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Agriculture drought assessment based on remote sensing, cloud computing, multi-temporal analysis. A case study: the Mostiştea Plain (Romania)

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Abstract

Agricultural drought is one of the most important natural hazards worldwide, affecting a significant proportion of the global population. Earth Observation multi-spectral imagery satellites can provide a comprehensive picture of all land and sea areas of the Earth. Free of charge and open access imagery from missions such as Sentinel-2 provides high quality imagery with rapid high revisit period. Earth Engine© developed by Google Inc. provides the possibility to view and analyse petabytes of remote sensing data in archives that include more than thirty years of satellite imagery and scientific datasets. This paper proposes a cloud-based computation approach and analysis of multi-temporal, high resolution Sentinel-2 imagery on the Mostiștea Plain (Romania) in order to evaluate the agriculture drought. Custom javascript code was created in the Code Editor for calculating and analyzing remote sensing-based indices between 2017 and 2019. The results were classified into six classes: Water, No drought, Light drought, Moderate drought, Heavy drought, Severe drought. According to the classification, the southern half of Mostiștea Plain was the most affected area by a heavy agricultural drought during 2017-2019 period.

Keywords: *agricultural drought, Google Earth Engine, remote sensing, Sentinel-2.*

Rezumat. Evaluarea secetei agricole bazată pe analiza multi-temporală în cloud a imaginilor satelitare. Studiu de caz: Câmpia Mostiștei (Romania)

Seceta agricolă este unul din cele mai însemnate hazarde la nivel mondial, afectând o proporție semnificativă a populației globale. Imaginile satelitare multispectrale de observare a Pământului oferă o imagine cuprinzătoare a tuturor suprafețelor terestre și marine ale Pământului. Imaginile disponibile online și gratuite ale misiunilor precum Sentinel-2 oferă imagini de înaltă calitate și o perioadă scurtă de revizitare. Earth Engine© dezvoltat de Google Inc oferă posibilitatea de a vizualiza și analiza petabyți de date de satelitare regăsite în arhive ce includ mai bine de treizeci de ani de imagini satelitare și seturi de date științifice. Această lucrare propune o soluție bazată pe calcularea și analiza în sisteme de tip "cloud" a seriilor de imagini multitemporale, de înaltă rezoluție Sentinel-2, asupra Câmpiei Mostiștei (România) în vederea evaluării secetei agricole. Un cod de tipul javascript a fost creat prin intermediul interfeței Code Editor în vederea cal-culării și analizării indicilor spectrali de teledetecție pentru anii 2017-2019. Rezultatele au fost clasificate în șase clase: Apă, Fără secetă, Secetă slabă, Secetă moderată, Secetă puternică și Secetă severă. Conform clasificării, jumătatea sudică a Câmpiei Mostiștei a fost cea mai afectată de o secetă agricolă puternică în intervalul 2017-2019.

Cuvinte-cheie: *secetă agricolă, Google Earth Engine, teledetecție, Sentinel-2.*

Introduction

Drought is a major and complex hazard, with a lot of implications in many different fields around the world (Hu et al., 2019). Because it affects various socio-economic sectors, several definitions have been developed considering the field affected (Wilhite, 1993) According to the researchers Wilhite and Glantz (1985), drought can be grouped, by type, in four categories: meteorological, hydrological, agriculture and socio-economic. Each of them can have a certain duration, intensity, spatial coverage and socio-economic impact and they can also influence each other. Agricultural drought is linked, especially, to some characteristics of the meteorological drought, such as: high temperatures, precipitation shortages and evapotranspiration (Wilhite and Glantz, 1985). It appears when the soil moisture availability to plants decreased so much that the crop yield is affected and hence the agricultural profitability (Mannocchi et al., 2004).

There are several ways to monitor the agricultural drought, one of them being the use of satellite images. Earth Observation satellites provide a comprehensive temporal and spatial perspective of the land, that helps us obtain detailed analyses for large areas. Several remote sensing indices have been developed to monitor the agriculture drought. For instance, the Normalized Difference Vegetation Index (NDVI) is one of the most efficient and commonly used, because the value of this index can be used to distinguish the area with vegetation from those without and can also provide information about the vegetation health (Hu et al., 2019). According to studies (Heim, 2002; Hu et al., 2019), NDVI alone is not able and is not recommended to be used to identify vegetation drought, because some factors

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such as land cover or pest infestation can lead to an NDVI anomaly similar to that caused by drought. So, other indices have been proposed, such as Normalized Difference Water Index (NDWI), Normalized Drought Index (NDDI), Vegetation Condition Index (VCI), Vegetation Temperature Condition Index (VTCI), Visible and Shortwave Drought Index (VSDI) or Normalized Multiband Drought Index (NMDI).

With the development of Earth Observation techniques, several studies have applied remote sensing data in order to map, monitor and analyze the agricultural drought and its effects on a large scale (Yağcı Levent, 2014; Lee et al., 2016; Hu et al., 2019; Crocetti et al., 2020; Jiménez-Donaire et al., 2020), including for South-Eastern Europe. For example, Pascoa et al. (2020) performed a detailed study of the impact of drought event on vegetation activity in this part of Europe, having as case studies Romania and the Republic of Moldova. The authors evaluated the response of vegetation's photosynthetic activity to drought conditions from 1998 to 2014 over these countries, using a multi-scale drought indicator (SPEI) and a vegetation index (NDVI).

Romania is one of the European countries affected by drought. The phenomena have extended as a result of cumulative transformations that took place over vast regions nationwide (deforestations, soil erosion and others) and on the basis of climatic im-balance (Vizitiu et al., 2016). According to Stăncălie et al. (2014), most of the agricultural lands in Romania are affected by drought (about 7 million ha). The areas with the biggest problems are located in the South, South-East and East of the country (Mateescu et al., 2013).

In the national studies, Stăncălie et al. (2014) showed that the most suitable indices for agricultural drought characteristics monitoring are NDVI, NDWI and NDDI. Angearu et al. (2018) used Normal-ized Difference Drought Index (NDDI) together with the Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) in the evaluation of the extent and intensity of drought in Dobrogea (Romania), thus identifying three types: moderate, severe and extreme drought.

The paper aims to present an approach to monitoring agriculture drought in Romania, by using Sentinel-2 imagery from the ESA Copernicus Programme. In this sense, a time series analysis of the satellite-derived indices such as NDVI, NDWI and NDDI were performed for three years (March, 28th, 2017 - December, 31st, 2019). As a case study, it has been chosen the geomorphological unit named the Mostiștea Plain.

Study area

The Mostiștea Plain is located in the South-East of Romania and, according to the geographer Vintilă Mihăilescu (1925), it is part of the Southern Bărăgan Plain (Fig. 1), which is a subunit of the Wallachian Plain with an area of about 1000 sq km.

From a geomorphological point of view, the Mostiștea Plain has a smooth appearance, covered with a thick layer of loess and loess deposits, with micro-depressions known in literature as "crovuri", mounds and terraced valleys.

Mostiștea Plain is a warm and moderately dry region, with an average annual temperature of +10.5 to +11°C and average annual precipitations of 480 to 500 mm/year (Grecu et al., 2012). Due to the rich soils and suitable landforms, it is an important agricultural area, but the relatively low annual precipitation values make it susceptible to land degradation, associated with prolonged drought seasons.

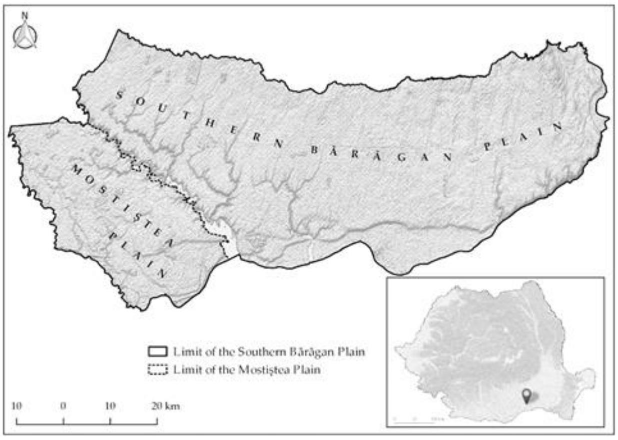

Fig. 1: Location of the study area (Source: authors)

Materials and methods

For this study, NDDI was calculated in order to assess the severity of the drought phenomena during 2017, 2018 and 2019. NDDI is based on the strong relationship between NDVI and NDWI values and it is a very good indicator of summer drought (Renza et al., 2010).

As shown by Lee et al. (2016), NDDI has a strong relation with gross primary production (GPP), especially during spring and fall, making it a good indicator for evaluating crop damages induced by drought. The index combines information from RED, NIR and SWIR spectral bands. NDDI was generated using the equation:

$$NDDI=(NDVI-NDWI)/(NDVI+NDWI)$$

NDVI is based on the properties of green vegetation to absorb radiation in the RED electromagnetic spectrum and reflect radiation in the electromagnetic spectrum of NIR. The index was first proposed by Rouse et al., (1973) by normalizing the simple ratio, while conducting a test with ERTS-1 (Landsat-1) imagery, for measuring green biomass values. Nowadays, the NDVI is the most widely used remote sensing index for estimating green vegetation cover. The formula for this index is:

NDVI=(NIR-RED)/(NIR+RED)

NDVI values represent the plant chlorophyll content, so this is the reason why the index is suitable for identifying agriculture drought. The limitations of its use are related to the fact that the values may show non-drought stress conditions, because it can be affected by other factors, such as: the effects of the soil humidity, pest infection, land cover/land use changes, flood or fire (Jiménez-Donaire et al., 2020; Yağcı Levent et al., 2014). Therefore, it is important to use NDVI index in combination with other vegetation indices for drought assessment.

Plant canopy water content can be determined using two near infrared channels (Gao, 1996) thus resulting NDWI. Previous research studies have shown a good correlation between NDWI values and soil moisture content making it a prime indicator of drought phenomena (Serrano et al., 2019). It is computed using the near infrared (NIR) and the short wave infrared (SWIR) reflectance, the mathematical formula to compute NDWI is:

NDWI=(NIR-SWIR)/(NIR+SWIR)

For this case study, high spatial resolution Copernicus Sentinel-2 data were used. Sentinel-2 mission consists in a pair of two satellites, designed to capture multispectral images of the Earth's land masses and coastal areas, with a combined revisit rate of 5 days at the equator and spatial resolution up to 10 m. The satellite constellation is orbiting at 786 km on a near polar sun synchronous orbit. Sentinel-2A started the mission on the 23rd of June 2015, followed by Sentinel-2B on the 7th of March 2017. Onboard the satellites, multispectral optical sensors acquire information on 13 spectral bands in the visible light spectrum, near infrared and short wave infrared (Table 1) making it proper for calculating NDDI.

Sentinel-2 mission is designed to provide continuity for missions such as SPOT or Landsat on acquiring high quality remote sensing data. The free full open data policy for all the Copernicus data makes Sentinel-2 imagery an easy to access and highly valuable asset for scientists and researchers. Every day, Sentinel-2 satellites acquire more than 1TB of remote sensing imagery data combined. The vast amount of data makes impractical the workflow of downloading, processing and analyzing of large scale or multiyear time series on local hardware. Cloud computing platforms offer both the processing power and also eliminate the need for downloading and storing large amounts of data sets. This method of processing remote sensing imagery greatly reduces the cost for the end user, the services can be accessed with low end specs desktop or laptop PC, only a reliable internet connection being required.

Table 1 Sentinel-2 spectral bands used in the study

Band Number	Central Wavelenght (nm)	Bandwidth (nm)	Spatial Resolution (m)
Red (B4)	665	31	10
NIR (B8)	842	106	10
SWIR (B11)	1610	91	20

Source: https://sentinel.esa.int/

In this case study, a number of 80 images corresponding to granules 35TMK and 35TMJ were used in order to calculate NDDI over the study area. The images were accessed and processed using Google Earth Engine (Fig. 2), a free to use online cloud based platform, which grants access to a library of multi-petabyte of remote sensing imagery spanning for more than forty years. The remote sensing imagery collection consists in multiple Earth observation missions including: Sentinel, Landsat, Terra, Aqua, and other.

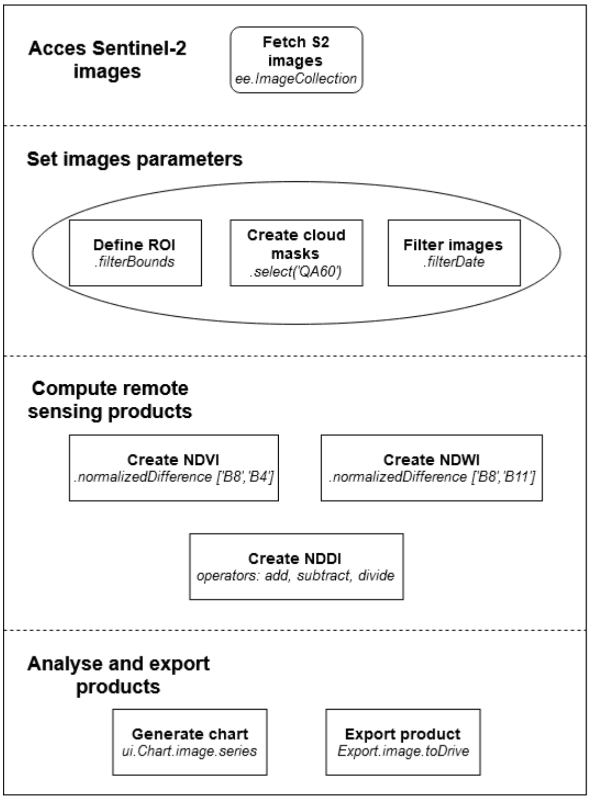

Fig. 2: Google Earth Engine processing workflow

Google Earth Engine was accessed through the Code Editor, an integrated development environment

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(IDE) that allows users to access all the functions directly within the web browser. Analysis of multi-temporal series requires that the images to be atmospherically corrected in order to eliminate the disturbances caused by the atmosphere which can greatly differ from a day to another. Starting with the 28th of March 2017, Google Earth Engine automatically processes Sentinel-2 images from Level-1C (Top of Atmosphere reflectance) to Level-2A (Bottom of Atmosphere reflectance), using Sen2Cor processor developed by ESA. For this analysis, Level-2A atmospherically corrected images were used, ranging from March, 28th, 2017 until December, 31st, 2019.

The first and one of the most important steps in fetching the imagery for the analysis is to filter the cloudy pixels. In the case of passive optical remote sensing, clouds make the data useless for Earth surface observations. Clouds captured by the sensors of Sentinel-2 were masked out using the quality assurance product (QA60). QA60 is automatically generated during the atmospheric correction processing step, by using Band 10 in the range of 1374 nm and with a spatial resolution of 60m. The QA60 band can have three values: 0 for cloud-free pixels, 1 for dense cloud pixels and 2 for cirrus cloud pixels. In this case, images were filtered using the value 0 of the QA60 band.

Alongside the cloudy pixel masks, query filters were set for the images, by date, using filter Date function and by the region of interest (ROI) filterBounds. The region of interest was defined by ingesting as an asset a vector in CSV (Comma-separated values) format containing the limits of the Mostiștea Plain, in polygon type.

The computation of the NDDI spectral index requires several steps. The first one was the computation of NDVI and NDWI indices by selecting the appropriate bands and using the normalized Difference function, specially designed to provide users the means to quickly calculate normalized difference indices between two bands. In the case of NDVI, bands 8 and 4 were used, and for NDWI - bands 8 and 11. NDDI was calculated combining the previous two spectral indices using simple operators: var NDDI= NDVI.subtract (NDWI). Divide (NDVI.add(NDWI)rename ('NDDI')).

Ui.Chart.image.series function was used in order to generate multi-temporal charts with values of the selected products. The chart values can be exported as CSV files for future analyses. The resulting products were exported in Google Drive using Export.image.toDrive function in Geotiff format than downloaded and stored on the computer. The average size of every product generated in Earth Engine is of about 100 MB. Taking into account that storing a single, unprocessed multispectral Sentinel-2 image takes up about 700 MB of storage space, the possibility of storing only the final product is a great advantage.

The NDDI products were reclassified in ArcMap in six classes using *Reclassify* function from the *Spatial Analyst Toolbox*. In order to calculate the surfaces of each class, the reclassified raster was transformed into vector format. The raster was dissolved by class and the values for each class were calculated in the attribute table.

Results and discussions

The resulting data show a good distribution of satellite images through the entire analysis period, except for late spring and the beginning of summer 2019, when cloud cover over the study area was present for many days in a row.

Fig. 3 illustrates the values of NDVI, NDWI and NDDI during the study period. It can be seen a good correlation between all indices, high values of NDDI being illustrated in periods with low NDWI and NDVI values with a decrease of drought phenomena in periods with green vegetation and high level of plant canopy water.

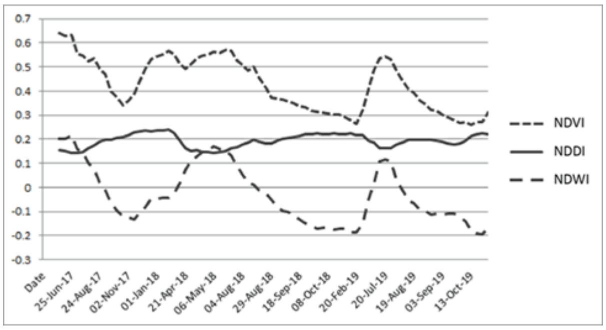

Fig. 3: NDVI, NDWI and NDDI values

The end of summer and the beginning of autumn, a period that in the context of the Mostiștea Plain coincides with the harvesting of the spring crops and pre-sowing period of the autumn crops, shows an increase in drought values. These phenomena affect the autumn crops, especially rapeseed, which is more sensitive to the lack of water than barley or wheat. The lack of vegetation cover during this period exposes soil to different natural external agents such as wind and water, which by means of specific geomorphologic processes contributes to land degradation.

Based on Fig. 3, we can see that NDDI values in the autumn of 2017 are higher than NDDI values of the same season in 2018. The NDVI values for the autumn of 2017 are showing us that a large part of the study area was seeded with autumn crops. When comparing the same interval with the NDWI values, it can be clearly seen that the vegetation water content is low.

A prolonged drought phenomena spanning from the autumn of 2018 until the spring of 2019 can be observed in the constant high values of NDDI. This translates in a short vegetation period during the summer of 2019 described by all three indices.

NDDI values were grouped in five categories in order to better illustrate the magnitude of drought. Values below 0.05 represent water bodies, 0.05 – 0.1 surfaces where drought did not occur, 0.1 – 0.15 light drought, 0.15 – 0.2 moderate drought, 0.2 – 0.25 heavy drought and values above 0.25 represent severe drought. Calculating the surfaces according to the predefined classes, involved the conversion of the raster into vector format, dissolving the vector layer by class and calculating the area for each class. The results were exported into Excel format and charts of the values were produced.

The charts (Fig. 4-6) illustrate hat during 2017 and 2018 approximately 10 sq km were affected by severe drought, while in 2019 severe drought occurred on more than 40 sq km, which count for 4% of the total area. Also, in 2019, heavy drought occurred on 481 sq km (48.23%), making it the most affected year form the study period.

2018 is less affected with 225 sq km (20.83%) of land on which light drought occurred and more than 8 sq km (0.86%) where the drought phenomena did not occur.

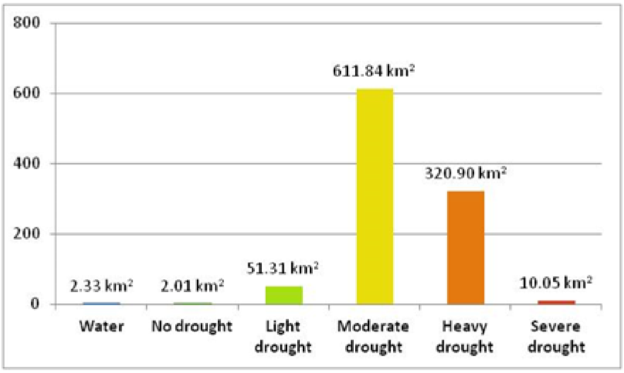

Fig. 4: 2017 NDDI Values

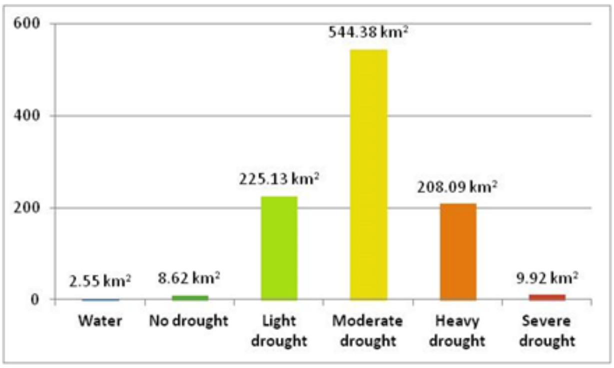

Fig. 5: 2018 NDDI Values

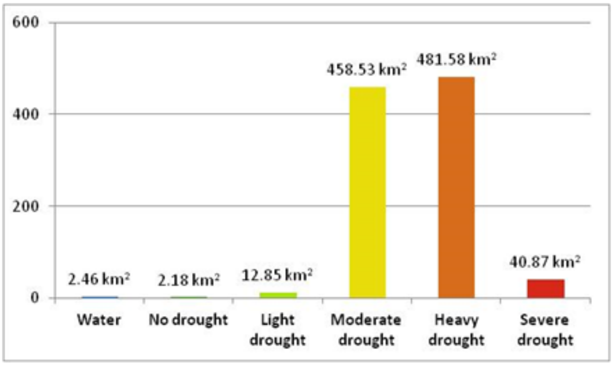

Fig. 6: 2019 NDDI Values

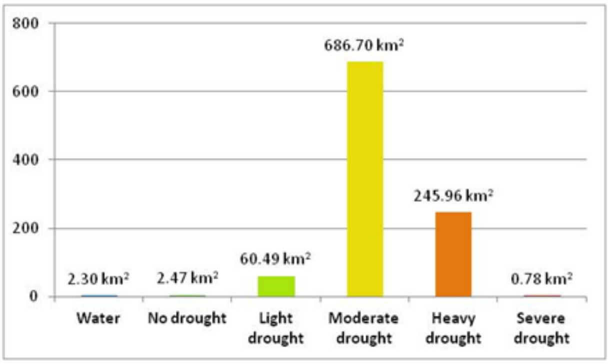

Fig. 7: 2017-2019 average NDDI values

The chart displaying average NDDI values for the entire study area was created by computing the arithmetic average of 2017, 2018 and 2019 (Fig. 7). It shows that during the study period, the Mostiștea Plain mainly experienced moderate drought on 686 sq km counting for approximately 68% of the total area, while heavy drought occurred on 245 sq km (24%).

In order to better illustrate the spatial distribution of the mean annual NDDI values during the study period, four maps of the Mostiștea Plain are presented in Fig. 8. It can be observed that the most affected year by drought is 2019 and the least affected is 2018. The 2017-2019 map represents the arithmetic average of the values for all three years, indicating that drought severity is greater in the center and south eastern region, and less severe in the north western region.

The central part of the Mostiștea Plain coincides with an area with a higher fragmentation of the land parcels. This can be a clue that management of smaller parcels by many farmers is more prone to agriculture drought.

Based on this information, we can conclude that large areas of the Mostiștea Plain are susceptible to agricultural drought. The recent studies such as Dai (2011), shows that because of the current climate change trends, drought events will be more frequent and with greater magnitude. Nowadays, Remote

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Sensing and GIS can greatly improve the knowledge about natural hazards.

Results like the ones presented in this paper are essential for acting in accordance with the extent of drought phenomena in order to reduce or even eliminate its negative effects. One the priorities of the United Nations, in the framework of the 2030 Agenda for Sustainable Development, is the end of hunger by ensuring food production and sustainable agricultural practices. Using such kind of data, local and regional legislators are provided with punctual and reliable data in order to take the best actions.

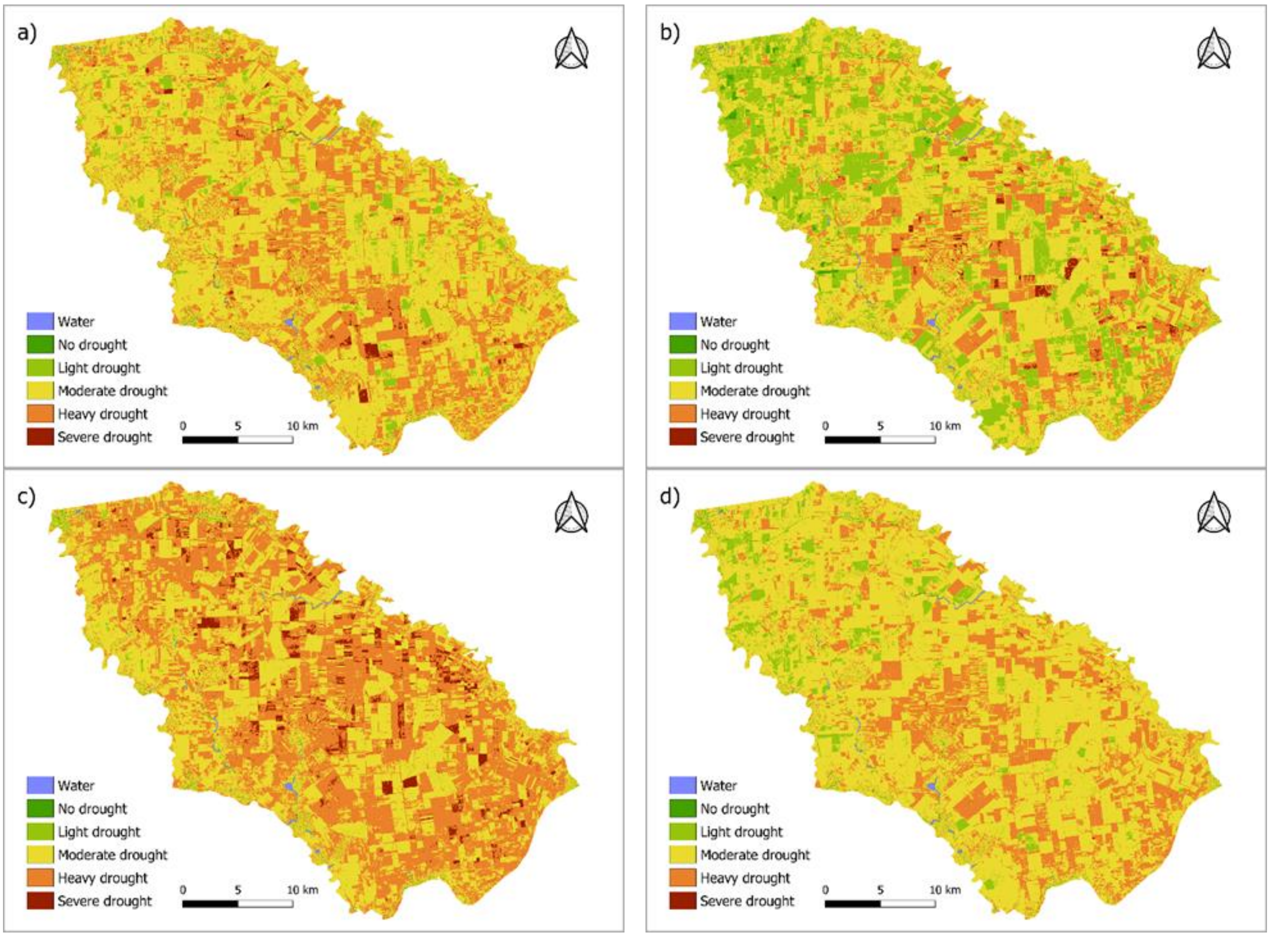

Figure 8: Spatial distribution of agricultural drought in Mostiștea Plain

a) 2017; b) 2018; c) 2019; d) 2017-2019 (Source: authors)

Conclusion

Drought, including the agricultural drought, can have substantial negative impact on economic and social systems. Remote sensing is one of the components that helps identify and evaluate the intensity and spatial distribution over large areas and multiple years. In this instance, Sentinel-2 imagery was used to conduct an assessment of drought phenomena over three years. Google Earth Engine proved to be a very powerful and relatively easy to use application. The vast documentation provided by Google Earth Engine development team enables rapid on understanding how to perform simple and even complex analysis for users with minimum programming knowledge. Sentinel-2 imagery demonstrated to be a good and reliable data source. The high resolution of the images enabled to precisely evaluate the agriculture drought even for small areas.

This application was used to calculate NDVI, NDWI and NDDI for Mostiștea Plain. The results showed that the southern half of the Mostiștea Plain is affected by heavy agricultural drought during 2017-2019 period. The resulting maps show that small parcels, especially in the center of the study area, are the most affected (Fig. 8, d). This can be caused by the uneven exploitation of the land by multiple property owners that are unable to employ sustainable agriculture practices.

At a local level, the good spatial resolution of the Sentinel-2 imagery of 10m, can help farmers assess their parcels. Already, a large number of services targeted at farmers offers remote sensing products based on Sentinel-2 imagery. A product such as NDDI can enable farmers to better understand drought phenomena that affects their farms.

For the future work, we propose to extend the area of interest over the entire Southern Bărăgan Plain, which is one of the most important agricultural areas of Romania.

References

Angearu, C., Irimescu, A., Mihailescu, D. & Vîrsta, A. (2018). Evaluation of Drought and Fires in the Dobrogea Region, using Modis satellite data. ”Agricultural for Life Life for Agriculture” Conference Proceedings, 1, 336-345.

Crocetti, L., Forkel, M., Fischer, M., Jurečka, F., Salentining, A., Trnka, M., Anderson, M., Ng, W-T., Kokalj, Z., Bucur, A. & Dorigo, W. (2020). Earth Observation for agricultural drought monitoring in the Pannonian Basin (southeastern Europe): current state and future directions. Reg Environ Change 20, 123.

Dai, A. (2011). Drought under global warming: a review. *Wiley Interdisciplinary Reviews: Climate Change*, 2, 45-65.

Gao, B. (1996). Difference water index for remote sensing of vegetation liquid water from space. *Remote Sens. Environ*., 58, 257-266.

Grecu, G., Zaharia, L., Ghiță, C., Comănescu, L., Cîrciumaru, E. & Albu, M. (2012). *Sisteme hidrogeomorfologice din Câmpia Română. Hazard – Vulnerabilitate – Risc.* Editura Universității din București.

Heim, R. R. J. (2002). A review of twentieth-century drought indices used in United States. *Bull. Am. Meteolorol. Soc*., 83 (8), 1149-1165.

Hu, X., Ren, H., Tansey, K., Zheng, Y., Ghent, D., Liu, X. & Yan, L. (2019). Agriculture drought monitoring using European Space Agency Sentinel 3A land surface temperature and normalized differ-ence vegetation index imageries. *Agricultural and Forest Meteorology*, 279, 2019, 107707.

Jiménez-Donaire, M., Tarquis, A. & Vicente Giráldez, J. (2020). Evaluation of a combined drought indicator and its potential for agricultural drought prediction in southern Spain. *Nat.Hazards Earth.Sci*,20, 21-33.

Lee, S.J., Cho, J., Hong, S., Ha, K.J., Lee, H. & Lee, Y.W. (2016). On the relationships between satellite-based drought index and gross primary produc-tion in the North Korean croplands, 2000–2012. *Remote Sens. Lett*., 7 (8), 790-799.

Mannocchi, F., Todisco, F. & Vergni, L. (2004). Agricultural drought: indices, definition and analysis. The Basis of Civilization-Water Science: Proceeding of the UNESCO/IAHS/IWHA Symposium.

Mateescu, E., Smarandache, M., Jeler, N. & Apostol, V. (2013). Drought conditions and management strategies in Romania. Retrieved from the https://www.droughtmanagement.info/literature/UNW-DPC_NDMP_Country_Report_Romania_2013.pdf.

Mihăilescu, V. (1925). Vlăsia și Mostiștea. Evoluția geografică a două regiuni din Câmpia Română. Buletinul Societății Regale Române de Geografie, XLIII.

Renza, D., Martinez, E., Arquero, A. & Sanchez, J. (2010). Drought Estimation Maps by Means of Multidate Landsat Fused Images. Remote Sensing of Science, Education and Natural and Cultural Heritage, 275-282.

Rouse, J.W., Haas, R.H., Schell, J.A. & Deering, D.W. (1973) Monitoring the vernal advancement and retrogradation (green wave effect) of natural vege-tation. *Prog. Rep*. RSC 1978-1.

Serrano, J., Shahidian, S. & Marques da Silva, J. (2019) Evaluation of Normalized Difference Water Index as a Tool for Monitoring Pasture Seasonal and Inter-Annual Variability in a Mediterranean Agro-Silvo-Pastoral System. Water, 11, 62.

Stăncălie, G., Nertan, A. & Șerban, F. (214). Agricultural Drought Monitoring Using Satellite-Based Products in Romania. Proceedings of the Third International Conference on Telecommunications and Remote Sensing, 100-106.

Vizitiu, O-P., Claciu, I.C. & Simota, C.C. (2016). Drought intensity on arable land in Romania – processes and tendencies. *Lucrările Seminarului Geografic Dimitrie Cantemir*, Vol. 42, 67-80.

Wilhite, D.A. & Glantz, M.H. (1985) Understanding: the Drought Phenomenon: The Role Of Definitions. Water International, 10 (3), 111-120.

Wilhite, D.A. (1993) Understanding the Phenomenon of Drought. *Hydro Review*, 12:5.

Yağcı Levent, A., Liping, D. & Meixia, D. (2014). The influence of land cover-related changes on the NDVI-based satellite agricultural drought indices. *International Geoscience and Remote Sensing Symposium* (IGARSS), 2054-2057.