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Review

A Review of Earth's Surface Soil Moisture Retrieval Models via Remote Sensing

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Abstract: Soil moisture is essential parameter in the Earth's surface. The information provided by soil moisture plays a vital role in agricultural production, eco-environmental protection, water and land resources management, etc. Meanwhile, the accurate monitoring of the spatial and temporal distribution of soil moisture is of great significance for the engineering geological assessment and geological disaster prevention. Monitoring and retrieving soil moisture via remote sensing data and mathematical models are the main research methods at present and the crucial issue is how to eliminate the influence of other surface and soil parameters like roughness and soil bulk density, and the interference of vegetated areas to electromagnetic waves. Nowadays, many branches of retrieval methods have been developed, and researchers are integrating multiple models to improve the retrieval accuracy. This paper summarizes the present research status and progress of soil moisture retrieval via remote sensing based on four kinds of models: empirical model, semi-empirical model, physical model, and machine learning. The soil moisture products are summarized and listed at the same time. The difficulties and issues in the present research are discussed and the future outlook is explored.

Keywords: soil moisture; remote sensing; model; retrieval methods

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1. Introduction

The Earth's surface soil moisture (SM) is widely used in atmospheric and agricultural sciences. It refers to the water content in the surface soil layer, and plays a key role in the material and energy exchange between soil and atmosphere. It is a crucial factor affecting global water vapor circulation, ecological evolution, and energy exchange [1]. SM provides information in multiple fields such as meteorology, hydrology, and agriculture, and provides information support for production and life. For example, in agricultural science, soil moisture is a key indicator for monitoring crop growth, estimating yield, and drought monitoring and prediction [2,3], and is of great significance for local agriculture and water resource management. In addition, soil moisture has important value for weather forecasting, climate change, and monitoring floods and droughts worldwide [4].

So far, the large-scale and high-precision retrieval of soil moisture has been a troublesome issue. Traditional methods are restricted by manpower and financial and environmental factors, so it is difficult for large-area and long-time observation. Since the 1950s, from basic field observations to the development of remote sensing methods, various data sources like optical, thermal, and microwave have been deeply studied and investigated, providing a large number of algorithms, models, and products that have been extensively used in practical production and life. Currently, the most effective and convenient technical methods for monitoring soil moisture in the research area is using optical and radar remote

sensing technology to construct a mathematical statistics or physical model of electromagnetic wave and surface soil parameters. Sensors on remote sensing satellites can track and record the Earth's surface frequently, and with the launch of subsequent satellites and the establishment of constellations, it is possible to use satellite remote sensing images to monitor surface soil moisture over large areas and long-time series. Optical remote sensing images have the advantages of high spatial and spectral resolution; therefore, they are widely used to remove the interference of vegetation coverage, among which water cloud models are most commonly used. Microwave has strong penetration ability, and its corresponding bands are highly sensitive to water molecules in the soil. Due to the linear arrangement of water molecules under the action of electric fields, the dielectric constant is usually high [5]. According to this physical mechanism, the corresponding physical model is constructed and used in the retrieval of surface soil moisture. Presently, microwave remote sensing is mainly divided into passive and active microwave remote sensing. Passive microwave remote sensing has low spatial resolution, which leads to poor performance in monitoring soil moisture at small scales. As an active microwave remote sensing, synthetic aperture radar (SAR) not only has high spatial and temporal resolution, but can also provide rich ground polarization information for the retrieval of soil moisture. Therefore, using active polarized SAR information to obtain high accuracy and high spatial–temporal resolution, soil moisture is one of the hot research directions in this field [6].

The current reviews are mainly based on the classification of data sources, while there is less of a summary of the retrieval model. The structure of most current reviews are subdivided into optical (further subdivided into visible, near-infrared, and some including short-wave infrared), thermal, and microwave (further subdivided into active and passive) based on the types of remote sensing data sources [7], and the combination of these as secondary headings. For example, Petropourlos [8], Lizhaoliang et al. [7]—based on the above three categories—have summarized the achievements and opinions of the current soil moisture research. The advantage of this structure is that the reader can find the corresponding retrieval algorithm and mechanism according to their own data source. However, there are a large number of models that each data source can use, so it is not convenient if a reader wishes to find an introduction for a specific type of retrieval model. In addition, Babaeian et al. [9] provided a detailed introduction to ground-based and proximal sensing methods and summarized the applications of spaceborne products. Peng et al. [10] further analyzed the gap between current SM product characteristics and application requirements according to different fields. In a word, a review of the retrieval model categories is currently lacking. Therefore, the main objective of this review is to summarize the current models of remote sensing according to four types, empirical model, semi-empirical model, physical model, and machine learning, and analyze their advantages and disadvantages. The development status and the problems of the retrieval models and algorithms used in soil moisture research are summarized, and the future directions are explored. Meanwhile, the selection of references in this review is based on the search for keywords of different models in the current Chinese and English mainstream journals of remote sensing and agriculture, up to 150 articles were searched. Finally, the articles were selected according to the structure and chapter arrangement.

2. Retrieval Model

Researchers have conducted copious research on the remote sensing retrieval of soil moisture, and four kinds of retrieval models have been established. Among them, the empirical, semi-empirical, physical models (based on mathematical statistics), and physical meaning have been studied comprehensively and in-depth, and many corresponding soil moisture products have been introduced. In addition, with the development of computer technology and artificial intelligence, the machine learning direction has developed rapidly. Training methods like neural networks were applied to retrieve soil moisture, obtaining a series of satisfactory results and attracting high attention.

2.1. Empirical Model

The empirical model is a statistical model based on the parameters obtained by remote sensing image and soil moisture. Common parameters include surface temperature, radar backscatter coefficient, optical index like normalized vegetation index (NDVI), etc., in the form of:

$$SM = f(\rho \text{ or } i) \quad (1)$$

ρ refers to spectral reflectance and i refers to index established by combining ρ from different bands. For microwave data sources, they can be divided into active and passive types, and their retrieval forms are as follows:

$$\text{Active microwave: } SM = f(\sigma, VWC) \quad (2)$$

$$\text{Passive microwave: } SM = f(Tb, \tau \text{ or } VWC) \quad (3)$$

σ is the backscatter coefficient, Tb is the brightness temperature, and VWC is the vegetation water content.

Soil moisture is correlated with the reflectance of the visible light band of soil. Previous research results have shown that the linear relationship between spectral reflectance and SM is remarkable, but some studies have also found nonlinear relationships [11,12]. The variation of soil moisture is reflected by the difference between the absorption and reflection of spectra under different surface conditions. Different absorption characteristics are usually used to establish SM retrieval methods. Therefore, changes in soil moisture can be monitored based on the optical reflectance characteristics of the soil [13]. Optical methods generally associate the spectral characteristic of images with soil moisture content, and estimate soil moisture by using spectral data or calculating the spectral reflectance index. Although this method has the advantage of simplicity and convenience, it can be easily affected by weather conditions. Among them, the most widely used method is the thermal infrared method, which estimates soil moisture by calculating thermal inertia and other parameters according to the thermal characteristics of the soil. However, in some areas with high vegetation coverage, soil radiation information is obscured by vegetation, which affects the accuracy of soil moisture estimation. Therefore, these methods are generally only applicable to monitoring soil moisture in bare soil and sparsely vegetated areas under cloud-free conditions [14]. The normalized multi-band drought index (NMDI) formed by a combination of information from multiple near-infrared and short-wave infrared channels has better sensitivity to drought and is suitable for estimating soil and vegetation water content [15]. Ghulam et al. [16] proposed the modified perpendicular drought index (MPDI) based on the bare soil perpendicular drought index (PDI), and removed the interference of vegetation information in mixed pixels via fractional vegetation coverage (FVC) and vegetation reflectance in the corresponding band (Figure 1).

$$PDI = \frac{1}{\sqrt{M^2 + 1}}(B_{red} + M \bullet B_{NIR}) \quad (4)$$

$$MPDI = \frac{B_{vred} + M \bullet B_{NIR} - FVC(B_{vred} + M \bullet B_{VNIR})}{(1 - FVC)\sqrt{M^2 + 1}} \quad (5)$$

Among them, M is the slope of the soil line, B_{vred} and B_{VNIR} refer to the reflectance of vegetation in the red and near-infrared bands, and *FVC* is the fractional vegetation coverage.

Since the soil has a linear relationship in the two-dimensional spectral feature space of the red and near-infrared bands, the fitting lines are called soil lines, shown as the line BC in Figure 1. Rnir and Rred are near infrared and red spectral reflectance, respectively. L is made to be perpendicular to the soil line BC through the coordinate origin, whereby the smaller the distance from any point E (Rred, Rnir) to the line L, the wetter the soil, and vice versa.

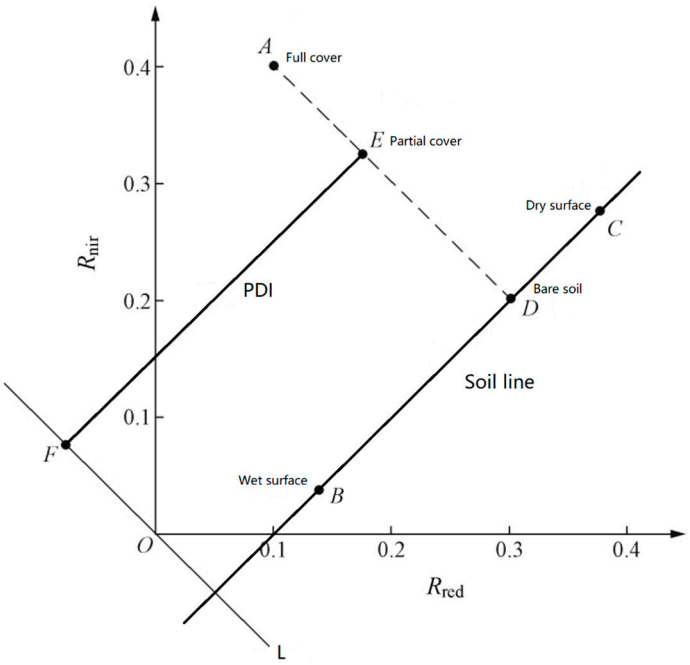

Figure 1. Sketch of PDI (adapted with permission from Ref. [17]. 2021, Danyang Yang).

In empirical models, many researchers estimate soil moisture based on the close relationship between land surface temperature (LST) and vegetation conditions using the triangle feature space method. Sandholt et al. [18] proposed a triangle feature space constructed via LST and NDVI (Figure 2).

$$\mathrm{TVDI} = (\mathrm{T} - \mathrm{T_{min}})/(\mathrm{T_{max}} - \mathrm{T_{min}}) \quad (6)$$

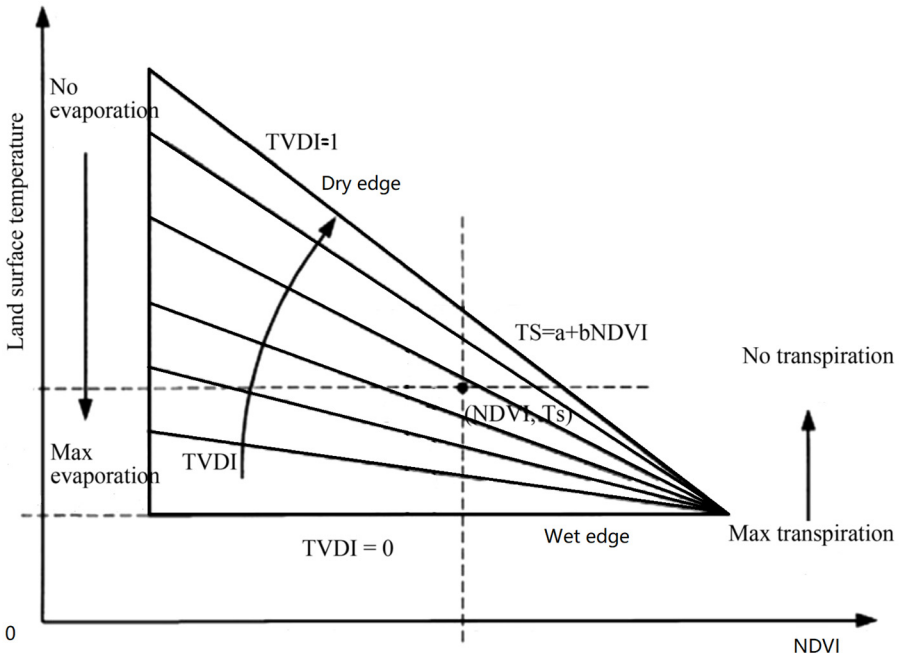

Figure 2. Sketch of NDVI–LST triangle feature space (feature space of the TVDI) (adapted with permission from Ref. [13]. 2019, Junxia Wang).

In the formula, T is the surface temperature; T_{min} is the lowest temperature in the feature space, representing the wet edge; $T_{max} = a + b \times NDVI$, which represents the highest

temperature corresponding to a NDVI value; and a and b are the coefficients obtained by linear fitting.

The wet edge is composed of the lowest LST under different vegetation conditions, indicating the maximum humidity. The dry edge represents the minimum value of surface evapotranspiration (ET), formed by the scatter of the highest LST under different NDVI values. As shown in Figure 2, if the vegetation coverage range extends from bare soil to dense coverage, the SM range extends from extreme drought to extreme humidity, and the NDVI–LST scatter plot forms a triangle.

Apart from the above feature spaces, the drought index constructed by LST and NDVI (TVDI) is also closely related to SM [19]. Based on this, a method combining LST, NDVI, and TVDI triangle feature space has been developed for SM retrieval [20–22]. Using Landsat 8's visible light band of the satellite remote sensing image and thermal infrared band data to calculate LST and NDVI, a TVDI model was constructed to retrieve soil moisture in the Heihe River Basin and the average accuracy is 80.3% [23]. Yang et al. [17] used GF-1 multi-spectral images and measured data from ground observation stations to establish a soil moisture retrieval model based on four drought indices—PDI, MPDI based on NDVI, MPDI based on enhanced vegetation index (EVI), and vegetation-adjusted perpendicular drought index (VAPDI)—and evaluated their accuracy. R^2 was 0.6985, 0.7133, 0.7143, and 0.7552, respectively, which indicate that the accuracy of the four models is similar, but the latter three are higher than PDI. Due to the fact that some satellites do not have thermal infrared data sources, a new model named the Optical Trapezoid Model (OPTRAM) based on shortwave infrared transformed reflectance (STR) was established [24]. This model uses Sentinel-2 and Landsat-8 STR data instead of LST calculated from TIR data to construct the feature space. The result indicated that the OPTRAM can obtain SSM estimates with high accuracy, where RMSE was below 0.04 with local calibration and below 0.05 without calibration.

2.2. Semi-Empirical Model

The semi-empirical model is a semi-quantitative model combining physical meaning and empirical data to not only reduce the impact of vegetation coverage and soil roughness, but also obtain a higher accuracy.

For areas with bare soil or low vegetation coverage, the interference of the vegetation layer is rare. Typical semi-empirical models like the Dubois model and OH model based on radar data have been developed [25,26]. Dubois et al. constructed a semi-empirical relationship between the surface root-mean-squared height and soil moisture. The OH model is a semi-empirical model based on measured data, which constructs the relationship among the backscattering polarization ratio, soil moisture, and surface roughness from different radar bands and polarization modes. On account of the limitations on radar frequency, incident angle, and soil roughness, the model is not suitable for obtaining soil moisture under complex vegetation conditions. The formulas of these two models are as follows:

Dubois model:

$$\sigma^0_{vv} = 10^{-2.35}\frac{\cos^3\theta}{\sin\theta}10^{0.046\,\varepsilon_r\tan\theta}(s\ \sin^3\theta)^{1.1}\lambda^{0.7} \tag{7}$$

$$\sigma^0_{vh} = 10^{-2.75}\frac{\cos^{1.5}\theta}{\sin\theta^5}10^{0.028\,\varepsilon_r\tan\theta}(s\ \sin^{1.4}\theta)\lambda^{0.7} \tag{8}$$

OH model:

$$\frac{\sigma^0_{hv}}{\sigma^0_{vv}} = 0.23\sqrt{\Gamma_0}(1-e^{-s}) \tag{9}$$

$$\frac{\sigma^0_{hh}}{\sigma^0_{vv}} = [1-(\frac{2\theta}{\pi})^{(\frac{1}{3\Gamma_0})}e^{-s}]^2 \tag{10}$$

$$\Gamma_0 = |\frac{1-\sqrt{\varepsilon_r}}{1+\sqrt{\varepsilon_r}}|^2 \quad (11)$$

where ε_r is the real part of the dielectric constant, λ is the wavelength, s is the root-mean-squared height, θ is the incidence angle, and Γ_0 is the soil Fresnel reflection coefficient. σ^0_{pq} represents the backscattering coefficient and pq is the polarization state.

Obtaining high-precision soil moisture results in areas with dense vegetation has always been a challenge. Based on the physical characteristics of electromagnetic wave scattering via vegetation canopy, a series of retrieval models are developed by combining the measured data with the methods of statistical regression. Among them, the typical one is the water-cloud model proposed by Attema and Ulaby in 1978 [27], which is a scattering model that simulates the vegetation layer when studying crops. It has two premises: first, it assumes that the scattering particles in the vegetation layer not only have the same size and shape, but are also distributed uniformly throughout the vegetation layer; second, it ignores multiple scattering between vegetation and the soil surface. The sketch is shown in Figure 3, and the specific formulas are as follows:

$$\sigma^0 = {\sigma_{veg}}^0(\theta) + \tau^2(\theta) * {\sigma_{soil}}^0(\theta) \quad (12)$$

$${\sigma_{veg}}^0(\theta) = A * V_1 * \cos\theta * (1 - \tau^2(\theta)) \quad (13)$$

$$\tau^2 = e^{(\frac{-2BV_2}{\cos\theta})} \quad (14)$$

where τ^2 is the double attenuation factor (transmittance) of the vegetation layer; θ is the incidence angle of the electromagnetic wave; A and B are empirical coefficients of the water-cloud model, which depend on the vegetation type and frequency of the incident electromagnetic wave; and V_1 and V_2 are two parameters that describe the vegetation.

The water-cloud model is currently widely applied. Based on Sentinel-1 SAR data and ground measurements, radar backscatter coefficients were used to monitor and retrieve typical grassland soil moisture in Inner Mongolia. [28]. The water-cloud model was used to revise the retrieval results by removing the interference of vegetation coverage in the study area. The retrieved soil moisture is significantly correlated with the measured soil moisture; R^2 was 0.87. It was believed that Sentinel-1 SAR data can effectively monitor large-scale grassland soil drought problems. Xiong et al. [29] used Sentinel-1A SAR data and combined them with the water-cloud model to extract the spatial distribution information of crop waterlogging with high spatiotemporal resolution. The spatial distribution of the relative volume water content of the soil surface layer with a 12-day interval was extracted as the estimated parameter. At the same time, the Kalman filter interpolation method [30] was used to extract the daily spatial distribution information of the relative volume water content. A method was proposed to jointly retrieve surface soil moisture under local vegetation coverage through a combination of Sentinel-1 SAR data and Landsat 8 optical data [31]. A vegetation water content estimation model based on Landsat OLI spectral index was established to eliminate the interference of vegetation, and the model was incorporated into the original water-cloud model to establish an improved water-cloud model with spectral index. The RMSE was 0.053, and the correlation coefficient between the estimated and measured SM was 0.911. Xie et al. [32] also chose to fuse optical and SAR microwave radar data to eliminate vegetation interference through the water-cloud model and calculate the surface backscattering coefficient combined with ground observation data for comparative analysis. Most validation sites have R values greater than 0.6 and some are greater than 0.8. It is believed that this method can improve the credibility of long-term soil moisture retrieval. Katarzyna [33] used Sentinel-1 VH and VV data to retrieve soil moisture based on the influence of vegetation on backscattering under different soil moisture levels. It was found that the vegetation status reflected by NDVI can be described by the difference between σ_o VH and VV or the ratio of σ_o VV/VH calculated from the Sentinel images

in the logarithmic domain. Meanwhile, the retrieval method of the water-cloud model can accurately estimate the average moisture of wetlands. It was concluded that the soil moisture retrieval algorithm based on Sentinel-1 data is suitable for wetland ecosystems with soil moisture values several times higher than those in agricultural areas.

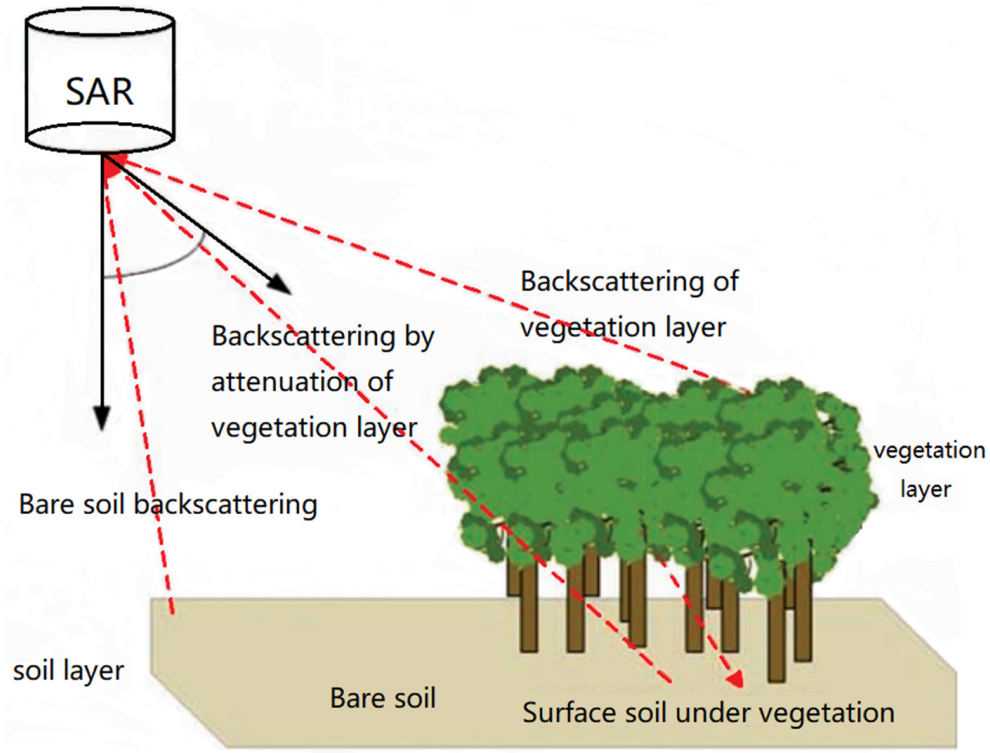

Figure 3. Sketch for water-cloud model.

In recent years, besides the water-cloud model, researchers have also developed many different semi-empirical models. An optical and radar remote sensing semi-empirical coupling model was proposed, which distinguishes the scattering contribution under crop cover and the direct scattering of bare ground, and combines the water-cloud model and the PROSAIL model to retrieve soil moisture in farmland areas [34]. It was believed that there is a good linear relationship between the backscattering coefficient and the measured value in this method; R^2 increased from 0.645 to 0.809, and RMSE decreased by 0.006 compared with the single water-cloud model. Sekertekin [35] used ALOS-2 L band and Sentinel-1 C band SAR data to retrieve surface soil moisture on bare and vegetated farmland during the dry season without irrigation, and studied the sensitivity of the two polarization modes to the bare surface and vegetated surface. A bare soil surface empirical model based on MLR analysis was proposed. It was found that for bare soil surfaces, the sensitivity of ALOS-2 HH polarization and Sentinel-1 VV polarization is the highest. At the same time, compared with the Dubois semi-empirical model, MLR analysis model, and water-cloud model, it was found that the Dubois semi-empirical model has low sensitivity, the accuracy of the MLR model in estimating SM by Sentinel-1 is higher than that of ALOS-2, and the WCM can effectively eliminate the backscattering effect of vegetation. Lei [36] proposed a prototype framework that integrates high-resolution TIR and SAR remote sensing data into a soil–vegetation–atmosphere transfer (SVAT) model to better estimate surface and root-layer soil moisture and optimize irrigation management. It was found that the surface- and root-layer soil moisture accuracy levels predicted by the SVAT model were both enhanced by assimilation based on heat and radar retrieval. Using multi-temporal C band SAR data of the Sentinel-1 satellite, the Alpha approximation model was constructed to establish the soil moisture observation equation group that realized the retrieval of farmland surface soil moisture by solving the equation group [37]. It was believed that the Alpha approximation

model is more effective in areas where soil scattering dominates and the retrieved RMSE is 0.06. The following table summarizes the soil moisture product retrieved by empirical and semi-empirical models (Table 1).

Table 1. Typical soil moisture product retrieved by empirical and semi-empirical models.

Satellite Program	Spatial Resolution	Band	Temporal Resolution	Time Range	Publisher
SMOS	25 KM	L	1 d	2 November 2009 ongoing	The European Space Agency (ESA)
ASCAT MetOp-B	25 KM 50 KM	C	1 d	17 September 2012 ongoing	ESA
Terra-Sar	2 M	X	1 d	June 2007 ongoing	ESA
Sentinel-1	1 KM	C	1 d	3 April 2014 ongoing	ESA
SMAP	36 KM	L	1 d	31 January 2015 ongoing	The National Aeronautics and Space Administration (NASA)

2.3. Physical Model

The physical models were first introduced in the 1950s and have since been developed. The common models include the small perturbation method (SPM) [38], the Kirchhoff approximation (KA) [39], and the integral equation model (IEM) [40]. Among them, the SPM model has strict requirements for surface roughness that the root-mean-squared height is required to be far lower than the wavelength and is only suitable for slightly rough surfaces. The Ka model is suitable for the situation where the intensity of land surface change exceeds the wavelength [41]. The most widely used physical model for soil moisture retrieval is the IEM model proposed by Fung et al., as well as the advanced integral equation model AIEM developed by Chen et al. [42]. The IEM model is a surface scattering model based on the electromagnetic wave microwave radiation transfer equation, which is applicable to a wide range of surface roughness. AIEM introduces a new way of calculating the Fresnel scattering coefficient and the autocorrelation function; thus, the surface autocorrelation function can smoothly transition between rough and smooth states, which can further improve the simulation accuracy of the model.

The AIEM model divides the surface field into two parts: Kirchhoff facet field and its compensating field.

$$\sigma_{pq}^{0} = \sigma_{pq}^{k} + \sigma_{pq}^{c} + \sigma_{pq}^{kc} \tag{15}$$

Among them, p and q represent the polarization characteristics (H or V) of the radar signals emitted and received, respectively. σ_{pq}^{0} represents the backscattering coefficient, and σ_{pq}^{k}, σ_{pq}^{c}, σ_{pq}^{kc} represent the Kirchhoff term, the compensating term, and the cross term of the Kirchhoff term and the compensating term, respectively. The specific formulas are as follows:

$$\sigma_{pq}^{0} = \frac{k^2}{2} e^{(-2k_z^2 s^2)} \sum_{n=1}^{\infty} \left| I_{pq}^{n} \right|^2 \frac{W^{(n)}(-2k_x, 0)}{2} \tag{16}$$

$$I_{pq}^{n} = (2k_z)^n f_{pq} e^{(-2k_z^2 s^2)} + \frac{k_z^n F_{pq}}{2} \tag{17}$$

where k is the wave number, s is the root-mean-squared height, $k_z = k\cos\theta$, $k_x = k\sin\theta$, θ is the incidence angle, f_{pq} is the Gustav Kirchhoff coefficient, F_{pq} is the compensation field coefficient, and pq is the polarization state.

The AIEM model can simulate the response relationship between the backscattering coefficient and the radar incidence angle (θ), soil moisture (SM), root-mean-squared height (S), and correlation length (L) under different conditions [43]. Shi et al. [44] developed the Qp model based on the AIEM model simulation data regression and combined it with satellite observation data to eliminate the influence of roughness under different polarization modes. This algorithm does not rely on surface roughness data and is adopted

by China FY-3B satellite microwave soil moisture product. Cui et al. [45,46] improved the vegetation correction part in the dual-channel algorithm, and used the Qp model to remove the influence of roughness, which improved the retrieval accuracy that was increased by R^2 between retrievals and measurements, by approximately 10.1% to 18.4%; RMSE decreased by about 5% to 8.5%. The NASA soil moisture retrieval algorithm of AMSR-E is based on the microwave radiation transfer model, using the least squares method to retrieve soil moisture by minimizing the cost function between the observed brightness temperature value and the simulated brightness temperature value [47]. The NASA AMSR-E JAXA soil moisture product is based on the lookup table algorithm developed from the DMRT-AIEM physical model, which is based on the physical radiation transfer model that uses the theory of radiative transfer to calculate the multiple scattering effects of soil particles and simulates the surface roughness effects of soil particles through AIEM [48].

In addition to the AIEM model, other physical models have also been applied to soil moisture retrieval. Ulaby [49] proposed the MIM-ICS model based on measured data of soil, vegetation, crops, rocks, and other surface objects covered with vegetation. This model is a first-order solution to the microwave radiation transfer equation. Owe and De [50] used polar orbit passive microwave data to retrieve vegetation optical thickness and soil dielectric constant, and The Land Parameter Retrieving Model (LPRM) is proposed to calculate soil moisture using the soil dielectric constant. In China, LPRM was also used to retrieve surface soil moisture and compared it with measured data, and it is believed that the result retrieved by the radiation transfer model based on FY-3 data can accurately describe the temporal and spatial variation characteristics of soil moisture. The results showed that the R of most sites was 0.7; RMSE was less than 0.06 [51]. The AMSR-2 uses a zero-order radiation transfer model as the forward model. The algorithm introduces soil moisture index and microwave vegetation polarization difference index, and combines simulation databases of vegetation coverage, vegetation water content, and soil moisture in different ranges to construct a lookup table to retrieve soil moisture [52]. The following table summarizes the soil moisture product retrieved by physical model (Table 2).

Table 2. Soil moisture product retrieved by physical model.

Satellite Program	Spatial Resolution	Band	Temporal Resolution	Time Range	Publisher
ERS-1	50 km × 50 km	C	1 d	17 July 1991–10 March 2000	ESA
ERS-2	25 km × 25 km	C	1 d	21 April 1995–5 September 2011	ESA
AMSR-E	50 km	C, X	1 d	1 June 2002–4 October 2011	NASA
AMSR-2	50 km	C, X	1 d	10 August 2012 ongoing	NASA
FY-3B	25 km × 25 km	X	1 d	12 July 2011–19 August 2019	China Meteorological Administration (CMA)
FY-3C	25 km	X	1 d	29 May 2014 ongoing	CMA

2.4. Machine Learning

Machine learning is currently a rapidly developing direction in the field of computer remote sensing, and techniques like neural networks, random forest (RF), support vector machine (SVM), decision tree (Figure 4) and deep learning have been applied to soil moisture remote sensing retrieval with remarkable results.

Li et al. [53] evaluated the importance of polarimetric features in soil moisture retrieval by using a decision tree-based random forest regression method, and selected the optimal polarimetric feature combination to construct a high-precision soil moisture retrieval model for different vegetation coverage in winter wheat areas; the total sample RMSE is about 0.06. An Improved Convolutional Neural Network (ICNN) method was proposed by combining multi-polarization radar and multispectral data sources to solve the problem of an ineffective estimation of vegetation and soil roughness effects in wide-area soil moisture retrieval [54]. The correlation coefficient between the model prediction value

and the sample data is 0.934, and the RMSE is 0.0145. This method does not require a separate estimation of vegetation and soil roughness effects, nor does it require the collection of measured parameters. The error in estimating the influence of vegetation and soil roughness is avoided. Wu et al. [55] combined Sentinel-1 incidence angle information, backscattering coefficients, optical data of vegetation index extracted from Sentinel-2, and ground measured data to construct a back propagation (BP) neural network soil moisture retrieval model and applied it to soil moisture retrieval in the experimental area with a 0.045 RMSE, concluding that the Sentinel-1 VV polarization mode is more suitable for soil moisture retrieval than the VH polarization mode. Based on fully polarimetric Radarsat-2 C band data and measured data, multiple retrieval models were constructed and optimized using three different machine learning algorithms, RF, SVM, and BP artificial neural networks [56]. Meanwhile, a 10-fold cross-validation was used to comprehensively evaluate the accuracy of each model, select the best model to retrieve soil moisture in the study area, and analyze its spatial distribution pattern and impact factors. Using data collected from the Sentinel-1 SAR sensor, Hachani et al. [57] proposed a soil moisture retrieval algorithm based on artificial neural networks (ANNs). They used auxiliary information like the digital elevation model, local incidence angle, NDVI, and combined satellite measurement with electromagnetic model simulation data (based on the IEM model) to obtain a special strategy for training, which not only made the algorithm robust and almost independent of the experimental location, but also allowed it to obtain a high value of the correlation coefficient between the estimated value and the measured value (R= 0.77, RMSE = 0.0184). Cheng et al. [58] took the Shandianhe River Basin as an example, using MODIS vegetation index, related LST, and measured soil moisture data as input parameters, establishing an extreme random tree model by using shortwave infrared transformed reflectance (STR) to predict soil moisture with a higher accuracy (RMSE = 0.054, R = 0.69) than support vector machines and random forest models.

The physical model can be also integrated into machine learning. Guo et al. [59] used the OH model, support vector regression model (SVR), and generalized regression neural network (GRNN) models to quantitatively retrieve soil moisture based on Sentinel-1 and Sentinel-2 data, in order to reduce the influence of vegetation. They believed that the retrieval accuracy of the OH model was improved after removing the influence of vegetation using the water-cloud model, and the retrieval effect of the multi-feature parameter combination based on the SVR model (dual-polarization radar backscattering coefficient, altitude, local incidence angle, and modified soil-adjusted vegetation index) was the optimal solution with an RMSE of around 0.015; R 0.903. Geng et al. [60] used the backscattering coefficient data of ground-based synthetic aperture radar (cGBSAR) and BP neural network to train the simulation dataset output using the AIEM–OH model for soil moisture retrieval. They believed that selecting the radar incidence angle based on the surface roughness can improve the accuracy of soil moisture retrieval. The R is 0.8080 and RMSE is 0.0385 when the radar incidence angle is 41°. AIEM multi-parameter retrieval method was proposed based on bidirectional deep neural networks [61]. It is pointed out that the bidirectional deep neural network can not only better predict the backscattering coefficient with an RMSE reduced to 0.1%, but also retrieve the surface parameters and improve the accuracy to over 90%.

In addition to improving retrieval accuracy, machine learning is also commonly used to improve the spatial resolution of soil moisture products. Currently, the spatial resolution of internationally published soil moisture products is mainly at large and medium scales, and microwave soil moisture products such as AMSR-E, FY-3B, AMSR-2, SMOS, and SMAP have spatial resolutions of 25 km or 36 km, which are only suitable for large-scale or global studies. Some researchers have used random forest models in machine learning to downscale SMAP and AMSR-E products and obtained soil moisture data with a spatial resolution of 1 km [62,63].

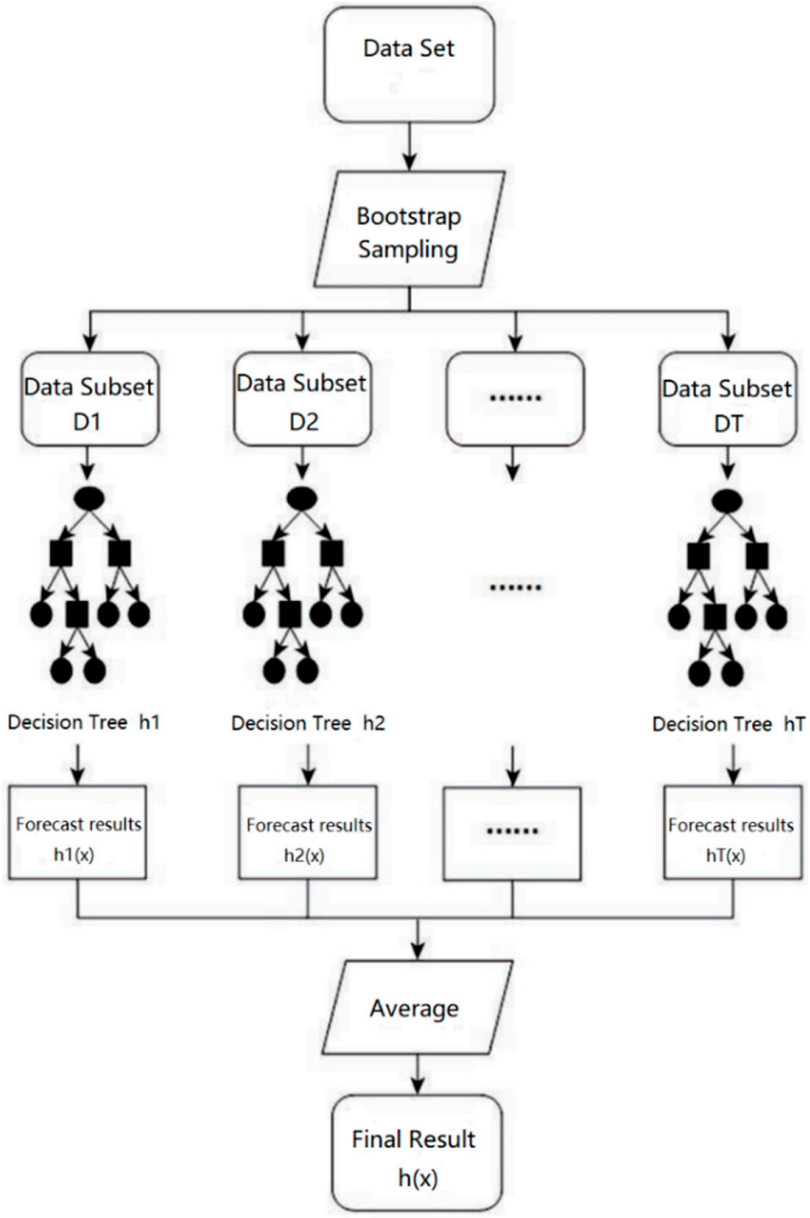

Figure 4. The structure of random forest (adapted with permission from Ref. [58]. 2021, Yuan Cheng.

3. Future Perspective

Although the soil moisture retrieval models have made steady progress in recent decades, there remains great prospects for improvement. Different retrieval methods and models are pursuing higher spatial–temporal resolution, longer time series monitoring, shorter transmission delays, higher accuracy, and better model performance and interpretability [64]. Meanwhile, with the continuous introduction of SM products, there is still a long way before successfully meeting the actual demand of users and improving their accuracy, time resolution, interpretability, and applicability. Future optimization is thus required in the following aspects.

3.1. Multi-Source Data Matching

It is known that optical remote sensing data are more sensitive to vegetation information, while SAR remote sensing data are more sensitive to soil moisture information [65], their combined retrieval method has been extensively applied and has achieved relatively noticeable results. However, there are still some barriers. Due to the differences in data formats, resolutions, and imaging principles of the two data sources, it is inevitable to

introduce errors and reduce the accuracy of the final result. Therefore, matching the data from multiple sources should be considered. In addition, most of the data sources at present are visible light, near-infrared, thermal infrared, and microwave. The research and model based on short-wave infrared is relatively few, which can be further studied in the future.

3.2. Spatial–Temporal Resolution

Frequently and accurately obtaining soil moisture is helpful to forecast the sowing time, crop irrigation during the growth period, geohazards mitigation, and drought prediction, etc. However, the spatial–temporal resolution of the majority of SM products currently cannot meet the requirements. It is necessary to adapt to small-scale applications like field scale and hourly scale. Daily or hourly monitoring data can be used to study irrigation, effectively reducing the waste of water resources and serving precision agriculture. Furthermore, root zone soil moisture has a greater impact on vegetation growth. The commonly used radar bands are mainly X, C, and L bands, which cannot penetrate the vegetation root zone. Therefore, the development of P-band radar retrieval methods with a deeper penetration depth is worthy of attention.

3.3. Long Time Series, Low Latency

In the field of climate change, geohazards identification, etc., soil moisture information of long time series is conductive to better research and application. Therefore, it is essential to continuously extend the time range of SM datasets. Building new ground networks, launching satellites, organizing observation networks, using machine learning models, and improving the materials of satellites and observation instruments to extend their operation life can effectively enlarge the acquisition of time series.

3.4. Model Accuracy and Meaning

An empirical model based on an optical data source is difficult to be applied while there are clouds or a high degree of vegetation coverage. The semi-empirical model is severely constrained by prior data in large-scale soil moisture monitoring. Due to the various calibration parameters under different surface coverage types, the general applicability under large-scale complex surface coverage still requires to be improved. The physical model involves a large number of parameters and calculation, making it difficult to achieve universality. Meanwhile, most of the studies are based on empirical data and requires measured data for comparison; as a result, it is necessary to investigate the parameter differences under various ground cover types. In terms of machine learning, the interpretability of the model should be emphasized. Although many articles on machine learning provide different retrieval algorithms, models, and corresponding validation processes and result evaluations, there currently remains a scarce amount of discussion and explanation on the models themselves. Combining the physical model with artificial intelligence methods to develop a joint model can probably improve the interpretability of the model [58]. In addition, because there are many methods of machine learning to choose, how to rapidly determine and optimize the method is also an issue worth considering. For all current models, different types of auxiliary data are still required to constrain them. Therefore, developing SM retrieval algorithms that are independent of auxiliary data or that rely only on a small number of them, which can be accurately obtained from satellite observations, is another future direction [60].

4. Summary and Conclusions

The following is a summary of the advantages and disadvantages of the four common types of soil moisture model categories (Table 3):

Table 3. Summary of advantages and disadvantages of different models.

Model	Advantages	Disadvantages
Empirical model	(1) Less variable parameters, simple and fast calculation; (2) Easy access to parameters	(1) Accuracy is affected by parameter selection; (2) The physical meaning of parameters is weak—a lack of logical relation
Semi-empirical model	(1) More parameters, higher accuracy; (2) Certain physical meaning, improved model interpretability	(1) Constrained by the accuracy of prior data, empirical data have a higher impact on results; (2) Some parameters are more complex
Physical model	(1) Has practical physical meaning, the model has good interpretability, and a high degree of quantification; (2) The model has a higher accuracy when applied in bare soil areas	(1) The most complex parameters—some parameters are difficult to obtain and require a large amount of calculation; (2) Greater regional limitations, difficult to use for large-scale research
Machine learning	(1) High accuracy, high degree of automation; (2) Improved efficiency, can process larger amounts of data and perform long-term analysis	(1) Subject to the training accuracy of simulation data; (2) Higher requirements for computer hardware and environment configuration; (3) The principle of the model is difficult to explain—lacks physical meaning

From the above table, although the advantages and disadvantages of the four types of models are different, all of them provide methods and a theoretical basis for current soil moisture acquisition. In this review, the current soil moisture retrieval models are divided into four categories, the common models are gathered, their advantages and disadvantages are analyzed, and the current research difficulties are discussed. The main conclusions, problems, and meaning of this review can be summarized as follows:

1. According to the acquisition of data sources and the characteristics of the study area, researchers select the appropriate model that makes the accuracy in a specific area satisfactory. Empirical model is widely used because of its few parameters and because it is easy to be obtained, but its accuracy is seriously restricted by the empirical data and it has no physical meaning. Semi-empirical model introduces physical meaning on the basis of empirical data and calibrates the coefficient from a certain theoretical formula by using empirical data, which improves the model's scientificalness and interpretability to a certain extent. However, it is still subject to empirical data. A physical model is constructed in strict accordance with the laws of physics, containing complex formulas and a wide range of parameters for constraints. It has good model meaning, but because of the large number of parameters and the large amount of calculation, it is difficult to obtain some parameters directly, and the parameter values vary greatly in different regions; therefore, it cannot be applied to large-scale studies. Machine learning is the most rapidly developing model in recent years; by using computer technologies like artificial intelligence to process and train remote sensing data, the precision of large-scale research has been improved, the scope of application has been broadened, and the retrieval speed has been accelerated. However, similar to the empirical model, the model still lacks interpretability and the influence of the accuracy of training data cannot be ignored.
2. At present, apart from the problems of the model itself, the characteristics of remote sensing data sources and terrain types also affect the retrieval accuracy. The relationship between SM and soil reflectance is uncertain due to the limitation of atmospheric conditions on optical data. The lack of penetration depth makes it difficult to precisely estimate the soil moisture in the root-zone layer. It is still inconvenient to eliminate the influence of the vegetation layer under the covered area. In addition, it is also a challenge to decrease the interference such as the angle of incidence of electromagnetic waves and surface roughness. Future optimization is suggested in the following

aspects: multi-source data matching, spatial–temporal resolution, time series, latency, model accuracy, and meaning.

3. The objective of this review is to provide readers with a more comprehensive introduction of the types and mechanisms of soil moisture retrieval models. At the same time, it should be emphasized that the applicability of the relevant model introduced in this review depends on the scope of the study area (space and time) and the availability of data. So far, there is no single model and data source that can be used as a common solution with high accuracy. In order to retrieve soil moisture more accurately and meet the actual demands, a growing number of scholars begin to consider multiple models to retrieve soil moisture. A common multi-source data and model retrieval flow chart is shown below (Figure 5).

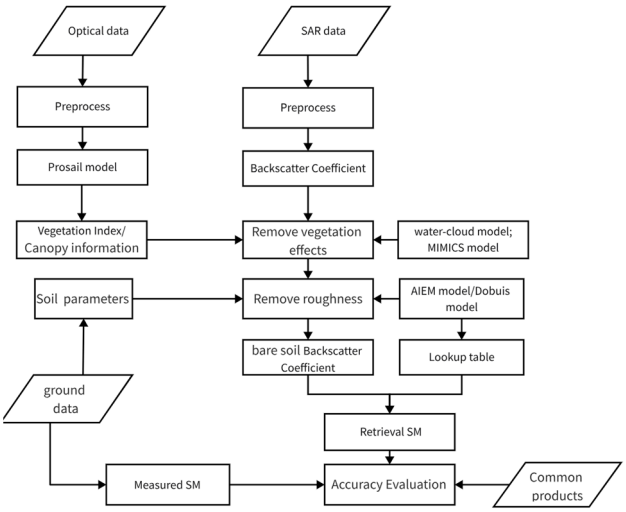

Figure 5. The flow chart of multi-source data and model retrieval.

Meanwhile, the machine learning method is used to optimize the existing products. This review does not provide a detailed description of specific data sources, products, and applications. Therefore, with the development of new data sources, new products, and applications of soil moisture, these aspects can be summarized and evaluated in future work, especially with regard to the applications that can provide a comprehensive reference for researchers in related fields. For example, soil salinization is closely related to a large amount of evaporation of surface soil moisture. A considerable amount of research has focused on the long-term monitoring of soil salinization [66], and the spatiotemporal evolution trend of soil salinization has become an emerging research topic; the application of soil moisture in these fields will be of great benefit. In conclusion, although there are still many problems to be solved, due to the rapid development of remote sensing technology, along with the optimization and development of soil moisture retrieval models, by making full use of various remote sensing information and then combining them with mathematics, physics, and even computer algorithms, it is hence the main direction to improve the stability, applicability, and accuracy of retrieval model and generate high-quality soil moisture products in the future.

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