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Proximal Soil Moisture Sensing for Real-Time Water Delivery Control: Exploratory Study over a Potato Farm

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Abstract: New sensing technologies are at the cusp of providing state-of-the-art infrastructure to precisely monitor crop water requirements spatially so as to optimize irrigation scheduling and agricultural productivity. This project aimed to develop a new smart irrigation system that uses an L-band radiometer in conjunction with an irrigation boom, allowing for a precision water delivery system using derived high-resolution soil moisture information. A potato farm was selected due to its sensitivity to water and an existing irrigation system where the radiometer could be mounted. A field experiment was conducted to capture the soil moisture variation across the farm using the radiometer. A greenhouse trial was also conducted to mimic the actual growth of potatoes by controlling the soil moisture and exploring the impact on their growth. It was found that 0.3 cm^3/cm^3 was the optimal moisture level in terms of productivity. Moreover, it was demonstrated that on-farm soil moisture maps could be generated with an RMSE of 0.044 cm^3/cm^3. It is anticipated that through such technology, a real-time watering map will be generated, which will then be passed to the irrigation software to adjust the rate of each nozzle to meet the requirements without under- or over-watering.

Keywords: soil moisture; real-time watering; smart irrigation; L-band radiometer; crop production

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1. Introduction

The importance of crop production cannot be overstated, especially in light of the fact that the world's population is expected to reach 9 billion by 2050 [1]. This projected increase in population places tremendous pressure on the global food supply, necessitating a substantial increase in agricultural productivity to meet the growing demand [2,3]. However, the challenge lies in the fact that this increased demand must be fulfilled using the same, or even a diminished, amount of land and water resources. As urban areas continue to expand, encroaching upon prime agricultural land, the available arable land for cultivation becomes increasingly limited. The conversion of fertile farmlands into housing developments, infrastructure, and industrial zones poses a significant threat to crop production [4]. Consequently, farmers are compelled to maximize the productivity of the remaining agricultural land, often resorting to intensive farming practices and the use of advanced technologies to optimize yields.

Moreover, the impact of climate change further exacerbates the difficulties faced by farmers worldwide. Rising temperatures, shifting rainfall patterns, and more frequent extreme weather events pose significant challenges to agricultural systems. Erratic weather conditions, including droughts, floods, and heatwaves, can cause crop failures, reducing overall productivity. The unpredictability of weather patterns necessitates the development and implementation of climate-resilient farming practices and the adoption of drought-tolerant and disease-resistant crop varieties.

In addition to land constraints and climate change, water scarcity presents a formidable obstacle to achieving sustainable crop production. National water reforms and the effects of climate change are expected to reduce the available water resources for irrigation, thereby increasing reliance on efficient water management practices. Farmers must adopt innovative irrigation techniques such as drip irrigation, precision watering, and the use of moisture sensors to optimize water usage and reduce waste. Furthermore, sustainable water management strategies, including rainwater harvesting, water recycling, and water-use efficiency programs, are essential to mitigate the impacts of water scarcity on agricultural production. Consequently, meeting the escalating global demand for food in the face of limited land and water resources, urban expansion, climate change, and water scarcity poses a significant challenge to crop production.

With around 62% of both surface and ground water being used presently for agricultural irrigation in Australia, conserving even a small percentage of this water at the point of use, through more efficient irrigation application, can have a significant impact on the sustainability of our limited freshwater resources [5]. Not only can this result in irrigating longer into the growing season, but it can also provide the much-needed capacity to irrigate more marginal land. To address this issue, society needs to find new ways to use water efficiently, increase crop productivity, and utilize available land more effectively. With crop production being crucial for ensuring food security, reducing poverty, and promoting economic growth in rural areas [6], it is important that investment be made in the research and development of new agricultural technologies to help produce more food with fewer resources.

Water is an essential resource for crop production, and optimal watering is crucial for achieving high crop yields. Over- or under-watering can lead to reduced crop productivity and even crop failure. To meet the growing demand for food, it is imperative that water be used more efficiently [7,8]. This does not just mean saving water but also using it wisely and effectively. One way to achieve this is to vary the amount of water applied to different areas of the farm based on the actual soil moisture levels resulting from variations in soil properties and topography. For instance, extra watering can be applied to drier patches while reducing watering on the wetter ones. To accomplish this, it is necessary to monitor the soil moisture of each patch across the farm. By doing so, the water application can be tailored to each patch, ensuring that every part of the crop receives the optimal amount of water. Therefore, by implementing optimal watering practices, crop productivity can be increased while meeting the challenge of feeding a growing population and making efficient use of our water resources.

The main objective of this study was to determine the optimal soil moisture requirement for a particular crop type so that it could be combined with a soil moisture map across the entire farm, allowing a real-time watering map to be generated. It is therefore important to also be able to obtain an accurate real-time soil moisture map at an appropriate spatial scale. Remote sensing technologies offer a powerful means of monitoring soil moisture and improving agricultural productivity [9–11], with optical and microwave sensing being two widely used methods. While optical data from the visible and near-infrared range of the electromagnetic spectrum are readily available at high spatial resolution, they are heavily impacted by clouds making the data infrequent in time. Moreover, the ability to convert this information into accurate soil moisture information that relates to the present time is challenging. In contrast, microwave sensors can penetrate cloud cover and provide accurate measurements of soil moisture for a near-surface layer of soil through their strong relationship with the dielectric properties of water. Among the various microwave frequencies and approaches, the L-band passive microwave has been shown to be the most accurate method for retrieving soil moisture at the top 5 cm layer [12,13], though it has poor retrieval resolution. This is because the L-band signals can penetrate through vegetation, allowing for more accurate measurements of soil moisture beneath the canopy. Accordingly, this approach has been adopted for the global mapping of soil moisture by the SMAP and SMOS satellites [13,14]. However, the spatial resolution from these satellites is currently limited to 40 km, meaning that a proximal implementation is required to achieve the spatial resolution required for precision irrigation.

This paper outlines a smart irrigation system that can address the needs outlined above. Moreover, the optimal moisture for growing potato crops is determined, and a proximal L-band soil moisture mapping technology is demonstrated, providing all the elements needed to produce a data-driven precision irrigation system.

2. Smart Irrigation System

While satellite-based soil moisture retrieval methods such as SMAP and SMOS offer high accuracy, their spatial resolution is limited due to their orbit height of 600–800 km [13,14]. This results in a resolution of approximately 40 km, which is inadequate for precise agricultural applications such as precision irrigation, where soil moisture conditions can vary significantly within a single field. To overcome this limitation, the proposed study suggests leveraging the same technology but at a much closer distance to the ground.

The proximal-based approach aims to enhance spatial resolution by mounting the L-band radiometer directly onto the irrigation boom. By doing so, the observations are made in close proximity to the soil surface, allowing for a much finer resolution of 5 m or even less. This proximity-based setup offers the potential to capture detailed variations in soil moisture across the field, enabling more precise irrigation management.

In the current study, a single fixed-point installation on the irrigation boom is being tested. However, there are possibilities for further advancements to map soil moisture across the entire length of the boom. One approach involves incorporating multiple fixed-point installations along the boom, strategically positioned to capture a comprehensive picture of soil moisture distribution. Alternatively, a rail system could be implemented to enable scanning back and forth along the irrigator, covering the entire area of interest.

The soil moisture mapping system demonstrated in this study is based on a proximal installation of the European-Space-Agency L-Band Radiometer (ELBARA), which operates at 1.42 GHz with -3 dB full-beamwidth of 12 degrees and provides both h- and v-polarized brightness temperature data [15–17]. As seen in Figure 1, the ELBARA system sits on the irrigation boom with a height of 4.5 m and with a looking angle of 40 degrees. The resolution of the final soil moisture product obtained from this system is approximately 5 m, with the ELBARA radiometer observing the ground as the linear shift irrigator transits the field. In the smart irrigation system envisaged here, the collected data from ELBARA would be converted to soil moisture in real time and sent back to the irrigation system controller to adjust the water application rate from each nozzle head. Although the ELBARA system as shown in Figure 1 is large and cumbersome, this was for demonstration purposes only, and in principle, a much more compact solar-powered system could be developed and deployed.

The innovative aspect of this study is the demonstration of a proximal sensing system that will be cost-efficient and easy to implement, utilizing a precise positioning and real-time recording system. Such as system will significantly reduce time commitments and make image processing automatic, providing a high-resolution and cost-efficient method for soil moisture acquisition at farm scales. There is a great and accelerating interest in using proximal sensing in precision agriculture worldwide. Therefore, access to real-time data on the soil moisture content will not only allow growers to control their water application rates but also raise yields and in turn maximize profit. This state-of-the-art irrigation scheduling system, with its unique sensing technology for optimal water use, can also provide the capability to self-adapt irrigation rates to each user's situation and business objectives and operate autonomously. Accordingly, irrigators with a smart irrigation system will be more inclined to irrigate when the crops need water, not just when it suits the irrigator, so as to fulfill more viable farming as well as an improved lifestyle.

Figure 1. (**a**) Control unit and battery of the L-band radiometer ELBARA; (**b**) Horn antenna of ELBARA; (**c**) Waterproof house of ELBARA components; (**d**) Setup of ELBARA system onto a linear shift irrigator; and (**e**) Soil moisture monitoring over a potato farm by the Smart Irrigation System.

3. Data and Method

The study farm was situated in Cora Lynn, Victoria, Australia, encompassing an area of 200 m by 600 m. This location was specifically chosen as it predominantly focused on potato cultivation. The selection of the farm was influenced by several factors, including the water sensitivity of potato plants, the presence of existing soil moisture monitoring stations, and the implementation of a linear shift irrigation system equipped with variable-rate nozzle heads for precise and efficient water delivery. Due to the water sensitivity of potatoes, this farm provided an ideal setting for observing and analyzing the growth of potato plants throughout their lifecycle, from germination to harvesting. Furthermore, the farm's irrigation system offered an advantageous infrastructure for implementing the proposed proximal-based approach. This system has the potential to deliver water at varying rates across different areas of the field, based on the real-time soil moisture data obtained from the L-band radiometer. The integration of this technology allowed for more precise and efficient water delivery, addressing the specific moisture requirements of different potato growth stages and varying soil conditions.

In addition to field experiments, greenhouse trials were conducted to simulate on-farm potato growth under controlled conditions. These greenhouse trials provided a controlled environment where different growing conditions and treatments could be tested accurately. The ability to replicate and manipulate various factors provided the opportunity to assess the impact of different moisture levels on potato growth and yield, aiding in the refinement of irrigation strategies and optimizing water usage.

3.1. Optimal Moisture Level Determination from Greenhouse Experiment

One purpose of the greenhouse trial was to mimic the actual growth status of the potato plant on the farm under different moisture conditions to study the optimal moisture level requirements for potatoes by controlling the moisture level for each pot to a different level. As seen in Figure 2, there were, in total, 6 watering levels: air dry, 0.1 cm^3/cm^3, 0.2 cm^3/cm^3, 0.3 cm^3/cm^3, 0.4 cm^3/cm^3, and 0.5 cm^3/cm^3, with 5 replicates for each level.

Except for the different water content levels, it is assumed all other conditions were the same for all potato pots in the greenhouse, with the soil taken from the farm under study. In order to maintain a similar water content for each pot over time, the soil moisture value was monitored twice a week using the handheld Hydraprobe Data Acquisition System (HDAS, [18]), and the pots were watered when necessary, according to HDAS values. Height and density for each pot were recorded on a weekly basis, and the number and weight of potatoes were recorded at harvest so as to track and compare the yield status and thus determine the best moisture level.

Figure 2. Potato cultivation in the greenhouse (top row) and on the farm (bottom row) under similar conditions, including close seeding date, similar spacing between rows and between plants. Six watering levels were set for the greenhouse trial: W1 = air dry, W2 = 0.1 cm^3/cm^3, W3 = 0.2 cm^3/cm^3, W4 = 0.3 cm^3/cm^3, W5 = 0.4 cm^3/cm^3 and W6 = 0.5 cm^3/cm^3, each with 5 replicates.

3.2. Real-Time Soil Moisture Mapping from ELBARA

Three farm experiments were undertaken to capture the variation of soil moisture values over time: two during the growing stage (10 December 2018 and 23 January 2019) and one close to harvesting (25 February 2019). For each experiment, brightness temperature data were collected from ELBARA on a single run of the linear shift (at a speed of 200 m/h), covering a strip with a size of approximately 5 m wide by 600 m long. Ground sampling activities were conducted at the same time (Figure 3), including top 5 cm soil moisture monitoring using the HDAS at 10 m intervals along the strip, vegetation spectral sampling at ~10 m interval, surface roughness sampling using a pin profiler, and destructive vegetation sampling for obtaining the vegetation water content.

Figure 3. Instruments used during the farm experiment, including (**a**) ELBARA radiometer mounted on a linear shift irrigator, (**b**) a roughness pin profiler, (**c**) a spectral radiometer for vegetation index, and (**d**) HDAS for soil moisture monitoring as ground truth.

Based on the collected brightness temperature data, and the ancillary ground data such as roughness and vegetation data, a soil moisture map was generated through an established retrieval method. Current algorithms for passive microwave soil moisture retrieval are based on inversion of a radiative transfer model that simulates the passive microwave emission from the land surface using ancillary information such as vegetation-related indices or vegetation water content, soil surface roughness, and soil temperature. The *tau-omega* mode, which is well-known in the passive microwave soil moisture community and used by the SMOS mission and also applied in the SMAP mission [14], was used here. The core of this algorithm is based on this model and requires two main parameters representing the vegetation attenuation properties and the scattering effects within the canopy layer: the optical depth of the canopy τ and the single-scattering albedo ω.

Details on the *tau-omega* model can be found in both [19,20]. Apart from τ and ω, other model parameters include a soil roughness parameter *HR* and a vegetation parameter *b*. The optical depth τ has been linearly related to the Vegetation Water Content (VWC) using the empirically fitted *b* parameter through $\tau = \mathrm{b} \times \mathrm{VWC}$. The effective soil temperature required in the model was calculated using near-surface (2–5 cm) temperature T_{SURF} and deep-soil temperature (∼50 cm) T_{DEEP} from a nearby in-situ station according to

$$T_{EFF} = T_{DEEP} + (T_{SURF} - T_{DEEP}) \times (\theta/w_0)b_0, \tag{1}$$

where θ is the surface soil moisture, and w_0 and b_0 are semi-empirical parameters depending on specific soil characteristics. The vegetation temperature T_{VEG} required in the model was considered to be equal to T_{SURF}. The retrieved soil moisture product is compared against the ground truth from HDAS.

Due to the immobility of ELBARA along the irrigation boom in its setup, there was only a single strip of data collected for each experiment, but as mentioned above, it is anticipated that the whole farm can be covered if the radiometer can move freely on the boom, requiring a mechanical modification when using existing irrigation systems. As an exploratory investigation, this study aimed to show the capability of proximal L-band radiometry for accurately monitoring real-time soil moisture across the farm, and its potential to generate a detailed watering map when integrated with an optimal moisture level.

4. Results and Discussion

4.1. Optimal Moisture Level Determination from Greenhouse Trial

The pot moisture level was monitored regularly by the HDAS and maintained at its set level for each pot. The heights and number of branches were recorded from 18 November 2018 to 10 February 2019; the quantity and weight of harvested potatoes were also recorded at the end. It is noted from Figure 4 that plants at condition W4 (moisture level 0.3 cm^3/cm^3) had the best performance in terms of height, especially from the end of December 2018 (growing stage). Heights were only recorded till mid-February 2019, as from the beginning of February the leaves of all plants become yellow and started shrinking and drying. Potatoes in the greenhouse were harvested on 19 March 2019. The average weight of potatoes per pot was 0 g for W1, 70 g for W2, 270 g for W3, 550 g for W4, 580 g for W5, and 540 g for W6. The weight jumped to about double from W3 to W4, with similar average weights measured for W4, W5, and W6.

It was assumed at the start of the trial that the condition was homogenous in the greenhouse for each pot except for the moisture level. However, it was found that plants near the greenhouse window grew faster and taller than others, especially during the floral stage, as highlighted in Figure 4c and also shaded in Figure 4e, likely due to more sunlight near the window. However, each row was equally affected, and so, while this impacted variability within each moisture regime, it did not bias the results of any one regime. Another issue encountered was an aphid infection, as there were no natural predators (ladybugs) in the greenhouse, which may have impacted the quality and quantity of potatoes. However, it is expected that all plants were affected by the aphids proportionally, meaning that the impact of moisture conditions could still be reliably derived. To this end, condition W4 (0.3 cm^3/cm^3) was determined to be the optimal soil moisture; however, more studies with better controlled environments should be conducted before drawing any definitive conclusions.

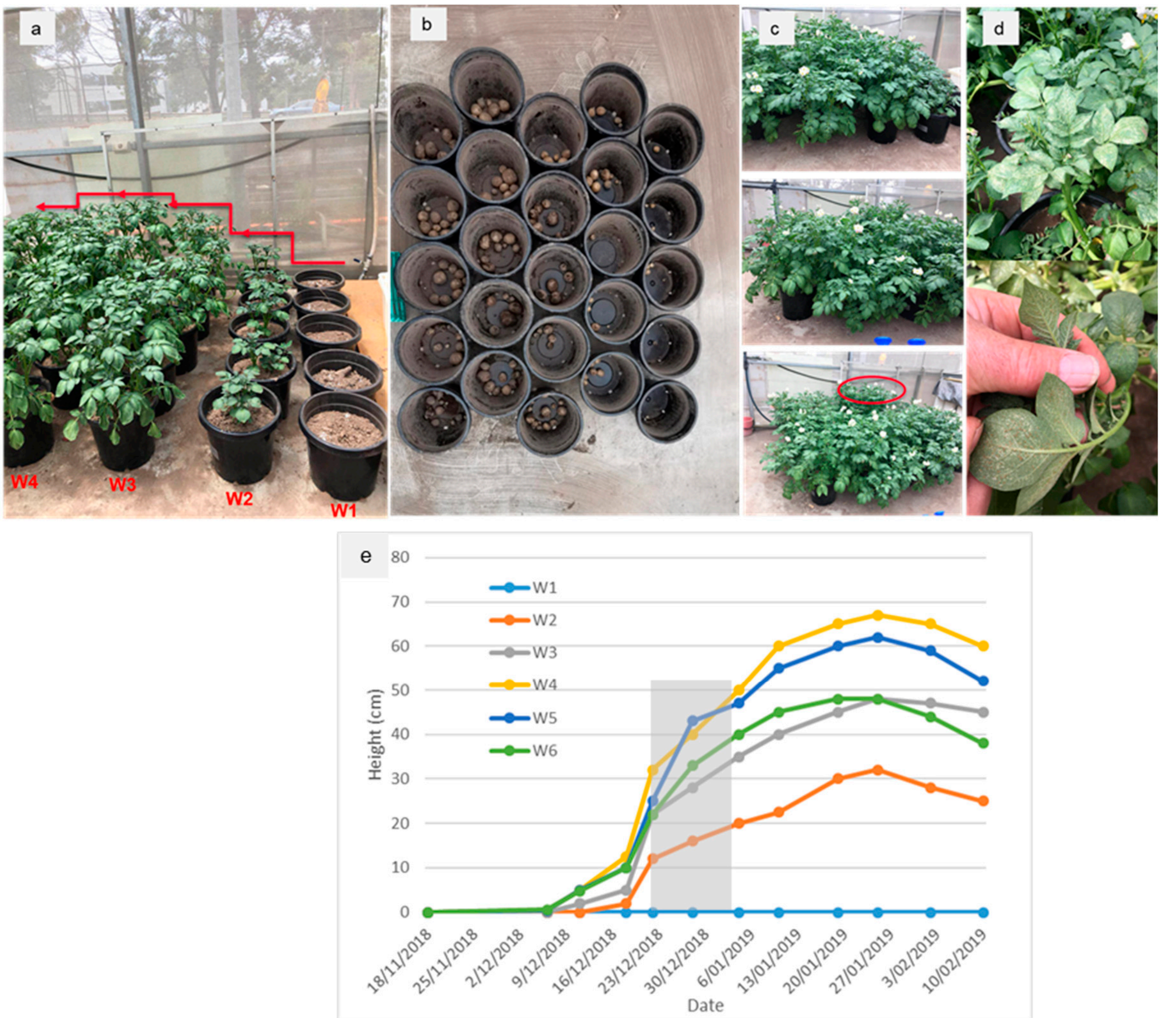

Figure 4. (**a**) Potato growing stage with different moisture conditions; (**b**) Harvesting of potatoes; (**c**) Potato growth status at floral stage with circle highlighting the impact of light variation on growth; (**d**) Pest infection; (**e**) Plots of height variation over time for each condition. The average height at each condition was calculated and displayed; shaded area indicates the floral stage.

4.2. Real-Time Soil Moisture Mapping from ELBARA

Brightness temperature data were collected on 10 December 2018, 23 January 2019, and 25 February 2019, together with ground sampled data, including HDAS data at 10 m resolution and other ancillary surface parameters relating to roughness and vegetation. The brightness temperature data were calibrated and then converted to soil moisture using the *tau-omega* model. The results from 23 January 2019 are displayed in Figure 5. ELBARA observed the ground while the irrigation boom moved from right (distance 0 m) to left (distance 600 m) in Figure 5a. By comparing against the ground measurements, the Root-Mean-Square-Error (RMSE) of the retrieved soil moisture was calculated to be 0.046 cm^3/cm^3, and the correlation coefficient R was 0.85 for 23 January 2019. Either from the ELBARA-retrieved soil moisture or from the HDAS-measured soil moisture, it shows that the soil moisture on the right side of the farm was substantially higher than that of the left side. Additionally, a noticeable difference in plant height was observed during the sampling day, with plants on the right side appearing visibly taller than those on the left.

These observations suggest that the plants on the left side require more water to support their growth and development, with the required amount of water to be decided through the integration of the soil moisture map retrieved from ELBARA and the optimal moisture level from the greenhouse trial.

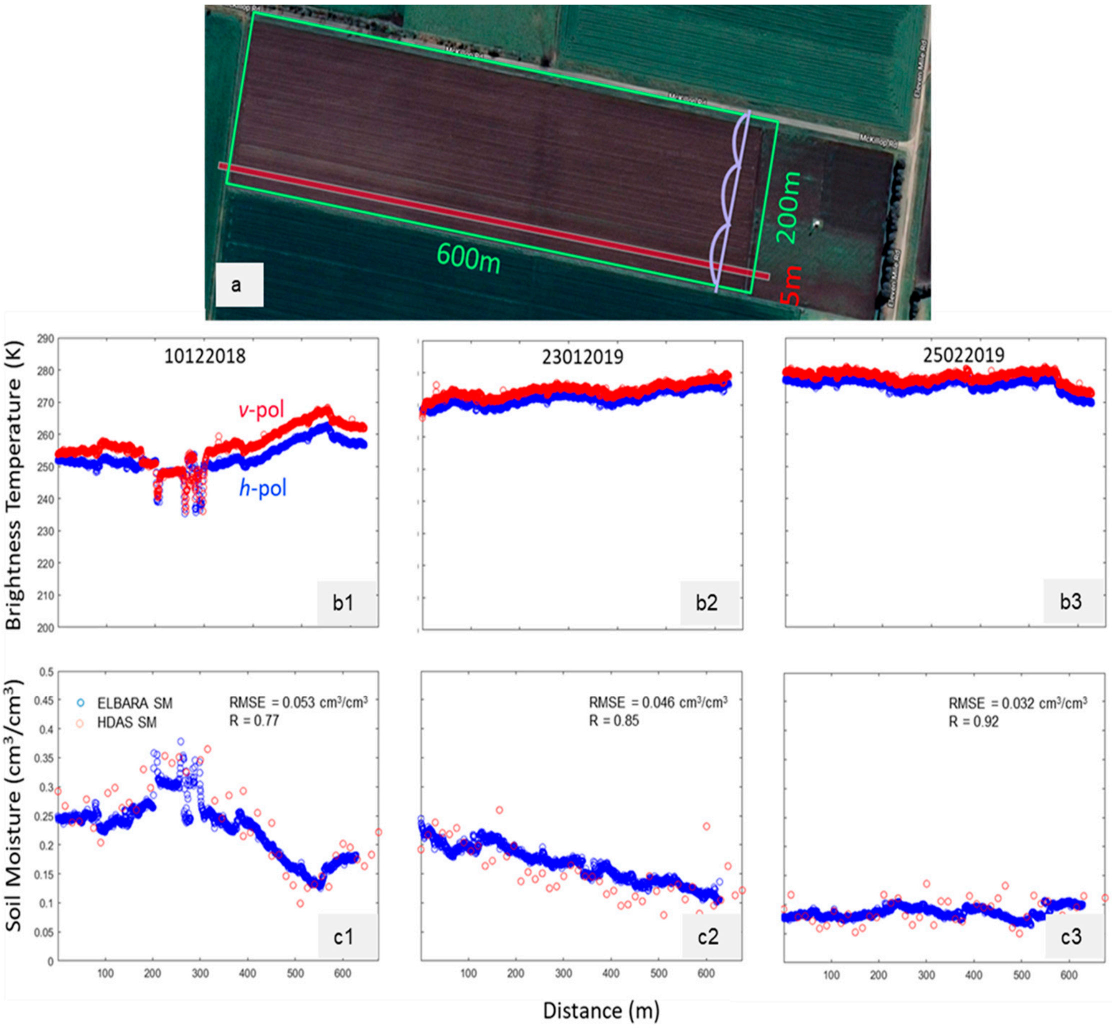

Figure 5. (**a**) Potato farm (200 m × 600 m; in green) and ELBARA monitoring strip (5 m × 600 m; in red); (**b1**–**b3**) Brightness temperature values from ELBARA along the strip at *h*- and *v*-pol, on 10 December 2018, 23 January 2019 and 25 February 2019 respectively; and (**c1**–**c3**) Comparison between ELBARA retrieved soil moisture and the ground sampled soil moisture using HDAS along the strip on 10 December 2018, 23 January 2019 and 25 February 2019 respectively.

Analysis was also conducted for the two additional days, as shown in Figure 5, yielding an RMSE of 0.053 cm^3/cm^3 for 10 December 2018 and 0.032 cm^3/cm^3 for the 25 of February 2019. On these days, the correlation coefficient R was found to be 0.77 and 0.92. The average RMSE and R from the three days were 0.044 cm^3/cm^3 and 0.85.

5. Discussion and Conclusions

In Australia, irrigation water is limited and contributes a significant part of overall farming cost, and/or limits the area that can be put under crop. Readily available soil moisture data will help farmers to better optimize their irrigation scheduling and minimize water consumption. By monitoring soil moisture in real time, farmers can quickly detect changes in soil moisture levels and take appropriate action to prevent crop damage or loss.

The proposed smart irrigation system has the potential to generate soil moisture maps in real-time with an accuracy of approximately 0.04 cm^3/cm^3, which together with the 0.3 cm^3/cm^3 soil moisture requirement found for potatoes, will facilitate the creation of a precise water delivery map. Such a system can play an enormous role in contributing to fresh water savings. Importantly, conservation techniques used in farm management save not only water but also money, time, and effort, in addition to benefiting the natural environment. Making irrigated agriculture more productive will not only increase production but also create more jobs, as improved water efficiency means more land can be irrigated, and therefore, as a result of the increased work, more jobs will be created.

Further work should include additional greenhouse trials to confirm the optimal moisture conditions for potato growth under stable and controlled environmental conditions. These trials would involve carefully manipulating and monitoring the moisture levels to determine the precise range that promotes optimal growth and yield. This would provide valuable insights into the water requirements of potatoes and help fine-tune irrigation practices for maximum efficiency. Moreover, in order to implement these optimized irrigation techniques on a larger scale, a field-deployable L-band radiometer specifically designed for integration with irrigation booms should be developed. This radiometer would need to provide an accurate narrow field of view measurement of brightness temperature. The aim would be to create a device that is cost-effective and suitable for mass production, enabling widespread adoption by farmers. Once this has been established, the generated soil moisture map from the L-band radiometer can be utilized in real time with the optimal moisture level to produce an accurate water delivery map for input to the variable rate irrigation system software. This water delivery map can be used to continuously adjust the water application rate across the entire paddock to ensure that the optimal moisture level is maintained for optimal crop growth and yield. To assess the effectiveness of this innovative approach, a comparison between the growth and yield of the potato crop under the optimized irrigation techniques and traditional non-optimized techniques should be conducted. Two adjacent paddocks could be selected for this purpose, with one paddock utilizing the optimized irrigation practices based on real-time soil moisture mapping and the other using conventional irrigation methods. By comparing the results from these two paddocks, it would be possible to quantify the benefits of the optimized approach in terms of improved crop growth and higher yields.

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Conflicts of Interest: The authors declare no conflict of interest.

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