



Machine Learning for Monitoring Vegetation Dynamics and Soil Salinity in Arid and Semi-Arid Regions: A Comprehensive Review and Change-Oriented Conceptual Framework

Hassan Fathizad^{1*} , Mahsa Kohzadi² 

¹ Department of Arid and Desert Region Management, Faculty of Natural Resources and Desert Studies, Yazd University, Yazd, Iran. Email: h.fathizad@yazd.ac.ir

² Department of Rangeland and Watershed Management, Faculty of Agricultural, Ilam University, Ilam, Iran.

Article Info.

Article type:

Research Article

Article history:

Received: 26 May 2026

Received in revised from: 16 Jul. 2026

Accepted: 25 Jul. 2026

Published online: 27 Jul. 2026

Keywords:

Machine Learning,

Remote Sensing,

Soil Salinity,

Vegetation Dynamics,

Hybrid Models,

Arid and Semi-Arid Regions.

ABSTRACT

The ecosystems characterized by arid and semi-arid climate conditions are threatened heavily by processes of degradation, especially due to vegetation loss and soil salinization. However, despite the revolution in environmental monitoring that has been caused by the development of Remote Sensing (RS) and Machine Learning (ML) approaches, it is hard to synthesize rapidly evolving developments in this field. In the current paper, we offer an overview of the application of RS and ML approaches for vegetation dynamics and soil salinization monitoring. Thus, our review proposes a new, change-oriented, and comprehensive conceptual framework that goes beyond linear processing with the use of multi-temporal features extraction, hybrid predictive modeling, and adaptive decision-making (MCDM inclusion). In our work, we emphasize several crucial methodological bottlenecks, such as data scarcity, spatial autocorrelation, and the black box of advanced algorithms. With the increasing use of ML frameworks in environmental decisions, issues related to ethics, reproducibility, and open science should be considered carefully. The combination of high-resolution remote sensing techniques, including those using Unmanned Aerial Vehicles (UAVs), can pose privacy problems and requires strict compliance with local data governance. In addition, this review tackles institutional barriers along with the pressing need for Open Science, which involves the development of benchmark datasets and reproducible methodologies. In essence, this paper offers a clear strategy to guide researchers and policy makers towards developing ML-enabled monitoring systems for managing arid areas sustainably.

Cite this article: Fathizad, H., Kohzadi, M. (2026). Machine Learning for Monitoring Vegetation Dynamics and Soil Salinity in Arid and Semi-Arid Regions: A Comprehensive Review and Change-Oriented Conceptual Framework. DESERT, 31 (2), DOI: 10.22059/jdesert.2026.108911



© The Author(s).

DOI: 10.22059/jdesert.2026.108911

Publisher: University of Tehran Press

List of Abbreviations

AHP: Analytic Hierarchy Process
ANN: Artificial Neural Network
CNN: Convolutional Neural Network
DEM: Digital Elevation Model
EVI: Enhanced Vegetation Index
GAN: Generative Adversarial Network
GIS: Geographic Information System
LIME: Local Interpretable Model-agnostic Explanations
LST: Land Surface Temperature
MAE: Mean Absolute Error
MCDM: Multi-Criteria Decision-Making
ML: Machine Learning
MLP: Multi-Layer Perceptron
NDVI: Normalized Difference Vegetation Index
PINN: Physics-Informed Neural Network
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RF: Random Forest
RMSE: Root Mean Square Error
RNN: Recurrent Neural Network
RS: Remote Sensing
SAR: Synthetic Aperture Radar
SAVI: Soil Adjusted Vegetation Index
SCV: Spatial Cross-Validation
SHAP: SHapley Additive exPlanations
SVM: Support Vector Machine
TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution
UAV: Unmanned Aerial Vehicle
XAI: Explainable Artificial Intelligence
XGBoost: Extreme Gradient Boosting

1. Introduction

Soil salinity and vegetation cover are important components of natural resource management in arid and semi-arid regions. Soil salinity is recognized as a major constraint on agricultural production and vegetation development in these environments and can affect natural ecosystems and agricultural productivity at large spatial scales (Morgan *et al.*, 2018; Chen *et al.*, 2022; Kaplan *et al.*, 2023). Soil salinity, particularly in sandy and semi-arid soils, can substantially alter soil physical and chemical properties, resulting in reduced productivity and biodiversity (Mzid *et al.*, 2023). Sustainable resource management therefore requires effective monitoring of the spatial and temporal dynamics of soil salinity and vegetation cover.

Remote sensing (RS) provides an effective means of monitoring these dynamics by offering spatially and temporally consistent observations of vegetation and soil conditions. For example, Yaghobi *et al.* (2026) applied the Standardized Precipitation Index (SPI) and NDVI to quantify drought impacts on vegetation cover in western Iran, reporting a 15–20% reduction in NDVI values during extreme drought years. Recent studies have also demonstrated the applicability of machine learning (ML) methods, including ensemble and neural network approaches, for mapping soil properties in desert environments (Fathizad *et al.*, 2025). These developments

highlight the potential of integrating remote sensing and machine learning to characterize vegetation condition, soil salinity, and their temporal dynamics (Allbed and Kumar, 2013; Sulieman *et al.*, 2023).

Several machine learning algorithms, including Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost), have been increasingly applied to soil salinity mapping because of their ability to capture nonlinear relationships between environmental variables and remotely sensed observations (Ivushkin *et al.*, 2019; Wang *et al.*, 2021). However, much of the existing literature remains focused on improving predictive accuracy within individual study areas rather than developing generalized approaches for long-term environmental monitoring. Temporal variability is also frequently represented using a limited number of observation dates, restricting the ability of models to characterize continuous salinity dynamics under changing climatic and land-use conditions (Wang *et al.*, 2023; Chen *et al.*, 2025).

Despite the increasing use of multi-temporal remote sensing and machine learning, several methodological challenges remain. Many studies are constrained by limited temporal continuity and insufficient integration of multi-source remote sensing data, which can reduce the ability to characterize long-term environmental changes and progressive land degradation (Reisi Gahrouei *et al.*, 2024; Samadzadegan *et al.*, 2025). Model transferability across climatic and ecological conditions is another challenge because environmental characteristics and training data distributions vary substantially among regions (Meyer *et al.*, 2018). In addition, spatial autocorrelation, uncertainty quantification, and spatial cross-validation are not consistently addressed, while the integration of predictive outputs into operational decision-support systems remains limited (Ploton *et al.*, 2020; Roberts *et al.*, 2017). These limitations are particularly relevant in arid and semi-arid environments, where low-quality ground-reference data, high soil surface reflectance, environmental heterogeneity, and class imbalance can further complicate predictive modelling.

This review critically examines recent advances in the application of remote sensing and machine learning for monitoring vegetation dynamics and soil salinity in arid and semi-arid regions. Particular emphasis is placed on studies integrating multi-temporal Landsat and Sentinel imagery with widely used machine learning algorithms, including RF and ANN, as well as on the integration of multi-source remote sensing data. Rather than proposing a new empirical modelling technique, the review synthesizes existing approaches and identifies methodological priorities for improving long-term, change-oriented environmental monitoring.

In terms of its scope and scientific contribution, this study adopts a hybrid structure combining a systematic review with a conceptual framework. Three main synthetic contributions are developed. First, a comparative analysis evaluates studies conducted in arid and semi-arid environments, with particular attention to the challenges associated with ground-reference data quality, soil surface reflectance, environmental heterogeneity, and class imbalance. Second, the review critically examines attempts to integrate multi-criteria decision-making (MCDM) techniques with machine learning algorithms for environmental monitoring, an area that has received comparatively limited attention in previous reviews. Third, a change-oriented conceptual framework is proposed to synthesize existing approaches and identify methodological priorities for future research, including multi-temporal analysis, hybrid machine learning, spatial cross-validation, uncertainty assessment, and Explainable Artificial Intelligence (XAI).

The proposed framework is presented in Figure 1. In contrast to conventional remote sensing workflows that are often implemented as linear processes, the proposed framework adopts an

iterative, feedback-based structure. It integrates data from multiple sources, including optical satellite imagery, Sentinel-1 radar observations, and UAV data, with machine learning methods. Spatial cross-validation is incorporated to address the effects of spatial autocorrelation, while uncertainty assessment and explainable modelling provide additional information for interpreting predictive outputs and supporting adaptive land management.

For the systematic presentation of the literature through the PRISMA framework, three main research questions (RQs) guide the review:

RQ1: What are the common remote sensing databases and machine learning techniques employed in analyzing vegetation dynamics and soil salinity in arid and semi-arid areas?

RQ2: What are the major methodological limitations, including spatial autocorrelation, limited reference data, and computational costs, that hinder the practical application of these predictive models?

RQ3: How can approaches such as XAI and MCDM help connect the outputs of machine learning models with adaptive land management practices?

The principal aim of this hybrid review is therefore to critically synthesize current approaches, identify methodological gaps, and develop a change-oriented conceptual framework for integrating remote sensing, machine learning, spatial validation, uncertainty assessment, and decision-support approaches in the monitoring and management of arid and semi-arid ecosystems.

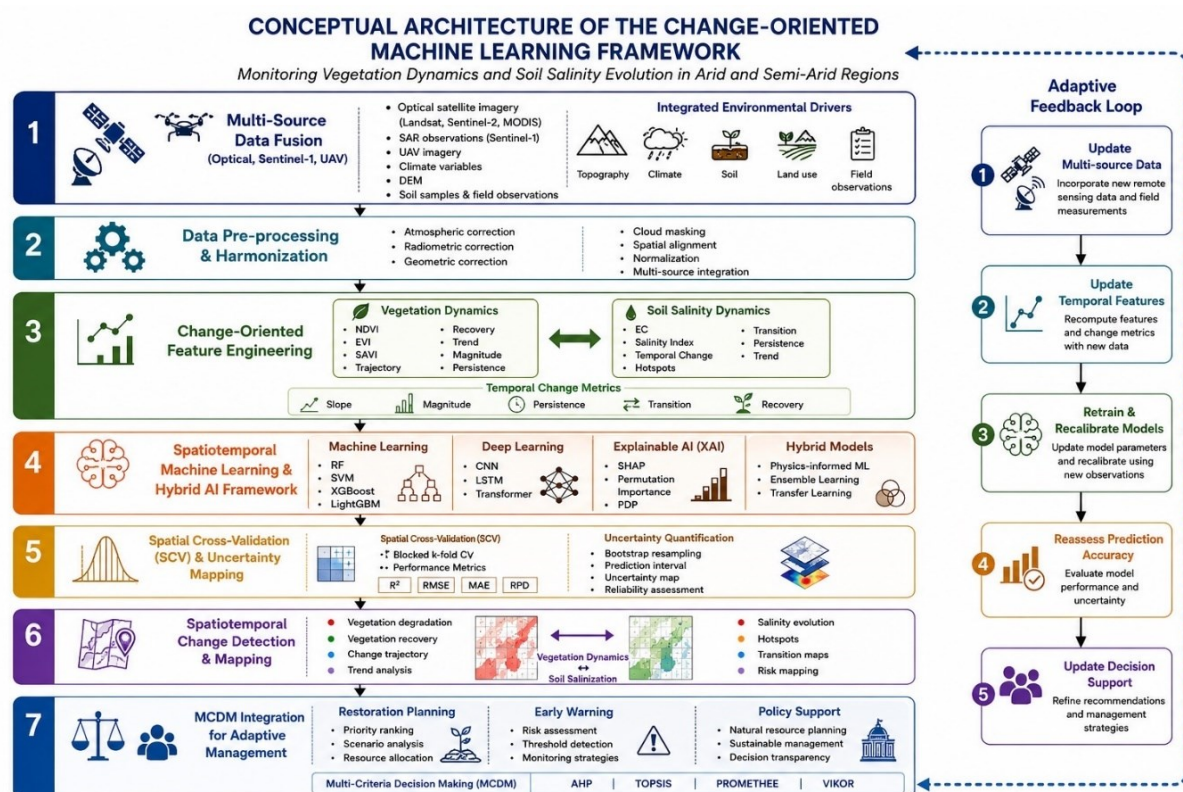


Figure 1. Conceptual framework integrating remote sensing, machine learning, spatial cross-validation, and uncertainty mapping for adaptive monitoring of arid ecosystems. Developed with assistance from ChatGPT (OpenAI).

Table1. Recent Studies on Soil Salinity and Vegetation Analysis Using Machine Learning and Remote Sensing

Key Findings	Evaluation Metrics	Data Used	Machine Learning Models	Study Area	Reference
Sentinel-2 data provided higher accuracy; integrating TCW improved salinity mapping.	R ² , RMSE	Landsat 8, Sentinel-2	Cubist Model	Northwest China	Wang <i>et al.</i> , (2020)
Combining radar and optical data improved salinity prediction.	RMSE, R ²	Sentinel-1, Sentinel-2	RF, BPNN, SVR	Nile Delta, Egypt	Mohamed <i>et al.</i> , (2023)
XGBoost performed best using spectral indices and texture features.	R ² , RMSE, MAE	Multispectral Data	XGBoost, RF, BPNN	Heihe River Basin, China	Zhao <i>et al.</i> , (2024)
MU-NET model effectively simulated soil salinity across vegetation periods.	Prediction Accuracy	UAV, Remote Sensing Data	MU-NET (CNN-based)	China	Cui <i>et al.</i> , (2023)
Transformer models outperformed traditional methods in soil quality analysis	Prediction Accuracy	Remote Sensing Data	Transformer-based Models	Iran	Saki <i>et al.</i> , (2024)

1.1. Conceptual Workflow of the Proposed Change-Oriented Framework

The proposed change-oriented conceptual framework is intended as a synthesis of current methodological advances in remote sensing (RS) and machine learning (ML) rather than as a novel predictive algorithm or operational workflow. Based on the critical evaluation of the reviewed literature, the framework integrates the principal methodological components required for monitoring vegetation dynamics and soil salinity in arid and semi-arid environments. Unlike conventional static workflows, the proposed framework emphasizes the continuous integration of multi-temporal observations, adaptive model refinement, uncertainty assessment, and decision-support processes to support dynamic environmental monitoring.

1.2. Multi-temporal Data Integration

The first component of the framework involves the integration of multi-temporal and multi-source datasets acquired from complementary remote sensing platforms. Optical imagery (e.g., Landsat and Sentinel-2) provides detailed spectral information for vegetation and soil characterization, whereas Synthetic Aperture Radar (SAR) supplies structural information that is largely independent of cloud cover and illumination conditions. Thermal observations provide information on land surface temperature and moisture stress, while LiDAR and UAV-derived products improve the representation of vegetation structure and surface topography. Climate variables, digital elevation models (DEMs), and field observations further complement remotely sensed data by providing environmental and ground-reference information. The integration of these heterogeneous datasets improves the characterization of land degradation processes while reducing the limitations associated with single-sensor observations (Reisi Gahrouei *et al.*, 2024; Samadzadegan *et al.*, 2025).

1.3. Temporal Feature Extraction

Following data acquisition, all observations are conceptually harmonized through standard preprocessing procedures, including atmospheric correction, radiometric calibration, geometric co-registration, cloud masking, temporal harmonization, and spatial normalization. Temporal features are subsequently extracted from sequential observations to characterize environmental dynamics rather than isolated environmental conditions. These features include vegetation indices (e.g., NDVI, SAVI, and EVI), soil salinity indices, land surface temperature, texture measures, terrain derivatives, and temporal descriptors representing long-term trends, seasonal variability, and change trajectories. Temporal feature extraction enables machine learning algorithms to capture complex non-linear relationships and long-term environmental dynamics that cannot be adequately represented using single-date observations (Meyer *et al.*, 2018; Ivushkin *et al.*, 2019).

1.4. Machine Learning and Hybrid Modeling

The extracted temporal and environmental variables are subsequently incorporated into machine learning models for environmental prediction and spatiotemporal change analysis. Rather than recommending a single algorithm, the proposed framework highlights the complementary roles of conventional machine learning algorithms, deep learning architectures, hybrid modeling approaches, and multi-source data fusion techniques. Model selection should be guided by the characteristics of the available datasets, monitoring objectives, computational requirements, and environmental complexity. Recent studies have demonstrated that hybrid approaches integrating multiple data sources and learning algorithms frequently improve prediction accuracy, robustness, and model generalization across heterogeneous landscapes (Taghadosi *et al.*, 2021; Reisi Gahrouei *et al.*, 2024; Samadzadegan *et al.*, 2025).

1.5. Model Evaluation and Uncertainty Assessment

Reliable environmental monitoring requires rigorous model evaluation beyond conventional random validation approaches. Previous studies have shown that random cross-validation frequently overestimates predictive performance because spatial autocorrelation violates the assumption of independent observations (Ploton *et al.*, 2020). Therefore, the proposed framework explicitly incorporates spatial cross-validation, independent validation datasets, uncertainty quantification, and Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME to improve model reliability, interpretability, and transferability. Integrating these components enables researchers and decision-makers to evaluate not only predictive performance but also the confidence associated with spatial predictions under different environmental conditions (Roberts *et al.*, 2017; Ploton *et al.*, 2020).

1.6. Adaptive Feedback Mechanism

A key feature of the proposed framework is the incorporation of an adaptive feedback mechanism that supports continuous environmental monitoring. Unlike conventional static workflows, the proposed feedback loop is not intended to represent a mathematical optimization algorithm. Instead, it operates as an iterative conceptual process in which model evaluation results, uncertainty estimates, newly acquired remote sensing observations, and updated field measurements are continuously incorporated into successive monitoring cycles.

Following each prediction cycle, model performance is evaluated using independent validation datasets, spatial cross-validation, and uncertainty assessment techniques. When model performance no longer satisfies predefined validation criteria or when newly acquired

observations become available, the monitoring workflow is updated by re-extracting temporal features, incorporating additional multi-temporal remote sensing observations, recalibrating the machine learning model, and generating revised prediction maps. The updated outputs are subsequently re-evaluated before being integrated into the next monitoring cycle. This iterative process continues until model performance stabilizes and newly available observations no longer provide substantial improvements in predictive capability.

Consequently, the adaptive feedback mechanism enables continuous refinement of feature extraction, model calibration, and prediction strategies, thereby improving the robustness, adaptability, and long-term applicability of environmental monitoring systems. Adaptive monitoring frameworks are increasingly recognized as essential for sustainable natural resource management under rapidly changing environmental and climatic conditions (Roberts *et al.*, 2017; Meyer *et al.*, 2018; Ploton *et al.*, 2020; Samadzadegan *et al.*, 2025).

Overall, the proposed framework should be interpreted as a conceptual synthesis of current scientific knowledge rather than as a novel predictive algorithm. Its primary contribution lies in systematically integrating the major methodological components identified across the reviewed literature into a unified change-oriented framework that supports future research, improves methodological consistency, and facilitates evidence-based environmental decision-making in arid and semi-arid regions.

Beyond generating spatial prediction maps, the proposed framework is intended to support evidence-based environmental decision-making. The outputs generated throughout the workflow, including vegetation change maps, soil salinity predictions, uncertainty maps, and model interpretation results, provide valuable information for identifying land degradation hotspots, prioritizing field surveys, optimizing restoration strategies, and evaluating the effectiveness of land management practices. Rather than representing an end in themselves, these outputs are designed to provide scientifically robust evidence that supports adaptive management and informed policy development in arid and semi-arid regions.

The integration of spatial cross-validation, uncertainty assessment, and Explainable Artificial Intelligence (XAI) further strengthens the reliability and transparency of model predictions. These components enable decision-makers to evaluate the confidence associated with spatial predictions while improving understanding of the environmental variables driving vegetation change and soil salinity. Consequently, the framework facilitates risk-informed decision-making by supporting the identification of priority intervention areas and guiding future monitoring and field verification efforts.

A key feature of the framework is the adaptive feedback mechanism, which enables the monitoring system to evolve as new remote sensing observations and field measurements become available. By continuously incorporating updated information, the framework supports iterative model refinement and the regular updating of monitoring products. This adaptive process enhances the ability of environmental agencies to evaluate management outcomes, revise restoration priorities, and adjust land management strategies in response to changing climatic and land-use conditions. Therefore, the proposed framework should be viewed as a conceptual decision-support system that strengthens the connection between scientific evidence and sustainable natural resource management rather than as a standalone predictive model (Cash *et al.*, 2003; Jakeman *et al.*, 2006; McNie, 2007).

1.7. Decision-Making Component of the Proposed Framework

The Decision-Making component represents the final stage of the proposed framework, where the outputs generated throughout the monitoring workflow are translated into practical

environmental management actions. Rather than relying solely on spatial prediction maps, the framework integrates vegetation change maps, soil salinity predictions, uncertainty maps, and model interpretation results to support evidence-based decision-making. This integrated information enables decision-makers to identify priority areas for restoration, optimize field survey planning, support sustainable land and water management, prioritize soil salinity mitigation measures, and allocate financial and technical resources more efficiently (Malczewski, 2006; Geneletti, 2008).

The framework also promotes transparent and reliable decision-making by explicitly incorporating uncertainty assessment and model interpretability into the evaluation process. Instead of assuming that all model predictions are equally reliable, uncertainty maps identify areas where additional field observations or further analyses are needed before management actions are implemented. At the same time, model interpretation techniques help explain the environmental factors driving vegetation change and soil salinity, providing greater confidence in management decisions and reducing the risk of inappropriate interventions (Ascough *et al.*, 2008; Mahmoud *et al.*, 2009).

Finally, the adaptive feedback mechanism ensures that decision-making remains dynamic rather than static. As new remote sensing observations, field measurements, and monitoring results become available, management priorities and restoration strategies can be periodically reassessed and updated. This iterative process supports adaptive management by allowing decisions to evolve in response to changing environmental conditions, land-use dynamics, and newly available scientific evidence. Consequently, the proposed framework provides a flexible decision-support approach that strengthens the link between scientific evidence and sustainable natural resource management while facilitating continuous improvement of environmental monitoring and management practices (Williams *et al.*, 2009; Gregory *et al.*, 2012).

1.8. Illustrative Decision-Making Scenario

Regarding the application of predictive models within the domain of natural resources management, their translation into practical conservation actions necessitates the combination of machine learning with MCDM approaches (Malczewski, 2006; Nguyen & Liu, 2019). Based on the existing literature, although ML-based models generate accurate and relevant spatial information in the form of, for example, maps of soil salinity risks as well as maps of spatial uncertainties related to them (Ascough *et al.*, 2008), MCDM techniques, including AHP, are crucial for prioritizing socio-economic and ecological objectives (Saaty, 1980). In other words, when it comes to choosing between alternative solutions that should be implemented in order to address the land degradation problem (such as extensive biological rehabilitation vs passive grazing), there are several aspects that need to be considered besides the environmental risk (Geneletti, 2008).

As a result, regions that are at high risk of land degradation and have low ML prediction uncertainty are allocated more investments for costly land restorations. On the other hand, in those regions where ML algorithms have high uncertainty in their predictions owing to the lack of ground truth information on heterogeneous landscapes, MCDM methods will discourage expensive treatments, and encourage passive management approaches or even sample collection from the field (Mahmoud *et al.*, 2009).

2. Systematic Review Methodology

In order to conduct a systematic, thorough, and replicable synthesis of the literature, PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines were

employed in this research. The method involved three main stages which include literature search, criteria for inclusion/exclusion, and data extraction.

2.1. Search Strategy

A thorough review of the literature has been carried out from three prominent scientific sources namely Web of Science (Core Collection), Scopus, and Google Scholar. The search was confined to articles up to June 2026 for the latest updates in the field of machine learning and remote sensing. The search approach used a combination of Boolean logic operators (AND, OR) based on title, abstract, and keyword fields. The main search query was constructed as follows: ("*machine learning*" OR "*deep learning*" OR "*artificial intelligence*") AND ("*remote sensing*" OR "*satellite imagery*" OR "*UAV*") AND ("*soil salinity*" OR "*vegetation dynamics*" OR "*land degradation*") AND ("*arid*" OR "*semi-arid*" OR "*dryland*").

2.2. Inclusion and Exclusion Criteria

Criteria for selection of the reviewed literature have been set to ensure its validity and relevancy. The following criteria were used for inclusion of the articles: (1) they had to be peer-reviewed primary and secondary sources of research; (2) they had to be written in English; (3) they had to be specifically dedicated to the use of machine learning and remote sensing; and (4) they had to be carried out in arid or semi-arid climates. For exclusion, the following criteria were used: (1) grey literature and preprints; (2) studies that did not contain any modeling or machine learning techniques; (3) research conducted in tropical or humid climates (environmental variables are different from those of drylands); and (4) full text inaccessibility.

2.3. Paper Screening and PRISMA Workflow

From the search of the initial database, 620 documents were retrieved. After the elimination of 140 duplicates through reference management software, 480 unique documents remained to be reviewed during the first round of screening. In this stage, titles and abstracts of all documents were scrutinized, and 285 of them were subsequently filtered out from further consideration due to the non-relevance of their themes. Afterwards, the full-text review was conducted to check the applicability of the 195 remaining articles in accordance with strict inclusion/exclusion criteria. After such a meticulous process, 93 papers have been discarded due to inadequate methodological information, irrelevant climatic aspects, or absence of machine learning applications. As a result, 102 high-quality peer-reviewed documents were included into the scope of data extraction and synthesis to develop the suggested theoretical framework.

3. Remote Sensing Data and Foundations

3.1. Remote sensing to be used in Environmental Analysis

Remote sensing (RS) is considered as the most important approach to monitor vegetation and soil salinity in areas where water is scarce. Landsat and Sentinel are two of the most commonly used satellite data (Almalki *et al.*, 2022). Vegetation indices, including NDVI (Tucker, 1979) and EVI (Yan *et al.*, 2025), are reliable indicators of the state of vegetation. Moreover, the salinity of the soil can also be determined indirectly using some spectral indices. For example, Salimi *et al.*, (2019) conducted a study where they applied indices that are particularly sensitive to salinity to model soil salinity over the area of Iran. These approaches are especially necessary in situations where field data are scarce (Allbed & Kumar, 2013). Still, dependent on one index, like NDVI, one has to face some drawbacks. NDVI might get blocked in highly vegetated regions or produce contaminated data in the case of areas where soil has high reflectance.

To give an example, Fathizad *et al.* (2020) deployed advanced predictive machine learning models to the study of soil salinity mapping in the central desert of Iran. The outcomes were characterized by R^2 values in the interval of 0.84–0.89 and RMSE of 0.12–0.15 dS/m over several locations which, in fact, indicated that combining RS data with machine learning provides reliable estimates even in remote data-scarce arid regions. Likewise, Fathizad *et al.*, (2022) made use of ML models to monitor soil organic carbon fluctuations and gave spatiotemporal predictions with over 85% accuracy.

3.2. The Multi-source and Multi-temporal Data Role.

Data fusion from diverse sources leads to more precise analysis. Among them were optical, radar (SAR), and thermal data (Gorelick *et al.*, 2017; Chen *et al.*, 2022). Multi-temporal data gives a picture of the environment during the time of the study (. Fathizad *et al.*, (2025) showed that the combination of multi-source RS data with support from ML models (MLP, Decision Tree, and RF) results in soil texture mapping with the coefficient of determination (R^2) reaching 0.91 and root mean square error (RMSE) dropping to 0.10 (see Table 2).

Table 2. Role of Remote Sensing Data in Vegetation and Soil Salinity Analysis

Remote Sensing Data Type	Features and Benefits	Application in Vegetation and Soil Salinity Analysis
Optical Data	Wide coverage, free access, various spectral indices	Vegetation monitoring, NDVI, SAVI extraction
Thermal Data	Surface temperature measurement, plant stress analysis	Analysis of temperature-salinity/drought relationship
Radar Data	Cloud-independent, sensitive to soil moisture	Identification of moisture and soil texture changes
Elevation Data (DEM)	Topography, slope, slope aspect	Examining the role of physiography in salinity distribution
Multitemporal Data	Temporal changes analysis	Long-term vegetation and soil salinity trend monitoring

A comparison of multitemporal, multisource, and textual/unstructured data in remote sensing is shown in Table 3, highlighting the features and applications of each.

3.3. Methodological Synthesis

The core conceptual synthesis in this review is the shift from a conventional, single-day predictive mapping design to an evolutionary, change-oriented monitoring framework. Through the assessment of recently published literature, this review illustrates how authors handle multi-temporal remote sensing datasets to monitor continuous temporal dynamics in vegetation indices and salinity-related spectral characteristics. Furthermore, our synthesis demonstrates that integrating these multi-temporal parameters into machine learning frameworks serves as an excellent approach for assessing the spatiotemporal changes in vegetation and soil salinity.

3.4. Role of 3D Structural Data in Supporting Soil Salinity Mapping

Three-dimensional (3D) remote sensing data, particularly those derived from LiDAR and UAV photogrammetry, do not directly measure soil salinity. Instead, they provide detailed information on terrain morphology, micro-topography, surface roughness, and vegetation structure, all of which influence hydrological processes, water redistribution, drainage patterns,

and ultimately the spatial distribution of soil salinity. These structural variables can be incorporated as auxiliary predictor variables within machine learning models, together with optical, thermal, SAR, and field-derived data, to improve the accuracy and robustness of soil salinity mapping. Therefore, the contribution of 3D structural data is indirect, enhancing model performance by providing complementary information on the environmental factors controlling salinity distribution rather than directly detecting soil salinity itself (Reisi Gahruei *et al.*, 2024; Samadzadegan *et al.*, 2025).

Table 3. Comparison of Multi-temporal and Multi-source Remote Sensing Data for Environmental Monitoring

Feature	Multi-temporal Data	Multi-source Data
Definition	Sequential satellite observations acquired over different time periods	Integration of complementary datasets from multiple remote sensing platforms
Primary purpose	Monitoring temporal dynamics and environmental changes	Improving environmental characterization through complementary information
Typical data sources	Landsat, Sentinel-2, MODIS, PlanetScope	Optical, SAR, Thermal, LiDAR, UAV, DEM
Extracted information	Temporal trends, seasonal variability, change trajectories	Spectral, structural, thermal, topographic and geometric information
Applications	Vegetation dynamics, soil salinity evolution, drought monitoring, land degradation assessment	Soil salinity mapping, vegetation classification, land cover mapping, environmental monitoring
Advantages	Captures long-term environmental changes and change rates	Improves prediction accuracy, robustness, and environmental representation
Limitations	Sensitive to missing observations, cloud contamination, and temporal inconsistency	Requires data harmonization, co-registration, and computational resources
Representative examples	Multi-year Landsat time series for vegetation monitoring	Integration of Sentinel-1 SAR and Sentinel-2 optical imagery for soil salinity assessment

3.5. Hyperspectral remote Sensing Role

Though multispectral remote sensing is popular, hyperspectral remote sensing can provide more superior services in the specific analysis that can be carried out on the soil salinity. Hyperspectral sensor, as opposed to multispectral sensors collect hundreds of narrow spectral bands and spectra adjacent to each other. This spectral resolution enables the detection of distinctive absorption characteristics of salinity-related minerals and physiological stresses in vegetation, which are not easily detected (Allbed and Kumar, 2013). It has been demonstrated in many studies that the hyperspectral data can generate soil salinity maps that are much more accurate than multispectral data (Farifteh *et al.*, 2007). Nevertheless, such factors as the cost of data are high and the size of data has restricted its use.

3.6. Positioning of UAV Remote Sensing in Multiscales Research

The Unmanned Aerial Vehicle (UAV) remote sensing device is a field that warrants special attention because it is a special tool in multi-scale studies. The UAVs can obtain data on extremely high spatial scales (i.e. centimeter level) that are in the gap between ground-based point data and lower quality satellite data. The large level of resolution allows identifying very

small-scale pictures of soil salinity or vegetation stress. The ability of UAVs to schedule flights enables researchers to take data at key time points and thus it is a key instrument towards calibrating satellite-based models and creating accurate and field-scale management models (Feng *et al.*, 2015).

The use of UAVs successfully fills the critical spatial gap between sparse field observations and moderate-resolution satellite images (e.g., Landsat or Sentinel). The ability of UAVs to generate ultra-high-resolution data makes them extremely useful in monitoring small-scale spatial heterogeneities of arid landscapes by mapping individual plant canopies and microtopography linked to surface soil salinity. Within machine learning applications, UAV images serve as a valuable source of highly accurate training data that improves the calibration and validation of complex models, such as Convolutional Neural Networks (CNNs) and tree ensembles.

Modern UAVs may be equipped with a range of advanced sensors (multispectral, hyperspectral, thermal cameras, and LiDAR), which allows for creating a comprehensive environmental profile. Nonetheless, there are certain practical obstacles related to the extensive use of UAVs in desert areas. These obstacles include limited flight times because of battery capacity, sensitivity to adverse meteorological conditions (e.g., strong winds and dust storms that are common in arid environments), strict airspace regulations, and the heavy computation needed to process large amounts of photogrammetric and hyperspectral data.

3.7. Model Selection, Hyperparameter Tuning, and Computational Trade-offs

The successful adoption of machine learning algorithms in environmental monitoring depends heavily on rigorous model selection and hyperparameter optimization techniques. In spatial applications, model selection often requires a difficult balance among predictive performance, interpretability, and input data demands (Maxwell *et al.*, 2018). Although highly advanced Deep Learning (DL) algorithms offer superior performance when modeling complex non-linear spatiotemporal relationships, their lack of transparency and massive data requirements make ensemble tree-based models (such as Random Forest and XGBoost) more desirable in regions with sparse ground-truth data (Belgiu & Drăguț, 2016).

Optimizing these models also demands extensive computational resources associated with hyperparameter tuning. Recent studies highlight the need to move away from the conventional exhaustive Grid Search toward more efficient techniques, such as Randomized Search and Bayesian Optimization, which decrease computational costs while mitigating overfitting (Schratz *et al.*, 2019). This brings up another critical practical issue: computational trade-offs. Scaling high-resolution predictive models across vast arid landscapes requires substantial processing power and memory. Consequently, an increasing number of researchers rely on cloud-computing platforms, such as Google Earth Engine (GEE), which alleviate local hardware limitations but simultaneously restrict the ability to deeply configure models and optimize their hyperparameters (Gorelick *et al.*, 2017; Tamiminia *et al.*, 2020).

3.8. Benchmark Datasets and Standardized Test Sites

While great progress in machine learning algorithms has been made due to the availability of benchmark datasets in general remote sensing applications (such as Sen12MS for land cover classification), a critical problem remains: the lack of standard benchmark datasets specifically designed for arid and semi-arid environments. Currently, almost all research devoted to studying vegetation dynamics or soil salinity relies on localized, proprietary field sampling data. This fragmentation greatly hinders the reproducibility of studies and the objective

comparison of different machine learning frameworks (Wadoux *et al.*, 2020).

To improve the practical application of machine learning in monitoring desertification and soil degradation processes, developing open-access benchmark datasets is vital. Such initiatives could include creating a global spectral library for saline soils and assembling annotated datasets for arid vegetation characteristics acquired from UAVs. Furthermore, establishing globally recognized standardized test sites (similar to LTER networks) will allow researchers to conduct rigorous evaluations of novel algorithms, standardize hyperparameter tuning procedures, and ultimately develop more transferable predictive models (Schmitt *et al.*, 2019).

4. Methods of Environmental Modeling using Machine Learning

The application of machine learning (ML) models to analyze remote sensing data has seen continuous growth due to the unprecedented availability of spatial data. Furthermore, the use of Multi-Criteria Decision-Making (MCDM) models together with ML models in hybrid techniques helps to enhance natural resource management. For example, the use of ML models alongside the Analytic Hierarchy Process (AHP) technique can assist in determining the priority areas for the management of vegetation and soil salinity in arid regions (Nguyen & Liu, 2019).

4.1. Introduction to Machine Learning Models

In order to handle large volumes of information and analyze environmental patterns, non-linear models like Random Forest (RF) (Breiman, 2001) and Artificial Neural Networks, especially the Multi-Layer Perceptron (MLP), are commonly selected (Ouma *et al.*, 2023; Su *et al.*, 2024). As an example, RF has been extensively used to simulate vegetation cover variations (Rezaei *et al.*, 2025); meanwhile, MLP and Digital Soil Assessment approaches have proven to be effective instruments for forecasting soil salinity and soil quality dynamics in a long perspective with great accuracy and up to 30 years ahead (AbdelRahman, 2023; Fathizad *et al.*, 2020). The second trend caused by the growing complexity of spatial data is the shift towards deep learning algorithms. CNNs and RNNs have become the standard tools for feature detection in the context of images and time series data; the efficiency of these algorithms has been significantly improved in terms of both accuracy and computational speed (Zhu *et al.*, 2017; Ma *et al.*, 2019; Table 4).

There are a number of machine learning approaches used to monitor vegetation and forecast soil salinity in the recent decade. All these algorithms differ from one another concerning their methodological framework, computer requirements, and applications. Rather than finding out what approach performs better than others, recent literature reviews prove that the performance of models depends on various factors including geographical characteristics of the area under analysis, variables used for forecasting, sample size, spatial and temporal resolution, data quality, and validation method (Belgiu & Drăguț, 2016; Maxwell *et al.*, 2018; Ma *et al.*, 2019). In addition, some recent methodological developments showed that the use of standard random validation leads to a large overestimation of prediction accuracy when spatial models are analyzed because of spatial autocorrelation (Meyer *et al.*, 2018; Ploton *et al.*, 2020). That is why comparisons presented in Tables 4 and 5 should be seen as a qualitative summary of evidence regarding methodological features, benefits, weaknesses, and common applications. of evidences regarding methodological features, benefits, weaknesses, and common applications.

Table 4. Characteristics of Common Machine Learning Algorithms for Vegetation and Soil Salinity Monitoring

Machine Learning Algorithm	Typical Applications	Commonly Reported Strengths	Commonly Reported Limitations
Random Forest (RF)	Vegetation classification, soil salinity prediction, digital soil mapping	Robust to noisy and high-dimensional data; captures nonlinear relationships; provides variable importance	Higher computational cost; reduced interpretability compared with simpler models
Artificial Neural Network (ANN)	Vegetation dynamics, soil property prediction, environmental modeling	Effectively models complex nonlinear relationships; highly flexible	Requires extensive hyperparameter tuning; susceptible to overfitting; computationally demanding
Extreme Gradient Boosting (XGBoost)	Soil salinity mapping, vegetation prediction, regression and classification	High predictive performance; efficient optimization; handles nonlinear interactions	Sensitive to hyperparameter tuning; lower interpretability
Support Vector Machine (SVM)	Land-cover classification, vegetation mapping, soil salinity prediction	Effective for small and medium-sized datasets; strong generalization capability	Sensitive to kernel and parameter selection; computationally intensive for large datasets
K-Nearest Neighbor (KNN)	Image classification, land-cover mapping	Simple implementation; no explicit training phase	Sensitive to feature scaling and irrelevant predictors; computationally expensive for large datasets

Note: The aforementioned characteristics provided in the table are based on the synthesized literature and reflect general methodological trends in machine learning performance instead of universal rankings. The performance of machine learning models is dependent on the purpose of the research, environmental conditions, predictor variables, number of observations, remote sensing datasets, feature extraction, and validation process. In addition, to facilitate clarity, the qualitative ratings are defined as follows: Computational Cost: "Low" implies models that can be executed using typical CPUs; "High/Very High" requires cloud-based computing or Graphics Processing Units (GPUs). Data Requirement: "Low/Medium" implies models working well with small samples; "High/Very High" implies the necessity of using large, contiguous spatial datasets.

4.2. Deep Learning

With a multi-layer neural network (CNN and RNN), Deep Learning has a remarkable capacity to produce features of data in remote sensing images. Such techniques have worked especially well in tasks such as object detection, image recognition, and in time-series analysis. Ma *et al.*, (2019) also applied CNN in classifying Sentinel-2 satellite images with improved results compared to the traditional models such as SVM. The application of the CNN and RNN in Zhu *et al.*, (2017) contributed to the study of vegetation shifts over the years; the F1 score was raised by the mean of 8.

4.3. Reinforcement Learning

With the capability to come up with the best decisions when dealing with dynamic environments, Reinforcement Learning has become a promising process of analysing remote sensing data. These models have a practical use in such areas as the management of resources and monitoring the natural phenomena. Diaz-Vitor *et al.*, (2025) applied the TD3 algorithm to optimize the routes of drones to track fire. Furthermore, Ganapathi Subramanian *et al.*, (2018)

demonstrated that the reinforcement learning might become a potent predictor of the fire spread path by considering satellite images.

4.4. *Transformer Models and Attention Mechanism*

Another missing point in most of the classic reviews is the aspect of Transformer models, which are fast becoming a norm of processing remote sensing time-series data. Transformer models were originally designed to be used with natural language processing, but they feature a strong module known as the self-attention that is used to reflect long-range dependencies in sequential data (Vaswani *et al.*, 2017). Transformers are able to attend time-steps unlike RNNs or LSTMs that process information sequentially. This parallel processing enables them to create better complex and non-linear temporal patterns. It has been proven that Transformer-based models are more efficient than the older ones because they are more capable of learning temporal dynamics, which has proven to be effective in specific tasks such as crop classification and drought prediction (Garnot *et al.*, 2021; Saki *et al.*, 2024).

4.5. *New Frontiers: Generative Models and Physics-Informed Neural Networks*

In addition to the architectures mentioned above, there are two new areas of study that are transforming the landscape of environmental modeling. The former is Physics-Informed Neural Networks (PINNs). As opposed to being strictly data-driven, PINNs encode the governing physical laws of a phenomenon into the loss function of the neural network when being trained, in a way that makes predictions physically sensible, even where field data are sparse (Willard *et al.*, 2022).

The second one is Generative Models, including Generative Adversarial Networks (GANs). They are important and ubiquitous in their remote sensing applications. As an example, they can be applied to data augmentation, removing clouds in satellite images, and image super-resolution to address some of the inherent weaknesses of satellite data (Dash *et al.*, 2023).

4.6. *How to solve Data Scarcity by transfer learning*

Transfer learning is a critical approach that can be used to overcome the problem of data scarce in arid areas. The method consists of fine-tuning a model (usually a deep neural network) that was initially trained on a large, general data set with a smaller, task-specific data set. The model does not have to learn everything and uses the rich feature representations as an initial point obtained through the large dataset. It is a common method of remote sensing to substantially enhance the performance of models, particularly when the number of labeled data is small (Zhu *et al.*, 2017; Kussul *et al.*, 2017).

4.7. *Spatial Decision-Making Models (MCDM) Integration*

Decision-making in the natural resource management requires multi-criteria and integrative decision-making. Multi-Criteria Decision-Making (MCDM) models, including AHP, ANP, and TOPSIS can be viewed as effective prioritization and risk assessment tools in this scenario (Saaty 1980; Zengxiang *et al.*, 2016). The combination of ML models and MCDM techniques allows conducting data analysis more accurately and in-depth and facilitates effective decision-making (Nguyen & Liu, 2019). Further evolution of hybrid models of MCDM and machine learning could introduce new perspectives of accurate forecasting and intelligent management of the environmental crisis (Rezaei *et al.*, 2025). Since the current machine learning algorithms used in remote sensing are varied, the performance of different algorithms in various aspects is important in the selection of the correct method in different applications. In this section, three

major categories of models have been compared analytically. The comparison is performed... as well as takes into account such practical aspects as computational complexity, data training needs, flexibility, and generalization ability (Table 5 and Table 6).

Table 5. Analytical Comparison of Modern Machine Learning Models in Remote Sensing

Feature	Hybrid Models	Deep Learning	Reinforcement Learning
Primary concept	Integration of complementary algorithms and/or data sources	Hierarchical feature learning directly from data	Learning optimal actions through interaction with the environment
Typical applications	Soil salinity prediction, vegetation monitoring, environmental modeling	Image classification, semantic segmentation, object detection, change detection	Adaptive environmental management, resource allocation, autonomous monitoring
Training data requirements	Moderate to high	Generally large labeled datasets	Environment interaction or simulation-based learning
Computational requirements	Moderate to high	High	High
Interpretability	Moderate (model-dependent)	Generally limited	Generally limited
Major strengths	Combines complementary information; improves robustness and predictive performance	Automatically extracts complex spatial and temporal features	Supports adaptive decision-making under dynamic conditions
Major limitations	Increased model complexity and parameter tuning	Large computational cost and data demand	Limited practical applications in environmental remote sensing
Representative software	Scikit-learn, XGBoost, R	TensorFlow, PyTorch	RLlib, Stable-Baselines

Note: The aforementioned characteristics provided in the table are based on the synthesized literature and reflect general methodological trends in machine learning performance instead of universal rankings. The performance of machine learning models is dependent on the purpose of the research, environmental conditions, predictor variables, number of observations, remote sensing datasets, feature extraction, and validation process. In addition, to facilitate clarity, the qualitative ratings are defined as follows: Computational Cost: "Low" implies models that can be executed using typical CPUs; "High/Very High" requires cloud-based computing or Graphics Processing Units (GPUs). Data Requirement: "Low/Medium" implies models working well with small samples; "High/Very High" implies the necessity of using large, contiguous spatial datasets.

Table 6. Integration of Machine Learning Models with Multi-Criteria Decision-Making (MCDM) Methods in the Analysis of Spatial Changes in Vegetation and Soil Salinity in Arid and Semi-Arid Regions

Machine Learning Model	MCDM Method	Potential Synergy / Strength	Advantages	Application Domain
Random Forest	AHP	High Potential	Ability to combine data-driven patterns with expert knowledge	Identification of priority zones for vegetation and soil salinity changes
ANN	TOPSIS	High Potential	Effective for ranking alternatives based on complex non-linear predictions	Prediction and prioritization of vegetation and salinity trends
XGBoost	ELECTRE	Very High Potential	High predictive power combined with robust outranking method	Analysis and ranking of spatio-temporal changes in vegetation and salinity
SVM	AHP	Moderate Potential	Low sensitivity to noisy data combined with structured expert weighting	Modeling and prioritizing spatial changes in arid and semi-arid regions

The application of ML and MCDM aims to address the key gap between the generation of predictive maps and active land management (e.g., Shang *et al.*, 2023; Ghosh, 2021). Thus, when applying AHP, continuous probability maps generated via ML methods such as the spatial prediction of high soil salinity risk can be reclassified and used as a primary criterion in the quantitative assessment of suitability. This ML-derived criterion is then organized within a decision matrix and weighted by experts alongside other socio-environmental factors, such as proximity to agricultural infrastructure, slope, and water availability (Rabie *et al.*, 2025). The final result is a suitability map that highlights priority zones for soil reclamation in arid regions.

In the same manner, methods such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) can directly incorporate the outputs of ML algorithms to rank specific management actions (Parsian *et al.*, 2021). For example, if an ensemble machine learning algorithm predicts the future level of vegetation degradation across different land parcels, TOPSIS can evaluate these specific parcels against various operational constraints. This comparison integrates both the ML-predicted vegetation degradation level and other variables, such as intervention costs and ease of access. This process helps to identify the optimal management parcel that minimizes economic costs while maximizing conservation impacts (Batar & Watanabe, 2021).

5. Model Evaluation, Uncertainty and Validation

Rather than treating these challenges as isolated methodological limitations, the proposed change-oriented framework integrates several complementary strategies to address them systematically. Specifically, the integration of multi-source and multi-temporal remote sensing data reduces information gaps associated with individual sensors and improves the characterization of environmental dynamics. Hybrid machine learning approaches enhance model robustness under heterogeneous environmental conditions, while spatial cross-validation and uncertainty assessment improve the reliability and generalizability of predictive models. In addition, Explainable Artificial Intelligence (XAI) techniques increase model transparency by facilitating the interpretation of predictor importance and model behavior. Accordingly, the following section provides a critical synthesis of the principal methodological challenges identified in the reviewed literature and discusses how each challenge is addressed within the proposed conceptual framework through an integrated monitoring strategy rather than as an isolated methodological issue.

The precise evaluation of ML-RS models is fundamental as the trustworthiness of the model literally speaks through its applications and, hence, decision-making (Belgiu & Dragut, 2016). The standard measures for regression models are the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) (Emadi *et al.*, 2020; Heung *et al.*, 2014). Nash-Sutcliffe efficiency (NSE) is often the preferred metric in hydrology studies (Nash & Sutcliffe, 1970; Melsen *et al.*, 2025). For classifiers the confusion matrices give access to the computations of overall accuracy, precision, recall, and F1 score.

K-fold cross-validation is the go-to method for small data sets or non-uniform distributions as a means to counteract overfitting (Rodriguez-Galiano *et al.*, 2012). Validation datasets kept independent are of utmost strength when it comes to the assessment of generalizability (Wang *et al.*, 2021).

5.1. Spatial Cross-Validation and Transferability

The challenge of data scarcity and spatial heterogeneity in drylands presents a unique hurdle for predictive modeling. Spatial Cross-Validation (SCV) addresses this issue by partitioning a

geographical region into separate, non-overlapping blocks to account for spatial autocorrelation and provide highly reliable accuracy estimations (Roberts *et al.*, 2017). For example, Fathizad *et al.* (2020) applied SCV in the central Iranian desert; this approach successfully reduced the overestimation of soil quality predictions by 12% compared to standard random sampling.

Transferability describes a model's ability to maintain predictive performance across different geographic regions. In this context, Domain Adaptation involves applying transfer learning to fine-tune a model-originally trained on a data-rich source region for application in a data-poor target region (Tuia *et al.*, 2016). Demonstrating this capability, Fathizad *et al.* (2025) showed that Random Forest (RF) and Multilayer Perceptron (MLP) models, after undergoing transfer learning, provided highly accurate soil texture maps ($R^2=0.87-0.90$) across varying desert subregions in Iran.

5.2. Uncertainty Analysis

Beven & Freer (2001) posited that in order to distinguish between reliable and unreliable areas, the models should estimate prediction uncertainties. One of the uses of uncertainty maps is to indicate the locations where more field data is needed. In a case study, Fathizad *et al.*, (2022) produced uncertainty maps for soil organic carbon, pinpointing spots with over 15% uncertainty that called for extra sampling and thus, increasing the trust of the overall model.

The proposed framework addresses this challenge by combining multi-source remote sensing datasets with an adaptive feedback mechanism. As new remote sensing and field observations become available, they are incorporated into the monitoring process to update and refine the model. This iterative approach helps reduce information gaps, improves the temporal consistency of environmental observations, and increases the reliability of machine learning predictions under changing environmental conditions.

5.3. Ground Truthing

Ground truth data (field samples, GPS surveys, or high-resolution images) are essential to adjust and verify predictive models (Foody & Atkinson, 2002). The optimal spatial distribution of these ground data significantly enhances a model's applicability and generalization capabilities (Heung *et al.*, 2014). For instance, Fathizad *et al.* (2020) utilized 201 field samples in the central Iranian desert to test soil salinity models. The collection of these ground-truth samples was not random; rather, it was rigorously designed to address the high environmental heterogeneity of the site. Specifically, a Conditioned Latin Hypercube Sampling (cLHS) strategy was employed to allocate the sampling points (Minasny & McBratney, 2006). This advanced sampling method ensured proportional coverage across the multidimensional space of the environmental covariates (e.g., topographic gradients, remote sensing indices, and land cover types). By utilizing cLHS, the potential problem of sample clustering in easily accessible locations was avoided, ensuring that the full spectrum of environmental variability was represented. Consequently, the Random Forest (RF) predictions achieved high accuracy, with an RMSE of 0.13 dS/m and an R^2 of 0.86.

Beyond robust data collection, a critical challenge in modern spatial modeling is the interpretability of complex algorithms. The proposed framework addresses this challenge by incorporating Explainable Artificial Intelligence (XAI) techniques as an integral component of the model evaluation stage. Rather than relying solely on prediction accuracy, the framework emphasizes understanding how different environmental variables contribute to model predictions. Methods such as SHAP and LIME can be used to identify the relative importance of predictor variables and to improve the transparency of machine learning models. This

information helps researchers and decision-makers better interpret model outputs and increases confidence in the application of machine learning for environmental monitoring and natural resource management (Ribeiro *et al.*, 2016; Lundberg & Lee, 2017; Ploton *et al.*, 2020).

5.4 Specific Challenges in Arid Regions

Heterogeneous land cover along with soil reflectance variability has made it difficult to make predictions using remote sensing in arid regions (Chlingaryan *et al.*, 2018). It is a common phenomenon to have class imbalance, for example, datasets might not include highly saline areas which would then lead models to favor the majority class (Sun *et al.*, 2009). One of the solutions for this problem is employing SMOTE for sampling and using evaluation metrics that are resistant to imbalance, like F1-score or Kappa coefficient.

Within the proposed framework, computational complexity is addressed through a flexible model selection strategy rather than by recommending a single machine learning algorithm. The choice of model depends on the monitoring objective, the availability and quality of input data, computational resources, and the required level of prediction accuracy. Simpler models may be appropriate for routine monitoring tasks, whereas more advanced hybrid or deep learning approaches can be adopted when sufficient data and computational capacity are available. This flexibility allows the framework to be applied under different environmental and operational conditions without relying on a single modeling approach (Belgiu & Drăguț, 2016; Maxwell *et al.*, 2018; Ma *et al.*, 2019).

5.5. Model Evaluation and Uncertainty Assessment

For reliable environmental monitoring, it is crucial that models are evaluated strictly to provide more realistic estimation of their prediction capabilities. As neighboring pixels in remote sensing datasets are usually spatially auto-correlated, the traditional method of random cross-validation will lead to an optimistic prediction assessment of the model (Roberts *et al.*, 2017; Ploton *et al.*, 2020). That is why the proposed model includes spatial cross-validation as one of the essential elements of the model evaluation process. In the spatial cross-validation technique, the study area is divided into independent spatial folds.

Along with the spatial validation of predictions, the framework includes uncertainty mapping that helps measure the reliability of the predictions spatially. It is possible to estimate the prediction uncertainty by using any of the following methods: ensemble models, bootstrap sampling, or the prediction variance from multiple models. The produced maps of uncertainties show the zones in which the model predictions have lower reliability.

In the suggested system, the results from the spatial cross-validation and uncertainty analysis are included in the adaptive feedback loop. Those areas with large uncertainty in predictions and low validity are selected for further data collection and modeling iterations. This leads to improvements in feature selection, model calibration, and prediction accuracy through each monitoring cycle, making the monitoring system more robust and sustainable.

6. Challenges, Policy Implications and Opportunities

6.1. Real-Life Problems and Obstacles

Models of machine learning (ML) and remote sensing (RS) provide a great deal of support for the sustainable management and monitoring of natural resources in the dry regions. One of their main advantages is the detection and analysis of complex and intricate patterns, which makes them perfect candidates if data are weak or noisy (Kuhn & Johnson, 2013). The near real-time monitoring implemented by RS when partnering with ground observance, which is a process

always advantageous in difficult-to-access desert regions where field surveys are extremely expensive and time-consuming (Chlingaryan *et al.*, 2018), is one of the main benefits of this technology in such areas.

Yet, there are some challenges:

1. **Data Quality and Availability:** A major challenge in spatial modeling is the lack of high-quality and reliable datasets for most remote and arid regions (Grimm *et al.*, 2008). For instance, according to the findings by Fathizad *et al.* (2020), only one-third of the collected soil salinity field measurements could be utilized. This significant data attrition occurred because the rest of the data was compromised by logistical constraints inherent to harsh desert conditions, such as extreme weather events and severe accessibility issues.

2. **Model Complexity and Black-Box Nature:** In many cases, it is very difficult to extract the reasoning behind the decisions made by deep learning systems and hybrid ML models, which can adversely affect their acceptance and also create distrust among local in decision-making authorities (Molnar, 2022).

3. **Computational Costs:** In many instances, the use of high-resolution, multi-temporal datasets along with complex ML models entails huge computational costs that may not be easily met by developing countries.

Possibilities:

1. **Free and Open-Access Data:** The data provided by Sentinel and Landsat satellites combined with the use of cloud computing like Google Earth Engine allow for fast and low-cost large-scale analyses (Gorelick *et al.*, 2017).

2. **Hybrid ML Approaches:** The ML technology together with Multi-Criteria Decision-Making (MCDM) allows better identification of actionable insights. For instance, Fathizad *et al.*, (2026) combined NDVI trends with standardized precipitation indices for the purpose of identifying drought-prone vegetation areas. Figure 2 shows a conceptual map that explains the correlation between these main challenges and opportunities.

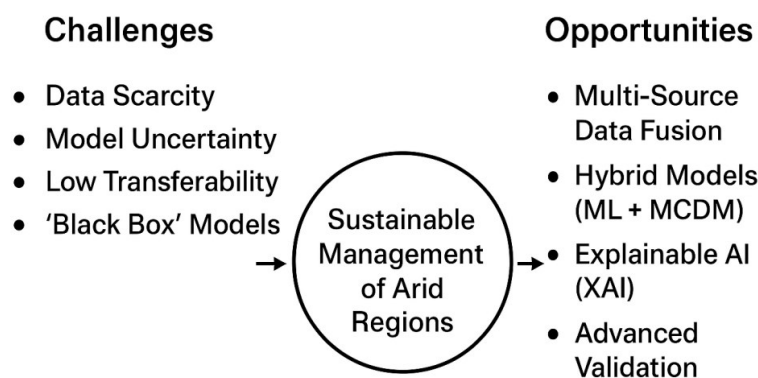


Figure 2. Conceptual synthesis of key challenges and future directions in ML-based environmental monitoring of arid regions.

6.2. Accessibility and Software Development

Advanced software like Google Earth Engine (GEE), ENVI, and QGIS provide the ability to conduct multiple satellite data analysis with very little local computing resources. The majority of cloud-based computing power is dedicated to the processing of massive data sets for environmental conservation and prediction (Matejicek, 2012).

To illustrate, Fathizad *et al.*, (2019) deployed MLP neural networks on GEE to model land use changes in the 500 km² area of central Iran, which was faster by 70% than the local systems.

6.3. Implications of the Environmental Policy

The effective development of environmental policies in dryland regions consistently requires a balance among ecology, economy, and society (Meadowcroft, 2002). Historically, policy-makers in arid countries have depended on reactive approaches, which often fail due to the absence of accurate spatial data. Today, evidence-based policy-making is entirely dependent on the availability of continuous, high-resolution data. The combination of ML and RS facilitates a proactive approach that translates complex spatial predictions into actionable policies.

Case Study of Iran: Iran's national programs addressing soil salinity and land degradation have previously relied on post-crisis engineering approaches that are expensive and temporary. However, a new approach for predicting soil salinity at the watershed scale using remote sensing techniques, geographical information systems, and spatial modeling has recently been adopted (Fathizad *et al.*, 2020; Khajehzadeh *et al.*, 2022). By generating highly accurate spatial vulnerability maps, the government can implement targeted interventions. From a national policy perspective, this entails imposing restrictions on excessive groundwater extraction in highly vulnerable regions, optimizing the distribution of scarce freshwater resources, and treating severely degraded lands through bioremediation.

Egypt's Nile Delta: In Egypt, the agricultural sector is at severe risk due to seawater intrusion and land overexploitation. In this regard, modern spatial algorithms directly support national policies aimed at ensuring food security. For example, the joint application of Sentinel-1 radar and Sentinel-2 optical imagery led to a 15–20% enhancement in the precision of salinity predictions compared to previous methods based on a single data source (Abou Samra & Ali, 2023). This specific achievement is crucial for Egyptian policy-makers, as it allows them to adapt land reclamation projects (e.g., in the Western Desert), optimize the spatial planning of agricultural expansion, and implement early warning systems for farmers in the Nile Delta.

In conclusion, these localized cases demonstrate that the integration of modern ML-RS tools into national policy frameworks extends beyond academic mapping; it enables the creation of Spatial Decision Support Systems (SDSS). These systems are vital for implementing adaptive management, ensuring efficient resource utilization, and supporting long-term sustainable development in sensitive dryland environments.

6.4. Ethical Considerations, Reproducibility, and Open Science

Given the increasing role that machine learning platforms play in the process of decision-making related to environmental issues, it is essential to consider ethical implications, reproducibility issues, and open science methods. The incorporation of high-resolution data from remote sensing using UAVs poses privacy problems that call for a strict adherence to data policy and ethical data collection in the region where the study takes place.

Moreover, the reproducibility crisis in artificial intelligence is an important impediment in environmental modelling. A lot of scientific papers do not include details of hyperparameters used, selection of features, and data preparation procedures that make their models hardly reproducible. Thus, future research should be conducted according to the principle of Open Science in which annotated field data, algorithm source code and model weights should be shared via public repositories such as GitHub or Zenodo. What is more, creating standardized benchmark data sets aimed at soil salinity and vegetation measurements in drylands will ensure that the algorithms under development can be compared with each other fairly and reliably.

6.5. Institutional Barriers and Capacity Building

However, despite the rapid technical development of ML and RS tools, substantial institutional constraints persist, hampering their implementation in dryland environmental management (Benos *et al.*, 2021). The first major constraint is an acute shortage of properly trained staff. Although environmental ministries typically employ professionals in soil science and ecology, they frequently lack experts in advanced data science, cloud computing, and spatial analytics (Klerkx *et al.*, 2019). This skills gap hampers governments' ability to independently update and maintain complex algorithms long after academic research projects conclude.

Moreover, restrictive data-sharing practices and the fragmentation of institutional governance constitute major challenges to the effective utilization of these tools. In many developing countries located in arid regions, critical environmental data (such as local meteorology, groundwater extraction rates, and historical soil profiles) are housed separately across different ministries (Klerkx *et al.*, 2019; Meinard *et al.*, 2021). The reluctance of authorities to share these data prevents the creation of the consolidated and standardized geodatabases required to properly train machine learning algorithms.

7. Conclusion and Future Research Recommendations

Changes in vegetation and soil salinity are among the most critical environmental issues in arid and semi-arid lands, exerting widespread effects on the sustainability of natural resources and food security. In recent years, the integration of advanced machine learning models, remote sensing data, and Geographic Information Systems (GIS) has created new opportunities for monitoring, analyzing, and controlling these changes. This article aimed to review these models and their ability to detect and forecast spatiotemporal changes in vegetation and soil salinity. Based on this synthesis, the main findings are outlined below, followed by recommendations for future research.

Finally, it is important to recognize the limitations of this review. While a systematic search strategy was adopted across key academic databases, the strict exclusion of grey literature—such as government reports and policy papers—may have caused an important set of regional case studies and practical experiences to be overlooked. Additionally, because the inclusion criteria focused exclusively on English-language peer-reviewed journals, there is a possibility that a language bias was introduced to this study. Consequently, this constraint may have caused valuable localized information published in native languages to be excluded from the analysis.

7.1. Summary of Findings

This comprehensive review proves that the incorporation of modern machine learning (ML) tools with RS and GIS data offers a powerful method to monitor vegetation changes and soil salinity in arid and semi-arid environments. Through critical analysis of the literature, this paper concludes that there are several important lessons:

Predictive Stability and Data Integration: Machine learning techniques including Random Forest (RF), Artificial Neural Networks (ANN), and XGBoost exhibit high stability when it comes to the prediction of spatio-temporal environmental changes (Fathizad *et al.*, 2020). Moreover, the incorporation of multiple source high-resolution data (spectral, radar, UAV data) significantly improves the efficiency and accuracy of models in heterogeneous desert areas (Fathizad *et al.*, 2025).

Efficiency of Hybrid Frameworks: The combination of ML predictions with Multi-Criteria Decision-Making (MCDM) techniques has higher practical significance. Such hybrids can be effectively used to prioritize and monitor drought-affected vegetation (Yaghibi *et al.*, 2026).

Change in Focus towards Multi-Temporal Dynamics: Static modeling is not enough when dealing with gradual degradation processes. It is vital to use continuous, multi-temporal RS data to detect long-term trends in spatiotemporal changes of soil properties and vegetation cover (Fathizad *et al.*, 2022).

In summary, the move from a fragmented predictive mapping model to a more holistic, transformative concept is likely to improve the accuracy of environmental monitoring while ensuring the sustainable management of natural resources.

7.2. Future Research Recommendations

The methodological gaps and weaknesses that were found for the conceptual framework need to be addressed, and these include the following priorities:

- **Maximizing Data Fusion:** In order to deal with the bottleneck of having sparse and noisy data from the field in remote arid regions, future researchers should aim at maximizing the data fusion of optical, radar, thermal, and UAV datasets. For example, combining Sentinel-1 radar datasets with UAV images was successful in increasing the resolution of salinity mapping by 18% in central Iran (Fathizad *et al.*, 2025).
- **Dealing with "Black-Box" Models Using XAI Techniques:** In order to solve the problem of the black-box approach in using complex models such as deep learning or hybrid models, future frameworks should use Explainable Artificial Intelligence (XAI). This will increase interpretability and build trust among policymakers and local managers regarding feature importance in model predictions.
- **Addressing the Problem of Uncertainty through Proactive Analysis:** In order to overcome the bottleneck of model uncertainty caused by inconsistent prediction errors in different environments, future models should be characterized by proactive analysis of uncertainty and sensitivity. Creating uncertainty maps for particular areas allows scientists to identify precisely which places need further field studies, and hence helps avoid the misclassification of saline soils (Fathizad *et al.*, 2020).
- **Solving the Problem of Poor Transferability Using Localized Models:** In order to address the issue of poor performance of models when it comes to their transferability, future research needs to concentrate on adjusting particular models according to local climatic conditions. Adapting neural networks (e.g., MLP) specifically for regional desert climates results in highly accurate and transferable models (Fathizad *et al.*, 2019).
- **Overcoming Short-Term Static Observation with Temporal Modeling:** In order to overcome the shortcomings of short-term and static observation models, research needs to use multi-decade datasets (for example, Google Earth Engine time-series). Spatiotemporal modeling is needed in order to discover long-term degradation trends such as declines in soil organic carbon during decades (Fathizad *et al.*, 2022).
- **Implementing Evidence-Based Action Through ML-MCDM Hybrid Early Warning Systems:** To finally close the loop between modeling and management, future models need to incorporate ML outputs along with MCDM to produce effective early warning systems. The combination of NDVI and drought indexes can help produce very accurate seasonal alerts, allowing for appropriate action to be taken on time (Yaghobi *et al.*, 2026).

Acknowledgment

The authors wish to express their gratitude to the individuals and organizations that contributed to the preparation of this review article.

Author Contributions

Conceptualization, H.F. and M.K.; methodology, H.F. and M.K.; software, H.F.; validation, H.F. and M.K.; formal analysis, H.F.; investigation, H.F. and M.K.; resources, H.F.; data curation, H.F.; writing-original draft preparation, H.F.; writing-review and editing, H.F. and M.K.; visualization, H.F.; supervision, H.F. and M.K.; project administration, H.F. and M.K.; funding acquisition, M.K. All authors have read and agreed to the published version of the manuscript.

Funding

Yazd University and Ilam University supported this study. No specific grants were received from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interests

The authors declare no competing interests.

Data Availability Statement

No new datasets were generated or analyzed during this study. All information discussed in this review article was compiled from previously published sources.

Ethical considerations

This review article did not involve human participants, human subjects, animals, or the collection of personal data; therefore, ethical approval and informed consent were not required.

Conflict of interest

The authors declare that they have no conflicts of interest.

References

- AbdelRahman, M. A. E. (2023). An overview of land degradation, desertification and sustainable land management using GIS and remote sensing applications. *Rendiconti Lincei. Scienze Fisiche e Naturali*, 34(3), 767–808. <https://doi.org/10.1007/s12210-023-01155-3>
- Abou Samra, R. M., & Ali, R. R. (2018). The development of an overlay model to predict soil salinity risks by using remote sensing and GIS techniques: A case study in soils around Idku Lake, Egypt. *Environmental Monitoring and Assessment*, 190(12), 706. <https://doi.org/10.1007/s10661-018-7079-3>
- Abuelgasim, A., & Ammad, R. (2019). Mapping soil salinity in arid and semi-arid regions using Landsat 8 OLI satellite data. *Remote Sensing Applications: Society and Environment*, 13, 415–425. <https://doi.org/10.1016/j.rsase.2018.12.010>
- Adelle, C., Weiland, S., Dick, J., González Olivo, D., Marquardt, J., Rots, G., & Zasada, I. (2016). Regulatory impact assessment: A survey of selected developing and emerging economies. *Public Money & Management*, 36(2), 89–96. <https://doi.org/10.1080/09540962.2016.1118930>
- Allbed, A., & Kumar, L. (2013). Soil salinity mapping and monitoring in arid and semi-arid regions using remote sensing technology: A review. *Advances in Remote Sensing*, 2(4), 373–385. <https://doi.org/10.4236/ars.2013.24040>

- Almalki, R., Khaki, M., Saco, P. M., & Rodriguez, J. F. (2022). Monitoring and mapping vegetation cover changes in arid and semi-arid areas using remote sensing technology: A review. *Remote Sensing*, 14(20), 5143. <https://doi.org/10.3390/rs14205143>
- Aly, A. A., Al-Omran, A. M., Sallam, A. S., Al-Wabel, M. I., & Al-Shayaa, M. S. (2016). Vegetation cover change detection and assessment in arid environment using multi-temporal remote sensing images and ecosystem management approach. *Solid Earth*, 7(2), 713–725. <https://doi.org/10.5194/se-7-713-2016>
- Ascough, J. C., Maier, H. R., Ravalico, J. K., & Strudley, M. W. (2008). Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. *Ecological Modelling*, 219(3–4), 383–399. <https://doi.org/10.1016/j.ecolmodel.2008.07.015>
- Baltrušaitis, T., Ahuja, C., & Morency, L. P. (2019). Multimodal machine learning: A survey and taxonomy. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 41(2), 423–443. <https://doi.org/10.1109/TPAMI.2018.2798607>
- Batar, A. K., & Watanabe, T. (2021). Landslide susceptibility mapping and assessment using geospatial platforms and weights of evidence (WoE) method in the Indian Himalayan region: Recent developments, gaps, and future directions. *ISPRS International Journal of Geo-Information*, 10(3), 114. <https://doi.org/10.3390/ijgi10030114>
- Belgiu, M., & Drăguț, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 114, 24–31. <https://doi.org/10.1016/j.isprsjprs.2016.01.011>
- Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. *Sensors*, 21(11), 3758. <https://doi.org/10.3390/s21113758>
- Beven, K., & Freer, J. (2001). Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of Hydrology*, 249(1–4), 11–29. [https://doi.org/10.1016/S0022-1694\(01\)00421-8](https://doi.org/10.1016/S0022-1694(01)00421-8)
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>
- Cash, D. W., Clark, W. C., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., & Mitchell, R. B. (2003). Knowledge systems for sustainable development. *Proceedings of the National Academy of Sciences*, 100(14), 8086–8091. <https://doi.org/10.1073/pnas.1231332100>
- Cashmore, M., Bond, A., & Sadler, B. (2009). Introduction: The effectiveness of impact assessment instruments. *Impact Assessment and Project Appraisal*, 27(2), 91–93. <https://doi.org/10.3152/146155109X454285>
- Che, X., Feng, M., Sexton, J., Channan, S., Sun, Q., Ying, Q., & Wang, Y. (2019). Landsat-based estimation of seasonal water cover and change in arid and semi-arid Central Asia (2000–2015). *Remote Sensing*, 11(11), 1323. <https://doi.org/10.3390/rs11111323>
- Chen, J., Chen, S., Fu, R., Li, D., Jiang, H., Wang, C., & Hicks, B. J. (2022). Remote sensing big data for water environment monitoring: Current status, challenges, and future prospects. *Earth's Future*, 10(2), e2021EF002289. <https://doi.org/10.1029/2021EF002289>

- Chen, X., Yang, S., Wen, X., Wang, Y., & Wang, W. (2025). Study on soil salinity inversion of different crop types based on multi-time series. *Plant and Soil*, 514(1), 1187–1203. <https://doi.org/10.1007/s11104-025-07455-x>
- Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture*, 151, 61–69. <https://doi.org/10.1016/j.compag.2018.05.012>
- Cord, A. F., Klein, D., Mora, F., & Dech, S. (2014). Comparing the suitability of classified land cover data and remote sensing variables for modeling distribution patterns of plants. *Ecological Modelling*, 272, 129–140. <https://doi.org/10.1016/j.ecolmodel.2013.09.011>
- Cui, J., Chen, X., Han, W., Cui, X., Ma, W., & Li, G. (2023). Estimation of soil salt content at different depths using UAV multi-spectral remote sensing combined with machine learning algorithms. *Remote Sensing*, 15(21), 5254. <https://doi.org/10.3390/rs15215254>
- Dash, A., Ye, J., & Wang, G. (2023). A review of generative adversarial networks (GANs) and its applications in a wide variety of disciplines: From medical to remote sensing. *IEEE Access*, 12, 18330–18357. <https://doi.org/10.1109/ACCESS.2023.3242060>
- Diaz-Vilor, C., Lozano, A., & Jafarkhani, H. (2025). A reinforcement learning approach for wildfire tracking with UAV swarms. *IEEE Transactions on Wireless Communications*, 24(4), 2766–2782. <https://doi.org/10.1109/TWC.2024.3524324>
- Ding, Y., Xu, J., Wang, X., Peng, X., & Cai, H. (2020). Spatial and temporal effects of drought on Chinese vegetation under different coverage levels. *Science of the Total Environment*, 716, 137166. <https://doi.org/10.1016/j.scitotenv.2020.137166>
- Emadi, M., Taghizadeh-Mehrjardi, R., Cherati, A., Danesh, M., Mosavi, A., & Scholten, T. (2020). Predicting and mapping of soil organic carbon using machine learning algorithms in Northern Iran. *Remote Sensing*, 12(14), 2234. <https://doi.org/10.3390/rs12142234>
- Emmanuel, T., Maupong, T., Mpoeleng, D., Semong, T., Mphago, B., & Tabona, O. (2021). A survey on missing data in machine learning. *Journal of Big Data*, 8, 1–37. <https://doi.org/10.1186/s40537-021-00516-9>
- Farifteh, J., Farshad, A., & George, R. J. (2006). Assessing salt-affected soils using remote sensing, solute modelling, and geophysics. *Geoderma*, 130(3–4), 191–206. <https://doi.org/10.1016/j.geoderma.2005.02.003>
- Fathizad, H., Ardakani, M. A. H., Heung, B., Sodaiezhadeh, H., Rahmani, A., Fathabadi, A., & Taghizadeh-Mehrjardi, R. (2018). Evaluating desertification using remote sensing technique and object-oriented classification algorithm in the Iranian central desert. *Journal of African Earth Sciences*, 145, 115–130. <https://doi.org/10.1016/j.jafrearsci.2018.04.012>
- Fathizad, H., Ardakani, M. A. H., Heung, B., Sodaiezhadeh, H., Rahmani, A., Fathabadi, A., & Taghizadeh-Mehrjardi, R. (2019). Modeling land use change process by integrating the MLP neural network model in the central desert regions of Iran. *Desert*, 24(2), 241–254.
- Fathizad, H., Ardakani, M. A. H., Heung, B., Sodaiezhadeh, H., Rahmani, A., Fathabadi, A., & Taghizadeh-Mehrjardi, R. (2020). Spatio-temporal dynamic of soil quality in the central Iranian desert modeled with machine learning and digital soil assessment techniques. *Ecological Indicators*, 118, 106736. <https://doi.org/10.1016/j.ecolind.2020.106736>

- Fathizad, H., Hakimzadeh Ardakani, M. A., & Eshghi, B. (2025). Digital mapping of soil texture with the use of MLP, decision tree and RF models in Iran's desert region. *Modeling Earth Systems and Environment*, 11(6), 1–24. <https://doi.org/10.1007/s40808-025-02469-x>
- Fathizad, H., Rostami, N., & Faramarzi, M. (2015). Detection and prediction of land cover changes using Markov chain model in semi-arid rangeland in western Iran. *Environmental Monitoring and Assessment*, 187, 1–12. <https://doi.org/10.1007/s10661-015-4805-y>
- Fathizad, H., Taghizadeh-Mehrjardi, R., Hakimzadeh Ardakani, M. A., Zeraatpisheh, M., Heung, B., & Scholten, T. (2022). Spatiotemporal assessment of soil organic carbon change using machine-learning in arid regions. *Agronomy*, 12(3), 628. <https://doi.org/10.3390/agronomy12030628>
- Feng, K., Wang, T., Liu, S., Kang, W., Chen, X., Guo, Z., & Zhi, Y. (2022). Monitoring desertification using machine-learning techniques with multiple indicators derived from MODIS images in Mu Us Sandy Land, China. *Remote Sensing*, 14(11), 2663. <https://doi.org/10.3390/rs14112663>
- Feng, Q., Liu, J., & Gong, J. (2015). UAV remote sensing for urban vegetation mapping using random forest and texture analysis. *Remote Sensing*, 7(1), 1074–1094. <https://doi.org/10.3390/rs70101074>
- Foody, G. M., & Atkinson, P. M. (Eds.). (2002). *Uncertainty in remote sensing and GIS*. John Wiley & Sons. <https://doi.org/10.1002/0470035269>
- Ganapathi Subramanian, S., & Crowley, M. (2018). Using spatial reinforcement learning to build forest wildfire dynamics models from satellite images. *Frontiers in ICT*, 5, 6. <https://doi.org/10.3389/fict.2018.00006>
- Garnot, V. S. F., Landrieu, L., Giordano, S., & Chehata, N. (2020). Satellite image time series classification with pixel-set encoders and temporal self-attention. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 12325–12334). <https://doi.org/10.1109/CVPR42600.2020.01234>
- Geneletti, D. (2008). Incorporating biodiversity assets in spatial planning: Methodological proposal and development of a planning support system. *Landscape and Urban Planning*, 84(3–4), 252–265. <https://doi.org/10.1016/j.landurbplan.2007.08.005>
- Ghamisi, P., Rasti, B., Yokoya, N., Wang, Q., Höfle, B., Bruzzone, L., & Benediktsson, J. A. (2018). Multisource and multitemporal data fusion in remote sensing. *arXiv*. <https://doi.org/10.48550/arXiv.1812.08287>
- Ghosh, B. (2021). Spatial mapping of groundwater potential using data-driven evidential belief function, knowledge-based analytic hierarchy process and an ensemble approach. *Environmental Earth Sciences*, 80(18), 625. <https://doi.org/10.1007/s12665-021-09921-y>
- Gislason, P. O., Benediktsson, J. A., & Sveinsson, J. R. (2006). Random forests for land cover classification. *Pattern Recognition Letters*, 27(4), 294–300. <https://doi.org/10.1016/j.patrec.2005.08.011>
- Google Earth Engine Team. (2021). *Google Earth Engine: A cloud-based platform for planetary-scale environmental monitoring*. <https://earthengine.google.com>

- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Gregory, R., Failing, L., Harstone, M., Long, G., McDaniels, T., & Ohlson, D. (2012). *Structured decision making: A practical guide to environmental management choices*. John Wiley & Sons.
- Grimm, R., Behrens, T., Märker, M., & Elsenbeer, H. (2008). Soil organic carbon concentrations and stocks on Barro Colorado Island—Digital soil mapping using Random Forests analysis. *Geoderma*, 146(1–2), 102–113. <https://doi.org/10.1016/j.geoderma.2008.05.008>
- Haidarh, M., Mu, C., & Liu, Y. (2025). Hybrid multiscale spectral-spatial Swin transformer for hyperspectral image classification. *Optics & Laser Technology*, 192, 113923. <https://doi.org/10.1016/j.optlastec.2025.113923>
- Heung, B., Bulmer, C. E., & Schmidt, M. G. (2014). Predictive soil parent material mapping at a regional-scale: A Random Forest approach. *Geoderma*, 214, 141–154. <https://doi.org/10.1016/j.geoderma.2013.09.016>
- Hoa, P. V., Giang, N. V., Binh, N. A., Hai, L. V. H., Pham, T. D., Hasanlou, M., & Tien Bui, D. (2019). 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 Sensing*, 11(2), 128. <https://doi.org/10.3390/rs11020128>
- Huang, I. B., Keisler, J., & Linkov, I. (2011). Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends. *Science of the Total Environment*, 409(19), 3578–3594. <https://doi.org/10.1016/j.scitotenv.2011.06.022>
- Huang, J., Yu, H., Guan, X., Wang, G., & Guo, R. (2020). Accelerated dryland expansion under climate change. *Nature Climate Change*, 10(6), 487–492. <https://doi.org/10.1038/s41558-020-0751-4>
- Ivushkin, K., Bartholomeus, H., Bregt, A. K., Pulatov, A., Kempen, B., & De Sousa, L. (2019). Global mapping of soil salinity change. *Remote Sensing of Environment*, 231, 111260. <https://doi.org/10.1016/j.rse.2019.111260>
- Jakeman, A. J., Letcher, R. A., & Norton, J. P. (2006). Ten iterative steps in development and evaluation of environmental models. *Environmental Modelling & Software*, 21(5), 602–614. <https://doi.org/10.1016/j.envsoft.2006.01.004>
- Jordan, A., & Lenschow, A. (2010). Environmental policy integration: A state of the art review. *Environmental Policy and Governance*, 20(3), 147–158. <https://doi.org/10.1002/eet.539>
- Kaplan, G., Gašparović, M., Alqasemi, A. S., Aldhaheri, A., Abuelgasim, A., & Ibrahim, M. (2023). Soil salinity prediction using machine learning and Sentinel-2 remote sensing data in hyper-arid areas. *Physics and Chemistry of the Earth, Parts A/B/C*, 130, 103400. <https://doi.org/10.1016/j.pce.2023.103400>
- Khajehzadeh, M., Afzali, S. F., Honarbakhsh, A., & Ingram, B. (2022). Remote sensing and GIS-based modeling for predicting soil salinity at the watershed scale in a semi-arid region of southern Iran. *Arabian Journal of Geosciences*, 15(5), 423. <https://doi.org/10.1007/s12517-022-09762-4>

- Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS: Wageningen Journal of Life Sciences*, 90(1), 100315. <https://doi.org/10.1016/j.njas.2019.100315>
- Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling*. Springer. <https://doi.org/10.1007/978-1-4614-6849-3>
- Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geoscience and Remote Sensing Letters*, 14(5), 778–782. <https://doi.org/10.1109/LGRS.2017.2681128>
- Lefsky, M. A., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar remote sensing for ecosystem studies. *BioScience*, 52(1), 19–30. [https://doi.org/10.1641/0006-3568\(2002\)052\[0019:LRSFES\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2002)052[0019:LRSFES]2.0.CO;2)
- Liu, Z., Chen, D., Liu, S., Feng, W., Lai, F., Li, H., & Zan, M. (2022). Research on vegetation cover changes in arid and semi-arid region based on a spatio-temporal fusion model. *Forests*, 13(12), 2066. <https://doi.org/10.3390/f13122066>
- Lu, L., Kuenzer, C., Wang, C., Guo, H., & Li, Q. (2015). Evaluation of three MODIS-derived vegetation index time series for dryland vegetation dynamics monitoring. *Remote Sensing*, 7(6), 7597–7614. <https://doi.org/10.3390/rs70607597>
- Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., & Johnson, B. A. (2019). Deep learning in remote sensing applications: A meta-analysis and review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 152, 166–177. <https://doi.org/10.1016/j.isprsjprs.2019.04.015>
- Mahmoud, M., Liu, Y., Hartmann, H., Stewart, S., Wagener, T., Semmens, D., & Winter, L. (2009). A formal framework for scenario development in support of environmental decision-making. *Environmental Modelling & Software*, 24(7), 798–808. <https://doi.org/10.1016/j.envsoft.2008.11.010>
- Malczewski, J. (2006). GIS-based multicriteria decision analysis: A survey of the literature. *International Journal of Geographical Information Science*, 20(7), 703–726. <https://doi.org/10.1080/13658810600661508>
- Matejicek, L. (2012). Environmental modelling using cloud computing tools: Case studies and examples. In *iEMSs 2012—Managing resources of a limited planet: Proceedings of the 6th Biennial Meeting of the International Environmental Modelling and Software Society*. International Environmental Modelling and Software Society.
- McNie, E. C. (2007). Reconciling the supply of scientific information with user demands: An analysis of the problem and review of the literature. *Environmental Science & Policy*, 10(1), 17–38. <https://doi.org/10.1016/j.envsci.2006.10.004>
- Meadowcroft, J. (2002). Politics and scale: Some implications for environmental governance. *Landscape and Urban Planning*, 61(2–4), 169–179. [https://doi.org/10.1016/S0169-2046\(02\)00111-1](https://doi.org/10.1016/S0169-2046(02)00111-1)
- Meinard, Y., Barreteau, O., Boschet, C., Daniell, K. A., Ferrand, N., Girard, S., & Zarate, P. (2021). What is policy analytics? An exploration of 5 years of environmental management applications. *Environmental Management*, 67(5), 886–900. <https://doi.org/10.1007/s00267-020-01408-z>

- Melsen, L. A., Puy, A., Torfs, P. J., & Saltelli, A. (2025). The rise of the Nash-Sutcliffe efficiency in hydrology. *Hydrological Sciences Journal*, 1–12. <https://doi.org/10.1080/02626667.2025.2475105>
- Metwaly, M. M., AbdelRahman, M. A., & Mohamed, S. A. (2024). A machine learning model and multi-temporal remote sensing for sustainable soil management in Egypt's Western Nile Delta. *Earth Systems and Environment*, 1–21. <https://doi.org/10.1007/s41748-024-00499-6>
- Meyer, H., Reudenbach, C., Hengl, T., Katurji, M., & Nauss, T. (2018). Improving performance of spatio-temporal machine learning models using forward feature selection and target-oriented validation. *Environmental Modelling & Software*, 101, 1–9. <https://doi.org/10.1016/j.envsoft.2017.12.001>
- Minasny, B., & McBratney, A. B. (2006). A conditioned Latin hypercube method for sampling in the presence of ancillary information. *Computers & Geosciences*, 32(9), 1378–1388. <https://doi.org/10.1016/j.cageo.2005.12.009>
- Morgan, R. S., El-Hady, M. A., & Rahim, I. S. (2018). Soil salinity mapping utilizing Sentinel-2 and neural networks. *Indian Journal of Agricultural Research*, 52(5), 524–529. <https://doi.org/10.18805/IJARE.A-316>
- Mzid, N., Boussadia, O., Albrizio, R., Stellacci, A. M., Braham, M., & Todorovic, M. (2023). Salinity properties retrieval from Sentinel-2 satellite data and machine learning algorithms. *Agronomy*, 13(3), 716. <https://doi.org/10.3390/agronomy13030716>
- Nan, L., Yang, M., Wang, H., Miao, P., Ma, H., Wang, H., & Zhang, X. (2024). Assessment of spatio-temporal dynamic vegetation evolution and its driving mechanism on the Kubuqi Desert using multi-source satellite remote sensing. *Remote Sensing*, 16(24), 4769. <https://doi.org/10.3390/rs16244769>
- Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I—A discussion of principles. *Journal of Hydrology*, 10(3), 282–290. [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6)
- Nguyen, T. T. N., & Liu, C. C. (2019). A new approach using AHP to generate landslide susceptibility maps in the Chen-Yu-Lan Watershed, Taiwan. *Sensors*, 19(3), 505. <https://doi.org/10.3390/s19030505>
- Nguyen, V. V., Pham, B. T., Vu, B. T., Prakash, I., Jha, S., Shahabi, H., & Tien Bui, D. (2019). Hybrid machine learning approaches for landslide susceptibility modeling. *Forests*, 10(2), 157. <https://doi.org/10.3390/f10020157>
- OpenAI. (2026). *ChatGPT (GPT-5.6)* [Large language model]. <https://chatgpt.com/>
- Ouma, Y. O., Keitsile, A., Nkwae, B., Odirile, P., Moalafhi, D., & Qi, J. (2023). Urban land-use classification using machine learning classifiers: Comparative evaluation and post-classification multi-feature fusion approach. *European Journal of Remote Sensing*, 56(1), 2173659. <https://doi.org/10.1080/22797254.2023.2173659>
- Paluba, D., Saux, B. L., & Stych, P. (2023). Estimating optical vegetation indices and biophysical variables for temperate forests with Sentinel-1 SAR data using machine learning techniques: A case study for Czechia. *arXiv*. <https://doi.org/10.48550/arXiv.2311.07537>

- Parsian, S., Amani, M., Moghimi, A., Ghorbanian, A., & Mahdavi, S. (2021). Flood hazard mapping using fuzzy logic, analytical hierarchy process, and multi-source geospatial datasets. *Remote Sensing*, 13(23), 4761. <https://doi.org/10.3390/rs13234761>
- Ploton, P., Mortier, F., Réjou-Méchain, M., Barbier, N., Picard, N., Rossi, V., & Pélissier, R. (2020). Spatial validation reveals poor predictive performance of large-scale ecological mapping models. *Nature Communications*, 11(1), 4540. <https://doi.org/10.1038/s41467-020-18321-y>
- QGIS Development Team. (2021). *QGIS Geographic Information System*. Open Source Geospatial Foundation Project. <https://qgis.org>
- Rabie, A. B., Elhag, M., & Subyani, A. (2025). Remote sensing, GIS, and machine learning in water resources management for arid agricultural regions: A review. *Water*, 17(21), 3125. <https://doi.org/10.3390/w17213125>
- Reed, M. S., Evely, A. C., Cundill, G., Fazey, I., Glass, J., Laing, A., Newig, J., Parrish, B., Prell, C., Raymond, C., & Stringer, L. C. (2010). What is social learning? *Ecology and Society*, 15(4), Article r1. <https://doi.org/10.5751/ES-03564-1504r01>
- Reisi Gahrouei, O., Côté, J. F., Bournival, P., Giguère, P., & Béland, M. (2024). Comparison of deep and machine learning approaches for Quebec tree species classification using a combination of multispectral and LiDAR data. *Canadian Journal of Remote Sensing*, 50(1), 2359433. <https://doi.org/10.1080/07038992.2024.2359433>
- Rezaei, M., Moghaddam, M. A., Piri, J., Azizyan, G., & Shamsipour, A. A. (2025). Drought prediction using advanced hybrid machine learning for arid and semi-arid environments. *KSCE Journal of Civil Engineering*, 29(4), 100025. <https://doi.org/10.1016/j.kscej.2024.100025>
- Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., & Dormann, C. F. (2017). Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography*, 40(8), 913–929. <https://doi.org/10.1111/ecog.02881>
- Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 67, 93–104. <https://doi.org/10.1016/j.isprsjprs.2011.11.002>
- Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resources allocation*. McGraw-Hill.
- Saki, M., Keshavarz, R., Franklin, D., Abolhasan, M., Lipman, J., & Shariati, N. (2024). Precision soil quality analysis using transformer-based data fusion strategies: A systematic review. *arXiv*. <https://doi.org/10.48550/arXiv.2410.18353>
- Salcedo, F. P., Cutillas, P. P., Cabañero, J. J. A., & Vivaldi, A. G. (2022). Use of remote sensing to evaluate the effects of environmental factors on soil salinity in a semi-arid area. *Science of the Total Environment*, 815, 152524. <https://doi.org/10.1016/j.scitotenv.2021.152524>
- Salimi, K. H., Ahmadi Sani, N., & Jalilnejad, N. (2019). Mapping soil salinity using remote sensing technology (Case study: South lands of West Azarbaijan province). *Water and Soil Science*, 29(2), 115–128.

- Samadzadegan, F., Toosi, A., & Dadrass Javan, F. (2025). A critical review on multi-sensor and multi-platform remote sensing data fusion approaches: Current status and prospects. *International Journal of Remote Sensing*, 46(3), 1327–1402. <https://doi.org/10.1080/01431161.2024.2429784>
- Sarker, I. H. (2021). Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions. *SN Computer Science*, 2(6), 1–20. <https://doi.org/10.1007/s42979-021-00815-1>
- Saurette, D. D., Heck, R. J., Gillespie, A. W., Berg, A. A., & Biswas, A. (2024). Sample size optimization for digital soil mapping: An empirical example. *Land*, 13(3), 365. <https://doi.org/10.3390/land13030365>
- Schmitt, M., Hughes, L. H., Qiu, C., & Zhu, X. X. (2019). SEN12MS—A curated dataset of georeferenced multi-spectral Sentinel-1/2 imagery for deep learning and data fusion. *arXiv*. <https://doi.org/10.48550/arXiv.1906.07789>
- Schratz, P., Muenchow, J., Iturrutxa, E., Richter, J., & Brenning, A. (2019). Hyperparameter tuning and performance assessment of statistical and machine-learning algorithms using spatial data. *Ecological Modelling*, 406, 109–120. <https://doi.org/10.1016/j.ecolmodel.2019.06.002>
- Shafeian, E., Fassnacht, F. E., & Latifi, H. (2023). Detecting semi-arid forest decline using time series of Landsat data. *European Journal of Remote Sensing*, 56(1), 2260549. <https://doi.org/10.1080/22797254.2023.2260549>
- Shang, H., Su, L., Chen, W., Tsangaratos, P., Ilia, I., Liu, S., & Duan, Z. (2023). Spatial prediction of landslide susceptibility using logistic regression (LR), functional trees (FTs), and random subspace functional trees (RSFTs) for Pengyang County, China. *Remote Sensing*, 15(20), 4952. <https://doi.org/10.3390/rs15204952>
- Su, T., Wang, X., Ning, S., Sheng, J., Jiang, P., Gao, S., & Li, Z. (2024). Enhancing soil salinity evaluation accuracy in arid regions: An integrated spatiotemporal data fusion and AI model approach for arable lands. *Land*, 13(11), 1837. <https://doi.org/10.3390/land13111837>
- Sui, D. Z., & Maggio, R. C. (1999). Integrating GIS with hydrological modeling: Practices, problems, and prospects. *Computers, Environment and Urban Systems*, 23(1), 33–51. [https://doi.org/10.1016/S0198-9715\(98\)00052-0](https://doi.org/10.1016/S0198-9715(98)00052-0)
- Suliman, M. M., Kaya, F., Elsheikh, M. A., Başayığit, L., & Francaviglia, R. (2023). Application of machine learning algorithms for digital mapping of soil salinity levels and assessing their spatial transferability in arid regions. *Land*, 12(9), 1680. <https://doi.org/10.3390/land12091680>
- Sun, Y., Wong, A. K. C., & Kamel, M. S. (2009). Classification of imbalanced data: A review. *International Journal of Pattern Recognition and Artificial Intelligence*, 23(4), 687–719. <https://doi.org/10.1142/S0218001409007326>
- Taghadosi, M. M., & Hasanlou, M. (2021). Developing geographic weighted regression (GWR) technique for monitoring soil salinity using Sentinel-2 multispectral imagery. *Environmental Earth Sciences*, 80(3), 75. <https://doi.org/10.1007/s12665-020-09345-0>

- Talebi, H., & Samadianfard, S. (2024). Integration of machine learning and remote sensing for drought index prediction: A framework for water resource crisis management. *Earth Science Informatics*, 17(5), 4949–4968. <https://doi.org/10.1007/s12145-024-01437-w>
- Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., & Brisco, B. (2020). Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 164, 152–170. <https://doi.org/10.1016/j.isprsjprs.2020.04.001>
- Tifafi, M., Guenet, B., & Hatté, C. (2018). Large differences in global and regional total soil carbon stock estimates based on SoilGrids, HWSD, and NCSCD: Intercomparison and evaluation based on field data from USA, England, Wales, and France. *Global Biogeochemical Cycles*, 32(1), 42–56. <https://doi.org/10.1002/2017GB005678>
- Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, 8(2), 127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0)
- Tuia, D., Persello, C., & Bruzzone, L. (2016). Domain adaptation for the classification of remote sensing data: An overview of recent advances. *IEEE Geoscience and Remote Sensing Magazine*, 4(2), 41–57. <https://doi.org/10.1109/MGRS.2016.2548504>
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30, 5998–6008.
- Verstraete, M. M., Scholes, R. J., & Smith, M. S. (2009). Climate and desertification: Looking at an old problem through new lenses. *Frontiers in Ecology and the Environment*, 7(8), 421–428. <https://doi.org/10.1890/080119>
- Wadoux, A. M. C., Minasny, B., & McBratney, A. B. (2020). Machine learning for digital soil mapping: Applications, challenges and suggested solutions. *Earth-Science Reviews*, 210, 103359. <https://doi.org/10.1016/j.earscirev.2020.103359>
- Wang, F., Han, L., Liu, L., Bai, C., Ao, J., Hu, H., & Wei, Y. (2024). Advancements and perspective in the quantitative assessment of soil salinity utilizing remote sensing and machine learning algorithms: A review. *Remote Sensing*, 16(24), 4812. <https://doi.org/10.3390/rs16244812>
- Wang, J., Ding, J., Yu, D., Teng, D., He, B., Chen, X., & Su, F. (2020). Machine learning-based detection of soil salinity in an arid desert region, Northwest China: A comparison between Landsat-8 OLI and Sentinel-2 MSI. *Science of the Total Environment*, 707, 136092. <https://doi.org/10.1016/j.scitotenv.2019.136092>
- Wang, J., Peng, J., Li, H., Yin, C., Liu, W., Wang, T., & Zhang, H. (2021). Soil salinity mapping using machine learning algorithms with the Sentinel-2 MSI in arid areas, China. *Remote Sensing*, 13(2), 305. <https://doi.org/10.3390/rs13020305>
- Wehr, A., & Lohr, U. (1999). Airborne laser scanning—An introduction and overview. *ISPRS Journal of Photogrammetry and Remote Sensing*, 54(2–3), 68–82. [https://doi.org/10.1016/S0924-2716\(99\)00011-8](https://doi.org/10.1016/S0924-2716(99)00011-8)

- Willard, J., Jia, X., Xu, S., Steinbach, M., & Kumar, V. (2020). Integrating physics-based modeling with machine learning: A survey. *arXiv*. <https://doi.org/10.48550/arXiv.2003.04919>
- Williams, B. K., Szaro, R. C., & Shapiro, C. D. (2007). *Adaptive management: The U.S. Department of the Interior technical guide*. U.S. Department of the Interior, Adaptive Management Working Group.
- Wu, W., Muhaimeed, A. S., Al-Shafie, W. M., & Al-Quraishi, A. M. F. (2020). Using radar and optical data for soil salinity modeling and mapping in Central Iraq. In *Environmental remote sensing and GIS in Iraq* (pp. 19–40). Springer. https://doi.org/10.1007/978-3-030-21344-2_2
- Yaghobi, S., Daneshi, A., Faramarzi, M., Azadi, H., Fathizad, H., & Islami, I. (2026). Drought impacts on vegetation cover in Western Iran: Application of standardized precipitation and normalized difference vegetation index. *International Journal of Environmental Science and Technology*, 23(1), 35. <https://doi.org/10.1007/s13762-025-06795-6>
- Yan, K., Gao, S., Yan, G., Ma, X., Chen, X., Zhu, P., & Wang, Q. (2025). A global systematic review of the remote sensing vegetation indices. *International Journal of Applied Earth Observation and Geoinformation*, 139, 104560. <https://doi.org/10.1016/j.jag.2025.104560>
- Yang, X., & Lo, C. P. (2003). Modelling urban growth and landscape changes in the Atlanta metropolitan area. *International Journal of Geographical Information Science*, 17(5), 463–488.
- Yuan, F., & Liu, R. (2020). Mining social media data for rapid damage assessment during Hurricane Matthew: Feasibility study. *Journal of Computing in Civil Engineering*, 34(3), 05020001. [https://doi.org/10.1061/\(ASCE\)CP.1943-5487.0000877](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000877)
- Zarei, A., Hasanlou, M., & Mahdianpari, M. (2021). A comparison of machine learning models for soil salinity estimation using multi-spectral earth observation data. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, V-3-2021, 257–263. <https://doi.org/10.5194/isprs-annals-V-3-2021-257-2021>
- Zengxiang, Q., Jianjun, L., & Weihua, X. (2015). Suitability analysis of mountain settlements in Qinling using a GIS system. *Acta Ecologica Sinica*, 35(4), 1274–1283. <https://doi.org/10.5846/stxb201305020899>
- Zhu, X. X., Tuia, D., Mou, L., Xia, G. S., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep learning in remote sensing: A comprehensive review and list of resources. *IEEE Geoscience and Remote Sensing Magazine*, 5(4), 8–36. <https://doi.org/10.1109/MGRS.2017.2762307>