Role of Drones in Characterizing Soil Water Content in Open Field Cultivation

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Soil water content is a central topic in open field cultivation. In Finland's boreal region with four thermal seasons it has many roles which alter throughout the year. Climate change is changing the weather patterns, affecting all water-related processes and challenging the current farming practices. Better understanding of soils and their characteristics regarding response to water processes is called for, and data collection has a key role in this. Precision agriculture has been driving data-intensification in farming. Unmanned aerial vehicles, or drones, have many applications and overall wide interest as an emerging technology in agriculture. Yet they lack an established role in day-to-day farming practices. Regarding data collection in open field cultivation, drones can be compared – or combined – with satellites, rovers, stationary devices as well as plain old on-site observations by the farmer. In this study we give an overview of recent published literature, looking at data collection from the perspective of soil water information. We assess the opportunities and challenges of using drones in characterizing soil water content, mainly using soil and plant properties as proxies for it. Drones are useful in on-demand, non-intrusive, high-resolution spatial mapping of field properties. Soil moisture monitoring however requires frequent measurements, limiting the applicability of current drones.

1. Introduction

Open field cultivation relies on a complex interdependent system of plants, soil and weather. Water, essential for plant growth and the upkeep of soil biota, is a critical component in this system. Its movement between and within each part of the system (Figure 1) is guided by equally complex hydrological factors. Weather largely determines how much water enters a non-irrigated crop field and how much exits through evaporation loss. Water in the plants is essential for photosynthesis and other biological functions as well as for transport of soluble nutrients. Roots of most plants also need oxygen, therefore excess water at root level can damage the crops by creating anaerobic conditions.

Besides being crucial to plant growth plants, water can influence working conditions, soil biota and soil morphology, all of which can in turn lead to lasting qualitative changes in the soil. Heavy machinery in wet, soft soil can lead to compaction in the soil (Alaoui and Diserens, 2018) while freeze-thaw-cycles can alleviate it (Jabro *et al.*, 2014).

Soil water can be naturally recharged from above by precipitation under gravitational force and from below by capillary forces on ground water. How the soil responds to incoming water is defined by soil hydrological properties which are largely a function of mineral texture, aggregate structure and soil organic content. These properties show significant spatial variation at scales small enough to show heterogenous distributions between fields and even within individual fields, both horizontally and vertically. A combination of multiple sensor platforms and measurements help in forming a complete picture of the water dynamics within a field: satellites, aircrafts, ground vehicles, weather stations, ground probes – and drones.

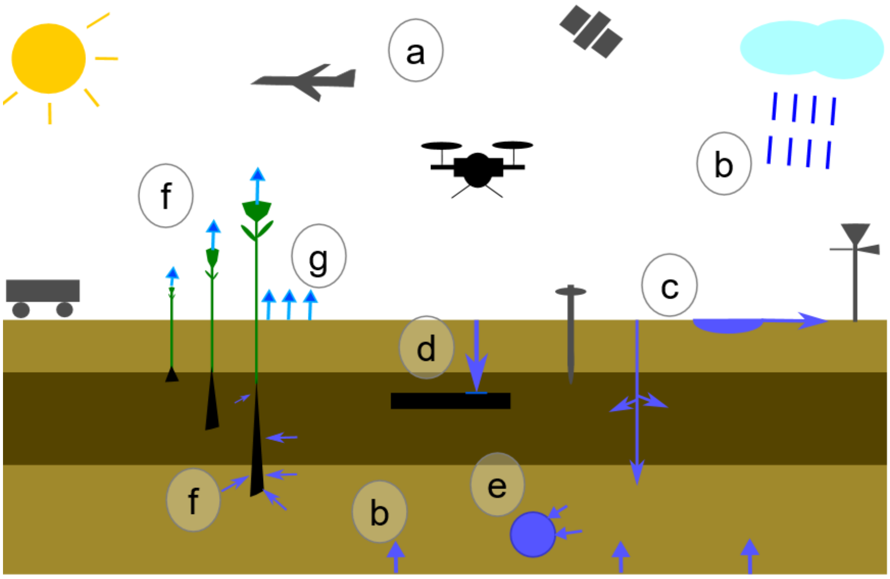

Figure 1 Weather, soil and plants form a dynamic system. a) A combination of sensor platforms is needed for comprehensive measurements. b) Soil water can be naturally recharged from above by precipitation and gravity and from below by ground water and capillary rise. c) Rainwater needs to infiltrate the surface or it accumulates in puddles and flows overland. d) Percolation to deeper layers may be prevented by a compacted hardpan. e) Excess water is drained through underground drainage pipe. f) Plants take in water through their roots and transpire water vapor through their leaves. g) Part of the water is evaporated back to the atmosphere.

1.1. The Need for Water Data

Knowing the current and forecasted state of soil water content and its availability to plants has significant implications to optimizing resources. Indeed, an ecologically sound management of the farm requires this information. Understanding the dynamics of this soil-water-plant system requires data that can characterize it and help explain the underlying processes. As this understanding develops, more needs for additional data collection can be identified. Improvements in technology enable us to measure properties of this system that has previously been out of reach. They can also increase the quantity and quality of the collected data in general as well as the efficiency of the data collection process itself.

Climate change is expected to disrupt water related phenomena. The outlook in western Finland is more precipitation from Autumn to Spring, less snow coverage, longer dry periods during growing season although more intense rainfall events (Ruosteenoja, Räisänen and Pirinen, 2011). Predicting water content in different weather scenarios can help in assessing the risk to crop production. The current crop growth models in use that depend on soil moisture content are typically calibrated for regional water patterns of recent history. If these patterns are to change then it becomes essential to re-calibrate management practices. In addition, increasing awareness of and drive to end inefficient practices that lead to nutrient leaching, or water wastage, has made soil moisture monitoring an important aspect in open field farming.

1.2. Measuring Soil Water Content

Soil hydrology and measurement of true soil water content have been presented comprehensively by Novák et al. (Novák and Hlaváčiková, 2019). While providing accuracy these methods are labor, time and resource intensive, which limit their practical application in everyday farming context. Notably, the *gravimetric method* requires extracting a soil sample and drying it in an oven. They do however serve an important role in ascertaining the true value with some confidence, in instrument calibration and model development. Data on features whose correlation with soil-water is established can also be used, albeit with lower confidence. If a correlation can be established, there is value in low fidelity characterization of soil-water with high acquisition ease and resolution. Remote sensing methods together with the necessary data post-processing steps can be computationally more intensive and also laborious to set up but are more conducive for automation.

Water content varies with space and time. Spatial variation is, for example, due to differences in soil properties, topology, precipitation level, relative location respective to underground drainage, which makes reliable extrapolation from point measurements difficult. The rate of change can be high especially during growing season.

In this study, instead of direct measurement, we look at the most common methods for estimating the soil water content through indirect proxy measurements that correlate with the actual soil moisture. For the purposes of this study, we divide these proxy variables into *soil proxies* and *plant proxies,* which measure soil water content through soil or plant properties, respectively. Soil proxies measure properties of the bare ground, such as its dielectric permittivity or spectral reflectance. Plant proxies measure for example the plant canopy's spectral reflectance or temperature. The list of variables here is not meant to be exhaustive. Any variable that correlates with soil water content could be included. Well-known examples are given while the focus of the study is in the methodology.

A conceptual model is presented in Figure 2 describing how, for the purposes of this study, the water related phenomena and variables are assumed to be related to the measurements of proxy indicators. As an example, the Normalized Difference

Water Index NDWI (sometimes called moisture index NDMI) uses two infrared spectral bands of an image sensor to measure liquid water content of vegetation canopies. Similarly, the commonly used vegetation index NDVI is calculated from red and near-infrared channels, measuring chlorophyll related leaf reflectance in the plants (Gao, 1996). Plant available water is a necessary, although not sufficient, condition for the existence of chlorophyll in leaves. Thus, both NDWI and NDVI are plant related proxies for plant available water. However, as virtually all proxies, they are influenced by many other factors. Two main factors, namely soil characteristics and plant type, are shown in the figure as *parameters*, which may need to be calibrated for when interpreting proxy measurements.

The model in Figure 2 is static, depicting the state of the system at a given moment. Each arrow represents an assumed causal influence in the direction of the arrow. This framework is used as a guiding structure for organizing the literature overview in this study.

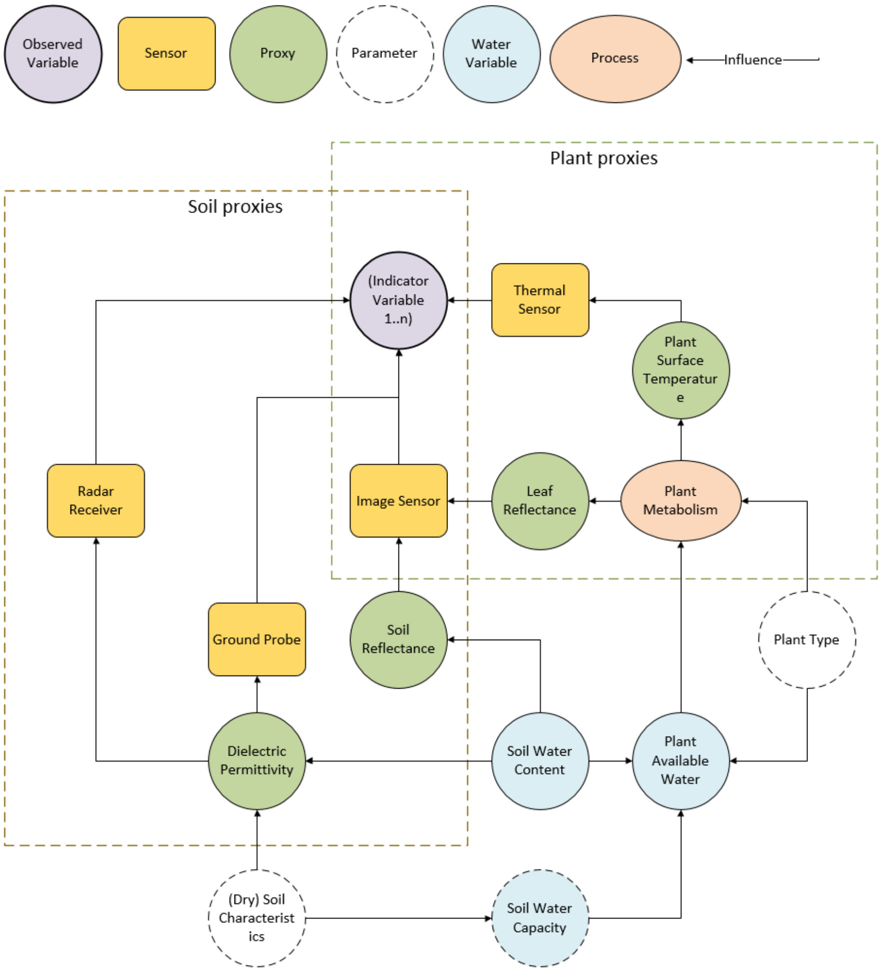

Figure 2 Soil and plant properties as proxies for water related information in the soil. Measurements are typically several steps apart from the actual phenomena of interest. There are several paths that can be taken, depending on the situation, available technology and resources. Outputs from multiple sensors can be combined for more reliable indicators.

1.3. Drones in Agriculture

The use of drones, or more formally – unmanned aerial vehicles (UAV), in agriculture is increasing rapidly. UAVs are used in crop production, forestry and disaster risk reduction. Applications in crop production range from crop health monitoring and irrigation planning to weed detection and insurance. (FAO and ITU, 2018)

Broadly speaking, the role of drones can be seen either as passive or active, depending on how much they interact with their environment. Active drones can spray pesticides or take physical samples. This study is focused on passive data collection. The actual end application of the data can be crop stress monitoring, crop detection, seasonal planning, loss estimation, etc. In these roles, drones can be seen as an alternative or a complementary tool for acquiring the needed information. In addition, drones have been used in ancillary roles, such as in collecting data from wireless sensor networks (Uddin *et al.*, 2018; Zhan, Zeng and Zhang, 2018).

Drones, ground vehicles, airplanes and satellites can all be equipped with same or similar measurement technology. Therefore, much of the literature regarding soil water measurement is presented under the topic of the given technology. Data acquisition by drones typically has specific advantages and constraints in terms of spatial and temporal resolution of the data as well as practical considerations of operating a drone. The wide and growing range of different types and sizes of drones from large military drones to 'smart dust', their properties in terms of endurance, range, weight, altitude as well as their applications has been reviewed and classified by Hassanalian and Abdelkefi (Hassanalian and Abdelkefi, 2017).

The ability to do on-demand high-resolution mapping of fields without disturbing either soil or plants is a main advantage of a drone in open-field farming. Constraints on a drone as a sensor carrier platform are due to factors such as weight of the instruments, required proximity to ground and flight-time. Airborne vehicles measuring soil and canopy surface only through reflectance and spectrometry have limitations. Some of the sub-surface properties can be estimated from these images, if the data generating processes are known. Using manual sampling to acquire reference data on parameters such as soil texture, soil structure and organic content, for example would allow for more accurate estimates compared to visual examination of the obtained images alone.

Drones themselves are becoming commodity items. The value of drones in data collection however would come from their capabilities and limitations as a sensor carrying platform. Utility for a farmer additionally requires a mature data processing workflow that can routinely turn the raw collected data into relevant information that improves their field management decisions.

1.4. Objectives

This is a preliminary study to map out the different aspects related to measuring water content in a crop field and to provide an overview of recent literature on the topic. We approach the crop field as system from two different perspectives – water state and soil properties. We look at methods to measure the water state on the field at a given moment, as a snapshot of the dynamic system. That enables water stress detection in monitored conditions. We also look at measuring system properties, those relatively stable soil hydrologic properties that could aid in characterization of soil's response to water events. Knowledge of this response would allow us to better estimate the soil moisture conditions at a given time, even with scarce data. It would also enable forecasting the availability of water to plants and simulate the behavior of the field in different scenarios such as prolonged drought or excess rainfall. We look at how drones have been used in these tasks and what is the future outlook.

2. Measurement Targets

The target is to estimate the actual water content in the soil, and the plant available water specifically. As discussed above and shown in Figure 2, we focus on measuring the variables of interests indirectly through proxies in soil and plants. There are also other variables, such as weather data, that covary with soil water content and could therefore be used to improve estimations of it.

2.1. Soil proxies

Spectral properties of soil correlate with soil moisture and can be used to monitor moisture conditions in bare soil (Fabre, Briottet and Lesaignoux, 2015), such as drying of the soil in Spring. Remote sensing soil surface reflectance has limited utility as a proxy, as it provides information mostly about the soil surface, which can differ considerably from moisture below. Soil surface characteristics in itself have a large role in determining the amount of infiltration and runoff, especially with crusting (Corbane *et al.*, 2012). Furthermore, even the soil surface is hidden below the crop canopy during the growing season.

Soil relative dielectric permittivity is a typical soil proxy and can be measured using ground probes (Novák and Hlaváčiková, 2019) as well as radar (Klotzsche *et al.*, 2018), (Chantasen *et al.*, 2020).

When there is plant canopy, the soil is typically not directly observable using reflectometry, but a soil probe or radar is needed.

2.2. Plant proxies

Plant physiological properties can be used to detect water stress, which in turn is an indicator of plant available water content at root level. Gago et al. (Gago *et al.*, 2015) reviewed literature on using UAVs to measure water stress by using leaf reflectance and temperature and called for studies measuring leaf chlorophyll fluorescence as a more direct indicator of photosynthesis.

Spectral imaging, both within and beyond the visible spectrum, is the main method for measuring plant proxies. Information from different spectral bands is combined into specialized indices that target specific phenomena of interest, for example NDVI for crop vegetation vigor, NDWI for water content of crop canopy (Gao, 1996) and Leaf Area Index LAI for estimating evapotranspiration among other properties (Zheng and Moskal, 2009). Candiago et al. evaluated vegetation indices for precision farming applications from multispectral UAV images in (Candiago *et al.*, 2015).

Hassan-Esfahani et al. (Hassan-Esfahani *et al.*, 2015) used plant proxy together with gravimetric reference samples to produce a machine learning model for surface soil moisture estimation. In addition to multispectral and thermal images, their best performing input combinations required knowledge of field capacity, derived from soil texture samples.

2.3. Soil Characteristics

Soil characteristics are those relatively stable properties of the soil that affect the interaction between soil and water: i.e. how rainfall infiltrates the surface, percolates through soil layers, how much of it is retained in the soil, and how much available for plants to use (Novák and Hlaváčiková, 2019). Mineral texture and aggregate structure of the soil as well as its organic matter content are the main components. These are relatively stable properties, which can be considered constant at least within a single season. There can however be considerable spatial variation within a field, both on the surface and sub-surface. The presence, type and condition of underground drainage systems and other installed infrastructure that affect the water dynamics of the field are similarly stable factors in the system.

Soil characteristics don't generally vary with water content, but knowledge of them can aid in the estimation of water content and its behavior over time, as they affect the sensor measurements and may need to be calibrated for. They can also be used as inputs to *pedotransfer functions (PTF)* to estimate soil hydrological properties, such as field capacity and wilting point, based on their statistical relationships in large soil data sets (Van Looy *et al.*, 2017). The traditional way to characterize soils is by collecting soil samples and analyzing them in a laboratory. Technologies that would measure soil properties in-situ or reducing the number of needed soil samples would therefore also help in estimating soil water content.

3. Measurement Technology

Technology for measuring proxies for soil water content in soil and plants is divided here into image sensors, radar and ground probes. As same or similar sensors can be mounted on different platforms, sensor specific reviews irrespective of platform are also included here for broad perspective and summarized in Table 1. Selected case studies that exhibit utility of drones as a platform are summarized in Table 2. An overview on the literature is given briefly below.

Table 1 Generic sensor related reviews

Ref	Title	Sensor
(Gago *et al.*, 2015)	UAVs challenge to assess water stress for sustainable agriculture	RGB, multispectral, hyperspectral, thermal
(Barbedo, 2019)	A Review on the Use of Unmanned Aerial Vehicles and Imaging Sensors for Monitoring and Assessing Plant Stresses	RGB, multispectral, hyperspectral, thermal
(Adão *et al.*, 2017)	Hyperspectral Imaging: A Review on UAV-Based Sensors, Data Processing and Applications for Agriculture and Forestry	Hyperspectral
(Lu *et al.*, 2020)	Recent advances of hyperspectral imaging technology and applications in agriculture	Hyperspectral
(Messina and Modica, 2020)	Applications of UAV Thermal Imagery in Precision Agriculture: State of the Art and Future Research Outlook	Thermal
(Brocca *et al.*, 2017)	A Review of the Applications of ASCAT Soil Moisture Products	Radar (ASCAT)

(Edokossi *et al.*, 2020)	GNSS-Reflectometry and Remote Sensing of Soil Moisture: A Review of Measurement Techniques, Methods, and Applications	Radar (GNSS-R)
(Liu, Dong and Leskovar, 2016)	Ground penetrating radar for underground sensing in agriculture: a review	GPR
(Klotzsche *et al.*, 2018)	Measuring Soil Water Content with Ground Penetrating Radar: A Decade of Progress	GPR
(Zajícová and Chuman, 2019)	Application of ground penetrating radar methods in soil studies: A review	GPR
(Corwin and Scudiero, 2020)	Field-scale apparent soil electrical conductivity	Apparent Electrical Conductivity sensor
(Babaeian *et al.*, 2019)	Ground, Proximal, and Satellite Remote Sensing of Soil Moisture	Ground, proximal, satellite
(Hardie, 2020)	Review of Novel and Emerging Proximal Soil Moisture Sensors for Use in Agriculture. Sensors	Proximal sensors
(Jackisch *et al.*, 2020)	Soil moisture and matric potential – an open field comparison of sensor systems	Ground probe

Table 2 Selected case studies, estimating soil water content using UAV mountable technology through proxies in soil and plants or characterizing stable, water related soil properties

Ref	Title	Sensors	Metrics	Target
(Hassan-Esfahani *et al.*, 2015)	Assessment of Surface Soil Moisture Using High-Resolution Multi-Spectral Imagery and Artificial Neural Networks	RGB, NIR, thermal	surface soil moisture	plant proxy
(Matese *et al.*, 2015)	Intercomparison of UAV, Aircraft and Satellite Remote Sensing Platforms for Precision Viticulture	Multispectral	NDVI intra-vineyard vegetation variability	plant proxy
(Christiansen *et al.*, 2017)	Designing and Testing a UAV Mapping System for Agricultural Field Surveying	Lidar	crop height and volume	plant proxy
(Ge *et al.*, 2019)	Combining UAV-based hyperspectral imagery and machine learning algorithms for soil moisture content monitoring	Hyperspectral	soil moisture content monitoring	plant proxy
(Wu *et al.*, 2019)	A new drone-borne GPR for soil moisture mapping	GPR	soil moisture mapping	soil proxy
(Chantasen *et al.*, 2020)	Mapping the Physical and Dielectric Properties of Layered Soil Using Short-Time Matrix Pencil Method-Based Ground-Penetrating Radar	GPR	dielectric properties, dielectric constant, bulk density	soil

3.1. Ground probes

Ground measurements can be used to collect continuous time series data such as soil moisture data with sub-surface sensors. Calibration can be an issue, as there is no generic method that works across all manufacturers. Many manufacturers don't give access to either to the raw data or the internally applied conversion functions. (Jackisch *et al.*, 2020)

One challenge is that ground probes measure point-data. This point data needs to be interpolated over potentially highly variable soil properties. In addition to point sensors, mobile sensors for apparent soil electrical conductivity have been used for soil spatial variability mapping (Corwin and Scudiero, 2020).

The use of drones here is limited. Using drone mounted ground probes would require a mechanism for inserting the probe into the soil without damaging it. The soil around the inserted probe also needs time to settle for accurate reading. Otherwise, drones could be used to collect data from sensors with wireless connectivity or in combination with a ground vehicle.

3.2. Radar

Radar is an active remote sensing method, where the device sends an electromagnetic pulse and records the reflected or scattered return wave. Depending on the wavelength, radar signal can penetrate the plant canopy or soil. Radar signal frequencies range from high frequency radio waves (MHz) to around 100 GHz microwaves. Soil moisture can be derived from the dielectric constant extracted from the return signal (Kornelsen and Coulibaly, 2013).

Advanced Scatterometer ASCAT on board of satellites has been used in measuring surface soil moisture, but is in its own not enough for precision agriculture applications (Brocca *et al.*, 2017) due to coarse (1km+) resolution.

Global Navigation Satellite System Reflectometry GNSS-R is a method that combines active satellite signals with an on or near-ground passive receiver and has been used to measure surface soil moisture (Edokossi *et al.*, 2020). A prototype for UAV mounted GNSS-R for retrieving soil moisture was presented by Jia et al. (Jia *et al.*, 2015).

Ground penetrating radar (GPR) is a term used for radars capable of subsurface measurements, with signals in 10 – 2000 MHz range. They have been used in civil engineering (Wai-Lok Lai, Dérobert and Annan, 2018) and archeology (Catapano *et al.*, 2019) for applications such as object detection and assessing structural health. Resolution and maximum measurement depth depend on the signal frequency: higher frequency detects finer details but attenuates faster. In agriculture the depth of interest is approximately from the surface down to the depth of 2 meters. With a proper frequency it is possible to characterize the soil in agriculture-relevant depth (Liu, Dong and Leskovar, 2016).

GPR has been used in characterizing soil characteristics and dielectric properties (Chantasen *et al.*, 2020). It can also give information about the soil water content, which affects the dielectric permittivity of the soil, which in turn affects the radar signal (Klotzsche *et al.*, 2018). Zajícová and Chuman (Zajícová and Chuman, 2019) reviewed applications of GPR in soil studies, concluding that it can assist in estimating soil moisture and in detecting soil horizons, especially in sandy soils with low cation exchange capacity (CEC). They point out that while clay soils have been found to be unfavorable for GPR surveys, more due to CEC than grain size, with high attenuation of the radar signal, even a penetration depth of 0.5 m would be sufficient for many applications.

GPR has been has been mounted on drones for landmine detection by Fernández et al. in (Garcia Fernandez *et al.*, 2018), using synthetic aperture radar (SAR) algorithm. Wu et al. (Wu *et al.*, 2019) described using a 1.5 kg radar system operating at 500-700MHz range to map moisture in the top 10-20 cm of the soil.

3.3. Spectral imagery

Cameras are typically categorized as visible light (RGB) cameras, multispectral, hyperspectral and thermal cameras depending on the electromagnetic spectral range within which the sensors operate. RGB camera operate within the visible spectrum (red, green and blue spectral bands). Multispectral cameras include the visible range as well as selected bands in the near-infra-red (NIR) short-wave infra-red (SWIR) range. Hyperspectral cameras work in the same spectral range, but while both RGB and multispectral cameras capture distinct spectral bands, hyperspectral cameras capture a contiguous spectral range. A basic premise in spectral imagery is that certain plant phenological phenomena can be correlated to reflectance values in specific wavelengths. These wavelengths, or bands, can be further refined into specialized indices. For example, NDWI is a combination of two near-infrared channels which correlates with liquid water molecules in vegetation canopy (Gao, 1996).

Drone mounted hyperspectral cameras were reviewed by Adão et al (Adão *et al.*, 2017). They saw potential for drones as platform as the hyperspectral devices are becoming smaller and lighter, although the amount of data collected by these devices can be huge and the required processing complex. Hyperspectral camera was used by Ewing et al. for soil gradation in laboratory conditions (Ewing *et al.*, 2020). Hyperspectral devices have previously been out of reach for many farmers due to high price, but more affordable technologies and options are being developed and productized. One approach is combining regular digital cameras with passive diffraction grating filter and machine learning (Toivonen, Rajani and Klami, 2021). Even open-source do-it-yourself cameras have been built and tested, such as in (Salazar-Vazquez and Mendez-Vazquez, 2020).

Barbedo reviewed the use of drone imaging for monitoring plant stresses. He concluded that all approaches for water stress detection found had limitations for practical adoption. Combining data from multiple complementary sources was seen as the way forward, along with improved sensor technology, computer vision and machine learning techniques (Barbedo, 2019).

Thermal cameras, operating mostly in the mid infrared wavelengths (3-8μm) have been used for assessing water stress with Crop Water Stress Index CWSI. This and other promising applications of UAV thermal imagery such as subsurface drainage mapping are reviewed by Messina and Modica (Messina and Modica, 2020). They pointed out that low resolution compared to RGB images, low number of applications for thermal data and required knowledge of thermography in the process are all limiting the adoption of thermal cameras. López and Giraldo proposed a method for planning an optimal irrigation route and rate, based on CWSI (Lopez and Giraldo, 2019).

Drones have been used to provide variability maps to produce better extrapolations from point measurements. They have been used when the availability of satellite imagery has been limited or when the spatial resolution hasn't been high enough. The minimum pixel size for multispectral imagery of the Sentinel 2 satellite from European Space Agency is 10x10m (Ambrosone *et al.*, 2020) while drones can achieve sub-centimeter resolution.

3.4. Other Measurement Technology

Light detection and ranging (LiDAR) has been used to create digital elevation models (Rayburg, Thoms and Neave, 2009) and to map canopy volume and height for biomass (Christiansen *et al.*, 2017). This data can be used as proxies for crop vigor which in turn can be used with models for field water balance, water flows and accumulation points. Fitzpatrick et al. proposed using thermoacoustic imaging that combines a microwave source with an ultrasound receiver to overcome some of the limitations of current technology, especially GPR (Fitzpatrick, Singhvi and Arbabian, 2020). Hardie reviewed a range of soil moisture sensors for use in agriculture, identifying their limitations and concluding that current technology for soil moisture measurement generally don't often meet the practical requirements in farming (Hardie, 2020). Babaeian et al. did an extensive review on ground, proximal and satellite remote sensing of soil moisture, touching also other methods such as neutron scattering, nuclear magnetic resonance and gamma ray sensors (Babaeian *et al.*, 2019). They found that many common methods only measure surface soil moisture, and then proceeded by reviewing modeling approaches for root zone soil moisture estimation.

4. Discussion

Measuring plant available water content at the field scale with confidence requires combining data from multiple data sources. Making conclusive inferences about soil water content based solely on remote sensing data can be difficult, if not impossible. This uncertainty in the estimations could be reduced by combining the empirical models for spectral data with physically based models such as hydrological and crop growth models (Babaeian *et al.*, 2019). The cause of the detected features can be hard to identify because many causes can lead to similar data patterns. While ground probes provide point data with comparatively more proximal sensing of data, remote sensing technology can be used for gaining spatial distribution information and drones can be mounted with several types of instruments to measure additional data on demand.

Opportunities for using drones in information collection are found when looking at the gaps left by other technologies and seeing how the strengths of drones such as spatial resolution, adaptability for different instruments and non-intrusiveness can help. Satellites with 10m+ spatial resolution can provide approximate information at field level, but within-field variability may require higher resolution, which can be acquired using drone-mounted cameras. For example, estimation of LAI using Sentinel-2 data was studied and found to be unsatisfactory especially in precision agriculture when within-field variability is a concern (Kganyago *et al.*, 2020).

Satellite based radars (C-band, L-band) can typically measure soil to a vertical depth of 2-7cm of surface soil, but their horizontal surface resolution can be above 1km (Brocca *et al.*, 2017). On the other hand, near-surface ground penetrating radars can characterize soils in deeper layers with much higher resolution, both vertically and horizontally (Klotzsche *et al.*, 2018; Wu *et al.*, 2019; Zajícová and Chuman, 2019; Chantasen *et al.*, 2020). UAVs have the advantage of non-intrusiveness which allows it to be used during growing season to get information about subsurface conditions while also enables quick mapping of the whole field. High spatial resolution opens up the possibility of measuring chlorophyll fluorescence which could provide a more direct indicator of photosynthesis and allow for detection of water stress (Gago *et al.*, 2015).

The conceptual model presented in the introduction is a static model with the main purpose of guiding the literature research. It could be further extended for use as a basis for a numerical model for estimating individual unknown variables, when other variables are known. Each arrow would then add uncertainty to the estimate as proxies move further away from the actual measurement target. For a useful dynamic model, weather and evapotranspiration would need to be included as well.

All the different methods of measuring soil moisture described here are based on indirect measurements of proxy variables and therefore unlikely to be satisfactory individually. They are subject to various degrees of uncertainty from multiple different sources, including measurement error, and model error. When proceeding from estimation of current state to forecasting, this uncertainty will be further amplified. An important task is to quantify the different sources of uncertainty and their contribution to the overall prediction. This uncertainty can then be reduced by targeted data collection, including complementary measurements from different types of sensors (Dietze, 2017).

5. Conclusions

The interaction of soil and water is a central topic in open field farming and the changing weather patterns call for re-evaluating current field management practices. Measuring soil water content is a multi-faceted spatio-temporal problem with varying degrees of uncertainty. A tractable solution can be to measure soil properties and assess plant canopy condition. Soil characteristics define the more stable part of the system, while the highly variable water content can be estimated through plant and soil related proxies.

In this study, several key variables related to soil and plant available water content along with their relationships were identified and presented as a conceptual graph model. This graph was then used to guide a literature search to find applications of for drones in measuring soil water content and characteristics in open field cultivation. This graph can be used as a tool to choose measurement methods and targets, diagnostics and understanding the field water dynamics in general. It could further be used as a basis for developing a model to estimate the yield gap on a given field due to water issues. In the future this graph can be iteratively expanded upon as the need to include additional features and processes to the model arises.

Drones have characteristics that make them useful in measuring water content in open field cultivation, especially in on-demand, high-resolution spatial mapping. Visual range and multispectral cameras are commonplace in drones, but hyperspectral and thermal cameras along with radar technology can be mounted on drones as well, taking into account weight and cost limitations in practical applications.

Continuous monitoring and forecasting soil moisture require frequent measurements. Autonomous drones may be able to do this in the future, but at the moment this information needs to be provided by ground probes and other devices deployed at the field. In these cases, drones may still have a role in measuring the more stable properties and patterns of the field that can be used to improve the soil moisture estimates.

Even with collected data – with or without drones – the challenge of combining and analyzing data from different sources remains, before the results can be useful in practical decision making for a farmer. The amount of data collected and the number of, potentially computationally intensive, post-processing steps required can quickly become overwhelming, calling for proper infrastructure and high level of automation throughout the data processing chain.

6. References

Adão, T. *et al.* (2017) 'Hyperspectral Imaging: A Review on UAV-Based Sensors, Data Processing and Applications for Agriculture and Forestry', *Remote Sensing*. MDPI AG, 9(11), p. 1110. doi: 10.3390/rs9111110.

Alaoui, A. and Diserens, E. (2018) ‘Mapping soil compaction – A review’, *Current Opinion in Environmental Science & Health*, 5, pp. 60–66. doi: 10.1016/j.coesh.2018.05.003.

Ambrosone, M. *et al.* (2020) ‘Retrieving soil moisture in rainfed and irrigated fields using Sentinel-2 observations and a modified OPTRAM approach’, *International Journal of Applied Earth Observation and Geoinformation*, 89, p. 102113. doi: 10.1016/j.jag.2020.102113.

Babaeian, E. *et al.* (2019) ‘Ground, Proximal, and Satellite Remote Sensing of Soil Moisture’, *Reviews of Geophysics*, 57(2), pp. 530–616. doi: 10.1029/2018RG000618.

Barbedo, J. G. A. (2019) ‘A Review on the Use of Unmanned Aerial Vehicles and Imaging Sensors for Monitoring and Assessing Plant Stresses’, *Drones*, 3(2), p. 40. doi: 10.3390/drones3020040.

Brocca, L. *et al.* (2017) ‘A Review of the Applications of ASCAT Soil Moisture Products’, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. Institute of Electrical and Electronics Engineers, 10(5), pp. 2285–2306. doi: 10.1109/JSTARS.2017.2651140.

Candiago, S. *et al.* (2015) ‘Evaluating Multispectral Images and Vegetation Indices for Precision Farming Applications from UAV Images’, *Remote Sensing*. MDPI AG, 7(4), pp. 4026–4047. doi: 10.3390/rs70404026.

Catapano, I. *et al.* (2019) ‘Applying Ground-Penetrating Radar and Microwave Tomography Data Processing in Cultural Heritage: State of the Art and Future Trends’, *IEEE Signal Processing Magazine*, 36(4), pp. 53–61. doi: 10.1109/MSP.2019.2895121.

Chantasen, N. *et al.* (2020) ‘Mapping the Physical and Dielectric Properties of Layered Soil Using Short-Time Matrix Pencil Method-Based Ground-Penetrating Radar’, *IEEE Access*. Institute of Electrical and Electronics Engineers Inc., 8, pp. 105610–105621. doi: 10.1109/ACCESS.2020.2999894.

Christiansen, M. *et al.* (2017) ‘Designing and Testing a UAV Mapping System for Agricultural Field Surveying’, *Sensors*. Multidisciplinary Digital Publishing Institute, 17(12), p. 2703. doi: 10.3390/s17122703.

Corbane, C. *et al.* (2012) ‘Multitemporal analysis of hydrological soil surface characteristics using aerial photos: A case study on a Mediterranean vineyard’, *International Journal of Applied Earth Observation and Geoinformation*, 18, pp. 356–367. doi: 10.1016/j.jag.2012.03.009.

Corwin, D. L. and Scudiero, E. (2020) ‘Field-scale apparent soil electrical conductivity’, *Soil Science Society of America Journal*, 84(5), pp. 1405–1441. doi: 10.1002/saj2.20153.

Dietze, M. C. (2017) ‘Prediction in ecology: a first-principles framework’, *Ecological Applications*. Ecological Society of America, 27(7), pp. 2048–2060. doi: 10.1002/eap.1589.

Edokossi, K. *et al.* (2020) ‘GNSS-Reflectometry and Remote Sensing of Soil Moisture: A Review of Measurement Techniques, Methods, and Applications’, *Remote Sensing*. MDPI AG, 12(4), p. 614. doi: 10.3390/rs12040614.

Ewing, J. *et al.* (2020) 'Utilizing Hyperspectral Remote Sensing for Soil Gradation', *Remote Sensing*. MDPI AG, 12(20), p. 3312. doi: 10.3390/rs12203312.

Fabre, S., Briottet, X. and Lesaignoux, A. (2015) 'Estimation of soil moisture content from the spectral reflectance of bare soils in the 0.4–2.5 µm domain', *Sensors (Switzerland)*. doi: 10.3390/s150203262.

FAO and ITU (2018) *E-agriculture in action: drones for agriculture*, *Journal of Chemical Information and Modeling*. Edited by G. Sylvester. Bangkok: FAO, ITU.

Fitzpatrick, A., Singhvi, A. and Arbabian, A. (2020) 'Spatial Reconstruction of Soil Moisture Content using Non-Contact Thermoacoustic Imaging', in *2020 IEEE SENSORS*. IEEE, pp. 1–4. doi: 10.1109/SENSORS47125.2020.9278654.

Gago, J. *et al.* (2015) 'UAVs challenge to assess water stress for sustainable agriculture', *Agricultural Water Management*. Elsevier, 153, pp. 9–19. doi: 10.1016/j.agwat.2015.01.020.

Gao, B. (1996) 'NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space', *Remote Sensing of Environment*, 58(3), pp. 257–266. doi: 10.1016/S0034-4257(96)00067-3.

Garcia Fernandez, M. *et al.* (2018) 'Synthetic Aperture Radar Imaging System for Landmine Detection Using a Ground Penetrating Radar on Board a Unmanned Aerial Vehicle', *IEEE Access*, 6, pp. 45100–45112. doi: 10.1109/ACCESS.2018.2863572.

Ge, X. *et al.* (2019) 'Combining UAV-based hyperspectral imagery and machine learning algorithms for soil moisture content monitoring', *PeerJ*. PeerJ, 7, p. e6926. doi: 10.7717/peerj.6926.

Hardie, M. (2020) 'Review of Novel and Emerging Proximal Soil Moisture Sensors for Use in Agriculture', *Sensors*. MDPI AG, 20(23), p. 6934. doi: 10.3390/s20236934.

Hassan-Esfahani, L. *et al.* (2015) 'Assessment of Surface Soil Moisture Using High-Resolution Multi-Spectral Imagery and Artificial Neural Networks', *Remote Sensing*, 7(3), pp. 2627–2646. doi: 10.3390/rs70302627.

Hassanalian, M. and Abdelkefi, A. (2017) 'Classifications, applications, and design challenges of drones: A review', *Progress in Aerospace Sciences*. Elsevier Ltd, 91, pp. 99–131. doi: 10.1016/j.paerosci.2017.04.003.

Jabro, J. D. *et al.* (2014) 'Repeated Freeze-Thaw Cycle Effects on Soil Compaction in a Clay Loam in Northeastern Montana', *Soil Science Society of America Journal*, 78(3), pp. 737–744. doi: 10.2136/sssaj2013.07.0280.

Jackisch, C. *et al.* (2020) 'Soil moisture and matric potential – an open field comparison of sensor systems', *Earth System Science Data*. Copernicus GmbH, 12(1), pp. 683–697. doi: 10.5194/essd-12-683-2020.

Jia, Y. *et al.* (2015) 'GNSS reflectometry for remote sensing of soil moisture', in *2015 IEEE 1st International Forum on Research and Technologies for Society and Industry, RTSI 2015 - Proceedings*. Institute of Electrical and Electronics Engineers Inc., pp. 498–501. doi: 10.1109/RTSI.2015.7325147.

Kganyago, M. *et al.* (2020) 'Validation of sentinel-2 leaf area index (LAI) product derived from SNAP toolbox and its comparison with global LAI products in an African semi-arid agricultural landscape', *Remote Sensing Letters*. Taylor and Francis Ltd., 11(10), pp. 883–892. doi: 10.1080/2150704X.2020.1767823.

Klotzsche, A. *et al.* (2018) 'Measuring Soil Water Content with Ground Penetrating Radar: A Decade of Progress', *Vadose Zone Journal*. Soil Science Society of America, 17(1), p. 180052. doi: 10.2136/vzj2018.03.0052.

Kornelsen, K. C. and Coulibaly, P. (2013) 'Advances in soil moisture retrieval from synthetic aperture radar and hydrological applications', *Journal of Hydrology*, 476, pp. 460–489. doi: 10.1016/j.jhydrol.2012.10.044.

Liu, X., Dong, X. and Leskovar, D. I. (2016) 'Ground penetrating radar for underground sensing in agriculture: a review', *International Agrophysics*. Walter de Gruyter GmbH, 30(4), pp. 533–543. doi: 10.1515/intag-2016-0010.

Van Looy, K. *et al.* (2017) 'Pedotransfer Functions in Earth System Science: Challenges and Perspectives', *Reviews of Geophysics*. Blackwell Publishing Ltd, 55(4), pp. 1199–1256. doi: 10.1002/2017RG000581.

Lopez, C. D. and Giraldo, L. F. (2019) 'Optimization of Energy and Water Consumption on Crop Irrigation using UAVs via Path Design', in *2019 IEEE 4th Colombian Conference on Automatic Control (CCAC)*. IEEE, pp. 1–5. doi: 10.1109/CCAC.2019.8921148.

Lu, B. *et al.* (2020) 'Recent Advances of Hyperspectral Imaging Technology and Applications in Agriculture', *Remote Sensing*. MDPI AG, 12(16), p. 2659. doi: 10.3390/rs12162659.

Matese, A. *et al.* (2015) 'Intercomparison of UAV, Aircraft and Satellite Remote Sensing Platforms for Precision Viticulture', *Remote Sensing*. MDPI AG, 7(3), pp. 2971–2990. doi: 10.3390/rs70302971.

Messina, G. and Modica, G. (2020) 'Applications of UAV Thermal Imagery in Precision Agriculture: State of the Art and Future Research Outlook', *Remote Sensing*. MDPI AG, 12(9), p. 1491. doi: 10.3390/rs12091491.

Novák, V. and Hlaváčiková, H. (2019) *Applied Soil Hydrology*. Cham: Springer International Publishing (Theory and Applications of Transport in Porous Media). doi: 10.1007/978-3-030-01806-1.

Rayburg, S., Thoms, M. and Neave, M. (2009) 'A comparison of digital elevation models generated from different data sources', *Geomorphology*. Elsevier, 106(3–4), pp. 261–270. doi: 10.1016/j.geomorph.2008.11.007.

Ruosteenoja, K., Räisänen, J. and Pirinen, P. (2011) 'Projected changes in thermal seasons and the growing season in Finland', *International Journal of Climatology*. John Wiley & Sons, Ltd, 31(10), pp. 1473–1487. doi: 10.1002/joc.2171.

Salazar-Vazquez, J. and Mendez-Vazquez, A. (2020) 'A plug-and-play Hyperspectral Imaging Sensor using low-cost equipment', *HardwareX*. Elsevier Ltd, 7, p. e00087. doi: 10.1016/j.ohx.2019.e00087.

Toivonen, M. E., Rajani, C. and Klami, A. (2021) 'Snapshot hyperspectral imaging using wide dilation networks', *Machine Vision and Applications*. Springer Science and Business Media LLC, 32(1), pp. 1–11. doi: 10.1007/s00138-020-01136-8.

Uddin, M. A. *et al.* (2018) 'UAV-Assisted Dynamic Clustering of Wireless Sensor Networks for Crop Health Monitoring', *Sensors*, 18(2), p. 555. doi: 10.3390/s18020555.

Wai-Lok Lai, W., Dérobert, X. and Annan, P. (2018) 'A review of Ground Penetrating Radar application in civil engineering: A 30-year journey from Locating and Testing to Imaging and Diagnosis', *NDT and E International*. doi: 10.1016/j.ndteint.2017.04.002.

Wu, K. *et al.* (2019) 'A new drone-borne GPR for soil moisture mapping', *Remote Sensing of Environment*. Elsevier Inc., 235, p. 111456. doi: 10.1016/j.rse.2019.111456.

Zajícová, K. and Chuman, T. (2019) 'Application of ground penetrating radar methods in soil studies: A review', *Geoderma*. Elsevier B.V., 343, pp. 116–129. doi: 10.1016/j.geoderma.2019.02.024.

Zhan, C., Zeng, Y. and Zhang, R. (2018) 'Energy-Efficient Data Collection in UAV Enabled Wireless Sensor Network', *IEEE Wireless Communications Letters*, 7(3), pp. 328–331. doi: 10.1109/LWC.2017.2776922.

Zheng, G. and Moskal, L. M. (2009) 'Retrieving Leaf Area Index (LAI) Using Remote Sensing: Theories, Methods and Sensors', *Sensors*, 9(4), pp. 2719–2745. doi: 10.3390/s90402719.