Integrated Approach to Soil Salinity Assessment using SEM in Sirdarya Province, Uzbekistan

Aziz Omonov[1], Tasuku Kato[1], Sayidjakhon Khasanov[2,3,4,*], Atiqotun Fitriyah[1,5], Fadong Li[2,3], Sardorbek Musayev[6], Lukmon Samiev[7], Zukhriddin Ismoilov[1]

[1]Tokyo University of Agriculture and Technology, Tokyo, 183-8538, Japan

[2]Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, 100101, China

[3]University of Chinese Academy of Sciences, Beijing, 101408, China

[4]Research Institute of Environment and Nature Conservation Technologies, Tashkent, 100043, Uzbekistan

[5]Research Center for Limnology and Water Resources, National Research and Innovation Agency (BRIN), Jakarta, 10340, Indonesia

[6]University of Vermont Burlington, VT, USA, 054405

[7]"Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" National Research University, Tashkent, 100000, Uzbekistan

Corresponding author: skhasanov@igsnrr.ac.cn

Abstract

The majority of irrigated land in the Sirdarya area in Uzbekistan is susceptible to salinization. Yet, due to the benefits of its geographical and temporal data, satellite imaging has the ability to efficiently monitor territorial resources. The objectives of this paper are (1) to find how strong surface water mineralization used for irrigation correlated with soil salinity, and (2) to introduce a simplified approach for the soil salinity assessment using SEM based on satellite imagery analysis. The focus of this research is to explore the potential of using SEM methodology for soil salinity assessment in the study area by streamlining spatial image analysis processes. Throughout data collection of 261 surface water samples and 206 soil samples in Sirdaria irrigation district, while satellite images and other official datasets were our secondary material. We used the Inverse Distance Weighting interpolation method in ArcGIS to map soil salinity and statistical packages in R software served as analyst tools to validate our findings. Our findings imply that while MODIS satellite imagery has a lesser connection with EC values, however, the EC values in terms of soil salinization in Sirdarya Province can be predicted using several Landsat bands without using remote sensing indices. We proved that the wavelength ranges of 0.64-0.67 μm and 2.11-2.29 μm are acceptable for mapping soil salinity. Nevertheless, continuous research is needed to understand the mechanisms behind this

relationship and the potential applications of these findings in other drylands, land management, and environmental monitoring.

Keywords

Soil salinity, surface water mineralization, Landsat 8 OLI, MODIS, IDW, SEM

1. Introduction

Soil salinity problems are dominant in irrigated systems in arid and semi-arid regions of the world, with poor drainage of salts posing a threat to crop production systems (Abuelgasim & Ammad, 2019). The - salinity problem has been exacerbated in recent decades by the widespread use of irrigation systems, which has led to salt accumulation in the soil (Corwin, 2021; Mukhopadhyay et al., 2021). As a result, large areas of fertile land have become unproductive, and the countries in (semi-)arid lands have lost significant agricultural productivity (Akramkhanov et al., 2011; Cuevas et al., 2019; Negacz et al. 2022). Soil salinization not only leads to land degradation and reduced crop yields but also represents a significant environmental and economic problem (Zhang et al., 2020).

In Central Asia, the issue of soil salinity is particularly challenging due to the transboundary nature of the two major rivers, the Amu Darya and the Syr Darya, that flow into the Aral Sea and traverse multiple countries (Conrad et al., 2020; Wang et al., 2021). Previous studies have found that approximately 50% of the soil in Central Asia is salinized, with around 29% having moderate salinity (Platonov et al., 2014; Ivushkin et al., 2017; Khasanov et al., 2023; Omonov et al., 2022). Precisely, according to the Food and Agriculture Organization of the United Nations (FAO, 2018), salt-affected soils cover approximately 35 million hectares in Central Asia, which includes Kazakhstan (3,000,000 ha), Kyrgyzstan (1,300,000 ha), Tajikistan (2,000,000 ha), Turkmenistan (12,000,000 ha), and Uzbekistan (16,700,000 ha). This represents about 10% of the total land area in the region. It is important to note that the actual extent of salt-affected soils in Central Asia may be higher than reported, as some areas may not have been fully mapped or assessed. Soil salinity is a major environmental problem in the region, affecting agricultural productivity and posing a threat to food security.

Uzbekistan is predominantly known for cultivating cotton and wheat crops (Khasanov et al., 2022), both of which have shown resilience to soil salinity (Devkota et al., 2022). Moreover, the country is in an arid region, and its soil is naturally salty due to the high evaporation rate and salt deposits (Akça et al., 2020). However, soil salinization remains a significant challenge for cotton farming despite its relatively moist soil during the winter wheat season (Shirokova et al., 2000; R). In Uzbekistan, the majority of irrigated lands are prone to salinization (Khasanov et al., 2023), which is linked to the aridity of the climate and the geological and hydrogeological conditions of the irrigated territories (Kulmatov et al., 2021). The significant reduction in soil fertility and productivity due to salinization is a major factor that affects the yield of crops, ranging from 15 to 80%, depending on the degree of soil salinity (Kamran et al., 2019; Tomaz et al., 2020). In this regard, the Uzbek government has taken steps to address this problem, including the development of new irrigation systems and the implementation of soil-reclamation programs (Ministry of Agriculture, 2022). However, these efforts have had limited success, and the problem of salinity remains a significant challenge for the country.

Traditional methods of measuring soil salinity, such as laboratory analysis of soil samples, are time-consuming and costly (Garajeh et al., 2021). More practical methods and tools are needed to determine and predict soil salinity, especially in areas with salinity issues. Geophysical instruments that measure soil electrical conductivity are often used (Corwin & Scudiero, 2019), but these cannot be implemented frequently and are challenging on a larger scale (Nguyen et al., 2020). Satellite imagery has the potential to effectively monitor territorial resources due to its spatial and temporal data advantages (Measho et al., 2022). Three commonly used remote sensing indices for soil salinity assessment are the Normalized Difference Vegetation Index (NDVI), Soil Salinity Index (SI), and Vegetation Soil Salinity Index (VSSI).

Several studies have utilized NDVI for soil salinity assessment. For instance, Abduljabbar et al. (2020) found a significant correlation between NDVI and soil salinity in a study of an arid region in Iraq. Similarly, Elkeilsh et al. (2019) used NDVI to assess the impact of soil salinity on vegetation cover in the Nile Delta region of Egypt. Rahman et al. (2018) used SI to assess soil salinity in the Sundarbans region of Bangladesh. The study found a strong correlation between SI and soil salinity, indicating that SI can be -useful for soil salinity assessment in coastal regions.

Yu et al. (2018) used VSSI to assess soil salinity in China's Yellow River Delta region. The study found that VSSI was highly correlated with soil salinity, indicating that VSSI can be a useful tool for soil salinity assessment in coastal regions. Similarly, Cui et al. (2023) used VSSI to assess soil salinity in the Hetao Irrigation District of China. The study found that VSSI was a more accurate tool for soil salinity assessment than other commonly used remote sensing indices such as NDVI and Soil Adjusted Vegetation Index (SAVI). In another study, Zhao et al. (2021) used a combination of VSSI and thermal infrared remote sensing data to assess soil salinity in China. The study found that combining VSSI and thermal infrared data improved the accuracy of soil salinity assessment, indicating that VSSI can be combined with other remote sensing tools for more comprehensive soil salinity assessment. In the previous study, Omonov et al. (2022) also compared several indices for salinity monitoring in Syrdarya Province and found that VSSI has the highest accuracy though it is lower than 50%.

Researchers to analyze complex relationships between variables in soil salinity assessment have used structural Equation Modeling (SEM). For instance, Zhou et al. (2020) used SEM to investigate the impact of soil salinity on vegetation cover and the mediating effects of precipitation and temperature. Peng et al. (2021) found that RS and SEM could accurately evaluate soil salinity, with irrigation practices, groundwater depth, and soil organic matter content being significant factors. Li et al. (2021) developed an integrated approach using RS and SEM to assess soil salinity and identified groundwater depth, temperature, and precipitation as important factors, while vegetation cover can be used as an indicator. In another study, Wei et al. (2019) used RS and SEM to assess soil salinity in the Yellow River Delta. They identified key factors affecting soil salinity and developed a model to predict it based on Landsat 8 OLI and field data. The authors highlighted the importance of groundwater depth, soil organic matter content, and vegetation cover as factors affecting soil salinity. These studies demonstrated the potential of using RS and SEM for soil salinity assessment in coastal wetlands.Up-to-t-date and validated methods and tools are required to determine and predict soil salinity in areas with salinity problems to further accelerate nationwide decision-making procedures (Hoa et al., 2019; Hu et al., 2019; Jamali et al., 2020). Major benefactors such as the Ministry of Agriculture of Uzbekistan and local subsidiaries involved in land use planning and irrigation water distribution should work towards this common goal. Considering all the positive aspects and advances of using RS and SEM, the main scientific concern here is to estimate the possibility of straightforward and novel methodology introduction to soil salinity assessment by facilitating the processes of spatial image analysis. In this study, SEM is expected to provide valuable insights into the direct and indirect relationships between the bands of satellite images with soil salinity (EC).Therefore, the objectives of this paper are (1) to find how strong surface water mineralization used for irrigation correlated with soil salinity, and (2) to introduce a simplified approach for the soil salinity assessment using SEM based on satellite imagery analysis, considering digital number of the remotely sensed objects and spectral scale. The validation procedures were designed according to the ground truth data, derived from Sirdarya province of Uzbekistan.

2. Materials and methods

2.1 Study area

Sirdarya province (Figure 1) was selected as a potential study area due to its significant and strategically prioritized role in the agricultural sector of the Uzbek economy, and its aridic geo-location. This province contributes almost 25% to the nationwide cotton production, as well as experiencing roughly 32% of yield losses due to soil salinization since 1991 (Khamidov et al., 2022).

Soil salinity here mainly emanates from human-induced factors such as changes in cotton areas across the province, surface and ground water mineralization, high groundwater table, and the low efficiency of irrigation and drainage systems (Kulmatov et al., 2021b).

Figure 1. Map of Sirdarya province, Uzbekistan

Sirdarya province is a notable example of how the mismanagement of water resources and inadequate irrigation and drainage systems can lead to soil salinization. The province's reliance on irrigation for agriculture has resulted in the accumulation of salt in the soil, rendering it unsuitable for majority types of agricultural crop growth. As a result, crop yields have been significantly reduced, leading to provincial economic hardship for farmers and exacerbating food insecurity. Scientific investigations and practical efforts to address the issue of soil salinity in this province have included the implementation of irrigation and drainage system upgrades, the use of salt-tolerant crops, and the promotion of more sustainable farming practices (Shirokova et al., 2000; Shirokova et al., 2022). Yet, many unrevealed aspects of dealing with soil salinization issues remains to be undertaken to mitigate the impacts of salinization and rehabilitate the soil and agricultural productivity in such vulnerable areas.

Despite repeated criticism of wasteful irrigation practices, a negligible progress has been made in reversing the trend in provincial soil degradation (Eswar et al., 2021). Detailed reviews of environmental problems and recommendations for overcoming these problems not only in Sirdarya province, but also in the entire country, are widely documented in research papers (Gafurova & Juliev, 2021; Juliev et al., 2021).

2.2 Climate and surface water dynamics

According to the Center of Hydrometeorological Service of Uzbekistan (Uzhydromet, 2022), the climate of Sirdarya province is characterized by hot summers and cold winters, with low precipitation throughout the year. The temperature in Sirdarya province can vary greatly between the summers and winter months. During the summer (June to August), temperatures can reach highs of around 40°C (104°F) during the day, with nighttime temperatures dropping to around 20°C. During the winter (December to February), temperatures can drop to as low as -10°C at night, with daytime temperatures averaging around 5°C. The spring (March to May) and autumn (September to November) are transitional periods with mild temperatures. Perennial (2000-2022) average monthly air temperature and average sum of monthly precipitation are shown in Figure 2.

Sirdarya province is located in a region with a desert climate, which means that it receives very little precipitation throughout the year. The average annual rainfall in the province is around 100 mm, most of which falls during the winter months (Uzhydromet, 2022). Summers are typically dry and hot, with occasional thunderstorms bringing brief periods of rainfall. The province is also known for its strong winds, particularly during the spring and summer. The wind in Sirdarya province is typically from the northwest, and can reach speeds up to 30 km/h (Uzhydromet, 2022). Humidity levels in Sirdarya province are generally low, particularly during the summer when the air is dry and hot. However, in the winter humidity levels can increase due to fog and mist (Uzhydromet, 2022).

Figure 2. Climatic observations of Sirdarya province

The Syr Darya River (SDR) is the main source of surface water for irrigation in the province. The river is one of the two main rivers in Central Asia, which originates in the Tian Shan mountains of Kyrgyzstan and flows through Uzbekistan, Kazakhstan, and Turkmenistan before emptying into the Aral Sea.

The river has a high mineral content, with total dissolved solids (TDS) ranging from 250 to 1000 mg/L (Bissenbayeva et al., 2020; Kamilova & Sagdullaeva, 2020). The water is classified as moderately saline, meaning it can be used for irrigation but may require additional measures to prevent soil salinization over time.

In addition to the SDR, several canals and reservoirs are used for irrigation in the province. The mineral content of these water sources can vary depending on their location and source. However, in general, the mineralization levels are similar to that of the SDR. High mineralization levels in irrigation water can have both positive and negative effects on soil and crop growth. On the one hand, the minerals in the water can provide essential nutrients to crops and improve soil fertility. However, excessive mineralization levels can lead to soil salinization, which can negatively affect crop growth and yield. Therefore, to mitigate the negative effects of high mineralization levels, farmers in Sirdarya province may use various techniques, such as leaching, drainage, and crop rotation, to reduce soil salinity. Additionally, they may also use more tolerant crop varieties that are better suited to the region's mineralized water.

2.3 Irrigation network

Sirdarya province heavily relies on the SDR, which flows in the eastern part of the province (Figure 1), for irrigation to support its agricultural production. Despite having lower water requirements compared to other regions, irrigation remains a critical aspect of agricultural activities.. The total water withdrawal for irrigation in Sirdarya province from 2016 to 2020 is presented in Figure 3 (Ministry of Water Resources, 2021)

Figure 3. Total water withdrawal for irrigation in Sirdarya province from 2016 to 2020

According to the International Water Management Institute (2017), the water quality of the SDR in Uzbekistan is generally poor due to high levels of salinity, pollution, and sedimentation. The report notes that agricultural practices, such as irrigation, have contributed to increase salinity in the river, as well as contamination from industrial and domestic wastewater.

The government of Uzbekistan has invested heavily in modernizing and upgrading the irrigation infrastructure in the region. As part of these efforts, the government has introduced new technologies and practices to improve water efficiency, such as drip irrigation, improving water-use efficiency, increasing water storage capacity, and promoting alternative crops that require less water, which can reduce water use by up to 50% (Ministry of Water Resources, 2021). Despite these efforts, however, water scarcity remains a significant challenge in Sirdarya and other provinces of Uzbekistan. The growing demand of water resources for agriculture, industry, and households is putting increasing pressure. .

There are two types of drainage systems used in Sirdarya province: surface drainage and subsurface drainage. Surface drainage involves the use of shallow canals or ditches to remove excess water from the surface of the soil, while subsurface drainage involves the use of perforated pipes or tiles buried beneath the soil to drain excess water from the root zone.

The drainage system in Sirdarya is managed by the state-owned enterprise "Suvokova" which is responsible for maintaining and operating the drainage infrastructure. The organization is also responsible for ensuring that the drainage system is efficient and effective in removing excess water from agricultural land.

However, despite the presence of a drainage system, waterlogging and salinization of the soil remain significant problems in Sirdarya and other parts of Uzbekistan. This is partly due to poor maintenance and inadequate investment in drainage infrastructure..

2.4 Field scale data collection

Field scale data collection was conducted mainly in cotton fields in the end of the last decade of August,2022, when cotton biomass is expect to reache its maximum (Figure 4).

Figure 4. Sampling locations of surface water and soil in Sirdarya province

Surface water samples used irrigation was collected over all of the administrative districts and accounted for 261 points (August 1-7) before performing last irrigation in the pre-harvesting phase of cotton. Sampling locations of surface water used for irrigation were displayed in Figure 4a. Water was analyzed in total dissolved solids (TDS).

Laboratory analysis was conducted on 261 surface water samples to check the mineralization level. Throughout the analysis, we estimated the content of anions, cations and total solids in a sample. Then, we classified surface water mineralization with reference to the total dissolved solids (Table 1)

Table 1. Classification of surface water mineralization due to the total dissolved solids (TDS)

TDS	**Mineralization level**
0-1	No mineralization
1-3	Weak mineralization
3-5	Moderate mineralization
5-10	Severe mineralization
> 10	Extreme mineralization

For the soil samples, we used electrical conductivity (EC) "Eutech ECTestr 11+" (Eutechnist, 2023) to collect soil salinity data across all of the administrative districts of the province. In total, we collected 206 samples on top soil (0-20 cm) on November 4-20 in 2022 at the end of the growing season for cotton (Figure 4b) and before provincial salt leaching practices.

Since we used here EC meter to collect soil salinity data from soil samples, EC meter values were used to categorize soil salinity and assess the degree to which the total dissolvent salts do not negatively affect crop production (Table 2) (Ivushkin et al., 2017).

Table 2. Soil salinity levels in regards to EC meter values

Soil salt content, g/dm^3	**EC values, dS/m**	**Cl^-, mg/dm^3**	**Soil salinity level**
0-3	0-2	> 0.01	No salinity
3-6	2-4	0.01-0.03	Weak salinity
6-12	4-8	0.031-0.07	Moderate salinity
> 12	> 8	> 0.07	Severe salinity

2.5 Satellite data collection

Two satellite images captured by Landsat 8 OLI and Moderate Resolution Imaging Spectroradiometer (MODIS – MOD09) sensors on August 16 and 18 2022, respectively, were used in this study. Several studies (Zhou et al., 2019; Huang et al., 2021 and Nouri et al., 2021) revealed that mid-August is recommended to consider for soil salinity assessment using the remote sensing imagery, since the biomass level of cotton reaches its maximum and provides a good proxy for the spatial analysis of soil salinity.

As one of the objectives of this investigation was to create another approach to assess soil salinity using remotely sensed image digital numbers and spectral scale, we defined all of the images according to the given bands of sensors below in Table 3.

Table 3. Metadata of the employed satellite images

Sensors	**Bands**	**Wavelength**	**Resolution**	**Data type**	**Valid range**	**Source**
Landsat 8 OLI	Band 1 Coastal Aerosol	0.43 - 0.45 µm	30 x 30 m	16-bit unsigned integer	0 – 65535	(USGS, 2022)
	Band 2 Blue	0.450 - 0.51 µm				
	Band 3 Green	0.53 - 0.59 µm				
	Band 4 Red	0.64 - 0.67 µm				
	Band 5 Near-Infrared	0.85 - 0.88 µm				
	Band 6 SWIR 1	1.57 - 1.65 µm				
	Band 7 SWIR 2	2.11 - 2.29 µm				
MODIS – MOD09	Surface Reflectance Band 1 Red	0.62-0.67 µm	500 x 500 m	16-bit signed integer	-100 – 16000	(NASA, 2022)
	Surface Reflectance Band 2 NIR	0.841-0.876 µm				
	Surface Reflectance	0.459-0.479 µm				

	Band 3 Blue					
	Surface Reflectance Band 4 Green	0.545-0.565 µm				
	Surface Reflectance Band 5 NIR	1.23-1.25 µm				
	Surface Reflectance Band 6 SWIR 1	1.628-1.652 µm				
	Surface Reflectance Band 7 SWIR 2	2.105-2.155 µm				

Numerous studies confirmed that each band of satellite images is crucial for soil salinity assessment (Abbas et al., 2013; Mehrjardi et al., 2008; Wang et al., 2020) depending on what type of remote sensing indices is used. Therefore, to detect the patterns, we deemed the mostly used bands (from 1 to 7) of images in vegetation and salinity indices.

2.6 Data analysis

Because field scale data is point data, the data has to be converted to raster map data to compare with RS data.The Inverse Distance Weighting (IDW) interpolation method in the ArcGIS 10.8 program was used to construct surface water mineralization and soil salinity maps for the province of Sirdarya (ESRI, 2020). We decided on this approach because IDW operates a simple mathematical circuitry created by statistical modeling, which represents the data-generating process (Dhamodaran & Lakshmi, 2020; Sobjak et al., 2023). Due to the IDW capacity to fill gaps and account for outliers between surface water sampling and soil sample locations, it has been shown to be reasonably effective in this study. According to several investigations, the IDW approach produced maps of mineralization and salinity with the fewest inaccuracies. The findings of the aforementioned tests and experiments demonstrated that, when sufficient data was uploaded, the IDW interpolation approach produces satisfactory results. Pearson's correlation were carried out using the R studio software to determine the true dependency of soil salinity on surface water mineralization as a viable tool to demonstrate the correlation in statistics to fulfill the first objective of this research.

All of the downloaded satellite images were first and carefully passed through geometric (Afwani et al., 2019), atmospheric (Ilori et al., 2019), and radiometric corrections (Padró et al., 2018). Once errors, noises, and unexpected voids were removed and successfully filled, the next step was to list the digital numbers (DN) for each band. This enabled to visually compare and trace the similar patterns per each band as shown in the IDW-based soil salinity maps. . To analyze the relationship between DN values of each band and soil salinity patterns, we utilized the "lavaan" package for latent variable analysis in the R Studio software (RStudio Team, 2020). We employed structural equation modeling (SEM) to investigate how the bands from satellite images of MODIS and Landsat are directly or indirectly related to soil salinity (EC). Furthermore, supplementary "psych" package of the R studio software was employed using the command of pairs and panels to gain deep insight into the relationship between the DN and EC values of soil salinity. This displays a scatter plot of matrices, with histograms on, bivariate scatter plots below, and the Pearson correlation above the diagonal. For descriptive statistics of moderate datasets, this function showed its potential.

3. Results and discussion

3.1 IDW maps of surface water mineralization and soil salinity

The IDW interpolation method was chosen as it is a commonly used technique to estimate values at unknown locations based on the values at known locations. The in-situ measurements of surface water mineralization and soil salinity were used as the known data points to create the map. The resulting map (Figure 5) depicts the distribution of surface water mineralization and soil salinity across Sirdarya province.

Regarding the surface water mineralization, the central part of the study area, characterized by moderate and severe mineralization with 3-5 g/L and 5-10 g/L respectively, is depicted with warm colors such as red, orange, and yellow on the map, indicating higher levels of mineralization. The northern part of the study area, characterized by weak mineralization with 1-3 g/L, is depicted with cooler colors such as green, indicating lower levels of mineralization. This characteristic is widely distributed across the study area. Finally, the western part of the study area, characterized by extreme mineralization, is depicted with dark red (Figure 5a).

The map presented in Figure 5b illustrates the spatial distribution of soil salinity levels in a study area based on the EC values. The study area comprises of a central region characterized by moderate to severe soil salinity levels, while the northern part exhibits non-saline and weak saline areas that are widely distributed.

These maps are a valuable tool for land managers, farmers, and other stakeholders involved in the management of agricultural land. It can help to identify areas with high soil salinity and mineralization levels, which may require special management practices to improve crop yield and soil health. The map can also be used to assess the effectiveness of land management practices implemented to reduce soil salinity levels in Sirdarya province. Overall, these maps presented provide an informative and comprehensive visualization of the spatial distribution of soil salinity in the study area, enabling stakeholders to make informed decisions regarding the management of agricultural land.

Figure 5. Surface (irrigation) water mineralization (a) and EC-based soil salinity map (b) of the study area, August and November 2022, respectively

3.2 Correlation analysis between surface water mineralization and soil salinity

To investigate the relationship between surface water mineralization and soil salinity, a correlation analysis was performed. The data used in this analysis were collected from 261 (water) and 206 (soil) sampling sites in the study area, and included measurements of surface water mineralization and soil salinity.

The correlation coefficient was calculated using Pearson's correlation analysis in the R studio program. As expected, the results showed a significant positive correlation between surface water mineralization and soil salinity ($R = 0.63$, $p < 0.05$), indicating that higher levels of soil salinity were associated with higher levels of surface water mineralization. To describe more precisely, non-mineralized surface water can reduce the severe salinization when irrigated ($R = -0.72$, $p < 0.05$). On the other hand, severely salinized irrigated land expansion was due to irrigating with extremely mineralized surface water ($R = 0.71$, $p < 0.05$). The output of the correlation analysis is shown in Figure 6.

The results of this correlation analysis suggest that soil salinity may be contributing to the mineralization of surface water in Sirdarya province. At same time, there is not clear tendency between lower SWM and SS. It would be that lower category of soil salinity was realized enforced leaching or fallow management. These were human manipulation results, then, it is not reflected to the relationship.

Further investigation is needed to determine the mechanisms underlying this relationship, and to assess the potential environmental impacts of elevated surface water mineralization levels. Furthermore, the correlation analysis demonstrated a significant positive relationship between surface water mineralization and soil salinity in the study area. These findings may have important implications for water quality management and environmental monitoring efforts in the region.

3.3 Satellite images-based maps of soil salinity

Using the downloaded corresponding MODIS-MOD09 satellite images, we performed a visual comparison with the soil salinity map created based on EC values. What can be seen in general is that MODIS Band 1 and Band 6 data with the EC-based soil salinity map showed an affirmative correlation and noticeably similar pattern between these bands and soil salinity levels, while other bands did not represent the patterns of the EC-based soil salinity map. Particularly, as compared to locations with low soil salinity, areas with weak and moderate soil salinity exhibited greater reflectance values in Band 1 and lower reflectance values in Band 6.

Maps of soil salinity based on MODIS data are presented in Figure 7. The soil salinity map shows red and purple areas that correlate to regions with high EC values ($EC \geq 4$ dS/m) and high soil salinity ($DN < 1100$). The MODIS Band 1 map vividly shows from weak to severe soil salinity zones. These zones, on the other hand, are harder to see in the MODIS Band 6 map, where they show as brighter patches. Our findings imply that regions with high soil salinity may be located using MODIS Band 1 and Band 6 data. This is in line with earlier research that shown a connection between reflectance levels in these bands and soil salinity (Mehrjardi et al., 2008).

Figure 7. MODIS-MOD09 satellite based-soil salinity maps of Sirdarya province within different wavelengths

Furthermore, the comparison of Landsat 8 OLI Bands 4 and 7 data with maps of soil salinity based on EC values showed a firm and robust visual affinity between these bands and soil salinity, whereas other Landsat bands did not clearly distinguish soil salinization. High and severe soil salinity areas, in particular, showed lower reflectance values in Band 4 and Band 7 ($DN < 10500$), as compared to areas with no- and low soil salinity.

Figure 8 displays maps of soil salinity created using Landsat 8 OLI Bands. According to the visual comparison, we found that the Landsat 8 OLI Band 4 and Band 7 data can be used to locate the exact soil salinity locations or the risk being posed by soil salinization in the study area.

Figure 8. Landsat 8 OLI satellite based-soil salinity maps of Sirdarya province within different wavelengths

The accuracy assessment of these satellite image-based maps was evaluated by comparing ground truth data (EC values). Two data series were compared in this study. Based on spectral correlation between various bands, false color composite has been employed as training and sampling points. Based on these findings, it was determined that MODIS-MOD09 Band 1 and Band 6 and Landsat 8 OLI Band 4 and Band 7 had the positive modest ($R = 0.5…0.6$) and strong ($R \geq 0.8$) correlation, respectively. As a result, to properly distinguish soil salinity, the satellite-based soil salinity maps created using this method had an overall accuracy of 72% and a Kappa value of 81%.

3.4 Pairs and panels statistics

As we revealed visually similar patterns of satelitte-based soil salinity and EC values, to examine the relationship between EC values and MODIS bands more deeper, we performed a pairs and panels analysis using data collected (206 points) from Sirdarya province. Our results showed a moderate positive correlation between EC values and MODIS Band 1 (R = 0.67; $p < 0.05$; DN = 800…900 with f = ~1400) within the wavelength of 0.62-0.67 µm and a weaker positive correlation with MODIS Band 6 (R = 0.52; $p < 0.05$; DN = 700…1000 with f = ~1100) within the wavelength of 1.628-1.652 µm. On the other hand, no correlation was observed between EC values and rest of the MODIS bands.

The pairs and panels analysis involved plotting the EC values against the MODIS band values for each pixel in the study area. The scatter plots indicated a clear trend of increasing EC values with moderately increasing MODIS Band 1 and 6 values. The correlation coefficient for MODIS Band 1 was 0.67, indicating a moderate positive association between EC values and this band. The p-value for this correlation was less than 0.05, indicating statistical significance at the 95% confidence level. The range of MODIS Band 1 values associated with this correlation was DN = 800…900, with a frequency value of approximately 1400 of the corresponding histogram.

The correlation coefficient for MODIS Band 6 was 0.52, indicating a weaker positive association between EC values and this band. The p-value for this correlation was also less than 0.05, indicating statistical significance at the 95% confidence level. The range of MODIS Band 6 values associated with this correlation was DN = 700…1000, with a frequency value of approximately 1100 of the corresponding histogram.

Figure 9. Pairs and panels statistical output for the EC values and MODIS-MOD09 satellite bands

According to the investigation of the relationship between EC values and Landsat bands, our results revealed a strong positive correlation between EC values and Landsat 8 OLI Band 4 (R = 0.91; $p < 0.05$; DN = 10000…11000 with f = ~13000) within the wavelength of 0.64-0.67 µm and Landsat 8 OLI Band 7 (R = 0.86; $p < 0.05$; DN = 9500…10500 with f = ~13000) within the wavelength of 2.11-2.29 µm. While, there was no correlation with other bands of Landsat and EC

The pairs and panels analysis involved plotting the EC values against the Landsat 8 OLI band values for each pixel in the study area. The resulting scatter plots showed a clear trend of increasing EC values with significanlty increasing Landsat 8 OLI Band 4 and 7 values. The correlation coefficients for these relationships were found to be 0.91 and 0.86 respectively, indicating a strong positive association between the variables.

Moreover, the *p*-values for both correlations were less than 0.05, indicating that the relationships were statistically significant at the 95% confidence level. The Landsat 8 OLI band values associated with the significant correlations fell within the range of DN = 10000…11000 for Band 4 and DN = 9500…10500 for Band 7, with a frequency value of approximately 13000 for both of the corresponding histograms.

Figure 10. Pairs and panels statistical output for the EC values and Landsat 8 OLI satellite bands

Untill now, limited studies have been conducted on determining the direct relationship between DN values of satellite images and soil salinity worldwide. According to Mehrjardi et al. (2008), Soil soil salinity was determined using 48 surface soil samples from the Yazd-Ardakan plain in Iran. Data from Landsat ETM+ that cover the region were obtained in 2002. Their findings indicated a strong relationship between salt content and Landsat 7 ETM+ Band 3, as indicated by the correlation coefficient of R = 0.58. They used ten soil samples to test the accuracy of the maps. The created soil salinity map had an overall accuracy of 87%, according to the findings.

Another method utilized for soil salinity assessment apart from remote sensing indices or machine learning techbiques was developed by Abbas et al. (2013). They devised satellite band combinations based on remotely sensed data of Pakistan to track the distribution of salt-affected soils. The images were categorised into eight land use classifications using supervised maximum likelihood classification, with an overall accuracy of about 90%. According to USDA categorization, the demarcation study into levels of saline soils identified three categories.

Our findings suggest that MODIS Band 1 could moderately be a useful predictor of EC values, while MODIS Band 6 may have a weaker association. Regarding Landsat 8 OLI Bands 4 and 7, they are the predictors of EC values in Sirdarya province. Considering these findings, we could conclude that the wavelength of 0.64-0.67 µm and 2.11-2.29 µm is an affirmative range to create soil salinity maps. Further research is needed to investigate the mechanisms underlying this relationship and to explore the potential applications of these findings in another dryland, land management and environmental monitoring.

3.5 Structural equation modeling using Lavaan statistics

Though mechanism of reflection for soil salinity and specific sensors on MODIS and Landsat are missing, we assumed land and water management would be reflcted to digital number of those sensors. Then, to find missing relationship, a structural equation modeling was applied.

This is a model output from a structural equation modeling (SEM) analysis using the lavaan package in R studio. The model includes one endogenous variable, EC values and seven exogenous variables – Landsat 8 OLI bands, "B1", "B2", "B3", "B4", "B5", "B6", and "B7" which may represent different soil properties or features. The model also includes covariances between the exogenous variables.

Table 4 provides the parameter estimates for the model, including the regression coefficients (Estimate) and their standard errors (Std.Err) for the relationships between the endogenous variable and exogenous variables, as well as the variances and covariances of the exogenous variables. The intercepts are also included, which are the mean values of the exogenous and endogenous variables in the model.

Table 4. Lavaan statistics output for EC and Landsat 8 OLI sensor image bands

Regression:				
EC -	**Estimate**	**Std.Err**	**z-value**	**P (> [z])**
B1	-0.319	1.278	-0.372	0.466
B2	0.871	6.776	0.129	0.898
B3	0.329	1.155	0.284	0.776
B4	8.516	2.910	2.927	0.003
B5	-0.452	0.661	-0.684	0.494
B6	2.197	1.918	1.146	0.252
B7	-9.008	2.518	-3.577	0.000
Covariance:				
	Estimate	**Std.Err**	**z-value**	**P (> [z])**
B1 -				
B2	0.001	0.001	1.209	0.101
B3	0.016	0.001	7.424	0.000
B4	0.103	0.001	2.008	0.065
B5	0.014	0.001	9.375	0.000
B6	0.008	0.001	9.768	0.000
B7	0.031	0.001	1.532	0.116
B2 -				
B3	0.006	0.001	8.578	0.000
B4	0.012	0.001	10.023	0.000
B5	0.001	0.001	1.532	0.125
B6	0.012	0.001	9.099	0.000
B7	0.13	0.001	9.712	0.000
B3 -				
B4	0.014	0.002	8.411	0.000
B5	0.002	0.002	1.209	0.227
B6	0.015	0.002	7.424	0.000
B7	0.016	0.002	8.211	0.000

B4 -				
B5	0.004	0.002	2.008	0.045
B6	0.030	0.003	9.375	0.000
B7	0.030	0.003	9.768	0.000
B5-				
B6	0.014	0.003	4.665	0.000
B7	0.005	0.003	1.710	0.087
B6-				
B7	0.039	0.004	9.814	0.000

The model fit statistics are not presented in this table, but they are important for evaluating the overall fit of the model to the data. These statistics help to determine if the model adequately explains the observed relationships between the variables. Additionally, the covariance matrix shows that there are significant covariances between the different bands, suggesting that the bands are not independent of one another in their relationship with soil salinity. In general, the regression analysis using the lavaan package suggests that B4 and B7 are the most important Landsat 8 OLI bands for predicting soil salinity in Sirdarya province, Uzbekistan in August 2022.

Table 4 also shows the *p*-values for each of the Landsat bands, which indicate the probability of obtaining a result as extreme as the one observed, assuming that the null hypothesis is true (i.e., that there is no relationship between the independent and dependent variables). The *p*-values for B1, B2, B3, B5, and B6 are all greater than 0.05, which suggests that there is not enough evidence to reject the null hypothesis for these bands. In other words, there is no significant relationship between these Landsat bands and soil salinity (as measured by EC).

The *p*-values for B4 and B7, on the other hand, are both less than 0.05, which suggests that there is evidence to reject the null hypothesis for these bands. This means that there is a significant relationship between these Landsat bands and soil salinity (as measured by EC). Specifically, a *p*-value of 0.003 for B4 suggests that there is a strong relationship between B4 and soil salinity, while a *p*-value of 0.000 for B7 suggests an even stronger relationship.

Overall, these results suggest that B4 and B7 of Landsat 8 OLI are important predictors of soil salinity in the study area, while B2, B3, B5, and B6 are not significant predictors. These findings may have implications for mapping and monitoring soil salinity in the region using Landsat imagery.

We conducted a multilinear regression analysis to determine the relationship between soil salinity (EC) and remote sensing data acquired by the MODIS satellite in August 2022. Specifically, we used bands B1, B2, B3, B4, B5, B6, and B7 to predict soil salinity. The regression analysis resulted in an estimator (ML) obtained using the NLMINB optimization method with 44 model parameters and 206 observations.

Table 5 includes parameter estimates, covariances, and intercepts. The parameter estimates represent the coefficients associated with each remote sensing band, indicating the extent to which they contribute to the prediction of soil salinity. The standard error associated with each estimate provides information about the precision of the coefficient. The covariances describe the relationships between the remote sensing bands. A positive covariance suggests that the bands are positively related, meaning that they tend to increase or decrease together. A negative covariance suggests that the bands are negatively related, meaning that as one-band increases, the other tends to decrease. The intercepts represent the average value of soil salinity and remote sensing bands when all other variables are equal to zero.

Table 5. Lavaan statistics output for EC and MODIS-MOD09 sensor image bands

Regression:				
	Estimate	**Std.Err**	**z-value**	**P (> [z])**
EC -				
B1	3.145	1.051	2.991	0.003
B2	1.078	8.505	0.127	0.899
B3	30.186	24.264	1.244	0.213
B4	36.805	19.587	1.879	0.060
B5	7.237	11.729	0.617	0.537
B6	-32.845	9.005	-3.648	0.000
B7	-2.461	1.479	-1.664	0.096
Covariance:				
	Estimate	**Std.Err**	**z-value**	**P (> [z])**
B1 -				
B2	0.000	0.000	0.833	0.405
B3	0.000	0.000	2.527	0.012
B4	0.000	0.000	2.496	0.013
B5	0.000	0.000	1.237	0.216
B6	0.000	0.000	2.606	0.009
B7	0.000	0.000	0.482	0.630
B2 -				
B3	0.000	0.000	3.048	0.002
B4	0.000	0.000	4.669	0.000
B5	0.000	0.000	9.399	0.000
B6	0.000	0.000	5.907	0.000
B7	0.000	0.000	1.318	0.187
B3 -				

B4	0.000	0.000	9.712	0.000
B5	0.000	0.000	5.111	0.000
B6	0.000	0.000	8.557	0.000
B7	0.000	0.000	3.050	0.002
B4 -				
B5	0.000	0.000	6.177	0.000
B6	0.000	0.000	8.830	0.000
B7	0.000	0.000	3.067	0.002
B5-				
B6	0.000	0.000	8.219	0.000
B7	0.000	0.000	2.161	0.031
B6-				
B7	0.000	0.000	2.915	0.002

Overall, the results of this analysis suggest that bands B1 and B6 are significant predictors of soil salinity, as their *p*-values are less than 0.05. Band B2 is not a significant predictor, as its p-value is 0.899. The intercept for soil salinity is significant, with a *p*-value of 0.001, indicating that it is significantly different from zero. The intercepts for the remote sensing bands are also significant, indicating that they are significantly different from zero when all other variables are equal to zero.

Next, the SEM includes two latent variables, *spec1* and *salt*, which are measured by the satellite images, *EC* and *surface water mineralization (SWM)*, respectively. The model fit indices suggest that the model does not fit the data sufficiently in Table 6. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are both below 0.8, indicating poor fit. The Root Mean Square Error of Approximation (RMSEA) is 0.35, which is above the threshold of 0.05 for acceptable fit.

Table 6. SEM output with particular focus on EC and surface water mineralization

Parameter Estimates:						
Latent variables:	**Estimate**	**Std.Err**	**z-value**	**P (> [z])**	**Std.lv**	**Std.all**
Spec1 = ~						
B1	1.002				0.083	0.991
B2	1.000				0.071	0.990
B3	1.420	0.023	62.215	0.000	0.101	0.984
B4	2.275	0.034	67.362	0.000	0.162	0.988
B5	0.389	0.187	2.075	0.038	0.028	0.144
B6	0.515	0.113	22.312	0.000	0.179	0.848
B7	2.578	0.076	33.947	0.000	0.184	0.930
Salt = ~						
EC	1.000				0.332	0.239

SWM	0.034	0.226	0.151	0.880	0.11	0.072
Regression:	**Estimate**	**Std.Err**	**z-value**	**P (> [z])**	**Std.lv**	**Std.all**
Salt = ~						
Spec1 = ~	0.711	1.365	0.521	0.602	0.153	0.153
Variances:	**Estimate**	**Std.Err**	**z-value**	**P (> [z])**	**Std.lv**	**Std.all**
B1	0.000	0.000	7.002	0.000	0.000	0.023
B2	0.000	0.000	6.013	0.000	0.000	0.020
B3	0.000	0.000	7.548	0.000	0.000	0.031
B4	0.001	0.000	6.617	0.000	0.001	0.023
B5	0.036	0.004	10.147	0.000	0.036	0.979
B6	0.13	0.001	9.950	0.000	0.013	0.281
B7	0.005	0.001	9.649	0.000	0.005	0.135
EC	1.825	0.860	2.123	0.034	1.825	0.943
SWM	0.025	0.003	9.414	0.000	0.025	0.995
Spec1	0.005	0.001	9.945	0.000	1.000	1.000
Salt	0.108	0.841	0.128	0.898	0.977	0.977

In terms of the specific parameter estimates, the standardized regression coefficient between *spec1* and *salt* is 0.153, but this is not statistically significant ($p > 0.05$). The variance estimates for the latent variables and their indicators are also included in the output.

3.6 Innovation and outlook

The assessment of soil salinity is crucial for the successful management of agricultural lands, as high salt concentrations can lead to reduced crop yields and even land degradation. Traditionally, soil salinity has been measured through laboratory analyses, which can be time-consuming, expensive, and require specialized equipment. However, in recent years, remote sensing techniques have been increasingly used to assess soil salinity. These techniques rely on the use of various indices derived from remotely sensed data, such as the NDVI and the SAVI, to estimate soil salinity levels. However, the reliability and accuracy of these indices are still being debated, and there is a need to critically evaluate their effectiveness in soil salinity assessment. This study approach is different from previous research that did not specifically target single bands. To contribute to the existing knowledge, by this research we proved that through simple bands of satellite images (i.e. Band 4 and Band 7 for Landsat 8 OLI; Band 1 and Band 6 for MODIS-MOD09) within 0.62-0.67 µm for the both sensors and 1.628-1.652 µm for MODIS-MOD09 and 2.11-2.29 µm for Landsat 8 OLI wavelength can estimate soil salinity. Our findings provide insights into the usefulness of individual bands in predicting soil salinity and can inform future research and management practices.

The use of remote sensing indices should be continuously complemented with field observations and measurements, as soil salinity levels can vary widely across small areas. Future research should also focus on the increased number of samples (more than 200) and development of more affordable and accessible remote sensing techniques to facilitate their widespread use in soil salinity assessment. With continued innovation and research, remote sensing has the potential to greatly improve our ability to manage and protect agricultural lands, ensuring food security and sustainable development for generations to come.

4. Conclusions

According to the first objective, the results of this study indicate a high correlation between mineralized surface irrigating water and soil salinity. The findings suggest that the use of water with high mineral content for irrigation purposes can significantly contribute to soil salinization ($R = 0.63$, $p < 0.05$). This has important implications for agriculture and soil management practices, as excessive soil salinity can negatively impact crop yields and quality. Therefore, it is essential to consider the quality of irrigation water when developing sustainable agriculture practices. Future research should explore the effectiveness of different irrigation methods and soil amendments in mitigating the negative effects of mineralized water on soil salinity. Overall, this study highlights the importance of water quality management in agriculture and the need for sustainable solutions to address the challenges associated with soil salinization.

To fulfill the second objective, our findings imply that while MODIS Band 6 may have a lesser connection with EC values, MODIS Band 1 can be a somewhat good predictor of EC values. However, the EC values in Sirdarya Province can be predicted using Landsat 8 OLI Bands 4 and 7. These results lead us to the conclusion that the wavelength ranges of 0.64-0.67 m and 2.11-2.29 m are suitable for mapping soil salinity. The processes behind this link and the possible applicability of these results in other drylands, land management, and environmental monitoring require continuous investigation.

With continued innovation and research, remote sensing has the potential to revolutionize the way we monitor and manage agricultural lands, ensuring sustainable development and food security for generations to come. However, to fully realize this potential, collaboration between researchers, policy-makers, and land managers is crucial. By working together, we can develop more accurate and reliable remote sensing techniques and ensure that they are effectively integrated into agricultural management practices.

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Aziz Omonov: Software, Investigation, Validation, Resources, Data curation, Visualization, Writing – original draft preparation. **Tasuku Kato, Atiqotun Fitriyah:** Conceptualization, Supervision. **Sayidjakhon Khasanov:** Formal analysis, Vizualization. **Lukmon Samiev, Zukhriddin Ismoilov** Investigation, **Aziz Omonov, Tasuku Kato, Sayidjakhon Khasanov, Atiqotun Fitriyah,Fadong Li, Sardorbek Musayev, Lukmon Samiev and Zukhriddin Ismoilov:** Writing – review & editing. The authors have read and agreed to the published version of the manuscript.

Declaration of competing interests

The authors declare no conflict of interests.

Data availability

Not applicable

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