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Remote sensing data for drought stress and croplands productivity assessment in Kherson region

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ABSTRACT

Formulation of the problem. Remote sensing data might be used for indirect assessment of croplands conditions and drought stress through the calculation of specific vegetation indices, such as vegetation health index (VHI), agriculture stress index (ASI), and drought intensity or weighted mean vegetation health index (WMVHI). However, the accuracy of these indices is not clear for some territories. For example, the South of Ukraine is a zone of risky agriculture, because of low natural moisture supply and high evapotranspiration. Moisture supply is the main limiting factor for sustainable crop production in this region.

The goals of this study were: 1) to assess the reliability of the mentioned vegetation indices in drought assessment through the direct comparison with the UNEP aridity index; 2) to find out whether remote sensing drought indicators could be used for the yield prediction of major crops on the regional scale.

Methods. The study was conducted for Kherson region of Ukraine, as it is one of the most arid regions of the country with very high drought risks. The data on average weighted annual VHI, ASI, and WMVHI for the period 1984-2022 (Season 1) were collected and generalized from the FAO Earth Observation services. UNEP aridity index was calculated using the data from Kherson regional hydrometeorological center. Correlation and linear regression analysis were performed using common statistical methodology.

Results. As a result, it was found that 1) all the studied remote sensing drought indicators demonstrate poor correlation with the aridity index, therefore, they should not be used to determine meteorological drought in the region; 2) all the studied remote sensing indices, especially VHI, demonstrate moderate-to-strong correlation with the yields of certain crops, cultivated in Kherson region (R=0.54-0.86), and could be used for the yield prediction; 3) the aridity index have poor relation to the yields of major crops, cultivated in the studied area; 4) VHI-based linear regression models for the crops' yields prediction are reliable and reasonable for scientific and practical use just for cereal crops, and are much less accurate for grain corn and sunflower; 5) based on the study findings, it could be concluded that aridity index provides pure climatological characteristics of the region, while the studied vegetation indices are mainly focused on the level of drought stress that impacts crops during the growing season.

Scientific novelty and practical significance. The article provides novel insights on the implementation of remote sensing data in drought risks assessment in crop production, and their utilization for the purpose of croplands productivity prediction. The study has theoretical and practical importance for current agriculture, and the findings could be used both in scientific, educational, and practical purposes.

Keywords: *agriculture stress index, aridity index, drought intensity, vegetation health index, yield*.

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Introduction. Global climate change is one of the greatest challenges for modern agriculture, as this branch of economy is highly dependent on environmental conditions and weather [1]. Sustainable crop production is possible just under the satisfaction of crops' requirements for vital elements, such as light, heat, nutrition, and water. Lack of natural moisture supply, accompanied by significant increase in air temperature, is one of the most important limiting factors for sustainable agriculture in the arid and semi-arid regions of the world. In these areas, which are gradually increasing in the intercourse of global warming, stable crop yields could be harvested in the irrigated conditions only [2, 3]. However, global water resources scarcity limits irrigation capacities, therefore, current irrigation should be not only water-saving, but it should also be provided on the territories, where its positive effects are expected to be the best [4]. In order to judge about the necessity of irrigation in the concrete territory, modern agricultural and meteorological science provides direct and in-direct methods for drought risk assessment.

Among direct methods for the assessment of the level of climate aridity, the United Nations Environment Program (UNEP) aridity index (AI) calculations are simple and re-liable, and this meteorological indicator is widely used in international scientific community to estimate the impacts of current climate change. The method is based on the ratio of the precipitation amounts (PA) and evaporation (PET) rates (AI=PA/PET), observed in the territory for the stipulated period of time. According to the calculation results, six types of climate are marked out, namely: extremely arid or sub-desert (AI<0.05); arid (AI=0.05-0.20); semi-arid (AI=0.20-0.50); dry sub-humid (AI=0.50-0.65); humid (AI=0.65-0.75); hyper humid (AI>0.75) [5, 6]. UNEP aridity index is referred as the standard methodology for climatological assessment of the territories in many scientific studies, and it has proved its reliability [7].

At the same time, current science and technology offers great variety of alternative in-direct methods for drought risk and aridity assessment. Among them, remote sensing-based methods are of great importance and interest for agricultural science and practice.

For example, Food and Agriculture Organization of the United Nations (FAO) developed the agriculture stress index (ASI) as a measure for the operational assessment of water stress and drought in croplands. The ASI is based on the integration of the Vegetation Health Index (VHI) in temporal and spatial dimensions to assess drought events. The ASI is provided by administrative regions, and each administrative region is classified according to the percentage of the possibly affected by drought area into six classes (ASI<10; 10-25; 25-40; 40-55; 55-70; 70-85; >85) [8]. The ASI is not widely implemented, but it demonstrated good results in the estimation of El Nino's drought impacts on agriculture [9]. However, the role of the ASI in drought characteristics in different environments re-mains unclear, as well as the suitability of this index for crop yield prediction.

The Vegetation Health Index (VHI) is one of the most widely implemented vegetation indices, used for drought conditions assessment and monitoring. The VHI utilizes the Vegetation Condition Index (VCI) and the thermal Condition Index (TCI) to estimate drought [10]. Prior studies testified that the VHI is dependent on such features of the territory as geographical location and type of the vegetation cover [11]. Besides, it was deter-mined that the input of the VHI constituent indices VCI and TCI into the final assessment is also dependent on vegetation type and general climate parameters of the studied area [12]. Therefore, it is necessary to evaluate its capacity to represent drought stress conditions in croplands in every certain area. Besides, the VHI is also suitable for crop yield prediction, as it was proved by some scientific studies for rice and wheat, cultivated in different environments [13, 14].

Apart from ASI and VHI, FAO proposes another interesting index for assessment of the intensity of agricultural drought conditions, based on the Weighted Mean Vegetation Health Index (WMVHI in percents) aggregated per GAUL 2 region. The intensity of drought is assessed using the presumption that the poorer the vegetation health is, the more severe the drought is. The WMVHI-based drought intensity index subdivides the areas by agricultural drought manifestation into five classes (WMVHI<25; 25-35; 35-38; 38-42; >42) [15]. The index found very little scientific and practical implementation in drought monitoring and croplands productivity prediction, however, this neglection lacks scientific justification.

Therefore, remote sensing methods for drought assessment are represented by somewhat different approaches in the interpretation of the VHI. It should be noted that while VHI is commonly used for croplands health monitoring, the ASI and the WMVHI are less common and less studied indicators of drought. The goals of current study were: i) to assess the reliability of the ASI, VHI, and WMVHI in drought assessment through the establishment of their relationship with aridity index level; ii) to find out whether the studied vegetation indices could be used for the yield prediction of major crops, cultivated in the South of Ukraine. As the reliability of the methods for drought risk assessment should be better evaluated in the areas, where climate aridity and droughts are common, it was determined that Kherson region of Ukraine, representing the zone of risky agriculture because of lack of natural moisture supply and high evaporation, is a good one for such a purpose [16].

Materials and methods. The study was carried out for Kherson region of Ukraine for the period 1984-2022. Geographical location of the region is presented in the Figure 1. The region represents typical Steppe zone climate, which is characterized by [17, 18] as BSk or cold semi-arid climate. The region belongs to the zone of risky agriculture with systematic impacts of drought events on croplands [19].

The images of annual VHI for the Season 1 croplands were extracted for the calculations and analysis from the Global Information and Early Warning System on Food and Agriculture (GIEWS) Living Atlas map, presented via ArcGIS Online platform.

The Season 1 croplands represent growing season of most cultivated crops in the region, as by the FAO's definition it falls within the period March-August in the region (Figure 2).

The extracted images were analyzed using Pixel Color Counter (https://townsean.github.io/canvas-pixel-color-counter/) to obtain quantitative characteristics of the representation of each VHI class in the images. The final VHI score was calculated using the following equation (1):

$$VHI = a*n_a + b*n_b + c*n_c + d*n_d + e*n_e + f*n_f + g*n_g + h*n_h + i*n_i, \quad (1)$$

where a, b, c, d, e, f, g, h, i are corresponding classes of the VHI values, namely, 0.075, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.85; n_{a-i} are corresponding share of the pixels in the image, which represent particular VHI class, calculated as the ratio of the pixels of certain color band to the total number of cropland-representing pixels in the image.

The values of ASI and WMVHI were retrieved

Fig. 1. Location of Kherson region in the map of Europe (created with https://mapchart.net)

from the data, provided by FAO (could be accessed from https://www.fao.org/giews/earthobservation/country/index.jsp?lang=en&code=UKR). The association between the VHI, ASI, and WMVHI indicators is presented in the Figure 3 on the example of 2000 year.

The UNEP aridity index for the stipulated period was calculated using historical meteorological data obtained at Kherson regional hydrometeorological center and the open data from *meteoblue* service (https://www.meteoblue.com/en/). Further, mutual relationship between the VHI, ASI, WMVHI and the UNEP aridity index was calculated using common correlation analysis methodology in Microsoft Excel 365 statistical toolkit [20]. Strength of the relationship between the studied indicators was evaluated by the guidelines [21]. The methodological flow chart of this part of the study could be presented as follows (Figure 4).

Further, historical yielding data for the period 2005-2021 were retrieved from official statistical bodies of Ukraine. Five major crops, including winter wheat, spring wheat, barley, grain corn, and sunflower were analyzed. The yielding data were associated with every studied drought index and statistically processed to estimate whether they are appropriate for yield prediction through the procedure of linear regression analysis toolkit within Microsoft Excel 365 [22]. Finally, linear regression models of major crops yield prediction were developed, if reasonable. The models are developed based on the basic equation of linear regression (2):

$$\text{Yield} = a + b*x, \quad (2)$$

where Yield is the value of a certain crop productivity, t/ha; x – the value of a certain drought index; a – the interception of the regression model; b – regression coefficient.

Linear models were chosen because of small input sample size (less than 30), therefore, non-linear models, requiring bigger sample sizes, were concluded to be inappropriate in the study because of the overfitting hazard. Regression models were developed in BioStat v.7 software.

Results. The resulst of the study will be presented in the following sub-sections depending on their relevance to the stipulated tasks of the investigation.

3.1. Relationship between the studied drought indicators

As a result of correlation anlysis, it was found out that there is extremely strong relationship between FAO's drought intensity (MWVHI) and ASI indices, while there is almost no connection between the UNEP aridity index (AI) and all other studied indicators (Table 1).

Strong relationship was established between VHI, ASI, and MWVHI. It should be noted that the relationship is inverted for VHI – ASI, ASI – MWVHI, and ASI – AI pairs. It means that an increased VHI results in less ASI values, and so on. This is quite logical, because high VHI, and MWVHI

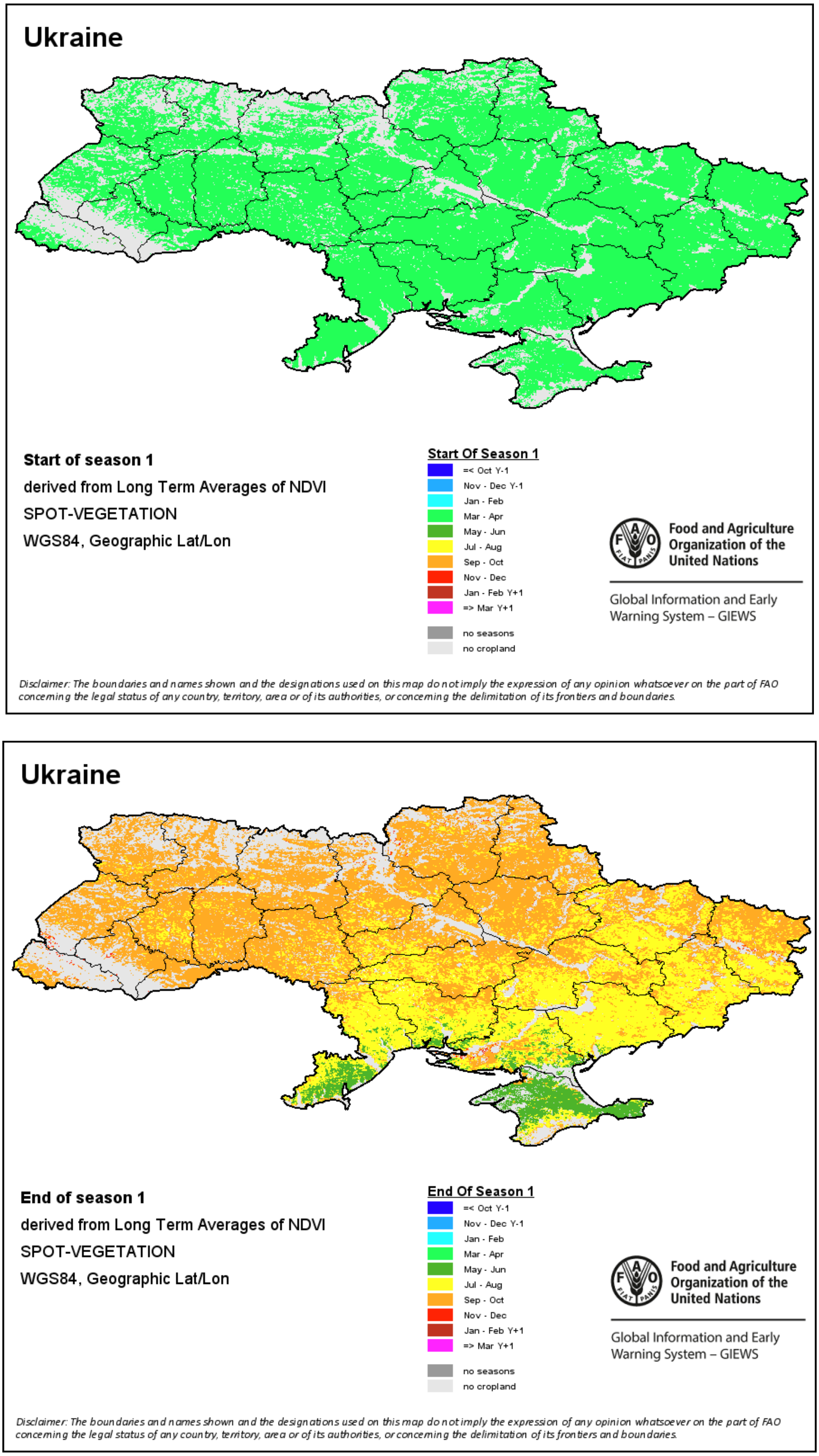

Fig. 2. Season 1 duration for Kherson region of Ukraine (retrieved from FAO Earth Observation services, https://www.fao.org/giews/earthobservation/country/index.jsp?lang=en&code=UKR)

Fig. 3. Association between the studied remote sensing drought indicators in Kherson region in 2000 year (extracted from ArcGIS Online platform)

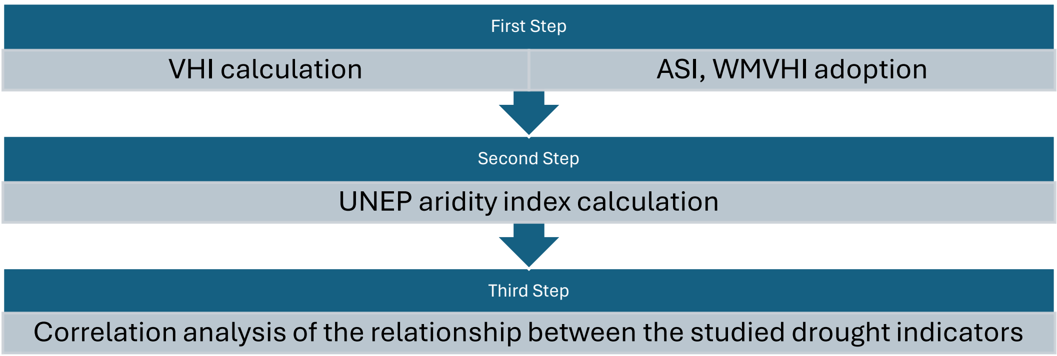

Fig. 4. Methodological flow chart of the study

Table 1

The results of correlation analysis between the studied drought indicators

Indicators pair	Correlation coefficient	Determination coefficient
VHI – ASI	-0.7975	0.64 (64%)
VHI – MWVHI	0.8071	0.65 (65%)
VHI – AI	0.2016	0.04 (4%)
ASI – MWVHI	-0.9625	0.93 (93%)
ASI – AI	-0.1269	0.02 (2%)
MWVHI – AI	0.1173	0.01 (1%)

values tell about better vegetation cover conditions and less stress in plants, while high ASI tells about higher affection of the area with drought stress. As well, higher UNEP AI values mean less arid and dry climate, therefore, it is logical, that higher UNEP AI shall correspond to lower ASI values.

3.2. Yields of major crops and drought stress indicators

The yields of major crops, cultivated in Kherson region, namely, winter and spring wheat, barley, grain corn, and sunflower are strongly dependent on the levels of natural moisture supply in the region, as well as irrigation [23]. Therefore, there should be a connection between the crops' productivity and drought indicators in the region. Tables 2–5 present generalized information on the mean annual yields of the studied crops in Kherson region, as well as their relationship with the studied drought indicators.

From the study results, it becomes evident that the strongest relationship between the crops' yields and drought indicators belongs to the pair "Yield – VHI", where determination coefficient, depending on the crop, fluctuates within 0.29-0.75. The weakest connection is determined for grain corn, while the strongest – for winter wheat. There is almost no statistically significant relationship between the crops' yields and UNEP aridity index. This is because the mentioned above indicator refers mainly to pure meteorological characteristics of the period and does not reflect real in-field conditions of drought intensity, which could be quite different because of additional parameters, affecting crops' state (irrigation, agrotechnological measures for moisture preservation, etc.). As for ASI and WMVHI, there is mild-to-moderate connection with crops' yields in the region. However, it is sufficiently lower than for VHI. Therefore, it is reasonable to create yield prediction models based on the VHI values, and other indices could be just supportive in this regard.

3.3. Crops' yield prediction models based on the vegetation health index

Based on the inputs, provided in the Table 2, linear regression models have been developed for each crop, cultivated in Kherson region. The statistics for the developed models are presented in Table 6.

Considering the results of linear regression analy-

Table 2

Historical mean annual yields of major crops, cultivated in Kherson region, and vegetation health index values

Year	VHI	Crops' yields, t/ha				
		Winter wheat	Spring wheat	Barley	Corn	Sunflower
2006	0.55	2.54	2.54	2.12	3.87	1.00
2008	0.61	3.28	3.28	3.09	5.99	1.11
2009	0.52	2.44	2.44	2.14	5.46	0.82
2010	0.52	2.43	2.43	1.63	5.29	1.23
2011	0.56	3.47	3.47	2.71	5.24	1.29
2013	0.51	2.41	2.41	1.97	4.97	0.77
2014	0.55	2.94	2.94	2.29	5.18	0.87
2015	0.68	3.54	2.86	3.10	7.10	1.70
2016	0.62	3.62	3.43	3.18	5.77	1.65
2017	0.53	3.49	3.00	3.05	5.97	1.34
2018	0.52	3.22	2.56	3.47	6.56	1.64
2019	0.60	3.49	3.14	4.09	8.03	1.79
2020	0.59	3.16	3.16	3.20	8.42	1.65
2021	0.74	4.22	4.22	4.42	6.70	2.00
2005	0.55	2.45	2.45	1.54	4.47	1.03
2007	0.26	1.85	1.85	0.90	4.13	0.57
2012	0.27	1.57	1.57	1.33	4.96	0.83
Correlation coefficient		0.86	0.86	0.78	0.54	0.73
Determination coefficient		0.75	0.74	0.61	0.29	0.54

Table 3

Historical mean annual yields of major crops, cultivated in Kherson region, and UNEP aridity index values

Year	UNEP AI	Crops' yields, t/ha				
		Winter wheat	Spring wheat	Barley	Corn	Sunflower
2006	0.35	2.54	2.54	2.12	3.87	1.00
2008	0.51	3.28	3.28	3.09	5.99	1.11
2009	0.48	2.44	2.44	2.14	5.46	0.82
2010	0.54	2.43	2.43	1.63	5.29	1.23
2011	0.20	3.47	3.47	2.71	5.24	1.29
2013	0.24	2.41	2.41	1.97	4.97	0.77
2014	0.23	2.94	2.94	2.29	5.18	0.87
2015	0.35	3.54	2.86	3.10	7.10	1.70
2016	0.38	3.62	3.43	3.18	5.77	1.65
2017	0.20	3.49	3.00	3.05	5.97	1.34
2018	0.27	3.22	2.56	3.47	6.56	1.64
2019	0.43	3.49	3.14	4.09	8.03	1.79
2020	0.23	3.16	3.16	3.20	8.42	1.65
2021	0.53	4.22	4.22	4.42	6.70	2.00
2005	0.49	2.45	2.45	1.54	4.47	1.03
2007	0.35	1.85	1.85	0.90	4.13	0.57
2012	0.23	1.57	1.57	1.33	4.96	0.83
Correlation coefficient		0.09	0.18	0.10	0.00	0.15
Determination coefficient		0.01	0.03	0.01	0.00	0.02

Table 4

Historical mean annual yields of major crops, cultivated in Kherson region, and agriculture stress index values

Year	**ASI**	**Crops' yields, t/ha**				
		Winter wheat	**Spring wheat**	**Barley**	**Corn**	**Sunflower**
2006	10.0	2.54	2.54	2.12	3.87	1.00
2008	10.0	3.28	3.28	3.09	5.99	1.11
2009	10.0	2.44	2.44	2.14	5.46	0.82
2010	10.0	2.43	2.43	1.63	5.29	1.23
2011	10.0	3.47	3.47	2.71	5.24	1.29
2013	17.5	2.41	2.41	1.97	4.97	0.77
2014	10.0	2.94	2.94	2.29	5.18	0.87
2015	10.0	3.54	2.86	3.10	7.10	1.70
2016	10.0	3.62	3.43	3.18	5.77	1.65
2017	10.0	3.49	3.00	3.05	5.97	1.34
2018	10.0	3.22	2.56	3.47	6.56	1.64
2019	10.0	3.49	3.14	4.09	8.03	1.79
2020	10.0	3.16	3.16	3.20	8.42	1.65
2021	10.0	4.22	4.22	4.42	6.70	2.00
2005	10.0	2.45	2.45	1.54	4.47	1.03
2007	77.5	1.85	1.85	0.90	4.13	0.57
2012	47.5	1.57	1.57	1.33	4.96	0.83
Correlation coefficient		-0.64	-0.62	-0.59	-0.40	-0.53
Determination coefficient		0.41	0.38	0.35	0.16	0.28

Table 5

Historical mean annual yields of major crops, cultivated in Kherson region, and drought intensity (weighted mean vegetation health index) index values

Year	**WMVHI**	**Crops yield, t/ha**				
		Winter wheat	**Spring wheat**	**Barley**	**Corn**	**Sunflower**
2006	71.0	2.54	2.54	2.12	3.87	1.00
2008	71.0	3.28	3.28	3.09	5.99	1.11
2009	71.0	2.44	2.44	2.14	5.46	0.82
2010	71.0	2.43	2.43	1.63	5.29	1.23
2011	71.0	3.47	3.47	2.71	5.24	1.29
2013	71.0	2.41	2.41	1.97	4.97	0.77
2014	71.0	2.94	2.94	2.29	5.18	0.87
2015	71.0	3.54	2.86	3.10	7.10	1.70
2016	71.0	3.62	3.43	3.18	5.77	1.65
2017	71.0	3.49	3.00	3.05	5.97	1.34
2018	71.0	3.22	2.56	3.47	6.56	1.64
2019	71.0	3.49	3.14	4.09	8.03	1.79
2020	71.0	3.16	3.16	3.20	8.42	1.65
2021	71.0	4.22	4.22	4.42	6.70	2.00
2005	71.0	2.45	2.45	1.54	4.47	1.03
2007	30.0	1.85	1.85	0.90	4.13	0.57
2012	36.5	1.57	1.57	1.33	4.96	0.83
Correlation coefficient		0.66	0.64	0.58	0.37	0.50
Determination coefficient		0.43	0.41	0.34	0.14	0.25

Table 6

Regression statistics for the developed models of the crops' yields prediction based on the values of vegetation health index

Statistical criteria	**Crop name**				
	Winter wheat	**Spring wheat**	**Barley**	**Grain corn**	**Sun-flower**
Number of inputs (N)	17	17	17	17	17
Correlation coefficient (R)	0.8644	0.8583	0.7802	0.5360	0.7349
Coefficient of determination (R^2)	0.7471	0.7367	0.6088	0.2873	0.5401
Adjusted R^2	0.7302	0.7192	0.5827	0.2398	0.5094
Predicted R^2	0.6873	0.6421	0.5223	0.1509	0.4242
Mean square error (MSE)	0.1323	0.1138	0.3963	1.2219	0.0879
Standard deviation (SD)	0.3637	0.3373	0.6295	1.1054	0.2965
Mean average percentage error (MAPE)	10.40%	9.67%	20.96%	13.90%	21.89%

sis. Five regression models have been developed for the yield prediction based on the VHI values (Table 7). However, it should be noted that the accuracy of the developed models is unequal, and the best quality of the prediction was achieved for winter and spring wheat. The greatest errors were established for grain corn and sunflower predictions, while barley yield prediction model has the lowest error and high fitting quality, taking into account the values of correlation and determination coefficients.

Therefore, the models for wheat and barley could be recommended for practical use, while the lower accuracy and fitting quality of the models for grain corn and sunflower makes these models contradictive and does not allow to recommend them for practitioners.

Table 7

Linear regression models for the studied crops' yields prediction based on vegetation health index values

Crop name	**Model**
Winter wheat	Yield=0.2296+5.0346*VHI
Spring wheat	Yield=0.3548+4.5446*VHI
Barley	Yield=-0.8136+6.3248*VHI
Grain corn	Yield=2.7183+5.65358VHI
Sunflower	Yield=-0.1453+2.5882*VHI

Discussion. Current study provides first scientific insight on the relationship between different drought risk indicators, both remotely sensed and directly measured. Special attention has been paid to comparatively rarely used in science and practice indicators, such as Agri-culture Stress Index (ASI), and FAO's drought intensity indicator (based on the Weighted Mean Vegetation Health Index WMVHI). These drought risk indicators are specific for agricultural use, but they found narrow implementation in science and practice. For example, the ASI was applied in several studies to assess drought impacts of the El Niño phenomenon on agricultural lands [15, 24] and as a remotely sensed indicator for crop insurance [25]. But none of the quoted studies investigated the relationship between the real meteorological drought and/or aridity indicators, as well as other remotely sensed drought indicators. This statement is also true for the FAO's drought intensity indicator. But the situation with the VHI is absolutely different.

The vegetation health index is one of the most well-studied drought and vegetation cover conditions indicators, which are computed based on the remote sensing data. The study [12] evaluated the relationship between the VHI and SPEI (Standardized Precipitation-Evapotranspiration Index) and found that these two indices are moderately correlated with each other. The study [26] revealed that the VHI moderately correlates with the NDVI (Normalized Difference Vegetation Index), and weakly correlates with the LST (Land Surface Temperature). The study [27] on the optimization of the VHI computation technique revealed that the correlation between the original VHI and scaled PDSI (Palmer's Drought Severity Index) was mild-to-moderate (0.38), while the optimized calculations resulted in better correlation between the two drought indicators (enhanced to 0.51). In the study [28] the authors revealed presence of moderate correlation between the VHI and SMI (Soil Moisture Index), favoring for the assumption that vegetation health index could be a reliable predictor of soil drought. Another study [29] claims that both VHI and SPI-3 (Standardized Precipitation Index) can clearly explain the relationship between meteorological drought and agricultural drought in Indonesia; the VHI and SPI-3 are strongly correlated with each other. Therefore, it is evident that vegetation health index is vastly studied in terms of its reliability in drought assessment and its connection with other popular meteorological indicators, calculated based on actual meteorological data. Not-withstanding the fact, there is no study available in scientific literature, devoted to the investigation on the relationship between the VHI and UNEP-AI. Thus, current study pro-vides novel insight into this subject, pointing out on extremely weak correlation between all the studied remote sensing-based drought indicators and aridity index. At the same time, it has been proved that all the remote sensing indicators are moderately-to-strong correlated with each other. Considering the study outcomes regarding the correlation be-tween the crops' yields in Kherson region and the studied indicators, it is possible to conclude that the UNEP aridity index provides pure climatological characteristics, while the ASI, MWVHI, and VHI provide indirect characteristics of drought effects on the croplands.

As for the crops' yields prediction, it was found out that vegetation health index is the only one to be implemented in this purpose, because the relationship between the yields and ASI/MWVHI is much weaker. Current study is not the first one to build up the models for crops' yields prediction based on remote sensing VHI data; although, it is the first study made for the specific conditions of Kherson region, which is characterized as the zone of risky agriculture. Kussul et al. (2015) refer to the VHI-based empirical models for regional crop yield prediction as commonly used in agricultural science [30]. VHI-based empirical models were developed and successfully used in scientific purposes for such crops as rice, cultivated in Bangladesh (R = 0.71-0.83) [31]; winter wheat, cultivated in Australia (R ≥ 0.70) [14], India (mean absolute percentage error of the predictive models was less than 10%) [32], Ukraine (VHI-based model outperformed NDVI-based and FAPAR-based ones having the lowest root mean square error of 0.51 t/ha) [33] etc.; grain corn, cultivated in Bulgaria (strong correlation between the crop yields and VHI was detected) [34]. Thus, it is evident that the VHI-based approach is well-known in modern agricultural science, but still not widely implemented. Current study provides some additional insights on the relationship between the VHI and regional yields of wheat, barley, grain corn and sunflower crops, pointing out that there is a great difference in this relationship for each of the studied crops. If cereal crops are strongly related to vegetation health index, grain corn and sunflower are much less related to this indicator, thus, making VHI-based yield prediction less reliable and reasonable. Such a discrepancy could be put upon different reaction of the studied crops on drought conditions, as well as great inequality in the areas under irrigation for each crop.

Conclusions. Current study is devoted to the investigation of the inter-relationship between drought indicators, such as ASI, MWVHI, VHI, and UNEP AI, as well as their correlation with the yields of major crops, cultivated in Kherson region of Ukraine. It was revealed that UNEP AI is weakly related both to remote sensing drought indicators and crops' yields in the region, providing mainly pure climatological characteristics, while other studied indicators are moderately-to-strong related to the yields of the studied crops, providing the information on how the cultivated plants react to drought conditions in the region. VHI-based linear regression models were developed to predict the yields of the studied crops for Kherson region. It was established that the best accuracy and reliability of the models is attributed to cereal crops, e.g., wheat and barley, while late-spring crops (grain corn and sunflower) have much less relation to the VHI. The developed models could be applied in scientific and practical purposes to predict the yields of the studied crops in Kherson region of Ukraine. Further studies will be conducted to learn more details about the patterns and features of the relationship between the remote sensing drought indicators and real-life productivity of crops.

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Дані дистанційного зондування для оцінки стресу від посухи та продуктивності сільськогосподарських угідь у Херсонській області

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Дані дистанційного зондування Землі є цінним джерелом інформації про стан навколишнього середовища в цілому та сільськогосподарських угідь зокрема. У статті описано результати вивчення застосування індексу здоров'я рослинності (VHI), індексу сільськогосподарського стресу (ASI) та індексу інтенсивності посухи (WMVHI) для оцінки інтенсивності негативної дії посушливих явищ на агрофітоценози у контексті їх кореляції з метеорологічним індексом аридності та продуктивністю сільськогосподарських земель Херсонської області. Дослідження базувалося на даних, знятих у період 1984-2022 рр., щодо врожайності основних сільськогосподарських культур у регіоні (озима та яра пшениця, ячмінь, кукурудза, соняшник) та величині вегетаційних індексів, розрахованих у відповідності до методики ФАО ООН за супутниковими знімками сервісу FAO Earth Observation Services. Індекс аридності було оцінено за методикою UNEP за даними Херсонського обласного гідрометеорологічного центру. Статистичну обробку даних виконували згідно традиційних методик кореляційно-регресійного аналізу та моделювання у Microsoft Excel 365 та BioStat v.7. У результаті досліджень встановлено, що супутникові вегетаційні індекси тісно корелюють із продуктивністю досліджуваних сільськогосподарських культур, та можуть бути успішно використані для стратегічного та оперативного прогнозування їх урожайності. Щодо метеорологічного індексу аридності, то він слабо корелює з урожайністю культурних рослин, і є суто кліматологічним показником, який має другорядне значення для оцінки стану та прогнозування продуктивності агрофітоценозів. Таким чином, запропоновано новий підхід до оцінки інтенсивності впливу посушливих явищ на агрофітоценози півдня України та прогнозу їх продуктивності за даними дистанційного зондування Землі, що має високу науково-теоретичну та практичну цінність.

Ключові слова: *індекс сільськогосподарського стресу, індекс аридності, інтенсивність посухи, індекс здоров'я рослинності, урожай.*

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