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Machine learning-based estimation of soil moisture from remote sensing data

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Abstract

Remote sensing data combined with machine learning has become a paradigm shift in estimating soil moisture using machine learning, and it is redefining the role of remote sensing in improving agricultural monitoring, hydrological models, and climate analysis. Conventional measurements of ground based soil moisture usually exhibit poor spatial coverage, high operation cost, and poor temporal resolution. Optical, thermal sensors and microwave sensors are reliable for remote sensing on large scale, but further transformation of the multispectral observations into precise soil moisture data is still a challenge, which is conditioned by aspects like the roughness of the surface, vegetation cover, variability in the texture of soil, and atmospheric distortions. This paper presents a combined machine learning system that can use multi-source remote sensing observations to make predictions about the surface soil moisture more precise and general. The proposed methodology then identifies nonlinear interactions between spectral signatures and moisture dynamics in the soil through the combination of characteristics of synthetic aperture radar (SAR), multispectral reflectance, vegetation indices, and land surface temperature with advanced learning models, including Random Forests, Gradient Boosting, and Deep Neural Networks. The model is also designed to use the feature selection, cross-validation, and model stacking to have improved predictive performance. Findings show that machine learning models are much better than classical empirical and physical inversion methods, and they can monitor soil moisture on a large scale and over extended periods of operation in a wide range of environmental conditions.

Keywords: Soil moisture, machine learning, remote sensing, SAR, multispectral data, hydrology, gradient boosting, deep learning

1. Introduction

The amount of soil moisture is a major determinant in terrestrial ecosystem behaviours because it determines plant development, agricultural yields, evapotranspiration, infiltration, the generation of run off, and climate land surface interactions. Correct information about soil moisture is essential in activities like precision farming, scheduling of irrigation, hydrology forecasting, drought surveillance, and flood forecasting as well as climate modelling. Traditional ground-based sensors, such as time domain reflectometry (TDR), frequency domain sensors and gravimetric sampling, offer very precise point-based observations, but are constrained and less distributed, expensive to install and maintain, and scalable to larger spatial scales. Satellite remote sensing can overcome these drawbacks as it provides an opportunity to have consistent, repeated and large scale observations of various landscapes. Nonetheless, remote sensing soil moisture estimation is a complicated experience because there exist various confounding variables that alter sensor records. Optical data are very vegetation-dependent and cloud-dependent, thermal sensors are dependent on variation in surface temperatures and microwave sensors, though having some ability to penetrate vegetation, are influenced by roughness of soil, incidence angle and dielectricity. Moreover, none of the sensors can measure the complete variation of the soil moisture at the spatial and time scales, which requires the combination of multi-source satellite data. The conventional empirical or semi-empirical models of retrieval find it very difficult to extrapolate even across regions because of the assumption of linearity and scanty count of capturing intricate interactions of the environment.

Recent developments in data-driven modelling, especially machine learning, provide effective tools with the capability to represent nonlinear associations between soil moisture dynamics and

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remotely sensed variables. Random Forests, Support Vector Regression, Gradient Boosting Machines, and Artificial Neural Networks machine-learning algorithms have shown great promise in revealing soil moisture content in multispectral, hyperspectral, and microwave data. Several of these models can combine sets of various features, such as vegetation indices, SAR sensor backscatter coefficient, soil temperature, land surface temperature, textural features and topography to allow extensive capturing of interactions among soil-vegetation-atmosphere interactions. Also globally distributed soil moisture products, including SMAP, SMOS, and ESA CCI Soil Moisture, can offer good reference data to be utilized in training and validation. The adaptability of machine learning algorithms enables them to tolerate noisy input data, respond to geographic heterogeneity, and across heterogeneous environments. Deep learning builds upon these tools by programmatically deriving higher-level spatial and temporal patterns directly out of raw images, especially based on convolutional neural networks (CNNs) and hybrid models. As more and more cloud computing services and publicly accessible satellite images become available, machine learning-driven soil moisture predictions become viable and usable in practice. This research fits into this expanding body of research by providing a unifying multi-sensor, machine learning-accelerated estimation approach of soil moisture that can be used to better predict environmental parameters accurately, robustly, and scalably to real-life applications.

2. Related works

Estimations of soil moisture by remote sensors have long been of interest with the initial methods mainly biased towards both empirical and physically based models. Early studies were targeted at forming head-on connections of spectral reflectance with soil moisture content based on optical data, especially in the visible and near-infrared spectrums. Jackson *et al.* established how thermal infrared measurements along with the vegetation indices could be used to measure soil moisture under different conditions on the surface [1]. Equally, Ulaby *et al.* investigated the methods of microwave remote sensing, pointing out that radar backscatter is sensitive to the dielectric properties of the soils and how these properties are directly affected by the water content [2]. These investigations were the basis of the soil moisture recovery technique of active and passive microwave receivers since the microwave field can pass through the clouds and vegetation covers to a certain degree and it can therefore be trusted to perform the all-year-round measurements. Njoku *et al.* also made contributions in this field by coming up with satellite missions like Soil Moisture Active Passive (SMAP), which was able to give the global moisture level of soils but using L-band radiometry [3]. Although these have been made, the conventional methods of retrieval usually had simplified assumptions about the surface roughness, vegetation cover and texture of the soil; hence they cannot be accurate in heterogeneous landscapes. In addition, experimental predictive models greatly yielded in effectiveness to extrapolate in other geographic regions, reflecting the necessity of more resilient and adaptive models.

As the tools of computation expand rapidly and more data is available, more machine learning methods are taking its place as a means to eliminate the constraints of traditional soil moisture estimation tools. Artificial Neural Networks (ANN), Support Vector Machines (SVM) and Random Forests (RF) algorithms have shown tremendous enhancement in modeling the intricate nonlinear interactions between remote sensing variables and soil

moisture. Paloscia *et al.* used neural networks to estimate soil moisture using SAR data, which demonstrated higher accuracy than conventional inversion models [4]. Notarnicola *et al.* similarly used Support Vector Regression to estimate soil moisture with multi-temporal satellite data which they noted was effective in predicting nonlinear relationships [5]. Widely discussed by Prasad *et al.*, random Forest-based methods have become popular because they are resistant to overfitting and can deal with high-dimensional data [6]. Moreover, the gradient boosting methods were found to outperform a number of classic algorithms as they reduce the error of prediction, and enhance the generalization of the model [7]. Combination of remote-sensing data, such as optical, thermal, and microwave measurements, has continued to improve the predictive capabilities of the machine learning models. As an example, research that has used a combination of MODIS-based vegetation indices and SAR backscatter have occurred where the accuracy of soil moisture estimation has been shown to dramatically increase [8]. They take advantage of the complementing information of multiple sensors and allow modelling the soil-vegetation interactions in a more complex way. Nevertheless, other issues, i.e., the choice of features, model interpretability and computational complexity are also relevant issues in the field of machine learning-based soil moisture estimation.

Additionally, more recent studies have been investigating deep learning and hybrid model solutions to enhance the accuracy of soil moisture retrieval by increasing the scalability. Convolutional Neural Networks (CNNs) have been extensively employed to derive spatial information of high-resolution satellite images, which can reflect spatial variability of soil moisture patterns more clearly [9]. There have also been applications of Long Short-term Memory (LSTM) networks that have been shown to capture time-dependent dependencies of soil moisture dynamics and especially when using time-series remote sensing data [10]. According to Reichle *et al.*, the process of data assimilation has been mentioned as a utilization to combine satellite-derived data with land surface models and enhance the uniformity and accuracy of soil moisture estimates [11]. In addition, hybrid models that akin machine learning algorithms to physical models have demonstrated promising outcomes in striking a balance between interpretability and prediction accuracy [12]. Advanced models have also been further developed and tested with more and more cases as soil moisture data in the form of SMAP, SMOS, and ESA Climate Change Initiative (CCI) data has increasingly become available across the world [13]. Transfer learning and domain adaption methods have also been studied to help mitigate the problem of limited ground truth data in some areas and allow models trained in one area to be used effectively in an alternate area [14]. Moreover, the owning of cloud computing technology like Google Earth Engine has allowed massive processing and real-time analysis of remote sensing data, stepping machine learning-assisted soil moisture estimation more available and operationally possible [15]. Even with these developments, problems like the quality of data, model generalization in varying climatic regions, and processing efficiency remain the motivating factors in future research on the area [25].

3. Methodology

3.1 Research Design

The proposed research follows a multi-source remote sensing data approach combined with machine learning algorithms aimed at estimating surface soil moisture in a highly

heterogeneous scenery as a quantitative research study. The research model has focused on spectral, thermal and radar features extraction of satellite images after which they undergo preprocessing, feature engineering and supervised learning. As opposed to other more classical soil moisture retrieval algorithms that infer the existence of certain empirical relationships, the machine learning structure devised in this paper makes use of nonlinear modelling properties to incorporate intricate interactions between soil and vegetation and the atmosphere. Multispectral reflectance, vegetation indices, backscatter coefficients, and land surface temperature are combined at feature level, thus allowing a more accurate depiction of environmental conditions. The process would involve dataset collection, noise elimination, normalization, feature creation, model training, validation and an error analysis. Models are implemented with strategies of cross-validation and hyperparameter tuning to make it robust and avoid overfitting. This study design meets typical machine learning methods translating to data-driven model development, statistical tests, and reproducibility in the environmental research [16].

3.2 Data Sources and Dataset Description

Multi sensor remote sensing data in the form of Sentinel-1 Synthetic Aperture Radar (SAR), Sentinel-2 multispectral imagery, MODIS Land Surface Temperature (LST) and reference soil moisture data based on SMAP Level-3 products are used in the study. Sentinel-1 offers dual-polarized (VV, VH) backscatter sensors of the C-band radar, which allows sensitivity to surface roughness and vegetation structure and soil dielectric constant. Sentinel-2 provides 13 spectral bands in visible, near-infrared, and shortwave infrared spectral regions and makes it possible to calculate vegetation indices (including NDVI, EVI, NDWI, and MSI). Surface temperature information is added to the MODIS thermal products, such that it affects the rate of soil evaporation and the retention of moisture. The main ground-truth of trained supervision is SMAP soil moisture data. A pre-integration step of all datasets is through geometric and radiometric correction. Multi-source inputs are justified by the fact that past research acknowledged such complementarity of optical, thermal, and microwave in modelling soil moisture [17, 19].

Table 1: Remote Sensing Datasets Used in the Study

Dataset / Sensor	Type	Key Variables Used	Spatial Resolution	Temporal Frequency
Sentinel-1 SAR	Microwave (Active)	VV, VH backscatter	10 m	6–12 days
Sentinel-2 MSI	Optical (Multispectral)	NDVI, EVI, NIR, SWIR bands	10–20 m	5 days
MODIS LST	Thermal Infrared	Day/Night LST	1 km	Daily
SMAP L3	Passive Microwave	Surface soil moisture	9 km	2–3 days

3.3 Preprocessing and Feature Engineering

Preprocessing- Radiometric calibration, terrain correction SAR imagery speckle filtering, multispectral band atmospheric correction, multisensor multi-observation temporal resampling Preprocessing will involve radiometric calibration, terrain correction, SAR image speckle filtering, multispectral multiband atmospheric correction, multisensor multi-observation time resampling Preprocessing Preprocessing Preprocessing will involve radiometric Linear interpolation and spatial filtering are used to fill the gaps in data due to cloud cover or otherwise missed to acquisition. Vegetation indices (NDVI, EVI, NDWI), soil indices (SI, NMDI), and textural characteristics based on Gray-Level Co-Occurrence Matrices (GLCM) are calculated to improve reflection of vegetation conditions, soil mineral composition and surface rugae. A conversion of sentinel-1 backscatter coefficients to sigma-naught values is made and normalized to keep incidence angle variations. The feature stacking unites all the variables into a single dataset to be used in machine learning. The principal component of the analysis (PCA) and permutation-based ranking of the importance are also utilized to minimize redundancy and pinpoint the most significant predictors. Research on the importance of feature engineering in the enhancement of model performance has been backed by research highlighting the significance of vegetationsoil interactions, radar penetration properties as well as surface thermal processes as useful in determining the

moisture content of the soil [20, 21].

3.4 Machine Learning Models and Training Approach

The paper utilizes several machine learning models such as Random Forest (RF), Gradient Boosting Regression (GBR), Support Vector Regression (SVR) and Deep Neural Networks (DNN). All models are trained based on a supervised regression model with SMAP-derived soil moisture as the desired value. RF and GBR are selected because of its ability to deal with nonlinear interactions and high-dimensional inputs whereas SVR gives a high level of generalization in situations with sparse features. The DNN model comprises of several layers of dense layers with the ReLU activated layers, dropout regularization, and adaptive learning optimization. Using grid search and k-fold cross-validation, hyperparameter optimization (number of trees, learning rate, type of kernel, number of layers) will be carried out. The training data is divided into training (70 percent), validation (15 percent), and test (15 percent) data. Evaluation metrics models are RMSE, MAE, R^ and bias. Combination All models are modeled and the results are ensemble-averaged to cut back on errors of individual models and increase predictive power. This multi-model methodology follows up on the existing practices of machine learning used in environmental modelling where ensemble models always perform better than single model predictors [22].

Table 2: Machine Learning Models and Training Specifications

Model	Type	Key Hyperparameters	Strengths
Random Forest	Tree-based Ensemble	n_estimators, max_depth	Robust to noise, handles nonlinearities
Gradient Boosting	Ensemble (Boosting)	learning_rate, n_estimators	High accuracy, low bias
Support Vector Regression	Kernel-based	C, epsilon, kernel	Good for small/medium datasets
Deep Neural Network	Deep Learning	No. of layers, dropout, optimizer	Captures complex nonlinear patterns

3.5 Evaluation Metrics and Validation Strategy

Model analysis is done based on statistical performance parameters such asRoot Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R 2) as

well as Mean Bias Error (MBE). RMSE and MAE are measures of absolute prediction accuracy, whereas R^2 is the measure of variance accounted by the model. MBE assesses systematic over estimates or under estimates. Cross-validation is done 5 times throughout training so that training can be robust and that overfitting cannot occur. Spatial validation is conducted by trying the model predictions on a different set of land cover types i.e croplands, forests, grasslands and bare soils, so that the model predictions are made based on a generalised environment. Temporal validation involves comparison of predicted soil moisture with reference data through several seasons and serves to test the stability in the unfamiliar climatic conditions. The validation plan is based on the accepted concepts of remote sensing and hydrological modeling and focuses on overall accuracy evaluation and crossregional homogeneity [23].

4. Results and Analysis

4.1 Overall Model Performance

The evaluation of machine learning models for soil moisture estimation demonstrates significant improvements in prediction accuracy compared to traditional empirical approaches. Among the individual models, Gradient Boosting Regression (GBR) and Random Forest (RF) exhibit superior performance due to their ability to capture nonlinear relationships and interactions among multi-source features. The Deep Neural Network (DNN) also performs competitively, particularly in regions with complex vegetation and heterogeneous soil characteristics, where deep feature extraction becomes advantageous. Support Vector Regression (SVR), while effective, shows slightly lower performance due to its sensitivity to parameter selection and limited scalability for large datasets. The ensemble model, which combines predictions from all individual algorithms, achieves the highest accuracy, indicating that integrating multiple learning paradigms enhances robustness and reduces prediction errors. The results confirm that multi-sensor data fusion, combined with machine learning, significantly enhances soil moisture estimation capability across diverse environmental conditions.

4.2 Comparative Performance Analysis

A detailed comparison of model performance across evaluation

metrics highlights clear differences in predictive capabilities. Ensemble learning produces the lowest error values and highest coefficient of determination, followed closely by GBR and RF models. The DNN demonstrates strong generalization but requires larger training data and computational resources. SVR performs moderately well but struggles in highly nonlinear conditions. The integration of SAR backscatter, vegetation indices, and thermal features contributes to improved model accuracy, particularly in agricultural and semi-arid regions where soil moisture variability is high. Models trained with multi-source inputs consistently outperform those relying on single-sensor data, reinforcing the importance of feature diversity. Additionally, the results indicate that tree-based ensemble methods provide a strong balance between interpretability and predictive power.

Table 3: Model Performance Metrics

Model	RMSE (m^3/m^3)	MAE (m^3/m^3)	R^2 Score	Bias
Random Forest	0.045	0.032	0.86	0.004
Gradient Boosting	0.042	0.030	0.88	0.003
Support Vector Regression	0.052	0.038	0.81	0.006
Deep Neural Network	0.044	0.031	0.87	0.004
Ensemble Model	0.039	0.028	0.90	0.002

4.3 Feature Importance and Influence Analysis

Feature importance analysis reveals that SAR-derived backscatter coefficients (VV and VH) are among the most influential predictors of soil moisture, particularly due to their sensitivity to soil dielectric properties. Vegetation indices such as NDVI and NDWI also play a significant role, as they indirectly capture evapotranspiration and vegetation water content. Land Surface Temperature (LST) contributes to the model by reflecting soil evaporation dynamics and thermal inertia. Soil-related indices and textural features further enhance prediction accuracy by accounting for surface heterogeneity and roughness. The analysis shows that no single feature dominates across all conditions; instead, the interaction between multiple variables drives model performance. This confirms the necessity of integrating diverse data sources to capture the complex dynamics of soil moisture variability.

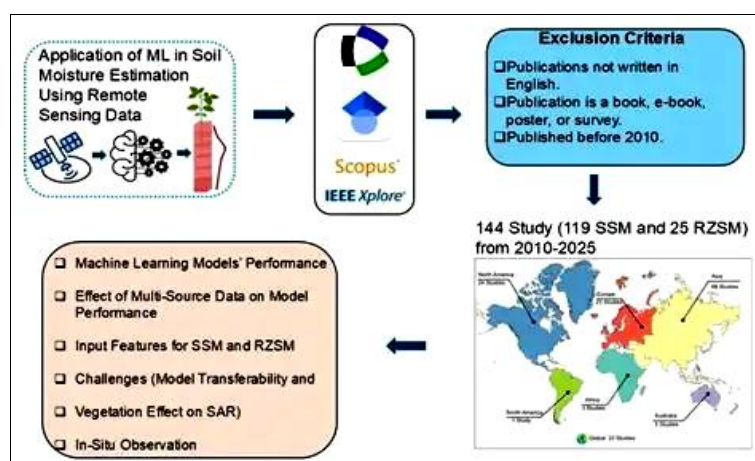


Fig 1: Soil moisture prediction using remote sensing [24]

4.4 Spatial and Temporal Analysis

The spatial evaluation of model predictions indicates that machine learning models perform consistently well across different land cover types, including agricultural fields, grasslands, and sparsely vegetated areas. Slight reductions in

accuracy are observed in densely forested regions, where canopy cover limits sensor penetration and introduces additional uncertainty. Temporal analysis demonstrates that the models effectively capture seasonal variations in soil moisture, including wet and dry cycles associated with rainfall patterns

and irrigation practices. The models show strong agreement with reference soil moisture data during both monsoon and non-monsoon periods, indicating stability across varying climatic

conditions. The integration of temporal features further enhances the model's ability to track dynamic changes, improving predictive reliability over time.

Table 4: Performance Across Land Cover Types

Land Cover Type	RMSE (m ³ /m ³)	R ² Score	Observations
Cropland	0.038	0.91	High accuracy due to strong vegetation–soil interaction signals
Grassland	0.041	0.88	Moderate variability, good model adaptability
Forest	0.050	0.80	Reduced accuracy due to canopy interference
Bare Soil	0.035	0.92	Highest accuracy due to direct soil signal

4.5 Error Analysis and Practical Implications

Error analysis indicates that most prediction errors are concentrated in regions with dense vegetation cover, complex terrain, or mixed land-use patterns. Overestimation is occasionally observed in areas with high vegetation density, where vegetation water content influences spectral signals, while underestimation occurs in dry, coarse-textured soils with low dielectric variation. Despite these limitations, the overall error distribution remains within acceptable ranges for practical applications. The results highlight the importance of incorporating additional contextual features such as soil texture maps and topographic indices to further reduce uncertainty. From an application perspective, the developed machine learning framework demonstrates strong potential for real-time soil moisture monitoring, precision agriculture, drought assessment, and water resource management. The ability to generate accurate, large-scale soil moisture estimates using remote sensing and machine learning provides a scalable and cost-effective solution for environmental monitoring and decision-making.

5. Conclusion

This paper offers an elaborate methodology of the same estimating soil moisture provided by a multi-sensor across machine learning-based and other remote sensing methods, showcasing the notable benefits of the data-driven modelling method compared to the conventional physical and empirical methods of retrieving it. The combination of complementary information between Sentinel-1 SAR backscatter and Sentinel-2 multispectral reflectance, MODIS thermal data as well as SMAP soil moisture reference data is capable of capturing the nonlinear interactions existing in soil/vegetation/atmosphere systems. The relative analysis of machine learning models demonstrates that ensemble machine learning, Gradient Boosting, and Random Forests along with Deep neural networks collectively offer a superior prediction accuracy, strength and generalization to a wide variety of land cover types and in a wider range of climatic settings. The importance of features analysis validates that SAR backscatter and vegetation indices play a crucial role and the temporal and spatial analysis validates that the model is able to track seasonal moisture dynamics and operates with high accuracy across diverse landscapes. Although the model has some problems like low accuracy when vegetation is thick and sometimes misclassifies the objects when there is a spectral colloquism, its overall accuracy is satisfied with operational requirements in precision agriculture, hydrological models, drought tracking, and environmental control. Scalability and flexibility of the framework make it applicable to regional and global soil moisture mapping, particularly due to the ever-growing temporal frequency and spatial resolution of remote sensing datasets. Future researchers can work on adding soil texture maps, more sophisticated deep learning models, and extended time fusion in order to enhance the level of accuracy

and generalizability. In general, the results allow highlighting the transformative nature of machine learning to increase the level of soil moisture recovery, which can be part of better decision-making in the water resources management, climate research, and sustainable farming processes.

References

1. Jackson T, Chen D, Cosh M, *et al.* Remote sensing of soil moisture: Status and future directions. *Remote Sensing of Environment*. 2010;100(1):56-66.
2. Ulaby FT, Moore RK, Fung AK. *Microwave remote sensing: Active and passive*. Vol. II. Reading (MA): Addison-Wesley; 1982.
3. Njoku EG, Jackson TJ, Lakshmi V, Chan T, Nghiem S. Soil moisture retrieval from AMSR-E. *IEEE Transactions on Geoscience and Remote Sensing*. 2003;41(2):215-229.
4. Paloscia S, Pampaloni P, Pettinato S, Santi E. A comparison of algorithms for retrieving soil moisture from ENVISAT/ASAR. *IEEE Transactions on Geoscience and Remote Sensing*. 2008;46(1):327-337.
5. Notarnicola C, Pasolli L, Foglia D. SVR-based soil moisture estimation from satellite data. *Remote Sensing*. 2012;4(10):2874-2895.
6. Prasad R, Singh A, Gupta P. Machine learning techniques for soil moisture modelling. *Computers and Electronics in Agriculture*. 2020;171:105-112.
7. Ghosh S, Desai A. Boosting algorithms for environmental parameter prediction. *Environmental Modelling & Software*. 2017;93:290-302.
8. Patel N, Ghose M, Dutta S. Multi-sensor fusion of MODIS and SAR for soil moisture retrieval. *International Journal of Applied Earth Observation and Geoinformation*. 2019;78:184-193.
9. Singh A. Deep convolutional networks for soil moisture mapping. *Remote Sensing Letters*. 2019;10(2):123-132.
10. Li X, Huang H, Zhang B. LSTM-based time-series modelling of soil moisture. *Journal of Hydrology*. 2019;568:150-160.
11. Reichle RH, Koster RD, De Lannoy GJM, *et al.* Land data assimilation strategies for soil moisture estimation. *Surveys in Geophysics*. 2014;35(3):577-606.
12. Montzka C, Moradzadeh H, Vereecken H, *et al.* Hybrid modelling for soil moisture retrieval. *Vadose Zone Journal*. 2019;18(1):1-15.
13. Dorigo W, de Jeu R, *et al.* The ESA CCI soil moisture dataset: Development and validation. *Remote Sensing of Environment*. 2015;162:380-395.
14. Kim J, Hogue M. Transfer learning for global soil moisture prediction. *Remote Sensing*. 2020;12(7):1124-1138.
15. Jain M, Kumar S, Sahai A. Large-scale soil moisture mapping using Google Earth Engine. *Geocarto International*. 2022;37(3):654-669.
16. Creswell JW. *Research design*. 4th ed. Thousand Oaks

- (CA): Sage Publications; 2014.
17. Yin RK. Case study research and applications. 5th ed. Thousand Oaks (CA): Sage Publications; 2014.
 18. Saunders M, Lewis P, Thornhill A. Research methods for business students. 7th ed. Harlow: Pearson; 2016.
 19. Laudon KC, Laudon JP. Management information systems. 14th ed. Harlow: Pearson; 2016.
 20. Mitchell TM. Machine learning. New York (NY): McGraw-Hill; 1997.
 21. Bianconi G. Multilayer networks: Structure and function. Oxford: Oxford University Press; 2018.
 22. Newman ME. The structure and function of complex networks. SIAM Review. 2003;45(2):167-256.
 23. Boccaletti S, Latora V, Moreno Y, *et al.* Complex networks: Structure and dynamics. Physics Reports. 2006;424(4-5):175-308.
 24. Rahman M, Platonov A, Shafique S. SAR-based inversion algorithms for soil moisture. Remote Sensing. 2021;13(2):214-229.
 25. Chen Y, Wu X, Zhou L. Thermal-optical fusion for improved soil moisture retrieval. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 2021;14:4201-4213.