Review

Applications of Machine Learning and Remote Sensing in Soil and Water Conservation

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Posted Date: 1 October 2024

doi: 10.20944/preprints202410.0048.v1

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 doi:10.20944/preprints202410.0048.v1

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Applications of Machine Learning and Remote Sensing in Soil and Water Conservation

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Abstract: The application of machine learning (ML) and remote sensing (RS) in soil and water conservation has become a powerful tool. As analytical tools continue to advance, the variety of ML algorithms and RS sources has expanded, providing opportunities for more sophisticated analyses. At the same time, researchers are required to select appropriate technologies based on research objectives, topic, and scope of the study area. In this paper, we present a comprehensive review on the application of ML algorithms and RS that has been implemented to advance research in soil and water conservation. The key contribution of this review paper is that it provides an overview of current research areas within soil and water conservation and their effectiveness in improving prediction accuracy and resource management in categorized subfields, including biomass-vegetation, soil properties, hydrology and water resources, and wildfire management. We also highlight challenges and future directions based on limitations of ML and RS applications in soil and water conservation. This review aims to serve as a reference for researchers and decision-makers by offering insights into the effectiveness of ML and RS applications in the field of soil and water conservation.

Keywords: Machine learning; Remote sensing; Soil conservation; Water conservation; Environmental analysis; Data-driven decision-making; Resource management

1. Introduction

Soil and water play a pivotal role in various ecological processes, including nutrient cycling, water filtration, and habitat provision, which collectively support biodiversity and ecosystem stability. Soils contribute to the cycling of carbon, nitrogen, and phosphorus critical for plant growth and ecosystem productivity [1–3]. Water is essential for maintaining hydrological cycles, regulating temperature, and sustaining terrestrial and aquatic habitats [4,5]. These resources are fundamental to ecosystem resilience and functionality, impacting not only natural processes, but also human activities such as agriculture and urban development [6,7].

In addition to their ecological significance, soil and water resources are crucial for sustainable agricultural practices and food security [8]. However, their integrity is increasingly compromised by anthropogenic factors including climate change, population growth, deforestation, and unsustainable land use practices [9]. Climate change can exacerbate soil erosion, disrupt nutrient cycles, and affect water availability by altering precipitation patterns and increasing frequencies of extreme weather events [10]. Population growth and urban expansion place additional pressures on these resources, leading to overexploitation, pollution, and habitat loss [11]. Deforestation can further undermine soil structure and reduce land's capacity to retain water, while poor land management practices can accelerate soil degradation and water contamination [12,13].

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Addressing these challenges requires a comprehensive approach to soil and water conservation that encompasses a range of strategies aimed at mitigating negative effects of these stressors [14,15]. Effective soil conservation involves practices such as erosion control, moisture retention through irrigation management and organic amendments, and sustainable land use planning. Similarly, water conservation encompasses measures to enhance water quality, improve storage capacity, and promote efficient usage. These conservation practices are important not only for sustaining ecosystem health and agricultural productivity, but also for supporting broader environmental management goals, including wildfire mitigation and recovery. To address this, numerical models have traditionally been important tools in soil and water conservation [16,17]. However, their reliance on a limited set of variables and specific assumptions often results in prediction accuracy being heavily dependent on given input data [18–21]. Additionally, they may fail to account for uncertainties in the detection of climate change [18]. Thus, advanced tools that can complement or even replace traditional numerical models are needed. Integration of machine learning (ML) and remote sensing (RS) data presents a promising solution to limitations of traditional methods in soil and water conservation [22]. Advances in usage of RS data provide extensive spatial and temporal data, capturing environmental changes with high precision across large areas [23,24]. RS techniques such as multispectral and hyperspectral imaging, LiDAR, and synthetic aperture radar (SAR) enable the collection of data on various environmental parameters, including soil moisture, vegetation cover, land surface temperature, and water quality. When combined with ML techniques such as Random Forest (RF), Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), and Gradient Boosting Machines (GBMs), these data can be analyzed to identify patterns, make predictions, and develop more effective conservation strategies. Combined with ML, these data can be analyzed to identify patterns of spatial and temporal data, make predictions, and establish more effective conservation strategies [25,26]. The ability of ML to process vast amounts of RS data enables extraction of valuable insights from complex, unstructured datasets, leading to improved accuracy in predicting soil and water resource changes. Additionally, the fusion of ML and RS allows for real-time monitoring and assessment, offering dynamic and responsive tools for decision-making in conservation practices [27,28]. This integrated approach can enhance resource optimization, increase precision of policy implementations, and facilitate data-driven decision-making in soil and water management.

The objective of this review is to explore the potential of ML and RS technologies in advancing soil and water conservation. This review aims to provide an overview of current research areas within soil and water conservation and to present how a combination of ML and RS can overcome limitations of traditional methods. The review will highlight applications of various ML techniques and RS data in different subfields of soil and water conservation, demonstrating their effectiveness in improving prediction accuracy and resource management. Additionally, this paper will discuss future research directions, focusing on integrating ML with RS and development of innovative solutions for sustainable soil and water conservation. The scope includes a detailed examination of how these advanced tools can be applied across diverse conservation challenges and implications for future policy and practice.

2. Materials and Methods

2.1 Searching/Classification Methodology

The literature review focused on collecting published journals that applied ML algorithms and RS data to conduct research related to soil and water conservation, as summarized in Figure 1.

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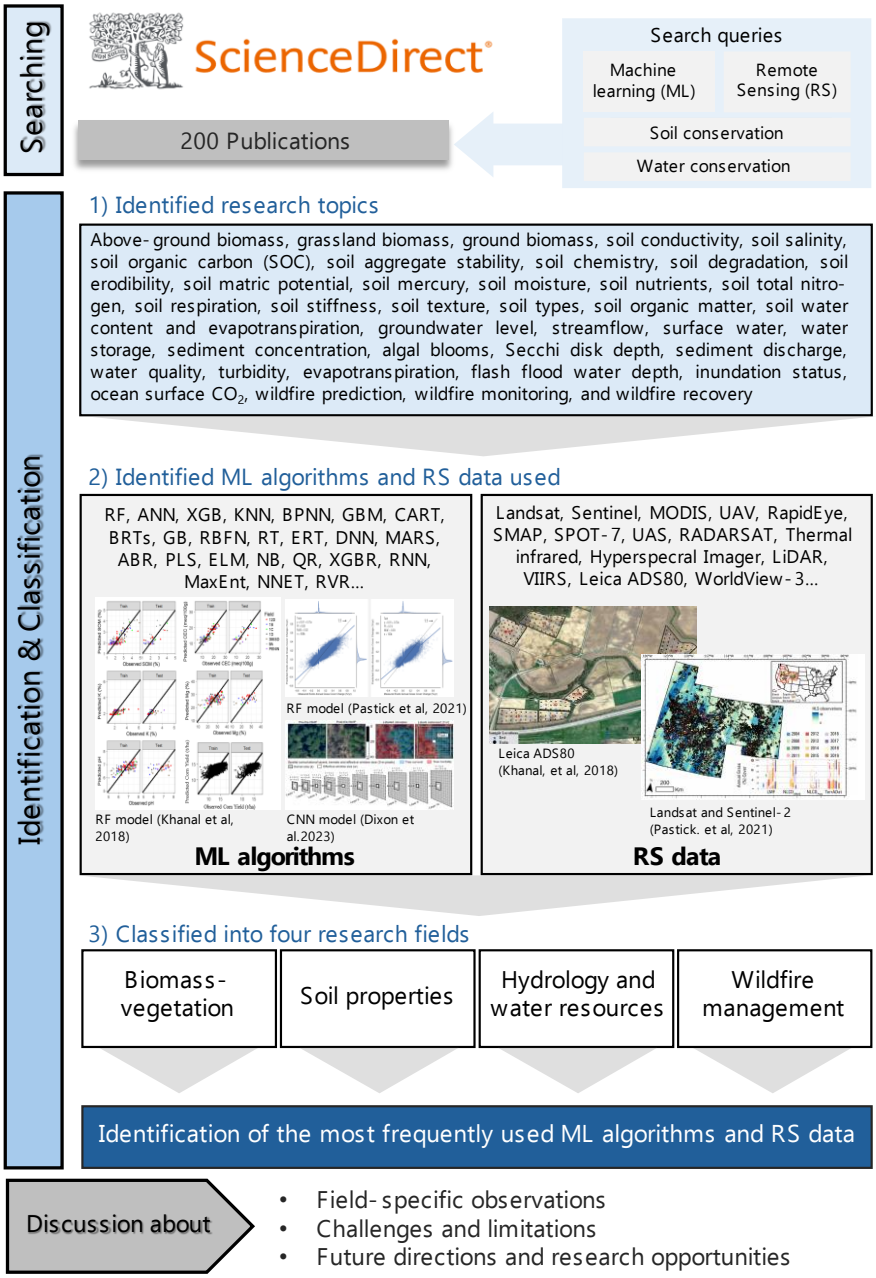

Figure 1. An overview of the study's process, highlighting the search methodology, identification of research topics, employed ML algorithms and RS data, classification and sub-classification criteria, as well as key discussion points

To identify relevant publications, we utilized the web-based bibliographic database 'ScienceDirect' to identify relevant publications, using specific keywords such as "machine learning," "remote sensing," "soil conservation," and "water conservation". This search resulted in the identification of 200 studies conducted across 47 countries, as shown in Figure 2. Studies conducted in China, the United States, and Iran, with smaller but notable frequencies in Australia, Canada, Russia, and several European countries showed the highest frequencies. Studies conducted in other locations around the world, including parts of Africa, South America, and South Asia, were also marked, indicating their relative frequency in the data. Figure 3 illustrates trends in reviewed publications across four key research areas from 2006 to 2024. Wildfire management exhibited a dramatic increase in publications, peaking in 2022, likely due to the increasing impact of climate change, advances in ML and RS technologies, and increased global awareness driven by initiatives such as the UN's SDGs and the Paris Agreement. Research studies on soil properties, hydrology, and water resources also peaked around the same time, although they showed a more gradual rise

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and fall. Frequency of research on biomass-vegetation remained relatively low in comparison, with minimal fluctuations throughout the period.

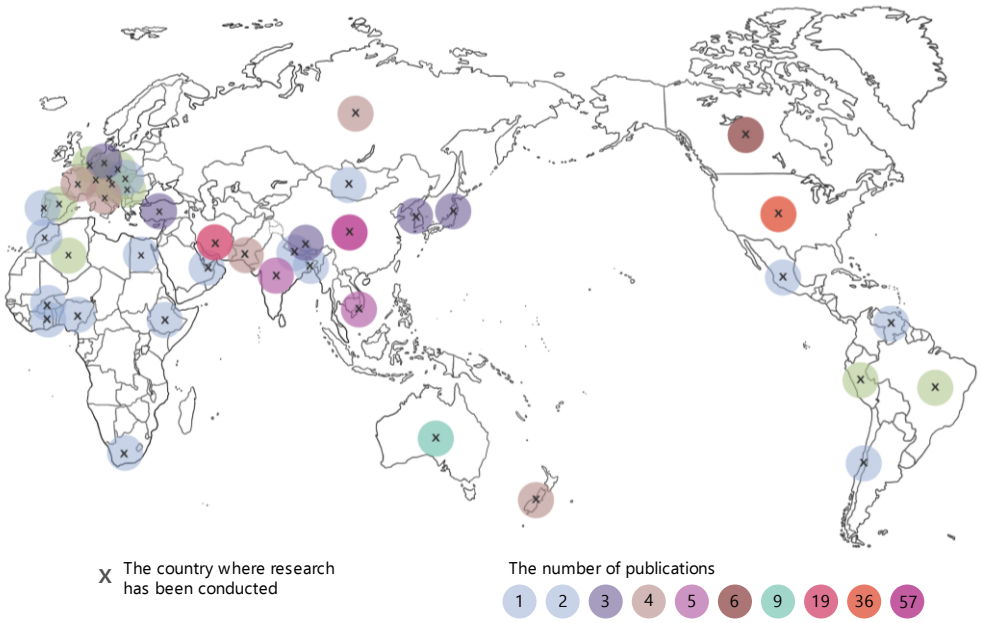

Figure 2. A world map depicting 47 countries where research has been conducted, marked by 'x'. Colored circles represent the number of publications in each country, with the corresponding numbers shown in the legend.

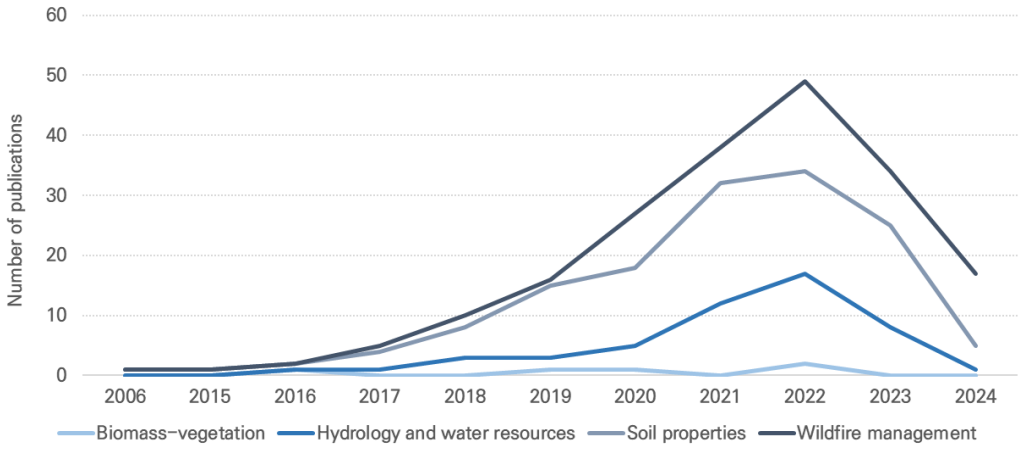

Figure 3. Number of publications from 2006 to 2024 in four research areas: wildfire management, soil properties, hydrology and water resources, and biomass-vegetation. A notable peak in publications on wildfire management occurred around 2022.

Research subjects of 200 studies were then identified and categorized into a total of 37 specific research topics, referred to as "subcategorized subjects," including above-ground biomass, grassland biomass, ground biomass, soil conductivity, soil salinity, soil organic carbon (SOC), soil aggregate stability, soil chemistry, soil degradation, soil erodibility, soil matric potential, soil mercury, soil moisture, soil nutrients, soil total nitrogen, soil respiration, soil stiffness, soil texture, soil types, soil organic matter, soil water content and evapotranspiration, groundwater level, streamflow, surface water, water storage, sediment concentration, algal blooms, Secchi disk depth, sediment discharge, water quality, turbidity, evapotranspiration, flash flood water depth, inundation status, ocean surface CO_2, wildfire prediction, wildfire monitoring, and wildfire recovery as shown in Table 1. These subcategorized subjects were then reclassified into four research fields: 1) biomass-vegetation, 2) soil properties, 3) hydrology and water resources, and 4) wildfire management. While some subcategorized subjects of collected studies were closely related and ambiguous to distinguish, the

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classification focused on the objective of this study. The research field of soil properties had the highest number of publications, followed by wildfire management, hydrology and water resources, and biomass-vegetation research fields. Publications were distributed as follows: 93 (47%) papers on soil properties, 52 (26%) papers on wildfire management, 50 (25%) papers on hydrology and water resources, and 5 (2%) papers on biomass-vegetation as shown in Figure 4.

Table 1. Classification of 200 research studies into four research fields based on their subcategorized subjects (this table lists the number of publications associated with each research field and specific subcategorized subjects within them. The four fields include biomass-vegetation, soil properties, hydrology and water resources, and wildfire management, encompassing a total of 37 subcategorized subjects)

Research fields	Subcategorized subjects	Number of publications
Biomass-vegetation	Above-ground biomass[29–31], grassland biomass[32], ground biomass[33,34]	5
Soil properties	Soil conductivity[35–37], soil salinity[28,38–57], SOC [58–72], soil aggregate stability[73,74], soil chemistry[75,76], soil degradation[77], soil erodibility[78–81], soil matric potential[82], soil mercury[83], soil moisture[84–110], soil nutrients[111–113], soil total nitrogen[114], soil respiration[115], soil stiffness[116], soil texture[117–119], soil types[120], soil organic matter[121–124], soil water content and evapotranspiration[125]	93
Hydrology and water resources	Groundwater level[126], streamflow[127], surface water[128,129], water storage[130], sediment concentration[131], algal blooms[132], Secchi disk depth[133], sediment discharge[134], waters quality[135–159], turbidity[160–165], evapotranspiration[166,167], flash flood water depth[168], inundation status[169], ocean surface CO_2[170]	50
Wildfire management	Wildfire prediction[171–192], wildfire monitoring[25,193–218], wildfire recovery[219,220]	52

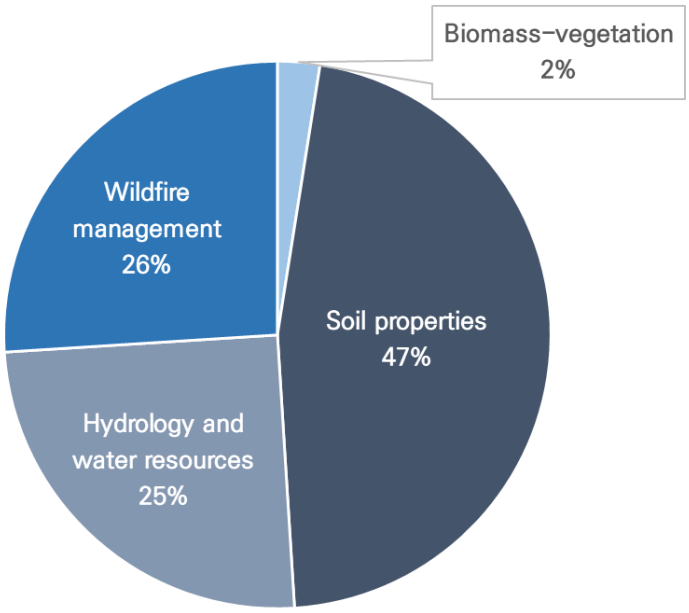

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Figure 4. Distribution of 200 research studies across four research fields. This pie chart illustrates the percentage of publications dedicated to each field: soil properties (47%), hydrology and water resources (25%), wildfire management (26%), and biomass-vegetation (2%).

3. Results and Discussion

3.1. Types and Frequencies of RS Data Used in Soil and Water Conservation Research

Of 200 studies collected, a total of 41 different types of RS techniques were identified (Table A2). Figure 5 depicts the number of publications that utilized each RS data, highlighting only those RS data used more than twice across the 200 studies. The following RS data were used only once each: AGRS, ALOS-2, AVIRIS-NG, GF-1, Triplesat, PALSAR-2, Terra, ZH-1, ETM+, SVC, SRTM, NLCD, Himawari-8, TDC, AMSR-E, MERIS, MERRA-2, Chinese Environmental 1A satellite, GOES-16, TM, SAR, and SPOT-4. This study analyzed types and frequencies of RS data used across different research fields in soil and water conservation. RS data were classified based on four research fields. Below is an overview of the most frequently used RS data types within each field. Table 3 summarizes the number of publications and the top three most commonly used RS data in different environmental research fields, including biomass-vegetation, soil properties, hydrology and water resources, and wildfire management. In the field of biomass-vegetation, MODIS and UAVs were the most commonly used algorithms, appearing two times. These tools are crucial for large-scale biomass estimation and vegetation monitoring. For Soil Properties, Landsat 8 was the most frequently used (32 times). Its high-resolution images and multispectral capabilities are particularly effective for evaluating soil characteristics. In hydrology and water resources, Landsat 8 was again predominant. It was used 18 times for tracking changes in water bodies, flood monitoring, and resource management. Lastly, in wildfire management, MODIS was the leading algorithm. It was used 20 times, offering vital support for real-time fire monitoring and management across damaged areas.

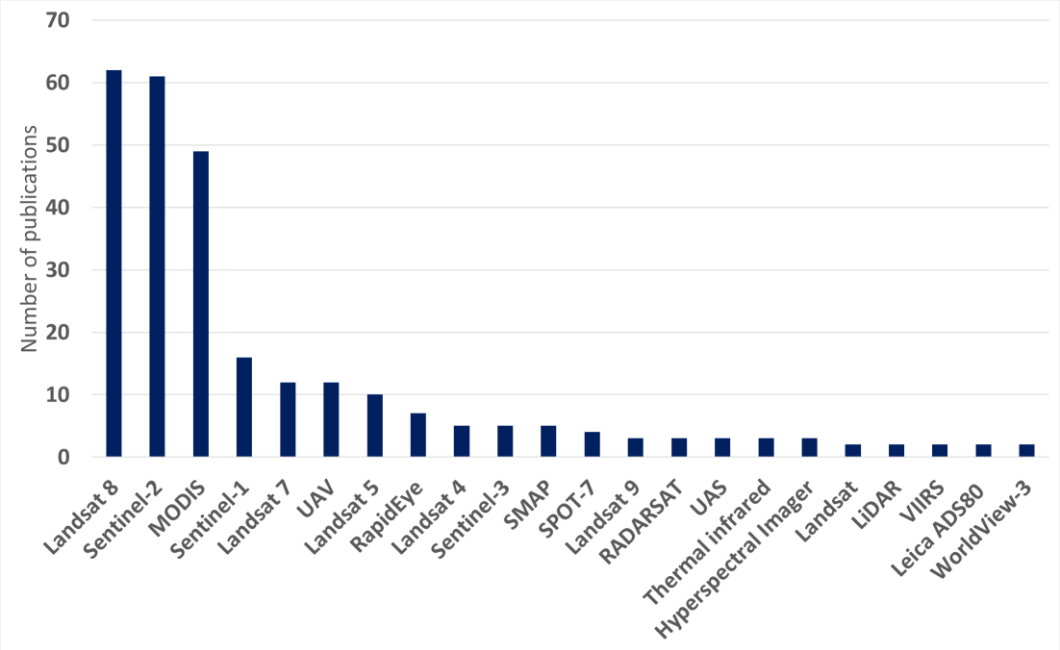

Figure 5. Frequency of usage for RS data in soil and water conservation research. A total of 41 different RS techniques were identified. Only those used more than twice are shown in the figure. RS data used only once are not shown in the figure, including AGRS, ALOS-2, AVIRIS-NG, GF-1, Triplesat, PALSAR-2, Terra, ZH-1, ETM+, SVC, SRTM, Himawari-8, and TDC.

Table 3. Overview of the number of publications and the top three most commonly used RS data in different research fields, including biomass-vegetation, soil properties, hydrology and water resources, and wildfire management

Research fields	Number of publications	Top three most commonly used RS data	
		Algorithms	Frequency of usages
Biomass-vegetation	5	(1) MODIS, UAV	2

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		(2) Landsat 8, Sentinel-2, ALOS-2, STRM	1
		N/A	N/A
Soil properties	93	(1) Landsat 8	32
		(2) Sentinel-2	28
		(3) MODIS	22
Hydrology and water resources	50	(1) Landsat 8	18
		(2) Sentinel-2	16
		(3) Rapid Eye	7
Wildfire management	52	(1) MODIS	20
		(2) Sentinel-2	15
		(3) Landsat 8	10

Landsat and MODIS are essential satellite sensors, each suitable for specific research applications due to differences in data characteristics and resolution. Landsat 8, Sentinel-2, and MODIS are frequently used in soil and water resource studies due to their technical features. Landsat, with its high spatial resolution of 30 meters, is ideal for detailed studies of soil characteristics and hydrology. It allows for precise analysis of small-scale features such as soil moisture and water flow. In contrast, MODIS with a lower resolution of 250 to 1,000 meters but a higher revisit frequency of twice daily is better suited for monitoring large-scale, rapidly changing events like wildfires. MODIS is particularly effective for wildfire management due to its ability to capture wide areas quickly and detect heat through infrared bands, while Landsat's detailed imagery is preferred for soil and hydrological research.

These RS data also provide broad spatial and temporal coverage. MODIS collects global data daily, while Landsat 8 and Sentinel-2 offer high-resolution imagery with revisit periods of 16 days and 5 days, respectively. This allows for long-term monitoring of environmental changes and time-series analysis of hydrological events or soil changes. Moreover, these RS data offer long-term historical datasets, which is a significant advantage. For instance, the Landsat program has been accumulating data since the 1970s, making it valuable for analyzing decades of environmental changes or soil erosion patterns. Similarly, Sentinel-2 and MODIS provide consistent datasets over the years, supporting accurate trend analysis and modeling. The preference for these applications reflects their efficiency in capturing crucial information for soil and water resource conservation.

3.2. Types and Frequencies of ML Algorithm Used in Soil and Water Conservation Research

A total of 50 distinct ML algorithms were identified and their usage frequencies are illustrated in Figure 6. Algorithms that appeared more than twice are shown, while those not depicted to prevent excessive clutter, each used only once, include RTM, ANFIS, ARD, BAGGING, BDT, SA, SCA-Elman, SoLIM, SOM, SR, PSO-SVR, B-CART, CBR, DR, DELM, GAN, BAYE, LGBM, GSC, GRNN, PCR, PKR, RPART, MR-CNN, LMM, EBP, ETR, ELR, EM, EFS, EPR, DBN, DRF, DMP, LDA, MDN, MLPR, MT, Nue-SICR, SICR, FR, FCN, FNN, AdaBag, BST, M5P, YOLO, and IF. The number of publications across research fields related to RS data and the top three most commonly used algorithms along with their frequency of usage is shown in Table 4. In the biomass-vegetation field, RF and ANN were used most frequently. The Soil properties field had the highest number of publications, with RF being the most prevalent algorithm. Similarly, hydrology and water resources and wildfire management also showed a preference for RF as the leading algorithm. In cases where algorithms were used with the same frequency, they were ranked equally. The total number of algorithm usages does not necessarily match the total number of publications due to the use of multiple algorithms in some studies.

RF, ANN, and SVM were the most commonly used ML algorithms across different research fields. RF is an ensemble learning method that constructs multiple decision trees during training and aggregates their outputs for prediction. This approach enhances accuracy and mitigates overfitting by averaging results of numerous trees, which can help manage noisy and high-dimensional datasets common in environmental research. RF is frequently used in environmental research due to its effectiveness in identifying feature importance, which helps researchers determine the most influential variables affecting environmental processes such as water quality prediction *[143,156]* and

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land cover classification[80] . Its robustness and capacity to manage large datasets enhance its utility across various ecological and hydrological applications. ANNs excel at modeling complex, non-linear relationships capturing intricate data patterns. Comprised of interconnected neurons that can adjust weights through iterative training, ANNs can optimize predictions for complex environmental variables. This adaptability makes them highly effective for tasks such as flood prediction and groundwater level forecasting, where capturing non-linear interactions is essential. Their ability to generalize from extensive datasets ensures precise modeling of dynamic environmental systems. This adaptability makes ANNs particularly useful for tasks such as flood prediction or groundwater level forecasting, where capturing non-linear interactions is crucial. Their capability to generalize from extensive training datasets enables accurate modeling of dynamic environmental systems and phenomena.

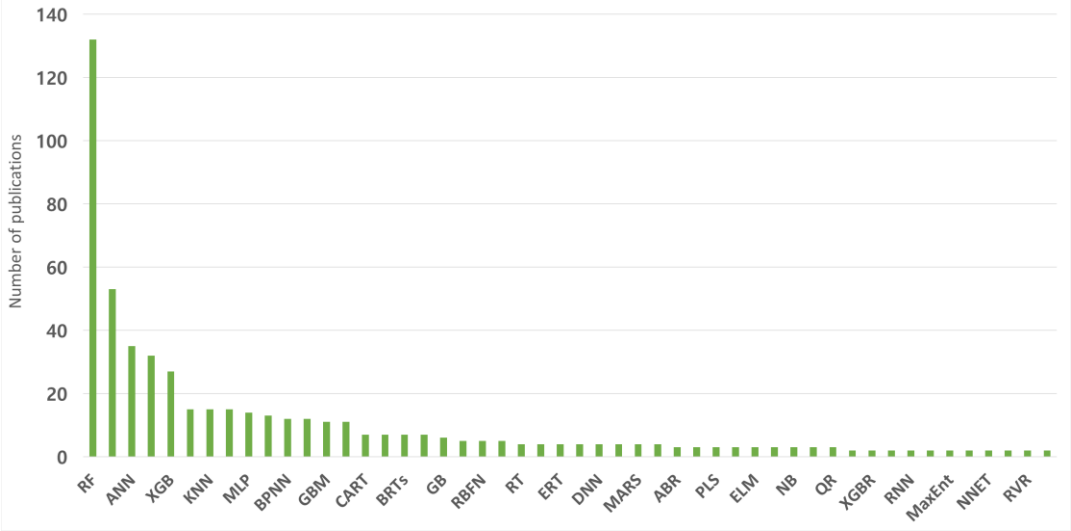

Figure 6. Frequency of usage for ML algorithm in soil and water conservation research. RF shows the highest frequency of usage. Only algorithms used more than twice are shown in the figure. RS data used only once are not shown in the figure.

Table 4. Overview of the number of publications and the top three most commonly used ML algorithms in different research fields, including biomass-vegetation, soil properties, hydrology and water resources, and wildfire management

Research fields	Number of publications	Top three most commonly used RS data	
		Algorithms	Frequency of usages
Biomass-vegetation	5	(1) RF, ANN	3
		(2) SVM, MLR	2
		(3) ANFIS, PLS, KNN, MARS	1
Soil properties	93	(1) RF	67
		(2) ANN	23
		(3) SVM	21
Hydrology and water resources	50	(1) RF	32
		(2) SVM, SVR	14
		(3) XGB	9
Wildfire management	52	(1) RF	30
		(2) SVM	16
		(3) MLP	7

3.3 Field-Specific Observations

3.3.1. Biomass-Vegetation

In the research field of biomass and vegetation, researchers frequently combine MODIS and UAV data with ML algorithms such as RF and ANN to assess vegetation conditions and estimate

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biomass. MODIS is effective for large-scale vegetation monitoring and tracking seasonal changes and long-term trends due to its global coverage and frequent revisit times. UAV, on the other hand, provides high spatial resolution and flexibility, capturing detailed images at plot or landscape levels. Equipped with sensors like RGB cameras, multispectral, hyperspectral, and LiDAR, UAVs can be utilized to detect specific wavelengths that indicate plant health, structure, and biomass. RF is particularly useful for managing large datasets and modeling complex relationships between spectral data and vegetation attributes such as Leaf Area Index (LAI), chlorophyll content, and biomass density.

3.3.2. Soil Properties

In the research field of soil properties, numerous studies have combined RS data from Landsat 8 and Sentinel-2 with RF. Landsat 8 and Sentinel-2 are widely utilized for mapping and monitoring soil properties at regional and global scales due to their high-resolution multispectral imagery. These satellites provide data that can be used to derive indicators related to soil properties such as organic carbon content, soil moisture, and soil texture. ML algorithms such as RF and SVM are particularly effective in this field because they can handle large and complex datasets and model nonlinear relationships between RS-derived variables and soil attributes. RF is especially useful for processing large amounts of data and analyzing complex patterns that link spectral information with soil properties, while SVM is often employed to classify and predict soil properties by maximizing the margin between different types of soil data. The integration of RS data and ML algorithms enables more accurate and efficient prediction and mapping of soil characteristics, which is essential for sustainable land management, agriculture, and environmental conservation.

3.3.3. Hydrology and Water Resources

In the research field of hydrology and water resources, studies have mainly focused on predicting river flow, groundwater levels, and water quality parameters. RS data from Landsat 8 and Sentinel-2 have been widely used due to their ability to capture detailed spatial and temporal information related to water bodies and terrain. These satellites can provide high-resolution multispectral imagery that is crucial for monitoring and assessing various hydrological variables such as surface water extent, vegetation cover, and soil moisture, which can directly influence hydrological processes. In this field, RF and SVR are preferred for modeling complex and nonlinear hydrological processes due to their robustness and accuracy. RF has been utilized to process large datasets and identify patterns in river flow and groundwater levels, while SVR has been employed to predict continuous variables such as water quality parameters, leveraging its ability to model relationships in data with limited observations. The combination of RS data from Landsat 8 and Sentinel-2 with ML algorithms such as RF and SVR can enhance the ability to accurately predict and manage water resources, which is essential for sustainable water resource management and planning.

3.3.4. Wildfire Management

In the research field of wildfire management, ML techniques are extensively used to predict and monitor wildfire occurrences. MODIS, known for its daily global coverage, is one of the most frequently utilized RS data sources in this domain. MODIS provides critical information for real-time monitoring and historical analysis of wildfires, enabling the detection of active fires, mapping of burn scars, and assessment of the extent of fire-affected areas. Its frequent revisit times are particularly useful for tracking wildfire progression and immediate impacts. To predict fire-prone areas and assess post-fire effects on soil and vegetation, MODIS data are commonly used with RF and SVM. RF is highly effective in identifying complex patterns among environmental variables, such as vegetation type, moisture content, and weather conditions, which can influence wildfire risk. SVM is also employed to classify regions based on fire vulnerability and to assess the severity of fires within ecosystems. The integration of MODIS data with ML algorithms such as RF and SVM can enhance the ability to predict wildfires, mitigate risks, and manage post-fire recovery efforts, contributing to more effective wildfire management strategies.

4. Challenges and Limitations

4.1. Data-Related Challenges

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One of the fundamental challenges in the application of ML to soil and water conservation lies in the availability, quality, and consistency of RS data. RS data are often characterized by varying spatial, spectral, and temporal resolutions, which can introduce significant variability into datasets used for model training and validation. For instance, while Landsat can provide data with moderate (15 ~ 120 m) spatial resolution and a long temporal record, Sentinel-2 offers higher spatial resolution (10 ~ 60 m) but with a shorter historical dataset. The integration of these diverse data sources can be problematic, as differences in resolution, sensor characteristics, and data acquisition periods can lead to discrepancies that need to be harmonized. In addition, inconsistent or incomplete datasets are a common issue, particularly in regions with limited historical monitoring or where cloud cover frequently obstructs satellite observations. These data gaps can introduce biases into ML models, leading to inaccurate results for prediction. For example, if training data are not representative of the full range of environmental conditions, the model may fail to generalize effectively, resulting in poor performance when applied to new or unseen conditions. Moreover, preprocessing of RS data, including tasks such as georeferencing, atmospheric correction, and resampling to a common spatial and temporal grid, can be technically demanding and resource-intensive. Harmonization of data from multiple sensors requires advanced techniques, such as data fusion and cross-calibration, to ensure consistency of inputs for ML models.

4.2. Technological Limitations

The implementation of ML in the context of soil and water conservation is often constrained by availability of computational resources and inherent complexity of algorithms employed. High-dimensional datasets—characterized by a large number of variables and extensive temporal records—are common in environmental studies. Processing these datasets requires significant computational power, including high-performance computing (HPC) clusters or cloud-based solutions, which may not be readily available in all research settings. The storage of such large volumes of data also poses challenges, as traditional data storage solutions might be insufficient to handle the scale and complexity of RS data. Furthermore, the complexity of ML algorithms—particularly those involving deep learning (e.g., convolutional neural networks, recurrent neural networks)—requires not only computational resources, but also specialized expertise. Deep learning models, for instance, often involve a large number of hyperparameters and require extensive tuning to achieve optimal performances. This complexity can be a significant barrier to the adoption of ML in resource-limited settings, where access to both infrastructure and skilled personnel might be limited. Model interpretability is another a significant concern in environmental applications. Many ML models, especially those classified as "black-box" models, offer limited insights into the underlying decision-making processes, which can hinder their acceptance and use in policy-making or by stakeholders. Decision-makers often require not only accurate predictions, but also an understanding of the rationale, which can be challenging to provide with complex ML models. Finally, the scalability limits the broader applicability of ML models across diverse geographic regions with availability constraints.

4.3. Implementation Issues

The practical application of ML in conservation efforts is also limited by challenges in model interpretation and transparency. Many ML techniques, particularly deep learning models, operate as "black boxes," making it difficult for stakeholders to understand the decision-making process. This lack of interpretability can hinder the integration of ML outcomes into policy and management strategies.

5. Future Directions and Research Opportunities

Future research on ML for soil and water conservation will benefit from advancements in big data analytics and cloud computing, which can address current limitations related to data processing and storage. The development of more interpretable ML models, such as explainable AI (XAI), is also expected to enhance the integration of ML into decision-making, making outputs more accessible to non-experts. There is also a growing need for research that focuses on the development of hybrid models that can strength various ML algorithms and RS data to enhance prediction accuracy and provide a comprehensive understanding of soil and water processes. Such approaches can improve

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prediction accuracy and provide a more holistic understanding of environmental processes. Additionally, research should explore the potential of integrating ground-based sensor networks with RS data, enhancing real-time monitoring and predictive capabilities. The adoption of ML in soil and water conservation has significant policy implications, particularly in the context of climate change adaptation and sustainable land management. Future research should emphasize the importance of interdisciplinary collaboration, bringing together experts in ML, environmental science, and policy to ensure that technological advancements can translate into practical conservation outcomes. Collaborative efforts should also focus on capacity-building initiatives to equip stakeholders with necessary skills and knowledge to implement ML-driven solutions effectively.

The selection of algorithms in each field is influenced by characteristics of the data, complexity of the problem, and objectives of the prediction. RF is popular in many environmental and resource management fields due to its ability to handle complex interactions among variables and manage nonlinearity effectively. SVM is useful for high-dimensional data or problems with nonlinear boundaries. Meanwhile, ANN and MLP excel at learning complex nonlinear patterns. The choice of these algorithms is made to optimize outcomes based on characteristics of the data and goals of problem-solving. The selection of ML algorithms varies depending on factors such as data characteristics, problem complexity, and interpretability. Future research should focus on optimizing algorithm selection and improvement by considering these factors. Additionally, comparing performances of various algorithms and conducting comprehensive evaluations will be crucial for proposing the most suitable methodologies for each field, offering significant insights into best practices.

Author Contributions: "Conceptualization, Jang, W.S., Yun, Y.J.; methodology, Jang, W.S., Kim,Y.I., and Park, W.H.; validation, Jang, W.S., Park, W.H., Shin, Y.; formal analysis, Yun, Y.J.; investigation, Park, W.H.; resources, Shin, Y.; writing—original draft preparation, Kim, Y.I.; writing—review and editing, Kim, Y.I., Park, W.H., Engel, B.; visualization, Kim, Y.I.; supervision, Jang, W.S., Yun, Y.J.; project administration, Jang. W.S.; funding acquisition, Jang, W.S. All authors have read and agreed to the published version of the manuscript."

Funding: "This study was supported by the research project, Developing of S-P-C experts for field-adaptive forest fire management (S: Smart, P: Professional, C: Confluence) (RS-2024-00402624), funded by the Korea Forest Service."

Data Availability Statement: The data used in this study are contained within the article. Additional data are available upon request from the corresponding author.

Conflicts of Interest: "The authors declare no conflicts of interest."

Appendix A

Table A1. A list of all the abbreviated ML algorithms used in the paper.

ML	Full of name
ABR	Adaptive Boosting Regression
AdaBag	Boosting and Bagging
AdaBoost	Boosted Classifier
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ARD	Automatic Relevance Determination
BAGGING	Bootstrap Aggregating Regression
BAYE	Bayesian
B-CART	Bagged Classification and Regression Trees
BDT	Bagging Decision Tree
BPNN	Back Propagation Neural Network
BRTs	Boosted Regression Trees
BST	Extreme Gradient Boosting Tree
CART	Classification and Regression Trees
CB	Cubist
CBR	Catboost Regression
CNN	Convolutional Neural Network
DBN	Deep Belief Network

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DELM	Deep Extreme Learning Machine
DL	Deep Learning
DMP	Dense Multilayer Perceptron
DNN	Deep Neural Networks
DR	Dmine Regression
DRF	Distributed Random Forest
DTr	Decision Tree
EBP	Error Back Propagation
EFS	Exhaustive Feature Selection
ELM	Extreme Learning Machine
ELR	Extreme Learning Machine Regression
EM	Evaluation metrics
EN	Elastic Net
EPR	Evolutionary Polynomial Regression
ERT	Extremely Randomized Tree
ETR	Extreme Tree Regression
FCN	Fully Connected Network
FNN	Feed forward Neural Networks
FR	Frequency Ratio
GAN	Generative Adversarial Networks
GB	Gradient Boosting
GBDT	Gradient Boosted Decision Tree
GBM	Gradient Boosting Machine
GBR	Gradient Boosting Regression
GBRT	Gradient Boosting Regression Tree
GEP	Genetic Expression Programming
GLM	Generalized Linear Model
GPR	Gaussian Process Regression
GRNN	General Regression Neural Network
GSC	Generalized Synthetic Control
Isolation Forest	Isolation Forest
KNN	K-nearest Neighbors
La-R	Lasso Regression
LARS	Least Angle Regression
LDA	Linear Discriminant Analysis
LGBM	Light Gradient Boosting Machine
Li-R	Linear Regression
LMM	Linear Mixed-Effects Model
Lo-R	Logistic Regression
LSTM	Long Short-Term Memory
M5P	M5-pruned
MARS	Multivariate Adaptive Regression Spline
MaxEnt	Maximum Entropy Model
MDN	Mixture Density Network
MLP	Multilayer Perceptron
MLPR	Multi-Layer Perceptron Regression
MLR	Multiple Linear Regression
MR-CNN	Mask Region-Based Convolutional Neural Network
MT	M5 Model Tree
NB	Naïve Bayes
Neu-SICR	Neural Network-Satellite and In situ sensor Collaborated Reconstruction
NN	Neural Networks
NNET	Feed-Forward Neural Network
OLS	Ordinary Least Squares
PCR	Principal Component Regression
PKR	Polynomial Kernel Regression
PLS	Partial Least Squares
PLSR	Partial Least Squares Regression

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PSO-SVR	Particle Swarm Optimization and Support Vector Machine
QR	Quantile Regression Forest
RBFN	Radial Basin Function Neural Network
RF	Random Forest
RNN	Recurrent Neural Network
RPART	Recursive Partitioning and Regression Trees
RR	Ridge Regression
RT	Regression Tree
RTM	Radiative Transfer Models
RVR	Relevance Vector Regression
SA	Sensitivity Analysis
SCA-Elman	Sine Cosine Algorithm-Elman
SGB	Stochastic Gradient Boosting
SICR	Sensor Collaborated Reconstruction
SLR	Stepwise Linear Regression
SoLIM	Soil–Landscape Inference Model (Fuzzy logic)
SOM	Self-Organizing Maps
SR	Simple Regression
SVM	Support Vector Machine
SVR	Support Vector Regression
XGB	EXtreme Gradient Boosting
XGBR	Extreme Gradient Boosting Regression
YOLO	You Only Look Once

Table A2. Descriptions for RS techniques implemented in reviewed publications. In the description of RS techniques related to satellites, the resolution, launching entity, and key features were included.

Note: Each asterisk level corresponds to a specific category (*Satellite name, ** Resolution of satellite, *** Launching entity, and **** Key features).

RS Techniques		Descriptions
Satellite	ALOS-2*	3m, 6m, 10m** JAXA (Japan Aerospace Exploration Agency) *** ALOS-2 is a Japanese Earth observation satellite equipped with a SAR sensor for monitoring land surface changes and natural hazards regardless of weather conditions such as clouds or rain****
	Chinese Environmental 1A	30m ~ 60m CRESDA (China Centre for Resources Satellite Data and Application) China's Earth observation satellite for monitoring environmental elements such as air, water, soil, and vegetation
	GF-1	2m, 8m China National Space Administration (CNSA) A high-resolution ground observation satellite from China's GaoFen series, known for its advanced imaging capabilities to monitor urban areas, natural resources, and environmental changes
	GOES-16	0.5km ~ 2km NOAA (National Oceanic and Atmospheric Administration) U.S. geostationary weather satellite that monitors weather conditions over North America in real time
	Himawari-8	0.5km, 1km, 2km JMA (Japan Meteorological Agency) A geostationary satellite for weather monitoring in the Asia-Pacific region, Himawari-8 provides continuous and detailed weather observations
	Landsat 4, 5	30m, 80m, 120m NASA (The National Aeronautics and Space Administration)/USGS (The United States Geological Survey) A satellite sensor designed to observe the Earth's land surface and monitor changes in land use and natural resources, both of which have

 doi:10.20944/preprints202410.0048.v1

	officially ended their missions
Landsat 7	15m, 30m, 60m NASA (The National Aeronautics and Space Administration)/USGS (The United States Geological Survey) A satellite sensor used for Earth observation, capable of capturing detailed imagery to monitor environmental changes, land use, and natural resources, and continues to provide valuable data since its launch in 1999
Landsat 8, 9	15m, 30m, 100m NASA (The National Aeronautics and Space Administration)/USGS (The United States Geological Survey) The latest satellite sensors in the Landsat series, launched in 2013 and 2021, providing high-quality Earth surface data for monitoring environmental changes, land use, and natural resources
RADARSAT	1m ~ 100m CSA (Canadian Space Agency) A Canadian-operated SAR (Synthetic Aperture Radar) satellite known for its capability to provide detailed, all-weather, day-and-night imagery for global environmental monitoring, disaster response, and resource management
RapidEye	5m, 6.5m BlackBridge Networks A satellite constellation that provides multi-spectral imagery, designed for applications in agriculture, forest management, and other areas
Sentitel-1	5 ~ 40m ESA (European Space Agency) A satellite sensor using Synthetic Aperture Radar (SAR) to observe the Earth in all weather conditions, both day and night, providing continuous and detailed surface monitoring
Sentitel-2	10m, 20m, 60m ESA (European Space Agency) A satellite sensor providing high-resolution multispectral images, useful for agriculture, forestry, and land cover monitoring
Sentitel-3	300m, 500m, 1km ESA (European Space Agency) A satellite sensor used to monitor sea and land surface temperature, color, and ocean conditions, equipped with multiple instruments for comprehensive Earth observation and environmental monitoring
SMAP	3km, 10km, 40km NASA (The National Aeronautics and Space Administration) A satellite primarily used for observing soil moisture and freeze/thaw conditions, crucial for climate research and agricultural monitoring, providing detailed data to support environmental and climate studies
SPOT-4	10m, 20m , 60m CNES (Centre national d'études spatiales) SPOT-4 is an Earth observation satellite that carries HRVIR, HRG, and VEGETATION sensors with an additional shortwave infrared band for agriculture, forestry, and environmental monitoring
SPOT-7	1.5m, 6m Airbus Defence and Space SPOT-7 is the latest satellite in the SPOT series, providing high-resolution Earth observation imagery with a NAOMI sensor that significantly improves spatial resolution
SRTM	30m, 90m NASA (The National Aeronautics and Space Administration) A global satellite mission that collects elevation data to create 3D terrain models of Earth's surface
Terra	250m, 500m, 1km

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		NASA (The National Aeronautics and Space Administration) A satellite that provides comprehensive observations of the Earth's environment, collecting data on the atmosphere, land, oceans, and energy systems to support environmental monitoring and research
	Triplesat	0.8m, 3.2m 21AT (The Twenty First Century Aerospace Technology) A high-resolution Earth observation satellite widely used for commercial purposes, offering detailed imagery for applications in agriculture, urban planning, and resource management
	WorldView-3	0.31m, 1.24m DigitalGlobe WorldView-3 is a commercial high-resolution Earth observation satellite that provides high-quality imagery data for use in a variety of industries
	ZH-1	10m CNSA (the China National Space Administration / ASI (the Italian Space Agency) A high-resolution Earth observation satellite from China, designed for detailed imaging to monitor urban areas, natural resources, and environmental changes
AGRS		A technology that utilizes aircraft and drones to gather detailed information about the Earth's surface and geology, AGRS provides valuable data for various applications
AMSR-E		A microwave radiometer that monitors various aspects of the Earth's water cycle, including precipitation, cloud water, water vapor, sea surface winds, sea surface temperature, ice, snow, and soil moisture
AVIRIS-NG		An airborne hyperspectral imaging sensor that captures detailed information across a wide range of spectral bands, including visible and infrared wavelengths
ETM+		ETM+ is a sensor on board the Landsat 7 satellite that is an enhanced version of ETM with a total of eight spectral bands
Thermal infrared		A remote sensing technology that measures surface temperatures by observing thermal infrared emissions, providing data for climate studies, weather monitoring, and environmental analysis
Leica ADS80		A high-resolution digital camera used for aerial photogrammetry, the Leica ADS80 captures detailed images from the air
LiDAR		A remote sensing technology that uses lasers to precisely measure the 3D structure of terrain, providing detailed topographic data for applications in mapping, forestry, and environmental monitoring
MERIS		A sensor with high spectral and radiometric resolution and dual spatial resolution that studies the Earth's water cycle, including precipitation, cloud water, water vapor, sea surface winds, sea surface temperature, ice, snow, and soil moisture
MODIS		A satellite sensor that captures comprehensive global data, viewing the entire Earth's surface every one to two days with high temporal resolution
PALSAR-2		An L-band SAR mounted on the ALOS-2 satellite, providing detailed surface information globally with high precision for applications in terrain mapping, disaster monitoring, and environmental assessment
SAR		A technology that uses electromagnetic waves to observe the Earth's surface, enabling data collection in all weather conditions and at any time, providing reliable information for environmental monitoring and disaster management
SVC		A spectroradiometer that measures the reflectance spectra of the Earth's surface, enabling detailed analysis of material composition and characterization for applications in geology, agriculture, and environmental monitoring
TDC		A thermal infrared sensor, which measures infrared radiation to detect temperature variations on the Earth's surface
Hyperspectral Imager		An instrument that measures hundreds of narrow wavelength bands, a

 doi:10.20944/preprints202410.0048.v1

	hyperspectral imager precisely analyzes the material composition of the Earth's surface
TM	A sensor on the Landsat 4 and 5 satellites with seven spectral bands, TM (Thematic Mapper) is optimized to collect detailed information on land surface characteristics
UAS / UAV	Remote sensing platforms using drones, including UAS (Unmanned Aerial Systems) and UAVs (Unmanned Aerial Vehicles), employed to collect high spatial resolution data for various applications such as mapping, agriculture, and environmental monitoring
VIIRS	A satellite sensor that observes the Earth's atmosphere, oceans, and land, providing valuable data for climate research, disaster monitoring, and various environmental applications with comprehensive multispectral imaging

Uncategorized References

1. Pereira, P., et al., *Soil ecosystem services, sustainability, valuation and management.* Current Opinion in Environmental Science & Health, 2018. **5**: p. 7-13.
2. Trap, J., et al., *Ecological importance of soil bacterivores for ecosystem functions.* Plant and Soil, 2016. **398**: p. 1-24.
3. Whitford, W.G., *The importance of the biodiversity of soil biota in arid ecosystems.* Biodiversity & Conservation, 1996. **5**: p. 185-195.
4. Allan, R.P., et al., *Advances in understanding large-scale responses of the water cycle to climate change.* Annals of the New York Academy of Sciences, 2020. **1472**(1): p. 49-75.
5. Peixoto, J.P. and M.A. Kettani, *The control of the water cycle.* Scientific American, 1973. **228**(4): p. 46-63.
6. Lal, R., *Soil conservation and ecosystem services.* International soil and water conservation research, 2014. **2**(3): p. 36-47.
7. Neary, D.G., K.C. Ryan, and L.F. DeBano, *Wildland fire in ecosystems: effects of fire on soils and water.* Gen. Tech. Rep. RMRS-GTR-42-vol, 2005. **4**(250): p. 42.
8. Ali, M. and M. Talukder, *Increasing water productivity in crop production—A synthesis.* Agricultural water management, 2008. **95**(11): p. 1201-1213.
9. Akhtar, N., et al., *Various natural and anthropogenic factors responsible for water quality degradation: A review.* Water, 2021. **13**(19): p. 2660.
10. Bungau, S., et al., *Expatiating the impact of anthropogenic aspects and climatic factors on long-term soil monitoring and management.* Environmental Science and Pollution Research, 2021. **28**(24): p. 30528-30550.
11. Zhang, X., et al., *Assessing the impact of urban sprawl on soil resources of Nanjing city using satellite images and digital soil databases.* Catena, 2007. **69**(1): p. 16-30.
12. Hajabbasi, M.A., A. Jalalian, and H.R. Karimzadeh, *Deforestation effects on soil physical and chemical properties, Lordegan, Iran.* Plant and soil, 1997. **190**: p. 301-308.
13. Syamsih, D., *Impacts of Deforestation on Soil Quality and Water Resources in Tropical Forest Areas of Sumatra.* Journal of Horizon, 2024. **1**(1): p. 16-22.
14. Blanco-Canqui, H., et al., *Soil and water conservation.* Principles of soil conservation and management, 2008: p. 1-19.
15. Côté, I.M., E.S. Darling, and C.J. Brown, *Interactions among ecosystem stressors and their importance in conservation.* Proceedings of the Royal Society B: Biological Sciences, 2016. **283**(1824): p. 20152592.
16. Gassman, P.W., et al., *The soil and water assessment tool: historical development, applications, and future research directions.* Transactions of the ASABE, 2007. **50**(4): p. 1211-1250.
17. Mansell, R., et al., *Adaptive grid refinement in numerical models for water flow and chemical transport in soil: a review.* Vadose Zone Journal, 2002. **1**(2): p. 222-238.
18. Kattenberg, A., et al., *Climate models: projections of future climate*, in *Climate Change 1995: the science of climate change. Contribution of WG1 to the Second Assessment Report of the IPCC*. 1996, Cambridge University Press. p. 299-357.
19. Kavetski, D., S.W. Franks, and G. Kuczera, *Confronting input uncertainty in environmental modelling.* Calibration of watershed models, 2003. **6**: p. 49-68.
20. Matott, L.S., J.E. Babendreier, and S.T. Purucker, *Evaluating uncertainty in integrated environmental models: A review of concepts and tools.* Water Resources Research, 2009. **45**(6).

 doi:10.20944/preprints202410.0048.v1

21. Refsgaard, J.C., et al., *Uncertainty in the environmental modelling process–a framework and guidance.* Environmental modelling & software, 2007. **22**(11): p. 1543-1556.
22. Zhong, S., et al., *Machine learning: new ideas and tools in environmental science and engineering.* Environmental science & technology, 2021. **55**(19): p. 12741-12754.
23. Huang, C., et al., *Detecting, extracting, and monitoring surface water from space using optical sensors: A review.* Reviews of Geophysics, 2018. **56**(2): p. 333-360.
24. Rogan, J. and D. Chen, *Remote sensing technology for mapping and monitoring land-cover and land-use change.* Progress in planning, 2004. **61**(4): p. 301-325.
25. Florath, J. and S. Keller, *Supervised machine learning approaches on multispectral remote sensing data for a combined detection of fire and burned area.* Remote sensing, 2022. **14**(3): p. 657.
26. Sun, A.Y. and B.R. Scanlon, *How can Big Data and machine learning benefit environment and water management: a survey of methods, applications, and future directions.* Environmental Research Letters, 2019. **14**(7): p. 073001.
27. Glasgow, H.B., et al., *Real-time remote monitoring of water quality: a review of current applications, and advancements in sensor, telemetry, and computing technologies.* Journal of experimental marine biology and ecology, 2004. **300**(1-2): p. 409-448.
28. Wang, S., et al., *Using soil library hyperspectral reflectance and machine learning to predict soil organic carbon: Assessing potential of airborne and spaceborne optical soil sensing.* Remote Sensing of Environment, 2022. **271**: p. 112914.
29. Han, L., et al., *Modeling maize above-ground biomass based on machine learning approaches using UAV remote-sensing data.* Plant methods, 2019. **15**: p. 1-19.
30. Sharma, P., et al., *Above-ground biomass estimation in oats using UAV remote sensing and machine learning.* Sensors, 2022. **22**(2): p. 601.
31. Quang, N.H., et al., *Comparisons of regression and machine learning methods for estimating mangrove above-ground biomass using multiple remote sensing data in the red River Estuaries of Vietnam.* Remote Sensing Applications: Society and Environment, 2022. **26**: p. 100725.
32. Ali, I., et al., *Modeling managed grassland biomass estimation by using multitemporal remote sensing data—A machine learning approach.* IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2016. **10**(7): p. 3254-3264.
33. Meng, B., et al., *Modeling alpine grassland above ground biomass based on remote sensing data and machine learning algorithm: A case study in east of the Tibetan Plateau, China.* IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2020. **13**: p. 2986-2995.
34. Lendzioch, T., et al., *Mapping the groundwater level and soil moisture of a montane peat bog using uav monitoring and machine learning.* Remote Sensing, 2021. **13**(5): p. 907.
35. Saygın, F., et al., *Different approaches to estimating soil properties for digital soil map integrated with machine learning and remote sensing techniques in a sub-humid ecosystem.* Environmental Monitoring and Assessment, 2023. **195**(9): p. 1061.
36. Rezaei, M., et al., *Incorporating machine learning models and remote sensing to assess the spatial distribution of saturated hydraulic conductivity in a light-textured soil.* Computers and Electronics in Agriculture, 2023. **209**: p. 107821.
37. Jia, P., et al., *Combination of hyperspectral and machine learning to invert soil electrical conductivity.* Remote Sensing, 2022. **14**(11): p. 2602.
38. Wang, N., et al., *Integrating remote sensing and landscape characteristics to estimate soil salinity using machine learning methods: A case study from Southern Xinjiang, China.* Remote Sensing, 2020. **12**(24): p. 4118.
39. Mohamed, S.A., et al., *Integrating active and passive remote sensing data for mapping soil salinity using machine learning and feature selection approaches in arid regions.* Remote Sensing, 2023. **15**(7): p. 1751.
40. Wang, Z., et al., *Regional suitability prediction of soil salinization based on remote-sensing derivatives and optimal spectral index.* Science of the Total Environment, 2021. **775**: p. 145807.
41. Cui, J., et al., *Estimation of soil salt content at different depths using UAV multi-spectral remote sensing combined with machine learning algorithms.* Remote Sensing, 2023. **15**(21): p. 5254.
42. Naimi, S., et al., *Ground observations and environmental covariates integration for mapping of soil salinity: a machine learning-based approach.* Remote Sensing, 2021. **13**(23): p. 4825.
43. Wang, S., et al., *Performance comparison of machine learning algorithms for estimating the soil salinity of salt-affected soil using field spectral data.* Remote Sensing, 2019. **11**(22): p. 2605.

44. Erkin, N., et al., *Method for predicting soil salinity concentrations in croplands based on machine learning and remote sensing techniques.* Journal of Applied Remote Sensing, 2019. **13**(3): p. 034520-034520.
45. Kaplan, G., et al., *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, 2023. **130**: p. 103400.
46. Jiang, X., et al., *Estimation of soil salinization by machine learning algorithms in different arid regions of northwest China.* Remote Sensing, 2022. **14**(2): p. 347.
47. Haq, Y.u., et al., *Spatial mapping of soil salinity using machine learning and remote sensing in Kot Addu, Pakistan.* Sustainability, 2023. **15**(17): p. 12943.
48. Wang, J., et al., *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, 2020. **707**: p. 136092.
49. Zhang, H., et al., *Mapping Multi-Depth Soil Salinity Using Remote Sensing-Enabled Machine Learning in the Yellow River Delta, China.* Remote Sensing, 2023. **15**(24): p. 5640.
50. Wei, Q., et al., *Inversion of soil salinity using multisource remote sensing data and particle swarm machine learning models in Keriya Oasis, northwestern China.* Remote Sensing, 2022. **14**(3): p. 512.
51. Hoa, P.V., et al., *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, 2019. **11**(2): p. 128.
52. Das, A., et al., *A novel method for detecting soil salinity using AVIRIS-NG imaging spectroscopy and ensemble machine learning.* ISPRS Journal of Photogrammetry and Remote Sensing, 2023. **200**: p. 191-212.
53. Nguyen, H.D., et al., *Soil salinity prediction using hybrid machine learning and remote sensing in Ben Tre province on Vietnam's Mekong River Delta.* Environmental Science and Pollution Research, 2023. **30**(29): p. 74340-74357.
54. Zhao, W., et al., *Soil salinity inversion model of oasis in arid area based on UAV multispectral remote sensing.* Remote Sensing, 2022. **14**(8): p. 1804.
55. Aksoy, S., et al., *Assessing the performance of machine learning algorithms for soil salinity mapping in Google Earth Engine platform using Sentinel-2A and Landsat-8 OLI data.* Advances in Space Research, 2022. **69**(2): p. 1072-1086.
56. Ma, G., et al., *Digital mapping of soil salinization based on Sentinel-1 and Sentinel-2 data combined with machine learning algorithms.* Regional Sustainability, 2021. **2**(2): p. 177-188.
57. Kalambukattu, J.G., et al., *Temporal remote sensing based soil salinity mapping in Indo-Gangetic plain employing machine-learning techniques.* Proceedings of the Indian National Science Academy, 2023. **89**(2): p. 290-305.
58. Zhang, T., Y. Li, and M. Wang, *Remote sensing-based prediction of organic carbon in agricultural and natural soils influenced by salt and sand mining using machine learning.* Journal of Environmental Management, 2024. **352**: p. 120107.
59. Odebiri, O., et al., *Modelling soil organic carbon stock distribution across different land-uses in South Africa: A remote sensing and deep learning approach.* ISPRS Journal of Photogrammetry and Remote Sensing, 2022. **188**: p. 351-362.
60. Zhang, X., et al., *Digital mapping of soil organic carbon with machine learning in dryland of Northeast and North plain China.* Remote Sensing, 2022. **14**(10): p. 2504.
61. Emadi, M., et al., *Predicting and mapping of soil organic carbon using machine learning algorithms in Northern Iran.* Remote Sensing, 2020. **12**(14): p. 2234.
62. John, K., et al., *Using machine learning algorithms to estimate soil organic carbon variability with environmental variables and soil nutrient indicators in an alluvial soil.* Land, 2020. **9**(12): p. 487.
63. Meng, X., et al., *An advanced soil organic carbon content prediction model* via *fused temporal-spatial-spectral (TSS) information based on machine learning and deep learning algorithms.* Remote Sensing of Environment, 2022. **280**: p. 113166.
64. Zeraatpisheh, M., et al., *Digital mapping of soil properties using multiple machine learning in a semi-arid region, central Iran.* Geoderma, 2019. **338**: p. 445-452.
65. Zhou, T., et al., *High-resolution digital mapping of soil organic carbon and soil total nitrogen using DEM derivatives, Sentinel-1 and Sentinel-2 data based on machine learning algorithms.* Science of The Total Environment, 2020. **729**: p. 138244.
66. Zhou, T., et al., *Prediction of soil organic carbon and the C: N ratio on a national scale using machine learning and satellite data: A comparison between Sentinel-2, Sentinel-3 and Landsat-8 images.* Science of the Total Environment, 2021. **755**: p. 142661.

 doi:10.20944/preprints202410.0048.v1

67. Abdoli, P., et al., *Use of remote sensing data to predict soil organic carbon in some agricultural soils of Iran.* Remote Sensing Applications: Society and Environment, 2023. **30**: p. 100969.
68. Paul, S., et al., *Mapping soil organic carbon and clay using remote sensing to predict soil workability for enhanced climate change adaptation.* Geoderma, 2020. **363**: p. 114177.
69. Hamzehpour, N., H. Shafizadeh-Moghadam, and R. Valavi, *Exploring the driving forces and digital mapping of soil organic carbon using remote sensing and soil texture.* Catena, 2019. **182**: p. 104141.
70. Matinfar, H.R., et al., *Evaluation and Prediction of Topsoil organic carbon using Machine learning and hybrid models at a Field-scale.* Catena, 2021. **202**: p. 105258.
71. Xie, B., et al., *Estimation of soil organic carbon content in the Ebinur Lake wetland, Xinjiang, China, based on multisource remote sensing data and ensemble learning algorithms.* Sensors, 2022. **22**(7): p. 2685.
72. Wang, B., et al., *High resolution mapping of soil organic carbon stocks using remote sensing variables in the semi-arid rangelands of eastern Australia.* Science of the Total Environment, 2018. **630**: p. 367-378.
73. Xing, C., et al., *A machine learning based reconstruction method for satellite remote sensing of soil moisture images with* in situ *observations.* Remote Sensing, 2017. **9**(5): p. 484.
74. Zeraatpisheh, M., et al., *Spatial prediction of soil aggregate stability and soil organic carbon in aggregate fractions using machine learning algorithms and environmental variables.* Geoderma Regional, 2021. **27**: p. e00440.
75. Mahjenabadi, V.A.J., et al., *Digital mapping of soil biological properties and wheat yield using remotely sensed, soil chemical data and machine learning approaches.* Computers and Electronics in Agriculture, 2022. **197**: p. 106978.
76. Khanal, S., et al., *Integration of high resolution remotely sensed data and machine learning techniques for spatial prediction of soil properties and corn yield.* Computers and electronics in agriculture, 2018. **153**: p. 213-225.
77. Rukhovich, D.I., et al., *Recognition of the bare soil using deep machine learning methods to create maps of arable soil degradation based on the analysis of multi-temporal remote sensing data.* Remote Sensing, 2022. **14**(9): p. 2224.
78. Alexakis, D.D., et al., *Integrated use of satellite remote sensing, artificial neural networks, field spectroscopy, and GIS in estimating crucial soil parameters in terms of soil erosion.* Remote Sensing, 2019. **11**(9): p. 1106.
79. Fernández, D., et al., *Comparative analysis of machine learning algorithms for soil erosion modelling based on remotely sensed data.* Remote Sensing, 2023. **15**(2): p. 482.
80. Do, T.A.T., H.D. Tran, and A.N.T. Do, *Classifying forest cover and mapping forest fire susceptibility in Dak Nong province, Vietnam utilizing remote sensing and machine learning.* Ecological Informatics, 2024. **79**: p. 102392.
81. Saygın, F., et al., *Estimation of soil erodability parameters based on different machine algorithms integrated with remote sensing techniques.* International Journal of Environmental Science and Technology, 2024: p. 1-14.
82. Maia, R.F., C.B. Lurbe, and J. Hornbuckle, *Machine learning approach to estimate soil matric potential in the plant root zone based on remote sensing data.* Frontiers in Plant Science, 2022. **13**: p. 931491.
83. Suleymanov, A., et al., *Mercury Prediction in Urban Soils by Remote Sensing and Relief Data Using Machine Learning Techniques.* Remote Sensing, 2023. **15**(12): p. 3158.
84. Senanayake, I., et al., *Estimating catchment scale soil moisture at a high spatial resolution: Integrating remote sensing and machine learning.* Science of The Total Environment, 2021. **776**: p. 145924.
85. Mao, T., et al., *A spatial downscaling method for remote sensing soil moisture based on random forest considering soil moisture memory and mass conservation.* Remote Sensing, 2022. **14**(16): p. 3858.
86. Babaeian, E., et al., *Estimation of root zone soil moisture from ground and remotely sensed soil information with multisensor data fusion and automated machine learning.* Remote sensing of environment, 2021. **260**: p. 112434.
87. Sun, H. and Y. Cui, *Evaluating downscaling factors of microwave satellite soil moisture based on machine learning method.* Remote Sensing, 2021. **13**(1): p. 133.
88. Senyurek, V., et al., *Machine learning-based CYGNSS soil moisture estimates over ISMN sites in CONUS.* Remote Sensing, 2020. **12**(7): p. 1168.
89. Araya, S.N., et al., *Advances in soil moisture retrieval from multispectral remote sensing using unoccupied aircraft systems and machine learning techniques.* Hydrology and Earth System Sciences, 2021. **25**(5): p. 2739-2758.
90. Kisekka, I., et al., *Spatial–temporal modeling of root zone soil moisture dynamics in a vineyard using machine learning and remote sensing.* Irrigation science, 2022. **40**(4): p. 761-777.
91. Greifeneder, F., C. Notarnicola, and W. Wagner, *A machine learning-based approach for surface soil moisture estimations with google earth engine.* Remote Sensing, 2021. **13**(11): p. 2099.
92. Liu, Y., et al., *Comparison of different machine learning approaches for monthly satellite-based soil moisture downscaling over Northeast China.* Remote Sensing, 2017. **10**(1): p. 31.
93. Zeng, L., et al., *Multilayer soil moisture mapping at a regional scale from multisource data* via *a machine learning method.* Remote Sensing, 2019. **11**(3): p. 284.

 doi:10.20944/preprints202410.0048.v1

94. Zhao, J., et al., *Retrieval of farmland surface soil moisture based on feature optimization and machine learning.* Remote Sensing, 2022. **14**(20): p. 5102.
95. Abowarda, A.S., et al., *Generating surface soil moisture at 30 m spatial resolution using both data fusion and machine learning toward better water resources management at the field scale.* Remote Sensing of Environment, 2021. **255**: p. 112301.
96. Wang, S., et al., *Remote sensing-based retrieval of soil moisture content using stacking ensemble learning models.* Land Degradation & Development, 2023. **34**(3): p. 911-925.
97. Im, J., et al., *Downscaling of AMSR-E soil moisture with MODIS products using machine learning approaches.* Environmental Earth Sciences, 2016. **75**: p. 1-19.
98. Karthikeyan, L. and A.K. Mishra, *Multi-layer high-resolution soil moisture estimation using machine learning over the United States.* Remote Sensing of Environment, 2021. **266**: p. 112706.
99. Araya, S.N., et al. *Machine learning based soil moisture retrieval from unmanned aircraft system multispectral remote sensing*. in *IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium*. 2020. IEEE.
100. Chen, Q., et al., *Downscaling of satellite remote sensing soil moisture products over the Tibetan Plateau based on the random forest algorithm: Preliminary results.* Earth and Space Science, 2020. **7**(6): p. e2020EA001265.
101. Nouraki, A., et al., *Spatial-temporal modeling of soil moisture using optical and thermal remote sensing data and machine learning algorithms.* Iranian Journal of Soil and Water Research, 2023. **54**(4): p. 637-653.
102. Chen, L., et al., *Estimating soil moisture over winter wheat fields during growing season using machine-learning methods.* IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2021. **14**: p. 3706-3718.
103. Hajdu, I., I. Yule, and M.H. Dehghan-Shear. *Modelling of near-surface soil moisture using machine learning and multi-temporal sentinel 1 images in New Zealand*. in *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium*. 2018. IEEE.
104. Santi, E., et al., *Combining machine learning and compact polarimetry for estimating soil moisture from C-band SAR data.* Remote Sensing, 2019. **11**(20): p. 2451.
105. Park, S., et al. *AMSR2 soil moisture downscaling using multisensor products through machine learning approach*. in *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. 2015. IEEE.
106. Bueno, M., et al., *Watershed scale soil moisture estimation model using machine learning and remote sensing in a data-scarce context.* Scientia Agropecuaria, 2024. **15**(1): p. 103-120.
107. Cui, Y., et al., *A soil moisture spatial and temporal resolution improving algorithm based on multi-source remote sensing data and GRNN model.* Remote Sensing, 2020. **12**(3): p. 455.
108. Chen, S., et al., *Spatial downscaling methods of soil moisture based on multisource remote sensing data and its application.* Water, 2019. **11**(7): p. 1401.
109. Tong, C., et al., *Spatial gap-filling of SMAP soil moisture pixels over Tibetan plateau* via *machine learning versus geostatistics.* IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2021. **14**: p. 9899-9912.
110. Nadeem, A.A., et al., *Spatial downscaling and gap-filling of SMAP soil moisture to high resolution using MODIS surface variables and machine learning approaches over ShanDian River Basin, China.* Remote Sensing, 2023. **15**(3): p. 812.
111. Zhang, W., et al., *Mapping cropland soil nutrients contents based on multi-spectral remote sensing and machine learning.* Agriculture, 2023. **13**(8): p. 1592.
112. Song, Y.-Q., et al., *Predicting spatial variations in soil nutrients with hyperspectral remote sensing at regional scale.* Sensors, 2018. **18**(9): p. 3086.
113. Hengl, T., et al., *Soil nutrient maps of Sub-Saharan Africa: assessment of soil nutrient content at 250 m spatial resolution using machine learning.* Nutrient Cycling in Agroecosystems, 2017. **109**: p. 77-102.
114. Kaur, G., K. Das, and J. Hazra. *Soil nutrients prediction using remote sensing data in western india: An evaluation of machine learning models*. in *IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium*. 2020. IEEE.
115. Liu, Y., J. Lin, and H. Yue, *Soil respiration estimation in desertified mining areas based on UAV remote sensing and machine learning.* Earth Science Informatics, 2023. **16**(4): p. 3433-3448.
116. Ewing, J., et al., *Characterizing soil stiffness using thermal remote sensing and machine learning.* Remote Sensing, 2021. **13**(12): p. 2306.

117. Forkuor, G., et al., *High resolution mapping of soil properties using remote sensing variables in south-western Burkina Faso: a comparison of machine learning and multiple linear regression models.* PloS one, 2017. **12**(1): p. e0170478.
118. Mirzaeitalarposhti, R., et al., *Digital soil texture mapping and spatial transferability of machine learning models using sentinel-1, sentinel-2, and terrain-derived covariates.* Remote Sensing, 2022. **14**(23): p. 5909.
119. Zhai, Y., et al., *Soil texture classification with artificial neural networks operating on remote sensing data.* Computers and Electronics in Agriculture, 2006. **54**(2): p. 53-68.
120. Haq, Y.U., et al., *Identification of soil type in Pakistan using remote sensing and machine learning.* PeerJ Computer Science, 2022. **8**: p. e1109.
121. Heil, J., C. Jörges, and B. Stumpe, *Fine-scale mapping of soil organic matter in agricultural soils using UAVs and machine learning.* Remote Sensing, 2022. **14**(14): p. 3349.
122. Zhang, M., et al., *Mapping regional soil organic matter based on sentinel-2a and modis imagery using machine learning algorithms and google earth engine.* Remote Sensing, 2021. **13**(15): p. 2934.
123. Chen, D., et al., *Mapping dynamics of soil organic matter in croplands with MODIS data and machine learning algorithms.* Science of the Total Environment, 2019. **669**: p. 844-855.
124. Wu, T., et al., *Geo-object-based soil organic matter mapping using machine learning algorithms with multi-source geo-spatial data.* IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2019. **12**(4): p. 1091-1106.
125. Filgueiras, R., et al., *Soil water content and actual evapotranspiration predictions using regression algorithms and remote sensing data.* Agricultural Water Management, 2020. **241**: p. 106346.
126. Lee, J.-Y., M. Raza, and K.D. Kwon, *Land use and land cover changes in the Haean Basin of Korea: Impacts on soil erosion.* Episodes Journal of International Geoscience, 2019. **42**(1): p. 17-32.
127. Guo, D., et al., *How does wildfire and climate variability affect streamflow in forested catchments? A regional study in eastern Australia.* Journal of Hydrology, 2023. **625**: p. 129979.
128. Rahaman, M.H., M. Masroor, and H. Sajjad, *Integrating remote sensing derived indices and machine learning algorithms for precise extraction of small surface water bodies in the lower Thoubal river watershed, India.* Journal of Cleaner Production, 2023. **422**: p. 138563.
129. Acharya, T.D., A. Subedi, and D.H. Lee, *Evaluation of machine learning algorithms for surface water extraction in a Landsat 8 scene of Nepal.* Sensors, 2019. **19**(12): p. 2769.
130. Yang, H., et al., *Bathymetric mapping and estimation of water storage in a shallow lake using a remote sensing inversion method based on machine learning.* International Journal of Digital Earth, 2022. **15**(1): p. 789-812.
131. Dehkordi, A.T., H. Ghasemi, and M.J.V. Zoej. *Machine learning-based estimation of suspended sediment concentration along Missouri River using remote sensing imageries in Google Earth Engine*. in *2021 7th International Conference on Signal Processing and Intelligent Systems (ICSPIS)*. 2021. IEEE.
132. Izadi, M., et al., *A remote sensing and machine learning-based approach to forecast the onset of harmful algal bloom.* Remote Sensing, 2021. **13**(19): p. 3863.
133. Zhang, Y., et al., *Improving remote sensing estimation of Secchi disk depth for global lakes and reservoirs using machine learning methods.* GIScience & Remote Sensing, 2022. **59**(1): p. 1367-1383.
134. Mohsen, A., F. Kovács, and T. Kiss, *Remote sensing of sediment discharge in rivers using Sentinel-2 images and machine-learning algorithms.* Hydrology, 2022. **9**(5): p. 88.
135. Mondal, I., et al., *Assessing intra and interannual variability of water quality in the Sundarban mangrove dominated estuarine ecosystem using remote sensing and hybrid machine learning models.* Journal of Cleaner Production, 2024. **442**: p. 140889.
136. Song, W., et al., *Study on remote sensing inversion and temporal-spatial variation of Hulun lake water quality based on machine learning.* Journal of Contaminant Hydrology, 2024. **260**: p. 104282.
137. Yang, W., et al., *Monitoring multi-water quality of internationally important karst wetland through deep learning, multi-sensor and multi-platform remote sensing images: A case study of Guilin, China.* Ecological Indicators, 2023. **154**: p. 110755.
138. Qiao, Z., et al., *Retrieval of total phosphorus concentration in the surface water of miyun reservoir based on remote sensing data and machine learning algorithms.* Remote Sensing, 2021. **13**(22): p. 4662.
139. Borovskaya, R., et al., *Surface water salinity evaluation and identification for using remote sensing data and machine learning approach.* Journal of Marine Science and Engineering, 2022. **10**(2): p. 257.
140. Ahmed, M., et al., *A multi–step approach for optically active and inactive water quality parameter estimation using deep learning and remote sensing.* Water, 2022. **14**(13): p. 2112.

141. Zhu, X., et al., *An ensemble machine learning model for water quality estimation in coastal area based on remote sensing imagery.* Journal of Environmental Management, 2022. **323**: p. 116187.
142. Leggesse, E.S., et al., *Predicting optical water quality indicators from remote sensing using machine learning algorithms in tropical highlands of Ethiopia.* Hydrology, 2023. **10**(5): p. 110.
143. Zhao, X., et al., *Comparing deep learning with several typical methods in prediction of assessing chlorophyll-a by remote sensing: A case study in Taihu Lake, China.* Water Supply, 2021. **21**(7): p. 3710-3724.
144. Sun, X., et al., *Monitoring water quality using proximal remote sensing technology.* Science of the Total Environment, 2022. **803**: p. 149805.
145. Qian, J., et al., *Water quality monitoring and assessment based on cruise monitoring, remote sensing, and deep learning: A case study of Qingcaosha Reservoir.* Frontiers in Environmental Science, 2022. **10**: p. 979133.
146. Hoyek, A., L.F. Arias-Rodriguez, and F. Perosa, *Holistic approach for estimating water quality ecosystem services of danube floodplains: Field measures, remote sensing, and machine learning.* Hydrobiology, 2022. **1**(2): p. 211-231.
147. Wang, X., F. Zhang, and J. Ding, *Evaluation of water quality based on a machine learning algorithm and water quality index for the Ebinur Lake Watershed, China.* Scientific reports, 2017. **7**(1): p. 12858.
148. Li, N., et al., *Satellite and machine learning monitoring of optically inactive water quality variability in a tropical river.* Remote Sensing, 2022. **14**(21): p. 5466.
149. Peterson, K.T., V. Sagan, and J.J. Sloan, *Deep learning-based water quality estimation and anomaly detection using Landsat-8/Sentinel-2 virtual constellation and cloud computing.* GIScience & Remote Sensing, 2020. **57**(4): p. 510-525.
150. Najafzadeh, M. and S. Basirian, *Evaluation of river water quality index using remote sensing and artificial intelligence models.* Remote Sensing, 2023. **15**(9): p. 2359.
151. Maier, P.M. and S. Keller. *Machine learning regression on hyperspectral data to estimate multiple water parameters*. in *2018 9th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)*. 2018. IEEE.
152. Arias-Rodriguez, L.F., et al., *Monitoring water quality of valle de bravo reservoir, mexico, using entire lifespan of meris data and machine learning approaches.* Remote Sensing, 2020. **12**(10): p. 1586.
153. Cao, Q., et al., *Monitoring water quality of the Haihe River based on ground-based hyperspectral remote sensing.* Water, 2021. **14**(1): p. 22.
154. Xiao, Y., et al., *UAV multispectral image-based urban river water quality monitoring using stacked ensemble machine learning algorithms—A case study of the Zhanghe river, China.* Remote Sensing, 2022. **14**(14): p. 3272.
155. Cao, Z., et al., *A machine learning approach to estimate chlorophyll-a from Landsat-8 measurements in inland lakes.* Remote Sensing of Environment, 2020. **248**: p. 111974.
156. Adusei, Y.Y., et al., *Spatial prediction and mapping of water quality of Owabi reservoir from satellite imageries and machine learning models.* The Egyptian Journal of Remote Sensing and Space Science, 2021. **24**(3): p. 825-833.
157. Arias-Rodriguez, L.F., et al., *Global water quality of inland waters with harmonized landsat-8 and sentinel-2 using cloud-computed machine learning.* Remote Sensing, 2023. **15**(5): p. 1390.
158. Blix, K., et al., *Remote sensing of water quality parameters over Lake Balaton by using Sentinel-3 OLCI.* Water, 2018. **10**(10): p. 1428.
159. Cai, J., et al., *Using machine learning algorithms with* in situ *hyperspectral reflectance data to assess comprehensive water quality of urban rivers.* IEEE Transactions on Geoscience and Remote Sensing, 2022. **60**: p. 1-13.
160. Souza, A.P., et al., *Integrating remote sensing and machine learning to detect turbidity anomalies in hydroelectric reservoirs.* Science of the Total Environment, 2023. **902**: p. 165964.
161. Ma, Y., et al., *Remote sensing of turbidity for lakes in northeast China using Sentinel-2 images with machine learning algorithms.* IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2021. **14**: p. 9132-9146.
162. Rubin, H.J., et al., *Remote sensing of lake water clarity: Performance and transferability of both historical algorithms and machine learning.* Remote Sensing, 2021. **13**(8): p. 1434.
163. Zeng, W., et al., *Regional Remote Sensing of Lake Water Transparency Based on Google Earth Engine: Performance of Empirical Algorithm and Machine Learning.* Applied Sciences, 2023. **13**(6): p. 4007.
164. Magrì, S., et al., *Application of machine learning techniques to derive sea water turbidity from Sentinel-2 imagery.* Remote Sensing Applications: Society and Environment, 2023. **30**: p. 100951.
165. Lu, Q., et al., *Retrieval of water quality from UAV-borne hyperspectral imagery: A comparative study of machine learning algorithms.* Remote Sensing, 2021. **13**(19): p. 3928.

 doi:10.20944/preprints202410.0048.v1

166. Mosre, J. and F. Suárez, *Actual evapotranspiration estimates in arid cold regions using machine learning algorithms with* in situ *and remote sensing data.* Water, 2021. **13**(6): p. 870.
167. Loggenberg, K., et al., *Modelling water stress in a Shiraz vineyard using hyperspectral imaging and machine learning.* Remote Sensing, 2018. **10**(2): p. 202.
168. Elkhrachy, I., *Flash flood water depth estimation using SAR images, digital elevation models, and machine learning algorithms.* Remote Sensing, 2022. **14**(3): p. 440.
169. Zhang, L., Q. Hu, and Z. Tang, *Using Sentinel-2 imagery and machine learning algorithms to assess the inundation status of Nebraska conservation easements during 2018–2021.* Remote Sensing, 2022. **14**(17): p. 4382.
170. Fu, Z., et al., *Estimating spatial and temporal variation in ocean surface pCO2 in the Gulf of Mexico using remote sensing and machine learning techniques.* Science of the Total Environment, 2020. **745**: p. 140965.
171. Singha, C., et al., *Integrating geospatial, remote sensing, and machine learning for climate-induced forest fire susceptibility mapping in Similipal Tiger Reserve, India.* Forest Ecology and Management, 2024. **555**: p. 121729.
172. Kalantar, B., et al., *Forest fire susceptibility prediction based on machine learning models with resampling algorithms on remote sensing data.* Remote Sensing, 2020. **12**(22): p. 3682.
173. Tavakkoli Piralilou, S., et al., *A Google Earth Engine approach for wildfire susceptibility prediction fusion with remote sensing data of different spatial resolutions.* Remote sensing, 2022. **14**(3): p. 672.
174. Xie, L., et al., *Wildfire risk assessment in Liangshan Prefecture, China based on an integration machine learning algorithm.* Remote Sensing, 2022. **14**(18): p. 4592.
175. Cheng, S., et al., *Parameter flexible wildfire prediction using machine learning techniques: Forward and inverse modelling.* Remote Sensing, 2022. **14**(13): p. 3228.
176. Sulova, A. and J. Jokar Arsanjani, *Exploratory analysis of driving force of wildfires in Australia: An application of machine learning within Google Earth engine.* Remote Sensing, 2020. **13**(1): p. 10.
177. Saim, A.A. and M.H. Aly, *Machine learning for modeling wildfire susceptibility at the state level: an example from Arkansas, USA.* Geographies, 2022. **2**(1): p. 31-47.
178. Pérez-Porras, F.-J., et al., *Machine learning methods and synthetic data generation to predict large wildfires.* Sensors, 2021. **21**(11): p. 3694.
179. McCandless, T.C., B. Kosovic, and W. Petzke, *Enhancing wildfire spread modelling by building a gridded fuel moisture content product with machine learning.* Machine Learning: Science and Technology, 2020. **1**(3): p. 035010.
180. Rafaqat, W., et al., *Study of driving factors using machine learning to determine the effect of topography, climate, and fuel on wildfire in pakistan.* Remote Sensing, 2022. **14**(8): p. 1918.
181. Agrawal, N., P.V. Nelson, and R.D. Low, *A Novel Approach for Predicting Large Wildfires Using Machine Learning Towards Environmental Justice* via *Environmental Remote Sensing and Atmospheric Reanalysis Data across the United States.* Remote Sensing, 2023. **15**(23): p. 5501.
182. Jiang, W., et al., *Wildfire risk assessment using deep learning in Guangdong Province, China.* International Journal of Applied Earth Observation and Geoinformation, 2024. **128**: p. 103750.
183. Shirazi, Z., L. Wang, and V.G. Bondur, *Modeling Conditions Appropriate for Wildfire in South East China–A Machine Learning Approach.* Frontiers in Earth Science, 2021. **9**: p. 622307.
184. Valdez, M.C., et al., *Modelling the spatial variability of wildfire susceptibility in Honduras using remote sensing and geographical information systems.* Geomatics, Natural Hazards and Risk, 2017. **8**(2): p. 876-892.
185. Heisig, J., E. Olson, and E. Pebesma, *Predicting wildfire fuels and hazard in a central European temperate forest using active and passive remote sensing.* Fire, 2022. **5**(1): p. 29.
186. Zhao, Y., et al., *Saliency detection and deep learning-based wildfire identification in UAV imagery.* Sensors, 2018. **18**(3): p. 712.
187. Wang, G., et al., *M4SFWD: A Multi-Faceted synthetic dataset for remote sensing forest wildfires detection.* Expert Systems with Applications, 2024. **248**: p. 123489.
188. Velayati, A.H., et al., *Spatiotemporal analysis of wildfire in the Tigris and Euphrates basin: A remote sensing based wildfire potential mapping.* Remote Sensing Applications: Society and Environment, 2024. **34**: p. 101150.
189. Pelletier, N., K. Millard, and S. Darling, *Wildfire likelihood in Canadian treed peatlands based on remote-sensing time-series of surface conditions.* Remote Sensing of Environment, 2023. **296**: p. 113747.
190. Jin, S., et al., *A self-adaptive wildfire detection algorithm by fusing physical and deep learning schemes.* International Journal of Applied Earth Observation and Geoinformation, 2024. **127**: p. 103671.

191. Zhang, Q., et al., *Beyond being wise after the event: Combining spatial, temporal and spectral information for Himawari-8 early-stage wildfire detection.* International Journal of Applied Earth Observation and Geoinformation, 2023. **124**: p. 103506.
192. Dixon, D.J., et al., *Satellite detection of canopy-scale tree mortality and survival from California wildfires with spatio-temporal deep learning.* Remote Sensing of Environment, 2023. **298**: p. 113842.
193. Van, L.N., et al., *Enhancing wildfire mapping accuracy using mono-temporal Sentinel-2 data: A novel approach through qualitative and quantitative feature selection with explainable AI.* Ecological Informatics, 2024. **81**: p. 102601.
194. Huot, F., et al., *Next day wildfire spread: A machine learning dataset to predict wildfire spreading from remote-sensing data.* IEEE Transactions on Geoscience and Remote Sensing, 2022. **60**: p. 1-13.
195. dos Santos, S.M.B., et al., *Remote sensing applications for mapping large wildfires based on machine learning and time series in northwestern Portugal.* Fire, 2023. **6**(2): p. 43.
196. Iban, M.C. and A. Sekertekin, *Machine learning based wildfire susceptibility mapping using remotely sensed fire data and GIS: A case study of Adana and Mersin provinces, Turkey.* Ecological Informatics, 2022. **69**: p. 101647.
197. Mohajane, M., et al., *Application of remote sensing and machine learning algorithms for forest fire mapping in a Mediterranean area.* Ecological Indicators, 2021. **129**: p. 107869.
198. Janiec, P. and S. Gadal, *A comparison of two machine learning classification methods for remote sensing predictive modeling of the forest fire in the North-Eastern Siberia.* Remote Sensing, 2020. **12**(24): p. 4157.
199. Poon, P.K. and A.M. Kinoshita, *Estimating evapotranspiration in a post-fire environment using remote sensing and machine learning.* Remote Sensing, 2018. **10**(11): p. 1728.
200. Nur, A.S., Y.J. Kim, and C.-W. Lee, *Creation of wildfire susceptibility maps in plumas national forest using InSAR coherence, deep learning, and metaheuristic optimization approaches.* Remote Sensing, 2022. **14**(17): p. 4416.
201. Sim, S., et al., *Wildfire severity mapping using sentinel satellite data based on machine learning approaches.* Korean Journal of Remote Sensing, 2020. **36**(5_3): p. 1109-1123.
202. Ghorbanzadeh, O., et al., *Spatial prediction of wildfire susceptibility using field survey GPS data and machine learning approaches.* Fire, 2019. **2**(3): p. 43.
203. Gholamnia, K., et al., *Comparisons of diverse machine learning approaches for wildfire susceptibility mapping.* Symmetry, 2020. **12**(4): p. 604.
204. Di Napoli, M., et al., *Landslide susceptibility assessment of wildfire burnt areas through earth-observation techniques and a machine learning-based approach.* Remote Sensing, 2020. **12**(15): p. 2505.
205. Zikiou, N., et al., *Remote Sensing and Machine Learning for Accurate Fire Severity Mapping in Northern Algeria.* Remote Sensing, 2024. **16**(9): p. 1517.
206. Bahadori, N., et al., *Wildfire susceptibility mapping using deep learning algorithms in two satellite imagery dataset.* Forests, 2023. **14**(7): p. 1325.
207. Shmuel, A. and E. Heifetz, *Global wildfire susceptibility mapping based on machine learning models.* Forests, 2022. **13**(7): p. 1050.
208. Hamilton, D.A., et al., *Wildland fire tree mortality mapping from hyperspatial imagery using machine learning.* Remote Sensing, 2021. **13**(2): p. 290.
209. Schreck, J.S., et al., *Machine Learning and VIIRS Satellite Retrievals for Skillful Fuel Moisture Content Monitoring in Wildfire Management.* Remote Sensing, 2023. **15**(13): p. 3372.
210. Syifa, M., M. Panahi, and C.-W. Lee, *Mapping of post-wildfire burned area using a hybrid algorithm and satellite data: The case of the camp fire wildfire in California, USA.* Remote Sensing, 2020. **12**(4): p. 623.
211. Oliver, J.A., et al., *A machine learning approach to waterbody segmentation in thermal infrared imagery in support of tactical wildfire mapping.* Remote Sensing, 2022. **14**(9): p. 2262.
212. Ban, Y., et al., *Near real-time wildfire progression monitoring with Sentinel-1 SAR time series and deep learning.* Scientific reports, 2020. **10**(1): p. 1322.
213. Cui, Q., et al., *High Spatiotemporal Resolution PM2. 5 concentration estimation with machine learning algorithm: A Case Study for Wildfire in California.* Remote Sensing, 2022. **14**(7): p. 1635.
214. Pastick, N.J., et al., *Rapid monitoring of the abundance and spread of exotic annual grasses in the western United States using remote sensing and machine learning.* AGU Advances, 2021. **2**(2): p. e2020AV000298.
215. Serra-Burriel, F., et al., *Estimating heterogeneous wildfire effects using synthetic controls and satellite remote sensing.* Remote Sensing of Environment, 2021. **265**: p. 112649.
216. Nolè, A., et al., *Biogeographic variability in wildfire severity and post-fire vegetation recovery across the European forests* via *remote sensing-derived spectral metrics.* Science of the Total Environment, 2022. **823**: p. 153807.

 doi:10.20944/preprints202410.0048.v1

217. Guerra-Hernández, J., et al., *Impact of fire severity on forest structure and biomass stocks using NASA GEDI data. Insights from the 2020 and 2021 wildfire season in Spain and Portugal.* Science of Remote Sensing, 2024. **9**: p. 100134.
218. Chen, R., et al., *Estimation of potential wildfire behavior characteristics to assess wildfire danger in southwest China using deep learning schemes.* Journal of environmental management, 2024. **351**: p. 120005.
219. Ramsey, S., K. Reinke, and S. Jones, *Mapping the recovery of Mountain Ash (Eucalyptus regnans) and Alpine Ash (E. delegatensis) using satellite remote sensing and a machine learning classifier.* Remote Sensing Applications: Society and Environment, 2024: p. 101274.
220. Fernández-Guisuraga, J.M., et al., *FIREMAP: Cloud-based software to automate the estimation of wildfire-induced ecological impacts and recovery processes using remote sensing techniques.* Ecological Informatics, 2024. **81**: p. 102591.