Detecting the Chemical Changes of Sugar Beet by Using Remote Sensing Technology

Rutkay ATUN*, Önder GÜRSOY

Sivas Cumhuriyet University, Engineering Faculty, Department of Geomatics, Sivas / Turkey

** Corresponding author: ratun@cumhuriyet.edu.tr*

Abstract

The changes in spectral behavior of plants against chemical effects were investigated by using remote sensing and its terrestrial spectral data, in this study. Sugar beet plant was selected as test plants. The study area was split into 3 sections for the sugar beet plant and three different phosphorus fertilization were treated to these sections (300 kg P ha^{-1}, 150 kg P ha^{-1} and 0 kg P ha^{-1}). Terrestrial spectral measurements were carried out on the leaves of the sugar beets, after the development of them. The reflectance values obtained by terrestrial spectral measurement data were used as an end member in order to run spectral classification and Sentinel 2A satellite image was used for spectral classification. Vegetation indices also were produced in order to support the spectral classification results. As a result of the study, remote sensing and its terrestrial components' usability have been shown in order to prevent wrong fertilization, to increase product yield, to protect the health of the plant and soil.

Keywords: Spectroradiometer measurements, Spectral classification, Sugar beet

Research article
Received Date: 11 February 2020
Accepted Date:30 November 2020

INTRODUCTION

Remote sensing basically means that the information of an object is obtained without direct contact to that object. The science of remote sensing has also shown great improvement since the 1800s (Gibson, 2000). In addition, today there are many free satellite images available for remote sensing and it provides speed, practicality, and convenience in accessing the information (Gürsoy et. al., 2017; Gürsoy & Atun, 2019a; Canbaz et. al., 2018). Nowadays, the use of remote sensing has increased and the usage areas have varied with the developing technology. One of these areas is agricultural applications. Thanks to remote sensing, it has been possible to perform applications such as tracing, irrigation, fertilization, and product health quickly and effectively (Ramoelo et. al., 2015; He et al., 2016; Birdal et al., 2017).

There are many studies on agriculture by using remote sensing in today. In the study conducted by Özelkan et al. (2015), the vineyard areas in the Trakya region in Turkey were investigated by remote sensing and geographical information systems. In this context, using the remote sensing and GIS, the vineyard areas in the area of Trakya region, Tekirdağ and Tekirdağ Department of Viticulture Research Station were examined. The geographical location of the existing vineyard was determined by satellite image for this purpose. In addition, water stress and photosynthesis conditions of plants were investigated with the help of terrestrial hyperspectral remote sensing techniques and the most suitable areas for viticulture were evaluated in a GIS environment by considering various criteria.

The study carried out in 2017 by Gürsoy et al, it was treated various doses of cadmium and zinc to sugar beet plants grown in a greenhouse environment. Zinc was applied as 0 and 5.0 mg Zn / kg doses and cadmium doses were treated 0, 2.5, 5.0 and 10.0 mg Cd / kg ($CuSO_4$). As a result of the study, the wavelength ranges in which the spectral signatures change in the electromagnetic spectrum according to the doses and the elements applied to the plants were determined.

The study conducted Yousfi et al. in 2016, wheat and bread wheat in different irrigation conditions of vegetation indices and canopy temperatures were compared to different methodological approaches. The plants were periodically observed for two years, the spectrophotometry of the plants was examined and the images were taken with traditional cameras. Canopy temperatures were measured between 12.00 and 14.00 at noon simultaneously with spectroradiometer measurements. The GA, GGA and NDVI vegetation indices were produced to investigate the status of plants. The GA and GGA vegetation indices were calculated by the images taken from the camera. NDVI index was calculated by reflectance obtained from spectroradiometer. As a result of the study, the vegetation indices obtained by traditional cameras (GA, GGA) showed a significant correlation with the NDVI calculated by the reflectance obtained by the spectroradiometer.

In this study, unlike the experiments conducted in the literature, plants treated differently doses of fertilization were classified by spectral classification algorithms by using remote sensing and its terrestrial spectral components. Subsequently, different vegetation indices were utilized in order to support the classification results and the relationships between these indices were examined. As a result, differences in the amount of fertilizer in plants could be detected by remote sensing and its terrestrial spectral components.

MATERIAL and METHODS

The study was conducted field conditions in Sivas city of Ulaş region where located in the middle of Turkey (Figure 1). The study was carried out in 2017. Sugar beet which is very important for the regional economy has been selected as the test plant.

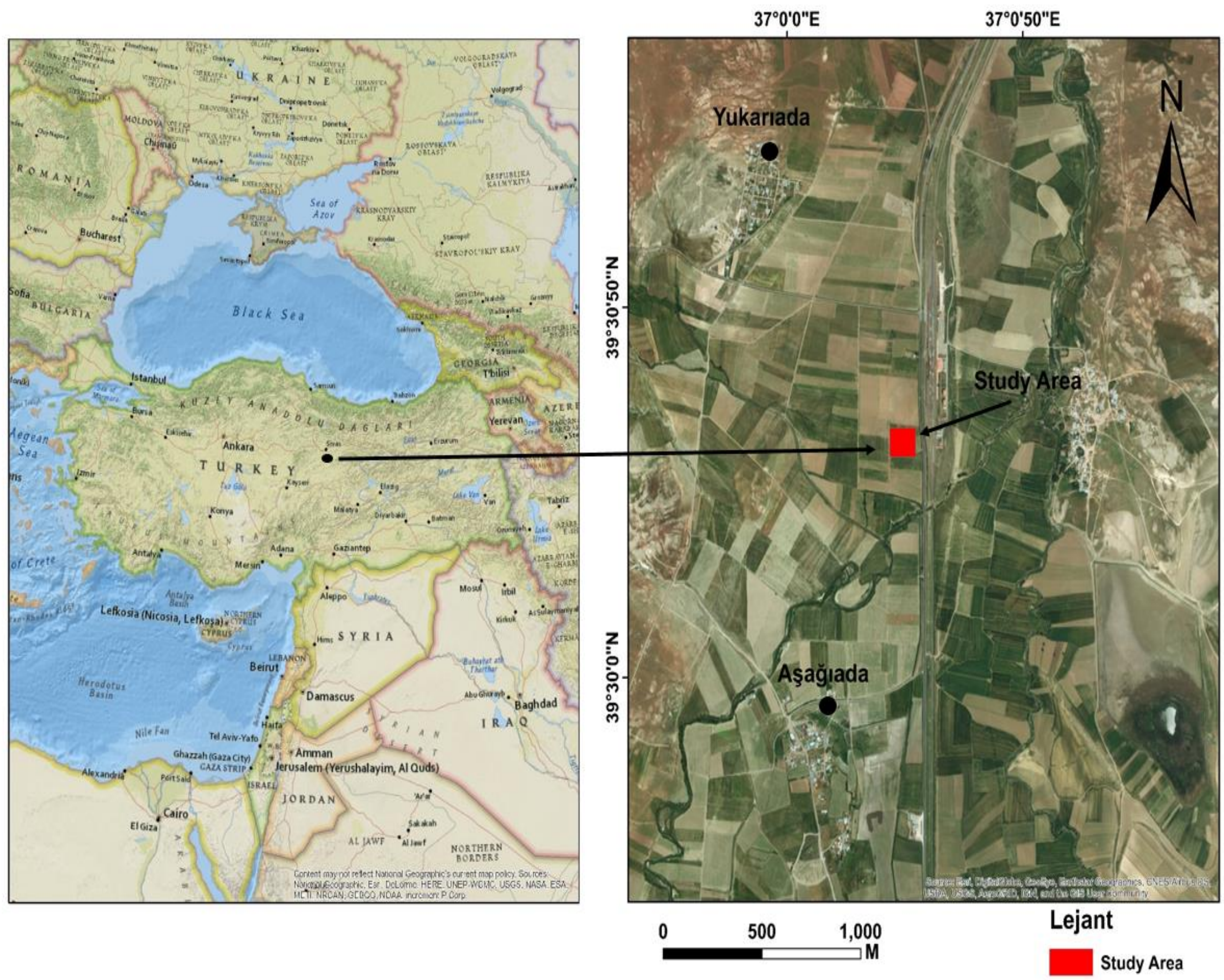

Figure 1. Study Area

Physical and chemical properties of soil structure were investigated before planting sugar beet seed (Table 1). The research was carried out in field conditions with randomized blocks as 3 replicates. The study area was divided into 3 zones and 300 kg P ha^{-1} and 150 kg P ha^{-1} phosphorus were applied to the north and middle of the region respectively. Phosphorus fertilizers weren't applied to the south of the study area. Phosphorus fertilizers were given as triple superphosphate with planting. Valentina type sugar beet seed was sown in the field after these operations.

Table 1. Physical and Chemical Properties of Soil Structure (Gürsoy & Atun, 2019b)

Soil Property	**Depth (0-30 cm)**
pH (H_2O)	7.42
Lime (%)	14.30
Salt (dS m^{-1})	0.41
Organic Matter (%)	1.30
Texture	CL
Total N (%)	0.10
Available P (kg ha^{-1})	53.50
Available K (kg ha^{-1})	948.10

After the plants mature, spectroradiometer measurements were performed in order to get reflectance values for each phosphorus group's sugar beets. The spectroradiometer measurements were made in order to obtain reference spectra to be used spectral classification. The measurements were carried out by Field Spec Pro 4 High - Res, which was able to measure between 350 and 2500 nm from ASD. Subsequently, these average reflectance values belonging to each phosphorus group were resampled to the band intervals of the Sentinel 2A satellite to obtain the end members to be used in the spectral classification (Table 2).

Table 2. Reflectance Resampled to Sentinel 2A Band Intervals

Wavelength (nanometer)	Mean 300 kg P ha^{-1} (micrometer)	Mean 1 50 kg P ha^{-1} (micrometer)	Mean 0 kg P ha^{-1} (micrometer)
443	0.040715	0.037593	0.019891
490	0.047850	0.045520	0.024314
560	0.095054	0.099328	0.055483
665	0.047529	0.043044	0.021635
705	0.136481	0.141598	0.083516
740	0.572003	0.604650	0.416171
783	0.730212	0.754632	0.532130
842	0.738143	0.760215	0.539149
865	0.740174	0.761540	0.541672
945	0.657524	0.683436	0.474532
1375	0.280079	0.281595	0.130788
1610	0.191399	0.186920	0.093105
2190	0.078668	0.069800	0.031734

It is necessary to make an atmospheric correction in order to reduce atmospheric, sensor and topography errors before making classification in satellite images (Canbaz et. al., 2017, Gürsoy & Kaya, 2016). Sentinel 2A, the satellite image used in the study, was provided free of charge from ESA. The image was prepared for classification by applying atmospheric correction. After the process of atmospheric correction, the resampled reflectance was used as an end member to run spectral classification.

Matched filtering, one of the most frequently used algorithm in classification has been chosen as a spectral classification algorithm. The matched filtering has been derived to remove the signal to noise ratio of a disturbed signal by noise. This algorithm is also used as the best method for detecting primary users of the transmitted signal is known (Harsanyi & Chang, 1994; Gürsoy & Atun, 2018; Gürsoy et. al., 2017).

Various vegetation indices were also used in order to support the result of the classification study. The indices were generated using spectral reflectance differences of the Sentinel 2A satellite. Vegetation indices used in the study were NDVI, CIgreen and CIrededge.

The most common vegetation index for determining plant status and vegetation is NDVI. In the NDVI index, the near infrared and red regions of the electromagnetic spectrum are used. The red and near-infrared region is a region sensitive to plants and dense vegetation (Rouse et. al., 1974; Welmann et. al., 2018; Gandhi et. al., 2015). It was produced to detect different phosphorus doses, in the scope of the study.

Green and near-infrared regions of the spectrum are used in CIgreen, which is called the green chlorophyll index (Clevers & Gitelson, 2013; Peng et. al., 2011). CIgreen was also used to display phosphorus fertilization at different doses in sugar beet.

The red region of the spectrum is utilized to generate the CIred-edge index used to estimate the amount of fertilizer and chlorophyll in plants (Clevers & Kooistra, 2012; Vina et. al., 2011). It was also utilized to monitor phosphorus fertilization at different doses in sugar beet plants.

RESULTS and DISCUSSION

As a result of the spectroradiometer measurements made in the leaves of sugar beet, the plants with the least reflectance were found to have no phosphorus applied plants. The sugar beet applied at 150 kg P ha^{-1} kg dose was the highest reflectance in most regions of the electromagnetic spectrum. In addition, increasing the application of phosphorus (300 kg P ha^{-1}) reduced reflection by comparison to 150 kg treated plants (Figure 2).

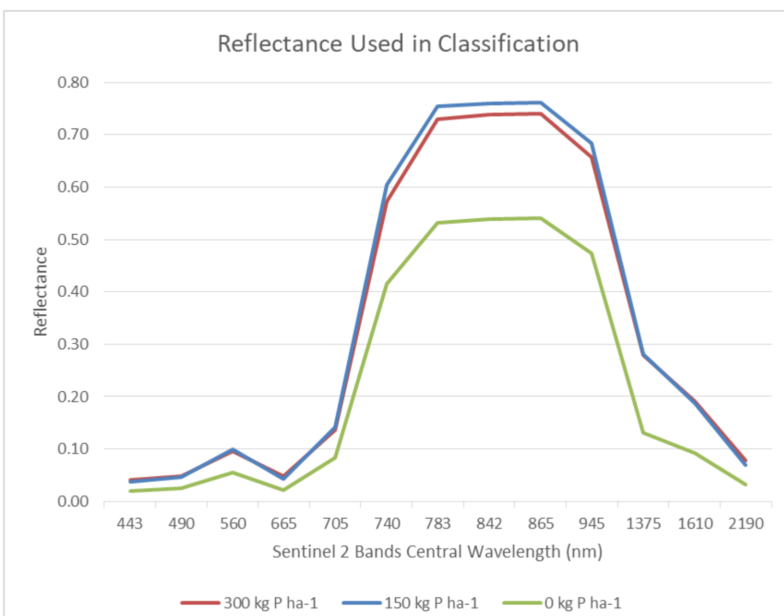

Figure 2. Mean Reflectance Values Belonging To Each Phosphorus Group

Spectral classification was performed by using the reflectance values obtained from the spectroradiometer. Sugar beet plants with different amounts of phosphorus applied were detected, with the spectral classification (Figure 3).

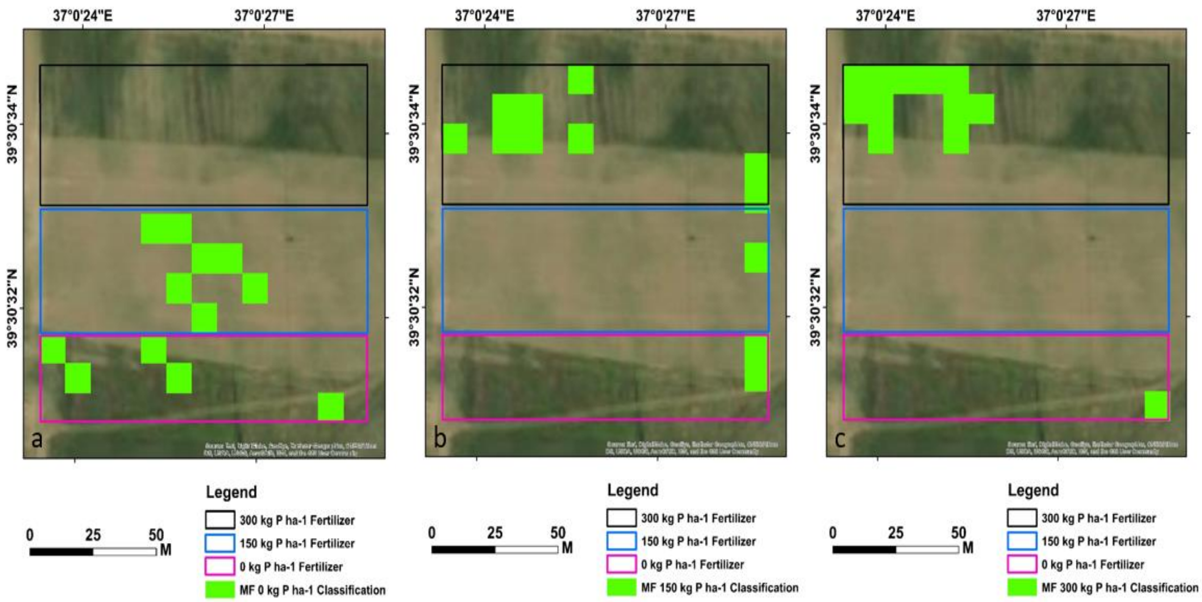

Figure 3. Spectral Classification Results of Matched Filtering. a) 0 kg P ha^{-1} kg Phosphorus Fertilizer Sugar Beets b) 150 kg P ha^{-1} kg Phosphorus Fertilizer Sugar Beets c) 300 kg P ha^{-1} kg Phosphorus Fertilizer Sugar Beets

As a result of the spectral classification, it is determined that some of the classified pixels are in non-own classes. The reason for this is that the farmer applied fertilizer to the entire area of the study field in the year prior to the start of the study. In addition, different amounts of phosphorus applied parcels are adjacent to each other in this study. Thus, phosphorus fertilizers applied in different amounts interacted with each other in the soil and the other control group also affected the sugar beet plants. This is another factor that negatively affects the outcome of the classification.

Vegetation index results showed that the index values of sugar beets that did not receive phosphorus were low. Thus, these plants could be easily distinguished from fertilized sugar beets plants. In addition, it is seen that the index values of the edge pixels of some areas where phosphorus fertilization was applied in the vegetation index maps were low. It was concluded that the phosphorus fertilizer did not penetrate sufficiently to the areas remaining at the endpoints of the study area and that the sugar beet plants were deprived of the fertilizer (Figure 4).

In addition, the correlation between vegetation indices was investigated. It was concluded that there was a high linear correlation between them (Figure 5).

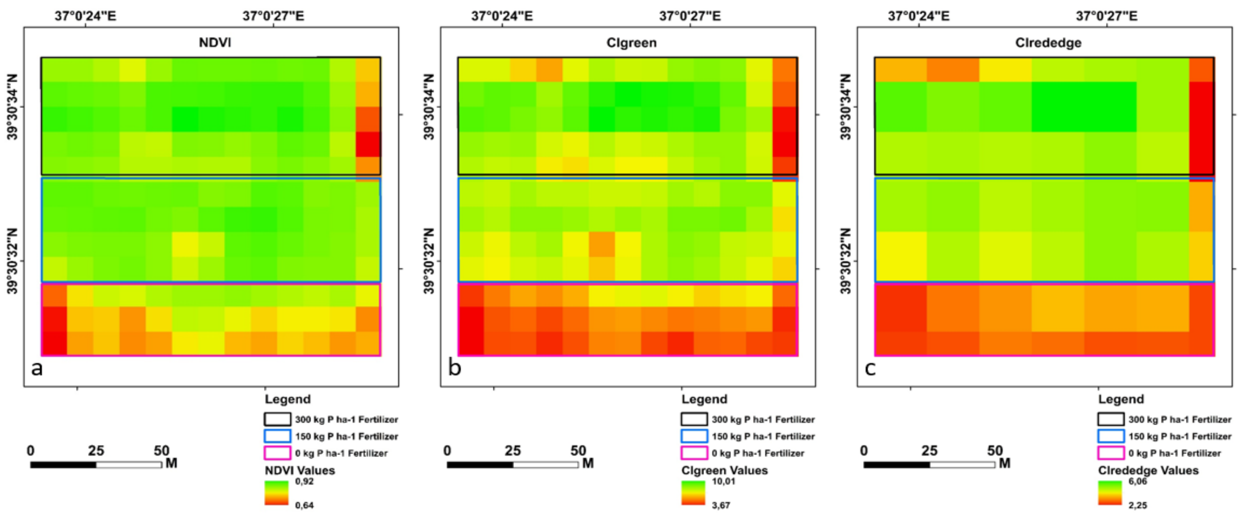

Figure 4. Vegetation Indices. a) NDVI Result b) CIgreen Result c) CIrededge Result

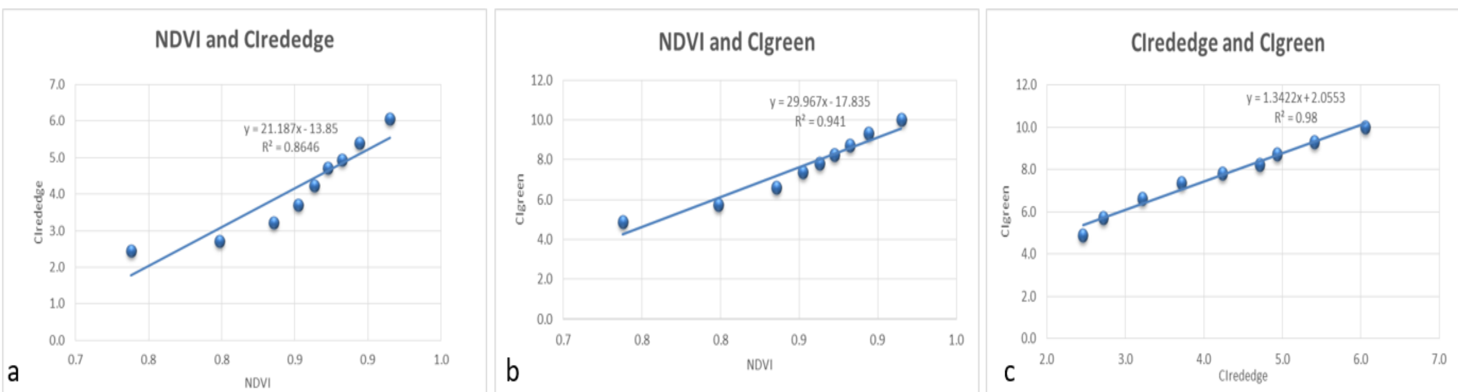

Figure 5. Correlations between Vegetation Indices. a) Correlation between NDVI and CIrededge b) Correlation between NDVI and CIgreen c) Correlation between CIrededge and CIgreen

CONCLUSIONS

As a result of the study, it has been shown that plants exposed to different amounts of fertilization doses could be detected by remote sensing and its terrestrial spectral components. It is thought that wrong fertilization could be prevented by applying the study to other agricultural lands. In addition, the effectiveness of Sentinel 2A in agricultural applications has also been demonstrated. However, it should be noted that the 10-meter spatial resolution of Sentinel 2A significantly affects the classification accuracy. It is thought that using a higher resolution satellite image or a multispectral aerial photograph will improve the accuracy. Besides, separating parcels with different amounts of fertilization, leaving more than one pixel in size, or carrying out the work in separate parcels will increase the accuracy of classification.

ACKNOWLEDGMENT

We want to thank CUBAP (Cumhuriyet University Scientific Research Projects) for M – 687 numbered project's data. We would like to thank Asst. Prof. Ahmet Demirbaş for his contribution to the field of study and plant selection. We also thank ESA for providing the Sentinel 2A satellite imagery free of charge.

REFERENCES

Birdal A. C., Avdan U. & Türk T. 2017. Estimating Tree Heights with İmages from an Unmanned Aerial Vehicle, *Geomatics Natural Hazards and Risk*, 8(2), 1144-1156.

Canbaz O., Gürsoy Ö. & Gökçe A. 2017. Determination of Hydrothermal Alteration Areas by Aster Satellite Images: Ağmaşat Plato- Zara (Sivas) / Turkey Sample, *Cumhuriyet Science Journal*, 38(3), 419-426.

Canbaz O., Gürsoy Ö. & Gökçe A. 2018. Detecting Clay Minerals in Hydrothermal Alteration Areas with Integration of ASTER Image and Spectral Data in Kösedag-Zara (Sivas), Turkey, *Journal of the Geological Society of India*, 91(4), 483-488.

Clevers J. G. P. W. & Gitelson A. A. 2013. Remote Estimation of Crop and Grass Chlorophyll and Nitrogen Content Using Red-Edge Bands on Sentinel-2 And -3, *International Journal of Applied Earth Observation and Geoinformation*, 23, 344-351.

Clevers J. G. P. W. & Kooistra L. 2012. Using Hyperspectral Remote Sensing Data for Retrieving Canopy Chlorophyll and Nitrogen Content, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 5(2), 574-583.

Gandhi M. G., Parthiban S., Thummalu N. & Christy A. 2015. Ndvi: Vegetation Change Detection Using Remote Sensing and Gis – A Case Study of Vellore District, *Procedia Computer Science*, 57, 1199-1210.

Gibson P. J. 2000. Introductory Remote Sensing: Principles and Concepts, 2 Park Square, Milton Park, Abingdon, Oxon, OX14 4RN, 176s, Abingdon, USA.

Gürsoy Ö. & Kaya Ş. 2016. Detecting Of Lithological Units by Using Terrestrial Spectral Data and Remote Sensing Image, *Journal of the Indian Society of Remote Sensing*, 45 (2), 1-11.

Gürsoy Ö., Demirbaş A., Atun R. & Durukan H. 2017. Farklı Dozlarda Zn Ve Cd Uygulamalarının Şekerpancarının Spektral Imzasına Etkisinin Belirlenmesi, *Tufuab Ix.Teknik Sempozyumu*, 9, 144-147.

Gürsoy Ö., Canbaz O., Gökçe A. & Atun R. 2017. Spectral Classification in Lithological Mapping; A Case Study of Matched Filtering, *Cumhuriyet Science Journal*, 38(4), 731-737.

Gürsoy Ö. & Atun R. 2018. Comparison of Spectral Classification Methods in Water Quality, *Cumhuriyet Science Journal*, 39(2), 543-549.

Gürsoy Ö. & Atun R. 2019a. The Investigation of Surface Water Pollution by Integrated Remotely Sensed and Field Spectral Measurement Data of Kızılırmak: A Case Study, *Polish Journal of Environmental Studies*, 28(4), 1-6.

Gürsoy Ö. & Atun R. 2019b. Using Remote Sensing in Detecting Sugar Beet Fields Treated with Different Doses of Phosphorus, *Fresenius Environmental Bulletin*, 28(2A), 1247-1253.

Harsanyi J. C. & Chang C. I. 1994. Hyperspectral Image Classification and Dimensionality Reduction: An Orthogonal Subspace Projection Approach, *IEEE Transactions on Geoscience and Remote Sensing*, 32(4), 779-785.

He L., Zhang H. Y. Zhang Y. S., Song X., Feng W., Kang G. Z., Wang C. Y. & Guo T.C. 2016. Estimation Canopy Leaf Nitrogen Concentration in Winter Wheat Based On Multiangular Hyperspectral Remote Sensing, *European Journal of Agronomy*, 73, 170-185.

Özelkan E., Karaman M., Candar S., Coşkun Z. & Örmeci C., 2015. Investigation of Grapevine Photosynthesis Using Hyperspectral Techniques and Development of Hyperspectral Band Ratio Indices Sensitive to Photosynthesis, *Journal of Environmental Biology*, 36, 91-100.

Peng Y., Gitelson A. A., Keydan G., Rundquist D. C. & Moses W., 2011. Remote Estimation of Gross Primary Production in Maize and Support for a New Paradigm Based on Total Crop Chlorophyll Content, *Remote Sensing of Environment*, 115, 978-989.

Ramoelo A., Dzikiti S., Deventer H. V., Maherry A., Cho M. A. & Gush M. 2015. Potential to Monitor Plant Stress Using Remote Sensing Tools, *Journal of Arid Environments*, 113, 134-144.

Rouse J. W., Haas R. H., Schell J. A. & Deering D.W. 1974. Monitoring Vegetation Systems in the Great Plains with ERTS, *NASA SP-351*, *Third ERTS-1 Symposium NASA*, 3, 309-317.

Vina A., Gitelson A. A., Robertson A. N. L. & Peng Y. 2011. Comparison of Different Vegetation Indices for the Remote Assessment of Green Leaf Area Index of Crops, *Remote Sensing of Environment*, 115, 3468-3478.

Welmann T., Haase D., Knapp S., Salbach C., Selsam P. & Lausch A. 2018. Urban Land Use Intensity Assessment: The Potential of Spatio-Temporal Spectral Traits with Remote Sensing, *Ecological Indicators*, 85, 190-203.

Yousfi S., Kellas N., Saidi L., Benlakehal Z., Chaou L., Siad D., Herda F., Karrou M., Vergara O., Gracia A., Araus J. L. & Serret M. D. 2016. Comparative Performance of Remote Sensing Methods in Assessing Wheat Performance under Mediterranean Conditions, *Agricultural Water Management*, 164(1), 137-147.