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Assessment of soil electrical conductivity using remotely sensed thermal data

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Abstract. Detection of heterogeneity (crop, soil, etc.) gained a lot of importance in the field of site-specific farming in recent years and became possible to be measured by different sensors. The thermal spectrum of electromagnetic radiation has a great potential today and experiments focused on describing a relation between canopy temperature and various vegetation characteristics are conducted. This paper was aimed to examine the relation between canopy temperature and electrical conductivity as one of staple soil characteristics. The related experiment was undertaken in Sojovice, Czech Republic, within an agricultural plot where winter wheat was grown in 2017 growing season. The examined plot was composed of three sub plots and 35 control points were selected within this area which the data were related to. A canopy was sensed by UAV (eBee carrying thermoMAP (FLIR TAU2) camera). Soil conductivity data were collected by terrestrial sampling using EM38-MK2 Ground Conductivity Meter in 1 m depth and 2 m sampling point distance. This dataset was later interpolated using the kriging method. The correlation analysis results showed a strong negative correlation between conductivity and thermal data (-0.82; $p < 0.001$). When comparing conductivity with NDVI representing the aboveground biomass, there was an opposite trend but also strong result (0.86; $p < 0.001$). Correlation coefficient of thermal data and NDVI comparison was -0.86; ($p < 0.001$). These preliminary results have a potential for further research in terms of soil characteristics studies.

Key words: precision agriculture, winter wheat, heterogeneity, UAV, kriging.

INTRODUCTION

The concept of Precision Agriculture (PA) has developed rapidly in recent decades. As the population grows and the field of specialized technologies are enhanced, the methods of site-specific farming more or less engage the common practice. Many studies are conducted with the aim to describe relations between various soil and vegetation characteristics and different kind of remotely sensed (RS) data. Such knowledge is essential to obtain a complex overview of how the natural processes may be explained by spectral imagery. The major advantage of such approach is especially the fact that the research may be carried out in a non-destructive mode. Related analyses may be thus undertaken repeatedly during one growing season, i.e. it is possible to evaluate crops on particular plot in different growth stages (Richards, 1993; Jones & Vaughan, 2010). It was determined that the spectral characteristics are related to various vegetation characteristics such as biochemical composition, physical structure or plant status (Sahoo et al., 2015). Based on this knowledge there is not only the possibility to evaluate the crop status at the canopy scale, but it is also possible to detect some within-field heterogeneity. This heterogeneity may be caused by variability of elevation or soil texture that in both cases affects at most the water distribution (Kumhálová et al., 2011; Sassenrath & Kulesza, 2017). Detecting of the within-field heterogeneity may be utilized to adjust the agricultural management and delineate so-called production zones. Initially, the concept of PA was based on responses in the visible and near-infrared (NIR) regions of the electromagnetic spectrum. Plenty of vegetation indices (VI) were developed as the ratios of reflectance in different wavelengths. Although many of them are considered to be very effective indicator of soil and vegetation characteristics, the research is focused on thermal infrared region of the spectrum in recent years. The major difference between these two approaches is that optical RS exploits the radiation reflected from the investigated surface, whereas thermal RS methods work with the amount of radiation that is emitted by the particular surface or object (Sabins Jr., 1997). As the temperature is such characteristic that is not visible under standard conditions, the thermal RS converts this information and displays the patterns as the visible image (Ishimwe et al., 2014). According to Khanal et al. (2017) this is especially useful for early detection of stressed vegetation based on the crop temperature on the contrary to optical RS methods, where the stress may be indicated only when visible symptoms appear. This statement is supported also by study of Camoglu et al. (2017), where thermal and hyperspectral data were analyzed to detect four levels of water stress on peppers (*Capsicum annuum L.*). Whereas spectral indices did not indicate the difference between 100% and 75% irrigated vegetation, thermal indices provided significant results. Initially, the obtaining of high resolution thermal imagery was limited by high acquisition costs. However, recently the low-costs platforms were developed. Especially, the utilization of Unmanned Aerial Vehicles (UAV) has lowered the costs and thus the thermal imagery became more accessible for various branches of agricultural research such as nursery and greenhouse monitoring, irrigation management, plant disease detection or yield prediction (Ishimwe et al., 2014). A number of studies focus on fruit trees yield prediction. An algorithm was developed by Stajnko et al. (2004) to estimate apple tree yield prediction using thermal data. Moreover, Bulanon et al. (2008) demonstrated the method how to estimate citrus fruit yield based on the fact that the fruits have approximately 1.6 °C higher temperature than leaves during the night. Nevertheless, the utilization of thermal imagery to predict cereals yield has still some limits in scientific literature. However, there are also studies describing the relation of thermal imagery and soil characteristics. Soil texture was found to be strongly related to a land surface temperature (Mattikalli et al., 1998). It is a factor that besides the others affects the amount of water held in soil profile that on the rebound influences the surface temperature. Soil electrical conductivity (EC) is considered to be a staple soil property. It determines capability of soil to transmit an electrical charge (Logsdon, 2008). According to various studies EC is associated to other soil attributes such as soil texture or soil water content (Corwin & Lesch, 2003; Logsdon, 2008; Malin & Faulin, 2013). Exploration of physical and chemical soil properties within examined area is often expensive and time consuming procedure. Therefore, in terms of PA applications EC became useful and most frequently obtained measurements to determine soil properties. Obtained values of EC are usually processed and thereafter presented as a map. This kind of map thus gives approximate information about soil texture and soil water distribution. It may be utilized not only for appropriate crop selection, but also for evaluation of drainage and irrigation management or spatio-temporal changes in soil properties.

Since thermal RS methods gained attention in recent years and the soil EC is considered to be a staple soil factor, this study aimed to describe the relation between these two variables. Experimental data presented in this paper are aimed to be analysed to determine the level of association of canopy temperature (T_c) and soil EC as the staple soil factor.

MATERIALS AND METHODS

Experimental Site

The experiment was conducted within an agricultural plot near the Sojovice town in Czech Republic. It is located approximately 25 km north-east from Prague [50°13'45"N, 14°45'54"E]. The whole experimental area has nearly 25 ha and it is composed of three smaller plots marked by numbers (Fig. 1). The west side plot [7] has 8.4 ha and there are cambisols as a staple soil type. The northern part of plot [9] has 10.0 ha and the southern one [5] has 5.8 ha. There are regosols as the staple soil type within both of these plots. According to the DEM the elevation ranges between 175–184 m a.s.l. thus there is no significant elevation variability over the area. This agricultural plot has already been monitored in recent years. Certain pattern in crop heterogeneity is observable on different kind of imagery during the growing season (Fig. 2).

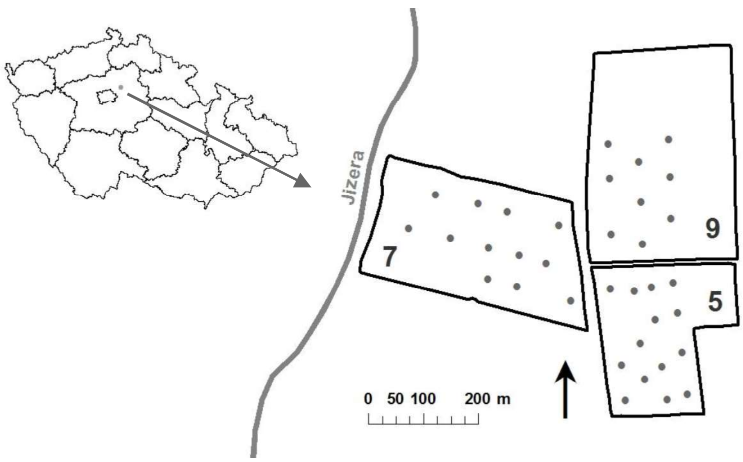
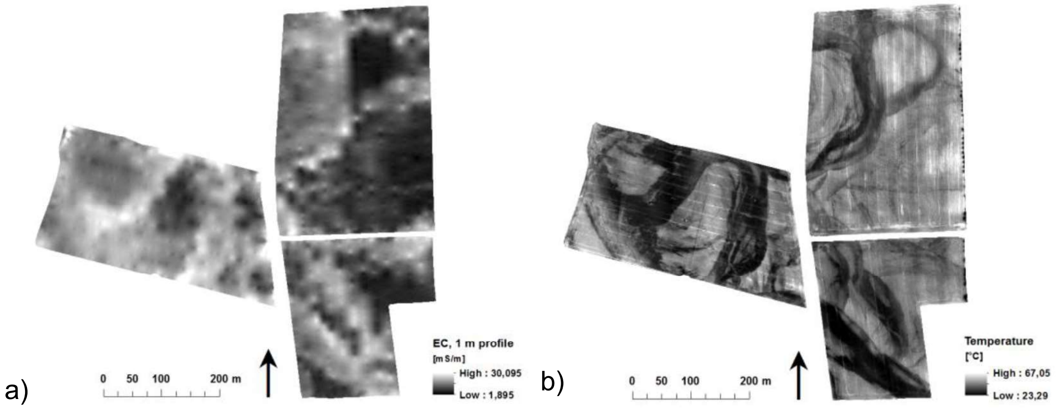


Figure 1. Experimental plot localization and composition (subplots marked by numbers 5, 7, 9) with 35 control points depicted within the field and Jizera river flow on the west side.



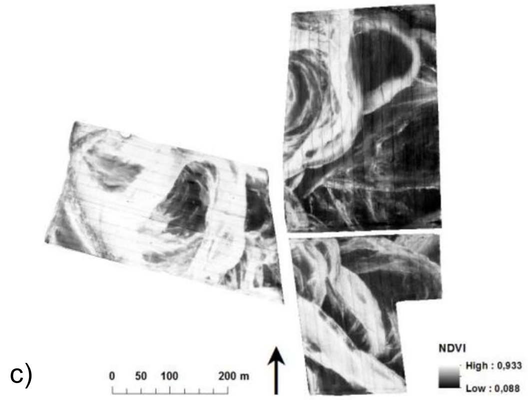


Figure 2. a) Soil electrical conductivity (EC), b) canopy temperature (T_c) and c) Normalized Difference Vegetation Index (NDVI) derived from remotely sensed imagery.

This heterogeneity is very likely influenced by the nearby flow of Jizera river and it is planned to be examined also in upcoming growing season. For a purpose of pedological research in total 35 control points were selected (Fig. 1). This control points selection was based on remotely sensed data from years 2015 and 2016 that were generally poor on precipitation. Therefore, zones of crops stressed by insufficient amount of water appeared in certain pattern during both examined growing season. Thus, points were selected to represent zones with different rate of crop water stress.

Agricultural management of the examined plot works with crop rotation of winter wheat and potato with one-year period. In 2017 growing season there was a winter wheat grown in two varieties. Variety *Patras* was sown on the southern part of the plot [5], while the other two parts were sown with *Epos* variety. Consequently all data analysis and results interpretation are related to winter wheat as one of the staple agricultural crops.

Remotely sensed Data

To obtain spectral data in sufficient spatial resolution the canopy of the experimental plot was sensed using UAV on 19th June 2017. A fully autonomous drone eBee (senseFly, Cheseaux-Lausanne, Switzerland) was utilized to carry two different types of camera. Canopy temperature data were obtained using thermal camera senseFly thermoMap. The images were processed and composed using specialized SW. In order to calculate Normalized Difference Vegetation Index (NDVI) sensing with multispectral camera senseFly multiSPEC 4C was done as well. To acquire absolute reflectance measurements the calibration with calibration target was necessary to be done before flight. This multispectral camera contains four separate sensors that acquire data in four bands – green, red, red-edge and NIR. Based on multispectral imagery NDVI index was calculated using ENVI 5.4 (Exelis Visual Information Solutions, Boulder, Colorado, USA). This index was derived and used in the analysis as the indicator of aboveground biomass. Technical specifications of utilized cameras and their settings for this particular sensing are given by Table 1, whereas Table 2. describes meteorological conditions during the process of data acquisition.

Table 1. Technical parameters of canopy remote sensing at 80 above ground level

	Thermal camera	MS camera
Typ of device	thermoMap	multiSPEC 4C
Sensor	FLIR TAU2, 640 × 512 px	4×1/3" CMOS
Ground resolution at 100 m, cm/px	19	10
Velocity, m s^{-1}	12–13	
Vertical overlap, %	80	
Horizontal overlap, %	80	
SW	eMotion, Pix4D	

Soil Electrical Conductivity Data

In order to gain the soil EC data, a terrestrial sampling was carried out using widely known probe for electromagnetic induction (EMI) (Corwin and Lesch, 2005) measurement EM38 MK2 (Geonics Limited, Ontario, Canada) on 13th September 2017. Weather conditions during the process of measurement are given in Table 2. The probe was pulled by quad by the speed approximately 2.8 m s^{-1}, while the data were acquired in the soil profile 0–1 m. The measurement was performed as the set of points with the distance of 2 m in the direction of quad motion. Weather conditions during the process of measurement are given in Table 2. The probe was pulled by quad by the speed approximately 2.8 m s^{-1}, while the data were acquired in the soil profile 0–1 m. The measurement was performed as the set of points with the distance of 2 m in the direction of quad motion. The distance between particular trajectories was approximately 20 m. Data from probe was recorded to the measuring unit together with DGPS signal each second. In order to eliminate recorded errors, some modifications on the original EC values were performed before processing. Data were treated at the extreme values. Data of conductivity were processed using statistical and geostatistical methods. The set of 7,428 points was interpolated in order to get coherent map

Table 2. Meteorological conditions by data collection

	T_c	EC
Date of sensing	19.6.2017	13.9.2017
Time of sensing	2–3 PM	2–4 PM
Aerial temperature, °C	29	16.4
Precipitation, mm	0.0	0.0
Wind velocity, k h^{-1}	8.6	18
Air pressure, hPa	1,020.3	1,005.8

representing the EC values distribution within the examined area. The maps were created using the kriging interpolation method (see Table 3). Software Microsoft office (Microsoft Corporation, Redmond, USA) and ArcGIS 10.5 (ESRI, Redlands, California, USA) were used.

Table 3. Parameters of Kriging as a method of interpolating the point electrical conductivity (EC) data

Method of estimation	Method of Moments (MoM)
Method of interpolation	Kriging
Variogram model	Spherical
Nugget variance	0.776
Distance parameter (r)	43.471
Partial sill	12.349

Data Analysis

Since the data were acquired and processed, it was possible to display numerical values of examined vegetation and soil characteristics in form of raster layer. This kind of visualisation showed certain pattern of data variability within examined agricultural plot. Nevertheless, the analysis needed to be done to describe the relation between T_c and EC more precisely. In addition, analysis of the relation between EC and NDVI, respectively T_c and NDVI was done as well to obtain complex information about the dataset. Since there was set of 35 control points selected within the experimental area, the other data analysis was related to those points. Values from raster layers (T_c, EC and NDVI) were extracted using the *Extract Multi Values to Points* tool in ArcMap 10.5 SW and added to the attribute table of 35 control point vector layer. Thus, the result was the table with in containing exact numerical information about T_c, the soil EC and NDVI at the particular point. Statistical analysis process was done in R Studio SW (RStudio Team, Boston, Massachusetts, USA). Pearson's correlation coefficient was calculated at three levels. At first the relation T_c and EC was evaluated, followed by the calculations for T_c and NDVI and also EC and NDVI.

RESULTS AND DISCUSSION

First, summary statistics of examined variables was done to acquire complex information about the dataset intended to be analysed. Results of the summary are given by Table 4. Mean value of EC was 10.306 mS m^{-1}, whereas median reached only 9.310 mS m^{-1}. These values were in accordance with possitive skewness (0.403) that indicated the data are more distributed on the right side of the mean value, i.e. the field is mostly characterized by lower values of EC, however the mean value is influenced by several parts with higher EC values. Mean canopy temperature was calculated to be 30.4 °C, median 31.6 °C. Negative skewness indicated higher vaules dominating among the dataset. NDVI mean value was 0.66 and slightly negative skewness showed on more values distributed on the left side of the mean.

Table 4. Summary statistics of soil electrical conductivity (EC), canopy temperature (T_c) and Normalized Difference Vegetation Index (NDVI)

	EC	T_c	NDVI
Count	35	35	35
Mean	10.306	30.440	0.660
Median	9.310	31.600	0.679
Sample variance	14.621	5.825	0.040
Standard deviation	3.824	2.413	0.199
Minimum	4.280	26.440	0.323
Maximum	18.048	33.910	0.901
Skewness	0.403	-0.215	-0.179

Relation of soil EC and T_c was evaluated within selected agricultural plot. Additionally, the NDVI was added to the analysis as the aboveground biomass indicator. The analysis was concentrated in 35 control points selected in terms of previous research. Correlation coefficients were calculated for combinations of three examined variables, however, the relation of EC and T_c was the most required one. Fig. 3 gives a complex overview of correlation analysis results. Significantly strong correlation was detected at all levels. Soil EC and T_c were negatively correlated with the correlation coefficient value -0.82. Even stronger negative correlation was observed by T_c and NDVI relation (-0.86), while conversely very strong positive correlation was found by EC and NDVI (0.86). Fig. 4 gives detailed information about the relation of EC and other two examined variables (T_c and NDVI).

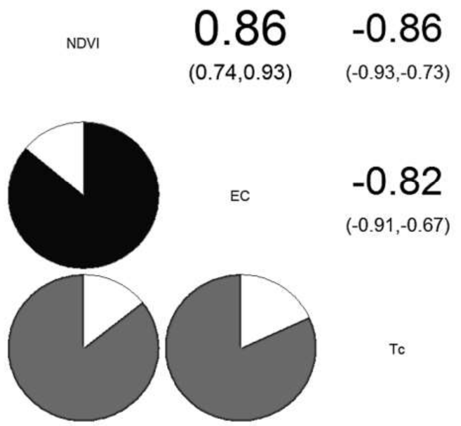


Figure 3. Results of correlation analysis presented as correlogram, where the dark grey colour within a pie chart represents a positive trend of correlation coefficient, while the light grey indicates a negative trend (*p-value* < *0.001*). Confidence intervals are given in round brackets.

Based on the results of correlation analysis the relation of soil property and canopy temperature may be described. The negative value of correlation coefficient is the indicator of indirect proportion. In fact, with lower values of EC the canopy temperature tends to increase. It is generally known that plant temperature is associated with the stomatal conductance that further links to the nutrient uptake and therefore it influences actual biomass of the crop (Cai & Cespedes, 2012). This fact is also in accordance with result of analysis of thermal data and NDVI representing aboveground biomass, where the correlation coefficient indicated indirect proportion as well.

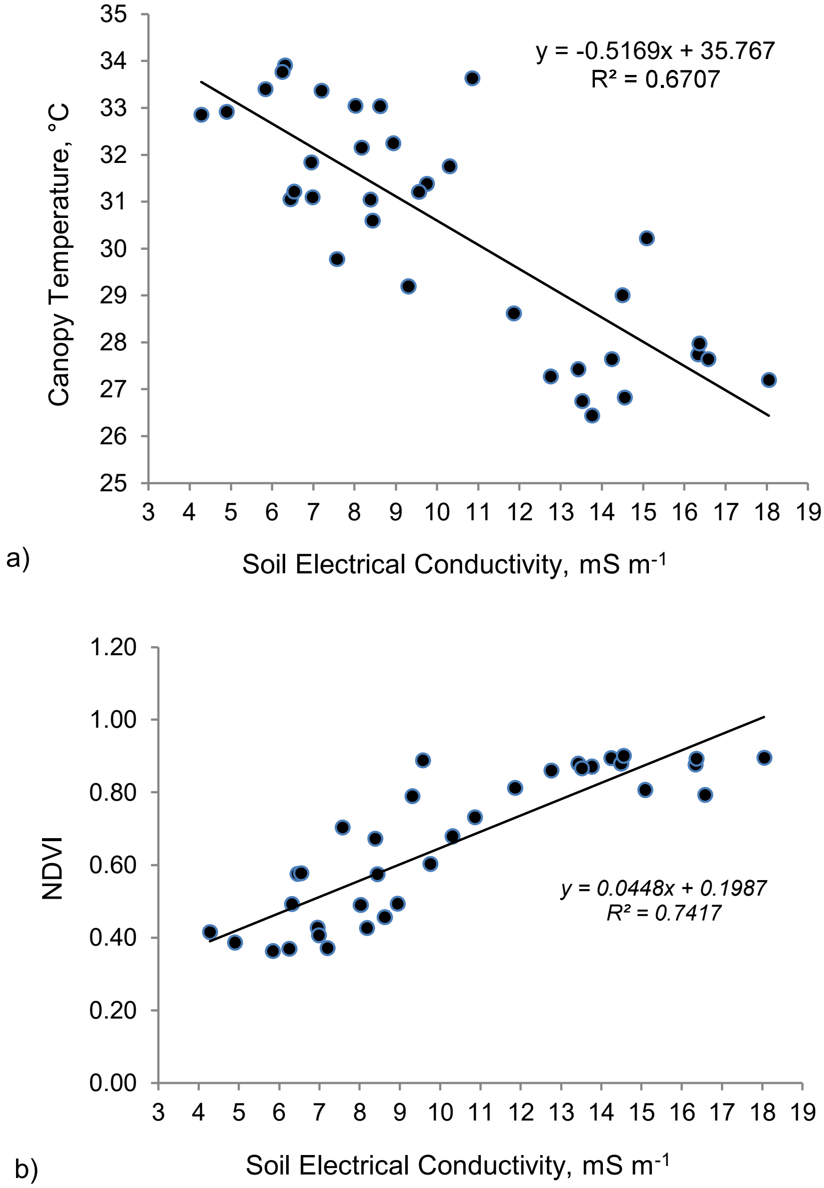


Figure 4. a) Trend of T_c and EC and b) trend of NDVI and EC relation based on the data from 35 control points.

Multispectral imagery can provide quick information about crop biomass within the field by calculating particular VI. In this case, NDVI values ranges from 0.323 to 0.901 and the heterogeneity is apparent also from attached map (Fig. 2, c). When having such information about the crop vegetation status, the cause of such differences should be determined. Various factors may influence the crop growth, e.g. topography (Kumhálová et al., 2011), soil properties variability or presence of pests or effect of plant disease. As was stated above, the elevation variability is not significant within the examined plot. Very likely the heterogeneity is caused by variable soil properties, but the soil sampling is difficult to be conducted during growing season. On the contrary, evaluation of vegetation cover using thermal RS techniques may be carried out regardless of time. T_c and EC correlation analysis showed the value -0.89 and thus the EC may be very likely explained by remotely sensed thermal data. There are studies that describe very tight correlation of EC and other soil properties (Corwin & Lesch, 2003). However, other studies were conducted with different results. Malin & Faulin (2013) evaluated two agricultural plots to determine the relation of EC and clay and water content. Significant results were found only on one of two evaluated plots, where spatial variability of soil texture was higher. Moreover, the study of Valente et al. (2012) found no significant results when evaluating EC and soil texture and moisture, respectively various chemical properties. It is clear that conclusions differ across the scientific literature, so the particular limiting soil factor may not be always identified precisely without soil sampling.

CONCLUSIONS

A number of studies were conducted to describe possible utilization of recently enhanced thermal RS data to predict yield of agricultural plot. However, the potential of thermal data to explain the soil properties that are a major factor influencing the crop growth, i.e. yield as well, is not described yet. In order to determine some basic relation of thermal response and soil characteristics this study was conducted. Soil electrical conductivity was chosen to be analysed as the factor subsuming most of other soil properties. At first, correlation analysis showed that aboveground biomass (presented by NDVI) is strongly influenced by EC (0.86). Based on this piece of information the correlation of canopy temperature and EC was examined and provided significant results, respectively close negative correlation (-0.82) was indicated. Such conclusion may be considered as some preliminary result supporting the thesis on possibility of soil properties to be explained by thermal RS. Further research may be conducted based on this conclusion to explore how are the thermal data capable to explain other soil properties.

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REFERENCES

Bulanon, D.M., Burks, T.F. & Alchantis, V. 2008. Study on temporal variation in citrus canopy using thermal imaging for citrus fruit detection. *Biosystems Engineering* **101**, 161–171.

Cai, J. & Cespedes, M. 2012. Plant temperature measurement and analysis from infrared images. In: *27th Conference on Image and Vision Computing New Zealand.* IVCNZ, Dunedin, pp. 406–411.

Camoglu, G., Demirel, K. & Levent, G. 2017. Use of infrared thermography and hyperspectral data to detect effects of water stress on pepper. Quantitative InfraRed Thermography Journal, DOI: 10.1080/17686733.2017.1331008.

Corwin, D.I. & Lesch, S.M. 2003. Applicaion of Soil Electrical Conductivity to Precision Agriculture: Theory, Principles, and Guidelines. *Agronomy Journal* **95**, 445–471.
Corwin, D.L. & Lesch, S.M. 2005. Apparent soil electrical conductivity measurements in agriculture. *Computers and Electronics in Agriculture* **46**, 11–43.
Ishimwe, R., Abutaleb, K. & Ahmed, F. 2014. Applications of Thermal Imaging in Agriculture – A Review. *Advances in Remote Sensing* **3**, 128–140.
Jones, H.G. & Vaughan, R.A. 2010. *Remote Sensing of Vegetation: Principles, techniques and applications*. Oxford University Press, Oxford, 353 pp.
Khanal, S., Fulton, J. & Shearer, S. 2017. An overview of current and potential applications of thermal remote sensing in precision agriculture. *Computer and Electronics in Agriculture* **139**, 22–32.
Kumhálová, J., Kumhála, F., Kroulík, M. & Matějková, Š. 2011. The impact of topography on soil properties and yield and the effects of weather conditions. *Precision Agriculture* **12**, 813–830.
Logsdon S.D. 2008. *Soil Science: Step-by-step Field Analysis*. ASA-CSSA-SSSA, Madison, 251 pp.
Malin, J.P. & Faulin, G.CH. 2013. Spatial and Temporal variability of soil electrical conductivity related to soil moisture. *Scientia Agricola* **70**, 1–5.
Mattikalli, N.M., Engman, E.T., Jackson, T.J. & Ahuja, L.R. 1998. Microwave remote sensing of temporal variations of brightness temperature and near-surface soil water content during a watershed-scale field experiment and its application to the estimation of soil physical properties. *Water Resources Research* **34**, 2289–2299.
Richards, J.A. 1993. *Remote Sensing Digital Image Analysis: An Introduction.* Springer-Verlag, Berlin, 340 pp.
RStudio Team 2016. RStudio: Integrated Development for R. RStudio, Inc., Boston, MA URL http://www.rstudio.com/.
Sabbins, Jr. F.F. 1997. *Remote Sensing: Principles and Interpretation, 3rd Edition*. W.H. Freeman, New York, 494 pp.
Sahoo, R.N., Ray, S.S. & Manjunath, K.R. 2015. Hyperspectral remote sensing of agriculture. *Current Science* **108**, 848–859.
Sassenrath, G.F. & Kulesza, S. 2017. Measuring Soil Electrical Conductivity to Delineate Zones of Variability in Production Fields. In: *SEARC Agricultural Research 2017*. Kansas State University, Manhattan, pp. 64–72.
Stajnko, D., Lakota, M. & Hočevar, M. 2004. Estimation of number and diameter of apple fruits in an orchard during the growing season by thermal imaging. *Computer and Electronics in Agriculture* **42**, 31–42.
Valente, D.S.M., DeQueiroz, D.M., Pinto, F.A.C., Santos, N.T. & Santos, F.L. 2012. The relationship between apparent soil electrical conductivity and soil properties. *Revista Ciência Agronômica* **43**, 683–690.