
IMPROVING METHODS FOR REMOTE DETECTION AND ANALYSIS OF SALINITY PATCHES VARIABILITY

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Abstract:

This article addresses the issue of salinity patches variability in irrigated areas, which is considered one of the most critical meliorative challenges. Traditional field surveys for detecting and monitoring soil salinization are time-consuming and costly; therefore, the study focuses on the application of modern remote sensing technologies. The research improves methodologies for identifying and analyzing saline spots based on satellite imagery and drone data. In particular, spectral indices such as NDVI, SI, and other vegetation–soil indicators were employed to assess the spatial and temporal dynamics of soil salinity. The results provide insights into the distribution and intensity of salinity processes, enabling better understanding of their variability across time and space. The findings are of practical importance for planning effective reclamation measures, optimizing water resource management, and ensuring sustainable agricultural production. Moreover, the proposed approach offers farmers and land management organizations a rapid and accurate tool for monitoring salinity processes in irrigated lands.

Keywords: Soil salinity, Salinity patches, Variability, Remote sensing, Spectral indices, NDVI, SI (Salinity Index), GIS analysis, Irrigated lands, Land reclamation, Water management.

Introduction:

Soil salinization is one of the most widespread and serious environmental and agricultural challenges in irrigated regions. The accumulation of salts in the soil not only reduces crop productivity but also accelerates land degradation, threatening sustainable agricultural development. In particular, the formation and variability of salinity patches within irrigated fields complicate land management and make it difficult to design effective reclamation measures. Traditional field-based methods for detecting and monitoring soil salinity require significant time, labor, and financial resources. In recent years, remote sensing technologies have emerged as a promising alternative, providing rapid, cost-effective, and large-scale monitoring capabilities. By utilizing satellite

images, unmanned aerial vehicles (UAVs), and spectral indices such as NDVI and SI, it has become possible to assess the spatial distribution and temporal dynamics of salinity with higher accuracy. This study aims to improve the methodologies for detecting and analyzing the variability of salinity patches through remote sensing techniques. The research not only enhances the scientific understanding of salinization processes but also provides practical solutions for optimizing water resource management, planning reclamation measures, and supporting sustainable agricultural practices in irrigated areas[1,5].

Materials and Methods:

The research was carried out in irrigated areas where soil salinity is considered one of the main constraints for agricultural productivity. To assess the variability of salinity patches, a combination of field surveys, remote sensing data, and geospatial analysis was employed. Satellite imagery from Landsat-9 OLI and Sentinel-2 MSI platforms was used to extract spectral information related to soil salinity. Additionally, unmanned aerial vehicle (UAV) images with high spatial resolution were applied for detailed mapping of saline spots. Preprocessing steps included radiometric and atmospheric corrections, image mosaicking, and normalization of spectral bands[2,3].

Several vegetation and soil indices were calculated, such as Normalized Difference Vegetation Index (NDVI), Salinity Index (SI), and Normalized Difference Salinity Index (NDSI). These indices were used to evaluate spatial patterns of salinity and to monitor their temporal dynamics. Ground truth data were collected through field soil sampling and electrical conductivity (EC) measurements, which served for calibration and validation of the remote sensing results. All spatial analyses and mapping were conducted using GIS software (ArcGIS and QGIS). Correlation and regression analyses were applied to determine the relationships between spectral indices and measured soil salinity parameters. This integrated approach allowed for improving the accuracy of salinity detection and for analyzing the variability of saline patches across the study area[4,8].

Among the remote sensing data studied, Landsat images are the most convenient source for studying salinity and land salinization due to the balanced combination of spatial, temporal, and spectral resolution. Landsat is a satellite with a large database that has been continuously improved since 1972. Its latest satellite, Landsat 9 (in 2021), was launched and is equipped with the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). These devices have significantly improved the ability to detect surface changes due to salinity and are of great importance in identifying salt spots. The following methodology was used to analyze remote sensing data in the dissertation[6,7].

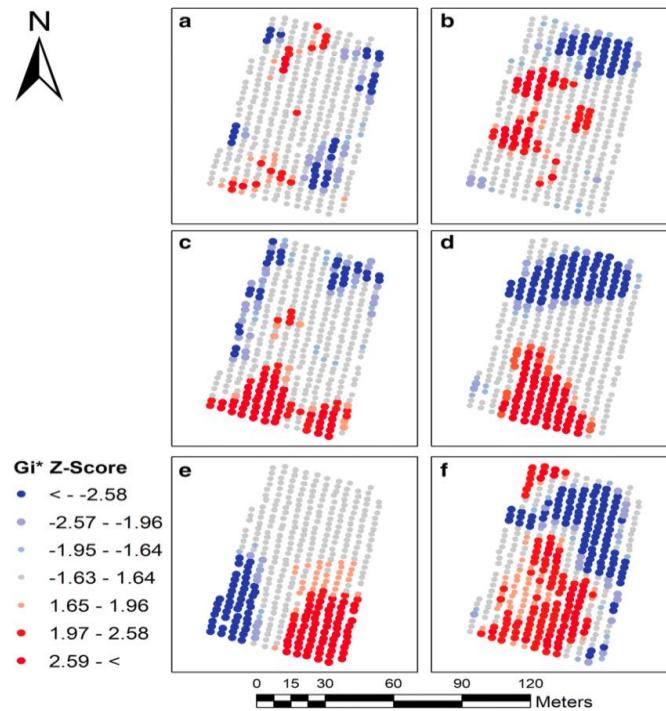
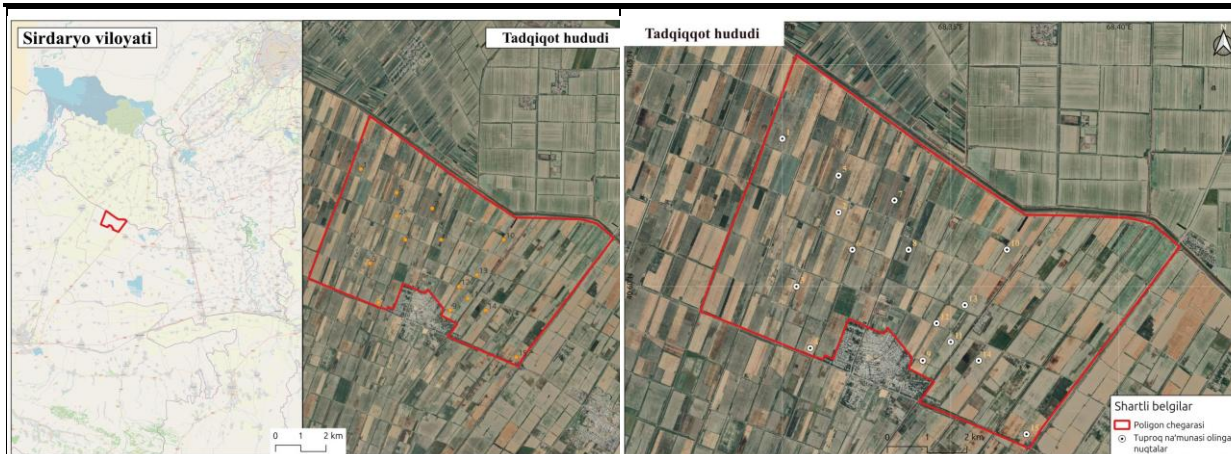


Figure 1. Clustering based on the Gettys-Ord G_i^* statistic.

The Getis-Ord G_i^* statistic was selected for the statistical analysis of NDSI and NDVI indices. Especially in this method, when combined with NDVI and NDSI, it is one of the most powerful and scientifically sound methods for identifying salinity clusters, anomaly zones, and hazard areas. This method complements zonal and index analysis with statistical depth. Therefore, NDSI was selected as the main index for determining salinity, and when used in combination with NDVI, it provides results with high accuracy and analytical efficiency [98; p. 2366]. This approach is particularly useful for multi-temporal analysis, clustering, and hazard zone identification[5,2].

In order to determine soil salinity and salt spots in the study area, agricultural lands located in the irrigated agricultural area of Syr Darya region were selected. The study area was defined by defined polygon boundaries, and the location and salinity status were depicted cartographically based on soil samples taken from 15 points. In the study area, the lands are mostly large-scale agricultural fields and are regularly irrigated. The color differences in the space images indicate different levels of salinity. The following analysis was carried out at each sampled point, with points 6–9–11–15 being identified as areas with potentially high salinity levels (yellowish or light brown tones).

Based on the presented maps, it is possible to analyze the location, intensity and distribution of the salinization process in the study area. By analyzing soil samples taken from each point in the laboratory, it is possible to assess the causes of the formation of salt spots, their relationship to hydrogeological conditions, and the state of land reclamation[2,6].



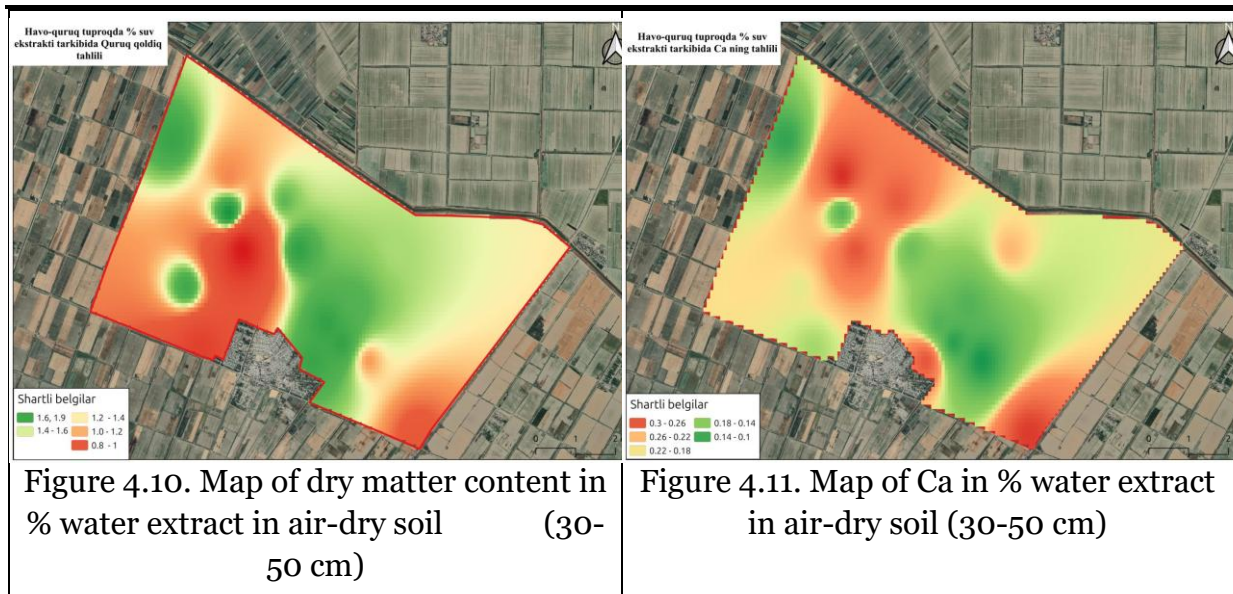


Table 4.4. Spatial distribution of chemical parameters by soil layers

Parametr	Deps (sm)	Intermediate	Color coding	Explanation
SO ₄ quacity (%)	0-30	0.1 – 0.88	Green → Red	Red - areas with high salinity, green - areas with low salinity
Dry residue (%)	0-30	0.31 – 1.6	Green → Red	Red - areas with high salinity, green - areas with low salinity
Ca quacity (%)	0-30	0.0044 – 0.068	Green → Red	Red - areas with high salinity, green - areas with low salinity
SO ₄ quacity (%)	30-50	0.14 – 1.4	Green → Red	Red - areas with high salinity, green - areas with low salinity
Dry residue (%)	30-50	0.078 – 0.21	Green → Red	Red - areas with high salinity, green - areas with low salinity
Ca quacity (%)	30-50	0.1 – 1.2	Green → Red	Red - areas with high salinity, green - areas with low salinity

SO content: Higher SO levels are recorded at a depth of 30–50 cm, indicating that SO accumulates in the deeper layer. The distribution within the area is characterized by higher concentrations in the center and red.

Dry matter: The upper layer (0–30 cm) has a wide range of variability (0.31–1.6%), while the lower layer is more stable (0.078–0.21%).

Ca content: Higher Ca values (0.1–1.2%) were detected at 30–50 cm, which is significantly different from the values in the 0–30 cm layer. This indicates an abundance of Ca in deeper layers.

Cartographic analysis shows that all indicators show higher concentrations in the center and southeastern regions, and a decrease is observed towards the edges.

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Figure 4.12. Salinity map (April 2024)

Figure 4.13. Salinity map (October 2024)



Figure 4.14. NDVI map (April 2024)

Figure 4.15. NDVI map (October 2024)

Using NDSI (Normalized Difference Salinity Index) and NDVI (Normalized Difference Vegetation Index) data obtained through remote sensing technologies, the state of salinity and vegetation in the Startli region was studied in the spring (April) and autumn (October) seasons of 2024. These indicators allow assessing salinity and plant health, as well as identifying hotspot zones. According to the results of the NDSI obtained in the spring (04.2024), the highest levels of salinity were recorded in the central and eastern zones. These areas were identified as hotspot zones using the Gettys-Ord G_i^* statistics. According to the color indicators, red color indicates a high level of salinity, and it is the zones of this color that are clusters of agricultural risk. In the NDSI maps obtained in the fall (10.2024), the salinity level has decreased compared to the spring indicators, especially in remote areas. However, the central hotspot areas have remained despite the seasonal decrease. This indicates the need for continuous monitoring for these areas. According to NDVI data, plant health is directly related to salinity levels. The red zones have extremely low vegetation levels, meaning that plants are either not growing at all or growing very slowly in these areas. This corresponds to the saline zones shown in red on the NDVI maps[2].

Conclusion:

The study confirmed that remote sensing technologies, particularly the integration of satellite imagery, UAV data, and ground-based measurements, provide effective tools for detecting and analyzing the variability of salinity patches in irrigated lands. The application of spectral indices such as NDVI, SI, and NDSI, combined with advanced statistical methods like the Getis-Ord G_i^* statistic, allowed for accurate identification of salinity clusters, hotspot zones, and anomaly areas.

The results revealed that salinity levels are not uniformly distributed but vary significantly across spatial and temporal scales, with central and eastern parts of the study area being the most vulnerable. Seasonal changes also influenced salinity intensity, indicating the need for continuous monitoring. NDVI analysis confirmed the direct relationship between vegetation health and salinity levels, emphasizing the negative impact of salt accumulation on crop growth.

These findings highlight the practical importance of remote sensing methods for sustainable land and water management. The improved methodology can assist farmers, researchers, and policymakers in planning reclamation measures, optimizing irrigation regimes, and mitigating soil degradation. In conclusion, integrating remote sensing and GIS-based analysis into agricultural monitoring systems is essential for addressing soil salinization challenges and ensuring sustainable agricultural productivity.

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