ON THE EFFECT OF MULTISEASONAL EARTH OBSERVATION AVAILABILITY FOR THE ASSIMILATION-SUPPORTED MODELLING OF WINTER WHEAT YIELD

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ABSTRACT

The challenges of sustainably securing food production for a growing world population require an increased efficiency of agricultural production. Site specific management is one key towards higher agricultural production efficiency. However, it is dependent on spatial information on crop status during the growth period. Such information may be provided by complex growth models, whose spatial parameterisations are enriched through assimilation of optical remote sensing data. Optical satellite observations again are highly dependent on weather conditions and sensor availability, resulting in a limited number of observations that can be acquired of a certain target during the course of a growing season. This study therefore investigates the effect of observation frequency on the spatial modelling of winter wheat yield in northern Germany. Based on the comparison of modelled and measured spatial yield maps, covering more than 500 ha of winter wheat, it is shown that the accuracy of the model results decreases significantly, if less than four spatial observations per season are available. Thereby, observations covering phenological growth stages from BBCH 70-90 proved to be best suited for the modelling of yield, followed by observations from BBCH 50-70, while satellite images taken during BBCH stages 30-40 turned out to be least suitable for yield modelling.

1. INTRODUCTION

Predominantly driven through the continuing growth of the world population, the competition between food, fibre, energy and environmental demands for bioproductive land surface is gradually becoming more severe [1]. The conflict between limited availability of bioproductive land surface on one hand and rising demands of biological production (food, energy, fibre, carbon sinks etc.) on the other, also has led to an increased public awareness of the necessity of increased agricultural production [2]. Due to climatic, pedogenetic, ecologic or logistic limitations, further spatial expansion of the currently cultivated farmland is rarely feasible. Although global simulations indicate that locations of potential farmland might change in the future, because some areas might become usable due to global warming, while others in future might not be suitable any more due to erosion or water scarcity as an effect of climatic shifts, the absolute area of potential farmland is supposed to more or less stay constant. An increase of agricultural production therefore has to be achieved by gaining higher amounts of yield from the already agriculturally exploited acreage, i.e. by reasonably and sustainably increasing the efficiency of agricultural production [3].

Being sensibly applied and thoroughly supported by up-to-date spatial information, smart farming practices, such as site specific seeding, fertilization or plant protection, as well as advanced computer aided farm management systems may significantly contribute to an increased efficiency of agricultural production [4]. Reliable information on crop status during the different development stages of a growth period thereby are the key to improved crop management. Above all, site-specific management approaches are based on the awareness of spatial heterogeneities of growth conditions. Therefore, only monitoring techniques able to deliver spatially explicit data may successfully be applied. Satellite-based earth observation (EO) currently represents the only technological solution capable of providing spatially continuous information on land surface heterogeneity. Furthermore, remote sensing may effectively be applied to the derivation of specific plant physiological variables, such as the concentration of chlorophyll pigments or the amount of photosynthetically active leaf area. In order to allow for the generation of agricultural application maps, spatially explicit information on crop status is required one or two days in advance of the scheduled execution of the site-specific management measure (seeding, fertilization, plant protection, harvesting etc.). The availability of information therefore is very time-critical. Due to various restrictions associated with optical remote sensing (e.g. weather conditions, sensor availability etc.), the number of observations that may be acquired of a specific target, such as a certain field, during a single growth period normally is rather small. However, the surface processes monitored by remote sensing, e.g. plant growth and development, are highly influenced by dynamic variables (weather conditions, human or animal interference, occurrence of pests and diseases etc.) and therefore cannot be assumed to follow a linear course. Bridging the gaps between satellite observations through simple interpolation over longer

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spans of time consequently will not allow for an adequate representation of crop development. To overcome these temporal constraints, advanced information systems have been developed, which are based on the assimilation of EO data into process-based models of agricultural production [5]. Model-based approaches are able to mechanistically combine spatially explicit information derived from EO data with temporally dynamic information, such as growth processes driven by hourly weather data. They thus may provide the desired information, e.g. the current distribution of aboveground biomass, in hourly intervals mostly independent from the date of the satellite data acquisition. Nonetheless, the assimilation-based model approaches largely depend on high-quality satellite observations that ideally should cover the major development stages of the crop. The conflict between the general necessity of routinely acquiring high quality EO data in order to produce high quality information products for smart farming on one hand and the difficulties of generating highly frequent (daily) monitoring series using optical sensors on the other, leads to two important research questions:

1. How many EO acquisitions actually are required during the course of one growing season to allow for the generation of a reasonably accurate agronomical information product?

2. Are there preferred periods of time during a growing season, where EO acquisitions may contribute more information to the final product than during other periods?

The presented study therefore aims at investigating the impact of satellite observation frequency on assimilation-based simulations of winter wheat yield. Thereby, also the question of preferable acquisition dates for the modeling of winter wheat yield is addressed.

2. MATERIALS & METHODS

2.1. The Model System

Remote sensing as a stand-alone technique is limited with respect to the derivation of information products of practical farming relevance. This on one hand is due to the fact that the derivation of absolute biomass from remote sensing remains difficult [6], but mostly results from the uncertain predictability of observations for specific dates/times, due to variable weather conditions. To overcome these limitations, an approach is proposed that combines information on the spatial heterogeneity of the land surface from EO data sources with information on the temporal dynamics of non-linear land surface processes from a physically based land surface model. For the land surface simulation component, the model PROMET (Process of Radiation, Mass and Energy Transfer; [7]) is used, while the optical remote sensing part of the combined model system is represented by the complex canopy reflectance model SLC (Soil-Leaf-Canopy; [8], [9]), as it is indicated in Fig. 1. SLC is used in inverted mode to derive spatially explicit maps of photosynthetically active leaf area (greenLAI) from EO data. At the same time, PROMET simulates greenLAI at an hourly time-step as the result of biomass allocation within the leaf

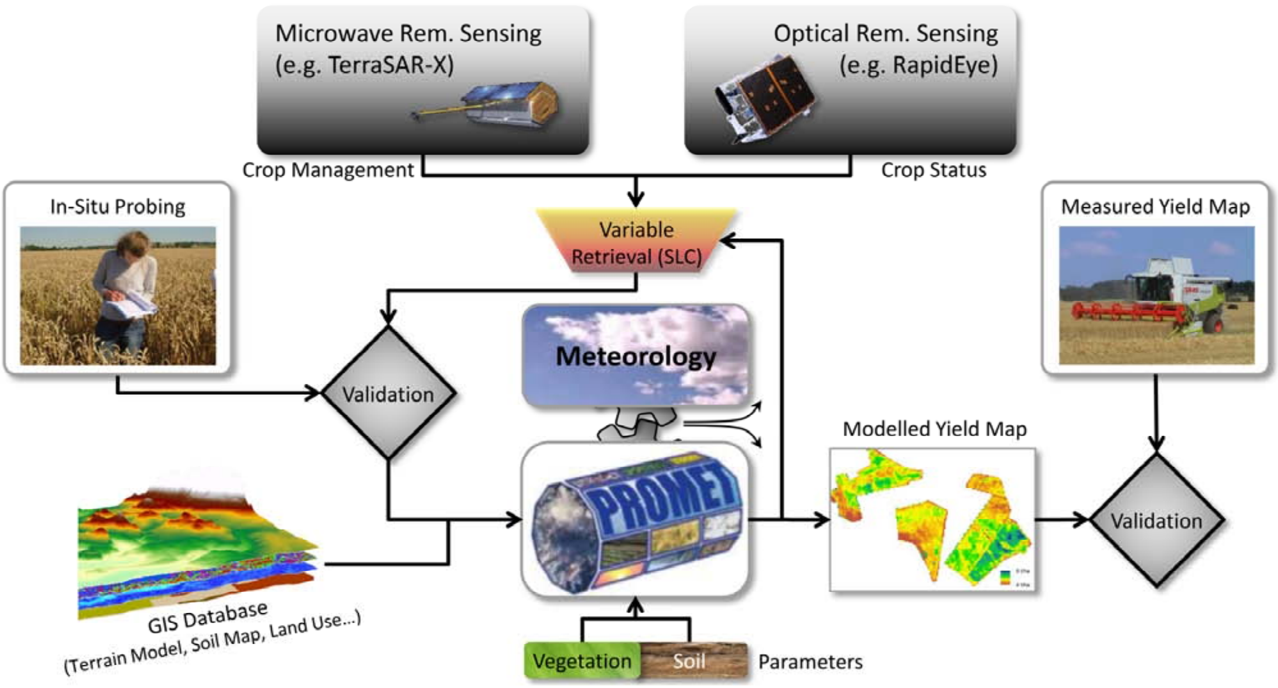

Figure 1. Overview of the combined (PROMET/SLC) assimilation system, including EO data sources, model parameters and components as well as different levels of validation options.

fraction of the modelled canopy. GreenLAI therefore may be used as spatial exchange variable between the land surface model and the satellite observation during run-time. Major management events, such as harvest, are derived from hyperfrequent X-band SAR time series and are made available to the land surface model on field level (Fig. 1).

With the help of this integrated EO/model system, it is possible to simulate a variety of land surface variables at an hourly time step, among them being highly sophisticated outputs such as agricultural yield. Yield is a variable that is extremely sensitive to growth conditions, mostly because all growth influencing factors, such as the duration of the single phenological stages, the water and nutrient supply during the course of the growing season, the occurrence of pests and diseases or unexpected natural hazards such as wind break or hail damage, more or less are aggregated within the final product. A correct simulation of yield therefore implies the correct representation also of other growth influencing variables in the model. Due to this interconnectedness of the variable yield and also due to the fact that yield more or less is the only biophysical variable that can be measured spatially without destroying the crop during the active growth phase, it was decided to use yield as the benchmark variable for the analyses of this study.

2.2. Test Area and Model Setup

The integrated EO/model approach is applied to a test site in Saxony-Anhalt, northern Germany, thus choosing one of the most intensively cultivated areas of Germany for the experiment. Winter wheat fields of two large farms in the vicinity of Blankenburg, east of the Harz low mountain range, were modelled for the growing seasons of the years 2010 and 2011. While for 2010 more than 280 hectares of wheat were modelled, the test site was cultivated with more than 560 hectares of winter wheat in 2011. The area is generally characterized through relatively large acreages, fertile soils (mostly chernozems) and low annual precipitation sums (approx. 600 mm), combined with a continentally dominated climate. The required spatial parameters for the model setup could mostly be derived from publicly available data sources (soil map from FAO/HWSD, DTM from NASA/SRTM) or from own observations respectively (land use), while the meteorological driver variables were commercially acquired from the European Weather Consult (EWC) measuring network. The geometric features of the modelled fields could be derived from the Farm Management Information Systems (FMIS) of the test farms.

The spatial resolution of the simulation should represent a compromise between the characteristics of the available satellite-based sensors, the computational efficiency and the requirements for information density on field level. All spatial input data sets thus were resampled to a common resolution of 20 x 20 meters.

2.3. EO Data

The applied assimilation concept, being based on the retrieval of greenLAI with help of an inverted canopy reflectance model, allows for the integration of multisensoral data. Accordingly, combinations of RapidEye and Landsat 5 TM images were used, both sensors providing adequate spectral and spatial information for the retrieval of greenLAI on the field scale. The images from both sensors were equally resampled to a resolution of 20 x 20 meters. Five satellite scenes could be obtained for the season of 2010, while even seven acquisitions were available for 2011 (Tab. 1).

Table 1. Earth Observation data available for assimilation into the PROMET model (OZA = Observer Zenith Angle, GSD = Ground Sampling Distance).

Acquisition Date	Sensor	OZA	GSD
May, 21st 2010	RapidEye	10.33°	5 m
June, 16th 2010	RapidEye	6.96°	5 m
June, 29th 2010	Landsat TM	Nadir	30 m
July, 8th 2010	Landsat TM	Nadir	30 m
July, 20th 2010	RapidEye	-12.04°	5 m
March, 3rd 2011	RapidEye	-19.55°	5 m
April, 2nd 2011	RapidEye	3.6°	5 m
April, 18th 2011	RapidEye	6.73°	5 m
May, 5th 2011	RapidEye	6.99°	5 m
June, 1st 2011	RapidEye	0.34°	5 m
June, 29th 2011	RapidEye	-6.18°	5 m
July, 1st 2011	Landsat TM	Nadir	30 m

In order to investigate the influence of the assimilation of single observations on the finally resulting modelled yield map, repeated model runs were performed for both growing seasons, while the absolute number of observations that were included in the assimilation were gradually varied. For each quantity of observations that were taken into account, the possible combinations of the available acquisitions were iteratively tested. This data mining approach is comparable to a study by Murakami et al. [10], who investigated the discrimination of favourable scene combinations for agricultural land cover classification. The five satellite observations from 2010 resulted in 32 different combinations of the available observation dates. Based on the seven observation dates available for 2011, even 128 combinations could be investigated.

2.4. Validation Data

For the validation of the model outputs, spatially explicit yield maps could be used that were supplied by the managers of the test sites. Being collected during the actual harvesting process through a GPS-supported combine harvester of the Type Claas Lexion 600, the yield maps allow for a spatial analysis of absolute wheat yield. The yield maps obtained with this method nonetheless suffer from some serious uncertainties, which partly can be reduced through sensible calibration [11]. The raw data provided by the combine harvester consists of data points that are spatially referenced, but do not have a defined spatial extent. They were converted into a spatially continuous raster through inverse distance interpolation (30 neighbours, weighting parameter = 0.5). Measurement outliers lower than 0.5 or higher than 18 t ha^{-1} were excluded. Although the yield maps indicate the spatial distribution of harvested yield, the absolute values recorded by the combine harvester may incorporate a strong bias. The yield map thus was calibrated with the absolute weights of the harvest mass of the respective fields. With the help of field-based moisture content measurements, the yield values of each field finally were standardized to a dry matter content of 86 %, which is the ideal percentage of dry matter aspired for wheat harvest and which is also assumed in the outputs of the PROMET model. After these corrective steps, the yield map was considered to represent a reliable spatial validation raster data set.

2.5. Assessing the Impact of Observation Frequency

Although the EO/model system is designed to serve as decision support instrument throughout the course of the vegetation period, spatial validation of intermediate model outputs, such as aboveground biomass distribution, would necessarily result in the destruction of the crop. Validation therefore was confined to the output variable ‘yield’, where spatial in-situ measurements were available.

The model was set up to calculate yield maps for the respective harvest days of the individual fields (around the middle of August) for both seasons. By gradually reducing the quantity of satellite observations included in the assimilation process and repeatedly comparing modelled against measured yield, the impact of observation frequency was assessed. Thereby, all possible combinations of the available satellite images for each observation quantity were iteratively applied to the model. To account for the intensive computational demands, the task was distributed to a 27-node cluster computer located at the Department of Geography of the LMU Munich.

The model outputs generated from each possible combination of included observation dates were individually compared to the validation data set through direct regression between the modelled and the measured yield map. Accounting for different aspects of model accuracy, two statistical indicators were calculated for each combination. While the coefficient of determination (R^2) indicates the agreement of spatial patterns, the Root-Mean-Squared-Error (RMSE) represents the agreement of absolute values between modelled and measured yield. The statistical results were averaged within categories of available observations (0, 1, 2, 3, 4, 5, 6*, 7*; *only 2011). The comparison of averaged results was preferred to the ranking of absolute values to give a more general indication of the change in confidence and stability of the model results with increasing temporal frequency of assimilated EO scenes.

In order to analyse the importance of single observation dates as well, the model results were mined to find the combination of satellite observations that resulted in a model output with the best overall results. Assessing the achieved model accuracy in spatial as well as in absolute terms, the two complementary error indices (R^2 and RMSE) were normalized to the actual data range, thus generating equally dimensionless quality measures. The average of the two normalized error indices then was used as overall quality indicator, ranking the model outputs according to their agreement with the measured yield. The 20 % best performing combinations of each season then were selected (6 out of 32 for 2010 and 26 out of 128 for 2011) and the actual observation dates that had been included in the simulation of the respective results were analysed, thus ranking the individual observation dates according to their positive impact on model accuracy.

3. RESULTS & DISCUSSION

3.1. Observation Frequency

The results obtained for the season of 2010 show that the accuracy of the modelled winter wheat yield increases with respect to spatial patterns (increasing R^2) as well as with respect to the simulation of absolute yield values (decreasing RMSE), when a higher number of EO data sets are included in the simulation process (Fig. 2).

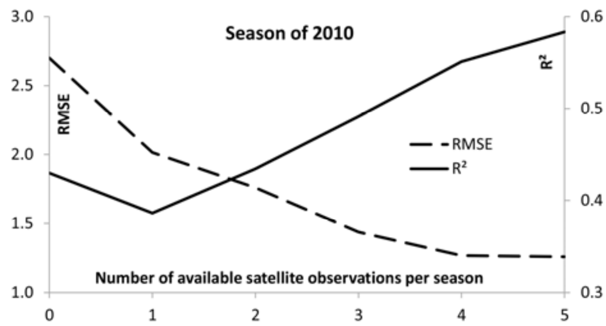

Figure 2. Statistical error indices derived from the spatial comparison of modelled and measured yield of winter wheat on >280 hectares on a test site in Saxony-Anhalt (Germany) for the season of 2010 in dependence of the absolute number of satellite observations that were assimilated into the model.

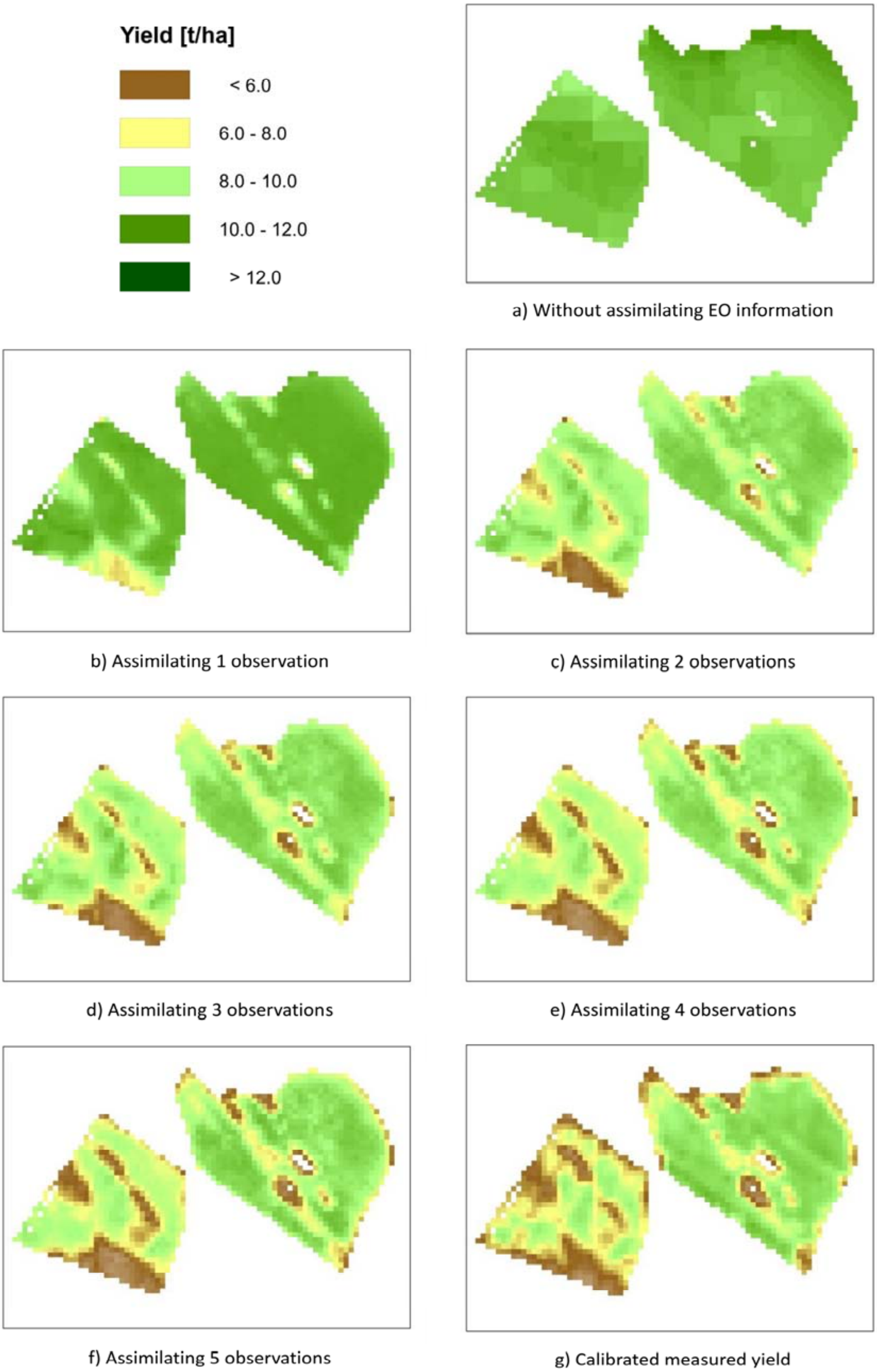

Figure 3. Results of modelled winter wheat yield (a-f) obtained for a subset of the test area (approx. 70 ha) for the season of 2010 in comparison to the calibrated measured yield map (g).

The gradual increase of agreement between model outputs and spatial validation measurement is visualized in Fig. 3. It can be observed in Fig. 3a that without EO information the model results represent optimal growth conditions and thus overestimate yield. The spatial patterns are determined through the rough resolution of the static spatial input data sets (DEM, soil map etc.). By adding more and more satellite observations to the assimilation chain, these drawbacks are gradually resolved.

It was also found in the results for 2010 that the RMSE decreased significantly, when up to four observations were included. The inclusion of a fifth satellite scene, however, did not result in a further improvement (Fig. 2). The agreement of spatial patterns, indicated through the R^2 value, nonetheless shows a definite increase with every observation that was added to the assimilation chain of the season 2010 with only one exception. Surprisingly, the model returned a slightly higher R^2 value without EO support compared to the average obtained when only one observation date was used. This is due to the fact that the variety specific parameterization of the PROMET model for the year 2010 returned two clusters of data points (one relatively high, one relatively low). The resulting correlation only indicates an agreement of field averages and should not be statistically misinterpreted as positive correlation of in-field heterogeneities. The bold decline of RMSE with the inclusion of a single observation date nonetheless clearly indicates the positive effect of the additionally assimilated information on the model results.

Also for 2011, a general increase of the regarded accuracy measures can be observed with an increasing number of EO scenes involved (Fig. 4).

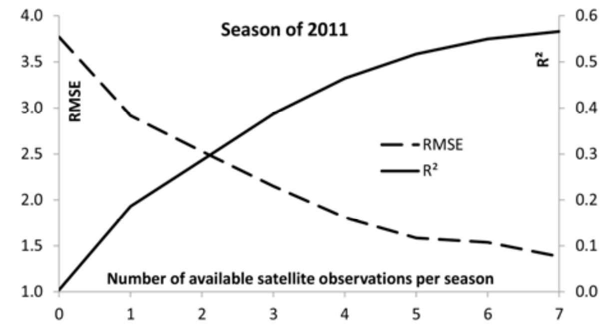

Figure 4. Statistical error indices derived from the spatial comparison of modelled and measured yield of winter wheat on >560 hectares on a test site in Saxony-Anhalt (Germany) for the season of 2011 in dependence of the absolute number of satellite observations that were assimilated into the model.

Again, the increase of accuracy is not linear, so that with an increasing number of included observations effects of saturation can be observed. While the gain in accuracy is strong when up to four scenes are successively added to the assimilation chain, including more than four scenes only led to a moderate but nonetheless positive increase of model accuracy. This saturation trend was equally observed for 2010 and 2011. Nonetheless, the best results could be achieved for both seasons by using the maximum number of available observations (Fig. 3f; Tab. 2).

Table 2. Statistical measures for the validation of both growing seasons (2010 & 2011), obtained under consideration of the respective maximum number of available observations.

	R^2	RMSE	Area
Season of 2010:	0.58	1.25 t ha^{-1}	> 280 ha
Season of 2011:	0.57	1.38 t ha^{-1}	> 560 ha

The results obtained for the season of 2011 (Fig. 3) seem to indicate more stable trends compared to the results for 2010 (Fig. 2). This on one hand may be due to the higher number of available EO acquisitions and the higher homogeneity of the EO data used for 2011 (6 out of seven from the same system, i.e. RapidEye, see Tab. 1) but on the other may also be traced to smoothing effects induced by the larger area that was covered by the 2011 experiment (see Tab. 2).

3.2. Observation Date

Assessing the importance of single observation dates is difficult, mostly because it is not the calendar date that determines the information content contributed to the model through an EO image, but more the phenological stage that is covered by the observation. Phenological information unfortunately was not consistently available for both growth periods. It nonetheless could be verified that phenological development between both respected seasons was very similar, only differing significantly during the month of May, where the development during 2011 was accelerated by approximately one week compared to 2010. The results achieved for the two growing seasons therefore may well be jointly interpreted.

It could be found for the season of 2010 that among the 20 % best performing combinations, the satellite observations from June 29th and from July 20th were selected most frequently (6 out of 6 times = 100 %), while the early observation from May 21st was least frequently represented among the best performing combinations (Fig. 5). Not only providing a higher number of available scenes, but also showing a more even distribution of observations in the course of the season, the analysis of the results achieved for the season of 2011 returned slightly different findings that nonetheless mostly confirm the results obtained for 2010. From the 20 % best performing combinations of available observation dates for 2011 (26 out of 128), the RapidEye observation from the 2nd of June was selected most frequently (26 out of 26 = 100 %). Unfortunately, for 2010 no observation exists close to that date, so that

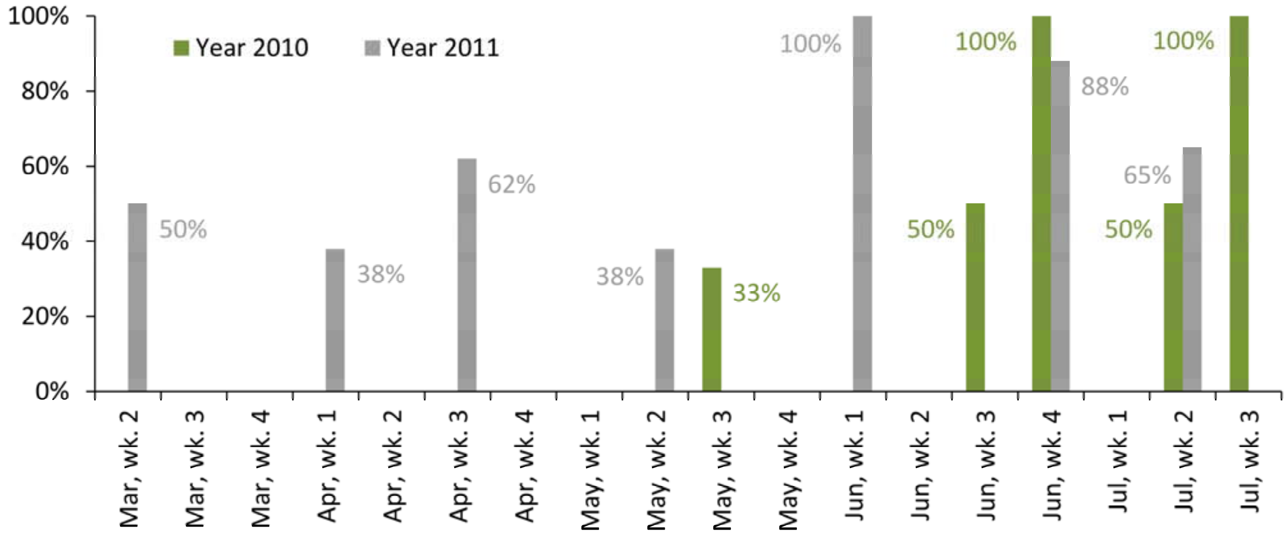

Figure 5. Frequency of selection of the EO dates that were available for the weeks of the seasons 2010 and 2011 among the 20 % of possible combinations (6 out of 32 for 2010 and 26 out of 128 for 2011) that performed best in comparison to the validation data.

the dominating importance of this observation cannot be confirmed. In accordance to the results found for 2010, the satellite observation from June 29th, which fortunately was available for both seasons, was second mostly selected (88 %). Additionally confirming the results achieved for 2010, the observation during May was significantly less often selected also for 2011, while the observation from the middle of July for both seasons seems to contribute average significant information, being selected 3 out of 6 times (50 %) for 2010 and 17 out of 26 times (65 %) for 2011. This may be due to the fact that satellite observations during late July are likely to capture spatial growth patterns that distinctly appear during the ripening phase of the crop. Very late observations additionally may be of increased importance, when unforeseen damages are affecting yield even at late development stages.
Interpreting the results, it has to be taken into account that, due to climatic differences, phenological development was approximately one week earlier during May 2011 compared to May 2010, while during the rest of the growth period the development was rather parallel between the two seasons. It therefore can be stated that observations covering the growth stages from BBCH 70 to 90 proved to be best suited for the modelling of yield, followed by observations from BBCH 50 to 70, while satellite images taken during BBCH stages 30 to 40 turned out to be least suitable for yield modelling. A sensor-related preference of observations could not be detected in the results.

4. CONCLUSIONS

Although the model results could only be validated through the variable yield, it can be assumed to some extent that correctly modelled yield is likely to be the result of equally correctly modelled plant development during the growing season, since many intermediate variables, such as phenological progress, photosynthetic performance, biomass accumulation etc., are directly influencing yield formation. According to our findings, the research questions posed in section 1 consequently may be answered as follows:

1. At least four observations per season are required for the generation of a reliable information product on crop status, when the entire growing season shall be covered. If more than four observations are available, they should also be integrated into the assimilation process to further improve the model performance. Nonetheless, the gain in accuracy shows some saturation effects, if more than four observations are used.

2. For the modelling of winter wheat yield in northern Germany, satellite observations from the end of June are ideal, followed by middle of July and end of April. Also high impact could be detected for one observation from 2010 that was taken shortly before the actual harvest (end of July). Unfortunately no corresponding observation was available for 2011, so that this effect could not be confirmed. Both seasons agree on the minimum information content of observations from middle of May.

Our study emphasizes that global efforts of improving agricultural efficiency may strongly be supported by satellite monitoring. However, the results also imply the necessity of careful selection of EO acquisition dates for agricultural applications. According to our results, global earth observation activities should aim at reliably providing at least four spatially continuous datasets on field level during the growing period/summer. Thinking globally, this would mean aiming for at least eight cloud-free data acquisitions at reasonable resolution for the monitoring of in-field heterogeneities (10-30 m) per year.

Taking the challenges of obtaining multi-seasonal optical remote sensing data series into account, this goal will still require a lot of effort. Nonetheless, some elaborated EO systems are about to be launched in the near future, which are ideally designed for agricultural applications at the field level, e.g. the twin configuration of ESAs Sentinel-2. These systems will complement the existing data sources, such as Landsat 8 or RapidEye, and thus will strongly contribute to the goal of improved multiseasonal EO coverage. With the help of continuous multisensoral earth monitoring data streams, it will also become possible to more carefully assess the growth stage dependent impact of acquisition selection on the quality of agronomical information products.

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