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The Use of Remote Sensing Techniques in the Analysis of the Influence of Forest Ecosystems over the Precipitation

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Abstract: The processing of remote sensing images and their integration into a Geographic Information System (GIS) to analyse and manage an area represents a modern approach that is increasingly used. In the present paper, a predominantly mountainous area was studied and analysed, located in Hunedoara County – Romania, near the city of Hateg and the Retezat Mountains. A satellite scene from 09.24.2019 from the RapidEye remote sensing system was retrieved, processed and subjected to complex remote sensing analyses. These remote sensing data were analysed and processed, and based on them a series of specific indices were calculated and interpreted, namely, for the characterisation of the vegetation: NDVI (Normalised Difference Vegetation Index), GNDVI (Green Normalized Difference Vegetation Index), NDRE (Normalised Difference Red Edge Index), SAVI (Soil Adjusted Vegetation Index), MSAVI (Modified Soil Adjusted Vegetation Index), CI Green (Chlorophyll Index Green), CI Red Edge (Red Edge Chlorophyll Index), RTVI core (Red Edge Triangular Vegetation Index), SR (Simple Ratio), Red Edge SR (Red Edge Simple Ratio), LAI (Leaf Area Index).

Keywords: GIS, monitoring, NDVI, rainfall interception

1. Introduction

Based on remote sensing, various studies have been carried out for monitoring the land surface: land cover (Vittek et al. 2013), forest cover (Hansen et al. 2013), forest pest monitoring (Rullan-Silva et al. 2013), deforestation (Achard et al. 2014), fires, urban changes (Huang et al. 2017), floods and precision agriculture (Redo & Millington 2011).

The relationship between precipitation and vegetation has been analysed and researched in many areas of the globe and various types of ecosystems on all continents (Maurer et al. 2020, Hawinkel et al. 2016). In the last 30 years, more and more such studies have used remote sensing technology as an investigative technique (Huete et al. 1997) in forest monitoring processes and for land cover mapping. Based on remote sensing images, many vegetation indices have been developed that allow the monitoring of very large areas and in a relatively short time. An evaluation of the response of vegetation to precipitation requires a differentiation of the types of vegetation analysed (Gallagher et al. 2019).

Remote sensing techniques are very useful in health assessment studies on the integrity of forest ecosystems. Forest biomass growth is closely related to global climate change, and the average annual temperature and average annual precipitation are the most important factors influencing forest biomass (Huang et al. 2021, Peng et al. 2014, Zhang et al. 2023).

Interception is the process by which part of the atmospheric precipitation is captured and retained by vegetation, after which it evaporates. Interception is one of the essential components of the hydrological cycle of water; it also influences the spatial distribution of water infiltration, soil erosion, and leakage, and vegetation canopies play a vital role in the hydrological process of ecosystems. This amount of water retained by vegetation canopies plays a significant role in the hydrological balance equation. It, therefore, cannot be neglected; in similar studies, it is called interception storage capacity. Evaluating these time and space variable hydrological parameters are the key elements for the sustainable development of water resources. Over time, several models have been developed to estimate the amount of rainfall interception. Still, the most used/known are the Gash and Rutter models, which have the canopy storage capacity as the basic component. The two rainfall interception models, the Rutter and Gash models, are different, the first being a conceptual model and the second being an analytical model (Muzylo et al. 2009).

The database available for this paper/research is not sufficient, so the quantification of these hydrological parameters by traditional methods is limited, therefore, satellite images were used. One of the parameters estimated based on remote sensing and used in calculating precipitation interception is the leaf surface index (LAI).

Compared to hardwood forests, softwood forests retain more water from the atmospheric precipitation. In the case of spruce and fir species, the water retention can reach up to 80%.

The main objective of this study is to analyse the existing relationship between forest ecosystems and precipitation using modern tools in the field of remote sensing and geographic information systems. Based on the images taken from the Rapid Eye system, several vegetation indices were determined that offer an overall vision in the monitoring process of the analysed forest ecosystem located in Romania – Hunedoare County.

2. Materials and Methods

2.1. Study area

The study area is predominantly mountainous in Hunedoara County near the town of Hateg and the Retezat Mountains and is part of the Mures river basin (Fig. 1).

The precipitations in the Mures river basin fall in different quantities. Thus, in the Carpathian chain compared to the western circulation, there are considerable differences between the quantities measured at different points from this river basin. The average annual rainfall per basin is between 480 mm and 980 mm, and the multiannual average is 610 mm.

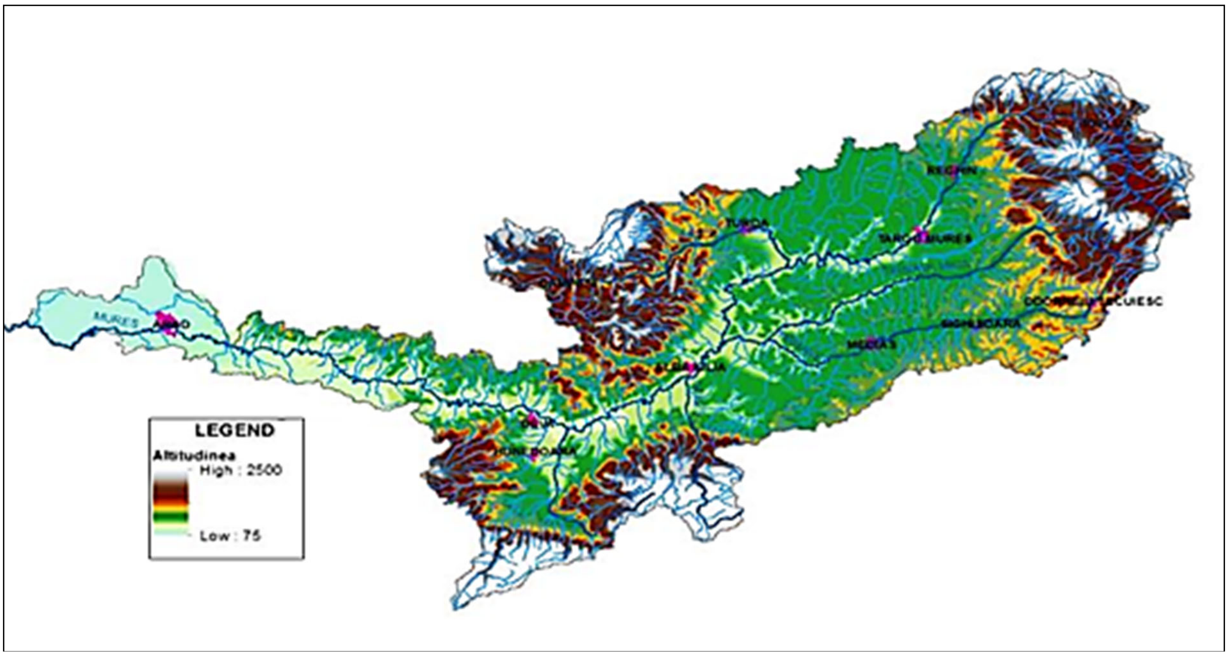

Fig. 1. DEM of Mures catchment

2.2. Satellite system and indices used

In the analysis, a satellite scene from 24 August 2019 from the Rapid Eye system (PlanetTeam, 2017) was used, which is composed of 5 spectral bands, namely, Red (630-685 nm), Green (520-590 nm), Blue (440-510 nm), Red Edge (690-730 nm) and Near Infrared (760-850 nm).

Also, for a morphological characterisation of the area, a Digital elevation model was used based on which the Aspect Map and the Slope Map were generated. This data was processed using ArcGIS Pro v. 2.60 software (Fig. 2).

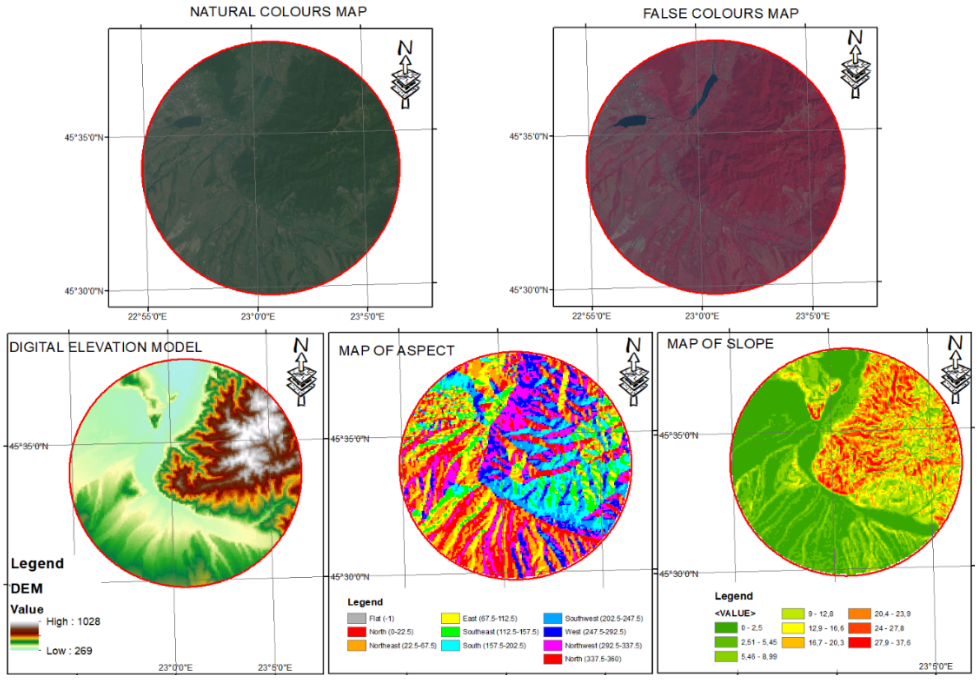

Fig. 2. Digital Elevation Model, Map of Aspect and Map of Slope

To carry out the proposed research, the NDVI (Normalised Difference Vegetation Index) (Rouse et al. 1973) and Leaf Area Index (LAI) were calculated for an analysis of the gas – vegetation exchange phenomenon (photosynthesis, evapotranspiration, precipitation interception, carbon flow).

$$\mathrm{NDVI} = \left(\frac{\mathrm{NIR}-\mathrm{Red}}{\mathrm{NIR}+\mathrm{Red}}\right) \tag{1}$$

2.3. Hydrological modeling

With the help of multispectral images and the NDVI index, the vegetation variables are determined, namely the Leaf Area Index (LAI) parameter, used in many hydrological models to determine evapotranspiration. The vegetation standardisation difference index (NDVI) is one of the most used indices for monitoring vegetation dynamics globally (Vrieling et al. 2013), with values between -1 and 1.

This paper uses the relation between LAI and NDVI, using the reflection properties of vegetation to assess the vegetation cover of the study area. The relation between the NDVI and LAI parameters is taken over from Tabarant (2000):

$$\mathrm{LAI} = 8.238 * \mathrm{NDVI} - 2.93 \tag{2}$$

The storage capacity depends on the vegetation type; thus, the capacity of a coniferous forest differs from that of deciduous trees. The maximum storage in the canopies parameter (Smax) is directly related to the LAI parameter, and to determine the calculation method, they will be adapted according to the vegetation types. In recent years, land use has undergone significant changes. This aspect participates along with other factors in climate change both in our country and globally. The rainfall retention capacity depends on the respective area's category/land cover types.

These land use changes disrupt the hydrological cycle of the river basin, in which there are changes between the input and output parameters of the system. Some anthropogenic activities such as deforestation and overgrazing reduce evaporation and initiate a feedback mechanism that leads to decreased rainfall (CLC 2006, CLC 2012, CLC 2018) and urbanisation over large areas causes several large-scale effects, which cause floods and increased flows on watercourses, or in some areas the reduction of these flows and the intensification of extreme phenomena – storms (Barbosa et al. 2020, Balazovicova & Skodova 2022).

Figures 3 and 4 show the study area after the classification process, in which the agricultural area has a percentage of 49.8%, followed by forested areas with a percentage of 42.39%. In this paper, based on the land cover maps generated with the GIS program, the types of vegetation required for the leaf area index (LAI) are estimated. The interception of precipitation by vegetation canopy is determined by the maximum storage capacity (Smax) (De Roo et al. 1996):

$$S_{max} = 0.935 + 0.498 \cdot \mathrm{LAI} - 0.00575 \cdot LAI^2 \tag{3}$$

where:
LAI – Leaf Area Index parameter

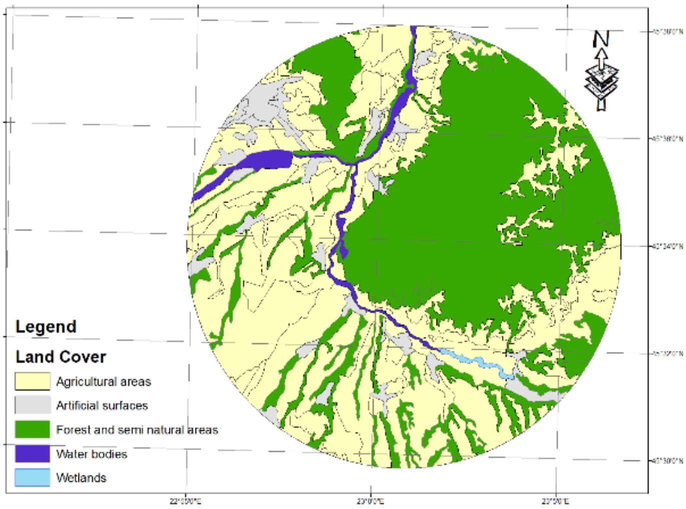

Fig. 3. The Map of Land Cover

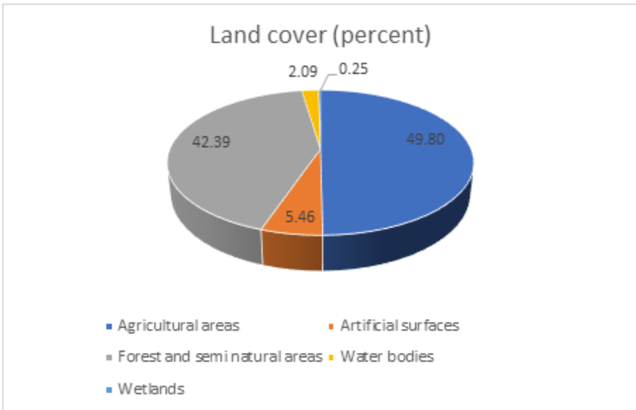

Fig. 4. The distribution of the land cover of the study area

3. Results and Discussion

LAI estimation based on remote sensing spectral data considers the green leaf characteristics. The vegetation index is a unique numerical value that indicates the reflectivity of ground objects using wavelength ranges and linear or nonlinear calculations to generate certain indications of vegetation and biomass increase.

Next, NDVI indices were determined for the study area, where values lower than zero indicate land without vegetation cover (desert, bare ground, cloud, snow, water formations, etc.), and values higher than zero indicate vegetation cover, respectively the LAI index (Leaf Area Index) an important variable used to estimate evapotranspiration (Fig. 5). Also the profile of NDVI and LAI are presented in Fig. 6 and Fig. 7.

The LAI index is one of the main parameters to estimate the precipitation interception rate. A coniferous forest from the Mures river basin was chosen as a study area to estimate the precipitation interception.

Interception is an important factor in understanding the hydrological effects of plant cover and modelling the hydrological balance/water cycle. This hydrological parameter is also helpful in estimating vegetation's effect on runoff in those areas. Based on the LAI indices obtained for this area under study, the maximum storage capacity (Smax) is determined (Fig. 8).

Scientific research on the basins in our country shows that the litter of a deciduous forest of about 90 years retains between 3 and 4 mm (Abagiu et al. 1980). From the specialised literature, the average annual transpiration for various tree species falls between the values: spruce 300-320 mm/year, beech 250-300 mm/year, oak 120-300 mm/year, pine 120-300 mm/year, larch up to 680 mm/year.

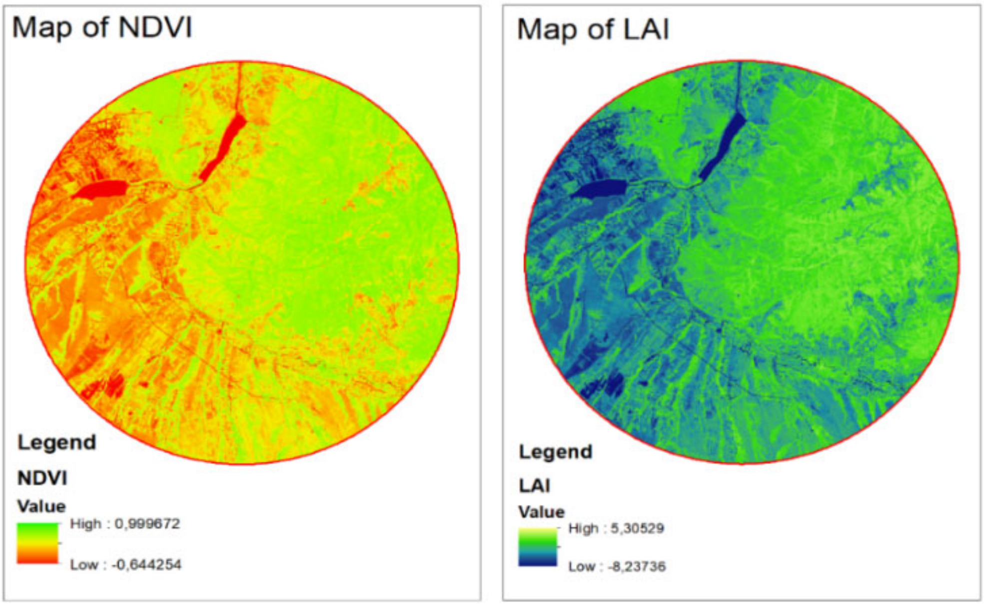

Fig. 5. The Map of NDVI Index and The Map of LAI parameter

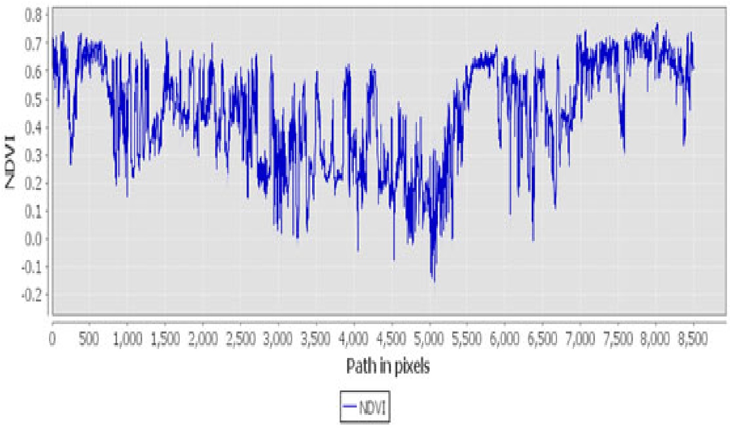

Fig. 6. Profile for NDVI

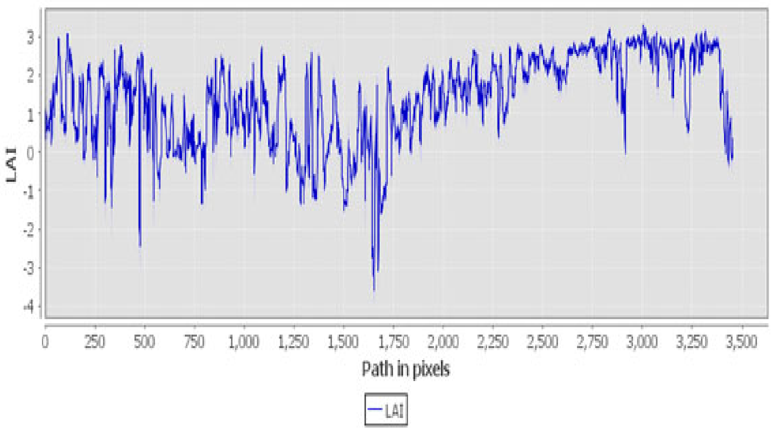

Fig. 7. Profile for LAI

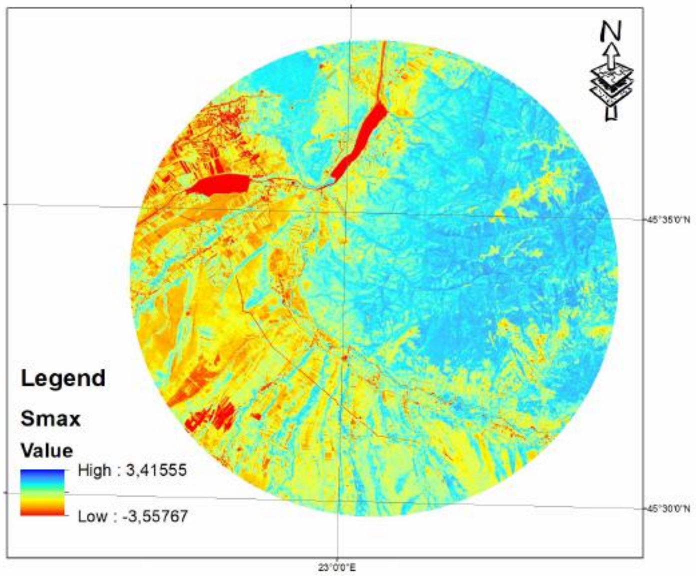

Fig. 8. Maximum storage capacity

The average monthly rainfall for Deva, Ruschita and Magureni is presented in Fig. 9. Based on ArcGIS software, precipitation data were interpolated by the IDW method using daily average precipi-tation values for August 2019 (https://chrsdata.eng.uci.edu/) (Fig. 10).

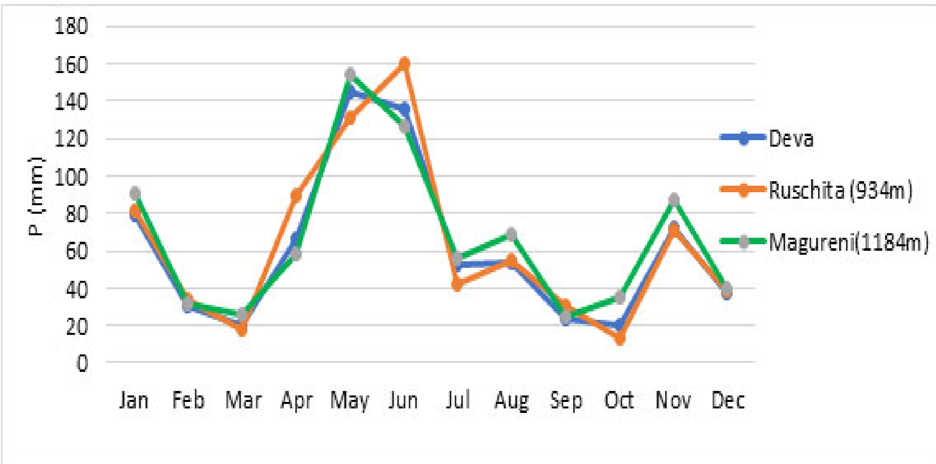

Fig. 9. Average monthly rainfall

The LAI parameter values calculated using the GIS program from the satellite image for our location are plotted against the NDVI values of the same study area (Fig. 11). Next is the linear regression analysis be-tween vegetation indices (NDVI) calculated in the previous stages based on remote sensing images and Leaf Area Index (LAI), respectively between the maximum storage capacity (Smax) and Leaf Area Index (LAI) (Fig. 12).

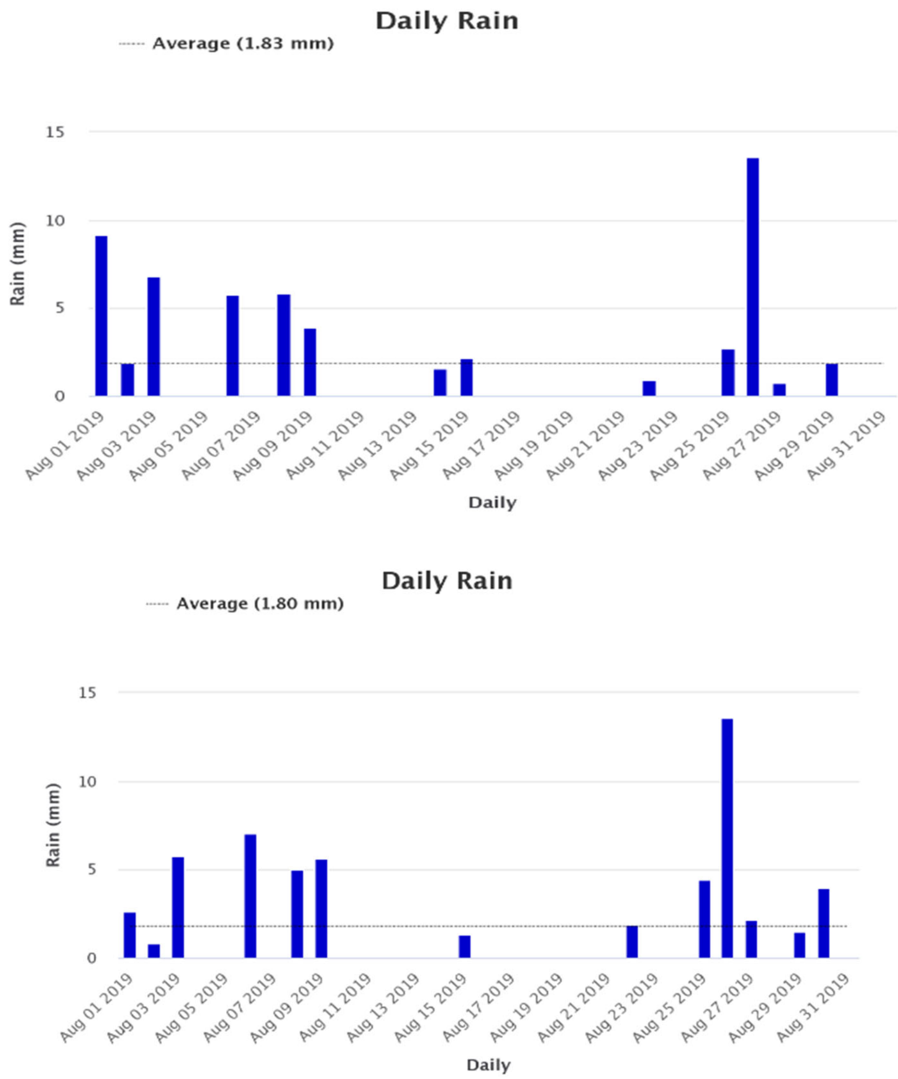

Fig. 10. Average daily rainfall (a) from Magura and (b) from Deva

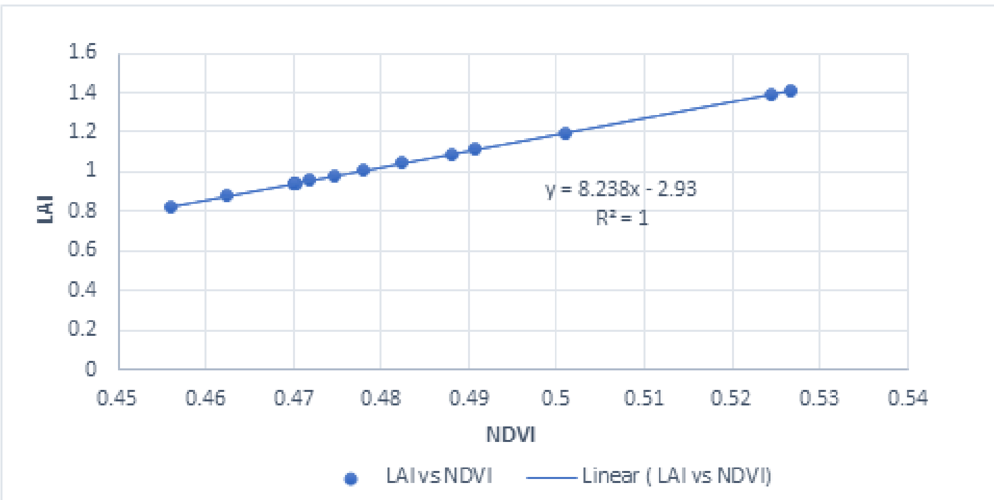

Fig. 11. Linear correlation between LAI and NDVI

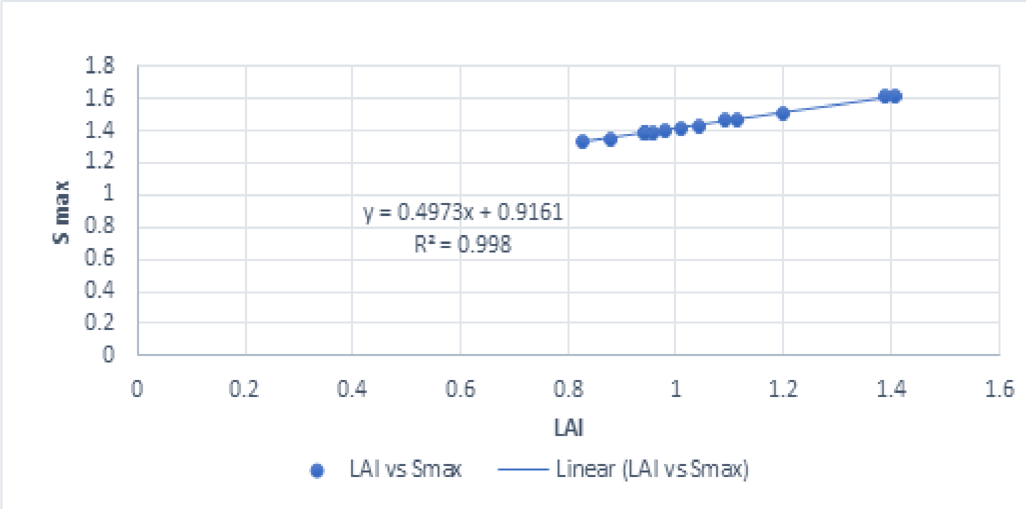

Fig. 12. Linear correlation between LAI and Smax

By applying the equation of 1st degree for the two parameters Smax and LAI, Table 1 is created. Similar studies demonstrated that high rainfall intensities coincide with high storage capacities due to dynamic storage (Keim et al. 2006).

Table 1. Regression analysis LAI – Smax

REGRESSION STATISTICS								
Multiple R					0.999015			
R Square					0.99803			
Adjusted R Square					0.997866			
Standard Error					0.004036			
Observations					14			
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0.099068	0.099068	6080.448	1.32E-17			
Residual	12	0.000196	1.63E-05					
Total	13	0.099263						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.916127	0.006793	134.8555	1.86E-20	0.901325	0.930928	0.90132	0.93092
LAI	0.497287	0.006377	77.97723	1.32E-17	0.483392	0.511182	0.48339	0.51118

4. Conclusions

This paper analysed the morphological variables of the canopy that affect the rate of interception of precipitation and demonstrated the importance of the spatial distribution of the canopy LAI. The NDVI index (Normalised Difference Vegetation Index) was determined based on the spectral bands to characterise the vegetation in the study area. The LAI index (Leaf Area Index) was determined for rainfall interception.

The LAI indicator is a variable used in various production, hydrological, and ecological models (Running & Coughlan 1988, Bonan 1998). The LAI parameter must be determined at moderate and high spatial resolutions To obtain a high precision. The NDVI – LAI relationship is a principal or unique approach for a high temporal resolution in regional and global scale studies.

Very strong correlations were found between the Leaf Area Index (LAI) and the Normalised Difference Vegetation Index (NDVI), respectively, between LAI and Maximum Storage Capacity (Smax).

LAI is an important biophysical parameter of vegetation and represents a ratio between the leaves' surface and the soil surface unit. In the long run, monitoring the LAI parameter can be useful in understanding the dynamic changes of climate impact on forest ecosystems.

References

Abagiu, P., Bumbu, G., Munteanu, St. (1980). *Determinarea parametrilor hidrologici ai pădurii în raport cu modul de gospodărire, scurgerea de suprafaţă şi intercepţia în coronament în arborete de fag şi molid*. Departamentul Ssilviculturii, Institutul de Cercetări şi Amenajări Silvice, Bucureşti.

Achard, F., Beuchle, R., Mayaux, P., Stibig, H.-J., Bodart, C., Brink, A., Carboni, S., Desclée, B., Donnay, F., Eva, H.D. (2014). Determination of tropical deforestation rates and related carbon losses from 1990 to 2010. *Glob. Chang. Biol.*, *20*, 2540-2554.

Balazovicova, L., Skodova, M. (2022). Vegetation and land use analysis for runoff estimation in small forested catchment: A case study of Tajovsky Brook in Slovakia. *Carpathian Journal of Earth and Environmental Sciences*, *17*(1), 81-92.

Barbosa, A.S., Pires, M.M., Schulz, U.H. (2020). Influence of land-use classes on the functional structure of fish communities in Southern Brazilian headwater streams. *Environmental management*, *65*(5), 618-629. https://doi.org/10.1007/s00267-020-01274-9

Bonan, G.B. (1998). The land surface climatology of the NCAR Land Surface Model coupled to the NCAR Community Climate Model. *Journal of Climate*, *11*(6), 1307-1326.

CLC, 2006. Corine Land Cover, v.2020_20u1. European Union, Copernicus Land Monitoring Service 2006, European Environment Agency (EEA). https://land.copernicus.eu/pan-european/corineland-cover/clc-2006?tab=download

CLC, 2012. Corine Land Cover, version v.2020_20u1. European Union, Copernicus Land Monitoring Service 2012, European Environment Agency (EEA) https://land.copernicus.eu/pan-european/corineland-cover/clc-2012?tab=download

CLC, 2018. Corine Land Cover, version v.2020_20u1. European Union, Copernicus Land Monitoring Service 2018, European Environment Agency (EEA) https://land.copernicus.eu/pan-european/corineland-cover/clc2018?tab=download

De Roo, A.P.J., Wesseling, C.G. LISEM (1996). A single event physically-based hydrological and soil erosion model for drainage basins,. I: *Theory, input, and output. Hydrol. Process*., *10*, 1107-1117.

Gallagher, R.V., Allen, S., Wright, I.J. (2019). Safety margins and adaptive capacity of vegetation to climate change. *Sci. Rep.*, *9*, 8241.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, *342*, 850-853.

Hawinkel, P., Thiery, W., Hermitte, S.L., Swinnen, E., Verbist, B., Van Orshoven, J., Muys, B. (2016). Vegetation response to precipitation variability in East Africa controlled by biogeographical factors. *J. Geophys. Res. Biogeosci.*, *121*, 2422-2444.

Huang, C., Liang, Y., He, H.S., Wu, M.M., Liu., B., Ma, T.X. (2021). Sensitivity of aboveground biomass and species composition to climate change in boreal forests of Northeastern China. *Ecol. Model.*, *445*, 109472.

Huang, X., Wen, D., Li, J., Qin, R. (2017). Multi-level monitoring of subtle urban changes for the megacities of China using high-resolution multi-view satellite imagery. *Remote Sens. Environ.*, *196*, 56-75.

Huete, A.R., Liu, H.Q., Batchily, K., van Leeuwen, W. (1997). A comparison of vegetation indices over a global set of TM images for EOS-MODIS. *Remote Sens. Environ.*, *59*, 440-451.

Keim, R.F., Skaugset, A.E., Weiler, M. (2006). Storage of water on vegetation under simulated rainfall of varying intensity*, Advances in Water Resources,* 29, 974-986. https://doi.org/10.1016/j.advwatres.2005.07.017

Maurer, G.E., Hallmark, A.J., Brown, R.F., Sala, O.E., Collins, S.L. (2020). Sensitivity of primary production to precipitation across the United States. *Ecol. Lett.*, *23*, 527-536.

Muzylo, A., Llorens, Pilar, P., Valente, F. Ernanda , Keizer, J.J., Domingo, F.rancisco, Gash, J.H.C. (2009). A Review of Rainfall Interception Modeling. *Journal of Hydrology*, 191-206. https://doi.org/10.1016/j.jhydrol.2009.02.058

Peng, J., Dan, L., Huang, M., 2014. Sensitivity of global and regional terrestrial carbon storage to the direct CO_2 effect and climate change based on the CMIP5 model intercomparison. *PLoS ONE*, *9*, e95282.

Planet Team (2017). *Planet Application Program Interface: In Space for Life on Earth*. San Francisco, CA.

Redo, D.J., Millington, A.C. (2011). A hybrid approach to mapping land-use modification and land-cover transition from MODIS time-series data: A case study from the Bolivian seasonal tropics. *Remote Sens. Environ.*, *115*, 353-372.

Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W. (1973). Monitoring Vegetation Systems in the Great Plains with ERTS (Earth Resources Technology Satellite). *Proceedings of 3rd Earth Resources Technology Satellite Symposium,* Greenbelt, 10-14 December, SP-351, 309-317.

Rullan-Silva, C.D., Olthoff, A.E., Delgado de la Mata, J.A., Pajares-Alonso, J.A. (2013). Remote Monitoring of Forest Insect Defoliation – A Review. *For. Syst.*, *22*, 377.

Running, S.W., Coughlan, J.C. (1988). A general model of forest ecosystem processes for regional applications I. Hydrologic balance, canopy gas exchange and primary production processes. *Ecological modelling*, *42*(2), 125-154.

Tabarant, F. (2000). *Apport de la télédetection et de la modélisation à l'étude de la dynamique de production d'un écosystème méditerranéen de Chênes verts dans le Sud de La France*. Report SPI 00.124, Ispra, Italy, JRC Space Applications Institute.

Vittek, M., Brink, A., Donnay, F., Simonetti, D., Desclée, B. (2013). Land cover change monitoring using landsat MSS/TM satellite image data over west Africa between 1975 and 1990. *Remote Sens*., *6*, 658-676.

Vrieling A, de Leeuw J, Said M.Y. (2013). Length of growing period over Africa: variability and trends from 30 years of NDVI time series, *Remote Sensing*, 5, 982-1000. https://doi.org/10.3390/rs5020982

Zhang, T., Ding, G.J., Zhang, J.P., Qi, Y.J. (2023). Stand, plot characteristics, and tree species diversity jointly dominate the recruitment biomass of subtropical forests. *For. Ecol. Manag*., *531*, 120814.