# Earth Observation Big Data for Soil Moisture Estimation Techniques in Precision Viticulture

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**Abstract.** Grapevine cultivation is one of the most relevant economic drivers of the Mediterranean basin, benefiting from favorable climate conditions, characterized by dry summers and wet winters. However, climate change poses new challenges that must be addressed and, thus, traditional farming expertise is no longer sufficient to ensure optimal wine productivity and quality. Among the key factors influencing grapevines, soil moisture plays a crucial role since it affects plant health, grape composition, and overall wine quality. Optimizing water management through advanced monitoring techniques is therefore essential for enhancing vineyard sustainability. The geomatic techniques, leveraging geospatial big data and information and communications technology, have emerged as powerful tools for monitoring vineyard health and optimizing wine productivity, quality, and sustainability. This paper presents the latest technological advancements in vineyard monitoring for soil moisture assessment, providing a comprehensive analysis of their strengths and weaknesses. The research methodology is structured into two key sections: the former focuses on monitoring technologies, while the latter describes the effectiveness and efficiency of these approaches, with particulat emphasis on machine learning applications and data fusion strategies to improve accuracy and decision-making in vineyard management. Up to now, most approaches have prioritized data acquisition and dissemination, leaving their full potential underexplored. This study outlines that integrating advanced earth observation techniques can lead to more data-driven, efficient, and sustainable viticulture.

**Keywords:** Precision Viticulture · Geomatics Techniques · Geospatial Big Data

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## 1 Introduction

Grapevine cultivation is widespread worldwide [1] and represents one of the most significant economic drivers, particularly in the Mediterranean Basin [2]. It is estimated that approximately 7.2 million hectares of land worldwide are dedicated to vineyards, with wine production reaching around 237 million hectoliters in 2023 [3, 4]. Thanks to their remarkable adaptability, grapevines can be cultivated in a wide range of environmental conditions. However, their quality and yield are influenced by a complex system of factors, including climate, soil, geography, variety, and terroir [5]. Among these, soil moisture and temperature are essential to optimizing the vineyard management system. Indeed, excessive water can stimulate plant growth and increase yield while, simultaneously, compromising quality by altering sugar content and acidity [6]. As a result, improving irrigation systems to optimize water efficiently and prevent the spread of plant diseases is essential [6]. Similarly, temperature significantly affects grape maturation and its sugar accumulation, consequently impacting the alcoholic content of the produced wine [5].

The Mediterranean climate provides an optimal substratum for enhancing grapevine quality, as its reproductive cycle is closely linked to temperature and water availability. Although weather patterns vary across the Mediterranean regions, the typical Mediterranean climate, characterized by wet winters and dry summers, favors grape maturation, enhancing both quality and yield [7, 8]. As a result, European countries, including Italy, Spain, and France, have long been recognized as leading contributors to this sector, benefiting from favorable climatic conditions. However, this privileged position is expected to change rapidly in the coming years due to climate change, as highlighted by the Intergovernmental Panel on Climate Change (IPCC) [9]. To address this challenge, the development of advanced monitoring approaches is essential for assessing vineyard conditions in real time in response to these evolving environmental challenges [10, 11].

Precision Agriculture (PA) has emerged as a transformative approach, encompassing a wide range of techniques and technologies for collecting both quantitative and qualitative data at field and sub-field scales, enabling precise estimation of crop parameters [12]. Recognized as one of the top ten developments in modern agriculture, PA allows farmers to "do the right thing, in the right place, at the right time" [13]. Although this discipline emerged in the mid-1980s, it has only recently begun to reach its full potential, driven by technological advancements that allow for precise, localized interventions. Unlike conventional agriculture, which assumes spatial homogeneity across fields, PA acknowledges intra-field variability and promotes tailored strategies that extend beyond traditional farmer expertise [14]. In such a way, the resulting management strategies optimize the use of site-specific resources, enhance product quality and yields, reduce environmental impacts, promote sustainability, improve plant health, and save costs while increasing benefits [15].

This process consists of three main steps: i) data collection through advanced geomatic techniques and sensors; ii) data manipulation and interpretation from an agronomic perspective; and, lastly, iii) execution of manual and/or automatic actions to preserve, correct, and mitigate potential issues. Data collection relies on various advanced technologies, including the Global Navigation Satellite System (GNSS)-based sensors for glocalization, proximal and remote sensors for extracting plant and soil parameters, and,

lastly, wireless sensor networks for monitoring plant health and resource needs [16, 17]. These techniques are often used in combination to overcome individual limitations and enhance data accuracy and effectiveness [18]. This integrated approach supports targeted, effective decision-making for vineyard management. Data manipulation and interpretation are typically performed using specialized software designed to manage spatial data, with Geographic Information Systems (GIS) providing an optimal platform for this purpose. Finally, management strategies are implemented manually and/or automatically through the use of Variable Rate Technologies (VRT)/Variable Rate Application (VRA) machines. These tools are designed to optimize input rates of pesticides, fertilizers, etc., based on site-specific requirements.

When PA is implemented in viticulture, the discipline is tagged as Precision Viticulture (PV). Despite the significant socio-economic interest in this sector, PV only gained traction in the mid-2000s, primarily due to challenges in vineyard feature extraction. Grapevines are organized in rows with discontinuous canopies, requiring high-resolution images to distinguish the vineyard from the background and extract plants' biophysical and biochemical traits [19]. Additionally, until now, PV has not been focused on site-specific applications but rather on detecting features that are relatively homogeneous within a field. This information is usually generated using multi/hyperspectral [20] and thermal imagery [21], along with geolocated data [22], and integrating some of these [23].

Multiple approaches could be adopted to produce such data. Spectral indices, based on the mathematical combination of spectral bands, enable rapid classification of large areas and provide insights into plant physiology [24, 25]. However, although some indices have also been shown to be effective in indirectly determining water status [26, 27], their accuracy remains unsatisfactory [27]. As a result, Machine Learning (ML) approaches offer a viable solution to overcome these limits.

Given the pivotal role of soil moisture in vineyard management, this study aims to evaluate a range of estimation methodologies through an extensive and critical literature review. The objective is to identify the most effective approaches for supporting precision viticulture, with the ultimate goal of optimizing water use and improving vineyard management practices.

This paper is structured as follows: Sect. 2 reports the methodology adopted to extract the main information concerning soil moisture data from the literature. On the contrary, Sect. 3 explores the relevance of soil moisture parameters in vineyard management, reviews methodologies for their measurements and estimation, and highlights the strengths and weaknesses of each. Finally, Sect. 4 reports the main conclusion and future research directions.

## 2 Material and Methods

### 2.1 Meta-analysis of Literature

To ensure a rigorous and transparent evaluation of the existing scientific literature, this study employed a systematic review methodology inspired by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Fig. 1) [28]. This structured approach facilitated the identification, screening, and selection of relevant

research focused on the application of geomatics technologies in viticulture for assessing surface soil moisture. The objective was to synthesize key advancements and highlight existing knowledge gaps pertinent to vineyard water status monitoring and sustainable management.

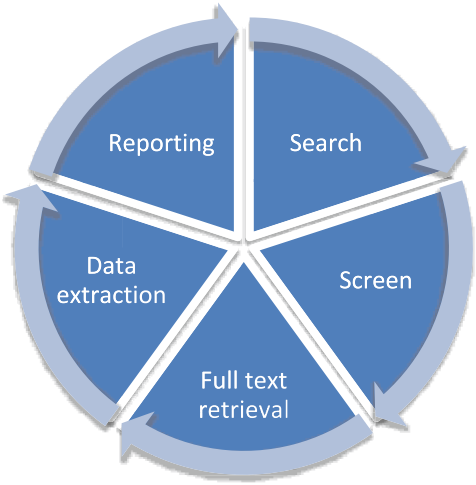


**Fig. 1.** Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology adopted for the literature review.

The first step of the PRISMA approach involved a comprehensive search across leading academic databases, including Web of Science (WoS), Scopus, and Google Scholar, targeting publications released between 2000 and 2025. The search strategy employed a combination of relevant keywords and Boolean operators to refine the query, ensuring the retrieval of studies that aligned with the research focus. The primary keywords included: i) "Geomatics in viticulture", ii) "Precision agriculture", iii) "Grapevine water status monitoring", iv) "Surface soil moisture in viticulture", v) "Vineyard sustainability", and vi) "Earth Observation for assessing vineyard water status". Additional terms were included to account for emerging technological advancements, such as "machine learning", "microwave techniques", and "data fusion in precision viticulture". Filters were applied to limit the search to English-language articles and studies explicitly focused on geomatic approaches to vineyard water status analysis.

The screening process followed a two-step approach to refine the dataset. First, an initial screening was conducted by reviewing paper titles, keywords, and abstracts to exclude studies not directly related to viticulture or the application of geomatic technologies. Articles focusing on non-grapevine crops or non-geomatic methodologies were systematically removed. In the second step, the remaining articles underwent an in-depth assessment to evaluate their methodological rigor and relevance to vineyard water status assessment and monitoring. The inclusion criteria required studies to: i) investigate geomatic technologies in vineyard monitoring, such as vine vigor mapping or water stress detection; ii) focus on Mediterranean vineyards or regions with comparable climatic

conditions; and iii) provide insights applicable to sustainable vineyard management and the development of advanced geospatial methodologies.

A total of 312 articles were selected and systematically analyzed to extract key findings relevant to the study objectives. The analysis emphasized methodologies such as spectral analysis, geospatial modeling, and machine learning-based extraction techniques.

## 3 Results and Discussion

### 3.1 EO-Based Approaches

Soil moisture monitoring is essential for balancing the grapevine reproductive cycle, as it regulates plant growth and pigment concentration [5]. This phenomenon influences several key factors, including evaporation, transpiration, biodiversity, and rainfall runoff, all of which affect ecosystem health. Specifically, excessive water levels can reduce grapevine quality by influencing sugar content and acidity [6], making the plants more susceptible to winter damage and diseases [6]. Conversely, water deficits may hinder proper plant growth, significantly lowering productivity and acidity while increasing sugar content [6]. Therefore, establishing an effective smart water management strategy is essential for improving grapevine quality and yield.

Traditionally, soil moisture has been measured using ground-based techniques, which offer several advantages, such as equipment portability, ease of installation, straightforward operation and maintenance, and methodological stability [30, 31]. However, these methods are not limitation-free. They tend to be expensive, often lack accuracy, and are difficult to scale due to their reliance on localized sensor data, which must be interpolated to obtain a broader spatial representation [32].

Thus, to go beyond these constraints, alternative methods have been developed to estimate soil moisture at various spatial and temporal scales [33]. Among them, EO-based approaches are currently recognized as the most efficient and cost-effective methods of assessing soil moisture variability within a field [34]. Instead of providing direct measurements, these methods estimate soil moisture by using spectral bands as input for physical and semi-empirical models, combined with inversion algorithms. Various algorithms have been developed for this purpose, each with own strengths and weaknesses [35]. Indeed, the first studies in soil moisture remote sensing started in the mid-1970s, just a few years after the introduction of satellite remote sensing. Over time, however, different parts of the electromagnetic spectrum, ranging from the optical to the microwave region, have been exploited. Previous studies have demonstrated the potential of near-infrared and thermal bands, as well as active and passive microwave remote sensing techniques [36], although the relationship between soil moisture content and sensor response varies depending on the spectral region. The benefits and constraints of each method are reported in Table 1.

**Optical Remote Sensing**

The potential of optical remote sensing has been explored since the early 20th century, albeit initial results were relatively coarse. In 1925, Angstrom observed an inverse relationship between reflectance and soil moisture content [37]. Later, Bowers and Smith [38]

**Table 1.** Advantages and challenges of EO-based approaches adopted for estimating soil moisture.

| Spectral Domain | Key Observations | Advantages | Challenges |
|---|---|---|---|
| *Optical* | Surface reflectance | High spatial resolution, wide coverage | Limited penetration depth, affected by cloud cover and atmospheric noise |
| *Thermal infrared* | Surface temperature | Good spatial resolution, well-established methodology | Shallow penetration, influenced by meteorological conditions and vegetation |
| *Passive microwave* | Emitted radiation, dielectric properties | Less atmospheric interference, moderate soil penetration | Low spatial resolution, sensitive to surface roughness and vegetation cover |
| *Active microwave* | Backscatter signal, dielectric properties | High spatial resolution, moderate soil penetration, minimal atmospheric effects | Narrow imaging swath, influenced by surface roughness and vegetation density |

established a linear relationship between water absorption bands and soil water content, while Dalal and Henry [39] used near-infrared absorbance values to estimate moisture levels. However, despite their potential, these approaches have proven inadequate for accurately assessing soil moisture, mainly due to optical bands' limited penetration depth and high sensitivity to atmospheric disturbances [40].

Recently, innovative spectral indices, derived from the mathematical integration of specific bands, have been introduced to estimate soil moisture. Although index-based approaches have been widely employed for land classification and biomass estimation, their application in viticulture remains limited. In fact, these indices have been used only nine times to assess and/or monitor water content in vine leaves [41]. Specifically, Normalized Difference Water Index (NDWI) [42], Global Vegetation Moisture Index (GVMI) [43], Moisture Stress Index (MSI) [43], and Shortwave Infrared Water Stress Index (SIWSI) [44]. The equations for these indices are summarized in Table 2. All of them rely on Near-Infrared (NIR) and Shortwave Infrared (SWIR) bands, as these are highly sensitive to water content, whereas Red, Green, and Blue (RGB) bands are ineffective for this purpose.

Previous studies have demonstrated the significant potential of spectral indices for estimating water content, although their accuracy ranges between 0.5 and 0.8. More sophisticated algorithms have been tested to improve the index-based method's performance.

**Table 2.** Summary of indices adopted to estimate water content.

| Index | Equation | Equation number |
|---|---|---|
| *Normalized Difference Water Index (NDWI)* | $\frac{NIR-SWIR_2}{NIR+SWIR_2}$ | (1) |
| *Global Vegetation Moisture Index (GVMI)* | $\frac{(NIR+0.1)-(SWIR+0.02)}{(NIR+0.1)+(SWIR+0.02)}$ | (2) |
| *Moisture Stress Index (MSI)* | $\frac{SWIR}{NIR}$ | (3) |
| *Shortwave Infrared Water Stress Index (SIWSI)* | $\frac{NIR-SWIR_1}{NIR+SWIR_1}$ | (4) |

**Thermal Infrared Remote Sensing**

Thermal infrared imagery can be used to estimate soil surface moisture either individually, as in the thermal inertia method, or in combination with other indices, as proposed by the thermal infrared index approach. The thermal inertia method, which is physically based, provides accurate soil moisture estimation; however, its reliability decreases in densely vegetated areas [45]. In this method, volumetric soil moisture ($W_s$) is calculated using the following equation:

$$W_s = a_0 * ATI + \alpha_1. \tag{5}$$

where $\alpha_0$ and $\alpha_1$ are the empirical parameter and ATI represents the Apparent Thermal Inertia, calculated as:

$$ATI = \frac{1-\alpha}{\Delta T}. \tag{6}$$

In this equation, ΔT denotes the diurnal temperature range, while α represents the surface albedo. ATI serves as an approximate measure of thermal inertia, which describes a material's ability to resist temperature fluctuations [46].

An alternative approach estimates $W_s$ based on its relationship with the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) within a given area. This method, commonly referred to as the "Universal Triangle," is expressed as follows:

$$W_s = \sum_{i=0}^{n}\sum_{j=0}^{n} a_{ij} * NDVI^* * T^*. \tag{7}$$

where $\alpha_{ij}$ are the regression coefficients while $T^*$ and $NDVI^*$ are the scaled LST and NDVI, respectively. These scaled values are computed as:

$$T^* = \frac{T - T_0}{T_s - T_0}. \tag{6}$$

$$NDVI^* = \frac{NDVI - NDVI_0}{NDVI_s - NDVI_0}. \tag{7}$$

where the subscripts 0 and s indicate the minimum and maximum values, respectively.

Due to the strong theoretical foundation and effectiveness of this approach, various modifications have been introduced over time, including Temperature-Vegetation conteXtual approach (TVX) [47], TemperatureVegetation Dryness Index (TVDI) [48], moisture index [49], and the VI/Trad relation [50].

**Microwave Remote Sensing**

Microwave remote sensing provides a direct method to measure soil moisture across the microwave band (0.5–100 cm), distinguishing itself from the other techniques discussed previously. In this portion of the electromagnetic spectrum, the atmosphere remains almost completely transparent, and the significant difference in dielectric properties, approximately 80 for water versus less than 4 for soil particles, greatly facilitates the retrieval of soil moisture data [51].

Depending on the sensor type and its operating mode, microwave remote sensing is classified into two main categories: active and passive. Active systems, such as Synthetic Aperture Radars (SAR), function by emitting microwave pulses and recording the energy that bounces back from the Earth's surface, whereas passive systems, like radiometers, measure the natural microwave emissions originating from the surface.

Microwave signals in the L-band (1–2 GHz), often termed the "water frequency channel," are particularly sensitive to moisture in the upper 5 cm of the soil and can effectively penetrate low to moderately dense vegetation covers [52]. In contrast, higher frequency bands, namely the C-band (4–8 GHz) and X-band (8–12.5 GHz), are responsive to very shallow soil layers and can only pass through sparse vegetation [53]. At the lower end of the spectrum, the P-band (<1 GHz) offers deeper soil penetration, making it particularly valuable for subsurface moisture estimation and biomass monitoring. However, its use is limited by Radio Frequency Interference (RFI) and stringent regulatory constraints.

Over recent decades, specialized inversion algorithms have been developed to estimate surface soil moisture, each tailored to specific frequencies, measurement principles, and the characteristics of various microwave sensors aboard satellites. This focused research effort has led to the development of a range of EO microwave soil moisture products, spanning from 1978 to the present.

Five quasi-operational satellite soil moisture products are currently available in Near Real-Time (NRT) or within a few days of acquisition:

- Soil Moisture and Ocean Salinity (SMOS), an Earth Explorer mission operational since January 2010, is expected to conclude by the end of 2025. It provides free, open-access data with a 35 km resolution [54];
- Advanced Microwave Scanning Radiometer 2 (AMSR2), aboard the Global Change Observation Mission for Water (GCOM-W), active since July 2012 and set to operate until late 2026. Its products offer a 10 km resolution [55];
- BEC L4, a soil moisture dataset derived from SMOS and refined using high-resolution MODIS (Aqua/Terra) data, has been in operation since January 2010. It currently provides 1 km resolution NRT soil moisture maps over the Iberian Peninsula [56];
- Sentinel-1 C-band Synthetic Aperture Radar Ground Range Detected (SAR GRD), launched in 2014 under the European Space Agency's Copernicus Program, delivers 10 m resolution images with a temporal revisit cycle of 6–12 days [57];

- NASA-ISRO SAR (NISAR), jointly developed by NASA and ISRO and launched in 2023, provides 7 m resolution data. Its L- and S-band capabilities enable precise global monitoring of above-ground biomass, which is particularly useful for vineyard health assessment and productivity analysis [58].

While these products enable large-scale soil moisture monitoring, their spatial resolution remains insufficient for field-scale applications in viticulture. To overcome these limitations, upcoming satellite missions, such as ESA Biomass, ROSE-L, HARMONY, TanDEM-L, ALOS-4, and Sentinel-1 C/D, will introduce improvements in spatial resolution, revisit frequency, and wavelength range. These advancements will enable more accurate and frequent moisture assessments, improving applications in environmental monitoring, precision agriculture, and hydrology. Further details on these missions are provided in Table 3.

**Table 3.** Summary of the main characteristics of new microwave missions.

| Satellite Missions | Agency | Launch Date | Band | Frequency (GHz) | Revisit period (days) |
|---|---|---|---|---|---|
| *ALOS-4* | JAXA | 1st July 2024 | L | 1.26 | 14 |
| *Sentinel-1C* | ESA | 5th December 2024 | C | 5.41 | 12 |
| *Biomass* | ESA | 2025 (planned) | P | 0.44 | 25 |
| *Sentinel-1D* | ESA | 2025 (planned) | C | 5.41 | 12 |
| *TanDEM-L* | DLR | 2028 (planned) | L | 1.27 | 16 |
| *ROSE-L* | ESA | 2028 (planned) | L | 1.26 | 6 |
| *Harmony* | ESA | 2029 (planned) | C | passive | 12 |
| *Sentinel-1 NG* | ESA | 2032 (planned) | C | 5.41 | <6 |

Due to the limitations discussed above, these products have had limited application in vineyards, particularly for soil moisture estimation. In 2014, Ballester-Berman et al. [59] evaluated three different approaches for estimating soil moisture in vineyards using RADARSAT-2 polarimetric data and ground measurements: a two-component model, a classical three-component model enhanced with a physically constrained volume power, and a modified version of the latter incorporating the Integral Equation Model (IEM). While all three models yielded promising results, the IEM approach proved to be the most accurate.

Similarly, the C-SSM soil moisture product, derived from Sentinel-1 data and provided by the Copernicus Global Land Service for Europe at a 1 km resolution, demonstrated good performance. However, Bazzi et al. [60] found that it tends to overestimate soil moisture in forested and vineyard areas.

Other studies have explored the fusion of microwave data with optical remote sensing and terrain information to enhance soil moisture estimation. Further details on data fusion techniques using microwave data are discussed in the following section.

**Data Fusion**

To address the limitations of individual methodologies and enhance the accuracy of soil moisture estimation, several studies have explored the integration of multiple geomatics techniques [61]. This multidisciplinary approach is essential for improving water resource management and optimizing irrigation strategies in viticulture.

Thus, Lei et al. [62] investigated the fusion of high-resolution thermal infrared (TIR) data and Sentinel-1 SAR imagery within a soil–vegetation–atmosphere transfer (SVAT) model to refine soil moisture estimates in vineyards. Their study, based on a two-component polarimetric model using C-band radar data, demonstrated the potential of remote sensing and data assimilation techniques in monitoring evapotranspiration and soil moisture dynamics.

Similarly, Mendes et al. [63] analyzed the combined use of Sentinel-1 and Sentinel-2 data along with terrain parameters to identify low soil moisture areas in a drip-irrigated vineyard affected by agricultural drought. Their findings highlighted the cost-effectiveness of remote sensing for soil moisture monitoring and its ability to predict regions at risk of salinization, an issue that is expected to worsen with climate change. The study also emphasized the advantages of multi-sensor approaches, as different wavelengths exhibit varying sensitivities to environmental parameters, thereby improving the reliability of assessments. Conversely, Efremova et al. [64] explored the application of Sentinel-1 and Sentinel-2 Earth observation data for soil moisture prediction in vineyards using a cycle-consistent adversarial network (CycleGAN). They compared the performance of multiple ML algorithms, including linear regression, random forest, support vector regression, and neural networks. Among these, the random forest model yielded the most accurate results, while linear regression suffered from significant overfitting. Additionally, the study evaluated CycleGAN's effectiveness in translating imagery between Sentinel-1 and Sentinel-2, finding that, while the model could extract features from different spectral domains, its translation accuracy remained imperfect.

The Vineyard Data Assimilation (VIDA) system integrates remote sensing data with a soil water balance model to support vineyard irrigation decisions, demonstrating its ability to capture daily variations in soil moisture [65]. Effective soil moisture monitoring is crucial for optimizing irrigation strategies, including deficit irrigation. Technologies such as SAR and thermal-infrared sensing enable high-resolution soil moisture assessment. While VIDA has shown promise in improving irrigation efficiency, challenges remain, particularly in correcting biases in irrigation input data and accurately representing subsurface water flow processes.

### 3.2 Challenges in Soil Moisture Estimation in Vineyards Ecosystem

Accurately estimating soil moisture in vineyards using EO data presents several challenges, primarily due to the spatial and temporal resolution of currently available products. Soil moisture dynamics in viticultural environments occur at a fine scale, influenced by factors such as soil texture, vineyard management practices, and microclimatic variability [51]. However, EO-derived products often lack the necessary resolution to capture these variations effectively, limiting their applicability for irrigation management and hydrological modeling at the vineyard scale [51].

Another critical limitation is the penetration depth of EO signals, which affects the ability to retrieve soil moisture beyond the surface layer. Optical and infrared sensors, as well as certain microwave wavelengths, provide information only on the uppermost soil layer, resulting in an incomplete representation of soil moisture profiles. This is particularly problematic for vineyard applications, where deeper soil moisture measurements are essential for assessing irrigation needs. Moreover, the dense vine canopy during the growing season can introduce significant errors in soil moisture estimation, necessitating correction models that account for vegetation effects on soil reflectance and emissivity. Recent studies using L-band data have shown promising results in integrating soil moisture retrieval with vegetation index estimation [56].

Data acquisition conditions further complicate soil moisture estimation. Optical and thermal methods are ineffective under cloudy conditions, while microwave observations, although capable of providing all-weather measurements, are susceptible to Radio Frequency Interference (RFI), which can degrade data quality [66]. Additionally, the heterogeneous nature of vineyard parcels, often featuring alternating rows of bare soil, vegetation cover, or mulching, leads to significant spectral variability that can affect soil moisture retrieval accuracy. The presence of free-standing water within the sensor's footprint, particularly after heavy rainfall, can further distort measurements [66, 67].

Another major challenge is the frequency of data acquisition. Current microwave sensors operating in polar orbits provide observations only at specific times of the day, typically at dawn and dusk, limiting their usefulness for applications requiring sub-daily soil moisture monitoring [68]. A potential solution to this limitation could be the deployment of geostationary microwave sensors or the integration of polar-orbiting microwave data with geostationary optical and thermal observations [56].

Uncertainty in soil moisture estimates directly impacts irrigation management in vineyards, highlighting the need for a comprehensive characterization of errors associated with operational products. To enhance reliability and practical usability, increased validation efforts are required across different soil, climate, and vegetation conditions [29]. Incorporating sensitivity analyses into data verification processes could also help refine retrieval methodologies and reduce measurement uncertainties [69].

## 4 Conclusion

Soil moisture plays a fundamental role in vineyard management, directly influencing grapevine growth, yield, and quality. The precise assessment of soil moisture levels is essential for optimizing irrigation strategies, mitigating the risks of water stress, and ensuring sustainable viticulture practices. Traditional ground-based methods, while effective at local scales, present limitations in terms of spatial coverage, scalability, and cost. Consequently, Earth Observation-based approaches have emerged as a powerful alternative, enabling large-scale monitoring of soil moisture variability with enhanced efficiency and cost-effectiveness.

Among EO techniques, optical, thermal infrared, and microwave remote sensing methods have been widely investigated for their potential in soil moisture estimation. Optical and thermal sensors provide high spatial resolution and well-established methodologies but suffer from limitations such as shallow penetration depth and sensitivity to

atmospheric conditions. Conversely, microwave techniques, both active and passive, offer greater penetration capabilities and reduced atmospheric interference, but often face challenges related to spatial resolution and surface roughness effects.

Recent advancements in remote sensing technology, including the development of spectral indices and machine learning algorithms, have significantly improved the accuracy of soil moisture estimation. While spectral indices provide a straightforward means of assessing water content, their application in viticulture remains limited. In contrast, machine learning approaches offer promising results by integrating multi-source data and capturing complex relationships between spectral signatures and soil moisture levels.

Despite the progress made, further research is needed to refine EO-based methodologies for vineyard-specific applications. Future studies should focus on integrating multiple remote sensing techniques, leveraging data fusion approaches, and improving algorithm robustness to enhance predictive accuracy. Additionally, the development of real-time monitoring systems and decision-support tools will be crucial for translating research findings into actionable vineyard management strategies.

Ultimately, the implementation of EO-based soil moisture assessment within the framework of precision viticulture represents a transformative step toward sustainable, resource-efficient, and climate-resilient grape production. By embracing these innovative technologies, vineyard managers can optimize water use, improve grape quality, and better adapt to the evolving challenges posed by climate change.

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