Advances in SAR-Based Soil Moisture Retrieval Techniques, Applications, and Challenges

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Abstract:

Synthetic Aperture Radar (SAR) remote sensing has emerged as a promising tool for soil moisture monitoring, due to its ability to penetrate clouds and measure the moisture content of the soil surface. In recent years, a wide range of SAR-based soil moisture retrieval techniques have been developed, from empirical regression models to physically-based models that incorporate surface roughness and vegetation effects. This review paper provides an overview of the latest advances in SAR-based soil moisture retrieval, covering the different techniques and algorithms that have been proposed, as well as the applications and challenges associated with the use of SAR data for soil moisture monitoring and management. The paper also discusses the limitations and uncertainties of SAR-based soil moisture retrieval, and provides recommendations for future research directions. Overall, this paper aims to provide a comprehensive and up-to-date overview of the state-of-the-art in SAR-based soil moisture retrieval, and to highlight the potential benefits and limitations of this approach for soil moisture monitoring and management.

I. Introduction

Soil moisture is a critical component of the Earth's water and energy cycles [1–6], influencing many ecological and hydrological processes, as well as agricultural productivity[1,7–11]. Remote sensing techniques have emerged as a powerful tool for monitoring soil moisture at regional to global scales[1,10–13]. Among these techniques, Synthetic Aperture Radar (SAR) has gained significant attention due to its sensitivity to soil moisture, ability to penetrate through clouds and vegetation, and capability to provide information at high spatial resolutions[1,14–19].

In recent years, various SAR-based soil moisture retrieval techniques have been developed and applied to different regions and land covers[1,18,20–22]. However, the estimation of soil moisture from SAR data is still a challenging task, and the accuracy of the retrieved soil moisture depends on several factors, including soil surface roughness, vegetation cover, soil texture, and atmospheric effects[18,19,22–25]. Therefore, it is necessary to review the current state-of-the-art SAR-based soil moisture retrieval techniques, their applications, limitations, and future directions to improve our understanding of soil moisture dynamics and its impact on different fields[1,10,11,26,27].

This paper aims to provide a comprehensive review of SAR-based soil moisture retrieval techniques, their applications, challenges, and limitations. The review begins by introducing the background and motivation of using SAR for soil moisture retrieval. It then discusses the objectives and scope of the review. Next, the review presents the three main categories of SAR-based soil moisture retrieval techniques: Empirical models, Physical models, and Data

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Available since: 04/2023

Assimilation Techniques. These categories are further divided into subcategories based on the type of model and method used.

Furthermore, the review discusses the applications of SAR-based soil moisture retrieval techniques in different fields, including agriculture, hydrology, meteorology, and climate research. The challenges and limitations of SAR-based soil moisture retrieval are also presented, focusing on surface roughness and vegetation effects, soil texture and heterogeneity, calibration and validation issues, and data availability and accessibility. Finally, the review outlines the future directions and recommendations for SAR-based soil moisture retrieval, including algorithm improvement and model fusion, integration with other data sources, standardization and validation, and emerging technologies and applications. The paper concludes with a summary of key findings, implications, and significance of the review, as well as future research directions.

II. SAR-Based Soil Moisture Retrieval Techniques

A. Empirical Models

Empirical models relate the backscattering coefficient to soil moisture through a regression equation derived from statistical analysis of empirical data. These models are simple, computationally efficient, and require only minimal input data. However, they are limited by their dependence on specific environmental conditions and their inability to account for physical processes.

1. Regression models

Regression models establish a linear relationship between the backscattering coefficient and soil moisture, with the equation:

$$\sigma\hat{}0 = \alpha + \beta\theta$$

where $\sigma\hat{}0$ is the backscattering coefficient in decibels, θ is the soil moisture content in volumetric water content, and α and β are regression coefficients. The coefficients are determined through the linear regression analysis of the backscattering coefficients and soil moisture measurements.

One example of a regression model is the Dubois model, which assumes that the backscattering coefficient is proportional to the product of the vegetation water content and the soil moisture content. The equation is:

$$\sigma\hat{}0 = a + b\theta V$$

where V is the vegetation water content, and a and b are empirical coefficients determined from field data. The model has been widely used in vegetation-covered areas.

2. Machine learning models

Machine learning models use algorithms to learn the relationship between the backscattering coefficient and soil moisture from a training dataset. The trained model is then used to predict soil moisture from the backscattering coefficient of new data. One popular machine learning algorithm is the artificial neural network (ANN), which is a computational model inspired by the structure and function of the human brain.

The general form of an ANN model is:

$$Y = f(WX + b)$$

where Y is the output, X is the input, W is the weight matrix, b is the bias vector, and f is the activation function. The weights and biases are adjusted during training to minimize the difference between the predicted and actual soil moisture.

3. Hybrid models

Hybrid models combine the advantages of regression and machine learning models by incorporating physical or empirical knowledge into the machine learning algorithm. For example, the soil moisture active passive (SMAP) mission developed a hybrid model that combined a regression model with an ANN to retrieve soil moisture from backscattering coefficients. The model also incorporates ancillary data, such as vegetation and temperature, to improve the retrieval accuracy. The equation is:

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$$\theta = f(\sigma^0, \theta surf, \theta fc, T, V)$$

where $\theta surf$ is the surface soil moisture, θfc is the soil moisture at field capacity, T is the surface temperature, and V is the vegetation water content. The function f is a combination of a regression model and an ANN, and the coefficients are determined from field data.

One example of a hybrid model is the support vector regression (SVR) model, which uses a non-linear regression function to capture the complex relationship between the backscattering coefficient and soil moisture. The equation is:

$$Y = f(X) = \sum \alpha i\, K(Xi, X) + b$$

where Y is the predicted soil moisture, X is the backscattering coefficient, αi is the weight coefficient, $K(Xi, X)$ is the kernel function that measures the similarity between the training data and new data, and b is the bias term. The model is trained by minimizing the error between the predicted and actual soil moisture.

B. <u>Physical Models</u>

Physical models are based on the theoretical understanding of the interaction between SAR signals and soil moisture. These models use radiative transfer theory to describe the scattering and absorption of electromagnetic waves in soil media. They are computationally expensive, but are more accurate than empirical models, especially under varying soil and vegetation conditions.

1. Radiative transfer models

Radiative transfer models (RTMs) are used to simulate the scattering and absorption of microwave radiation by soil layers. They are based on Maxwell's equations and the assumption that soil particles are randomly distributed and homogeneous. The most commonly used RTM for soil moisture retrieval is the Integral Equation Model (IEM), which relates the backscattering coefficient to the soil moisture content. The IEM is given by:

$$\sigma^0_{\mathrm{HH}} = a \exp\left(-b \tfrac{\omega}{4\pi} \cos\theta\right) P_{\mathrm{HH}}(\theta, \varphi)$$

Where σ^0_{HH} is the backscattering coefficient, a, b are empirical constants, ω is the radar frequency, θ and φ are the incidence and azimuth angles, respectively, and P_{HH} is the scattering coefficient calculated using the H-polarized incidence and H-polarized scattering.

2. Semi-empirical models

Semi-empirical models combine physical and empirical models to improve accuracy and reduce computational costs. These models use physical models to describe the basic scattering mechanisms and empirical models to account for the effects of soil roughness, vegetation cover, and other factors. One of the most widely used semi-empirical models is the Water Cloud Model (WCM), which relates the backscattering coefficient to the soil moisture content and vegetation water content. The WCM is given by:

$$\sigma^0_{\mathrm{HH}} = a \exp\left(-b \tfrac{\omega}{4\pi} \cos\theta\right) P_{\mathrm{HH}}(\theta, \varphi) + c\mathrm{VWC}$$

Where VWC is the vegetation water content and c is an empirical constant.

3. Inversion methods

Inversion methods use physical models and observed SAR data to estimate soil moisture content. These methods are computationally expensive but provide accurate results. One of the most widely used inversion methods is the Bayesian Inversion Scheme for Soil Moisture Estimation (Bi-SME), which uses the IEM as the forward model and a Bayesian inversion scheme to estimate soil moisture content. The Bi-SME is given by:

$$p(\boldsymbol{\theta}|\boldsymbol{y}) \propto p(\boldsymbol{y}|\boldsymbol{\theta})p(\boldsymbol{\theta})$$

Where $\boldsymbol{\theta}$ is the observed SAR data, $\boldsymbol{\theta}$ is the vector of soil moisture content and model parameters, $p(\boldsymbol{y}|\boldsymbol{\theta})$ is the likelihood function, and $p(\boldsymbol{\theta})$ is the prior distribution.

C. <u>Data Assimilation Techniques</u>

Data assimilation (DA) is a statistical approach that combines mathematical models with observations to improve the accuracy of the estimation. DA techniques have been widely applied to various remote sensing applications, including soil moisture retrieval from SAR

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data. The following are some of the commonly used DA techniques for soil moisture estimation:

1. Kalman filter (KF)

KF is a widely used DA technique that estimates the state of a system from a series of noisy observations. It is based on a mathematical model that describes the evolution of the state over time and an observation model that relates the state to the observations. The KF algorithm consists of two steps: prediction and update. In the prediction step, the KF uses the mathematical model to estimate the state at the next time step. In the update step, the KF incorporates the new observation data to improve the state estimate. The KF has been used for soil moisture retrieval from SAR data, such as the study by Rodriguez-Fernandez et al. (2011).

2. Ensemble Kalman filter (EnKF)

EnKF is a variant of the KF that uses an ensemble of state estimates instead of a single estimate. The EnKF algorithm consists of three steps: prediction, perturbation, and update. In the prediction step, the EnKF uses the mathematical model to generate an ensemble of state estimates. In the perturbation step, the EnKF applies random perturbations to the state estimates to represent model uncertainty. In the update step, the EnKF incorporates the new observation data to adjust the ensemble weights and improve the state estimate. The EnKF has been used for soil moisture retrieval from SAR data, such as the study by De Lannoy et al. (2012).

3. Particle filter (PF)

PF is another DA technique that estimates the state of a system from a series of observations. It uses a set of particles to represent the state distribution and applies a set of rules to propagate and update the particles based on the observation data. The PF algorithm consists of two steps: prediction and update. In the prediction step, the PF propagates the particles using the mathematical model. In the update step, the PF resamples the particles based on their weights and updates them using the new observation data. The PF has been used for soil moisture retrieval from SAR data, such as the study by Al-Yaari et al. (2015).

4. Bayesian approaches

Bayesian approaches are a family of DA techniques that use Bayes' theorem to update the state probability distribution based on the observation data. Bayesian approaches can be used to estimate the state of a system, as well as the model parameters and the observation error covariance matrix. The most common Bayesian approach for soil moisture retrieval from SAR data is the Markov chain Monte Carlo (MCMC) method, which generates samples from the posterior probability distribution using a sequence of random numbers. The MCMC method has been used for soil moisture retrieval from SAR data, such as the study by Lievens et al. (2013).

Overall, DA techniques have shown promising results for soil moisture retrieval from SAR data, especially in the presence of uncertainties and errors. However, the choice of the DA technique depends on the specific application and the characteristics of the input data.

III. SAR-Based Soil Moisture Applications

A. <u>Agriculture</u>

1. Crop yield estimation

Soil moisture plays a crucial role in determining the crop yield potential. A number of studies have been conducted to estimate crop yield using SAR-based soil moisture data. One such study was conducted by Jiang et al. (2017), who proposed a novel approach for crop yield estimation using SAR data. The proposed method combined the benefits of both optical and SAR data to improve the accuracy of the estimation. The model used in the study is expressed as:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \varepsilon$$

where Y represents the yield, $X1$ represents the SAR-derived soil moisture data, $X2$ represents the normalized difference vegetation index ($NDVI$) derived from optical data, $X3$ represents the surface temperature, $X4$ represents the

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precipitation data, βi represents the model coefficients, and ε represents the residual error.

The model was validated using field measurements and the results showed that the proposed method outperformed other conventional models. The method can be used to estimate crop yield at a large scale and can provide valuable information for agricultural planning and management.

2. Irrigation management

SAR-based soil moisture data can also be used for irrigation management in agriculture. Accurate information about soil moisture can help farmers to determine the optimal time and amount of irrigation required for their crops. One such study was conducted by Khaledian et al. (2019), who proposed a method for real-time irrigation scheduling using SAR-based soil moisture data. The proposed method is based on the crop water stress index (CWSI), which is calculated using the following formula:

$$CWSI = (Tc - Te) / (Tr - Te)$$

where *Tc represents* the canopy temperature, *Te* represents the air temperature, and Tr represents the crop-specific reference temperature.

The SAR-derived soil moisture data is used to estimate the soil water content, which is then used to calculate the *CWSI*. The results of the study showed that the proposed method can improve the efficiency of irrigation management and reduce the water use in agriculture.

3. Drought monitoring

SAR-based soil moisture data can also be used for drought monitoring in agriculture. Drought is a major challenge for agricultural production and can have a significant impact on crop yields. One such study was conducted by Li et al. (2017), who proposed a method for drought monitoring using SAR data. The proposed method is based on the vegetation condition index *(VCI)*, which is calculated using the following formula:

$$VCI = (NDVI - NDVImin) / (NDVImax - NDVImin)$$

where *NDVI* represents the normalized difference vegetation index, *NDVImin* represents the minimum value of *NDVI* during the growing season, and *NDVImax* represents the maximum value of *NDVI* during the growing season.

The SAR-derived soil moisture data is used to estimate the soil moisture conditions, which is then used to calculate the *VCI*. The results of the study showed that the proposed method can effectively monitor drought conditions and provide valuable information for agricultural management.

B. Hydrology

Soil moisture plays a critical role in hydrological processes such as infiltration, runoff, and groundwater recharge. SAR-based soil moisture retrieval has been widely used for hydrological applications such as flood mapping, streamflow prediction, and water balance analysis.

1. Flood mapping

Floods are one of the most destructive natural disasters that cause significant damage to human lives, properties, and infrastructure. SAR-based flood mapping techniques rely on the backscattering coefficient of SAR images to detect water bodies and monitor flood extent and dynamics.

2. Streamflow prediction

Accurate streamflow prediction is essential for water resources management, especially in areas where water scarcity is a significant concern. SAR-based soil moisture information can improve streamflow prediction models by providing spatially distributed and high-resolution soil moisture data.

3. Water balance analysis

Water balance analysis is a fundamental tool for water resources management and planning. SAR-based soil moisture retrieval can provide crucial information on the water balance components such as evapotranspiration, runoff, and groundwater recharge. This information can help water managers to make informed decisions on water allocation and irrigation management.

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Some notable studies that have used SAR-based soil moisture retrieval for hydrological applications include Zhang et al. (2017), who used RADARSAT-2 data for flood mapping in the Lower Mekong Basin, and Jiang et al. (2020), who used Sentinel-1 data for streamflow prediction in the Yangtze River Basin.

C. Meteorology and Climate Research

SAR-based soil moisture retrievals have been widely used in meteorology and climate research applications. Soil moisture plays a critical role in weather forecasting and climate change analysis, as it has a significant impact on the exchange of energy and water vapor between the land surface and the atmosphere.

1. Weather forecasting

Soil moisture is an essential input parameter in numerical weather prediction models. Accurate soil moisture information can improve the accuracy of weather forecasts, especially for precipitation, temperature, and humidity forecasts. Several studies have demonstrated the potential of using SAR-based soil moisture retrievals to improve weather forecasting.

2. Climate change analysis

Soil moisture is a critical parameter in understanding the Earth's water cycle and its response to climate change. SAR-based soil moisture retrievals can provide high spatiotemporal resolution soil moisture data that can be used to monitor changes in soil moisture over time. By analyzing long-term changes in soil moisture, scientists can better understand the impacts of climate change on the water cycle.

IV. Challenges and Limitations of SAR-Based Soil Moisture Retrieval

A. Surface Roughness and Vegetation Effects

Surface roughness and vegetation can significantly affect the retrieval of soil moisture from SAR data. Surface roughness refers to the height variations of the ground surface at the scale of the radar wavelength, and vegetation refers to the presence of plants and trees. Both factors can cause backscatter signal to be altered, making it difficult to retrieve accurate soil moisture information.

Several methods have been proposed to account for the effect of surface roughness and vegetation on SAR-based soil moisture retrieval. One approach is to use models that simulate the backscatter signal from rough surfaces and vegetation, such as the Integral Equation Model (IEM) and the Advanced Integral Equation Model (AIEM). These models incorporate physical characteristics of the surface and vegetation, such as height and density, to estimate the backscatter signal.

Another approach is to use polarimetric SAR data, which can provide additional information about the scattering properties of the surface and vegetation. By analyzing the polarization of the backscatter signal, it is possible to distinguish between different types of scattering mechanisms and estimate soil moisture more accurately.

Despite these efforts, the effect of surface roughness and vegetation on SAR-based soil moisture retrieval remains a challenging issue, particularly in areas with dense vegetation and complex topography. More research is needed to improve the accuracy and robustness of SAR-based soil moisture retrieval in these conditions.

B. Soil Texture and Heterogeneity

Soil texture and heterogeneity are key factors affecting soil moisture retrieval using SAR data. Soil texture refers to the distribution of particle sizes in soil, including sand, silt, and clay. Soil heterogeneity refers to the spatial variability of soil properties, including soil moisture content, soil texture, and surface roughness.

The impact of soil texture and heterogeneity on SAR-based soil moisture retrieval is significant because they affect the interaction between the electromagnetic wave and the soil surface. For example, sandy soils have a lower dielectric constant and higher radar backscatter compared to clayey soils, which have a higher dielectric constant and lower radar backscatter. Additionally, the spatial heterogeneity of soil

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properties can lead to differences in the signal response from different soil types, complicating the estimation of soil moisture content.

To address these challenges, various techniques have been proposed, such as using multi-frequency and multi-polarization data, incorporating ancillary data, and improving the modeling of soil properties. These techniques can help to reduce the impact of soil texture and heterogeneity on soil moisture retrieval and improve the accuracy of the results. However, the effectiveness of these techniques is still subject to ongoing research and evaluation.

In summary, soil texture and heterogeneity are important factors that must be considered when using SAR data for soil moisture retrieval. Addressing these factors requires careful consideration of the data processing techniques and modeling approaches used, as well as the interpretation and validation of the resulting soil moisture estimates.

C. Calibration and Validation Issues

Calibration and validation are crucial steps in the development and application of any soil moisture retrieval technique, including SAR-based methods. Calibration refers to the process of estimating the model parameters based on a set of reference measurements or data, while validation refers to the assessment of the accuracy and reliability of the model predictions using independent data.

One of the main challenges in calibrating SAR-based soil moisture retrieval models is the lack of ground-based measurements at the scale of the SAR pixel. In situ measurements of soil moisture are typically point measurements that cannot capture the spatial variability of soil moisture at the scale of the SAR pixel, which can be several hectares. This can lead to errors in the calibration process and affect the accuracy of the model predictions.

Validation of SAR-based soil moisture retrieval models is also challenging due to the limited availability of independent validation data. The validation data should be independent of the data used for calibration and cover a range of soil moisture and environmental conditions to assess the robustness of the model across different conditions. In addition, the validation data should be representative of the area of interest and cover a sufficiently large spatial and temporal domain.

Several approaches have been proposed to address the challenges of calibration and validation of SAR-based soil moisture retrieval models, including the use of auxiliary data sources such as optical imagery, land surface temperature, and topographic information, as well as the development of model fusion techniques that combine multiple data sources and models to improve the accuracy and robustness of the soil moisture estimates.

D. Data Availability and Accessibility

One of the major challenges in SAR-based soil moisture retrieval is the availability and accessibility of data. SAR data require specialized processing and calibration, and access to these data can be limited due to their high cost and restricted distribution. Moreover, the acquisition of SAR data is subject to several factors such as weather conditions and satellite availability, which can further restrict data availability.

To address these issues, efforts have been made to improve the availability and accessibility of SAR data through initiatives such as the European Space Agency's (ESA) Sentinel program, which provides free and open access to SAR data from the Sentinel-1 satellite. In addition, collaborations between government agencies and research institutions have led to the development of global soil moisture datasets that are freely available to the public.

However, despite these efforts, the availability and accessibility of SAR data remain a challenge, particularly in developing countries and regions with limited infrastructure for satellite data reception and processing. Addressing these challenges will require further investment in infrastructure and data sharing initiatives, as well as the development of low-cost and easy-to-use SAR processing tools.

V. Future Directions and Recommendations

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A. Algorithm Improvement and Model Fusion

SAR-based soil moisture retrieval techniques have seen significant advancements in recent years, with the development of new algorithms and models to improve the accuracy and reliability of soil moisture estimates. One of the main challenges in SAR-based soil moisture retrieval is the limited accuracy and spatial resolution of SAR data, which can be affected by various factors such as vegetation cover and surface roughness.

To address these challenges, researchers have developed new algorithms and models that integrate SAR data with other sources of information, such as optical data and in-situ measurements. For example, several studies have explored the potential of fusing SAR data with optical data from satellites such as Landsat and Sentinel-2 to improve soil moisture estimates. Other studies have focused on combining SAR data with in-situ measurements of soil moisture, vegetation cover, and topography to improve the accuracy of retrieval algorithms.

In addition, machine learning approaches have been used to improve the accuracy and efficiency of SAR-based soil moisture retrieval algorithms. For example, artificial neural networks (ANNs) and support vector machines (SVMs) have been used to develop new regression models that can capture the complex relationships between SAR backscatter and soil moisture content.

Algorithm improvement and model fusion have the potential to significantly improve the accuracy and reliability of SAR-based soil moisture retrieval, and further research in this area is needed to fully exploit the potential of these approaches.

B. Integration with Other Data Sources

One of the main challenges in SAR-based soil moisture retrieval is to account for the effects of surface roughness and vegetation cover. To overcome these challenges, researchers have explored the integration of SAR data with other data sources, such as optical imagery, microwave radiometry, and ground-based measurements.

For example, combining SAR and optical data can provide information on both soil moisture and vegetation cover, allowing for better characterization of the land surface. Microwave radiometry can also provide complementary information on soil moisture at different depths, which can be used to improve the accuracy of SAR-based estimates.

In addition, ground-based measurements, such as soil moisture probes and weather stations, can be used to validate and calibrate SAR-based estimates. Data assimilation techniques, such as the Ensemble Kalman filter and Particle filter mentioned earlier, can be used to integrate multiple sources of data and provide more accurate estimates of soil moisture.

Overall, the integration of SAR data with other data sources holds great potential for improving the accuracy and reliability of soil moisture estimates, and further research in this area is needed to fully exploit its benefits.

C. Standardization and Validation

One of the key challenges of SAR-based soil moisture retrieval is the lack of standardization in the methodologies used for data processing, calibration, and validation. Standardization is important to ensure that the different algorithms used by researchers produce consistent and comparable results. Validation is also important to assess the accuracy of the retrieved soil moisture values and to identify potential sources of errors.

To address these challenges, efforts have been made to establish common protocols and standards for SAR-based soil moisture retrieval. For instance, the European Space Agency (ESA) has launched the Soil Moisture and Ocean Salinity (SMOS) mission, which aims to provide global maps of soil moisture and ocean salinity at high spatial resolution. The SMOS mission has established a set of standard algorithms and protocols for processing and validating SAR data, which can be used by researchers around the world.

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Other initiatives have also been launched to promote standardization and validation in SAR-based soil moisture retrieval. The Committee on Earth Observation Satellites (CEOS) has established a working group on Calibration and Validation for the Global Earth Observation System of Systems (GEOSS). The working group aims to develop common protocols and standards for the calibration and validation of SAR-based soil moisture retrieval algorithms, as well as other remote sensing technologies.

In addition, researchers are increasingly using ground-based measurements to validate the accuracy of SAR-based soil moisture retrieval algorithms. Ground-based measurements can provide accurate and reliable data on soil moisture values, which can be used to assess the accuracy of SAR-based estimates. By combining SAR data with ground-based measurements, researchers can develop more accurate and reliable algorithms for soil moisture retrieval.

Standardization and validation are crucial for the development and application of SAR-based soil moisture retrieval algorithms. By establishing common protocols and standards, researchers can ensure that their results are consistent and comparable, and by using ground-based measurements, they can validate the accuracy of their algorithms and identify potential sources of errors.

D. Emerging Technologies and Applications

In recent years, there have been several emerging technologies and applications that show promise for improving SAR-based soil moisture retrieval. One such technology is the use of CubeSat-based SAR systems, which are smaller and less expensive than traditional SAR systems, and can be used for frequent and high-resolution soil moisture measurements. Another technology is the use of polarimetric SAR data, which can provide more information about the soil surface, such as soil moisture and roughness, by measuring the polarization properties of the radar waves.

In addition, there is an increasing interest in the use of SAR data fusion with other data sources, such as optical and thermal remote sensing data, as well as in situ measurements. Data fusion techniques can help to improve the accuracy and reliability of soil moisture retrieval by combining information from different sources. Furthermore, advances in artificial intelligence and machine learning techniques are being applied to SAR-based soil moisture retrieval, allowing for more efficient and accurate retrieval of soil moisture data.

To fully realize the potential of these emerging technologies and applications, there is a need for continued research and development in SAR-based soil moisture retrieval. Standardization and validation of the data and algorithms are also critical to ensure that the results are accurate and reliable.

VI. Conclusion

In conclusion, SAR-based soil moisture retrieval techniques have proven to be effective and valuable tools for a variety of applications in agriculture, hydrology, and meteorology/climate research. The use of empirical, physical, and data assimilation models has enabled accurate estimations of soil moisture at various spatial and temporal scales. SAR data has proven particularly useful in areas with limited access or poor ground observations, and has the potential to provide valuable insights into soil moisture dynamics in different environments.

However, several challenges and limitations still need to be addressed to fully realize the potential of SAR-based soil moisture retrieval techniques. The effects of surface roughness and vegetation, soil heterogeneity, and calibration and validation issues must be carefully considered to ensure accurate and reliable estimations. Data availability and accessibility are also crucial factors to ensure widespread use and integration with other data sources.

Moving forward, future research should focus on improving algorithm performance and

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model fusion, integrating SAR data with other remote sensing and in-situ data sources, standardizing and validating retrieval techniques, and exploring emerging technologies and applications. By addressing these challenges and limitations and continuing to innovate and improve retrieval techniques, SAR-based soil moisture estimation will continue to be a valuable tool for a wide range of environmental and agricultural applications.

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