ПОЧВЕННО-ЗЕМЕЛЬНЫЕ РЕСУРСЫ

SOIL AND LAND RESOURCES

ГЛЕБАВА-ЗЯМЕЛЬНЫЯ РЭСУРСЫ

ISSN 1810-9810 (Print)
УДК 528.8+631.4

B. Zhao, A. Chervan

*Belarusian State University, Minsk, Belarus,
e-mail: geozhao@outlook.com, e-mail: Chervan@bsu.by*

SPATIAL DISTRIBUTION OF SOILS BY SALINIZATION LEVEL IN SOLIGORSK DISTRICT OF BELARUS

Abstract. The article discusses the problem of soil salinization in the Soligorsk region of Belarus and emphasizes the importance of monitoring the level of soil salinization. Methods of using Sentinel-2 satellite data to assess the spatial differentiation of soil salinization are presented. Based on soil information, the causes and risks of soil salinization are studied, geographical and environmental characteristics of the territory of Soligorsk district are briefly described. Analysis of methodological principles of Sentinel-2 satellite use for soil salinization assessment and monitoring is presented, taking into account the choice of monitoring indicators and data processing methods. Results of a spatial assessment of temporal and spatial variability of soil salinity level are presented. Measures to improve the environmental situation and recommendations on soil salinization management are proposed.

Keywords: soil salinization, Sentinel-2 satellite, monitoring, remote sensing, interpretation, Soligorsk district

Б. Чжао, А. Червань[1]

*Белорусский государственный университет, Минск, Беларусь,
e-mail: geozhao@outlook.com, e-mail: Chervan@bsu.by*

ПРОСТРАНСТВЕННОЕ РАСПРЕДЕЛЕНИЕ ПОЧВ ПО УРОВНЮ ЗАСОЛЕНИЯ В СОЛИГОРСКОМ РАЙОНЕ БЕЛАРУСИ

Аннотация. Рассматривается проблема засоления почв в Солигорском районе Беларуси и подчеркивается важность мониторинга уровня засоленности почв. Приведены методы использования данных спутника Sentinel-2 для оценки пространственной дифференциации засоления почвенного покрова. Исследованы причины и риски засоления почв, кратко описаны географические и экологические характеристики территории Солигорского района. Проведен анализ методических принципов использования спутника Sentinel-2 для пространственной оценки засоления почвенного покрова с учетом выбора показателей мониторинга и методов обработки данных. Представлены результаты пространственной оценки временной и пространственной изменчивости уровня засоления почв. Предложены меры по улучшению экологической ситуации и даны рекомендации по управлению засолением почв.

Ключевые слова: засоление почв, спутник Sentinel-2, мониторинг, дистанционное зондирование, дешифрирование, Солигорский район

Б. Чжао, А. Чэрвань

*Беларускі дзяржаўны ўніверсітэт, Мінск, Беларусь,
e-mail: geozhao@outlook.com, e-mail: Chervan@bsu.by*

ПРАСТОРАВАЯ АЦЭНКА ЎЗРОЎНЮ ЗАСАЛЕННЯ ГЛЕБЫ САЛІГОРСКАГА РАЁНА БЕЛАРУСІ

Анатацыя. Разглядаецца праблема засалення глебы ў Салігорскім раёне Беларусі і падкрэсліваецца важнасць маніторынгу ўзроўню засоленасці глебы. Прыведзены метады выкарыстання даных спадарожніка Sentinel-2 для адзнакі прасторавай дыферэнцыяцыі засалення глебавага покрыва. Даследаваны прычыны і рызыкі засалення глебы, коратка апісаны геаграфічныя і экалагічныя характарыстыкі тэрыторыі Салігорскага раёна. Праведзены аналіз метадычных прынцыпаў выкарыстання спадарожніка Sentinel-2 для прасторавай ацэнкі засалення глебавага покрыва з улікам выбару паказчыкаў маніторынгу і метадаў апрацоўкі даных. Прадстаўлены вынікі прасторавай ацэнкі часовай і прасторавай зменлівасці ўзроўню засалення глебы. Прапанаваны меры па паляпшэнні экалагічнай сітуацыі і дадзены рэкамендацыі па кіраванні засаленнем глебы.

Ключавыя словы: засаленне глебы, спадарожнік Sentinel-2, маніторынг, дыстанцыйнае зандзіраванне, дэшыфраванне, Салігорскі раён

Introduction. Soil salinization, as one of the important components affecting soil degradation, has a major impact on the sustainability of agriculture and environmental sustainability changes. Soil plays a major role in supporting the growth of plants, including crops. Soil acts as a physical support for plants, providing the nutrients and water they need to grow. This undoubtedly makes soil the most important component of the environment. However, soil salinization due to various reasons, such as irrational mineral extraction, has many unforeseen effects on soil fertility and plant growth [1].

The production process in industrial environments can cause impacts on the surrounding environment, including, but not limited to, an increase in the salinity of the soil and the release of related pollutants. When these impacts continue over a long period of time, they can lead to changes in the soil structure, which can have an impact on the growth of plants. This change is soil salinization, which poses an unspeakable threat to agricultural activities, crop production, and ecological activities in general.

The Soligorsk region of Belarus, territory of the production of potash, makes the soil more vulnerable to the risk of soil salinization. Mining and industrial processes in the region result in the release of large quantities of pollutants into the environment through the water cycle and direct contamination of the soil, leading to an increase in soil chemical pollution in the region.

In the face of such a serious crisis of soil salinization in the Soligorsk region, it is necessary to use appropriate and efficient means of monitoring. The use of satellite image data based on remote sensing technology is an effective instrument of monitoring the level of soil salinization in the Soligorsk district.

This approach is made possible by the use of multispectral Sentinel-2 satellite data, which are based on high resolution format, have a short re-entry period and are easy to use. Therefore, the main objective of the present study was to use Sentinel-2 data to monitor the level of soil salinization in the Soligorsk district of Belarus. By interpreting the high light remote sensing image data of the study area, it is possible to obtain a suitable model for assessing soil salinization as well as the spatial distribution and temporal pattern of soil salinity evolution, which will provide suitable references for understanding local soil pollution and future land management systems, and will be an important reference for the environmentally sustainable development of the Soligorsk district.

Background. Remote sensing techniques, especially using satellite-based platforms, are widely used to monitor soil salinity and alkalinity. Their ability to provide synoptic and repeat coverage over large areas has made them invaluable in this regard. The use of satellite data and its waveband characteristics has been recognized since the 1980s. In the 1990s, the availability of hyperspectral data from satellites like Terra, TM, Quickbird, SPOT, IRS, Hymap, AME, and Hyperion facilitated the development of multi-band, wide-range, and multi-temporal remote sensing satellites dedicated to land observation and soil monitoring [2, 3].

Spectral characteristics of saline soils play a key role in identifying and monitoring soil salinity through remote sensing. For instance, Csillag identified specific bands in the visible, near-infrared, and mid-infrared zones that distinguish different stages of salinization and alkalinization. Frequency bands such as 550–770 nm, 900–1030 nm, 1270–1520 nm, and 1940–2150 nm have been identified for detecting land salinization [4].

Various methods have been used to extract salinity information through remote sensing, including visual interpretation, range-band selection, K-T variation, principal component analysis, IHS variation, image ratio operation, maximum similarity classification, decision tree, neural network, fuzzy classification, surface decomposition elements and integrated modeling of multi-source data. In addition, the integration of remote sensing data with ground-based data and vegetation cover accounting facilitate accurate and reliable land and soil monitoring [5–7].

In recent years the Sentinel-2 satellite imagery an ESA mission has been widely used to monitor soil salinity and alkalinity. Sentinel-2 provides valuable data for monitoring studies with high-resolution optical imagery and multispectral imager spanning 13 spectral bands across multiole regions, including visible, near-infrared, and shortwave infrared zones [8]. Studies have successfully used Sentinel-2 data and various indices such as Normalized Difference Salinity Index (NDSI) and Soil-adjusted Vegetation Index (SAVI) to map and assess soil salinity and alkalinity [9].

Previous studies around the world and in regions such as Belarus have demonstrated the effectiveness of remote sensing, especially using Sentinel-2 data, for monitoring soil salinity and alkalinity [10]. Belarusian research is focused on soddy-podzolic soils, common in temperate and boreal forest regions. Remote sensing data including Sentinel-2 imagery have been used to monitor soil properties, including spectral response analysis, index identification, and integrated modeling [11].

The researchers identified specific wavelength ranges and indices that are sensitive to soil salinity and alkalinity in soddy-podzolic soils by analyzing the relationship between remote sensing data and soil properties. Integrating remote sensing data with other geospatial information, such as soil sampling and climate data, improves the accuracy and reliability of soil monitoring in Belarus.

Thus remote sensing techniques, especially satellites such as Sentinel-2, offer a reliable tool for monitoring soil salinity and alkalinity. The spectral characteristics of saline soils combined with various statistical analysis methods make it possible to identify and extract information about salinity. Integration of remote sensing data with ground-based data and land cover recording facilitate accurate and reliable monitoring at regional and local levels. Sentinel-2 data has proven its effectiveness in global studies and in regions such as Belarus, highlighting its potential for accurate and reliable monitoring of soil salinity and alkalinity.

Object and method. *Study area and satellite image selection.* The study focused on the northern part of Soligorsk (Belarus), known for the production of potash fertilizers. The geographical coordinates of the study area range from 52°44' to 52°56'N latitude and 27°21' to 27°43'E longitude, as shown in Figure 1.

The technological impact on the soil cover of the Soligorsk mining region is due to the activities of JSC "Belarusian Potassium" ("Belaruskali"). These pollutants include halite dust from salt dumps, leakage of saline solution from a slurry pond, discharge of pollutants from stacks of a cassiterite processing plant, transport of salt due to wind erosion of salt dumps, as well as dissolution of the saline solution by precipitation, leading to the formation of a concentrated salt solution [9] . The salt dumps cover an area of 608.3 hectares with a waste volume of 980 million tons; the sludge dumps cover an area of 939.9 hectares with a total weight of clay-salt-sludge waste of 115 million tons [12]. The uniqueness of the clay-salt waste from mine site No. 4 lies in the fact that the halogenation method is used in the production of potassium chloride fertilizers. Previous studies have found low salt content, consisting mainly of water (79.4 %), sodium chloride (7.7 %), potassium chloride (5.6 %) and calcium sulfate (5.3 %) [13]. The sludge contains 0.25 % calcium chloride and 0.42 % magnesium chloride which significantly affects the local soils of Soligorsk.

Remote sensing data was collected from ESA's Sentinel-2 satellite, specifically the S2A satellite on April 4, 2018 and the S2B satellite on March 19, 2023. The selection of remote sensing image time series from the spring season is choosen given the minimal vegetation cover and melting snow during this period. This choice ensures effective monitoring of soil conditions and eliminates the influence of vegetation and snow on the accuracy of the data.

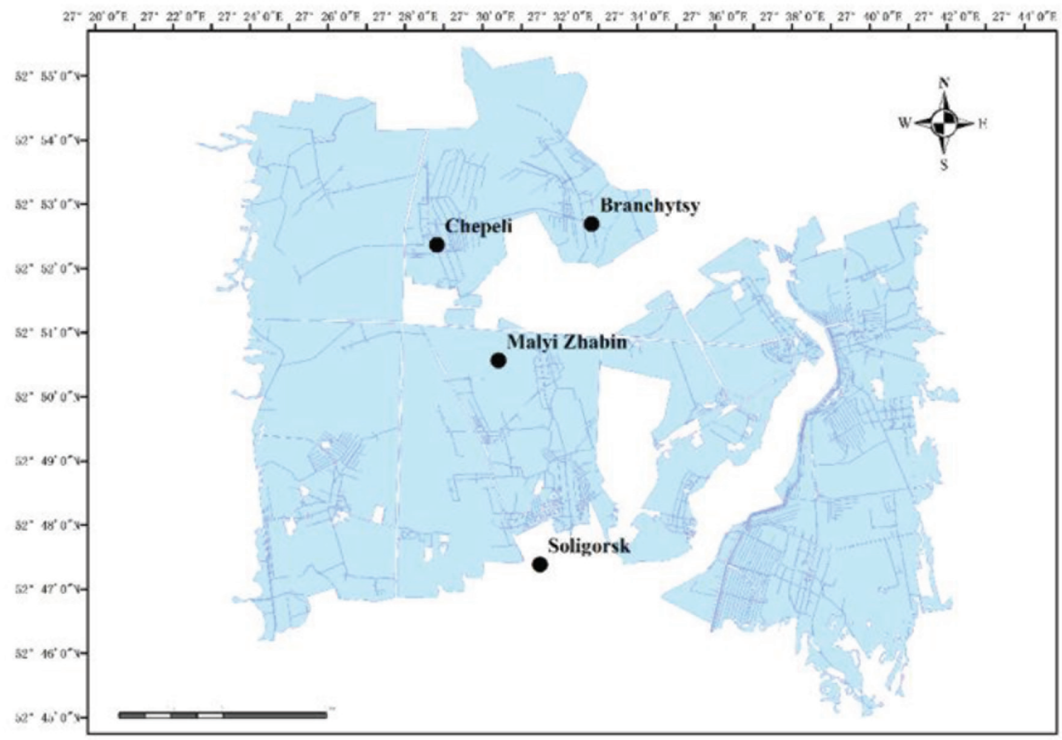


Fig. 1. The geographical location of the study area

Method. The remote sensing images used in this study were selected on the principle that the images were acquired as close as possible to the sampling time of the study area and without cloud cover. A total of seven salinity-related factors such as vegetation index, salinity index, substrate factor, intrinsic space, TCT coefficient, stripe reflectivity and topographic factor were identified as supporting information for salinity monitoring. The specific classification is presented in Table 1.

Table 1. **Salinization-related indexes extracted for prediction model in Soligorsk district**

Abbreviation	Equation	Reference
NDVI	$(NIR - R) / (NIR + R)$	Celleri et al. 2019 [14]
EVI	$2{,}5(NIR - R) / (NIR + 6R - 7{,}5B + 1)$	Peng et al. 2019 [15]
RVI	NIR / R	Celleri et al. 2019 [14]
ENDVI	$(NIR + SWIR2 - R) / (NIR + SWIR2 + R)$	Wang et al. 2017 [16]
MSAVI	$\left[2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - R)}\right] / 2$	Celleri et al. 2019 [14]
ARVI	$(NIR - 2R + B) / (NIR - 2R - B)$	Guo et al. 2018 [17]
VSSI	$2G - 5(R + NIR)$	Dehni et al. 2012 [18]
S3	$(G{*}R) / B$	Allbed et al. 2014 [19]
SI-T	$100(R - NIR)$	Wang et al. 2017 [16]
SI	$\sqrt{BR}$	Allbed et al. 2014 [19]
S6	$(NIR{*}R) / G$	Allbed et al. 2014 [19]
WI	$0{,}151R + 0{,}197G + 0{,}328B + 0{,}341NIR - 0{,}711SWIR1 - 0{,}457SWIR2$	Crist. 1985 [20]
GVI	$-0{,}285B - 0{,}244G - 0{,}544R + 0{,}724NIR + 0{,}084SWIR1 - 0{,}180SWIR2$	Crist. 1985 [20]
WSI	$\sqrt{(1 - WI)^2 + SI^2}$	Li et al.2015 [21]
NWI	$\sqrt{(MSAWI - 1)^2 + (WI - 1)^2}$	Li et al. 2015 [21]
NSI	$\sqrt{(MSAWI - 1)^2 + SI^2}$	Li et al. 2015 [21]
α_{Vis}	$0{,}44B + 0{,}170G + 0{,}240R$	Liang et al. 2023 [22]

Result and analysis. *Map of soil species distribution in the study area based on field measurements.* To train the predictive model 200 control points were selected based on historical data, field measurements and various soil types in the study area (Figure 2). A schematic diagram of soil types and the proportion of the area occupied by the various soil in the study area are shown in Figure 3 and Table 2.

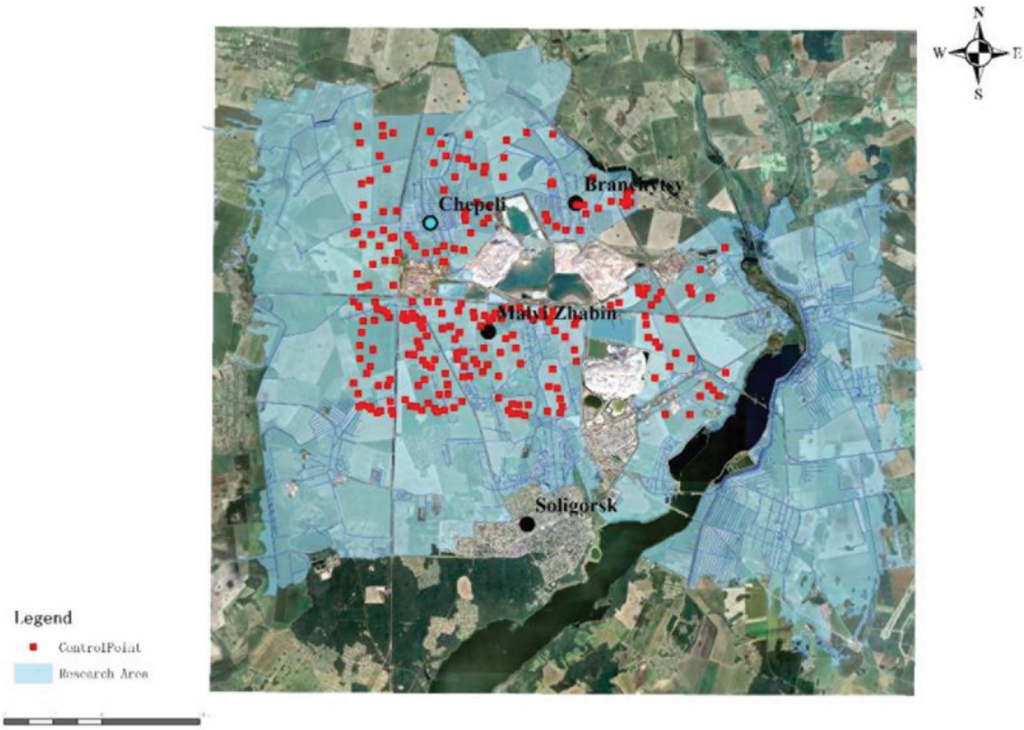


Fig. 2. Accuracy assessment prediction model derived from remote sensing data

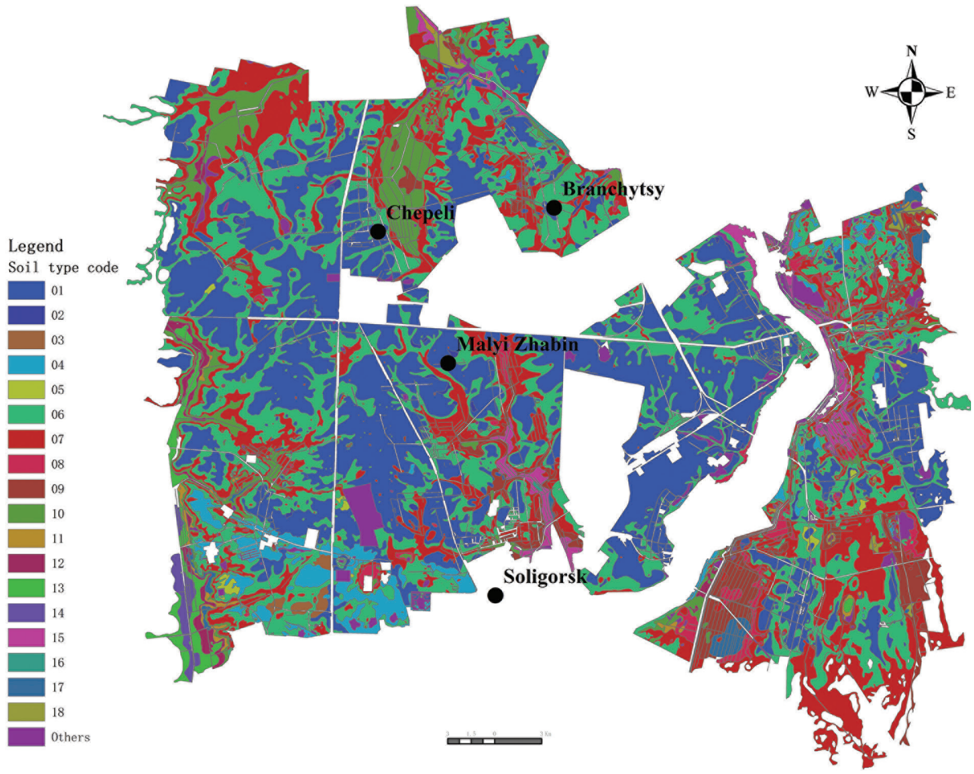


Fig. 3. The soil cover characteristics of the study area

Table 2. **The proportion of the study area occupied by the various soils**

Soil	Hectares	Percentage
01. Soddy-pale-podzolic loamy soils on loess-like light loams, underlain by cohesive rocks from a depth of 0.5–1.0 m	6 154.2	31.9
06. Soddy-podzolic, temporarily excessively moist (slightly gleyic) loamy soils on loess-like light loams	5 645.8	29.3
07. Soddy-podzolic gleyic loamy soils on loess-like light loams, underlain by cohesive rocks from a depth of 0.5– 1.0 m	3 772.9	19.6
10. Sod-gley medium-deep loamy soils on loess-like light loams, underlain by loose rocks with a depth of 0.5– 1.0 m	932.1	4.8
09. Soddy-gley medium-deep loamy soils on loess-like light loams, underlain by loose rocks with a depth of 0.5– 1.0 m	584.9	3.0
04. Soddy-podzolic sandy soils on fluvio-glacial cohesive sands, underlain by loose rocks with a depth of up to 0.5 m.	317.1	1.6
15. Alluvial sod-gley soils on light loamy alluvium, replaceable sandy alluvium	312.0	1.6
08. Sod-podzolic gley loamy soils on loess-like light loams, underlain by loose rocks with a depth of 0.5–1.0 m	281.3	1.5
13. Medium-deep peat soils (peat thickness up to 1.0–2.0 m) on sedge peat, underlain by loose rocks	188.5	0.9
12. Peat thin soils (peat thickness up to 0.5–1.0 m) on sedge-reed and reed-sedge peats, underlain by loose rocks	147.9	0.8
02. Soddy-pale-podzolic slightly washed away sandy loam lands on loess-like cohesive sandy loams, underlain by loose rocks with a level of 0.5–1.0 m	130.8	0.7
17. Degropeat peat-mineral residual gleyed moderately mineralized (organic matter 30.1–40 %) soils, underlain by loose rocks	126.6	0.7
14. Thick peat soils (peat thickness more than 2.0 m) on sedge peat underlain by loose rocks	86.3	0.7
11. Peat-gley relief soils (peat thickness up to 0.3–0.5 m) on sedge peats underlain by loose rocks	75.8	0.4
18. Degropeat mineral residual-peaty (mineral residual-peaty) dark gray (organic matter 10.1–20 %) cohesive sandy soils	70.9	0.4
03. Soddy-pale-podzolic contact gleyed susoid soils on forest-sandy cohesive sandy loams, underlain by binder rocks	53.1	0.3
05. Soddy-podzolic gleyed lower sandy areas on fluvio-glacial cohesive sands, underlain by loose rocks with a depth of up to 0.5 m	50.5	0.3
16. Silty - peaty medium-deep soils (peat thickness up to 1.0–2.0 m) on reed peats, underlain by loose rocks	43.7	0.2
Others	315.9	1.6

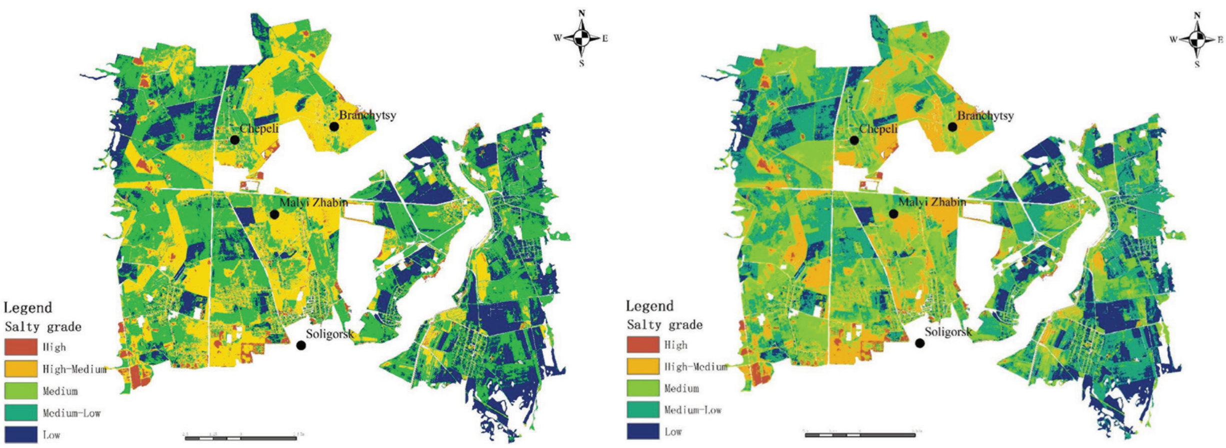
Remote sensing index analysis based on actual control points. In addition, 200 samples were selected from the study area to test the correlation between the above indicators and the ground cover, which were calculated in the RStudio software in order to obtain the following matrix (Figure 4).

P	NSI	NWI	WSI	αVis	GVI	WI	S6	SI	GDVI	SI_T	SI3	ENDVI	VSSI	ARVI	NDVI	RVI	EVI
NSI		0.0000	0.434	0.0811	0.0000	0.4738	0.0000	0.0328	0.0000	0.0000	0.0683	0.4484	0.0000	0.0000	0.0000	0.0000	0.4484
NWI	0.0000		0.0000	0.0063	0.0000	0.0000	0.0000	0.0011	0.0000	0.0000	0.0058	0.7156	0.0000	0.0000	0.0000	0.0000	0.7156
WSI	0.434	0.0000		0.0015	0.0289	0.0000	0.0000	0.0004	0.7143	0.6484	0.0017	0.0086	0.0028	0.4992	0.9954	0.0223	0.0086
αVis	0.0811	0.0063	0.0015		0.0034	0.0069	0.0000	0.0000	0.0000	0.8343	0.0000	0.0032	0.0000	0.0000	0.0000	0.0000	0.0032
GVI	0.0000	0.0000	0.0289	0.0034		0.0364	0.0000	0.0009	0.0000	0.0000	0.0034	0.6749	0.0000	0.0000	0.0000	0.0000	0.6749
WI	0.4738	0.0000	0.0000	0.0069	0.0364		0.0000	0.0020	0.5824	0.6543	0.0076	0.0106	0.0083	0.6225	0.8568	0.0368	0.0106
S6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SI	0.0328	0.0011	0.0004	0.0000	0.0009	0.0020	0.0000		0.0000	0.8573	0.0000	0.0015	0.0000	0.0000	0.0000	0.0000	0.0015
GDVI	0.0000	0.0000	0.7143	0.0000	0.0000	0.5824	0.0000	0.0000		0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0001
SI_T	0.0000	0.0000	0.6484	0.8343	0.0000	0.6543	0.0000	0.8573	0.0000		0.8932	0.3162	0.0000	0.0000	0.0000	0.0000	0.3162
SI3	0.0683	0.0058	0.0017	0.0000	0.0034	0.0076	0.0000	0.0000	0.0000	0.8932		0.0019	0.0000	0.0000	0.0000	0.0000	0.0019
ENDVI	0.4484	0.7156	0.0086	0.0032	0.6749	0.0106	0.0000	0.0015	0.0001	0.3162	0.0019		0.0002	0.0333	0.0004	0.2647	0.0000
VSSI	0.0000	0.0000	0.0028	0.0000	0.0000	0.0083	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002		0.0000	0.0000	0.0003	0.0002
ARVI	0.0000	0.0000	0.4992	0.0000	0.0000	0.6225	0.0000	0.0000	0.0000	0.0000	0.0000	0.0333	0.0000		0.0000	0.0000	0.0333
NDVI	0.0000	0.0000	0.9954	0.0000	0.0000	0.8568	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000		0.0000	0.0004
RVI	0.0000	0.0000	0.0223	0.0000	0.0000	0.0368	0.0000	0.0000	0.0000	0.0000	0.0000	0.2647	0.0003	0.0000	0.0000		0.2647
EVI	0.4484	0.7156	0.0086	0.0032	0.6749	0.0106	0.0000	0.0015	0.0001	0.3162	0.0019	0.0000	0.0002	0.0333	0.0004	0.2647	

Fig. 4. Spectral indices of study area obtained by the Sentinel 2 satellite

The above-mentioned spectral indices demonstrate a statistically substantiated tendency to correlate with the type of vegetation cover and soil salinity in the area. However, this correlation is not considered significant and is used as an additional test to build the model.

Best estimate model inversion was used to obtain the distribution of soil salinity classes in the spring for two consecutive years (Figure 5). The corresponding proportion of each class of soil salts in the area was tabulated (Table 3).



a *b*

Fig. 5. Distribution map of soil salt content 2018 (*a*) and 2023 (*b*) graph in spring

In the study area, soil salinization is graded, with a central focus on the main reservoirs and a symmetrical distribution towards the periphery. The overall range indicates higher salinity in the west compared to the east.

Analysis of regional changes in the salinity composition of soils shows a decrease in non-saline and highly saline soils and a significant increase in moderately saline soils. Using the formula for calculating soil salinity in the study area, the salinity index was determined to be 17.2347 in 2018 and 12.1527 in 2023. This indicates a general trend towards improvement of soil condition in the study area.

By combining the resulting soil salinity class maps for 2018 and 2023 with images of land cover data, the information presented in the following table can be obtained (Table 4).

Most soil types in the study area have code 27 Soddy-pale-podzolic loamy soils on loess-like light loams, which is more evenly distributed in the study area, where for all soils of this type the average salinity level

Table 3. **Proportion of areas with different soil salinity in 2018 and 2023 according to the model, %**

Year	Non-saline soils	Mildly saline soils	Moderately saline soils	Heavily salinized soils	Saline soil
2018	20.42	32.02	24.611	22.939	0.01
2023	13.52	34.09	33.45	18.91	0.02

Table 4. **Land salinity for different surface cover**

Soil type code	Salinity minimum	Salinity maximum	Average salinity	Standard Deviation
01	1	5	3.39589	0.958251
06	1	5	3.403881	0.971077
07	1	5	3.514184	1.014814
10	1	5	3.099974	0.927744
09	1	5	3.410117	1.058277
04	1	5	2.92498	1.00748
15	1	5	3.360177	0.937621
08	1	5	3.609232	1.003174
13	1	5	2.650213	1.167214
12	1	5	2.93332	1.071109
02	1	5	3.714051	1.038917
17	1	5	3.426266	0.821902
14	1	4	2.380997	0.965918
11	1	5	3.287623	0.926658
18	1	5	3.249312	0.91649
03	1	5	2.740132	0.650477
05	1	5	3.571712	1.026592
16	1	4	2.445605	0.658049

of 3.39 is more close to the general soil salinity of the region as a whole, higher, with a standard deviation of 0.96, which corresponds to the soil being regional. The standard deviation is 0.96, which corresponds to the distribution pattern of this soil type as the main soil of the region. Soil types codes 230, 229, and 82 are predominantly grasslands. The salinity of these soils is basically the same as that of code 27 soils, which also corresponds to the geography conditions of Soligorsk district. The change in standard deviation is mainly reflected in the influence of the moistering on soil salinity.

Discussion of soil salinity changes. It was found that the green, red and near-infrared bands had the highest light reflectance, which correlated with soil salinity, which was basically consistent with the results of related studies.

In order to minimize the influence of vegetation on soil salinity acquisition, this study first selected springs with low vegetation cover, and secondly representative areas with relatively uniform vegetation cover were selected as the sampling area to account for factors by remote sensing methods.

In general, soil salinity in the study area is generally moderate – slightly saline and moderately saline soils predominate. The spatial distribution is influenced by the main wastewater ponds of potash mines with high mineralization of groundwater, which leads to severe salinization, and the eastern part is influenced by fresh-water flow, which mitigates soil salinization to a certain extent. The overall level of salinity in the study area has not changed significantly, but the overall dynamics show a softening trend.

In addition, based on the IDW method, the main salinity centers of the forecasting area were mapped using the soil salinity inversion model of the soil cover type.

Combined with the research results of this paper, the application of saline and alkaline land reclamation in the study area should be based on different salinity characteristics and their modification rules, and suitable soil improvement measures should be selected according to local conditions.

Conclusion. In the represented paper, an index of soil salinity content was constructed by taking into account soil types and multi-temporal and spatial remote sensing data in the northern part of the Soligorsk potash field as the study area. The soil salinity dynamics in the study area was statistically analyzed by using an inversion model of soil salinity. The following conclusions were drawn:

The sensitive bands of soil salinity are green light B3, red light B4, and near-infrared band B8, remote sensing indices constructed on the basis of the above bands are more helpful in detecting soil salinity. Based on this stripe, a soil model can be built to detect the soil in an area with domination of soddy-podzolic soils.

During the period of 2018-2023 the degree of soil salinity in the study area shows a slightly mitigating trend, and the degree of soil salinity change is not high.

Based on the main potassium fertilizer mining area north of Soligorsk this study proposes an effective method for remote sensing inversion and monitoring the soil salinity dynamics, which provides a better understanding of the features and patterns of soil salinity dynamics in the study area. It provides the scientific tools and framework for management of saline land resources caused by potash mining.

References

1. *Sahbeni G., Ngabireet M., Musyimi P., Székely B.* Challenges and Opportunities in Remote Sensing for Soil Salinization Mapping and Monitoring: A Review. Remote Sensing, 2023, vol. 15, iss.10, pp. 25–40.

2. *Allbed A., Kumar L., Aldakheel Y. Y.* Assessing soil salinity using soil salinity and vegetation indices derived from IKONOS high-spatial resolution imageries: Applications in a date palm dominated region. Geoderma, 2014, 230–231, pp. 1–8.

3. *Bouaziz M., Matschullat J., Gloaguen R.* Improved remote sensing detection of soil salinity from a semi-arid climate in Northeast Brazil. Comptes Rendus Geoscience, 2011, 343:795–803.

4. *Csillag F., Pásztor L., Biehl L. L.* Spectral band selection for the characterization of salinity status of soils. Remote Sensing of Environment, 1993, vol. 43, iss. 3, pp. 231–242.

5. *Shang R., Zhu Z.* Harmonizing Landsat 8 and Sentinel-2: A time-series-based reflectance adjustment approach. Remote Sensing of Environment, 2019, vol. 235. P. 111439.

6. *Wang Z., Zhang F., Zhang X., Chan N. W., Kung H., Zhou X., Wang Y.* Quantitative Evaluation of Spatial and Temporal Variation of Soil Salinization Risk Using GIS-Based Geostatistical Method. Remote Sensing, 2020, vol. 12, iss. 15. P. 2405.

7. *Zhang Z., Niu B., Li X., Kang X., Hu Z.* Estimation and Dynamic Analysis of Soil Salinity Based on UAV and Sentinel-2A Multispectral Imagery in the Coastal Area, China. Land, 2022, vol. 11, iss. 12. P. 2307.

8. *Ali A., Martelli R., Lupia F., Barbanti L.* Assessing Multiple Years' Spatial Variability of Crop Yields Using Satellite Vegetation Indices. Remote Sensing, 2019, vol. 11, iss. 20. P. 2384.

9. *Zhang J., Zhang Z., Chen J., Chen H., Jin J., Han J., Wang X., Song Z ., Wei G.* Estimating soil salinity with different fractional vegetation cover using remote sensing. Land Degradation & Development, 2021, vol. 32, iss. 2, pp. 597–612.

10. *Guo S., Xia Y., Wan H., Shang S.* Characterizing the spatiotemporal evolution of soil salinization in Hetao Irrigation District (China) using a remote sensing approach. International Journal of Remote Sensing, 2018, vol. 39, no. 20, pp. 6805–6825.

11. *Xu H., Chen Ch., Zheng H., Luo G., Yang L., Wang W., Wu Sh., Ding J.* AGA-SVR-based selection of feature subsets and optimization of parameter in regional soil salinization monitoring. International Journal of Remote Sensing, 2020, vol. 41, no. 12, pp. 4470–4495.

12. *Khairulina E. A., Khomich V. S., Liskova M. Yu.* Geoecological problems of developing potassium salt deposits. News of Tula University. Geosciences, 2018, vol. 2, pp. 112–126 (in Russian).

13. *Chervan A. M., Ustinova A. M., Tsyrybko V. B.* Spatiotemporal Changes of Soil Salinization in the Soligorsk Mining Region. Eurasian Soil Science, 2019, vol. 52, no. 8, pp. 998–1006.

14. *Celleri C., Zapperi G., González Trilla G., Pratolongo P.* Assessing the capability of broadband indices derived from Landsat 8 Operational Land Imager to monitor above ground biomass and salinity in semiarid saline environments of the Bahía Blanca Estuary, Argentina. International Journal of Remote Sensing, 2019, vol. 40, no. 12, pp. 4817–4838.

15. *Peng J., Biswas A., Jiang Q., Zhao R., Hu J., Hu B., Shi Z.* Estimating soil salinity from remote sensing and terrain data in southern Xinjiang Province, China. Geoderma, 2019. vol. 337, pp. 1309–1319.

16. *Wang, F., Ding J., Wei Y., Zhou Q.-qian, Xiaodong Y., Wang Q.-feng.* Sensitivity Analysis of Soil Salinity and Vegetation Indices to Detect Soil Salinity Variation by Using Landsat Series Images: Applications in Different Oases in Xinjiang, China. Acta Ecologica Sinica, 2017, vol. 37, no. 15, pp. 5007–5022 (in Chinese).

17. *Guo B., Yang F., Fan Y., Han B., Chen Sh., Yang W.* Dynamic monitoring of soil salinization in Yellow River Delta utilizing MSAVI–SI feature space models with Landsat images. Environmental Earth Sciences, 2019, vol. 78, no. 10. P. 308.

18. *Dehni A., Lounis M.* Remote Sensing Techniques for Salt Affected Soil Mapping: Application to the Oran Region of Algeria. Procedia Engineering, 2012, vol. 33, pp.188–198.

19. *Allbed A., Kumar L., Sinha P.* Mapping and Modelling Spatial Variation in Soil Salinity in the Al Hassa Oasis Based on Remote Sensing Indicators and Regression Techniques. Remote Sensing, 2014, vol. 6, no. 2, pp. 1137–1157.

20. *Crist E. P.* A TM Tasseled Cap equivalent transformation for reflectance factor data. Remote Sensing of Environment, 1985, vol. 17, no. 3, pp. 301–306.

21. *Li Y., Ding J., Sun Y.* Remote Sensing Monitoring Models of Soil Salinization Based on the Three Dimensional Feature Space of MSAVI-WI-SI. Research of Soil and Water Conservation, 2015, vol. 22, no. 4, pp. 117–121 (in Chinese).

22. *Liang S.* Narrowband to broadband conversions of land surface albedo I. Remote Sensing of Environment, 2001, vol. 76, no. 2, pp. 213–238.

Received 16.01.2024