

<https://doi.org/10.26565/1992-4224-2026-45-01>

UDC: 631.427:528.8:912

A. B. ACHASOV¹, DSc (Agriculture),

Professor of the Department of Ecology and Environmental Management

e-mail: achasov@karazin.ua

ORCID ID: <https://orcid.org/0000-0003-2446-3707>

O. Y. SELIVERSTOV¹,

Senior Lecturer of the Department of Ecology and Environmental Management

e-mail: oleg.seliverstov@karazin.ua

ORCID ID: <https://orcid.org/0000-0002-8477-274X>

G. V. TITENKO¹, PhD (Geography),

Associate Professor of the Department of Ecology and Environmental Management

e-mail: titenko@karazin.ua

ORCID ID: <https://orcid.org/0000-0002-8477-0672>

R. R. KALASHNIKOV¹,

Bachelor Student

e-mail: ruslan.kalashnikov@student.karazin.ua

ORCID ID: <https://orcid.org/0009-0002-3616-400X>

¹V.N. Karazin Kharkiv National University,

4, Svobody, Sq., Kharkiv, 61022, Ukraine

EXPERIENCE IN MAPPING ERODE SOILS BASED ON REMOTE SENSING DATA

Purpose. Demonstration of the capabilities of modern Earth remote sensing data and geoinformation technologies for the identification and large-scale mapping of eroded soils with a special emphasis on the detection of sheet water erosion, which remains insufficiently represented on the existing soil maps of Ukraine.

Methods. Data processing was performed on the Google Earth Engine platform by generating a bare soil composite image based on the Bare Soil Index (BSI), scene classification masks, and median pixel reduction. Identification of eroded areas was carried out by visual interpretation taking into account spectral, spatial, and morphological features of water erosion.

Results. The study was conducted within the territory of the Novoodeska territorial community of Mykolaiv region using archival maps of agro-production soil groups at a scale of 1:10,000 and multitemporal Sentinel-2 satellite images for the period 2020–2025. Significant discrepancies were identified between archival soil maps and the current spatial distribution of eroded soils, indicating an intensification of degradation processes over recent decades. The application of multitemporal bare soil composites ensured reliable delineation of severely eroded soils and outcrops of parent materials within agricultural landscapes. As a result, an updated large-scale map of severely eroded soils at a scale of 1:10,000 was created, which significantly exceeds existing cartographic materials in terms of detail and reliability.

Conclusion. It has been proven that the integration of multitemporal Sentinel-2 satellite imagery and cloud-based geoinformation analysis significantly increases the accuracy of water erosion mapping, especially its sheet forms. The proposed approach is an effective tool for updating soil-cartographic materials.

KEYWORDS: *water erosion, eroded soils, Earth remote sensing, Sentinel-2, Google Earth Engine, soil mapping*

Як цитувати: Achasov A. B., Seliverstov O. Y., Titenko G. V., Kalashnikov R. R. Experience in mapping erode soils based on remote sensing data. *Людина та довкілля. Проблеми неоекології*. 2026. Вип. 45. С. 8–20. <https://doi.org/10.26565/1992-4224-2026-45-01>

In cites: Achasov, A. B., Seliverstov, O. Y., Titenko, G. V., & Kalashnikov, R. R. (2026). Experience in mapping erode soils based on remote sensing data. *Man and Environment. Issues of Neoeology*, (45), 8–20. <https://doi.org/10.26565/1992-4224-2026-45-01>

Introduction

The current state of land resources of Ukraine is characterized by critical levels of degradation, which leads to annual economic

losses in the amount of 40–50 billion hryvnias [1]. Water erosion occupies a leading position among degradation processes. According to

© Achasov A. B., Seliverstov O. Y., Titenko G. V., Kalashnikov R. R., 2026



This is an open access article distributed under the terms of the [Creative Commons Attribution License 4.0](https://creativecommons.org/licenses/by/4.0/)

expert estimates, the area of land affected by water erosion reaches 13.4 million hectares, including 10.6 million hectares of arable land [2]. Water erosion, as the dominant degradation process, not only reduces fertility due to the washout of the upper humus layer, but also causes a number of indirect negative consequences: disturbance of the hydrological balance, pollution of water bodies, and intensification of organic matter mineralization, which leads to an increase in greenhouse gas emissions [3].

In the context of global climate change and intensification of agricultural production, monitoring and accurate mapping of eroded soils become strategic tasks for ensuring food security and sustainable land use. Such mapping should be based on the use of Earth remote sensing (ERS) data in combination with geographic information systems (GIS), which provides prompt, objective, and high-precision analysis of the state of the soil cover [4].

There are many examples of successful application of ERS and GIS for mapping eroded soils. Seutloali et al. [5] used 30-meter multispectral Landsat TM5 satellite data to map the degree of soil erosion in Transkei, demonstrating the importance of 30-meter multispectral Landsat sensors for detecting soil erosion at the regional scale.

In paper [6], the process of mapping the ϕ coefficient is described, which characterizes the type and degrees of erosion in the empirical erosion model that is widely used in the process of creating soil erosion maps using the Erosion Potential Method (EPM). The mapping was based on the use of satellite images obtained from the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) missions over a ten-year period. Mapping and identification of erosion processes were carried

out on the Google Earth Engine (GEE) platform based on the Bare Soil Index (BSI).

Czech researchers [7] tested a remote sensing method for determining eroded areas at the regional scale using a combination of time series of Sentinel-2 image data, aerial orthophotos, and ground data. A high potential of this approach for obtaining valuable data on actual soil degradation as a result of erosion was demonstrated.

Radek Malinowski et al. [8] carried out automated mapping of rill erosion based on remote sensing data. The studies showed that the use of UAVs provides high detail for automated mapping of erosion rill networks using machine learning methods, in particular the Random Forest algorithm.

Wang et al. [9] used seven Google Earth images with different spatial resolutions combined with auxiliary data to detect gullies in parts of the chernozem region in northeastern China.

Despite the significant level of research on the topic of mapping eroded soils, it remains relevant for Ukraine primarily due to the specificity of its soil cover. In particular, most existing global publications relate to the interpretation and mapping of rill water erosion. At the same time, the issue of recording sheet erosion remains practically unconsidered. In our opinion, this is due to the fact that chernozems, which prevail on the territory of Ukraine, occupy approximately 230 million hectares, which constitutes about 1.8% of the total land area of the Earth [10].

Chernozems are characterized by high reserves of organic carbon (humus), which gives them their characteristic dark gray color, and by a deep profile. Accordingly, at the medium and strong stages of soil washout, weakly humus-enriched genetic layers reach the surface, which allows them to be sufficiently clearly identified on satellite images [3].

Objects and materials. Research methodology

The research was conducted within the territory of the Novoodeska territorial community (NTC) of Mykolaiv region (Fig. 1). The Novoodeska territorial community has 54,773 ha of agricultural land with high potential for crop production (grain crops, industrial crops) and livestock production (cattle, pigs, poultry).

The community has a high-quality soil cover represented by typical chernozems,

southern chernozems, with inclusions of meadow-chernozem soils. At the same time, there is numerous evidence of significant degradation of the soil cover, primarily due to water erosion, which requires the adoption of appropriate environmental protection measures. An example is a satellite image (Google Earth Pro service) of the territory of the NTC near the village of Novopavlivka, on which some exam-



Fig. 1 – Territory of the Novoodeska territorial community of Mykolaiv region

ples of manifestations of water erosion are highlighted with black arrows (Fig. 2).

The research was conducted within the framework of the project “DIY4Change for Green Recovery and Sustainable Development of Two Communities in Mykolaiv Region”, implemented by the NGO Mykolaiv City Development Fund. One of the project objectives was to prepare local communities for the development of a Comprehensive Spatial

Development Plan. A priority task of the project was to support the Nova Odesa community in the preparation of such a plan, which required updating and refining data on land resources. Given the agricultural profile of the community and the significant level of arable land degradation, particular emphasis was placed on mapping severely eroded soils and exposures of parent material as the most critical and environmentally vulnerable areas.



Fig. 2 – Examples of water-erosion degradation of soil cover within the territory of the Nova Odesa territorial community, Mykolaiv region

In the research, archival maps of agro-production soil groups at a scale of 1:10,000 were used, which were compiled in 1994 and 2001. All of them were georeferenced to the geographic coordinate system in the QGIS geoinformation system.

The identification of eroded soils on the images was carried out by the method of visual interpretation. Visual interpretation is a classical method of analysis of aerospace images, which is based on the recognition of objects by their characteristic features without the use of

complex software. The specialist uses direct features (color, shape, structure, etc.) and indirect relationships between them, carrying out a complex logical-intuitive process inherent specifically to humans. Due to the difficulty of full automation of such analysis, this method remains a relevant and highly effective tool that successfully complements modern methods of machine object recognition.

The image presented in Fig. 2 also shows the main drawback of the Google Earth Pro service – it presents high spatial resolution images over a period of more than 20 years, but without the possibility of ordering an image for a specific time. As can be seen in the figure, part of the fields in any image will always be covered with vegetation or its residues, which significantly complicates the interpretation process.

It is possible to partially eliminate this problem by using images from the Sentinel-2 satellite [11], which are freely available for any date range and any territory. However, in order to find high-quality images with bare soil for each field, download them, and interpret them using traditional methods, enormous time and labor costs would be required.

An alternative to this is the use of the Google Earth Engine (GEE) service. GEE [12] is a specialized cloud platform for geospatial data analysis at the planetary scale. Unlike

traditional GIS packages, GEE combines a multi-petabyte archive of satellite data with Google's high-performance computing capabilities. This makes it possible to perform complex mathematical and statistical processing of large data arrays without the need to download them to local storage media [13].

For the detection of eroded areas, a key advantage of GEE is the possibility of generating multitemporal composite images of bare soil. The algorithm is based on the analysis of time series of Sentinel-2 satellite data over several years. The software script performs an iterative review of each pixel in the data archives and applies vegetation masking based on vegetation indices.

From the stack of images where a pixel is identified as bare soil, the most representative value of spectral reflectance is selected using statistical reduction functions. This makes it possible to eliminate the influence of cloudiness, shadows, and random noise, creating a single seamless image of the entire territory of the Novoodeska community, where each field is displayed in the state after plowing or before crop emergence. The process of constructing such a composite image for the territory of the NTC will be described in detail in the next section

Results

At the first stage of the research, archival maps of agro-production soil groups for the territory of the Novoodeska community were analyzed. In particular, a vector layer of severely eroded soils was created, the legend of which is given in Table 1. The total area of eroded soils on the territory of the NTC according to archival maps is 26,013.2 ha; the area of severely washed soils is 5,214.3 ha, moderately washed soils – 10,009.7 ha, weakly washed soils – 10,789.2 ha.

A preliminary visual integrated analysis of remote sensing data and archival maps showed that far from all severely eroded soils are represented (Fig. 3). For example, plot 751 (Fig. 3a) is marked as moderately washed, whereas the satellite image indicates severe erosion (red arrow, Fig. 3b).

This is quite understandable considering the date of map compilation – the 1990s. Moreover, these dates most likely indicate not the actual conducting of field soil surveys, but only the updating of the cartographic material

itself. Over the past time, soil degradation processes could have introduced their negative corrections into the structure of the soil cover. It should also be added that at the time of map compilation, the information-technological capabilities available now – free remote sensing data and advanced geoinformation technologies – were absent, which objectively did not allow the creation of highly detailed soil maps.

Water erosion is differentiated into two main types: sheet (surface) and linear (rill) erosion. Sheet erosion is characterized by a relatively uniform washout of the topsoil layer across the entire area of the plot, which leads to the appearance of large-scale eroded zones.

Remote diagnostics of this type is based on changes in spectral properties: eroded areas appear lighter due to the exposure of sub-humus horizons. At the same time, this fact alone is not sufficient, as the light color of the soil may be caused by its natural genesis, for example podzolization or formation on parent rocks of light granulometric composition. In addition to

Table 1

Explication of eroded soils in the Nova Odesa territorial community

Agro-production soil group code	Agro-production soil group name	Area, ha
65е	Ordinary Chernozems, slightly eroded, silty light-clay, on simple slopes	504,8
65л	Ordinary Chernozems, slightly eroded, light-clay, on loess of narrow erosion-prone plateaus	3509,1
66л	Ordinary Chernozems, moderately eroded, light-clay, on loess	1771,1
66е	Ordinary Chernozems, moderately eroded, low-humus, light-clay, on loess	1076,1
67е	Ordinary Chernozems, low-humus, thin, severely eroded, heavy-loamy, on loess-like loams of complex slopes	83,7
67л	Ordinary Chernozems, severely eroded, on loess of complex exposure slopes	237,5
74е	Southern Chernozems, low-humus, slightly eroded, heavy-clay, on loess-like loams of complex slopes	256,2
74л	Southern Chernozems, low-humus, slightly eroded, light-clay, on loess of narrow erosion-prone plateaus	6433,7
74д	Chernozems, low-humus, slightly eroded, medium-loamy, on loess-like loams underlain by limestone from 150 cm.	33,1
75д	Southern Chernozems, low-humus, moderately eroded, medium-loamy, on loess-like loams	573,3
75е	Southern Chernozems, low-humus, moderately eroded, heavy-loamy, on loess-like loams of complex slopes	1710,9
75л	Southern Chernozems, low-humus, moderately eroded, light-clay, on loess of slopes	4095
76д	Southern Chernozems, low-humus, severely eroded, medium-loamy, on loess-like loams underlain by limestone eluvium from 150 cm.	99,8
76е	Southern Chernozems, low-humus, severely eroded, heavy-loamy, on loess-like loams of complex slopes	179,2
76л	Southern Chernozems, low-humus, severely eroded, light-clay, on loess of complex slopes	151,6
85л	Chernozems, slightly eroded, non-saline and slightly saline, light-clay, on dense clays	16,9
85е	Chernozems, slightly eroded, medium-clay, on dense clays of complex slopes	33,6
86е	Chernozems, moderately eroded, medium-clay, on dense clays of complex slopes	304,4
86л	Chernozems, moderately eroded, light-clay, on dense clays of complex slopes	86,7
87е	Chernozems, slightly eroded, non-saline and slightly saline, light-clay, on dense clays	1,8
87л	Chernozems, severely eroded, light-clay, on dense clays of complex slopes	10,1
93д	Chernozems, moderately eroded, medium-loamy, on sands	0,9
102е	Chernozems, moderately and severely eroded, skeletal heavy-loamy, on simple slopes	687
103д	Chernozems, moderately eroded, medium-loamy, on limestone eluvium of complex slopes	391,3
104д	Chernozems, severely eroded, medium-loamy, on limestone eluvium in complex with limestone outcrops (10–30%), on complex slopes	3603,1
104е	Ordinary Chernozems, low-humus, shallow, severely eroded, heavy-loamy, on loess-like loams underlain by limestone eluvium at 0.5–1.0 m	162,3

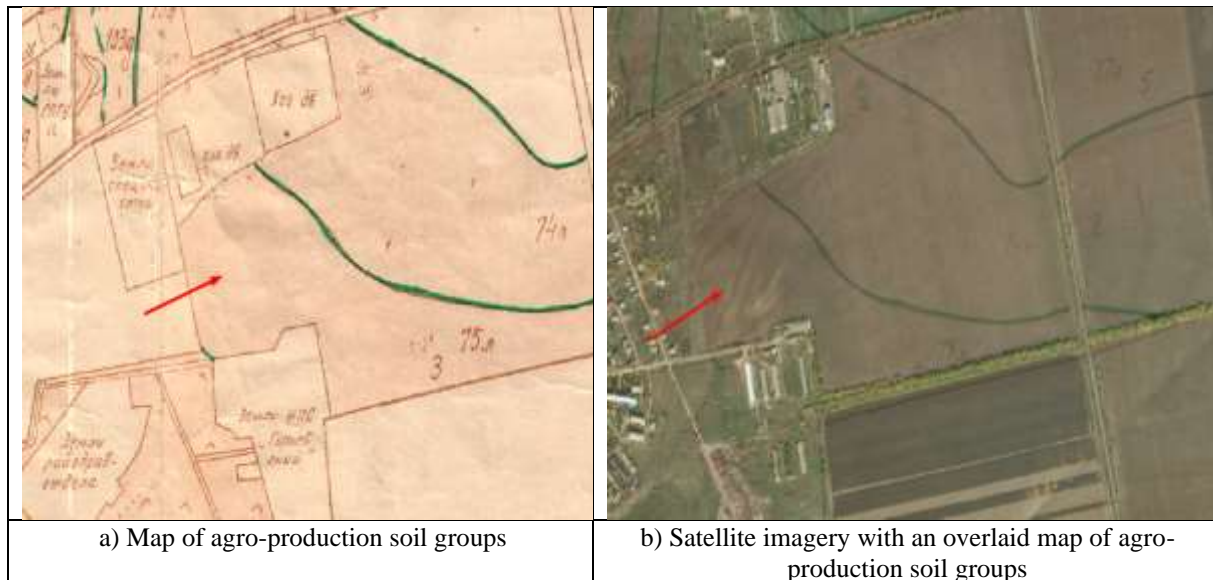


Fig. 3 – Example of the obsolescence of existing maps of agro-production soil groups

color, it is necessary to take into account the presence of a characteristic feathery structure of the image – alternating light and dark stripes oriented parallel to each other. These stripes represent the alternation of runoff depressions, which are weakly manifested in the relief. An

additional important characteristic is the orientation of these stripes perpendicular to the landscape thalwegs (Fig. 4).

For the recognition of linear erosion on satellite images, a set of interpretive features is used, allowing the identification of gullies



a) Mykolaiv region



b) Kharkiv region

Fig. 4 – Example of water erosion identification from remote sensing data

based on their morphology and optical properties. In particular, attention is paid to the specific winding shape and dendritic (tree-like) structure of networks, whose sizes correspond to the scales of fields. In addition, key indicators include: clear alignment of new gullies with old erosion forms, such as ravines; repeatability and preservation of object contours across different

image series; pronounced brightness contrast and characteristic heterogeneous coloring compared to the background image of adjacent arable plots [14].

It should be noted that the distinction between sheet and linear erosion is fairly conditional. On agricultural lands, water does not move as a continuous flow; temporary

streams of equal size always form. Accordingly, in the interpretation of eroded soils, a general delineation is carried out without dividing by erosion types [15,16].

To correct archival cartographic data, a composite image of bare soil was created (based on Sentinel-2 satellite data). To obtain the composite using the Gemini 3.0 artificial intelligence service, a software algorithm was generated for Google Earth Engine.

The algorithm used archival satellite data from the Sentinel-2 constellation for the period 2020–2025. To ensure correct identification of the soil cover specifically, the script applied selection for specific months – March, April, August, September, October. This corresponds to periods of the agricultural cycle when vegetation cover is minimal. Spatially, the search was limited to the boundaries of the NTC with prior filtering by cloudiness level – less than 60% of cloud pixels in the scene.

A key element of the algorithm is the calculation of the Bare Soil Index (BSI). The calculation is performed using a formula that combines the shortwave infrared (SWIR), red (Red), near-infrared (NIR), and blue (Blue) channels:

$$BSI = \frac{(B11 + B4) - (B8 + B2)}{(B11 + B4) + (B8 + B2)}$$

where: B2 - Blue

- B4 - Red

- B8 - NIR (Near-Infrared)

- B11 - SWIR1 (Short-wave Infrared 1)

This index allows effective differentiation of bare soil areas from vegetation and built-up territories. BSI is a normalized difference index, its values theoretically range from -1 to 1. Positive values correspond to areas with high reflectance in the shortwave infrared and red spectra compared to near-infrared and blue. This is characteristic of bare soils, sand, and anthropogenic objects.

Negative values are typical for surfaces with high chlorophyll content (active vegetation) or water bodies. Since vegetation intensely reflects light in the NIR range (B8), the denominator of the formula increases, and the numerator becomes negative, resulting in negative index values.

To select “pure” soil pixels, a two-level filtering system is implemented in the algorithm. At the first level, masking is carried out using the Scene Classification classifier. This is a built-in Sentinel-2 layer, where only pixels classified as “vegetation” and “bare soil” remain. At the second level, filtering is performed by BSI values > 0. This allows exclusion of residual dry vegetation and pastures, leaving only arable land or areas with minimal chlorophyll content in the collection..



a) satellite image, Google



b) Bare Soil Index

Fig. 5 – Result of constructing the Bare Soil Index in the Google Earth Engine service.

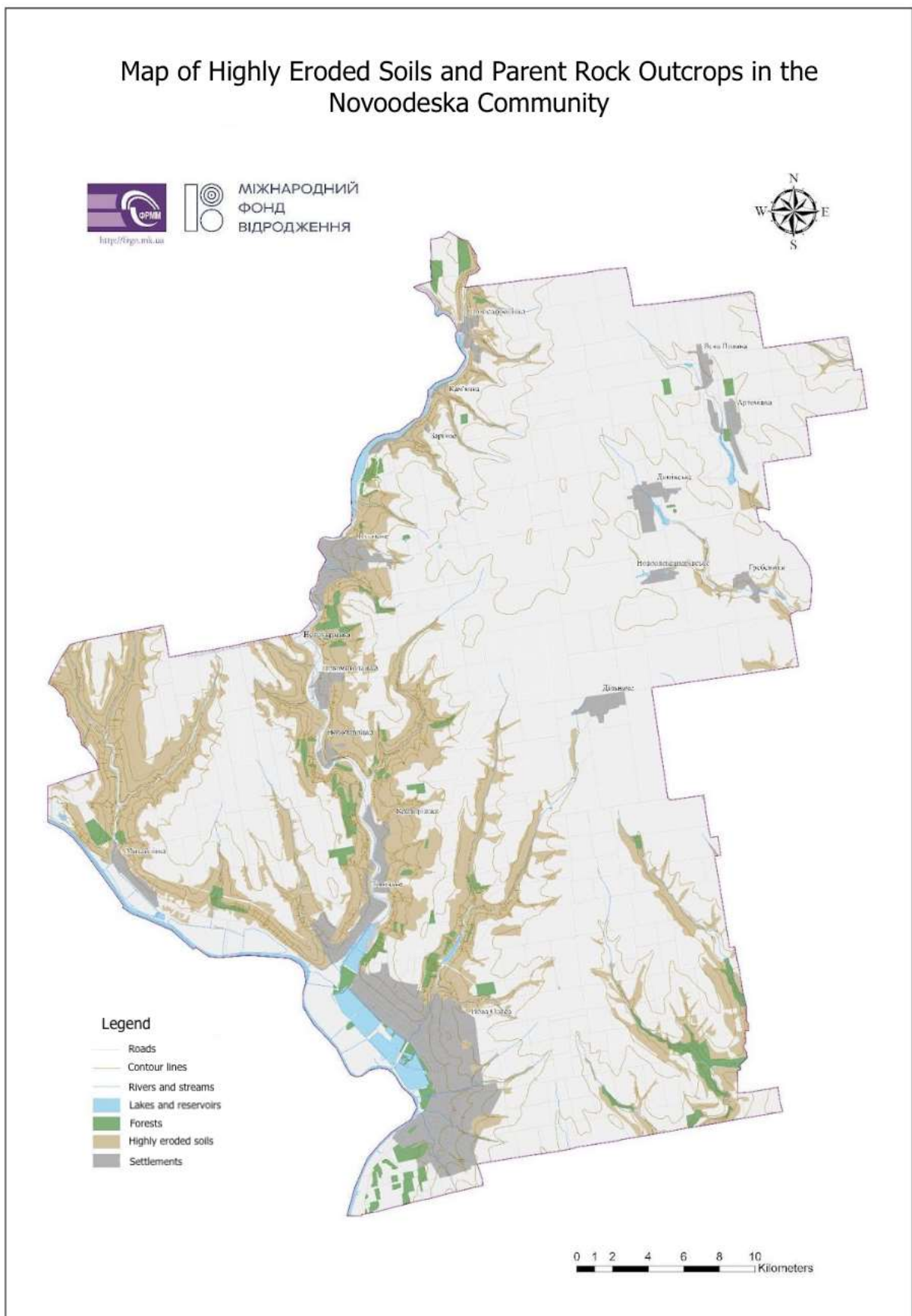


Fig. 6 – Map of severely washed soils and outcrops of parent rocks in the territory of the Novoodeska territorial community

To obtain the final result, a median reduction method is applied to the filtered image collection. Choosing the median instead of the mean minimizes the influence of random outliers, such as residual cloud shadows or artifacts, and provides the most spectrally representative state of the soil over a five-year period.

The final image includes spectral channels B2, B3, B4, B8, B11, and a separate BSI layer (Fig. 5). Export of the results is configured in the “UTM zone 36N” coordinate system with a spatial resolution of 10 meters per pixel. Analysis of the BSI layer (Fig. 5) shows that it is not

possible to completely eliminate the influence of vegetation, which is manifested as a mosaic in the image along the field boundaries. This is due to the short five-year period of analysis and the widespread use of no-till technology, under which the surface is constantly covered with vegetation or its residues. At the same time, combining the BSI layer with high-resolution images (Google, Bing, ESRI) made it possible to create a map of severely washed soils and outcrops of parent rocks of the Novoodeska community (Fig. 6) at a scale of 1:10,000 [17]. According to updated data, their area is 12,027.6 ha

Discussion

The results of the conducted study confirm the need to update cartographic data on the state of Ukraine’s soil cover, since soil maps compiled in the 1990s – early 2000s are now significantly outdated. Comparative analysis showed that archival data do not reflect the actual scale of degradation. For instance, according to old maps, the area of severely washed soils in the Novoodeska community was about 5,214 ha, whereas according to refined remote sensing data, this figure increased to 12,027.6 ha. This discrepancy is explained not only by the intensification of erosion processes over the last 20–30 years but also by the limited technical capabilities of the previous century, which did not allow for high-resolution monitoring.

The use of the cloud platform Google Earth Engine (GEE) demonstrates a significant methodological advantage in the processing of large geospatial data, providing the scientific community with free access to vast remote sensing datasets. GEE fundamentally changes not only the location of computations but also the strategy for geospatial research development, as it enables instant work with multi-year satellite archives without the need to download data or manage local storage. This opens opportunities for implementing multi-scale and multi-temporal projects, such as global time series, which are often infeasible on conventional desktop computers [18,19].

The platform eliminates the need for separate stages of data acquisition and preprocessing, instead offering globally consistent and reproducible workflows based on curated collections. The latter term refers to a set of carefully selected, systematized, and preprocessed datasets [20]. Specialists from Google and partner organizations (e.g., NASA)

perform extensive preparatory work on standardization, preprocessing, quality control, and data updating.

Thanks to automatic parallelization of analysis within Google’s infrastructure, processing geospatial data at a planetary scale is reduced from months to mere hours. A striking example of such efficiency is the study by Hansen et al. [21], in which approximately 707 terabytes of Landsat-7 imagery were processed to create a global forest map in just 100 hours – a task that would have taken a million hours outside of GEE.

An important analysis tool was the Bare Soil Index (BSI), which allows clear differentiation of bare surfaces from vegetation by combining spectral channels, where high reflectance in the shortwave infrared and red bands indicates exposed soil. However, as the study showed, even a five-year analysis period and the use of BSI do not entirely eliminate the influence of vegetation. This is due to the specifics of modern agriculture, particularly the widespread adoption of no-till technology, where soil remains constantly covered with crop residues, creating a “mosaic” in the imagery.

Combining automated indices with visual analysis allowed the creation of an updated map of severely washed soils of the community at a scale of 1:10,000, which will be useful in the development of the Comprehensive Plan for Spatial Development of the Territory.

The resulting layer of severely washed soils can also serve as a training dataset for further remote studies of the soil cover in Mykolaiv region.

The conducted mapping is also strategically important for ensuring food security and reducing greenhouse gas emissions, as

erosion intensifies the mineralization of organic matter. The use of artificial intelligence for algorithm development in GEE (as was done

with Gemini 3.0 in this work) opens new prospects for operational monitoring of land resources at regional and national levels

Conclusions

Existing soil maps of the Novoodeska territorial community, compiled at the end of the 20th century, significantly underestimate the current scale of land degradation. A substantial portion of areas previously classified as moderately washed now exhibit signs of severe erosion.

The use of the cloud platform Google Earth Engine and Sentinel-2 satellite data is an effective method for creating seamless bare soil maps. This allows mitigation of disturbances from vegetation and cloud cover, ensuring high-accuracy monitoring over large areas.

Within the study, a new map of severely

washed soils and outcrops of parent rocks of the NTC was developed at a scale of 1:10,000. The area of severely washed soils is 12,027.6 ha, more than twice the archival data. The resulting map is important for the development of the Comprehensive Plan for Spatial Development of the Territory and for implementing soil protection measures.

For achieving maximum accuracy, it is advisable to combine automated indices (BSI) with visual interpretation of linear and sheet erosion features, which helps avoid errors associated with the natural heterogeneity of the soil cover.

Conflict of Interest

This work was carried out within the framework of the project “DIY4Change for green recovery and sustainable development of 2 communities of Mykolaiv region,” implemented by the NGO “Mykolaiv City Development Fund” with support from the International Renaissance Foundation. The material represents the position of the authors and does not necessarily reflect the position of the IRF.

The authors declare that there is no conflict of interest regarding the publication of this manuscript. The authors fully adhered to ethical standards, including issues of plagiarism, data fabrication, and duplicate publication.

Author Contributions: The authors contributed equally to this work.

AI Statement

Gemini 3.0 artificial intelligence was used to write a software algorithm for generating composite images of open ground using Sentinel-2 data (Google Earth Engine).

References

1. Verkhovna Rada of Ukraine. (2022). On approval of the Concept of the National Target Program for land use and protection (Order No. 70-r). <https://zakon.rada.gov.ua/laws/show/70-2022-%D1%80#Text> (in Ukrainian).
2. *Overview of soil conditions of arable land in Ukraine*. (2020). FAO. <https://doi.org/10.4060/ca7761en> (in Ukrainian).
3. Achasov, A., Achasova, A., Titenko, G., Seliverstov, O., & Krivtsov, V. (2021). Assessment of the Ecological Condition of Soil Cover Based on Remote Sensing Data: Erosional Aspect. *SHS Web of Conferences*, 100, 05014. <https://doi.org/10.1051/shsconf/202110005014>
4. Wang, J., Yang, J., Li, Z., Ke, L., Li, Q., Fan, J., & Wang, X. (2024). Research on Soil Erosion Based on Remote Sensing Technology: A Review. *Agriculture*, 15(1), 18. <https://doi.org/10.3390/agriculture15010018>
5. Seutloali, K. E., Dube, T., & Mutanga, O. (2017). Assessing and mapping the severity of soil erosion using the 30-m Landsat multispectral satellite data in the former South African homelands of Transkei. *Physics and Chemistry of the Earth, Parts A/B/C*, 100, 296–304. <https://doi.org/10.1016/j.pce.2016.10.001>
6. Polovina, S., Radić, B., Ristić, R., & Milčanović, V. (2024). Application of Remote Sensing for Identifying Soil Erosion Processes on a Regional Scale: An Innovative Approach to Enhance the Erosion Potential Model. *Remote Sensing*, 16(13), 2390. <https://doi.org/10.3390/rs16132390>
7. Žižala, D., Juřicová, A., Zádorová, T., Zelenková, K., & Minařík, R. (2018). Mapping soil degradation using remote sensing data and ancillary data: South-East Moravia, Czech Republic. *European Journal of Remote Sensing*, 52(sup1), 108–122. <https://doi.org/10.1080/22797254.2018.1482524>

8. Malinowski, R., Heckrath, G., Rybicki, M., & Eltner, A. (2022). Mapping rill soil erosion in agricultural fields with UAV-borne remote sensing data. *Earth Surface Processes and Landforms*. <https://doi.org/10.1002/esp.5505>
9. Wang, B., Zhang, Z., Wang, X., Zhao, X., Yi, L., & Hu, S. (2021). The Suitability of Remote Sensing Images at Different Resolutions for Mapping of Gullies in the Black Soil Region, Northeast China. *Remote Sensing*, 13(12), 2367. <https://doi.org/10.3390/rs13122367>
10. Britannica Editors (2019, September 24). Chernozem. Encyclopedia Britannica. <https://www.britannica.com/science/Chernozem-FAO-soil-group>
11. Sentinel-2. Copernicus Data Space Ecosystem. <https://dataspace.copernicus.eu/data-collections/copernicus-sentinel-data/sentinel-2>
12. Google Earth Engine. Google Earth Engine. <https://earthengine.google.com/>
13. Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., Moghimi, A., Mirmazloumi, S. M., Moghaddam, S. H. A., Mahdavi, S., Ghahremanloo, M., Parsian, S., Wu, Q., & Brisco, B. (2020). Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 5326–5350. <https://doi.org/10.1109/jstars.2020.3021052>
14. Achasov, A., & Achasova, A. (2020). Features of Visual Decoding of Water Erosion by Remote Sensing Data. *Man and Environment. Issues of Neoeology*, (33). <https://doi.org/10.26565/1992-4224-2020-33-13> (in Ukrainian).
15. Achasov, A. B., Achashova, A. O., Buligin, S. Yu., et al. (2010). *Large-scale soil mapping using integrated analysis of remote sensing data and digital elevation models: Methodological recommendations*. Kharkiv National Agrarian University. (in Ukrainian).
16. Achasov, A. B. (2016). *Anti-erosion optimization of agricultural landscapes: A geoinformation approach*. Kharkiv National Agrarian University. (in Ukrainian).
17. Achasov, A., Dyadin, D., Sinna, O., & Siedov, A. (2026). *Maps for the EcoProfile: Novoodeska territorial community*. International Renaissance Foundation; Foundation for the Development of Modern Media. https://nodmr.gov.ua/images/kontent/side_menu/Stratehiya_ta_investytsiyina/2025/ЕкоПро-фільм_A4_HTГ_1.pdf (in Ukrainian).
18. Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., & Brisco, B. (2020). Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 164, 152–170. <https://doi.org/10.1016/j.isprsjprs.2020.04.001>
19. Velastegui-Montoya, A., Montalván-Burbano, N., Carrión-Mero, P., Rivera-Torres, H., Sadeck, L., & Adami, M. (2023). Google Earth Engine: A Global Analysis and Future Trends. *Remote Sensing*, 15(14), 3675. <https://doi.org/10.3390/rs15143675>
20. Schmitt, M., Hughes, L. H., Qiu, C., & Zhu, X. X. (2019). SEN12MS & NDASH; A curated dataset of georeferenced multi-spectral Sentinel-1/2 imagery for deep learning and data fusion. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, IV-2/W7, 153–160. <https://doi.org/10.5194/isprs-annals-iv-2-w7-153-2019>
21. Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, 342(6160), 850–853. <https://doi.org/10.1126/science.1244693>

Submission received: 24.01.2026 / Revised: 26.02.2026 / Accepted: 06.03.2026 / Published: 30.05.2026

А. Б. АЧАСОВ¹, д-р с.-г. наук, проф.
професор кафедри екології та менеджменту довкілля
e-mail: achasov@karazin.ua ORCID ID: <https://orcid.org/0000-0003-2446-3707>

О. Ю. СЕЛІВЕРСТОВ¹,
викладач кафедри екології та менеджменту довкілля
e-mail: oleg.seliverstov@karazin.ua ORCID ID: <https://orcid.org/0000-0002-8477-274X>

Г. В. ТІТЕНКО¹, канд. географ. наук, доц.,
доцент кафедри екології та менеджменту довкілля
e-mail: titenko@karazin.ua ORCID ID: <http://orcid.org/0000-0002-8477-0672>

Р. Р. КАЛАШНИКОВ¹,
Бакалавр
e-mail: ruslan.kalashnikov@student.karazin.ua ORCID ID: <https://orcid.org/0009-0002-3616-400X>

¹Харківський національний університет імені В. Н. Каразіна,
майдан Свободи, 4, м. Харків, 61022, Україна

ДОСВІД КАРТОГРАФУВАННЯ ЕРОДОВАНИХ ҐРУНТІВ НА ОСНОВІ ДАНИХ ДИСТАНЦІЙНОГО ЗОНДУВАННЯ

Мета. Можливості сучасних даних дистанційного зондування Землі та геоінформаційних технологій для ідентифікації та великомасштабного картографування еродованих ґрунтів з особливим акцентом на виявлення площинної водної ерозії, яка залишається недостатньо представленою на наявних ґрунтових картах України.

Методи. Обробку даних виконано на платформі Google Earth Engine шляхом формування композитного зображення відкритого ґрунту на основі індексу Bare Soil Index (BSI), масок сенової класифікації та медіанної редукції пікселів. Ідентифікацію еродованих ділянок здійснювали методом візуального дешифрування з урахуванням спектральних, просторових і морфологічних ознак водної ерозії.

Результати. Дослідження проведено на території Новоодеської територіальної громади Миколаївської області з використанням архівних карт агропромислових груп ґрунтів масштабу 1:10 000 та багатотемпоральних супутникових знімків Sentinel-2 за період 2020–2025 рр. Встановлено суттєві розбіжності між архівними ґрунтовими картами та сучасним просторовим розподілом еродованих ґрунтів, що свідчить про посилення деградаційних процесів упродовж останніх десятиліть. Застосування багатотемпоральних композитів відкритого ґрунту забезпечило надійне виділення сильноеродованих ґрунтів і виходів материнських порід у межах сільськогосподарських ландшафтів. У результаті створено актуалізовану великомасштабну карту сильноеродованих ґрунтів у масштабі 1:10 000, яка істотно перевищує за детальністю та достовірністю наявні картографічні матеріали.

Висновок. Інтеграція багатотемпоральних супутникових знімків Sentinel-2 та хмарного геоінформаційного аналізу значно підвищує точність картографування водної ерозії, особливо її площинних форм. Запропонований підхід є ефективним інструментом для оновлення ґрунтово-картографічних матеріалів.

КЛЮЧОВІ СЛОВА: водна ерозія, еродовані ґрунти, дистанційне зондування Землі, Sentinel-2, Google Earth Engine, ґрунтове картографування

Конфлікт інтересів

Робота виконана в рамках проекту «DIY4Change для зеленого відновлення та сталого розвитку 2 громад Миколаївської області», що реалізується ГО «Фонд розвитку міста Миколаїв» за підтримки Міжнародного фонду «Відродження». Матеріал відображає позицію авторів і не обов'язково відображає позицію IRF.

Автори заявляють про відсутність конфлікту інтересів щодо публікації цього рукопису. Автори повністю дотримувалися етичних стандартів, включаючи питання плагіату, фальсифікації даних та дублювання публікацій.

Внесок авторів: Автори зробили рівний внесок у цю роботу.

Декларація про використання ШІ

Штучний інтелект Gemini 3.0 застосовано для написання програмного алгоритму для генерації композитних знімків відкритого ґрунту за даними Sentinel-2 (сервіс Google Earth Engine).

Список використаної літератури

1. Верховна Рада України. Про схвалення Концепції Загальнодержавної цільової програми використання та охорони земель. 2022. № 70-р, ст. 141. URL: <https://zakon.rada.gov.ua/laws/show/70-2022-%D1%80#Text> (дата звернення: 21.01.2026).
2. Огляд стану ґрунтів орних земель України – дослідження для степової та лісостепової зон. Будапешт, Угорщина : FAO, 2020. 64 с. <https://doi.org/10.4060/ca7761en>
3. Achasov A., Achasova A., Titenko G., Seliverstov O., Krivtsov V.. Оцінка екологічного стану ґрунтового покриву на основі даних дистанційного зондування: ерозійний аспект. *SHS Web of Conferences*. 2021. Т. 100. С. 05014. <https://doi.org/10.1051/shsconf/202110005014>
4. Wang J., Yang J., Li Z., Ke L., Li Q., Fan J., Wang X.. Дослідження ерозії ґрунтів на основі технологій дистанційного зондування: огляд. *Agriculture*. 2024. Т. 15, № 1. С. 18. <https://doi.org/10.3390/agriculture15010018>
5. Seutloali, K.E.; Timothy, D.; Onisimo, M. Оцінювання та картографування інтенсивності ерозії ґрунтів із використанням 30-м багатоспектральних супутникових даних Landsat на території колишніх південноафриканських голландів Транскею. *Phys. Chem. Earth*. 2016. Т. 100. С. 296–304.
6. Polovina S., Radić B., Ristic R., Milčanović V. Застосування дистанційного зондування для ідентифікації ерозійних процесів ґрунтів на регіональному рівні: інноваційний підхід до вдосконалення моделі ерозійного потенціалу. *Remote Sensing*. 2024. Т. 16, № 13. С. 2390. <https://doi.org/10.3390/rs16132390>
7. Žižala D., Juřicová A., Zádorová T., Zelenková K., Minařík R.. Картографування деградації ґрунтів із використанням даних дистанційного зондування та допоміжних даних: Південно-Східна Моравія, Чеська Республіка. *European Journal of Remote Sensing*. 2018. Т. 52, дод. 1. С. 108–122. <https://doi.org/10.1080/22797254.2018.1482524>
8. Malinowski R., Heckrath G., Rybicki M., Eltner A.. Картографування борознаної ерозії ґрунтів на сільськогосподарських полях за допомогою БПЛА-даних дистанційного зондування. *Earth Surface Processes and Landforms*. 2022. <https://doi.org/10.1002/esp.5505>
9. Wang, B.; Zhang, Z.; Wang, X.; Zhao, X.; Yi, L.; Hu, S. Придатність дистанційних знімків різної просторової роздільної здатності для картографування ярів у регіоні чорноземів Північно-Східного Китаю. *Remote Sens.* 2021, 13, 2367. <https://doi.org/10.3390/rs13122367>
10. Britannica Editors Chernozem. Encyclopedia Britannica. 2019. URL: <https://www.britannica.com/science/Chernozem-FAO-soil-group> (дата звернення: 21.01.2026)
11. Sentinel-2. Copernicus Data Space Ecosystem. URL: <https://dataspace.copernicus.eu/data-collections/copernicus-sentinel-data/sentinel-2>
12. Google Earth Engine. Google Earth Engine. URL: <https://earthengine.google.com>
13. Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., ... & Brisco, B. (2020). Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 5326–5350. <https://doi.org/10.1109/jstars.2020.3021052>
14. Ачасов А. Б., Ачасова А. О. Особливості візуального дешифрування водної ерозії за даними дистанційного зондування. *Людина та довкілля. Проблеми неоекології*. 2020. № 33. <https://doi.org/10.26565/1992-4224-2020-33-13>
15. Ачасов А. Б., Ачасова А. О., Булигін С. Ю. та ін. Великомасштабне картографування ґрунтів за допомогою інтегрального аналізу даних дистанційного зондування й цифрових моделей рельєфу. Методичні рекомендації. Харків : ХНАУ, 2010. 47 с.;
16. Ачасов А. Б. Протиерозійна оптимізація агроландшафтів: геоінформаційний підхід. Харків : Харк. нац. аграр. ун-т, 2016. 409 с.
17. Ачасов А., Дядін Д., Сінна О., Седов А.. Карти до ЕкоПрофілю – Новоодеська територіальна громада. Міжнародний фонд «Відродження», ФРММ, 2026. 16 с. URL:[https://nodmr.gov.ua/images/kontent/side menu/Stratehiya ta investytsiyana/2025/ЕкоПрофіль_A4_НТГ_1.pdf](https://nodmr.gov.ua/images/kontent/side_menu/Stratehiya_ta_investytsiyana/2025/ЕкоПрофіль_A4_НТГ_1.pdf)
18. H. Tamiminia, B. Salehi, M. Mahdianpari, L. Quackenbush, S. Adeli, B. Brisco. Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing*. 2020. Т. 164. С. 152–170. <https://doi.org/10.1016/j.isprsjprs.2020.04.001>
19. Velastegui-Montoya, A., Montalván-Burbano, N., Carrión-Mero, P., Rivera-Torres, H., Sadeck, L., Adami, M. Google Earth Engine: A Global Analysis and Future Trends. *Remote Sensing*. 2023. Т. 15(14). С. 3675. <https://doi.org/10.3390/rs15143675>
20. Schmitt M., Hughes L., Qiu C., Zhu X.. SEN12MS & NDASH; A curated dataset of georeferenced multi-spectral Sentinel-1/2 imagery for deep learning and data fusion. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*. 2019. IV-2/W7. С. 153–160. <https://doi.org/10.5194/isprs-annals-iv-2-w7-153-2019>
21. Hansen M. C., Potapov P. V., Moore R., Hancher M., ... Townshend J. R. G.. High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*. 2013. Т. 342, № 6160. С. 850–853. <https://doi.org/10.1126/science.1244693>

Отримано: 24.01.2026 / Переглянуто: 26.02.2026 / Прийнято: 06.03.2026 / Опубліковано: 30.05.2026