УДК 631.432.2: 528.88
DOI https://doi.org/10.32848/agrar.innov.2026.35.25

AGROECOLOGICAL MODELING OF WATER CONDITIONS IN FALLOW FIELDS USING REMOTE SENSING DATA

LYKHOVYD P.V. – Doctor of Agricultural Sciences,
orcid.org/0000-0002-0314-7644
Institute of Climate-Smart Agriculture of National Academy of Agrarian Sciences of Ukraine
CHABAN V.O. – Doctor of Agricultural Sciences
orcid.org/0000-0003-0900-2128
Kherson State Maritime Academy
MAKSYMOV D.O. – Candidate of Agricultural Sciences
orcid.org/0009-0001-7461-6321
Institute of Climate-Smart Agriculture of National Academy of Agrarian Sciences of Ukraine

Problem statement. Global warming impacts Earth's ecosystems on almost every scale. Climate change has become one of the most dangerous threats to humanity in the 21st century. The strongest effect is on food security, as global shifts in climate patterns have resulted in dramatic changes in the sustainability of agricultural ecosystems, reducing their productivity and making it harder to gather high-quality crops in the most vulnerable regions. The main driving forces behind the decrease in agricultural productivity are high temperatures combined with prolonged drought events and inequality in natural moisture income. Insufficient precipitation under extreme air temperatures leads to severe soil and air drought events, which in turn cause great harm to the yields of agricultural crops [1]. When combined with adverse meteorological phenomena like strong winds, hailstorms, and pest attacks, climatic events become even more harmful, sometimes leading to complete yield loss in the vulnerable arid and semi-arid regions of the planet.

To ensure the sustainable development of agriculture, food security, and the environmental safety of agrotechnologies, it is essential to carefully control the usage of natural resources in agriculture. As freshwater becomes one of the most vulnerable and deficient resources, studying novel ways of monitoring moisture accumulation becomes one of the most urgent tasks of modern agricultural science [2]. On-land surveys are not always possible or convenient, as they require specialists, high expenditures, and time availability. Although they remain the standard in the field of agricultural meteorology, novel technologies are being studied to enhance the efficiency of agrometeorological monitoring and make it less expensive and laborious.

Analysis of recent research and publications. Remote sensing has become a cornerstone in monitoring moisture accumulation from precipitation, offering global, high-resolution, and near-real-time data on soil moisture, precipitation, and related hydrologic variables. These technologies are crucial for understanding the water cycle, improving drought and flood forecasting, and supporting water resource management, especially in regions with sparse ground observations. For example, remote sensing is applied for drought monitoring, where it has its strong points (high spatial/temporal coverage, reasonable accuracy with multivariate assimilation) and drawbacks (lower reliability in dense vegetation, topographic effects, and distortions due to atmospheric events) compared to traditional agrometeorological methods [3, 4]. Also, remote sensing data have been applied to precipitation estimation and proved to be in good agreement with on-land observation data but sometimes fail because of data gaps and uncertainties in complex relief [5]. Apart from their low time and cost consumption, remote sensing methods are extremely helpful in mapping water objects and moisture income [6]. Integration with robust data analysis techniques has increased the value of remote sensing data in natural moisture prediction in recent decades, aiding in filling data gaps and providing the best forecasting algorithms [7]. Ongoing research focuses on refining downscaling techniques to bridge the gap between coarse satellite data and the needs of local hydrologic applications. Efforts continue to improve validation methods and quantify uncertainties, particularly in data-scarce or complex regions [8, 9].

In general, remote sensing has revolutionized the monitoring of moisture accumulation from precipitation, enabling accurate, timely, relatively cheap, and spatially comprehensive assessments compared to traditional methods. While challenges remain – such as data resolution, validation, and performance in complex environments – ongoing advances in data assimilation, machine learning, and downscaling are rapidly improving the utility of these datasets for hydrologic science and water management.

Purpose – the main goal of our study was to establish whether remotely sensed indices like the normalized difference water index (NDWI) and soil moisture index (SMI) are suitable for dynamic control of moisture accumulation in fallow fields in the semi-arid climate zone of southern Ukraine, where moisture deficit is one of the greatest threats to sustainable agriculture and food security.

Materials and methods. The study was carried out in 2025 on fallow fields of the Agricultural Farm “Vostok”, located in the Kherson region, southern Ukraine. The experimental site is situated within the geographic extent 46°40–46°44′ N and 32°13–32°50′ E. The soil in the study area is represented by dark-chestnut slightly saline soil. In climatic relation, this zone belongs to the zone of risky agriculture because of semi-arid Steppe climate and consistent deficiency in natural humidification.

Remote sensing data were obtained from the OneSoil precision farming platform, based on Sentinel-2 imagery with 10-m spatial resolution [10]. Only cloud-free scenes (cloud coverage < 5%) with no corruption and distortions were used. Two vegetation-water indices were analyzed: the NDWI and SMI. OneSoil platform provides indices, calculated using common international methodologies [11, 12]. Ground-truth data on soil moisture accumulation (MA) were collected using field gauge measurements and further associated with corresponding remote sensing data on spatial indices.

In total, 250 paired observations were obtained for "NDWI–soil moisture" and 250 for "SMI–soil moisture", as well as 103 observations for complex "NDWI-SMI-soil moisture" pairs. The relationships between remote sensing indices and measured soil moisture were modeled using ordinary least squares (OLS) linear regression [13]. Model performance was assessed with Pearson's correlation coefficient (r), coefficient of determination (R^2), mean square error (MSE), and mean absolute percentage error (MAPE) [14]. All statistical analyses were conducted in BioStat v.7 software at 95% confidence interval (CI).

Cluster analysis of the datasets was performed by unsupervised K-means learning algorithm with computation of the silhouette score and inertia to identify natural groupings of soil moisture conditions using Python 3 with external libraries from scikit learn and matplotlib modules [15].

Research results. The results clearly indicate that the NDWI-based model provides a more accurate and robust estimation of soil moisture accumulation compared to the SMI-based model (Table 1).

The NDWI-based model demonstrated superior performance across all statistical metrics. The strong positive correlation (r=0.9160) indicates a highly linear relationship between NDWI and soil moisture accumulation. This is further supported by the high coefficient of determination (R^2=0.8391), which suggests that approximately 84% of the variability in soil moisture accumulation can be explained by the NDWI. The model's acceptable value of mean square error (MSE = 37.48 mm) confirms its high predictive accuracy and lower error margin compared to the SMI-based model. As for the mean absolute percentage error value (MAPE = 26.56%), it must be noted that the model's performance could be considered reasonably good according to the modern classification recommendation [16].

In contrast, the SMI-based model showed a weaker correlation (r=0.6884) and a significantly lower coefficient of determination (R^2=0.4739). This means that the SMI accounts for only about 47% of the variability in soil moisture, indicating a less reliable relationship. The higher error metrics (MSE = 108.84 mm and MAPE = 54.93%) further underscore its reduced predictive capability and greater average error.

Special attention should be paid to the models themselves. The negative coefficient suggests an inverse relationship, meaning as the NDWI value decreases (which is often associated with drier conditions in some contexts), moisture accumulation increases. Common NDWI interpretations tell that positive values within the range 0.2-1.0 are usual for water surface areas, while -1.0-0.2 are usually used to describe various water conditions of non-water objects, such as soil. For example, NDWI of 0.0-0.2 usually corresponds to highly humid or flooded areas, while NDWI of -0.3-0.0 is common for non-aqueous surfaces experiencing slight to moderate drought [17]. Considering the fact that the minimum value of NDWI in our case was -0.54, while the maximum value reached 0.09, it is obvious that the NDWI of the studied area corresponds to moderately dry to dry soil, which is absolutely right for the dark-chestnut soil in southern Ukraine, as this agricultural zone is subjected to moderate and severe droughts, and there is a constant natural moisture deficit in the soils of the zone [18]. Therefore, the NDWI-based model perfectly reflects the real-life moisture accumulation patterns in the zone of the study conduction but has some limitations because no variants close to the edge values of the index were included in the training dataset.

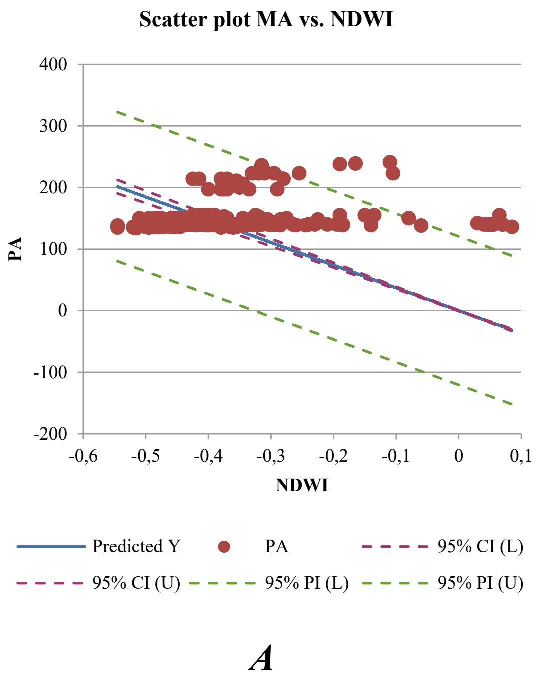
With the SMI index, there is a different situation. The values of this indicator usually fluctuate between 0 and 1, so the values close to 0 reflect extreme drought, while those close to 1 reflect extremely wet conditions [12]. The SMI-based model equation provides a positive direct relationship, where an increase in the SMI value is associated with an increase in moisture accumulation, which aligns with the general interpretation of the soil moisture index provided above. However, despite this logical relationship, the overall predictive power of the model is significantly lower than that of the NDWI model.

Additional information could be received from the visualization (Fig. 1). Based on the scatter plots, there is a negative correlation between moisture accumulation and NDWI, and a positive correlation between moisture accumulation and SMI. The regression line in the NDWI plot slopes downward, while the one in the SMI plot slopes upward. The dashed lines around the regression lines represent the prediction confidence intervals. The wider spread of these lines in the SMI plot compared to the NDWI plot suggests a lower predictive accuracy for the SMI-MA relationship. However, the data points in the NDWI plot are

Table 1

Results of Modeling Soil Moisture Accumulation (MA) in Fallow Fields Using Normalized Difference Water Index (NDWI) and Soil Moisture Index (SMI)

Metrics	NDWI	SMI
r	0.9160	0.6884
R^2	0.8391	0.4739
MSE	37.48 mm	108.84 mm
MAPE	26.56%	54.93%
Model (MA)	MA = -369.27×NDWI	MA = 716.53×SMI



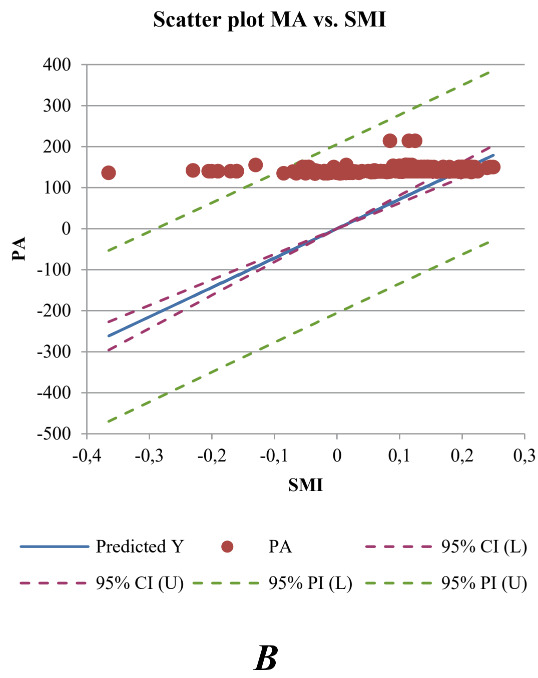


Fig. 1. Scatter plots for the NDWI- and SMI-based Models of Soil Moisture Accumulation (MA) in Fallow Fields

more scattered, while the points in the SMI plot are more tightly clustered.

As for the combined model, its performance beat both solo-index models: R^2 reached 0.8778, with MSE of 26.22 mm and MAPE of 26.02%, respectively. The model could be expressed as the following linear equation: MA = -159.05×SMI – 344.09×NDWI. Quite surprisingly, the combined model suggests negative regression coefficients for both remote sensing indices, that is unusual for SMI. Future research with larger datasets is required to clarify this feature, which could be dependent on the noise in data, regression analysis limitations or could be a characteristic of complex relationship between soil moisture and remote sensing indices for the area of study conduction.

As for clustering analysis results, based on the value of silhouette score (0.47), they are reasonable and could be considered for theoretical interpretation, while lacking strength of evidence for practical recommendations (Fig. 2).

Each cluster represents a specific soil moisture regime, defined by a unique combination of values for the three indices:

1) Teal/Green Cluster: The “Dry” Regime. This cluster occupies the region with the lowest values on the MA axis, generally below 150 mm. It also has a wide range of SMI and mostly negative NDWI values. It represents dry, arid, or heavily water-stressed conditions in the fallow fields.

2) Yellow Cluster: The “Moderate” Regime. This cluster is found at intermediate MA values, typically ranging from 150 mm to around 170 mm. It shows a tight grouping on the SMI axis but a wider spread of NDWI values. It represents moderately humid or transitional conditions. This is a common state for fallow fields under rainfed conditions.

3) Purple Cluster: The "Wet" or "Saturated" Regime. This cluster is clearly distinguished by its high values on the MA axis, generally above 180 mm. It has a significant spread on both the SMI and NDWI axes, often with the highest positive values in the dataset. It represents areas with high soil moisture, saturated conditions, or even standing water. It could be put upon the fact that in some cases data were collected almost immediately after heavy rainfall.

The visualization effectively shows that Moisture Accumulation (MA) is the most dominant variable for separating the clusters. The MA axis acts as the primary differentiator, with SMI and NDWI providing additional dimensions that refine the classification within each moisture level. This analysis is valuable for applications such as drought monitoring, hydrological modeling, and precision agriculture, as it provides a clear and intuitive classification of a landscape's soil moisture status.

Discussion. Remote sensing, particularly using indices like the NDWI, has become a key tool for monitoring soil moisture dynamics, especially in agricultural enterprises and agroecological surveys. Accurate soil moisture estimation is crucial for rational agricultural water management, assisting in drought monitoring and prediction, as well as providing for optimizing agricultural plant cultivation practices.

Recent studies point out that NDWI is sensitive to soil moisture variations and can track water stress and accumulation, especially when integrated with other indices and ground measurements [19]. NDMI, closely related to NDWI, has also demonstrated strong correlation with soil moisture in precision agriculture settings [20].

Recent research leverages machine learning (e.g., Random Forest, long short-term memory, convolutional neural network) and data fusion (optical, thermal, microwave) to improve soil moisture predictions at field and regional scales. These models, when fed with NDWI/NDMI and auxiliary data (climate, soil texture, topography), achieve high accuracy (R^2 up to 0.99 in some cases)

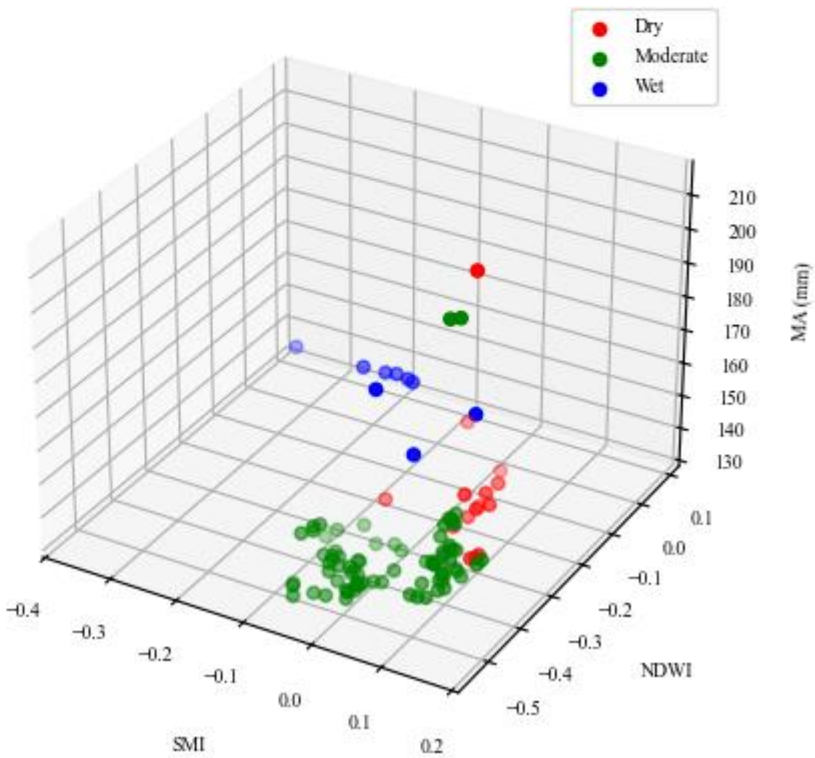


Fig. 2. Clustering 3D Plot for the NDWI, SMI and Soil Moisture Accumulation (MA) in Fallow Fields

and robustness, even under varying vegetation cover or noise [20, 21]. Stacking and ensemble approaches further enhance prediction reliability [22].

While most studies focus on cropped fields, the principles extend to fallow fields, where bare soil or sparse vegetation allows NDWI to directly reflect soil moisture status. However, there is very limited data on fallow field applications of NDWI-based moisture predictions. Therefore, our outcomes are pilot ones and provide novel insights on the remote sensing index implementation for soil moisture content estimation.

As for the SMI, it is increasingly used to estimate and monitor soil moisture dynamics, especially in croplands and fallow fields where in-situ measurements are sparse. SMI leverages satellite data to provide spatially explicit, timely, and cost-effective soil moisture assessments critical for water management, drought monitoring, and precision agriculture.

SMI is frequently derived from the relationship between land surface temperature (LST) and vegetation indices (e.g., normalized difference vegetation index referred to as NDVI) using satellite data such as Landsat or the Moderate Resolution Imaging Spectroradiometer (MODIS). These methods are effective for mapping soil moisture and drought severity, with validation showing strong correlation to field measurements and utility in drought risk assessment [12, 23].

SMI models usually achieve high correlation with ground data (R^2 up to 0.87), with root mean square errors (RMSE) often below 8% [22, 24]. Machine learning and data fusion approaches further enhance prediction accuracy, especially in heterogeneous or semi-arid landscapes, where the relationships are often broken. However, it should be noted that notwithstanding relatively high correlation with real soil moisture content, its performance is still inferior to NDWI- or NDMI-driven models in most cases. In addition, SMI limitations include reduced accuracy in areas with dense vegetation, complex terrain, or limited ground truth data [25, 26].

In general, remote sensing SMI is a robust, scalable indicator for modeling soil moisture accumulation on agricultural fields, with best results achieved by integrating multiple sensor types and advanced modeling techniques. While highly effective, ongoing challenges include improving accuracy under dense and sparse vegetation, as well as enhancing root-zone moisture estimation. As was mentioned before and was proved by our study, NDWI is a better option for practical soil moisture monitoring and assessment. Besides, the results also support the idea of combined usage of different water stress indices, as far as the combined NDWI-SMI model performed best in our study.

Conclusions. Based on the study results, the NDWI is a far more effective remote sensing index for modeling soil moisture accumulation in the dark-chestnut soils of southern Ukraine. Its high correlation, strong explanatory power, and low error rates make it a more reliable tool for land reclamation and irrigation management. The SMI, while showing a positive relationship with soil moisture, is less suitable for accurate quantitative modeling. The best performance is achieved using combined NDWI-SMI model for soil moisture prediction. This model is suitable both for scientific and practical purposes.

For scientific applications, the NDWI model can be used to monitor and estimate soil moisture accumulation with a high degree of confidence. This model can be used for studies related to decision-making in irrigation scheduling and water resource management. Although the model provides relatively high accuracy, it should be used cautiously for practical purposes.

Further research will be aimed to enlarge the dataset including more edge cases in the data, collecting data for multiple years so that more robust and reliable models of soil moisture accumulation could be developed.

BIBLIOGRAPHY:

1. Lykhovyd P. V. Study of climate impact on vegetation cover in Kherson oblast (Ukraine) using normalized difference and enhanced vegetation indices. *Journal of Ecological Engineering*. 2021. Vol. 22 (6). P. 126–135. DOI: 10.12911/22998993/137362
2. Ingrao C., Strippoli R., Lagioia G., Huisingh D. Water scarcity in agriculture: An overview of causes, impacts and approaches for reducing the risks. *Heliyon*. 2023. Vol. 9 (8). P. e18507. DOI: 10.1016/j.heliyon.2023.e18507
3. Sehler R., Li J., Reager J., Ye H. Investigating relationship between soil moisture and precipitation globally using remote sensing observations. *Journal of Contemporary Water Research & Education*. 2019. Vol. 168. P. 106–118. DOI: 10.1111/j.1936-704X.2019.03324.x
4. Gaona J., Quintana-Seguí P., Escorihuela M., Boone A., Llasat M. Interactions between precipitation, evapotranspiration and soil-moisture-based indices to characterize drought with high-resolution remote sensing and land-surface model data. *Natural Hazards and Earth System Sciences*. 2022. Vol. 22. P. 3461–3478. DOI: 10.5194/nhess-22-3461-2022
5. Chiaravalloti F., Brocca L., Procopio A., Massari C., Gabriele S. Assessment of GPM and SM2RAIN-ASCAT rainfall products over complex terrain in southern Italy. *Atmospheric Research*. 2018. Vol. 205. P. 151–162. DOI: 10.1016/J.ATMOSRES.2018.02.019
6. Akbar R., Gianotti D., Salvucci G., Entekhabi D. Mapped hydroclimatology of evapotranspiration and drainage runoff using SMAP brightness temperature observations and precipitation information. *Water Resources Research*. 2019. Vol. 55. P. 3391–3413. DOI: 10.1029/2018WR024459
7. Iamampai S., Talaluxmana Y., Kanasut J., Rangsiwanichpong P. Enhancing rainfall–runoff model accuracy with machine learning models by using soil water index to reflect runoff characteristics. *Water Science and Technology*. 2024. Vol. 89 (2). P. 368–381. DOI: 10.2166/wst.2023.424
8. Latif S., Hazrin N., Koo C., Ng J., Chaplot B., Huang Y., El-Shafie A., Ahmed A. Assessing rainfall prediction models: Exploring the advantages of machine learning and remote sensing approaches. *Alexandria Engineering Journal*. 2023. Vol. 85. P. 387–400. DOI: 10.1016/j.aej.2023.09.060
9. Peng J., Loew A., Merlin O., Verhoest N. A review of spatial downscaling of satellite remotely sensed soil moisture. *Reviews of Geophysics*. 2017. Vol. 55. P. 341–366. DOI: 10.1002/2016RG000543
10. Lykhovyd P. V. The use of spatial normalized difference vegetation index for determination of humus content in the soils of southern Ukraine. *Ecological Engineering & Environmental Technology*. 2023. Vol. 24 (4). P. 223–228. DOI: 10.12912/27197050/162698
11. Yang X., Zhao S., Qin X., Zhao N., Liang L. Mapping of urban surface water bodies from Sentinel-2 MSI imagery at 10 m resolution via NDWI-based image sharpening. *Remote Sensing*. 2017. Vol. 9 (6). P. 596. DOI: 10.3390/rs9060596
12. Saha A., Patil M., Goyal V. C., Rathore D. S. Assessment and impact of soil moisture index in agricultural drought estimation using remote sensing and GIS techniques. *Proceedings*. 2019. Vol. 7 (1). P. 2. DOI: 10.3390/ECWS-3-05802
13. Burton A. L. OLS (linear) regression. In: *The Encyclopedia of Research Methods in Criminology and Criminal Justice*. Wiley-Blackwell, 2021. P. 509–514. DOI: 10.1002/9781119111931.ch104
14. Tatachar A. V. Comparative assessment of regression models based on model evaluation metrics. *International Research Journal of Engineering and Technology*. 2021. Vol. 8 (9). P. 853–860.
15. Sinaga K. P., Yang M. S. Unsupervised K-means clustering algorithm. *IEEE Access*. 2020. Vol. 8. P. 80716–80727. DOI: 10.1109/ACCESS.2020.2988796
16. Moreno J. J. M., Pol A. P., Abad A. S., Blasco B. C. Using the R-MAPE index as a resistant measure of forecast accuracy. *Psicothema*. 2013. Vol. 25 (4). P. 500–506. DOI: 10.7334/psicothema2013.23
17. McFeeters S. K. Using the normalized difference water index (NDWI) within a geographic information system to detect swimming pools for mosquito abatement: A practical approach. *Remote Sensing*. 2013. Vol. 5 (7). P. 3544–3561. DOI: 10.3390/rs5073544
18. Lykhovyd P. V. Irrigation needs in Ukraine according to current aridity level. *Journal of Ecological Engineering*. 2021. Vol. 22 (8). P. 11–18. DOI: 10.12911/22998993/140478
19. Ainiwaer M., Ding J., Kasim N., Wang J., Wang J. Regional scale soil moisture content estimation based on multi-source remote sensing parameters. *International Journal of Remote Sensing*. 2020. Vol. 41. P. 3346–3367. DOI: 10.1080/01431161.2019.1701723
20. Koohikeradeh E., Gumiere S. J., Bonakdari H. NDMI-derived field-scale soil moisture prediction using ERA5 and LSTM for precision agriculture. *Sustainability*. 2025. Vol. 17 (6). P. 2399. DOI: 10.3390/su17062399
21. Adab H., Morbidelli R., Saltalippi C., Moradian M., Ghalhari G. A. F. Machine learning to estimate surface soil moisture from remote sensing data. *Water*. 2020. Vol. 12 (11). P. 3223. DOI: 10.3390/w12113223
22. Das B., Rathore P., Roy D., Chakraborty D., Jatav R. S., Sethi D., Kumar P. Comparison of bagging, boosting and stacking algorithms for surface soil moisture mapping using optical–thermal–microwave remote sensing synergies. *CATENA*. 2022. Vol. 217. P. 106485. DOI: 10.1016/j.catena.2022.106485
23. John J., Jaganathan R., Shylesh D. D. Mapping of soil moisture index using optical and thermal remote sensing. In: *International Conference on Structural Engineering and Construction Management*. Springer International Publishing, 2021. P. 759–767. DOI: 10.1007/978-3-030-80312-4_65

24. Liu Z., Xia Z., Chen F., Hu Y., Wen Y., Liu J., Liu H., Liu L. Soil moisture index model for retrieving soil moisture in semiarid regions of China. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. 2020. Vol. 13. P. 5929–5937. DOI: 10.1109/JSTARS.2020.3025596
25. Babaeian E., Sadeghi M., Jones S., Montzka C., Vereecken H., Tuller M. Ground, proximal, and satellite remote sensing of soil moisture. *Reviews of Geophysics*. 2019. Vol. 57. P. 530–616. DOI: 10.1029/2018RG000618
26. Celik M., Isik M., Yuzugullu O., Fajraoui N., Erten E. Soil moisture prediction from remote sensing images coupled with climate, soil texture and topography via deep learning. *Remote Sensing*. 2022. Vol. 14. P. 5584. DOI: 10.3390/rs14215584

REFERENCES:

1. Lykhovyd, P. V. (2021). Study of climate impact on vegetation cover in Kherson oblast (Ukraine) using normalized difference and enhanced vegetation indices. *Journal of Ecological Engineering*, 22(6), 126–135. DOI: 10.12911/22998993/137362
2. Ingrao, C., Strippoli, R., Lagioia, G., & Huisingh, D. (2023). Water scarcity in agriculture: An overview of causes, impacts and approaches for reducing the risks. *Heliyon*, 9(8), e18507. DOI: 10.1016/j.heliyon.2023.e18507
3. Sehler, R., Li, J., Reager, J., & Ye, H. (2019). Investigating relationship between soil moisture and precipitation globally using remote sensing observations. *Journal of Contemporary Water Research & Education*, 168, 106–118. DOI: 10.1111/j.1936-704X.2019.03324.x
4. Gaona, J., Quintana-Seguí, P., Escorihuela, M., Boone, A., & Llasat, M. (2022). Interactions between precipitation, evapotranspiration and soil-moisture-based indices to characterize drought with high-resolution remote sensing and land-surface model data. *Natural Hazards and Earth System Sciences*, 22, 3461–3478. DOI: 10.5194/nhess-22-3461-2022
5. Chiaravalloti, F., Brocca, L., Procopio, A., Massari, C., & Gabriele, S. (2018). Assessment of GPM and SM2RAIN-ASCAT rainfall products over complex terrain in southern Italy. *Atmospheric Research*, 205, 151–162. DOI: 10.1016/J.ATMOSRES.2018.02.019
6. Akbar, R., Gianotti, D., Salvucci, G., & Entekhabi, D. (2019). Mapped hydroclimatology of evapotranspiration and drainage runoff using SMAP brightness temperature observations and precipitation information. *Water Resources Research*, 55, 3391–3413. DOI: 10.1029/2018WR024459
7. Iamampai, S., Talaluxmana, Y., Kanasut, J., & Rangsiwanichpong, P. (2024). Enhancing rainfall–runoff model accuracy with machine learning models by using soil water index to reflect runoff characteristics. *Water Science and Technology*, 89(2), 368–381. DOI: 10.2166/wst.2023.424
8. Latif, S., Hazrin, N., Koo, C., Ng, J., Chaplot, B., Huang, Y., El-Shafie, A., & Ahmed, A. (2023). Assessing rainfall prediction models: Exploring the advantages of machine learning and remote sensing approaches. *Alexandria Engineering Journal*, 85, 387–400. DOI: 10.1016/j.aej.2023.09.060
9. Peng, J., Loew, A., Merlin, O., & Verhoest, N. (2017). A review of spatial downscaling of satellite remotely sensed soil moisture. *Reviews of Geophysics*, 55, 341–366. DOI: 10.1002/2016RG000543
10. Lykhovyd, P. V. (2023). The use of spatial normalized difference vegetation index for determination of humus content in the soils of southern Ukraine. *Ecological Engineering & Environmental Technology*, 24, 223–228. DOI: 10.12912/27197050/162698
11. Yang, X., Zhao, S., Qin, X., Zhao, N., & Liang, L. (2017). Mapping of urban surface water bodies from Sentinel-2 MSI imagery at 10 m resolution via NDWI-based image sharpening. *Remote Sensing*, 9(6), 596. DOI: 10.3390/rs9060596
12. Saha, A., Patil, M., Goyal, V. C., & Rathore, D. S. (2019). Assessment and impact of soil moisture index in agricultural drought estimation using remote sensing and GIS techniques. *Proceedings*, 7(1), 2. DOI: 10.3390/ECWS-3-05802
13. Burton, A. L. (2021). OLS (linear) regression. In *The Encyclopedia of Research Methods in Criminology and Criminal Justice* (pp. 509–514). Hoboken: Wiley-Blackwell. DOI: 10.1002/9781119111931.ch104
14. Tatachar, A. V. (2021). Comparative assessment of regression models based on model evaluation metrics. *International Research Journal of Engineering and Technology*, 8(9), 853–860.
15. Sinaga, K. P., & Yang, M. S. (2020). Unsupervised K-means clustering algorithm. *IEEE Access*, 8, 80716–80727. DOI: 10.1109/ACCESS.2020.2988796
16. 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(4), 500–506. DOI: 10.7334/psicothema2013.23
17. McFeeters, S. K. (2013). Using the normalized difference water index (NDWI) within a geographic information system to detect swimming pools for mosquito abatement: A practical approach. *Remote Sensing*, 5(7), 3544–3561. DOI: 10.3390/rs5073544
18. Lykhovyd, P. V. (2021). Irrigation needs in Ukraine according to current aridity level. *Journal of Ecological Engineering*, 22(8), 11–18. DOI: 10.12911/22998993/140478
19. Ainiwaer, M., Ding, J., Kasim, N., Wang, J., & Wang, J. (2020). Regional scale soil moisture content estimation based on multi-source remote sensing parameters. *International Journal of Remote Sensing*, 41, 3346–3367. DOI: 10.1080/01431161.2019.1701723
20. Koohikeradeh, E., Gumiere, S. J., & Bonakdari, H. (2025). NDMI-derived field-scale soil moisture prediction using ERA5 and LSTM for precision agriculture. *Sustainability*, 17(6), 2399. DOI: 10.3390/su17062399
21. Adab, H., Morbidelli, R., Saltalippi, C., Moradian, M., & Ghalhari, G. A. F. (2020). Machine learning to estimate surface soil moisture from remote sensing data. *Water*, 12(11), 3223. DOI: 10.3390/w12113223
22. Das, B., Rathore, P., Roy, D., Chakraborty, D., Jatav, R. S., Sethi, D., & Kumar, P. (2022). Comparison of bagging, boosting and stacking algorithms for surface soil moisture mapping using optical–thermal–microwave remote sensing synergies. *Catena*, 217, 106485. DOI: 10.1016/j.catena.2022.106485
23. John, J., Jaganathan, R., & Shylesh, D. D. (2021). Mapping of soil moisture index using optical and thermal remote sensing. In *International Conference on Structural Engineering and Construction Management*

(pp. 759–767). Cham: Springer International Publishing. DOI: 10.1007/978-3-030-80312-4_65

24. Liu, Z., Xia, Z., Chen, F., Hu, Y., Wen, Y., Liu, J., Liu, H., & Liu, L. (2020). Soil moisture index model for retrieving soil moisture in semiarid regions of China. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 5929–5937. DOI: 10.1109/JSTARS.2020.3025596
25. Babaeian, E., Sadeghi, M., Jones, S., Montzka, C., Vereecken, H., & Tuller, M. (2019). Ground, proximal, and satellite remote sensing of soil moisture. *Reviews of Geophysics*, 57, 530–616. DOI: 10.1029/2018RG000618
26. Celik, M., Isik, M., Yuzugullu, O., Fajraoui, N., & Erten, E. (2022). Soil moisture prediction from remote sensing images coupled with climate, soil texture and topography via deep learning. *Remote Sensing*, **14**, 5584. DOI: 10.3390/rs14215584

Лиховид П.В., Чабан В.О., Максимов Д.О.
Агроекологічне моделювання вологи на парових полях із застосуванням даних дистанційного зондування

Глобальне потепління загострило екологічну проблему дефіциту вологи в сільському господарстві, що робить динамічний моніторинг водних ресурсів необхідним для сталого рослинництва. Традиційні наземні дослідження є дорогими та трудомісткими, що підкреслює потребу в економічно ефективних рішеннях на базі даних дистанційного зондування.

Мета. Це дослідження мало на меті визначити придатність індексів дистанційного зондування – нормалізованого диференційного водного індексу (NDWI) та індексу вологості ґрунту (SMI) – для динамічного контролю накопичення вологи (MA) на парових полях у напівпосушливій кліматичній зоні.

Методи. Дослідження проводили у 2025 році в дослідному господарстві «Восток» Херсонської області. Ґрунт дослідних полів був представлений типовим темно-каштановим слабозасоленим ґрунтом. У кліматичному відношенні район проведення досліджень відноситься до зони напівпосушливого Степу. Супутникові знімки платформи OneSoil забезпечували необхідні показники з відповідною рівномірною просторовою роздільною здатністю 10 м із супутника Sentinel-2, а метеорологічний манометр вимірював MA на досліджуваних полях. Регресійний аналіз проводився для 500 пар даних (250 для «NDWI-MA» і 250 для «SMI-MA») і 103 комплексних пар даних («NDWI-SMI-MA») за звичайним алгоритмом найменших квадратів (OLS). Ефективність регресії оцінювали за допомогою коефіцієнта кореляції Пірсона (r), коефіцієнта детермінації (R^2), середньої квадратичної помилки (MSE) і середньої абсолютної процентної помилки (MAPE). Крім того, кластеризація була виконана за алгоритмом K-means.

Результати. Результати демонструють, що NDWI має значно сильнішу кореляцію (0,9160 проти 0,6884) і тісніший регресійний зв'язок з MA, ніж SMI. Отже, NDWI є кращим для динамічного моніторингу в цих середовищах. Комбінована модель «NDWI-SMI-MA» забезпечила найкращу загальну продуктивність для оцінки MA з найменшим MAPE 26,02%. Кластерний аналіз успішно розрізнив три основні групи вологості, виявивши, що більшість перелогових полів належали до «сухого кластера», що вказує на серйозний дефіцит вмісту вологи в ґрунті.

Висновки. Виходячи з результатів, NDWI є кращим просторовим індексом для оцінки накопичення вологи в ґрунті. Показник SMI, демонструючи позитивний зв'язок із вологістю ґрунту, менше підходить для точного кількісного моделювання. Найкраща точність досягається за допомогою комбінованої моделі NDWI-SMI для прогнозування вологості ґрунту. Незважаючи на переконливість, необхідно підкреслити, що ці моделі слід використовувати обережно на практиці, оскільки їм все ще не вистачає надійності, побудованої на тривалості спостережень і аналізу більшої кількості даних. Подальші дослідження будуть спрямовані на розширення набору даних, включаючи більше граничних випадків у даних, збираючи дані за кілька років, щоб можна було розробити більш надійні та надійні моделі накопичення вологи в ґрунті.

Ключові слова: агроекологічний моніторинг, кластеризація, посуха, нормований індекс різниці води, регресійне моделювання, індекс вологості ґрунту.

Lykhovyd P.V., Chaban V.O., Maksymov D.O.
Agroecological modeling of water conditions in fallow fields using remote sensing data

Global warming has intensified the ecological challenge of moisture deficit in agriculture, making the dynamic monitoring of water resources essential for sustainable crop production. Traditional on-land surveys are costly and time-intensive, highlighting the need for cost-effective remote sensing solutions.

Purpose. This study aimed to determine the suitability of remotely sensed indices – the Normalized Difference Water Index (NDWI) and the Soil Moisture Index (SMI) – for the dynamic control of Moisture Accumulation (MA) in fallow fields within a semi-arid climate zone.

Methods. Trials were conducted in 2025 at the "Vostok" experimental farm in the Kherson region. The soil of the experimental fields was represented by typical dark-chestnut slightly saline soil. Climatically, the area of the study conduction belongs to the semi-arid Steppe zone. Satellite imagery from the OneSoil platform provided the required indices with corresponding uniform spatial resolution of 10 m from Sentinel-2 satellite, while a meteorological gauge measured MA in the studied fields. Regression analysis was performed on 500 data pairs (250 for "NDWI-MA" and 250 for "SMI-MA") and 103 complex data pairs ("NDWI-SMI-MA") by the ordinary least square (OLS) algorithm. The regression performance was assessed with Pearson's correlation coefficient (r), coefficient of determination (R^2), mean square error (MSE), and mean absolute percentage error (MAPE). Besides, clustering was performed by the K-means algorithm.

Results. The results indicate that NDWI exhibits a significantly higher correlation (0.9160 vs. 0.6884) and stronger regression relationship with MA than SMI. Consequently, NDWI is preferred for dynamic monitoring in these environments. The combined "NDWI-SMI-MA" model provided the best overall performance for estimating MA with the least MAPE of 26.02%. Cluster analysis successfully distinguished three major moisture groupings, revealing that most fallow fields belonged to a "dry cluster," indicating a severe deficit of soil moisture content.

Conclusions. Based on the results, the NDWI is a better spatial index for soil moisture accumulation assessment. The SMI, while showing a positive relationship with soil moisture, is less suitable for accurate quantitative modeling. The best performance is achieved using combined NDWI-SMI model for soil moisture prediction. Though convincing, it is necessary to emphasize that these models should be used cautiously in practice, as they still lack the robustness built on the longevity of observations and bigger data analysis. Further research will be aimed to enlarge the dataset including more edge cases in the data, collecting data for multiple years so that more robust and reliable models of soil moisture accumulation could be developed.

Key words: agroecological monitoring, clustering, drought, normalized difference water index, regression modeling, soil moisture index.

Дата першого надходження статті до видання: 03.02.2026
Дата прийняття статті до друку після рецензування: 30.03.2026
Дата публікації (оприлюднення) статті: 06.05.2026