RELATIONSHIPS BETWEEN LAND DEGRADATION AND CLIMATE CHANGE VULNERABILITY OF AGRICULTURAL WATER RESOURCES

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ABSTRACT

According to the methodology for determining land degradation adopted by the UN for the calculation of the sustainable development goal's (SDG) indicator 15.3.1, land productivity on the basis of remote sensing data is one of the three sub-indicators. At the same time, the process of land degradation is very complex and it has not yet been studied how it is affected by climate changes. This task is complicated by the fact that climate change has consequences in the future. However, satellite data have a long history of observations and therefore we can see, how climate indicators affect the process of land degradation in historical terms. In this paper, we used MODIS satellite data to calculate land productivity and estimated the relationship between land productivity and climate change vulnerability of agricultural water resources (CCV) obtained by SWAT model for Ukraine. Correlation and regression analysis show that the climate change vulnerability of agricultural water resources is one of the indicators of land degradation.

***Index Terms*—** SDG, land degradation, Trends.earth, SWAT, climate change

1. INTRODUCTION

Land degradation is a complex phenomenon that needs further study to monitor it and reduce the negative impact on the environment. One of the definitions of land degradation used in modern practice is a long-term decline in the functioning of the ecosystem, which can be expressed in reduced biophysical indicators of vegetative biomass [1, 2]. This definition makes it possible to use remote sensing tools to calculate and monitor areas that have manifestations of land degradation [3]. Further research in this direction made it possible to calculate the sustainable development goal's indicator 15.3.1 "Proportion of land that is degraded over total land area", adopted by the UN for goal 15 "Life on Land" [4]. This technology is already used for the SDG support and provided great results on the land degradation assessment in different countries of Europe [5] and Asia [6]. The core product for SDG monitoring based on this technology is MODIS NDVI collection that have moderate 250 m. spatial resolution and has been updated daily since the 2000s. The main reason why this data are most used is the long time series of satellite images. However, modern approaches to harmonization of the Sentinel-2 and Landsat-8 satellite data [7] make it possible to improve the methodology for the NDVI trend calculation and obtain land productivity maps with higher spatial resolution [8]. These modifications as well as use of local data, such as land cover or crop type maps [9,10], are very important, because they give possibility to improve agricultural monitoring and food security in countries under development by support of UN SDGs [11]. In addition to the development of technology for monitoring land degradation, there are also software solutions that implement these technologies through the cloud environment. One of the projects developing tools for monitoring land degradation indicators is the Trends.earth, which is a convenient plugin for the QGIS, which through the Google Earth Engine platform makes it possible to build productivity maps and indicator 15.3.1 maps for any area in the world.

An important issue that arises in the study of the phenomenon of land degradation is the impact on this process of climate change and the role of human activities in the climate change. Climate change due to the impact on agroclimatic indicators significantly influence the water balance in ecosystems [12, 13], which has a particularly negative impact on the condition and development of crops. This effect can be seen through models that provide information on soil and water status through impact analysis of land use, land management practices, and climate change. Such a model is the SWAT, which is widely used in the world to assess climate change on the water balance of territories [14]. To conduct this research, several outputs produced in the scope of the 'EnviroGRIDS: Building Capacity for a Black Sea Catchment (BSC) Observation and Assessment System supporting Sustainable Development' were used. [15]. To conduct hydrological analyses of the 2.2 mio km^2 catchment area, the Soil and Water Assessment Tool was set up and calibrated by Rouholahnejad [16]. All the resulting datasets of this project are freely available on a web platform (http://blacksea.grid.unep.ch).

2. STUDY AREA

Ukraine has a total area of more than 600,000 km^2 and is bordered by two seas to the South: The Sea of Azov and the Black Sea. Agriculture represents 68% of the country's total area and more than 10% of its Gross Domestic Product (GDP). We can usually distinguish three to four agro-climatological zones in Ukraine:

- The *humid zone*, with temperatures ranging from -4°C to 17°C, covers most of the northwestern part of the country, including the Carpathian Mountains. The average annual precipitation is 600mm (including snow).
- The *warm* and *semi-arid zones*, with temperatures ranging from -6°C to 21°C, cover half the country, mostly in the eastern and central forested steppe. The average annual precipitation lies between 450 and 500mm.
- The *arid zone*, with temperatures ranging from 0°C to 23°C, covers the south of the country and gets an average of 360mm precipitation per year.

Industry and agriculture are the two main drivers of water withdrawals in the country, extracting respectively 48% et 30% of total withdrawals. Irrigation has traditionally been developed in the arid zone (Southern Ukraine) and it is estimated that more than 2 mio ha of agricultural land are equipped for irrigation. However, in 2003, only a third of these lands were actually irrigated.

3. DATA

3.1 SWAT data

To assess vulnerability, as defined by the Intergovernmental Panel on Climate Change (IPCC), three climate change scenarios should be considered: an increase in temperature, a decrease in precipitation and the combination of both. For our study, we focus on the third scenario to analyze climate change impacts on agricultural water resources. To achieve this research's objectives, we used a dataset produced by Bär et al. [12], who assessed the vulnerability of agricultural water resources to climate change in the BSC. As virtually all the territory of Ukraine is part of the BSC, we used the results pertaining to our study area (fig. 1).

There are usually three main inputs required to run a simulation of SWAT for a given water catchment: a digital elevation model (DEM), used to build river networks and determine topography, a soil type map and a landuse map. Based on the DEM, the model will delineate the watershed and create subbasins. Further, each unique combination of slope, soil type and landuse will define Hydrological Response Units (HRUs). For this study, results were presented at the subbasin scale, while analyses were performed at the HRU scale.

Through the model, outputs were simulated for the period 1970 – 2006. To conduct the vulnerability assessment, a simulation with a climate change scenario of +3°C and -30% precipitation rate was also performed. The agricultural vulnerability to climate change defined by analyzing the yearly change in the number of days where climatic conditions allow for plant growth, taking into account the days where there is potential for irrigation. When a subbasin has a negative change in plant growth days, it is vulnerable to a change in climatic conditions. A subbasin with additional plant growth days benefits from climate change.

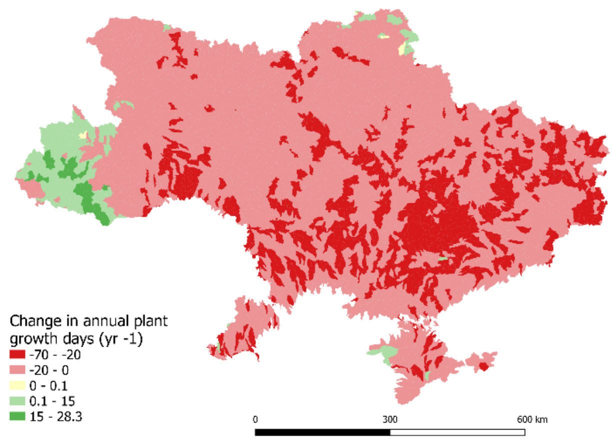

Figure 1. climate change vulnerability of agricultural water resources for Ukraine

3.2 Trends.Earth plugin usage

To calculate the indicator 15.3.1 for a certain area, three sub-indicators should be computed: trends in land cover, land productivity and carbon stocks. If one of these indicators has a declining trend for a certain land unit, then the land unit will be classified as degraded, even if the other two indicators are improving ("One Out, All Out" principle). The second sub-indicator, land productivity, is the biological capacity of land to produce food and is usually approximated by vegetation indices, notably the Normalized Difference Vegetation Index (NDVI) (UNCCD, 2017). This sub-indicator is core product in our study, because it reflects the ecosystem functionality in terms of vegetation quality.

In our study, we used Trends.Earth (TE) to calculate NDVI trend, using global, publicly available datasets. TE is a free and open-source Quantum GIS plugin created as part of the project "Enabling the use of global data sources to assess and monitor land degradation at multiple scales", which is funded by the Global Environment Facility (GEF) TE uses Google Earth Engine cloud computing facilities to perform complex calculations.

For the purpose of this study, we used the default datasets, which are the following: the ESA Climate Change Initiative-Land Cover (CCI-LC) global dataset, at 300m spatial resolution (7 land cover classes), and MODIS NDVI 250m spatial resolution dataset.

4. DATA ANALYSIS

For the experiment we firstly masked not agricultural areas on NDVI trend map by land cover map. After, we calculated mean NDVI trend values for each subbasin polygon and removed all polygons with high percentage of non-agriculture areas. In addition, we normalized values of NDVI trend and CCV. The values between 0 and 0.2 for CCV were removed, in this interval due to the appearance of noise for these small number of points. As the result we obtained 2406 subbasin with NDVI trends and CCV values. For the analysis we used two techniques: correlation analysis and regression analysis. In the correlation analysis Pearson r coefficient is used to evaluate the linear dependence between two values. In the regression analysis we fit linear and polynomial regression function to evaluate how CCV can represent variance of NDVI trend by R-squared coefficient. Also for the linear regression function, the angular a1 coefficient represent the dependences between changes of two values. Taking into account the difference in the spatial resolution of both datasets, we conducted analysis for the all values as well as for mean values of NDVI trend for each 411 unique values of CCV.

5. RESULTS

Figure 2 represent the dependence between CCV and NDVI trend. We can see a weak correlation equal 0.44 and linear regression function represent a small variance. But the a1 coefficient is 0.77.

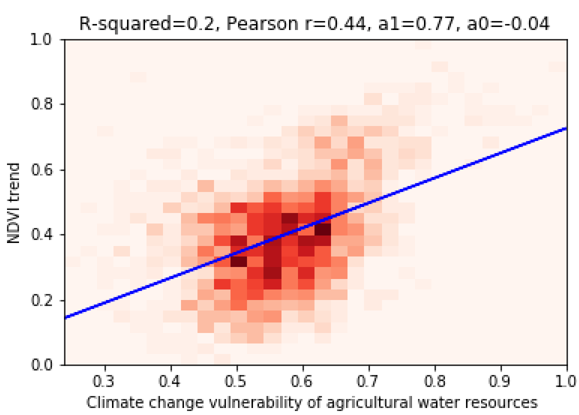

Figure 2. 2-d histogram and regression function for the CCV and NDVI trend dependence.

The figure 3 represent square dependence between CCV and NDVI trend. The Pearson correlation was calculated for CCV square and NDVI trend. We can see that R-squared and Pearson r are better than for linear function, but they are steal reflect weak dependence. It can be explained by the fact that spatial resolution of NDVI trend map is 250 m, while CCV are modeling results based on the large subbasin units and, thus CCV has much smaller variability then NDVI trend. Thus, we aggregated the values of NDVI trend by the unique values of CCV. The figure 4 represent the linear dependence between aggregated CCV and NDVI trend by mean value for each HRU. Now we can see strong correlation between this two values as well as the goodly fitted linear regression function with R-squared equal to 0.49. This result show that CCV is strongly correlated. However, we also see the quadratic patterns of the dependences of this values. The figure 5 represent square dependence between aggregated CCV and NDVI trend.

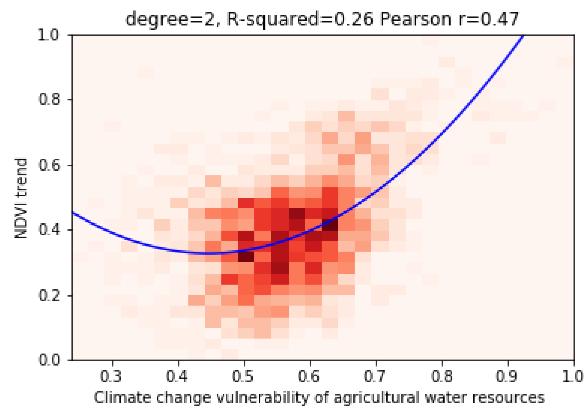

Figure 3. 2-d histogram and square regression function for the CCV and NDVI trend dependence.

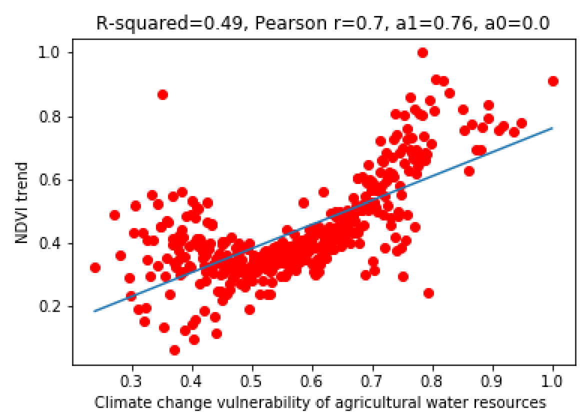

Figure 4. Linear regression function for the aggregated CCV and NDVI trend

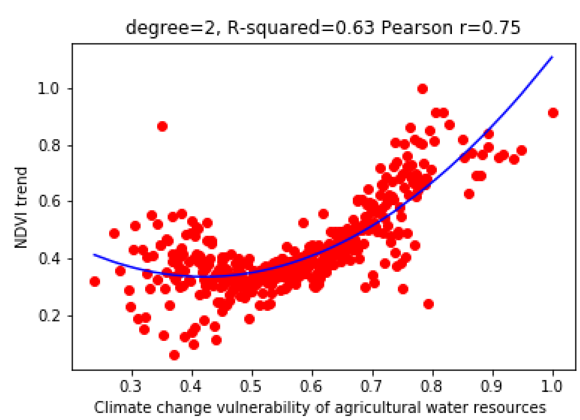

Figure 5. Square regression function between aggregated CCV and NDVI trend

Now we can see very good representation of variance by regression function with R-square coefficient equal 0.63. and Pearson r coefficient 0.75. The strong correlation of this values means that CCV can be used as one of the indicator of land degradation that reflect the changes of NDVI trend influenced by climate change.

6. DISCUSSION AND CONCLUSIONS

Land degradation is a serious challenge to humanity. The main driver of this process has long been considered anthropogenic impact on ecosystems, while factors related to climate change have been ignored. However, climate change is also partly an anthropogenic process and therefore its impact needs to be assessed in relation to land degradation. The experiment showed a strong relationship between climate change and land degradation, which is reflected in the quadratic relationship between climate change vulnerability of agricultural water resources and NDVI trend.

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11. REFERENCES

[1] Bai, Z. G., et al. Global assessment of land degradation and improvement: 1. identification by remote sensing. No. 5. ISRIC-World Soil Information, 2008.

[2] Kolotii, A., et al. "COMPARISON OF BIOPHYSICAL AND SATELLITE PREDICTORS FOR WHEAT YIELD FORECASTING IN UKRAINE." International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences (2015).

[2] Giuliani, Gregory, et al. "Knowledge generation using satellite earth observations to support sustainable development goals (SDG): A use case on Land degradation." International Journal of Applied Earth Observation and Geoinformation 88 (2020): 102068.

[3] Prince, S. D. (2019). Challenges for remote sensing of the Sustainable Development Goal SDG 15.3. 1 productivity indicator. Remote Sensing of Environment, 234, 111428.

[4] Giuliani, Gregory, et al. "Monitoring land degradation at national level using satellite Earth Observation time-series data to support SDG15–exploring the potential of data cube." Big Earth Data 4.1 (2020): 3-22.

[5] Wang, Tuo, et al. "Supporting SDG 15, Life on Land: Identifying the Main Drivers of Land Degradation in Honghe Prefecture, China, between 2005 and 2015." ISPRS International Journal of Geo-Information 9.12 (2020): 710.

[6] Claverie, Martin, et al. "The Harmonized Landsat and Sentinel-2 surface reflectance data set." Remote sensing of environment 219 (2018): 145-161.

[7] Kussul, Nataliia, et al. "A workflow for Sustainable Development Goals indicators assessment based on high-resolution satellite data." International Journal of Digital Earth 13.2 (2020): 309-321.

[8] Kussul, Nataliia, et al. "Deep learning classification of land cover and crop types using remote sensing data." IEEE Geoscience and Remote Sensing Letters 14.5 (2017): 778-782.

[9] Shelestov, Andrii, et al. "Cloud approach to automated crop classification using Sentinel-1 imagery." IEEE Transactions on Big Data 6.3 (2019): 572-582.

[10] Kussul, Nataliia, et al. "Crop inventory at regional scale in Ukraine: developing in season and end of season crop maps with multi-temporal optical and SAR satellite imagery." European Journal of Remote Sensing 51.1 (2018): 627-636.

[11] Kussul, Nataliia N., et al. "The wide area grid testbed for flood monitoring using earth observation data." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 5.6 (2012): 1746-1751.

[12] Kravchenko, A. N., et al. "Water resource quality monitoring using heterogeneous data and high-performance computations." Cybernetics and Systems Analysis 44.4 (2008): 616-624.

[11] White, Eric D., et al. "Development and application of a physically based landscape water balance in the SWAT model." Hydrological Processes 25.6 (2011): 915-925.

[12] Bär, R., Rouholahnejad, E., Rahman, K., Abbaspour, K. C., & Lehmann, A. (2015). Climate change and agricultural water resources: A vulnerability assessment of the Black Sea catchment. Environmental Science & Policy, 46, 57-69.

[13] Lehmann, A., Guigoz, Y., Ray, N., Mancosu, E., Abbaspour, K. C., Freund, E. R., ... & Giuliani, G. (2017). A web platform for landuse, climate, demography, hydrology and beach erosion in the Black Sea catchment. Scientific data, 4(1), 1-15.

[14] Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2011). Soil and water assessment tool theoretical documentation version 2009. Texas Water Resources Institute.

[15] EnviroGRIDS: http://envirogrids.net/

[16] Rouholahnejad, Elham, et al. "Water resources of the Black Sea Basin at high spatial and temporal resolution." Water Resources Research 50.7 (2014): 5866-5885.