

Use of modern digital techniques for mapping and assessment of salt-affected soils

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Soil salinity is a growing global challenge, threatening agricultural productivity and food security. Conventional methods for diagnosing salt-affected soils such as visual inspection, field sampling, and laboratory testing have long provided essential insights but remain time-consuming, costly, and limited in spatial coverage. Recent advances in geospatial technologies, particularly remote sensing, geographic information systems (GIS), and machine learning (ML), are transforming how soil salinity is detected, mapped, and managed. Optical remote sensing now enables large-scale monitoring by capturing spectral signals linked to salinity stress, while predictive algorithms such as random forests, support vector machines, and neural networks enhance mapping accuracy across diverse landscapes. Digital Soil Mapping (DSM) builds on these innovations by integrating multi-source environmental data with advanced models to generate high-resolution, continuous maps of soil salinity, offering actionable intelligence for precision agriculture. In India, pioneering applications of DSM have shown promising results, from improving fertilizer efficiency and water use in Maharashtra to large-scale initiatives like the Soil Intelligence System in Andhra Pradesh, Bihar, and Odisha. The ICAR-Central Soil Salinity Research Institute (CSSRI) has also advanced national-level salinity mapping efforts, combining legacy soil data with remote sensing and ML approaches. Emerging tools such as UAVs further add local-scale precision, enabling dynamic monitoring of soil health. Together, these developments illustrate how DSM is reshaping salinity diagnostics, bridging science and practice, and paving the way for more sustainable land management strategies in the face of climate change and increasing soil degradation.

Keywords: Digital soil mapping, Machine learning, Remote sensing, Soil salinity

SOIL salinity, the accumulation of excessive salts in the soil, is one of the primary causes of soil degradation globally. According to the Food and Agriculture Organization (FAO), salt-affected soils (SAS) cover 1381 million hectares or 10.7 % of total land area globally, with the extent increasing in regions that depend heavily on irrigation. The spread of SAS is expected to worsen due to the dual impacts of climate change and unsustainable agricultural practices (FAO 2024).

Classification and diagnostic methods for salt-affected soils

SAS can be classified into saline and sodic soils based on their composition and properties. Saline soils have high concentrations of soluble salts, while sodic soils are characterized by excess sodium. Diagnosing the

presence of these soils traditionally involves measuring the electrical conductivity (EC) and sodium adsorption ratio (SAR) of the soil.

While traditional diagnostic methods are critical for soil health assessments, they face significant challenges, including being labour-intensive and spatially limited. Furthermore, such methods often lack the ability to provide high-resolution spatial data on soil salinity, especially across large areas.

Advancements in geospatial technologies for salt-affected soil diagnostics

Recent advancements in geospatial technologies have revolutionized the monitoring and mapping of SAS. Remote sensing (RS), geographic information systems

(GIS), and machine learning (ML) techniques have enabled the large-scale, high-resolution mapping of salt-affected areas. The integration of these technologies allows for the creation of digital soil maps that provide predictive, continuous data on soil salinity across vast regions.

Remote sensing and soil salinity detection

Salt-affected soils (SAS) are a major challenge for farmers, especially in arid and semi-arid regions where white crusts of salt often appear on the surface, stunting crops and reducing yields. Traditionally, diagnosing and mapping these soils relied on physical inspections, soil testing, and expert judgment. For instance, farmers and soil scientists would look for visible salt crusts, poor vegetation cover, or stressed plants as warning signs. Field surveys and sampling at different depths then helped determine the extent and severity of salt accumulation. In the 1990s, researchers even started using satellite images in “false colour” mode, where experts drew boundaries around areas that looked similar in colour, brightness, or texture—essentially hand-mapping salinity based on experience. While these conventional methods have played a crucial role, they are far from perfect: They are time-consuming, labour-intensive, and limited to discrete sampling points that cannot capture the full variation of salinity across large landscapes.

This is where modern geospatial technologies have changed the game. By combining remote sensing, GIS, and machine learning, scientists can now map salinity with much greater accuracy and efficiency. Instead of collecting hundreds of soil samples, satellite data can be fed into predictive models to estimate soil salinity over entire districts or regions. This approach provides a continuous picture of salt distribution and allows for large-scale monitoring something that was impossible with traditional methods.

RS in particular has become a powerful ally in the fight against soil salinity. Satellites can capture information from areas that are difficult to reach, track changes over time, and even distinguish subtle differences in soil or vegetation health. Optical remote sensing uses spectral reflectance—how soils and plants reflect light at different wavelengths to infer salinity levels. For example, stressed plants or bare salty patches reflect light differently from healthy vegetation, providing clues about underlying soil conditions. With frequent satellite passes, scientists can monitor how salinity changes over months or years, offering valuable insights for land management.

Studies have shown that newer satellites like Sentinel-2 perform better than older ones like Landsat, largely due to their higher resolution (10 meters vs. 30 meters) and more frequent coverage (every 5 days instead of 16). Sentinel data has been found to predict soil salinity with about 70% accuracy, compared to 66% for Landsat. But satellites alone are not enough—scientists also use algorithms ranging from simple regression models to advanced machine learning techniques like Random Forest (RF), Support Vector Machines (SVM),

and neural networks offering superior predictive performance compared to traditional geostatistical methods like Kriging. Each has its strengths: Neural networks can capture complex non-linear relationships, while RF reduces the risk of overfitting. Although no universal algorithm has emerged as the global “best fit,” machine learning consistently outperforms traditional methods for salinity prediction.

However, challenges remain. For example, in agricultural areas, spectral signatures of saline soils can be confused with other bright surfaces like roads, buildings, or even nearby salt ponds. Vegetation-based indices such as NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), or the Canopy Responsive Salinity Index (CRSI) are often used as indirect measures, since salinity affects crop growth and canopy temperature. Yet no single index works equally well across all regions. The Vegetation Soil Salinity Index (VSSI), for instance, is effective in coastal zones but often misclassifies dry, bare soils as saline in arid regions.

To overcome these hurdles, scientists are increasingly turning to Digital Soil Mapping (DSM). DSM combines remote sensing data with environmental variables such as climate, topography, and land use, and uses predictive models to generate continuous maps of soil salinity. Unlike conventional mapping or simple index-based methods, DSM can capture spatial variability more accurately and is adaptable to diverse landscapes. In effect, DSM is helping move soil salinity studies from isolated observations toward dynamic, data-driven solutions that support precision agriculture and sustainable land management.

Digital soil mapping (DSM)

DSM is a powerful approach for predicting soil properties over large areas using geospatial data and advanced modeling techniques. The SCORPAN model is often used in DSM to predict soil properties by integrating spatial and environmental covariates such as climate, topography, parent material, and vegetation. The equation for DSM is typically represented as SCORPAN model given below:

$$S = f(S, C, O, R, P, A, N) + \epsilon$$

Where S, Soil attributes at an unvisited location; f, Numerical model (e.g. decision tree, random forest, deep learning); C, Climatic properties; O, Organisms, vegetation, or human activity; R, Relief or slope; P, Parent material, lithology; A, Time factor (age); N, Location or relative spatial information; ϵ , Auto-correlated random spatial variation.

So, DSM can be defined as computer-assisted production of digital interpolated maps of soil properties using machine learning, deep learning, ensemble models or other statistical models that pool information from soil observations with information contained in correlated environmental variables as mentioned earlier in the previous paragraph as climate, organisms (presented through various remote sensing based indices), relief and parent material.

The application of DSM for salt-affected soils helps in producing high-resolution, continuous maps that overcome the limitations of traditional polygon-based mapping. DSM also benefits from the integration of remote sensing data, GIS, and other environmental data sources, allowing for real-time updates and dynamic monitoring of soil salinity.

Case studies related to use of DSM in India

DSM is quietly transforming Indian agriculture, with several success stories showing how data and technology can reshape the way farmers manage their soils. In Maharashtra's Vidarbha region, often associated with low productivity and farmer distress, digital soil health mapping using IoT sensors and geospatial tools has helped cotton and soybean growers cut fertilizer use by nearly 15%, save 20% water, and still boost yields by 25–30%. In Odisha's Khordha district, GIS-based nutrient maps revealed that more than 70% of farmland was acidic and nitrogen-deficient, giving farmers and policymakers the evidence they needed for targeted soil amendments. Further east, in Assam's Upper Brahmaputra Valley, researchers applied machine learning to predict soil organic carbon across silk-producing landscapes, providing vital insights into carbon storage and sustainable land management. In Tamil Nadu, scientists used legacy soil data with advanced models like Random Forest to generate 250-meter resolution maps of soil depth, texture, and coarse fragments, producing invaluable tools for precision farming and environmental planning. Large-scale initiatives are also underway: Soil Intelligence System (SIS) in Andhra Pradesh, Bihar, and Odisha is combining soil health card data, geo-statistics, and digital dashboards to create user-friendly soil maps built on FAIR data principles, while Bihar Agricultural University has embarked on a state-wide digital soil mapping programme aiming to cover all 38 districts by 2028. Together, these efforts demonstrate how DSM can empower farmers with actionable knowledge, reduce costs, improve soil health, and set Indian agriculture on a more sustainable and resilient path.

CSSRI's initiatives in digital soil mapping of salt-affected soils

The ICAR-Central Soil Salinity Research Institute (CSSRI) had developed a computerized database and visual interpretation-based maps of salt-affected soils, including saline, sodic, and saline-sodic categories, covering the entire country. Over time, significant advancements

have been made in the tools and methodologies used for soil salinity mapping. Recently, Mandal *et al.* (2023) generated a coastal salinity map using linear regression models, integrating laboratory-measured electrical conductivity of saturation paste extract (EC_e) data from various coastal locations with remote sensing indices. Their study estimated that approximately 1.294 million hectares of coastal land are affected by salinity. However, a comprehensive and high-resolution map of salt-affected soils across the entire country is still lacking.

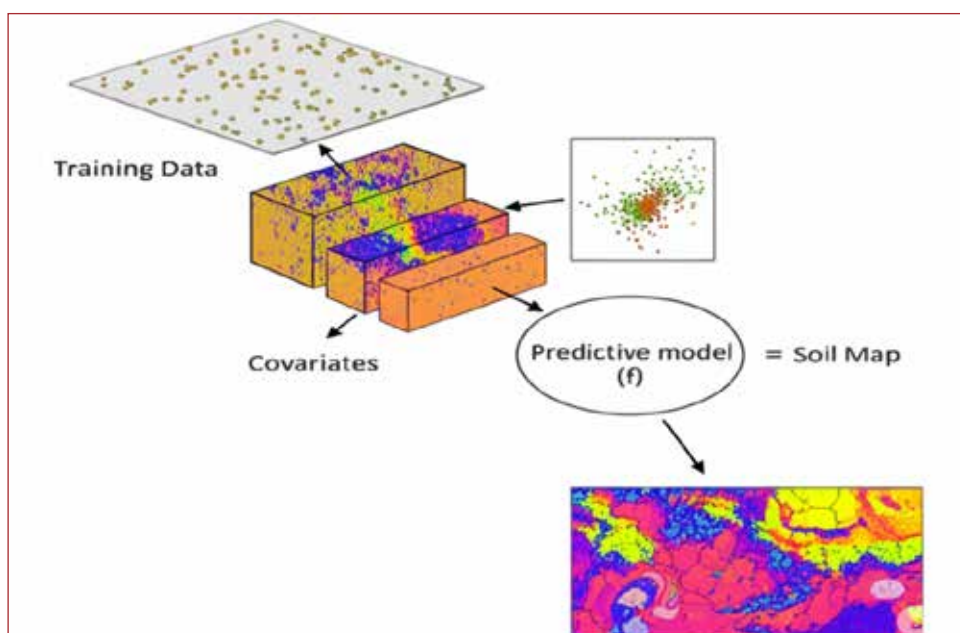
To address this gap, CSSRI has initiated the development DSM of salt-affected soils at the national level using advanced machine learning algorithms. These models integrate field observations with multi-source remote sensing datasets to generate predictive maps of salt-affected areas across India, offering improved spatial accuracy and aiding in evidence-based management and reclamation strategies.

Integration of UAVs in DSM for salt-affected soils

Unmanned Aerial Vehicles (UAVs) have emerged as an important tool in DSM, particularly for local-scale soil mapping. UAVs offer high-resolution data acquisition, flexibility in data collection, and the ability to operate in inaccessible areas. Studies have demonstrated their potential for mapping soil organic carbon (SOC) and other soil properties, which are essential for assessing soil salinity.

Future perspectives and challenges

The future of DSM in salt-affected soils will rely on further integration of machine learning, remote sensing, and environmental covariates to enhance predictive accuracy. Challenges remain in handling large-scale datasets, overcoming the impact of cloud cover, and improving sensor fusion techniques for better salinity detection across diverse land uses. The development of



Flow chart of digital soil mapping technique (AI-generated image)