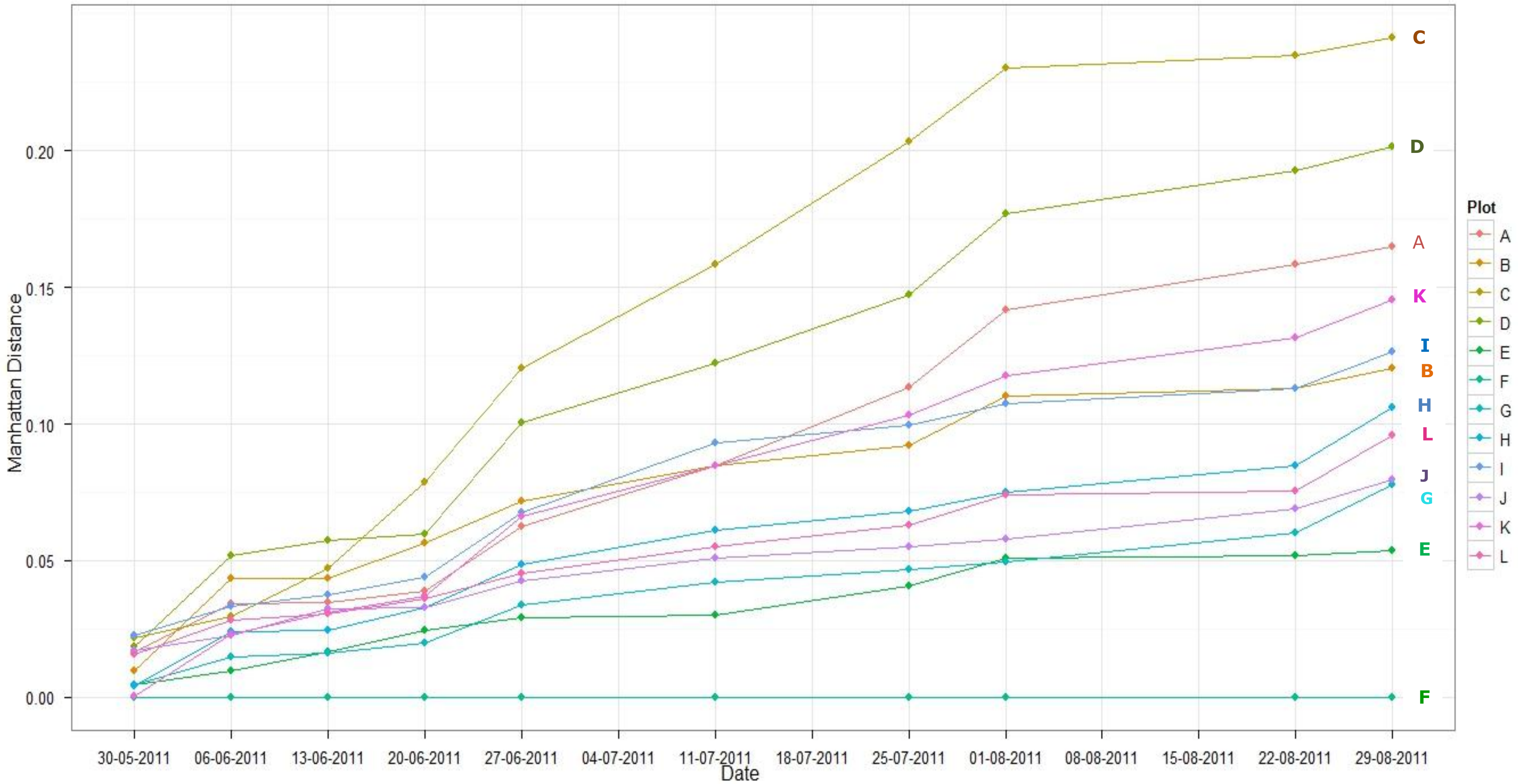


Figure 20*:* Time series similarity measure using Manhattan distance measure. The similarity is performed using Plot F as a reference plot and compared with the rest of the plots. The Y-axis represents the Manhattan distance difference between the reference plot F TCARI/OSAVI value and the rest of the plots at each specific moment of the growing season. The X-axis represents the weekly dates when the data were collected.

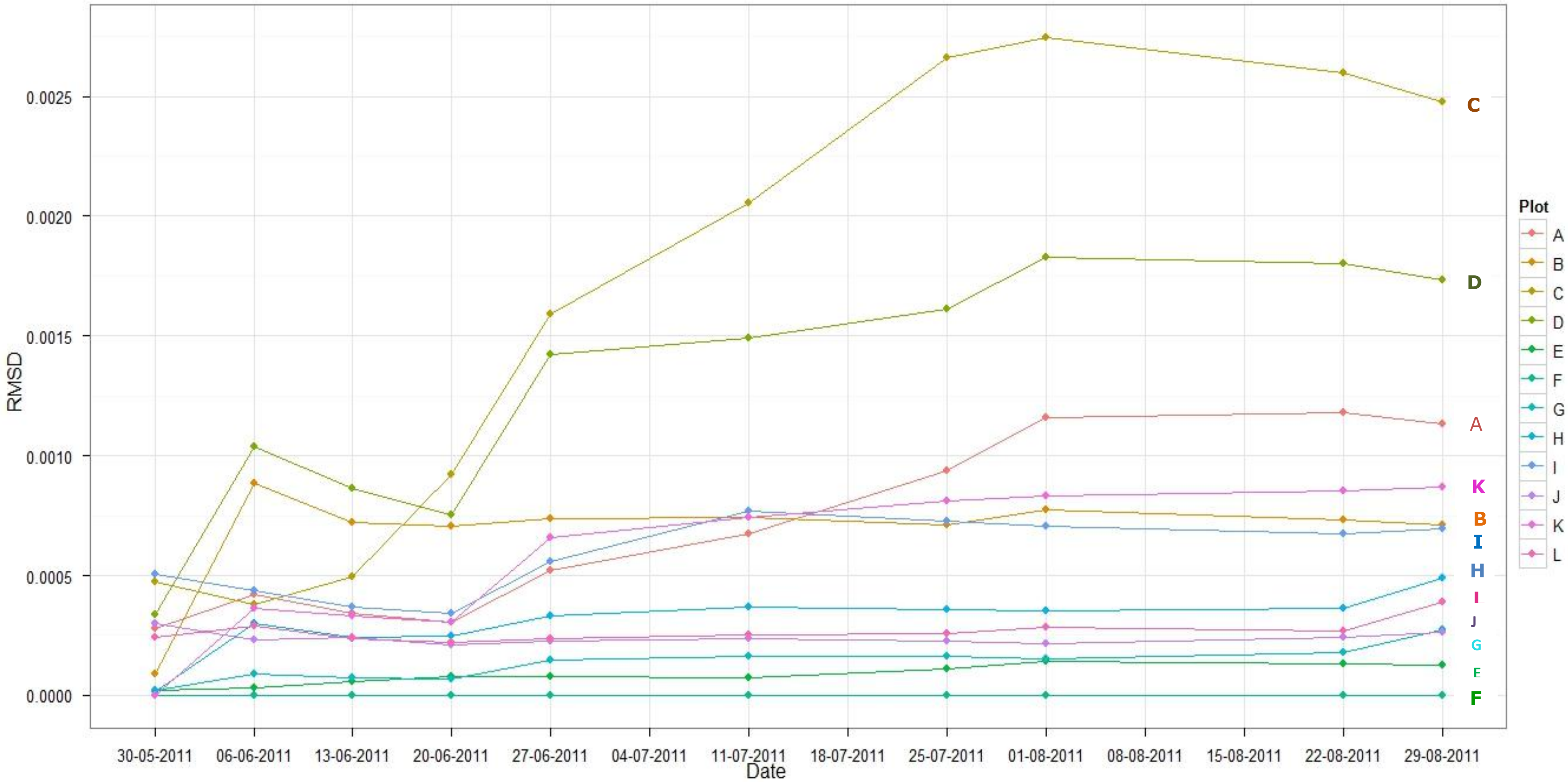


Figure 21: Time series similarity measure using Root Mean Square Distance (RMSD) measure. The similarity is performed using Plot F as a reference plot and compared with the rest of the plots. The Y-axis represents the RMSD difference between the reference plot F TCARI/OSAVI value and the rest of the plots at each specific moment of the growing season. The X-axis represents the weekly dates when the data were collected.

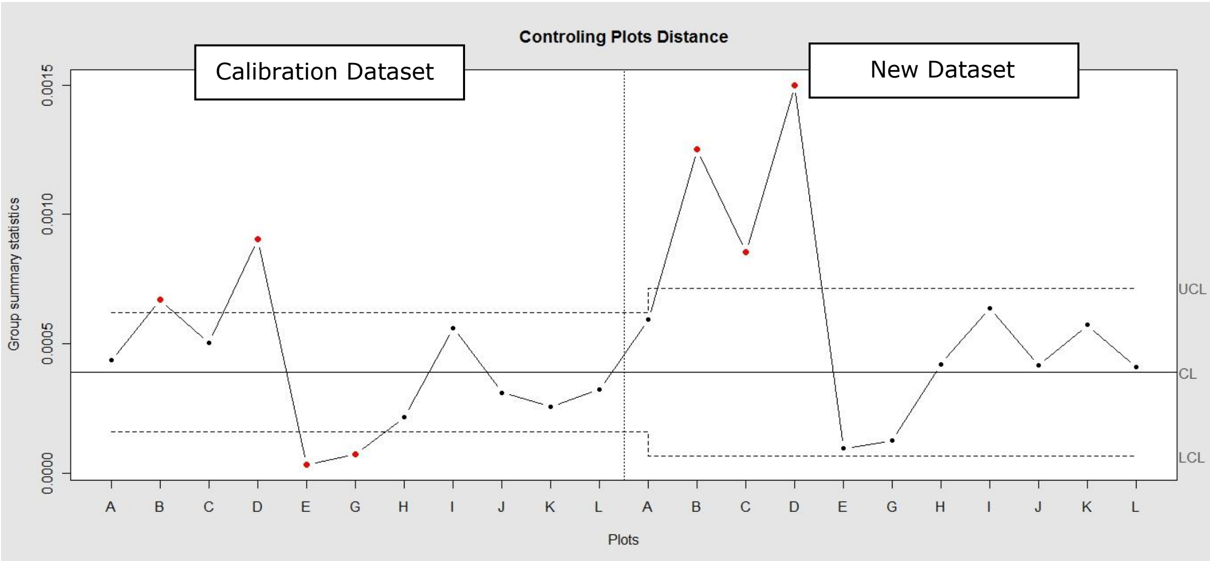
4.7 Checking threshold values of each plot at each specific dates using control charts concept

Figure 22 shows the result of the control charts being used to determine threshold values based on Euclidean distance values. The top graph shows when the third measurement i.e. from June 13 is plotted. The first data set from May 30 and June 6 (on the left side of the broken line) is used as a calibration data and the new dataset (on the right side of the broken line) is the measurement from June 13 for all the plots. On the first graph (top), 1 standard deviation from the mean is used to check which of the plots are within 1 standard deviation from the mean. It is clearly visible that plots B, C and D (red dots) are out of the upper control limit and this shows as they are far away from the reference plot at this specific date. The rest of the plots are within 1 standard deviation from the mean. On the second graph (bottom), 2 standard deviations from the mean are used to check which of the plots are in the warning limits and which one of them are still out of control. The bottom graph revealed that plots B and D are still out of the control limits but plot C is now within the 2 standard deviation from the mean range. By using this concept, all the data from each of the specific measurement dates are used to check which plots are close to the reference plot and which are far from the reference plot. Table 12 summarizes the status of each of the plots at each specific date. The yellow circle shows as the plot's Euclidean distance from the reference plot is within 2 standard deviations from the mean whereas the green circle shows as the plot's Euclidean distance from the reference plot is within 1 standard deviation from the mean. Based on the concept of control charts, plots which are red are out of the control limits and the plots which are green are under control and plots which are yellow are within the warning limits. This concept is used to check the crop status of each plot after a measurement on a specific date has been taken.

From Table 12 we can see that plots B and D are out of control starting from the third measurement date (June 13) until end of the growing season while plots E and G are within the control limits. Plots J and L are under control until July 25 but are in the warning limit starting from August 1. Plots I and K are under control until June 20 but are going out of control after June 27. A change in the status of a specific plot, for example a change from green to yellow can be used by the farmer to take necessary measures. In general this type of ranking list based on control charts concept can be used to check the status of a specific plot immediately a measurement is taken.

Table 12: Summary of the status of each of the plots at each specific measurement date compared to the reference plot F in terms of the Euclidean distance. Green means plot is under control (1 S.D from the mean), yellow means plot is in warning limit (2 S.D from the mean) and red means out of control i.e. above 2 S.D from the mean.

Date	A	B	C	D	E	G	H	I	J	K	L
June 13	Green	Red	Yellow	Red	Green	Green	Green	Green	Green	Green	Green
June 20	Green	Red	Red	Red	Green	Green	Green	Green	Green	Green	Green
June 27	Red	Red	Red	Red	Green	Green	Yellow	Red	Green	Red	Green
July 11	Red	Red	Red	Red	Green	Green	Yellow	Red	Green	Red	Green
July 25	Red	Red	Red	Red	Green	Green	Yellow	Red	Green	Red	Green
August 1	Red	Red	Red	Red	Green	Green	Yellow	Red	Yellow	Red	Yellow
August 22	Red	Red	Red	Red	Green	Green	Red	Red	Yellow	Red	Yellow
August 29	Red	Red	Red	Red	Green	Yellow	Red	Red	Yellow	Red	Red



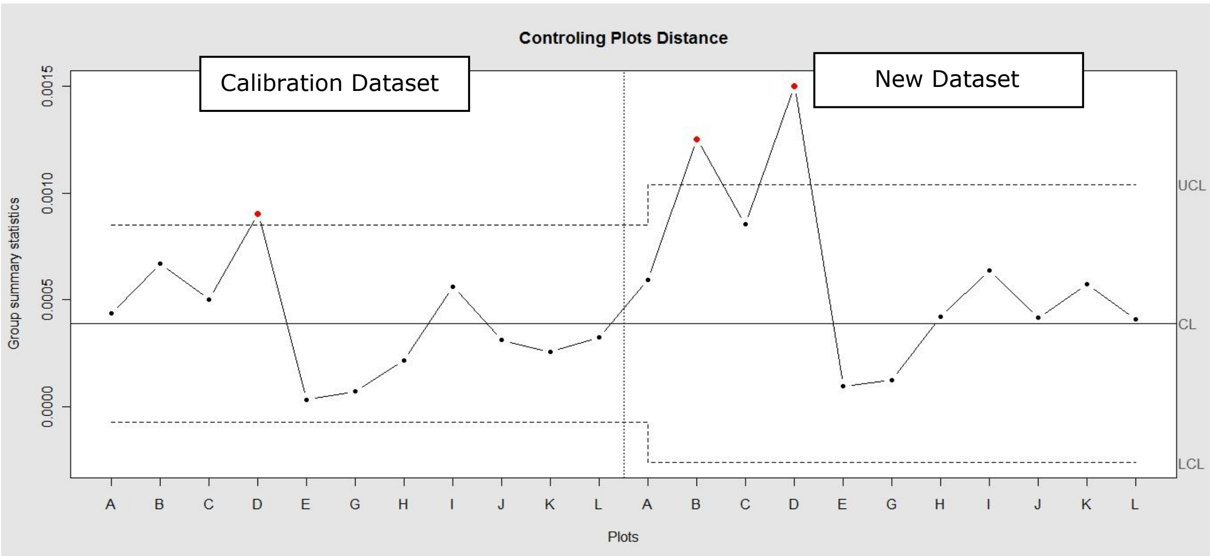


Figure 22: Status of each plot during the third measurement date (June 13). The first group (May 30 and June 6) measurements are used as a calibration dataset. The Y-axis describes the group summary statistics and on the X-axis are the plots names. Where UCL = Upper Control Limit, CL = Control Limit (mean) and LCL = Lower Control Limit. The top figure is within 1 standard deviation from the mean and bottom one is within 2 standard deviations from the mean.

5. Discussion

5.1 Relationship between Plant Sap and SPAD readings

The overall relationship between the concentrations of nitrate in Plant Sap and the chlorophyll content from the SPAD chlorophyll meter as it is revealed by Figure 8 is moderate with an R^2 of 0.599 (*P* value: < 2.2e-16) . Vos and Bom (1993) found a strong correlation between the two when a subset of data with one application of nitrogen in spring was used to identify the relationship. However, there was weak correlation (r=0.76) between the Plant Sap and SPAD readings when all the data from their experiment were bulked. Like Vos and Bom (1993) the results of this study show as the relationship between the two is significant when sub-sets of data based on initial fertilization are used. For example the relationship between the two on the plots which has an initial fertilization of 23 kg h^{-1}, is very strong with R^2 of 0.7881 (p = 3.259e-09) (Figure 5). But when all the data are used the relationship is moderate (R^2 = 0.5256). The reason for this as explained by Vos and Bom (1993) was due to the much stronger response in petiole nitrate than in chlorophyll to split N dressings. The seasonal trends presented in Figure 10 and 11 show both the Plant Sap and SPAD chlorophyll meter values have higher values early in the growing season and the values from both decreases over the temporal development of the potato crop. The reason for this decrease is that when the crop grows, from planting to biophysical maturity, crop chlorophyll content (N) decrease as its biomass and LAI increases (Plénet and Lemaire 1999). Figure 10 and 11 also reveal that the Plant Sap is more sensitive to the variation in fertilization than SPAD chlorophyll readings. This is typically visible during the measurements between June 27 and July 4 when the Plant Sap values for all the plots show higher values while the SPAD values were still declining. This shows that the Plant Sap values are more sensitive to the N variation than the SPAD readings and this is also confirmed by Vos and Bom (1993). This variation can also be explained from a plant physiological perspective: SPAD is related to chlorophyll while Plant Sap is related to mobile nitrogen components in the plant and this mobility behavior might be the cause for the Plant Sap to be more sensitive to variation than SPAD. Also as it can be seen from Table 6 the relationship between Plant Sap and SPAD in general is strong early in the growing season than later in the growing season. The strongest relationship is on June 6 with an R^2 of 0.9418. The other factor for the moderate relationship between the two could be the difference in the acquisition dates by the two methods. The dates considered to determine the relationship between the two are not exactly the same. As it can be seen from Table 5 there is a minimum of one day and a maximum of two days difference when the relationship between the two is determined.

Mostly the SPAD measurements were taken one day before the Plant Sap measurements. The dates Plant Sap measurements were taken (Table 4) and application of additional fertilization for plots B and D (Table 3) coincides on June 21 and July 20. This means the Plant Sap values on these dates (June 21 and July 20) were higher for plots B and D than the previous day measurement using the SPAD. This acquisition date's difference together with the application of the additional fertilizer on the same date when the Plant Sap measurements were taken could also be the reason for the moderate relationship. The other reason could also be the type of N measured using the two methods. The SPAD chlorophyll meter measures the chlorophyll content on top of the newly grown young leaves (Gianquinto, Goffart et al. 2004) while the Plant Sap measures the concentration of nitrate in petioles (Vos and Bom 1993). Therefore, the physiological bases for measuring the N content of the leaf are different between the two types of systems and this could also be the other additional reason for the identified moderate relationship between the two methods. In general there is no relationship between the two with extreme N fertilization levels applied to the plots.

The relationship between Plant Sap and vegetation indices was also done by Kooistra (2011). Plant Sap compared to SPAD does not seem to relate to vegetation indices, while from this study it is found that SPAD shows very good relation with sensor based vegetation index measurements and this makes it a better candidate to be used with sensor driven fertilization methods. The reasonable relationship between the nitrate concentration from Plant Sap method and chlorophyll content from SPAD which is revealed in this research is a good indicator as the SPAD method can also be used as an alternative operational method like the Plant Sap method.

5.2 Relationship between LAI-2000 and LAI Mijnakker

The relationship between LAI-2000 and LAI Mijnakker as it is revealed by Figure 12 is strong when data from a single date are used. However, the overall relationship between the two when all the data are bulked is moderately strong with R^2 of 0.6888. We can see from Figure 12 that the relationship is strong on May 30 and June 27. The relationship is moderate on June 6 and August 18. The strongest relationship is on June 27 with an R^2 of 0.9064. The relationship between vegetation indices and crop parameters as it is presented on Table 6 also shows as the relationship was strong on this date. The reason for this strong relationship on this specific date could be very good weather condition during acquiring the measurements on the farm and management activities applied before this date. Since both the ground based and remote sensing measurements are highly affected by weather conditions, a day with a good weather condition has a significant contribution to the relationship and as a result can enhance the final relationship. From table 5 we can see that the dates considered for determining the relationship between the LAI-2000 and LAI from Mijnakker are not exactly the same. There is a minimum of one and a maximum of four days difference on the acquisition dates from the two sources. Considering the period of maximum of four days between the dates of acquisition of LAI-2000 and LAI_MJ, we can also assume that the temporal variations of LAI can also be a major source explaining the moderate relationship between the two. From Figure 9 we can see that LAI values from Mijnakker are often smaller compared to the LAI-2000 values. The difference in LAI values can be explained by the difference in the size of the area (pixel size) under measurement using the two methods. The Mijnakker products have a pixel size of 10*10 m while the field of view of the LAI-2000 is adjustable depending on the size of the plot under measurement (LI-COR 2012). This feature of the LAI-2000 helps to minimize the effect of background reflectance which might underestimate or overestimate the LAI depending on the time of the growing season. However, in the case of the LAI from Mijnakker reflectance from the background soil will especially have a significant effect on estimating the LAI early in the growing season. This difference in size of the area under measurement (pixel size) might be the other important reason for the moderate relationship. Besides the pixel size difference, Mijnakker LAI data were originally in a raster format and later it was converted to vector and during the vectorization process the surrounding bare soil values were also contributed for the final calculated value for each pixel and this might have an effect on the final value of a pixel.

5.3 Relationship between Mijnakker N top of the leaf and SPAD/PlantSap

The result of the regression model between chlorophyll content from SPAD and N top of the leaf from Mijnakker shows as there is a relationship between the two. This is already revealed by Appendix IV. The R^2 from the regression equation is 0.6744. The relationship is better than the relationship between SPAD and Plant sap. This shows as the N top of the leaf product from Mijnakker can also give an information to the farmer about the N status of the crop at a specific moment of the growing season. The chlorophyll content from the SPAD was measured by clamping the instrument on randomly selected first full-grown leaves from the top. This makes the SPAD instrument to measure the chlorophyll content only on top of the leaf while the Mijnakker N top of the leaf product could be affected by the background soil reflectance. The measurement with the SPAD might not been affected by any external factor like soil background reflectance. Raymond (2004) explained as optical measurements at leaf level do not necessarily provide detailed information on plant and crop performance, as that is co-determined by many factors and because of this reason chlorophyll contents measured by remote sensing methods have a better indicator of the N status of the plant since it integrates from all parts of the plant. Although it is not clear how the N top of the leaf product from Mijnakker is derived from the remote sensing crop reflectance, the result of the relationship with SPAD shows as it is also a good method to determine the N status of the potato crop.

5.4 Relationship between vegetation indices from different sensors

Vegetation indices which are designed to relate to the biomass of a crop from different sensors were related to investigate the relationship between similar vegetation indices from the different sensors. Figure 13 shows the result of the relationship between NDVI derived from the Cropscan (NDVI_CS) data and NDVI from Mijnakker (NDVI_MJ). The overall relationship from the two sensors is strong with R^2 of 0.7659 ($P < 0.05$). From Table 5 it is evident that the relationship is determined only using data from four dates of measurements. Since the acquisition dates from the two sensors are not exactly the same, selection of closest dates from both sensors is done and there is a minimum of one and a maximum of four days difference on the respective dates. This difference in the acquisition dates could be a reason for the weak relationship especially on June 6 and August 29. For the case of June 6, the data from Mijnakker was acquired on June 2 while the data from Cropscan was acquired on June 6. For the case of August 29, the data from Mijnakker was acquired on September 1 while the data from Cropscan was acquired on August 29. Besides, since there is no metadata about the Mijnakker products which describes when exactly the acquisition was done, still there might be a date difference when the acquisition of the image and calculating the NDVI from Mijnakker data was done. The other reason for the difference in the relationship between the NDVI from the two sources could be the size of the field of view under measurement. For the Cropscan, depending on the height of the radiometer above the canopy, the sampling FOV for one scan can range from 1 to 2 m^2 (Goffart, Olivier et al. 2008) and it has a pixel size of 0.6m (Kooistra 2011) while the Mijnakker products have a pixel size of 10m. This pixel size difference could also be the reason for the weak relationship especially early in the growing season since NDVI from the Mijnakker might have been influenced by the background soil reflectance.

The result of the relationship between NDVI from Mijnakker (NDVI_MJ) and GreenSeeker (NDVI_GS) is presented in Figure 14. The relationship is very weak when both the dates are considered separately. Early in the growing season (May 3) the NDVI from both the GreenSeeker and Mijnakker have smaller values and this is because at this stage the crop was at its early stage and for both sensors the background soil has a major effect for the low NDVI values. Late in the month; May 25 the relationship is still weak but the NDVI values from both sensors have higher values than early May. This is because of the development of the crop over the month. However, when the data from the two dates are bulked together, the relationship has significantly improved with R^2 of 0.9831. It is significant at p – value < 2.2e-16. However, the relationship is based on only two point clouds and it doesn’t tell as there is a strong relationship between the two over the growing season. The growth of the plants during this time is explaining the variation of the NDVI from the two sensors. The NDVI was small during early in the growing season and higher in the middle of the growing season. Even though the R^2 tells as the relationship between the two is strong based on the two dates, the model diagnostic plots for the goodness of fit of the model show as the variance is not constant over the fitted values and this indicates performing the relationship analysis using only the two dates data is not enough to show the strong relationship between the NDVI from the two sensors. It only tells as there is a strong relationship only on the selected dates. The variation in the values of the NDVI could be because of the pixel size difference between the two sensors. Like the other sensors the acquisition dates by these two sensors were also different and only two dates which were close to each other were used to determine the relationship.

5.5 Relationship between vegetation indices and crop chlorophyll content

As nitrogen is the most important nutrient for the development of the crop, timely assessment of the N status of the crop is the most crucial one. Consequently, one of the main objectives of this thesis research is to identify the most robust vegetation index which can detect changes in the potato crop N status and condition over the growing season. A range of chlorophyll and nitrogen indices which are more applicable to the context of precision agriculture based on recommendations from Haboundane et al (2002) and Clevers (2011) were tested to explore their potential in detecting changes in the N status or chlorophyll content of the potato crop over the growing season. Results confirmed that the chlorophyll ratio index TCARI/OSAVI is related in a highly non-linear way with the chlorophyll content from SPAD measurements. The result also confirmed the result of (Haboudane, Miller et al. 2002) and (Haboudane, Tremblay et al. 2008) on simulated and corn chlorophyll content. They stated that indices like TCARI which are based on the calculation of chlorophyll absorption depth combined with a vegetation index OSAVI that minimizes soil effects to give the ration index TCARI/OSAVI have a nonlinear strong relationship with the measured chlorophyll content. On the contrary Jain et al (2007) and Herman et al (2010) found as the original TCAR/OSAVI was insensitive to changes in the N status of the potato crop. However, when band 670 nm was replaced with band 1505 nm, the TCARI/OSAVI was found sensitive to changes in the N status of the crop (Herrmann, Karnieli et al. 2010). Nevertheless, for the case of this study as Table 7 reveals, the relationship between TCARI/OSAVI with the measured chlorophyll content early in the growing season especially for the month of June and late in the growing season i.e. on August 22 and 29 is very weak while the other chlorophyll indices (REP, NDRE and CI $_{red\ edge}$) are related much better than the TCARI/OSAVI. Even though the overall relationship between TCARI/OSAVI with the chlorophyll content is significant, it seems TCARI/OSAVI is slightly more sensitive to LAI changes especially during the month of June and late August. Haboudane, Tremblay et al. (2008) explained as the ratio index TCARI/OSAVI has a significant relationship with the measured chlorophyll content and their experiment on the effect of crop type on the canopy structural attributes showed as there is a clear effect of the crop type on the performance of the combined ratio indices like TCARI/OSAVI. Indeed, the potato dataset from this study revealed significant correlations between the TCARI/OSAVI index and chlorophyll content with R^2 of 0.6131 (P < 2.2e-16) with some noticeable sensitivity to LAI influence.

5.6 Time series similarity measures

The other main objective of this thesis research was to investigate the capability of time series analysis techniques to detect changes on the N status of the potato crop. The starting point for this analysis is based on the idea proposed by Lambin and Ehrlich (1997). To measure land cover changes using remote sensing methods lambin and Ehrlich (1997) defined three aspects which need to be defined before performing the land cover change analysis. These points are (1) a biophysical indicator strongly related to land-cover conditions that can be measured by remote sensing (2) a reference state for the land cover at every location as a standard against which to compare current situations and (3) a technique for detecting changes (Lambin and Ehrlich 1997).

By adapting Lambin and Ehrlich (1997) idea to detect changes in the N status of a crop using remote and ground based methods, three points relevant to the context of agricultural fields are defined. (1) a biophysical indicator which is strongly related to the N status of the crop over the growing season (2) a reference plot which is used as a standard against which to compare current status of other plots and (3) a technique for detecting the change in the N status of the crop. The biophysical indicator which is strongly related to the N status of the potato crop is identified from the relationship between chlorophyll indices and chlorophyll content from SPAD measurements. Based on the best correlation with the chlorophyll content from SPAD measurements, the identified biophysical indicator to the N status of the crop is the TCARI/OSAVI vegetation index (Section 5.5). In order to perform the similarity between two time series, a reference time series has to be determined in which the time series of the other object will be compared with. For the case of this research, plot F was selected as the reference plot. It was selected based on the analysis done by one of the agricultural advisory companies involved in the experiment. The analysis result of the company revealed as plot F was the most optimal plot (both in amount and quality of the potato yield) with respect to fertilizer application. The techniques selected for detecting the change in the N status of the crop were time series similarity methods based on distance measures and correlation measures.

The capabilities of the most commonly used time series similarity measures to detect changes on the N status of a potato crop were explored. Results confirmed that all of the time series similarity methods based on distance measures are capable of detecting changes on the N status of a potato crop based on the N content of a reference plot (Fig.19, Fig.20 and Fig.21). On the other hand the results from the time series similarity methods based on correlation measures show as there is strong correlation between the values from the reference plot and the rest of the plots over the growing season regardless of the amount of total N applied to the plots. This strong correlation occurs when time series values are correlated between different temporal observations within one time series and this results the occurrence of serial correlation (Lhermitte, Verbesselt et al. 2011). As a result of the influence by the serial correlation, it is difficult to clearly visualize the difference between the reference plot and the other plots under similarity comparison (Appendix IX). Since the plots had different levels of N fertilization over the growing season, it is expected that the plots would also have a different temporal profile. However, in the case of the similarity measure based on correlation, there is no as such a significant difference on the temporal profile when the correlation values are plotted as a function of time.

As we can see from the results (Fig.19, Fig.20 and Fig.21) it is clearly visible that the distance difference between the reference plot and the rest of the plots is smaller in the case of the Euclidean distance measures while it is bigger in the case of Manhattan and RMSD distance measures. The reason for this is by definition Euclidean distance is the shortest possible distance between two points (Jain, Murty et al. 1999) while the Manhattan distance measures distance following only axis-aligned directions (Mimmack, Mason et al. 2001) and this makes the Euclidean distance values to be smaller while the Manhattan distance measure values are bigger. The RMSD distance measure also quantify the possible straight-line inter-point distance in a multi-temporal space, where low values reflect high temporal similarity (Lhermitte, Verbesselt et al. 2010).

Time series similarity based on distance measures to detect the N status of a potato crop on a specific plot based on the N status of a reference plot is a mechanism to check the status of a plot at each specific measurement date. It can be used by the farmer to check the N status of the crops at a specific location. This indicates the method is a spatio-temporal approach that employs time series similarity and spatial context to check the N status of a crop on a specific plot based on the N status of the reference plot. For this approach to be able to determine the N status of the plots under comparison, selection of the right reference plot plays the major role. Like the variable rate application methods selection of the right reference plot with optimum amount of N should be done carefully. The reference plot is a way to keep the confounding factors constant and focus on the distinctive effect of nitrogen status at measurement (Mellgren 2008). As Samborski, Tremblay et.al (2009) recommended the N-rich strip reference plot should probably be placed in the field so as to traverse as many soil types and growing conditions as possible. Such an approach will allow obtaining an average value of the N status of the reference plot. Besides the appropriate field representative selection of the reference plot elimination of more fundamental field management problems such as water-logging, fertilization application mistakes, wrong herbicide, fungicide, and lime application (Samborski, Tremblay et al. 2009) need also be taken into consideration for the successful implementation of this time series similarity approach.

In this research, data from the 2011 growing season were used and the time series similarity comparison was performed only based on this growing season data. However, in order to use the approach to compare the N status of a specific plot based on the reference dataset from a different year some points need to be taken into account. For example the date when the measurements of the N status both for the reference dataset plot and the current plot under comparison need to coincide. For example a dataset which was taken 50 days after crop emergence need to be compared with the crop which is also 50 days old. The type of crop which was on the field in the previous year also needs to be taken into account. In summary, to compare current growing season time series data of a specific plot with previous or other year's acquisition date data of a reference plot, the dates of acquisition, and other environmental variables like soil texture, soil water content, weather conditions and a like need to be taken in to account. To compare the N status of a plot with the reference plot in which both the plots are located on the same field and on the same growing season also need to consider the environmental variables. The soil structure, soil water content and other additional environmental factors of the reference plot have to be representative of the whole filed.

The other important point which needs to be taken into account is the selection of the distance measures. Although the three types of distance measures used in this study are able to detect the status of a specific plot based on the reference plot by measuring the distance difference between the two points (TCARI/OSAVI values) on a multi-temporal space, still there are differences on the results. Lhermitte Verbesselt et al (2011) describe as the main advantage of the Minkowski distances i.e. Euclidean and Manhattan are easy to calculate and interpret. This makes them to be used and applied in a variety of approaches, ranging from change vector analysis to landcover classification (Lhermitte, Verbesselt et al. 2011). However, care has to be taken on the selection since some of them are vulnerable for some environmental conditions e.g. noise. For example, the Euclidean distance measures are sensitive to outlier values (Lhermitte, Verbesselt et al. 2011) and because of this it is advisable not to use the Euclidean measures in a dataset where there is a lot of noise. The other thing about the Minkowski distance is the tendency of the largest-scaled feature to dominate the others and solutions to this problem includes normalization of the continuous features to a common variance or other weighting schemes (Jain, Murty et al. 1999).

The other important thing which also needs to be considered is the temporal resolution. The temporal resolution is another important factor as the time interval between consecutive observations can vary significantly (Lhermitte, Verbesselt et al. 2011). As it is revealed from the results (Fig.19, Fig.20 and Fig.21), there were no measurements on July 4, July 18, August 8 and August 15 and as a result it is difficult to know whether the N status of the different plots is changing or not on those days when measurements are missing. In other words it is difficult to know what the N status of a plot is. For this study a weekly measurement of the N status of a potato crop was used. On the days when the weekly measurements were available it is relatively easy to check the status of the plots immediately after the measurement is done. For example from Table 12 we can see that plots A and K were under control (Green circle) until the fourth measurement i.e. until June 20 but immediately on June 27 both the plots were out of control (Red circle). This shows how the N status of a plot can change within a week time. If there was a measurement in between it would have been very helpful for the farmer to determine the status of these plots before it is late to take the necessary management activities. Although it is possible to see the status of the plots using the weekly measurement data, to have a more control on the N status of the potato crop a high temporal resolution data is very crucial. As Veraverbeke et al (2010) recommended for rapidly changing dynamics, a high temporal resolution will be essential and from the results we see that depending on the type of treatments applied the N status of a potato crop is changing within a short period of time and this confirms as a high temporal resolution data helps the modern farmer to have a more control on the N status of the potato field especially during the critical physiological stages of the crop.

After calculating the distance differences between the reference plot and the plot under comparison, the next step is to check if the distance difference is within the range of the threshold or not. Figure 22 reveals as control charts can be used to determine the threshold values based on the distance differences between the reference plot and the plot under comparison. By using data from few date measurements it is possible to define the control limit (CL), upper control limit (UCL) and lower control limit (LCL) of the chart. In this study measurements from May 30 and June 6 were used as calibration datasets. Once the control limit (in this case the mean) is determined, the status of a crop on a specific plot can be determined by calculating the standard deviation (S.D) from the mean. The different colors of the dots on Table 12 have their own meanings. The green dots shows as the plot's distance from the reference plot is within 1 standard deviation from the mean whereas the yellow dots shows as the plot's distance from the reference plot is within 2 standard deviations from the mean.

The red dot shows as the plot's distance from the reference plot is beyond 2 standard deviations from the mean. Based on the concept of control charts, plots which are green are under control, plots which are yellow are in the warning limit and plots which are red are out of the control limits. The top graph of Figure 22 shows when the third measurement i.e. from June 13 is plotted. The first data set (on the left side of the broken line) is used as a calibration data and the new dataset (on the right side of the broken line) is the measurement from June 13 for all the plots. On the first graph (top), 1 standard deviation from the mean is used to check which of the plots are within 1 standard deviation from the mean. It is clearly visible that plots B, C and D (red dots) are out of the upper control limit and this shows as they are far away from the reference plot at this specific date. The rest of the plots are within 1 standard deviation from the mean (green dots). On the second graph (bottom), 2 standard deviations from the mean are used to check which of the plots are in the warning limits and which one of them are still out of control. The bottom graph revealed that plots B and D are still out of the control limits but plot C is now within the 2 standard deviation from the mean range. By using control charts concept, all the data from each of the specific measurement dates can be used to check which plots are close to the reference plot and which are far from the reference plot. This concept can be used to check the crop status of each plot after a measurement on a specific date has been taken.

From Table 12 we can see that plots B and D are out of control starting from the third measurement date (June 13) until end of the growing season while plots E and G are within the control limits. Plots J and L are under control until July 25 but are in the warning limit starting from August 1. Plots I and K are under control until June 20 but are going out of control after June 27. A change in the status of a specific plot, for example a change from green to yellow can be used by the farmer to take necessary measures. In general this type of ranking list based on control charts concept can be used to check the status of a specific plot immediately a measurement has been taken. The control charts concept can only tell the status of the plot reference to the reference plot. It doesn't recommend the modern farmer what type of management activity or additional fertilization is required.

6. Conclusions and recommendations

Since nitrogen is the most important nutrient for the development of the potato crop, timely assessment of the N status of the crop is very crucial. In this study, multi-temporal ground based measurements of crop parameters data; remote sensing data and ground based near sensing data were used to identify and quantify the relationship between the field observations of crop parameters and sensing measurements at one moment in the growing season. The study has investigated the relationship between the concentrations of nitrate in Plant Sap and the chlorophyll content from the SPAD chlorophyll meter and revealed as there is a moderate relationship between the two. It also showed as there is no any relationship between the two at extreme N levels. The study has also investigated the relationship between the LAI from LAI-2000 and LAI from Mijnakker. Investigating the relationships between N top of the leaf from Mijnakker and SPAD chlorophyll meter were also part of this study.

Comparison of the most relevant vegetation indices in the context of precision agriculture to detect the N status of the potato crop over the growing season was performed by considering the temporal, spatial, initial fertilization, treatment types and total fertilization applied on the experimental plots into consideration. Then, using the identified most robust vegetation index for detecting the N status of the potato crop over the growing season in all the conditions, a time series similarity between a reference plot with optimum N amount and a plot with suboptimum N amount were performed. Based on the results of this study the following conclusions are made:

- It is clearly visible from the results that there is a relationship between the concentrations of nitrate in Plant Sap and chlorophyll content from SPAD chlorophyll meter. However, the strength of the relationship totally depends on the amount of total and initial fertilizer applied. This means, there is no relationship between the two in both the extreme levels of N applied to the crop.

- The reasonable relationship between the nitrate concentration from Plant Sap method and chlorophyll content from SPAD is a good indicator as the SPAD method can also be used as an alternative operational method like the Plant Sap method.

- The relationship between concentrations of nitrate in Plant Sap and chlorophyll content from SPAD chlorophyll meter can be significantly improved by considering additional variables besides the SPAD chlorophyll content. For example the relationship can be improved by considering the total fertilization applied on the plots in the regression analysis.
- Crop physical or biochemical parameters which are acquired using field measurements and using vegetation index derived from remote sensing methods and close sensing methods can be related and quantified based on values determined by the determination of coefficients (R^2). However, the size of the spot area (pixel size) under measurement using the different methods needs to be taken into account. The same is true when the same vegetation index but from different sensors is related.
- Regarding the performance of the indices in detecting the N status of the potato crop over the growing season based on the R^2 and RMSE has allowed the following conclusions to be drawn:
    - The ratio index TCARI/OSAVI seems to be the best N content detector for the potato crop over the growing season when the relationship is considered under different circumstances i.e. with different treatment types, fertilization levels and time of the growing season.
    - TCARI/OSAVIs sensitivity at low LAI values or early in the growing season shows as care has to be taken when the index is used to detect the N status of the potato crop during early in the growing season with low LAI values.
- Analysis results also revealed that changes in the N status or abnormal changes of a plot can be detected by means of the commonly used time series similarity measures which are based on distance measures.
- By using the results from the time series similarity measures the threshold values can be determined by employing the concept of control charts which have been mainly used in industrial applications. Based on the output of the control charts the farmer can be in a position to prepare an operational ranking list for the different plots.
- A change in the status of a specific plot based on control charts result, for example a change from under control (green) to yellow (warning limit) can be used by the modern farmer to take necessary measures. In general this type of ranking list based

on control charts concept can be used by the modern farmer to check the status of a specific plot immediately a measurement is taken.

- Results from this study also revealed that by using the weekly near-sensing time series data it is possible to control the N status of a plot based on the N status of a reference plot with optimal N content. However, to have a more control of the N status of the potato crop on a specific field a data with high temporal resolution like daily acquired data need to be investigated for its possible additional contribution for the more robustness of the method.

- Results from time series similarity methods indicate only the status of a specific field or plot in terms of its N content in reference to the other plot. Results cannot be used to determine the amount of additional N fertilization or management activities needed. For future studies, improvements to the proposed analysis may include the recommendations based on the results from time series similarity measures.

Recommendations

- In this study weekly measurement data have been used to investigate the potential applicability of time series methods to determine the N status of a crop based on the N status of a reference plot. However, further study need to be done by using high temporal resolution (for example daily data) to see the additional value of using a high temporal resolution data for the time series similarity methods
- As explained before, the method cannot be used to determine the amount of additional N fertilization to be applied or the required management activity needed. However, it would be very helpful for the farmer if the method can also be in a position to recommend the additional fertilization to be applied based on the distance differences.

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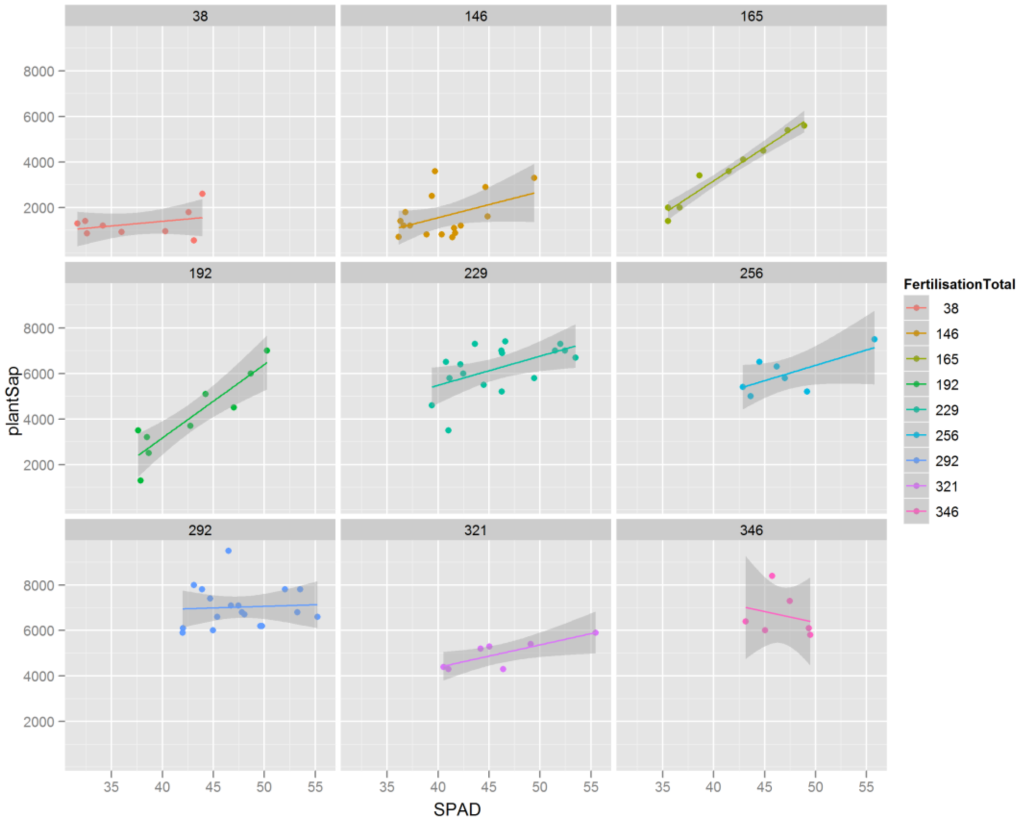
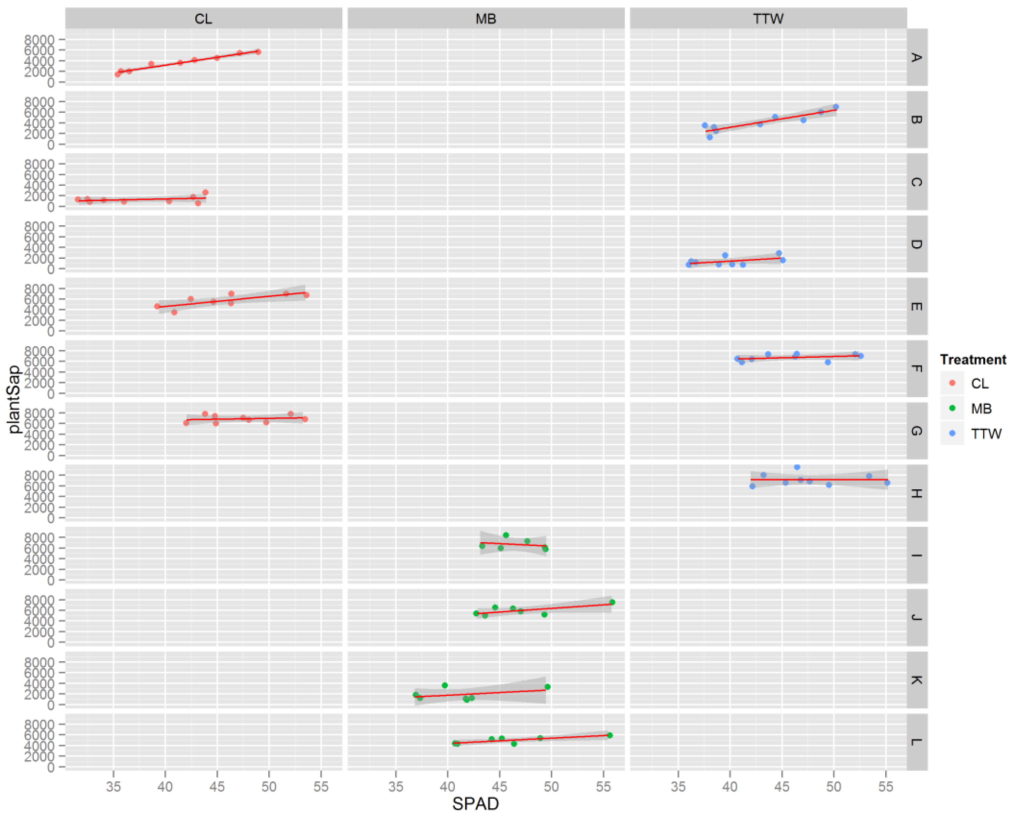
Appendices

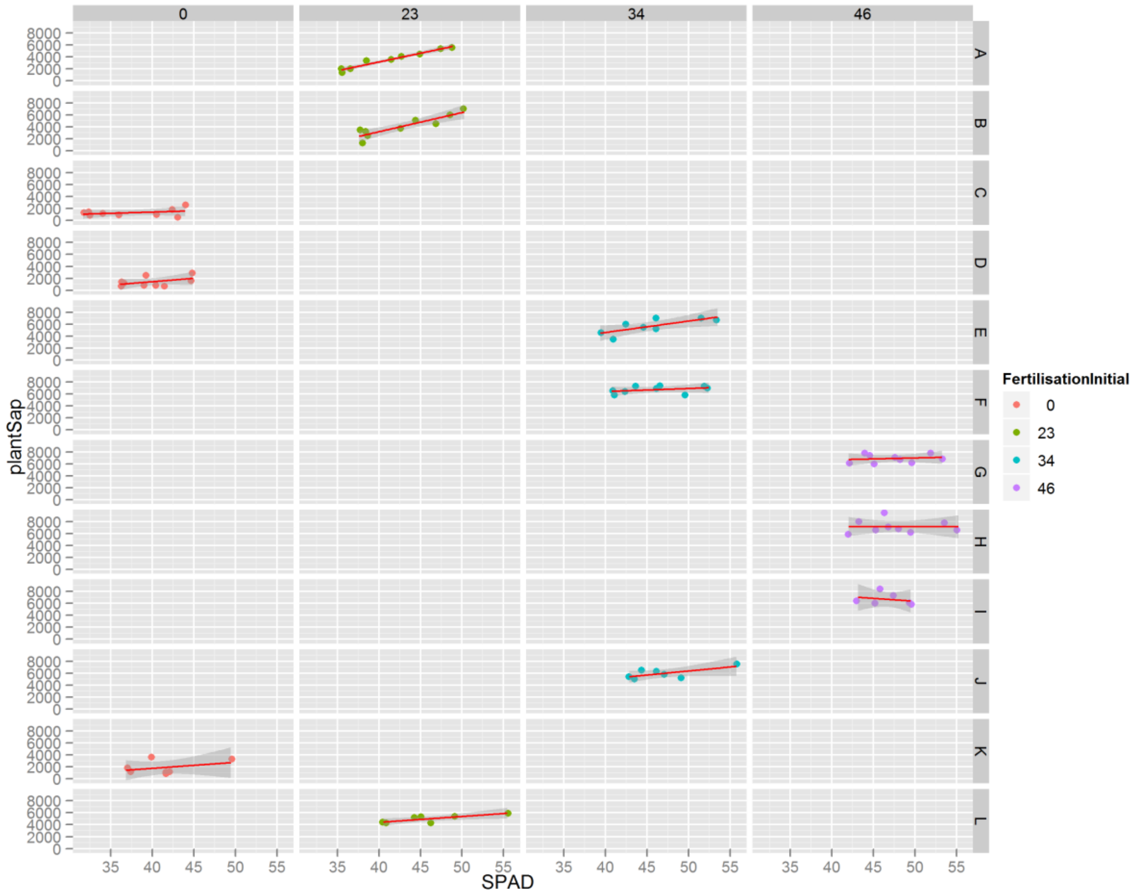
Appendix I: Relationship between SPAD and Plant Sap based on total fertilization applied



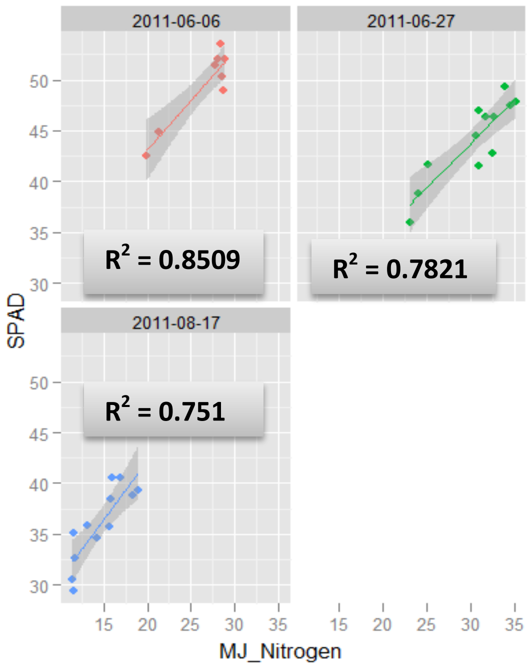
Appendix II: Relationship between SPAD and Plant Sap per plot per treatment types

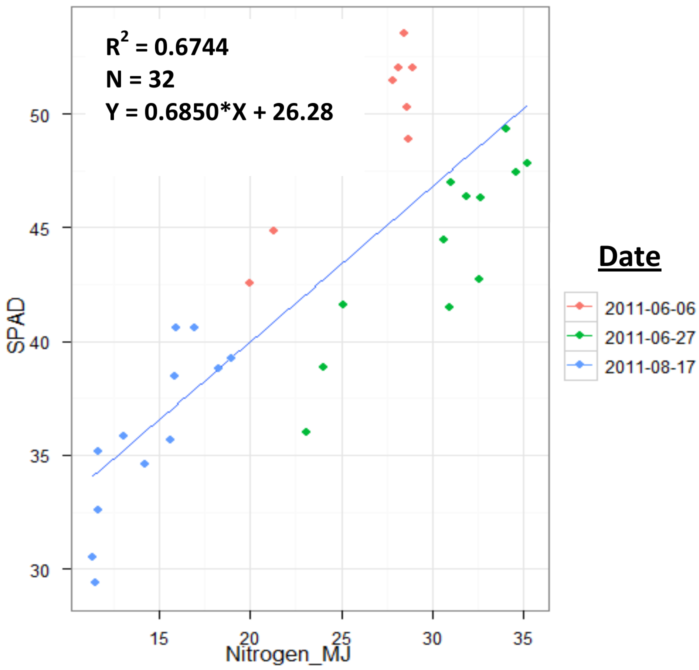


Appendix III: Relationship between SPAD and Plant Sap per plot per initial fertilization level

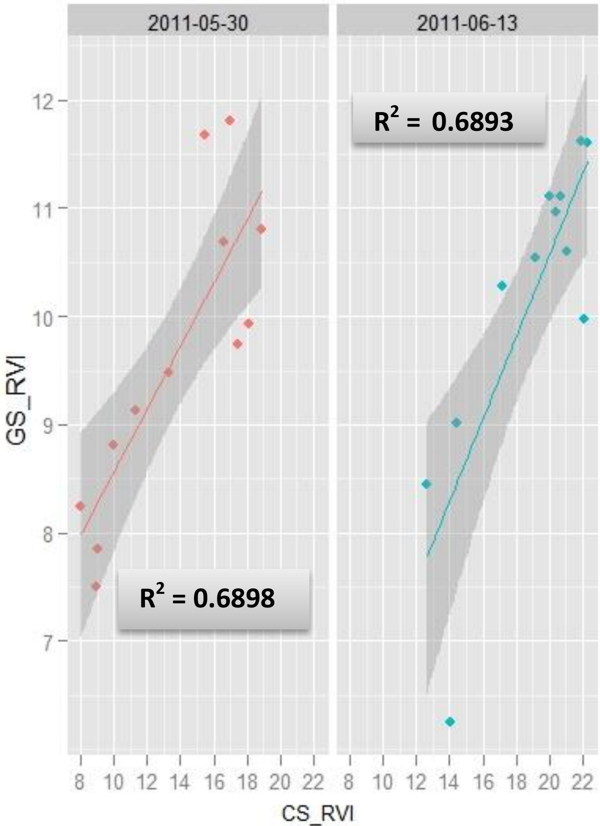


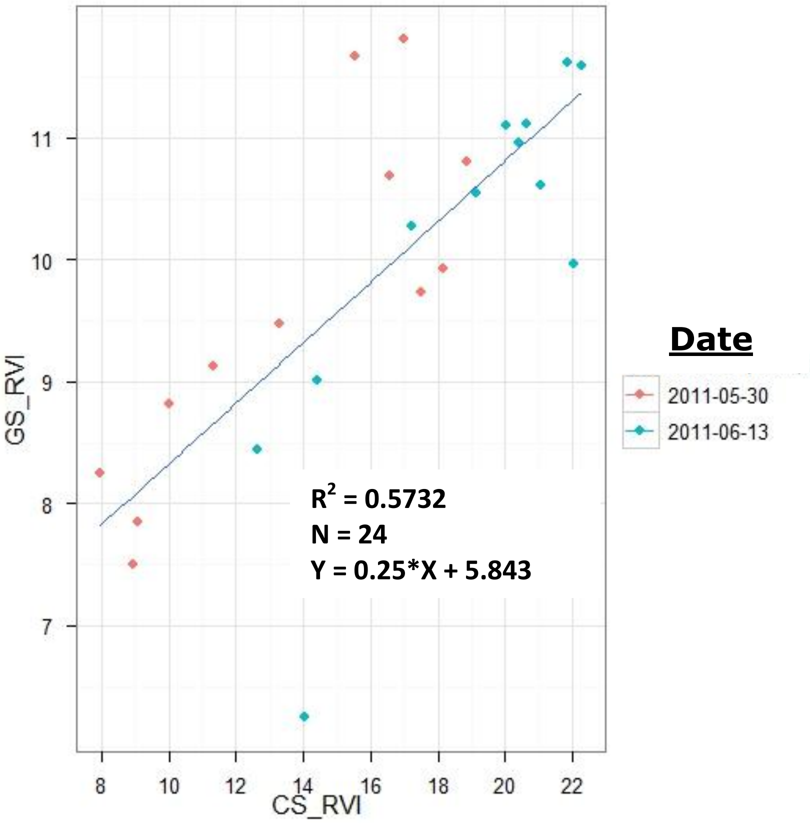
Appendix IV: Relationship between N top of the leaf from Mijnakker and SPAD readings on specific dates



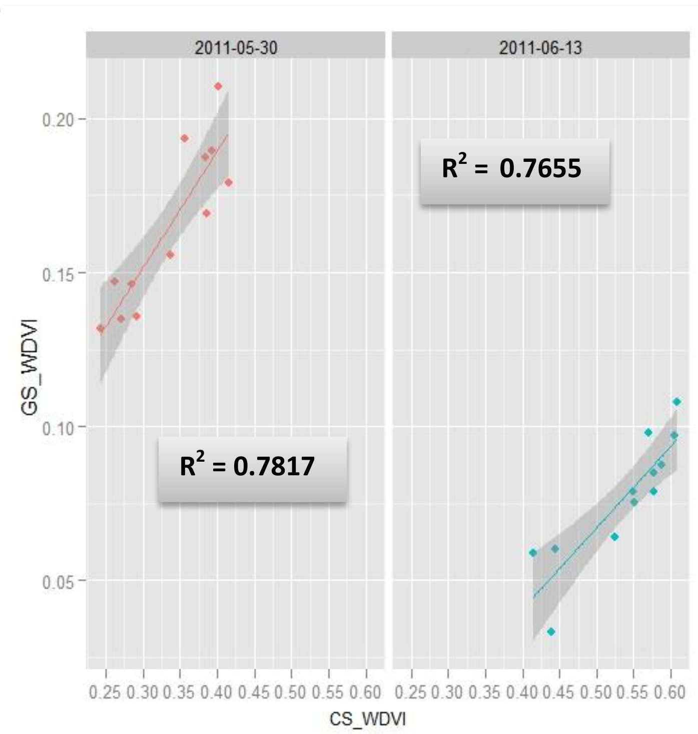


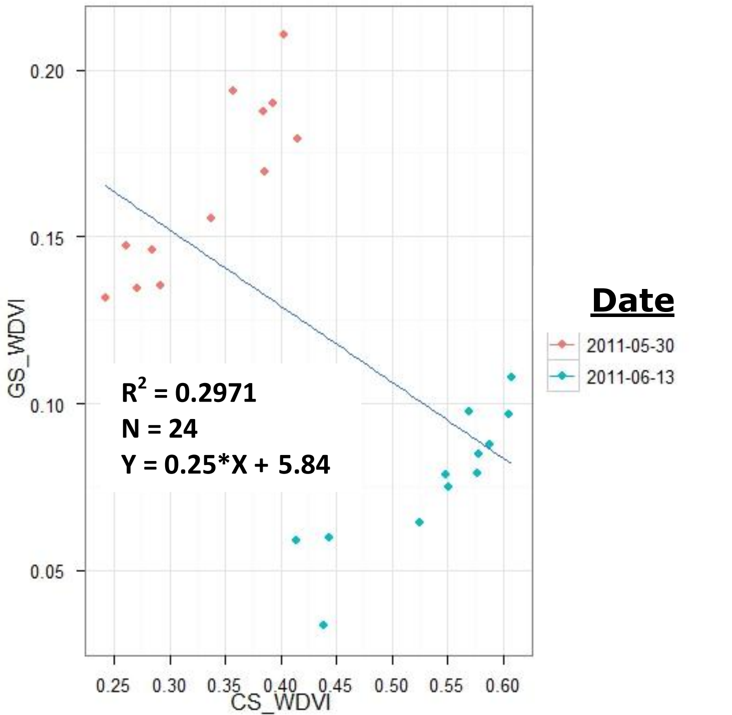
Appendix V: Relationship between RVI from Cropscan and GreenSeeker values on specific dates



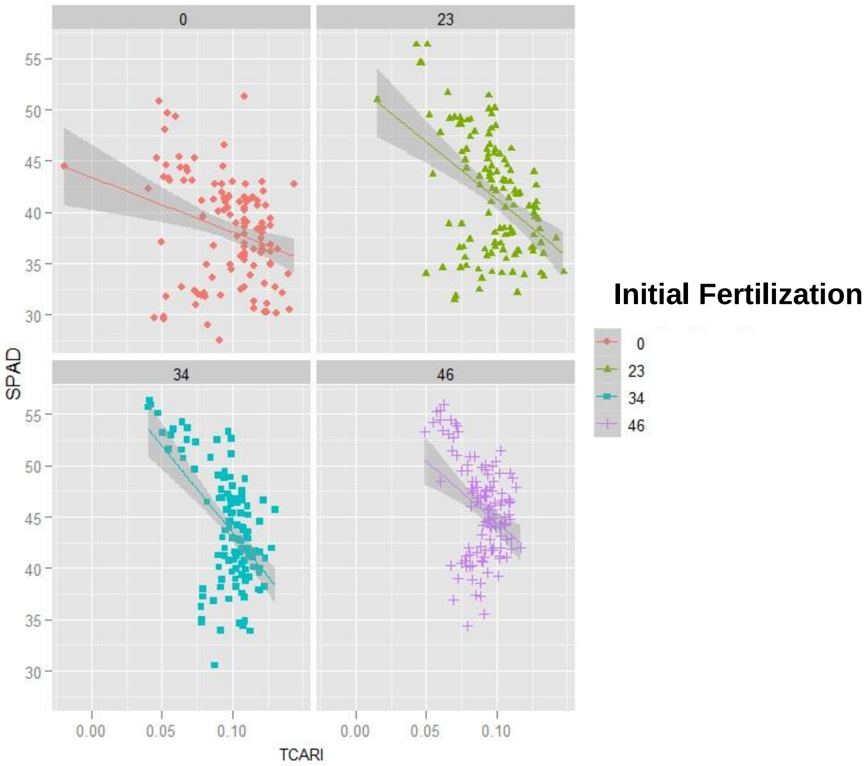


Appendix VI: Relationship between WDVI from Cropscan and GreenSeeker values on specific dates

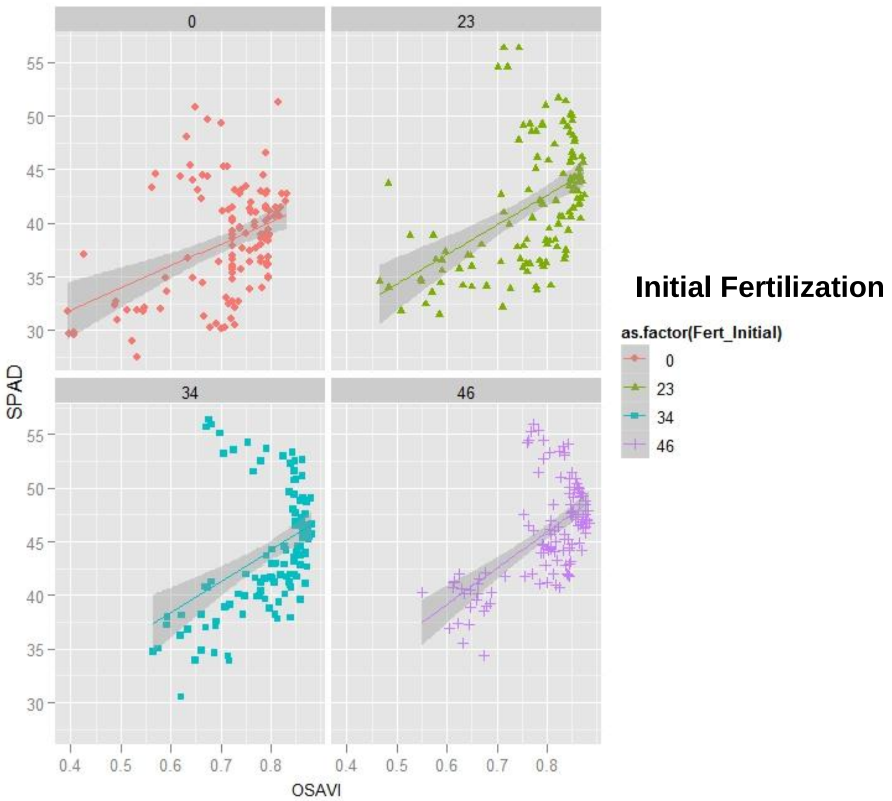




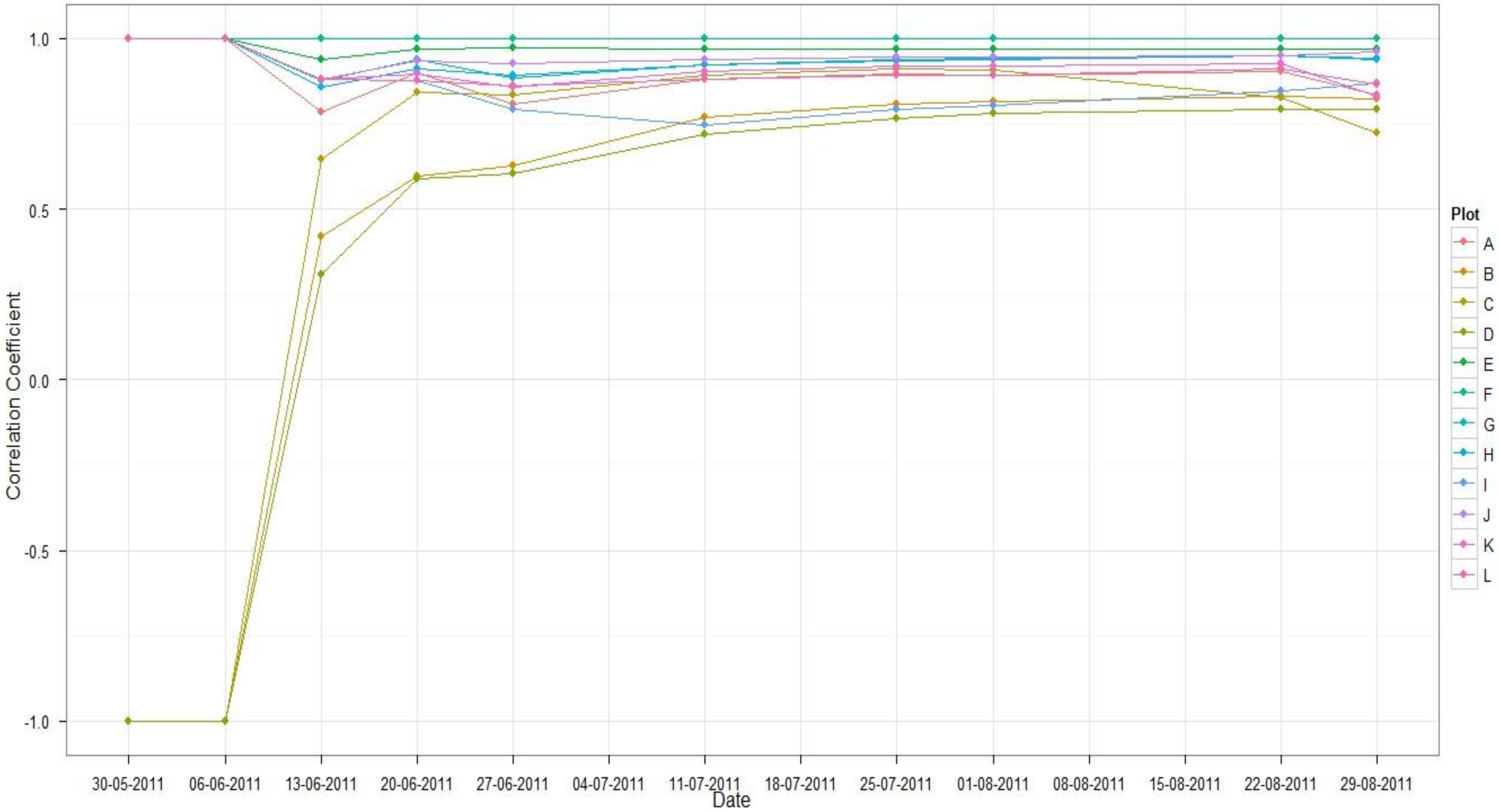
Appendix VII: Relationship between chlorophyll index TCARI and potato chlorophyll content from SPAD measurements based on the initial fertilization levels



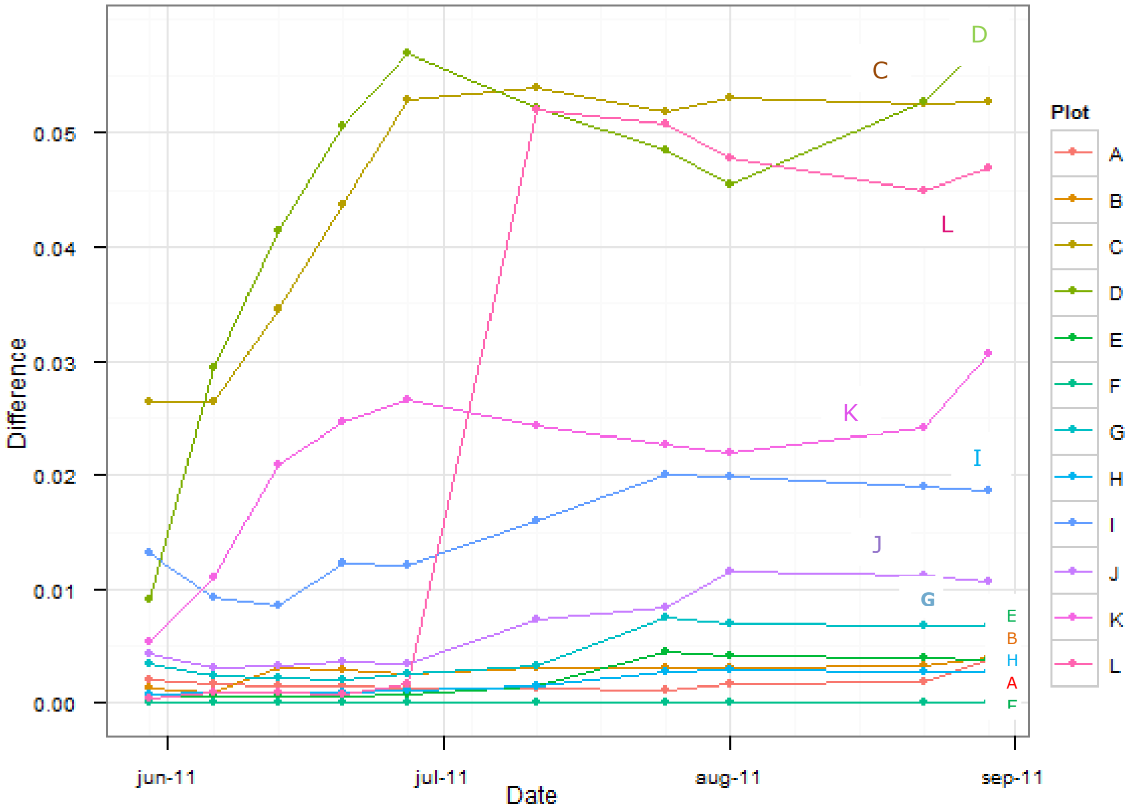
Appendix VIII: Relationship between chlorophyll index OSAVI and potato chlorophyll content from SPAD measurements based on the initial fertilization levels



Appendix IX: Time series similarity measure using correlation measures



Appendix X: Time series similarity measure using RMSD measure by using time series of the WDVI biomass index



Appendix XI: Time series similarity measure using Manhattan distance measure by using time series of the WDVI biomass index