remote sensing

Review

Challenges and Opportunities in Remote Sensing for Soil Salinization Mapping and Monitoring: A Review

Ghada Sahbeni [1,*], Maurice Ngabire [2,3], Peter K. Musyimi [1,4] and Balázs Székely [1]

1 Department of Geophysics and Space Science, Eötvös Loránd University, Pázmány Péter stny. 1/C, 1117 Budapest, Hungary; musyimipeter@student.elte.hu (P.K.M.); balazs.szekely@ttk.elte.hu (B.S.)
2 University of Chinese Academy of Sciences, Beijing 100039, China; ngabire01@mails.ucas.ac.cn
3 Key Laboratory of Desert and Desertification, Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou 730000, China
4 Department of Humanities and Languages, Karatina University, Karatina P.O. Box 1957-10101, Kenya
* Correspondence: gsahbeni@caesar.elte.hu

Abstract: Meeting current needs without compromising future generations' ability to meet theirs is the only path toward achieving environmental sustainability. As the most valuable natural resource, soil faces global, regional, and local challenges, from quality degradation to mass losses brought on by salinization. These issues affect agricultural productivity and ecological balance, undermining sustainability and food security. Therefore, timely monitoring and accurate mapping of salinization processes are crucial, especially in semi-arid and arid regions where climate variability impacts have already reached alarming levels. Salt-affected soil mapping has enormous potential thanks to recent progress in remote sensing. This paper comprehensively reviews the potential of remote sensing to assess soil salinization. The review demonstrates that large-scale soil salinity estimation based on remote sensing tools remains a significant challenge, primarily due to data resolution and acquisition costs. Fundamental trade-offs constrain practical remote sensing applications in salinization mapping between data resolution, spatial and temporal coverage, acquisition costs, and high accuracy expectations. This article provides an overview of research work related to soil salinization mapping and monitoring using remote sensing. By synthesizing recent research and highlighting areas where further investigation is needed, this review helps to steer future efforts, provides insight for decision-making on environmental sustainability and soil resource management, and promotes interdisciplinary collaboration.

Keywords: environmental sustainability; monitoring; salinization mapping; soil; remote sensing

Citation: Sahbeni, G.; Ngabire, M.; Musyimi, P.K.; Székely, B. Challenges and Opportunities in Remote Sensing for Soil Salinization Mapping and Monitoring: A Review. *Remote Sens.* **2023**, *15*, 2540. https://doi.org/10.3390/rs15102540

Academic Editor: Greg Okin

Received: 31 March 2023
Revised: 3 May 2023
Accepted: 10 May 2023
Published: 12 May 2023

1. Introduction

Soil salinization is a major environmental hazard affecting agricultural productivity and food security worldwide [1]. It adversely influences soil structure, nutrient availability, and plant growth, leading to reduced crop yields and, in extreme scenarios, desertification [2,3]. The increasing levels are caused by diverse natural and anthropogenic factors, such as inadequate irrigation practices, fertilizer overuse, and land use changes [4]. In addition, climate change impacts on soil salinization are a significant concern, with weather patterns playing a fundamental role in increasing salt content around the rhizosphere [5,6]. This is particularly noticeable in areas with shallow water tables and degraded groundwater quality [7]. Therefore, real-time monitoring of soil salinity levels is essential for effective soil management and sustainable agriculture [8,9].

Subsequently, remote sensing has proven to be an attractive alternative for mapping and monitoring salinization in large-scale and heterogeneous landscapes, especially under different land use and land cover types and areas where socio-culturally different farming cultivation techniques are maintained [10,11]. Remote sensing data from satellite imagery and aerial photography offer valuable information on various environmental parameters, including vegetation cover, soil composition, and moisture content, which are interconnected to salt content [12]. By analyzing and interpreting such data, researchers and practitioners can generate detailed maps and spatial models of salinity distribution, which inform land management decisions and support the development of effective strategies for risk mitigation [13,14]. Over the past few decades, remote sensing has undergone significant advancements, enabling the collection of high-resolution data on various scales [15,16]. As research progresses, various tools have emerged [17–19], including multispectral imaging sensors which capture information at different wavelengths, leading to more accurate results with higher spatial resolution [20]. This enables the extraction of auxiliary data on soil properties such as moisture content, organic matter, and salt content by analyzing the reflected radiation from the surface [21]. To map soil salinization, many researchers have used the concept of spectral index, a combination of pixel values from two or more spectral bands [22–24]. As they rely on the variance in reflectance between the visible (VIS), near-infrared (NIR), and shortwave infrared (SWIR) bands, they can be useful in detecting changes in salt content [25].

In addition to multispectral imaging, synthetic aperture radar (SAR) has recently become one of the most efficient remote sensing tools for soil salinity detection due to its insensitivity to weather conditions, unlike optical remote sensing [26]. SAR uses microwave signals to penetrate the soil and retrieve information on soil moisture [27] and structure [28]. Therefore, it can generate relevant information on soil's electrical conductivity (EC), which is closely related to its salt content [29,30]. The backscatter coefficient (sigma-0), as a measure of the microwave energy reflected back to the sensor, is a commonly used parameter for mapping soil salinity by integrating it into empirical models [31].

The accuracy of salinity mapping has been significantly improved by the fusion of multiple data sources, such as optical and SAR data [32]. As optical sensors can capture surface reflectance and vegetation cover, SAR sensors penetrate the vegetation and retrieve information on soil properties [33]. Moreover, integrating remote sensing data with other data types, such as those on land cover, land use and topographic features, provides even more accurate estimations [4,34]. By combining data from different sensors and platforms, researchers can take advantage of the complementary strengths of each data source and overcome their limitations.

As the field of salinization mapping continues to progress, it has become increasingly evident that integrating remote sensing data with machine learning offers a more robust framework for effectively processing large datasets and generating more accurate products [35]. Machine learning algorithms, such as random forest [36] and support vector machines [37], have been remarkably efficient at data processing and analysis, enabling prediction models to learn from the spectral and spatial patterns and produce estimations based on input features [38,39].

Despite the remarkable growth, remote sensing applications for salinization assessment pose significant challenges, including issues with data resolution, spatial and temporal coverage, acquisition costs, data processing and storage. In this regard, a comprehensive review of remote sensing's current state can help identify areas for further research and technological development while providing a valuable resource for researchers, policy-makers, and stakeholders concerned with environmental sustainability and land management.

2. Remote Sensing for Mapping Soil Salinization

Not only do environmental factors, such as soil type, land use, topography, and climate, play a leading role in salinization expansion, but anthropogenic actions, such as the inadequacy of drainage systems and ineffective irrigation activities over an extended period, also have a direct impact on this dynamic process [4,40,41]. In light of this, the availability of spaceborne and airborne platforms has significantly facilitated the monitoring of environmental hazards by providing vast amounts of data that can be applied to diverse fields, from sustainable agriculture, land surveys, and climate change to risk mitigation [42]. Enhanced data in terms of spatiotemporal and spectral resolutions offered by these systems have enabled researchers to monitor changes inland and identify salinity patterns at various spatial scales. In addition, when combined with geospatial data, ground-based systems such as the electromagnetic induction instrument (EMI) give valuable insights into the salinization status at both local and canopy scales, allowing policy-makers to gain a more comprehensive understanding of the complex dynamics of salinization at the field level [43].

Integrating remote sensing data with robust analytical techniques has shown great promise in salinization mapping, as suggested by many researchers. A study conducted in Qom Valley in Iraq demonstrated that combining Landsat 8 OLI's spectral indices and topographic features can accurately predict and map soil salinity [44]. Further, jointly using Sentinel-2 Multispectral Imager (MSI) data with laboratory measurements to build a machine learning model for soil salinity estimation in the northern margin of the Tarim Basin (China) provided a timeless scientific reference for futuristic scenarios related to salinization expansion in arid areas [45]. Field observations, Landsat 5 TM and radar data retrieved from ALOS (Advanced Land Observing Satellite) and PALSAR (Phased Array L-Band Synthetic Aperture Radar) have provided a promising solution for salinity monitoring in central Iraq with lower costs, as suggested by the authors of [46]. In the Great Hungarian Plain, the authors of [47] employed spectral indices and principal components derived from Landsat 8 OLI data coupled with multiple linear regression analysis to map salt content distribution in the area. The study proved the potential of multispectral data, with the outperformance of ridge regression, yielding an overall accuracy of 75%. Thus, linear regression modeling using remote sensing-based variables can be significantly effective for locally assessing soil salinity.

As pattern changes in land use and land cover supposedly vary with salinization magnitude, relevant data can be effectively employed to predict soil salinity levels [48,49]. In Europe, among several land cover inventories, the CORINE system has solely provided this information for over two decades, which fortunately could be used to map salinization by many researchers [4,50,51]. In addition, a study conducted in Dakhla Oasis, located in the western desert of Egypt, showed a discrepancy in soil salinity estimations based on the linear spectral unmixing (LSU) related to land surface temperature over different land cover types and altitudes [52]. These findings are consistent with another study conducted in Korat province (Thailand), emphasizing the importance of vegetation cover, soil characteristics, and seasonal fluctuations in mapping soil salinization via remote sensing [53].

Over the past decade, research focus has shifted from traditional, labor-intensive methods of measuring salt content through field surveys and laboratory analysis towards a greater reliance on remotely sensed data often used with limited reference datasets for calibration purposes [54]. Based on a qualitative analysis of the Scopus database, we have run an advanced search query to find available peer-reviewed research papers, with the following terms: soil salinization, monitoring, and remote sensing. Significant progress was made in spaceborne and airborne remote sensing systems between 2014 and 2023, which was fundamentally driven by the launch of Landsat 8 in 2013 and the subsequent launches of Sentinel 1 and Sentinel 2 in 2014 and 2015. Figure 1 demonstrates a positive trend in research studies that employed remote sensing for salinization assessment in the same timeframe. However, the sudden drop in 2021 is attributed to a shift in research focus toward other areas or technologies, funding limitations, and reference data unavailability due to the geographic inaccessibility caused by extreme global events such as COVID-19. Given the rise in technology availability and professional knowledge worldwide, this increasing trend is expected to continue in 2023.

Extensive data have been used to assess salinization by measuring the changes in reflectance along the spectrum from visible to infrared (IR) for different salinity levels accompanied by vegetated and sparsely vegetated profiles to distinguish the disparities. Usually, the interaction between soil and spectral energy differs based on the emitted radiation and the surface properties, whereas salt-affected soils often exhibit whitish or grayish crust on the topsoil [55,56]. In this regard, the authors of [57] found an increase in reflectance in the visible range, particularly in the blue (450 nm) range with excessively saline soils. Moreover, higher reflectance occurs in the SWIR region (1100–3000 nm), revealing more sensitivity to salt content, as discovered by the authors of [58] and [59]. According to the authors of [60], alterations in surface roughness caused by salinity induce shifts in spectral reflectance. Many studies have used SWIR and thermal infrared (TIR) spectroscopy to quantify salt content [61,62]. This means various properties influence salt-affected land identification, including soil color, texture and moisture content.

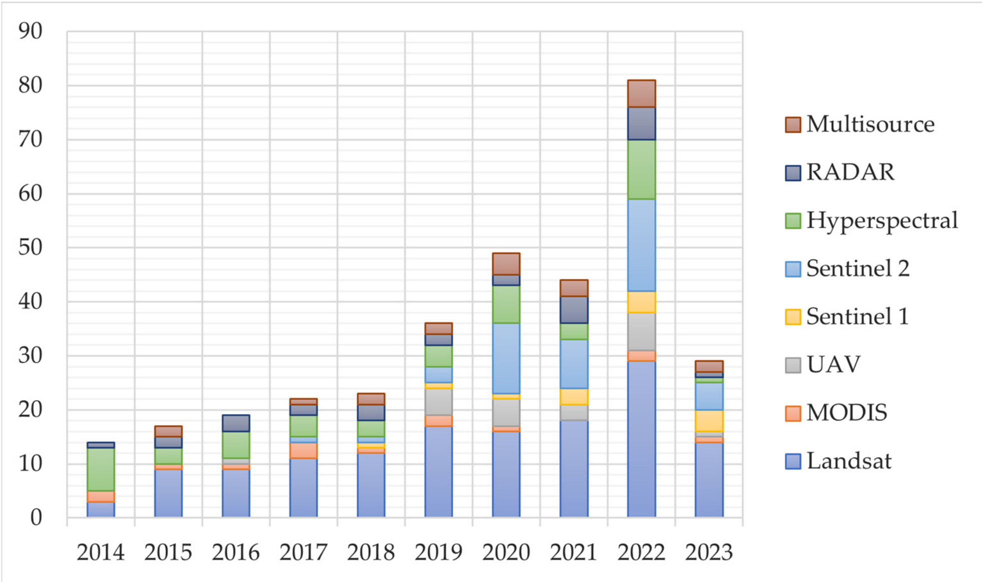

Figure 1. Progress of remote sensing application in salinization mapping based on available studies in Scopus between 2014 and 2023. The yearly number of studies using various sensors has significantly increased from 14 in 2014 to 81 in 2022. The availability of satellite data and the development of sophisticated instruments with higher spectral and spatial resolutions have contributed to this growth.

Consequently, hyperspectral remote sensing has facilitated salt characterization by establishing predictive models to estimate salt content more accurately [63] or through creating spectral libraries for various salt types based on their narrow continuous bands [64], which cover the entire spectrum from visible, near-infrared to SWIR and TIR [64]. The situation is quite different in vegetated areas since reduced crop growth induced by saline stress causes chlorophyll and other pigment alterations and increases heat emissions. This presents a potential avenue to use thermal remote sensing for qualifying vulnerable areas based on vegetation status, except for halophytes [65].

While remote sensing has provided new opportunities for soil salinization assessment, this task complexity highlights the need for addressing data availability, investigation scale, and mapping approaches, which are discussed in the following section.

3. Uncovering Data Availability: Investigating the Scope and Scale of Accessible Data

While remote sensing has become a valuable tool for salinization assessment, its successful implementation depends on data availability and the investigation scale. Many studies have applied thermal, multispectral, hyperspectral, and microwave sensors to quantify salt content [66–70]. As these sensors have varying spectral, spatial, radiometric, and temporal resolution properties, this has a massive impact on the scope and relevance of the study [71]. Table 1 illustrates the most common sensors used in soil salinization detection and their properties.

Table 1. An overview of commonly used sensors for salinization assessment and their characteristics, including spatial, spectral, and temporal resolutions, acquisition cost, and applicable mapping scale. The listed sensors range from regional/global-scale sensors such as MODIS to high-resolution pixel-plot sensors such as UAV-based ones and are used for mapping at different scales depending on their spatial coverage.

Sensor	Spatial Resolution (m)	Spectral Resolution	Temporal Resolution (Day)	Acquisition Cost	Applicable Mapping Scale
MODIS	250–500	36	1	Free	Regional/Global
Landsat	30–120	8–11	16	Free	Local/Regional
Sentinel 2	10–60	13	5	Free	Local/Regional
ASTER	15–90	14	16	Low	Local/Regional
IKONOS	4	5	3	High	Local
PlanetScope	3	8	1	Low/Medium	Local/Pixel plot
Worldview	<5	9	1	Low/Medium	Local/Pixel plot
Sentinel 1	5		6	Free	Local/Regional
RADAR	5			High	Local/Regional
Hyperspectral	1	>200		High	Pixel-plot
Unmanned Aerial Vehicle (UAV)	~2.5 cm	>200		Medium/High	Pixel-plot

Up to this point, these sensors have demonstrated their ability to detect patterns at spatiotemporal scales, thanks to their spatial resolution ranging from a few centimeters to several hundred meters with a revisit time from one day to two weeks [72]. Therefore, selecting a remote sensing system for salinization assessment depends on the sensor's technical characteristics and data availability. In this regard, Sentinel missions, i.e., Sentinel-1 and Sentinel-2, have recently dominated the European imaging systems as part of the Copernicus program funded and developed by the European Space Agency (ESA). The Copernicus program is an Earth observation program that examines Earth's surface and its environment for the benefit of the European community and provides free information services [73]. Due to their high spatial resolution (ranging from 10 to 60 m) and fast revisit time (ranging from five days for Sentinel-2 and six to 12 days for Sentinel-1), Sentinel products have become a valuable data resource for many Earth observation research projects, including salinization risk management [74].

On the other hand, fewer studies have used hyperspectral data to mainly focus on specific areas, usually distinguished by an extremely saline environment, e.g., [75–77]. As such, the authors of [78] studied salinity variation across the Yellow River Delta region in China using a combination of laboratory and hyperspectral data retrieved from EO-1 Hyperion. A soil salinity spectral index (SSI) was developed from continuum-removed reflectance (CR-reflectance) in 2052 and 2203 nm to examine the spectral absorption properties of salt-affected soils, yielding a correlation coefficient (R^2) of 0.91. The Hyperion reflectance image was processed using the final model, resulting in a quantitative salinity map with an RMSE of 1.921 g/kg and an R^2 of 0.63. The study elucidated the reliability of hyperspectral data in estimating salt content due to their high spectral resolution. This aligns with [79], the authors of which used HJ-1A hyperspectral data to detect topsoil salt components across another study area in China. The research successfully established a robust relationship between salt content and reflectance spectra.

We performed a quick query on the Scopus database to identify the most widely used remote sensing platforms for soil salinization assessment in peer-reviewed research papers. We used the following search keywords: Landsat, Sentinel-2, MODIS, UAV, ASTER, IKONOS, hyperspectral, radar, remote sensing, and soil salinization. Figure 2 illustrates the overall distribution of remote sensing data used in soil salinization-related studies.

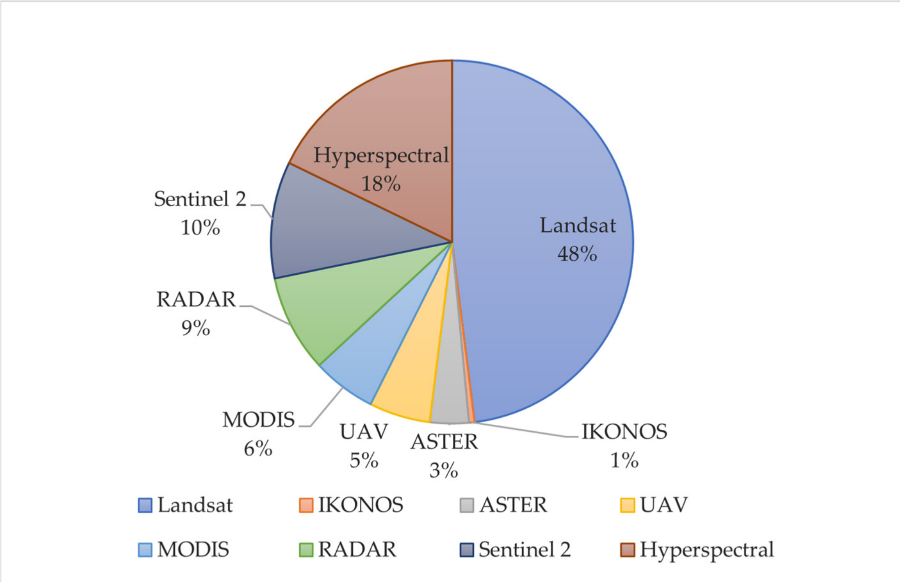

Figure 2. Distribution of data types used in accessible research papers related to soil salinization assessment. Remote sensing data selection considers several factors, such as cost, accessibility, spatial and spectral resolutions, and the research scale. Available studies have used various instruments, such as multispectral, hyperspectral, and microwave sensors. Open-access satellite data has gained popularity among researchers recently due to their cost-effectiveness and widespread availability, unlike those of commercial platforms.

Optical remote sensing has been widely applied due to its practicality in data processing and storage, as well as its moderately extended spatial coverage and high resolution, which is in alignment with [71]. In contrast, fewer studies have used high-resolution commercial sensors such as ASTER (~15 m), IKONOS (~4 m), and UAV-based ones (<1 m), which is consistent with [72]. The associated high costs and limited coverage are the primary causes why its application is restricted to narrow geographic regions. Nevertheless, accessing valuable information at different scales is essential in adopting appropriate mitigation strategies.

Although the potential of active remote sensing in assessing soil salinization is well recognized [80], the search yielded fewer research papers, reflecting the challenges of limited access to such data. A study conducted in Keriya River Basin, Northwest China, highlighted the efficacy of active remote sensing to map soil salinity by applying an integrated threshold of backscattering values from PALSAR and Radarsat-2 polarimetric images. The research yielded enhanced results in separating moderately and extremely saline soils [81]. Further, another study by the authors of [33] used ERS-1/2 and Sentinel-1 SAR time-series data acquired between 2000 and 2018 to identify salinity levels in Hortobágyi National Park in Hungary, one of the most naturally alkaline environments in Europe. The research demonstrated the usefulness of SAR data in salt detection with an outperformance of Sentinel-1 SAR products over ERS-1/2 due to its higher resolution and its operation with a dually polarized antenna which could identify better subtle changes in salinity levels.

Based on Figure 2, limited research focused on radar and hyperspectral data compared to multispectral data application (i.e., MODIS, Landsat, and Sentinel 2 MSI). This can be associated with many factors, including data availability and resolution, spatial coverage, acquisition costs, and processing and storage infrastructures since those products require high processing and storage capacities.

3.1. Local Scale

Remote sensing has proven valuable for accurately and timely detecting excessive soil salinity, enabling automated and reproducible monitoring of salinization processes in agricultural systems. This is fundamental for soil conservation and agricultural productivity at the local scale. Notably, data retrieved from thermal and hyperspectral sensors have shown particular sensitivity to saline stress, making them advantageous in characterizing vegetation conditions and estimating salt content [82]. By capturing synoptic information on various physiological processes under saline conditions, such as thermal energy release and canopy health and vigor, they portray the situation on the surface [83]. This information helps detect minimal changes in the landscape early on, allowing prompt interventions to avoid soil fertility and biodiversity losses [84]. Intensive research has focused on studying salinity distribution on the field scale [85–87]. Although each study has been conducted in a specific spatiotemporal context on different cropping systems from rice to olive trees and in diverse geographical locations (i.e., Portugal, China, and Tunisia) under different environmental conditions, from semi-arid to irrigated systems, indicating the versatility and applicability of remote sensing under various agricultural settings. The common conclusion is that remote sensing data, specifically satellite imagery with relatively high spatial resolution, i.e., Landsat and Sentinel-2, can be used to assess salinity in agricultural lands with high accuracy when combined with electromagnetic induction techniques to measure reference values.

The operational capabilities of remote sensing at the farm scale have significantly improved due to the increasing availability of high-resolution platforms such as UAVs [88]. In recent years, UAVs have shown their utility in improving accuracy and providing more insights into intensive soil monitoring [89]. Likewise, imaging spectroscopy techniques, such as matched filtering (MF) and mixture tuned matched filtering (MTMF) with multi-spectral advanced spaceborne thermal emission and reflection radiometer (ASTER) images, have been successfully used to map saline soils and determine crop yield reduction and land degradation caused by salinization at the farm level [90].

Integrating remote sensing has become a fundamental component of precision agriculture, enabling the detection and monitoring of changes in salinity levels at the plot scale. Accordingly, accurate monitoring can support soil conservation efforts and mitigate the adverse impacts of climate change on agriculture. By optimizing the use of resources and inputs offered by remote sensing, farmers can effectively manage salt-affected lands and optimize crop yield while contributing to sustainable agriculture practices.

3.2. Regional Scale

As a practical and cost-effective tool, remote sensing generates valuable information about salinization risks and vulnerable areas requiring intervention, efficiently covering large areas and detecting hotspots that traditional field-based surveys fail to cover [91]. Recent research has well established that incorporating it with field surveys can provide a more comprehensive understanding of salinization dynamics, at least on a smaller scale, due to the coarse spatial resolution of most satellite imagery products. As such, many studies have employed it to regionally assess salinization under different scenarios, from complex agricultural systems to drylands [92,93]. A study by the authors of [94] used imaging spectroscopy data from an SR-3500 spectrometer combined with machine learning to map soil's electrical conductivity in the northern Yinchuan Plain (China). Among the six models, the extremely randomized trees-based model performed the best, with R^2 values of 0.96 and 0.98. Another study by the authors of [95] assessed soil salinity in San Joaquin Valley (CA, USA) using multi-year Landsat 7 ETM+ data in combination with canopy reflectance and the canopy response salinity index (CRSI). The research yielded an estimation model with R^2 values of 0.61 and 0.73, where CRSI, crop type, rainfall, and temperature were the most influential variables. This further proves that recent research efforts have provided significant theoretical support for salinization mapping and monitoring at the regional scale.

Nonetheless, a more comprehensive understanding of salinization dynamics will enable targeted intervention strategies to mitigate its risks and keep it under control [96]. Despite the advantages brought on by remote sensing-based approaches in this regard, fundamental challenges must be addressed to ensure its valid representativeness. Not only must the spatial and spectral resolutions of sensors be carefully selected to ensure that the data obtained are suitable for the study scale, but atmospheric interference and calibration issues should be addressed to optimize the product's accuracy [97]. To fully harness the potential of remote sensing, it is crucial to develop robust techniques that can address the associated challenges and ensure the accuracy and validity of acquired data. By doing so, we can access reliable and up-to-date information to develop effective strategies to mitigate soil salinization impacts inland.

3.3. Global Scale

Salinization is expanded over more than 1 billion hectares worldwide and constantly increasing, according to FAO and ITPS report [98]. Other estimations of total salt-affected lands differ somewhat substantially. According to [99], the disparity in current estimates of saline soils is frequently caused by discrepancies in methodology for data collection and analysis; hence, only a rough estimate can be provided.

Currently, the Harmonized World Soil Database represents the most popular database that delivers a global coverage of soil salinity data [100]. While this database represents a valuable resource for global studies, it has a few limitations to consider, such as the discontinuity of pixel values, the coarse spatial resolution (>1 km), and outdated information on soil salinity, with its most recent version (v1.2) released in 2012 [101]. A lack of spatial resolution and accurate data highlights an urgent need for an updated worldwide soil salinity map.

To address this issue, the Global Soil Partnership (GSP) and the Food and Agriculture Organization (FAO) have initiated efforts to create a more comprehensive global map of salt-affected soils, the Global Map of Salt-affected Soils (GSASmap V1.0.0), which was released in 2020 [102]. The product includes contributions from over 118 countries, with more than 350 national experts involved in the harmonization process [103]. Each country subsequently generated its maps following approved technical standards set by FAO. The map illustrates SAS spatial distribution at the topsoil (0–30 cm) and subsoil (30–100 cm). According to GSASmap, which covers 85% of the worldwide land surface, salinization affects around 424 million ha of topsoil and 833 million ha of subsoil [104], with nearly two-thirds of global SAS falling under arid and semi-arid climates [105].

Despite the progress made, monitoring salinization is an ongoing process, and there is still much to be done to improve the accuracy of available maps [106]. This emphasizes the necessity for further research and international collaborations to address this growing issue in real-time and promote sustainable land management practices.

4. Mapping Approaches

Although diverse approaches are available for generating accurate salt content estimates, including in situ and laboratory analysis, they are time-consuming and require intensive sampling and enormous labor costs, making them impractical for larger-scale studies [107]. Alternatively, indirect methods such as remote sensing can provide relatively useful information at lower costs based solely on electromagnetic energy, enabling continuous monitoring of saline environments at a broader range [108]. Recent progress in machine learning and artificial intelligence has tremendously supported the establishment of more robust digital soil mapping approaches, providing reliable predictive tools for salinization assessment [109].

Substantially, changes in land cover due to excessive salinity, such as deterioration of soil structure, organic matter loss, changes in water balance, and loss of biodiversity, result in detectable differences in reflectance characteristics, which can be detected by sensors in high to extreme scenarios [110]. The most commonly used methodologies can be broadly categorized into three main types: statistical models, machine learning algorithms, and physical models. Statistical models such as those based on linear regression [111,112] use an empirical approach to analyze the correlation between variations in remote sensing derivatives such as spectral indices and principal components with field measurements. These models are simple and easy to develop but fail to capture complex interactions between variables. As a result, this affects the methodology's replicability since there may be other factors involved that interact in synergy or solely, which are not captured by simple estimation models. Therefore, the model fails to yield accurate results without considering these influential indicators when replicating the research workflow. In this context, hybrid modeling techniques are increasingly integrated for salinity prediction [113,114], particularly in poorly sampled locations. These methods combine the strengths of various models and sensors to generate more accurate and reliable estimates. Geostatistical models such as co-kriging and regression kriging rely on a spatial correlation, assuming that locations closer to each other have similar properties, while a regression analysis between two variables or more is exploited to predict the dependent variable's distribution in lowly sampled areas [4,115]. Although hybrid models' main goal is to overcome individual models' limitations by combining them, their effectiveness highly depends on the nature of the data, the significance of the correlation between covariates, and the research question. Thus, a hybrid technique application becomes irrelevant if no significant correlation exists between the model covariates. Consequently, it is crucial to carefully select and combine the models based on the research scope and available data to obtain the most accurate and reliable estimations. For instance, cubist models are based on a hybrid approach that combines regression analysis and decision tree modeling techniques to enable accurate predictions based on input data while employing boosting with multiple training data points to improve accuracy and balance the variables' weights [116]. Through generating a set of rules to combine input variables, each rule is associated with a linear model [117]. This method involves constructing a series of decision trees, each with adjusted weights, to produce a model that accurately reflects the patterns in the data [118]. It can be advantageous in cases where the relationship between input variables and the predicted outcome is complex and difficult to discern using traditional statistical models such as soil salinity modeling [119,120]. Nevertheless, this is quite different for geostatistical models [121–123], although they rely on statistical assumptions about underlying spatial variability to estimate salinity at unsampled locations. Some geostatistical methods, such as the stochastic simulation technique [124], can be considered process-based modeling, as it involves using physical parameters and equations to estimate the parameter of interest. On the other hand, machine learning-based models [125], such as neural networks [126], support vector machines [127], random forests [128], and extreme gradient boosting [129], use advanced mathematical models to analyze enormous and complex datasets for prediction. These models can be computationally intensive and may not be as easy to interpret as most statistical models. Physical models, such as the soil, vegetation and atmosphere transfer (SVAT) model [130], are process-based and numerical models that simulate the physical processes controlling salt accumulation and vegetation growth. While they can be computationally demanding, they provide a more in-depth understanding of the underlying physicochemical mechanisms at play. Their simulation capabilities allow physical models to test various hypotheses and scenarios that may not be directly observable in the field. A comparative study conducted by the authors of [131] between a physical model and three ML models, including distributed random forest (DRF), gradient boosting machine (GBM), and deep learning (Deeplearning) for salinity estimation at the canopy scale, found that machine learning-based models have predictive power similar to physical-based models; however, their performance primarily depends on the prediction scenarios and input variables. In the coastal rural areas of Bangladesh, research was carried out by the authors of [132] to explore the potential of salinity using Landsat 8 OLI data. The study used various vegetation and salinity indices in a linear regression analysis-based approach to determine the statistical association between these indices and ground-measured electrical conductivity to yield a low correlation between the ground EC and the pixel values of generated maps, suggesting that the indices are not sufficient to assess salinity. This eventually contradicts other research work carried out in the same context, which suggests differently. In the oasis lands of Egypt, a study conducted by the authors of [133] to map salinity using different statistical models based on Landsat 8 OLI and imaging spectroscopy data revealed that the used spectral indices had low to moderate correlations with EC values, with an R^2 ranging between 0.27 and 0.64. Although this research recommended Landsat-based spectral indices to produce spatial distribution maps, a further investigation is suggested to explore the produced models' dependencies and their validity under other climatic conditions. In the Ebinur Lake region in China, a bootstrap hybrid machine-learning framework was established by combining Sentinel-2 MSI data and environmental covariates [134]. The research initially compared four machine learning methods (i.e., bagging, classification and regression tree, random forest, and gradient boosting regression tree (GBRT)) to conclude that the models driven by spectral information and environmental covariates explained up to 88% of data variability, with the superiority of GBRT. The proposed approach offers a soil salinity mapping strategy with a 10 m resolution and high accuracy in poorly sampled locations, which can eventually help in future land restoration projects.

Although several remote sensing methods have been proposed for determining soil salinity, no widely accepted standard can consistently generate accurate data across diverse environmental conditions [135]. The accuracy of these methods can vary significantly across different regions, indicating the challenge of creating a globally harmonized data system. Consequently, producing a comprehensive and reliable global soil salinity map remains complicated.

Ideally, combining the abovementioned approaches and fusing multi-source data allow extracting the maximum amount of information from remotely sensed data while considering the complex interactions between environmental factors. The choice usually depends on the research scope, the available data, and the computational resources. Table 2 provides an overview of the most commonly used methods for salinization assessment.

Table 2. Comparison of modeling techniques for soil salinization mapping based on remote sensing data. This table provides an overview of commonly used modeling techniques for remote sensing data analysis, their estimated accuracy range, and their strengths and weaknesses. The estimated accuracy range of each method is based on the existing literature and may vary depending on the specific application and data used.

Modeling Technique/Algorithm	Estimated Accuracy Range (%)	Strengths	Weaknesses	Example Studies
Linear Regression	40–50	Simple and efficient; can identify linear relationships	Assumes only linear relationships	[136]
Multiple Linear Regression	60–80	Can account for multiple variables	Assumes only linear relationships	[20,137]
Decision Trees	70–85	Easy to interpret; can handle nonlinear relationships	Prone to overfitting	[23]
Random Forest	80–90	Good for nonlinear relationships	Can be slow with large datasets	[138,139]
Support Vector Machines	75–90	Can handle high-dimensional data	Prone to overfitting	[140,141]
Artificial Neural Networks	80–95	Can learn complex relationships	Can be prone to overfitting	[142,143]
Spectral Indices	60–80	Simple and fast, it can provide helpful information about vegetation and soil properties.	Limited to specific vegetation and soil types, and sensitive to atmospheric interferences	[144,145]
Deep Learning	90–95	Can learn complex relationships	Requires large amounts of data and computing power	[146,147]
Maximum Likelihood Classification	60–80	Simple and easy to implement	Requires accurate training data and assumes a normal distribution of pixel values	[148,149]

Table 2 summarizes the main approaches used in recent studies, encompassing the estimated accuracy range, strengths, and weaknesses of each method. Deep learning and artificial neural networks have the highest estimated accuracy ranges of 90–95% and 80–95%, respectively. While multiple linear regression and spectral indices have significantly lower accuracy ranges of 60–80%, linear regression has the lowest expected accuracy. This can be explained by the fact that deep learning approaches focus more on the complex nonlinear connections between covariates, which is more realistic than the assumption of linearity. Researchers must consider the available data, investigation scale, and desired accuracy to choose an appropriate mapping approach for salinization assessment. The specific characteristics of the study area, such as vegetation cover, land use, and soil type, should also be studied.

It is crucial to address the challenges associated with this topic, including data availability, spatial resolution, and investigation scale. By considering the strengths and weaknesses of different methodologies, researchers can build more practical tools for assessing soil salinization based on remote sensing data.

5. Challenges in Salinization Mapping

Soil salinization assessment via remote sensing poses several challenges that must be addressed to deliver reliable information on a spatiotemporal framework. Substantially, the remote sensing community faces a trade-off between data quality, spatial coverage, acquisition costs, and high accuracy [150]. One of the primary challenges is the limited spatial coverage. As most sensors have low spatial coverage, this has restricted soil salinization studies mainly to a local scale [151].

When tracking changes in soil salinity over an extended period, the limited temporal coverage of remote sensing data presents another challenge. Since salinity can frequently fluctuate in response to various factors, such as climate variability, irrigation practices, and land management activities [152], it must be continuously evaluated to identify the causes and impacts in the long term. Collecting and comparing remote sensing data at different time intervals allows the detection of patterns and trends in soil salinization, enabling a better understanding of its dynamics for more effective intervention strategies to be developed. In the Yellow River Delta, the authors of [153] established a novel remote sensing monitoring index of salinization based on a three-dimensional feature space model using Landsat data. The research showed an increasing trend in salinization intensity between 1984 and 2022 due to the inadequate agricultural systems adopted. The authors of [154] extracted Sentinel-2 MSI-based indices to monitor soil salinity in a typical saline zone in the Weigan River–Kuqa River Delta Oasis. The study proved that using remote sensing-based monitoring models in this context is fundamental to comprehensively grasp the salinization magnitude and enhance land management practices on the watershed scale. Therefore, the concept of temporal variation is fundamental for the success of remote sensing-based monitoring efforts, as proven by these studies.

Landsat missions have continuously acquired data since the 1970s, providing extensive temporal coverage for analyzing land use and cover changes [155]. This can be leveraged to monitor salinization and even predict future trends based on past data. In comparison, other space missions, such as MODIS and Sentinel 2, have had less archived data since 2002 and 2015, respectively. Although they provide relevant information, more extended coverage remains essential for temporal analysis-related studies, given the climate and land cover changes that have gradually accelerated salinization expansion in some regions in recent decades [156].

While hyperspectral data have shown higher efficiency [157], they are limited in use compared to multispectral data, which have lower efficiency but broader spatial coverage [158]. The application of hyperspectral data is constrained by their high cost, low temporal resolution, and restricted spatial coverage. These limitations make it difficult to develop comprehensive and accurate salinization maps that could inform and assist in developing soil management strategies. Nevertheless, the emergence of new generations of hyperspectral satellites such as the Italian *PRecursore IperSpettrale della Missione Applicativa* (PRISMA), American Hyperspectral InfraRed Imager (HyspIRI), Japanese Hyperspectral Imager Suite (HISUI), and German Environmental Mapping and Analysis Program (EnMAP) is revolutionizing soil mapping by providing higher spatial and spectral resolution data [159–161]. With their advanced capabilities, these satellites can offer a wealth of information on the composition and properties of the land surface, allowing more detailed and accurate soil salinity mapping.

Additional challenges may arise in some regions, such as those with dense vegetation and high cloud cover [162]. Under dense vegetation cover, remote sensing data acquisition and accuracy can be limited, with the obstructed view of the soil surface making it impossible to directly detect salt content variations from bare soil, reducing mapping accuracy. Similarly, cloud cover can hinder the acquisition of optical data, resulting in limited temporal coverage and mediocre accuracy, which can be addressed by implementing radar data instead to avoid the atmospheric effects associated with optical data [163].

Validation based on ground truth data can improve salinization products derived from remote sensing, but obtaining reliable field data can be complex due to factors such as the heterogeneity of soil properties and salinity distribution, the lack of uniformity in the methods used to collect and analyze soil samples, and the inaccessibility of some locations [164]. Standardized methods for collecting and analyzing field data are essential to account for soil heterogeneity and salinity distribution across various regions. This task requires the involvement of soil experts and environmental scientists with local knowledge to ensure the representativeness of field surveys.

Moreover, data processing and analysis pose another challenge to accurately assessing soil salinity spatiotemporal distribution. With the enhancement of data quality retrieved from sensors, the amount and dimension of generated information can reach the terabyte scale, making it necessary to adopt efficient methods for processing, analysis, and storage without affecting data quality [165]. Integrating multi-sensor data should also be further explored to improve the accuracy of salinization maps, though it requires supplementary efforts in terms of data processing and management, as well as high-performance computing resources. Addressing these challenges involves establishing processing algorithms that meet the operational requirements of soil experts and remote sensing scientists [166].

Despite these challenges, remote sensing offers opportunities to better monitor and map soil salinization. Establishing new data processing and analysis methods, adopting standard variables for monitoring, and integrating multi-sensor data may provide an opportunity to improve our ability to assess salt-affected lands. Further, recent research has demonstrated the potential of using composite images in soil mapping by combining information from multi-temporal data [167]. By integrating temporal information with spectral data, such as surface reflectance values obtained from remote sensing, researchers have developed accurate models for mapping soil attributes [168]. Composite images have several advantages over single-date images, including noise reduction, the ability to capture the dynamic nature of soil processes [169], and identifying long-term trends and patterns. Thus, it is worth investigating in future studies for soil salinity mapping.

Furthermore, cloud-based systems, such as the Google Earth engine and Microsoft's Planetary Computer, have granted an opportunity to manage and analyze large amounts of data and track temporal changes in soil salinity [170,171]. These systems are time-efficient for time series data processing and interpretation, which are difficult to fulfill using conventional computing methods. As such, cloud-based systems enable easier collaboration and data sharing among researchers and policy-makers. For soil salinity monitoring, they merit further investigation to explore their full potential.

Developing innovative remote sensing tools, such as imaging spectroscopy and UAV-based systems, has tremendously improved our capacity to conduct a more thorough and detailed local assessment. Specifically, UAV technology has emerged as an attractive option for acquiring high-resolution data at the field scale and upscaling satellite images covering larger geographic areas [172,173]. Future work should examine the efficiency and potential of recent technologies in validating the findings retrieved from space-borne remote sensing systems.

6. Conclusions

The significance and relevance of salinization assessment using remote sensing in the scientific community were assessed in this review paper. The number of research papers published on this topic increased over the last decade, highlighting the need for further development. This review underlines the advantages of remote sensing tools in salinization mapping but also emphasizes the need for continued research and technological development to improve the accuracy and effectiveness of salinization products to achieve sustainable land management practices.

While hyperspectral data outperformed multispectral data regarding salt-affected land characterization and detection due to its higher spectral resolution, less research has been carried out using commercial sensors, including most hyperspectral instruments, due to their high costs, limited spatial coverage, and restricted public access.

Given the limitations of current remote sensing systems, it is essential to investigate alternative options. With the growing accessibility of open-access data, such as Sentinel-1 synthetic aperture radar (SAR) data, radar remote sensing has emerged as a promising approach for salinization mapping. Microwave sensors have the potential to provide valuable information due to their capacity to penetrate vegetation and measure soil moisture content, which has been demonstrated to have a strong correlation with salinization processes.

Data retrieved from high-resolution sensors have shown their full potential in identifying plant canopy conditions and detecting soil moisture and salinity-induced stress at the plot and local scale. Therefore, further research should prioritize regional monitoring at the landscape scale to maintain environmental sustainability and explore the efficiency of emerged hyperspectral remote sensing systems such as EnMap, PRISMA, and UAVs to validate the findings from open-access satellite data.

Finally, it should be noted that no universally recognized approaches have been established for estimating soil salinity using remote sensing that could be applied to multiple scenarios and still produce accurate data under various climatic conditions.

Author Contributions: Conceptualization, G.S. and B.S.; initial draft writing, G.S., M.N. and P.K.M.; final manuscript writing, G.S.; review and editing, G.S. and B.S.; supervision, B.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The authors would like to thank the editor and the anonymous reviewers for their valuable comments and suggestions made to enhance this review article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. FAO. Soil Salinization as a Global Major Challenge | ITPS Soil Letter #3. Available online: https://www.fao.org/global-soil-partnership/resources/highlights/detail/en/c/1412475/ (accessed on 7 March 2023).
2. Shahid, S.A.; Zaman, M.; Heng, L. Introduction to Soil Salinity, Sodicity and Diagnostics Techniques. In *Guideline for Salinity Assessment, Mitigation, and Adaptation Using Nuclear and Related Techniques*; Springer: Cham, Switzerland, 2018; pp. 1–25. [CrossRef]
3. Daba, A.W.; Qureshi, A.S. Review of Soil Salinity and Sodicity Challenges to Crop Production in the Lowland Irrigated Areas of Ethiopia and Its Management Strategies. *Land* **2021**, *10*, 1377. [CrossRef]
4. Kaya, F.; Schillaci, C.; Keshavarzi, A.; Başayiğit, L. Predictive Mapping of Electrical Conductivity and Assessment of Soil Salinity in a Western Türkiye Alluvial Plain. *Land* **2022**, *11*, 2148. [CrossRef]
5. Shrivastava, P.; Kumar, R. Soil salinity: A serious environmental issue and plant growth promoting bacteria as one of the tools for its alleviation. *Saudi J. Biol. Sci.* **2015**, *22*, 123–131. [CrossRef] [PubMed]
6. Okur, B.; Orcen, N. Soil Salinization and Climate Change. In *Climate Change and Soil Interactions*; Prasad, M.N.V., Pietrzykowski, M., Eds.; Elsevier: Amsterdam, The Netherlands, 2020; pp. 331–350. [CrossRef]
7. Corwin, D.L. Climate Change Impacts on Soil Salinity in Agricultural Areas. *Eur. J. Soil Sci.* **2020**, *72*, 842–862. [CrossRef]
8. Hussain, S.; Shaukat, M.; Ashraf, M.; Zhu, C.; Jin, Q.; Zhang, J. Salinity Stress in Arid and Semi-Arid Climates: Effects and Management in Field Crops. In *Climate Change and Agriculture*; IntechOpen: London, UK, 2019. [CrossRef]

9. Hassani, A.; Azapagic, A.; Shokri, N. Global Predictions of Primary Soil Salinization under Changing Climate in the 21st Century. *Nat. Commun.* **2021**, *12*, 6663. [CrossRef]
10. Wu, W. A Brief Review on Soil Salinity Mapping by Optical and Radar Remote Sensing. In *Research Developments in Saline Agriculture*; Dagar, J.C., Yadav, R.S., Sharma, P.C., Eds.; Springer: Singapore, 2019; pp. 23–40. [CrossRef]
11. Corwin, D.L.; Scudiero, E. Review of Soil Salinity Assessment for Agriculture across Multiple Scales Using Proximal and/or Remote Sensors. *Adv. Agron.* **2019**, *158*, 1–130. [CrossRef]
12. Metternicht, G.I.; Zinck, J.A. Remote sensing of soil salinity: Potentials and constraints. *Remote Sens. Environ.* **2003**, *85*, 1–20. [CrossRef]
13. Xu, S.; Xu, Y.; Fu, Y.; Wang, Q. Soil Salinization and Mitigation Measures in Land Reclamation Regions. In *Soil Contamination—Current Consequences and Further Solutions*; Larramendy, M.L., Soloneski, S., Eds.; IntechOpen: London, UK, 2016. [CrossRef]
14. Singh, A. Soil salinity: A global threat to sustainable development. *Soil Use Manag.* **2022**, *38*, 39–67. [CrossRef]
15. Taghadosi, M.M.; Hasanlou, M.; Eftekhari, K. Soil salinity mapping using dual-polarized SAR Sentinel-1 imagery. *Int. J. Remote Sens.* **2018**, *40*, 237–252. [CrossRef]
16. Kasim, N.; Maihemuti, B.; Sawut, R.; Abliz, A.; Dong, C.; Abdumutallip, M. Quantitative Estimation of Soil Salinization in an Arid Region of the Keriya Oasis Based on Multidimensional Modeling. *Water* **2020**, *12*, 880. [CrossRef]
17. Azabdaftari, A.; Sunar, F. Soil Salinity Mapping Using Multitemporal Landsat Data. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.* **2016**, *XLI-B7*, 3–9. [CrossRef]
18. Abuelgasim, A.A.; Ammad, R. Mapping soil salinity in arid and semi-arid regions using Landsat 8 OLI satellite data. *Remote Sens. Appl. Soc. Environ.* **2019**, *13*, 415–425. [CrossRef]
19. Günal, E.; Wang, X.; Kılıc, O.M.; Budak, M.; Al Obaid, S.; Ansari, M.J.; Brestic, M. Potential of Landsat 8 OLI for mapping and monitoring of soil salinity in an arid region: A case study in Dushak, Turkmenistan. *PLoS ONE* **2021**, *16*, e0259695. [CrossRef] [PubMed]
20. Avdan, U.; Kaplan, G.; Küçük Matcı, D.; Yigit Avdan, Z.; Erdem, F.; Tuğba Mizik, E.; lknur Demirtas, I. Soil salinity prediction models constructed by different remote sensors. *Phys. Chem. Earth* **2022**, *128*, 103230. [CrossRef]
21. Sahbeni, G. A PLSR model to predict soil salinity using Sentinel-2 MSI data. *Open Geosci.* **2021**, *13*, 977–987. [CrossRef]
22. Aceves, E.Á.; Guevara, H.J.P.; Enríquez, A.C.; Sánchez, M.F.; Mora, E.M. Determining Salinity and Ion Soil Using Satellite Image Processing. *Pol. J. Environ. Stud.* **2019**, *28*, 1549–1560. [CrossRef]
23. Merembayev, T.; Amirgaliyev, Y.; Saurov, S.; Wójcik, W. Soil Salinity Classification Using Machine Learning Algorithms and Radar Data in the Case from the South of Kazakhstan. *J. Ecol. Eng.* **2022**, *23*, 61–67. [CrossRef]
24. Smanov, Z.M.; Laiskhanov, S.U.; Poshanov, M.N.; Abikbayev, Y.R.; Duisekov, S.N.; Tulegenov, Y.A. Mapping of Cornfield Soil Salinity in Arid and Semi-Arid Regions. *J. Ecol. Eng.* **2023**, *24*, 146–158. [CrossRef]
25. Khan, N.M.; Rastoskuev, V.V.; Sato, Y.; Shiozawa, S. Assessment of Hydro Saline Land Degradation by Using a Simple Approach of Remote Sensing Indicators. *Agric. Water Manag.* **2005**, *77*, 96–109. [CrossRef]
26. Ouchi, K. Recent Trend and Advance of Synthetic Aperture Radar with Selected Topics. *Remote Sens.* **2013**, *5*, 716–807. [CrossRef]
27. Barrett, B.; Dwyer, E.; Whelan, P. Soil Moisture Retrieval from Active Spaceborne Microwave Observations: An Evaluation of Current Techniques. *Remote Sens.* **2009**, *1*, 210–242. [CrossRef]
28. Beale, J.; Snapir, B.; Waine, T.; Evans, J.; Corstanje, R. The Significance of Soil Properties to the Estimation of Soil Moisture from C-Band Synthetic Aperture Radar. *Hydrol. Earth Syst. Sci. Discuss.* **2019**, 1–28. [CrossRef]
29. Muhetaer, N.; Nurmemet, I.; Abulaiti, A.; Xiao, S.; Zhao, J. A Quantifying Approach to Soil Salinity Based on a Radar Feature Space Model Using ALOS PALSAR-2 Data. *Remote Sens.* **2022**, *14*, 363. [CrossRef]
30. Wu, K.; Lambot, S. Analysis of Low-Frequency Drone-Borne GPR for Root-Zone Soil Electrical Conductivity Characterization. *IEEE Trans. Geosci. Remote Sens.* **2022**, *60*, 1–13. [CrossRef]
31. Hoa, P.; Giang, N.; Binh, N.; Hai, L.; Pham, T.-D.; Hasanlou, M.; Bui, D.T. Soil Salinity Mapping Using SAR Sentinel-1 Data and Advanced Machine Learning Algorithms: A Case Study at Ben Tre Province of the Mekong River Delta (Vietnam). *Remote Sens.* **2019**, *11*, 128. [CrossRef]
32. Dehni, A.; Lounis, M. Remote Sensing Techniques for Salt-Affected Soil Mapping: Application to the Oran Region of Algeria. *Procedia Eng.* **2012**, *33*, 188–198. [CrossRef]
33. Sahbeni, G.; Székely, B. Salinity Levels Discrimination Using ERS-1/2 and Sentinel-1 SAR Time Series Data in Hortobágyi National Park, Hungary. In Proceedings of the 2022 IEEE Mediterranean and Middle East Geoscience and Remote Sensing Symposium (M2GARSS), Virtual, 7–9 March 2022; pp. 194–197. [CrossRef]
34. Shahrayini, E.; Noroozi, A.A. Modeling and Mapping of Soil Salinity and Alkalinity Using Remote Sensing Data and Topographic Factors: A Case Study in Iran. *Environ. Model. Assess* **2022**, *27*, 901–913. [CrossRef]
35. Sarker, I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Comput. Sci.* **2021**, *2*, 160. [CrossRef]
36. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
37. Vapnik, V.; Golowich, S.; Smola, A. Support vector method for function approximation, regression estimation, and signal processing. In *Advances in Neural Information Processing Systems 9*; Mozer, M.C., Jordan, M.I., Petsche, T., Eds.; MIT Press: Cambridge, MA, USA, 1997; pp. 281–287.

38. Vermeulen, D.; Van Niekerk, A. Machine learning performance for predicting soil salinity using different combinations of geomorphometric covariates. *Geoderma* **2017**, *299*, 1–12. [CrossRef]
39. Wang, F.; Yang, S.; Yang, W.; Yang, X.; Ding, J. Comparison of machine learning algorithms for soil salinity predictions in three dryland oases located in Xinjiang Uyghur Autonomous Region (XJUAR) of China. *Eur. J. Remote Sens.* **2019**, *52*, 256–276. [CrossRef]
40. Hillel, D.; Braimoh, A.K.; Vlek, P.L.G. Soil Degradation Under Irrigation. In *Land Use and Soil Resources*; Braimoh, A.K., Vlek, P.L.G., Eds.; Springer: Dordrecht, The Netherlands, 2008; pp. 97–120. [CrossRef]
41. Yuvaraj, M.; Subash Chandra Bose, K.; Elavarasi, P.; Tawfik, E. Soil Salinity and Its Management. In *Soil Moisture Importance*; Meena, R.S., Datta, R., Eds.; IntechOpen: London, UK, 2021; Volume 1, Chapter 5. [CrossRef]
42. Zhao, Q.; Yu, L.; Du, Z.; Peng, D.; Hao, P.; Zhang, Y.; Gong, P. An Overview of the Applications of Earth Observation Satellite Data: Impacts and Future Trends. *Remote Sens.* **2022**, *14*, 1863. [CrossRef]
43. Scudiero, E.; Corwin, D.L.; Anderson, R.G.; Skaggs, T.H. Moving Forward on Remote Sensing of Soil Salinity at Regional Scale. *Front. Environ. Sci.* **2016**, *4*, 65. [CrossRef]
44. Habibi, V.; Ahmadi, H.; Jafari, M.; Moeini, A. Mapping Soil Salinity Using a Combined Spectral and Topographical Index with Artificial Neural Network. *PLoS ONE* **2021**, *16*, e0228494. [CrossRef]
45. Wang, J.; Peng, J.; Li, H.; Yin, C.; Liu, W.; Wang, T.; Zhang, H. Soil Salinity Mapping Using Machine Learning Algorithms with the Sentinel-2 MSI in Arid Areas, China. *Remote Sens.* **2021**, *13*, 305. [CrossRef]
46. Wu, W.; Muhaimeed, A.S.; Al-Shafie, W.M.; Al-Quraishi, A.M.F. Using Radar and Optical Data for Soil Salinity Modeling and Mapping in Central Iraq. In *Environmental Remote Sensing and GIS in Iraq*; Al-Quraishi, A., Negm, A., Eds.; Springer Water: Cham, Switzerland, 2020; pp. 19–32. [CrossRef]
47. Sahbeni, G. Soil Salinity Mapping Using Landsat 8 OLI Data and Regression Modeling in the Great Hungarian Plain. *SN Appl. Sci.* **2021**, *3*, 587. [CrossRef]
48. Saad, K.; Kallel, A.; Rebah, Z.B.; Solaiman, B. Spatio-temporal monitoring of soil salinity and land cover changes using remote sensing techniques: Zaghouan case study (Tunisia). In Proceedings of the 6th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP), Sfax, Tunisia, 24–27 May 2022; pp. 1–5. [CrossRef]
49. Biro Turk, K.; Aljughaiman, A. Land use/land cover assessment as related to soil and irrigation water salinity over an oasis in arid environment. *Open Geosci.* **2020**, *12*, 220–231. [CrossRef]
50. Lekka, C.; Petropoulos, G.P.; Triantakonstantis, D.; Detsikas, S.E.; Chalkias, C. Exploring the spatial patterns of soil salinity and organic carbon in agricultural areas of Lesvos Island, Greece, using Geoinformation Technologies. *Environ. Monit. Assess.* **2023**, *195*, 3. [CrossRef]
51. Bakacsi, Z.; Tóth, T.; Makó, A.; Barna, G.; Laborczi, A.; Szabó, J.; Szatmári, G.; Pásztor, L. National level assessment of soil salinization and structural degradation risks under irrigation. *Hung. Geogr. Bull.* **2019**, *68*, 141–156. [CrossRef]
52. Masoud, A.A.; Koike, K.; Atwia, M.G.; El-Horiny, M.M.; Gemail, K.S. Mapping Soil Salinity Using Spectral Mixture Analysis of Landsat 8 OLI Images to Identify Factors Influencing Salinization in an Arid Region. *Int. J. Appl. Earth Obs. Geoinform.* **2019**, *83*, 101944. [CrossRef]
53. Shrestha, R.P.; Qasim, S.; Bachri, S. Investigating Remote Sensing Properties for Soil Salinity Mapping: A Case Study in Korat Province of Thailand. *Environ. Chall.* **2021**, *5*, 100290. [CrossRef]
54. El-SayedGad, M.M.; Mohamed, M.H.A.; Mohamed, M.R. Soil salinity mapping using remote sensing and GIS. *Geomatica* **2022**, *75*, 295–309. [CrossRef]
55. Howari, F.M.; Goodell, P.C.; Miyamoto, S. Spectral Properties of Salt Crusts Formed on Saline Soils. *J. Environ. Qual.* **2002**, *31*, 1453–1461. [CrossRef] [PubMed]
56. Li, S.; Li, C.; Fu, X. Characteristics of Soil Salt Crust Formed by Mixing Calcium Chloride with Sodium Sulfate and the Possibility of Inhibiting Wind-Sand Flow. *Sci. Rep.* **2021**, *11*, 9746. [CrossRef]
57. Metternicht, G.I.; Zinck, J.A. Spatial Discrimination of Salt- and Sodium-Affected Soil Surfaces. *Int. J. Remote Sens.* **1997**, *18*, 2571–2586. [CrossRef]
58. Bannari, A.; Guedon, A.M.; El-Harti, A.; Cherkaoui, F.Z.; El-Ghmari, A. Characterization of Slightly and Moderately Saline and Sodic Soils in Irrigated Agricultural Land using Simulated Data of Advanced Land Imaging (EO-1) Sensor. *Commun. Soil Sci. Plant Anal.* **2008**, *39*, 2795–2811. [CrossRef]
59. Sahbeni, G. Comparative Study of Machine-Learning-Based Classifiers for Soil Salinization Prediction using Sentinel-1 SAR and Sentinel-2 MSI Data. In Proceedings of the 2022 10th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), Valencia, Spain, 7–9 July 2022; pp. 1–4. [CrossRef]
60. Goldshleger, N.; Chudnovsky, A.; Ben-Binyamin, R. Predicting Salinity in Tomato Using Soil Reflectance Spectral. *Int. J. Remote Sens.* **2013**, *34*, 6079–6093. [CrossRef]
61. Wu, S.; Wang, C.; Liu, Y.; Li, Y.; Liu, J.; Xu, A.; Pan, K.; Li, Y.; Pan, X. Mapping the Salt Content in Soil Profiles Using Vis-NIR Hyperspectral Imaging. *Soil Sci. Soc. Am. J.* **2018**, *82*, 1259–1269. [CrossRef]
62. Rajakumari, S.; Mahesh, R.; Sarunjith, K.J.; Ramesh, R. Building spectral catalogue for salt marsh vegetation, hyperspectral and multispectral remote sensing. *Reg. Stud. Mar. Sci.* **2022**, *53*, 102435. [CrossRef]

63. Nguyen, K.A.; Liou, Y.A.; Tran, H.P.; Hoang, P.P.; Nguyen, T.H. Soil Salinity Assessment by Using Near-Infrared Channel and Vegetation Soil Salinity Index Derived from Landsat 8 OLI Data: A Case Study in the Tra Vinh Province, Mekong Delta, Vietnam. *Prog. Earth Planet. Sci.* **2020**, *7*, 2–16. [CrossRef]
64. Ramos, T.B.; Castanheira, N.; Oliveira, A.R.; Paz, A.M.; Darouich, H.; Simionesei, L.; Farzamian, M.; Gonçalves, M.C. Soil salinity assessment using vegetation indices derived from Sentinel-2 multispectral data. Application to Lezíria Grande, Portugal. *Agric. Water Manag.* **2020**, *241*, 106387. [CrossRef]
65. Metternicht, G.I.; Zinck, J.A. *Remote Sensing of Soil Salinization: Impact on Land Management*; CRC Press: Boca Raton, FL, USA, 2008. [CrossRef]
66. Hu, J.; Peng, J.; Zhou, Y.; Xu, D.; Zhao, R.; Jiang, Q.; Fu, T.; Wang, F.; Shi, Z. Quantitative Estimation of Soil Salinity Using UAV-Borne Hyperspectral and Satellite Multispectral Images. *Remote Sens.* **2019**, *11*, 736. [CrossRef]
67. Ma, G.; Ding, J.; Han, L.S.; Zhang, Z.; Ran, S. Digital mapping of soil salinization based on Sentinel-1 and Sentinel-2 data combined with machine learning algorithms. *Reg. Sustain.* **2021**, *2*, 177–188. [CrossRef]
68. Zhu, K.; Sun, Z.; Zhao, F.; Yang, T.; Tian, Z.; Lai, J.; Zhu, W.; Long, B. Relating Hyperspectral Vegetation Indices with Soil Salinity at Different Depths for the Diagnosis of Winter Wheat Salt Stress. *Remote Sens.* **2021**, *13*, 250. [CrossRef]
69. Yu, X.; Chang, C.; Song, J.; Zhuge, Y.; Wang, A. Precise Monitoring of Soil Salinity in China's Yellow River Delta Using UAV-Borne Multispectral Imagery and a Soil Salinity Retrieval Index. *Sensors* **2022**, *22*, 546. [CrossRef] [PubMed]
70. Guo, B.; Han, B.; Yang, F.; Fan, Y.; Jiang, L.; Chen, S.; Yang, W.; Gong, R.; Liang, T. Salinization Information Extraction Model Based on VI–SI Feature Space Combinations in the Yellow River Delta Based on Landsat 8 OLI Image. Geomat. *Nat. Haz. Risk* **2019**, *10*, 1863–1878. [CrossRef]
71. Allbed, A.; Kumar, L. Soil Salinity Mapping and Monitoring in Arid and Semi-Arid Regions Using Remote Sensing Technology: A Review. *Adv. Remote Sens.* **2013**, *2*, 404–420. [CrossRef]
72. Zhu, L.; Suomalainen, J.; Liu, J.; Hyyppä, J.; Kaartinen, H.; Haggren, H. *A Review: Remote Sensing Sensors, Multi-Purposeful Application of Geospatial Data*; IntechOpen: London, UK, 2017. [CrossRef]
73. Phiri, D.; Simwanda, M.; Salekin, S.; Nyirenda, V.R.; Murayama, Y.; Ranagalage, M. Sentinel-2 Data for Land Cover/Use Mapping: A Review. *Remote Sens.* **2020**, *12*, 2291. [CrossRef]
74. Frampton, W.J.; Dash, J.; Watmough, G.; Milton, E.J. Evaluating the Capabilities of Sentinel-2 for Quantitative Estimation of Biophysical Variables in Vegetation. *ISPRS J. Photogramm. Remote Sens.* **2013**, *82*, 83–92. [CrossRef]
75. Kobayashi, C.; Lau, I.C.; Wheaton, B.; Cater, D.; Bourke, L.; Asada, N.; Kashimura, O.; Ong, C.C.; Cudahy, T. Estimating soil salinity using hyperspectral data in the Western Australian wheat belt. In Proceedings of the 2013 IEEE International Geoscience and Remote Sensing Symposium—IGARSS, Melbourne, Australia, 21–26 July 2013; pp. 4325–4328. [CrossRef]
76. Rocha Neto, O.; Teixeira, A.; Leão, R.; Moreira, L.; Galvão, L. Hyperspectral Remote Sensing for Detecting Soil Salinization Using ProSpecTIR-VS Aerial Imagery and Sensor Simulation. *Remote Sens.* **2017**, *9*, 42. [CrossRef]
77. Abd El-Hamid, H.T.; Hong, G. Hyperspectral remote sensing for extraction of soil salinization in the northern region of Ningxia. *Model. Earth Syst. Environ.* **2020**, *6*, 2487–2493. [CrossRef]
78. Weng, Y.; Gong, P.; Zhu, Z. A Spectral Index for Estimating Soil Salinity in the Yellow River Delta Region of China Using EO-1 Hyperion Data. *Pedosphere* **2010**, *20*, 378–388. [CrossRef]
79. Jiang, H.; Shu, H.; Lei, L.; Xu, J. Estimating soil salt components and salinity using hyperspectral remote sensing data in an arid area of China. *J. Appl. Remote Sens.* **2017**, *11*, 016043. [CrossRef]
80. Chen, Y.; Du, Y.; Yin, H.; Wang, H.; Chen, H.; Li, X.; Zhang, Z.; Chen, J. Radar remote sensing-based inversion model of soil salt content at different depths under vegetation. *PeerJ* **2022**, *10*, e13306. [CrossRef] [PubMed]
81. Nurmemet, I.; Sagan, V.; Ding, J.L.; Halik, U.; Abliz, A.; Yakup, Z. A WFS-SVM Model for Soil Salinity Mapping in Keriya Oasis, North-western China Using Polarimetric Decomposition and Fully PolSAR Data. *Remote Sens.* **2018**, *10*, 598. [CrossRef]
82. Calzone, A.; Cotrozzi, L.; Lorenzini, G.; Nali, C.; Pellegrini, E. Hyperspectral Detection and Monitoring of Salt Stress in Pomegranate Cultivars. *Agronomy* **2021**, *11*, 1038. [CrossRef]
83. Turhan, H.; Genc, L.; Smith, S.E.; Bostanci, Y.B.; Turkmen, O.S. Assessment of the Effect of Salinity on the Early Growth Stage of the Common Sunflower (Sanay Cultivar) Using Spectral Discrimination Techniques. *Afr. J. Biotechnol.* **2008**, *7*, 761–767.
84. Gorji, T.; Tanik, A.; Sertel, E. Soil Salinity Prediction, Monitoring and Mapping Using Modern Technologies. *Procedia Earth Planet. Sci.* **2015**, *15*, 507–512. [CrossRef]
85. Gerardo, R.; de Lima, I.P. Sentinel-2 Satellite Imagery-Based Assessment of Soil Salinity in Irrigated Rice Fields in Portugal. *Agriculture* **2022**, *12*, 1490. [CrossRef]
86. Kılıç, O.M.; Budak, M.; Gunal, E.; Acir, N.; Halbac-Cotoara-Zamfir, R.; Alfarraj, S.; Ansari, M.J. Soil salinity assessment of a natural pasture using remote sensing techniques in central Anatolia, Turkey. *PLoS ONE* **2022**, *17*, e0266915. [CrossRef]
87. Gharsallah, M.E.; Aichi, H.; Stambouli, T.; Ben Rabah, Z.; Ben Hassine, H. Assessment and mapping of soil salinity using electromagnetic induction and Landsat 8 OLI remote sensing data in an irrigated olive orchard under semi-arid conditions. *Soil Water Res.* **2022**, *17*, 15–28. [CrossRef]
88. Yao, H.; Qin, R.; Chen, X. Unmanned Aerial Vehicle for Remote Sensing Applications—A Review. *Remote Sens.* **2019**, *11*, 1443. [CrossRef]
89. Del Cerro, J.; Cruz Ulloa, C.; Barrientos, A.; de León Rivas, J. Unmanned Aerial Vehicles in Agriculture: A Survey. *Agronomy* **2021**, *11*, 203. [CrossRef]

90. Melendez-Pastor, I.; Navarro-Pedreño, J.; Koch, M.; Gómez, I. Applying Imaging Spectroscopy Techniques to Map Saline Soils with ASTER Images. *Geoderma* **2010**, *158*, 55–65. [CrossRef]
91. Daliakopoulos, I.N.; Tsanis, I.K.; Koutroulis, A.G.; Kourgialas, N.N.; Varouchakis, A.E.; Karatzas, G.P.; Ritsema, C.J. The threat of soil salinity: A European scale review. *Sci. Total Environ.* **2016**, *573*, 727–739. [CrossRef]
92. Wang, Z.; Zhang, F.; Zhang, X.; Chan, N.W.; Kung, H.; Ariken, M.; Wang, Y. Regional suitability prediction of soil salinization based on remote-sensing derivatives and optimal spectral index. *Sci. Total Environ.* **2021**, *775*, 145807. [CrossRef]
93. Ma, L.; Ma, F.; Li, J.; Gu, Q.; Yang, S.; Wu, D.; Ding, J. Characterizing and modeling regional-scale variations in soil salinity in the arid oasis of Tarim Basin, China. *Geoderma* **2017**, *305*, 1–11. [CrossRef]
94. Jia, P.; Zhang, J.; He, W.; Hu, Y.; Zeng, R.; Zamanian, K.; Jia, K.; Zhao, X. Combination of Hyperspectral and Machine Learning to Invert Soil Electrical Conductivity. *Remote Sens.* **2022**, *14*, 2602. [CrossRef]
95. Scudiero, E.; Skaggs, T.H.; Corwin, D.L. Regional-scale soil salinity assessment using Landsat ETM+ canopy reflectance. *Remote Sens. Environ.* **2015**, *169*, 335–343. [CrossRef]
96. Basak, N.; Barman, A.; Sundha, P.; Rai, A.K. Recent Trends in Soil Salinity Appraisal and Management. In *Soil Analysis: Recent Trends and Applications*; Rakshit, A., Ghosh, S., Chakraborty, S., Philip, V., Datta, A., Eds.; Springer: Singapore, 2020. [CrossRef]
97. Kholdorov, S.; Gopakumar, L.; Katsura, K.; Jabbarov, Z.; Jobborov, O.; Shamsiddinov, T.; Khakimov, A. Soil salinity assessment research using remote sensing techniques: A special focus on recent research. *IOP Conf. Ser. Earth Environ. Sci.* **2022**, *1068*, 012037. [CrossRef]
98. FAO; ITPS. *Status of the World's Soil Resources (SWSR)—Main Report*; Food and Agriculture Organization of the United Nations and Intergovernmental Technical Panel on Soils: Rome, Italy, 2015. Available online: https://www.fao.org/documents/card/en/c/c6814873-efc3-41db-b7d3-2081a10ede50/ (accessed on 7 March 2023).
99. FAO. Salt-Affected Soils. Available online: http://www.fao.org/soils-portal/soil-management/management-of-some-problem-soils/salt-affected-soils/more-information-on-salt-affected-soils/en/ (accessed on 8 March 2023).
100. FAO. Legacy Soil Maps and Soils Databases. Available online: https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/en/ (accessed on 8 March 2023).
101. Ivushkin, K.; Bartholomeus, H.; Bregt, A.K.; Pulatov, A.; Kempen, B.; de Sousa, L. Global Mapping of Soil Salinity Change. *Remote Sens. Environ.* **2019**, *231*, 111260. [CrossRef]
102. Szatmári, G.; Bakacsi, Z.; Laborczi, A.; Petrik, O.; Pataki, R.; Tóth, T.; Pásztor, L. Elaborating Hungarian Segment of the Global Map of Salt-Affected Soils (GSSmap): National Contribution to an International Initiative. *Remote Sens.* **2020**, *12*, 4073. [CrossRef]
103. FAO. World Map of Salt-Affected Soils Launched at Virtual Conference. 2021. Available online: www.fao.org/newsroom/detail/salt-affected-soils-map-symposium/en (accessed on 8 March 2023).
104. Omuto, C.T.; Vargas, R.R.; El Mobarak, A.M.; Mohamed, N.; Viatkin, K.; Yigini, Y. *Mapping of Salt-Affected Soils: Technical Manual*; FAO: Rome, Italy, 2020. [CrossRef]
105. Corwin, D.L.; Yemoto, K. Measurement of soil salinity: Electrical conductivity and total dissolved solids. *Soil Sci. Soc. Am. J.* **2019**, *83*, 1–2. [CrossRef]
106. Singh, A. Soil Salinization Management for Sustainable Development: A Review. *J. Environ. Manag.* **2021**, *277*, 111383. [CrossRef] [PubMed]
107. Hussain, G.; Al-Hawas, I.A. Salinity sensor: A reliable tool for monitoring in situ soil salinity under saline irrigation. *Int. J. Soil Sci.* **2008**, *3*, 92–100. [CrossRef]
108. Asfaw, E.; Suryabhagavan, K.V.; Argaw, M. Soil salinity modeling and mapping using remote sensing and GIS: The case of Wonji sugar cane irrigation farm, Ethiopia. *J. Saudi Soc. Agric. Sci.* **2018**, *17*, 250–258. [CrossRef]
109. Pradipta, A.; Soupios, P.; Kourgialas, N.; Doula, M.; Dokou, Z.; Makkawi, M.; Alfarhan, M.; Tawabini, B.; Kirmizakis, P.; Yassin, M. Remote Sensing, Geophysics, and Modeling to Support Precision Agriculture—Part 1: Soil Applications. *Water* **2022**, *14*, 1158. [CrossRef]
110. Rafik, A.; Ibouh, H.; El Alaoui El Fels, A.; Eddahby, L.; Mezzane, D.; Bousfoul, M.; Amazirh, A.; Ouhamdouch, S.; Bahir, M.; Gourfi, A.; et al. Soil Salinity Detection and Mapping in an Environment under Water Stress between 1984 and 2018 (Case of the Largest Oasis in Africa-Morocco). *Remote Sens.* **2022**, *14*, 1606. [CrossRef]
111. Alqasemi, A.; Ibrahim, M.; Fadhil Al-Quraishi, A.; Saibi, H.; Al-Fugara, A.; Kaplan, G. Detection and Modeling of Soil Salinity Variations in Arid Lands Using Remote Sensing Data. *Open Geosci.* **2021**, *13*, 443–453. [CrossRef]
112. Elmetwalli, A.M.H.; Tyler, A.N.; Hunter, P.D.; Salt, C.A. Detecting and distinguishing moisture-and salinity-induced stress in wheat and maize through in situ spectroradiometry measurements. *Remote Sens. Lett.* **2012**, *3*, 363–372. [CrossRef]
113. Zare, S.; Shamsi, S.R.; Abtahi, S.M. Weakly-coupled geostatistical mapping of soil salinity to Stepwise Multiple Linear Regression of MODIS spectral image products. *J. Afr. Earth Sci.* **2019**, *152*, 101–114. [CrossRef]
114. Wei, Y.; Shi, Z.; Biswas, A.; Yang, S.; Ding, J.; Wang, F. Updated information on soil salinity in a typical oasis agroecosystem and desert-oasis ecotone: Case study conducted along the Tarim River, China. *Sci. Total Environ.* **2020**, *716*, 135387. [CrossRef]
115. Jantaravikorn, Y.; Ongsomwang, S. Soil Salinity Prediction and Its Severity Mapping Using a Suitable Interpolation Method on Data Collected by Electromagnetic Induction Method. *Appl. Sci.* **2022**, *12*, 10550. [CrossRef]
116. Kuhn, M.; Weston, S.; Keefer, C.; Coulter, N.; Quinlan, R. *Cubist: Rule-and Instance-Based Regression Modeling, R Package Version 0.0.18*; CRAN: Vienna, Austria, 2014.

117. Zhou, J.; Li, E.; Wei, H.; Li, C.; Qiao, Q.; Armaghani, D.J. Random Forests and Cubist Algorithms for Predicting Shear Strengths of Rockfill Materials. *Appl. Sci.* **2019**, *9*, 1621. [CrossRef]
118. Quinlan, R. Combining instance based and model based learning. In Proceedings of the Tenth International Conference on Machine Learning, Amherst, MA, USA, 27–29 June 1993; pp. 236–243.
119. Peng, J.; Biswas, A.; Jiang, Q.; Zhao, R.; Hu, J.; Hu, B.; Shi, Z. Estimating soil salinity from remote sensing and terrain data in southern Xinjiang Province, China. *Geoderma* **2019**, *337*, 1309–1319. [CrossRef]
120. Peng, J.; Li, S.; Makar, R.S.; Li, H.; Feng, C.; Luo, D.; Shen, J.; Wang, Y.; Jiang, Q.; Fang, L. Proximal Soil Sensing of Low Salinity in Southern Xinjiang, China. *Remote Sens.* **2022**, *14*, 4448. [CrossRef]
121. Sahbeni, G.; Székely, B. Spatial Modeling of Soil Salinity Using Kriging Interpolation Techniques: A Study Case in the Great Hungarian Plain. *Eurasian J. Soil Sci.* **2022**, *11*, 102–112. [CrossRef]
122. Hateffard, F.; Balog, K.; Tóth, T.; Mészáros, J.; Árvai, M.; Kovács, Z.A.; Szűcs-Vásárhelyi, N.; Koós, S.; László, P.; Novák, T.J.; et al. High-Resolution Mapping and Assessment of Salt-Affectedness on Arable Lands by the Combination of Ensemble Learning and Multivariate Geostatistics. *Agronomy* **2022**, *12*, 1858. [CrossRef]
123. Lu, L.; Li, S.; Wu, R.; Shen, D. Study on the Scale Effect of Spatial Variation in Soil Salinity Based on Geostatistics: A Case Study of Yingdaya River Irrigation Area. *Land* **2022**, *11*, 1697. [CrossRef]
124. Zakeri, F.; Mariethoz, G. A review of geostatistical simulation models applied to satellite remote sensing: Methods and applications. *Remote Sens. Environ.* **2021**, *259*, 112381. [CrossRef]
125. Sahbeni, G.; Székely, B. Machine Learning Models for Estimating Soil Salinity Using Sentinel-1 SAR and Landsat-8 OLI Data. *J. Adv. Geospat. Sci. Technol.* **2022**, *2*, 1–10.
126. Garajeh, M.K.; Malakyar, F.; Weng, Q.; Feizizadeh, B.; Blaschke, T.; Lakes, T. An automated deep learning convolutional neural network algorithm applied for soil salinity distribution mapping in Lake Urmia, Iran. *Sci. Total Environ.* **2021**, *778*, 146253. [CrossRef] [PubMed]
127. Xiao, C.; Ji, Q.; Chen, J.; Zhang, F.; Li, Y.; Fan, J.; Wang, H. Prediction of soil salinity parameters using machine learning models in an arid region of Northwest China. *Comput. Electron. Agric.* **2023**, *204*, 107512. [CrossRef]
128. Li, Z.; Li, Y.; Xing, A.; Zhang, J.; Liu, X. Spatial prediction of soil salinity in a Semi-arid Oasis: Environmental Sensitive Variable Selection and Model Comparison. *Chin. Geogr. Sci.* **2019**, *29*, 784–797. [CrossRef]
129. Zhang, W.; Zhang, W.; Liu, Y.; Zhang, J.; Yang, L.; Wang, Z.; Mao, Z.; Qi, S.; Zhang, C.; Yin, Z. The Role of Soil Salinization in Shaping the Spatio-Temporal Patterns of Soil Organic Carbon Stock. *Remote Sens.* **2022**, *14*, 3204. [CrossRef]
130. Burke, E.J.; Banks, A.C.; Gurney, R.J. Remote sensing of soil-vegetation- atmosphere transfer processes. *Prog. Phys. Geogr. Earth Environ.* **1997**, *21*, 549–572. [CrossRef]
131. Lei, G.; Zeng, W.; Yu, J.; Huang, J. A comparison of physical-based and machine learning modeling for soil salt dynamics in crop fields. *Agric. Water Manag.* **2023**, *277*, 108115. [CrossRef]
132. Hossen, B.; Yabar, H.; Faruque, M.J. Exploring the Potential of Soil Salinity Assessment through Remote Sensing and GIS: Case Study in the Coastal Rural Areas of Bangladesh. *Land* **2022**, *11*, 1784. [CrossRef]
133. Fadl, M.E.; Jalhoum, M.E.M.; Abdelrahman, M.A.E.; Ali, E.A.; Zahra, W.R.; Abuzaid, A.S.; Fiorentino, C.; D'Antonio, P.; Belal, A.A.; Scopa, A. Soil Salinity Assessing and Mapping Using Several Statistical and Distribution Techniques in Arid and Semi-Arid Ecosystems, Egypt. *Agronomy* **2023**, *13*, 583. [CrossRef]
134. Ge, X.; Ding, J.; Teng, D.; Wang, J.; Huo, T.; Jin, X.; Wang, J.; He, B.; Han, L. Updated soil salinity with fine spatial resolution and high accuracy: The synergy of sentinel-2 MSI, environmental covariates and hybrid machine learning approaches. *CATENA* **2022**, *212*, 106054. [CrossRef]
135. Abdelrahman, M.A.E.; Afifi, A.A.; D'Antonio, P.; Gabr, S.S.; Scopa, A. Detecting and Mapping Salt-Affected Soil with Arid Integrated Indices in Feature Space Using Multi-Temporal Landsat Imagery. *Remote Sens.* **2022**, *14*, 2599. [CrossRef]
136. Hihi, S.; Ben Rabah, Z.; Bouaziz, M.; Chtourou, M.; Bouaziz, S. Prediction of Soil Salinity Using Remote Sensing Tools and Linear Regression Model. *Adv. Remote Sens.* **2019**, *8*, 77–88. [CrossRef]
137. Ngabire, M.; Wang, T.; Xue, X.; Liao, J.; Sahbeni, G.; Huang, C.; Duan, H.; Song, X. Soil Salinization Mapping across Different Sandy Land-Cover Types in the Shiyang River Basin: A Remote Sensing and Multiple Linear Regression Approach. *Remote Sens. Appl. Soc. Environ.* **2022**, *23*, 100618. [CrossRef]
138. Suleymanov, A.; Gabbasova, I.; Komissarov, M.; Suleymanov, R.; Garipov, T.; Tuktarova, I.; Belan, L. Random Forest Modeling of Soil Properties in Saline Semi-Arid Areas. *Agriculture* **2023**, *13*, 976. [CrossRef]
139. Mohamed, S.A.; Metwaly, M.M.; Metwalli, M.R.; AbdelRahman, M.A.E.; Badreldin, N. Integrating Active and Passive Remote Sensing Data for Mapping Soil Salinity Using Machine Learning and Feature Selection Approaches in Arid Regions. *Remote Sens.* **2023**, *15*, 1751. [CrossRef]
140. Zhao, J.; Nurmemet, I.; Muhetaer, N.; Xiao, S.; Abulaiti, A. Monitoring Soil Salinity Using Machine Learning and the Polarimetric Scattering Features of PALSAR-2 Data. *Sustainability* **2023**, *15*, 7452. [CrossRef]
141. Guan, X.; Wang, S.; Gao, Z.; Lv, Y. Dynamic Prediction of Soil Salinization in an Irrigation District Based on the Support Vector Machine. *Math. Comput. Model.* **2013**, *58*, 719–724. [CrossRef]
142. Jiang, H.; Rusuli, Y.; Amuti, T.; He, Q. Quantitative Assessment of Soil Salinity Using Multi-Source Remote Sensing Data Based on the Support Vector Machine and Artificial Neural Network. *Int. J. Remote Sens.* **2018**, *40*, 284–306. [CrossRef]

143. Morgan, R.S.; El-Hady, M.A.; Rahim, I.S. Soil Salinity Mapping Utilizing Sentinel-2 and Neural Networks. *Indian J. Agric. Res.* **2018**, *52*, 524–529. [CrossRef]
144. Hernández, E.I.; Melendez-Pastor, I.; Navarro-Pedreño, J.; Gómez, I. Spectral Indices for the Detection of Salinity Effects in Melon Plants. *Sci. Agric.* **2014**, *71*, 324–330. [CrossRef]
145. Matinfar, H.R.; Zandieh, V. Efficiency of Spectral Indices Derived from Landsat-8 Images of Maharloo Lake and Its Surrounding Rangelands. *J. Rangeland Sci.* **2016**, *6*, 334–343.
146. Gu, Q.; Han, Y.; Xu, Y.; Ge, H.; Li, X. Extraction of Saline Soil Distributions Using Different Salinity Indices and Deep Neural Networks. *Remote Sens.* **2022**, *14*, 4647. [CrossRef]
147. Mohammadifar, A.; Gholami, H.; Golzari, S. Assessment of the Uncertainty and Interpretability of Deep Learning Models for Mapping Soil Salinity Using DeepQuantreg and Game Theory. *Sci. Rep.* **2022**, *12*, 15167. [CrossRef] [PubMed]
148. Elnaggar, A.; Noller, J. Application of Remote-sensing Data and Decision-Tree Analysis to Mapping Salt-Affected Soils over Large Areas. *Remote Sens.* **2010**, *2*, 151–165. [CrossRef]
149. Wu, J.; Vincent, B.; Yang, J.; Bouarfa, S.; Vidal, A. Remote Sensing Monitoring of Changes in Soil Salinity: A Case Study in Inner Mongolia, China. *Sensors* **2008**, *8*, 7035–7049. [CrossRef] [PubMed]
150. Turner, W. Sensing Biodiversity. *Science* **2014**, *346*, 301–302. [CrossRef]
151. Yan, Y.; Kayem, K.; Hao, Y.; Shi, Z.; Zhang, C.; Peng, J.; Liu, W.; Zuo, Q.; Ji, W.; Li, B. Mapping the Levels of Soil Salination and Alkalization by Integrating Machining Learning Methods and Soil-Forming Factors. *Remote Sens.* **2022**, *14*, 3020. [CrossRef]
152. Ding, J.; Yu, D. Monitoring and evaluating spatial variability of soil salinity in dry and wet seasons in the werigan–kuqa oasis, China, using remote sensing and electromagnetic induction instruments. *Geoderma* **2014**, *235–236*, 316–322. [CrossRef]
153. Guo, B.; Lu, M.; Fan, Y.; Wu, H.; Yang, Y.; Wang, C. A novel remote sensing monitoring index of salinization based on three-dimensional feature space model and its application in the Yellow River Delta of China. *Geomat. Nat. Hazards Risk* **2022**, *14*, 95–116. [CrossRef]
154. Ma, Y.; Tashpolat, N. Remote Sensing Monitoring of Soil Salinity in Weigan River–Kuqa River Delta Oasis Based on Two-Dimensional Feature Space. *Water* **2023**, *15*, 1694. [CrossRef]
155. Potapov, P.; Hansen, M.C.; Kommareddy, I.; Kommareddy, A.; Turubanova, S.; Pickens, A.; Adusei, B.; Tyukavina, A.; Ying, Q. Landsat Analysis Ready Data for Global Land Cover and Land Cover Change Mapping. *Remote Sens.* **2020**, *12*, 426. [CrossRef]
156. Thiam, S.; Villamor, G.B.; Faye, L.C.; Sène, J.H.; Diwediga, B.; Kyei-Baffour, N. Monitoring land use and soil salinity changes in coastal landscape: A case study from Senegal. *Environ. Monit. Assess.* **2021**, *193*, 259. [CrossRef] [PubMed]
157. Jia, P.; Zhang, J.; He, W.; Yuan, D.; Hu, Y.; Zamanian, K.; Jia, K.; Zhao, X. Inversion of Different Cultivated Soil Types' Salinity Using Hyperspectral Data and Machine Learning. *Remote Sens.* **2022**, *14*, 5639. [CrossRef]
158. Lagacherie, P.; Gomez, C.; Bailly, J.; Baret, F.; Coulouma, G. The Use of Hyperspectral Imagery for Digital Soil Mapping in Mediterranean Areas. In *Digital Soil Mapping*; Progress in Soil Science; Boettinger, J.L., Howell, D.W., Moore, A.C., Hartemink, A.E., Kienast-Brown, S., Eds.; Springer: Dordrecht, The Netherlands, 2010; Volume 2, pp. 99–114. [CrossRef]
159. Ward, K.J.; Chabrillat, S.; Brell, M.; Castaldi, F.; Spengler, D.; Foerster, S. Mapping Soil Organic Carbon for Airborne and Simulated EnMAP Imagery Using the LUCAS Soil Database and a Local PLSR. *Remote Sens.* **2020**, *12*, 3451. [CrossRef]
160. Mzid, N.; Castaldi, F.; Tolomio, M.; Pascucci, S.; Casa, R.; Pignatti, S. Evaluation of Agricultural Bare Soil Properties Retrieval from Landsat 8, Sentinel-2 and PRISMA Satellite Data. *Remote Sens.* **2022**, *14*, 714. [CrossRef]
161. Gasmi, A.; Gomez, C.; Chehbouni, A.; Dhiba, D.; El Gharous, M. Using PRISMA Hyperspectral Satellite Imagery and GIS Approaches for Soil Fertility Mapping (FertiMap) in Northern Morocco. *Remote Sens.* **2022**, *14*, 4080. [CrossRef]
162. Fan, X.; Weng, Y.; Tao, J. Towards decadal soil salinity mapping using Landsat time series data. *Int. J. Appl. Earth Obs. Geoinf.* **2016**, *52*, 32–41. [CrossRef]
163. Eibedingil, I.G.; Gill, T.E.; Van Pelt, R.S.; Tong, D.Q. Combining Optical and Radar Satellite Imagery to Investigate the Surface Properties and Evolution of the Lordsburg Playa, New Mexico, USA. *Remote Sens.* **2021**, *13*, 3402. [CrossRef]
164. Salas, E.A.; Subburayalu, S.K.; Slater, B.; Dave, R.; Parekh, P.; Zhao, K.; Bhattacharya, B. Assessing the effectiveness of ground truth data to capture landscape variability from an agricultural region using gaussian simulation and geostatistical techniques. *Heliyon* **2021**, *7*, e07439. [CrossRef]
165. Sekrecka, A.; Kedzierski, M. Integration of Satellite Data with High-Resolution Ratio: Improvement of Spectral Quality with Preserving Spatial Details. *Sensors* **2018**, *18*, 4418. [CrossRef]
166. Zhang, G.L.; Feng, L.I.U.; Song, X.D. Recent Progress and Future Prospect of Digital Soil Mapping: A Review. *J. Integr. Agric.* **2017**, *16*, 2871–2885. [CrossRef]
167. Safanelli, J.L.; Chabrillat, S.; Ben-Dor, E.; Demattê, J.A.M. Multispectral Models from Bare Soil Composites for Mapping Topsoil Properties over Europe. *Remote Sens.* **2020**, *12*, 1369. [CrossRef]
168. Meng, X.; Bao, Y.; Liu, H.; Zhang, X.; Wang, X. A new digital soil mapping method with temporal-spatial-spectral information derived from multi-source satellite images. *Geoderma* **2022**, *425*, 116065. [CrossRef]
169. Lindsay, E.; Frauenfelder, R.; Rüther, D.; Nava, L.; Rubensdotter, L.; Strout, J.; Nordal, S. Multi-Temporal Satellite Image Composites in Google Earth Engine for Improved Landslide Visibility: A Case Study of a Glacial Landscape. *Remote Sens.* **2022**, *14*, 2301. [CrossRef]
170. Ma, S.; He, B.; Xie, B.; Ge, X.; Han, L. Investigation of the spatial and temporal variation of soil salinity using Google Earth Engine: A case study at Werigan–Kuqa Oasis, West China. *Sci. Rep.* **2023**, *13*, 2754. [CrossRef]

171. Aksoy, S.; Yildirim, A.; Gorji, T.; Hamzehpour, N.; Tanik, A.; Sertel, E. Assessing the performance of machine learning algorithms for soil salinity mapping in Google Earth Engine Platform using Sentinel-2A and Landsat-8 OLI data. *Adv. Space Res.* **2021**, *69*, 1072–1086. [CrossRef]
172. Gao, M.; Xu, X.; Klinger, Y.; Van Der Woerd, J.; Tapponnier, P. High-Resolution Mapping Based on an Unmanned Aerial Vehicle (UAV) to Capture Paleo Seismic Offsets along the Altyn-Tagh Fault, China. *Sci. Rep.* **2017**, *7*, 8281. [CrossRef]
173. Nex, F.; Armenakis, C.; Cramer, M.; Cucci, D.A.; Gerke, M.; Honkavaara, E.; Kukko, A.; Persello, C.; Skaloud, J. UAV in the Advent of the Twenties: Where We Stand and What Is Next. *ISPRS J. Photogramm. Remote Sens.* **2022**, *184*, 215–242. [CrossRef]