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Integrating remote-, close range- and in-situ sensing for high-frequency observation of crop status to support precision agriculture

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Abstract: The objective of the study presented in this paper is to develop innovative approaches for the integration and analysis of information from multiple sensors which allow timely detection and diagnosis of crop status in precision agriculture. Our hypothesis was that sensing based nutrient management of crops can be improved by combining structure and bio-chemistry based vegetation indices and also taking into account the spectral changes over the growing season. Good relations were found between the sensor measured vegetation index WDVI and LAI and TCARI/OSAVI with nitrogen status based on SPAD measurements which were consistent over different growing seasons. Based on the calculated Euclidian distance of individual plot vectors with the reference plot vector, the development of crop status over time could be assessed. This approach will be further developed including the assignment of thresholds based on a so-called control chart approach.

Keywords: nitrogen fertilization, leaf area index, vegetation indices, time-series analysis

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1. Introduction

Changing needs in food production and associated food safety issues are challenging the agricultural sector to develop a new generation of sustainable agricultural systems. The use of global navigation satellite systems, remote sensing, tractor-based near-sensing instruments and in situ wireless sensor networks provides the modern farmer with a wealth of data [1,2]. For example in the case of fertilization, novel practices are required that improve nitrogen use efficiency by adjusting nutrient application rates based on precise estimation of crop needs [3]: type of fertilizer, improved timing, and placing nitrogen more precisely in the soil or on leaf. Therefore, to improve site-specific nitrogen management, plant growth models require accurate information on the whole cropping system, including the crop nitrogen status, and supply and losses from the soil with high temporal and spatial resolution [4]. However, there is still a lack of scientific knowledge and models to convert complementary data streams into spatial-temporal data products which can be used for optimizing field operations and use of resources in precision agriculture. Currently, the spatial resolution and also the temporal coverage of satellite sensors (e.g., Worldview-2, RapidEye, DMC, future Sentinel-2) are approaching the required specifications (< 10 m on a weekly basis). However, in temperate regions cloud cover is still limiting continuous data acquisition. To improve the frequency of spectral measurements, sensor data-streams of remote sensing and ground-based sensors on tractors need to be combined. In addition, the use of Unmanned Aerial Vehicles (UAV) provides a flexible intermediate observation platform which could improve the continuous aspect of data-acquisition. As a result there is a need to standardize vegetation indices from different sensor systems [5] and establish cross-sensor relationships. Such capability diminishes the trade-off of spatial resolution at the expense of temporal resolution (and vice versa), thus allowing observation of short-term variations in biochemical processes.

The objective of the study presented in this paper is to develop innovative approaches for the integration and analysis of information from multiple sensors which allow timely detection and diagnosis of crop status in precision agriculture. Our hypothesis is that sensing based nutrient management of crops can be improved by combining structure and bio-chemistry based vegetation indices and also taking into account the spectral changes over the growing season. We investigated the hypothesis based on a detailed field experiment which was conducted for two potato fields in the South of the Netherlands. This paper describes an overview of this case study, the available sensor data streams and the time-series analysis techniques.

2. Material and methods

During the 2011 growing season a broad range of sensors was adopted to monitor the status of a potato crop for an agricultural parcel (51° 19’ 04.55” N and 5° 10’ 11.29” E) in the South of the Netherlands close to the village of Reusel. Within the field different fertilization treatments were prepared resulting in a total of 12 different treatment levels (Figure 1). Within every treatment level, a plot of 30 by 30 m was laid out in which on a weekly basic crop conditions were determined (LAI, biomass, nitrogen status) and for which measurements with satellite-, ground-based and hand-held sensors were taken. In the next section these measurements shortly will be elaborated.

Monitoring of crop parameters

The potato crop status was monitored on a weekly basis in the period May 30 till August 29, 2011 resulting in 13 observations. For the 12 experimental plots (Figure 1), the nitrogen status was measured using the Minolta SPAD-502 chlorophyll meter. Within every plot, four rows were measured and for every row six plants and for every plant three leafs to characterize the variability within the plot. For this study, an average SPAD reading as proxy for nitrogen was used as input for the data analysis.

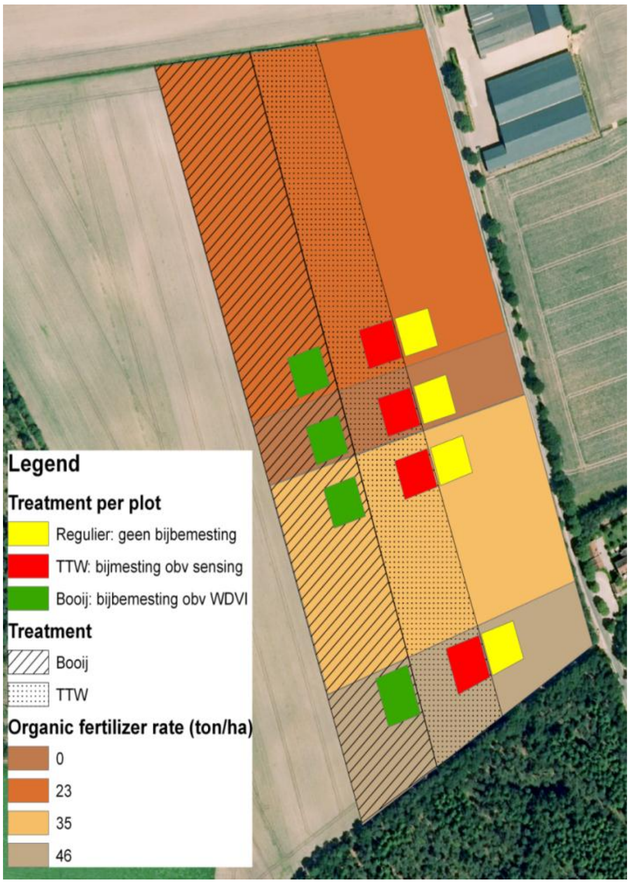

Figure 1: Overview of fertilizer treatments in the experimental potato field near the village of Reusel in the Netherlands

Simultaneously, the leaf area index (LAI) was measured with the LAI-2000 instrument for the same rows in the experimental plots. At the beginning and end of the row an incoming radiance measurement above the canopy was taken, and divided over the row six measurements below the canopy. Based on these measurements and with the LAI-2000 accompanying processing software a LAI value per row was calculated. In addition, three PASTIS-57 (PAI Autonomous System from Transmittance Instantaneous Sensors oriented at 57°) sensors were positioned in one of the plots for continuous monitoring of plant area index. The PASTIS-57 sensors are made of photodiodes that measure the incoming light in the blue wavelength to maximize the contrast between vegetation and sky and limit multiple scattering effects in the canopy. The measurements of the PAI gave additional information on the diurnal cycle of the vegetation and could be used to both validate ground based, close and remote sensing LAI or cover products.

Acquisition of sensing data

Crop reflectance was measured weekly with a Cropscan Multispectral Radiometer (MSR16R) for 12 observations in the period May 30 till August 29, 2011. The Cropscan is a handheld 16-band radiometer, which measures simultaneously the reflected and incoming radiation in narrow spectral bands [6]. Reflectance is measured through a 28° field-of-view (FOV) aperture and incoming radiation is measured through a cosine-corrected sphere. Calibration is performed by pointing the 28° FOV aperture towards the sun using an opal glass. Using this calibration, spectral reflectances are derived.

Next to this close sensing data were acquired in the first 6 weeks of growing season for five observations using the commercial greenseeker (GS) instrument. The GS sensor measures crop reflectance using an integrated LED emitting light in the red (656 nm) and NIR (774 nm). Six GS sensors were mounted on the spraying beam behind the tractor resulting in a regular point sampling of the field depending on the velocity during acquisition. Sensor measurements were acquired during regular agricultural management activities (e.g., fungicide application).

Finally, remote sensing imagery acquired with the UK-DMC-2 satellite (B1: 520 - 610 nm; B2: 630 - 690 nm; B3: 770 - 900 nm) were available on a regular basis resulting in a total of 8 observations over the growing season between May 30 till August 29, 2011.

Data analysis

In this study the following vegetation indices have been evaluated for the remote estimation of SPAD nitrogen content: REP, MTCI, MCARI/OSAVI, TCARI/OSAVI, CI_{green} and $CI_{red\ edge}$ [6]. NDVI and WDVI have been evaluated for the estimation of LAI. For the cropscan spectra all indices could be evaluated, while for the greenseeker and remote sensing imagery only the WDVI and NDVI were available for estimation of the LAI. Based on the R^2 and RMSEP for the relations between crop parameters and vegetation indices optimal relationships were established and also the comparison with found relations in previous years was evaluated.

Normally, sensing data of one moment in the growing season often the most actual one is used to assess the crop status. However, it would be relevant to take also the crop development into account in crop status assessment as this can give an indication of nitrogen use history or biomass development. This means that although at a certain stage two cropping locations can have a comparable nitrogen status but their nitrogen use history can be completely opposite (e.g., exhaustion vs. reserve) which requires different management strategies. To investigate these processes we applied time-series analysis methods to the cropscan sensing data to investigate if these processes are present and if they can be identified. For this study we adopted the Minkowski distance between two individual time series $f^p(t)$ and $f^q(t)$ collected at time t for pixels p and q respectively which is given by [7]:

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

Where is the $f^p(t)$ time series value at moment *t* and is the $f^q(t)$ time series value at moment *t.* N is the number of samples in the time series and r is a user defined integer where for r=2 it defines the Euclidean distance (D_E). In this analysis the most optimal fertilized plot (plot F) was used as reference, and the Euclidean distance between this plot and the other 11 plots over time was calculated. This means that an increasing distance from the reference plot indicates deviating nitrogen conditions and a potential need for a management action.

3. Results

A total of 144 observations was available to relate sensor derived vegetation indices with field measured LAI development and crop nitrogen status over the growing season (Figure 2). The WDVI gave the best relationship with LAI with a linear relation when all observations were included. The relation for NDVI gave the characteristic saturation effect resulting in uncertain LAI in the range 3-8. Figure 2 shows the gradual increase of LAI till the end of June when the potato crop its establishing its maximum LAI. The relation between WDVI and LAI for 2011 was compared to a relation which was derived in a comparable experiment for the growing season 2010. For higher LAI values the relation is comparable, however in the lower LAI range till 4 a clear deviation can be observed. This could be attributed to difference in aboveground structure of the potato canopy at the end of the growing season.

The TCARI/OSAVI index gave the best relation with the nitrogen status of the potato crop (Figure 2) with relations which also have been observed for other agricultural crops. An important advantage of the TCARI/OSAVI index compared to indices like REP and NDRE (result not shown) is the robustness to background effects like soil. Comparison of the 2011 and 2010 relationship gave a high degree of similarity which indicates that the established relations are robust over different growing seasons.

Figure 3 and 4 present the results of the time-series analysis, showing the difference based on Euclidian distance between vegetation index measurements for 11 experimental plots compared to the reference plot. It can be observed that at the start of the growing season already three plots which got a low initial fertilization (C, D, L) start to deviate from the growth of the reference plot F (Figure 3). Apart from plot K and I which also deviate at a later stage, the plots stay quit close together which indicates that in general the development of aboveground biomass (as indicated by WDVI) over the field is comparable for higher fertilization levels. This shows that fertilization effects on aboveground biomass only can be observed for plots with extreme (low) nitrogen availability. However, when we evaluate the difference in Euclidian distance for the TCARI/OSAVI index (Figure 4), then clear difference can be observed between clusters of experimental plots over the growing season. From the start of the growing season, plot B en D with low initial fertilization levels are already deviating. After two weeks also plot C and after three weeks a group of plots (A, K en I) start to deviate from the reference plot F. This latter process cannot be observed from the WDVI data (=biomass) but is mainly related to the nitrogen condition of the plant.

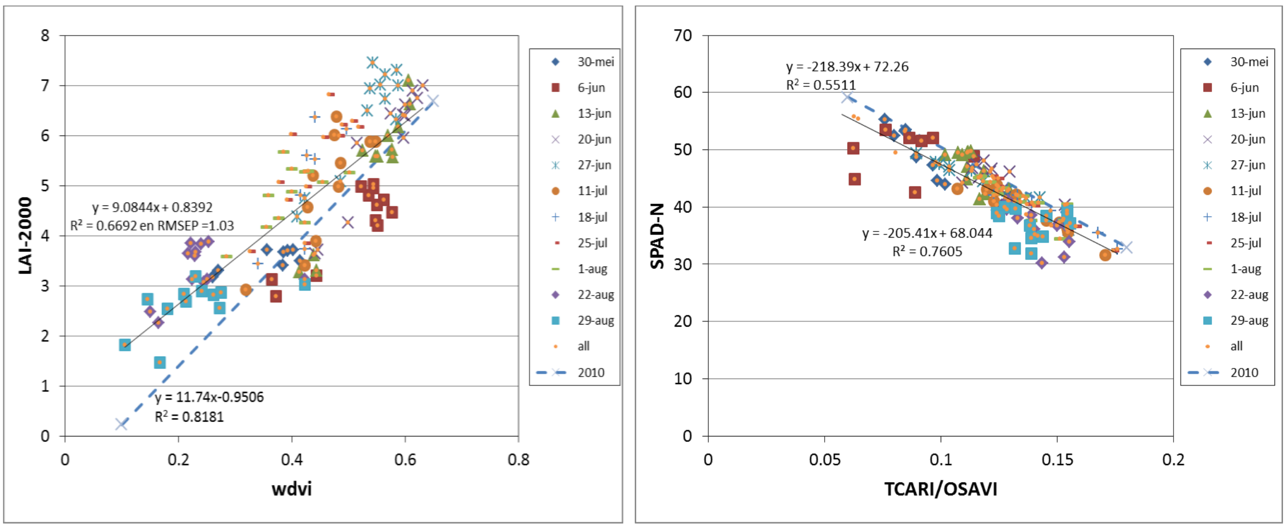

Figure 2: Relation for weighted difference vegetation index and Leaf Area Index for experimental plots in 2011 compared to regression line for field in 2010 (left); and relation for TCARI/OSAVI vegetation index and nitrogen determined with SPAD instrument for for experimental plots in 2011 compared to regression line for field in 2010 (right).

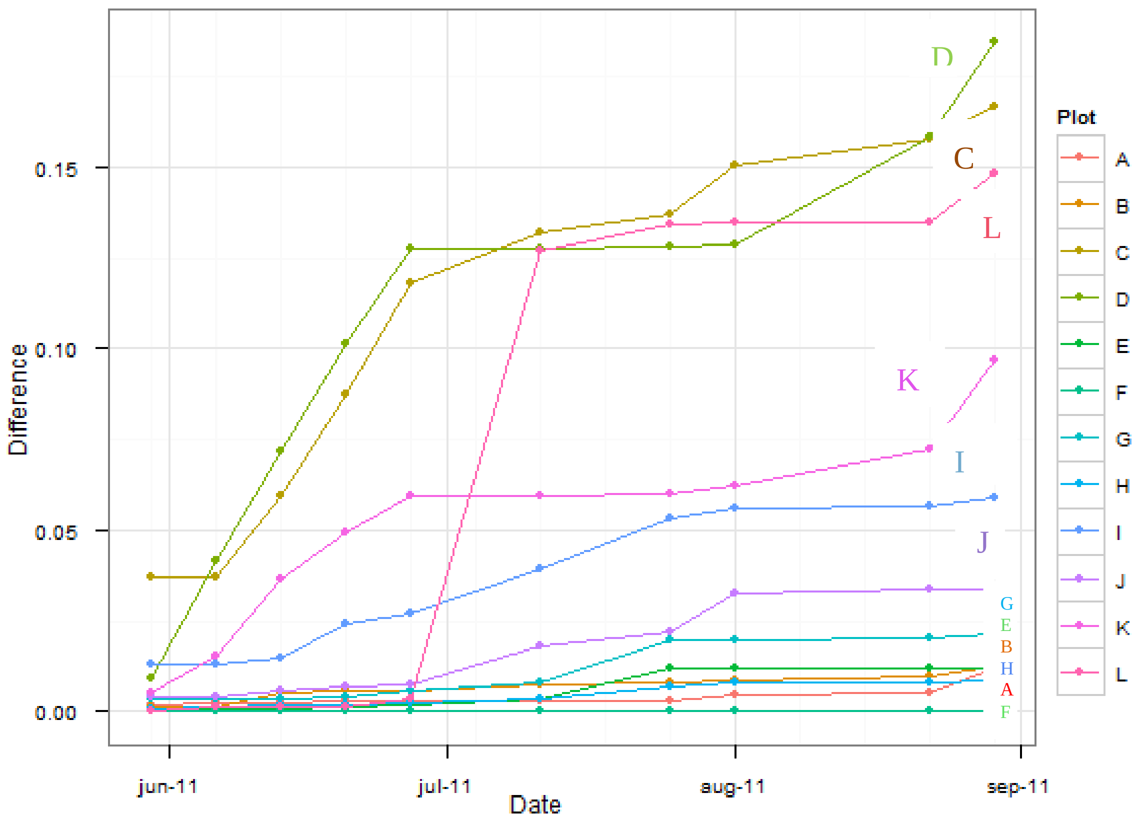

Figure 3: The difference based on Euclidian distance based on WDVI for 11 experimental plots compared to the reference plot F for sensor observations over the 2011 growing season.

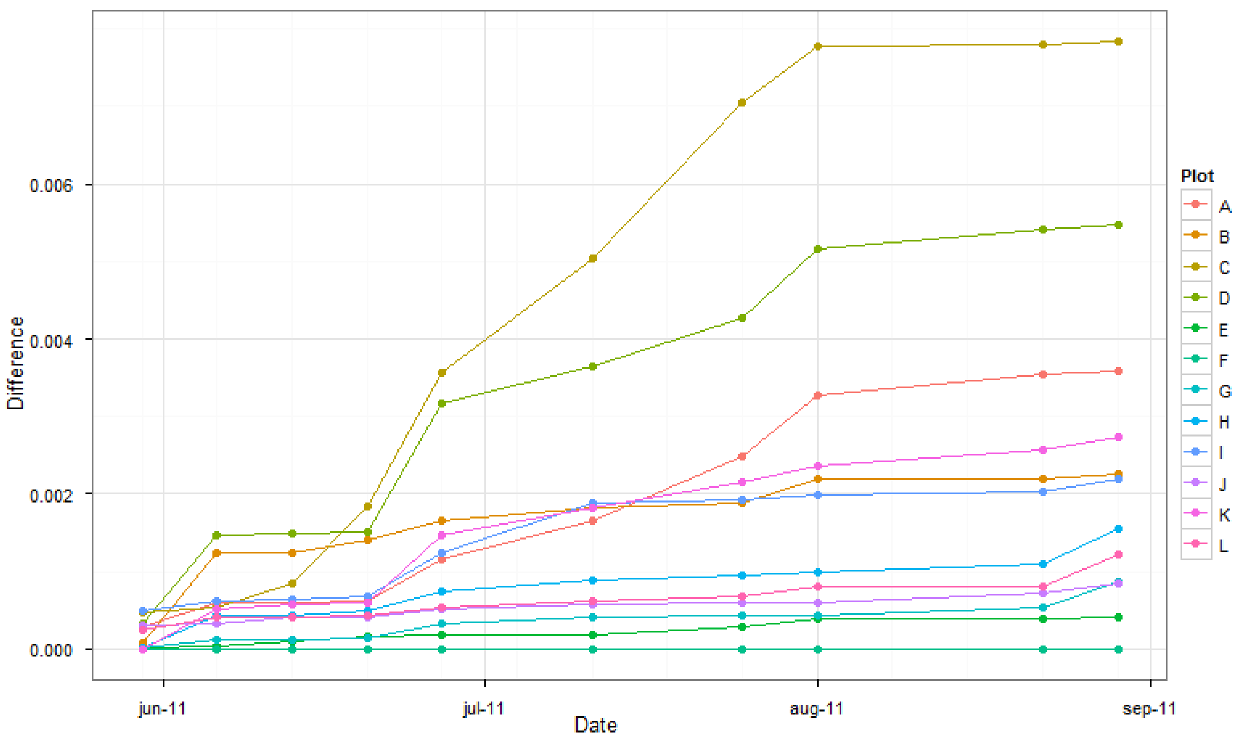

Figure 4: The difference based on Euclidian distance based on TCARI/OSAVI for 11 experimental plots compared to the reference plot F for sensor observations over the 2011 growing season.

4. Conclusions and outlook

In this paper, we have presented a multi-temporal dataset on the relation between close and remote sensing observations and potato crop characteristics in order to monitor crop status for precision agriculture applications. Good relations were found between the vegetation index WDVI and LAI and TCARI/OSAVI with nitrogen status based on SPAD measurements. The relations found for the potato field in 2011 showed comparable trends compared to these relations measured for another potato parcel in 2010. This shows that these relations seem to be generic over time and even over different potato varieties.

As a next step, instead of assessing differences in fertilizer treatments at one moment in time, we compared time-series of vegetation index values of all treatment plots with the reference plot for which optimal yields were observed. Based on the calculated the Euclidian distance of the individual plot vectors with the reference plot vector, the development of crop status over time could be assessed. Clear differences between plots could be observed at specific points over the growing season. This approach will be further developed including the assignment of thresholds based on a so-called control chart approach. This would allow the detection of areas within an agricultural parcel which are above a pre-defined warning limit or which pass an action limit defining the application of additional fertilizer. In 2012, the TCARI/OSAVI will be tested for operational implementation of variable rate application of nitrogen fertilizer over the growing season.

References and Notes

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