Satellite data spectral analysis under critical hydrogeological-amelioratory conditions of Golodnostepsky irrigation lands

Z.A. Onglassynov[*], *L.V.* Shagarova, *M.M.* Muratova

Satbayev University, Ahmedsafin Institute of Hydrogeology and Environmental Geoscience, 050010, Almaty, Kazakhstan

Abstract. The article presents the analysis of widespread spectral indexes of the results of the Earth remote sensing data thematic processing to reveal the most representative one for applying under conditions of critical increase of groundwater level and salinity as well as salinized soil. Long-term monitoring data and multispectral images of the LandSat-8 satellite were collected for the Golodnostepsky irrigation land. Sites with the most disturbing ameliorative conditions were identified using GIS. 74 sites comply with this criterion where cotton, rice, and cucurbits crops are cultivated. Seasonal multispectral data of the region covering emphasised sites and spectral indexes were processed and calculated: NDVI, SAVI, MSAVI-2, GEMI, ARVI, IPVI, MTVI, TDVI, NDWI, MNDWI, NDSI. The following results turned out to be the most informative vegetation indexes: NDVI (yearly changes variation range 0.40) and SAVI (yearly changes variation range 0.44). At the same time the least informative vegetation indexes became IPVI (yearly changes variation range 0.19) and GEMI (yearly changes variation range 0.11). It was shown that vegetation indexes data are highly correlated with the amount of precipitation, an average air temperature and crop yield. Among water indexes, NDWI (yearly changes variation range 0.32) turned out to be more preferable than MNDWI (yearly changes variation range 0.15). The information value of the index of salinity NDSI for the sample turned out to be low (yearly changes variation range 0.17), which can be explained by agricultural and ameliorative activity at the site under research (ploughing, sprouting, vegetation, saline washing, etc.)

1 Introduction

One of the most pressing problems in the Republic of Kazakhstan's agro-industrial sector today is the increase in productivity and competitive ability of agricultural products including cotton. A major part of lands in the south of Turkestan oblast (Kazakhstan) where cotton is cultivated comprises mainly light grey soils [1].

The country's President in his Address to the people of Kazakhstan on September 2, 2019, talked about the necessity of a staged increase of the area of irrigated land up to 3 mln hectares

[*] Corresponding author: zhuldyzbek.onlasynov@mail.ru

by 2030. This will ensure 4.5 times the growth of agricultural produce volume. The process of the country's Chief Address is implementable accompanied by quality monitoring and evaluation of the ameliorative status of the irrigated lands. In addition, Clause 15 of the Law of the Republic of Kazakhstan on agro-industrial complex and rural territories development government regulation # 66 dated July 8, 2005 (as amended and supplemented on 24.11.2021) says that information-marketing support to the agro-industrial complex is provided by a provision of agrometeorological and satellite monitoring data.

Up-to-date space technology makes an important contribution to the development of the Republic of Kazakhstan agroindustrial complex. For Kazakhstan with its horizonless scope, special topicality is represented by the use of the Earth remote sensing data to monitor land of agricultural designation [2].

Administratively, Golodnostepsky irrigation land is situated in the southern part of the Turkestan region (Kazakhstan) and covers 2 administrative districts (Zhetysai, Maktaaral) (figure 1).

In Golodnostepsky irrigation land cotton is watered 1 - 2 times within the vegetation period. This is caused by an irrigation water deficit. Besides, during the irrigation period, 250-600 mln m3 of groundwater is discharged beyond irrigation networks by collectors. Collector and drainage water pollute water-and-land resources of downstream irrigated land [3].

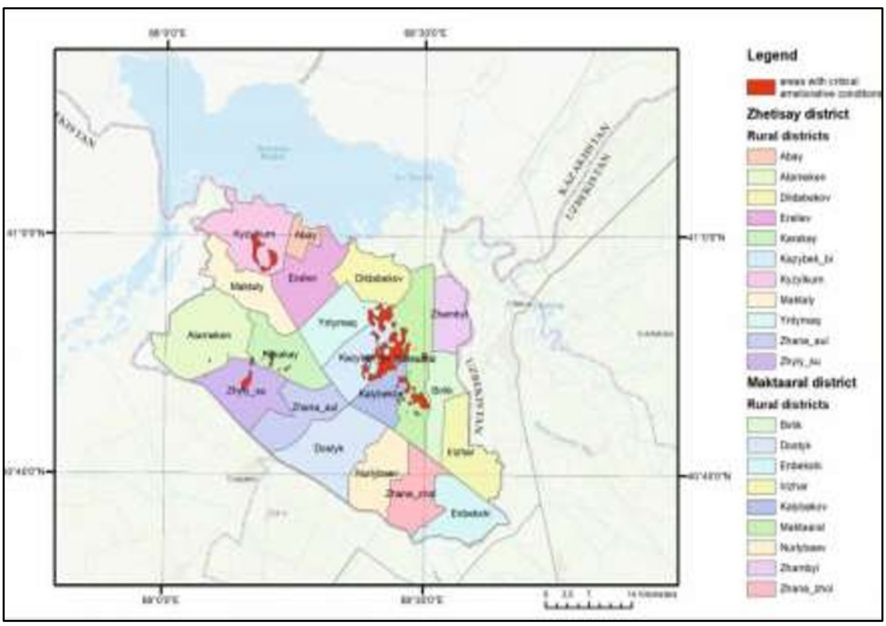

Fig. 1. Schematic map of Golodnostepsky irrigation lands location Caption of the.

Considerable areas of Golodnostepsky irrigation land and irrigated fields are exposed to salinization. Soil salinization in its turn adversely impacts crop yield.
A network of vertical drainage wells was created in the irrigation land territory as a preventive measure against soil salinization and irrigated sites submersion. According to data of monitoring works carried out by State Entity "South-Kazakhstan hydrogeological-meliorative expedition" of RK Ministry of Agriculture, in 2021, the area of irrigated fields of Zhetysai and Maktaaral districts within limits of Golodnostepsky irrigation land was 146,500 hectares (Zhetysai district – 83,281 hectares, Maktaaral district – 63,211 hectares). Sites with groundwater levels above 2 metres (above critical) in the Zhetysai district occupy 41% (37,660 hectares) and in the Maktaaral district 66% (41,690 hectares). Sites with

groundwater salinization above 3 g/l (above critical) in Zhetysai district occupy 36% (30,673 hectares), in Maktaaral district 26% (16,446 hectares). Sites with cumulative salt content above 1.5% (salinized) in the soil in Zhetysai district occupy 40% (33,536 hectares), in Maktaaral district 34% (21,331 hectares).

Figure 2 shows fluctuation dynamics of groundwater levels in the range of 2 m above/below the surface in the areas of irrigated lands for the period from 2013 to 2021. According to the graph, the area of lands with a high groundwater level (above 2 m) tends to increase, which may indicate a low efficiency of the collector-drainage network, including vertical drainage wells.

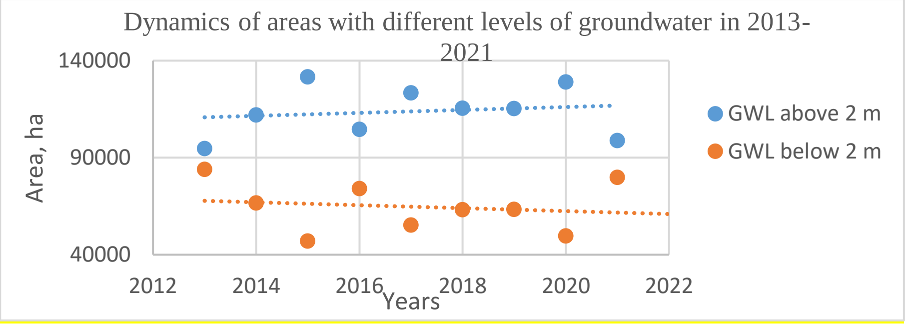

Fig. 2. Dynamics of areas with different levels of groundwater in 2013-2021.

To analyse crop yield and as a preventive measure against soil salinization impact, irrigated lands ameliorative status monitoring with the use of the Earth remote sensing data (ERS) and geoinformation technologies have enormous potential.

ERS data are widely used in hydrogeological-ameliorative and geological-hydrogeological studies. Organisation of work aimed at the Earth surface studies based on a combination of remote methods with ground observations at key sites allows for an increase of studies' information value [4]. Many aspects of hydrology and hydrogeology can be displayed in ERS including geological, soil, or geomorphological units, drainage structure, slopes, vegetation, water bodies, lineaments, geological structures, man-made facilities, reservoirs and villages [5].

The research objective is to reveal the most representative profiles of index images to use GIS-analysis under conditions of groundwater level critical increase and salinity, as well as salinized soil. For quality implementation and maintaining irrigated farming satellite monitoring, it is important to take into account global experience that shows intense development of scientific and remote methods in this area [6-21].

2 Materials and Methods

To deeply analyse the current ameliorative status, data from reports on monitoring works carried out by the State Entity “South-Kazakhstan hydrogeological-meliorative expedition" of the Ministry of Agriculture of the Republic of Kazakhstan were collected. Maps of groundwater level occurrence and salinity for vegetation periods 2013 - 2021 were digitised with the help of GIS systems. Relevant maps of soil salinization of Golodnostepsky irrigation land for 2016 and 2021 were digitised. While comparing all generated digital maps from 2013 to 2021, revealed were sites with critical ameliorative conditions, that is increased level and salinity of groundwater, and also with salinized soil. These sites with an area of 5,081 hectares are situated within borders of rural districts Kazybek bi, Maktaaral, Kalybekov, Kyzylkum, Zhyly-su, Karakai, Yntymak, schematic map of their location is given in figure 3.

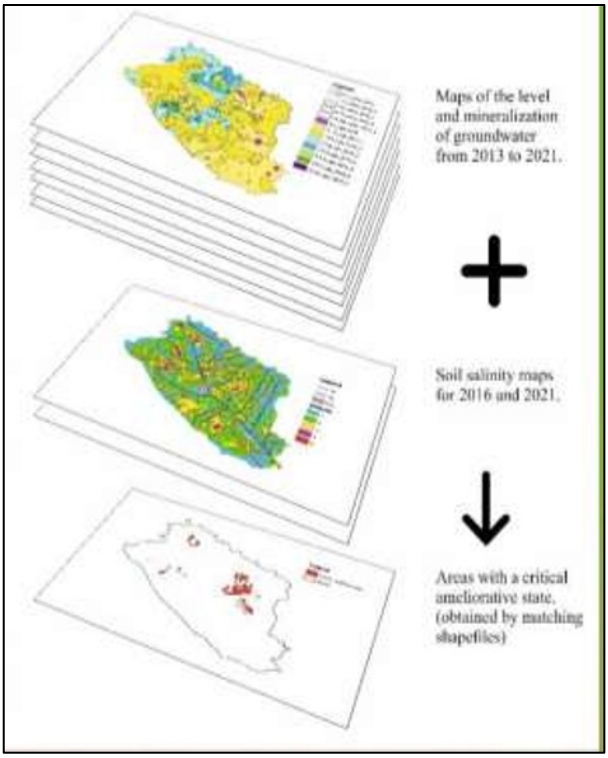

Fig. 3. Methodology for determining areas with a critical ameliorative condition.

Thematic processing of archived cloudless images with a medium spatial resolution (30 m per pixel) for vegetation periods from 2013 to 2021 was carried out for the territory under research to calculate spectral indexes and identify seasonal and long-term changes. For selecting Landsat-8 data, it is very important to take into account the correspondence between the survey period and the main stages of the vegetation phenophase for the study area. The world practice shows, that remote sensing data are widely used to study the phenophase of vegetation in cropland investigations [22]. In our case, all available cloudless Landsat-8 images during 2021 were used to highlight the main stages of crop growth. For all selected images, the SAVI vegetation index was calculated for the main grown crops, and a graph of the dynamics of the average SAVI values during 2021 was compiled (Figure 4).

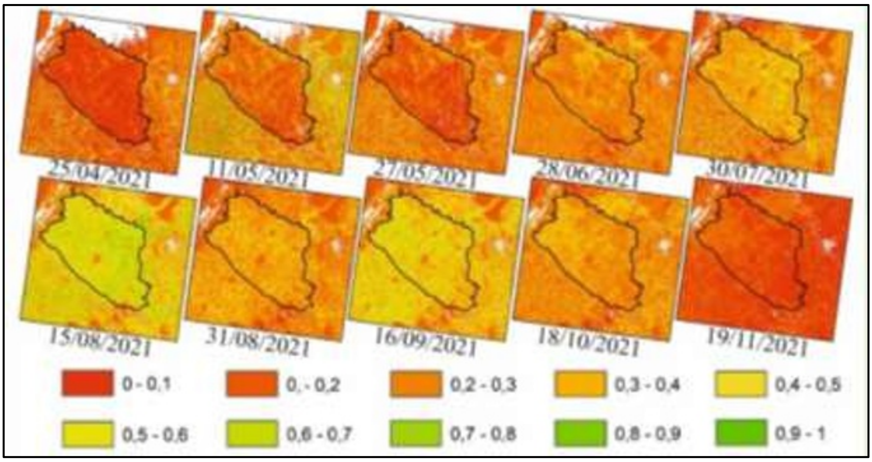

Fig. 4. Dynamics of SAVI in 2021.

According to the SAVI dynamics graph for the period of the year, there are 3 main time zones of vegetation maturation were identified. Landsat-8 archival data from 2013 to 2021 were selected according to the period of plant maturation, 3 images per year. The sampling principle of Landsat-8 data is shown in Figure 5. Licensed software ArcGIS and Geomatica 2016 were used to work with ERS data.

With the purpose of ERS data interpretation and information value increase, base space image spectral transformation was performed. Based on the analysis of irrigated fields spectral profiles on space images with the use of spectral libraries, atmospheric corrections of satellite images were carried out with account to calibration factors from Landsat metadata for OLI radiometer spectral data, design information in azimuth /the Sun zenith as of the moment of satellite taking images.

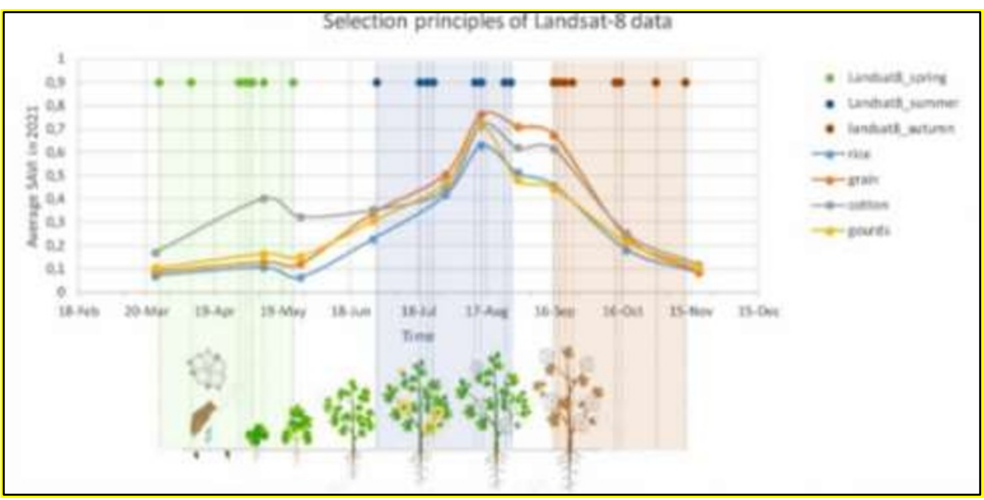

Fig. 5. Selection principles of Landsat-8 data.

The correction was made by the following formulae 1,2:

$$\rho\lambda = \frac{\rho\lambda'}{coscos\,(\theta SZ)} = \frac{\rho\lambda'}{sinsin\,(\theta SE)} \quad (1)$$

$$\rho\lambda' = M\rho * Qcal + A\rho \quad (2)$$

where: $\rho\lambda$ = TOA planetary reflectance;
θSE = Local sun elevation angle; the scene centre sun elevation angle in degrees is provided in the metadata;
θSZ = Local solar zenith angle; $\theta SZ = 90° - \theta SE$;
$\rho\lambda'$ = TOA Planetary Spectral Reflectance, without correction for solar angle;
$M\rho$ = Reflectance multiplicative scaling factor for the band;
$A\rho$ = Reflectance additive scaling factor for the band;
$Qcal$ = Level 1 pixel value in DN.

To distinguish limits of irrigated fields with different cultivated crops based on LandSat-8 satellite processed data, a spectral analysis of the image with the identifier LC08_L1TP_154032_20210815_20210826_01_T1 was carried out. (figure 6; table 1) Based on the results of this spectral analysis, there were limits (ROI) of the following crops: cotton, rice, cucurbits, forage, vineyards, and unused fields. These field limits were digitised with the relevant attributive data and a geodatabase (GDB) was created. GDB included volumetric information of 2,970 irrigated fields in the Golodnostepsky district.

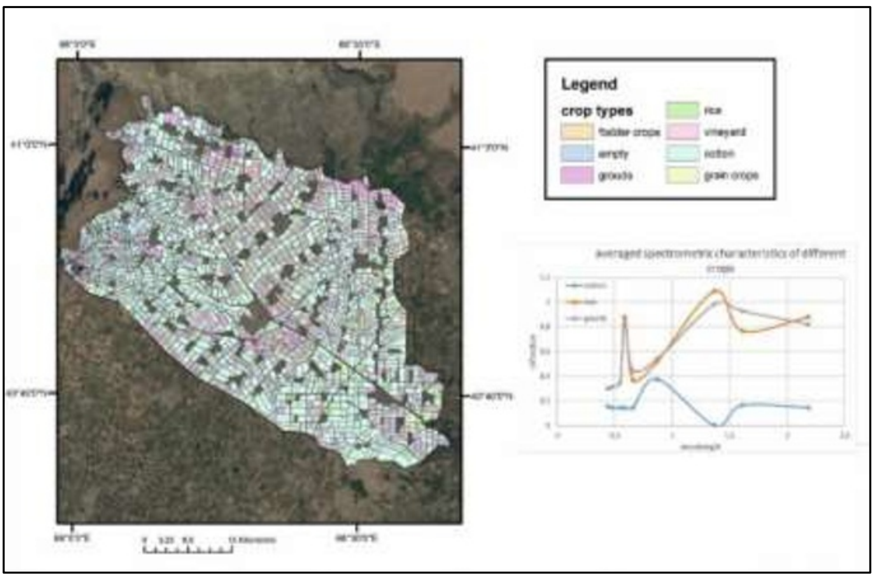

Fig. 6. Spectral characteristics of cultivated crops in Golodnostepsky irrigation lands.

Surface reflectance values matrices resulting from calculations made were used for mathematical analysis — calculation of many indexes.

Table 1. Reflectance values of cultivated crops.

Identifier	Spectral channels	Bands	Wavelength	Cotton	Rice	Grouds
LC08_L1TP_154032_20210815_20210826_01_T1	Coastal / Aerosol, New Deep Blue	b1	0.43-0.45	0.16	0.30	0.30
	Blue	b2	0.45-0.51	0.14	0.31	0.31
	Green	b3	0.53-0.59	0.15	0.35	0.35
	Panchromatic, PAN	b8	0.50-0.68	0.15	0.88	0.82
	Red	b4	0.64-0.67	0.15	0.37	0.44
	Near Infrared, NIR	b5	0.85-0.88	0.38	0.52	0.54
	Cirrus	b9	1.36-1.38	0.00	1.09	0.98

	Short Wavelength Infrared, SWIR-1	b6	1.57-1.65	0.16	0.77	0.93
	Short Wavelength Infrared, SWIR-2	b7	2.11-2.29	0.15	0.88	0.82

Taking into account the global experience of using Earth remote sensing data, and to reveal the most representative indexes under conditions of the Golodnostepsky irrigation land critical ameliorative status, the following widely distributed indexes were selected: NDVI [3, 7,13,16], SAVI [10], MSAVI2 [12,15], GEMI [11,14], ARVI [23], IPVI [8], MTVI [24], TDVI [6], NDWI [9,25], MNDWI [21], NDSI [26]. These indexes are calculated based on all the selected satellite images

Then numerical values (min, max, mean) of indexes for each individual irrigated field (figure 7) were obtained with the help of the Zonal Statistics as Table function. After that, out of 2,970 fields selected were 74 located in the area of sites with critical ameliorative conditions. Within the borders of these sites, cotton, rice, and cucurbits crops are cultivated in irrigated fields.

At the next stage, 74 selected fields were subdivided by three cultivated crops, and for each of them, spectral indexes change dynamics charts were generated by seasons from 2013 to 2021. Indexes' numerical data were correlated with weather data and crop yield. Weather data were obtained from ameliorative reports, and crop yield data were taken from the Agency for Strategic planning and reforms of the Republic of Kazakhstan Bureau of National statistics.

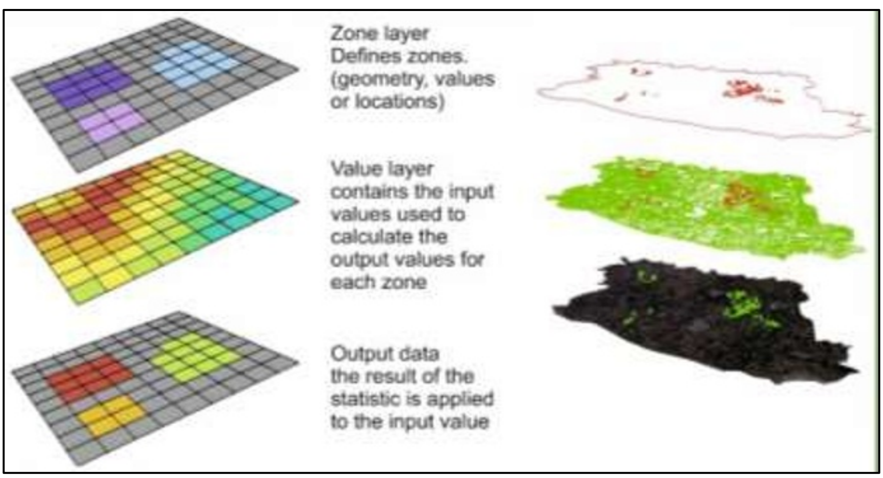

Fig. 7. Methodology of spectral indexes numerical data retrieval from a bit-mapped source with Zonal statistics as table tool.

3 Results and Discussion

As the result of spectral analysis, spectrometric characteristics curves were obtained for different cultivated crops grown on sites with a critical ameliorative condition.

Spectral curves for LandSat-8 data for 15.08.2021 show that notable difference in the reflectance of cotton, rice and cucurbits crops us noted within wavelengths range: 0.50-0.68 (cotton – 0.15; rice – 0.88; cucurbits – 0.82); 1.36 – 1.38 (cotton – 0.00; rice – 1.09; cucurbits – 0.98); 1.57-1.65 (cotton – 0.16; rice – 0.77; cucurbits – 0.93); 2.11-2.29 (cotton – 0.15; rice – 0.88; cucurbits – 0.82) (figure 8).

The following indexes turned out to be the most informative vegetation ones: NDVI (yearly changes variation range 0.40) and SAVI (yearly changes variation range 0.44). Figure

9 represents the correlation of SAVI and NDVI average values for the summer season images with the official statistics data on cotton yields in the Turkestan region. The correlation coefficient R2 does not exceed 0.2, but official statistics are given for the entire region, and not for the study area. The correlation coefficient R2 between SAVI and NDVI is equal to 0.8 (figure10). The following turned out to be the least informative vegetation indexes IPVI (yearly changes variation range 0.19) and GEMI (yearly changes variation range 0.11). It was shown that the vegetation indexes data are highly correlated with the amount of precipitation, the average air temperature, and the crop yield (figure 11).

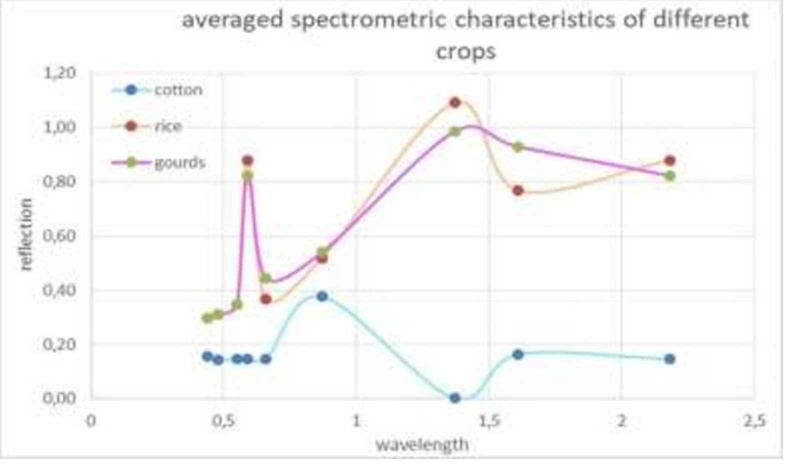

Fig. 8. Spectral characteristics of the cultivated crops.

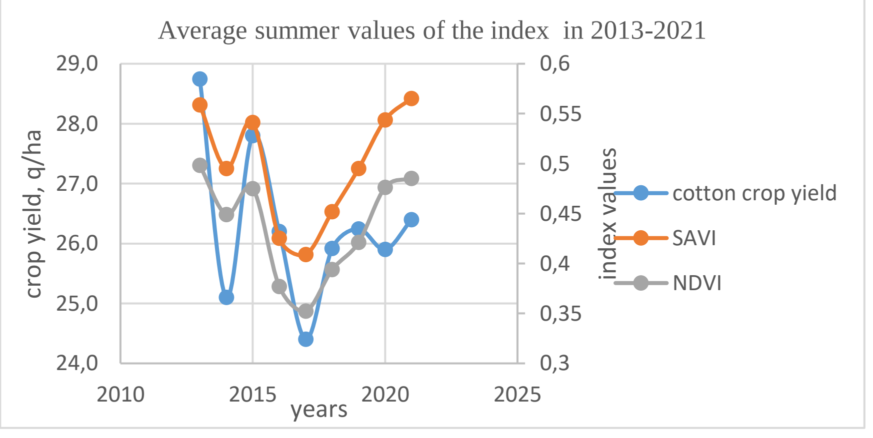

Fig. 9. Average summer values of the SAVI and NDVI in 2013-2021.

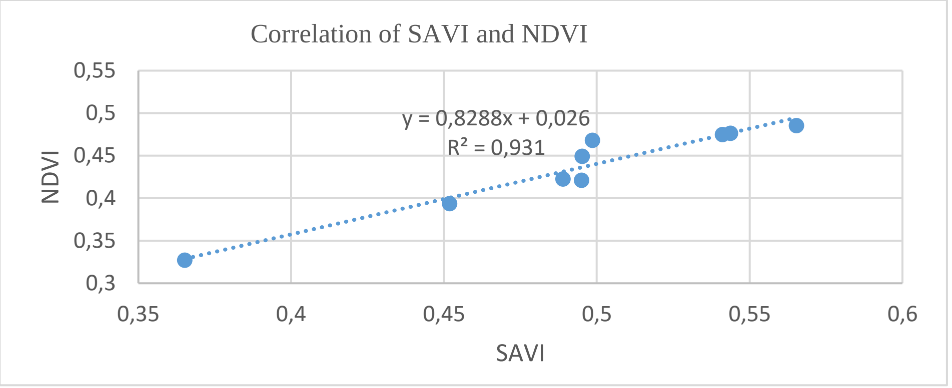

Fig. 10. Correlation of SAVI and NDVI.

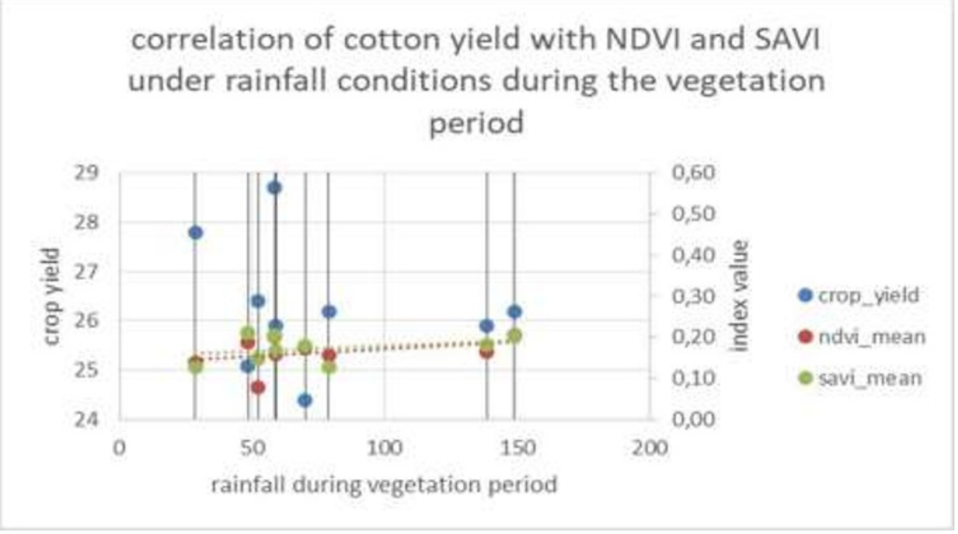

Fig. 11. Charts of vegetation indexes correlation with crop yield, under different precipitation conditions.

Among water indexes, NDWI (yearly changes variation range 0.32) turned out to be more preferable than MNDWI (yearly changes variation range 0.15). The information value of the salinity index NDSI for the sample turned out to be low (yearly changes variation range 0.17), which can be explained by agricultural and ameliorative activity at the site under research (ploughing, sprouting, vegetation, saline washing, etc.). Also, NDSI does not correlate with the soil salinization map generated based on ground and laboratory studies (figure 12). Spectral index dynamics trend is shown in figure 13.

Obtained spectral curves for various crops show that the spectral analysis can be applied while classifying irrigated lands by cultivated crops.

Figure 14 shows the dynamics of the ameliorative state of the Golodnostepsky irrigated lands. Despite the measures taken to improve the ameliorative state (salt leaching, collector-drainage network, vertical drainage wells), the situation no longer changed a lot. To improve the conditions, it is necessary to involve new technologies to conduct the monitoring of the ameliorative state. The method of deep machine learning in the processing of remote sensing data and correctly calculated water balance using numerical modeling of groundwater can contribute to the optimization of the monitoring network and the network of vertical drainage wells [25,27-30].

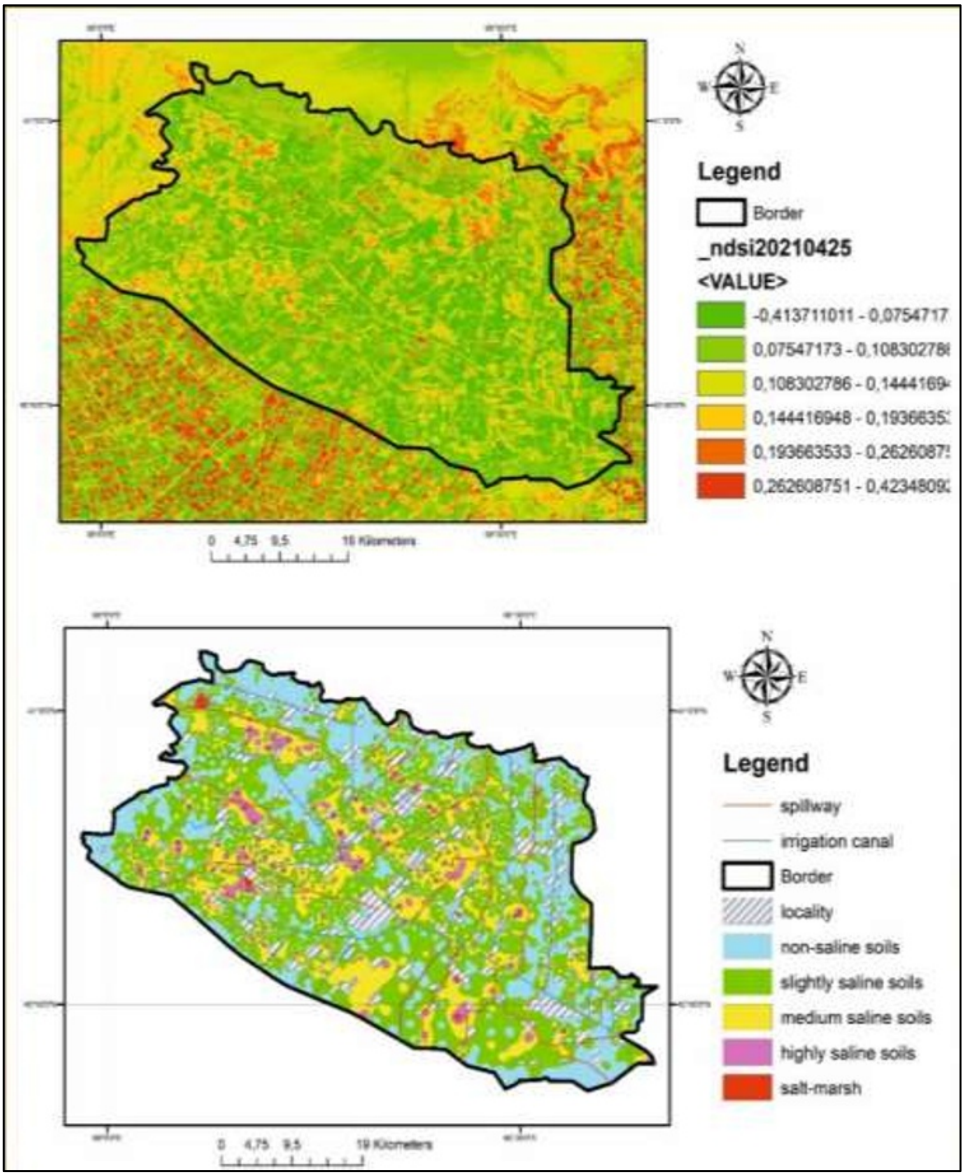

Fig. 12. NDSI in comparison with the soil salinity map of the Golodnostepsky irrigation array.

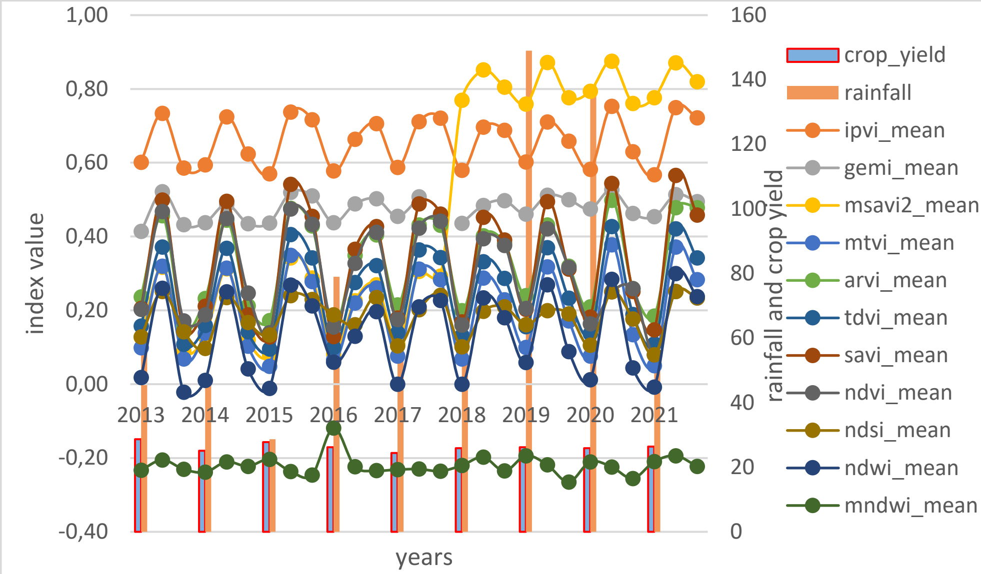

Fig. 13. Chart of spectral indexes dynamics within vegetation periods from 2013 to 2021.

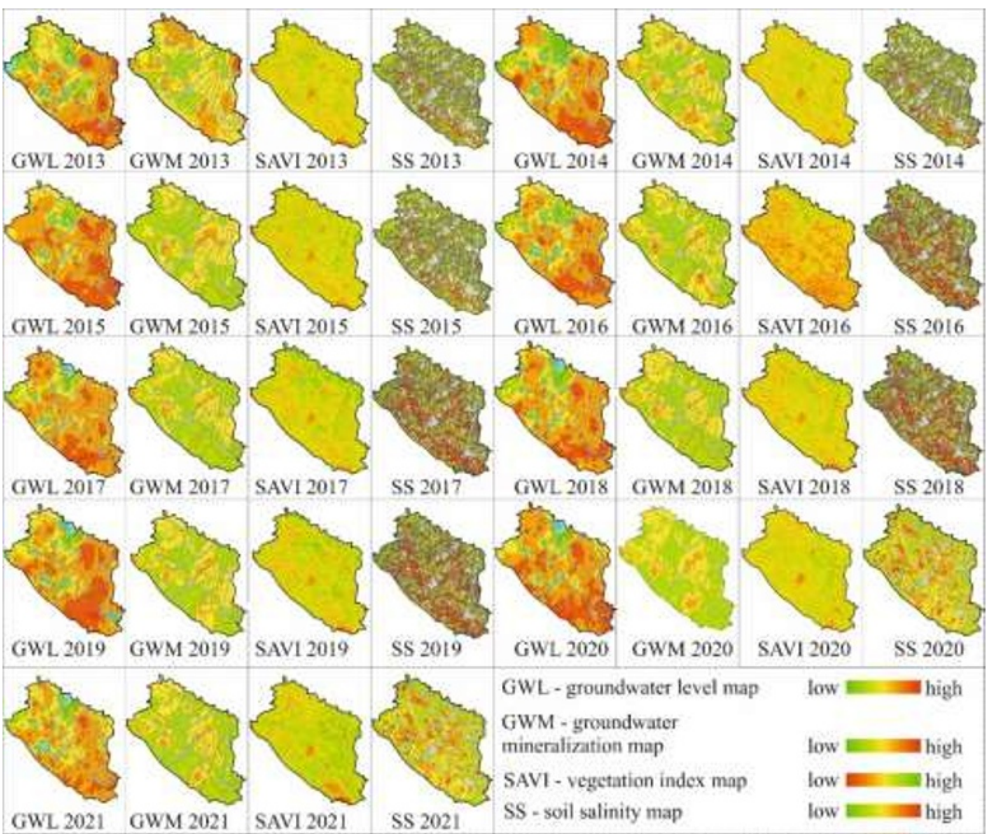

Fig. 14. Dynamics of the ameliorative state of the Golodnostepsky irrigation lands during from 2013-2021.

The authors managed to obtain valuable results thanks to the availability of ground monitoring works. However, ground monitoring works must also be automated with the use of various pressure and water salinity measuring sensors. This may reduce the occurrence of human factors while ground measurements and may have a significant impact on data quality and scientific findings. To improve spectral analysis results, it is also possible to use field spectrometers or UAVs with installed multispectral sensors. In the case of the circumscribed budget of the research, this methodology is well applicable. It is also possible to use other satellite data such as Sentinel-2 with a resolution of up to 10 m per pixel.

4 CONCLUSIONS

Based on the results obtained, the following conclusions can be made.

1.The ameliorative situation in the Golodnostepsky irrigation land is unpromising. Areas with a groundwater increased level can be observed in the central and south-east part, meanwhile, groundwater salinity is increased within central and north-west parts. Vertical drainage wells do not exert a considerable impact on irrigation land ameliorative status.

2. Classification of satellite images of irrigation lands by cultivated crops by spectral analysis is a well-applicable method.

3.Spectral vegetation indexes SAVI and NDVI are more informative than other indexes (MSAVI2, GEMI, ARVI, IPVI, MTVI, TDVI) under critical amelioratory conditions of the Golodnostepsky irrigation land.

4. Water index NDWI is more informative than MNDWI under critical amelioratory conditions of the Golodnostepsky irrigation land.

5. Salinity index NDSI under critical amelioratory conditions of the Golodnostepsky irrigation land is not informative and this can be explained by farming agriculture activities (irrigation, vegetation, ploughing, saline washing, works, etc.).

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