

Original Article

Modelling Techniques in Synthetic Aperture Radar (SAR) for Geophysical Parameter Retrieval

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Abstract

When cloud cover or poor light impair optical data, Synthetic Aperture Radar (SAR) modelling is crucial for deriving geophysical information from radar observations. The main SAR backscatter modelling techniques are examined in this article, including theoretical, semi-empirical, and empirical models including Oh, Dubois, and the Integral Equation Model (IEM). They are compared in terms of their assumptions, input specifications, retrieval efficiency, and suitability for soil moisture, surface roughness, and dielectric characteristics. Limitations pertaining to surface heterogeneity, model calibration, incidence angle, and vegetation effects are also covered in the paper. Future studies should concentrate on combining machine learning and multi-source SAR data with hybrid, site-adaptive, and physically limited models.

Keywords: Synthetic aperture radar; microwave scattering; backscatter modelling; geophysical retrieval; soil moisture

Introduction

Remote sensing has become an important tool for researching the surface of the earth, providing the means to detect physical and environmental properties over huge areas without having to take measurements at each point. Traditionally, optical sensors have supplied significant information for land-cover mapping, vegetation evaluation and environmental monitoring. However, their observations are limited by cloud cover and illumination conditions, which can impede data collecting when continuous or weather-independent observations are required. Microwave remote sensing is a supplementary capacity since active microwave systems provide their own radiation and can take measurements both day and night and in the presence of clouds. More crucially, microwave signals are sensitive to the dielectric and structural properties of natural surfaces, which can be used to study soil moisture, surface roughness, vegetation qualities and other geophysical variables [1]. One of the main active microwave systems for high-resolution imaging of the Earth's surface is Synthetic Aperture Radar (SAR). In a SAR system the sensor transmits microwave pulses toward the target and records the returning signals as it moves along its flight path. The readings performed at successive sensor sites are processed coherently to synthesize an aperture, thus providing a rather high spatial resolution. The recorded radar response is influenced by numerous elements such as radar wavelength, polarization, incidence angle, surface dielectric qualities, roughness and vegetation features. These characteristics have permitted the use of SAR in diverse fields such as agricultural monitoring, hydrological applications, soil-moisture estimate, forestry, geological investigations and environmental assessment [1], [2]. The radar backscatter coefficient (σ^0) is of central importance for quantitative interpretation of SAR observations.

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It represents the normalized strength of the microwave signal reflected back to the radar, and it provides information about the interaction between the electromagnetic wave and the surface examined. The magnitude of σ^0 for soil surfaces depends on soil moisture, dielectric constant, surface roughness, radar wavelength, polarization and incidence angle. Soil dielectric characteristics and the radar response generally change with increasing soil moisture. Simultaneously, roughness governs how the incident wave is distributed from the surface. Hence a change in σ^0 cannot be regarded as a change in soil moisture alone. One of the major issues in the quantitative recovery of soil properties from SAR measurements is this interplay of multiple components [3], [4].

Scattering models are often used to study the connection between radar backscatter and surface properties. A forward scattering model estimates the radar response for the appropriate surface and sensor characteristics. In the inverse problem, unknown surface properties are inferred from the radar readings collected. This approach is very beneficial for extracting characteristics such as soil moisture, dielectric constant, surface roughness and correlation length. However, the inverse problem is generally ill-posed since diverse combinations of surface properties may give similar radar responses. The quality of retrieval is thus dependent on the physical assumptions of the model, the availability of reliable ground measurements, the radar setup and the range of conditions across which the model has been evaluated [4]. The SAR backscatter models can be typically grouped into three types, empirical, semi-empirical and physical or theoretical techniques. Empirical models generally rely on experimental observations and statistical correlations. They are usually rather basic and computationally efficient, which makes them attractive for operational purposes. The key restriction is that their validity may be constrained by the conditions represented in the datasets used to create the model. Semi-empirical models represent a compromise between simplicity and scientific interpretation, incorporating physical factors while keeping experimentally derived relationships. Physical-based models, in contrast, are based on electromagnetic scattering theory and aim to characterize the interaction between the incident wave and the surface more explicitly. These models may give additional physical understanding, but they usually need more information about surface roughness, dielectric characteristics and radar geometry [1], [5]. One of the key advancements in empirical radar backscatter modeling was the work of Oh, Sarabandi and Ulaby [1]. Their work was based on polarimetric measurements of bare soil surfaces for different moisture and roughness conditions on L-, C- and X-band frequencies. The derived formulation connected radar backscatter to surface roughness and dielectric characteristics. An inversion technique to estimate surface rms height and soil moisture from multipolar zee radar images was presented [6]. The Oh model thereafter became an essential reference for investigations dealing with bare-soil scattering and geophysical parameter retrieval, as it provided a somewhat easy link between observable radar numbers and surface properties.

Another extensively used empirical method for soil moisture retrieval is the Dubois model. Dubois, van Zyl and Engman have constructed an empirical relation to estimate soil moisture and surface roughness using imaging radar images [7]. The equation links the radar backscatter to parameters like the incidence angle, the wavelength of the radar, and soil properties. The empirical approaches such as the Dubois model have a benefit in that they can be applied without the entire computing complexity of electromagnetic scattering simulations. At the same time, their performance can be sensitive to the parameters of the environment and of the radar under which they are employed. In the original study the effect of vegetation was also studied and the reliability of the retrieval was assessed by independent soil-moisture observations [7]. The Integral Equation Model (IEM) is based on electromagnetic scattering theory and provides an alternative modeling point of view. Fung, Li and Chen formulated the backscattering from randomly rough dielectric surfaces, in which the scattering response depends upon the dielectric properties and statistical parameters of the surface [8]. In soil surface applications, IEM provides a framework for connecting radar backscatter to factors including dielectric constant, surface roughness, wavelength and incidence angle. It has a physical basis and can be used for forward modeling and sensitivity analysis. The accuracy of a theoretical model, however, depends on how well the assumed surface statistics resemble the actual topography. This is especially relevant for agricultural surfaces because roughness can be spatially variable and can vary following cultivation or rainfall events. The theoretical scattering ideas like the Small Perturbation Method (SPM), the Kirchhoff approximation and Bragg scattering provide more basis for understanding the microwave interaction with rough surfaces. Their applicability depends on the relative relation between the surface roughness, the correlation length and the radar wavelength. These approaches helps to explain the reason why a surface behaves differently when measured at different frequencies or angles of incidence. They also offer the physical basis for more general surface scattering formulae used in radar remote sensing [8]. This is much more obvious when the predictions of these modeling methodologies are compared to real SAR measurements. Baghdadi and Zribi assessed the IEM, Oh, and Dubois models using C-band SAR data and in situ measurements of soil moisture and surface roughness. They showed that the differences between the observed and modeled radar responses were due to factors such as incidence angle, soil wetness and rms surface height [9]. This study shows an important issue for SAR modeling. Model performance cannot be considered independent of the conditions under which the observations are made. A model that works well for one combination of soil, roughness, wetness and radar setup may behave differently for another set of variables. Surface roughness is of special interest because it may alter radar backscatter in a way that is difficult to disentangle from the effect of soil moisture. Roughness is often defined in terms of metrics such as rms height and correlation length. Measurement of these features in the field can be difficult, especially across agricultural area. Moreover, a single parameter of roughness might not be sufficient to characterize the spatial organization of a natural soil surface. This issue was resolved by Baghdadi et al. who calibrated the IEM based on radar observations combined with field measurements of moisture and surface roughness. Their work showed the possibility of using semi-empirical calibration to improve the match between modeled and observed backscatter [10]. Such calibration may be valuable for a specific research region, but the derived relationship needs to be validated before transfer to other soil types or environmental situations.

Vegetation offers another level of complexity to the interpretation of radar readings. If a soil surface is covered by plants, the measured signal may have contributions from soil scattering, canopy scattering and attenuation in the vegetation layer. The Water Cloud Model, proposed by Attema and Ulaby [11], was an early conceptual model of vegetation impacts in microwave remote sensing. The challenge is especially difficult in agricultural applications because of the simultaneous changes in crop growth, soil moisture, and surface roughness. Therefore, the soil contribution has to be separated from the total radar response either by means of extra observations, an appropriate vegetation model or a retrieval approach able to account for these interaction effects. The drawbacks of modern scattering models have led to several comparative investigations. The model behavior was shown to fluctuate with the radar frequency and vegetation cover by Khabazan et al., who tested the IEM, Oh and Dubois models using L- and C-band SAR observations under different vegetation and soil-depth circumstances [12]. Paloscia et al. next compared a number of popular backscatter models with a huge dataset of SAR observations and actual soil measurements. Their investigation showed the differences between the Oh, Dubois, IEM and advanced IEM methods and indicated the relevance of model calibration and validation in the estimation of soil properties [13]. The results support the idea that model selection should be based not only on theoretical formulation but also on the features of the target surface, the radar observations and the available field data. There are still a number of research issues on the recovery of geophysical parameters from SAR data. Empirical models are computationally cheap, but their transferability may be limited beyond the calibration domain. Physically based models are more closely tied to electromagnetic scattering theory, although they can require precise knowledge regarding surface roughness and dielectric characteristics. The combined effects of soil moisture and roughness are still a substantial source of uncertainty. Vegetation, incidence angle, polarization, wavelength and dielectric modeling may bring further mistakes [4], [9], [13]. Representative ground observations are also important for reliable validation. These limitations become more severe when models generated with controlled or region-specific information are applied to heterogeneous agricultural landscapes or satellite images obtained across greater geographic areas.

Recent breakthroughs have promoted a trend toward a combination of physical modeling and data-driven techniques. Machine learning approaches can capture nonlinear correlations between SAR data and geophysical parameters and can take into account several input variables concurrently. Multi-temporal and multi-polarization observations can provide more information about the changing surface, while multi-frequency observations can increase the sensitivity to different scattering mechanisms. Hybrid approaches, which combine electromagnetic scattering models with machine-learning algorithms are especially intriguing, because they can keep the physical information, while taking advantage of the flexibility provided by data-driven methods. Nevertheless, the reliability of such methods still depends on the quality, diversity and representativeness of the training and validation datasets. So future advancements should address physical restrictions, independent validation, uncertainty estimation and enhanced field observations in addition to greater model complexity. In this context, a comprehensive study of SAR modeling approaches is needed to determine their applicability for geophysical parameter retrieval. This review considers empirical, semi-empirical and physically based modeling methodologies with specific reference to the Oh, Dubois and Integral Equation Model frameworks. Their theoretical basis, input requirements, assumptions, applications, strengths and limitations are reviewed from the point of view of geophysical parameter retrieval. The effect of soil moisture, dielectric characteristics, surface roughness, vegetation, wavelength, polarization and incidence angle on the model performance is discussed in detail. The review also discusses limitations of existing approaches and future research directions on calibrated and hybrid models, multi-configuration SAR observations, machine-learning-assisted inversion, physically constrained retrieval, improved ground-truth datasets and uncertainty analysis. The general objective is to provide a clear scientific basis for the selection and refinement of SAR modeling methodologies for more reliable retrieval of geophysical information.

Fundamentals of SAR Backscatter and Surface Scattering

This section establishes the physical basis required to understand SAR backscatter modelling and geophysical parameter retrieval. The radar response from a natural surface is controlled by the interaction between the electromagnetic wave and the physical and dielectric characteristics of the target. For soil surfaces, moisture, dielectric properties, surface roughness, wavelength, incidence angle, and polarization are particularly important. These variables are also strongly coupled, which makes direct interpretation of SAR backscatter in terms of a single geophysical parameter difficult.

1. Synthetic Aperture Radar

Synthetic Aperture Radar (SAR) is an active microwave remote-sensing technique in which an antenna transmits electromagnetic pulses toward the Earth's surface and records the energy scattered back toward the sensor. Because the radar provides its own source of illumination, SAR observations do not depend on sunlight and can be acquired during both day and night. Microwave wavelengths also allow radar observations to be obtained under cloudy conditions, making SAR suitable for repeated monitoring of terrestrial surfaces [14]. SAR normally operates in a side-looking geometry. The radar illuminates the surface obliquely, and the returned signal contains information about the interaction between the microwave field and the target. The direction along the flight path is referred to as the azimuth direction, while the direction associated with the distance between the sensor and the illuminated ground is the range direction. The high azimuth resolution of SAR is obtained by exploiting the movement of the radar platform. As the sensor travels along its flight path, a target remains within the antenna beam for a period of time and produces a sequence of radar echoes. These echoes contain amplitude and phase information that can be coherently processed to form an effective or *synthetic aperture*. Thus, a physically large antenna is not required to achieve the azimuth resolution associated with a much larger aperture [14]. When a microwave signal reaches the Earth's surface, its interaction depends on the electromagnetic and geometric characteristics of the target. Part of the incident energy may be reflected, part may penetrate the material, and part may be scattered in different directions. The relative contribution of these processes depends on

wavelength, incidence angle, polarization, dielectric properties, surface roughness, and the internal structure of the target [15]. For soil surfaces, the radar response is particularly sensitive to soil moisture and surface roughness. Water changes the effective dielectric properties of soil, whereas surface roughness controls the spatial distribution of scattering from the soil surface. Vegetated surfaces introduce additional effects because leaves, stems, branches, and other canopy components can attenuate and scatter the microwave signal. Therefore, SAR backscatter should be considered as the combined electromagnetic response of the observed surface rather than as a direct measurement of one physical parameter.

2. Radar Backscatter Coefficient

The normalized radar backscattering coefficient, denoted by σ^0 , is one of the principal quantities used for quantitative SAR analysis. It describes the normalized radar return from a surface and allows observations to be compared despite differences associated with the illuminated area and radar geometry [14].

Conceptually, the linear backscattering coefficient can be expressed as

$$\sigma^0 = \frac{\sigma}{A} \quad \text{equ.1}$$

Where

1. σ^0 = normalized radar backscattering coefficient,
2. σ = radar cross section (m^2),
3. A = illuminated surface area (m^2).

The logarithmic representation is

$$\sigma^0_{dB} = 10 \log_{10}(\sigma^0) \quad \text{equ.2}$$

Where

σ^0_{dB} = is the backscatter coefficient expressed in decibels.

$$\epsilon_r = \frac{\epsilon}{\epsilon_0} \quad \text{equ.3}$$

where:

1. ϵ_r = relative dielectric constant, dimensionless;
2. ϵ = absolute permittivity of the material (F/m);
3. ϵ_0 = permittivity of free space (F/m).

The value ϵ_0 of is approximately

$$\epsilon_0 = 8.854 \times 10^{-12} \text{ F/m. } \quad \text{equ.4}$$

3. Electromagnetic Properties of the Surface

The electromagnetic properties of soil determine how microwave radiation is reflected, transmitted, absorbed, and scattered at and within the surface. Among these properties, dielectric behaviour is particularly important because soil moisture produces a substantial change in the effective dielectric response of soil-water mixtures [17], [18].

1. Dielectric Constant

The relative dielectric constant is defined as where is the relative dielectric constant, is the absolute permittivity of the material, and is the permittivity of free space. The dielectric constant influences the interaction between the microwave field and the soil surface. Dry soil consists primarily of mineral particles and air-filled pores and therefore has a relatively low effective dielectric response. Addition of water increases the effective dielectric constant because water has a much stronger dielectric response at microwave frequencies. Experimental investigations have shown that the dielectric behaviour of wet soil depends on water content, soil texture, frequency, and temperature. Hallikainen et al. measured the dielectric properties of different soil types over the microwave frequency range and demonstrated the influence of both moisture and texture [17].

2. Complex permittivity

For a lossy dielectric medium, complex relative permittivity can be represented as

$$\epsilon^* = \epsilon' - \epsilon'' \quad \text{equ.5}$$

where:

1. ϵ^* = complex relative permittivity;
2. ϵ' = real component;
3. $-\epsilon''$ = imaginary component;
4. $j = \sqrt{-1}$

The real part under this sign convention defines the energy-storage behavior of the medium. The imaginary part represents dielectric loss.

3. Volumetric soil moisture

Volumetric soil moisture can be defined as

$$\theta_v = \frac{V_w}{V_t} \quad \text{equ.6}$$

where:

1. θ_v = volumetric soil-moisture content (m^3/m^3);
2. V_w = volume of water in the soil (m^3);
3. V_t = total soil volume (m^3).

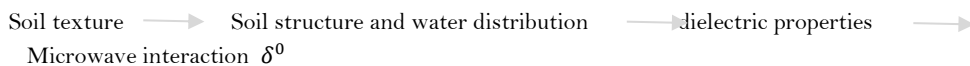
If expressed as percentage:

$$\theta_v(\%) = \frac{V_w}{V_t} * 100 \quad \text{equ.7}$$

This parameter is of particular importance, because an increase of water content usually leads to a change of the effective dielectric properties of the soil and, consequently, to a change of its microwave response. The dependence of the dielectric properties of soil on water content, soil texture and frequency has been experimentally established by Hallikainen et al. [18].

4. Soil Texture

Soil texture is defined as the relative proportion of sand, silt and clay. These components influence the pore structure, bulk density, water retention and distribution of water within the soil. Consequently, the texture influences the dielectric response of soil-water mixtures [17], [18]. The physical relationship can be expressed as:



Hallikainen et al. [17] discovered that soil texture affects the dielectric behavior across all the microwave frequencies studied but more so at the lower frequencies. Dielectric mixing models were later established by Dobson et al. relating soil moisture and texture to the effective dielectric response of soil [18].

Surface Roughness

1. RMS surface elevation

The RMS surface height can be computed from N observed surface-height observations:

where:

$$s = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (Z_i - \bar{Z})^2} \quad \text{equ.8}$$

1. s = RMS surface height (m);
2. N = number of measurements;
3. Z_i = surface height at measurement (m);
4. $\bar{Z}$ = mean surface height (m).

This parameter represents the vertical magnitude of surface-height variation.

2. RMS slope

If a one-dimensional surface profile is represented by , the RMS slope can be expressed as

$$m_{rms} = \sqrt{\frac{1}{N-1} \sum_{i=1}^N \left(\frac{dz}{dx} \right)^2} \quad \text{equ.9}$$

where m_{rms} is dimensionless if the horizontal and vertical dimensions have the same units.

RMS height and RMS slope are two distinct roughness parameters. The RMS height is a measure of the amount of vertical fluctuations while the RMS slope is a measure of the change in local surface inclination .

3. Correlation length

The surface correlation function can be represented generally as

$$\rho(\Delta x) = \frac{\langle [z(x) - \bar{z}][z(x + \Delta x) - \bar{z}] \rangle}{s^2} \quad \text{equ.10}$$

Where:

1. $\rho(\Delta x)$ = normalized surface autocorrelation function;
2. Δx = horizontal separation distance (m);
3. $z(x)$ = surface height at position;
4. $\bar{z}$ = mean surface height;
5. s = RMS surface height;
6. $\langle \rangle$ = spatial averaging operation.

The correlation length is then found by the definition used for the correlation function. So, never propose a universal formula for correlation length without providing the convention for the correlation function.

4. Common correlation functions

An exponential correlation function may be written as

$$\rho(\Delta x) = \exp \left(-\frac{|\Delta x|}{l} \right) \quad \text{equ.11}$$

Where ι is the correlation length.

A Gaussian correlation function can be written as

$$\rho(\Delta x) = \exp \left[- \left(\frac{|\Delta x|}{\iota} \right)^2 \right] \quad \text{equ.12}$$

The precise interpretation of ι depends on the selected mathematical definition. This is important when comparing roughness parameters from different studies.

5. Radar wavenumber and electromagnetic roughness

The radar wavenumber is

$$k = \frac{2\pi}{\lambda} \quad \text{equ.13}$$

where:

1. k = radar wavenumber (rad/m);
2. λ = radar wavelength (m).

A commonly used dimensionless roughness parameter is ks where s is RMS surface height.

This parameter has the physical size of the surface roughness relative to the radar wavelength. Thus the same physical surface may interact with radars differently at different wavelengths.

Radar Observation Parameters

1. Frequency and wavelength

The relationship between frequency and wavelength is

$$c = f\lambda \quad \text{or} \quad \lambda = c / f \quad \text{equ.14}$$

where:

1. c = speed of electromagnetic radiation in free space, approximately m/s;
2. f = radar frequency (Hz);
3. λ = wavelength (m).

For Sentinel-1: $f = 5.405$ GHz

and therefore

$$\lambda \approx \frac{3 \times 10^8}{5.405 \times 10^9} \approx 0.0555 \text{ m}$$

or approximately

$$\lambda \approx 5.55 \text{ cm}$$

ESA identifies Sentinel-1 as a C-band SAR operating at 5.405 GHz [17].

2. Incidence angle

The incidence angle can be represented geometrically as

where:

$$\theta_i = \cos^{-1} \left(\frac{k \cdot n}{|k||n|} \right) \quad \text{equ.15}$$

1. θ_i = incidence angle;
2. k = propagation-direction vector of the incident wave;
3. n = local surface-normal vector.
4. In practical SAR analysis, the incidence angle is usually obtained from the sensor geometry and associated metadata rather than calculated directly from raw radar data. Important: For sloping terrain, distinguish between the nominal incidence angle and the local incidence angle. The local terrain orientation can substantially modify the actual illumination geometry.

3. Polarization

There is no need to introduce an artificial mathematical formula for HH, VV, HV, and VH. They represent transmit/receive polarization combinations:

Polarization	Meaning
HH	Horizontal transmit, Horizontal receive
VV	Vertical transmit, Vertical receive
HV	Horizontal transmit, Vertical receive
VH	Vertical transmit, Horizontal receive

HH and VV are **co-polarized**, whereas HV and VH are **cross-polarized**.

For your later OH/Dubois modelling, this distinction is important because the models use particular polarization combinations and polarization ratios [16].

2.5.4 SAR spatial resolution

For a simplified range-resolution relationship, the slant-range resolution is related to signal bandwidth by where:

$$\delta R_s = \frac{c}{2B} \quad \text{equ.16}$$

1. δR_s = slant-range resolution (m);
2. c = speed of light (m/s);
3. B = transmitted radar bandwidth (Hz).

The corresponding ground-range resolution depends on incidence angle:

$$\delta R_g = \frac{\delta R_s}{\sin \theta_i} \quad \text{equ.17}$$

where δR_g is the ground-range resolution.

However, SAR azimuth resolution is more complex than simply applying the real-aperture radar equation, because SAR processing synthesizes the aperture using the motion of the platform. Therefore, avoid presenting an oversimplified azimuth-resolution equation unless you specifically discuss the SAR processing geometry.

6. Physical Relationship Between Surface Parameters and SAR Backscatter

The fundamental relationships discussed above can be summarized through the following physical chain:

Soil moisture > dielectric properties> Electromagnetic interaction > surface scattering > δ^0

Surface roughness provides another pathway:

Surface roughness> surface geometry > scattering mechanism > δ^0

These two effects are not independent. A soil surface with a particular moisture condition may produce different backscatter values depending on its roughness. Similarly, the same physical surface can produce different responses when observed at different wavelengths, incidence angles, or polarization configurations. This coupling is the fundamental reason why SAR-based geophysical retrieval requires scattering models rather than a simple one-to-one conversion between and soil moisture. Empirical models attempt to represent these relationships through observations, whereas physically based models describe them using electromagnetic scattering theory. Comparative evaluations of the Oh, Dubois, and IEM approaches have demonstrated that model errors can depend on soil moisture, RMS surface height, and radar incidence angle [20].

Table 1. Principal Parameters Used in SAR Backscatter Modelling

Parameter	Symbol	Unit	Physical significance	Parameter	Role in SAR modelling
Radar frequency	f	Hz	Frequency of transmitted radiation	Radar frequency	Determines wavelength and scattering regime
Wavelength	λ	m	Electromagnetic wavelength	Wavelength	Controls interaction with surface scale
Backscatter coefficient	δ^0	Dimensionless	Normalized returned radar power	Backscatter coefficient	Main SAR observable
Backscatter in dB	δ^0_{dB}	dB	Logarithmic representation of δ^0	Backscatter in dB	Common SAR image representation
Soil moisture	θ_v	m^3/m^3	Volumetric water content	Soil moisture	Major geophysical retrieval variable
Relative dielectric constant	ϵ_r	Dimensionless	Relative dielectric response	Relative dielectric constant	Controls electromagnetic interaction
Complex permittivity	ϵ^*	Dimensionless	Real and loss components	Complex permittivity	Used in electromagnetic models
RMS surface height	s	m	Vertical roughness magnitude	RMS surface height	Controls relative roughness
RMS slope	m_{rms}	Dimensionless	Variation of local slope	RMS slope	Describes surface geometry
Correlation length	l	m	Horizontal roughness scale	Correlation length	Describes spatial roughness structure
Correlation function	ρ	Dimensionless	Spatial correlation of surface heights	Correlation function	Used in physical scattering models
Incidence angle	θ_i	Degree	Radar illumination geometry	Incidence angle	Influences δ^0

Polarization	HH, VV, HV, VH	—	Electric-field orientation	Polarization	Determines scattering sensitivity
Spatial resolution	δR	m	Ability to resolve surface features	Spatial resolution	Determines spatial averaging

Table 2. Influence of Major Parameters on SAR Backscatter

Parameter	Main physical effect	Influence on σ^0	Modelling consideration
Soil moisture	Changes effective dielectric properties	Generally increases backscatter under many bare-soil conditions	Must account for roughness and geometry
Dielectric constant	Changes reflection/transmission	Changes scattering magnitude	Important input to physical models
RMS surface height	Changes surface geometry	Can increase diffuse scattering	Relative to wavelength through
Correlation length	Controls horizontal roughness structure	Changes angular/scattering behaviour	Correlation model must be specified
Wavelength	Changes scale of electromagnetic interaction	Changes sensitivity to roughness and vegetation	Determines scattering regime
Incidence angle	Changes illumination geometry	Changes σ^0	Must be considered during comparison
Polarization	Changes field-surface interaction	Changes scattering response	Important for empirical models
Spatial resolution	Controls spatial averaging	Affects observed heterogeneity	Important for field-SAR comparison
Soil texture	Changes water retention and dielectric response	Indirectly influences σ^0	Important in dielectric modelling

3. Classification of SAR Modeling Techniques

SAR scattering models are mathematical relationships between radar observations and the electromagnetic and geometric properties of the observed surface. Their development has gone from approximate electromagnetic formulations to more complete analytical models and, more recently, to hybrid approaches which mix physical models with empirical calibration and machine-learning methods. The choice of the model mainly depends on the roughness regime, dielectric properties, radar frequency, polarization, incidence angle and the geophysical parameter to be retrieved. The classical rough surface scattering approaches are Kirchhoff approximation, Physical Optics (PO), Geometric Optics (GO) and Small Perturbation Method (SPM). Integral Equation Model (IEM) was developed to provide a more general analytical treatment of the rough surface scattering [21], [22]. The difference between these approaches is important for geophysical parameter retrieval. Models are mostly based on electromagnetic theory (theoretical models), offer a mathematically tractable formulation of the scattering problem (analytical models), are based on observations (empirical models) or try to combine physical understanding with statistical flexibility (hybrid or data-driven models). There is no better category as such. The suitability of model depends on characteristics of surface and radar observation.

4. In-depth Review of Major SAR Backscatter Models

1. Kirchhoff Approximation 4.1.1

The Kirchhoff approximation is one of the basic theoretical methods used for the description of electromagnetic scattering from rough surfaces. The surface is locally approximated by planar facets and the scattered field is computed from the electromagnetic response of these local surface elements. Validity of the approximation depends on the ratio of surface dimensions, surface slopes and radar wavelength. It provides an important theoretical basis for the understanding of rough-surface scattering and the creation of more advanced scattering formulation [1], [2]. Two limiting descriptions often discussed within the Kirchhoff framework are the Physical Optics (PO) and Geometrical Optics (GO) approximations. Physical Optics addresses the comparable electromagnetic currents created on the lighted surface, whereas Geometrical Optics stresses the role of locally oriented surface facets. The distinction is crucial because the major scattering mechanism changes with the electromagnetic roughness of the surface [2]. For a perfectly conducting surface, the Physical Optics approximation employs the equivalent surface current $J_s = 2\hat{n} \times H_i$ equ.18 Where J_s is the induced surface current density, $\hat{n}$ is the unit normal to the surface, and H_i is the incident magnetic field. The scattered electromagnetic field is then obtained from the radiation generated by the equivalent current distribution [2]. The main advantage of the Kirchhoff approximation is the physical insight together with the comparatively simple mathematical treatment. However, the approximation fails when the surface comprises quickly varying features, or when multiple scattering, shadowing and strong interactions between neighboring surface elements become essential. Therefore, it is better to consider it as a theoretical basis rather than a general model for soil retrieval [1], [2].

Advantage: helpful theoretical basis and robust physical interpretation.

Limitation: validity highly depends on surface roughness and wavelength.

2. Small Perturbation Model (SPM)

The minor Perturbation Model (SPM) treats scattering from a rough surface as a minor perturbation of an ideal reference plane. The scattered electromagnetic field is expressed in powers of the surface-height variation. The approach is especially suitable for the case when the fluctuation in surface-height is minimal compared with the radar wavelength and the surface slopes are in the perturbation regime [21].

The perturbation expansion can be expressed as

$$E_S = E_S^1 + E_S^2 + E_S^3 + E_S^4 + \dots \quad \text{equ.19}$$

where E_S^n represents the contribution of the n -th order in surface height. In practical remote-sensing applications, first- and second-order terms are commonly emphasized because higher-order formulations rapidly increase in mathematical complexity [21].

For first-order perturbation theory, the scattered intensity is related to the statistical spectrum of the surface roughness. The dependence can generally be expressed through the surface power spectral density $W(q)$, the radar wavenumber k , and polarization-dependent electromagnetic factors. The precise form depends on the dielectric boundary conditions and the selected surface correlation function [21]. The SPM provides a useful theoretical description of scattering from relatively smooth surfaces and helps establish the relationship between surface statistics and radar observations. Its principal limitation is its restricted validity for increasingly rough surfaces. Studies of perturbation scattering have shown that higher-order terms become important as increases, where denotes RMS surface height [21]. Advantage: suitable for relatively smooth surfaces and provides a clear theoretical relationship between roughness and scattering. Limitation: validity decreases as electromagnetic roughness increases

3. Integral Equation Model (IEM)

The Integral Equation Model is a physically based formulation for electromagnetic scattering from randomly rough dielectric surfaces. Unlike simpler asymptotic approaches, IEM incorporates both the dielectric properties of the surface and statistical descriptions of its roughness. This makes it particularly relevant to soil surfaces, where moisture-dependent dielectric behaviour and roughness jointly influence radar backscatter [8]. The principal variables involved in the model include complex dielectric constant, RMS surface height, correlation length, radar wavelength, incidence angle, polarization, and the selected surface correlation function. The model dependence can therefore be represented conceptually as

$$\delta_{pq}^0 = F(\varepsilon^*, k, s, l, \rho, \theta_i, p, q) \quad \text{equ.20}$$

Where ε^* is complex permittivity, $k=2\pi/\lambda$ is the radar wavenumber, s is RMS surface height, l is correlation length, ρ describes the surface correlation function, and p, q represents the transmit and receive polarization states [8].

The dielectric component is critical for soil moisture retrieval because the dielectric constant varies strongly with water content increase. A suitable dielectric mixing model may describe the dielectric characteristics and soil moisture relationship, and then the dielectric response is incorporated into the electromagnetic scattering formulation [17], [18].

$$\theta_v = \varepsilon_r = \delta_{IEM}^0 \quad \text{equ.21}$$

The conceptual retrieval chain can therefore be written as

where θ_v is volumetric soil moisture and ε_r is the effective relative dielectric constant [8], [18].

A key property of IEM is its dependence on the statistical representation of the surface roughness. The RMS height alone is not adequate to fully characterize a random rough surface; the scattering response calculated is additionally influenced by the correlation length and correlation function.

Therefore, the uncertainty in the roughness measurements might immediately propagate into the expected backscattering [8], [9].

The main advantage of IEM is that it provides a physical representation of the combined effects of the dielectric characteristics and the surface roughness.

Mathematical complexity, sensitivity to the characterization of roughness and the need for a number of input factors which are not always available from normal field measurements [8], [10].

Advantage: physically based treatment of dielectric properties and roughness.

Limitation: relatively high input and computational requirements.

4. Advanced Integral Equation Model (AIEM)

An Advanced Integral Equation Model has been created to better handle rough-surface scattering in the integral-equation approach. The AIEM formulation keeps the surface-current terms of the Kirchhoff field and gives a more complete consideration of the scattering contributions than simple IEM formulations [22]. The initial AIEM study considered bistatic scattering explicitly and compared the model with IEM, SPM, Geometrical Optics and Kirchhoff approximations over their respective validity regimes.

The AIEM dependence can be commonly written as

$$\delta_{pq}^0 = F_{AIEM}(\varepsilon^*, k, s, l, \rho, \theta_i, p, q) \quad \text{equ.22}$$

where the variables have the same physical significance as in IEM. The main distinction is in the treatment of surface-current and complementary-field contributions electromagnetically, instead of introducing a totally different set of geophysical variables [22]. AIEM is beneficial when a more thorough electromagnetic treatment is needed, notably for studying scattering behavior over a broader variety of roughness conditions. However, the added mathematical terms also raise the computational needs. Moreover, the model still needs a proper description of the surface correlation function and dielectric characteristics [22]. The comparative investigations have demonstrated that the selected roughness correlation function can affect the performance of both IEM and AIEM. This illustrates that the uncertainty resulting from the lack of surface characterization is not eliminated by an improvement of the electromagnetic formulation alone [5], [22]. Advantage: better electromagnetic treatment than with simpler approximations. Limitation: more mathematical complexity, more sensitive to surface statistics.

5. Oh Model

The Oh model is a semi-empirical model, based on measurements of radar scattering from bare-soil surfaces. It correlates radar measurements to soil dielectric characteristics, surface roughness, incidence angle and polarization. The model has been widely used for soil moisture and roughness retrieval because of its very simple design [3]. A major aspect of the Oh formulation is the utilization of the polarization ratios. Two quantities typically employed are

$$p = \frac{\delta_{HH}^0}{\delta_{VV}^0} \quad \text{equ.23}$$

and

$$q = \frac{\delta_{HV}^0}{\delta_{VH}^0} \quad \text{equ.24}$$

where p is a co-polarized ratio and q is a cross-polarized ratio [3]. Polarization ratios provide extra information on the scattering mechanism and can minimize some of the dependence on absolute backscatter amplitude. This makes the model handy for polarimetric soil research where numerous polarization channels exist [3]. The main advantage of the Oh model is its computational simplicity compared to physically sophisticated electromagnetic models. However, given the model is based on empirical relationships, its performance is dependent on the range of surface and radar circumstances provided in its development dataset. It has been independently verified that the performance can be affected by the polarization, incidence angle, roughness and soil conditions [3], [5], [9]. Advantage: easy, effective and useful for polarimetric retrieval. Limitation: empirical calibration; limited transferability.

6. Dubois-Model

The Dubois model is an empirical model created for soil moisture retrieval using imaging radar readings. It links co-polarized radar backscatter to soil dielectric characteristics, surface roughness, radar wavelength and incidence angle [7]. The paradigm is often described in terms of discrete HH and VV relationships. The usual formulation links the HH and VV backscatter coefficients with empirical power-law functions of the dielectric constant, incidence angle, normalized roughness, and wavelength [7]. For example, the structure as a whole can be written as:

$$\delta_{HH}^0 = F_{HH}(\epsilon, \theta, ks, \lambda) \quad \text{equ.25}$$

and

$$\delta_{VV}^0 = F_{VV}(\epsilon, \theta, ks, \lambda) \quad \text{equ.26}$$

Where ks represents electromagnetic surface roughness [7].

The Dubois model is promising because it requires relatively few observations and is computationally inexpensive. So, it is useful for retrieving soil moisture across broad areas. However, its empirical calibration limits the transferability especially when the circumstances of soil, roughness, wavelength or incidence angle are significantly different from those employed in the model creation [7], [9]. Independent assessments have indicated that the performance of the Dubois formulation may vary between HH and VV observations, and can be significantly affected by surface conditions. Therefore, calibration and validation with actual field observations are still required when deploying the model into a new study region [5], [9], [12].

Advantage: easy formulation and cheap computing costs.

Limitation: empirical validity range and surface conditions sensitivity

7. Comparison of Models Assumptions and Applicability

The models discussed above have varied levels of physical complexity. Kirchhoff and SPM provide theoretical descriptions under certain surface regimes, IEM and AIEM provide more extensive electromagnetic formulations, and oh and Dubois provide computationally efficient empirical alternatives [1]–[3], [7], [8], [22].

Table 3. Comparison of Model Assumptions and Applicability

Model	Category	Main parameters	Roughness representation	Polarization	Complexity	Main strength	Main limitation
Kirchhoff	Physical	$\varepsilon, \theta, s, \lambda$	Surface geometry/statistics	Multiple	Medium	Physical basis	Approximation regime
SPM	Physical	$\varepsilon, \theta, s, \lambda$	Perturbation spectrum	Multiple	Medium	Smooth surfaces	Limited roughness range
IEM	Analytical	$\varepsilon, \theta, s, \lambda, l$	RMS + correlation	Multiple	High	Physical representation	Parameter sensitivity
AIEM	Analytical	$\varepsilon, \theta, s, \lambda, l$	Extended statistical treatment	Multiple	High	Improved electromagnetic formulation	Computational demand
Oh	Semi-empirical	$\delta^0 \varepsilon, \theta, s$	RMS roughness	Polarimetric	Low	Efficient retrieval	Calibration dependence
Dubois	Empirical	$\delta^0 \varepsilon, \theta, s, l$	RMS roughness	HH/VV	Low	Simple implementation	Limited empirical domain

Comparative evaluations show that no one model is consistently top performing under all scenarios. Model accuracy depends on surface roughness, dielectric characteristics, angle of incidence, polarization, wavelength and quality of the field data used for validation [5], [9], [12]. Therefore, the model selection for practical geophysical retrievals should be determined by the available SAR measurements and the expected surface-scattering regime. Physically based models are attractive when specific surface parameters are available but empirical models might be better when computational simplicity and speedy processing are more relevant [4], [5], [9].

4. Novel Hybrid, Machine Learning, and Physics-Informed Approaches

The limitations of individual scattering models has motivated the development of hybrid methodologies combining physical modeling with empirical calibration and data-driven techniques. The goal is to keep the physical interpretation of the existing scattering models, while minimizing systematic errors and better representing the nonlinear interactions between SAR measurements and the geophysical parameters [4], [5].

5. Hybrid physics-empirical models

A simple hybrid representation can be expressed as

$$\sigma_{hybride}^0 = \delta_{physical}^0 + \delta_{empirical}^0 \quad \text{equ.27}$$

Where $\delta_{physical}^0$ is the backscatter predicted by a physical model and $\delta_{empirical}^0$ represents a correction obtained from observations. Such a strategy is particularly useful when a physical model correctly represents the general scattering behaviour but exhibits systematic local errors. Semi-empirical calibration of IEM using measured soil moisture and roughness has demonstrated the practical value of this approach [10].

Physics + Machine Learning

Machine-learning methods can model nonlinear relationships between multiple SAR variables and geophysical parameters. A generalized soil-moisture retrieval relationship can be expressed as

$$\hat{\theta}_v = f_{ML}(\sigma_{VV}^0, \sigma_{VH}^0, \theta_I, \lambda, X_{anc}) \quad \text{equ.28}$$

where X_{anc} represents ancillary variables such as vegetation, terrain, or soil information.

The main advantage of standard ML is its ability to model non-linear interactions without needing an explicit analytical formulation for each relationship. However, the representativeness of training dataset is highly dependent on the reliability of learned model. A model trained in one environmental regime may not generalize well to another region or season [4]. Recent studies have shown the potential of combining SAR and optical observations with machine-learning algorithms for soil-moisture estimation, especially in situations where complementary information from different sensors can help reduce retrieval ambiguity.

5.3 Physics-Constrained Machine Learning

In physics-informed machine learning, the known physical relations are embedded into the learning. A general objective function can be written as

$$L = L_{data} + \lambda_p L_{physics} \quad \text{equ.29}$$

where L_{data} represents the mismatch between predictions and measured observations, $L_{physics}$ represents violation of a physical constraint, and controls the relative importance of the physical constraint.

For SAR retrieval, the physical term could be related to the difference between observed and λ_p model-predicted backscatter:

$$L_{physics} = [\sigma_{obs}^0 - \sigma_{model}^0(\hat{\theta}_v, \hat{s}, \varepsilon_r, \theta_i)]^2 \text{ equ.30}$$

This approach provides a feasible route to combine the nonlinear learning ability of machine learning with the physical limits of electromagnetic scattering theory. But the physical model employed as constraint must be appropriate for the surface and observation conditions themselves.

Problems and constraints

Soil moisture retrieval from SAR data is hampered by the intrinsic ambiguity between soil moisture and surface roughness. Both variables can influence the radar backscatter, complicating the separation of the individual contributions from a small number of measurements [3], [7]–[10]. The link between dielectric constant and soil moisture is also affected by soil texture and frequency. Strong correlations between dielectric behavior and soil moisture have been demonstrated in experimental experiments [17], [18], although the parameters of these relationships are dependent on the soil composition and measurement conditions. Surface roughness creates further uncertainty as RMS height and correlation length might vary significantly over agricultural areas. A field measurement may be only a small fraction of the surface area of a SAR pixel, generating a mismatch in spatial scale between ground truth and satellite observation [8]–[10]. plant additionally complicates the soil retrieval as the plant can attenuate the radar signal and add its own volume scattering component. The water-cloud approach proposed by Attema and Ulaby gives a conceptual basis for modeling vegetation effects, although more complicated vegetation conditions may require further modeling [11]. Another key limitation is that of model transferability. Evaluations of IEM, Oh and Dubois [5], [9], [12] have shown that model performance varies between sensors, polarizations, soil conditions, vegetation states and surface roughness regimes. Computational complexity also suggests a practical trade-off. IEM and AIEM are more demanding in terms of physical factors and processing work than empirical models. Therefore, satellite applications at a wide scale require a trade-off between physical fidelity, computational efficiency and availability of accurate input data [2], [8], [22].

Directions for Future Research

Future work in SAR retrieval should focus on the simultaneous consideration of soil moisture and surface roughness rather than considering them as fully independent variables. A multi-parameter state vector can be defined as where is soil moisture, is relative dielectric constant, is RMS surface height, and is correlation length [8], [10]. Another major research direction is site-specific calibration of physically-based models. The physical structure of the scattering model can be maintained while local parameter biases can be identified from field observations. This approach has already been examined for the IEM based soil moisture retrieval [10]. Multi-temporal SAR data provide another potential since the temporal information can assist in discriminating between relatively constant roughness and changing soil-moisture conditions. The inversion problem can be further constrained by combining the temporal information with numerous polarization channels [4], [5]. Hybrid physical/machine-learning models are very interesting for future retrieval systems. Rather than entirely replacing electromagnetic models, machine learning may be used to estimate model residuals, calibrate uncertain parameters, or discover nonlinear relations that are difficult to characterize analytically [4], [5]. The methodology can be further improved by physics-informed learning by enforcing electromagnetic consistency during the model training. Such methodologies should be tested on independent datasets gathered over diverse soil types, seasons and moisture conditions and radar configurations to evaluate whether the learned connections remain transferable. Finally, future retrieval systems should offer uncertainty information together with the calculated geophysical parameter. Reporting uncertainty would enable users to separate valid retrievals from observations which are heavily impacted by roughness, vegetation, model assumptions or measurement mistakes.

Conclusion

The relation between microwave observations and geophysical features of the Earth's surface is based on the SAR backscatter modeling. The models addressed in this study include theoretical methods such as Kirchhoff and SPM, analytical methods such as IEM and AIEM, and empirical or semi-empirical methods such as Oh and Dubois [1]–[3], [7], [8], [22]. The comparison highlights the various trade-offs involved in terms of physical interpretability, computational complexity, input requirements and calibration dependence of the models. The IEM and AIEM provide more thorough descriptions of dielectric and roughness effects, while Oh and Dubois provide more straightforward formulations that are attractive for practical retrieval applications [3], [5], [7]–[10]. The key problem still lies in the joint effect of soil moisture, surface roughness, soil texture, vegetation, incidence angle, polarization and wavelength. Therefore a reliable retrieval requires not only a suitable scattering model, but also precise ground observations and careful matching of field and SAR measurements [5], [9], [10], [12]. Future research should thus focus on calibrated physical models, hybrid physical-empirical methodologies, multi-temporal and multi-polarization SAR observations and physics-informed machine learning algorithms. The aim should not be to make the models more complex in them, but rather to provide physically meaningful, computationally efficient and transferable retrieval methods with a sound uncertainty estimate.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the Publication of this paper.

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