Mapping soil degradation using remote sensing data and ancillary data: South-East Moravia, Czech Republic

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ABSTRACT

Data on the real extent of soil that is degraded by erosion represent important information for the purposes of conservation policy. However, this type of data is rarely available for large areas. A remote-sensing-based method for identifying of eroded areas at the regional scale has been tested using a combination of time series of free access Sentinel-2 image data, airborne orthoimages and ground-truth data. The unsupervised classification ISODATA of the Sentinel-2A images has been performed. The minimum distance method has been applied for the assignment of unsupervised classes to four erosion classes using the ground-truth data. The automatic classification of eroded soils achieved an overall accuracy of 55.2% for three distinguished classes. An accumulated class has been eliminated as no unsupervised classes were assigned to this erosion class. A simplified classification of two classes (strongly eroded and other soils) reached an accuracy of 80.9%. The overall accuracy of the simplified classification increased to 86.9% after the visual refinement using orthoimages. This study shows the potential of the tested approach to produce valuable data on actual soil degradation by erosion. The limitations of the method are related to the soil cover variability, masking effect of clouds, vegetation or litter and the spectral separability of individual classes.

Introduction

Soil erosion that causes the loss of a high-quality soil material is perceived as one of the most problematic and visible forms of soil degradation both in Europe (Boardman & Poesen, 2006; EEA & JRC, 2010; Grimm, Jones, & Montanarella, 2002; Panagos et al., 2016; Stolte et al., 2016) and on a global scale (FAO and ITPS, 2015). The total rate of actual soil erosion and the real extent of eroded areas, however, are often known only at the local scale based on the information from spatial limited field campaigns (Evans, 2013; Verheijen, Jones, Rickson, & Smith, 2009). At the regional and global scales, information on soil erosion is available only in the forms of potential erosion risk, expert-knowledge estimations or computations using empirical models of potential soil loss rates (Novotný et al., 2016; Panagos et al., 2015). The validation using field data is usually limited (Evans, 2013). According to the calculations of the potential erosion risk, water erosion threatens more than 50% of the arable land in the Czech Republic (Novotný et al., 2016). More than 10% of the arable soils are endangered by wind erosion (Podhrážská, Kučera, Chuchma, Středa, & Středová, 2013).

The erosion risk differs significantly in different soils and geographical regions. Our study is located in the Chernozem region in southern Moravia, which is one of the most threatened areas in the Czech Republic (Novotný et al., 2016; Žízala, Kapička, & Novotný, 2016). Based on the empirical models, 84% of the arable land in this region is under threat from water erosion and approximately 86% is under threat from wind erosion. The first study on tillage erosion performed in the study area (Hrabáliková et al., 2016) also showed a significant impact of this form of erosion on the degradation of the soil cover.

Several studies based on field assessments and measurements of soil erosion indicate a discrepancy between modelled values and real field or plot data (Evans, 1998, 2013; Prasuhn, 2011; Žízala et al., 2016). The results point out considerable uncertainty in the quantification of real soil erosion. Moreover, the model-based approaches show a limited potential in the assessment of the erosion intensity and the spatial extent of degraded soils, namely, due to internal drawbacks of models and inaccuracy and uncertainty in the input data. However, despite a long-term criticism of empirical models by erosion scientists (Boardman, 2007; Evans & Boardman, 2016a,
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Lin, Zhou, Wu, Zhu, & Dang, 2014; Schmid et al., 2012, 2016; Žižala, Zádorová, & Kapička,
2017). Soil properties affected by erosion pro-
cesses that have a spectral response in soil spectra at the same time can be identified as spectral soil erosion indicators. These properties are either affected by the preferential removal and transportation of light surface particles, such as soil organic matter content and soil texture (Schmid et al., 2016), or are related to the removal of topsoil and its mixture with subsoil, such as the content of carbonates (Curzio & Magliulo, 2010b; Žižala et al., 2017), content of iron oxides (Chabrillat, 2006; Frazier & Cheng, 1989; Lin et al., 2014; Mathieu, Cervelle, Rémy, & Pouget, 2007), or content of coarse fragments (Hill, Mégier, & Mehli, 1995; Hill, Mehli, & Altherr, 1994; Hill & Schütt, 2000). The possibility and accuracy of the delineation of eroded soils using spectral images is highly dependent on the intensity of the erosion processes on the one hand, and on the corresponding changes in the spectral characteristic of disturbed soils on the other hand.

Remote sensing methods, traditionally used for the detection of eroded areas, include the visual interpretation of aerial images based on the interpretation of the soil colour and its changes related to the erosion processes (Fulajtár, 2001; Fulajtár, Jenčo, & Saks, 2016; Servenay & Prat, 2003). Recently, the progress in satellite data and digital RS utilization, including computer pre-processing of images (Fulajtár, 2001; Kolejka & Manakos, 2000; Šarapatka & Netopil, 2010) and the development of automatic classification methods (Alatorre & Beguéría, 2009; Curzio & Magliulo, 2010a; Martínez-Casasnovas, 2003; Mohammadi & Nikip, 2008), has enabled the analyses of larger areas in a time-saving manner, and the quantification of the classifications’ accuracy. Spectra-based per-pixel classification methods are easily implemented (Li, Zang, Zhang, Li, & Wu, 2014). However, their application can be problematic in cases of a significant, within-class spectral variability and mixture effect of different surfaces, particularly in conditions of a highly heterogeneous soil cover. Fulajtár (2001) noted that additional ancillary data is needed for the classification of erosion patterns with required accuracy, and other authors have also recommended a combination of automatic classification approach and visual interpretation (Báčová & Krása, 2016; Pilesjoe, 1992; Šarapatka & Netopil, 2010; Smetanová, 2009). The application of the fuzzy classification (Meléndez-Pastor, Pedreño, Lucas, & Zorpas, 2017), the spectral mixture (sub-pixel) analysis (Haboudane, Bonn, Royer, Sommer, & Mehl, 2002; Rabah & Farah, 2016; Schmid et al., 2016) or the object classification (“spatio-contextual” image classification) (Mayr, Rutzinger, Bremer, & Geitner, 2016; Nobrega et al., 2006; Wang, Huang, Du, Hu, & Han, 2013) represents another solution to overcome the above-mentioned difficulties related to the pixel-based methods (Li et al., 2014). Simultaneously, using higher resolution data in the spectral domain (hyperspectral data) promises an increase in the accuracy of the classification of erosion-degraded soils (Chabrillat et al., 2003, 2014; Haubrock, Chabrillat, & Kaufmann, 2004, 2005; Hill et al., 1994; Schmid et al., 2016; Žižala et al., 2017). The further development and wider application of this method can be expected with the forthcoming spaceborne hyperspectral sensors, such as German EnMAP, Italian PRISMA, Japanese HISUI, Israeli-Shalom or Chinese TianGong-1 (Demattè et al., 2015). So far, multispectral Landsat series and SPOT data or high resolution data, such as IKONOS and QuickBird have been the most commonly used satellite data in soil erosion research (Luleva, Van Der Werff, Van Der Meer, & Jetten, 2012; Sepuru & Dube, 2017; Vrieling, 2006). Newly launched satellites, such as Landsat-8 and
Sentinel-2 with their improved spectral, radiometric and spatial characteristics provide freely available multi-temporal data suitable for soil erosion mapping. The verification of their applicability is currently required.

Despite the progress in the classification methods and development of new types of optical sensors, the still-existing gaps in our knowledge limit a regular use of these methods for the assessment of eroded soils.

Several main limitations can be distinguished: (i) Assessment of large areas with field plots characterized by varying soil conditions (soil moisture, soil roughness, soil covered with vegetation, litter, dust or soil crust). It is necessary to use a multi-temporal approach and methods enabling a reduction of these effects. So far, most of the studies have focused on local scale assessment (Sepuru & Dube, 2017), and a substantial progress at regional and global scaled research is needed. (ii) Indispensability of precise atmospheric corrections and masking of the clouds and their shadows. (iii) Heterogeneity of environmental settings, especially of the soil cover structure (occurrence of different soil types and parent material, historical human-induced disturbances (Zádorová, Penížek, Žížala, Matějovský, & Vaněk, 2018). (iv) Specificities related to the erosion/accumulation process. Erosion and redeposition of soil material may lead to similar soil surface properties of eroded and AC soils (Zádorová et al., 2013, 2015). (v) Lack of historical data and related difficulties in the determination of original soil thickness, soil properties and erosion impact even at a local scale.

The aim of this study is to assess the potential of a combined use of time series of optical multispectral images from newly launched Sentinel-2 satellites, and time series of aerial orthoimages and field data for the (i) identification of the erosion spatial pattern at the regional scale and, (ii) delineation of the soils impacted by soil erosion processes at the regional scale. This study presents a multi-temporal classification approach, assessing the erosion-related soil pattern at a larger spatial extent compared to previous studies. The presented approach promises to produce a practical method usable in a frequent monitoring of degradation of soils due to erosion in large agricultural areas.

Regional settings

The study is located in the agricultural region in South-East Moravia, Czech Republic (Figure 1). The study area represents a region with the highest degradation risk by erosion on one the hand, and with some of the most fertile soils in the Czech Republic on the other hand. The area is delimited by longitudes 16.64 and 17.37E and latitudes 48.83 and 49.27N. The limits of the study area correspond with the occurrence of the Chernozem soil type and with boundaries of a region characterized by an undulating topography. The study area covers approximately 1,222 km². Arable land covers 815 km² (66%) of the study area. The area has undulating relief with an elevation ranging between 163 m a.s.l. and 477 m a.s.l.; the mean slope at the arable land is 4.2° (with a standard deviation of 3.08°), but it reaches up to 20° in the steepest parts. The climate is characterized by a mean annual precipitation of 540 mm and a mean annual temperature of 8.4°C. The area is formed by upper Eocene molasse facies (sandstones, conglomerates and marls) and Oligocene sandstones covered by a Pleistocene loess layer with a variable depth ranging from several metres up to several tens of metres (Chlupáč, Brzobohatý, Kovanda, & Straník, 2002).

Calcic Chernozem on loess is the original dominant soil type in the study area. During the centuries of...
agricultural practices, the soil cover has been transformed into a diversified mosaic of different soil units along with variable erosion and deposition processes (Figure 2). In addition to the former Chernozems, which are currently preserved in places with minimal slope, Haplic Calcisols have developed on steep slopes and slope shoulders (Hrabovská, 2013; Vopravil et al., 2011; Zádorová, Penížek, Šefrna, Rohošková, & Borůvka, 2011). By contrast, deep colluvial soils have been formed in concave parts of the slopes (Zádorová et al., 2013, 2011; Zádorová et al., 2015). The intensive response to soil erosion can be attributed to several factors: a high erodibility of soils determined by their silty texture, a segmented landscape locally with high inclination, the excessive size of farmers’ fields caused by forced collectivization of agricultural land in 1950s, an inappropriate management of arable land (intensive cultivation of crops susceptible to erosion, lack of manuring), and the destruction of landscape elements with an anti-erosion effects and unfavourable weather conditions (frequent episodes of drought) (Fukalová, Středová, & Vejtasová, 2014; Krása, Středová, Dostál, & Novotný, 2014).

Materials and methods

Soil data collection

The soil data contained in the datasets used for calibration and validation purposes originate from recently performed field campaigns carried out in the study area. The first part of the dataset is represented by the data acquired from field campaigns, where soil cover was surveyed in detail. All sites are characterized by high spatial variability of soil cover in response to soil erosion. Although the area is limited, all defined erosion and accumulation classes were found. This subset contains information from three local field campaigns:

- 50 samples from the site Sardice field survey performed in 2016 (Hrabáliková et al., 2016; Žižala et al., 2017),
- 75 samples filtered using stratified random sample selection from 600 samples acquired within the detailed campaign at the site Poresice in 2009 (Brodský, Vašát, Klement, Zádorová, & Jakšík, 2013; Vašát, Kodešová, Klement, & Jakšík, 2015; Zádorová et al., 2011) and
- 78 samples from the site Oulehle surveyed in 2016.

This part of the dataset was used as a calibration set for the classification, or more precisely, as support data for supervised cluster categorization during post-processing after unsupervised classification. The second part of the dataset contains data from a sparse sampling campaign that was performed across the study area in 2016 and 2017. The sampling points’ locations were selected from the database of an historical soil campaign, “Systematic soil survey of agricultural land in Czechoslovakia”, carried out between 1960 and 1970 (Němec, 1967; Zádorová & Penížek, 2011). The selection was performed using a stratified random strategy. The terrain attributes and spectral data were used as feature space variables for stratification. This part of the dataset, containing 115 samples, was used for validation purposes. The positions of all samples were measured by GNSS with a post-processing sub-meter accuracy. The information about soil profiles-soil unit, soil depth, profile stratigraphy and thickness of horizons was obtained by the description of a gouge auger core. The distribution of soil samples is depicted in Figure 3.

All soil samples from both datasets were classified into four classes with various stages of degradation by erosion. The determination of each class was based on the observation of soil erosion evidence on the sampling sites and the descriptions of the soil profiles. Four established classification classes consist of three erosion classes and one accumulation class. According to Žižala et al. (2017), the groups are defined as follows:

- NE soils – autochthon soils with a negligible evidence of soil loss or accumulation;
- Eroded soils with various stage of degradation – moderately eroded (ME) and strongly eroded (SE) soils – soil profiles with an evidence of soil loss and soil profile truncation; and
- Accumulation soils – soil profiles with an evidence of soil accumulation.
AC soils – soil profiles with an evidence of accumulation of new material and with increased thickness of the A horizon or burial of former surface horizons.

Soil samples were classified into erosion classes according to the description of soil profiles. The samples with the profile stratigraphy corresponding to the characteristics of the original Calcic Chernozems were classified as NE soils (59 samples in the calibration dataset and 26 samples in the validation dataset). These soils particularly cover the areas with minimal slope (0–2°). Calcic Chernozems occurring in the areas with increased slope and having significantly reduced thickness of A horizon were classified as ME (41 samples in the calibration dataset and 34 samples in the validation dataset). Soils with the truncated profiles were determined in the exposed areas with steep slopes (water erosion influence) and in the areas with high slopes gradients (tillage erosion influence). The profile stratigraphies of these soils corresponded to the Haplic Calcisol and were classified as SE soils (77 samples in the calibration dataset and 36 samples in the validation dataset). Deep colluvial soils with thick humus horizons were identified in the slope concavities, mainly in the toe-slopes, slope depressions and side valleys. These soils were classified as AC (26 samples in the calibration dataset and 19 samples in the validation dataset).

Images and image pre-processing

Sentinel-2 satellite images were used in the study. The time series of the seven Sentinel-2A MSI imagery (processing Level-1C) from 2015, 2016 and 2017 were downloaded from the Copernicus Open Access Hub (Table 1). The product Level 1C includes radiometric and geometric corrections with sub-pixel accuracy (European Space Agency, 2015). These data were processed to a Level-2A (atmospherically corrected) data product using Sentinel-2 Toolbox (Sentinel Application Platform, SNAP v5.0) with an integrated Sen2cor processor (Sentinel to Correction, v2.3.1).

All Level-2A data were pre-processed in Envi 5.4.1 to obtain a layer stack of 10 spectral bands (10 and 20 m resolution bands), resampled to the resolution of 10 m for all bands by the nearest neighbour method, and co-registered. The data from each image was masked as follows: the arable land mask, cloud cover mask and bare soil mask. The arable land mask was delimited by field boundary polygons obtained from the Land parcel identification system (LPIS – © Ministry of Agriculture of the

Table 1. Details of Sentinel-2 images.

| No. | Tile    | Sensing time | Sun zenith * | Sun azimuth * | Clouds [%]  | Thin cirrus [%] | Cloud shadow [%] | Bare soil [%] |
|-----|---------|--------------|--------------|---------------|-------------|----------------|------------------|--------------|
| 1   | 33UXQ   | 2015/08/30 10:05 | 41.21        | 162.92        | 4.90        | 12.90          | 0.05             | 27.99        |
| 2   | 33UXQ   | 2015/09/29 10:06 | 52.06        | 168.94        | 40.24       | 0.83           | 3.62             | 13.82        |
| 3   | 33UXQ   | 2016/05/23 9:54  | 30.22        | 155.73        | 2.04        | 17.54          | 1.91             | 10.72        |
| 4   | 33UXQ   | 2016/09/30 9:50  | 53.06        | 166.10        | 7.44        | 4.85           | 0.05             | 31.38        |
| 5   | 33UXQ   | 2017/03/29 9:50  | 47.32        | 159.70        | 6.66        | 5.73           | 0.73             | 58.44        |
| 6   | 33UXQ   | 2017/04/21 10:00 | 38.21        | 162.80        | 16.23       | 8.75           | 2.14             | 18.07        |
| 7   | 33UXQ   | 2017/05/18 9:50  | 31.22        | 156.46        | 8.90        | 7.73           | 0.05             | 13.58        |

* Mean sun angle.
*Based on L2A quality indicators.
Czech Republic). The cloud mask was obtained from the scene classification maps of the L2A product. The classes of clouds (low, medium and high probability), thin cirrus, cloud shadows, dark areas, saturated pixels and defective pixels, were extracted and reclassified into one layer. For detecting the bare soils for each image scene, the “soil line” concept was implemented (Baret, Jacquemoud, & Hanocq, 1993a; Baret, Jacquemoud, & Hanocq, 1993b; Richardson & Wiegand, 1977), and the relationship between band 8 (Near-infra Red) and band 4 (Red) was explored. On the basis of the brightness detection, all pixels marked in the scatter plot tool were detected and visualized in the image.

Classification

A preliminary assessment of the spectral purity of the training samples showed very poor spectral separability of some classes based on the ground-truth training samples. The statistics and analysis of variance showed that the calibration set is inappropriate for supervised classification purposes (Figure 4). Therefore, an

Figure 4. Spectral separability of erosion classes based on ground-truth training samples. B1 – B12 represents Sentinel2 spectral bands. *, **, *** indicates level of significance of difference of mean (*p ≤ 0.05, **p ≤ 0.01, ***p ≤ 0.001), NS = non-significant difference.
unsupervised clustering algorithm ISODATA – Iterative Self-Organizing Data Analysis (Tou & Gonzalez, 1974) mixture with supervised cluster categorization Minimum Distance Method was used for the classification of the erosion classes. Due to possibly different soil conditions on each image, each satellite image was classified separately. All post-processed classified rasters were merged into one final classification synthesis using the recalculation according to the most frequent class value for each pixel of the classified area.

The main advantage of the automatic image classification is the speeding up of the data processing. It is a relatively simple, time-saving and inexpensive method that can be used for large areas (Gómez, White, & Wulder, 2016). In comparison with the supervised classifications that require a certain amount of representative training samples, the unsupervised classification algorithm is not dependent on training samples and their spectral separability (Sepuru & Dube, 2017). Moreover, unsupervised methods provide the opportunity to identify clusters that could not be identified with the training samples. It is guaranteed by internal algorithms in case of unsupervised classifiers.

The ISODATA clustering technique uses the minimum spectral distance measurements to form clusters in an image. Different numbers of temporal clusters were generated with the following modelling parameters: number of classes (min: 8; max: 12), maximum number of iterations (30), change threshold (5%), minimum number of pixels in a class (1,000), maximum class standard deviation (1), minimum class distance (5), and maximum number of merge pairs (2). Once this classification was completed, the automatic cluster categorization Minimum Distance Method, based on a calibration point dataset, was applied to the clusters to define the erosion classes (NE, ME, SE, AC).

Validation of results

An independent validation dataset comprising 115 soil samples distributed across the study area was used for validation. A confusion matrix was calculated for both the classification synthesis and visual refinement of the output using point soil data as a ground truth. The user’s and producer’s accuracy, the overall accuracy and kappa coefficient were calculated to evaluate the final classification synthesis.

The flowchart of the whole process is depicted in Figure 5.

Results

Seven Sentinel-2A images were used for the classification. The images were masked by an arable soil layer, cloud non-affected pixels and bare soil pixels identified by the soil line concept. The extent of the bare soil for each image scene is depicted in Table 2. The maximum bare soil extent (53.4% from the total arable land) was obtained in September 2016; a significant extent of the bare soil was identified also in September 2015 and April 2017. The minimum bare soil extent (18.1% from the total arable land) occurred in May 2017. The final bare soil extent of the classification synthesis covered a total area of 733.6 km², which was 90.1% of the total arable land of the study area.

The final synthesis map with erosion classes was produced using the ISODATA classification and cluster categorization Minimum Distance Method (MDM) performed on the Sentinel-2 images. Due to the high spectral heterogeneity of the AC soils and their very poor spectral separability from other classes (Figure 4), the AC was not assigned to any ISODATA class by the MDM. Therefore, only three eroded classes were determined (NE, ME, SE). In total, there are 6,711 arable land fields within the study area. The SE soils cover 18%, the ME soils cover 38% and the NE soils cover 44% of the total area.

Figure 6 shows the descriptive statistics of the classified erosion classes in respect to the spectral characteristics derived from the Sentinel-2 images. The overall values of the spectral data correspond to the general shape of the spectral curves of the
Chernozem soils. The results show low reflectance values in the visible wavelengths (B2, B3, B4 bands), with a gradual increased reflectance towards the infrared wavelengths (B5, B6, B7, B8 and B8A). The highest values were obtained from the SWIR region (B11 and B12). The NE soils have a lower reflectance than the ME and SE soils in every spectral band, except for the NE...
and ME in the SWIR region where the difference is not significant.

The validation based on ground-truth data showed a low overall accuracy of the classification (see Table 3). It reached 55.2% (Kappa coefficient 0.34). The main misclassification is connected with an incorrect classification of ME to NE (19 cases). Other classification errors are represented by misclassifications between SE–NE (7 cases) and SE–ME (13 cases). The AC soils were classified mainly as NE soils (13 cases); in the six cases, they were assigned to eroded soils (ME and SE).

The overall accuracy increased significantly after an adjustment of the erosion classes. The performance of the classification scheme in distinguishing two classes (SE and other soils) was satisfactory. The overall accuracy reached 80.9% (Kappa coefficient 0.52). When considering each single image, the images captured in early spring months – March and April – showed better overall accuracy (83.3–86.7%) than the images acquired in autumn (73.1–77.8%).

Finally, the samples-independent refinement of the SE was performed using orthoimages. The overall accuracy of the SE class classification reached 86.9%. Only one SE sample was misclassified into the other category and 10 samples of NE and ME were classified as SE (see Table 4). There were 4 from 19 AC samples that were located within the area of the SE class.

Table 4. Confusion matrix of the erosion stages classification based on refinement.

| Ground truth        | NE | ME | SE | AC | Classification overall | Producer accuracy (%) |
|---------------------|----|----|----|----|------------------------|-----------------------|
| Orthophoto refinement results | SE | 1  | 9  | 35 | 49                     | 71.4                  |
| Others              | 25 | 25 | 1  | 15 | 66                     | 98.5                  |
| Truth overall       | 26 | 34 | 36 | 19 | 115                    |                       |
| User Accuracy       | –  | –  | –  | 97.2| –                      |                       |
| Overall accuracy (%)|   |    |    |    | 86.9                   |                       |

Figure 6. Descriptive statistics of reflectance values in the classified erosion classes.

Figure 7. Delineation of eroded classes using the unsupervised classification and the refinement based on visual interpretation of orthoimages.
A delineation of erosion classes using the unsupervised classification and SE class refinement is shown in Figure 7. Generally, the classification shows that a highly diversified soil cover formed in the areas that were originally covered with Chernozems. In both cases, the SE class was distinguished on the most exposed terrain positions in terms of tillage and water erosion. The ME class was classified on the milder slopes and positions with lower slope gradients adjacent to the SE class. The NE class was distinguished on plateaus and low slopes up to 2°.

**Discussion**

The main goal of this study was to analyse the possibilities of a direct delineation of eroded soil in agricultural land at a regional scale using optical multispectral images. Up to now, the majority of studies dealing with the direct delineation of eroded soils in agricultural land have been performed at a local scale, usually on small study sites consisting of one or few agriculture fields (Báčová & Krása, 2016; Fulajtár, 2001; Kolejka & Manakos, 2000; Sarapatka & Netopil, 2010; Smetanová, 2009). Other studies that have focused on the direct detection of eroded areas have delineated highly eroded non-agricultural areas characterized by bare soil or rock outcrops, such as badlands (Alatorre & Beguería, 2009; Beguería, 2006; Liberti et al., 2009; Pérez & García, 2017; Servenay & Prat, 2003). In these regions, different methods of eroded soils’ delineation, based mainly on the land cover classification, have been applied.

The results of the unsupervised classification of three degradation stages of soils showed a low overall accuracy of up to 55.2%. The accuracy is lower than that observe in studies performed at a local scale. Floras and Sgouras (1999) used Landsat 5 images for a k-means supervised classification of land cover, including eroded soils in marls, and reached an overall accuracy of 83.94%. Fulajtár (2001) reached the accuracy of 60% of the unsupervised classification of eroded soils on loess using a SPOT panchromatic image at the local scale. Similarly, Sarapatka and Netopil (2010) used the unsupervised classification of aerial photographs for the delineation of eroded soils on loess at the local scale. Kolejka and Manakos (2000) used a single Landsat 7 image for the delineation of SE soils in different geosystems.

In the present study, the main source of the classification error is connected with the incorrect classification of the ME class. A similar problem of distinguishing more erosion classes, especially the transitional classes between the NE and SE classes, has been reported in the literature (Schmid et al., 2016; Zádorová et al., 2011; Žižála et al., 2017). The ME class has achieved the lowest values of both user and producer accuracy. The main misclassification has been determined in the classification of ME to NE and vice versa. The results showed that distinguishing between these classes is very problematic using the present approach. The reasons for these inconclusive results lie in the character of the ME class. The ME class is characterized by a decrease of the A horizon thickness, but not under the depth of tillage. The tillage operations do not cause mixing of the humic A horizon with the contrasting subsoil (A/C horizon or loess). Thus, the properties of the topsoil are not significantly affected by soil removal, in contrast with SE soils, and the spectral differences of the NE and ME classes are observable with difficulties.

The performance of the ME delineation can be potentially increased using fuzzy methods, object-oriented classification methods or data with a higher spectral resolution, such as hyperspectral data (Schmid et al., 2016; Žižála et al., 2017).

A preliminary assessment of the spectral purity of the training samples in this study showed very poor spectral separability of the classes based on ground-truth samples. According to Sepuru and Dube (2017), the low separability of classes limits the applicability of the supervised classification methods, particularly in spatially complex erosion areas. The methods of machine learning, such as Support vector machine or the determination of a set of endmembers for different soil erosion and accumulation classes, represent a possible solution to overcome the limitations of the supervised classification methods (Schmid et al., 2016).

Despite the low accuracy of the automatic classification, the study showed a potential for the applied approach to distinguish SE soils from NE soils. Nevertheless, it still has many limitations. The use of refinement of the eroded classes based on the visual interpretation of time series of aerial orthomages leads to the increase of the classification accuracy, as was shown in the present study. However, the visual interpretation represents a time-consuming and subjective method that is limited to the visible RGB spectra (Fulajtár, 2001; Šarapatka & Netopil, 2010). The main difficulty lies in the fact that the level of soil degradation changes gradually. However, the operator must assess the crisp boundaries of the erosion classes.

Moreover, the accuracy of the erosion classification may also be influenced by other factors. The pattern of the spectral reflectance differs due to not only the erosion processes but also the characteristics influencing the spectral response, which are soil moisture, the geometric properties of the soil surface (roughness) and the variability of other soil properties, such as soil texture, soil aggregate sizes or the presence of a soil crust (Ben-Dor & Dematté, 2015; Dematté et al., 2015; Goldshleger, Ben-Dor, Lugassi, & Eshel, 2010; Schmid et al., 2016). Additionally, spectral satellite
data are influenced by different light beam geometries according to the date of acquisition (solar zenith and azimuth). This joint effect cannot be completely eliminated by image corrections.

The multi-temporal approach represents a possible solution to map soil properties in temperate regions. First, the soil composite concept presented by Diek, Fornallaz, Schaepman, and de Jong (2017) or Rogge et al. (2018) can be applied. Second, each image can be processed separately to overcome the issue of different surface and geometry conditions. This approach was used successfully in this study. Nevertheless, a reference study is needed to compare both approaches.

The classification can be even more difficult in the case of the combined influence of more erosion and sedimentation processes. The study area is characterized by the combined effect of water, tillage and wind erosion. This combination of soil redistribution processes leads to a highly complex erosion pattern and, for example, similar soil surface properties of the eroded and AC soils (Hill et al., 1995; Zádorová et al., 2013; Žízala et al., 2017).

The variability of soil types is also an important restraint in the assessment of larger areas. The erosion processes ongoing in soils with different stratigraphy and properties can result in significantly different spectral properties of the soil surface (Šarapatka & Netopil, 2010; Schmid et al., 2016; Smetanová, 2009; Žízala et al., 2017). The present approach is therefore limited to pedologically homogeneous areas.

The direct classification approaches of arable soils can also be limited by the masking effects of vegetation, litter or cloud cover on images. Therefore, especially in the condition of a temperate climate, a multi-temporal approach must be applied to avoid problems related to masked surfaces in large areas (Gómez et al., 2016; Meléndez-Pastor et al., 2017; Topaloglu, Sertel, & Musaoglu, 2016). Our study confirmed that the use of periodically acquired images, such as time series of aerial orthoimages or satellite data with continuous acquisition of images from Sentinel-2 or Landsat satellites, is appropriate. In our study, the mask consisting of the LPIS, cloud mask, and bare soil mask was created. The main difficulty was associated with the bare soil mask. The spectral behaviour of the vegetation cover and the bare soil is, in some cases, very similar, and the distinguishing of the litter cover is also problematic (Šarapatka & Netopil, 2010). The time series of seven images covering the spring-autumn period were used. Then, it was possible to identify almost 90% of the area with bare soils by the concept of the bare soil line. Every single image was characterized by certain specifics in vegetation cover. The sparse vegetation cover often occurred in the spring (March, April, and May). Through the summertime (August), only a very small area was covered by the bare soil. The presence of crops during the phase of harvesting (cereals, corn) was typical for September’s images. These fields covered with ripened crops and stubble fields had the spectral characteristics similar to SE areas in the VIS/NIR domain and could not be identified by the soil line methods. They were removed manually. Therefore, a more complex approach is needed to increase the accuracy of the bare soils’ identification (Richardson & Wiegand, 1977). Additionally, other more accurate methods (e.g. fmask – Zhu, Wang, & Woodcock, 2015) for the identification of the areas affected by clouds influence need to be tested.

Conclusions

The present study tested the potential of the processing of time series of Sentinel-2 images and aerial orthoimages to assess the erosion stages of agricultural soils. The assessment has been performed at a regional scale, in a study area comprising hundreds of square kilometres. The impact of erosion at the study sites was evaluated by an unsupervised classification of satellite images combined with the visual interpretation of aerial images.

This study reveals that the applied approach enables the accurate distinction of NE and SE soils. However, the performance of method for more detailed classification of different erosion stages, including transitional classes (ME soils), was not satisfactory. An automatic unsupervised classification achieved an overall accuracy of 55.2% for distinguishing two eroded (strongly and moderately) and a NE class, and 80.9% for only one eroded class. The accuracy of the classification reached 86.9% after a visual refinement based on the orthoimages. Despite this high accuracy of the visual interpretation method, there are still many limitations, and more automatic and objective approaches need to be developed and tested. Moreover, some considerable limitations and gaps were identified in the automatic classification. The practical and routine implementation of this approach entails several problems related to soil cover variability, the masking effect of different objects (clouds, vegetation, litter), or the spectral separability of individual classes. Therefore, further research is required, especially in terms of the automatic selection and preprocessing of the images, reduce and overcome the negative effects of the masking properties, and a progressive statistical method should be applied in the classification process. The applicability of the presented approach is also limited to the pedologically and geologically homogeneous areas. A different approach, enabling the distinguishing of diverse spectral characteristics of degraded soil on different parent materials, should be adopted in heterogeneous areas.

Our study focused on the applicability of the presented multi-temporal approach at a larger spatial
extent compared to previous studies. Although the accuracy achieved by the automatic classification was not satisfactory and the method requires further testing and improvements, the presented approach promises to produce valuable data on the actual degradation of soils by erosion. This type of information, available at the regional scale, is strongly needed for conservation policy purposes, and therefore, further progress in improving this approach is required.

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