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Normalised difference moisture index in water stress assessment of maize crops

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Abstract. Remote sensing is a promising technique for better management of water resources in agriculture through improvement of dynamic control and operational scheduling on irrigated croplands. The main goal of this study was to identify the possibilities of application of the normalised difference moisture index (NDMI) to water stress monitoring in maize crops, and to determine the relationship between the index and soil moisture content. The study was carried out in 2019–2021 in the experimental fields of disturbed maize, cultivated on dark-chestnut soils in the Southern Ukraine at the NAAS Institute of Climate-Smart Agriculture. The crop cultivation technology was common for the conditions of the steppe zone of Ukraine. Actual soil moisture content was determined by gravimetric method in the pre-sowing and post-harvest period. The NDMI values were calculated using cloudless aerospace images from the satellites Landsat 8, Sentinel-2, and MODIS with 250 m resolution. It was revealed that the seasonal NDMI dynamics perfectly reflected the water-supply conditions of the disturbed maize, and could be used for operational monitoring and scheduling of irrigation. The parameters of the water-supply conditions were determined in 2021, which was the wettest year of the study: the cumulative seasonal NDMI reached 1.71, while the highest water stress was recorded in the driest year, 2020, – the cumulative NDMI was 0.15. Additionally, there was a moderately strong negative correlation between NDMI and soil moisture content, and the coefficient of determination was 0.62. The linear regression models, developed to predict soil moisture content in the 0–100 cm layer depending on the NDMI values, had good fitting quality and reasonable accuracy, but they required further calibration and extension of the initial dataset to provide more robust and reliable results for practical implementation. Based on the results of the study, spatial NDMI could be considered a good and reliable tool for improving irrigation water management. Further studies should focus on the practical implementation of the NDMI-based model of moisture-content estimation, as well as on the possibilities of the index usage for mapping irrigated lands.

Keywords: aerospace monitoring; irrigation; NDMI; remote sensing; soil moisture; steppe zone.

Introduction

The normalised difference moisture index (hereafter referred to as NDMI) belongs to the family of the least studied remote sensing vegetation indices. Although aerospace monitoring importance in environmental and agricultural studies increases each year, there is a lack of robust scientific research regarding the practical use of NDMI in ecological and agronomic studies. According to the explanation by Rahman & Mesev (2019), NDMI is a marker of moisture content in plants canopy, and therefore, its main scope of implementation is identification of water-stress levels. The general interpretation of the water stress and canopy characteristics of the plant by the NDMI values is presented in Table 1.

Strashok et al. (2022) applied NDMI to evaluate the functional status of vegetation cover, as well as its reaction to meteorological conditions, and found that this index is highly sensitive to water content in plant tissues and sum of active air temperatures. Hosseini Chamani et al. (2019) successfully used NDMI values as a predictor of soil moisture content. Peng et al. (2016) determined that NDMI is closely related to land surface temperature (LST), and therefore could be used in LST estimation models based on remote sensing data. Another interesting study revealed the effectiveness of NDMI screening for the monitoring of the disturbed forest areas, and it generally provided relevant and accurate information about the forest status after outbreaks of bark beetle (Lastovicka et al., 2020).

There are some interesting and valuable scientific studies related to the implementation of NDMI in agricultural science. The study by Herbei et al. (2023) provided novel insights on the correlation between different spatial vegetation indices, as well as on the possibility of their implementation for sunflower yield prediction.

Table 1
NDMI interpretation in terms of water stress levels and canopy cover characteristics

NDMI value	Interpretation
–1.0…–0.8	bare soil
–0.8…–0.6	canopy cover is almost absent
–0.6…–0.4	extremely weak vegetation cover
–0.4…–0.2	weak vegetation cover, severe water stress
–0.2…0.0	moderately weak vegetation, high water stress, or extremely weak vegetation cover under moderate water stress
0.0…0.2	moderate vegetation cover under high water stress, or moderately weak vegetation cover under moderate water stress
0.2…0.4	moderately strong vegetation cover under high water stress, or moderate vegetation cover under low water stress
0.4…0.6	strong vegetation cover, no water stress
0.6…0.8	very strong vegetation cover, no water stress
0.8…1.0	absolute vegetation cover of soil, no water stress, or waterlogging because of excessive water supply

The researchers found very strong correlation between NDMI and NDVI (correlation coefficient 0.975), and NDMI and NBR (correlation coefficient 0.997), which are normalised difference vegetation index (Huang et al., 2021) and normalised burn ratio, respectively (Delcourt et al., 2021). This conclusion allows us to assume that NDMI could also be considered as a marker of vegetation health status in cultivated crops. The multiple regression model, created based on the results of sunflower field trials, included three input variables, namely NDMI, NDVI, and NBR, and provided impressive precision of crop productivity prediction. Berca & Horoias (2022) found that NDMI values were strongly related to the levels of water stress and the yields of winter wheat, cultivated in southern Romania, while Borca et al. (2023) reported that the best accuracy of rapeseed yield prediction was obtained by using vegetation indices of NDVI or NDMI according to the results of statistical evaluation of regression models by the values of P, RMSEP, and R^2.

Another important branch of NDMI application is mapping of the irrigated lands. Compared to other vegetation indices (NDVI and EVI), the seasonal maximum algorithm of NDMI-based detection and mapping of the irrigated lands provided the highest reliability and accuracy according to the best RMSE and R^2 values (Chance et al., 2017). Sharma et al. (2018) demonstrated the possibility of accurate identification of irrigated croplands through the combination of NDVI, NDMI, and EVI (enhanced vegetation index) within the framework of SVM (support vector machine) algorithm of machine learning. Application of NDMI is not limited to irrigation mapping, and it is also used in irrigation scheduling during crop cultivation, as Gaznayee et al. (2023) reported its efficiency in irrigation control due to high sensitivity to changes in soil moisture. Verma & Verma (2023) also claim that remote sensing with NDMI could be used in precision agricultural systems to control and maintain soil moisture at the optimal level for cultivated crops. Furthermore, if properly screened, this spatial index allows for a more efficient irrigation through identification of the most vulnerable areas with the greatest insufficiency of water supply, while not irrigate the field on the whole, thus providing the best practice of water-resource management. Safi et al. (2022) also used NDMI values (so called hot spot and average) to determine the deficiency levels of water supply in such crops as irrigated wheat, potatoes, and grapes as a part of general methodology for estimating plants stress.

Considering the abovementioned scientific evidence for the opportunities, opening with NDMI implementation in crop production, it is out of question that scientific investigation of the index implementation in agriculture is doubtless. Therefore, the main objective of this study was to determine whether NDMI could be used for water-stress levels in irrigated maize crops, cultivated in the steppe zone of Ukraine, and to identify the correlation between soil moisture content and NDMI in maize.

Materials and methods

The study was carried out in 2019–2021 at the experimental fields of the Institute of Climate-Smart Agriculture of NAAS, located in the neighborhood of the Naddniprianske village of Kherson Oblast. The soil of the experimental fields was represented by a slightly saline dark chestnut soil with low content of available nitrogen, moderate content of phosphorus, and high content of available potassium in the arable layer (0–30 cm). The humus content was 3.0%. The bulk density of the arable layer was 1.28 g/cm^3, field capacity – 22.1%, and wilting point – 9.2%. The general properties of the soil were favourable for cultivation of maize. The weather conditions during the growing season of crops were quite different by the years of the study, but in general they were typical for the conditions of the southern steppe zone of Ukraine. Detailed characteristics of the weather conditions in the years of study are presented in Tables 2–4. The weather conditions were recorded at the Kherson regional hydrometeorological station. The driest year was 2020, while the best natural conditions for maize cultivation formed in 2021.

The experiments were carried out with maize, which was irrigated using water from the Inhulets irrigation system, while general cultivation technology was common for the southern steppe zone of Ukraine (Lavrynenko et al., 2011). It should be stressed that the area of a single experimental plot was 50 m^2. Two maize hybrids (Tronka and Stepovyi) were used as biological material of maize. The soil-moisture content was estimated using the standard gravimetric methodology (Reynolds, 1970). Irrigation scheduling was performed using the methodlogy by Ushkarenko (1994).

The results of the field analysis of soil moisture were related to the results of calculation of the NDMI values. The NDMI values were calculated using the following equation (1) from the corresponding bands of the combined images form the satellites Landsat 8, Sentinel-2, and MODIS:

$$NDMI = \frac{NIR-SWIR}{NIR+SWIR} \quad (1)$$

where NIR – near-infrared band value of the aerospace image; SWIR – Shortwave infrared band value of the aerospace image (Taloor et al., 2021).

Table 2
Weather conditions of the field experiment in 2019

Month	Average air temperature, ºC				Precipitation, mm				Relative air humidity, %			
	ten-day periods			monthly average	ten-day periods			monthly sum	ten-day periods			monthly average
	I	II	III		I	II	III		I	II	III	
I	–2.3	–0.3	0.6	–0.6	7.9	12.9	19.4	40.2	92	87	93	91
II	2.5	2.7	–1.0	1.4	1.3	0.0	8.5	9.8	92	80	80	84
III	5.8	5.4	6.3	5.8	0.3	5.6	1.4	2.4	70	69	27	55
IV	9.6	8.8	13.4	9.3	5.3	37.6	0.0	42.9	57	79	51	62
V	14.1	18.2	20.1	17.5	6.8	3.8	24.5	35.1	74	74	72	73
VI	23.4	25.1	24.3	23.8	84.2	3.9	4.5	92.6	67	60	55	64
VII	22.7	21.5	25.1	23.1	42.3	2.7	3.7	48.7	60	58	57	58
VIII	21.4	23.1	25.5	23.3	21.4	0.7	0.0	22.1	66	60	48	58
IX	22.0	18.1	14.2	18.1	6.2	1.5	4.4	12.1	58	53	64	58
X	12.2	13.7	9.0	11.6	56.1	4.6	2.2	62.9	80	83	90	84
XI	11.3	8.0	1.8	7.1	19.0	1.6	17.4	38.0	84	91	84	86
XII	2.0	5.2	5.7	4.3	7.6	6.1	12.1	25.8	87	95	91	91
Annual average				12.2	Annual sum			437.5	Annual average			72

Table 3
Weather conditions of the field experiment in 2020

Month	Average air temperature, ºC				Precipitation, mm				Relative air humidity, %			
	ten-day periods			Monthly average	ten-day periods			Monthly sum	ten-day periods			Monthly average
	I	II	III		I	II	III		I	II	III	
I	–0.1	0.3	2.4	0.9	1.3	0.0	16.0	17.3	85	90	78	84
II	0.3	3.3	4.8	2.7	35.0	11.7	9.7	56.4	85	81	79	82
III	10.1	6.5	6.4	7.6	0.3	1.7	4.2	6.2	71	62	62	65
IV	7.9	10.1	11.3	9.8	0.0	2.0	0.8	2.8	50	55	52	52
V	14.4	15.5	14.2	14.7	9.2	6.3	13.8	29.3	63	60	68	64
VI	20.3	23.3	24.6	22.7	2.8	20.1	22.2	45.1	60	69	62	64
VII	26.1	23.4	24.5	24.7	33.3	4.9	20.8	59.0	54	52	58	55
VIII	25.2	22.4	23.7	23.8	1.1	19.7	4.5	25.3	46	53	55	51
IX	23.5	20.2	18.8	20.8	2.6	0.0	22.4	25.0	56	50	66	57
X	17.6	15.8	13.3	15.5	8.0	13.0	0.5	21.5	81	80	85	82
XI	8.6	2.0	4.2	4.9	10.3	0.0	0.0	10.3	90	84	82	85
XII	0.2	1.7	3.1	1.7	0.0	5.1	9.3	18.2	88	93	91	90
Annual average				12.5	Annual sum			312.6	Annual average			69

Table 4
Weather conditions of the field experiment in 2021

Month	Average air temperature, °C				Precipitation, mm				Relative air humidity, %			
	ten-day periods			Monthly average	ten-day periods			Monthly sum	ten-day periods			Monthly average
	I	II	III		I	II	III		I	II	III	
I	3.3	–7.5	2.9	–0.4	31.0	4.9	19.2	39.8	92	85	96	92
II	2.0	–5.6	2.4	–0.6	12.2	6.1	0.4	18.7	90	77	80	82
III	2.2	3.8	3.9	3.3	0.3	26.5	8.4	27.9	71	78	75	75
IV	7.0	9.8	9.9	8.9	19.7	18.0	3.7	41.4	70	72	71	71
V	13.9	15.2	18.5	16.0	14.9	56.4	26.4	97.7	67	73	68	69
VI	16.6	20.4	25.1	20.7	38.1	46.5	4.6	89.2	81	79	72	77
VII	23.7	27.0	25.3	25.3	68.3	0.9	7.5	76.7	72	57	57	62
VIII	25.7	23.9	23.6	24.4	1.8	4.5	1.2	7.5	61	61	61	61
IX	16.9	19.0	12.2	16.0	1.1	8.3	2.5	11.9	53	61	69	61
X	11.2	10.3	9.0	10.1	0.0	4.6	0.5	5.1	53	70	72	65
XI	9.7	3.7	6.2	6.5	19.3	0.9	13.4	33.6	89	84	86	86
XII	6.0	3.5	3.2	–3.3	1.9	17.4	31.9	64.1	92	91	87	90
		Annual average		11.7		Annual sum		523.3		Annual average		74

Cloudless images, free from distortion, were used to identify the corresponding values of NDMI. Cascade diagrams, created using Microsoft Excel 365 spreadsheet processor, were used to visualize the possibilities of NDMI in demonstration of changes in water supply of maize crops during the growing season under irrigation. Statistical evaluation of the connection between the actual soil-moisture content and the corresponding NDMI, screened at the time of soil analysis, was performed using standard correlation and regression analysis within BioStat v.7 software at $P < 0.05$. A regression model was proposed for the derivation of soil moisture from NDMI values based on the results of statistical data processing (Pal et al., 2019).

Results

Our study provides the insights on the possibility of NDMI application to evaluate the level of water supply in the crops of irrigated maize during its growing season, as well as correlation between the spatial index and soil-moisture content in the surface layer was identified. Fist, NDMI data, retrieved from the cloudless aerospace images, were generalised by the years of the study. Unfortunately, optical disturbances and cloud issues did not allow developing datasets that were equal in numbers for each year of the study. The largest dataset was recorded for 2021 – 16 datapoints, while the smallest dataset was in 2020 – just 8 datapoints. The total number of datapoints was 37, and it corresponded to a large data set according to the central limit theorem rule (CLT) for the standard normal distribution of data (Montgomery & Runger, 2020). The generalised NDMI for the growing season of irrigated maize (which was sown in the 3rd ten-day period of April and harvested in the 3rd ten-day period of September) data set is presented in Table 5.

Table 5
NDMI values during the growing season of irrigated maize in 2019–2021

2019		2020		2021	
Date	NDMI	Date	NDMI	Date	NDMI
5 May	–0.20	19 May	–0.13	4 May	-0.28
20 May	–0.01	8 June	–0.10	9 May	-0.26
30 May	–0.09	18 July	0	8 June	-0.01
9 June	0.02	7 August	0.05	13 June	-0.01
4 July	0.10	17 August	0.11	18 June	0.18
19 July	0.16	27 August	0.07	3 July	0.15
24 July	0.16	6 September	–0.03	8 July	0.27
3 August	0.10	26 September	–0.12	18 July	0.26
8 August	0.15			23 July	0.26
18 August	0.10			28 July	0.29
28 August	–0.02			2 August	0.27
7 September	–0.04			12 August	0.19
12 September	–0.03			17 August	0.21
				22 August	0.21
				1 September	–0.02
				16 September	0

The cascade diagrams, presented in Figures 1–3, demonstrate dynamical changes in the water supply of irrigated maize. It is evident that before irrigation (conducted in mid-late June), the crop suffered unfavourable moisture supply, expressed by negative NDMI values. The start of the irrigation season resulted in a steep improvement of the water regime in the crops' fields, and a negative water balance occurred just at the end of the growing season due to cessation of the artificial water supply to let the mass of the plant vegetation and grain dry to the moisture level that was suitable for combined harvesting. The highest positive NDMI balance was recorded in August by the years of the study. Generally, NDMI dynamics is good in explaining changes in conditions of maize water stress throughout the growing season.

It should also be noted that in the driest, 2020 year, even irrigation was unable to fully compensate for the water deficit in the fields of maize. If in 2019 and 2021, the cumulative NDMI value by the growing season of the crop was 0.40 and 1.71, respectively; in the driest 2020, it was –0.15, pointing to the negative water balance in the field regardless of artificial moisture supply. Therefore, NDMI is a simple and convenient tool for monitoring water stress in crops and adjusting irrigation scheduling.

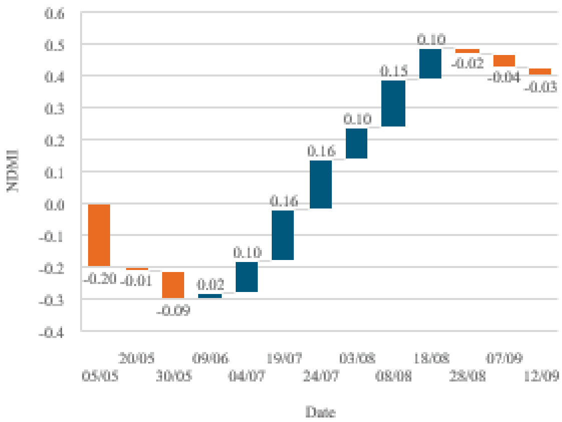

Fig. 1. Cascade diagram of water supply in maize crops expressed by NDMI values dynamics in 2019

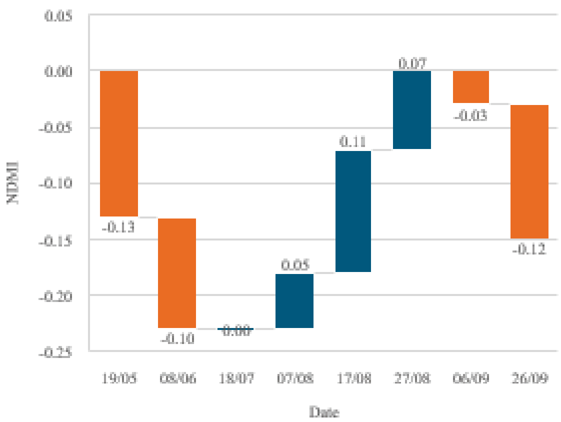

Fig. 2. Cascade diagram of water supply in maize crops expressed by NDMI values dynamics in 2020

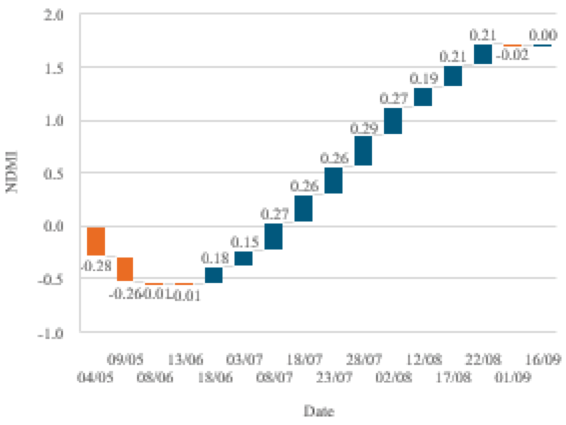

Fig. 3. Cascade diagram of water supply in maize crops expressed by NDMI values dynamics in 2021

In order to provide additional scientific substantiation of the implementation of NDMI in crop water supply, the analysis of the interconnection between soil moisture content and NDMI values was performed during the pre-sowing and post-harvest period of maize. The results of the study are presented in Table 6, indicating strong reverse connection between the studied indices (Schober et al., 2018), that means that the higher soil moisture content is, the lower NDMI values are, mainly due to the higher water intake by well-developed plants cover.

Table 6
Analysis of interconnection between soil moisture content in the 0–100 cm layer in maize crops and NDMI

Year	Terms of estimation	Soil moisture content, mm (W)	NDMI
2019	Pre-sowing period	151.3	–0.20
	Post-harvesting period	55.2	–0.03
2020	Pre-sowing period	155.8	–0.13
	Post-harvesting period	50.8	–0.12
2021	Pre-sowing period	150.7	–0.28
	Post-harvesting period	51.2	0
Pearson's correlation coefficient R		–0.79	
Coefficient of determination R^2		0.62	

Small dataset (N = 6) allows identifying only linear relationship between the studied indices. Therefore, linear regression models of NDMI soil moisture content in the 0–100 cm layer were developed (Table 7). The developed model with the intercept estimation had a moderate prognostic reliability and a reasonable predicting accuracy (Moreno et al., 2013). It suggests that by every single point of NDMI increment, soil moisture content in maize crops declined by 415.25 mm. Although the Fischer's Criterion indicates statistical significance of the model, P-values, calculated for the intercept and X argument of the model, were higher than 0.05. Therefore, the model cannot be considered statistically true. The model with no intercept estimation (Model 2) had a greater statistical significance and had been proved to be reliable both by the Fischer's and P-criteria. Accuracy of Model 2 was somewhat lower than Model 1, but still fell within the reasonable range. Visual approximation of both models is presented in Figure 4.

The interpretation of the results of the soil moisture content modelling (Model 2) shows that every time the NDMI value increased by one point and the soil moisture content decreased by 667.1 mm due to increased water uptake by plants. The negative values of the regression coefficients in both regression models provide additional evidence in support of the reverse correlation between the parameters studied.

Discussion

Remote sensing is a promising technology for improving crop cultivation management. It is especially relevant in the context of transfer to environmentally friendly, economically rational crop production technologies within the framework of climate-smart and low-carbon precision agriculture systems (Butrym et al., 2023). Various vegetation indices, calculated using aerospace images screened in different spectral bands, are inexhaustible source of valuable information about plants and agroecosystem conditions, and are used in agroecological zoning, phenological monitoring, yields prediction, soil qualities assessment, etc. (He et al., 2021; Ji et al., 2021; Liu et al., 2022; Lykhovyd, 2023). In this study, the main features of the implementation of NDMI for monitoring maize water stress and assessing soil moisture content are presented.

Table 7
A linear regression model of soil moisture content in the 0–100 cm layer prediction in maize crops depending on NDMI

Statistical parameter	Value
Model 1 (with an intercept estimation)	
Pearson's correlation coefficient R	–0.79
Coefficient of determination R^2	0.62
Normalized coefficient of determination R^2	0.53
Predicted coefficient of determination R^2	0.37
Standard deviation SD	37.81 mm
Fischer's criterion	6.55
Fischer's criterion (at $P < 0.05$)	0.06
P-value for Intercept	0.12
P-value for X (NDMI)	0.06
Mean absolute percentage error MAPE	27.9%
Model 1 equation	W = 49.90–415.25NDMI
Model 2 (no intercept estimation)	
Pearson's correlation coefficient R	0.93
Coefficient of determination R^2	0.86
Normalized coefficient of determination R^2	0.66
Predicted coefficient of determination R^2	0.36
Standard deviation SD	47.14
Fischer's criterion	30.16
Fischer's criterion (at $P < 0.05$)	0.005
P-value for X (NDMI)	0.003
Mean absolute percentage error MAPE	38.81%
Model 2 equation	W = –667.1NDMI

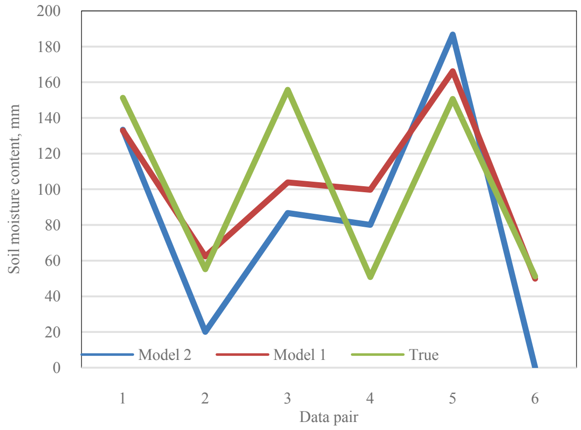

Fig. 4. Approximation of soil moisture content by NDMI-based linear regression models

Mimić et al. (2022) used NDMI values to evaluate the levels of crop moisture supply in maize and sunflower. The study by Dhaloiya et al. (2023) showed that NDMI is related not only to humidification conditions and water availability for plants, but also to air temperature and health of vegetation cover, making it a universal indicator of general water stress. Masina et al. (2020) provided the proof that NDMI, calculated using the aerospace imagery from Sentinel-2 satellite, is a promising substitute for CWSI (crop water stress index) to evaluate and predict water stress levels in maize crops. In addition, NDMI is significantly correlated with surface moisture, and it is applied to facilitate more accurate estimation of field water capacity in the arable (0–30 cm) soil layer and provide the best decisions on irrigation (Brom et al., 2021). In the current study, cascade diagrams and cumulative NDMI calculation provided reliable and convenient estimation of the water supply status in maize crops, as the index was strongly dependent on moisture income and intake by the plants. In addition, the outcomes support the idea of further implementation of NDMI in dynamical monitoring and management of irrigation in the systems of precise agriculture. It is promising not only for irrigation scheduling and precise identification of areas that are under water stress, but also can be used to determine the integrity and damage to irrigation system itself (Granshaw, 2019; Verma & Verma, 2023).

Previous studies on the given subject are in strong agreement with the obtained results. Thus, Mallick et al. (2012) found a strong negative correlation between the values of NDMI and soil moisture content: the determination coefficient reached 0.95, which was even higher than in our research. Interestingly, the direction of the relationship between these two variables was the same as in our study, reverse. Bidgoli et al. (2020) reported a significant advantage of NDMI over other vegetation indices for soil moisture assessment (correlation coefficients were 0.57–0.61), although none of the studied aerospace indices was suitable for accurate measurement of soil moisture content in arid climate. However, the issue of remote sensing screening of soil moisture content in desert and arid regions remains debatable, as Koohbanani & Yazdani (2018) provided the evidence that NDMI is an appropriate indicator to screen soil moisture content, especially in the zones with poor vegetation cover. The study, recently conducted in Indonesia, provided strong evidence to support the possibility of deriving soil moisture content from spatial NDMI values using a linear regression function with the average error of less than 5% and 94.6% linearity (Cahyono et al., 2022). Another scientific evidence in support of the possibility of estimating soil moisture content using NDMI values was provided by Kılıç & Gündoğan (2022), who found that NDMI had a moderately significant positive correlation with soil moisture content, identified by the gravimetric method. Considering the claims mentioned above and the results of the current study, there is evidence in support of the implementation of remote sensing NDMI in soil moisture monitoring both in irrigated and non-irrigated conditions. To obtain the best results, it is believed that NDMI screening should be performed for bare soil or during periods of low presence of vegetation cover.

Further research will be directed on the comparison of NDMI and NDWI (normalised difference water index) performance in estimating of crop water stress, as well as development of algorithms to implement the mentioned spatial indices in the systems of automated mapping of irrigated areas to facilitate the best management of water resource in agriculture (Sharma et al., 2018). Besides, NDMI, together with some other spatial vegetation indices, is strongly related not only to the levels of water supply in crops, but also to their general vigor, biomass accumulation, and nitrogen uptake from soil. Therefore, the combination of NDMI and EVI could be used to create maps for precision irrigation and nitrogen application in the systems of digital agriculture (Šuslikova et al., 2023).

Conclusions

The results of current research provide scientific evidence for rational use of aerospace-derived NDMI values in the monitoring of water stress in irrigated maize crops. The index reflects the dynamics of watering conditions throughout the growing season of crop and could be used to adjust irrigation scheduling in the systems of precise agriculture. In addition, strong reverse correlation between NDMI and gravimetric soil moisture content in the layer 0-100 cm was measured, and linear regression model was designed to facilitate rough predictions of changes in soil moisture content using the values of remote sensing with NDMI. Further research will be directed to provide stronger evidence on the relationship between NDMI and soil moisture content in different types of soil, as well as application of the index in mapping irrigated land.

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