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Study of Climate Impact on Vegetation Cover in Kherson Oblast (Ukraine) Using Normalized Difference and Enhanced Vegetation Indices

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ABSTRACT

Remote sensing is a convenient tool for the study of vegetation cover conditions and dynamics using normalized difference and enhanced vegetation indices. Determination of the connection between weather and vegetation indices plays an important role in better understanding peculiarities of ecosystems reaction to changing climate conditions. The study devoted to the evaluation of annual and long-term dynamics under vegetation cover conditions, and its reaction to the climate factor, was performed through the establishment of the link between remote sensing information (smoothed time series data on normalized and enhanced vegetation indices) and results of on-land hydrometeorological observations for air temperature and precipitation amounts in Kherson oblast of Ukraine during the period from 2012 to 2019 by the means of linear regression analysis of the data. The values of the studied vegetation indices (Terrain MODIS NDVI and MODIS EVI 250 m smoothed time series) were calculated and generalized by the means of GDAL raster analysis toolkit in QGIS 3.10. Statistical data processing was performed using BioStat v7 software. It was found that there is a strong tendency towards the enhancement of vegetation in the region year by year. Climate has strong effect on the vegetation, and the main input belongs to air temperature, while precipitation amounts cannot be considered as a driving force of changes in the growth of vegetation. Enhanced vegetation index seems to be more reliable for the estimation of vegetation cover conditions in comparison to normalized difference vegetation index.

Keywords: MODIS NDVI; MODIS EVI; vegetation cover; local meteorology.

INTRODUCTION

Modern methods used for the study of ecosystems and their conditions include remote sensing of environment. The capacities of this technique are used in precision agriculture [Seelan et al., 2003] and ecology for determination of flora conditions, e.g., forest [Morales et al., 2008], wetlands [Martínez-López et al., 2014], grasslands [Marsett et al., 2006] status, through the implementation of various spatial vegetation indices. Two of them have become mostly implemented both by scientists and practitioners: normalized difference vegetation index (hereinafter referred as NDVI) and enhanced vegetation index (hereinafter referred as EVI).

NDVI was firstly proposed in 1974 [Rouse et al., 1974]. The calculation of the index is based on the ratio (1):

$$NDVI = ((NIR - Red))/((NIR + Red)) \quad (1)$$

where: Red and NIR represent the spectral reflectance, measurements obtained in the red and near-infrared regions (Gutman 1991).

EVI is an improved version of NDVI, which is introduced as a replacement for NDVI. The index is less dependent on soil and atmospheric influences; however, some studies reported about the difficulties in creation of long EVI time-series [Jiang et al., 2008]. Standard EVI is calculated as follows (2):

$$EVI = \\ = G \times ((NIR - Red))/ \\ /((NIR + C1 \times Red - C2 \times Blue + L)) \quad (2)$$

where: Red, $Blue$ and NIR represent the corrected surface reflectance,
L is the canopy adjustment argument (in Moderate Resolution Imaging Spectroradiometer it is taken as 1.0),
$C1$ and $C2$ are the adjustment coefficients to diminish the distortion related to the influence of aerosols (in Moderate Resolution Imaging Spectroradiometer they are taken as 6.0 and 7.5, respectively),
G is the gain factor (it is taken as 2.5) [Matsushita et al., 2007].

Vegetation cover conditions monitoring and control is an important part of the environmental studies directed to conservation of biodiversity. Annual and long-term observations for vegetation provide valuable information on the patterns of flora reaction to human activities and natural changes on the response of vegetation to the changes in climate conditions. While direct observation and measurements remain the most precise way of obtaining information on the status of vegetation [Lykhovyd, 2020], the use of spatial indices provides an opportunity for fast assessment of vegetation conditions on a large area [Kim et al., 2010], which is impossible using direct on-land methods. This is the main reason for their use in large-scale ecological monitoring and modeling.

The main aim of the study was determination of annual and long-term dynamics in spatial vegetation indices, which indirectly represent the dynamics in the vegetation cover status, strength and direction of climate factors impact on vegetation through the interconnection of spatial NDVI and EVI to air temperature and precipitation amounts to better understand the patterns of flora reactions to climate and its dynamics under the pressure of its change.

MATERIALS AND METHODS

MODIS NDVI and EVI 250 m smoothed time series 16-day terrain data for the period from 01/01/2012 to 01/01/2020 for Kherson oblast of Ukraine (Fig. 1) provided by the University of Natural Resources and Life Sciences (Vienna) were used in the study.

Square screens of Kherson oblast were cut using GDAL raster cutting engine within QGIS 3.10 software by the mask of vegetation cover of the region (Fig. 2) obtained at NEXTGIS Data service to exclude distortion in the values of the studied indices connected with accounting the areas, which are free from vegetation, e.g., sands, lakes, buildings, etc.

The data were processed using QGIS 3.10 raster statistics function to calculate mean values

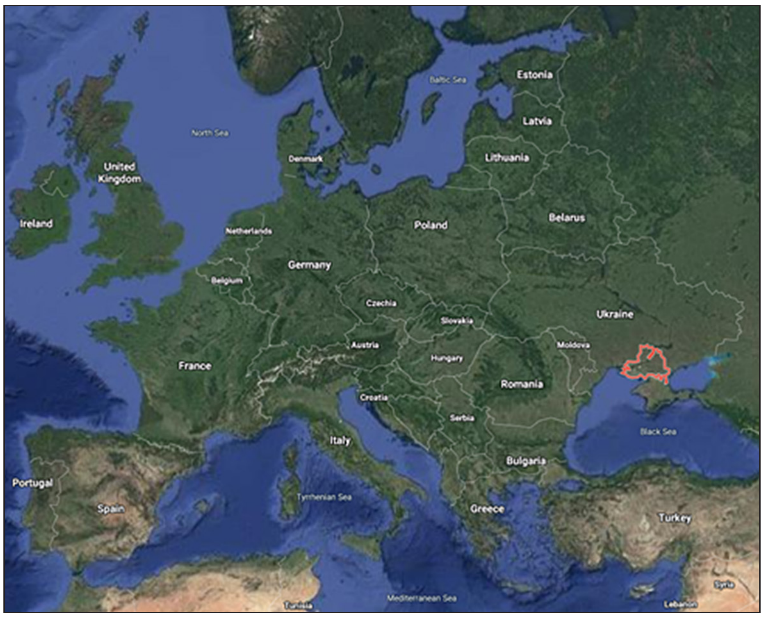

Figure 1. Kherson oblast in the map of Europe (the region is marked with a red boarder)

Figure 2. The mask of Kherson oblast used to cut the screens of the region to extract only the information on vegetation cover (the mask was purchased at NEXTGIS Data)

of NDVI and EVI by each month. The results were generalized annually (Table 1, Table 2).

Regional climate data for the period from 01/01/2012 to 01/01/2020, including air temperature and precipitation amounts, were recorded at the Kherson hydrometeorological station, and generalized (Table 3, Table 4).

The connection between the meteorological and vegetation indices was estimated using statistical analyses: linear Pearson correlation [Zou et al., 2003], multiple linear regression [Seber & Lee, 2012] with calculation of mean absolute percentage error (MAPE) [De Myttenaere et al., 2016]. All the statistical calculations were performed using BioStat v7 add-in within Microsoft Excel 365. Coefficient of variation (CV) for the studied vegetation indices were calculated by generally accepted methodology [Everitt, 1998]. Trend lines for the vegetation indices with a polynomial regression forecast were built by the

Table 1. NDVI values for the vegetation cover of Kherson oblast for the period of 2012–2019

Year	Month												Mean	CV (%)
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII		
2012	0.34	0.31	0.33	0.39	0.46	0.50	0.51	0.50	0.49	0.47	0.46	0.42	0.43	16.02
2013	0.39	0.40	0.43	0.47	0.50	0.51	0.50	0.49	0.48	0.47	0.47	0.45	0.46	8.05
2014	0.42	0.42	0.45	0.49	0.52	0.52	0.49	0.46	0.43	0.42	0.40	0.36	0.45	10.53
2015	0.35	0.38	0.44	0.50	0.55	0.57	0.55	0.51	0.46	0.42	0.40	0.39	0.46	15.55
2016	0.39	0.40	0.45	0.51	0.56	0.57	0.56	0.53	0.49	0.46	0.42	0.38	0.48	14.02
2017	0.36	0.37	0.42	0.49	0.53	0.54	0.52	0.49	0.47	0.47	0.47	0.31	0.45	15.43
2018	0.44	0.43	0.46	0.50	0.53	0.53	0.53	0.51	0.48	0.45	0.42	0.39	0.47	9.71
2019	0.39	0.41	0.46	0.52	0.56	0.56	0.54	0.51	0.50	0.51	0.53	0.55	0.50	10.65
CV (%)	8.89	9.69	9.94	8.41	6.42	5.05	4.67	4.14	4.64	6.43	10.02	17.50	4.59	

Table 2. EVI values for the vegetation cover of Kherson oblast for the period of 2012–2019

Year	Month												Mean	CV (%)
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII		
2012	0.14	0.14	0.16	0.20	0.25	0.29	0.29	0.29	0.26	0.25	0.23	0.21	0.23	23.78
2013	0.19	0.20	0.22	0.26	0.29	0.31	0.30	0.27	0.25	0.24	0.22	0.21	0.25	15.54
2014	0.20	0.20	0.24	0.28	0.31	0.31	0.29	0.26	0.23	0.20	0.18	0.15	0.24	21.32
2015	0.16	0.18	0.23	0.29	0.34	0.35	0.33	0.29	0.24	0.20	0.17	0.15	0.24	28.93
2016	0.15	0.18	0.23	0.28	0.33	0.35	0.33	0.30	0.26	0.23	0.20	0.17	0.25	25.97
2017	0.16	0.17	0.21	0.27	0.31	0.32	0.31	0.28	0.25	0.23	0.21	0.19	0.24	22.11
2018	0.18	0.19	0.23	0.28	0.31	0.32	0.31	0.28	0.25	0.22	0.19	0.18	0.25	21.02
2019	0.17	0.19	0.24	0.30	0.34	0.35	0.33	0.30	0.27	0.25	0.25	0.24	0.27	20.06
CV (%)	12.04	10.81	11.90	11.37	9.60	6.98	5.55	4.96	4.96	8.71	12.94	16.81	4.82	

Table 3. Air temperature in Kherson oblast for the period of 2012–2019, Celsius degrees

Year	Month												Mean
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	
2012	-1.3	-7.2	2.4	12.8	20.5	23.3	26.4	23.9	19.2	14.9	7.0	-0.4	11.8
2013	0.1	2.5	3.3	11.6	20.5	23.0	23.6	24.2	15.1	9.3	7.5	0.5	11.8
2014	1.1	0.0	6.8	11.0	18.1	20.8	25.0	24.5	18.4	9.3	3.3	0.4	11.6
2015	-0.4	0.9	5.2	9.4	17.0	21.3	23.5	24.1	20.9	9.6	7.4	2.6	11.8
2016	-3.1	3.9	6.2	12.7	16.3	22.1	24.3	24.9	18.0	8.4	4.0	-1.2	11.4
2017	-4.7	-0.8	7.0	9.3	16.3	22.0	23.4	25.4	19.9	11.3	5.4	5.9	11.7
2018	-0.3	-0.2	1.5	14.1	19.5	22.9	24.2	25.5	18.7	13.5	2.7	0.1	11.9
2019	-0.6	1.4	5.9	10.5	18.0	23.8	23.2	23.4	18.1	11.6	7.1	4.3	12.2
Mean	-1.2	0.1	2.4	11.4	18.3	22.4	24.2	24.5	18.5	11.0	5.6	1.5	11.8

Table 4. Precipitation amounts in Kherson oblast for the period of 2012–2019, mm

Year	Month												Sum
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	
2012	56.2	15.1	26.7	18.7	65.4	25.6	19.0	49.1	3.5	22.4	7.3	31.2	340.2
2013	39.8	22.2	41.3	8.0	12.0	70.1	48.1	12.4	43.7	53.9	4.0	3.7	359.2
2014	39.5	7.8	17.7	23.6	42.6	85.9	18.6	24.8	65.1	31.1	19.0	45.5	421.2
2015	32.2	39.9	57.7	57.8	44.8	60.6	64.2	25.7	3.8	19.1	50.7	5.2	461.7
2016	61.1	28.5	24.2	55.0	82.6	72.6	19.4	34.2	33.2	74.4	34.2	26.3	545.7
2017	27.5	20.3	5.1	87.9	25.6	10.3	39.8	4.8	0.7	12.0	40.6	35.4	310.0
2018	24.1	33.3	61.0	1.6	35.7	23.1	90.8	0.0	42.8	9.6	31.1	56.3	409.4
2019	23.0	9.8	7.3	56.0	72.8	92.6	48.7	22.1	12.1	10.4	37.9	26.3	419.0
Mean	37.9	22.1	30.1	38.6	47.7	55.1	43.6	21.6	25.6	29.1	28.1	28.7	408.3

means of Microsoft Excel 365 prediction tool [Heiberger et al., 2009]. All statistical analyses were performed for the probability level of 95%.

RESULTS AND DISCUSSION

Annual dynamics of vegetation cover in Kherson oblast

As any biological system, flora also has its fluctuations in time [Tsimring, 2014]. Annual dynamics in vegetation cover are well-known and seem to be evident. It is known by the local inhabitants that in Kherson oblast, grass starts to grow in early spring, trees blossom during the late spring and summer time, fruits appear in the late summer and autumn, and at the end of the autumn period gradual senescence and death of most vegetation, except evergreens can be observed. However, this evidence and knowledge based on common wisdom cannot be considered as a reliable source for the scientific knowledge of the processes, which take place in ecosystems. As a results of 8-year MODIS NDVI and EVI data generalization, the main annual trends in the vegetation growth in the region were determined (Fig. 3).

It was determined that the peak in the vegetation growth in the region is reached in the May–July period that is proved by the highest values of spatial vegetation indices at this time span: NDVI is 0.53–0.54, EVI is 0.31–0.32, respectively. The winter period (December–February) is characterized by the least live vegetation (average NDVI for the period is 0.39, and EVI is 0.18, respectively), which is represented by evergreens only. The spring period (March–May) is characterized by a substantial increase in the indices from 0.43 to 0.54 for NDVI and 0.22 to 0.31 for EVI, testifying about the regrowth of most vegetation in the studied region. The peak of vegetation growth is in the summer (June–August), when the average values of spatial indices reach 0.52 for NDVI and 0.30 for EVI, respectively. However, August (the end of summer) is a turning-point in the vegetation development. The flora comes into the period of gradual senescence, which continues through all the autumn period (September–November) and finishes (reaches the minimum) in January, which is simultaneously the coldest month of a

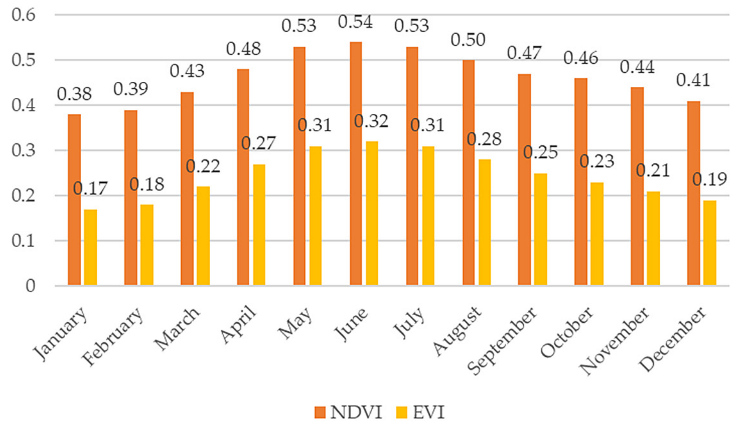

Figure 3. Annual dynamics of the vegetation cover in Kherson oblast by NDVI and EVI values averaged for each month of the studied (2012–2019) period

year (the only month with an average air temperature that is below zero).

The dynamics of the decrease in spatial vegetation indices starting from the August period can also be attributed to the fact that most crops cultivated on agricultural lands of the region have been already harvested before this period or are entering into the stage of ripening when green biomass is wilting.

Surprisingly, the senescence of vegetation in Kherson oblast is not completed in November or December, as it was usually stated by local hydro meteorologists and agricultural scientists who claim that usually cessation of vegetation at the beginning of November [Ushkarenko, 1994]. It could be attributed to the increase of air temperatures in these months over the last years, resulting in better conditions for continuous growth of some cold-resistant flora species.

Long-term (2012–2019) dynamics of the vegetation cover in Kherson oblast

The study of the long-term dynamics of the flora conditions in Kherson oblast showed that there is a strong tendency towards the improvement of vegetation growth conditions in the region, which is proved by the gradually increasing values of both studied spatial vegetation indices (Fig. 4, 5).

Polynomial regression trend lines testify about the highly likely ($R^2 > 0.80$) further increase in the vegetation indices, i.e., further enhancement of vegetation in the region [Taylor, 1990]. There are numerous factors affecting vegetation, e.g., climate, soil, biological interactions within ecosystems, anthropogenic activities (especially, on agricultural lands), etc. The next stage of the study was to define the role of climate impact on the vegetation cover conditions in Kherson oblast.

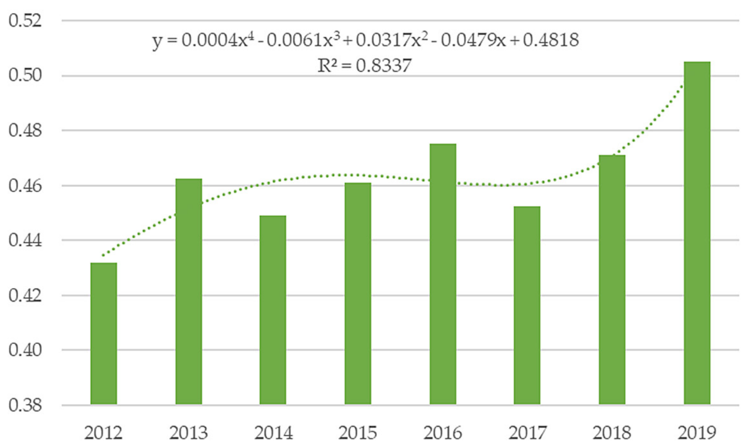

Figure 4. Long-term dynamics of the vegetation cover in Kherson oblast by NDVI values averaged for each year of the studied (2012–2019) period

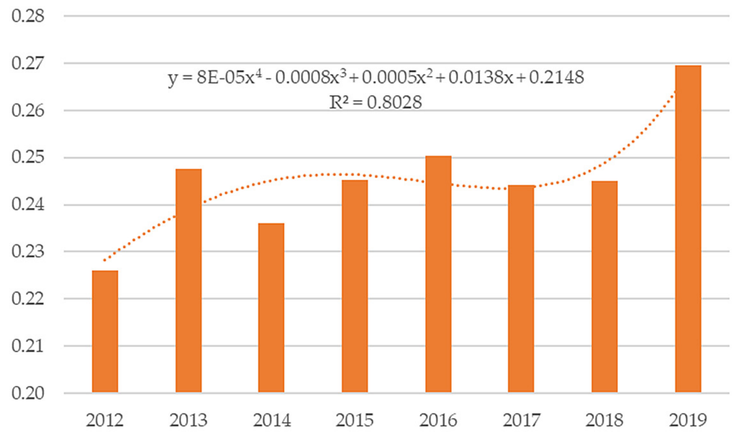

Figure 5. Long-term dynamics of the vegetation cover in Kherson oblast by EVI values averaged for each year of the studied (2012–2019) period

Dependence of vegetation cover in Kherson oblast on climate

Monthly air temperature and precipitation amounts were applied as the indices of climate characteristics in the study. The connection between the vegetation indices and climatic indices was determined by the linear Pearson correlation and multiple linear regression analysis. It was found out that both NDVI and EVI are closely related to the air temperature (linear Pearson correlation coefficient R values were 0.77 and 0.85, respectively), and at the same time there was almost no connection between the vegetation indices and precipitation amounts (correlation coefficient R values were 0.24 and 0.28, respectively).

Multiple linear regression analyses resulted in the determination of stronger connection between the climatic indices and EVI (Table 5), while their inter-connection with NDVI was considerably lower (Table 6).

Regression equations (3), (4) describing the dependence of the studied vegetation indices on climate inputs confirm the above-mentioned statement that the greatest impact on vegetation cover is made by air temperature, while precipitation amounts have very slight effect on it.

$$NDVI = 0.3903 + 0.0050 \times A + 0.0004 \times B \quad (3)$$

where: *NDVI* is a value of the spatial vegetation index,

Table 5. Multiple linear regression analysis results for the model "air temperature; precipitation amounts – EVI" in Kherson oblast for the period of 2012–2019

Regression statistics criteria	Values of criteria
Multiple correlation coefficient (R)	0.8745
Mean square (MS)	0.1165
Mean square error (MSE)	0.0008
Multiple determination coefficient (R^2)	0.7647
Adjusted R^2	0.7596
Root mean square error (RMSE)	0.0282
Mean absolute percentage error (MAPE)	9.5655
F value	151.0948
Multiple determination coefficient for the prediction (R^2)	0.7497
Regression model coefficients	
Slope	0.1711
A (for air temperature in Celsius degrees)	0.0050
B (for precipitation amounts in mm)	0.0005

Table 6. Multiple linear regression analysis results for the model "air temperature; precipitation amounts – NDVI" in Kherson oblast for the period of 2012–2019

Regression statistics criteria	Values of criteria
Multiple correlation coefficient (R)	0.7893
Mean square (MS)	0.1165
Mean square error (MSE)	0.0015
Multiple determination coefficient (R^2)	0.6230
Adjusted R^2	0.6149
Root mean square error (RMSE)	0.0394
Mean absolute percentage error (MAPE)	6.7064
F value	76.8292
Multiple determination coefficient for the prediction (R^2)	0.6019
Regression model coefficients	
Slope	0.3903
A (for air temperature in Celsius degrees)	0.0050
B (for precipitation amounts in mm)	0.0004

A is air temperature in Celsius degrees, and
B is precipitation amounts in mm.

$$EVI = 0.1711 + 0.0050 \times A + 0.0005 \times B \quad (4)$$

where: $NDVI$ is a value of the spatial vegetation index,
A is air temperature in Celsius degrees, and
B is precipitation amounts in mm.

The developed models, in particular the model for EVI, can be proposed as a reliable tool for the climate-based prediction of the vegetation cover status in Kherson oblast (prediction accuracy of the EVI model is 75% with MAPE of 9.57% < 10%) [Moreno et al. 2013].

DISCUSSION

NDVI is an easy and commonly used index for characterizing vegetation, especially, in precision agriculture systems [Oliver, 2010]; however, doubt on its usefulness for the determination of subsequent changes in vegetation cover and estimation of the dynamics in vegetation was cast [Elmore et al., 2010], mainly because of its tendency towards distortion due to soil reflection ability and cloudiness [Huete, 1988; Koslowsky, 1993; Hobbs, 1997]. EVI seems to be more reliable and less dependent on the above-mentioned hindrances, although it can be distorted by topography [Matsushita et al., 2007]. It was found that both NDVI and EVI trends on annual and long-term scales are remarkably close. However, it seems that terra NDVI tends to somewhat overestimate the livelihood of vegetation cover in the cold season of a year, maybe, because of the above-mentioned dependence on the soil reflection abilities, which cause some distortions in the winter period, as it is reported by the scientists [Lange et al., 2017]. Notwithstanding the fact that NDVI imaginary is subjected to additional noise under the conditions of high (exceeding 3.0) leaf area index [Gao, 1996], under different sunshine peculiarities [Huete et al., 1999], it is still widely used for vegetation cover estimation [Miura et al., 2019]. Besides some errors occurring due to the imperfection of the calculation algorithm, it should also be kept in mind that NDVI is mainly dependent on the chlorophyll content in green mass of vegetation and is less sensible to the area of canopy cover [Lillesaeter, 1982]. All these drawbacks seem to be replaced in the EVI computation algorithm [Matsushita et al., 2007]. Although this statement is quite debatable [Wardlow & Egbert, 2010], the performed study showed that NDVI is considerably less variable by the years and inter-annually than EVI (see CV values presented in Tables 1, 2) that drives us into the idea of its less reaction to seasonal changes, thus making NDVI less suitable for the estimation of fluctuations in vegetation cover depending on the internal and external factors of effect. All in all, the authors agree with [Karkauskaite et al., 2017; Qiu et al., 2018] that EVI is slightly better choice in case of studying the vegetation cover dynamics.

The study of long-term trends in spatial indices revealed a strong tendency towards their increase. The discovered trends have high reliability at the probability level of 95% ($p < 0.05$), representing the idea of a positive effect of climate changes, the main tendency of which is an increase in the average annual air temperature [Lykhovyd 2018; Vozhehova et al., 2018], on the vegetation cover in Kherson oblast. This conclusion is supported by the report on the results of long-term (for the periods of 2051–2060 and 2090–2098) vegetation cover changes modelling due to the climate changes. The modelling provided the results that vegetation cover will be considerably dense (by 21% and 36% for the periods of 2051–2060 and 2090–2098, respectively) because of the changes in climate, especially, this statement is true for the middle and northern latitudes of the Earth [Jiang et al., 2011]. However, scientists emphasize the inequality in vegetation feedback on global warming, pointing out that it will have a positive effect for the higher latitudes, and an adverse effect, which mainly will manifest itself through thinning of vegetation cover and gradual desertification of land, for the lower latitudes [Woodward et al., 1998].

Another debatable question is the dependence of the spatial indices on precipitation amounts. While the current study results showed almost no dependence of EVI and NDVI on the rainfall, there are several research works claiming the opposite. Statistically significant dependence of the studied indices on precipitation was proven in the studies of Zoungrana et al. [2015], Wang et al. [2003]. This contradiction was resolved by Schultz & Halpret [1993], who have drawn the conclusion that the NDVI dependence on air temperature and precipitation amounts variates by the climate zones, because the importance of rainfall and temperature for growth of vegetation varies in different regions of the world. For example, in cold regions with high rainfall, NDVI will mostly correlate with temperature, and in hot arid regions, this index will mainly depend on rainfall [Schultz & Halpert, 1993]. This conclusion is also supported by the work [Ding et al., 2007], showing that the NDVI correlation with rainfall is different in different years and areas of the Tibetan Plateau.

Statistical evaluation of the relations between climate and spatial vegetation indices revealed that EVI reacts on climate changes more than NDVI; thus, EVI will be better for the prediction of vegetation cover changes depending on climate conditions. It may result from less atmospheric noise in EVI [Wang et al., 2003]. Better performance of EVI for the estimation of agricultural land was also proven by previous studies [Lijun et al., 2008]. However, some reports on the worse performance for prediction of vegetation cover status of EVI-based models compared to the NDVI -based ones were found. For example, the study conducted in Northern Hebei Province of China testified about a significant advantage of the NDVI-based vegetation prediction over the EVI-based [Li et al., 2010]. Better performance of NDVI for vegetation cover evaluation and mapping was proven by the study conducted in Brazil, where NDVI outscored EVI in classification accuracy and showed better performance in the assessment of seasonal fluctuations of the regional flora [Eduarda et al., 2007]. Although there are a number of reports claiming better NDVI performance for vegetation cover assessment, it should be mentioned that the different feature of the performed study is an additional linkage of spatial vegetation indices to climate indices, and in this relation it was found significant benefit of EVI-based estimation of the vegetation in the studied region. Besides, EVI can be much more accurately predicted by air temperature and precipitation amounts, which makes this index more suitable for vegetation cover status forecasting. Similar attempts for EVI-based forecasting of vegetation cover changes were successfully made by other scientific groups using other techniques and inputs for the models [Gurung et al., 2009]. In order to support the results of current study, it should be mentioned that Moreira et al. have also proven strong correlation between climate indices, viz., air temperature and rainfall, and EVI [Moreira et al., 2019]. They also discovered that EVI–temperature and EVI–rainfall correlation is dependent on the El Nino and La Nina events.

Taking into account all the above-mentioned scientific statements and the results of current study, it is evident that it is too early to answer the questions on investigation of vegetation cover through spatial vegetation indices and their linkage with climate. Great discrepancies and serious contradictions between the results of the studies conducted under different climate conditions using different techniques for statistical analysis testify about the necessity of conducting further robust studies in this field to improve the current knowledge on the patterns of the "climate– vegetation" interactions both on local and global scales.

CONCLUSIONS

On the basis of the results of the current study it was found out that:

1. Annual dynamics in vegetation cover of Kherson oblast, studied by means of spatial vegetation indices, is characterized with a peak in the May–July period, gradual senescence since August and active regrowth since March;
2. There is a strong tendency towards the improvement of vegetation conditions in the region, which is proven by the gradually increasing values both of EVI and NDVI on the long-term scale of the studied (2012–2019) period;
3. Spatial vegetation indices and, hence vegetation cover of the region, strongly depend on air temperature and had a slight correspondence to rainfall; therefore, precipitation amounts cannot be considered as a major force for the improvement of vegetation status in the studied area;
4. Both EVI and NDVI could be predicted with sufficient accuracy by the climate indices; however, for this purpose, it is much better to apply the proposed modelling technique to EVI than NDVI because of higher forecasting precision.

REFERENCES

1. De Myttenaere, A., Golden, B., Le Grand, B., & Rossi, F. 2016. Mean absolute percentage error for regression models. Neurocomputing, 192, 38–48. DOI: 10.1016/j.neucom.2015.12.114

2. Ding, M., Zhang, Y., Liu, L., Zhang, W., Wang, Z., & Bai, W. 2007. The relationship between NDVI and precipitation on the Tibetan Plateau. Journal of Geographical Sciences, 17, 259–268. DOI: 10.1007/s11442–007–0259–7
3. Eduarda, M. D. O., de Carvalho, L. M., Junior, F. W. A., & de Mello, J. M. 2007. The assessment of vegetation seasonal dynamics using multitemporal NDVI and EVI images derived from MODIS. pp. 1–5. In: 2007 International Workshop on the Analysis of Multi-temporal Remote Sensing Images; IEEE. DOI: 10.1109/MULTITEMP.2007.4293049
4. Elmore, A. J., Mustard, J. F., Manning, S. J., & Lobell, D. B. 2010. Quantifying vegetation change in semiarid environments: precision and accuracy of spectral mixture analysis and the normalized difference vegetation index. Remote Sensing of Environment, 73, 87–102. DOI: 10.1016/S0034–4257(00)00100–0
5. Everitt, B. 1998. The Cambridge Dictionary of Statistics. Cambridge University Press: UK New York.
6. Gao, B. C. 1996. NDWI – A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment, 58, 257–266. DOI: 10.1016/S0034–4257(96)00067–3
7. Gurung, R. B., Breidt, F. J., Dutin, A., & Ogle, S. M. 2009. Predicting enhanced vegetation index (EVI) curves for ecosystem modeling applications. Remote Sensing of Environment, 113, 2186–2193. DOI: 10.1016/j.rse.2009.05.015
8. Gutman, G. G. 1991. Vegetation indices from AVHRR: An update and future prospects. Remote Sensing of Environment, 35, 121–136. DOI: 10.1016/0034–4257(91)90005-Q
9. Heiberger, R. M., & Neuwirth, E. 2009. Polynomial regression. pp. 269–284. In: R Through Excel , Springer: New York, USA. DOI: 10.1007/978–1-4419–0052–4_11
10. Hobbs, T. J. 1997. Atmospheric correction of NOAA-11 NDVI data in the arid rangelands of Central Australia. International Journal of Remote Sensing, 18, 1051–1058. DOI: 10.1080/014311697218566
11. Huete, A. R. 1988. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25, 295–309. DOI: 10.1016/0034–4257(88)90106-X
12. Huete, A., Justice, C., & Van Leeuwen, W. 1999. MODIS vegetation index (MOD13). Algorithm theoretical basis document 3(213).
13. Jiang, D., Zhang, Y., & Lang, X. 2011. Vegetation feedback under future global warming. Theoretical and Applied Climatology, 106, 211–227. DOI: 10.1007/s00704–011–0428–6
14. Jiang, Z., Huete, A. R., Didan, K., & Miura, T. 2008. Development of a two-band enhanced vegetation index without a blue band. Remote Sensing of Environment, 112, 3833–3845. DOI: 10.1016/j.rse.2008.06.006
15. Karkauskaite, P., Tagesson, T., & Fensholt, R. 2017. Evaluation of the plant phenology index (PPI), NDVI and EVI for start-of-season trend analysis of the Northern Hemisphere boreal zone. Remote Sensing, 9, 485. DOI: 10.3390/rs9050485
16. Kim, Y., Huete, A. R., Miura, T., & Jiang, Z. 2010. Spectral compatibility of vegetation indices across sensors: band decomposition analysis with Hyperion data. Journal of Applied Remote Sensing, 4, 043520. DOI: 10.1117/1.3400635
17. Koslowsky, D. 1993. The influence of viewing geometry on annual variations of NDVI. pp. 1140 – 1142. In: Proceedings of IGARSS'93-IEEE International Geoscience and Remote Sensing Symposium; IEEE. DOI: 10.1109/IGARSS.1993.322136
18. Lange, M., Dechant, B., Rebmann, C., Vohland, M., Cuntz, M., & Doktor, D. 2017. Validating MODIS and Sentinel-2 NDVI products at a temperate deciduous forest site using two independent ground-based sensors. Sensors, 17, 1855. DOI: 10.3390/s17081855
19. Li, Z., Li, X., Wei, D., Xu, X., & Wang, H. 2010. An assessment of correlation on MODIS-NDVI and EVI with natural vegetation coverage in Northern Hebei Province, China. Procedia Environmental Sciences, 2, 964–969. DOI: 10.1016/j.proenv.2010.10.108
20. Lijun, Z., Zengxiang, Z., Tingting, D., & Xiao, W. 2008. Application of MODIS/NDVI and MODIS EVI to extracting the information of cultivated land and comparison analysis. Transactions from the Chinese Society of Agricultural Engineering, 24, 167–172. DOI: 10.3969/j.issn.1002–6819.2008.3.033
21. Lillesaeter, O. 1982. Spectral reflectance of partly transmitting leaves: laboratory measurements and mathematical modeling. Remote Sensing of Environment, 12, 247–254. DOI: 10.1016/0034–4257(82)90057–8
22. Lykhovyd, P. V. 2020. Sweet corn yield simulation using normalized difference vegetation index and leaf area index. Journal of Ecological Engineering, 21, 228–236. DOI: 10.12911/22998993/118274
23. Lykhovyd, P. V. 2018. Global warming inputs in local climate changes of the Kherson region: Current state and forecast of the air temperature. Ukrainian Journal of Ecology, 8, 39–41. DOI: 10.15421/2018_307
24. Marsett, R. C., Qi, J., Heilman, P., Biedenbender, S. H., Watson, M. C., Amer, S., Weltz, M., Goodrich, D., & Marsett, R. 2006. Remote sensing for grassland management in the arid southwest. Rangeland Ecolohy & Management, 59, 530–540. DOI: 10.2111/05–201R.1
25. Martínez-López, J., Carreño, M. F., Palazón-Ferrando, J. A., Martínez-Fernández, J., & Esteve, M.

A. 2014. Remote sensing of plant communities as a tool for assessing the condition of semiarid Mediterranean saline wetlands in agricultural catchments. International Journal of Applied Earth Observation, 26, 193–204. DOI: 10.1016/j.jag.2013.07.005

26. Matsushita, B., Yang, W., Chen, J., Onda, Y., & Qiu, G. 2007. Sensitivity of the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) to topographic effects: a case study in high-density cypress forest. Sensors, 7, 2636–2651. DOI: 10.3390/s7112636
27. Miura, T., Nagai, S., Takeuchi, M., Ichii, K., & Yoshioka, H. 2019. Improved characterisation of vegetation and land surface seasonal dynamics in central Japan with Himawari-8 hypertemporal data. Scientific Reports, 9, 1–12. DOI: 10.1038/s41598–019–52076-x
28. Morales, R. M., Miura, T., & Idol, T. 2008. An assessment of Hawaiian dry forest condition with fine resolution remote sensing. Forest Ecology and Management, 255, 2524–2532. DOI: 10.1016/j.foreco.2008.01.049
29. Moreira, A., Fontana, D. C., & Kuplich, T. M. 2019. Wavelet approach applied to EVI/MODIS time series and meteorological data. ISPRS Journal of Photogrammetry and Remote Sensing, 147, 335–344. DOI: 10.1016/j.isprsjprs.2018.11.024
30. Moreno, J. J. M., Pol, A. P., Abad, A. S., & Blasco, B. C. 2013. Using the R-MAPE index as a resistant measure of forecast accuracy. Psicothema, 25, 500–506. DOI: 10.7334/psicothema2013.23
31. Oliver, M. A. 2010. Geostatistical applications for precision agriculture. Springer Science & Business Media, London New York. DOI: 10.1007/978–90–481–9133–8
32. Qiu, J., Yang, J., Wang, Y., & Su, H. 2018. A comparison of NDVI and EVI in the DisTrad model for thermal sub-pixel mapping in densely vegetated areas: a case study in Southern China. International Journal of Remote Sensing, 39, 2105–2118. DOI: 10.1080/01431161.2017.1420929
33. Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. 1974. Monitoring vegetation systems in the Great Plains with ERTS. NASA special publication, 351, 309.
34. Schultz, P. A., & Halpert, M. S. 1993. Global correlation of temperature, NDVI and precipitation. Advances in Space Research, 13, 277–280. DOI: 10.1016/0273–1177(93)90559-T
35. Seber, G. A., & Lee, A. J. 2012. Linear regression analysis. Vol. 329. John Wiley & Sons.
36. Seelan, S. K., Laguette, S., Casady, G. M., & Seielstad, G. A. 2003. Remote sensing applications for precision agriculture: A learning community approach. Remote Sensing of Environment, 88, 157–169. DOI: 10.1016/j.rse.2003.04.007
37. Taylor, R. 1990. Interpretation of the correlation coefficient: a basic review. Journal of Diagnostic Medical Sonography, 6, 35–39. DOI: 10.1177/875647939000600106
38. Tsimring, L. S. 2014. Noise in biology. Reports on Progress in Physics, 77, 026601. DOI: 10.1088/0034–4885/77/2/026601
39. Ushkarenko, V. O. 1994. Irrigated Agriculture. Urozhai: Kyiv, Ukraine.
40. Vozhehova, R., Kokovikhin, S., Lykhovyd, P., Vozhehov, S., & Drobitko, A. (2018): Artificial croplands and natural biosystems in the conditions of climatic changes: Possible problems and ways of their solving in the South Steppe zone of Ukraine. Research Journal of Pharmaceutical, Biological and Chemical Sciences, 9, 331–340.
41. Wang, J., Rich, P. M., & Price, K. P. 2003. Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. International Journal of Remote Sensing, 24, 2345–2364. DOI: 10.1080/01431160210154812
42. Wang, Z., Liu, C., & Huete, A. 2003. From AVHRR-NDVI to MODIS-EVI: Advances in vegetation index research. Acta Ecologica Sinica, 23, 979–987.
43. Wardlow, B. D., & Egbert, S. L. 2010. A comparison of MODIS 250-m EVI and NDVI data for crop mapping: a case study for southwest Kansas. International Journal of Remote Sensing, 31, 805–830. DOI: 10.1080/01431160902897858
44. Woodward, F. I., Lomas, M. R., & Betts, R. A. 1998. Vegetation-climate feedbacks in a greenhouse world. Philosophical Transactions of The Royal Society B Biological Sciences, 353, 29–39. DOI: 10.1098/rstb.1998.0188
45. Zou, K. H., Tuncali, K., & Silverman, S. G. 2003. Correlation and simple linear regression. Radiology, 227, 617–628. DOI: 10.1148/radiol.2273011499
46. Zoungrana, B. J. B., Conrad, C., Amekudzi, L. K., Thiel, M., & Da, E. D. 2015. Land use/cover response to rainfall variability: A comparing analysis between NDVI and EVI in the Southwest of Burkina Faso. Climate, 3, 63–77. DOI: 10.3390/cli3010063