SATELLITE IMAGE SIMULATIONS FOR MODEL-SUPERVISED, DYNAMIC RETRIEVAL OF CROP TYPE AND LAND USE INTENSITY

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ABSTRACT:

To support food security, information products about the actual cropping area per crop type, the current status of agricultural production and estimated yields, as well as the sustainability of the agricultural management are necessary. Based on this information, well-targeted land management decisions can be made. Remote sensing is in a unique position to contribute to this task as it is globally available and provides a plethora of information about current crop status.
M^{4}Land is a comprehensive system in which a crop growth model (PROMET) and a reflectance model (SLC) are coupled in order to provide these information products by analyzing multi-temporal satellite images. SLC uses modelled surface state parameters from PROMET, such as leaf area index or phenology of different crops to simulate spatially distributed surface reflectance spectra. This is the basis for generating artificial satellite images considering sensor specific configurations (spectral bands, solar and observation geometries). Ensembles of model runs are used to represent different crop types, fertilization status, soil colour and soil moisture. By multi-temporal comparisons of simulated and real satellite images, the land cover/crop type can be classified in a dynamically, model-supervised way and without in-situ training data. The method is demonstrated in an agricultural test-site in Bavaria. Its transferability is studied by analysing PROMET model results for the rest of Germany. Especially the simulated phenological development can be verified on this scale in order to understand whether PROMET is able to adequately simulate spatial, as well as temporal (intra- and inter-season) crop growth conditions, a prerequisite for the model-supervised approach.
This sophisticated new technology allows monitoring of management decisions on the field-level using high resolution optical data (presently RapidEye and Landsat). The M^{4}Land analysis system is designed to integrate multi-mission data and is well suited for the use of Sentinel-2's continuous and manifold data stream.

1. INTRODUCTION

To support food security, information products about the actual cropping area per crop type, the current status of agricultural production and estimated yields, as well as the sustainability of the agricultural management are necessary. Based on this information, well-targeted land management decisions can be made. Remote sensing is in a unique position to contribute to this task as it is globally available and provides a plethora of information about current crop status.

With the SENTINEL sensor family, a fleet of Earth Observation (EO) satellites is starting to become available, which will continuously monitor the land surface at different spatial scales (10 – 300 m) and with different systems (optical, microwave) (Berger, 2011). For an optimal translation of this data stream of different resolutions and wavelength ranges into land management information, an integrated analysis of the complete image data stream is required. This can be achieved through embedding the analysis in a continuous spatial modeling of land surface processes covering also the intervals between acquisitions.

In the frame of the M^{4}Land project (**M**odel based, **M**ulti-temporal, **M**ulti scale and **M**ulti sensorial retrieval of continuous land management information), a method to derive products for a sustainable management of the land surface is being developed. The method combines the full bandwidth of the spatial information provided by the future SENTINEL series within a land surface process model to generate spatially explicit and temporally continuous land surface management information products, such as dynamic land use, degree of ecological intensification, irrigation status, calamities etc. The system uses a dynamic classification of land cover, which is physically based and without training by a combination of the reflectance model SLC (Soil-Leaf-Canopy) (Verhoef, 2003) and (Verhoef, 2007) and the land surface process model PROMET (Processes of Radiation, Mass and Energy Transfer) (Mauser, 2009).
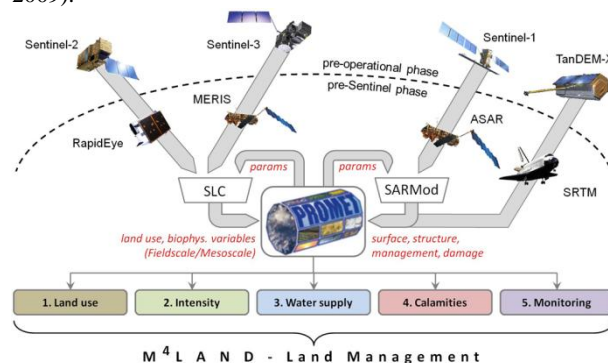

Figure 1. The M^{4}Land concept, showing the sensors employed during the development phase as well as in the pre-operational phase after the SENTINEL launch (Klug, 2014)

This paper explains the M^4Land concept and demonstrates it using time series of high resolution, optical data (RapidEye). Focus is laid on the principle of the new methodology as well as on its geographical transferability, for which the model-based approach is essential. This leads us to calling the methodology a "model-supervised" classification in contrast to common supervised or unsupervised classifications. Our assumption is that when we understand the land surface processes, which cause crop growth and phenological development as well as the radiative transfer of the canopy and soils (absorption, scattering and reflectance) adequately, we are able to simulate satellite images that are similar to real observations. Using this technique in an inverse mode we are then able to derive management information (like decisions on land use or seeding dates) that cannot be perfectly simulated and therefore rely on e.g. satellite image information. This synergistic concept shall be demonstrated in this paper.

2. METHODS

Two types of physically-based models are used in M^4Land in an integrative way, a crop growth agro-hydrological model and a radiative transfer model for simulating satellite measurements of reflectances. They are introduced below.

2.1 Crop growth modeling with PROMET

PROMET allows simulating all relevant water and energy fluxes related to radiation balance, vegetation, soil, snow and aerodynamic exchange processes on the land surface in a spatially distributed way. A detailed description of the model physics and components is given in (Mauser, 2009). The model results have been validated in different test sites on different scales (from 5 m to 1 km) with good results (Hank, 2015), (Migdall, 2009), (Mauser, 2009).

PROMET uses spatial data like soil maps and a digital terrain model as well as meteorological forcing data as input for hourly simulations. The meteorological data consists of hourly information on temperature, precipitation, relative humidity, wind speed and cloud cover, as offered by national weather services.

The development of crops is simulated in PROMET dynamically depending on the environmental conditions (mainly temperature, radiation and moisture conditions) while standard farming practices (e.g. seeding and harvest dates) are taken into account. The growth and accumulation of biomass is the result of an explicit simulation of photosynthetic processes based on the Farquhar concept (Farquhar, 1980). The assimilates are distributed within the canopy depending on the phenological progress of the different crop types.

The necessary parameterization of the crop types (from which 23 are implemented in PROMET) are kept generic and not optimized for a specific site, in order to allow for the geographical transferability of the M^4Land approach.

2.2 Radiative transfer modeling with SLC

The used surface reflectance model SLC (Soil-Leaf-Canopy) is an integrated radiative transfer model for the simulation of top-of-canopy spectral reflectance. The model consists of a modified Hapke soil BRDF model, a robust version of the PROSPECT leaf optical properties model, and the canopy radiative transfer model 4SAIL2, a two-layer robust version of SAILH (Verhoef, 2003).

In the M^4Land system, SLC is configured to use spectral configurations and acquisition parameters from the used satellite sensors (in this case RapidEye), soil spectral properties (single scattering albedo values for various soil types), as well as leaf parameters like chlorophyll content, leaf water, leaf dry matter and mesophyll structure, which can be predefined for every simulated crop type. SLC also allows to use PROMET outputs as input, like canopy parameters such as leaf area index (LAI), leaf angle distribution (connected to phenological development) and degree of maturity (fraction of brown leaves).

2.3 Satellite data and test site

As test site for a first demo application an agricultural area near Neusling in Bavaria, Germany, is selected. Land use and crop type were mapped during the growing season of 2010 for an area of approx. 4 km by 3 km. Winter wheat, winter barley, silage maize, potato and sugar beet are the relevant crops in this region.

A total of 10 almost cloud free RapidEye scenes were available for the growing season of 2010 (Table 1). With exception of September 2010, at least one RapidEye image is available for every month, guaranteeing a good and evenly distributed coverage of the entire growing season. The satellite images were resampled to a 20 m grid and an atmospheric correction was carried out using a MODTRAN Interrogation Technique (Verhoef, 2003) to retrieve bottom of atmosphere reflectance values.

March 26th	July 11th
April 8th	July 31st
May 11th	August 21st
June 6th	October 12th
June 25th	October 22nd

Table 1. List of cloud-free RapidEye images used in the test site Neusling during the growing season 2010.

2.4 Classification approach

Figure 2 gives an overview on the methodology of the classification.
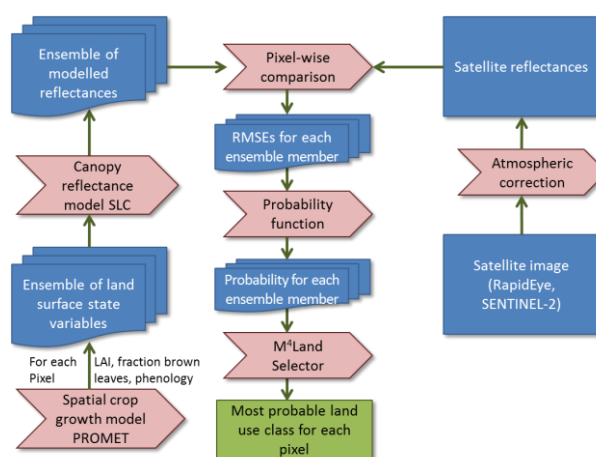

Figure 2. Flowchart illustrating the methodology of the model-supervised classification (Klug, 2014)

Surface state variables as modelled by PROMET (green leaf area index, phenology and degree of maturity) are used as input to the spectral reflectance simulations with SLC. This is the

basis for allowing a pixel-wise comparison of the simulated to the measured reflectances (after atmospheric correction of satellite data). The RMSE criterion is used to compare these two sets of spectral reflectances and is converted into probability via an arithmetic function (exponential form with a RMSE of less than 1 assigned a probability of 1, and a RMSE higher than 5 a probability of 0). The probability thus determines how likely it is that the respective pixel belongs to a specific land use class. A multi temporal application of this procedure provides the most probable land use class for each pixel by averaging the probabilities in the M^{4}Land selector.

PROMET is used to model the temporal dynamics of state variables for various crop types in a spatially distributed way. Figure 3 illustrates such simulation results for the leaf area index and the crop types of one pixel in the test area and the investigation period 2010. LAI is selected in this figure, since this state variable is the most significant factor for the temporal variation of spectral reflectances on the land surface (in the absence of snow and flooding). Each crop type in Figure 3 shows a distinctively different temporal pattern of LAI development that is connected to their phenological development. These different temporal courses form the baseline that allows for a model-based multi temporal classification. In Figure 3 an idealized crop development is assumed, without nutrient stress and assuming normal phenological development. In reality, crops are very likely confronted with nutrient stress at some points during their life cycle. This can be caused by different fertilization intensities, but can also be a consequence of poor soil water holding capacities that lead to insufficient soil moisture. The phenological development also varies with seeding date, crop variety, or occurrence of water stress. Accordingly there is a variability of LAI development in reality that is not yet covered in Figure 3.
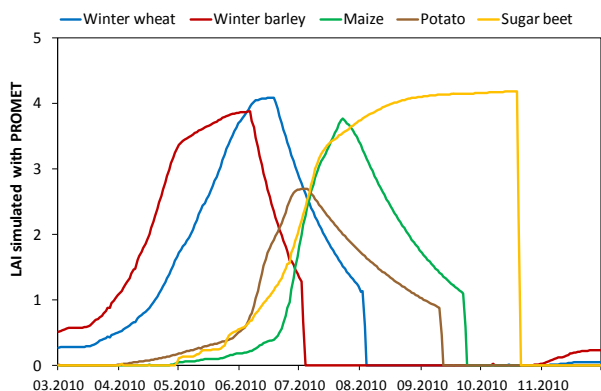

Figure 3. Modelled leaf area index development for the growing season of 2010 for the crop types in the test site, corresponding to scenarios with optimal plant development.

In order to consider this variability, the modeling for each crop type is carried out not only for optimal conditions but also for a variety of ensemble members (scenarios), in which the nutrition situation and the pace at which phenological development of the plants takes place can vary. The results are shown in Figure 4 for maize. Instead of a single curve for the LAI development of maize a set of possible courses is now provided. Reducing the nutrition supply of the maize plants, results in a decrease of biomass accumulation over the growing season and therefore in a decreased maximum leaf area index. A modified phenological development pace of the plants shifts the temporal course and with this also the date of maximum LAI. It can also have an

effect on the harvest date, which is however not the case for silage maize, since it is harvested before phenological maturity.
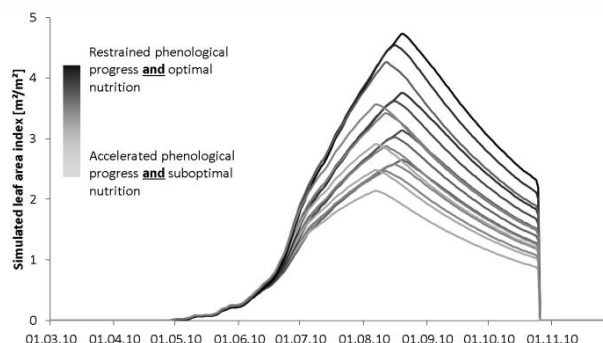

Figure 4. PROMET modeled leaf area index development ensemble for maize for the growing season 2010, with varying nutrition supply and phenological progress.

The use of scenarios thus allows for the representation of environmental conditions and management decisions of the farmer (e.g. fertilization level, crop variety or seeding date) providing a realistic range of possible land surface developments for each crop type.

These ensembles of crop developments are further depending on local meteorological conditions and thus are geographically variable. They also vary from year to year. This spatial and inter-annual heterogeneity is again simulated with PROMET, since the ensemble runs are performed for each individual pixel and variable meteorological conditions are thus considered.

In PROMET the phenological progress of agricultural crops is modelled using consecutive growth stages corresponding to the BBCH phenological classification system (Meier, 2001), a number system varying from 0 (seeding) to 100 (harvest). How PROMET is able to simulate geographical variations of phenological development is illustrated for model results for Germany in Figure 5. A point in time is selected (5th August 2014) when phenology of maize can range in Germany from leaf development to maturation. Accordingly also the temporal LAI development courses will strongly vary throughout Germany.
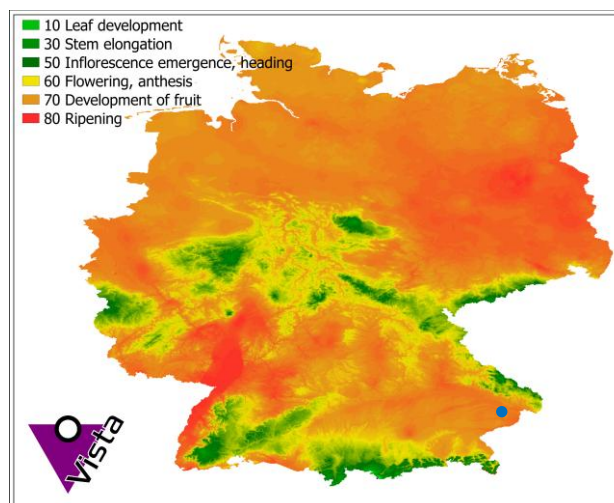

Figure 5. Simulated phenological stages for maize in Germany for the 5th August 2014 illustrating the heterogeneity of crop development (blue spot indicates location of Neusling)

3. RESULTS

3.1 Analyses of the transferability of the model-supervised approach

First the quality of the PROMET simulations shall be validated and their capability to adequately simulate the spatial and temporal patterns of crop growth. For this demonstration the phenological development for maize is selected. The first question is how well the intra-seasonal and inter-seasonal trends can be modelled.

For this we use in-situ measurements of phenology from 108 fields distributed over Germany that are provided by the German Weather Service DWD. To study the inter-annual variation, 4 years (2011 to 2014) were chosen. These in-situ observations are then compared with PROMET model results of the respective region. First averages of all fields were calculated for each year and related to the multi-annual average to understand how years can vary. These analyses based on the DWD observations are illustrated in Figure 6 as solid lines and compared to PROMET results (dashed lines).

Obviously 2011 showed Germany-wide a retarded phenological development of up to 7 days delay at stem elongation that is slowly caught up until ripening. This course is similarly simulated in PROMET. The accelerated phenological development of 6 days in 2013 is also simulated in PROMET but to a lesser degree. 2012 and 2014 are similar to the average, which is also depicted in the simulations. On average, measurements and simulated only differ by one day.
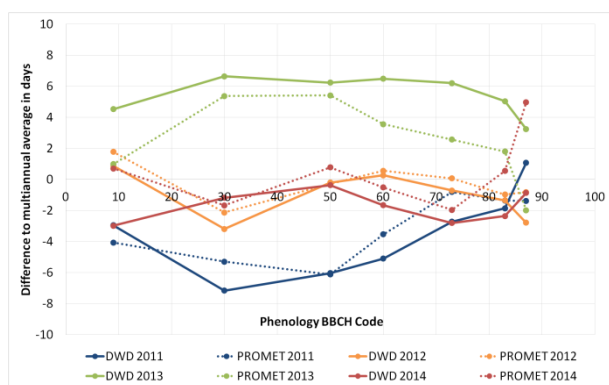

Figure 6. Validation of simulated phenological development of maize using in-situ measurements of the German Weather service DWD (averages over all 108 sites in Germany)

This validation on Germany-wide averages helps to study seasonal trends and inter-annual variations. Obviously both are well captured in the simulations. Another option is to compare the date of occurrence of a certain phenological state in measurement and simulation. This is illustrated in Figure 7 for all measurements of the 4 considered years and all 108 fields. It is evident that there is a very high concurrence. The points scatter very close around the 1:1 line. The Root Mean Square Error (RMSE) amounts to 10.9 days. This RMSE can be interpreted as the variability of the phenological development that is connected to management decisions of the farmer (seeding dates and crop variety for example) or local soil conditions (water stress leads to accelerated ripening).
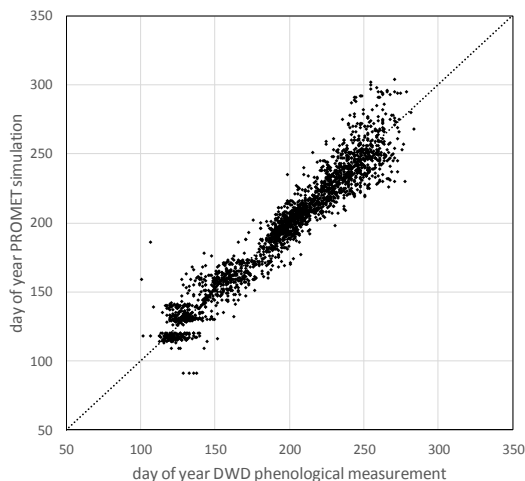

Figure 7. Simulated and measured dates (day of year DOY) of reaching a certain phenological stage for maize during the years 2011 to 2014.

3.2 Model-supervised classification of the Neusling test site

Results of the M[4]Land concept are presented for the Neusling test site in Bavaria. For the crop type classification the 10 RapidEye images of Table 1 were used. For each date of satellite acquisition, for each possible crop type and for each ensemble member spectral reflectances were simulated using SLC and the land surface state variables as provided by PROMET. These simulated spectral signatures can now be compared to the satellite measurement.

In a first step within one land use class the one ensemble member with the closest match with satellite derived spectrum is selected. An example for this step is illustrated in Figure 8. It shows, for a representative RapidEye acquisition date, the spectrum of each land use class for the most probable scenario in comparison to the RapidEye spectrum of one pixel. In this example the simulated spectrum of a maize pixel shows the closest congruence to the measured RapidEye spectrum. In order to quantify the match the RMSE criterion is used and the RMSE is transferred into a probability that ranges from 0 to 1.
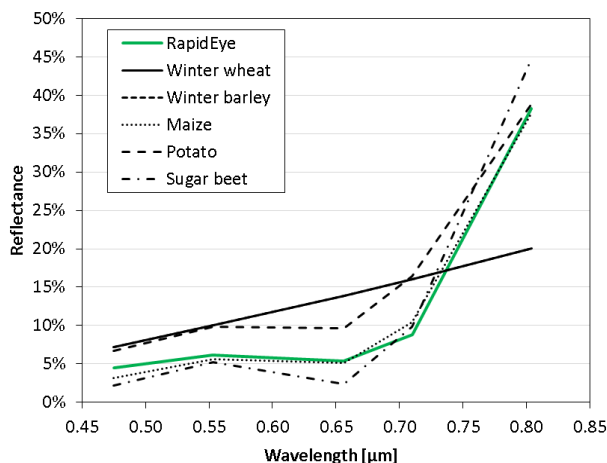

Figure 8. Comparison of a RapidEye observed spectrum (green) of one pixel on 21th of August 2010 with modelled spectra (black) for different land cover classes

The probabilities for each land use class and each acquisition date are aggregated by averaging the probabilities over all available image dates during the growing season. Figure 9 shows the aggregated mean probabilities of all crop types for the same pixel used in Figure 8. The probability for each acquisition date is calculated as the mean of all probabilities of the earlier acquisition dates including the current acquisition date. At the end of the growing season, the pixel is finally classified as the crop type with the highest aggregated probability. In our case it is maize. This is identical to the crop type that was mapped in the field.
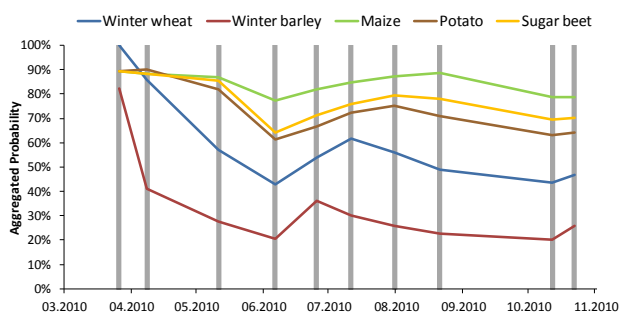

Figure 9. Aggregated probabilities for all modelled crop types of one maize pixel over the whole growing season of 2010. Grey vertical lines indicate satellite acquisitions.

The methodology demonstrated above for one pixel is repeated for each pixel in the satellite image. One of the intermediate outputs are simulated artificial satellite images that show the spectral reflectances with the best match to the EO data. For three selected dates these artificial images are compared with the measured satellite images in Figure 10. A false colour presentation was chosen with the green band in blue, the red band in green and the near infrared presented in red colour.

The images almost cover the whole crop cycle and illustrate well the high temporal dynamics of the spectral reflectance of agricultural areas. In the SLC simulation the soil reflectance is not assumed to be fix, however a soil background reflectance is selected pixel-wise from a set of typical soil spectra. Also the surface moisture of the soils that change the soil brightness is allowed to vary. This concept makes it possible to adequately simulate the soil reflectance and its effect on the canopy reflectance. Thus negative impacts on the classification accuracy can be avoided. This is also evident in the high

correspondence between simulated and measured images in Figure 10.

Figure 11 shows the resulting crop type map from the multi-temporal analyses. All pixels are classified with the most probable land cover class by the M^4Land framework. If the highest average probability is below a threshold of 70 %, pixels are left unclassified. They mostly occur in built-up areas and few fields that obviously are not sufficiently represented in the model setup.

The classification results were not filtered in order to be able to allow a fair evaluation of the model-supervised approach. The map reveals that most fields are uniformly classified. Only few fields share several different land cover classes, hardly any more than two.

Quantitative validation of the resulting land cover / crop type map was performed by pixel-wise comparing the classification with the mapped land use. A confusion matrix was created that allows the analysis of the product accuracy (see Table 2). The User's accuracy indicates how many pixels of a classified land cover class have actually been classified correctly, while the Producer's accuracy indicates how many pixels of the mapped land cover class have been classified correctly. User's and Producer's accuracies are both high. Mis-classifications occur to a larger extent for potato fields that were misinterpreted as maize or sugar beet. Winter wheat classification was almost 100 % correct, however some of the winter wheat fields were assigned winter barley which reduced the Producers' accuracy for winter wheat to 88 %. The overall accuracy of the achieved land cover map of the whole area is 85 %, which can be judged very high for an unsupervised autonomous methodology.

		Winter wheat	Winter barley	Maize	Potato	Sugar beet	Total	Users's accuracy
		GROUNDTRUTH						
CLASSIFIED	Winter wheat	3 249	8	3	2	0	3 262	**100%**
	Winter barley	269	305	0	0	0	574	**53%**
	Maize	8	1	1 354	293	113	1 769	**77%**
	Potato	169	4	42	1 082	288	1 585	**68%**
	Sugar beet	0	0	17	272	2 481	2 770	**90%**
	Total	3 695	318	1 416	1 649	2 882	9 960	
	Producer's accuracy	**88%**	**96%**	**96%**	**66%**	**86%**	**Overall**	**85%**

Table 2. Confusion matrix based on the comparison of in-situ-mapped and modelled land cover maps.
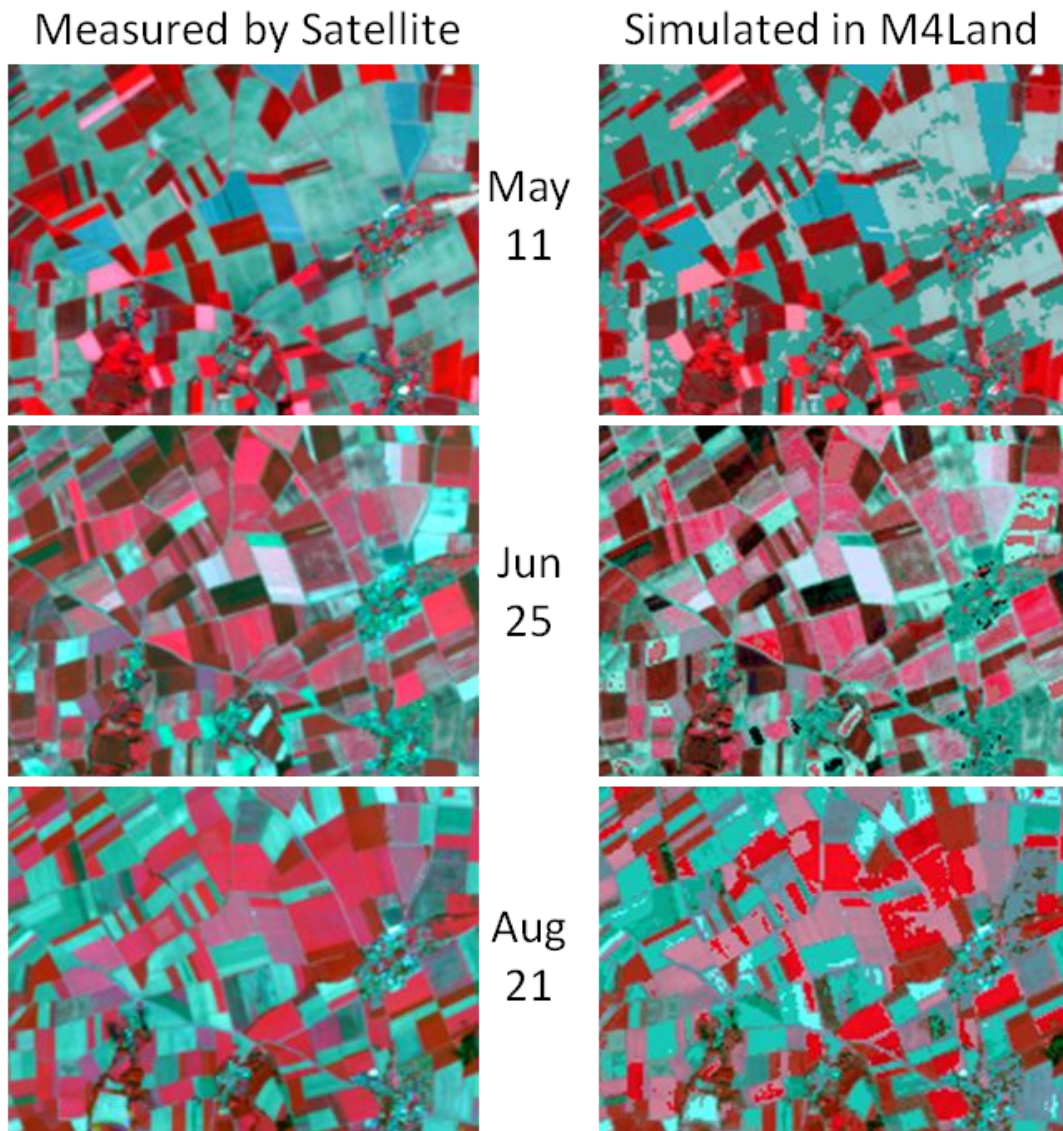
Figure 10. Real (left) compared with simulated (right) satellite images for selected dates during the growing season.
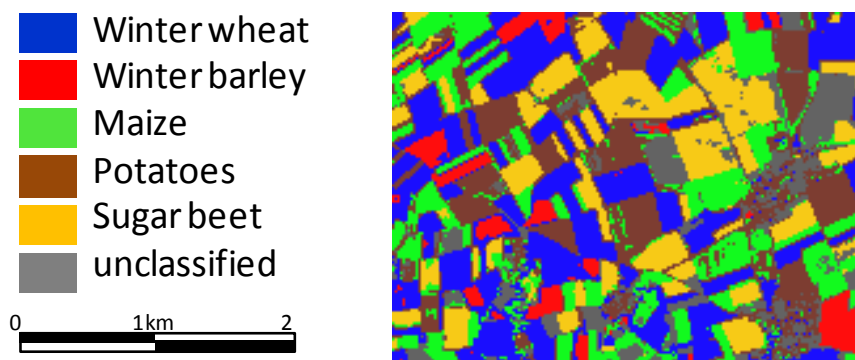

Figure 11. Land cover map derived by the model-supervised classification approach of assigning crop types to the highest average probability at the end of the growing season in 2010.

4. CONCLUSIONS AND OUTLOOK

The feasibility of the M^4Land concept has been successfully demonstrated. The model-supervised approach is able to dynamically classify multi-temporal RapidEye images based on physical and physiological principles and without training. It uses a combination of the reflectance model SLC and the land surface process model PROMET. The classification results have a high overall accuracy of 85%.

The fact that most fields are uniformly classified even though the M^4Land approach works pixel based and no post processing of the land cover product is performed, suggests that the model-supervised land cover classification is quite robust.

In a next step, the classification performance will be checked for other regions in Germany. Also several years shall be classified in order to allow the monitoring of the cropping cycle. It is further targeted to derive additional land surface management information products such as intensity of agricultural production, irrigation status or calamities using the ensemble information.

The M^4Land system shall also be extended to natural environments in a mesoscale setup. Demonstrations in climatologically different areas are currently performed. The generic character of the M^4Land approach will also allow for the extension towards the use of other satellite data apart from high resolution optical data (e.g. lower resolution optical or SAR data).

The required preprocessing chains for the inclusion of current and near-future optical Earth Observation Systems are already available within the M^4Land system, so that for example the SENTINEL data sets will be integrated as soon as they become available.

The M^4Land framework is designed to allow for an efficient handling of the rich data-stream of SENTINEL data that will soon be available. It therefore enables a continuous monitoring of non-linear processes at the land surface.

ACKNOWLEDGEMENTS

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