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Analysis of relationship between cereal yield and NDVI for selected regions of Central Europe based on MODIS satellite data

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ABSTRACT

Earth observation satellite technologies allow the status of crops to be assessed at various geographical scales. The most popular vegetation index for analyzing this status is the Normalized Difference Vegetation Index (NDVI). This article studies the relationship between the NDVI and cereal-grain yield in selected regions (corresponding to NUTS2 levels) of four Central European countries: Poland, Germany, the Czech Republic, and Slovakia. The remote sensing data cover the vegetation seasons (from the beginning of March until the end of June) of 2012–2016, and were obtained using the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor of NASA's Terra satellite. The average NDVI of the data was calculated for both the entire area and the arable-land area of the regions (according to the Corine Land Cover program). Statistical analysis includes correlation and linear regression analyses between cereal grain yield and mean NDVI for entire area and arable land of the regions in each year of the study. They are strongly correlated from the beginning of March until mid-May (most of the correlation coefficients for arable land are between 0.50 and 0.85), the strongest relationship being around the beginning of April in the Czech Republic and Slovakia (most of the correlation coefficients are between 0.80 and 1.00). In most regions of Poland, the relationships are quite strong, but in German regions they are weak and inconsistent. Regression coefficients (slopes) for relationships between the NDVI in the beginning of April and the grain yield of cereals range from 10.8 to 26.2. This means that an increase in the NDVI in early spring by 0.1 unit increases the grain yield of cereals by about 1.1–2.6 t/ha. The obtained results are promising because they prove the possibility of forecasting cereal grain yield at the regional level, three–four months before the harvest, which is important for planning food policy.

1. Introduction

Satellite-based remote sensing makes it possible to observe the current status of vegetation at various geographical scales. Satellite technology and devoted algorithms allow one to conduct various environmental analyses at the regional scale, thereby enabling the constant monitoring of environmental changes. Thanks to NASA projects, and the Terra satellite in particular, atmospheric correction of optical imagery has been available via the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor since 1999.

These data can be used to calculate vegetation indices. They are determined on the basis of spongy parenchyma, which has high reflectance value of near-infrared radiation, and plant chlorophyll, which absorbs the red light. Green vegetation in favorable conditions reflects infrared radiation, while poor vegetation with a lower chlorophyll concentration in the leaves absorbs most infrared radiation. Maximum chlorophyll absorbance occurs at the wavelengths of 0.42, 0.49, and 0.66 μm (Gausman, 1974; Collins, 1978; Sellers, 1985; Belward and Valenzuela, 1991; Zagajewski et al., 2007).

The most commonly used differential vegetation index is likely the Normalized Difference Vegetation Index (NDVI), which is based on the difference between reflectance in the near-infrared (NIR) band and that in the red (RED) band (Baret and Guyot, 1991; Chen, 1996; Rondeaux et al., 1996; Purevdorj et al., 1998; Thenkabail et al., 2000; Huete et al., 2002; Haboudane, 2004). The NDVI is believed to be sensitive enough to detect changes in small amounts of vegetation (Rouse et al., 1973; Wang et al., 2004).

Using Earth observation satellite data, it is possible not only to monitor the current state of the environment and the direction of its transformation, but also to predict crop yields and monitor the status of agricultural production at the local and regional levels. Many researchers from across the globe have emphasized that satellite data and

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the NDVI can help to predict crop yields (Smith et al., 1995; Purevdorj et al., 1998; Huete et al., 2002; Singh et al., 2002; Haboudane, 2004; Wang et al., 2004, 2019; Reeves et al., 2005; Ren et al., 2008; Becker-Reshef et al., 2010; Mkhabela et al., 2011; Rembold et al., 2013; Li et al., 2015; Lopresti et al., 2015; Ban et al., 2016; Zhang and Zhang, 2016; He et al., 2018; Petersen, 2018; Nagy et al., 2018; Yu and Shang, 2018).

Satellite data from sensors such as AVHRR or MODIS are used for the estimation of cereal-grain yield at the regional and global levels because of their reasonably small spatial resolution (from hundreds of meters to kilometers) (Reeves et al., 2005; Ban et al., 2016; Zhang and Zhang, 2016; He et al., 2018; Nagy et al., 2018; Petersen, 2018; Yu and Shang, 2018). One of the main advantages of such sources of satellite data is their daily temporal resolution and global coverage. For yield estimation, vegetation indices such as NDVI, enhanced vegetation index (EVI), or similar indices based on visible and infra-red reflectance are often used. In the simplest approach of yield estimation, NDVI (Lopresti et al., 2015) or cumulative NDVI (Ren et al., 2008) is used as the only predictor, and univariate linear regression is used as the statistical model. The results obtained in a study conducted in a selected region of Argentina (Lopresti et al., 2015) showed a strong relationship ($R^2 = 0.52$) between the grain yield of wheat and MODIS-NDVI at the anthesis (end of October–beginning of November, i.e., about one month before the harvest). An increase in NDVI by 0.1 units was related to an increase in wheat-grain yield of about 1.1 t/ha. In a study on Kansas (US) and the Ukraine, a strong relationship between maximum adjusted (by soil reflectance) NDVI derived from MODIS and the grain yield of winter wheat was observed (Becker-Reshef et al., 2010). Regression models allowed yield forecasts closely matched to the official reported production of winter wheat to be obtained for the studied regions with a 7% error for Kansas and a 10% error for the Ukraine. The forecast was done six weeks prior to harvest. In this study, the NDVI used for the analyses was only done for areas classified as wheat fields. In a study on selected counties in the eastern part of China (Ren et al., 2008), the relationship between MODIS-NDVI (from mid of March to end of May) and the grain yield of winter wheat was evaluated. Linear-regression models allowed the grain yield of winter wheat to be predicted with good accuracy ($R^2 = 0.88$; relative error about 5%) when using NDVI from the middle of April. In a study on regions of Canada, the relationships between MODIS-NDVI and the yield of barley, canola, peas, and wheat were quite strong but not exactly linear (Mkhabela et al., 2011). The best-fitted model was a multiplicative function (yield = a * NDVI^b) for barley and the coefficient of determination for wheat was in the range from 0.47 to 0.90 for NDVI at the flowering and grain-filling stages. In the study of Bu et al. (2017) strong relationships between satellite (RapidEye imagery) derived NDVI at flag leaf emergence with grain yield of spring wheat were found ($R^2 = 0.83$) but only in one year of two year study. In the same study strong relationships (R^2 from 0.77 to 0.84) were observed between NDVI from the end of June (three months before the harvest) and grain yield of maize. These relationships were evaluated on plots where different levels of nitrogen were applied. Very promising results for yield forecasting of various spring and winter crops including wheat, barley, maize and rye based on NDVI derived from AVHRR satellite sensors were obtained by Bognár et al. (2011). In this study yield forecast was possible with error less than 5% for counties of Hungary. High accuracy was possible to obtain 50 days before harvest of wheat and 70 days before the harvest of maize (Bognár et al., 2011). Another study for Hungary (Nagy et al., 2018) proved strong relationships (R^2 in range 0.7–0.8) between NDVI derived from MODIS and grain yield of winter wheat and maize at regional level. It allow to predict grain yield with high accuracy 6–8 weeks before the harvest. Besides simple yield models where NDVI is the only predictor of grain yield, more advanced approaches for yield estimation have been evaluated. MODIS data-derived variables can be used as additional predictors of grain yield in crop models such as CASA for wheat (Wang et al., 2019), WOFOST for wheat (Huang et al., 2015), CERES for maize (Fang et al., 2011), and DSSAT-CERES for wheat (Wang et al., 2010). This allows for better accuracy of grain yield prediction to be obtained. Better grain yield prediction is usually obtained when cropland classification data are used. Such data are of better quality in regions where crop fields are bigger and where certain crop species are concentrated. In the case of sparsely distributed croplands on small farms, for example, in most of Africa, the accuracy of yield prediction is worse (Zhang and Zhang, 2016).

Land-cover classification allows croplands and other types of land cover to be distinguished, and as a result, better yield prediction is obtained using satellite-derived vegetation indices. For the European Union area, the Corine Land Cover (CLC) database (Copernicus Programme) was created to allow the large-scale classification of particular types of land use and land cover. This database makes it possible to examine land-cover types and forms of land, e.g., arable land, other agricultural areas, forests, and anthropogenic areas. In this study, CLC was used to distinguish croplands for the analyses.

Yield prediction and monitoring the state of agricultural production is crucial due to the severe economic and social consequences of food shortage. This research mainly aims to determine the time of year when cereal grain yield can be precisely predicted using the NDVI (obtained from the MODIS sensor) at the regional level in Central Europe. An indication of this period is important because the results of various previous studies are not consistent and indicate different times as crucial. To study this, a long time range, with several days' interval, was analyzed, from early spring to the beginning of the harvest of most cereal species. This allows to estimate the grain yield of cereals with higher accuracy and, if possible, long before the harvest. Moreover, another aim of the study is a comparison of the relationships based on the NDVI for the total area versus the relationships based on NDVI for cropland area. It is important because cropland area is changing every year (e.g. because of urbanization) and it is difficult to distinguish crop masks, especially in areas where agricultural parcel size is very small (e.g. in southern Poland). To address these aims, the study uses data from the European Statistical System (EUROSTAT) for the selected regions (NUTS2) and the mean values of the MODIS-NDVI for 2012–2016.

2. Materials and methods

Atmospherically corrected MODIS multispectral satellite images with a pixel size of 250 m (product MOD09Q1) were obtained from the Global Agricultural Monitoring System (GLAM) by NASA, which provides a global NDVI dataset every eight days in near real time. The system was created as part of the Global Agricultural Monitoring project, which aims to provide the objective, timely, and regular assessment of global forecasts of agricultural production and conditions affecting global food security. The data were collected in 2012–2016, during a period close to the growing season in Central Europe, that is, from March 7 to June 28. The NDVI was read for each point (pixel centers located in the corresponding territorial [NUTS2] unit) of the data. For each region, the mean NDVI was calculated for all data points studied for both the entire regions (NUTS2) and their areas of arable land (Figs. 1 and 2, Table 1). Classification according to the Corine Land Cover (CLC, 2012 - Copernicus Programme) was used, so arable land included nonirrigated arable land, permanently irrigated arable land. The areas, defined in CLC nomenclature as Types 2.1.1—nonirrigated arable land, 2.4.2—complex cultivation patterns, and 2.4.3—land principally occupied by agriculture with significant areas of natural vegetation were used as a cropland mask for the analyses.

Cereal-grain yield data were obtained from the EUROSTAT database (EUROSTAT, 2019). The yield is weighted average for all species i.e. total production of all cereals species divided by total area of cereals. The following crop species were treated as cereals: wheat, barley, rye, oats, triticale, maize, and other cereals that are of negligible economic importance in the study area, such as buckwheat and millet. Vegetation of maize is shifted in comparison with other crops, harvest time in case of maize is about two months later (September–October) than other

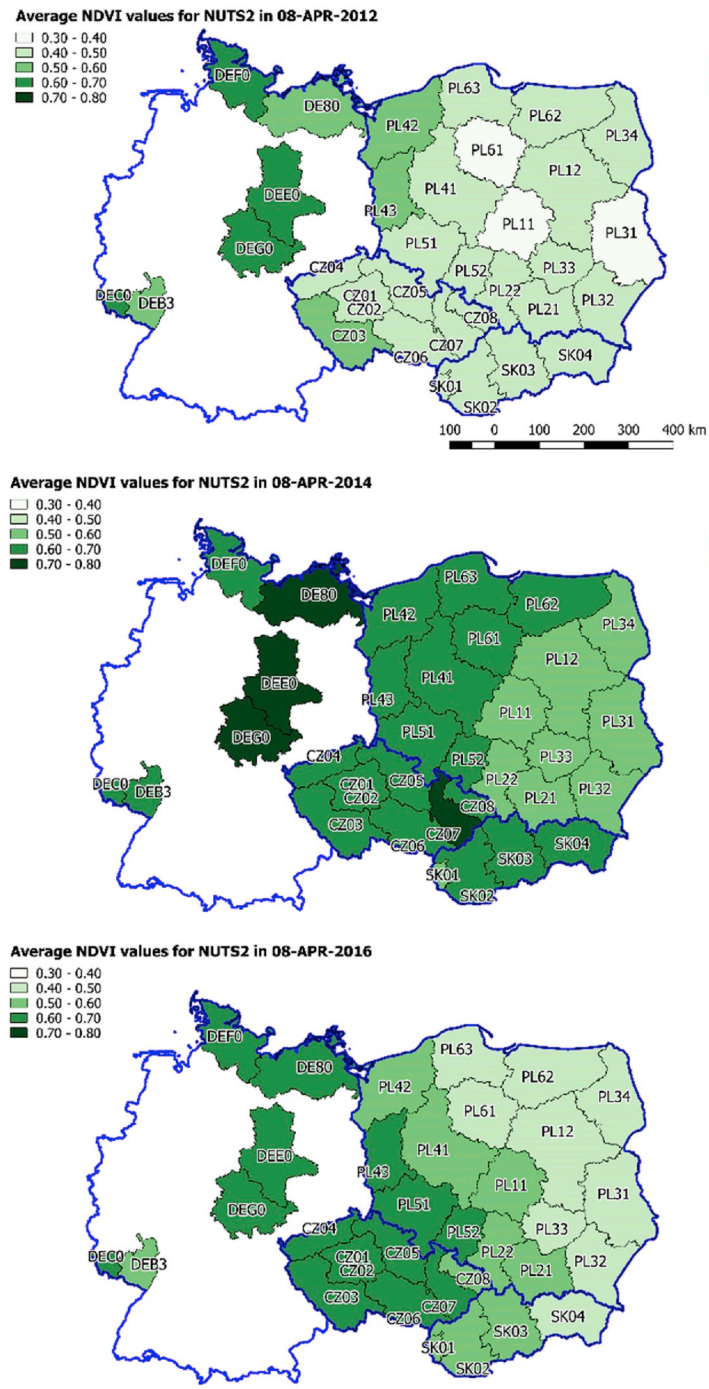

Fig. 1. Mean NDVI values of arable land for NUTS2 regions for dates in which strongest relationship between NDVI and cereal-grain yield was observed. Abbreviations and full names of the regions are presented in Table 4.

cereals (July–August).

2.1. Study area

The research covered all of Poland, Slovakia, and the Czech Republic, as well as selected regions of Germany. Analysis was based on cereal-grain yield data and the CLC 2012 land cover (Figs. 3 and 4) for 34 provinces (NUTS2). The included regions are characterized by similar climatic conditions and similar periods of crop development, including the date of the crop harvest (Rötter et al., 2012; Tutiempo Network, 2019). Cereals are important crops in Central Europe: their share in arable land is about 60% (Schils et al., 2018; EUROSTAT, 2019; FAOSTAT, 2019). Most of them are winter cereals, such as wheat, barley, rye, and triticale, which is why they were selected for the study. The largest area among these species was recorded to be occupied by wheat (almost half of the area of all cereals), and then by barley; other crops cover a smaller area (Table 2). In the case of Poland, quite a large area (about 20% of all cereals) was observed to account for triticale, and a large share of maize was recorded in Slovakia (about 25% of all cereals). Winter cereals with higher potential yield (especially winter wheat) are crops of bigger importance than spring cereals. In typical crop management, winter cereals are planted from the second half of September (northern part of the study area) to the beginning of October (southern part of the study area). Spring cereals are usually sown in the

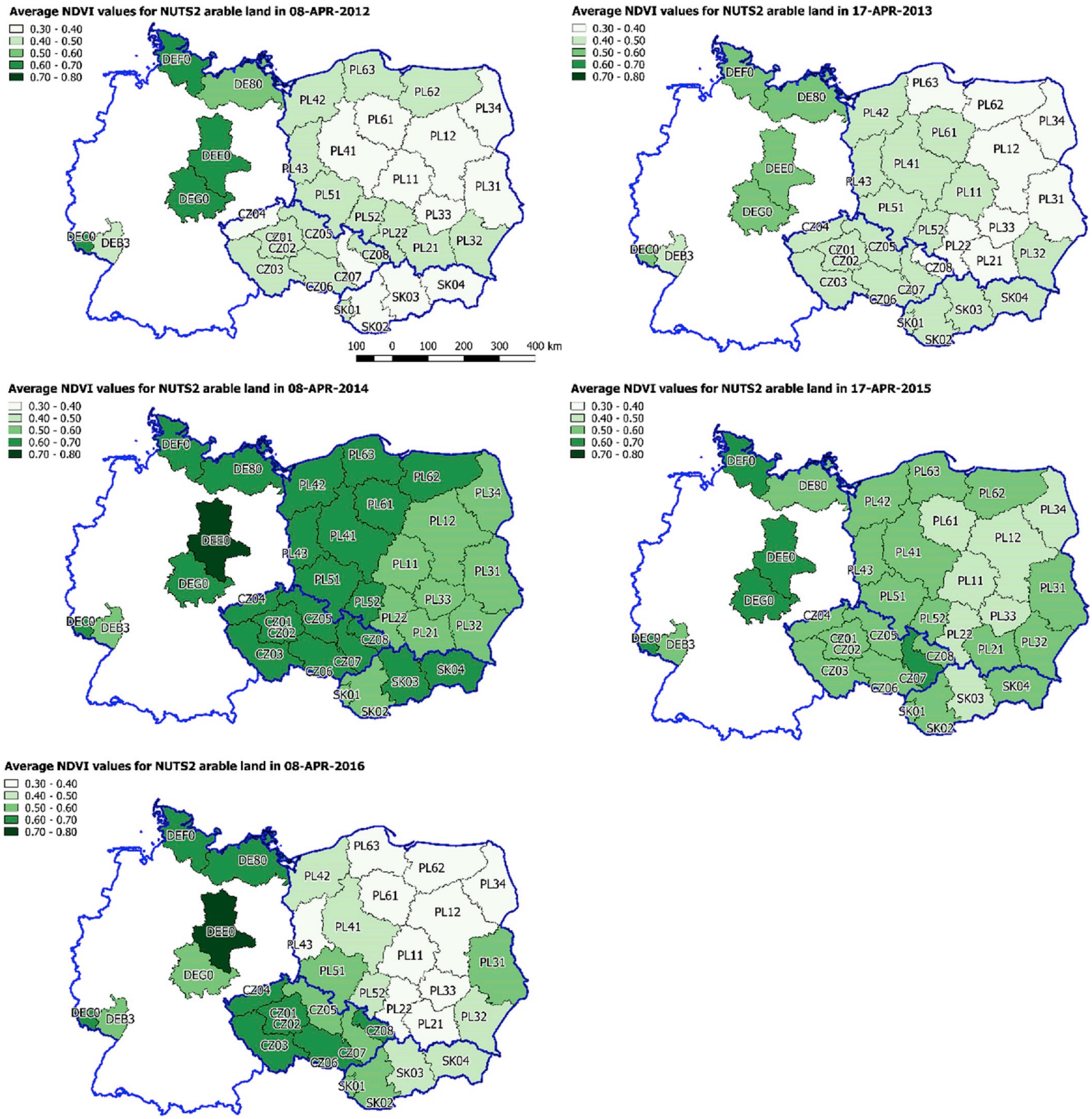

Fig. 2. Mean NDVI values for total area of NUTS2 regions for dates in which strongest relationship between NDVI and cereal-grain yield was observed. Abbreviations and full names of the regions are presented in Table 4.

second half of March or in the beginning of April. Maize is sown in the second half of April. Full maturity of most cereals, both winter and spring crops, is achieved in July, while maize reaches full maturity at the end of September or in October. Because of the high importance of national breeding companies, most cereal varieties cultivated in each country are different, but genetic yield potential of the cultivars in different countries is similar, as evidenced by the results of variety evaluation in each country. These results are available on the websites of national organizations for variety testing, i.e., http://eagri.cz/public/web/en/ukzuz/(Czech Republic); https://www.bundessortenamt.de/(Germany); http://coboru.pl/(Poland); http://www.vurv.sk/(Slovakia). Crop-management recommendations for the species and cultivars in each country within the area of study are similar, e.g., sowing density. The average annual precipitation for most parts of the study area is between 500 and 650 mm (Tutiempo Network, 2019). Higher precipitation is observed in the northern part of the study area, located by the seaside, and in the southern part of the study area with higher elevation (600–750 mm). Very high precipitation (800–1000 mm) is observed in the mountains next to the border of Poland with the Czech Republic and Slovakia, but such areas were excluded from cultivation.

Table 1
Means and SDs of the Normalized Difference Vegetation Index (NDVI) values for arable land and total area of all the studied regions (n = 34), from 7 March to 28 June in the period between 2012 - 2016.

Date	Arable land					Total area				
	2012	2013	2014	2015	2016	2012	2013	2014	2015	2016
7 Mar	0.340 ± 0.054	0.403 ± 0.037	0.454 ± 0.042	0.425 ± 0.046	0.451 ± 0.074	0.400 ± 0.051	0.438 ± 0.048	0.498 ± 0.046	0.469 ± 0.048	0.481 ± 0.104
15 Mar	0.345 ± 0.065	0.390 ± 0.051	0.478 ± 0.052	0.433 ± 0.047	0.443 ± 0.060	0.408 ± 0.054	0.464 ± 0.073	0.510 ± 0.053	0.476 ± 0.045	0.489 ± 0.053
23 Mar	0.405 ± 0.067	0.353 ± 0.090	0.546 ± 0.047	0.435 ± 0.052	0.460 ± 0.071	0.430 ± 0.059	0.459 ± 0.088	0.561 ± 0.045	0.475 ± 0.046	0.501 ± 0.056
1 Apr	0.438 ± 0.089	0.380 ± 0.090	0.548 ± 0.043	0.524 ± 0.050	0.505 ± 0.073	0.480 ± 0.067	0.424 ± 0.063	0.558 ± 0.042	0.538 ± 0.047	0.493 ± 0.075
8 Apr	0.438 ± 0.089	0.412 ± 0.047	0.619 ± 0.054	0.501 ± 0.055	0.507 ± 0.116	0.480 ± 0.067	0.432 ± 0.053	0.625 ± 0.053	0.523 ± 0.050	0.562 ± 0.069
17 Apr	0.585 ± 0.107	0.445 ± 0.055	0.628 ± 0.039	0.552 ± 0.052	0.598 ± 0.084	0.579 ± 0.052	0.478 ± 0.052	0.638 ± 0.038	0.571 ± 0.045	0.617 ± 0.064
25 Apr	0.547 ± 0.072	0.537 ± 0.059	0.675 ± 0.032	0.599 ± 0.051	0.615 ± 0.061	0.579 ± 0.052	0.560 ± 0.048	0.695 ± 0.032	0.618 ± 0.043	0.634 ± 0.049
3 May	0.590 ± 0.065	0.639 ± 0.059	0.700 ± 0.025	0.659 ± 0.038	0.644 ± 0.050	0.633 ± 0.051	0.660 ± 0.047	0.722 ± 0.026	0.683 ± 0.034	0.668 ± 0.043
11 May	0.658 ± 0.047	0.682 ± 0.043	0.722 ± 0.027	0.684 ± 0.029	0.660 ± 0.036	0.695 ± 0.039	0.716 ± 0.042	0.743 ± 0.032	0.714 ± 0.028	0.693 ± 0.036
19 May	0.693 ± 0.035	0.703 ± 0.040	0.718 ± 0.042	0.698 ± 0.031	0.697 ± 0.025	0.724 ± 0.034	0.729 ± 0.038	0.736 ± 0.037	0.729 ± 0.030	0.726 ± 0.028
27 May	0.713 ± 0.041	0.731 ± 0.029	0.706 ± 0.044	0.745 ± 0.030	0.724 ± 0.037	0.740 ± 0.037	0.754 ± 0.031	0.735 ± 0.039	0.765 ± 0.034	0.746 ± 0.034
04 Jun	0.730 ± 0.032	0.755 ± 0.039	0.725 ± 0.035	0.725 ± 0.033	0.741 ± 0.033	0.747 ± 0.032	0.770 ± 0.036	0.746 ± 0.034	0.753 ± 0.036	0.762 ± 0.035
12 Jun	0.742 ± 0.041	0.740 ± 0.028	0.750 ± 0.035	0.722 ± 0.040	0.742 ± 0.029	0.760 ± 0.039	0.760 ± 0.034	0.764 ± 0.032	0.749 ± 0.038	0.757 ± 0.036
20 Jun	0.737 ± 0.040	0.731 ± 0.021	0.705 ± 0.051	0.731 ± 0.037	0.718 ± 0.041	0.759 ± 0.040	0.754 ± 0.031	0.735 ± 0.038	0.756 ± 0.030	0.738 ± 0.040
28 Jun	0.695 ± 0.058	0.703 ± 0.040	0.678 ± 0.056	0.692 ± 0.047	0.701 ± 0.040	0.724 ± 0.046	0.729 ± 0.038	0.719 ± 0.041	0.734 ± 0.041	0.738 ± 0.040

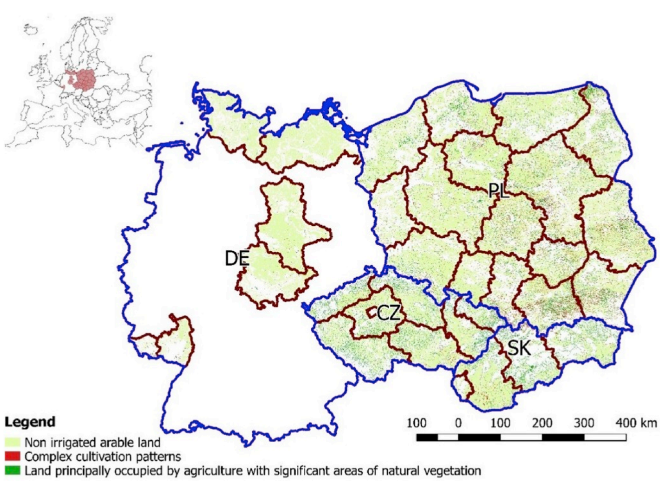

Fig. 3. Corine Land Cover 2012 map for the studied NUTS2 regions. Areas in yellow, red, and green were treated together as a cropland mask for statistical analysis. DE – Germany, PL – Poland, CZ – Czech Republic, SK – Slovakia. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

2.2. Statistical analysis

The means of NDVI values for MODIS image pixels within the total area of the regions or the area of croplands within the region were used for analysis as a statistical sample. A MODIS pixel with 250 m resolution cover 62500 m^2 (6.25 ha) The number of pixels for each region used for calculations of the NDVI means were from several thousands (for the smallest region—Praha) to near one million pixels (for the biggest region—Mazowieckie) for the total area of the regions, and about twice lower for the cropland area. For each date from 7 March to 28 June of each year, NDVI values based on the MODIS 8-day time series (MOD09Q1) were used for the analyses (NASA, 2019). The sample size was n = 34 (number of regions) for each year, while the sample size for the analyses across years separately for each region was n = 5 (number of years). Relationships between the NDVI values for the total area or only croplands and the cereal-grain yield were evaluated using Pearson's correlation and linear-regression analyses. Analyses were conducted for the following data subsets: (1) for each observation date (every 8 days over the studied period), separately for each year, and for all regions together; and (2) for each observation date, separately for individual regions, and for all years together. Values of correlation coefficients for each year across all regions are presented in graphical form for better evaluation of the change over time of the strength of the relationship between NDVI and grain yield. For dates where maximal values of correlation coefficients were observed, the results of linear regression are presented in graphical form, together with regression equations and coefficients of determination (R^2). Moreover, separate correlation coefficients for the regions across all years are presented in a table, with colors dependent on the value of the correlation coefficient (in heat-map form). Analyses were conducted using Statistica 13 (TIBCO Software Inc., Palo Alto, CA, USA) and the R 3.5 environment (R Foundation for Statistical Computing, Vienna, Austria). Spatial analyses were conducted, and maps were prepared using QGIS 2.18 software (QGIS Development Team, Gossau, Switzerland).

3. Results

3.1. Temporal and spatial variability of cereal-grain yield

In all years, the German regions—especially those in the northern part of the country—had the highest grain yields of cereals, while the eastern part of Poland had the lowest yields; this is visible on Fig. 2. Similar differences in grain yield were observed for individual species of

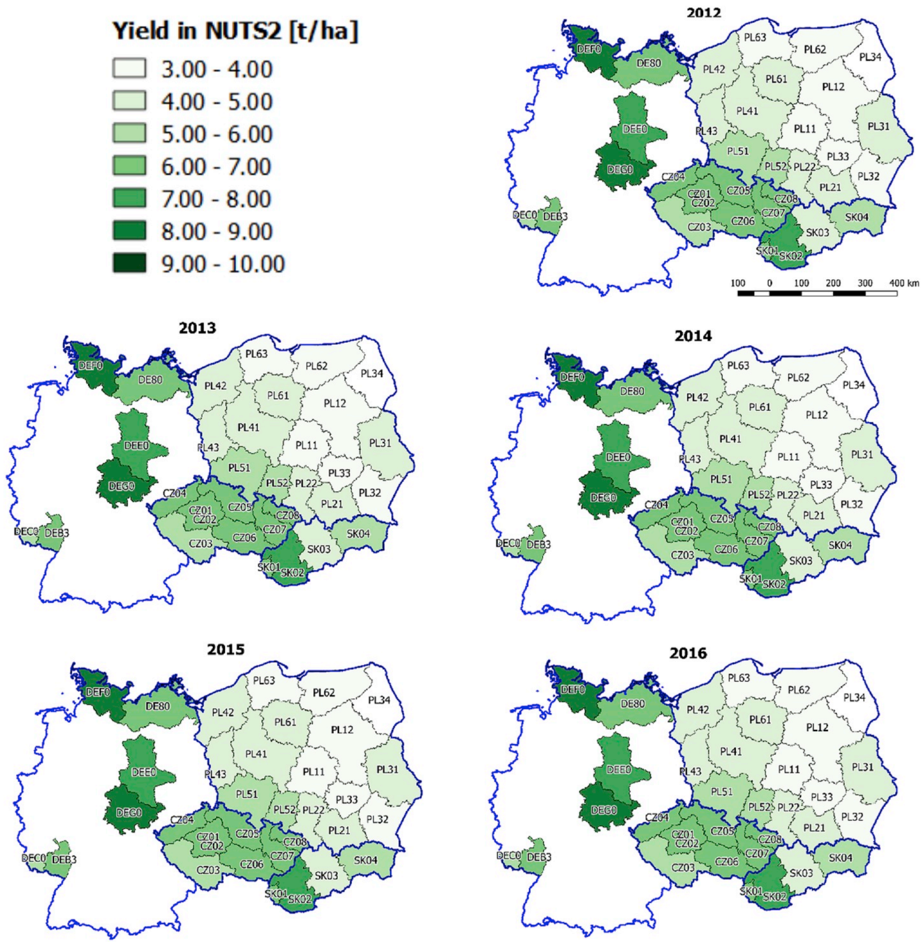

Fig. 4. Cereal grain yield in the NUTS2 regions in 2012–2016. Abbreviations and full names of the regions are presented in Table 4.

Table 2
General characteristics of the study area. Data from EUROSTAT (2019), FAOSTAT (2019), Olesen et al. (2012) and Joint Research Centre (2019).

Country	Czech Republic	Germany (eastern part)	Poland	Slovakia
Typical sowing date of winter cereals	End of September–first half of October	Second half of September	Second half of September	End of September–first half of October
Typical sowing date of spring cereals	Mid-March	End of March	End of March	End of March
Typical harvest date of	July	End of July–beginning of August	End of July–beginning of August	End of July–beginning of August
Percentage of cereals in arable area	~56%	~55%	~69%	~55%
Main species of cereals	wheat ~60%, barley ~26%	wheat ~50%, barley ~25%	wheat ~32%, triticale ~20%	wheat ~50%, maize ~26%
Average annual precipitation (mm)	550–700	500–650	500–650	600–750

cereals. These differences were mainly due to the higher intensity of crop production, including higher fertilizer consumption in Germany and the Czech Republic than in Poland and Slovakia. Similarly, in North Poland and Germany, soil quality and weather conditions had smaller effects on the grain yield of cereals; thus, crop management was the main factor in the differences between regions in terms of grain yield (Olesen et al., 2012). A greater yield gap value, defined as the difference between water-limited potential yield and the actual yield, was observed for Poland and Slovakia, mainly because of nonoptimal nitrogen fertilization.

Between-year differences in terms of the mean grain yield of all cereals across the regions (Table 3) were mainly due to weather conditions, such as very low temperatures during winter or droughts during spring and early summer. The highest grain yield of cereals was

Table 3
Means and standard deviations (SD) of grain yield in 2012–2016 based on data for all the studied regions.

Year	Grain yield (t/ha)	
	Mean	SD
2012	4.49	1.36
2013	4.84	1.45
2014	5.55	1.57
2015	5.06	1.61
2016	5.33	1.48

Table 4
Correlation coefficients between NDVI (from 7 March to 28 June) for arable land and cereal-grain yield for individual regions based on mean data across five years (2012–2106; n = 5). Background color of each cell depends on the correlation coefficient value; color assignment is presented in the color bar under the table (intensive red color indicates strongest positive correlations).

Country	Region code	Region	07 MAR	15 MAR	23 MAR	01 APR	08 APR	17 APR	25 APR	03 MAY	11 MAY	19 MAY	27 MAY	04 JUN	11 JUN	20 JUN	28 JUN
Czech Republic	CZ06	Jihovychod	0.99	1.00	0.84	0.70	0.87	0.61	0.82	0.91	0.95	0.86	0.61	0.72	0.78	−0.59	0.25
	CZ03	Jihozapad	0.92	0.86	0.73	0.94	0.92	0.75	1.00	0.75	0.35	0.45	0.44	0.55	0.75	−0.41	0.09
	CZ08	Moravskoslezsko	0.85	0.93	0.67	0.63	0.82	0.57	0.80	0.70	0.54	0.72	0.18	0.28	0.34	−0.71	−0.35
	CZ01	Praha	0.86	0.89	0.67	0.45	0.81	0.48	0.88	0.74	0.16	0.18	0.32	0.82	0.48	−0.03	0.22
	CZ05	Severovychod	0.95	0.97	0.81	0.77	0.89	0.72	0.91	0.59	0.68	0.58	0.42	0.28	0.71	−0.11	0.35
	CZ04	Severozapad	0.87	0.94	0.88	0.93	0.93	0.71	0.96	0.86	0.05	0.35	−0.15	0.73	0.33	−0.69	−0.08
	CZ02	Stredni Cechy	0.94	0.95	0.85	0.90	0.93	0.70	0.96	0.79	0.64	0.72	0.58	0.78	0.66	−0.36	0.10
	CZ07	Stredni Morava	0.97	0.88	0.93	0.91	0.93	0.87	0.92	0.76	0.16	−0.55	−0.22	−0.17	−0.43	0.16	0.81
Germany	DE80	Mecklenburg-Vorp.	−0.45	−0.57	−0.39	−0.13	−0.07	−0.57	−0.19	0.66	0.59	0.52	0.06	−0.97	−0.79	0.22	−0.40
	DEB3	Rheinhessen-Pfalz	−0.08	0.13	−0.43	−0.45	−0.25	−0.67	−0.45	0.68	0.54	0.51	−0.30	−0.79	−0.42	−0.40	−0.26
	DEC0	Saarland	−0.80	−0.75	−0.65	−0.66	−0.76	−0.53	−0.87	0.05	0.74	0.22	−0.67	−0.51	−0.38	−0.06	−0.11
	DEE0	Sachsen-Anhalt	0.76	0.66	0.45	0.23	0.53	0.37	0.31	0.30	0.04	0.34	−0.22	−0.10	0.90	−0.38	−0.22
	DEF0	Schleswig-Holstein	−0.28	−0.03	−0.06	0.11	0.28	−0.07	−0.10	0.54	0.64	0.33	−0.15	−0.86	−0.36	−0.57	−0.85
	DEG0	Thuringen	0.70	0.59	0.42	−0.07	0.35	0.08	0.31	0.04	−0.84	−0.67	−0.74	−0.30	−0.54	−0.11	0.80
Poland	PL51	Dolnoslaskie	0.70	0.69	0.86	0.80	0.77	0.85	0.72	0.63	0.57	0.44	−0.41	0.08	0.71	−0.23	−0.66
	PL61	Kujawsko-Pomorskie	0.55	0.51	0.65	0.48	0.61	0.52	0.57	0.41	0.52	0.94	−0.61	0.52	0.68	−0.41	−0.35
	PL11	Lodzkie	0.40	0.54	0.67	0.39	0.62	0.93	0.85	0.55	0.62	0.80	−0.53	0.71	0.92	0.84	0.53
	PL31	Lubelskie	0.99	1.00	0.96	0.93	0.98	0.95	0.95	0.99	0.92	0.28	−0.52	−0.81	−0.77	−0.87	−0.81
	PL43	Lubuskie	0.22	0.20	0.56	0.32	0.38	0.36	0.50	0.62	0.49	0.74	−0.48	0.34	0.68	−0.90	0.06
	PL21	Malopolskie	0.61	0.72	0.82	0.79	0.50	0.85	0.87	0.46	0.37	0.46	−0.49	−0.81	0.37	−0.50	−0.80
	PL12	Mazowieckie	0.71	0.69	0.86	0.53	0.67	0.74	0.84	0.63	0.62	0.66	−0.64	0.07	−0.04	0.31	0.43
	PL52	Opolskie	0.26	0.31	0.62	0.42	0.39	0.70	0.17	−0.07	−0.10	0.11	−0.90	−0.18	0.55	0.15	−0.11
	PL32	Podkarpackie	0.58	0.66	0.74	0.42	0.46	0.94	0.96	0.89	0.87	0.45	−0.68	−0.69	−0.04	−0.89	−0.71
	PL34	Podlaskie	0.59	0.87	0.89	0.04	0.83	0.74	0.81	0.47	0.48	0.33	−0.28	0.57	0.26	0.96	0.23
	PL63	Pomorskie	0.65	0.68	0.52	0.67	0.78	0.23	0.76	0.71	0.84	0.67	0.18	0.75	0.27	−0.02	0.11
	PL22	Slaskie	0.51	0.68	0.88	0.66	0.47	0.80	0.81	0.39	0.01	−0.15	−0.66	−0.30	0.19	−0.70	−0.14
	PL33	Swietokrzyskie	0.65	0.88	0.97	0.86	0.97	0.72	0.96	0.85	0.64	0.57	0.03	−0.84	−0.64	0.37	0.50
	PL62	Warminsko-Mazur.	0.88	0.52	0.67	0.38	0.86	0.29	0.48	0.68	0.59	0.40	0.40	0.23	0.31	−0.22	0.34
	PL41	Wielkopolskie	0.27	0.23	0.59	0.39	0.55	0.71	0.59	0.44	0.39	0.51	−0.58	0.45	0.83	−0.21	0.00
	PL42	Zachodniopomorskie	0.92	0.81	0.30	0.51	0.79	0.25	0.84	0.85	0.75	0.65	0.19	0.83	0.75	0.49	0.47
Slovakia	SK01	Bratislavsky kraj	0.98	0.93	0.40	0.53	0.87	0.51	0.65	0.73	0.68	0.92	0.35	0.54	0.80	0.06	0.60
	SK03	Stredne Slovensko	0.83	0.79	0.85	0.70	0.90	0.68	0.95	0.91	0.57	0.08	0.01	0.23	0.68	−0.87	−0.40
	SK04	Vychodne Slovensko	0.62	0.87	0.77	0.68	0.81	0.67	0.79	0.74	0.63	0.41	0.77	−0.67	−0.18	−0.97	−0.91
	SK02	Zapadne Slovensko	0.95	0.80	0.87	0.75	0.92	0.63	0.82	0.87	0.85	0.63	0.30	0.58	0.82	−0.51	0.32
		All regions	0.58	0.62	0.55	0.47	0.66	0.57	0.59	0.49	0.38	0.15	−0.02	−0.11	0.04	−0.11	−0.06

−1.0	−0.9	−0.8	−0.7	−0.6	−0.5	−0.4	−0.3	−0.2	−0.1	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0

very strong negative correlation — lack of correlation — very strong positive correlation

observed in 2014 (5.55 t/ha) and the lowest in 2012 (4.49 t/ha). The differences between years (Table 3) were smaller than those between regions (Fig. 4).

3.2. NDVI temporal and spatial variability

Table 3 shows the NDVI means and standard deviation calculated based on NDVI for all the regions (n = 34). The lowest NDVI was observed in the beginning of March, while the highest value was observed in the beginning of June, which is the period of the end of the flowering of winter cereals. The total areas of the regions had only slightly higher NDVI values (about a 0.03–0.05 unit) than the corresponding areas of arable land.

3.3. Relationship between NDVI at different dates and cereal-grain yield across regions

Figs. 1 and 2 present maps of the NDVI means in the regions for the selected periods. The periods were selected on the basis of having the strongest relationship between regional NDVI and the grain yield of cereals. This relationship was evaluated using correlation coefficients of which the values are presented in graphical form in Figs. 5 and 6. This allowed us to better evaluate when the correlation between the NDVI and cereal grain yield was the highest. For both arable land (Fig. 5) and the entire region area (Fig. 6), the strongest relationship occurred at the beginning of April, which then showed a downward trend until the end of the growing season. In 2012, 2014, and 2016, yield was most strongly correlated with the NDVI on 8 April, both for arable land and the entire NUTS2 region (Figs. 5 and 6). In 2013, the strongest correlation occurred eight days later (Figs. 5 and 6). In 2015, however, a discrepancy occurred: The strongest correlation between the NDVI of arable land with the grain yield of cereals occurred on 25 April, while for the NDVI of the entire region, it occurred on 17 April (Figs. 5 and 6).

For dates when this relationship was the strongest, linear regression was applied (Fig. 7). Such regression functions can be used to estimate the grain yield in a given year using the observed NDVI. The functions varied between years, which was likely due to weather conditions. Regression slopes were in the range from 10.8 to 26.2, so an increase by 0.1 in NDVI in early spring (at the beginning of April) would increase the predicted grain yield by 1.1–2.6 t/ha, with an average of close to 2 t/ha. The root mean square errors (RMSE) for the estimation of cereal-grain yield based on the regression models were in the range from 0.8 to 0.17 t/ha. Smaller RMSEs were observed for the relationships with NDVI for arable land than for the NDVI of the total area; the difference was from 0.04 to 0.23 depending on the year of study.

3.4. Relationship between NDVI at different dates and cereal-grain yield across years

Table 4 shows the relationships between NDVI and cereal-grain yield for individual regions for all years. The strongest relationships were observed for all regions of the Czech Republic and Slovakia. For the studied German regions, the relationships were either very weak or, because of negative correlations in some cases, ambiguous. The reason for such inconsistent relationships is unknown and suggests the need for more detailed studies for these regions. For example, in Figs. 5 and 6, relationships were stronger in early spring, and weaker in the late stages of growth. Much weaker relationships occurred from the end of May, which may have been caused by the saturation of NDVI (very intensive vegetation only in very small increases in degree of NDVI). Another reason for such a weak relationship is a decrease in NDVI after the flowering of cereals that, under typical weather conditions, begins from mid-May for winter cereals in Central Europe.

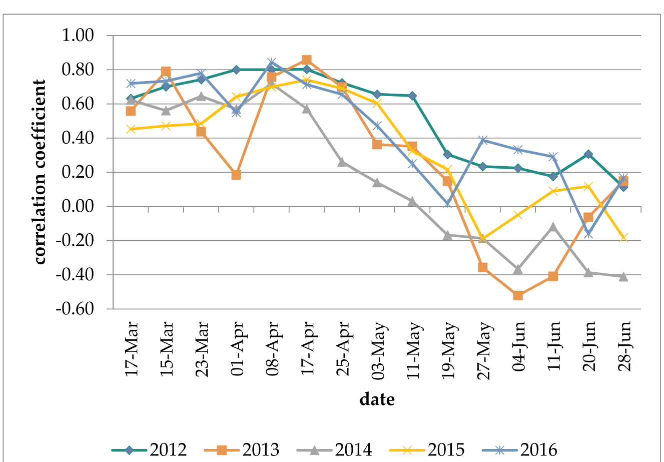

Fig. 5. Correlation coefficients between grain yield of cereals and NDVI for arable land from 7 March to 28 June in 2012–2016. Correlations were calculated using means of the regions (n = 34). Lines connecting points were added for better assessment of changes in the strength of the relationship over time.

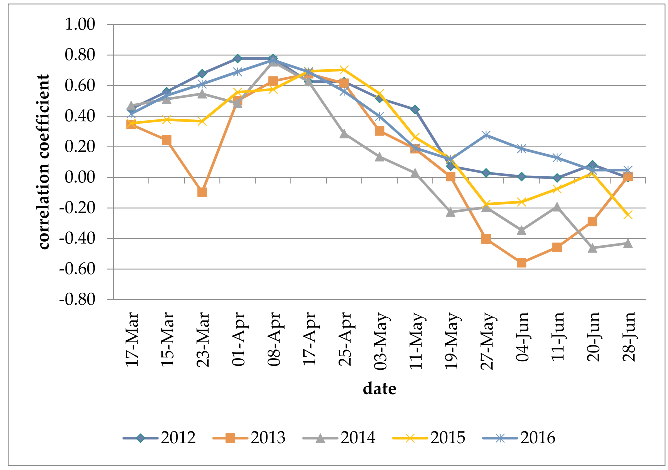

Fig. 6. Correlation coefficients between grain yield of cereals and NDVI for total area of NUTS2 regions from 7 March to 28 June in 2012–2016. Correlations were calculated using means of the regions (n = 34). Lines connecting points were added for better assessment of changes in the strength of the relationship over time.

4. Discussion

Monitoring agricultural production in regions can help in the planning and prediction of crop yields (Fig. 7), especially these days, as agriculture is facing changing climatic conditions, long-term droughts, and short periods of rainfall. Cereal-grain yield is essential for global food security, and continuous monitoring should provide information about threats to cereal production. Accurate and as early as possible estimation of grain yield is very important for proper food policy and trade. In the area of study (Central Europe) it is important not only because of too-low yields but, in some seasons, because of too-high yields at various spatial scales.

Together, these results prove that for winter cereals, which dominate agricultural production in Central Europe, the development stage in early spring is crucial for obtaining a high grain yield. A very similar approach to finding the optimal date for yield estimation based on MODIS derived by NDVI was applied by Mkhabela et al. (2011) in a study conducted in Canada. MODIS-NDVI was calculated using a cropland mask, but for all crops together, without distinguishing areas of particular crops. Values of correlation coefficients between NDVI and the grain yields of spring barley and spring wheat were analyzed every 10 days. The strongest correlations were observed from the end of June to early August for both crop species, which falls into the flowering and grain-filling periods of the species. These periods are much later than those observed in our study. The strength of the relationship was similar or even stronger (R^2 in the range of 0.47–0.90) in comparison with that found in our study (R^2 in the range of 0.49–0.71). Because the regression functions in the study of Mkhabela et al. (2011) are not linear, it is not possible to directly compare the regression coefficients. But the regression function was similar to line and based on graphs it is possible to evaluate the approximate increase. The approximate average increase in the grain yields of barley and wheat under Canadian conditions was about 0.8–1.0 t/ha, with an increase of 0.1 in NDVI value. This increase is lower in comparison with our result, probably because of the lower yield potential under Canadian conditions than in Central Europe; yields

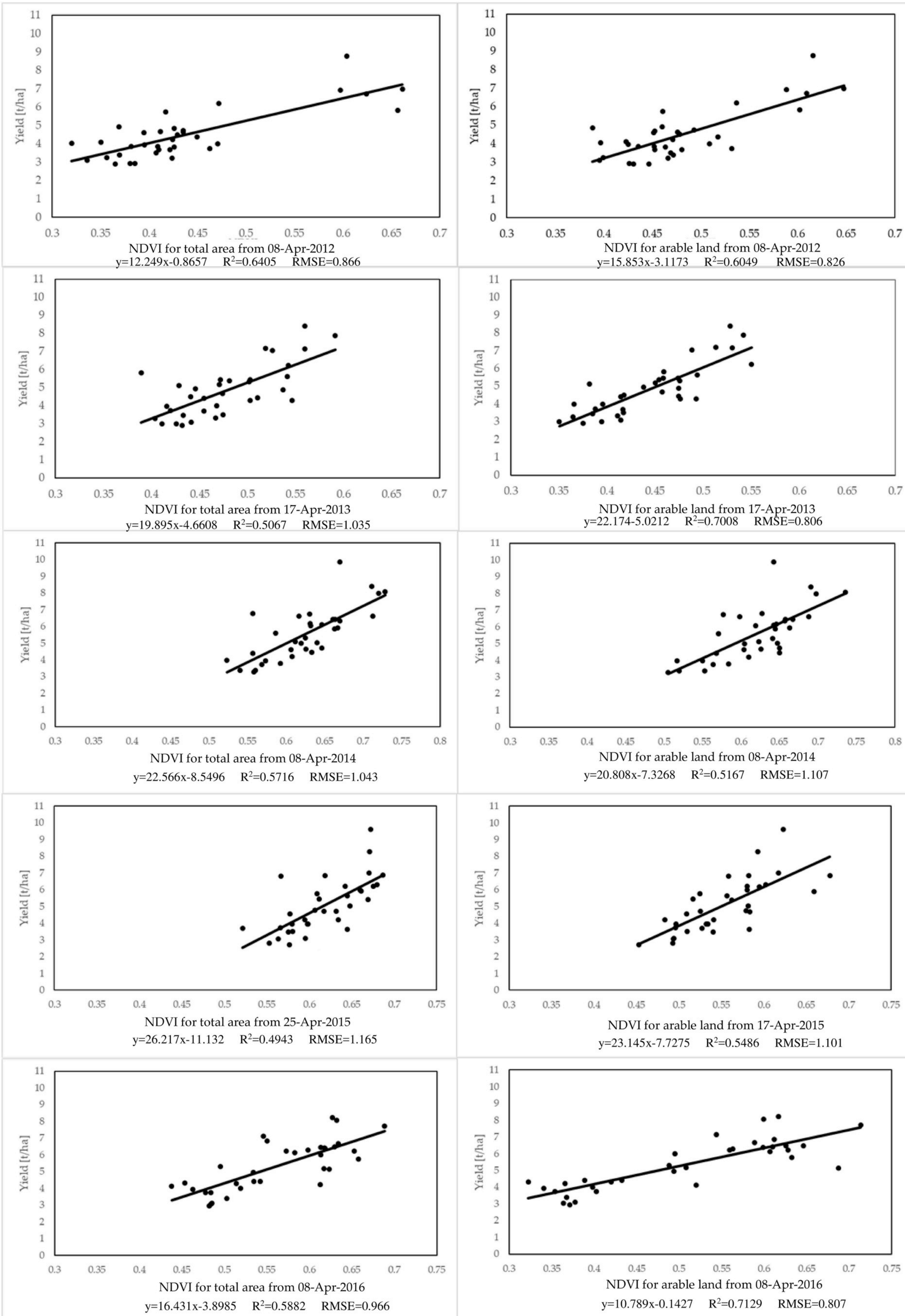

Fig. 7. Relationship between cereal-grain yield and the NDVI for the total area (left) and arable land (right) of the regions for the dates when their correlations reached maximum values in each year.

of barley and wheat in Canada were in the 1.5–3.5 t/ha range, while in Central Europe, cereal yields were two times higher.

In a study on predicting the grain yields of wheat in eastern Australia, Smith and others (1995) concluded that the greatest accuracy of crop prediction using the NDVI, derived from the NOAA-AVHRR sensor (pixel size ~1 km), was achieved for data within 3–5 months before harvest. These results are consistent with the results from our study, where the best yield prediction was observed at around 3 months before the harvest of cereals. In the study in Australian conditions (Smith et al., 1995), the observed grain yield of wheat was around three times lower in comparison with that in Central Europe, and the average increase of wheat grain yield, related to increase of NDVI value by 0.1, was in the range of 0.23–0.43 t/ha, which is much lower than that found in our study. Becker-Reshef et al. (2010) used a regression model for predicting winter wheat-grain yield based on eight years of MODIS-NDVI records (2000–2008). They found that the NDVI was a good predictor of yields in the eastern part of Ukraine (Becker-Reshef et al., 2010). Prediction accuracy was very high, i.e., the RMSE for the regression between the predicted yield of winter wheat and the official yield statistics was 0.18 t/ha, which is around five times lower than that found in our study. One of the reasons for the better prediction accuracy in that study was the use of a wheat crop mask in the study area. Moreover, the average grain yield for Ukraine was around twice lower in comparison with the grain yields in Central Europe. However, the relative accuracy measured as RMSE/mean grain yield was still much higher than that found in our study. Another difference between the study for Ukraine (Becker-Reshef et al., 2010) and our results was the much later occurrence of the best prediction, i.e., six weeks before harvest, when the maximal NDVI was observed. In the review study of Rembold et al. (2013), a significant relationship between the NDVI from low-resolution satellite sensors (e.g., MODIS) and the final yield of various crops, including cereals in North Africa, was found over a number of years. The same study proved that auxiliary variables like the percentage of cultivated land could improve the accuracy of yield prediction at a regional scale.

In the study of Wang et al. (2019), the CASA model based on satellite data from MODIS allowed the prediction of the grain yield of winter wheat with a relative error of about 6% ($R^2 = 0.56$, RMSE = 1.22 t/ha) for selected regions in China. Prediction accuracy was not very high, slightly worse than in our study, despite the application of a crop model with auxiliary variables (e.g., meteorological data).

According to Singh, the low-resolution satellite NDVI (from the IRS-1B-LISS-II satellite) could also be used for predicting the wheat yield in small areas in India, and it is possible to compare results from administrative regions at various levels (Singh et al., 2002). In this study, stratification was used to divide the areas into strata of different yield levels. For stratification, the NDVI at the flowering growth stage was used. The obtained results were very promising because of the very low error in wheat-grain yield estimation, i.e., in the range of 1.6%–6.7%.

Another study in which wheat-grain yield was predicted using MODIS-NDVI was conducted in Argentina (Lopresti et al., 2015). In the study, the best prediction ($R^2 = 0.75$) occurred in the late growth stages of wheat, 30 days before harvest, which is much later than in our study.

In the study of Nagy et al. (2018) high accuracy of prediction of grain yield of winter wheat and maize based on MODIS NDVI at regional level in Hungary was observed 6–8 weeks before the harvest. The relationships were evaluated only for areas which were classified as certain crop on the base of satellite images from April and July. Relative value of RMSE for predicted grain yield was not greater than 19% for both crops. In other study for Hungary (Bognár et al., 2011) NDVI derived from AVHRR satellite sensors allow to obtain high accuracy (error less than 5%) of grain yield prediction of wheat (50 days before harvest) and maize (70 days before the harvest).

Strong relationship between NDVI till anthesis proves the strong effect of the growth period before flowering for the grain yield of cereal variability (Ritchie et al., 1998; López-Lozano et al., 2015). During that period, the number of grains per unit area is determined, which is the most important yield component. The grain-filling period in moderate climates, such as Central Europe, is usually less important because it affects the weight of individual grains, which is a yield component of lower importance (Ugarte et al., 2007). Individual grain weight can be decreased in late growth stages by plant lodging or plant diseases, but such negative phenomena are limited by chemical plant protection (fungicides, herbicides, and plant-growth regulators), which is common in most of the study area (Joint Research Centre, 2019). Despite chemical plant protection, a substantial decrease of grain yield can occur in the late growth stages, mainly because of extreme weather events (e.g. storms, floods), but their extent is usually local and not regional.

Various studies have found different periods to be the most critical in terms of the estimation of cereal-grain yield. In most of them, the NDVI from the late growth stages (1–2 months before the harvest) is a good predictor of grain yield, but some studies, including our study, found a strong relationship between the NDVI from the early growth stages, which is the case for Central Europe in April.

5. Conclusions

MODIS-NDVI and cereal-grain yield were quite strongly related at the regional level when the NDVI data for both arable land and the whole area of the regions were used. Application of the cropland mask increased the strength of the relationship by only a small degree. This was likely due to the large share that cereals have in the agricultural area in Central Europe. A strong relationship between cereal-grain yield and NDVI was observed in early spring (in April), three to four months before the harvest. Such relationships were observed for most of regions in the study area, excluding regions of Germany. At later dates, the relationships were weaker, which may have been caused by NDVI saturation in the later growth stages of cereals. Such results are very promising for early yield forecasting in Central Europe because they allow to estimate cereal-grain production at the regional and country level long before harvesting. This allows the better planning of trade and food policy, which is strongly dependent on cereal-grain production.

Depending on season, an increase in mean NDVI in April by 0.1 units would bring about an increase of 1.0 to 2.6 t/ha in cereal-grain yield, with a mean of around 2 t/ha.

The obtained results prove that MODIS satellite data can help to improve the accuracy of cereal-grain yield prediction at the regional level in Central Europe from early spring. Further research is necessary to validate the equations in various weather scenarios, and to improve the strength of the relationship using auxiliary data.

Ethical statement

We declare that all ethical practices have been followed in relation to the development, writing, and publication of the article.

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Declaration of competing interest

The authors declare no conflict of interest.

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