EVALUATION OF BARE SOIL VARIABILITY FROM REMOTE SENSING DATA

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ABSTRACT

Main goal of the paper is to capture, examine and evaluate the variability of soils within each soil blocks with the use of digital records of remote sensing (RS). The evaluation was performed at the South Moravian Region with a total area of 1,100 km^2. RapidEye satellite images of the 2012 and borders of land blocks from iLPIS were used for this study. The first step was a selection of bare arable land through polygons of arable land from the system iLpis and pixels of arable land obtained through standard differential vegetation index (NDVI). An image classification was performed on these grounds in order to create class of information describing the spectrum of surfaces forming the bare soils. To classifications were included areas of bare soul with pixel count higher or equal to 50 % of the original number of pixels of bare soils in areas selected through data from the system iLpis. A coefficient of variation was used to rate variability. Information and The best images as far as for the information were images taken in March before the beginning of the growing season. This data was the most variable of all evaluated scenes, both in terms of assessment of statistical dispersion of the file and changes detectable by remote sensing. In subsequent phases of the project, all gathered results will be compared and refined with other information sources.

Key words: variability of bare soil, remote Sensing, iLpis, NDVI

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INTRODUCTION

In the field of precision agriculture, remote sensing (RS) is special, very powerful way to mapping soil variability performed by air or Satellite carriers of sensors. Lukas et al . (2011) states that remote sensing can detect changes in variability of land that affect crop yield formation during the growing season. According to Ben- Dor et al. (2009), a remote sensing is an important part of soil survey and aerial photography is one of the basic tools that are used in soil mapping. The high potential of remote sensing in precision agriculture is – according to Pierce et al. (1999), is the possibility of monitoring the spatial variability over time with high resolution and performance. Extensive areas can be mapped in a short time and with high complexity output. The spectral behavior of soil is described by Lillensand et al. (2008). He indicates the soil properties that affect reflectivity, such as organic matter content, soil moisture , grit and soil structure or presence of iron oxides (Lillensand et al., 2008). The reflectivity of the soil according to Lukas et al. (2011) decreases at higher soil moisture, a higher proportion of clay particles and organic matter content. Therefore, the soil with more poisture, heavier or humic appears darker. The presence of iron oxides then causes the color tint of the soil. Other factors affecting the spectral behavior are the mechanical properties of the soil, the degree of erosion and surface structure of the soil. Halounová at al . (2008) describes the different higher reflectivity of the surface soils with smaller particles. They indicate that this effect may in some cases overlap the effect of moisture. Similar fact is highlighted by Kroulík (2012). According to the author the soil moisture is closely related to grain size composition. Coarse sandy soil is usually drained and the result is lower moisture content and a relatively high reflectivity. Fine structure without natural drainage will have low reflectivity. But in the absence of water the soil itself will show opposite results. The coarser texture of the soil will appear darker than fine texture (Kroulík, 2012). Assessment of variability can be performed by the statistical measure of variability. These include variance, variation range, standard deviation and coefficient of variation. The rate of soil variability is expressed in this paper by the coefficient of variation (V_x). It is mentioned by Borůvka (2001), who discloses the use of V_x in the study of hydraulic conductivity, porosity and pH. Brodsky (2003) cites the work of Wollenhaupt et al. (1997), which shows V_x for available P, available K, organic matter and other factors ensuring higher yield.

MATERIAL AND METHODS

Four images (taken in March 2012, April 2012 and September 2012) were used as an input depicting the 1100 km^2 of South Moravian Region by the RapidEye satellite. At this time there was an assumption of the largest area of bare soil before the start of the growing season (March and April) and after harvest (September). Data from the RapidEye satellite is indicated as a good source of data for soil mapping eg by Brooke et al. (2010). This is the data with a resolution of 6.5 m radiometric and geometric corrections to the fundamental bands of the VIS , NIR and Red Edge. All data was ortho rectified before processing by digital elevation model from ASTER satellite and subsequently new bitmap mosaics were created in the Arc GIS 10.1. For each slide NDVI index (Halounová et al., 2008) was calculated using a Raster calculator and set a limit for arable land based on the values of the index. From thus obtained NDVI layer a bitmap was created where the value of 1 represents the intervals of arable land. A value of 0 then represents everything outside these intervals. The new bit map created this way is showing not only the arable land, but also build-up area, water surfaces and other categories of surfaces that fall in appropriate intervals. It was necessary to select areas from the layers which truly represent arable land. Other input data was therefore the polygon layer of arable land from the iLpis. The LPIS is a geographic information system for the registration of use of agricultural land in the Czech Republic, for which are given European and national subsidies to farmers. It does not, therefore, include all the arable land area. For each scene a new spatial query was made and some polygons were chosen representing arable land, which fully overlapped with the scene. Through these polygons areas of bare arable land were selected. However, this method of data selection (combination of intervals of arable land and polygons with arable land) considerably reduced the area which truly represents the arable land. Therefore, the blocks of bare arable land with the number of pixels greater than or equal to 50 % of the original number of pixels of areas of bare soil selected by data from the system iLpis were added to classification. This condition was implemented because of the highest possible selection of the most representative data in the respective periods. The selection of areas that meet that condition was carried out via the Tabulate area. Tabulate Area function creates two sets of data for a PivotTable. In a case like this, the table contains the number of pixels of each category which area is bordered by a polygon representing a soil block. Areas of pixels that met the specified condition, were subsequently converted into polygons and if their area was greater than 300 m^2, they entered as a training area into the process of supervised classification of all the scenes in ERDAS IMAGINE 2013. During usage of such created training areas some remarkable similarity of some classes were observed. Therefore, for all the scenes a PivotTable was created and also classes with similar spectral classes combined. After classifying the images were again analyzed in an Arc GIS 10.1 to calculate the coefficient of variation. To determine the coefficient of variation and descriptive statistics a tool called Zonall statistic was used. Areas of bare soil were divided, based on the values of the variation coefficient, according to the following clue:

Tab. 1:The clue for the classification of land according to the the coefficient of variation

The value of V_x	**Soil variability**	**Variability in Statistic**
0 - 49 %	slightly variable soil	Slightly sparse data set
50 - 100 %	variable soil	Strongly scattered data set
More then 100%	highly variable soil	extremely sparse data set

This clue is based on the classification of the coefficient of variation based on the statistics. More details on the value of the coefficient of variation are reported by Litschmannová (2009).

RESULT AND DISCUSSION

Table 2 shows the agricultural acreage blocks in iLpis system, which were found in the given classified scene. Due to the nature of the region of South Moravia, arable land predominates in all scenes and images and therefore represents an ideal material to study the variability of bare arable land. The trend of reduction of arable land, which was already used for analysis shows interesting but understandable reality. Data taken at the end of March make possible to evaluate the greatest amount of arable land and contain the most information of all 4 scenes. Bare soil, within all blocks of arable land, which are located outside of the whole scene, is represented by almost 67 %. The March picture confirms the appropriateness of the term for this kind of monitoring.

Tab. 2:Summary of arable land blocks and blocks satisfying the condition of coverage

Analyzed scenes	**Total area of blocks in the scene (ha)**	**The total area of arable**		**The total area of arable**	
		In ha	**% in total area of blocks**	**In ha**	**% in total area of blocks**
March 25 2012	209226	193445	92.46	129466	61.88
April 27 2012	222529	204092	91.71	73913	33.22
Sept 9 2012	209100	193024	92.31	113221	54.15
Sept11 2012	176805	155425	87.91	93360	52.80

Relatively low information value has data taken in September 2012. In both cases the bare arable land is represented on more than half of the given scene, but the variation is compared to the March data relatively low. The performance of the coefficient of variation for all four scenes is captured in the following figure:

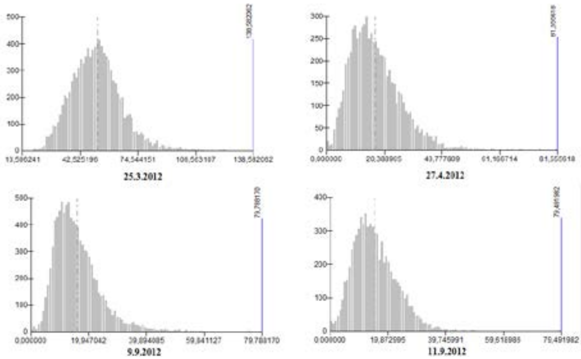

Figure 1:Histograms of V_x for each of the monitored period(mean by chain line)

Histograms in columns show the progress of the coefficient of variation at approximately same areas in the South Moravian Region. Data V_x obtained from the March image have almost normal distribution. The detected average of these data is 0.6 higher, which indicates a slightly positive left-sided distribution. The variability of the data is high. From the viewpoint of classical statistics it is an extremely sparse file. Beránek and Klement (2007) consider any land, for which the coefficient of variation of selected agrochemical properties of surveyed soil is more than 50 %, heavily unbalanced. Three more scenes have a left-sided positively skewed histogram with an excess of small values. From the perspective of the statistics, this data are weakly scattered files because most of the data is smaller than 50%. According to Beránek and Clement (2007), the soil with a coefficient of variation greater than 20 % are in some cases uneven .

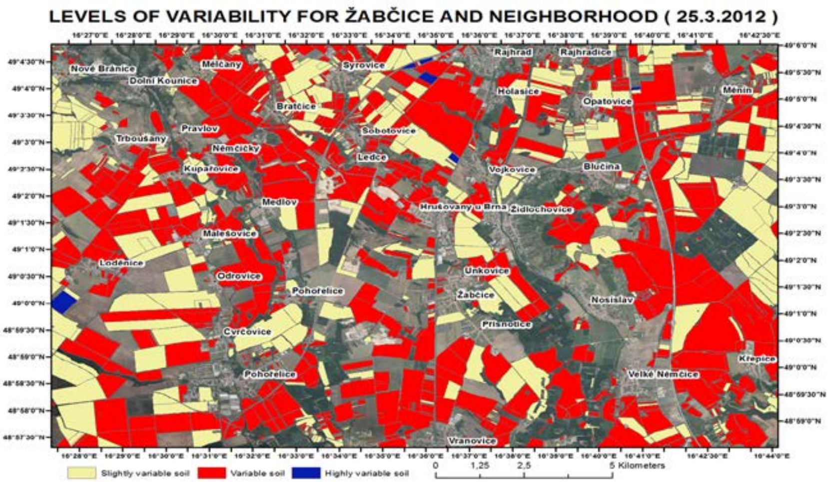

Figure 2:Levels of variability for Žabčice and neighborhood (25th 3rd 2012)

Figure 4 captures the variability of soil, determined from data taken on March 25, 2012, around the School Farm in Žabčice. Variable soil in this case has a majority representation. Categories of highly variable soil are represented only in a few cases.

CONCLUSIONS

Data taken by satellite Rapid Eye seem to be an appropriate means for mapping and assessing variability of bare soil. It very much depends though on the time of the acquisition of data. The most suitable period seems spring season before the growing season, when especially March data have a high variability. On the other hand, data taken after the harvest seem to be worse alternative. In these scenes, the substantial part of V_x is doesn't reach stronger distraction. In the event that the variability observed using remote sensing techniques is regarded as an indicator of variability of selected agrochemical properties of soil, analyzed arable land seems as unbalanced. As reported by Lukas et al. (2011), variability of soil conditions is often attributed to a number of factors which influence changes with regard to the spatial scale surveillance. At the field level, the variability is influenced by soil type, topography, previous crop and previous way of farming. Therefore, the obtained results will be compared and refined with analysis based on other sources of information, such as the relief of the terrain.

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