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Review Article

Detection of Soil Salinity Using Remote Sensing and Machine Learning: Innovative Approaches and Contributions

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Abstract

Soil salinity is a significant issue that threatens agricultural productivity and ecosystem balance worldwide. Analyzing soil salinity using traditional methods is a challenging, costly, and time-consuming process, as it relies on laboratory measurements, making it difficult to apply over large areas. Thus, there has been a rise in recent years in the trend toward utilizing remote sensing and machine learning methods to evaluate soil salinity quickly and effectively. Remote sensing can detect signs of salinity on the soil surface through spectral data obtained from satellites and aerial vehicles. Data from visible, near-infrared, and thermal bands, in particular, are widely used in mapping soil salinity. Machine learning algorithms process this spectral data to model complex relationships related to soil salinity and make predictions. Methods like Deep Learning, Artificial Neural Networks, Random Forests, and Support Vector Machines have attracted attention in this field due to their high accuracy rates. These methods hold great potential for monitoring changes in soil salinity, optimizing agricultural practices, and developing strategies to combat salinity. At the same time, they contribute to the advancement of sustainable agriculture by supporting soil management decisions, especially in large agricultural areas. In this context, the combination of machine learning and remote sensing technologies stands out as an effective solution for monitoring and managing soil salinity. Therefore, this research attempts to investigate the advantages and limitations of research conducted in this field and to provide a framework that can guide future studies.

Keywords: Detection of soil salinity, remote sensing, sustainable agriculture, machine learning

1. Introduction

Salinity of the soil is a significant environmental problem. Soil salinity does not have an immediate effect like some other environmental hazards do, but because of its long-term effects on human life, it is now regarded as a serious threat. Because it degrades soil quality and has an unfavourable effect on farm, water resources, and biodiversity, this condition poses a threat to food security and ecological sustainability (Kabiraj et al., 2022).

The negative consequences of salinization of soil are not limited to reducing agricultural productivity. This system can decrease the soil's ability to store and filter water, increase erosion, and disturb the structure of the soil. Additionally, natural habitats can be destroyed and biodiversity reduced by soil salinization (Peng et al., 2019). Furthermore, the increase in fertilizer use and human activities has significantly raised soil salinity levels. This further endangers agriculture, food security, water assets, and soil conservation (Ismaili et al., 2023). All things considered, conventional soil mapping techniques have frequently been expensive, minute, and inaccurate for current farm and ecological activities (Ismaili et al., 2024). As a result, the goal of research has been to use as little data as possible to predict soil properties fairly accurately. Consequently, they have significantly improved the efficiency and precision of soil property prediction by employing machine learning methods called smart mapping of soil (McBratney et al., 2003). The effectiveness of techniques for machine learning in predicting characteristics of soil has convinced numerous investigators to employ these techniques for estimating soil characteristics. Therefore, artificial neural networks, support vector machines, random forests, and other machine learning techniques have been used to increase forecast precision. (Padarian et al., 2019). These approaches enable more economical and effective monitoring of soil properties. As a result, it is possible to predict soil properties more accurately using DSM technology (Taghadosi et al., 2019). Due to the visibility of soil salinization and the significant impact on near-infrared reflectance, numerous spectral indices have been developed (Ramos et al., 2020). Based on this information, many researchers have predicted the spatial distribution of soil salinity using remote sensing (RS) and DSM methods (Singh, 2021). For example, the Hetao region of Inner Mongolia's soil salinity was correctly predicted by Jia et al. (2022). Ge et al. (2022) used spectral indices obtained out of Sentinel-2 satellite images to predict the salinity of the soil in western China.

Furthermore, Kaya et al. (2022) showed that machine learning techniques could accurately forecast Türkiye's soil salinity using Sentinel-2 satellite data and environmental parameters derived from Digital Elevation Models (DEM). In conclusion, machine learning techniques, they have become useful instruments in soil salinity research due to their capacity to process vast volumes of data and spot intricate patterns. These techniques can provide accurate predictions of soil salinity by analyzing temperature, moisture, and other environmental factors in addition to the chemical composition of the soil (Sulieman et al., 2023). The capacity of machine learning techniques to analyze vast amounts of information and determine intricate trends has made them popular instruments in soil salinity research. By analyzing moisture, temperature, soil chemical composition, and other environmental variables, they can provide accurate estimates of soil salinity. Machine learning and digital soil mapping techniques enable more precise and economical monitoring of soil salinity, becoming an essential tool for modern agricultural practices.

2. Soil salinity

Soil salinity, a common problem in arid and semi-arid regions, is a significant issue that both reduces agricultural productivity and disrupts environmental balance (Kaplan and Rufaioğlu, 2023). In these areas, low precipitation leads to the accumulation of dissolved salts in the soil, which degrades soil structure (Ülker et al., 2018). While soil salinization occurs in many parts of the world, the problem is more severe in arid regions with low rainfall and high evaporation rates. This is because rainwater is insufficient to leach away the salts (Zinck and Metternicht, 2008).

3. Primary and secondary stages of salinization

As the global population grows rapidly, the demand for food production is also increasing. However, a significant amount of agricultural land has been abandoned due to primary and secondary soil salinization. Salt buildup in the soil brought on by natural cycles like physical and chemical weathering or the movement of salts from parent materials, geological deposits, or groundwater is known as primary salinization. Traditional irrigation techniques and inadequate drainage systems are the main causes of secondary salinization (Daliakopoulos et al., 2016; Esetlili et al., 2018). This affects approximately 20% of irrigated land worldwide (Mayak et al., 2004). Zinck and Metternicht (2008) state that secondary salinization has damaged an area of about 77 million hectares. Figure 1 shows a simplified flow chart illustrating primary and secondary soil salinization.

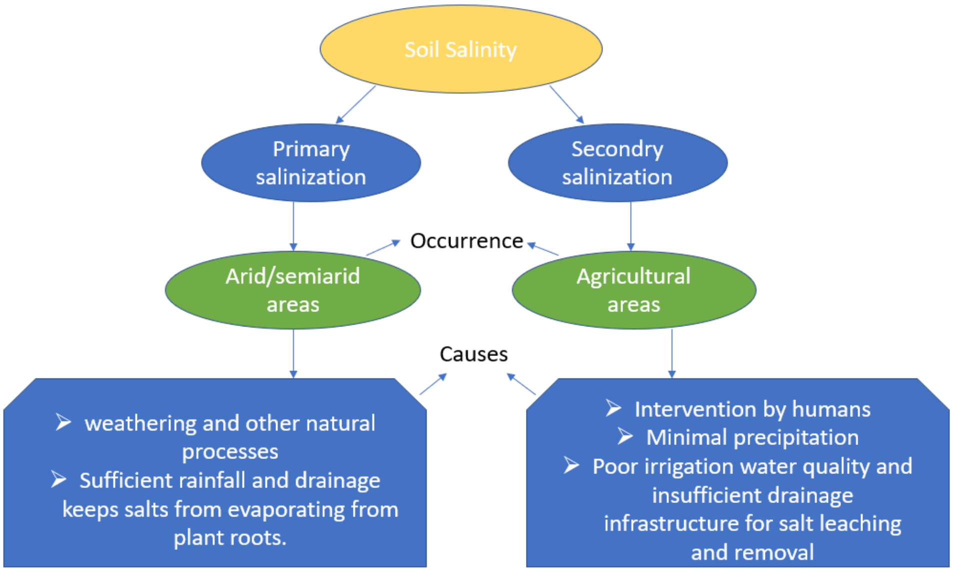

Figure 1. Flowchart showing the salinization of primary and secondary soils

a. Primary salinization **b.** Secondary salinization

Figure 2. Soil salinity (Primary salinity develops through natural processes, while secondary salinity results from human activities) (Sezen, 2021).

4. The effect of soil salinity on farming

Agricultural efficiency is genuinely endangered by soil salinity, a major problem that is particularly prevalent in arid and semi-arid areas. Salinity occurs because of the accumulation of dissolved salts (like sodium, chloride, calcium, and magnesium) in the soil, which can result from inadequate drainage, improper irrigation practices, or natural geological processes. Saline soils hinder plants' water and nutrient uptake, restrict growth, degrade soil structure, and reduce agricultural production. To address this problem, strategies such as proper irrigation techniques, drainage systems, the use of salt-tolerant plant varieties, and soil improvement methods (e.g., gypsum application) are implemented. Effective management of soil salinity is crucial for sustainable agriculture and food security (Matinfar et al., 2013). As emphasized, traditional irrigation practices play a significant role in soil salinization and the degradation of soil quality, leading to adverse outcomes and restricting plant growth and germination. Furthermore, the demand for food production is increasing as the world experiences rapid population growth. Consequently, this will lead to the conversion of more arid land into agricultural areas, primarily increasing the risk of salinization caused by irrigation. However, continuous monitoring and assessment of saline soils are of great importance in mitigating harmful effects such as land degradation and reduced crop yield (Allbed and Kumar, 2013).

5. Detection of soil salinity using remote sensing and machine learning methods

Enhancing land use requires real-time soil salinity monitoring and early warning sign detection due to the growing global population and increased demand for large agricultural lands. (Zinck and Metternicht, 2008). Decisions regarding the reclamation and management of such lands must be made with knowledge based on ongoing salinity monitoring. Traditional methods for salinity measurement include both field studies and laboratory analyses. Mapping the soil salinity of a region spatially requires collecting numerous samples, which is a challenging, costly, and labor-intensive process (Brunner et al., 2007; Haq et al., 2022; Ramzan et al., 2023). Approximately sixty-five years ago, information about different characteristics on the Earth's crust and soil salinity were measured using colored and black-and-white photos (Dale et al., 1986). Today, satellite-based remote sensing serves as a cost-effective tool for investigating salinity across various geographic and temporal scales. Remote sensing collects information about various objects by using electromagnetic energy represented from the surface of the Earth. This method facilitates soil salinity assessment. Remote sensing and geographic information systems methods have provided a technological opportunity to replace or complement traditional soil salinity assessment methods. Directly acquired spectral reflectance from detectors or spectral evolutions (Sahu et al., 2015), tasseled cap transformation (Li et al., 2016), and spectral indices (Dehni and Lounis, 2012; Wu, 2014) have yielded positive results in terms of prediction accuracy. Numerous researchers emphasize that spectral reflectance is highly significant in remote sensing studies and consider it a fundamental concept of the discipline (Ling et al., 2017; Aceves et al., 2019; Pandey et al., 2022). Many studies related to digital soil mapping have been conducted using various satellite data and geostatistical or statistical methods.

A study conducted in Uzbekistan found a relationship between vegetation temperature derived from MODIS data and soil salinity (Ivushkin et al., 2017). Hoa et al. (2019) produced a highly accurate model using Gaussian processes and contemporary machine learning models on SAR Sentinel-1 images, with an R^2 value of 0.808. This model successfully identified the relationship between EC and satellite data. Similarly, A study conducted in Morocco's Tafilalet plain showed that Landsat 8 OLI images could accurately determine the salinity of the soil (ElHafyani et al., 2019). Using a straightforward linear regression model, Hihi et al. (2019) found a moderate correlation (R2

= 0.48) between EC and spectral indices obtained from Sentinel images. The usefulness of polarized images derived from the VH and VV polarizations of SAR Sentinel-1 data in assessing soil salinity was shown by Taghadosi et al. (2019) The Support Vector Regression (SVR) strategy using an RBF kernel produced the most accurate results.

5.1. Soil salinity indices

Remote sensing technologies have been employed for mapping and determine soil salinity using a variety of spectral indices. These indices are used to detect salt accumulation in the soil either directly or indirectly. Table 1 lists a few widely used soil salinity indices.

Tablo 1. Soil salinity and vegetation ındices

Spectral indices	Expression	Reference
Normalized Difference Vegetation Index (NDVI)	(NIR-R)/(NIR+R)	(Rouse et al., 1974)
Normalized Difference Salinity Index (NDSI)	(R-NIR)/(R+NIR)	(Khan et al., 2005)
Soil Adjusted Vegetation Index (SAVI)	(NIR-R)/(NIR+R)+L*(1-L)	(Huete, 1988)
Simple Ration (SR)	(R-NIR)/(G+NIR)	(Abbas and Khan, 2007)
Differential Vegetation Index (DVI)	(NIR-R)	(Basso et al., 2000)
Ratio Spectral Index (RSI)	R/NIR	(Kahaer and Tashpolat, 2019)
Mosaic Simple Ratio (MSR)	NIR/R	(Vogelmann and Rock, 1985)
Vegetation Soil Salinity Index (VSSI)	2*G-5*(R+NIR)G-5*(R+NIR)	(Dehni and Lounis, 2012)
Salinity Index (SI1)	B/R	(Bannari et al., 2008)
Salinity Index (SI2)	(B-R)/(B+R)	(Abbas et al., 2013)
Salinity Index (SI3)	(G*R)/B	(Abbas et al., 2013)
Salinity Index (SI4)	NIR*R/G	(Abbas et al., 2013)

5.2. Commonly used machine learning models for soil salinity detection

Machine learning models are widely utilized to determine and map soil salinity. Among these models, Random Forest Regression (RFR) provides high accuracy in complex datasets such as spectral indices and soil properties, while Support Vector Regression (SVR) is preferred for modeling nonlinear relationships. Artificial Neural Networks (ANN) and Deep Learning Models yield effective results, especially with hyperspectral and high-resolution satellite images. Gradient Boosting Machines (GBM) and AdaBoost Regression (ABR) combine weak models to make strong predictions, while Partial Least Squares Regression and Ridge Regression (RR) analyze the connection among soil salinity and spectral data by addressing multicollinearity issues. Decision Tree Regression (DTR) is used as a simple and fast model for basic predictions, while Gaussian Processes (GP) provide uncertainty estimation with SAR data, as demonstrated in some studies using these models (Kaplan et al., 2023; Das et al., 2023; He et al., 2024). These models enable effective monitoring and management of soil salinity by integrating remote sensing technologies and ground measurements. Remote sensing and Landsat 8 OLI data offer an effective method for monitoring soil salinity. In their study, Haq et al. (2023) found that the Random Forest Regression (RFR) model carried out the strongest ($R^2 = 0.94$). Spectral indices such as DVI, SAVI, and NDVI showed strong correlations with salinity, while SI1-SI4 were ineffective in vegetated areas. These findings can support farmers against climate change by enabling the development of web-based applications for mapping soil salinity.

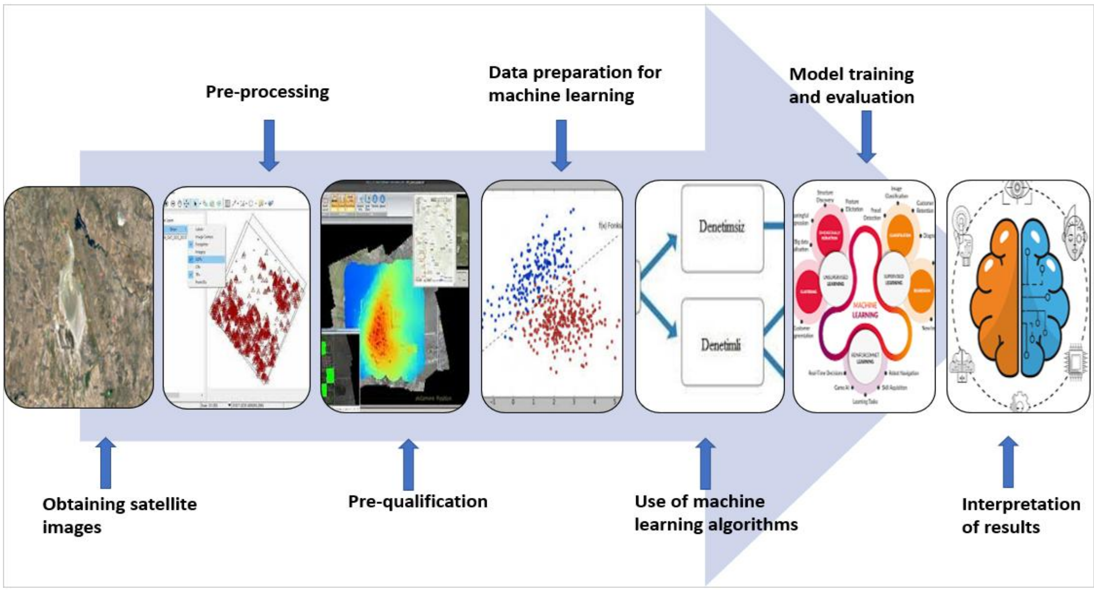

Figure 3. Steps followed when using satellite imagery ın machine learning

5.3. Error metrics used to test model accuracy

Metrics for evaluation are employed to measure the accuracy and error rate of a model. The primary performance evaluation metrics used in soil salinity studies are as follows.

5.3.1. Mean squared error (MSE)

The mean of the squared differences among the expected and true numbers is used to calculate the error rate, or MSE (Mean Squared Error). Because it penalizes larger errors more severely, MSE is a metric that is sensitive to the magnitude of errors (Chai and Draxler, 2014).

5.3.2. Root mean squared error (RMSE)

The magnitude of the forecast errors is better displayed by using the square root of MSE, or RMSE. RMSE is frequently used to assess the model's overall performance and shows how accurate yield forecasts are (Chai and Draxler, 2014).

5.3.3. Mean absolute error (MAE)

MAE averages the absolute values of the variations from the expected values and the true values. This metric helps understand the model performance by directly measuring the error rate of the model. This is especially useful in cases where there are no large errors (Willmott and Matsuura, 2005).

5.3.4. R^2 value

R2 shows the variance ratio of the model by the independent variables. The fit of the model increases as the R2 value approaches 1. It is used in plant breeding to evaluate how genetic and environmental variables affect plant yield (Montgomery and Peck, 2012).

5.3.5. Mean absolute percentage error (MAPE)

MAPE gives the error rate in proportion when comparing the estimated values with the real values. According to Makridakis and Hibon (2000), this metric shows the error rate of the model in percentage and allows comparison of data at various scales.

6. Conclusion

Soil salinity is a global issue that threatens agricultural productivity and ecosystem balance. Analyzing soil salinity using traditional methods is a time-consuming, costly, and challenging process to implement over vast regions. Then, in recent years, machine learning and remote sensing methods have increasingly been used to assess soil salinity quickly and effectively. Remote sensing technologies can detect signs of salinity on the soil surface through spectral data obtained from satellites and aerial vehicles, while machine learning algorithms process this data to model complex relationships and provide high accuracy rates. Techniques like Artificial Neural Networks, Random Forests, Deep Learning, and Support Vector Machines hold significant potential for monitoring and managing soil salinity. These methods offer important advantages in optimizing agricultural practices, developing strategies to combat salinity, and contributing to the advancement of sustainable agriculture. However, more research and development efforts are needed to effectively implement these technologies. Future studies can provide more effective solutions in the fight against soil salinity by examining the advantages and limitations of these methods in greater detail. In this context, the integration of machine learning and remote sensing technologies stands out as an effective tool for monitoring and managing soil salinity.

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