OPTIMIZATION OF SURFACE SOIL MOISTURE EXTRACTION USING SENTINEL-1A SAR AND MACHINE LEARNING IN NORTHWEST SHANDONG PLAIN, CHINA

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by

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LIST OF ABBREVIATIONS

AIEM	Advanced Integrated Equation Model
ANN	Artificial Neural Network
AVI	Anomaly Vegetation Index
CRNS	Cosmic Ray Neutron Sensing
CSMI	Cropland Soil Moisture Index
DDI	Distance Drought Index
DL	Deep Learning
ENVI	Environment for Visualizing Images
EO	Earth Observation
ERT	Electrical Resistivity Tomography
ESA	European Space Agency
FDR	Frequency Domain Reflectometry
GBM	Gradient Boosting Machines
GIS	Geographic Information System
GNSS-R	Global Navigation Satellite System-Reflectometry
IEM	Integral Equation Model
KNN	K-Nearest Neighbors
MATLAB	Matrix Laboratory
MDA	Mean Decreasing Accuracy
MDG	Mean Decreasing Gini
MEMS	Micro-Electro-Mechanical Systems
MIMICS	Michigan Microwave Canopy Scattering
ML	Machine Learning
MLP	Multi-layer Perceptron
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NMR	Nuclear Magnetic Resonance
OOB	out of bag
PDI	Perpendicular Drought Index
PolSARpro	Polarimetric SAR Data Processing and Educational Toolbox
RBF	Radial Basis Function

RF	Random Forest
RMSE	Root mean square error
SAR	Synthetic Aperture Radar
SLC	Single Look Complex
SM	Soil Moisture
SMAP	Soil Moisture Active Passive
SNAP	Sentinel Applications Platform
SNAP	Sentinel Applications Platform
SPM	Small Perturbation Model
SVM	Support Vector Machine
SWCI	Surface Water Content Index
SWCTI	Surface Water Content Temperature Index
TDR	Time Domain Reflectometry
TSMI	Triangular Soil Moisture Index
USGS	United States Geological Survey
VCI	Vegetation Condition Index
WCM	Water Cloud Model
WOS	Web of Science

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PENGOPTIMUMAN PENGEKSTRAKAN KELEMBAPAN PERMUKAAN TANIH MENGGUNAKAN SENTINEL-1A SAR DAN PEMBELAJARAN MESIN DI DATARAN BARAT LAUT SHANDONG, CHINA

ABSTRAK

Di kawasan separa lembap, kelembapan tanah (SM) memainkan peranan penting dalam mempengaruhi proses kitaran hidrologi dan keseimbangan tenaga. Walaupun pembelajaran mesin (ML) dan Radar Apertur Sintetik (SAR) menawarkan potensi dalam perolehan maklumat SM, prestasi dan keberkesanannya terhad dengan cabaran seperti pemilihan ciri dan sensitiviti terhadap variasi persekitaran mengikut musim yang berbeza. Cabaran ini menjadi lebih serius disebabkan oleh kekurangan rangka kerja yang komprehensif yang dapat mengintegrasikan parameter polarisimetri dengan pekali pantulan tradisional, yang boleh meningkatkan ketepatan perolehan SM berasaskan SAR. Oleh itu, penyelidikan ini bertujuan untuk membangunkan kaedah inovatif yang menggabungkan teknik penguraian polarisimetri maju dengan algoritma ML untuk perolehan SM yang kukuh di Dataran Barat Laut Shandong, China. Metodologi ini melibatkan pemprosesan data Sentinel-1A melalui analisis intensiti dan fasa standard, serta teknik penguraian Cloude-Pottier, untuk mengekstrak pekali pantulan dan parameter polarisimetri yang berkaitan dengan SM. Seterusnya, kepentingan faktor impak dan korelasi mereka dengan SM dianalisis secara kuantitatif. Pelbagai model ML kemudiannya dibina menggunakan pelbagai gabungan faktor impak dan dinilai secara menyeluruh melalui pengesahan silang K-lipatan untuk memastikan ketepatan, kejituan, dan kestabilan. Model yang memberikan prestasi terbaik akhirnya digunakan untuk perolehan dan analisis SM serantau. Penemuan

menunjukkan bahawa nilai eigen pertama (λ_1) dan entropi (H) memainkan peranan yang paling penting dalam perolehan SM, dengan komponen intensiti entropi Shannon menunjukkan pengaruh yang lebih besar daripada komponen polarisasinya. Perbandingan sistematik antara algoritma Random Forest (RF), Support Vector Machine (SVM), dan Artificial Neural Network (ANN) mendedahkan bahawa gabungan faktor impak yang optimum berbeza mengikut algoritma. Antara ini, model RF dengan 12 faktor yang dipilih dengan teliti (RF_{IM12}) mencapai prestasi yang unggul (R^2 = 0.55, RMSE = 6.12 vol.%), menjelaskan 90% variasi SM. Pendekatan ini menghapuskan pergantungan tradisional terhadap maklumat kekasaran permukaan yang eksplisit dan menyesuaikan dengan berkesan terhadap variasi musim melalui integrasi strategik data multi-temporal dan pemilihan ciri yang maju. Analisis spatial mendedahkan corak SM yang unik di Dataran Barat Laut Shandong, di mana paras SM di Taman Tanah Bencah Kebangsaan Sungai Kuning adalah jauh lebih tinggi berbanding kawasan sekitarnya dan menunjukkan variasi musim yang ketara. Penemuan ini memberikan pandangan baru tentang keberkesanan parameter polarisimetri untuk perolehan SM dan mewujudkan metodologi yang kukuh untuk keadaan temporal dinamik. Penyelidikan ini bukan sahaja memajukan pemahaman tentang perolehan SM berasaskan SAR, tetapi juga menawarkan penyelesaian praktikal untuk melaksanakan sistem pemantauan SM yang boleh dipercayai di kawasan separa lembap.

OPTIMIZATION OF SURFACE SOIL MOISTURE EXTRACTION USING SENTINEL-1A SAR AND MACHINE LEARNING IN NORTHWEST SHANDONG PLAIN, CHINA

ABSTRACT

In semi-humid regions, soil moisture (SM) plays a crucial role in influencing hydrological cycle processes and energy balance. While machine learning (ML) and Synthetic Aperture Radar (SAR) offer potential for SM information retrieval, their performance and applicability are limited by challenges such as feature selection and sensitivity to environmental variations across different seasons. This challenge is exacerbated by the lack of comprehensive frameworks that effectively integrate multiple polarimetric parameters with traditional backscatter coefficients, which could improve the accuracy of SAR-based SM retrieval. Hence, this research aims to develop an innovative method that combines advanced polarimetric decomposition techniques with ML algorithms for robust SM retrieval in the Northwest Shandong Plain, China. The methodology involves processing Sentinel-1A data through standard intensity and phase analyses, as well as Cloude-Pottier decomposition techniques, to extract backscatter coefficients and polarimetric parameters linked to SM. Next, the importance of the impact factors and their correlation with SM were quantitatively analyzed. Multiple ML models were then constructed using various combinations of impact factors and comprehensively evaluated through K-fold cross-validation to ensure precision, accuracy, and stability. The best-performing model was ultimately employed for regional SM retrieval and analysis. The findings show that the first eigenvalue (λ_1) and entropy (H) play the most important roles in SM retrieval, with the intensity component of Shannon entropy demonstrating greater influence than its polarization component. A systematic comparison of Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) algorithms reveals that the optimal combination of impact factors varies by algorithm. Among these, the RF model with 12 carefully selected factors (RF_{IM12}) achieves superior performance (R^2 = 0.55, RMSE = 6.12 vol.%), explaining 90% of SM variation. This approach eliminates the traditional dependence on explicit surface roughness information and effectively adapts to seasonal variations by strategically integrating multi-temporal data and advanced feature selection. Spatial analysis reveals distinctive SM patterns in the Northwest Shandong Plain, where SM levels in the Yellow River National Wetland Park are significantly higher than surrounding areas and exhibit pronounced seasonal variations. The findings provide new insights into the effectiveness of polarimetric parameters for SM retrieval and establish a robust methodology for dynamic temporal conditions. This research not only advances the understanding of SAR-based SM retrieval but also offers practical solutions for implementing reliable SM monitoring systems in semi-humid regions.

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Soil intersects the atmosphere, hydrosphere, lithosphere, and biosphere on the earth's surface and is the site of many physical, chemical, and biological processes (Cui et al., 2016). As an important component of the soil, soil moisture (SM) greatly influences soil properties and acts as an important solvent, acting as a water environment for various processes in the soil. At the same time, SM is an important parameter for hydrological, meteorological, and agro-environmental studies and is one of the key indicators of the water cycle. Estimates of SM are essential for climate prediction, flood hazard, and water recycling studies. Accurate monitoring of SM is therefore of great importance in the scientific study of land surface processes (Dusseux et al., 2014; Zhao et al., 2018).

In the context of global warming, desertification and salinization are becoming increasingly prominent and valued. SM is a key variable affecting the water and energy balance in the semi-humid zone and is the most effective driver of regional hydrological and vegetation processes, as well as one of the most important constraints on the evolution of semi-humid ecosystems (Hassaballa et al., 2014). Therefore, information on the spatial and temporal changes of SM is essential for the ecological protection and sustainable development of the semi-humid zone.

As research in hydrology, meteorology, and agro-environment continues to advance, higher demands are being placed on both high precision and high-resolution monitoring of SM. Current methods of SM acquisition include traditional ground measurements, proximal sensing, and remote sensing monitoring. Among them, traditional SM ground measurements and proximal sensing require complex process field operations, limited spatial and temporal resolution, high cost, and are difficult to measure on a large scale effectively. In recent years, with the rapid development of remote sensing technology, the use of satellite remote sensing for large-scale SM monitoring has become the most effective means of SM research. Compared with station observation, remote sensing can obtain information in a large area quickly and continuously, making up for the shortcomings of discrete point sampling observation methods.

Due to its all-weather, all-day, and penetrating characteristics, radar remote sensing technology has great application value in monitoring SM over large areas. In order to make full use of the scattering information contained in Synthetic Aperture Radar (SAR), some scholars have used various polarimetric decomposition methods to extract SAR polarimetric parameters, which are widely used in the research fields of feature classification, target identification, and retrieval of surface parameters, providing new ideas for SM retrieval.

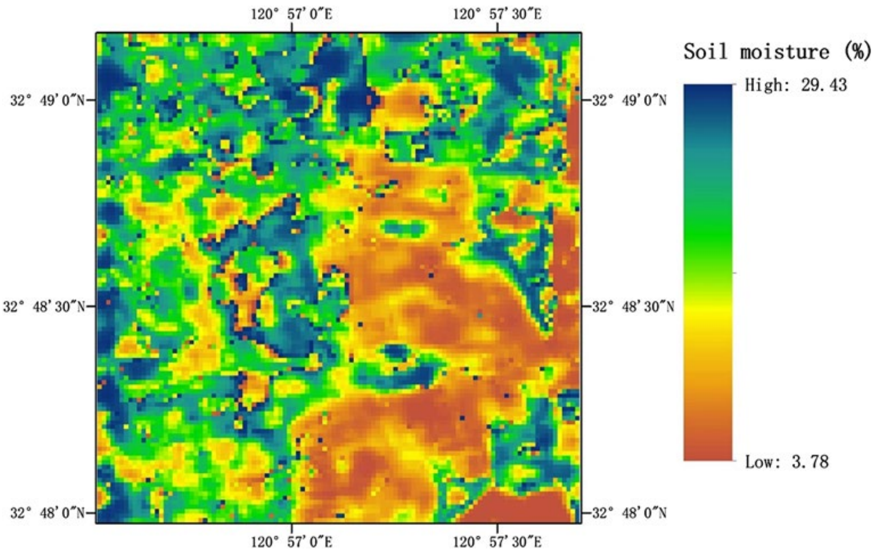

Figure 1.1 SM map captured by Sentinel-1A satellite (Wang et al., 2022).

The traditional method of applying simple linear regression to SM retrieval, which relies on a limited number of polarimetric parameters, fails to systematically and comprehensively assess the role of each polarimetric parameter in the retrieval process. To address this, there is an urgent need for a method that can fully integrate and utilize radar backscatter and polarization information for SM retrieval. Compared with traditional regression methods, machine learning (ML) is not restricted by the quantity and type of input factors. It can establish an optimal mapping from data to labels and learn the intrinsic patterns within the data, offering a viable approach to achieve the above-mentioned goal (Wang et al., 2021).

Located in the lower reaches of the Yellow River, the Northwest Shandong Plain has relatively scarce water resources, uneven seasonal distribution, and a relatively fragile ecological environment, with water being one of the most critical factors limiting the sustainable development of the local ecological environment and economy (Kong et al., 2022). At present, research on remote sensing monitoring of SM in this region is very limited. Moreover, the ecological protection and high-quality development of the Yellow River Basin has become a major national strategy in China, and the Yellow River Basin is an important ecological barrier and an important economic zone in China, which has a very important position in China's economic and social development and ecological security.

1.2 Problem Statements

SM is a critical environmental variable that significantly influences the water and energy exchange between the land surface and atmosphere, playing an essential role in agricultural production, water resource management, and ecosystem functioning. While passive microwave remote sensing is limited in monitoring SM at small scales due to its low spatial resolution, active microwave remote sensing through SAR technology not only provides high spatial resolution but also offers valuable polarisation characteristics beneficial for SM retrieval (Gherboudj et al., 2011; Notarnicola et al., 2008). However, current SAR-based SM retrieval methods face three major limitations: first, they often fail to comprehensively utilize the full range of available SAR parameters (backscatter coefficients, SAR indices, and polarimetric parameters) for SM estimation; second, the complex non-linear relationships between these parameters and SM are not fully understood or effectively modeled; third, there remains a fundamental challenge in developing models with robust cross-seasonal performance for regional applications.

First, while existing SM retrieval approaches primarily rely on backscatter coefficients and SAR indices (J. Wang et al., 2022), they often overlook the wealth of information contained within polarimetric parameters obtained through polarimetric decomposition. Although both backscatter coefficients and polarimetric parameters contain direct or indirect SM information, their complex non-linear relationships with SM remain inadequately understood (Bourgeau-Chavez et al., 2013; Wiseman et al., 2014). Current research lacks a comprehensive framework for quantifying the relative contributions of these various factors to SM retrieval accuracy, particularly regarding the role of polarimetric parameters in improving retrieval performance.

Second, traditional SM retrieval methods often employ simple linear regression analysis (Bai et al., 2016; Yang et al., 2019), which cannot effectively capture the complex relationships between multiple input factors and soil moisture. ML approaches offer significant advantages as they can handle multiple input variables simultaneously and model non-linear relationships without being constrained by the type and number of input factors (Ahmad et al., 2010). However, existing studies comparing different ML methods for SM retrieval have used varying datasets, pre-processing methods, and validation metrics, making it challenging to draw definitive conclusions about their relative effectiveness for operational SM retrieval applications.

Third, the Northwest Shandong Plain is a critical agricultural region in China where accurate SM monitoring is essential for agricultural management and water resource planning. While SAR-based SM retrieval methods have advanced, there remains a fundamental challenge in developing models with robust cross-seasonal performance. Cross-seasonal performance refers to a model's ability to maintain reliable accuracy when applied across different seasons without requiring recalibration or seasonal-specific adjustments, enabling the model to adapt to seasonal variations in environmental conditions, including changes in precipitation patterns, vegetation cover, surface roughness, and soil properties. Current SM retrieval approaches often require different models for different seasons, limiting their practical application for continuous monitoring. This limitation creates significant barriers to understanding long-term SM patterns and their implications for agricultural management in the region. Furthermore, the lack of a unified SM retrieval model with cross-seasonal performance capabilities for the Northwest Shandong Plain represents a significant gap in supporting effective regional water resource management. A unified SM retrieval model, as conceptualized in this study, integrates multiple SAR-derived parameters (backscatter coefficients, SAR indices, and polarimetric parameters) within a single comprehensive framework that maintains stable performance across different seasons, land cover types, and temporal conditions.

1.3 Research Questions

(i) What are the factors that affect the SM retrieval performance based on SAR satellite data?

(ii) Which ML methods perform better in retrieving SM from SAR satellite data?

(iii) What are the spatio-temporal changes of SM over the Northwest Shandong Plain?

1.4 Research Objectives

This study aims to develop an improved SM retrieval approach using SAR satellite data and ML methods, with enhanced cross-seasonal applicability for the Northwest Shandong Plain. To achieve this aim, the specific objectives are:

(i) To identify key factors that improve SM retrieval using SAR satellite data.

(ii) To evaluate the performance of different ML methods for retrieving SM from SAR satellite data.

(iii) To develop a unified SM retrieval model with better cross-seasonal generalization capability for assessing the spatial and temporal changes over the Northwest Shandong Plain.

1.5 Research Hypotheses

Based on the research objectives outlined above, this study is guided by three key hypotheses that address fundamental questions about SAR-based soil moisture retrieval:

Table 1.1 Research hypotheses of this study.

No.	Hypothesis
H1	Integration of remote sensing and ML can improve SM retrieval accuracy.
H2	Increasing the number of impact factors does not consistently improve model performance, and the optimal factor combinations vary across different ML models.
H3	ML models can achieve cross-seasonal generalization for SM retrieval by adapting to varying environmental conditions.

These hypotheses guide the research design and provide the foundation for testing the effectiveness of the proposed unified soil moisture retrieval approach. As shown in Table 1.1, the first hypothesis addresses the fundamental premise of combining SAR technology with machine learning. The second hypothesis challenges the assumption that more input parameters necessarily lead to better performance. The third hypothesis directly supports the primary research objective of developing cross-seasonal generalization capability.

1.6 Scope of Study

The scope of the study defines the boundaries, limitations, and specifications of the data and methods used in this research. This study encompasses the following key areas:

Sentinel-1A dual-polarization radar data were selected as the primary remote sensing data source after comparative evaluation of available SAR systems, including ALOS PALSAR. This selection was based on several key advantages: (i) Sentinel-1A provides free access to high spatial resolution (10 m) SAR data with consistent 12-day revisit intervals during the study period (2021-2022), ensuring temporal consistency required for cross-seasonal model development; (ii) C-band frequency demonstrates superior sensitivity to surface soil moisture variations (0-5 cm layer) compared to L-band systems, which despite deeper penetration capabilities, are more affected by vegetation interference in agricultural environments; (iii) the dual-polarization (VV+VH) configuration provides optimal information content for soil moisture applications without the complexity of quad-polarization processing; and (iv) proven effectiveness of C-band SAR for soil moisture retrieval in semi-humid agricultural regions aligns with the environmental conditions of the Northwest Shandong Plain.

The data processing workflow includes radiometric calibration, speckle filtering, terrain correction, and standard intensity and phase processing, as well as polarimetric decomposition techniques to extract comprehensive SAR parameters.

The Northwest Shandong Plain was selected as the study area, which experiences a temperate monsoon climate. Field measurements were conducted at strategically distributed sampling points during eight different time periods (28th June 2021, 1st December 2021, 13th December 2021, 12th April 2022, 24th April 2022, 6th May 2022, 18th May 2022, and 30th May 2022). These measurements included SM content at depths of 0-70 mm, using the TR-6D device. The geographic coordinates of each sampling point were recorded using GPS to ensure accurate spatial correspondence with SAR data. This multi-temporal sampling strategy was specifically designed to capture critical seasonal transitions in the temperate monsoon climate: summer monsoon conditions (June 2021), winter monsoon conditions (December 2021), and monsoon recovery period (April-May 2022). This temporal distribution enabled comprehensive capture of seasonal variations in SM conditions across the full annual cycle (detailed methodology in Section 4.2).

The study focused on developing and validating a unified ML model for SM retrieval using multiple SAR parameters derived from Sentinel-1A data. This unified modeling approach integrates various SAR-derived parameters within a single comprehensive framework, rather than developing separate models for different conditions or seasons. Three ML algorithms - RF, SVM, and ANN - were investigated, with their performance evaluated in terms of accuracy, computational efficiency, and generalization capability. Special attention was given to cross-seasonal model performance, addressing the challenge of developing a unified retrieval approach that maintains accuracy across different temporal conditions.

The scope also included the analysis of spatial variations in SM across different land cover types through the integration of land cover classification results with SM retrievals. This comprehensive approach allowed for a better understanding of how different land covers influence SM distribution and dynamics in the study area.

1.7 Significance of Study

This research makes substantial contributions to SM monitoring and management across international, national, and local scales through its innovative integration of SAR technology and ML approaches.

At the international level, this study advances the theoretical understanding and methodological approaches in SM retrieval using remote sensing technology. The comprehensive evaluation of 24 impact factors, including various backscatter coefficients and polarimetric decomposition components, provides new insights into the relative importance of different factors in SM estimation. This knowledge contributes to the global scientific understanding of how SAR signals interact with SM under different conditions. Furthermore, the development of a unified model with cross-seasonal generalization capability addresses a significant challenge in remote sensing applications worldwide. This cross-seasonal capability enables the model to maintain stable performance across varying seasonal conditions, reducing the need for seasonal-specific model development and supporting continuous operational monitoring throughout the annual cycle. The methodology's ability to maintain accuracy across different seasonal conditions without requiring surface roughness information makes it particularly valuable for international applications in areas with similar climatic characteristics.

At the national level, this research directly supports China's major strategy for ecological protection and high-quality development of the Yellow River Basin. The improved understanding of SM dynamics in the Northwest Shandong Plain provides essential information for implementing national policies on water resource management and sustainable agricultural development. The study's findings contribute to China's efforts to enhance agricultural water use efficiency and promote sustainable farming practices, particularly in regions experiencing similar semi-humid conditions. The methodology developed here can be applied to other agricultural regions across China, supporting the nation's goals for food security and sustainable agricultural development.

At the local scale, this research has immediate practical implications for agricultural management and water resource planning in the Northwest Shandong Plain. The improved SM monitoring capabilities enable more efficient irrigation scheduling and water resource allocation at the farm level. Local agricultural managers and farmers can benefit from more accurate SM information to optimize their irrigation practices and improve crop yields. The study's findings regarding SM variations across different land cover types provide valuable guidance for local land use planning and agricultural decision-making. Furthermore, the methodology's ability to operate without requiring surface roughness measurements makes it particularly practical for local implementation, reducing the cost and complexity of SM monitoring while maintaining high accuracy.

The research also makes significant methodological contributions that span all three scales. The comparative analysis of different ML algorithms (RF, SVM, and ANN) provides valuable insights for the remote sensing community globally, while the specific applications and findings offer practical solutions for national and local water resource management. The integration of multiple SAR parameters with advanced ML techniques represents an innovative approach that can be adapted and applied at various scales, from local agricultural management to national monitoring programs and international research initiatives.

By bridging the gap between theoretical research and practical applications, this study contributes to both the scientific understanding of soil-water dynamics and the development of operational tools for agricultural and environmental management. These contributions support sustainable agricultural practices and water resource management at local, national, and international scales, particularly in regions facing similar challenges in SM monitoring and management.

1.8 Organization of Chapters

The specific chapters of this research are organized as follows.

Chapter 1: Introduction. This chapter provides an overview of the research topic, including the background, problem statements, research questions, objectives, hypotheses, scope, and significance of the study.

Chapter 2: Literature Review. This chapter presents a comprehensive review of existing literature related to SM retrieval, focusing on various techniques including ground measurements, proximal sensing, and remote sensing. It also examines the application of ML algorithms in SM estimation and presents the conceptual framework guiding this research.

Chapter 3: Methodology. The conceptual research framework of the study is mainly described, and an overview of the geographical location and natural environment of the study area, the identification and distribution status of the sampling sites, soil sample collection and moisture content determination, and Sentinel-1A data presentation and pre-processing is presented. The theories, principles, and modelling processes related to the three ML models, RF, SVM, and ANN, as well as methods for model performance assessment, such as K-fold cross-validation and evaluation metrics such as coefficient of determination and root mean square error, are also introduced.

Chapter 4: Results. This chapter presents the results of the analysis, including the in-situ measurement results, the extraction of impact factors from satellite data, the importance and correlation analysis of these factors, the construction and evaluation of SM retrieval models, and the spatial distribution of SM across different land cover types.

Chapter 5: Discussion. This chapter provides a comprehensive discussion of the findings, addressing key themes such as seasonal variations and their impact on SM retrieval, the performance and limitations of different ML models, and the significance of model cross-seasonal migration capability. It also explores the challenges associated with soil surface roughness and the advantages of using models that do not require explicit roughness information.

Chapter 6: Conclusions and Recommendations. This chapter presents the concluding remarks of the study, summarizing the key findings, highlighting the contributions of the research, and providing recommendations for future research directions.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review of the literature pertinent to SM retrieval using remote sensing technology, focusing on the integration of SAR and ML methods. The review is structured to cover the theoretical background, current methodologies, technological advancements, and the application of these techniques in different environmental settings.

2.2 Soil Moisture

SM is a critical variable that plays a vital role in the Earth's water, energy, and carbon cycles. It refers to the amount of water held in the pore spaces between soil particles and is typically expressed as volumetric or gravimetric water content (Tuller et al., 2004; Vereecken et al., 2014). The spatial and temporal dynamics of SM are influenced by various factors, including precipitation, evapotranspiration, infiltration, runoff, and soil properties. Understanding SM dynamics is crucial for numerous applications in hydrology, climatology, agriculture, and environmental management (Liu et al., 2020).

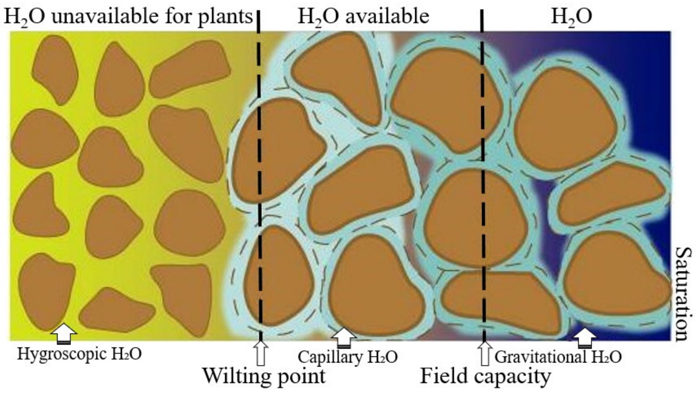

Figure 2.1 Types of soil moisture. This figure was adapted from Sanitation (2020).

When searching the Web of Science (WOS) with the keywords " soil moisture /soil water content", 105716 publications were found from January 2014 to December 2024, with an average annual publication of 9611 publications. As shown in Figure 2.2, the peak publication year was 2024 with 12753 publications, and the fastest growth rate occurred in 2018 at 15.1%, indicating rapid development in this research field. Currently, the field is in an upward trend. The top 30 countries/regions in terms of publication output in the field of SM research globally from January 2014 to December 2024 are shown in Figure 2.3. China leads with 35831 publications (33.89%), followed by the United States of America with 20101 publications (19.01%), and India with 6736 publications (6.37%), ranking second and third, respectively.

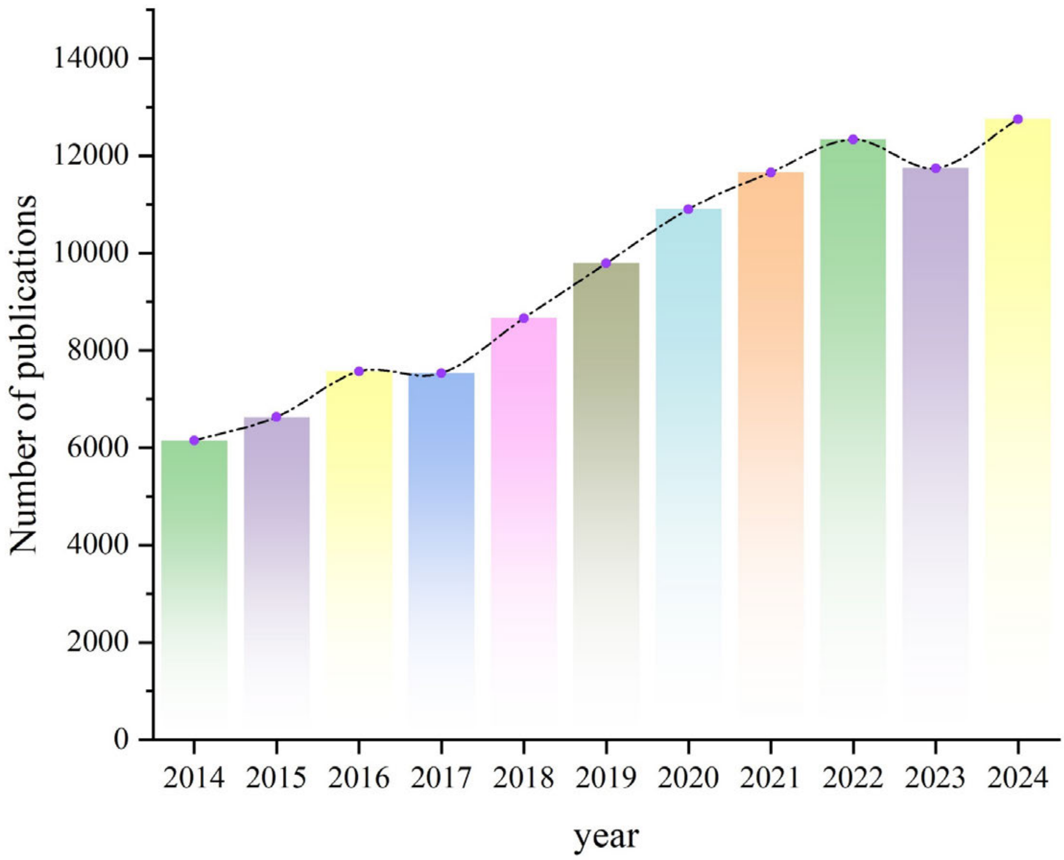

Figure 2.2 Annual publication trends of publications related to soil moisture/soil water content from January 2014 to December 2024.

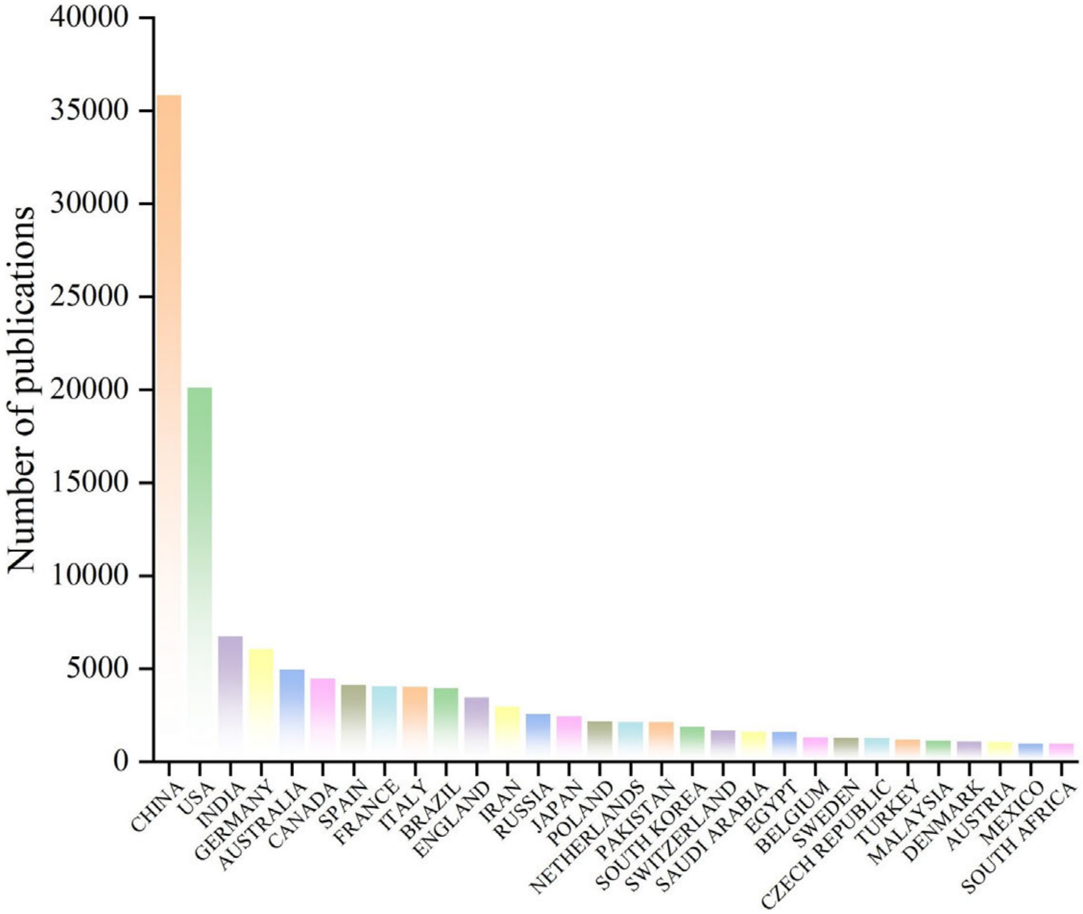

Figure 2.3 Top 30 countries in soil moisture/soil water content research.

SM is recognized as an Essential Climate Variable due to its significant impacts on weather and climate through land-atmosphere interactions (Dorigo et al., 2017). It affects the partitioning of incoming solar radiation into sensible and latent heat fluxes at the land surface, thereby influencing local and regional climate patterns. Higher SM content leads to increased evapotranspiration and latent heat flux, which has a cooling effect on surface temperatures. Conversely, dry soils result in greater sensible heat flux and warmer temperatures (Seneviratne et al., 2010). These SM-temperature feedbacks can amplify droughts and heat waves, potentially leading to more extreme weather events. Additionally, SM influences precipitation patterns by affecting atmospheric moisture content through evapotranspiration. SM-precipitation feedback can lead to the persistence of wet or dry anomalies in some regions, impacting long-term climate variability (Koster et al., 2004). The complex interactions between SM and climate highlight its importance in climate change research and the need for accurate SM monitoring at various scales.

In the hydrological context, SM is a key determinant of the partitioning of precipitation into infiltration, runoff, and evapotranspiration. It affects runoff generation and flooding potential, as saturated soils have limited additional water storage capacity, leading to increased surface runoff during rainfall events. This makes SM information crucial for flood forecasting and water resource management. Moreover, SM plays a critical role in groundwater recharge processes and the overall water balance of ecosystems. The vertical distribution of SM in the soil profile influences water movement and solute transport, impacting water quality and nutrient cycling (Vereecken et al., 2016).

From an agricultural perspective, SM is of paramount importance for crop growth and yield. It controls water availability for plant uptake and nutrient transport in the root zone. Drought stress due to SM deficits is a major cause of crop failures globally, making SM monitoring essential for agricultural risk assessment and management (Peng et al., 2021). Precise SM information can guide irrigation scheduling, helping to optimize water use efficiency in agriculture while maintaining crop productivity. Furthermore, SM affects soil temperature regimes, which influence seed germination, root development, and overall plant phenology. The relationship between SM and crop health also extends to pest and disease management, as soil water status can impact the susceptibility of crops to certain pathogens (Vereecken et al., 2014).

SM also plays a significant role in biogeochemical cycles, particularly in carbon and nitrogen dynamics. It regulates soil microbial activity and organic matter decomposition, thereby influencing soil carbon storage and greenhouse gas fluxes between land and atmosphere (Seneviratne et al., 2010). Soil water content affects the availability of oxygen in soil pores, which in turn influences microbial respiration rates and the balance between aerobic and anaerobic processes. Extreme SM conditions like flooding or drought can lead to increased emissions of methane and nitrous oxide from soils, contributing to climate change feedback. Additionally, SM impacts nitrogen mineralization and denitrification processes, affecting nutrient availability for plants and potential losses to the environment (Babaeian et al., 2019).

Divided into different spatial scales, SM measurements can range from point measurements all the way up to global scales (Miralles et al., 2010; Naeimi et al., 2009). As shown in Figure 2.4, SM can be obtained in three ways: ground measurements, proximal sensing, and remote sensing. Ground measurements and proximal sensing are limited by site distribution characteristics, surface heterogeneity, and other factors, making it difficult to monitor on a large scale (Rahimzadeh-Bajgiran et al., 2013). Remote sensing has become the most effective means of obtaining SM information on a large scale. Satellite-based SM products now provide global coverage at weekly to daily timescales, revolutionizing our ability to study SM dynamics over large areas.

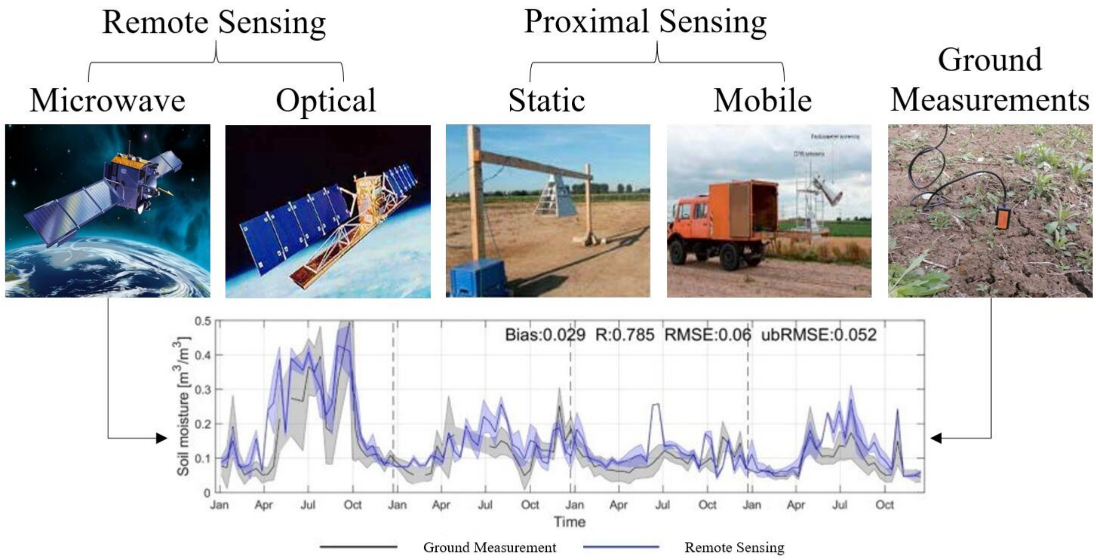

Figure 2.4 Classification of SM measurement methods. The bottom example shows the retrieval of the SM using SMAP compared to ground measurements in Yanco, Australia (Zhu et al., 2022).

2.3 Direct Soil Moisture Measurements

SM measurement techniques have evolved significantly over the past several decades, reflecting the critical importance of this parameter in hydrology, agriculture, and environmental sciences (Robinson et al., 2008). These techniques can be broadly categorized into direct and indirect methods, each with its own set of advantages and limitations.

Direct methods, primarily represented by the gravimetric technique, involve physical extraction and analysis of soil samples. The gravimetric method provides highly accurate measurements and serves as the calibration reference for other techniques (Walker et al., 2004). However, its destructive nature and inability to provide continuous measurements limit its applicability in many research scenarios.

Indirect methods infer SM content by measuring other soil properties influenced by water content. These methods have gained prominence due to their ability to provide non-destructive, rapid, and often continuous measurements. Among the indirect methods, nuclear techniques such as neutron scattering have been widely used, offering high accuracy but facing challenges related to radiation safety (Andreasen et al., 2017). Time Domain Reflectometry (TDR) has emerged as one of the most popular and reliable indirect methods. TDR utilizes the relationship between soil dielectric properties and water content to provide accurate, non-destructive measurements (Jagdhuber et al., 2019). Frequency Domain Reflectometry (FDR) operates on similar principles to TDR but uses different signal processing methods, offering a cost-effective alternative in some applications. Recent years have seen the development of innovative technologies such as Micro-Electro-Mechanical Systems (MEMS) and fiber optic sensors. These emerging techniques promise high-resolution, multi-parameter measurements with minimal soil disturbance. However, they are still overcoming challenges related to long-term field durability and calibration across diverse soil types.

The choice of SM measurement technique often depends on the specific requirements of the study, including desired accuracy, spatial and temporal resolution, soil type, and practical constraints such as cost and ease of use (Bogena et al., 2015). As research progresses, the integration of multiple measurement techniques and the development of improved calibration methods are enhancing our ability to accurately measure and understand SM dynamics across diverse environmental conditions.

Direct methods for SM measurement form the foundation of soil hydrology, providing highly accurate data through physical manipulation and analysis of soil samples. These techniques serve as the standard against which all other SM measurement methods are calibrated and validated (Klute, 1986).

The gravimetric method stands as the most widely recognized direct technique for SM determination. This approach involves extracting a soil sample, weighing it in its moist state, subjecting it to oven drying at 105°C for approximately 24 hours, and then reweighing the dried sample, as illustrated in Figure 2.5. The difference in mass before and after drying represents the water content, typically expressed as a percentage of the dry soil mass (Reynolds, 1970). Despite its unparalleled accuracy, the gravimetric method suffers from several significant drawbacks that limit its applicability in many research and practical scenarios. Its destructive nature precludes repeated measurements at the same location, potentially introducing spatial variability issues in temporal studies. The lengthy drying process, often exceeding 24 hours, renders it unsuitable for real-time monitoring applications, a critical limitation in dynamic environmental studies and precision agriculture (O'Kelly, 2004).

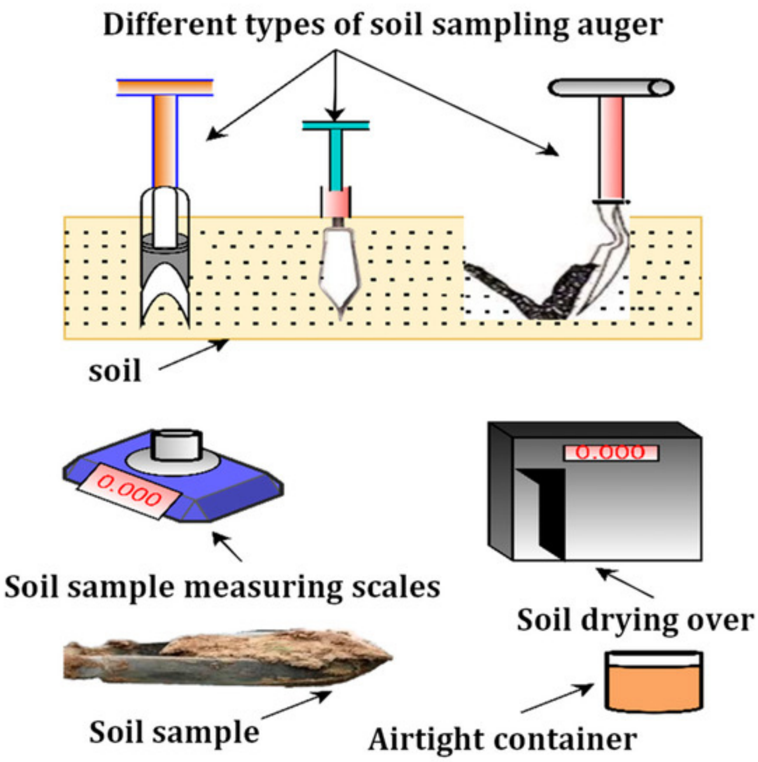

Figure 2.5 Schematic diagram illustrating moisture measurements using the Gravimetric method (Rasheed et al., 2022).

The thermo-volumetric method, an extension of the gravimetric technique, addresses the volumetric changes that occur in certain soil types with varying moisture content. This approach is particularly valuable when dealing with expansive clay soils or other materials prone to significant volume fluctuations. By measuring both the mass and volume of soil samples before and after drying, this method provides insights into soil shrinkage characteristics and bulk density changes associated with moisture variations (Abu-Hamdeh, 2003). However, like the gravimetric method, the thermo-volumetric approach is time-consuming, labor-intensive, and destructive, making it impractical for large-scale or frequent measurements.

While direct methods offer unparalleled accuracy, their limitations have spurred the development of indirect measurement techniques. These indirect methods aim to overcome the shortcomings associated with direct methods by providing non-destructive, rapid, and potentially continuous measurements of SM. Unlike direct methods, many indirect techniques allow for in-situ monitoring without disturbing the soil profile, making them ideal for studying temporal changes in SM at a fixed location. Additionally, the ability to automate data collection addresses the labor-intensive nature of direct methods, enabling high-frequency measurements over extended periods (Schmugge et al., 1980).

Nevertheless, direct methods maintain their importance as reference standards, even as new technologies emerge. They play a crucial role in calibrating and validating indirect techniques, ensuring the reliability and accuracy of SM data across various research and practical applications (Hillel, 2013). As the field of SM measurement continues to evolve, researchers are exploring ways to enhance the efficiency of direct methods, such as developing rapid drying techniques. However, for studies requiring high-frequency or continuous monitoring, indirect methods offer significant advantages over traditional direct approaches.

While direct methods provide the highest accuracy in SM measurement, their destructive nature, time-consuming process, and inability to provide continuous measurements have led to the widespread adoption of indirect techniques in many research and practical applications. The choice between direct and indirect methods often depends on the specific requirements of the study, balancing the need for accuracy with practical considerations such as measurement frequency, spatial coverage, and resource constraints.

2.4 Indirect Soil Moisture Measurements

2.4.1 Nuclear Methods

Nuclear methods for SM measurement represent a significant advancement in the field of soil hydrology, offering non-destructive and rapid assessment techniques. These methods utilize the interaction between subatomic particles or electromagnetic radiation and the hydrogen atoms in water molecules to infer SM content (Babaeian et al., 2019; Mukhlisin et al., 2021).

The neutron scattering technique, pioneered by Belcher (1950), has been widely adopted for SM measurement. This method employs a radioactive source to emit fast neutrons into the soil. These neutrons collide with hydrogen nuclei, primarily from water molecules, and are slowed down or "thermalized", as shown in Figure 2.6. The density of the resulting cloud of slow neutrons is proportional to the soil's water content (Visvalingam & Tandy, 1972). While highly accurate and capable of measuring large soil volumes, the neutron probe method has limitations. The use of radioactive materials poses safety concerns and requires strict regulatory compliance. Additionally, the sphere of influence varies with SM, complicating near-surface measurements (Chanasyk & Naeth, 1996).

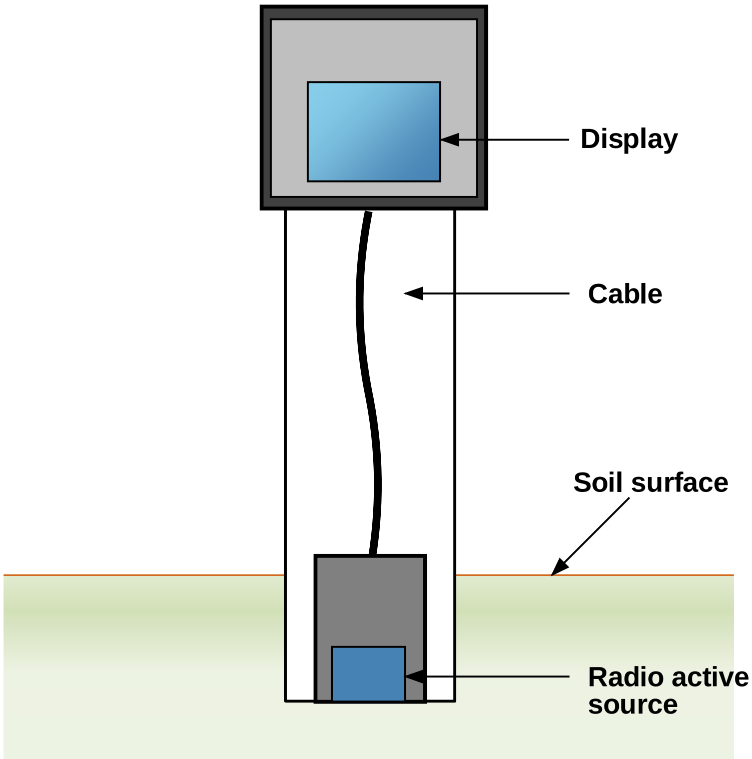

Figure 2.6 Schematic diagram showing moisture measurements using the Neutron scattering method. This figure was adapted from Su et al. (2014).

Gamma-ray attenuation, another nuclear technique, measures SM by quantifying the attenuation of gamma rays as they pass through the soil, as depicted in Figure 2.7. This method, first applied to SM measurement by Gurr (1962) and Gardner and Kirkham (1952), is based on the principle that water attenuates gamma radiation differently than soil particles. The gamma-ray technique offers high precision and can provide detailed SM profiles. However, it is limited by the need for specialized equipment and careful calibration to account for variations in soil density and composition (Mukhlisin et al., 2021).

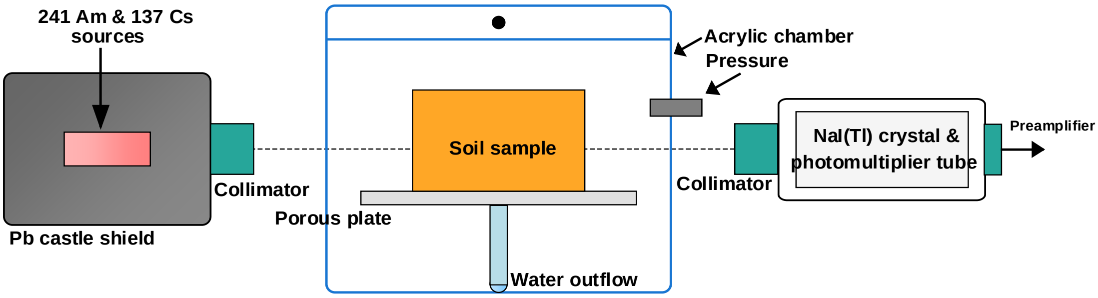

Figure 2.7 Schematic diagram depicting moisture measurements using the Gamma attenuation method. This figure was adapted from Rasheed et al. (2022).

Nuclear Magnetic Resonance (NMR) has emerged as a powerful tool for SM measurement, particularly in laboratory settings. This technique exploits the magnetic properties of hydrogen nuclei to directly measure water content in soils. NMR offers the advantage of distinguishing between different types of water in the soil matrix, such as bound water and free water (Prebble & Currie, 1970). While NMR provides detailed information about soil water dynamics, its application in field settings is limited due to equipment complexity and cost (Babaeian et al., 2019).

More recently, Cosmic Ray Neutron Sensing (CRNS) has been developed as a novel nuclear method for SM measurement. This technique utilizes naturally occurring cosmic-ray neutrons to estimate SM over large areas (hectare scale). CRNS offers the advantage of non-invasive measurement and can provide area-averaged SM estimates, bridging the gap between point measurements and remote sensing techniques (Zreda et al., 2008).

Despite their advantages, nuclear methods face challenges in widespread adoption. Safety concerns associated with radioactive sources, the need for specialized training, and high initial equipment costs can limit their use. Additionally, the influence of soil chemical composition, particularly the presence of elements with high neutron absorption cross-sections, can affect measurement accuracy and requires careful calibration (Mukhlisin et al., 2021).