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Crop type mapping using spectral-temporal profiles and phenological information

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Abstract

Spatially explicit multi-year crop information is required for many environmental applications. The study presented here proposes a hierarchical classification approach for per-plot crop type identification that is based on spectral-temporal profiles and accounts for deviations from the average growth stage timings by incorporating agro-meteorological information in the classification process. It is based on the fact that each crop type has a distinct seasonal spectral behaviour and that the weather may accelerate or delay crop development. The classification approach was applied to map twelve crop types in a 14 000 km² catchment area in Northeast Germany for several consecutive years. An accuracy assessment was performed and compared to those of a maximum likelihood classification. The 7.1 % lower overall classification accuracy of the spectral-temporal profiles approach may be justified by its independence of ground truth data. The results suggest that the number and timing of image acquisition is crucial to distinguish crop types. The increasing availability of optical imagery offering a high temporal coverage and a spatial resolution suitable for per-plot crop type mapping will facilitate the continuous refining of the spectral-temporal profiles for common crop types and different agro-regions and is expected to improve the classification accuracy of crop type maps using these profiles.

Key words: crop type mapping, NDVI temporal profiles, multi-temporal, phenological correction, agro-meteorological data

1 Introduction

Timely availability of large-scale information on the spatial distribution of crop types is required to support modeling and managing of agro-environmental systems from regional to national scales. Often this information is only available as averages at the level of administrative units and is usually not obtainable for areas with deviating boundaries, e.g. river basins (De Witt and Clevers, 2004). Many agro-environmental applications such as agricultural flood damage estimation or water quality modeling, however, require spatially distributed crop data.

For these applications remote sensing is nowadays an important source of information (Vincikova et al., 2010). Due to the dynamic character of agricultural systems, crop type mapping based on multi-temporal approaches is superior over single-date image analyses. While traditional approaches using parametric or non-parametric classification algorithms require ground truth data to train the classifier (e.g., Yang et al., 2011; Castillejo-González et al., 2009), the use of crop-specific spectral-temporal profiles is independent of ground truth data. The independence of ground truth data nevertheless facilitates operational monitoring of agricultural land use over large areas and longer time periods.

The use of spectral-temporal profiles for crop identification by satellite data was first proposed in the 1980s. Odenweller and Johnson (1984) presented characteristic profiles observed for a variety of crops by use of a vegetation indicator that measures the infrared reflectance relative to the reflectance in the visible range. The term 'spectral-temporal profile' refers to the spectral behaviour of a certain crop type throughout the year. Profile-based crop identification is based on the fact that profiles representing a specific crop are usually more similar than profiles representing different crops (Odenweller and Johnson, 1984). Several studies investigated the use of crop-specific seasonal profiles for crop discrimination and mapping at different spatial scales from local to state level (Wardlow et al., 2007; Murthy et al., 2003; Sakamoto et al., 2005; Jakubauskas et al., 2002). Most of the studies are based on temporal profiles of the Normalized Difference Vegetation Index (NDVI) as an effective indicator of the photosynthetically active vegetation (e.g., Bradley et al., 2007; Wardlow and Egbert, 2008). The NDVI is the most commonly used vegetation index applied in agricultural applications, however, several other vegetation indices have been proposed to reduce the influence of the canopy background and the atmosphere (Reed et al., 2003), such as the Soil Adjusted Vegetation Index (SAVI, Huete, 1988) or the Enhanced Vegetation Index (EVI, Huete et al. 1997). The NDVI is a measure of photosynthetic capacity of the vegetation cover, while the SAVI is more suitable to reflect the vegetation canopy structure (Reed et al., 2003). The EVI was found to be more sensitive to variations over high biomass areas, e.g. forests, when the NDVI tended to saturate (Huete et al., 2002). Furthermore, EVI may be advantageous in areas with high humidity since it is designed to minimize the effects of the atmosphere. Huete et al. (1997) conclude that each index had its strengths and weaknesses for certain applications.

Depending on the application at hand, satellite imagery ranging from low to high spatial resolution is applied for studying agricultural landscapes (Vincikova et al., 2010). For per-field crop type mapping, the spatial resolution of the imagery should be chosen relative to the typical field size. Apart from an adequate spatial resolution, the temporal resolution of the satellite data is critical for crop discrimination and mapping. Several authors have studied optimal times of image acquisition with respect to the growing stages (Murakami et al., 2001; Van Niel and McVicar, 2004).

The appearance of crop profiles is affected by regional variations in climate and management practices, which should be accounted for by setting-up individual crop profiles for each homogenous agro-region (Wardlow et al., 2007). Crop profiles, however, also vary from year to year resulting from specific weather conditions and, in particular, deviations in the temperature and precipitation distribution throughout the growing season (Siebert and Ewert, 2012). These inter-annual variations have so far hardly been accounted for in crop type mapping approaches.

In this study we therefore propose an efficient hierarchical classification algorithm that is based on spectral-temporal profiles of crop types and accounts for weather-induced inter-annual variations in the spectral-temporal behaviour through the use of agro-meteorological information. The proposed approach was tested using multi-temporal LANDSAT satellite imagery for the per-field crop type mapping of a large lowland river catchment in Germany.

2 Data basis and pre-processing

To set up characteristic temporal profiles for each crop, NDVI data from a sixteen year satellite image time series were combined with cultivation data collected from farming companies for the same time period and agro-meteorological data provided by the weather service. The

spectral-temporal profiles were then used to map crop types in the study area, the Havel River catchment, for the years 1994-2000 utilizing agro-meteorological data from the same period.
The study area is located in the north east of Germany (Figure 1). It comprises the catchment of the Havel River, a tributary of the Elbe River, excluding the Spree catchment, and covers a total area of 14 000 km². Arable land is the dominant land use covering 37.7 % of the total area. Soils are predominantly sandy with areas of high and low ground water. The average plot size is 21 ha. Major crops are winter rye (15 %), winter wheat (12 %), maize (12 %) and oilseed rape (10 %) (Amt fuer Statistik Berlin Brandenburg, 2010).

< Figure 1 >

2.1. Crop cultivation data

Cultivation data from the years 1987 to 2002 of 424 agricultural plots with a total area of 9021 ha were collected from six agricultural companies in the study area. More specifically, for each of these 424 plots information on the specific crops grown in the years of satellite image data acquisition was made available, resulting in a total of 3745 reference plot data (Table 1). These data served the development of the spectral-temporal profiles and were used to validate the final crop type map.
For the per-plot crop type mapping, a data set of the agricultural plots present in the study area is required in order to exclude other land use types from the classification process and enable a crop type identification at the plot level. This plot map may be either derived from official land cover data sets or from object-based image analysis (Blaschke, 2010). For our study area a digital land cover data set based on mapping CIR aerial photographs was available from the state ministry of environment.

< Table 1 >

2.2. Satellite image time series

Spectral information from 35 LANDSAT TM/ETM images acquired between the years 1987 and 2002 was used to set up the temporal crop type profiles. The image acquisition dates are listed in Table 2. LANDSAT images were chosen for this study for different reasons. They are available for several years to decades and are therefore suitable for long-term monitoring studies (Wulder et al., 2008). The spatial resolution of 30 m allows for single plot crop type identification and the image size of approximately 175 by 175 km encompasses the whole study area. The repetition rate of 16 days results in approximately two to five cloud-free coverages of our study area per year. The LANDSAT images were atmospherically and geometrically corrected to allow for multi-temporal analyses (Richter, 1996) andthe NVDI was then computed for each image We chose the most commonly used NDVI for this study, since our agricultural study area in Central Europe is characterized by low biomass and no particularly high humidity..

2.3. Agro-meteorological data

The different crop types undergo certain specific growth stages and agro-technical treatments throughout the growing season. These are for the example of cereals, sowing, seedling growth, tillering, stem elongation, flowering, grain-fill period (milk and dough development), ripening and harvest. As a result of specific weather patterns throughout individual years, particularly the temperature and precipitation characteristics, the onset and duration of the growth stages and the times of agro-technical treatments may deviate from an average year. Depending on the demands of the individual crop types, the timing not only differs among certain years but also among the individual crops in the same year. Growth stage timings in the study area can deviate up to approximately 20 days in both directions, i.e. ahead or behind the average development. To account for these deviations, agro-meteorological data were incorporated in the process of setting up spectral-temporal profiles and in the crop type classification. Nowadays many weather services provide such agro-meteorological data. For our study we used data made available by the German Weather Service (Deutscher Wetterdienst - DWD, www.dwd.de) for the period 1951-2003 collected at 40 stations within our study area. They contain information on times of growth stages, e.g. the onset of flowering, and agro-technical treatments for most common crop types in each year. Based on these data we calculated the average day of the year of each of these stages to obtain the average phenological pattern for each individual crop type present in the study area.

< Table 2 >

3 Methods

3.1 Spectral-temporal profiles of crop types including phenological correction

The spectral-temporal profiles represent the average phenological behaviour of each of the twelve most commonly grown crop types in North Germany. These comprise winter rye, winter wheat, winter barley, oilseed rape, sugar beets, maize, summer grain, potatoes, oilseed crops and legumes, first year and perennial field grass and fallow land. Based on the dates of image acquisition of the 35 LANDSAT images collected between the years 1987 and 2002, for each crop type the phenological day was determined according to the agro-meteorological information. Different from the actual day of the year, the term ‘phenological day’ refers to the phenological stage of a crop type in a certain year as a result of the temperature and precipitation pattern in that specific year. The phenological correction is shown schematically in

Figure 2. Dotted and dashed lines represent the deviation in days for two individual crop types and two different years as compared to the average year. The average is derived from the mean timings of the growth stages based on the agro-meteorological data from the weather service of the years 1951-2003. In the hypothetic Year 1, unfavourable temperature and precipitation conditions in spring may have led to a delay as compared to the average NDVI development. In the course of the year the lines slowly approach the average line as the delay reduces. Conversely, in the hypothetical Year 2 crop development in spring is ahead of the average due to favourable weather conditions, while in the later course of the year the crop development lags behind the average. The deviation among individual crop types in the same year is due to the crop types' different weather tolerability.

< Figure 2 >

The resulting list of phenologically corrected dates was combined with the average NDVI values for each of the 3745 agricultural reference plots. Subsequently, for each crop type the seasonal NDVI was plotted and studied in regard to its average development and variability throughout the season. While natural vegetation is characterized by a relatively continuous seasonal NDVI development, the seasonal NDVI of arable lands decreases more abruptly due to agro-technical treatments such as harvesting or mowing. These distinct NDVI declines are characteristic for each crop type and must therefore be contained in the individual NDVI temporal profiles. The final spectral-temporal profiles were then generated by interpolating the average NDVI values while retaining the characteristic decline features.

3.2 Crop type mapping by hierarchical classification

Once the NDVI temporal profiles are set up they can be used to map crop types for any year without the need of additional ground truth data. The study area should be located in the same broad agro-region to ensure transferability of the profiles.

A two-level hierarchical classification scheme was implemented. At the first level the three broad groups of summer crops, winter crops and perennial field grass / fallow land were classified. To separate perennial field grass / fallow land from the other two groups, those pixels that had high NDVI values in all available images throughout the growing season were classified as belonging to this group. Using a majority filter, the respective plots were excluded from the subsequent separation of summer and winter crops. This separation was based on two images, one acquired in winter / early spring and a second acquired in late spring / summer. While winter crops exhibit high NDVI values in both images, summer crops are characterized by a large difference in NDVI between both images with low values in winter / early spring and high values in late spring / summer. Again, a majority filter was used to assign the broad groups to the respective plots. As a result we obtained three separate masks containing plots with summer crops, winter crops and perennial field grass / fallow land.

At the second level single crop types within the three groups were classified based on their NDVI temporal profiles. For each date of image acquisition and each crop type, the phenological date, i.e. the day of the year corresponding to the actual phenological stage, was determined based on the agro-meteorological data. From the temporal profiles NDVI information was extracted for these phenologically corrected dates of image acquisition. This information was then used in the pixel-based classification using parallelepiped classification. The classification thresholds were defined by the standard deviation of the NDVI temporal profiles for each crop type and date. In cases of class overlap a minimum distance algorithm was applied using the image in which the classes to be separated show the largest difference in NDVI. In cases when the pixel was not within the thresholds, these were iteratively in-

creased. Finally, the classification results were combined in a joint crop type map. Using a majority filter, the dominant crop type per plot based on the plot boundaries was determined and assigned to each plot to derive the final crop type map for a certain year.
Additionally, a traditional maximum likelihood classification based on the same satellite imagery and on ground truth data was performed in order to assess the quality of the new classification algorithm based on NDVI temporal profiles.

4 Results

For each of the crop types the seasonal NDVI was plotted as exemplarily presented for winter rye and maize in Figures 3 and 4, respectively. The box plots show the variance of the NDVI values for each image acquisition date, while only those dates are included that have more than ten values. The NDVI exhibits a distinct seasonal pattern throughout the year with highest values between days 120 and 130 (early May) for winter rye and around 230 (mid August) for maize. The variability of NDVI values varies throughout the year and among different crops. For winter rye, the variability is largest during times of tillering until approximately day 115 (mid April) and after harvest from day 220 (early August) onwards, while it is smallest between days 115 (mid April) and 150 (end of May) during times of stem elongation and between days 200 (mid July) and 210 (end of July) during times of yellow-ripe. Maize shows a less distinct seasonal behaviour regarding NDVI variability. This can be attributed to the fact that maize shows a stronger dependence on the local soil and groundwater conditions, which the phenological correction does not account for. Hence the NDVI variability is higher throughout the year and the NDVI development is less continuous as compared to winter rye.

< Figure 3 >

< Figure 4 >

The spectral-temporal profiles for each of the 12 major crop types generated from the NDVI data can be clustered into three phenological groups (Figures 5 to 7). These are winter crops, summer crops and perennial field grass / fallow land. Among the groups each profile is specific in respect to the onset and duration of growth stages and agro-technical treatment times, the length of the growing period and the amount of photo-synthetically active vegetation present at the plots throughout the year.

< Figure 5, in colour >

< Figure 6, in colour >

< Figure 7, in colour >

Winter crops such as winter wheat and oilseed rape are sown in autumn. Accordingly, the NDVI values are characterized by a first increase in autumn and a second rapid increase in spring until reaching a maximum in early summer that is followed by a rapid decrease during the maturity stage in which harvesting and mowing dates are clearly distinguishable. Oilseed rape shows a characteristic temporary drop in NDVI values in May due to flowering.

Different from winter crops, summer crops are sown in spring and were therefore separable using spring images in the classification process. For other summer crops such as potatoes, maize and sugar beets, the increase in NDVI values starts only in mid May. While potatoes have a comparably short phenological cycle with a rapid NDVI decrease due to leaf senescence during maturing, sugar beets are characterized by high NDVI values until late October.

Fallow land and perennial field grass exhibit high NDVI values throughout the year with less variation as compared to summer and winter crops. Abrupt decreases in NDVI are due to mowing in the case of perennial field grass and the natural annual cycle of growth and withering in case of the natural vegetation on fallow land.

The presented hierarchical classification algorithm based on the generated NDVI temporal profiles was applied to map crop types in the study area for seven consecutive years 1994-2000. For each year two to five satellite images were available (cf. Table 2). Figure 8 shows the resulting crop type map of the entire study area for the year 2000. The distribution of the predominant crop types reflects the pattern of soil quality and water availability. On the sandy nutrient-poor areas, fallow land and winter rye predominate, while in the lowland areas with high soil quality and good water availability maize is the dominant crop type. Figure 9 presents crop type maps for a subset area of approximately 30 by 30 km for the years 1994-2000. Mapping crops of consecutive years allows the study of crop rotation patterns. We found that there are no fixed crop rotations, which was confirmed by the farmers.

< Figure 8, in colour >

< Figure 9, in colour >

A per-plot accuracy assessment was performed for the crop type map of the growing season 1994/1995, based on 144 agricultural plots comprising an overall area of 1°620°ha. For this growing season four satellite images were available (Table 3). Thus, the winter crops were represented by four images, while the summer crops were represented by three images. Table 3 also lists the phenologically corrected days of the year that were used in the classification process for each of the twelve crop types and each image.

< Table 3 >

The results of the accuracy assessment are summarized in Table 4. It presents the errors of commission (user's accuracy), omission (producer's accuracy), and the overall accuracy. The error of omission is the proportion of agricultural plots (given in hectare and percent) that is not correctly identified as belonging to a particular crop class. The error of commission is the proportion that is incorrectly identified as belonging to a particular class. The overall accuracy gives the proportion of correctly classified plots relative to the total number of validation plots. The overall accuracy was found to be 65.7 %. When interpreting this number, one has to bear in mind that the classification algorithm is transferable, i.e. no ground truth data are required in the classification process, and that the large number of twelve different crop types were distinguished. When summarizing the results at the hierarchical level of summer crops, winter crops and perennial field grass / fallow the overall accuracy increases to 86.3 %. While winter crops were classified with a high accuracy of 91.9 %, only 83.1 % of the summer crop plots were correctly classified. This may be primarily due to the different number and timings of images available for classifying summer and winter crops, while the information content of the July and August images is similar in regard to class separability. The misclassification between winter and summer crops at the first level of the hierarchical classification can be mainly attributed to the fact that an early spring image was not available in that particular growing season.

Highest crop-specific accuracies were obtained for winter wheat (91.7 %), oilseed rape (97.3 %) and oilseed crops and legumes (92.1 %), while moderate accuracies of more than 70 % were obtained for fallow land, winter barley and winter rye. Most of the classification error was associated with potatoes, sugar beets and maize. Only 14.5 % of maize plots were correctly classified, while 68.5 % were misclassified as being potatoes. Sugar beets were completely misclassified as being oilseed crops and legumes. This misclassification may be partly attributed to the unfavourable image acquisition dates, when a September image would allow a better differentiation between these crops. Furthermore, the end of July and early August 1995 were characterised by exceptionally low precipitation rates, leading to a negative water balance in the study area. The water stress led to a rapid withering of maize leaves in sandy locations with low groundwater making them appear spectrally similar to withered potato leaves. Maize that is cultivated in lowland areas with good access to groundwater does not show the withering phenomenon and is correctly classified as maize.

< Table 4 >

To assess the quality of the classification algorithm based on NDVI temporal profiles, a traditional maximum likelihood classification using the same four satellite images was performed. The results of the accuracy assessment are summarized in Table 5. With 72.8 % the overall accuracy was found to be higher as compared to the classification based on NDVI temporal profiles. This expected increase in classification accuracy can be attributed to the fact that the maximum likelihood classification is based on ground truth data and therefore the classifier is adjusted to the specific image statistics. When comparing the error matrices of both classification approaches (Table 4 and 5) similarities become apparent. In both approaches most classification error was associated with summer crops suggesting that the availability of images has a larger influence on the final result as compared to the type of classifier.

< Table 5 >

5 Discussion and conclusions

The classification approach proposed in this study allows an effective crop type mapping for large areas and several consecutive years. It can facilitate various environmental applications that require spatially explicit multi-year crop information such as water quality modeling (Krysanova et al., 1998) or agricultural flood loss estimation (Pantaleoni et al., 2007).

The hierarchical classification algorithm for per-plot crop type identification is based on distinct spectral-temporal profiles and accounts for inter-annual weather variations by incorporating agro-meteorological information in the classification process. The classification approach was applied to map twelve crop types in a 14 000 km² catchment in Northeast Germany for several consecutive years. Several recent crop mapping studies that compared the accuracy of supervised classification methods found the maximum likelihood classifier to perform best (Yang et al., 2011; Castillejo-González et al., 2009). Therefore the accuracy of the crop type mapping based on the spectral-temporal profiles was compared to that of a maximum likelihood classification (MLC). The overall accuracy increased from 65.7 % using the NDVI temporal profiles approach to 72.8 % using the ML classifier. While the MLC is based on training sets for each image used in the classification process, the NDVI temporal profiles approach is independent of ground truth data and solely requires information on the phenological stages of the individual crops at the time of image acquisition. The independence of ground truth data and therefore the transferability may justify the 7.1 % lower overall classification accuracy of the classification approach based on NDVI temporal profiles.

There are two major reasons for the slightly lower accuracy. These are the number and timing of image acquisitions and the occurrence of exceptional weather conditions. The classification based on the spectral-temporal profiles is more sensitive to the image acquisition dates than the MLC. This fact is illustrated by the confusion of summer grain and winter wheat in the growing season 1994/95 (cf. Tab. 4). The only major difference between the two spectral-temporal profiles is the later onset of NDVI increase of summer grain (around day 100) as compared to winter wheat (around day 70). If no image from this period is available, the classes will be confused. For the separability of all twelve crop type classes, the number and acquisition date of the images is therefore crucial. Optimal acquisition periods are those that allow the highest differentiation between crops, but are not necessarily peak growth times (Panigrahy and Sharma, 1997). For our study area these optimal acquisition periods were found to be early/mid April, mid May, early July, mid August and mid September. The second major reason for the slightly lower accuracies achieved with the spectral-temporal profile approach is the occurrence of unusual weather conditions, such as periods of exceptionally high or low temperature or precipitation that lead to strong deviations from the average spectral-temporal profiles for certain crop types in certain years. These deviations are particularly due to drought stress or changes in cultivation practices as a result to these weather conditions. They are not accounted for by the phenological correction using the agro-meterorological data, because this correction only implies a temporal shift of the spectral-temporal curve, but no modification in its shape or height. If the height of the profile strongly deviates from the average, e.g., due to exceptionally low NDVI values during drought conditions or some major management practices such as an earlier harvest, the spectral-temporal profile approach fails to classify correctly. One example for such an event is the summer drought period in 1994/95 that led to a rapid leave withering of (the water demanding crop) maize.

In both cases, i.e. if images of optimal acquisition periods are missing or the spectral-temporal profile is extremely deviating from the average, the accuracy of the spectral-temporal profiles approach is expected to be lower as compared to the MLC. This is due to the fact that the MLC uses image spectral information for a statistical adaption, while the spectral-temporal profile approach is solely relying on the average annual behaviour of the NDVI. Figure 10 compares the overall accuracy of both classification approaches for all twelve crop type classes for the growing season 1994/95. While the misclassification of summer grain and sugar beets using the spectral-temporal profiles approach can be mainly attributed to unfavourable image acquisition dates (missing early spring and September images, respectively), the misclassification of maize can be mainly explained as a result of the water stress maize plants at sandy locations experienced during the drought period in July and August of 1995. Figure 10 also shows that in the growing season 1994/95 for most crop types, i.e. fallow, perennial field grass, winter crops, oilseed rape, potatoes, and first year field grass, the results of the spectral-temporal profiles classification is comparable and even slightly better (by 0.6 % overall accuracy) as compared to the MLC. In case of the oilseed crops and legumes, the spectral-temporal profiles classification outperforms the MLC by 49 %, because in the MLC oilseed crops and legumes are often confused with perennial field grass. This points out the advantage of a hierarchical approach used in the spectral-temporal profile classification that separated in a first step perennial field grass and fallow land from summer and winter crops based on their high NDVI values throughout the year.

< Figure 10 >

The generated spectral-temporal profiles are only valid within one agro-region, i.e. a region of similar characteristics with regard to climate, soil and agro-technical conditions, and need to be adapted when applied to other agro-regions. However, even within an agro-region crops may develop differently depending on the soil and groundwater conditions, which may lead to misclassifications. While some crop types are characterized by a distinct continuous seasonal NDVI curve with low variation across the study area such as shown at the example of winter rye (Figure 3), other crop types such as maize (Figure 4) show a high variability across the study area as a result of its strong dependency on soil and groundwater conditions. Hence, the spectral-temporal profile is not valid for maize grown at different conditions. This suggests that the classification accuracy may be further improved by the inclusion of additional *a-*

priori information on the cultivation suitability for certain crop types such as soil quality or water availability. Apart from the spatial variation in crop phenology within and among different agro-regions, also a temporal development in crop phenology over the last few decades can be observed. Siebert and Ewert (2012) found out that the average temperature increase in Germany in the last 50 years resulted in an earlier onset and shortening of most phenological stages of oat. According to their study, the length of the growing season of oat in Germany decreased by about two weeks between 1959 and 2009. Consequently, the spectral-temporal profiles of crop types are subject to both spatial and temporal variations.

The further development of the proposed spectral-temporal profiles approach will benefit from the recent rapid increase in the availability of optical imagery, offering a high temporal coverage and a spatial resolution suitable for per-plot crop type mapping (Schreier and Dech, 2005). The increased availability of cloud-free images will facilitate the continuous refining of the spectral-temporal profiles for common crop types and different agro-regions under current climatic conditions and is expected to improve the classification accuracy of crop type maps using these profiles.

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Tab. 1: Cultivation data collected from six agricultural companies between the years 1987-2002 used for setting up the spectral-temporal profiles

Crop type	**Total number of plots**
Fallow	760
Field grass (perennial and first year)	120
Winter rye	890
Winter wheat	345
Winter barley	320
Oilseed rape	270
Summer grain	125
Sugar beets	60
Maize	365
Oilseed crops and legumes	325
Overall sum of plots	3745

Tab. 2: Acquisition dates of the 35 LANDSAT images sorted by the day of the year and respective crop development stages of winter wheat used for setting up the spectral-temporal profiles

Acquisition date of satellite image	Day of the year of image acquisition	Growth stage / agro-technical treatment
12.01.1989	12	Tillering (hibernation)
01.02.1996	32	Tillering (hibernation)
12.02.2000	43	Tillering (hibernation)
26.03.1998	85	Tillering
15.04.1988	105	Tillering
21.04.1996	111	Tillering
24.04.1997	114	Tillering
29.04.1987	119	Stem elongation
30.04.1999	120	Stem elongation
02.05.2000	122	Stem elongation
05.05.1995	125	Stem elongation
09.05.1988	129	Stem elongation
28.05.1992	148	Stem elongation
02.06.1997	153	Stem elongation
08.06.1996	169	Stem elongation
19.06.2000	170	Flowering
21.06.1998	172	Flowering
07.07.1989	188	Begin of yellow-ripeness
08.07.1995	189	Milk-ripeness
11.07.1999	192	Milk-ripeness
21.07.1994	202	Yellow-ripeness
09.08.1995	221	Shortly after harvest (stubbles)
11.08.1996	223	Yellow-ripeness
11.08.2002	223	Shortly after harvest (stubbles)
14.08.2000	226	Shortly after harvest (stubbles)
20.08.2002	232	Shortly after harvest (stubbles)
22.08.1994	234	After harvest
27.08.2002	239	After harvest
04.09.1987	247	After harvest
12.09.2002	255	After harvest
13.09.1999	256	After harvest
15.09.1991	258	After harvest
15.09.1997	258	After harvest
14.10.1996	287	Sowing
25.10.1994	298	Start of seeding development

Tab. 3: Acquisition dates of satellite images and phenologically corrected days of year used for crop type classification for the growing season 1994/1995

Acquisition date of satellite image		25.10.1994	05.05.1995	08.07.1995	09.08.1995
Day of year of image acquisition		298	125	189	221
	Fallow	293	132	184	226
	Perennial field grass	293	132	184	226
	Winter rye	298	128	193	221
	Winter wheat	293	132	184	226
	Winter barley	298	135	189	221
	Oilseed rape	298	135	183	221
	Summer grain		125	183	225
	Sugar beets		128	191	224
	Maize		128	189	218
	Oilseed crops and legumes		125	183	225
	Potatoes		128	191	224
	First year field grass		125	183	225

Tab. 4: Error matrix for classification based on NDVI temporal profiles using four images of the growing season 1994/1995

Reference data \ Classification results	Fallow	Perennial field grass	Winter rye	Winter wheat	Winter barley	Oilseed rape	Summer grain	Sugar beets	Maize	Oilseed crops and legumes	Potatoes	First year field grass	Area in ha	Correctly classified area in ha	Errors of omission (ha, %)
Fallow	76.6	1.6	0.4			6.7	1.6		0.4	4.4	3.2	5.1	328.6	251.7	76.9 23.4
Perennial field grass													0	0	0
Winter rye	10.1		71.1	8.8	6.1	1.6				0.4	1.9		299.0	214.1	84.9 28.9
Winter wheat	1.6		2.9	91.7		1.5	0.7					1.6	214.0	196.2	17.8 8.3
Winter barley	5.3		10.8		76.9	3.9				2.0	1.1		186.4	143.3	43.1 23.1
Oilseed rape	1.2			1.5		97.3							67.5	65.7	1.8 6.7
Summer grain				52.4		47.6							54.0	0	54.0 100
Sugar beets										100.0			27.7	0	27.7 100
Maize	0.4		6.2	1.4		1.3	0.6		14.5	1.8	68.5	5.2	271.0	39.5	231.5 85.5
Oilseed crops and legumes	2.1					1.0			3.1	92.1	1.7		167.5	154.3	13.2 7.9
Potatoes													0	0	0
First year field grass		100.0											3.7	0	3.7 100
Area in ha	300.9	9.1	257.4	255.6	161.6	133.6	8.4	0	45.5	206.2	206.8	34.2	Σ 1619.4*	1064.7	
Correctly classified area in ha	251.7	0	214.1	196.2	143.3	65.7	0	0	39.3	154.3	0	0	1064.7	Overall Accuracy	
Errors of commission (ha, %)	49.2 16.4	9.1 100	43.3 16.8	59.4 23.2	18.3 11.3	67.9 50.8	8.4 100	0	6.2 13.2	51.9 25.2	206.8 100	34.2 100		65.7 %	

* overall validation area

Tab. 5: Error matrix for maximum likelihood classification using four images of the growing season 1994/1995

		Classification result														
Reference data		Fallow	Perennial field grass	Winter rye	Winter wheat	Winter barley	Oilseed rape	Summer grain	Sugar beets	Maize	Oilseed crops and legumes	Potatoes	First year field grass	Area in ha	Correctly classified area in ha	Errors of omission (ha, %)
	Fallow	78.6	3.5	0.4	8.7	1.8			0.3	6.6				328.6	258.3	70.3 21.4
	Perennial field grass													0	0	0
	Winter rye	11.0	2.3	68.2	5.2	2.5	3.9	6.3						299.0	203.8	95.2 31.8
	Winter wheat			2.9	95.5		0.9			0.7				214.0	204.5	9.5 4.5
	Winter barley	2.0	4.2	5.0	3.7	71.7	12.3			1.1				186.4	133.6	52.8 28.3
	Oilseed rape				5.2		94.8							67.5	64.0	3.5 5.2
	Summer grain						27.8	72.2						54.0	39.0	15.0 27.8
	Sugar beets								100.0					27.7	27.7	0.0 0.0
	Maize	1.8		4.4	2.1		3.2		23.8	64.6				271.0	175.1	95.5 35.4
	Oilseed crops and legumes	1.4	47.7		1.0		1.0		1.0	4.7	43.2			167.5	72.3	95.2 56.8
	Potatoes													0	0	0
	First year field grass		67.6			32.4								3.7	0.0	3.7 100
	Area in ha	305.7	57.9	232.9	268.3	147.1	125.9	106.1	94.8	208.2	72.3	0	0	Σ 1619.4*	1178. 3	
	Correctly classified area in ha	258.3	0	203.8	204.5	133.6	64.0	39.0	27.7	175.1	72.3	0	0	1178.3	Overall Accuracy	
	Errors of commission (ha, %)	47.4 15.5	57.9 100	28.1 11.1	63.8 23.8	13.5 10.1	61.9 53.3	67.1 63.2	67.1 70.8	33.1 15.9	0.0 0.0	0	0		72.8 %	

* overall validation area

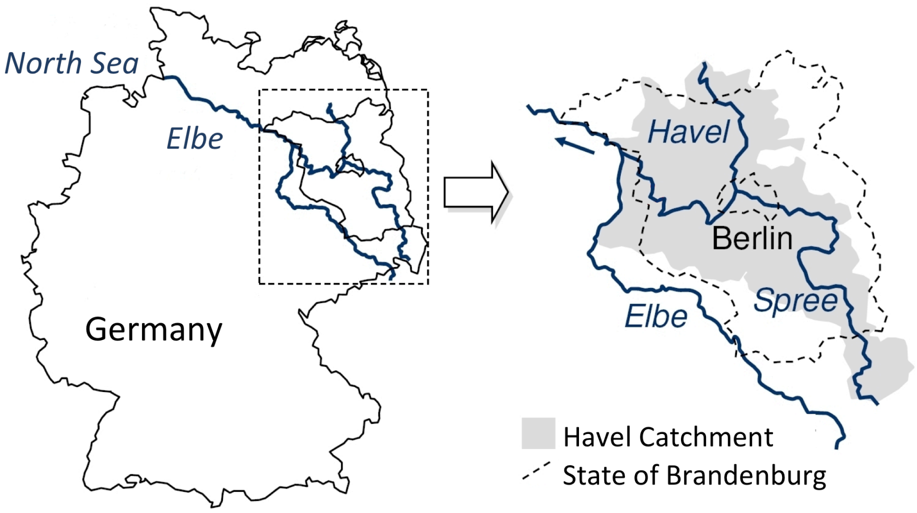

Fig. 1: Location of study area

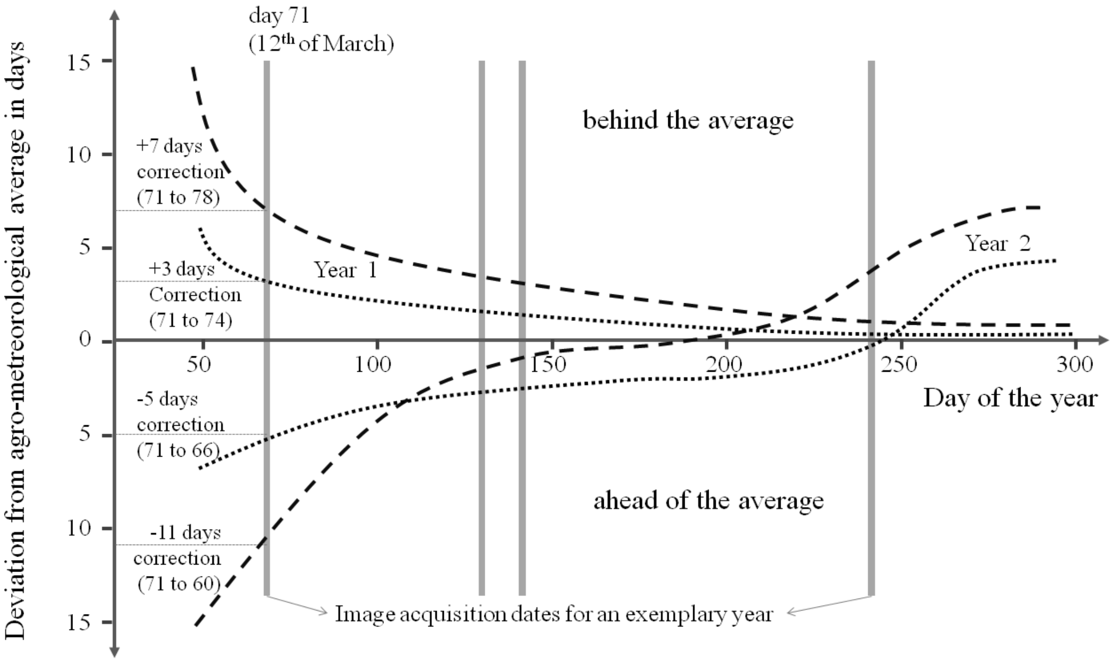

Fig. 2: Schematic graph of the phenological correction for two different years (marked as Year 1 and Year 2). Dotted and dashed lines represent the deviation from the average year in days for two different crop types. Positive values indicate a delayed crop development, negative values a crop development ahead of the average.

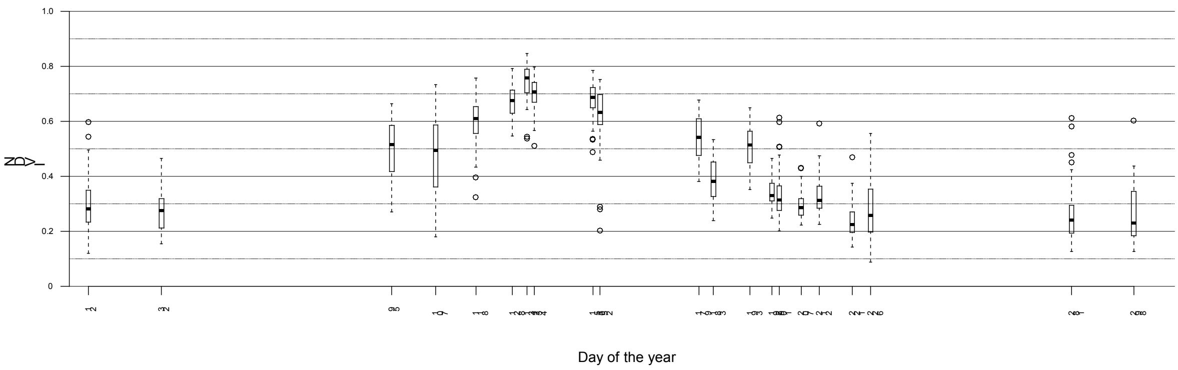

Fig. 3: NDVI response during the growing season of winter rye. Whiskers represent the 1.5 times interquartile range and the dots represent outliers.

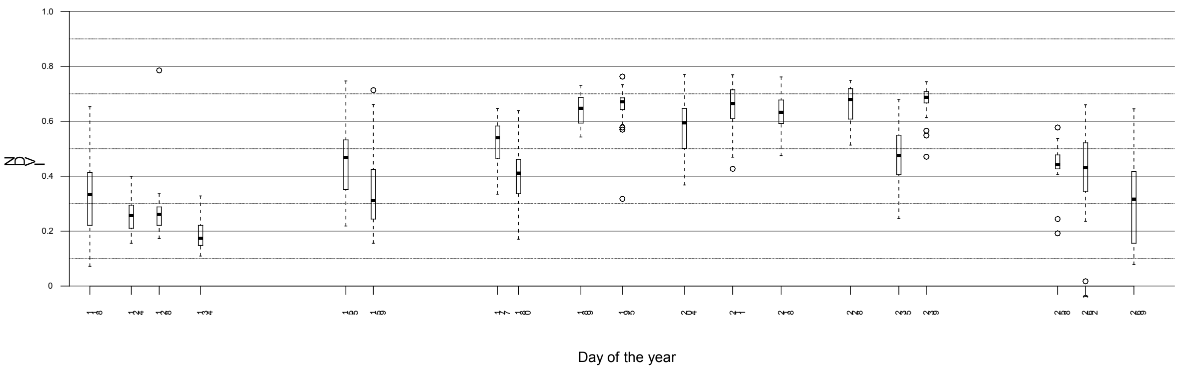

Fig. 4: NDVI response during the growing season of maize. Whiskers represent the 1.5 times interquartile range and the dots represent outliers.

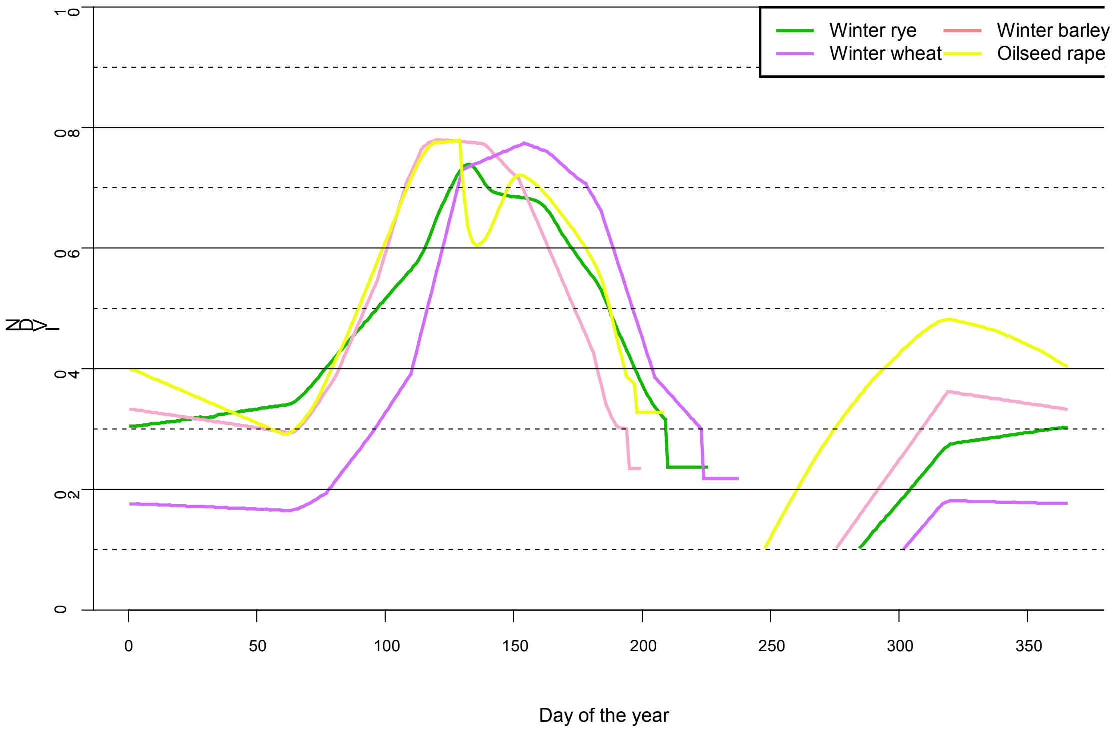

Fig. 5: NDVI temporal profile of winter crops

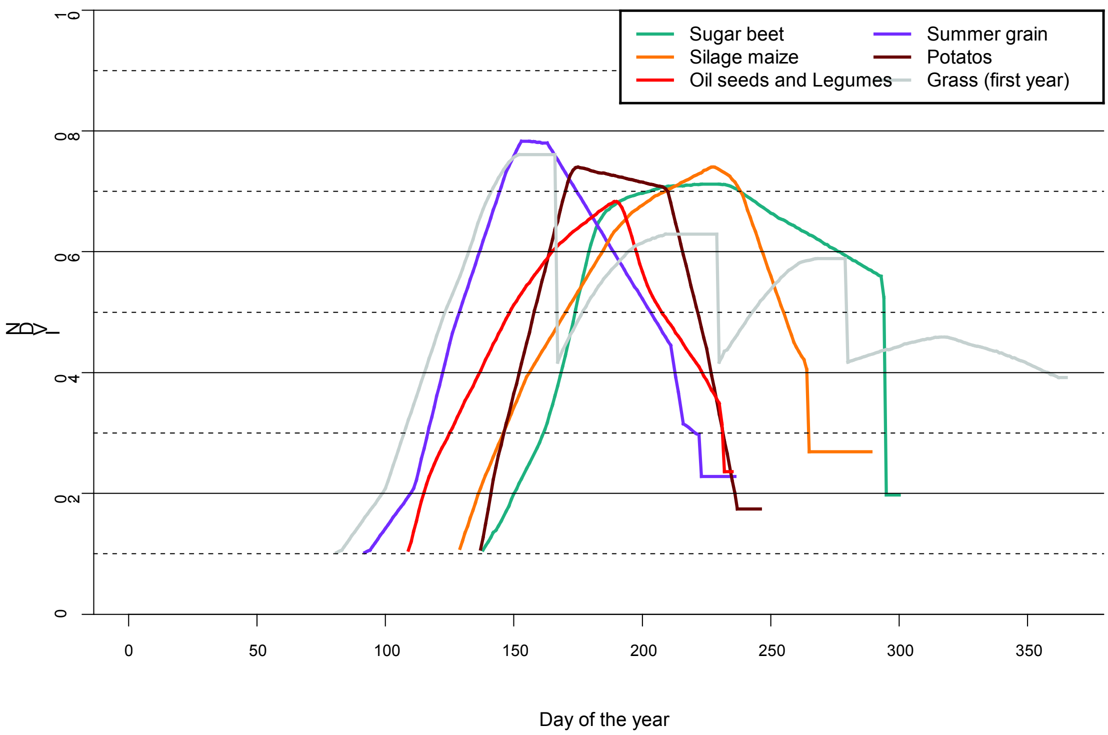

Fig. 6: NDVI temporal profile of summer crops

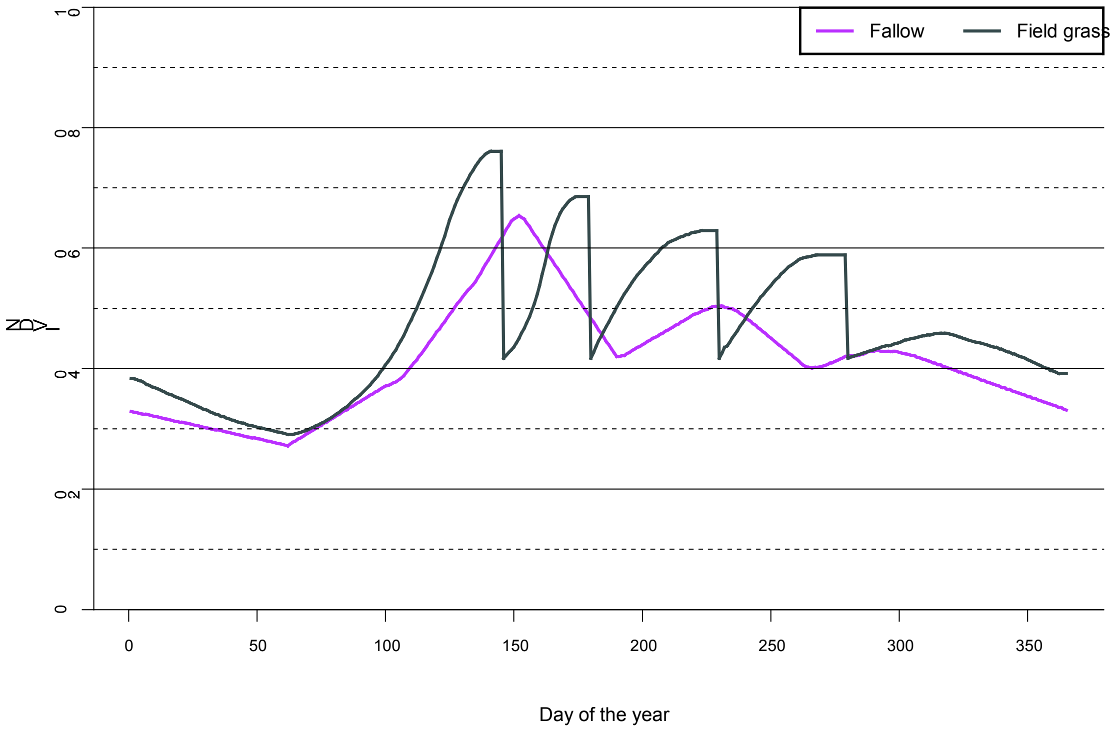

Fig. 7: NDVI temporal profile of perennial field grass / fallow land

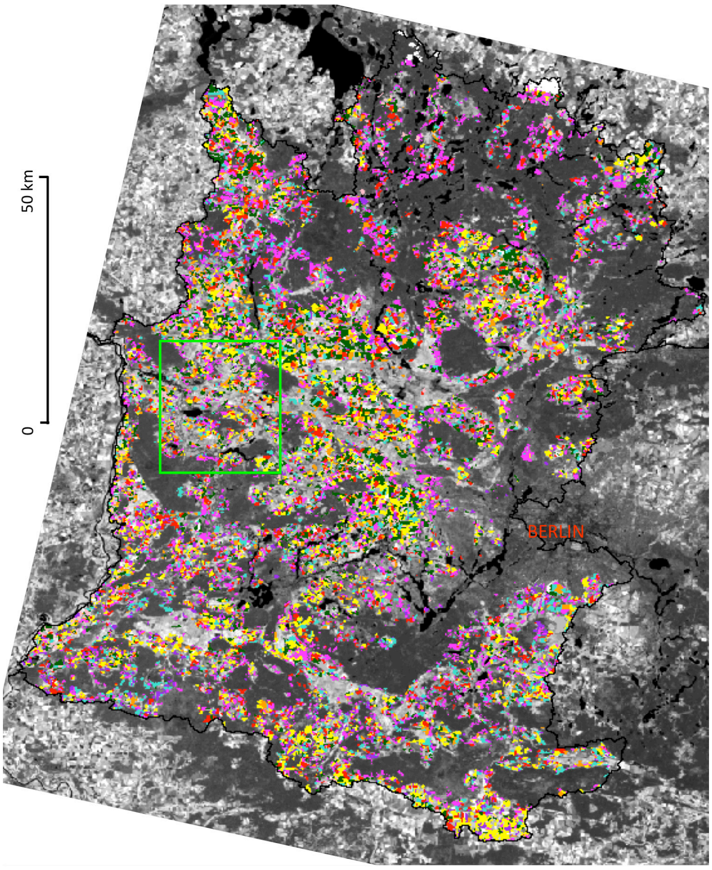

Fig. 8: Crop type map of the entire study area for the year 2000, subset region (Fig. 9) marked in green. For legend refer to Fig. 9.

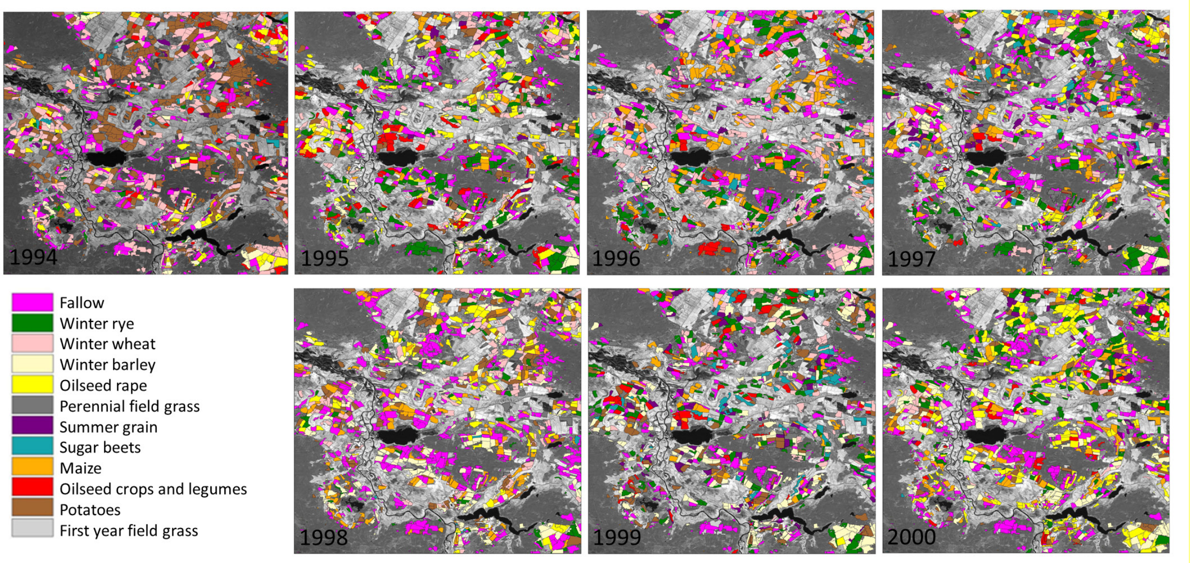

Fig. 9: Crop type maps for a subset region for the years 1994-2000

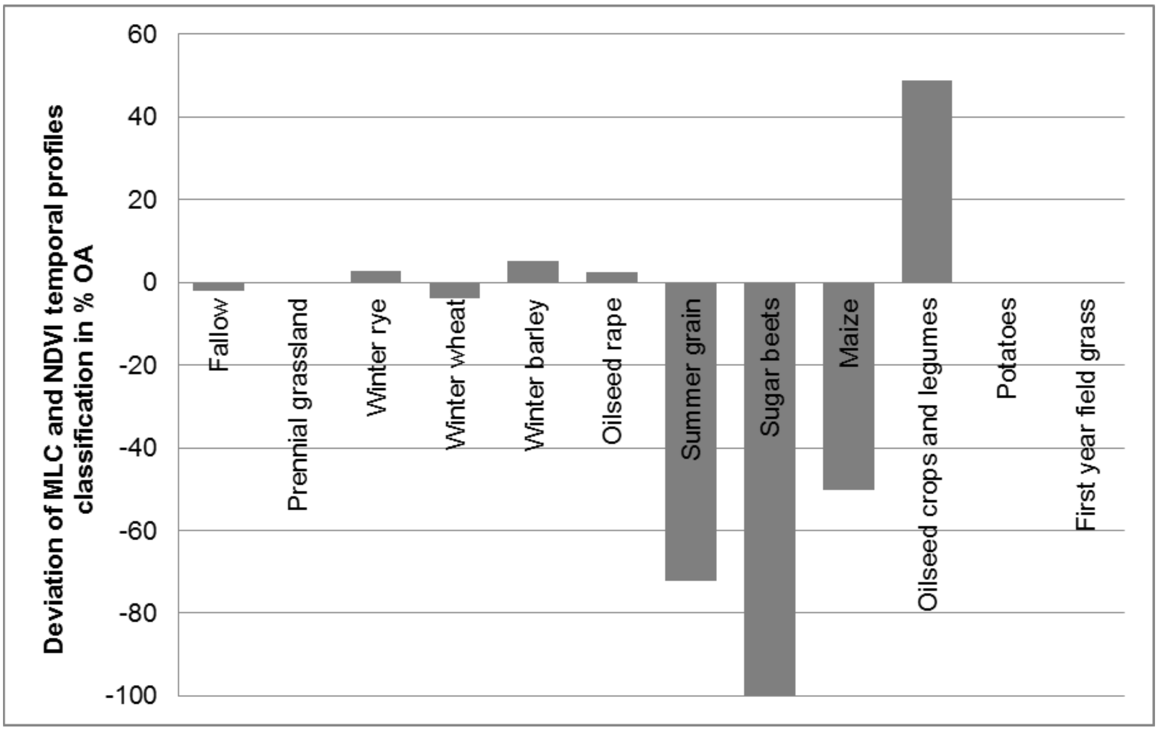

Fig. 10: Deviation of the overall accuracy (OA) between maximum likelihood classification (MLC) and spectral-temporal profiles classification per crop type class for the growing season 1994/95. Positive values indicate higher overall accuracies of the spectral-temporal profiles classification.