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Investigation of tempospatial variability of soil moisture in Ås, Norway

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Abstract

Accurate measurements of soil moisture are necessary for predicting weather patterns, mitigating floods and droughts, estimating precipitation and evapotranspiration, and calculating energy fluxes between the biosphere and the atmosphere. However, soil moisture variability is influenced by environmental conditions such as precipitation, soil properties, topography, temperature and vegetation cover. As part of the Hydrometeorology to Operations (H2O) project by the Norwegian Meteorological Institute, this study aims to investigate the temporal and spatial variability of soil moisture at Søråsfeltet in Ås, and to compare the effectiveness of satellite measurements to ground-based sensors.

Both ground-based and remote sensing methods were used to measure soil moisture, including the GroPoint Profile (SMIoT), SoilVUE10, COsmic-ray Soil Moisture Observing System (COSMOS), ThetaProbe ML2 (ADR), in addition to manual samples using the volumetric method, as well as data from the Sentinel-1 satellite. The data was collected from January to December 2022 at three locations in Ås with Søråsjordet as the main focus area.

The results showed significant temporal and vertical spatial variability of soil moisture. While ground-based sensors responded well to precipitation and provided reasonable soil moisture ranges, measurements from the Sentinel-1 satellite did not capture the same variability and its usage is not recommended. The ground truth data lies between the measurements of COSMOS and SoilVUE sensors, suggesting they provide a more accurate representation of surface soil moisture than the SMIoT sensors. However, the SoilVUE sensor experienced a malfunction or data transfer issue, resulting in incorrect data for soil moisture at depths of 10 and 50 cm.

The shallow soil moisture layers of the SMIoT and SoilVUE sensors exhibited more significant fluctuations than the deeper layers, consistent with the faster response of shallow soil layers to meteorological events. The overall trend suggests lower vertical and horizontal spatial variability when the soil is close to or at its saturation point.

The SoilVUE sensor consistently reported lower values than other in-situ sensors, but it showed an overestimation during heavy precipitation. A likely reason is poor contact with the soil due to the hysteresis effect of the soil's expansion/contraction characteristics, which resulted in air gaps after several wetting and drying cycles. This led to preferential flow during precipitation and poor soil contact during dry periods.

This study made several specific contributions to the understanding of soil moisture measurement in Ås: first, it compared various soil moisture sensors; second, it identified malfunctions in the SoilVUE sensor at Søråsfeltet; third, it contributed to the verification process for relocating a SMIoT sensor by discovering a drainage pipe that was affecting measurements in its original location; and fourth, it determined that satellite measurements are not appropriate for this region.

Sammendrag

Nøyaktige målinger av jordfuktighet er nødvendige for å predikere vær, forutsi flom- og tørkeperioder, estimere nedbør og evapotranspirasjon, og beregne energistrømmen mellom biosfæren og atmosfæren. Imidlertid påvirkes variasjonen i jordfuktighet av eksterne faktorer som temperatur, nedbør, vegetasjon, jordens egenskaper og topografi. Som en del av prosjektet "Hydrometeorology to Operations (H2O)" ledet av Meteorologisk Institutt, er målet med denne oppgaven å undersøke hvordan jordfuktighet varierer over tid og rom på Søråsfeltet i Ås, og å sammenligne nøyaktigheten av satellittmålinger med bakkebaserte sensorer.

For å måle jordfuktighet ble både bakkebaserte og fjernmålingsmetoder brukt, og måleinstrumentene som ble brukt var GroPoint Profile (SMIoT), SoilVUE10, COSmic-ray Soil Moisture Observing System (COSMOS), ThetaProbe ML2 (ADR), i tillegg til manuelle jordfuktighetsprøver og satellittdata fra Sentinel-1. Dataene ble samlet inn fra januar til desember 2022 på tre steder i Ås, med Søråsjordet som hovedområde.

Resultatene viste betydelig tidsmessig og vertikal romlig variasjon av jordfuktighet. Mens bakkebaserte sensorer responderte godt på nedbør og ga rimelige jordfuktighetsverdier, klarte ikke målingene fra Sentinel-1-satellitten å fange opp samme variasjon og bruken av satellittmålinger anbefales dermed ikke. De faktiske jordfuktighetsdataene ligger mellom målingene fra COSMOS- og SoilVUE-sensorene, noe som antyder at de gir en mer nøyaktig representasjon av overflatejordfuktighet enn SMIoT-sensorene. Imidlertid opplevde SoilVUE-sensoren en systematisk målefeil eller problem med dataoverføring, noe som resulterte i feil data for jordfuktighet på 10 og 50 cm dybde.

De grunneste jordfuktighetslagene viste større variasjon i jordfuktighet enn de dypere lagene, noe som samsvarer med den generelt raskere responsen av grunne jordlag på meteorologiske hendelser. Den overordnede trenden antydet lavere vertikal og horisontal romlig variasjon av jordfuktighet når jorda var nær eller på metningspunktet.

SoilVUE-sensoren rapporterte konsekvent lavere verdier enn andre in-situ-sensorer, men viste en overestimering under kraftig nedbør. En mulig årsak er jordas hystereseeffekt, der gjentakende sykluser med utvidelse og sammentrekning resulterte i dannelse av luftlommer. Dette førte til preferensiell strømning under kraftig nedbør og dårlig kontakt med jorda under tørre perioder.

Denne masteroppgaven har på flere måter bidratt til økt forståelse av måling av jordfuktighet i Ås: for det første sammenlignet den ulike jordfuktsensorer; for det andre identifiserte den feil på SoilVUE-sensoren på Søråsfeltet; for det tredje bidro den til verifiseringsprosessen for omplassering av en SMIoT-sensor ved å oppdage en dreneringsrør som påvirket målingene i den opprinnelige posisjonen; og for det fjerde fastslo den at satellittmålinger ikke er passende for denne regionen.

Preface and acknowledgments

I am pleased to present my master's thesis, which marks the end of my studies in Environmental Physics and Renewable Energy at the Norwegian University of Life Sciences (NMBU). This thesis is part of the project Hydrometeorology to Operations (H2O) by the Norwegian Meteorological Institute.

Firstly, I want to thank my supervisor Mareille Wolff and my co-supervisor Laura Ehrnsperger. Thank you for all your wisdom and all the help you have provided. Without your guidance, this thesis would not have been possible.

"I am also immensely grateful to ChatGPT for its invaluable assistance in coding and improving my language skills. Without its unwavering support and guidance, I would not have been able to successfully complete this thesis." - Written by ChatGPT

My parents, and my sister Lilliane (even though you specifically asked to be mentioned here), also deserve a special thank you. I want to thank you for instilling a love of learning in me, your willingness to be there when I needed you, and for making me the kind and humble man I am today. I look forward to making you proud as I continue to grow and learn in the years to come.

I also would like to thank my second family; the friends I made during my time as a student. I want to thank all my fellow student at my master room for having lunch together every day. I want to thank my roommates Kenneth, Sigurd and Daniil for taking my mind off of the thesis during stressful times. Finally, I would like thank my fellow student contacts at Tekna for the unforgettable memories we shared, and for the moments we can't quite remember.

"Last but not least, I wanna thank me
I wanna thank me for believing in me
I wanna thank me for doing all this hard work
I wanna thank me for having no days off
I wanna thank me for, for never quitting"
-*Snoop Dogg*

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1. INTRODUCTION

Soil moisture is defined as the total amount of liquid water in the unsaturated zone of the soil, which lies between the water table and the soil surface (American Meteorogical Society, 2023). Accurate measurements of soil moisture are essential for parameterizing numerical weather models. These models are used to forecast weather patterns, anticipate and mitigate the risk of floods and droughts, estimate cloud cover and precipitation, calculate evapotranspiration, and to calculate the energy fluxes in the land between the biosphere and the atmosphere (Cheng and Cotton, 2004, Crow and Wood, 2002, Guderle and Hildebrandt, 2015, Hubbard and Wu, 2005, Torres et al., 2013, Zhang et al., 2020a). However, the temporal and spatial variability of soil moisture is influenced by a variety of environmental conditions, such as temperature, precipitation, vegetation cover, soil properties and topography (Morgan et al., 2003, Robinson et al., 2008, Zhang et al., 2020b, Zhao et al., 2018). Despite existing research in the field, there is still a knowledge gap regarding how changes in environmental conditions impact soil moisture dynamics, emphasizing the significance of gaining a better understanding of this topic (Brye et al., 2000).

Measuring soil moisture has been a topic of interest for centuries, with early methods including manually digging up soil samples and weighing them before and after drying (Hillel, 1982). As technology advanced, more sophisticated methods were developed, such as the use of tensiometers and time domain reflectometry (TDR) in the mid-20th century (Kutilek and Nielsen, 2015). While these techniques allow for a continuous time series of soil moisture at greater depths and with greater accuracy, they rely on proxy measurements of soil moisture, such as dielectric conductivity or transmissivity (Moldoveanu and David, 2013). A drawback is that it can be influenced by external factors such as soil salinity, fluctuations in temperature, and poor probe/soil contact. Therefore, manual digging still remains the standard method and reference for all other techniques (Hillel, 1982). In recent years, remote sensing techniques such as satellite-based measurements have become increasingly popular, as they allow for the mapping of soil moisture over large areas. Additionally, advancements in sensor technology have led to the development of low-cost and portable soil moisture sensors that can be used for in situ measurements. Previous research found the need for comparing remote-sensing measurements of soil moisture to ground-based measurements to assess their accuracy and to determine whether these measurements are sufficiently accurate to represent variability of soil moisture of an area (Min et al., 2023).

The Hydrometeorology to Operations (H2O) project aims to improve the accuracy and reliability of numerical weather predictions by improving the representation of processes on the ground, with a particular focus on the link between water and the related fluxes of the biosphere (Kroken et al., 2009). This is being accomplished by utilizing advanced models of hydrological processes, such as how precipitation hitting the ground is distributed to streams, rivers and groundwater. Additionally, the project aims to improve the observational systems used to validate the prediction of short-term heavy precipitation events during summer by including soil moisture into the parameterization of land surface models. As a part of the H2O project, this thesis aims to deepen the understanding of tempospatial variability in soil moisture.

The motivation for this research is driven by the ongoing need to understand soil moisture and its variability in order to improve forecasting of weather, droughts, and floods (Hubbard and Wu, 2005, Torres et al., 2013, Zhang et al., 2020a). Understanding the temporal and spatial variability of soil moisture is important for managing and conserving natural resources, as well as predicting and mitigating the impacts of climate change on ecosystems (Hoegh-Guldberg et al., 2018). Additionally, research on soil moisture can also have practical applications such as improving irrigation management and crop planning for agriculture, and predicting the risk of wildfires (Marek et al., 2021, Torres et al., 2013). Understanding soil moisture dynamics can also contribute to better decision making for water resources management, disaster risk reduction and sustainable development (Robinson et al., 1985).

The focus of this thesis is to investigate the temporal and spatial variability of soil moisture in Ås, Norway, and to compare the effectiveness of satellite measurements with ground-based sensor. The study will employ time series analysis and perform statistical tests to analyze soil moisture measurements from different ground-based sensors. Furthermore, comparisons between satellite data and ground-based measurements will also be performed. Additionally, the study will investigate the effect of precipitation on soil moisture. The data will be collected from The Norwegian Water Resources and Energy Directorate (NVE), The Norwegian University of Life Sciences (NMBU) and the Norwegian Meteorological Institute, and the sensors that were used for this were GroPoint Profile (SMIoT), SoilVUE10 (SoilVUE), COsmic-ray Soil Moisture Observing System (COSMOS), ThetaProbe ML2 (ADR) in addition to manual soil moisture measurements and data from the Sentinel-1 satellite.

This master thesis will investigate the following questions:

Research question 1: How does soil moisture vary over time and space at Søråsfeltet in Ås?

Research question 2: How do satellite measurements compare to well-probed ground-based measurements to accurately estimate soil moisture levels?

2. THEORY

Soil moisture is an important component of the earth's water and energy cycle, and its knowledge is vital in various fields of study, including agriculture, forestry, hydrology, climate science, and natural resource management. It is important to understand the temporal and spatial variability of soil moisture as it influences plant growth and crop yield, floods and droughts, and water resource management.

In this chapter, an introduction to the hydrological cycle along with its significant processes is provided in subsection 2.1. Following this, subsection 2.2 is dedicated to the topic of soil, including its composition and formation. Subsequently, in subsection 2.3 the focus shifts towards subsurface water, with particular emphasis on ground water and soil moisture. The theory presented is primarily based on the works of Oke (1987), Hendriks (2010), Keller (2018), Hillel (1982) and Wallace and Hobbs (2006), unless otherwise noted.

2.1. Hydrological cycle

The hydrological cycle, also known as the water cycle, describes the continuous movement of water on, above, and below the Earth's surface. At any given moment, only a tiny fraction of the total water in the water cycle is found near the Earth's land surface. This includes water in the atmosphere, rivers, and subsurface environments, which amounts to just 0.3 % of the total water on Earth. The majority, 97 %, is in the oceans. The hydrological cycle is driven by solar energy and describes the process by which the sun heats water on the surface of the Earth, causing it to evaporate into water vapor which is carried in the atmosphere through circulation. This water vapor eventually condenses and falls back to the surface as precipitation, completing the cycle.

The water cycle is composed of several processes including evapotranspiration E, precipitation P, infiltration F, and runoff R, and together they constitute the water balance (Equation 1).

$$P = E + F + R + \Delta S \tag{1}$$

The definition of ΔS varies depending on the source. Hendriks (2010) defines it as the average change in storage, whereas Oke (1987) defines it as the net change in soil moisture content. Storage includes the water stored in rivers, lakes, soil water and groundwater. The American Meteorological Society (2023) defines soil moisture as the total amount of water in an unsaturated soil. Thus, soil moisture, also known

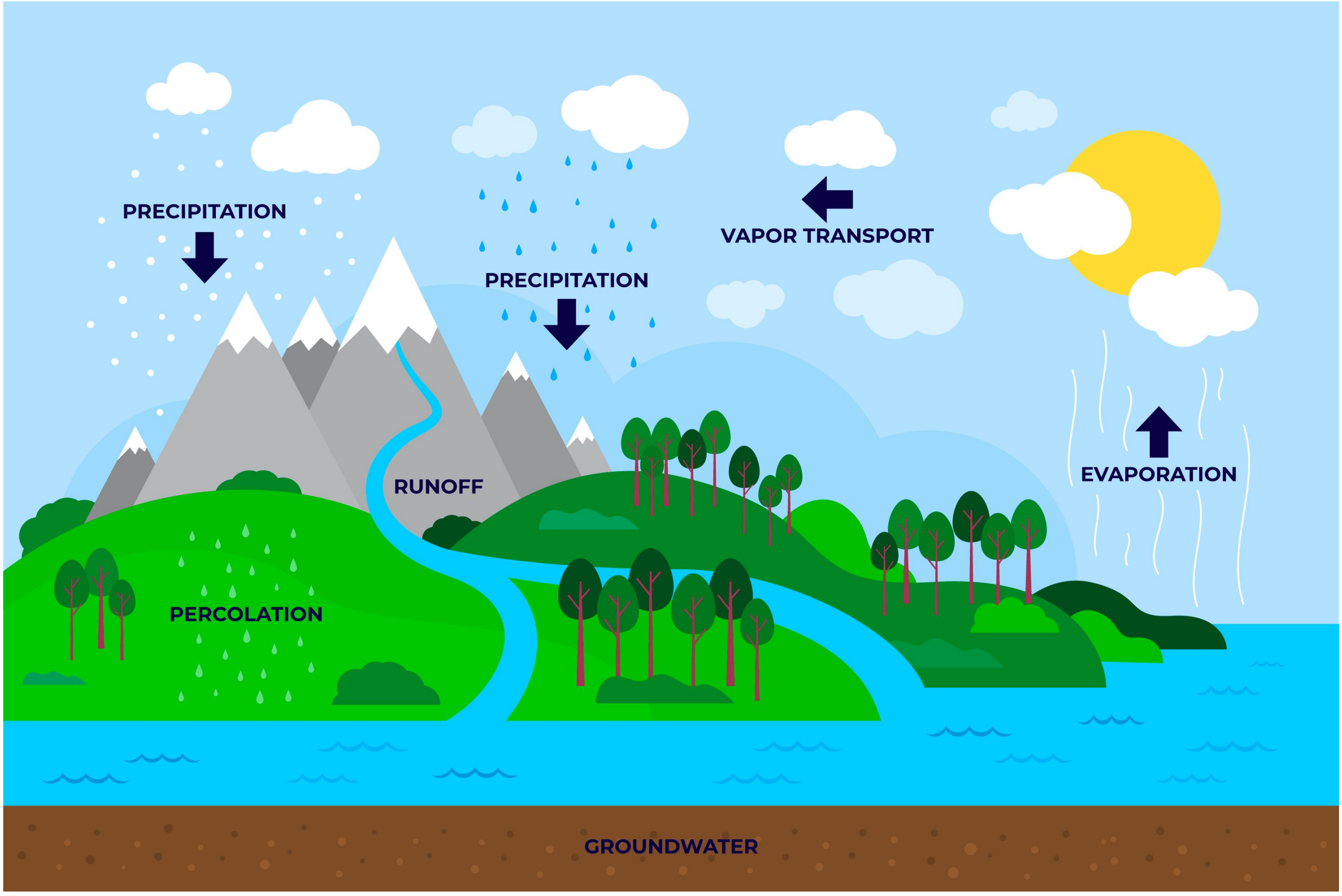


Fig. 1: Illustration of the water cycle, showing the various processes through which water moves within the land-atmosphere system. Image by Freepik.com

as soil water, represents the water in land surfaces that is not surface water or groundwater, but instead resides in the pores of the soil.

Evaporation of water is the change of water from liquid state into vapor. Water may evaporate from any wet surface, such as the ocean, lakes, or the soil, which purifies the water leaving salts behind on the surface (Figure 1). When water evaporates from the stomata, numerous openings or pores in the epidermis of plants, it is called transpiration (sto, 2022). Due to the fact that both evaporation and transpiration involve the movement of water into the atmosphere, they are often discussed jointly and referred to as evapotranspiration. Hydrologists sometimes describe evapotranspiration as a loss of water, even though it ultimately circles back to the surface. Precipitation is the process through which liquid and solid water fall from the atmosphere on the earth's surface. This includes both rain, snow and hail which replenishes water resources on earth. Infiltration is the process of water seeping through pores and cracks in the soil, sediments or rocks. Water movement through the unsaturated zone, where there is both water and air in the pores, is referred to as percolation. This process helps to refill groundwater. Understanding the balance between the aforementioned processes is important in managing and conserving water resources for both human and ecosystem use, as it determines the amount of water available.

Changes in land use, such as deforestation or urbanization, can alter the water balance through changes in evapotranspiration. Climate change, such as human-induced global warming, can also affect the water balance. For example, rising temperatures in mountainous areas can cause the snowline and the 0 °C isotherm to shift, leading to less snow storage in winter and decreased meltwater discharge in spring and summer. This, in turn, could have economic consequences, such as hindering cargo transport along rivers like the Rhine, as predicted by Kwadijk (1991). The impact of human-induced global climate change on the River Rhine discharge was the main subject of Kwadijk's study, which examined various climate scenarios for the years 1990 to 2100. The climate scenarios were based on scenarios of greenhouse gas emissions, and the conclusion was that even for scenarios anticipating decreases in annual precipitation, winter discharges should increase and summer discharges should decrease.

2.2. Soil

As water interacts with the subsurface, it also interacts with soil, which may be defined in different ways depending which perspective it is viewed from. From a soil scientist's point of view, soil is the result of physical, chemical, and organic processes that have transformed solid earth material, usually bedrock, into a medium that can support rooted plant life. From an engineering perspective, soil is any solid earth material that can be excavated without blasting (Keller, 2018). Hillel (1982) simply defines soil as the weathered and fragmented outer layer of the earth's terrestrial surface.

Soil formation involves both physical and chemical processes. Physical weathering occurs when rocks break down into smaller fragments due to temperature changes and mechanical stresses caused by water freezing and thawing. Roots also contribute to breaking down rocks, and particles transported by water, ice, and wind can erode rock surfaces. Chemical weathering processes break down parent materials through processes like hydration, oxidation, reduction, solution, dissociation, precipitation, and removal of components via volatilization or leaching. These processes create weathering products that can be transported by water, glaciers, or wind and deposited in different locations.

Soil is typically composed of mineral and organic matter, air and water. Figure 2 provides a visual

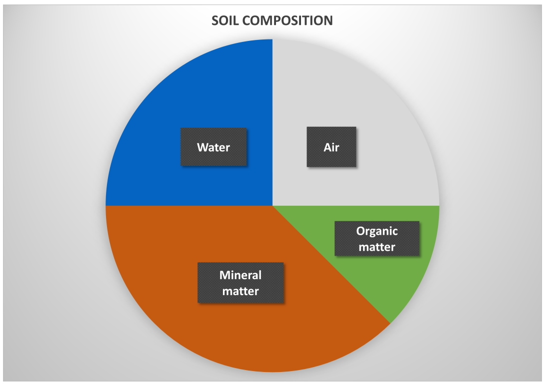


Fig. 2: The building blocks of healthy soil: a breakdown of the key components of soil composition. Adapted from Hillel (1982).

representation of the volume composition of a soil at an optimal condition for plant growth. Soil can be viewed as a three-phase system consisting of solid, liquid, and gaseous phases, with mineral and organic matter constituting the solid phase, water the liquid phase, and air the gaseous phase. The quantitative relationships between these phases' volumes and masses are of great interest in soil science. Table 1 presents the volume and mass of each phase, which defines the terms commonly used to describe the quantitative relationships between the main components of soil.

Table 1: Volume and Mass Relationships in Soil as a Three-Phase System: Solid, Liquid, and Gaseous Phases

	Volume	**Mass**
Air	V_a	$M_a \approx 0$
Water	V_w	M_w
Solids	V_s	M_s

The density of arable, mineral soils, ρ_s, is defined in Equation 2. According to Hillel (1982), typically values for the mean density are around 2.6-2.7 g/cm^3, while for clay it is approximately 2.9 g/cm^3 (Schjønning et al., 2017).

$$\rho_s = M_s/V_s \tag{2}$$

The dry bulk density, ρ_b, represents the mass of dried soil to its total volume, which includes the volume of solids, air, and water (Equation 3). Therefore, ρ_b is always smaller than ρ_s. If pores constitute half of the soil volume, then ρ_b is half the value of ρ_s, assuming the mass of air is negligible (M_A = 0). The typical value of ρ_b ranges from 1.3-1.35 g/cm^3, but can be as high as 1.6 g/cm^3 in sandy soils or as low as 1.1 g/cm^3 in clay soils.

$$\rho_b = M_s/V_t = M_s/(V_s + V_a + V_w) \tag{3}$$

The porosity f shown in Equation 4, is an indicator of the relative pore volume in the soil, and consists of the volume of fluids, V_f, namely water and air, over the total volume, V_t, and typical values are between 30-60 %.

$$f = V_f/V_t = (V_a + V_W)/(V_s + V_a + V_w) \tag{4}$$

Coarse-textured soils usually have less porosity than fine-textured soils. Clayey soils may undergo changes in volume due to various factors, such as moisture content, leading to swelling and shrinking. They can also form aggregates or disperse, depending on their composition and external forces. Additionally, these soils can experience compaction and cracking over time, which affects their porosity and overall structure.

Permeability is a property that characterizes how easily water flows through a material. In general, soils with large pores, such as clean gravels and sands, have high permeabilities, while soils with small pores, such as clays, have low permeabilities. The presence of fine particles in a mixture of clean gravel and sand can decrease permeability. The permeability of different soils can vary widely. For example, a study by Rawls et al. (1982) found the permeability of sand and loamy sand ranging from 10^{-2} to 10^{-5} cm/s, while the permeability of clay loam ranging from 10^{-5} to 10^{-7} cm/s.

2.3. Water in the ground

2.3.1. Ground water

Groundwater refers to water that is stored beneath the Earth's surface that fully saturates the pores and fractures within rock or soil. Nearly all groundwater is of atmospheric origin, which means that it stems from precipitation, followed by infiltration and percolation. Only a very little portion of the water, which is caught during sedimentation, is connate. There is groundwater beneath the surface of land across the entire planet, including the Sahara Desert, where there is estimated to be around 150 000 km^3 of water (Hendriks, 2010). Groundwater is a valuable resource that can be used for agriculture, industry, and drinking water. It has the ability to purify itself as it travels through the soil, making it a natural filtration system. A water table that can establish itself freely is by definition the level at which the water pressure is the standard atmospheric pressure of 101.325 kPa, and separates the saturated zone from the unsaturated zone.

2.3.2. Soil moisture

Soil moisture is defined as the total amount of liquid water in the unsaturated zone of the soil, which lies between the water table and the soil surface (American Meteorological Society, 2023). It constitutes a small fraction, only 0.15 %, of the liquid freshwater on Earth. Unsaturated soil refers to conditions where there is still air present in the pores. Soil water content, or soil moisture content, is an important determinant of the soil's properties, including its strength and its tendency to shrink or swell. When attempting to build a sand castle, it becomes clear that dry sand is structurally inadequate for construction, while moist sand can be compacted and shaped into stable vertical walls. This observation highlights the role that water plays in the engineering properties of soils.

The content of water in the soil can be expressed as a fraction of either volume or mass:

$$w = M_w/M_s, \tag{5}$$

$$\theta = V_w/V_t = V_w/(V_s + V_a + V_w), \tag{6}$$

where w, the gravimetric water content, is the dimensionless ratio of water mass M_w to dry soil mass, M_s, and θ, the volumetric water content, is the ratio of water volume V_w to total soil volume V_t. The two equations can be related to each other using the dry bulk density ρ_b and the density of water ρ_w:

$$\theta = w(\rho_b/\rho_w) \tag{7}$$

2.3.3. Subsurface water system

Groundwater and soil moisture are connected and interact with each other forming the subsurface water system. The movement of water in the subsurface is governed by physical properties of the soil, such as permeability and by the topography of the landscape. Groundwater and soil moisture can be replenished by precipitation and other surface water sources, and they can also discharge into surface water bodies. The hydrological cycle is important for determining soil moisture levels. Precipitation can increase soil moisture levels, while evapotranspiration can decrease soil moisture. Infiltration can also impact soil moisture levels by affecting how quickly water moves through the soil, and which amount of water is transported via surface runoff.

In practical terms, the lower limit of soil moisture in the field is not zero, but positive, due to the limitation of plants in extracting water beyond a certain level known as the wilting point. This bound on soil moisture has significant implications for its statistical properties in both space and time.

The movement of water in soil can occur horizontally or vertically through soil pores or fractures in the soil structure. Saturated flow refers to water movement in completely filled pores, whereas unsaturated flow is more common, occurring when only some of the pores are filled with water (Brady and Weil, 2002). Additionally, soil water flow can be classified into two other types: matrix and preferential flow, with their relative significance dependent on the soil type and rainfall intensity. Matrix flow refers to the uniform and slow movement of water through soil, while preferential flow is non-uniform and occurs through preferred pathways, such as cracks, wormholes, and root channels. These pathways, which make up a small portion of the total pore volume, can quickly transport water and solutes into deeper layers of soil, even below saturation levels. During heavy precipitation, water infiltrating the soil surface is often directed through these pathways. Although matrix flow is important, preferential flow may be responsible for most of the moisture and solute transport.

3. METHOD

In this chapter, a brief introduction to the research area and the soil moisture instrumentation is provided. The different techniques and instruments are presented and their locations are disclosed. Then, the manual measurements from the summer of 2022 are described, followed by a description of the processing methods used for the data. Finally, the approach for analyzing the data is discussed.

3.1. Research area

Søråsfeltet in Ås, Norway, is the primary location for the soil moisture data used in this study. The observations from The Norwegian University of Life Sciences (NMBU) at Søråsfeltet are among one of the longest and most comprehensive in Norway, with measurements since 1863 (Kroken et al., 2009). The field laboratory, BIOKLIM, is partially automated and provides meteorological and microclimatic data to the research communities in Ås. With its extensive measuring equipment, BIOKLIM enables continuous measurements of air temperature, precipitation, ground heat fluxes, radiation, and soil temperature profiles. The field station is located approximately 800 meters southeast of the Faculty of Science and Technology at NMBU. The are coordinates N 59° 39' 37", E 10° 46' 54", with an elevation of 93.3 meters above sea level. The field station, pictured in Figure 3, slopes 1 % towards the southwest and has 5 000 m^2 dedicated to field trials. It is surrounded by forests and residential areas, with a minimum distance of 200 meters from the fenced field station. As reported by Naalsund (2022), the soil in the vicinity of Søråsfeltet consists of 48 % clay, 42 % silt, and 10 % sand with a bulk density of 1.03 g/cm^3. The soil's porosity was calculated to be 61 %. According to Keller (2018), a soil with this composition will be classified as a silty clay. Given the availability of data and previous work done in this area, Søråsfeltet is an ideal location for this study, allowing for comparison of findings with previous studies and providing an opportunity for more comprehensive analysis of the data.

The COSMOS sensor, operated by The Norwegian Water Resources and Energy Directorate (NVE), is located in Kjerringjordet at N 59°39'51.9" E 10°45'42.8", roughly 1.2 km west of Søråsfeltet, which is also an agricultural site (Figure 4). The COSMOS sensor will be presented more thoroughly in section 3.3.3. Additionally, SMIoT sensor 3 was relocated to this location on 29.06.

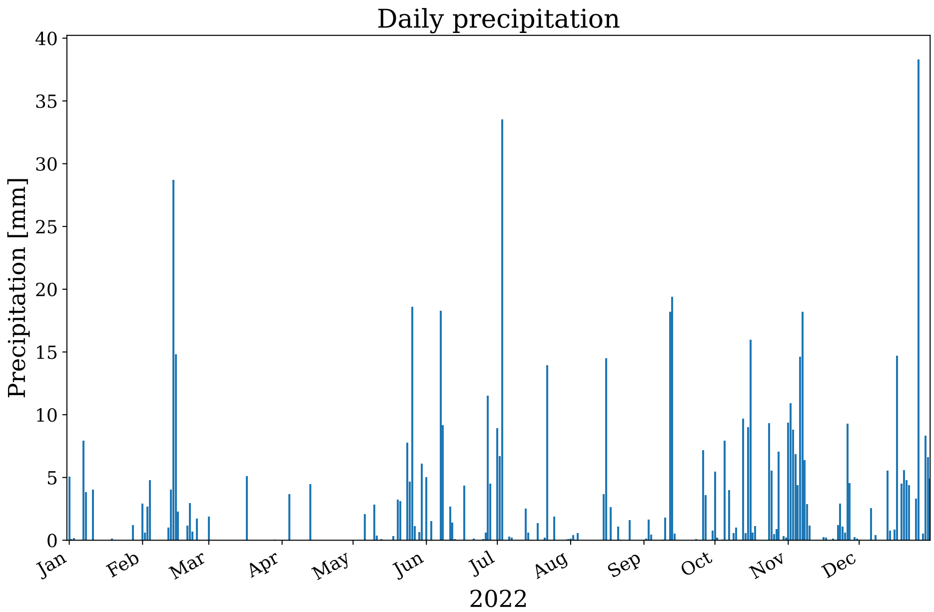
Fig. 3: A view of Søråsjordet, characterized by short grass and a flat terrain. Image from Laura Ehrnsperger.

Fig. 4: The map displays an aerial photograph of the Søråsfeltet area along with the Kjerringjordet. The Søråsfeltet area is located in the lower right corner of the map, while the Kjerringjordet is located in the upper left corner approximately 1.2 km away from each other. Image from Google Maps.

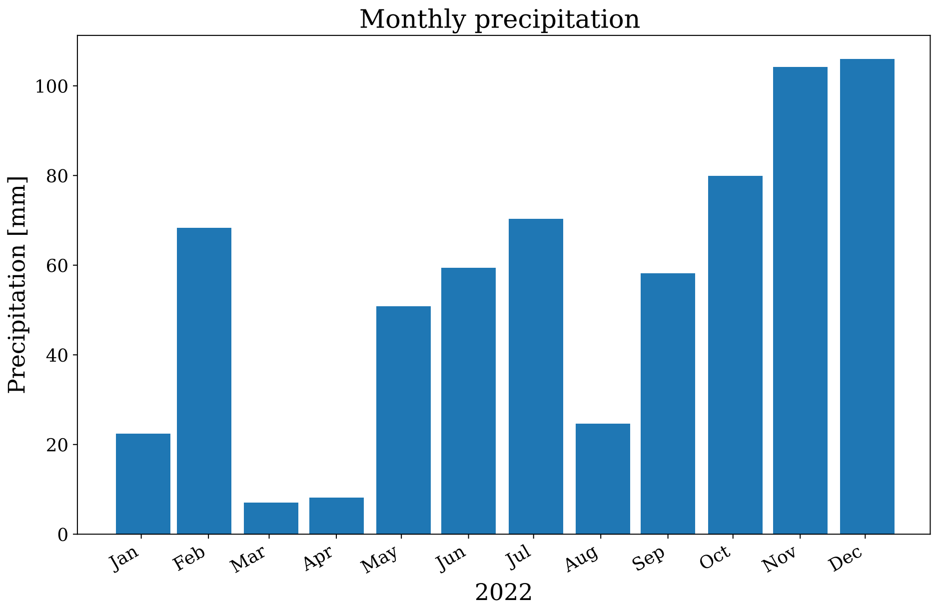
3.2. Meteorological conditions

The average temperature in Ås in 2022, was 7.3 °C, which is 1.0 °C higher than the average temperature for the normal period of 1991-2020. It was the third warmest year since weather observations began in Ås almost 150 years ago in 1874. The increase in temperature is consistent with global warming trends and may have significant implications for ecosystems and agriculture in the region (Hoegh-Guldberg et al., 2018). About 80 % of the normal amount of precipitation for Ås fell in 2022, making it a relatively dry year. The daily and monthly values for precipitation are shown in Figure 5. The dataset used in the analysis shows a yearly precipitation amount of 659 mm, which is 7.5 % lower than the reported value of 714 mm by Bioklim (Wolff, 2023). This could cause discrepancies in the dataset.

The winter varied between cold and mild periods, with occasional snow (Wolff, 2023). The spring was dry and mild, with very little rainfall in March and April, and slightly below-average precipitation in May. The summer had no heat waves or temperature records, but was characterized by 59 Nordic summer days (temperature above 20 °C) and eight high summer days (temperature above 25 °C). July was slightly colder than normal, while June and August were slightly warmer. August was particularly dry, with only one-third of the normal amount of precipitation. The autumn months were warmer than usual, with November being the third warmest November on record since 1874.



a)



b)

Fig. 5: *a)* Daily and *b)* monthly precipitation from January to December 2022. Based on data from Bioklim.

3.3. Soil moisture instrumentation

In this analysis, six different methods have been used to measure soil moisture, in addition to two datasets for precipitation, all presented in Table 2. The measurement campaign of 2022, mentioned in section 3.4, used the volumetric method, and the ThetaProbe ML2 sensor to measure soil moisture, which will be discussed more in section 3.3.2. The ThetaProbe ML2 sensor will hereafter be called ADR, named after the technology behind the sensor. The ScanMatic Internet of Things (SMIoT), SoilVUE 10 and COsmic-ray Soil Moisture Observing System (COSMOS) sensors were all permanently installed at Ås to measure soil moisture, and are all going to be elaborated on in their respective subsections in section 3.3.1. The data on precipitation was collected from the field laboratory BIOKLIM accessed via Seklima.met.no. The aforementioned methods and datasets are all ground-based. Additionally, satellite remote sensing data from the Sentinel-1 mission was also used to analyze soil moisture.

Table 2: Summary of dataset information, including depth of measurement, temporal resolution, period of time covered, accuracy and measured parameter.

Dataset	Depth	Resolution	Measuring period	Accuracy	Parameter
SMIoT x3	5 & 25 cm	10 min	07.02 - 17.07	±2 %	SM and temperature
SoilVUE	5, 10, 20, 30, 40 50, 60, 75 & 100 cm	10 min	01.01 - 30.12	±1.5 %	SM and temperature
COSMOS	25 cm	Hourly	01.05 - 30.11	±2 %	Soil moisture
ADR	5 cm	Weekly	09.06 - 08.09	±1 %	Soil moisture
Sentinel-1	5 cm	Weekly	01.01 - 31.12	-	Soil moisture
Volumetric	5 cm	Weekly	09.06 - 21.09	-	Soil moisture
Bioklim	-	10 min	01.01 - 31.12	-	Precipitation
SeKlima	-	Daily	01.01 - 31.12	-	Precipitation

There are various methods of measuring soil moisture, and they are divided into direct and indirect measurements. An example of a direct measurement technique is the thermo-gravimetric method where a soil sample, usually 100 g is oven dried for 24 hours at 100-105 °C (Lekshmi et al., 2014). The weight of the sample is recorded before and after drying, and the soil moisture content can be calculated. From this point on, the method for measuring soil moisture content will be referred to as the volumetric method, as volumetric soil moisture content is the most relevant. This technique is a destructive method, since the soil sample cannot be used for repetitive measurements as the soil structure gets disturbed. This technique ensures accurate measurements, as it does not depend on salinity or soil type, and is therefore regarded as the standard reference for determining soil moisture content (Hillel, 1982).

3.3.1. Electromagnetic sensors

Electromagnetic sensors are frequently used to estimate soil moisture due to their capacity to indirectly measure the electrical conductivity of the soil, which is closely related to the water content. Although indirect measurements may not provide a precise value, the advantage of using such sensors is that they are less invasive than the manual volumetric method. Additionally, continuous measurements can be obtained compared to the manual method, and the same soil column can be measured multiple times. In their study of soil electrical conductivity, Patel et al. (2018) confirmed the correlation between the dielectric constant (κ) of soil components, such as air, water, and dissolved salts.

The dielectric constant of air is approximately 1, while the dielectric constant of liquid water at room temperature is 81 as reported by Ling et al. (2016). The amount of water and air affects the total dielectric value of soils, which typically ranges between 2 and 5 for most dry soils. When soil is dry, there is less water present to conduct electricity, resulting in a lower electrical conductivity. Furthermore, when the soil is wet, the presence of water allows electricity to flow more easily, leading to a higher electrical conductivity. The dielectric constant is not only dependent on the amount of water present in the soil, but also on temperature. As mentioned, water exhibits a dielectric constant of 81 at room temperature, but at 0 °C, the dielectric constant increases to 88, while at 100 °C, it falls to 55 (Moldoveanu and David, 2013). As a result, it is important to calibrate electromagnetic sensors and account for temperature variations in order to obtain accurate and reliable soil moisture measurements.

Empirical equations can be used to establish the correlation between the dielectric constant of soil and soil moisture. For example, Topp et al. (1980) proposed an equation linking the dielectric constant of soil κ with its moisture content θ. This equation takes the following form:

$$\theta = -5.3 * 10^{-2} + 2.92 * 10^{-2}\kappa - 5.5 * 10^{-4}\kappa^2 + 4.3 * 10^{-6}\kappa^3, \tag{8}$$

In the plot depicted in Figure 6, a third-degree polynomial is displayed for κ-values ranging from 1 to

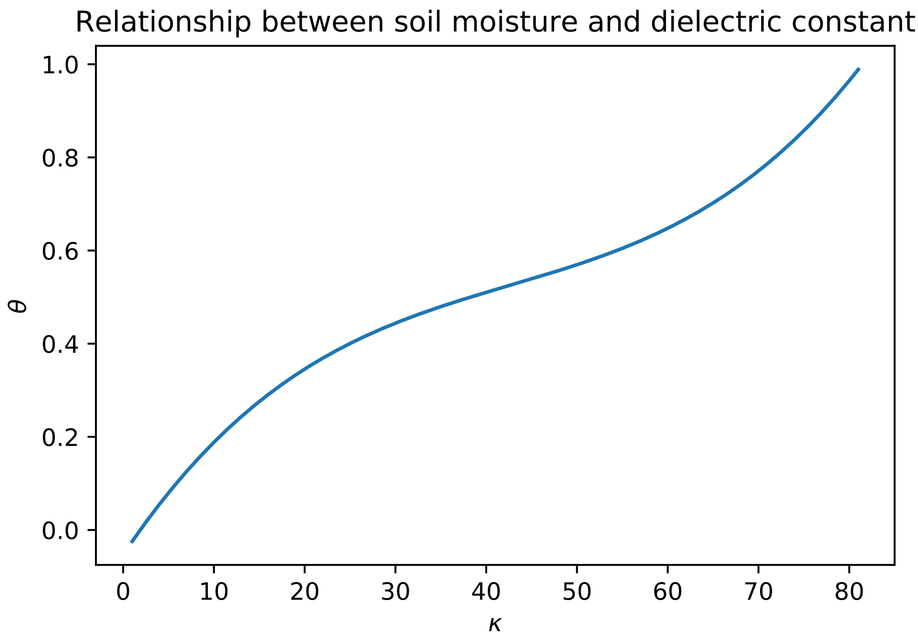


Fig. 6: Plot of the empirical equation describing the relationship between soil moisture and dielectric constant (κ) in the range of 1 to 81, as described in Equation 8. There is a strong positive correlation between soil moisture and dielectric constant.

81, which is the typical range for soil. The plot also includes the extreme values of 1 and 81, representing pure air and liquid water, respectively. At κ=1, there is no presence of water in the soil, while at κ=81 the soil moisture is at 100 %. The plot shows the correlation between soil moisture and changes in κ. According to Muñoz-Carpena (2021), the relationship in Equation 8 works for most mineral soils and for moisture below 50 %. For larger water content a specific calibration is required.

3.3.2. ThetaProbe ML2 (ADR)

The ThetaProbe ML2 from Delta-T Devices is a type of soil moisture sensor that uses amplitude domain reflectometry (ADR) technology to measure the volumetric water content of soil (Delta-T Devices Ltd, 1998). The sensor works by sending a low-frequency electromagnetic wave through the soil and measuring the amplitude of the reflected wave. The amplitude of the reflected wave is related to the dielectric constant of the soil, which in turn is related to the water content of the soil as seen in Equation 8. The ADR sensor is designed to be inserted vertically into the soil to a depth of up to 6 cm probing a soil volume of around 30 cm^3 surrounding the central rod. The ADR sensor provides several advantages over the traditional volumetric method, including its simplicity, reduced labor requirements, and shorter processing time. According to ICT-International (2021), ADR sensors permanently buried in landfills have demonstrated long-term durability, remaining operational for at least 15 years suggesting a reliable and robust technology.

The ThetaProbe ML2 sensor is connected to the HH2 Handheld Meter from Delta-T Devices. Together, these devices form the ADR-sensor, named after the technology used. The ADR-sensor has a measuring range of 5 to 50 % with full accuracy, and according to Van Bavel and Nichols (2010) the ADR-sensor does not require calibration for most applications. Additionally, it is possible to calibrate the sensor for general soil types, mineral or organic, or conduct a soil-specific calibration for a full range of 0 to 100 % with an accuracy of ± 1 % (The, Delta-T Devices Ltd, 1998). The ADR-sensor was used during the 2022 measurement campaign, which will be discussed further in Section 3.4.

3.3.3. COsmic-ray Soil Moisture Observing System (COSMOS)

The COSMOS sensor is a cosmic-ray sensor of type CRS-2000/B from Hydroinnova. The sensor works by detecting the naturally occurring cosmic ray neutrons that interact with the hydrogen atoms in soil water (Zreda et al., 2008). The sensor consists of two detectors that are placed several meters apart, and measures the difference in cosmic ray flux between the two detectors. Cosmic rays are high-energy particles that continuously bombard the Earth and produce secondary particles, including fast neutrons, when colliding with atoms in the air. The fast neutrons lose energy by colliding with other particles until they reach thermal equilibrium with the environment. The process of thermalization depends on the presence of hydrogen, which is abundant in air and soil. The cosmic-ray soil moisture method uses a sensor to count fast neutrons, which decreases with increasing hydrogen content due to their thermalization. To obtain soil moisture values from counts, there exist three distinct methods which are described in detail in Centre for Ecology & Hydrology (2021).

The COSMOS sensor is located at Kjerringjordet and is operated by The Norwegian Water Resources and Energy Directorate (NVE) (Figure 7 and Figure 8). A key characteristic of the Cosmic-Ray Neutron Sensing method is its large footprint, up to several square kilometers, and to a depth of up to 75 cm, but the one located at Kjerringjordet measures soil moisture at 15 and 30 meters distance from the sensor and at 25 and 50 cm depth (Naalsund, 2022). The accuracy is reported to be around $\pm$ 2 % for soil water content between 5 and 30 % according to Zreda et al. (2008).

Fig. 7: The map displays the location of the COSMOS-sensor together with the new position of SMIoT sensor 3 at Kjerringjordet. Image from Google Maps.

3.3.4. SoilVUE 10

The SoilVUE 10 sensor from Campbell Scientific is a soil water content profile sensor, see Figure 9. The sensor utilizes time domain reflectometry (TDR) technology to determine soil moisture content (Campbell Scientific Inc., 2022). It consists of TDR circuitry connected to a series of helical waveguides that make up part of a threaded design. The waveguides are embedded in threads and centered on the measurement depths of 5, 10, 20, 30, 40, 50, 60, 75, and 100 cm for the 1.0 m column version of the sensor. The goal of the threaded design is to maximize soil contact to minimize air gaps and preferential flow.

The TDR method measures the dielectric constant, κ, by transmitting an electromagnetic pulse along a transmission line placed in the soil and measuring the time it takes for the pulse to travel down and back along the transmission line. The propagation velocity, v, of the wave depends on κ, which means that κ is proportional to the square of the transit time, t, down and back along the transmission line. The formula for κ is given by

$$\kappa = \left(\frac{c}{v}\right)^2 = \left(\frac{c \cdot t}{2L}\right)^2, \tag{9}$$

where c is the velocity of electromagnetic waves in a vacuum, and L is the length of the transmission

Fig. 8: A view of the COSMOS sensor at Kjerringjordet. Image from Laura Ehrnsperger.

line (Patel et al., 2018). The dielectric constant is related to the volumetric water content using Equation 8. The accuracy for measuring volumetric water content is ±1.5 %, but for areas such as Søråsfeltet a soil-specific calibration due to the dispersive nature of soils with high clay content is recommended by the instrument manual (Campbell Scientific Inc., 2022). For the sensor, the range of the measurement of volumetric water content is 0 to 100 %.

The SoilVUE sensor is located at Søråsjordet, as can be seen in Figure 10. During the measurement period the sensor was relocated 18.07., with the new location being displayed in Figure 11.

3.3.5. ScanMatic Internet of Things (SMIoT)

The SMIoT sensor is a soil moisture sensor that utilizes the time domain transmission (TDT) method, a refined version of TDR, to measure soil moisture content (GroPoint™, 2021). The abbreviation SMIoT stands for ScanMatic Internet of Things. IoT generally describes situations in which network connectivity and computing capability are extended to objects, sensors, and common household items that are not

Fig. 9: SoilVUE sensor. Note the threaded design meant to optimize soil contact. Image from Laura Ehrnsperger.

typically thought of as computers. This enables these devices to generate, exchange, and consume data with little to no human intervention (Rose et al., 2015). The sensor consists of a 38 cm long probe that is inserted vertically into the soil at a desired depth. The TDT method measures the time it takes for an electromagnetic wave to propagate along a specific length of a transmission line in the soil. Moisture in the soil affects the dielectric properties of the soil, causing the electromagnetic wave to travel at different speeds in wet soil compared to dry soil. By detecting these differences in travel time, the TDT method provides a proxy measurement of soil moisture content using a calibration curve. The SMIoT sensor can measure soil moisture content over a range of depths from 5 cm to 1 meter, depending on the number of rods connected. The SMIoT sensors used in this analysis measure soil moisture at 5 and 25 cm depth. The range of measurement is 0-100 % with an accuracy of ± 2 %, and a 10-minute resolution (GroPoint™, 2021).

Generally, for most soils there is no calibration needed for the SMIoT sensor, but a specific calibration might be needed for the clayey soil at the research site (GroPoint™, 2021). In the beginning of the

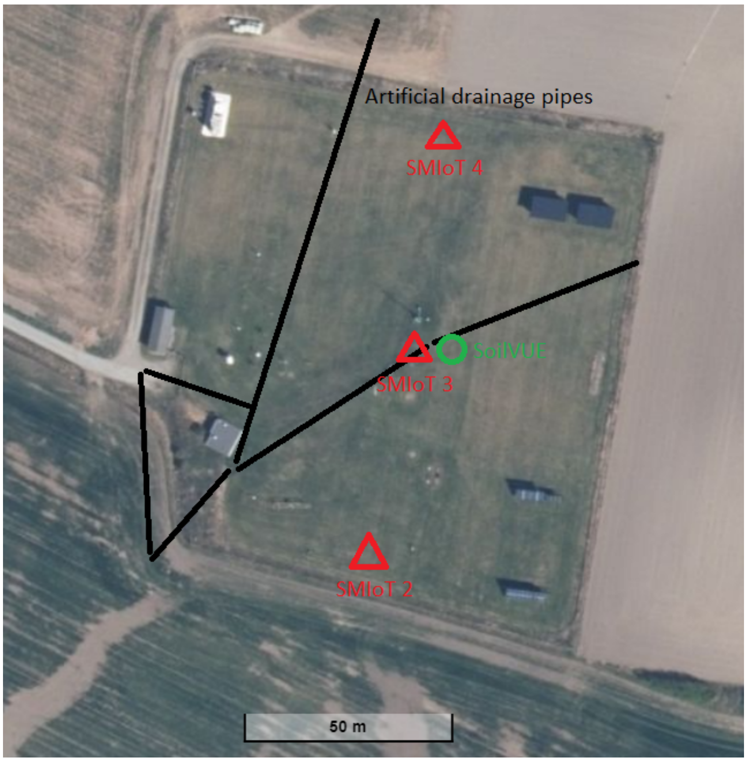


Fig. 10: The map displays the original location of the SoilVUE sensor together with the SMIoT sensors at Søråsjordet. Additionally, it displays the artificial drainage pipes installed beneath the ground, represented by black lines. Image from Google Maps.

measurement period, four SMIoT sensors where located at Søråsfeltet. The analysis considered data only from sensors 2 to 4 as sensor number 1 was unable to measure soil moisture, as shown in Figure 10. Additionally, sensor 3 was relocated to Kjerringjordet on 29.06, as depicted in Figure 11. Data was gathered utilizing GroPoint™ Lite Multi-Segment Soil Moisture Profiling Probe type 2 (GPLP-2 type), which were connected to SM5039 loggers from Scanmatic. These can be observed in Figure 12 and Figure 13, respectively.

3.3.6. Sentinel-1

Advances in satellite technology have shown that soil moisture can be measured by a variety of remote sensing techniques. The Sentinel-1 satellite from the European Space Agency (ESA) uses a Synthetic Aperture Radar (SAR) instrument to measure soil moisture (ESA-1, 2023). It consists of two polar orbiting satellites, Sentinel-1A and Sentinel-1B, each equipped with a C-band SAR instrument that generates high-

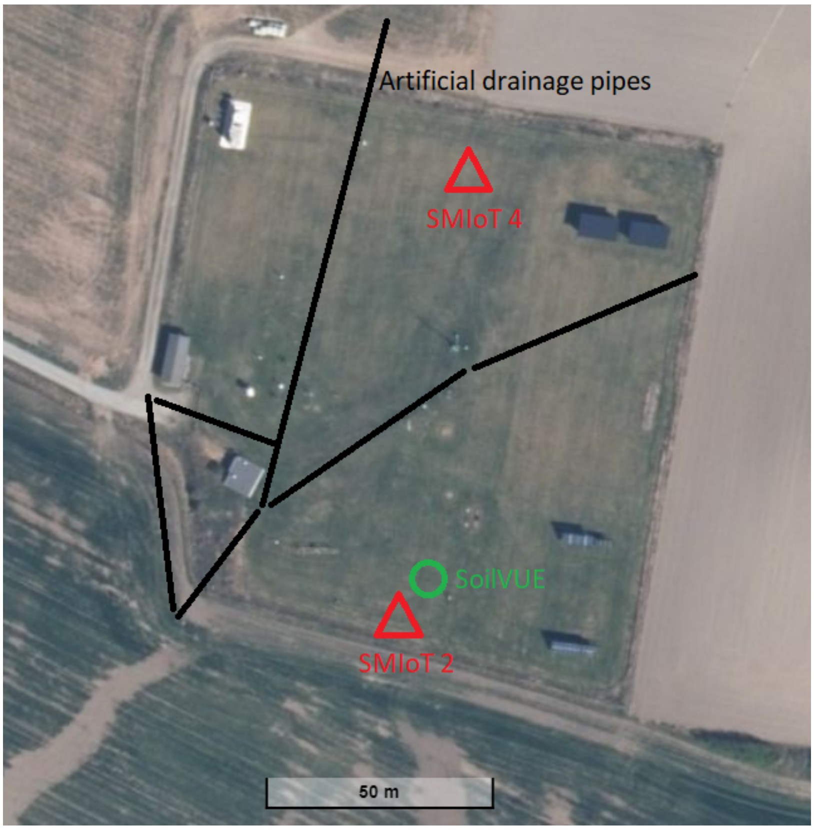


Fig. 11: The map displays the new location of the SoilVUE sensor together with the SMIoT sensors at Søråsjordet. Additionally, it displays the artificial drainage pipes installed beneath the ground, represented by black lines. Image from Google Maps.

resolution remote sensing imagery. C-band radars can penetrate through clouds and rain, making it useful for measuring soil moisture. The SAR instrument's ability to penetrate vegetation canopies or soils and measure soil moisture is limited to the uppermost layers, typically up to a depth of 5 cm.

The SAR sends microwave signals towards the Earth and measures the energy that bounces back, known as backscatter (ESA-2). The instrument's antenna receives the backscatter echo a short time later at a slightly different location as the satellite moves along its orbit. The amplitude and phase information of the returned signal is recorded to creates an image of the area. The increase in reflectivity due to moisture in the soil and vegetation affects the observed dielectric conductivity. This conductivity is closely related to the amount of moisture present, as presented in Equation 8.

The Sentinel-1 satellite carries the Synthetic Aperture Radar (SAR) instrument that measures soil moisture content from a height of around 700 km, enabling it to measure soil moisture content over large

Fig. 12: The SMIoT sensor before insertion into the ground. Image from Laura Ehrnsperger.

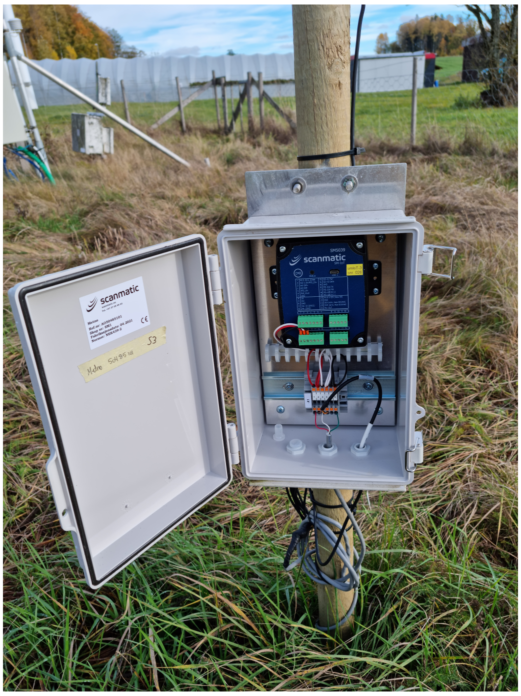


Fig. 13: The SM5039 logger from Scanmatic. Image from Laura Ehrnsperger.

areas. The satellite has four different modes and three different resolutions. The mode used in this analysis is Interferometric Wide Swath (IW) in high resolution, with Stripmap (SM), Extra Wide Swath (EW), and Wave (WV) being the other modes and full or high being the remaining resolutions.

3.4. Measurement campaign of 2022

As part of the H2O-project, a measurement campaign was conducted at Søråsfeltet, Ås, in the summers of 2022. The purpose of the campaign was to obtain manual soil moisture samples, which are considered to be ground truths (Hillel, 1982). These samples could then be compared to other sensors to assess their performance. Søråsfeltet was chosen for the manual measurements due to the availability of different sensors for comparison, along with the previous work done in this area regarding long time series of measurements. The measurement campaign involved soil moisture measurements using the volumetric and ADR sensor, as introduced in subsection 3.3 and subsubsection 3.3.2, respectively. Measurements of the 2022 campaign were conducted by H. Haaland and J. Fjeldså. For the volumetric method, data from 22.06 to 28.09, 2021, is available, while the ADR measurements stopped 05.08. of the same year.

3.5. Data processing

Processing of soil moisture data is important to ensure the accuracy and reliability of the analysis results. One common processing step is to remove outliers or spikes in the data that are not physically possible, which can be caused by environmental factors such as soil disturbance. Despiking methods like the interquartile range (IQR) method can be used to identify and remove these outliers. In data analysis, noise refers to unwanted random variations or errors in the data that can distort the analysis results and reduce the accuracy of the model. Time-averaging is a technique that can be used to remove noise from a dataset and uncover the underlying signal. By calculating averages over a certain time period, random variations or errors in the data can be reduced, resulting in a smoother and more stable signal (Raschka and Mirjalili, 2019). Postprocessing of soil moisture data often involves gap filling in missing values. This is especially important in long-term monitoring applications where sensors may fail or lose connection, resulting in missing data points. Methods such as linear or spline interpolation can be used to estimate the missing values based on surrounding data points, improving the accuracy and completeness of the dataset. Finally, data cleaning and quality control are necessary to ensure that the data is complete and consistent. Various techniques, including despiking, time-averaging, and data imputation, were used to preprocess the soil moisture datasets. The details of these preprocessing techniques will be described in the following sections.

3.5.1. SMIoT sensors

According to the manufacturer's specifications, the SMIoT sensor generates measurement data by transmitting 400,000 pulses through the sensing element and applying filtering to remove outliers before averaging the data and sending the measurement as SDI-12 output (GroPoint™, 2021). SDI-12 a standard communications protocol, which allows a microprocessor-based sensor, such as the SMIoT sensor, to transfer measurement data to a battery-powered data logger, as reported by METER-Environment (2020).

To postprocess the data obtained from SMIoT sensors, the Interquartile Range (IQR) method was used, which involves removing outliers that fall outside the 1.5 x IQR range. Upper and lower limits were defined based on the following equations:

$$IQR.Limit.lower = Quantile.lower + 1.5 \times IQR$$

$$IQR.Limit.upper = Quantile.upper + 1.5 \times IQR$$

where IQR.Limit.lower and IQR.Limit.upper are the limits applied to the outliers, Quantile.upper and Quantile.lower are the 25 % and 75 % percentiles, respectively, and IQR is the interquartile range. These limits were used to identify and remove any spikes in the data, ensuring the accuracy and reliability of the results. The processing of data was done by L. Ehrnsperger at The Norwegian Meteorological Institute.

3.5.2. COSMOS sensor

The COSMOS sensor measures soil moisture using the cosmic-ray technique on an hourly basis. However, this method results in noisy time-series. Therefore, it is recommended to average the counts over longer time periods, such as 6 or 24 hours, to reduce the impact of noise and obtain more reliable measurements (Centre for Ecology & Hydrology, 2021). Additionally, the presence of water above the soil surface during snow events can be mistakenly interpreted as soil moisture. To address this issue, a correction is applied to the daily volumetric water content when a snow day is detected. In this analysis, daily averages were used instead of 30-minute intervals. After examining a plot of the data, it became apparent that values equal to 50 % were likely to be a default value used for missing data. Consequently, these values were removed from the dataset to avoid any potential bias in the analysis.

3.6. Temporal and spatial variability in soil moisture measurements

To examine the temporal and spatial variability in soil moisture measurements across Søråsfeltet, multiple techniques were utilized. Time series data from the ADR sensor, SMIoT measurements, COSMOS sensor, volumetric method, and SoilVUE sensor were displayed, with precipitation events over 4 mm indicated to identify the impact of precipitation on soil moisture changes. The data from the different sensors were further analyzed to assess the spatial variability in soil moisture across the field. Additionally, satellite data was used to provide an overview of soil moisture variations across larger spatial scales. The combination of these different sensors and methods will hopefully provide a comprehensive understanding of how soil moisture varies both in space and time in Søråsfeltet and the surrounding area.

3.7. Statistical analysis

Statistical analysis plays an important role in understanding the dynamics of soil moisture, and several tests can be used to determine the distribution of the data and identify patterns and changes over time. It is important to first test for normal distribution using the Shapiro test, because many statistical methods rely on the assumption of normality (Brownlee, 2018). Depending on the distribution of the data, a suitable significance test can then be chosen. For normally distributed data, a t-test can be used to compare the means of two independent samples. This is important in soil moisture time series analysis because it can help to identify patterns and changes in soil moisture over time. For data that is not normally distributed, a Wilcoxon Rank Sum test can be employed to determine whether the distributions of two paired samples are equal or not. In addition, the Kolmogorov-Smirnov test can be used to test for similar distribution between two sets of samples. This test determines the likelihood of observing two sets of samples like this if they were drawn from the same, but unknown, probability distribution. This is important because it can help to identify similarities or differences between soil moisture data collected from different locations or at different times. For example, if soil moisture data collected from two different fields exhibit similar probability distributions, it may indicate that the two fields have similar soil properties and require similar irrigation or fertilization practices. On the other hand, if the soil moisture data collected from two fields exhibit different probability distributions, it may indicate that the two fields have different soil properties and require different management practices to optimize crop yields.

Exploratory data analysis uses statistical methods to find patterns that could be overlooked in a set of data Potter (2006). The box plot, illustrated in Figure 14, is one of these methods, which is used to graphically summarize and analyze sets of data. The plot consists of a rectangular box and two whiskers that extend from the box, which also gives it the name whisker plot. The box represents the interquartile range (IQR), which spans the middle 50 % of the data. The line inside the box represents the median, and the whiskers extend to the minimum and maximum values within 1.5 times the IQR from the box. Points beyond the whiskers are considered outliers, but are not visualized in Figure 14.

The Pearson's correlation coefficient measures the correlation between the two variables. This coefficient can vary from -1 (perfect negative correlation) through 0 (no correlation) to +1 (perfect positive correlation) and determines the strength and direction of the relationship between the variables (Mukaka, 2012). The strength of association is shown in Table 3.

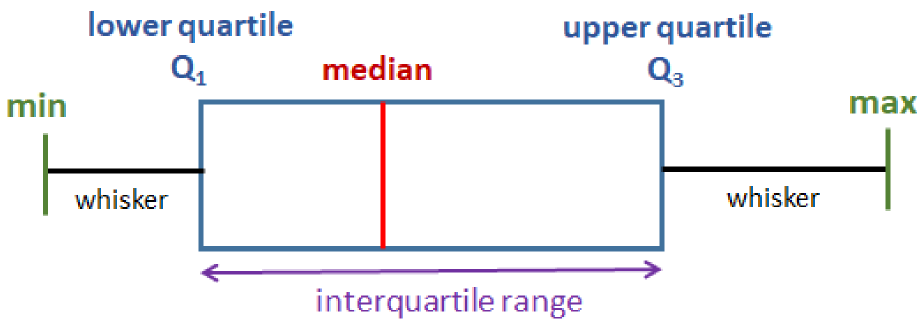


Fig. 14: Illustration of a box plot showing the median, lower and upper quartile ($Q1$ and $Q3$), interquartile range and minimum and maximum values of a dataset. Adapted from Potter (2006).

Table 3: Rule of thumb for interpreting the size of correlation coefficient (Mukaka, 2012).

Correlation coefficient (r)	Strength of correlation
±0.00 - 0.29	Negligible
±0.30 - 0.49	Low
±0.50 - 0.69	Moderate
±0.70 - 0.89	High
±0.90 - 1.00	Very High

All statistical analyses and graphics showing results were conducted using Python version 6.5.2. The quality of coding and English in this thesis was improved through the use of ChatGPT version 3.5.

4. RESULTS

The purpose of this study is to examine both temporal and spatial variability of soil moisture at Søråsfeltet in Ås and the surrounding area, as well as to compare satellite measurements to ground-based sensors. Additionally, the performance of the sensors under dry and wet conditions will be of interest.

This section presents the main outcomes obtained from the methods described in subsubsection 3.3.1. Specifically, subsection 4.1 presents time series for the sensors mentioned to show the temporal variability of soil moisture, while subsection 4.2 showcases the results concerning spatial variability. Both sections include plots illustrating interesting patterns before introducing satellite data. Subsequently, in subsection 4.3, the satellite data will be examined in more detail and compared to the different ground-based sensors. In subsection 4.4, statistical tests will be carried out to determine any similarities or patterns between the different sensors. Finally, in subsection 4.5, any potential errors or uncertainties will be addressed to provide a better understanding of the limitations and potential sources of inaccuracies in the results obtained.

4.1. Temporal variability

4.1.1. Intercomparison of different sensors

The time series obtained from the SMIoT sensor is showing considerable temporal variability at depths of 5 and 25 cm across the period from 07.02 - 17.07 (Figure 15). At 5 cm depth, the soil moisture reached a minimum 12.02 at 25 %, followed by an upward trend that culminated in a peak in April. Afterwards, soil moisture levels decreased during a dry period until mid-May, when precipitation occurred, leading to a rapid increase and an overall peak of 68 % 04.07. The fluctuations in soil moisture levels generally corresponded to precipitation events, although there was an anomalous increase in soil moisture from mid-March to the end of March, despite a lack of precipitation during this period.

The measurements from at 25 cm depth generally indicated higher soil moisture content with smaller fluctuations compared to the 5 cm depth, but it exhibited the same overall trend. The minimum is 13.02 at 34 % followed by an upward trend until the end of April. Thereafter, the soil moisture decreased due to the dry period, before it rapidly increased in end of May. Around mid-June the soil moisture plateaued and reached saturation at 68 %. Even though there were some precipitation events afterwards, the soil moisture content did not increase further. A time lag was observed between the soil moisture measurements at depths of 5 cm and 25 cm, with the sensor at 5 cm registering a faster response to precipitation. Furthermore, both depth exhibited an increase of soil moisture 26.05 where there is no displayed precipitation parallel to the steep increase of soil moisture.

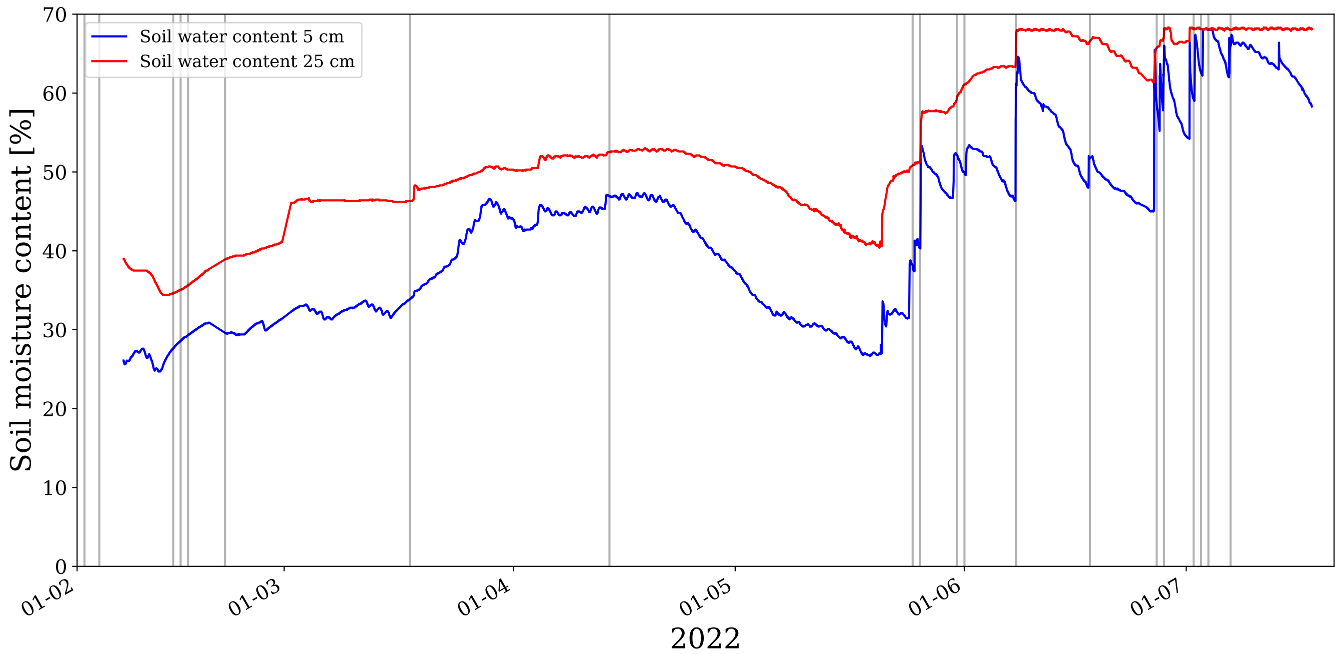


Fig. 15: Soil moisture measurements from the SMIoT sensor 2 at 5 and 25 cm depth from March to July 2022. The running mean of all samples is shown as a line and the standard deviation as a shaded area. The color blue represents soil moisture, and red represents temperature. The vertical grey lines represent days with more than 4 mm precipitation.

The SMIoT sensor measured diurnal fluctuations in soil moisture at a depth of 5 cm and ground-level temperature over a period of seven days from 14.04 to 21.03. This period was chosen due to the relatively stable soil moisture (Figure 15), which resulted in an interesting pattern for the entire week. The measurements were taken every 10 minutes, and there was no precipitation during this period.

During this period, soil moisture exhibited a sinusoidal pattern, with a trough at around 07 in the morning and a peak at 18 in the afternoon (Figure 16). Temperature followed a similar trend, with a trough at 06 in the morning and a peak at 15 in the afternoon (Figure 17). The running mean values showed that soil moisture was 46.6 % at the trough and 47.2 % at the peak, resulting in a difference of 0.6 percentage points. The temperature had a trough at 3 °C and a peak at 9 °C.

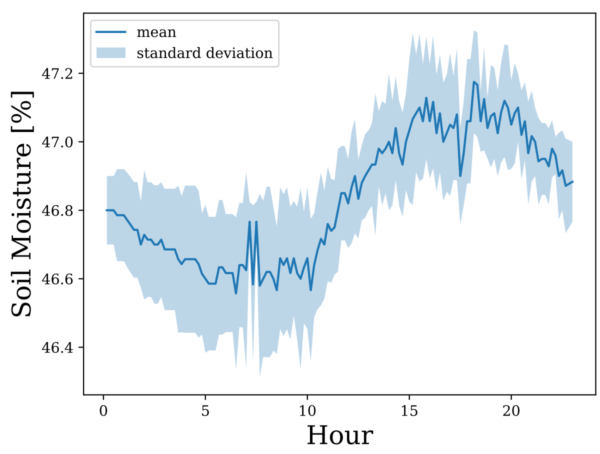


Fig. 16: Diurnal fluctuations of soil moisture measured at 5 cm depth of the SMIoT sensor.

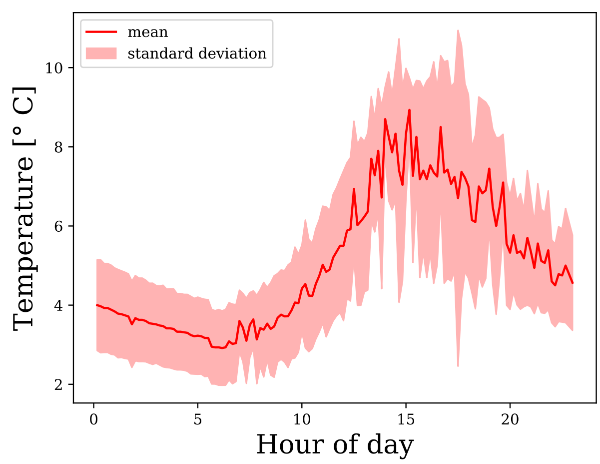


Fig. 17: Diurnal fluctuations of ambient temperature of the SMIoT sensor.

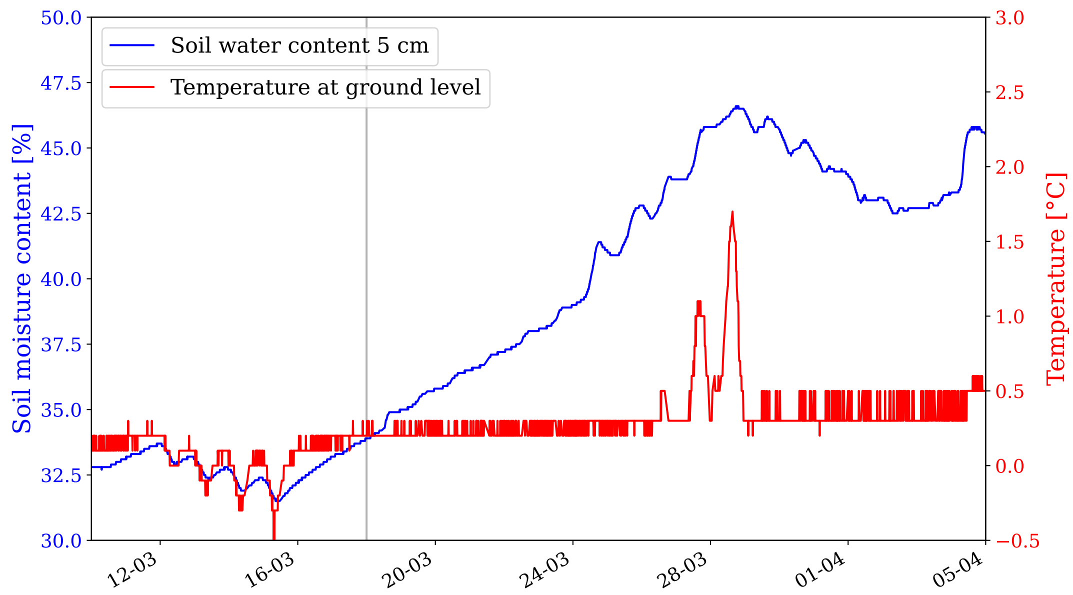


Fig. 18: Soil moisture content at 5 cm depth and ambient temperature from the SMIoT sensor in the period 10.03.22 to 05.04.22. The vertical grey line represents a day with more than 4 mm precipitation.

Figure 18 displays the soil moisture content at a depth of 5 cm, as well as the ambient temperature. The soil moisture plot is a subset of the larger graph shown in Figure 15, displaying only the period from 10.03 to 05.04 The temperature remains stable at or below zero until 26.03, when it experiences a few positive spikes. After these fluctuations, the temperature stabilizes again, but now in the positive region, between 0.4 and 0.5 °C. Meanwhile, the soil moisture exhibits some fluctuations around 32.5 %

between 10.03 and 17.03, but then begins to increase steadily until it reaches a peak of 47.5 % after 11 days. Notably, there is only one precipitation event over 4 mm, occurring on 19.03, during this time period.

The depth of 10, 75, and 100 cm for the SoilVUE sensor were stable during the whole period, with values ranging between 45 and 50 % (Figure 19). The SoilVUE sensor was moved to another location 18.07, which is clearly visible for the 100 cm sensor by the abrupt drop of soil moisture content. The 5 and 20 cm depths exhibited similar behavior to the SMIoT sensors, where the 5 cm depth always reported lower values than at 25 cm. The 5 cm depth showed overshooting during precipitation events in the wet period of November. The 50 cm depth consistently reported the lowest values out of all the depths during the first nine months with the lowest measurements being below 1 percent. During precipitation events in November, this depth also experienced extreme spikes. The 40 and 60 cm depths behaved similar, and experienced very stable values from January to mid-May without responding to precipitation events. After a long dry period, the values started to drop around mid-May. Overall, the different depths showed varying patterns and behavior, which could indicate differences in the moisture retention capacity of the different soil layers.

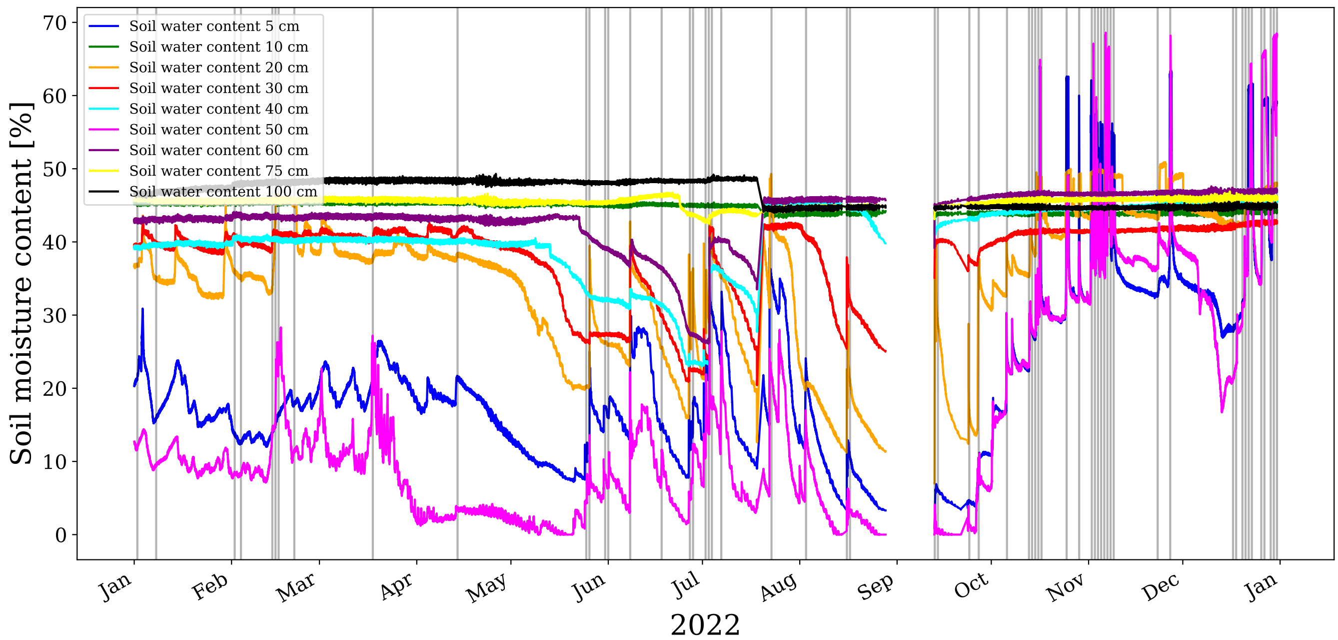


Fig. 19: Soil moisture measurements from SoilVUE sensor at nine depths from January to November 2022. The vertical grey lines represent days with more than 4 mm precipitation.

To validate the accuracy of the sensor such as ADR, SMIoT, SoilVUE and COSMOS, soil moisture samples were collected manually using the volumetric method. These samples were used as a benchmark or ground truth for comparison with the measurements obtained from the sensors that measure indirectly, as described by Hillel (1982). The resulting volumetric soil moisture content was plotted in Figure 20, with vertical grey lines indicating days with precipitation exceeding 4 mm. The measurement period spanned from 09.06 to 21.09, 2022.

The plot displayed a trend that was consistent with the observations made from the sensors measuring indirectly, indicating that precipitation events caused an increase in the soil moisture content. In early July, the measurements showed higher values compared to other days, with a maximum of 49 %, taken during a precipitation event. In contrast, the beginning of August recorded some of the lowest values, reaching 15 %, despite experiencing precipitation events during that time. On average, the measurements had a value of 26 % with a standard deviation of 6.5 %. Notably, measurements taken at Kroer are marked in red, and are shown to be 16.3 % and 14.6 %, respectively. Overall, these manual soil moisture samples will provide valuable confirmation of the trends observed in the sensor data, and help to ensure the accuracy and reliability of the measurements.

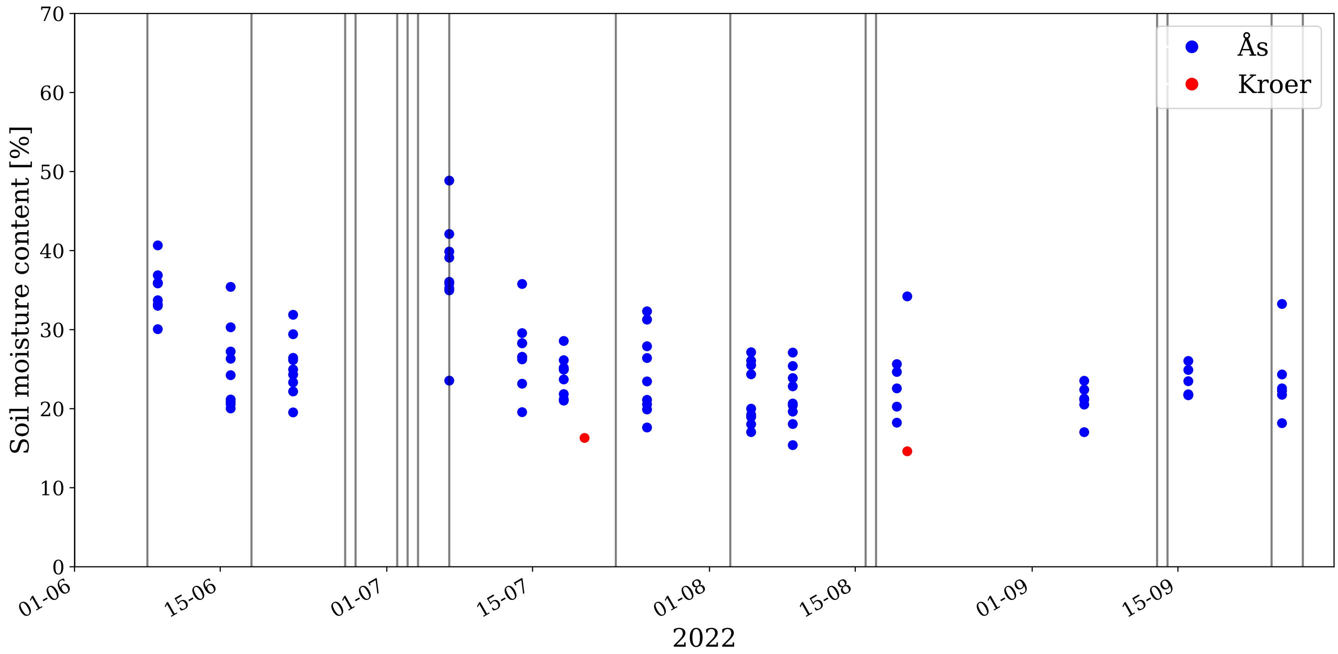


Fig. 20: Volumetric soil moisture content from the manual samples using the volumetric method. The vertical grey lines represent days with more than 4 mm precipitation.

4.1.2. Satellite versus ground measurements of soil moisture

Figure 21 displays soil moisture content from the top layer (5 cm depth), measured by the Sentinel-1 satellite, for the period spanning 01.01.22 to 31.12.22. The data showed a mean soil moisture content of 8.26 %, with a standard deviation of 2.97 %. The minimum soil moisture value of 3.4 % was recorded on 09.10.22, while the maximum value of 17.6 % was recorded on 23.01.22. Despite the presence of vertical grey lines indicating days with more than 4 mm of precipitation, there does not appear to be any discernible pattern in the soil moisture content over time. The data is characterized by numerous spikes and fluctuations, with no clear correlation between changes in soil moisture and precipitation events. Overall, the figure suggests that the satellite measurements do not represent the surface soil moisture observed in the ground-based measurements and are not reacting to precipitation, the main driver of changes in soil moisture.

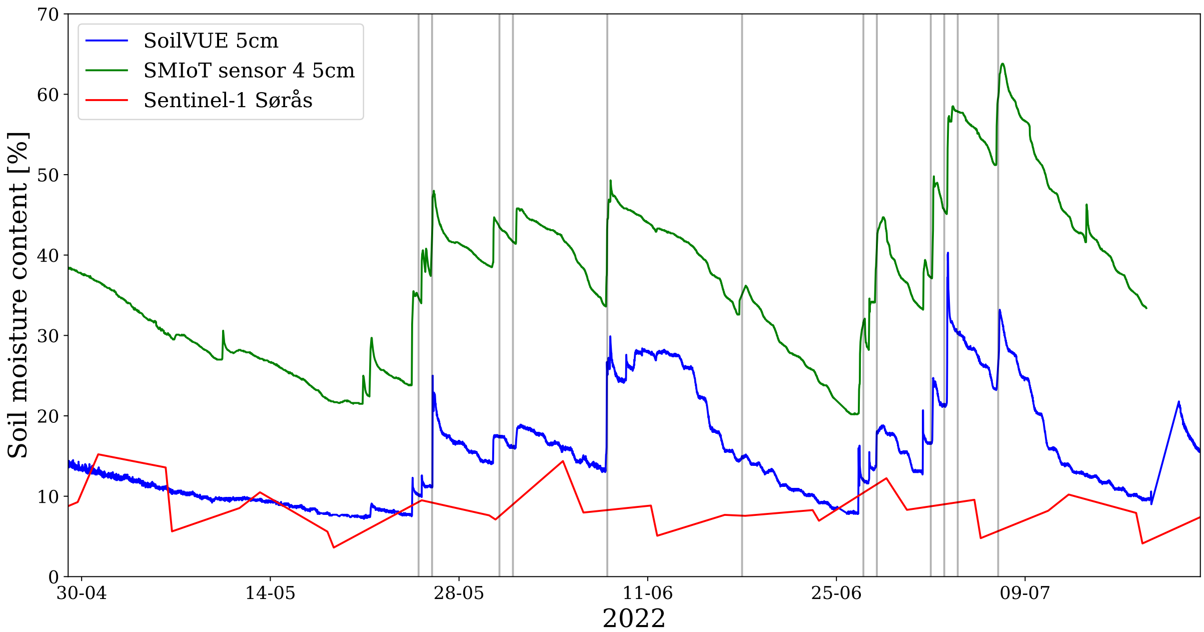


Fig. 21: Surface soil moisture content from the Sentinel-1 satellite in the period 01.01.22 to 31.12.22. The vertical grey lines represent days with more than 4 mm precipitation.

4.2. Spatial variability

In Figure 22, a time series obtained from all functioning SMIoT sensors is presented, displaying soil moisture content at depths of 5 cm and 25 cm. As sensor 1 malfunctioned, only sensor 2, 3, and 4 are displayed. In June, sensor 2 records much higher values compared to sensors 3 and 4, exhibiting the same trend for both the 5 cm and 25 cm sensors.

For sensor 3, some unrealistically low values were removed. On the 20.05, sensor 3 deviates from the other sensors, as it fails to record any increase in soil moisture. Throughout the time series, sensor 3 consistently reports the lowest values, displaying a surprisingly stable soil moisture content at 25 cm depth from 16.02 to 02.05 with a mean of 46 % and a standard deviation of only 0.66 %.

Sensor 4 exhibits a similar trend to sensor 2, gradually increasing from the beginning of the time series until the dry period, when it slowly decreases again. During the wet period, sensor 4 responds well to precipitation, reaching a peak of 67 % just below the peak recorded by sensor 2.

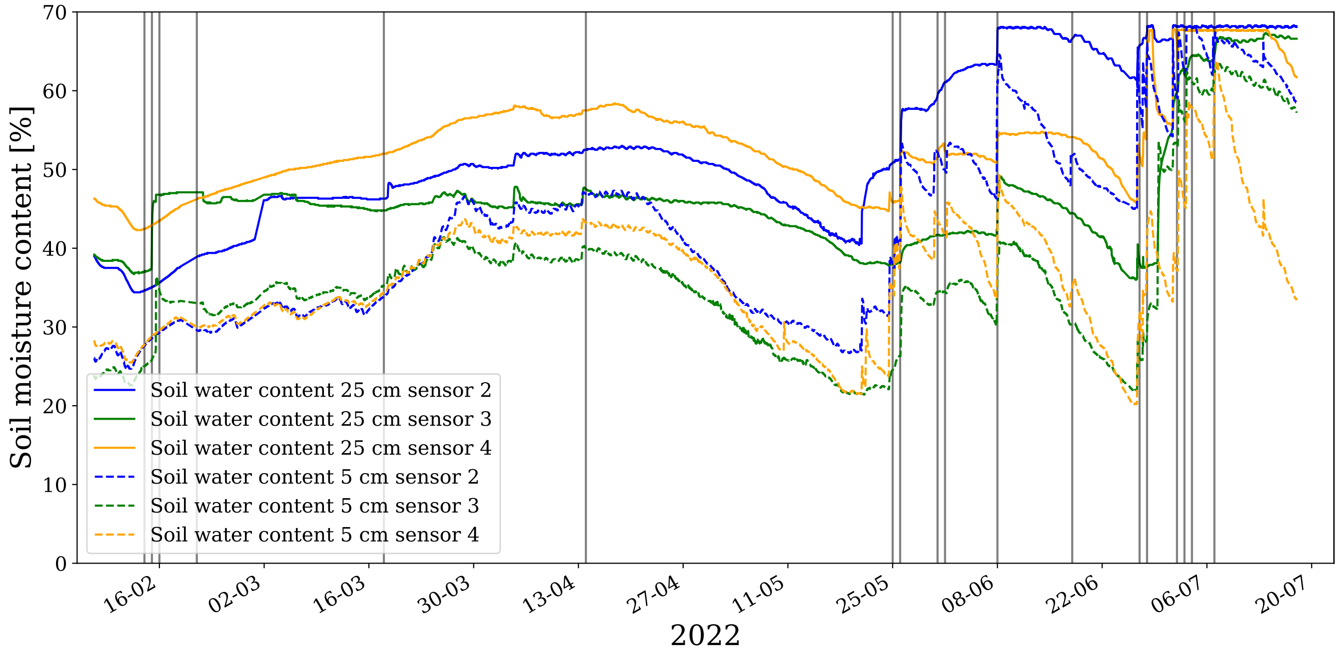


Fig. 22: Soil moisture measurements from three SMIoT sensors at 5 and 25 cm depth from February to July 2022. The vertical grey lines represent days with more than 4 mm precipitation.

The measurements from Sensor 3 of the SMIoT, which measures soil moisture at a depth of 25 cm, have exhibited remarkable stability over an extended period of time, as shown in Figure 23. Starting at 37.0 % on the 14.02, the sensor experienced a quick increase on the 15.02 up to 47.0 %, but then remained stable for the next three months. From the 16.02 to the 01.05, the mean soil moisture content for Sensor 3 was 46.00 %, with a low standard deviation of 0.66 %. This suggests that the soil moisture at this depth remained relatively constant during this period, despite a few precipitation events. In comparison, the

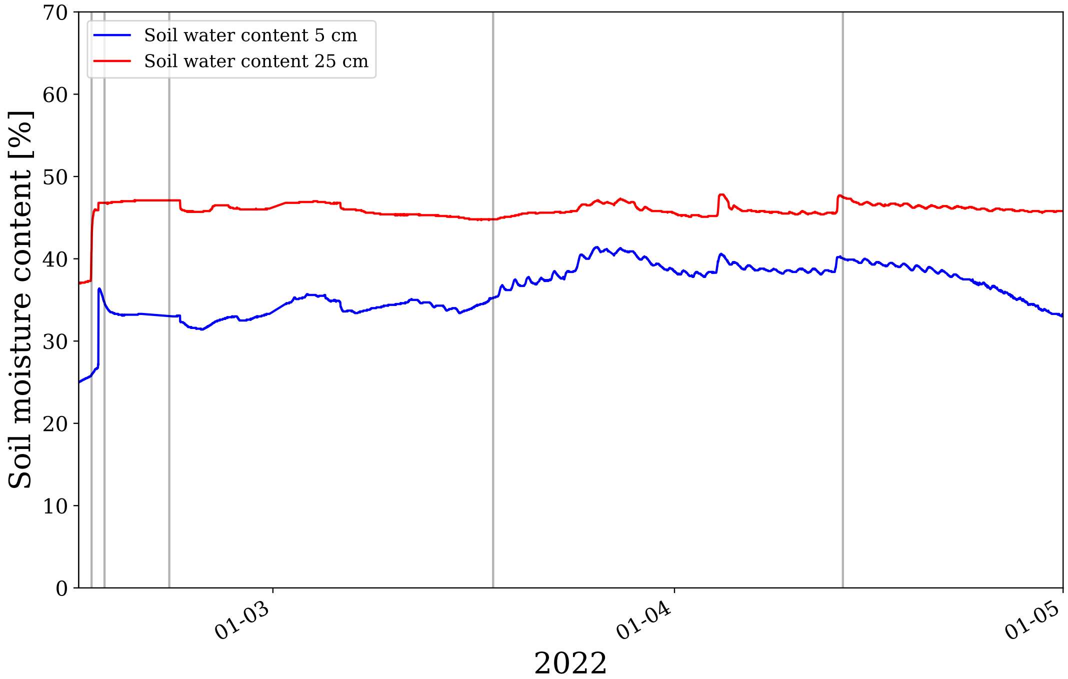


Fig. 23: Soil moisture measurements from the SMIoT sensor 3 at 5 and 25 cm depth from 14.02 to 01.05.2022. The vertical grey lines represent days with more than 4 mm precipitation.

mean soil moisture content for Sensor 3 at 5 cm depth was 36.6 %, with a higher standard deviation of 2.68 %. This indicates that the variability in soil moisture content was four times higher at the shallower depth.

In Figure 24, the soil moisture measurements obtained from the COSMOS sensor between 01.05 and 30.11 are presented. For the hourly data, one noteworthy observation is the high daily variability in soil moisture values. Further analysis of the dataset reveals a daily standard deviation of 3.9 %, while the mean for the entire period is 39.5 %, with a standard deviation of 9.6 %. The maximum soil moisture value recorded was 55 %, which occurred on three different occasions: 02.06, and 01.11 and 09.11. The lowest value, 17.9 %, was recorded on 08.05 towards the end of the drought period in April/May. Increases in soil moisture were generally observed after precipitation events, and soil moisture decreased during drier periods.

To obtain daily data, the hourly data from the COSMOS sensor was processed by removing values equal to 50 %, as described in subsubsection 3.5.2. This step resulted in gaps in the data mid-August and late-October. Nevertheless, the processed plot displays less noise, providing a clearer view of the daily

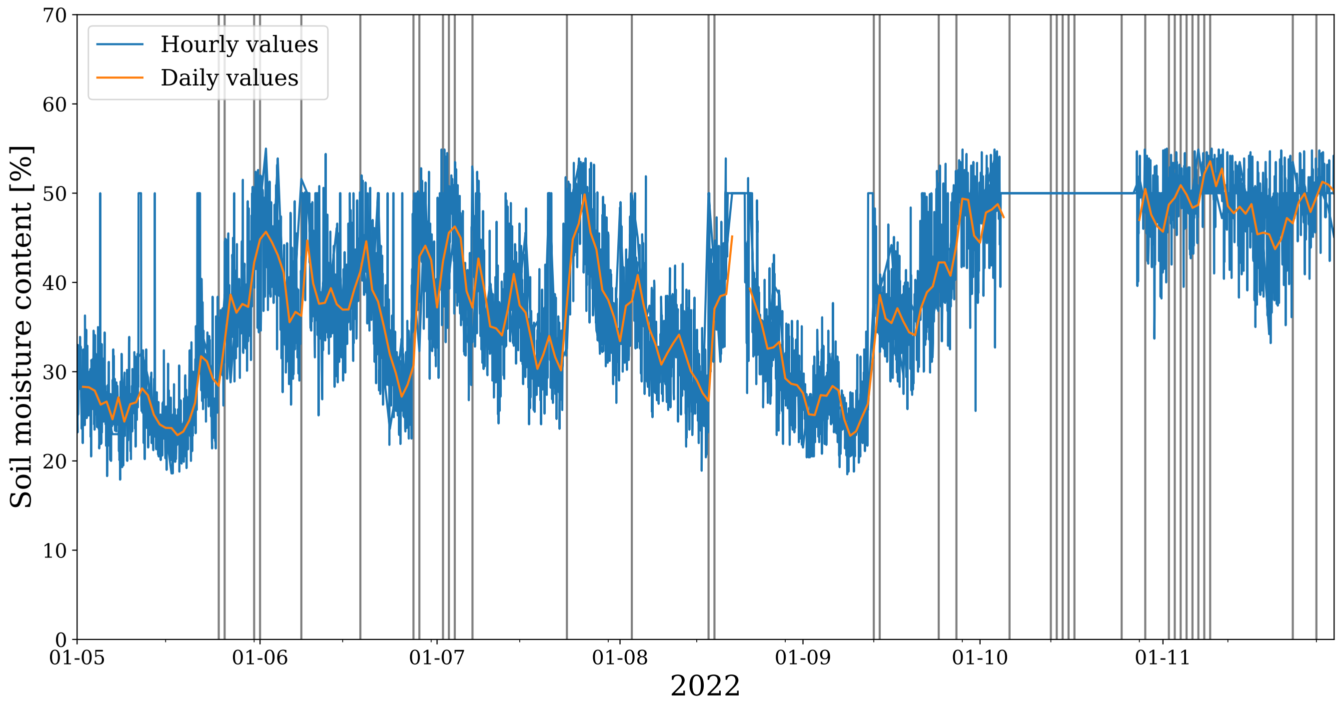


Fig. 24: Time series of soil moisture measured by the COSMOS sensor, showing the hourly and daily values from May to December. The straight lines of the hourly values in mid-August and October are due to gap-filling. The vertical grey lines represent days with more than 4 mm precipitation.

variability in soil moisture. The mean soil moisture value over the monitoring period is 37.7 %, with a standard deviation of 8.2 %. The highest soil moisture value of 53.6 % was recorded on 09.11, while the lowest value of 22.8 % was recorded on 09.09.

Analysis of the temporal trends reveals that soil moisture values were lowest after the dry periods in May and early September. On the other hand, the highest values were recorded in early November, following a period of heavy precipitation.

The soil moisture content from the top layer of ground was observed by the Sentinel-1 satellite at three different measurement sites over the course of the year, from 01.01. to 31.12. The results of these measurements are displayed in Figure 25. The measurements from the Kjerringjordet and Kroer show similar result to the measurements from Søråsjordet, with no apparent trends and no clear correlation with precipitation events. However, there is a noticeable difference in the mean soil moisture content between the three sites. Søråsjordet has an overall higher mean soil moisture content of 8.3 % with a mean of 3.0 %, while NVE has a mean of 7.4 % with a standard deviation of 2.3 %, and Kroer has the lowest mean

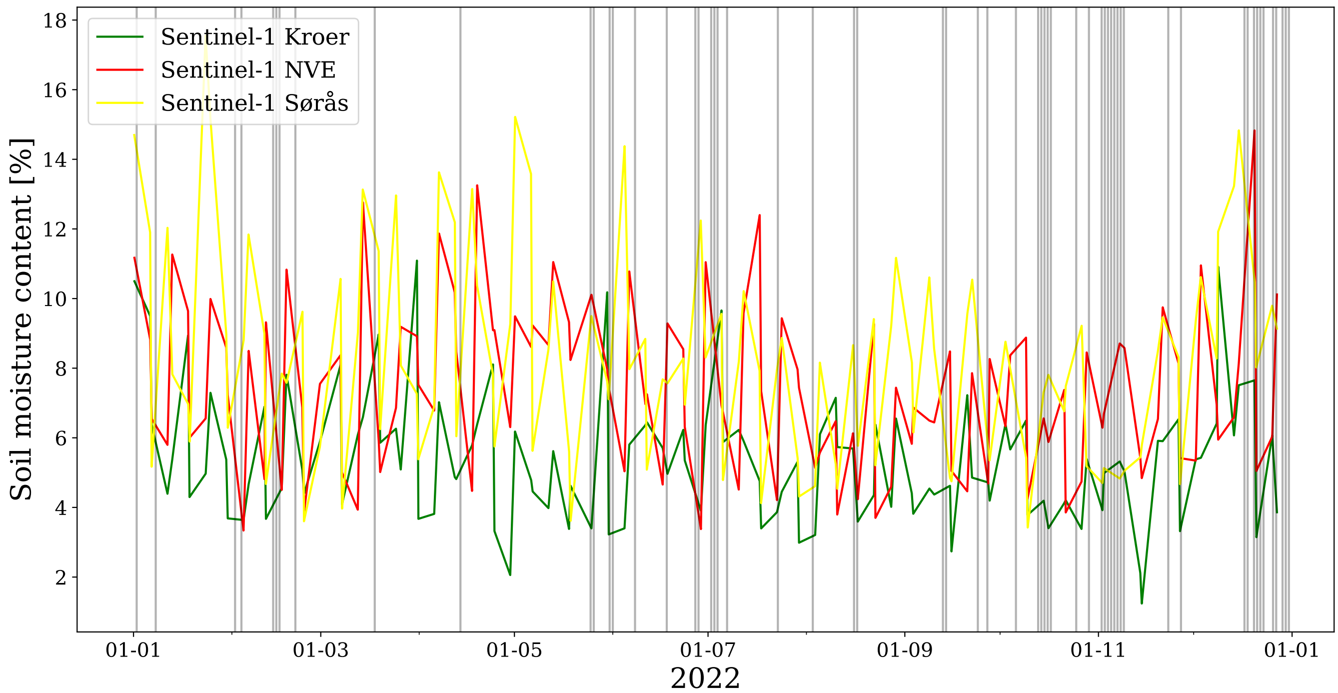


Fig. 25: Surface soil moisture content from the Sentinel-1 satellite displaying the locations Kroer, NVE-site (Kjerringjordet) and Søråsjordet in the period 01.01.22 to 31.12.22. The vertical grey lines represent days with more than 4 mm precipitation.

being 5.4 % with a standard deviation of 1.8 %. All these values are very low and probably not physically meaningful.

In Figure 26, the spatial variability of soil moisture is illustrated through a south-north transect of Søråsfeltet, based on five different days during the 2022 measurement campaign. Each day is represented by a different color. The results do not exhibit any significant trend for the spatial variability, with the exception of a slight positive spike near sampling point 9 and a negative spike near point 19. In contrast, the temporal effects are more noticeable, with the sample taken on 19.08 standing out due to a recent precipitation event two days prior. Similar trends are observed in Figure 27, where the only observable trend of the west-east transect is the higher soil moisture measurement on 19.08. Additionally, the soil moisture measurements from 24.08. are generally higher compared to remaining days.

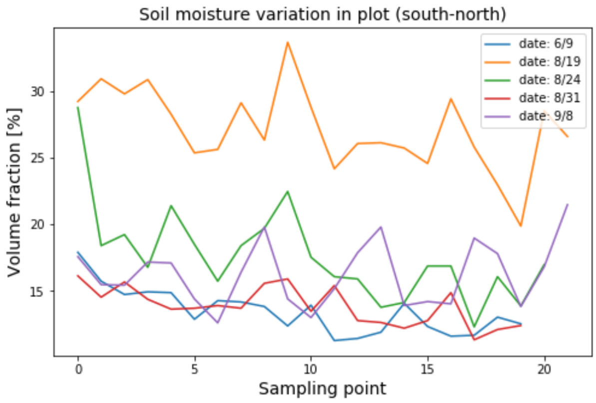


Fig. 26: South-north transect of Søråsfeltet showing soil moisture levels measured by ADR-sensor.

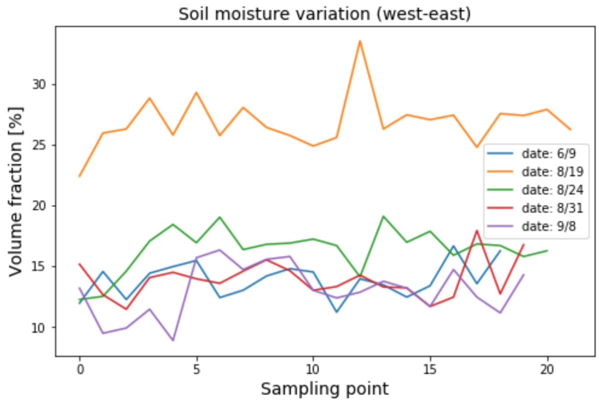


Fig. 27: West-east transect of Søråsfeltet showing soil moisture levels measured by ADR-sensor.

4.3. Comparison of sensors

The COSMOS, SMIoT, and SoilVUE sensors exhibit similar temporal patterns, although their absolute values differ (Figure 28). These sensors respond similarly to both dry and wet periods. The SMIoT sensor consistently records the highest values, occasionally exceeding the physical limit at 61 %. On the other hand, the SoilVUE sensor consistently records the lowest values of the three, with measurements below the wilting point at 18 %. The COSMOS sensor falls between the other sensors without surpassing the lower or upper limit for soil moisture.

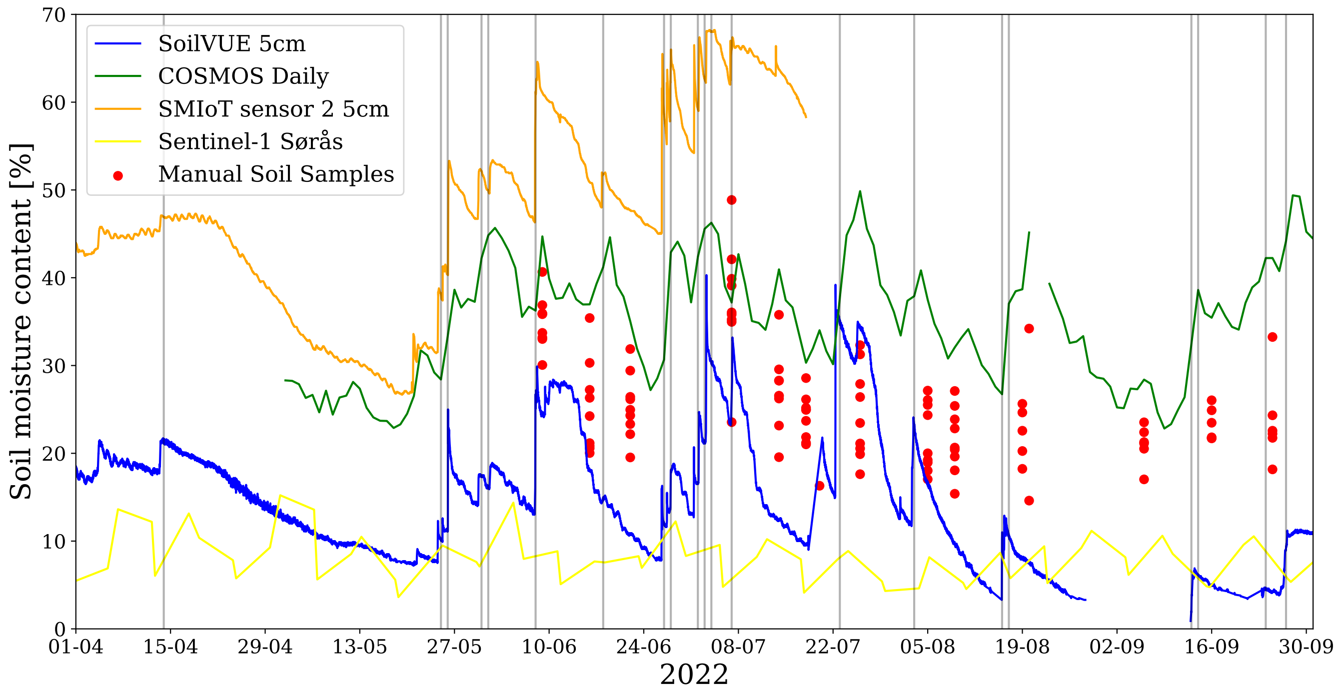


Fig. 28: Soil moisture measurements from SMIoT sensor 3 at 5 cm depth, from SoilVUE at 5 cm depth, the daily averaged values from the COSMOS sensor, measurements from the Sentinel-1 satellite, and the volumetric samples from 01.04 to 31.09.2022. The vertical grey lines represent days with more than 4 mm precipitation.

4.4. Statistical analysis

The results of the Shapiro-Wilk test for normality indicated that none of the p-values exceeded 0.05, leading to the rejection of the null hypothesis that the data follows a normal distribution. Moreover, none of the histograms showed a resemblance to a normal distribution. As a result, a t-test to compare the means of two independent samples was not performed due to the lack of normality in the samples. Instead, a Wilcoxon Rank Sum test was done to check whether the distributions of two paired samples were equal or not, all of which gave negative results. Additionally, the Kolmogorov-Smirnov test was performed to assess the similarity between two sets of samples, and all results were negative. Finally, the Levene test for equality of variances resulted in some p-values above 0.05, indicating the lack of significant differences between the variances of the samples. Only the tests that failed to reject the null hypothesis are shown in Table 4.

Table 4: Results of the Levene test for equality of variances

Comparison	Levene test statistic	p-value	Result
SoilVUE 20 cm vs Cosmos daily	0.0166	0.8973	Fail to reject null hypothesis
SMIoT Sensor 2 25 cm vs Cosmos hourly	0.7274	0.3937	Fail to reject null hypothesis
SMIoT Sensor 3 25 cm vs Manual Samples	0.9736	0.3238	Fail to reject null hypothesis
SoilVUE 20 cm vs SMIoT Sensor 3 5 cm	1.8223	0.1771	Fail to reject null hypothesis
SMIoT Sensor 3 5 cm vs Cosmos daily	0.0623	0.8030	Fail to reject null hypothesis

4.5. Possible errors and uncertainties

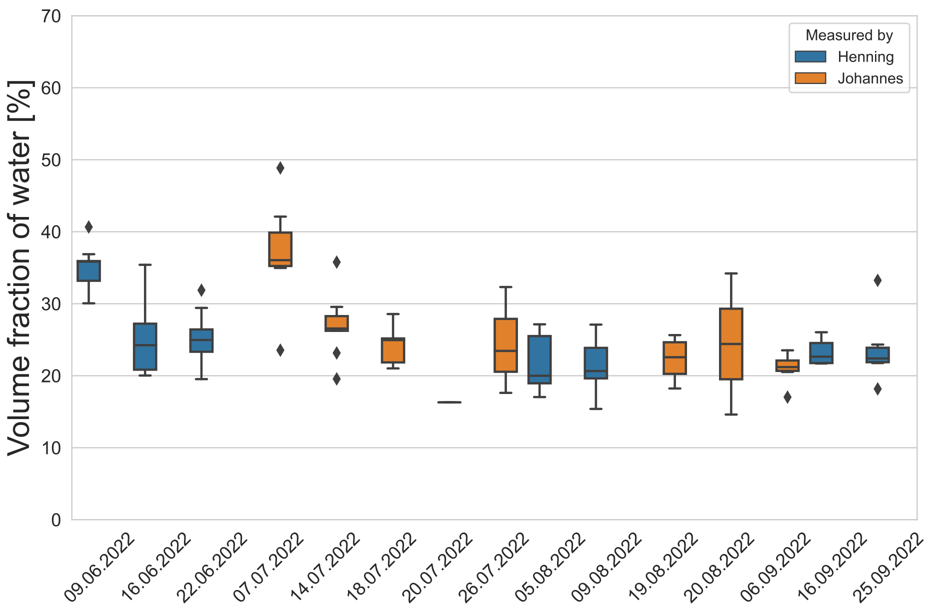


Fig. 29: This plot depicts box plots representing volume fractions of soil samples collected from Søråsfeltet. Each box is color-coded by the collector, and displays the median, quartiles, range, and outliers of the data.

In addition to providing a visual representation of the distribution of soil water in the Søråsfeltet, Figure 29 highlights any differences in measurements among the collectors, which could potentially be a source of systematic errors. It is worth noting that there is an outlier 07.07.2022 in the data due to a precipitation event, and thus should not be considered a human error. The color-coding of the box plots for each collector allows for easy identification of any differences in the measurements among them. By analyzing these differences, researchers can identify potential sources of systematic error, such as variations in the techniques used to collect the soil samples, or sampling at different depths. This information is valuable for improving the accuracy and reliability of future measurements and can help ensure that any systematic errors are properly addressed and minimized. This is especially relevant for the volumetric method as it is considered ground truth, so ensuring its accuracy is important for the validation and calibration of indirect measurement methods.

The lowest measured values are around 15 %, which matches decently with the wilting point at 18 % (Dingman, 2014). This could be used as a reference for filtering values. The maximum values are around 30-32 % for days with no precipitation, and up to 40-50 % for the rainy day.

5. DISCUSSION

The purpose of this study is to examine both temporal and spatial variability of soil moisture at Søråsfeltet in Ås and the surrounding area, as well as to compare satellite measurements to ground-based sensors. Furthermore, a comparison of sensors will be conducted across a diverse range of naturally occurring soil moisture conditions.

The chapter is divided into four sections, with subsection 5.1 and subsection 5.2 focusing on temporal and spatial variability of soil moisture in Søråsfeltet, respectively. subsection 5.3 provides a comparison of the soil moisture measurement techniques used in the study, while subsection 5.4 evaluates potential sources of error.

5.1. Temporal variability

In this section, the temporal variability of soil moisture will be investigated to address the research question. The analysis will include examining the time series data from various sensors, focusing on general trends, dry and wet periods, and other noteworthy patterns. Additionally, the temporal variability of the satellite measurements will also be evaluated and discussed.

SMIoT

The soil moisture generally responds well to precipitation, as shown in Figure 15, with a maximum value of 68 % at 25 cm depth. However, this value exceeds the porosity of the soil, which is estimated to be 61 % according to Naalsund (2022). The reason for this overestimation could be the lack of calibration for the soil type. Clayey soils typically require a special calibration to improve the accuracy of moisture measurements (GroPoint™, 2021). Another possible explanation could be the inaccuracy of the sensor for soil moisture values over 50 % (GroPoint™, 2021). Despite these limitations, the trend in the data is still considered representative and useful for those not requiring exact values.

It is a commonly observed phenomenon that there is a delay in the response of soil moisture in deeper soil layers, caused by the longer time taken for water to infiltrate after precipitation. However, this delay may vary depending on the soil type and other environmental factors, as noted by Xu et al. (2021). A study conducted by Naalsund (2022) investigated the response time of clayey soil at Søråsjordet and found that it had a response time of 0-2 hours. This means that after precipitation, it takes between 0 to 2 hours for the moisture to pass by the sensor at 5 cm and be detected at the depth of 25 cm. However, the soil can become increasingly compact due to the lack of tillage and the activity of shallower roots, which gradually reduces the infiltration rate. As the soil depth increases, the constant infiltration rates decline rapidly (Wang et al., 2015). This can result in a longer delay in soil moisture response patterns in deeper layers.

Another notable event in the data is the appearance of peaks 26.05, despite the apparent absence of precipitation during this time. After ruling out snowmelt and irrigation as potential causes, a closer examination of the precipitation data showed that there were two days with 3 mm of rainfall that were not included in the figure due to the 4 mm threshold. These two days explain the increase in soil moisture during this period. To avoid the issue of a threshold while keeping the plot clear, some studies, including He et al. (2023), have utilized dual x- and y-axes.

The figures 16 and 17 indicate a possible correlation between soil moisture and temperature, with both variables exhibiting a similar diurnal pattern. However, it is important to note that the daily variability of soil moisture is only 1.3 %, and the observed change is smaller than the accuracy of the SoilVUE sensor used to measure it. While this observation could imply the possibility of measurement error, determining the exact cause is challenging and requires further investigation.

A study by Young et al. (2008) examined a method for estimating volumetric water content of near-surface materials in which diurnal temperature variations can be as high as $\pm$ 20 °C. The study employed a Levenburg-Marquardt (LM) optimization of thermal conductivity, volumetric heat capacity, and drift in ambient temperature, resulting in the LM-Uncorrected method for calculation of water content, and an expansion of this method that incorporates temperature dependencies of soil thermal conductivity and optimizes on volumetric water content, apparent needle spacing, and drift in ambient temperature during the measurement, which is known as LM-Corrected. The LM-Uncorrected method revealed a diurnal variability of soil moisture ranging from $\pm$ 0.02-0.03 $\frac{m^3}{m^3}$, while the LM-Corrected method produced a time series of water content values that was much smoother at only $\pm$ 0.005 $\frac{m^3}{m^3}$. Further research is needed to confirm and comprehend the relationship between soil moisture and temperature with respect to diurnal variability, and it would be interesting to apply the LM-Corrected method to the measurement of the SMIoT sensor.

The mid to end of March saw an increase in soil moisture despite only one recorded precipitation event at 5.1 mm, as illustrated in Figure 18. It is unlikely that irrigation was the cause since there was no evidence of any irrigation activities in close proximity, and there was no snow to be melted (Kroken et al., 2009, Wolff, 2023). Other nearby sensors demonstrate similar water levels, decreasing the possibility of runoff. Additionally, data from the bio-climatic field station at Søråsfeltet show no snow cover, further reducing the likelihood of snowmelt being the cause. The stable temperature of about 0 °C in the area during the period indicates that the melting of frozen water in the soil could be the most likely explanation. Due to the latent heat of phase change, soil melting processes effectively dampen significant temperature variations from the surface down to the deep soil layer. The temperature of the ice remains constant as the ice melts (Tipler and Mosca, 2012). This melting process results in an increase in liquid water in the soil, leading to a rise of the dielectric conductivity as the conductivity of frozen and liquid water differ. The increase in measurable soil moisture is most significant at a depth of 5 cm and decreases with greater depths, as can be seen in Figure 22. In the soil thawing process, the upper and lower layers of frozen soil begin to melt first. However, the water from melted ice in the upper layer becomes obstructed by the frozen layer, allowing the soil moisture content to increase in the upper layer first (Musa et al., 2016).

An interesting question is whether the SMIoT sensors accurately measures soil moisture in frozen ground. When ice is present in the soil, the soil water potential and liquid water content are strongly influenced by temperature. As soil temperature drops further below the soil water freezing point, more water freezes, and liquid water content decreases. This drop in liquid water content during freezing is analogous to soil drying (Flerchinger et al., 2006). According to the manufacturer's specifications, the sensors can function in temperatures ranging from -20°C to 40°C (GroPoint™, 2021). Previous research by Yoshikawa and Overduin (2005) found that the accuracy of dielectric sensors in measuring unfrozen water content under frozen soil conditions is comparable to the manufacturer's claims.

In summary, soil moisture can increase due to sources other than precipitation, such as irrigation, runoff, snowmelt, or melting of frozen water in the soil. In this case, the stable temperature of about 0 °C during the observed period suggests the latter as the most likely explanation, where the melting of ice in the soil results in an increase in liquid water content and measurable soil moisture.

SoilVUE

Upon closer examination of Figure 19, inaccuracies are suspected in the measurements at depths of 10 and 50 cm. However, it is unclear whether the confusion in the depths is due to sensor malfunction or a data transfer issue to the online database. To gain a better understanding of the distribution of soil moisture at different depths, boxplots of the measurements are shown in Figure 30.

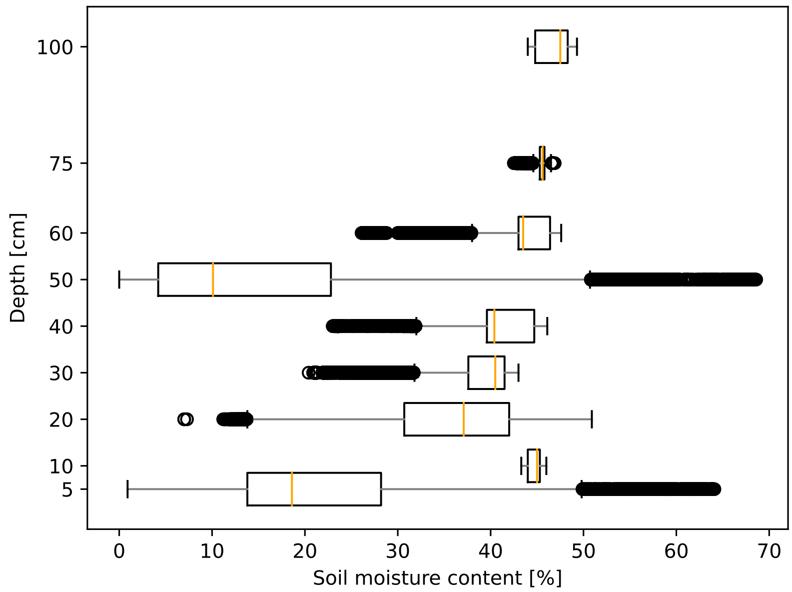


Fig. 30: Boxplots for the different depths of the SoilVUE sensor showing the distribution of soil moisture.

During periods of excessive rainfall, such as at the beginning of November and end of December, interesting observations can be made. Assuming that the 50 cm sensor is located at near-surface level, which seems more likely than it actually being positioned at a depth of 50 cm, the response time appears to be rapid. However, the measurements at 5 cm and 50 cm seem to overestimate the soil moisture content, while the same trend, albeit not as significant, can also be observed at a depth of 20 cm (Figure 15). The rapid increase and subsequent decrease in soil moisture content could be due to preferential flow, the movement of water through large, connected pores or cracks in the soil. This can cause water to bypass some soil layers, leading to rapid wetting of deeper soil layers and a quick response time in the sensors located at those depths.

Studies such as Demand et al. (2019) have found that preferential flow is strongly influenced by the initial soil water content and maximum rainfall intensity, with higher rainfall intensities leading to increased preferential flow. Additionally, preferential flow has been found to occur less frequently in spring and more frequently in summer and early autumn. These findings align with the observed spikes in soil moisture content during autumn when general soil moisture levels were already high (Figure 15). However, further investigation would be necessary to confirm the hypothesis of preferential flow causing the rapid increase and decrease in soil moisture content.

The SoilVUE sensor behaves abnormally during dry periods, such as the one observed in April/May, where both the 5 and 50 cm sensors report values well below the wilting-point of clay soils at 18 % (Dingman, 2014). The hysteresis effect of the soil's expansion/contraction characteristics can make it difficult to achieve a good contact with the soil. Additionally, after several wetting and drying cycles, the soil may not fit tightly around the probe, resulting in air gaps. In this clayey type of soil, moderate to severe surface cracks can appear when the soil dries out (Dingman, 2014).

A study by Wilson et al. (2023) found the SoilVUE sensor to generally have lower soil moisture content when compared to the HydraProbe by Stevens Water Monitoring Systems, the TDR-315L by Acclima Inc.. Additionally, the soil moisture content at a depth of 10 cm from the SoilVUE sensor were consistently about 0.09 m^3/m^3 lower than the gravimetric soil water content. This discrepancy suggests a potential limitation for the the SoilVUE sensing rods. A shortcoming of this study was that only measurements at 10 cm were looked at, as the HydraProbe and the TDR-315L do not measure at different depths. Despite this limitation, the study suggests that the SoilVUE sensor may be beneficial for monitoring the soil temperature profile, especially when precise soil moisture measurements are not crucial.

Marek et al. (2021) conducted a study analyzing soil water content data from a 100 cm SoilVUE sensor. They concluded that poor contact between the electrode and the soil resulted in underestimation of soil water content by the SoilVUE sensor. Moreover, this poor contact causes greater apparent spatial variability than what is actually present in the soil. In dry or drying soil, the SoilVUE sensor may report smaller water content values than the actual values, while in saturated soil, the reported values may sometimes be larger than the actual values due to water filling the gaps between the electrodes and the soil. Addressing this problem is not straightforward since detecting air gaps is difficult without disturbing the sensor and measurement site.

At agricultural sites, controlling the moisture level of soil through periodic irrigation can help reduce the variation in moisture content, which in turn can limit the expansion and contraction of soil and minimize the formation of air gaps between the probe and the soil (Centre for Ecology & Hydrology, 2021). However, if limiting the variation in moisture content is not possible, a technique of filling the gaps is suggested by GroPoint™ (2021). For instance, if the soil pulls away from the side of the probe after it has been inserted for some time, a slurry made by mixing soil from the immediate vicinity of the probe with water can be poured down the resulting crack to fill it. After drying out and shrinking, the slurry may need to be repeated a number of times before the crack remains filled. However, there are some potential problems associated with this method. The slurry may not have the same structure and properties as the natural soil. The repeated insertion of slurry to the soil can lead to changes in soil structure and moisture that may not be representative of the original conditions. Therefore, it is important to evaluate the potential impact of this method before implementing it. Adjusting the sensor placement or selecting a more suitable site, to improve the accuracy of the measurements without altering the natural soil moisture, might be a better idea.

Upon closer examination of the dry period in April/May, it appears that the soil moisture content begins to decrease from the top layers down. Soil moisture at 5 cm depth reacts first, while at 50 cm the data displays irregular behavior as usual. As time passes, the soil moisture content at 20 cm also begins to decrease. This trend continues downward to 75 cm, with the sensors recording lower soil moisture content as time passes. The sensor at 100 cm remains stable throughout the period, except for when the SoilVUE sensor was moved on 18.07. This observation is consistent with previous research by Xu et al. (2021), indicating that soil drying typically begins in the top layers. In general, temporal variability is higher at shallow depths, resulting in a greater range of both low and high soil moisture content values throughout the measuring period.

The observed pattern of decreasing soil moisture from top layers down during a dry period impacts ecosystems. According to Hoegh-Guldberg et al. (2018), decreasing soil moisture causing water stress in plants can lead to reduced growth, lower yields, and even plant mortality. The primary adaptation strategy for drought-tolerant plants to cope against water deficits is deeper rooting to access water from lower soil layers (Seleiman et al., 2021). However, not all plants have the ability to develop deeper root systems, and some may be more vulnerable to drought stress. This could result in a shift in vegetation towards more drought-resistant plant species. As stated by Hoegh-Guldberg et al. (2018), human-induced global warming has led to an increased risk of drought. This could have significant implications for ecosystems, particularly in areas where vegetation is already stressed due to water limitations.

Alternatively, if the soil is unable to absorb all the water from the precipitation, it can result in flooding, which can have severe consequences for both natural and human systems. These include environmental disturbance, habitat destruction, crop loss, nutrient deficiency in soil, property damage, and loss of human life (Aldardasawi and Eren, 2021). Therefore, understanding soil moisture patterns and their changes in response to climate change is important for managing the impacts of both droughts and floods.

Satellite measurements

The satellite measurements from Sentinel-1 are found to be comparable to the SoilVUE sensor at 5 cm depth during dry periods (Figure 21). As earlier mentioned, the SoilVUE sensor at 5 cm reports soil moisture content well below the wilting-point of silty clay soils at 18 % (Dingman, 2014). This means that also the data from the satellite falls below the wilting point. However, when compared to the SMIoT sensor which has data within the physically possible range, a significant mismatch is observed. The satellite data is around 30 percentage points lower than the SMIoT sensor data. Furthermore, the response of the satellite to precipitation is negligible. Calibration alone cannot fix the significant difference between the satellite and the ground based sensors, since the patterns also are different. The limitations of satellite retrievals of soil moisture are discussed by Entekhabi et al. (2004), including shallow vertical penetration depth, limited ability to penetrate vegetation or snow, sensitivity to surface roughness, discontinuous temporal coverage, and the short life span and high cost of satellite missions.

Figure 31 and 32 are showing data from Sentinel-1 in 2021 and 2022. The plots were provided by J. Blyverket, so the processing steps are not known. In particular, Figure 31 exhibits soil moisture values exceeding 80 %, surpassing measurements obtained from all other sensors in this study. On the other hand, Figure 32 displays a narrower range of values, ranging between 15 and 20 %, but there is no reaction to precipitation or dry periods, as can be seen in Figure 28. These plots further reinforce the limited utility of satellite data for soil moisture analysis in Ås.

A validation study conducted by Bauer-Marschallinger and Massart (2021), found that the surface soil moisture products derived from Sentinel-1 are currently in a ”pre-operational” stage with limited quality assessment. However, they are still deemed useful for distribution to mainstream users and can satisfy most applicable requirements. The study also showed that the product's temporal analyses demonstrated poor to medium performances when compared to in-situ data. Furthermore, it was observed that the satellite measurements do not accurately represent surface soil moisture as measured by ground-based methods and are not responsive to precipitation, the primary driver of soil moisture of this ecosystem. However, unlike in the study by Bauer-Marschallinger and Massart (2021), the results from this study indicate that the Sentinel-1 data is not useful.

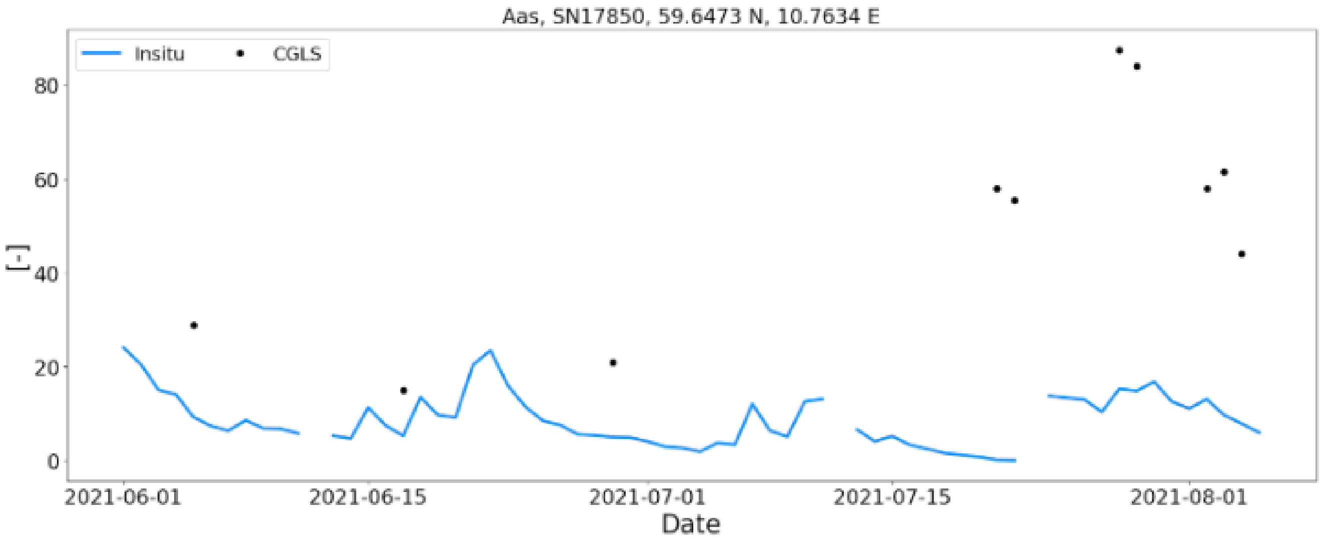


Fig. 31: Surface soil moisture content from Sentinel-1 (CGLS) together with in-situ data from Ås. The dataset corresponds to the year 2021 and was provided by Jostein Blyverket from the Norwegian Meteorological Institute.

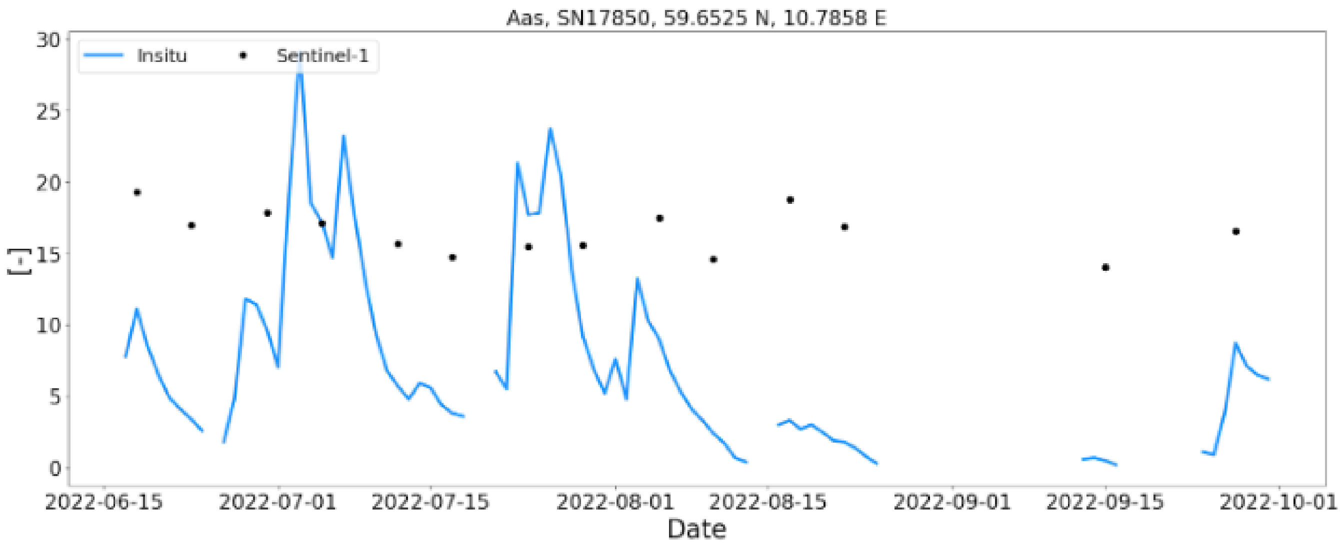


Fig. 32: Surface soil moisture content from Sentinel-1 together with in-situ data from Ås. The dataset corresponds to the year 2022 and was provided by Jostein Blyverket from the Norwegian Meteorological Institute.

5.2. Spatial variability

This section will address the research question by investigating the spatial variability of soil moisture, with a focus on both vertical and horizontal variability. The analysis will include a review of time series data from different sensors, highlighting general trends, dry and wet periods, and other significant patterns. The spatial variability of the satellite measurements will also be evaluated and discussed as part of the analysis.

Variability between SMIoT sensors

The vertical spatial variability of the three SMIoT sensors reveals distinct patterns at different depths (Figure 22). The 25 cm depth generally exhibits higher soil moisture levels compared to the 5 cm depth, a trend that is supported by the findings of Dingman (2014). The studies of Huang et al. (2022) and Xu et al. (2021) suggest that soil moisture generally increases first and then decreases with depth. Furthermore, fluctuations in soil moisture are observed to be larger at the 5 cm depth, which consistently decreases more rapidly in dry periods than the 25 cm depth. These observations are consistent with the faster response of shallow soil layers to meteorological events compared to deep soil layers, as reported by Xu et al. (2021). Precipitation responds faster in shallow soil layers and has a relatively slower response in deeper soil layers, which can be explained by the fact that the top layers are the first contact point for precipitation.

One of the SMIoT sensors, sensor 3, exhibited an interesting behavior during the spring season. The sensor measurements at a depth of 25 cm stabilized at a soil moisture level of 46 % after the precipitation event on 14.02, which was different from the measurements of the other sensors. Moreover, sensor 3 did not show any response to the precipitation event on 20.05, while sensors 2 and 4 at 5 cm and sensor 2 at 25 cm depth registered an increase in soil moisture. Upon investigation, it was discovered that sensor 3 was located directly above an artificial drainage pipe's inlet and outlet (Figure 10). This placement likely influenced the soil moisture in close proximity to the pipe. For heavy clay soils, installing drainage systems does not significantly increase soil storage capacity due to the absence of large pores. However, the installation of drainage systems can increase infiltration capacity by creating cracks during dry periods, which reduces surface runoff (Robinson and Rycroft, 1999). The dominant factors affecting flow rates vary depending on the site conditions (Robinson et al., 1985).

Looking at Figure 23, it is clear that there are no peaks in the spring season for sensor 3. Furthermore, upon closer inspection of Figure 22, it can be seen that sensor 3 does not experience the same peaks as the other sensors, except after relocating sensor 3 to Kjerringjordet on 29.06. These findings suggest that the placement of sensor 3 directly above the artificial drainage pipe has influenced its soil moisture measurements. While studies on clay soils generally demonstrate that drainage installations reduce peak flows (Robinson and Rycroft, 1999), a long-term investigation of grassland drainage on clay soil found only minor effects on peak and overall flows (Armstrong and Garwood, 1991). Therefore, the evidence is not conclusive, but it appears that the artificial drainage pipe is affecting the measurements of sensor 3. Unfortunately, no further work can be conducted as the sensor has been relocated.

The overall spatial variability of the soil moisture sensors reaches a low point on 07.07, which coincides with the end of the rainy period. This observation is consistent with the findings of Korres et al. (2015), who conducted a meta-analysis of spatiotemporal soil moisture patterns and reported negative linear relationships between the coefficient of variation and the mean soil moisture for all datasets. The trend suggests that there is a lower vertical and horizontal spatial variability when the soil is close to or at its saturation point. This suggests that soil moisture sensors may be more reliable in wetter conditions, but could be less reliable in drier conditions. In drought-prone regions, this could make it more difficult to accurately predict soil moisture dynamics and make models more prone to false predictions under dry conditions, or at least less reliable.

COSMOS

Area measurements can provide more representative information on soil moisture over a larger area, but the high variability can make it difficult to analyze temporal trends (Hendriks, 2010). Point measurements, on the other hand, can be affected by soil heterogeneity and disturbance caused by burying the instruments in the soil. The COSMOS sensor is a valuable tool for measuring soil moisture, but its footprints variability requires data processing for meaningful insights. Daily values have been compiled to reduce the variability, as shown in Figure 24, but this resolution makes it difficult to study the sensor's response time to precipitation events.

Precipitation is an essential factor affecting soil moisture's spatial variability, and COSMOS measurements have shown that after a rain event, soil moisture tends to be more spatially homogeneous due to runoff and infiltration. A study of soils in France, Spain, and Tunisia found that precipitation changes the mean soil water content but not the distribution of soil water, especially minima and maxima, through time (Vachaud et al., 1985). Additionally, the COSMOS sensor's neutron intensity varies with changes in barometric pressure, incoming cosmic radiation, snow, and atmospheric water vapor (Wien et al., 2021). Therefore, it is important to correct the measurements at the specific location using measured climate variables. Despite overall reasonable values from COSMOS measurements, missing data and spikes can still be challenging. Gap filling and removal of erroneous values may be necessary to avoid confusion.

Variability in ADR-transect measurements

Spatial patterns of near-surface soil moisture distribution are not easily discernible from the measurements presented in figures 26 and 27. One study found that heavier rains and higher mean moisture contents are often associated with lower spatial variability (Qiu et al., 2001), but this might not be the case here as there is still a relatively high variability even after a precipitation event right before 19.08. The dominant controls on spatial variability of soil moisture are land use, relative elevation, and hillslope position in the surface soil (0-5 cm) (Qiu et al., 2001), but as Søråsjordet only has 1 % slope with the same land use, none of these dominant factors should affect the spatial variability. Results from another study showed that spatial variability generally increases with extent scale, with the standard deviation increasing from 0.036 cm^3/cm^3 at the 2.5-m scale to 0.071 cm^3/cm^3 at the 50-km scale (Famiglietti et al., 2008). In non-uniformly wet profiles, the ADR-sensor seriously overestimates the water content when using calibrations from the manufacturer, as reported by Kargas and Kerkides (2009). This finding appears to be in line with the manufacturer's claim of full accuracy up to 50 % (Delta-T Devices Ltd, 1998). Since the ADR sensor's maximum value during the measurement campaign did not exceed this threshold, the accuracy beyond this level could not be assessed. However, it is important to note that the temporal variability observed in the measurements is greater than the spatial variability. Other studies that have observed spatial variability of soil moisture have incorporated significantly more measurement points, highlighting the need for further research to fully understand the spatial variability of soil moisture distribution using ADR-measurements.

Spatial variability of satellite measurements

According to the results of Bauer-Marschallinger and Massart (2021), the spatial analysis of satellite measurements was found to be more consistent than the temporal analysis when compared to in-situ measurements. The surface soil moisture measurements at Søråsjordet were slightly higher compared to Kjerringjordet, and Kroer showed the lowest values. The variation in vegetation cover among the sites may be a possible cause for the spatial variability in soil moisture measurements. Søråsjordet had short grass around 10 cm, Kjerringjordet had longer grass around 40-50 cm, and Kroer was located in a forested area with a steep slope and shallow, mostly organic soil dominated by litter. Consistent with the satellite measurements, the manual samples presented in Figure 20 also displayed consistently lower measurements at Kroer. However, the presence of apparent random noise makes it difficult to draw definitive conclusions from the dataset.

5.3. Comparison of soil moisture instruments

When looking at the SMIoT, SoilVUE, and COSMOS sensors, a similar temporal pattern is observed (Figure 28). However, consistently higher values are recorded by the SMIoT sensor, while the SoilVUE sensor records the lowest values. To provide validation of these measurements volumetric samples were collected as ground truth data (Hillel, 1982). These indicate that the COSMOS and SoilVUE sensors provide a more reasonable range of soil moisture content compared to the SMIoT sensor, which tends to overestimate during wet periods.

According to Hillel (1982), the conventional volumetric method for clay samples may not be completely reliable since some clay may still retain moisture even at a temperature of 105 °C. Additionally, certain organic matter in the sample can undergo oxidation and decomposition at this temperature, leading to weight loss that is not solely attributable to evaporation of moisture. Errors in the thermo-gravimetric method can be decreased by increasing the size and quantity of samples, or prolonging the time spent drying. However because sampling is a destructive process, it may disturb an observational site, which would lead to inaccurate data. Because of this, a lot of researchers use indirect techniques that enable repeated or continuous measurements at the same location. After the equipment is built and calibrated, these techniques take less time, labor, and cause fewer soil disturbances.

According to Graf et al. (2021), precipitation directly affects soil moisture content by increasing it. The SoilVUE and SMIoT sensors show an immediate response to precipitation due to their high 10-minute resolution. On the other hand, the COSMOS sensor has been plotted with daily values to reduce noise, as suggested by the manual, resulting in a delayed response to precipitation.

The satellite measurements show a significant discrepancy from the other sensors. The satellite measurements consistently report lower soil moisture content, do not exhibit any reaction to precipitation, and exhibit a different pattern compared to the other sensors. Due to these inconsistencies, the satellite measurements may not be suitable for various applications, such as numerical weather prediction, flood and drought prediction, and automatic irrigation. Furthermore, the non-continuous data makes it less preferable compared to other sensors with higher resolution. Therefore, caution is advised when using satellite-derived soil moisture data and further investigations are necessary to identify the underlying causes of these differences.

Currently, the challenge is to determine which soil moisture sensor is best suited for different conditions. To address this issue, the European Association of National Metrology Institutes (Euramet) is working on developing a multi-scale metrological system with traceable methods for soil moisture monitoring (Zboril, 2022). The goal of the project is to establish a metrological foundation for soil moisture measurements across multiple scales, ranging from decimeters to kilometers, with a relative uncertainty of 20 % or better. In other words, they want to create a system for measuring the tempospatial variability of soil moisture, ensuring that the different soil moisture measurement methods are standardized and accurate, allowing for reliable comparisons between data collected by different sensors. This will be important for a variety of applications, such as agriculture, drought and flood prediction, and climate modeling, where accurate and reliable soil moisture measurements are essential (Cheng and Cotton, 2004, Crow and Wood, 2002, Guderle and Hildebrandt, 2015, Hubbard and Wu, 2005, Torres et al., 2013, Zhang et al., 2020a).

5.4. Evaluation of possible sources of error

Sources of error associated with different soil moisture sensing methods can affect the reliability and validity of data, as stated by Robinson et al. (2008). This section discusses potential errors including improper installation, calibration, data handling, and sampling techniques. By identifying these sources of error, accuracy and precision of soil moisture measurements can be improved

Calibration of the sensors, or rather the lack thereof, can affect the accuracy of the soil moisture measurements. User manuals for soil moisture sensors commonly highlight the need for specific calibration when dealing with soils with high clay content (Campbell Scientific Inc., 2022, GroPoint™, 2021, Wijaya et al., 2003). According to a study conducted by Singh et al. (2019), correcting for the effects of clay could enhance the precision of measurements in clayey soils. The research revealed that in soils with clay content up to 50 % , soil moisture content was underestimated at low soil moisture levels and overestimated at high soil moisture levels. Direct soil sampling such as the volumetric method, do not face the same calibration issues as indirect methods (IAEA, 2008).

When installing soil moisture sensors, it is important to consider their placement carefully. For instance, inaccurate measurements may be produced by sensors placed in areas with high vegetation density due to potential interference from roots or leaves (Yang et al., 2018). During the study, unusual behavior was observed from SMIoT sensor 3, which was later found to be caused by an artificial drainage pipe. The sensor was relocated, and the impact is now being monitored. Locations were selected for all sensors at Søråsjordet to avoid interference from forests and buildings, or any other factors that may affect their measurements.

The accuracy of soil moisture measurements can be impacted by incorrect data handling practices, such as inaccurate recording or processing of the data. A delayed response to precipitation has been observed in the COSMOS sensor, which may be mitigated by modifying either the COSMOS sensor code or the precipitation handling method. Currently, soil moisture measurements from the COSMOS sensor are plotted at 23:59, the end of the day, while the total precipitation for a given day is plotted at the beginning of the day at 00:00, creating a potential weakness in the data handling approach due to the timing difference. Furthermore, the decision to use a 4 mm cutoff for precipitation was based on a similar approach used by Naalsund (2022), aiming to avoid cluttered plots. However, this approach has the drawback that occasionally precipitation below 4 mm actually may still have a noticeable impact on the soil moisture sensors.

The accuracy of soil moisture measurements can be affected by human error during the installation of sensing methods. Poor contact with the soil and preferential flow due to air gaps caused by improper installation were discussed in section 5.1. Systematic error due to different samplers was also considered (Figure 20), but no obvious error was found. Reynolds (1970) highlights another potential source of error caused by transferring samples from field containers to laboratory containers before drying. This method can lead to moisture condensation on the inside of the container, resulting in an underestimation of the moisture content. IAEA (2008) suggest using a portable electronic scale to weigh samples in the field to mitigate this issue.

6. CONCLUSION AND OUTLOOK

This study aimed to investigate the temporal and spatial variability of soil moisture at Søråsfeltet in Ås and surrounding areas, as well as to compare satellite measurements to ground-based sensors. The research covered the time frame from January to December 2022. The study uncovered significant fluctuations over time and in soil moisture levels across different depths, with some variability observed horizontally as well. The satellite measurements did not capture the same variability as the ground-based sensors.

The soil moisture sensors were observed to respond well to precipitation, with high correlation between the two. However, the SMIoT sensor exhibited overshooting during heavy precipitation in wet periods, exceeding the upper value limited by the porosity. It is worth noting that the SMIoT sensor, which generally measured the highest values compared to the other sensors, requires a specific calibration for soil moisture values over 50 %. The SMIoT and SoilVUE sensors reacted quickly to precipitation due to their high 10-minute resolution, while the COSMOS with a daily resolution naturally reacted slower. During the spring, the sensors showed an increase in soil moisture even without precipitation, attributed to melting of frozen soil leading to an increase of liquid water in the soil.

During the study, it was found that SMIoT sensor 3 had an unusually long period of stable soil moisture at a depth of 25 cm, with a standard deviation of 0.66 % over a three-month period. Further investigation revealed the presence of an artificial drainage pipe beneath the sensor, affecting the measurements. This highlights the importance of proper investigation and selection of sensor placement. To address the issue, the sensor was relocated, and the problem was resolved.

The soil at Søråsjordet has a high clay content, which presents a common challenge for most soil moisture sensors. The hysteresis effect of the soil's expansion and contraction characteristics can make it difficult to establish good soil contact with the probe. Furthermore, after several wetting and drying cycles, the soil may loosen and create air gaps around the sensor, leading to inaccurate measurements. Proper installation techniques and a special calibration for this type of soil would be beneficial to overcome this problem.

Regarding the vertical spatial variability, the shallow soil moisture layers exhibited larger fluctuations than the deeper layers, observed in both the SMIoT sensors and the SoilVUE sensor. The SMIoT sensors at 5 cm showed a diurnal pattern, potentially correlated with temperature, although this was inconclusive. This trend was less visible in the deeper layer, consistent with the faster response of shallow soil layers to meteorological events, such as temperature variations and precipitation, compared to deep soil layers. The overall trend for all sensors suggests lower vertical and horizontal spatial variability when the soil was close to or at its saturation point.

The volumetric samples collected as ground truth indicated that the COSMOS and SoilVUE provided a more reasonable range of soil moisture compared to the SMIoT sensor. However, the SoilVUE sensor had some sensors providing data at incorrect depths, possibly due to sensor malfunction or data transfer issues. The satellite measurements consistently showed soil moisture levels below the wilting point, did not react to precipitation, and did not exhibit the same pattern as the other sensors. Therefore, satellite measurements do not perform well compared to the well-probed ground based measurements.

The insights gained from this study will benefit a range of fields. By understanding the temporal and spatial variability of soil moisture, and how well different soil moisture sensors perform, there is potential for better water management, numerical weather prediction, disaster risk reduction, prediction and mitigation of the impacts of climate change, and sustainable development. This study made several specific contributions: first, it compared various soil moisture sensors in Ås; second, it identified malfunctions in the SoilVUE sensor at Søråsfeltet; third, it contributed to the verification process for relocating a SMIoT sensor by discovering a drainage pipe that was affecting measurements in its original location; and fourth, it determined that satellite measurements are not appropriate for this region. The practical applications of research on soil moisture make it an important area of study with far-reaching implications for the future.

6.1. Further work

To improve the accuracy of the SoilVUE sensor, it is recommended to refill any cracks that may be affecting the contact between the sensor and soil. If this does not result in more accurate measurements, reinstalling the sensor may be necessary. Additionally, further investigation into the 10 and 50 cm sensors is needed to determine the cause of malfunction or data transfer issue.

To improve the accuracy of the SMIoT sensors, a temperature correction using the LM-Uncorrected or LM-Corrected method by Young et al. (2008) could be applied to account for variations in temperature affecting soil moisture measurements.

The current state of soil moisture estimation using Sentinel-1 data exhibits a significant discrepancy from ground-based sensors, indicating a need for improvement. Fortunately, ESA is set to launch two new Sentinel-1 satellites in the near future, which are hoped to significantly enhance the quality and quantity of soil moisture data. These new satellites, Sentinel-1C and Sentinel-1D, will be equipped with advanced sensors and improved capabilities that will allow for higher resolution and more frequent soil moisture measurements (ESA-3, 2022).

Finally, there is also potential for using machine learning algorithms to improve the accuracy of soil moisture measurements and better understand the underlying patterns and drivers of soil moisture variability over time and space. These are all exciting directions for future work that could contribute significantly to the understanding of soil moisture dynamics and improve the reliability of soil moisture data for a wide range of applications.

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