Estimation of Soil Properties Based on Soil Colour Index

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Summary

Knowledge on soil properties is an important aspect in the implementation of precision agriculture. For this study was used an image taken by Sentinel 2 depicting fields of one farm with 8,261 ha in the South Moravian region of the Czech Republic.

For the determination of soil properties, soil samples were taken at a density of 1 sample per 3 hectares and analyzed by Mehlich III methodology. The content of available nutrients phosphorus, potassium, magnesium and calcium have been determined together with soil pH, soil texture and sand. The specified sampling revealed high variability for phosphorus, potassium and calcium. Lower variability has been observed with magnesium and pH. An identification of bare soil area without vegetation cover was tested by different threshold values of Normalized vegetation difference index (NDVI) (0.15 – 0.3).

The correlations between the multispectral bands and the soil properties were weak. In the analysis of soil samples was detected positive correlation (r = 0.505) between soil texture and Colour Index (CI). In area was found a negative correlation between CI and Ca (r = -0.618), then between CI and pH (r = -0.504). Weak correlation were found between CI, phosphorus and magnesium. At the level of lower NDVI values (0.16 - 0.15) we found correlation between CI and the sand content.

The observed level of correlation found in the data of remote sensing can predict some soil properties in fields that have not been subjected to soil sampling and facilitate learning about soil properties for decisions in precision agriculture.

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Introduction

Accurate information, needed to managing the variability in soil properties, is an important aspect in the implementation of site specific farming also known as precision agriculture (PA).

This information is critical for farmers to calculate the proper amount of inputs for best crop performance and at least environmental effect.

Conventional soil sampling and laboratory analyses, a traditional way to explore in-field soil variation, cannot efficiently provide this information, because they are slow, expensive, and could not retrieve all temporal and spatial variabilities (Zribi, Baghdadi, & Nolin, 2011). In order to obtain information about the spatial variability of soil properties in some optimal form were used such techniques as Proximal soil sensing (Viscarra Rossel and Adamchuk 2013) or Remote sensing (Carter and Young 2013), which can make it easier to get the right information. Remote sensing (RS) provides a tool for PA information gathering and has advantages of low cost, rapidity, and relatively high spatial resolution(Ge, Thomasson, & Sui, 2011).

According Hill et al. (2010) the soil spectra across the Visible (VIS, 0.4–0.7 μm), Near Infrared (NIR, 0.7–1.1 μm) and Short-Wave Infrared (SWIR, 1.1–2.5 μm) spectral regions are characterized by significant spectral features, that enable quantitative analysis of several soil properties such as soil texture (clay, silt, and sand percentages), organic matter (OM), nitrogen, pH or nutrients (phosphorous, P; potassium, K; calcium, Ca; magnesium, Mg; zinc, Zn; and sodium, Na) (Chang, Laird, Mausbach, & Hurburgh, 2001; Malley, Yesmin, Wray, & Edwards, 1999).

Remote sensing data are acquired by the multispectral or hyperspectral sensor types carried by satellite or airborne vehicles (Ben-Dor, 2002). Some of the multispectral data are free available.

Nowadays are as potential free source of multispectral data for study of bare soil used images from satellite Landsat 8 with the Operational Land Imager (OLI) or satellite Sentinel 2 with a Multispectral Imager (MSI). They are used to estimate soil properties like soil texture, organic carbon (Castaldi et al., 2016) or soil moisture (Roy et al., 2014).

As data analysis techniques is regression analysis, including multiple regression analysis (MLR), principal component regression (PCR), and partial least squares (PLS) regression, the most popular data analysis technique to relate soil properties to reflectance (Ge et al., 2011). To study the content of available nutrients or pH values regression analysis was used by J. A. Thomasson et al. (2001) or Malley et al. (1999).

Soil color is one of the most useful attributes for characterization and identification of soil texture that can also be derived from most operational multi- and hyperspectral sensor systems (Bigham, Ciolkosz, Torrent, & Barrón, 1993). Thus, the Colour Index can be a useful tool indicating change of soil texture in bare soil areas for this type of multispectral data. Soil color is a first order indicator to estimate soil organic carbon (SOC); typically, dark soils contain more soil organic matter than pale soils. This darkening of soil with higher SOC content is caused by saturated organic matter and to variation in the composition and quantity of black humic acid and soil moisture (Viscarra Rossel, Minasny, Roudier, & McBratney, 2006).

The Colour Index (CI) algorithm was developed to differentiate soils in the field (Pouget, Madeira, Le Floch, & Kamal, 1990).It is usually used for diachronic analysis, they help for a better understanding of the evolution of soil surfaces.

The main objective of this study was to evaluate free multispectral remote sensing data for purpose of predicting the spatial variability of main agrochemical soil properties through regression analysis in one of the main agricultural areas of the Czech Republic.

Material and methods

Study area

The study was conducted around Rostěnice-Zvonovice (Coordinates in WGS - 84: 49.238845, 16.965115) in the South Moravian Region in the Czech Republic. It is located approximately 35 km northeast of the city of Brno (Figure 1. Location of study area). The average annual temperature in the area is 9.8 °C. The average annual precipitation is 533 mm. From the point of view of soil conditions, the area under observation includes soils of warm,
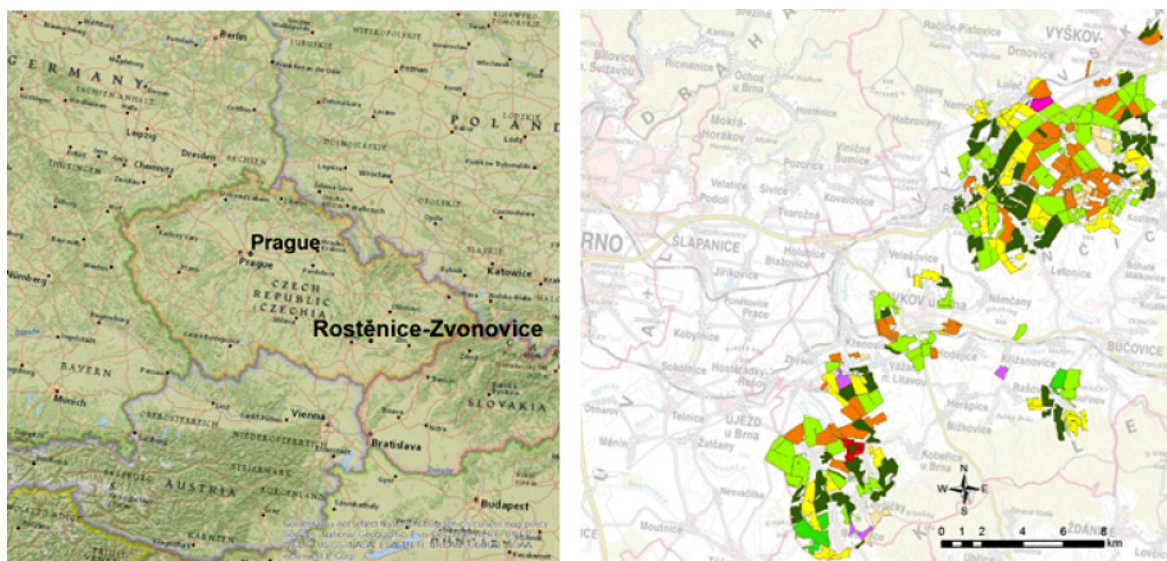

Figure 1. Location of study area

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Table 1. Spectral bands of Sentinel 2

Sentinel-2 Bands	Central Wavelength (μm)	Spatial resolution (m)
Band 1 – Coastal aerosol	0.443	60
Band 2 – Blue	0.490	10
Band 3 – Green	0.560	10
Band 4 – Red	0.665	10
Band 5 – Vegetation Red Edge	0.705	20
Band 6 – Vegetation Red Edge	0.740	20
Band 7 – Vegetation Red Edge	0.783	20
Band 8 – NIR	0.842	10
Band 8A – Narrow NIR	0.865	20
Band 9 – Water vapour	0.945	60
Band 11 – SWIR 1	1.610	20
Band 12 – SWIR 2	2.190	20

slightly humid to dry climatic region. Chernozem is predominant soil type in the whole area, to a lesser extent Fluvisol and Redzina. The main crops in this area are spring barley (32%), winter wheat (24%), maize (19%) and oilseed rape (16%).

Remote sensing data

As a source of remote sensing data, a image from Sentinel 2 for high spatial resolution in the VIS and NIR (10 m resolution) and presence of SWIR bands was selected for this study. Multispectral data were taken on 27th March 2016. In time of acquisition it was expected the greatest amount of bare soil. Sentinel-2,which was successfully launched in June 2015, has a MSI with a band in the SWIR region, between 2100 and 2280 nm and centered at 2190 nm, with a Ground Sampling Distance (GSD) of 20 m (Castaldi et al., 2016).

Data were obtained from European space agency (ESA) SciHub as L1C level (Product on Top-Of-Atmosphere level) and corrected in the SNAP application by the SEN2COR module to level L2A. L2A data, referred to as the "Bottom-Of-Atmosphere" (BOA) Product, contain, besides the orthocorrected bands of atmospheric corrected reflection, also a map of aerosol optical thicknesses (AOT), a water column map, a image classification map, and the clouds and snow probability map of that image (Uwe, Jerome, Rudolf, Ferran, & Marc, 2013). Through these data layers, various unwanted elements can be filtered from the image. In this case, clouds were removed.

The spectral bands captured in Table 1 were included in the study.

For the purposes of this study, soil indices including the Brightness Index, The Color Index and The Redness Index were derived in the SNAP application environment from the bands listed in Table 1. The most useful was The Colour Index, which was developed to differentiate soils in the field and is calculated from red and green band:

$$CI = \frac{R-G}{R+G} \qquad (1)$$

Soil sampling and laboratory analyses

Sampling was carried out on selected plots at a density of 1 sample per 3 hectares in 2014. Altogether 2136 samples were taken. The total area of the analyzed parcels was 8261 ha.

Soil samples were analyzed in laboratory according to the Czech valid methodology (J. Zbíral, 2002): for soil pH value (pHCaCl2), content of available nutrients (P, K, Mg, Ca) by Mehlich 3 method (Jirí Zbíral & Němec, 2000). Percentage of sand (>0.25 mm) were estimated by sedimentation method (J. Zbíral, 2002). Soil texture was determined based on United states department of agriculture
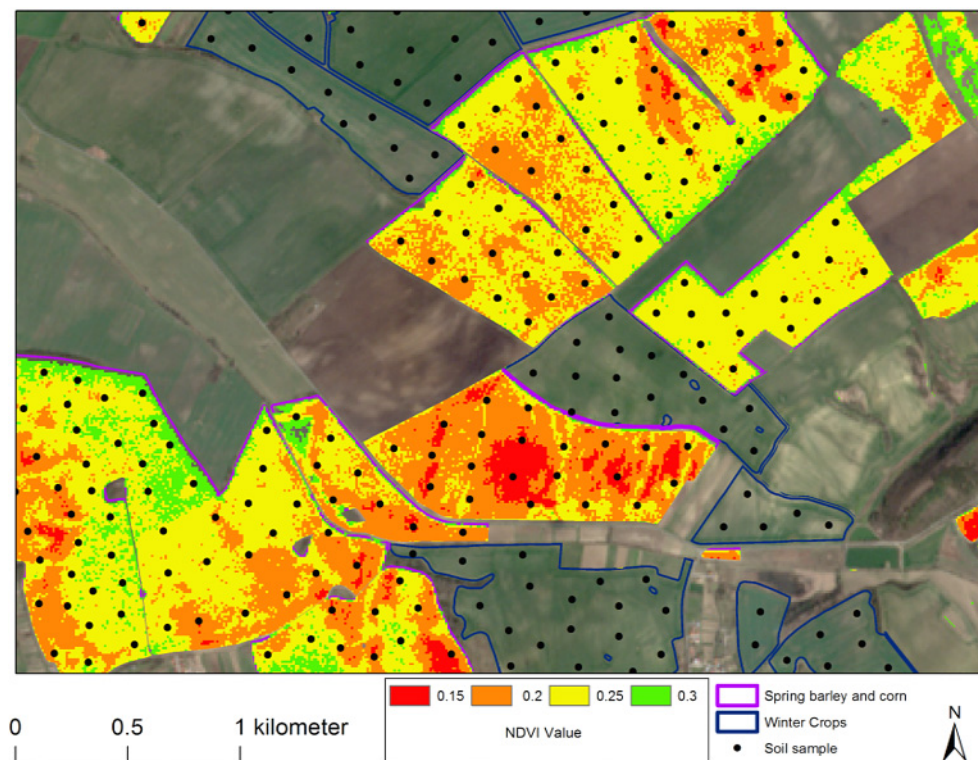
Figure 2.
NDVI values for bare soil in fields around Rostěnice - Zvonovice

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textural classification triangles (Brown, 1990). Main soil texture classes have been identified as sandy loam, sandy clay loam, loam and clay loam.

Data processing

The crucial problem of the study was the correct determination of bare soil within field boundaries. The most probable places of bare soil in the monitored area were fields with spring crops, which did not interfere with the spectral properties of the soil in the monitored area at the time of image acquisition. For the purposes of this study, field survey on bare soil in the study area was carried out using the ASD FieldSpec® HandHeld 2 spectral radiometer measurement and vegetation index NDVI calculation according to Rouse et al. (1974) for central wavelength (NIR-842nm, RED-665 nm) (Figure 2). The comparison of different NDVI threshold values was carried out for bare soil masking in the range of NDVI = 0.02 - 0.3. Mean value of NDVI for bare soil, determined from surface measurements in the entire area was 0.2 with a standard deviation of 0.07.

The threshold value was applied on spectral bands as the mask layer and derived soil indices and then extracted in ArcGIS 10.2 by the point layer representing the sampling points for different NDVI threshold values. ArcGIS is a geographic information system (GIS) for working with maps and geographic information. The correlation analysis among the variables was calculated. For strongest correlations were computed regression statistics. The correlation analysis and regression statistics both were carried out in Microsoft Excel. Basic statistic characteristics of soil sample results were also computed in this environment.

Results and discussion

The basic statistical characteristics of soil sampling results are preserved in Table 2. Results are related to samples in fields with spring crops up to 0.3 NDVI. The number of samples entering the analysis was therefore 1201. The specified sampling density revealed high variability especially for phosphorus (CV = 74.62), potassium (CV = 45.36) and calcium (CV = 44.54). Lower variability has been observed with magnesium (CV = 28.22) and pH (CV = 10.92). None of the variables has a normal distribution. In most cases, they are mixed with left-handed positively skewed data with an excess of data less than average. The exception is the pH, where it is a right-handed symmetric distribution, a span corresponding to the normal distribution, with an excess of values greater than mean.

Results of correlation analysis are shown in Table 3. All correlations were calculated at the significance level $p < 0.05$.

The correlations between the bands shown in Table 1 and the soil properties listed in Table 2 were weak. In areas of NDVI values

Table 2. Basic statistic characteristics of soil sample results (Units of nutrients - mg/kg)

	pH	Phosphorus	Potassium	Magnesium	Calcium
Mean	6.82	100.49	371.33	314.32	5566.73
Median	7.34	87.04	332.11	295.11	5242.21
Mode	7.53	68.12	240.12	257.03	3390.15
Max	7.83	1152.14	1630.07	1110.12	35560.23
MIN	4.57	9.08	134.06	97.08	1421.28
STD.	0.76	74.99	168.45	90.79	2479.58
Skewness	-0,95	6.15	2.04	2.40	2.49
Kurtosis	-0.33	62.31	7.08	10.22	19.87
CV	11.22	74.62	45.36	28.88	44.54

for bare soil less than 0.2, an increasing correlation between blue band and calcium content was recorded (r = 0.264 for 0.2 NDVI; r = 0.363 for 0.14 NDVI). In NDVI areas for bare soil above 0.2, higher correlations between SWIR 2 and magnesium (r = -0.32) or the same band and pH (r = -0.281) were observed at the observed levels.

Coleman et al. (1993) found significant correlations among remote–sensing reflectance data from Landsat TM in all seven Landsat bands and the soil variables studied: soil texture, O.M., and Iron content. Prediction equations generated from the same area with the data produced correlation coefficients of 0.665, 0.496, 0.633, 0.686, and 0.213 for sand, silt, clay, O.M., and Iron content, respectively.

However, the positive correlation (r = 0.426 – 0.504) between the soil texture and the soil Colour Index (CI) was found within the monitored area for all tested NDVI mask variants. The negative correlation between CI and Ca (r = -0.618), then between CI and pH (r = -0.543) was found throughout the area. Weak correlation links were found between the Colour Index, phosphorus and magnesium.

J. A. Thomasson et al. (2001) found significant correlations between groups of the averaged spectra and soil properties, but no single 50–nm band was highly correlated to any soil property. Soil nutrients were better correlated with spectra in one field, but texture was better correlated with spectra in the other. Only Ca and Mg in one field and clay and pH in the other had multiple–regressor model correlations with R^2 values greater than 0.50.

Stamatiadis et al. (2005) found correlations between soil surface reflectance and soil properties in the 0–0.3 m depth. The blue and green region of the spectrum had distinctively different correlation patterns to soil properties from the red and NIR bands. Soil water content, particulate OM, K and P were linearly related to soil

Table 3. Development of correlation values between CI and selected nutrients (p< 0.05)

NDVI Value	0.30	0.25	0.2	0.19	0.18	0.17	0.16	0.15
Number of samples	1201	1072	428	213	154	105	68	40
CI × soil texture	0.445*	0.451*	0.429*	0.457*	0.481*	0.426*	0.439*	0.504*
CI × calcium	-0.433*	-0.448*	-0.469*	-0.575*	-0.618*	-0.604*	-0.596*	- 0.575*
CI × pH	-0.293*	-0.317*	-0.308*	-0.412*	-0.480*	-0.505*	-0.494*	- 0.438*
CI × potassium	0.194*	-0.221*	-0.282*	-0.252*	-0.249*	-0.226*	-0.329*	- 0.265*
CI × magnesium	-0.295*	-0.309*	-0.296*	-0.252*	-0.254*	-0.182	-0.317	-0.184
CI × phosphorus	0.118	0.107	0.074	0.099	0.100	0.102	0.043	-0.023
CI × sand	-0.242*	-0.237*	-0.184*	-0.247*	-0.264*	-0.328*	-0.476*	-0.521*

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Table 4. Regression statistics for the strongest correlation relationships

NDVI Value	Soil property	N. of points	Mean (CI)	Slope (B$_1$)	Intercept (B$_0$)	R^2	RMSE
0.30	Calcium	1201	0.15	-46563.3	12477.05	0.188	2233
	pH	1201	0.15	-9.7102	8.2595	0.086	0.73
0.25	Calcium	1072	0.15	-49756.4	13054.34	0.206	2255
	pH	1072	0.15	-10.3395	8.3919	0.101	0.70
0.2	Calcium	429	0.14	-56857.93	14707.73	0.220	2554
	pH	429	0.14	-7.9352	8.2460	0.095	0.58
0.19	Calcium	214	0.14	-60099.15	15260.27	0.332	2149
	pH	214	0.14	-8.8985	8.4258	0.170	0.49
0.18	Calcium	154	0.14	-66289.67	16155.82	0.383	2154
	pH	154	0.14	-10.0930	8.5970	0.233	0.47
0.17	Calcium	105	0.13	-63706.12	15742.45	0.367	2218
	pH	105	0.13	-9.0377	8.4660	0.256	0.41
0.16	Calcium	68	0.13	-66225.79	16173.13	0.356	2368
	pH	68	0.13	-9.1743	7.468645	0.245	0.03
	Sand	68	0.13	-324.81	87.80	0.227	16
0.15	Calcium	40	0.13	-62802.04	15831.77	0.332	2334
	pH	40	0.13	-6.6590	8.1683	0.191	0.36
	Sand	40	0.13	-383.629	94.4122	0.271	16.46

reflectance in the blue and green region of the spectrum. However, the integration of surface soil reflectance and plant response variables in a multiple regression model did not substantially improve the prediction of soil properties in the root zone.

At the level of lower NDVI values (0.16 - 0.15) we found correlation between the Colour Index and the sand content. Low values of CI have been shown to be correlated with the presence of a high concentration of carbonates or sulfates and higher values to be correlated with crusted soils and sands in arid regions (Escadafal, 1989).

In Table 4, regression statistics for linear models created between observed soil properties and CI soil index for different soil reflection levels according to NDVI are captured. The best values of R^2 are described by the models describing the relation of calcium and soil index with CI, especially for NDVI values less than 0.18 NDVI. For the relationship between pH and CI, best R^2 values are at level of 0.17 NDVI. For lower NDVI values (0.16 - 0.15), sand correlations were also observed in the range of - 0.476 to - 0.521. R2 values for this relationship are in range from 0.227 to 0.271

Conclusion

The high resolution multispectral atmospherically corrected image captured by the Sentinel 2 satellite combined with a wide range of spectral bands gave hope for possible modeling of agrochemical properties of land from remote sensing data. The results in this study indicates that, while relationships between some soil spectral indices and the soil properties under consideration are detectable, they are not able to fully replaced soil sample mapping of soil chemical and physical properties with the methods examined. The relationships between individual multispectral bands and soil properties are only vague. The observed level of correlation found in the data of remote sensing can predict some soil properties in fields that have not been subjected to soil sampling and facilitate learning about soil properties for decisions in site specific farming.

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