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Towards data-intensive, more sustainable farming: advances in predicting crop growth and use of variable rate technology in arable crops in the Netherlands

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Abstract. Precision farming (PF) will contribute to more sustainable agriculture and the global challenge of producing 'More with less'. It is based on the farm management concept of observing, measuring and responding to inter- and intra-field variability in crops. Computers enabled the use of Farm Management Information Systems (FMIS) and farm and field specific Decision Support Systems (DSS) since mid-1980s. GIS and GNSS allowed since ca. 2000 geo-referencing of data and controlled traffic farming. Several types of soil and plant sensors provided site specific data on spatial variation in crops. Today we see the development of several cloud based data platforms, and apps for soil and crop monitoring and site-specific crop care. This R&D is likely to continue in the coming years, yielding more apps for tactical decisions and operational interventions in crops, and strategic decisions on more-complex crop rotation issues. PF requires these developments, needing 'big-data' to produce more with less.

In this paper, we show results of three research topics in which we evaluate 1) correlations between remote and near biomass sensing data, 2) correlations between biomass and yield sensing data and 3) the use of task maps based on biomass sensing. The studied crops are common in The Netherlands: winter wheat, potato and onion.

The studies showed acceptable correlation between remote and nearby measured biomass data. It is essential to remove irrelevant variation in order to get better biomass maps that can be used for yield prediction and task maps. In general we showed poor correlations and irregular trends in the correlation between biomass indices and final yield (winter wheat and onion). The correlation improved when seasonal mean biomass index was used.

Finally, we showed two examples in which biomass maps were successfully used in task maps for chemical haulm killing and N topdress fertilizer use. The task maps were made within the web-based Akkerweb GIS-platform (http://www.akkerweb.nl/). Inputs were reduced by 15 – 30 % when the task maps were applied.

Keywords. *Advisory system, smart farming, fertilizer use, crop protection*

Introduction

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Precision farming (PF) (Skotnikov & Robert, 1996; Kempenaar & Kocks, 2013) is an innovation in agriculture allowing the best treatment of crops and livestock at the right time and smallest scale possible (up to treatment of individual plants or animals). Other terms used to refer to this farm management concept, are data-intensive farming or smart farming. Notwithstanding the term, it requires a seamless integration of different technologies (sensors, Global Navigation Satellite Systems (GNSS), data-infrastructures (ICT), Farm Management Systems (FMS), implements) and intelligence (data, DSS, implement control software, auto-guidance systems). Optimisation of treatments at the lowest scale possible will improve yields and resource efficiency in agri-food chains, so reducing the agricultural footprint. More and more, PF will become the 'licence to produce' for modern farmers. Key technologies required for PF have become available for farmers, e.g. Farm Management Information Systems (FMIS) and GNSS, providing a basis for implementation of PF.

With the aim to further develop PF, we studied 1) correlations between remote and near biomass sensing data, 2) correlations between biomass and yield sensing data and 3) the use of task maps based on biomass sensing. The focus was on biomass sensor data and crop yield. We analysed data sets in which we had access to data from sensors that are used in practice. These sensors express the presence of green vegetation in NDVI (Normalize Difference Vegetation Index) and WDVI (Weighted Difference Vegetation Index). We analysed correlations between different biomass sensors and between biomass sensors and yield sensors. We give an outlook on how the biomass data can be used in variable rate task maps. These task maps are made in Akkerweb[1], a GIS-platform for farmers that supports the safe and easy use of spatial and temporal soil, crop, climate and management data for precision agricultural applications, and provides apps for variable rate application (VRA) of seeds, fertilizers and crop protection.

Materials & Methods

We collected and analysed data from several agricultural fields in The Netherlands in the period 2012 to 2016. We studied different crops for the goals of our research.

In topic 1 data, from seven potato crops in 2015, one onion crop and four potato crops in 2014, were analysed on the correlation between remote and near sensing of biomass. Out of these seven potato crops, 70 data pairs of remote and near sensing were analysed (Van Wee et al., 2016). In 2014, onion data by Spot 6/7 satellite and GreenSeeker RT100 sensor were selected (Lageweg et al., 2016) and nine observation dates with DMC satellite and N-sensor data on four potato fields were available (Holleman, 2015).

[1] www.akkerweb.nl, Geographic Information System for farmers

We studied a winter wheat (Feher, 2014) and an onion crop (Lageweg et al., 2016) to test the correlation between biomass data and yield in topic 2.

In topic 3 we studied two different potato crops to analyse the practical use of biomass data and task maps.

Field boundaries were available from the national governmental RVO-database which is connected with Akkerweb. Agronomic data on crops and crop management were provided by the farmers. Access to satellite, soil and weather data were obtained via Akkerweb. Intermediate service providers (Netherlands Geomatics & Earth Observation B.V.[NEO], WUR-Alterra) used reflection data from the public national satellite data portal[2] and provided NDVI and WDVI maps of the fields on the dates that satellite data were available in the database. The database contains images of three satellites: Formosat-2 and Spot 6/7 (resolutions < 10 m) and DMC (resolution > 20 m). Near sensing of crop reflection were measured with Yara N-sensor and Trimble Greenseeker RT100 sensors. The biomass indices provided by these sensors were analysed. Details on the sensors and indices are given in an earlier ICPA paper (Kempenaar et al., 2014). The annex also contains an overview of biomass indices. Crop yield data were collected with use of commercial systems on harvesting machines. The winter wheat was harvested with an 8-m wide Claas Lexion 600 series combine harvester with yield mapping unit (Feher, 2014). The gross yield of the onion field was measured on a 1.5 m wide onion swath lifter (Lageweg et al., 2016).

The data (both parameter values and coordinates) were analysed in their original form. This means that the data were analysed as provided by the sensor systems. We had point data and grid data. Pairs of data were made by a nearest neighbour approach. Regression analysis was applied to the data pairs to study correlations. We applied linear regression of the Microsoft Excel 2010 software program. Q-gis and Akkerweb were used to visualize data and to interpret crop growth conditions and farmer information in previous crops.

Results & Discussion

Topic 1: Correlation between remote and nearby biomass data

Analysis of data from seven potato crops in The Netherlands in September and October 2015 showed a rather poor correlation of R^2 = 0.39 (Fig. 1, details in Van Wee et al., 2016). The data set analysed consisted of 70 data pairs: ten remote sensing data points (DMC satellite; 22 x 22 m grids) were randomly chosen from each field and paired to in-grid near sensing data (nearest neighbour approach). Individual fields showed correlations from 0.12 to 0.75, ranging from very poor to good. A part of the poor correlation is explained by the fact that the near sensor data of the Yara N-Sensor (line scan) have a different resolution than the grid data. In Fig. 2 we show a rather good correlation between remote (DMC satellite) and near (N-Sensor) measured biomass indices of four potato

[2] www.spaceoffice.nl/nl/Satellietdataportaal, free satellite images

crops on nine observation dates in 2014 (R^2 = 0.69, Holleman, 2015). For the same fields Holleman also showed a good correlation between remote (Spot 6/7) and near (N-Sensor) biomass indices (R^2 = 0.71, data not shown). Lageweg et al. (2016) showed a good correlation between NDVI data of an onion crop in 2014 measured by Spot 6/7 satellite and NDVI data measured in the crop with GreenSeeker RT100 sensor (R^2 = 0.82, data not shown).

We conclude that correlation between remote and near biomass sensing data improves when the data set contains data from less fields. Variation between fields (for instance variety, previous crop, soil type) has a negative effect on correlations. It is important to remove irrelevant variation in data sets in order to get better biomass maps of arable crops that can be used for yield prediction and task maps.

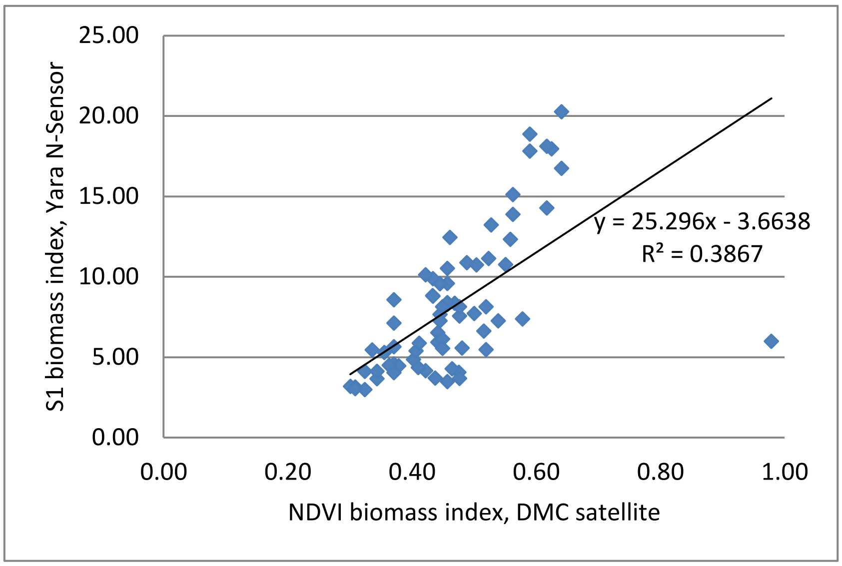

Figure 1. Biomass indices from tractor mounted line scan sensor (Yara N-Sensor, S1) and satellite mounted grid scan sensor (DMC satellite, NDVI) determined in September 2015 (end of season) in seven potato crops in The Netherlands plus statistics of the regression analysis (R^2 = 0.39).

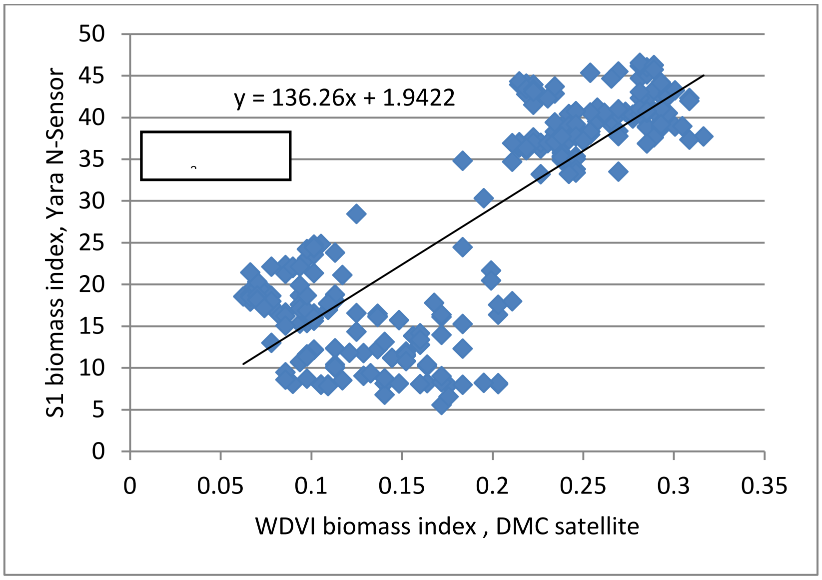

Figure 2. Biomass indices from tractor mounted line scan sensor (Yara N-Sensor, S1) and satellite mounted grid scan sensor (DMC satellite, NDVI) determined in may - September 2014 in four potato crops in The Netherlands plus statistics of the regression analysis (R^2 = 0.69).

Topic 2: Correlation between biomass data and crop yield

We analysed data from two crops: winter wheat and onion.

For winter wheat, we studied the correlation between remote (Formosat-2) measured NDVI data and site-specific yield data (season 2012-2013, see Fig 3a, and Feher, 2014). We had ten satellite sensor observation dates in the period May 1 until August 2, 2013. The correlation between NDVI and yield on individual observation dates was very poor to moderate, with R^2 ranging from 0.02 to 0.61 (Table 1). Best result in correlation between NDVI and final yield was obtained on July 8, 2013 and the worst on July 22. There was no trend to a better correlation towards the end of the season.

Table 1. R^2 correlation per date between mean NDVI values and final yield in 2013

	03.05.	27.05.	04.06.	06.06.	30.06.	06.07.	08.07.	18.07.	22.07.	02.08.
R^2	0,3174	0,4921	0,5349	0,3507	0,5135	0,315	0,6148	0,1294	0,0192	0,2315

Further analysis on the correlation between the seasonal mean NDVI (May 1 until August 2) and yield showed a high correlation (R^2 = 0.79, Fig 4a). The seasonal mean NDVI gives a better estimate of the final yield of the wheat crop than the individual NDVI data. We also observed that NDVI data measured in the tillering crop phase had very poor correlation with final yield. This can be explained by the fact that the crop can compensate less tillers with more and bigger kernels per tiller. The left part of the field (Fig. 3a) had half the plant density than the right part of the field. The lower plant density was compensated with more tillers per plant.

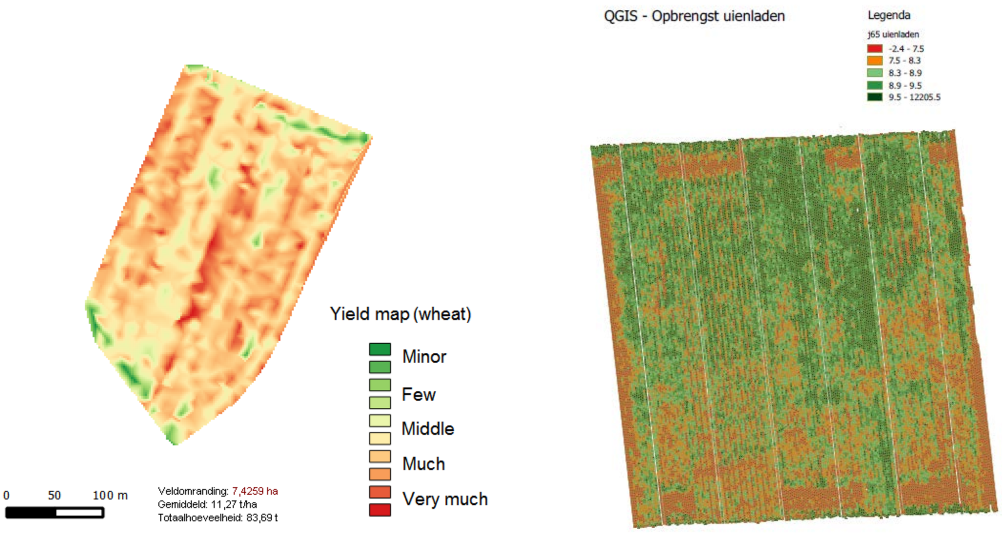

Figure 3a and 3b. Yield maps of winter wheat crop 2012 – 2103 (left, average 11.3 ton wheat per ha, gross) and onion crop 2014 (right, legend in kg per m^2, average 81 ton onion per ha, gross) in The Netherlands as presented in QGIS. Field size was ca 10 ha.

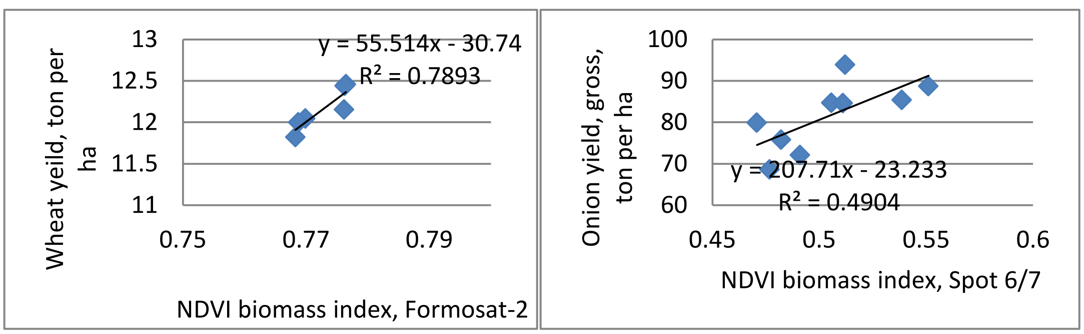

Figure 4a and 4b. Correlation between seasonal mean NDVI biomass data and crop yields in The Netherlands. On the left, data of a wheat crop and mean NDVI data from early May to early August R^2=0.79). On the right, data of an onion crop and NDVI data from June and July (R^2=0.49). See also Fig. 3a and 3b.

In the onion crop, we studied the correlation between nearby (GreenSeeker RT100) measured NDVI data and site-specific yield data (season 2014, see Fig 3b, and Lageweg et al., 2016). We analysed nine data pairs, observed in the period early June and July. The correlation between NDVI and yield on these observation dates was also very poor to moderate, with R^2 ranging from 0.10 to 0.74. Best result was obtained on July 22, 2013. However, similar as in the winter wheat case, we found an irregular trend in the correlation between NDVI and yield. The correlation between the seasonal mean NDVI (June 1 until July 31) and yield is shown in Fig 4b. The correlation between seasonal mean NDVI and yield was moderate to poor (R^2 = 0.49). The seasonal mean NDVI gave in this crop also a better estimate of the yield than the individual NDVI data. Visual inspection of plotted results and NDVI-patterns tended that field parts with high NDVI values also had more biomass.

We conclude that biomass maps can be used to estimate wheat and onion yield, as shown in this paper. Variation causing errors in the biomass sensing systems and the yield sensors do not allow accurate yield predictions yet. Efforts in R&D should be made to remove these errors.

Topic 3: Biomass data and task maps

We studied two different potato crops to analyse the practical use of biomass data and task maps. Although we sometimes observed poor correlations between sensor based biomass maps and yield, we expected that farmers can use the biomass maps in task maps. In Fig 5 we show two successful examples of use of biomass maps in task maps. Fig 5a shows a variable rate dosing map of Reglone (potato haulm killing) in potato based on a Spot 6/7 NDVI map measured in September 2015. Fig. 5b shows a variable rate top-dress N dosing map based on N-Sensor measurement in July 2015. Through smart integration of sensor data, decision support and implements, farmers can save on inputs even with the use of not yet optimal biomass maps.

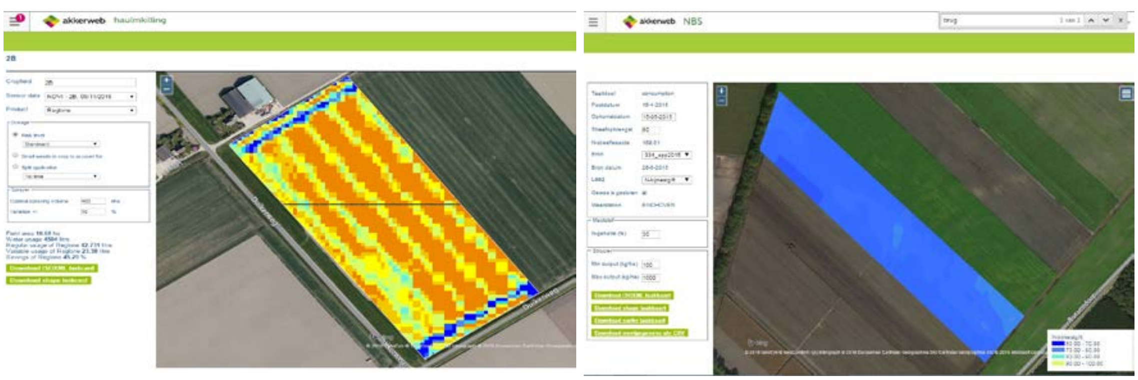

Figure 5a and 5b. Examples of use of biomass maps based dosing maps in The Netherlands. On the left, potato haulm killing dosing map based on Spot 6/7 data (September 2015). On the right, a top-dress nitrogen map for a potato crop (July, 2015)

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References

Feher, T., 2014. Comparing near and remote sensing datasets from experimental wheat parcel. BSc. Study report, CAH Vilentum, Dronten.

Kempenaar, C., Kocks, C.G., 2013. Van Precisielandbouw naar Smart Farming Technology. R&D program chair Precision farming. CAH Vilentum Hogeschool en Wageningen University en Research Center. 47 pages.

Kempenaar, C., Van Evert, F.K., Been, Th., 2014. Use of vegetation indices in variable rate application of potato haulm killing herbicides. In: Proceedings of ICPA conference, Sacramento, USA, July 2014. Paper 1413, https://www.ispag.org/icpa.

Holleman, K.C., 2015. De correlatie tussen vegetatie indices gemeten met de Yara N-sensor, Spot-6 en de DMC satellieten. BSc. Study report, Stoas Vilentum, Wageningen.

Lageweg, E., Kornegoor, J., Nortier, Y.J., 2016. Smart Farming. Analyse van data van twee telers in Flevoland. Study report, minor precision farming. CAH Vilentum.

Skotnikov, A., Robert, P., 1996. Site Specific Crop Management; A system approach. In: Proceedings of the Third International Conference on Precision Agriculture. American Society of Agronomy, Crop Science Society of America and Soil Science Society of America. Madison, USA, p. 1145-1151.

Van Wee, R., Algera, R., Doejaaren, S., Rentmeester, B., Stouwdam, H.J., 2016. Satellietbeelden en Yara N-Sensor bij variabele loofdoding. Study report Hona module. CAH Vilentum, Dronten.

Appendix

Table A-1. Overview of reflection based biomass indices (Kempenaar et al., 2014).

Index	Name	Formula	Authors (year)
NDVI	Normalized Difference Vegetation Index	$(R_{nir}-R_{red})/(R_{nir}+R_{red})$	(Rouse et al. (1974)
RVI	Ratio Vegetation Index	R_{nir}/R_{red}	Jordan (1969)
$WDVI_r$	$WDVI_r$, with red light reflection in formula	$R_{810}-(R_{810}-R_{660})xR_{660}$	Clevers (1989)
$WDVI_g$	$WDVI_g$, with green light reflection in formula	$R_{810}-(R_{810}-R_{560})xR_{560}$	Bouwman (1992)
REP-LI	Red Edge Position: Linear Interpolation method	$700+40x(Rre-R_{700})/(R_{740}-R_{700})$; and $Rre = (R_{670}+R_{780})/2$	Guyot et al. (1988)
MTCI	Meris Terrestrial Chlorophyll Index	$(R_{754}-R_{708})/(R_{708}-R_{680})$	Dash, Curran (2008)
TCARI	Transformed Chlorophyll Absorption in Reflectance Index	$3x((R_{700}-R_{670})-0.2x(R_{700}-R_{550})x(R_{700}/R_{670}))$	Haboudane et al. (2002)
TCARI/ OSAVI	TCARI with Optimized Soil-Adjusted Vegetation Index	$1.16x(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)$	Haboudane et al. (2002)
MCARI	Modified Chlorophyll Absorption Index	$(R_{700}-R_{670})-(0.2x(R_{700}-R_{550})x(R_{700}/R_{670}))$	Daughtry et al. (2000)
DCNI	Double-peak Canopy Nitrogen Index	$((R_{720}-R_{700})/(R_{700}-R_{670})/ (R_{720}-R_{670}+0.03))$	Chen et al. (2010)
NDRE	Normalized Difference Red Edge index	$(R_{780}-R_{720})/(R_{780}+R_{720})$	Eitel et al. (2010)

R_{nir} = reflection at near-infrared wavelengths, R_{red} at red light wavelengths, other reflections at specified wavelengths.