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RESEARCH ARTICLE

Agroecological zoning of Ukraine using remote sensing and unsupervised clustering

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Abstract

Current climate change, primarily driven by global warming, is significantly altering the suitability of agricultural lands for crop production. Given these dramatic climatic shifts in meteorological events and the advances in remote sensing and data science, providing an unbiased and scientifically sound agroecological zoning of Ukraine is a critical task for agricultural science. As a major food producer for Europe, developing an optimal agrarian policy in Ukraine is essential. This study used remote sensing vegetation indices, including NDVI, NDMI, and NRI, as primary features for clustering, as these indicators reflect vegetation vigor, water stress levels, and nitrogen availability. Index values were derived from the Ukrainian Crop Production Map web application for the period of 2005-2023. We implemented the K-means clustering algorithm to group agricultural lands into distinct zones. To ensure the study was unbiased, the optimal number of clusters (K) was determined using the Elbow method, and the quality of the clustering was confirmed with a silhouette score. As a result, four distinct agroecological zones were identified and mapped. The most prospective zone for crop production, given current climate conditions and soil nitrogen reserves, was established to be the western part of Ukraine. The southern region of Ukraine was identified as the riskiest for agriculture due to its drought-prone character. Meanwhile, the central and eastern parts of the country occupy an intermediate position, representing a balanced transitional zone.

Keywords: Agroecological mapping, Environmentology, Nitrogen reflectance index, Normalized difference moisture index, Normalized difference vegetation index

Introduction

Current climate change has caused substantial shifts in agricultural land suitability for crop production (Abd-Elmabod, et al. 2020). The increase in air temperature, unequal distribution of precipitation, frequent drought events, a shortage of freshwater available for agricultural purposes, land degradation because of erosion, and harmful anthropogenic activities, including military activities, land, air, and water pollution, have led to a deterioration of agricultural productivity. These effects are especially evident in risk-prone agricultural areas, which are most vulnerable to global warming. However, the consequences now extend beyond traditionally risky regions. In recent decades, even areas with fertile soils and favorable weather conditions have gradually transformed into risk-prone zones due to unpredictable natural humidification, rising air temperatures during crop growing seasons, widespread pollution, and overall ecological decline (Hultgren, et al. 2025). Therefore, a key challenge of modern agroecology is to develop strategies for continuous monitoring of agricultural ecosystems to enable timely and effective responses to environmental change.

The era of remote sensing and information technologies provides a wide choice of tools to perform cost- and time-effective agroecological monitoring. Most researchers tend to implement remote sensing data to calculate vegetation indices-indirect markers of vegetation cover, or more rarely, soil and water body conditions-to perform continuous dynamic monitoring of changes happening in the agroecological situation on different scales. Integrating remote sensing with geoinformation technologies provides valuable opportunities for visualizing and interpreting these changes (Willis, 2015).

Recent progress in machine learning has further enhanced the ability to extract insights from big data. It has become an essential component of modern agroecological research, supporting data interpretation, predictive analysis, and evidence-based decision-making. In particular, unsupervised learning methods are valuable because they allow data exploration without the biases introduced by human judgment (Ho, 2000).

Given these advances, it is unsurprising that modern agroecological research strongly integrates remote sensing and machine learning. Agroecological zoning-especially under the pressures of global warming and shifting meteorological patterns-requires thorough revision. Contemporary approaches to zoning now rely on robust computational algorithms that combine on-the-ground surveys with remote sensing data to provide scientifically substantiated assessments of regional suitability for agricultural activity (Møller, et al. 2021). Machine learning has greatly improved crop mapping, making it more precise and reliable (Dadrasi, et al. 2023). The most frequently used machine learning approaches include:

- Traditional models like Random Forest (RF), Support Vector Machine (SVM), Decision Trees, and k-Nearest Neighbors. Such models provide high accuracy (up to 96%-97%) with moderate computational demands, making them suitable for resource-limited setups (Rahaman, et al. 2025).

- Deep learning models including Convolutional Neural Networks (CNNs), U-Net, MANet, DeepLabv3+, and attention-based architectures excel at capturing complex spatial and temporal patterns, often outperforming traditional models, especially with large, multi-source datasets (Joshi, et al. 2023).

- Ensemble and Hybrid Models further boost accuracy and robustness, particularly in heterogeneous or challenging environments (Ofori-Ampofo, et al. 2021).

Machine learning and remote sensing have become essential for agroecological zoning and cropland mapping, offering high accuracy, scalability, and actionable insights. Continued advances in data integration, model development, and interpretability will further enhance their impact on sustainable agriculture and food security. However, the combination of machine learning and remote sensing is still rarely used to perform comprehensive agroecological zoning in Ukraine, notwithstanding the fact that aerospace imagery from satellites is recognized by domestic scientists as a valuable source of the information about environmental conditions (Tarariko, et al. 2025).

Nevertheless, Ukraine's traditional agroecological zoning remains outdated, and there is a notable gap in studies applying remote sensing and machine learning methods to update the distribution of its natural and agricultural zones. Many researchers continue to depend largely on expert opinion, with minimal or no use of unsupervised learning to support their assessments (Tarariko, et al. 2019). However, in recent years more attention is paid to optimizing natural resources and environmental management in Ukraine by the means of remote sensing data (Furdychko and Drebot, 2019).

Accordingly, the primary aim of this study is to conduct a comprehensive revision of Ukraine's agroecological zoning with respect to crop production suitability, using remote sensing data in combination with unsupervised machine learning clustering.

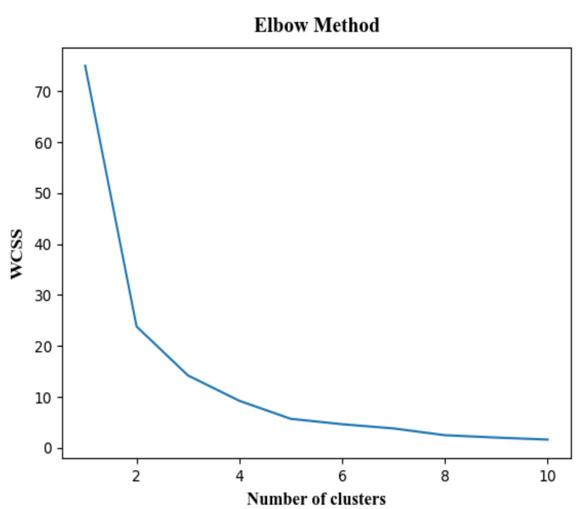
Materials and Methods

The study on agroecological zoning of Ukraine for the period 2005-2023 was performed using three major vegetation indices: Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), and Nitrogen Reflectance Index (NRI), which were retrieved from the open database Ukrainian Crop Production Map. The choice of these indicators is justified: NDVI indicates the general vigor and density of vegetation cover (Khan, et al. 2025); NDMI reflects vegetation water stress and overall soil moisture availability (Lykhovyd and Sharii, 2024); and NRI provides insights into nitrogen availability for plants, offering indirect information on overall soil fertility (Lykhovyd, et al. 2024). Therefore, the combination of these vegetation indices provides researchers with comprehensive information to assess the general suitability of agricultural lands for crop production through the evaluation of general vegetation conditions and soil nutrient and moisture status. Average annual values of each vegetation index for every region of Ukraine were used as a foundation for cluster-based agroecological zoning of the country.

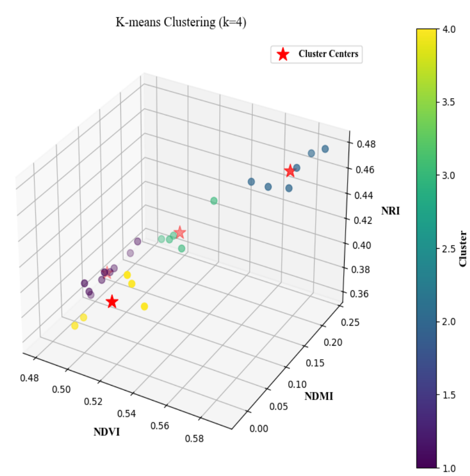
To avoid biased classification, it was decided to implement an unsupervised machine learning algorithm for remote sensing data clusterization. The K-means algorithm with four classes, previously established by the results of Elbow method, was applied (Sinaga and Yang, 2020). A silhouette score was calculated to evaluate the quality of the clusterization across different numbers of clusters (Januzaj, et al. 2023). Machine learning, related computations, and graphical constructions were performed using an original Python script. External modules (pandas, NumPy, scikit-learn, and Matplotlib) were used to simplify the workflow of script implementation. Finally, having received the clusterization results, a map of the agroecological zoning of Ukraine was built using the MapChart platform.

Results and Discussion

K-means clustering was performed for K=4 clusters, as this number was validated not only by the Elbow method (Fig. 1a) but also by the highest silhouette score (0.47 compared with 0.36 and 0.42 for 5 or 3 clusters, respectively). Therefore, unsupervised machine learning distinguished four clearly distinct agroecological zones of Ukraine (Fig. 1b), each with a unique combination of NDVI, NDMI, and NRI values. Cluster 1 is characterized by low NDVI, moderately low NDMI, and low NRI. Cluster 2 has high NDVI, NDMI, and NRI values. Cluster 3 is defined by moderate NDVI, NDMI, and NRI values. Cluster 4 is characterized by moderate NDVI, low NDMI, and moderately low NRI values.



a



b

Figure 1. K-means clustering results: a: Elbow method plot; b: Clustering 3D plot

Accordingly, using the most prominent features, each cluster zone was named: Cluster 1-Marginal Land and Conservation Zone; Cluster 2-High-Potential Arable Zone; Cluster 3-Balanced Transitional Zone; and Cluster 4-Drought-Prone Steppe Zone (Fig. 2).

Figure 2. Agroecological zoning of Ukraine based on the results of cluster analysis of remote sensing data for the period 2005-2023.

Spatial modeling and mapping are well-established techniques in scientific studies. Their benefits lie mainly in the fact that maps and colorful plots are usually better understood and easier to interpret than pure figures. For example, Breus and Skok, 2021 applied the ArcGIS system to visualize soil conditions in the Kherson region, while Hrynyk, et al. 2023 applied modern mapping technologies to provide a comprehensive evaluation of the suitability of certain agricultural landscapes for organic horticulture. However, most Ukrainian scientists have relied upon ground-based surveys and field assessments, in contrast to our study, which utilized remote sensing data. More importantly, no robust machine learning technique was applied to provide an unbiased evaluation, despite reputable scientists emphasizing that even the expertise of the best research groups may sometimes result in biased outcomes due to human subjectivity (Waldstein, et al. 2020). Considering agroecological zoning and making decisions on agricultural land suitability for crop production, biased estimation and misinterpretations may lead to a dramatic decrease in yields and aggravate food insecurity.

The results of machine learning-based agroecological zoning of Ukraine are of great importance because they provide an unbiased assessment of current environmental conditions based on a data-driven approach. This is the first time that such an approach to agroecological mapping of Ukraine has been implemented. Previous studies, conducted based on personal researcher interpretations or other scientific evidence, provided a somewhat similar vision regarding the current state of agricultural landscapes in Ukraine. However, closer examination shows that the K-means clustering-based zoning has distinct and novel features. For example, it agrees with the statements that the Southern Steppe of Ukraine is a zone of risky agriculture because of the drought-prone character of this region (Lykhovyd, 2021). Moreover, it has been recently established that the Steppe zone of Ukraine is extremely vulnerable and unstable from an ecological perspective due to imbalanced land use policies, insufficient adoption of climate-smart agricultural practices, and the impacts of military activities (Pichura, et al. 2023). Therefore, the main problems of Southern Ukraine are a lack of moisture (the lowest NDMI values) and severe technogenic degradation (Novakovska, et al. 2025).

As for the central and eastern parts of the country, these lands represent most Ukrainian croplands and could be labeled as lands with decreasing fertility and a slight, but still impactful, lack of moisture. Scientists agree that in recent decades, the climate of Central Ukraine, mostly represented by the Northern Steppe and Forest-Steppe natural zones, has shown an increasing tendency toward aridity and transformation into a Steppe zone (Sytnyk, et al. 2022). If the trend continues, gradual desertification of the zone is predicted, and as a result, these marginally suitable lands for crop production will transform into lands of risky agriculture (with Cluster 1 potentially merging with Cluster 4). This tendency can be observed in Fig. 1b, where Cluster 1 and Cluster 4 points are closely distributed in the 3D plot.

The balanced and high-potential zones for crop production represent less than half of the territory of Ukraine. These zones include mostly western and northern lands, which belong to the Forest zone and Polissia. They are the most favorable for the cultivation of major crops, and with good maintenance, will provide sustainable productivity. Current climate change has allowed for the transfer of some traditionally southern crops, such as sunflower and grain corn, to the north and west of the country (Vasylkovska, et al. 2024). However, considering recent sharp increases in air temperature in these regions and some deterioration in agricultural practices due to the ongoing full-scale war in Ukraine, it is difficult to say for how long these agricultural lands will preserve their optimal conditions if no steps are taken for soil conservation and climate change mitigation. Only a rational, scientifically based agricultural policy of land use and a transition to climate-smart agricultural practices can provide guarantees that Ukraine will not face a catastrophic crop production decrease in the near future (Kvasha, et al. 2024).

In case no measures are taken to prevent further land degradation and mitigate climate impacts on crop production, there is a risk of further blurring the borders between Clusters 1, 3, and 4, and a complete deterioration of almost 90% of Ukraine's agricultural lands with a sharp decrease in crop yields and consequent food insecurity and increased dependence on food imports. Currently, according to Dukhnytskyi and Pugachov, 2024, there is no statistically significant trend of increasing food imports in Ukraine, but the figures for 2023 are concerning, as they are substantially higher than in 2020 and 2022 for plant and animal products as well as ready-to-consume goods.

Conclusion

An integrated approach combining remote sensing and unsupervised clustering was used to create a modern agroecological zoning map of Ukraine. The analysis identified four distinct agroecological zones across the country. Most areas fall within drought-prone, high-risk agricultural or marginal land zones, while the western regions represent the most productive arable zone. The developed zoning map is recommended as a decision-support tool for crop cultivation planning and the selection of appropriate agrotechnological strategies.

References

Abd-Elmabod SK, Muñoz-Rojas M, Jordán A, Anaya-Romero M, Phillips JD, Jones L, Zhang Z, Pereira P, Fleskens L, van der Ploeg M, de la Rosa D. (2020). Climate change impacts on agricultural suitability and yield reduction in a Mediterranean region. Geoderma. **374**:114453.

Hultgren A, Carleton T, Delgado M, Gergel DR, Greenstone M, Houser T, Hsiang S, Jina A, Kopp RE, Malevich SB, McCusker KE, Mayer T, Nath I, Rising J, Rode A, Yuan J. (2025). Impacts of climate change on global agriculture accounting for adaptation. *Nature*. **642**:644-652.

Willis KS. (2015). Remote sensing change detection for ecological monitoring in United States protected areas. *Biol Conserv*. **182**:233-242.

Ho TB. (2000). Knowledge discovery from unsupervised data in support of decision making. Knowledge-Based Systems. *Techniques and Applications*. **2**:435-461.

Møller AB, Mulder VL, Heuvelink GB, Jacobsen NM, Greve MH. (2021). Can we use machine learning for agricultural land suitability assessment? *Agronomy*. **11**:703.

Dadrasi A, Chaichi M, Nehbandani A, Soltani E, Nemati A, Salmani F, Heydari M, Yousefi AR. (2023). Global insight into understanding wheat yield and production through agro-ecological zoning. *Sci Rep*. **13**:15898.

Rahaman M, Southworth J, Wen Y, Keellings D. (2025). Assessing model trade-offs in agricultural remote sensing: A review of machine learning and deep learning approaches using almond crop mapping. *Remote Sensing*. **17**:2670.

Joshi A, Pradhan B, Gite S, Chakraborty S. (2023). Remote-sensing data and deep-learning techniques in crop mapping and yield prediction: A systematic review. *Remote Sensing*. **15**:2014.

Ofori-Ampofo S, Pelletier C, Lang S. (2021). Crop type mapping from optical and radar time series using attention-based deep learning. *Remote Sensing*. **13**:4668.

Tarariko O, Demyanyuk O, Ilienko T, Solokha M, Lykhovyd P. (2025). Satellite information resource-modern potential for solving ecological problems of Ukraine's agrosphere. *Balanced Nature Using*. **1**:55-71.

Tarariko O, Ilienko T, Kuchma T, Novakovska I. (2019). Satellite agroecological monitoring within the system of sustainable environmental management. *Agric Sci Pract*. **6**:18-27.

Furdychko O, Drebot O. (2019). Control over Ukrainian agroresources by means of space distant exploration: Urgency and perspectives. *Bull Agrar Sci*. **6**:5-12.

Khan SN, Iqbal J, Khan MR, Malik NA, Khan FA, Khan K, Khan AN, Wahab A. (2025). Using remotely sensed vegetation indices and multi-stream deep learning improves county-level corn yield predictions. *EJA*. **164**:127496.

Lykhovyd PV, Sharii VO. (2024). Normalised difference moisture index in water stress assessment of maize crops. *Agrology*. **7**:21-26.

Lykhovyd P, Vozhehova R, Hranovska L, Bidnyna I, Shablia O, Kokoiko V, Koblai S, Solomonov R, Kulidzhanov E, Hnylytskyi Ye. (2024). Implementation of agroecological zoning index to map the suitability of agricultural lands of the Steppe zone of Ukraine for the cultivation of major crops. *Modern Phytomorphology*. **18**:41-46.

Sinaga KP, Yang MS. (2020). Unsupervised K-means clustering algorithm. *IEEE Access*. **8**:80716-80727.

Januzaj Y, Beqiri E, Luma A. (2023). Determining the optimal number of clusters using silhouette score as a data mining technique. *Int J Online Biomed Eng*. **19**:174-182.

Breus D. Skok S. (2021). Spatial modelling of agro-ecological condition of soils in steppe zone of Ukraine. *Indian J Ecol*. **48**:627-633.

Hrynyk I, Yehorova T, Bublyk M, Barabash L. (2023). Agricultural landscape zoning of the Forest-Steppe zone of Ukraine to develop organic gardening. *Plant Soil Sci*. **14**:21-32.

Waldstein SM, Seeböck P, Donner R, Sadeghipour A, Bogunović H, Osborne A, Schmidt-Erfurth U. (2020). Unbiased identification of novel subclinical imaging biomarkers using unsupervised deep learning. *Scientific Reports*. **10**:12954.

Lykhovyd PV. (2021). Irrigation needs in Ukraine according to current aridity level. *J Ecol Eng*. 22:11-18.

Lykhovyd PV. (2021). Study of climate impact on vegetation cover in Kherson oblast (Ukraine) using normalized difference and enhanced vegetation indices. *J Ecol Eng*. **22**:126-135.

Pichura V, Potravka L, Domaratskiy Y, Vdovenko N, Stratichuk N, Baysha K, Pichura I. (2023). Long-term changes in the stability of agricultural landscapes in the areas of irrigated agriculture of the Ukraine Steppe Zone. *J Ecol Eng*. **24**:188-198.

Novakovska I, Belousova N, Hunko L. (2025). Land degradation in Ukraine as a result of military operations. *Acta Scientiarum Polonorum Administratio Locorum*. **24**:129-145.

Sytnyk O, Bezlatnia L, Valchuk-Orkusha O, Denysyk B, Stefankov L. (2022). Anthropogenic landscapes of the interzonal geoecotones of «forest-steppe-steppe» of Ukraine as factores of its steppification. *Modern Sci, Prague*. **2022**:56-68.

Vasylkovska K, Andriienko O, Malakhovska V, Vasylkovskyi O, Andriienko A, Shepilova T. (2024). Analysis of effective sunflower cultivation zones using the example of Ukraine. *Agronomy Res*. **22**:1362-1376.

Kvasha S, Andrei P, Mancini MC, Vakulenko V. (2024). Food security in Ukraine today's conditions. *Int J Food Sci Nutr*. **75**:622-636.

Dukhnytskyi B, Pugachov V. (2024). Import of agri-food products to Ukraine. *Ekonomika APK*. **31**:27-35.