

Review

Remote Sensing, Geophysics, and Modeling to Support Precision Agriculture—Part 2: Irrigation Management

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Abstract: Food and water security are considered the most critical issues globally due to the projected population growth placing pressure on agricultural systems. Because agricultural activity is known to be the largest consumer of freshwater, the unsustainable irrigation water use required by crops to grow might lead to rapid freshwater depletion. Precision agriculture has emerged as a feasible concept to maintain farm productivity while facing future problems such as climate change, freshwater depletion, and environmental degradation. Agriculture is regarded as a complex system due to the variability of soil, crops, topography, and climate, and its interconnection with water availability and scarcity. Therefore, understanding these variables' spatial and temporal behavior is essential in order to support precision agriculture by implementing optimum irrigation water use. Nowadays, numerous cost- and time-effective methods have been highlighted and implemented in order to optimize on-farm productivity without threatening the quantity and quality of the environmental resources. Remote sensing can provide lateral distribution information for areas of interest from the regional scale to the farm scale, while geophysics can investigate non-invasively the sub-surface soil (vertically and laterally), mapping large spatial and temporal domains. Likewise, agro-hydrological modelling can overcome the insufficient on-farm physicochemical dataset which is spatially and temporally required for precision agriculture in the context of irrigation water scheduling.

Keywords: irrigation; crop growth; precision agriculture; remote sensing; agro-geophysics; modeling

1. Introduction

Because large amounts of freshwater are required to enhance crop yield, irrigation is crucial to ensure food security [1]. Globally, irrigated agriculture is responsible for around 70% of freshwater abstraction, 90% of water consumption, and 40% of food production [2]. However, the efficiency of irrigation water use is considered to be very low, as only 55% of freshwater withdrawal is consumed by the crop [3]. This unsustainable freshwater withdrawal leads to rapid surface water and groundwater depletion in many agricultural areas [4]. The challenge is more prominent in semi-arid and arid regions that are currently

under water stress and are relying on groundwater resources to support irrigation practices [5–7]. Furthermore, the expansion of global agriculture areas is expected to increase to meet the increasing demand for agricultural commodities due to population growth. Therefore, without proper irrigation water management techniques and practices, and considering the effect of climate change, freshwater preservation and future food production will be threatened.

A good understanding of the relationship between the soil water content and the plant is necessary, as the growth of the crop is governed by the water supply and demand in the soil-plant-atmosphere continuum [8]. In reality, the irrigation water requirement might vary in the field, depending on plant and soil properties and environmental status. Soil, water, and plant properties are not considered static parameters, but they constantly change over space and time [9]. Thus, the regular monitoring of soil water availability and crop growth is essential to establish precision water irrigation [10]. Moreover, the implementation of precision irrigation water would allow decision-makers and farmers to sustain limited freshwater resources while at the same time also enhancing on-farm productivity.

Nowadays, remote sensing, geophysics, and agrohydrological modeling have been widely applied as decision-making tools for site-specific irrigation water management. The use of the tools mentioned above is considered part of the innovation in precision agriculture. Dynamic processes in the soil-plant-atmosphere continuum, as well as the plant's physical properties such as soil moisture (SM), root water uptake (RWU), evapotranspiration (ET), crop chlorophyll, leaf area index (LAI) and plant water status content, could be retrieved through remote sensing or geophysical acquisition. In turn, these data could be used as inputs for agrohydrological modeling in order to provide an estimation of crop water requirements for optimal yields. That advanced information would be beneficial for the decision-making process at the farm-scale in order to achieve precision agriculture. The present paper intends to highlight applications of remote sensing, geophysics, and modeling to support proper irrigation water management. The overall concept is presented in the flowchart of Figure 1.

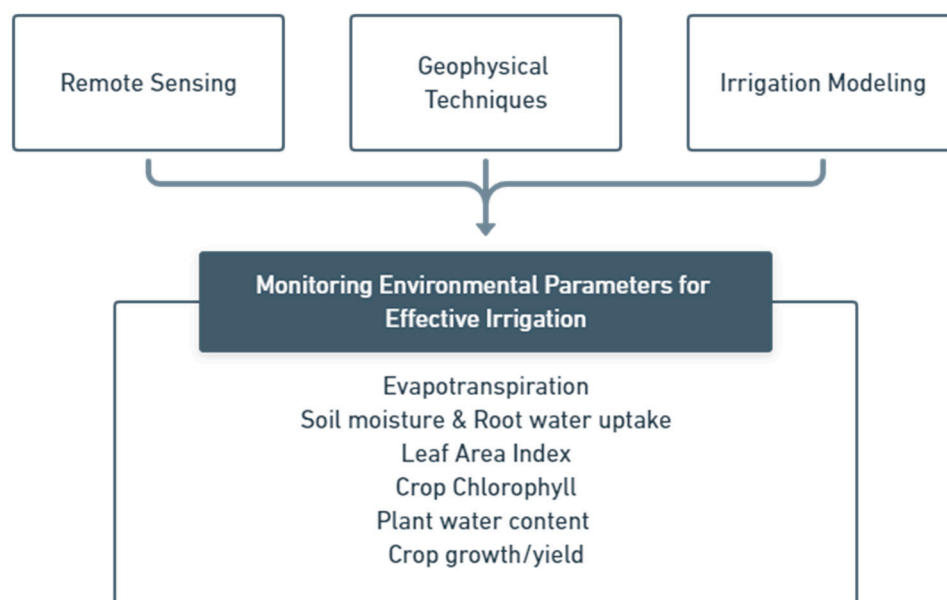


Figure 1. Flowchart of precision agricultural services to support proper irrigation management.

2. Irrigation and Crop Monitoring in Precision Agriculture

The adequate measurement of crop water requirements can be considered the first step toward implementing irrigation water efficiency. Quantifying the right amount of irrigation water supply typically involves the crop water requirement and soil water balance, where ET is the main component [11]. ET, which is a turbulent flux of water vapor from the surface

into the atmosphere involving soil evaporation and transpiration, can also be defined as the amount of water required by plants [12]. ET is regarded as the most significant outgoing water flux at the land surface, and any change of this variable will directly affect the water availability [13]. Thus, accurate knowledge of ET is crucial for a greater understanding of the water and energy balance, which is beneficial for numerous implementations such as irrigation water strategies.

Irrigation water allocation cannot be set in a uniform manner, as the biomass and soil texture might vary across the field, thus affecting the crop water requirement. Conventional techniques like lysimeter, eddy covariance, sap flow, pan measurement, and the Bowen ratio offer an accurate ET estimate at the individual crop and field scales. However, most of the aforementioned methods are difficult to extrapolate into a larger scale to identify on-farm spatial variability considering the heterogeneity of the land surface and heat transfer process. Hence, remote sensing is regarded as a suitable tool to overcome this gap due to its ability to provide adequate spatial and temporal information.

In the cultivated area, shallow soil characteristics (e.g., soil texture and structure) at a depth of 1–2 m might govern irrigation water distribution, the availability of nutrients, and root growth. Soil texture is defined as the relative proportion of gravel, sand, silt, and clay. At the same time, soil structure refers to the spatial arrangement of different solid constituents (e.g., mineral and organic matter) and the soil void. Coarser soil like sandy soil can be wetted by lesser irrigation, but it is easily dried up, resulting in frequent irrigation schedules. On the contrary, fine-textured soil is more fertile, and can hold soil water longer than coarser soil. Soil water movement and retention in the vadose zone are also influenced by the soil structure. Poor soil structure, such as soil with low permeability, could reduce the irrigation water infiltration and increase runoff. This characteristic might result from the compaction process due to the heavy equipment used in agricultural activity. Because these soil characteristics are not homogeneous within farm areas, they might affect the irrigation water management plan. Therefore, an accurate assessment of the subsurface soil at the field scale is required in order to support precision irrigation.

Other variables required for precision irrigation are the hydrological state and flux in the vadose zone, such as SM and RWU. Both variables are affected by each other; thus, understanding the spatiotemporal variability of SM and RWU would be beneficial to support decision making regarding the optimum irrigation scheme [14–16]. SM refers to the amount of water in the soil, and is commonly expressed as a percentage. SM is the essential variable influencing the transfer of energy, carbon, and water in the soil-plant-atmosphere continuum. In agricultural areas, a sufficient amount of SM is required by a crop to grow. This variable can be quantified through numerous approaches at various scales, from the point scale to the local and/or regional scale. The most traditional method is probably the application of gravimetric and volumetric soil water content equations after performing soil sampling. Another reliable technique at the point scale is the deployment of several electromagnetic sensors, such as time domain reflectometry (TDR), amplitude domain reflectometry (AWR), and frequent domain reflectometry (FDR) inside the soil to measure the volumetric water content [17]. At the proximal scale, several geophysics techniques can be employed, such as resistivity [18,19], ground-penetrating radar (GPR) [20], or electromagnetic induction (EMI) [17]. Nowadays, remote sensing approaches have been successfully proven to monitor surface soil moisture (SSM) at different scales. On the other hand, RWU is defined as the process of water extraction by plant roots for transpiration. In particular, the assessment of RWU is based on the adequate information of SM. The study of RWU typically focuses on the determination of the area where the water is extracted by plant roots, and the analysis of the major factor affecting RWU, such as changes of water availability or salinity [16].

Crop monitoring is one of the activities in precision agriculture that is commonly oriented towards retrieving key parameters such as the Leaf Area Index (LAI), chlorophyll content (e.g., leaf and canopy), and plant water status. Based on these three parameters, early agricultural yield can be calculated to affect farm planning and decision-making.

Water and nutrient supplies that vary in space and time are considered the most important variables influencing crop productivity [9]. Besides LAI and chlorophyll, several factors like pest, insect, and disease monitoring should be considered, as they could have adverse effects on crop development, such as yield reduction. The earlier these adverse factors can be identified, the easier the problem will be to address. Therefore, by implementing effective crop monitoring, the risk of economic loss can be potentially reduced.

Measuring leaf chlorophyll content, which is an indicator of photosynthesis and a principal parameter of crop productivity, could assist farmers in defining leaf nitrogen content. Among nutrients, nitrogen is regarded as the most important for crop productivity. Therefore, farmers should make an effort to balance the nitrogen supply to the crop's needs. Apart from increasing farm management costs, excess nitrogen supply could result in soil overloading, leaching or run-off and eutrophication to water bodies, causing soil and water degradation. On the other hand, a deficiency of the nitrogen supply might reduce the agricultural yield [21,22]. The early crop growth stage is a crucial period within the cultivation cycle, as it affects crop yield; thus, a sufficient rate of nitrogen to be applied across the field should be adequately determined [21].

The leaf chlorophyll concentration can be quantified through in situ measurements [23] or using remotely sensed observations [21,24,25]. The conventional and most accurate technique is chlorophyll extraction using organic solvent extraction and supercritical fluid extraction [26]. As a recent development, optical sensors offer a rapid, non-destructive, inexpensive technique to quantify leaf chlorophyll content through reflectance measurement [21,27,28]. The latter method has been widely applied due to its advantages, and can be adopted by in situ or remotely sensed observation. In addition, remote sensing provides opportunities in precision agriculture that require the scaling-up of the individual data from the plant level to the field level, as it could cover large monitoring areas. Through this approach, leaf chlorophyll is multiplied with LAI to obtain the total chlorophyll concentration per ground area [27,29,30]. However, the measurement of chlorophyll content by remote sensing at a large scale can be challenging, as the canopy reflectance is affected by structural factors that might mask the reflectance, such as canopy architecture, chlorophyll distribution, LAI, or soil background [27,31]. Thus, the acquired leaf reflectance within the same canopy might differ even for the same chlorophyll content [32].

Another critical index that reflects the biochemical and physiological process of vegetation, indicating plant productivity, is LAI [33,34]. This dimensionless variable is described as the leaf area ratio per unit of ground surface area [35]. The green leaf area is highly influenced by nitrogen, temperature, and water. Therefore, LAI measurement would be an effective method to understand crop responses to the implemented irrigation scheme. The leaf is also a medium in which photosynthesis takes place. Considering that the photosynthesis process governs crop production, LAI can be used for fertilization management, pruning, and spraying, and to predict crop growth and yield [36–38]. Given the importance of LAI for precision agriculture, new methods of LAI monitoring are emerging over the years. Remotely sensed observation can overcome the limitation of ground-based measurement that might be destructive and time-consuming. However, this approach still requires validation and calibration. In general, remote sensing observation for LAI measurement involves both satellites and unmanned aerial vehicles (UAVs).

Lastly, the quantitative measurement of the vegetation water content (VWC) is also necessary for crop yield estimation and precision irrigation. The VWC represents the total volume of water in the stem and canopy [39]. Basically, the canopy water content (CWC) is the product of the leaf water content (LWC) and LAI [39]. In other words, LWC and CWC can be defined as the water mass per leaf unit of area, and water mass of vegetation per unit of ground area, respectively [40]. LWC also can be referred to as the equivalent water thickness (EWT). Similarly to crop chlorophyll and LAI measurements, the remote sensing of VWC has recently become a popular method due to its rapid monitoring, time-efficiency, and cost-effectiveness.

3. Remote Sensing to Support Precision Agriculture in Irrigation Management

Many areas dedicated to crop production do not have sufficient field hydrological observations to support precision agriculture. Moreover, the field data commonly have different record lengths, and they are spatially limited, making agricultural monitoring more challenging. Due to the unprecedented development of earth science monitoring technology, remote sensing can address this issue by involving spaceborne and airborne observations. Unlike ground measurements, remote sensing has the advantages of regular spatial and temporal resolutions. Spaceborne or satellite data typically have a variety of spatial resolutions with consistent time acquisition, depending on the sensor. They can be used to observe areas of interest from the regional scale to the farm scale [41]. One of the airborne observations, UAV, offers better spatial resolution and can perform in smaller areas. Moreover, the acquisition time depends on the user, and could not be consistent with the satellite observation. For precision agriculture, the spatial resolution range should be from 0.1 m to 10 m, and the temporal resolution should be at least a few days [30,42].

3.1. Evapotranspiration

In particular, the quantification of ET through remote sensing involves numerous approaches, including the surface energy balance (SEB), vegetation index–surface temperature (VI-Ts), and water balance methods [43]. The SEB model calculates ET as a residual of the surface energy budget equation, and considers that the amount of energy entering the earth is equal to the amount of energy emerging from it [44]. This model is based on the principle of energy conservation to partition net radiation at the surface into ground heat, sensible heat, and latent heat flux, where the latter variable is referred to as the ET process [44–46].

SEB can be divided into single-source or two-source models [47]. A number of single-source SEB algorithms were developed to calculate ET through remote sensing, including the widely used model such as the Surface Energy Balance Algorithm for Land (SEBAL) [48], Mapping Evapotranspiration at High Resolution using Internalized Calibration (METRIC) [49], the Surface Energy Balanced System (SEBS) [45], and the Surface Temperature Initiated Closure (STIC) [50]. Single-source SEB models are relatively easy to perform, as they do not treat soil and vegetation as different components. However, the applications of single-source SEB models have limitations over a diverse range of surface conditions [47].

The basic principle of the two-source models is to quantify the contributions of both soil and vegetation components (evaporation and plant transpiration) to the total heat flux [51]. Moreover, the two-source models have been found to be practical to be applied, as they do not require prior calibration and additional input data from ground-based observations [44,47,52]. This is particularly useful for agricultural applications, as evaporation and transpiration are required to design proper irrigation management. The atmosphere land exchange inverse (ALEXI) [53], the Disaggregated Atmosphere Land Exchange Inverse Model (DisALEXI) [54], and the two-source energy balance model (TSEB) [51] are some representatives of the popular two-source SEB models. However, some conditions—such as fractional vegetation cover and soil water availability—might limit the accuracy of these models. In order to overcome this, several models based on two-source approaches have been developed lately, including the Soil Plant Atmosphere and Remote Sensing Evapotranspiration (SPARSE) [55], the Thermal-Based Two-Source Energy Balance for Different Seasons (TSEB-2S) [56], and the End-Member-Based Soil and Vegetation Energy Partitioning (ESVEP) [57]. SPARSE was designed to monitor ET in water-scarce environments, while TSEB-2S is practical to be implemented in a tree-grass ecosystem such as the savanna [55,56]. Lastly, ESVEP has the ability to separate the response of the SM at the upper layer to evaporation and at the deeper root zone to plant transpiration [57].

The input of SEB can be obtained from visible, near-infrared, and thermal infrared remote sensing bands ranging from the land surface temperature to albedo and VI [45,48]. These variables are then combined with ground-based meteorological data such as the air temperature, wind speed, and other near-surface variables to retrieve the net radiation, ground heat, and sensible heat flux [47]. Different satellite platforms have demonstrated

their capability to retrieve the required data for SEB input, including the Moderate Resolution Imaging Spectroradiometer (MODIS) [58–60] and Landsat [46,61,62] data. The uses of microwave sensors were also highlighted by several studies in order to overcome the major obstacle of visible, near-infrared, and thermal infrared remote sensing, which is a cloud cover. For instance, Bastiansseen et al. [63] and Mostafa et al. [64] utilized passive microwave remote sensing to retrieve SSM in order to estimate the soil evaporation in the two-source SEB models.

The VI-Ts triangle method is based on the vegetation index and land surface temperature (LST), which can be obtained from remote sensing. The VI-Ts method plots scatterplots of LST versus VI, forming triangular shape with a dry edge and a wet edge to estimate evaporative fraction (EF) and ET [65]. The wet edge is defined by the linear interpolation of pixels with minimum VI and maximum LST, while the dry edge is identified by an opposite response [43]. The VI-Ts approach is less complex, as it does not require a surface, meteorological, or land surface model as an ancillary dataset [58,66].

In order to obtain the best result of the VI-Ts method, the contrast variations of the land surface temperature and vegetation index are required; therefore, this method might not perform well in any areas characterized by a homogeneous land surface, such as desert or a rainfed agriculture area during the dry season [47,67]. Another factor restricting this method is atmospheric conditions, such as cloudiness, that can discontinue the LST retrieval [68]. Because temporally continuous ET is crucial for water resource management, previous studies have developed various techniques to address this issue. These techniques vary from the universal triangle method that transforms the VI-T feature space from the regional scale into the pixel scale [67], a gap-filling algorithm using a deep neural network (DNN) [69], and the fusion of a VI-Ts model and the LST construction method [68].

Another approach is the water balance method, which is quite simple in theory. This method estimates ET by quantifying it as a residual component using the water balance equation. The value of the ET can be obtained by subtracting the runoff (R) and change of water mass storage (ΔS) from precipitation (P) [70]. Currently, ΔS is only available from the Gravity Recovery and Climate Experiment (GRACE) satellite retrieval, which has coarser spatial resolution and suffers from periodic data gaps, thus limiting its use to the basin scale, and only with low temporal resolution [70–72]. In order to implement the water balance method in sub-basin-scale or smaller areas, further attempts commonly focused on improving the spatial resolution of GRACE through the downscaling process. For instance, Wan et al. [73] highlighted the use of the land surface model to downscale GRACE data for monthly ET monitoring in sub-basins across the United States. Yin et al. [74] explored the potential of statistical downscaling using numerous observations over a long period in order to apply the water balance method in the North China Plain. A brief overview of different remote sensing-based methods and products used to support irrigation water management is provided in Table 1.

Table 1. Brief overview of different remote sensing-based methods and products to estimate ET over irrigated areas.

Methods	Remote Sensing Platforms	Applications	References
Single-Sources Surface Energy Balance (SEBAL)	Lansat 8	Estimation of irrigated wheat requirement in the Ein Khosh Plain	[75]
Single-Sources Surface Energy Balance (STIC)	MODIS	ET mapping in the conterminous US	[76]
Two-Sources Surface Energy Balance (TSEB)	ASTER SPOT	Monitoring crop water consumption over the irrigated area of Tensift Basin	[77]
Two-Sources Surface Energy Balance (ETLook)	AMSR-E MODIS	ET mapping over irrigated area in the Indus Basin	[63]
Two-Sources Surface Energy Balance (SPARSE)	MODIS	Estimation of ET and water stress over several crop types and climates	[78]
VI-Ts triangle method	MODIS	ET estimation in the Haihe River Basin	[79]
Water balance method	GRACE	Detection of irrigation-induced ET in the Haihe River Basin	[80]

3.2. Soil Moisture

Commonly, the retrieval of SM through remote sensing mainly focuses on the use of microwave sensors, as they are strongly associated with the SM content [81,82]. At a large scale, passive microwave satellite observations such as AMSR, SMOS, and SMAP have been widely optimized and proven for their reliability to monitor SM variabilities in the top few centimeters (approximately 0–5 cm), i.e., referring to surface soil moisture (SSM) [83–86]. Recent studies have shown that SSM could serve as a basis to identify the spatial extent of irrigated regions [87,88], and to quantify the amount of water used for irrigation [89–92]. In addition to passive microwave remote sensing, active microwave satellites like Sentinel-1, RADARSAT-2, PALSAR/ALOS-2 and TerraSAR-X have feasibility for SM mapping [93–96]. Compared to passive microwave sensors, active microwave sensors offer a high spatial resolution. Hence, they can provide meaningful information at the farm scale. In contrast, passive microwave sensors would be helpful for agricultural decision-making at the local or regional scale. In terms of temporal resolution, the passive microwave has a higher revisit frequency compared to the active microwave. Both passive and active microwaves are sensitive to the soil-water dielectric constant that affects the emissivity and backscattering of microwaves, allowing them to measure SSM [97,98].

One of the limitations of spaceborne remote sensing is that it cannot capture the dynamic of SM in the deeper soil zone (root zone soil moisture (RZSM)). In cultivated areas, the information of the RZSM is important and required in order to have a meaningful impact for different applications, such as root water uptake (RWU) and soil hydraulic parameters [99]. Moreover, the ability of RZSM to reflect the actual soil water availability required by the crop is better than that of SSM [100]. In order to overcome this issue, several studies incorporated SM retrievals derived from passive microwave remote sensing into land surface or hydrological models through data assimilation schemes in order to predict RZSM [100–103]. Data assimilation is considered the most promising technique due to its ability to develop RZSM while quantifying uncertainties from observation data and output simulation [102].

Several factors, such as vegetation cover and soil characteristics, could influence the accuracy of SM retrieval. Sensor sensitivity tends to decrease with increasing vegetation density. Therefore, microwave sensors have better accuracy in areas characterized by sparse to moderate vegetation than densely vegetated areas [104]. In general, this issue can be minimized by using a longer wavelength. Among the existing passive microwave satellites, SMOS and SMAP have been widely used recently due to their L-band operation, which has the capability of penetrating vegetation cover, unlike the C-band [105–107]. Even though it is challenging, separating the effect of vegetation and soil characteristics such as soil roughness from SM would provide better accuracy, particularly for active microwave sensors, as these factors heavily perturb its backscattering. This is especially relevant at the farm or field scale, where precise irrigation management for a specific condition is necessary. In the past few years, the removal of the effect of the vegetation canopy over different crops and phenological periods through numerous methods has shown promising results, and is now feasible to be applied [94,108].

Alternative approaches to the assessment of SM are optical and thermal infrared satellite observations. Optical and thermal satellites are well-suited for small-scale observations because of their higher spatial resolutions. However, the applications of optical and thermal sensors solely for SM monitoring are still limited. The combination of both sensors (optical–thermal), known as the temperature–vegetation triangle approach, is more popular and widely used. The basic principle of the triangle approach is that SM is closely associated with the land surface temperature and vegetation index; thus, variations of SM can be estimated [109]. The visible (VIS), near- (NIR), and shortwave infrared (SWIR) bands emitted from the optical sensor can detect various plant parameters, such as greenness, canopy water, or photosynthetic parameters that related to plant water. In contrast, thermal infrared (TIR) wavebands are closely associated with soil thermal properties [110]. Numer-

ous studies have also exhibited the feasibility of combining optical and thermal sensors to determine SM variabilities [111–114].

Lately, the utilization of UAVs has become popular as part of modern agricultural management. Like satellite-based monitoring, UAV is a timesaving, non-destructive method, offers better spatial resolution, and supports real-time farm management. Wu et al. [115] demonstrated that SM could be observed by mounting ground-penetrating radar on UAVs. Another technique is the installation of optical and thermal sensors on UAVs [116,117]. Like satellites, these sensors capture vegetation index and land surface temperature information, which allow SM estimation. The overview of numerous remote sensing products for the retrieval of SSM and RZSM is depicted by Table 2.

Table 2. Overview of numerous remote sensing products and sensor types for the estimation of SSM and RZSM.

Applications	Remote Sensing Products	Sensor Types	References
Surface Soil Moisture	SMAP_SM	Microwave	[84]
	SMOS_SSM	Microwave	[85]
	AMSR2_SM	Microwave	[118]
	Sentinel-1, Sentinel-2	Microwave-Optical	[119]
	Sentinel-1 Landsat-8 OLI & TIRS	Microwave-Optical-Thermal	[93,120]
	Sentinel-2 Landsat-8 OLI & TIRS	Optical-Thermal	[114]
	MODIS_LST MODIS_Surface Reflectance	Optical-Thermal	[111]
	UAV	Optical-Thermal	[116,117]
Root Zone Soil Moisture	SMAP_SM SMOS_SSM SMOS_RZSM MODIS_LST MODIS_Surface Reflectance	Microwave-Optical	[100]
	AMSR-E_SSM MODIS_ET	Microwave-Optical	[103]

3.3. Crop Chlorophyll and LAI

Optical remote sensing in the VIS, NIR and SWIR spectra is widely used to estimate LAI and crop chlorophyll content [24,29,34,121,122]. Different materials and objects can be differentiated based on their spectral signature. Based on the number of spectral bands, optical remote sensing can be classified into several imaging systems, of which multispectral and hyperspectral sensors are the most used imaging sensors. Besides optical remote sensing, the potential of microwave remote sensing to retrieve LAI and crop chlorophyll was also explored by Clevers et al. [30]. Basically, multispectral and hyperspectral bands work by recording the electromagnetic energy reflected or emitted from the earth's surface in three to ten bands and more than ten bands, respectively. Compared to multispectral sensing, the utilization of the hyperspectral remote sensing has been increasing over the years due to its ability to provide continuous spectral coverage despite requiring more complex technical procedures [34]. However, both imageries can only provide satisfactory spatial resolution in clear atmospheric conditions.

Commonly, the estimation of the chlorophyll content and LAI relied on the empirical (statistical) spectral vegetation indices or the inversion of the radiative transfer model [123–126]. Empirical spectral vegetation indices are the simplest and most popular method that utilizes a statistical approach to determine the correlation between the observed object and vegetation indices or spectral reflectance [123,124]. However, the

complex internal and external factors affecting spectral reflectance might vary in time and space; thus, the relationship between the observed objects with their reflectance might be inadequate over heterogeneous conditions [127]. On the other hand, the inversion of a radiative model can explain the interaction of the radiation that occurred inside the canopy using physical laws; thus, the connection between the biophysical variables and canopy reflectance can be described [125]. The major limitation is that the radiative transfer model requires insitu-specific information that is not always available [24].

The quantitative estimates of some ecophysiological variables (e.g., leaf chlorophyll and LAI) are assessed using spectral reflectance in the VIS, NIR and SWIR domains. This is because leaf spectral reflectance is assumed to be related to pigment compositions, such as chlorophyll, carotenoids, and anthocyanins [28,128]. These spectral domains are then utilized to develop numerous vegetation indices (VI) to estimate the plant's biophysical parameters, including LAI. Among the developed VI, the normalized difference vegetation index (NDVI) is the most popular one. NDVI is also the VI which is least affected by soil background, and it has good accuracy, meaning that this index can be considered to be a reliable tool [31,129]. The most effective spectral reflectances used for LAI estimation are located in the NIR and SWIR regions, particularly at the wavelength of 820 nm, 1040 nm, 1200 nm, 1250 nm, 1650 nm, 2100 nm, and 2260 nm [130].

For the leaf chlorophyll estimation, Gitelson et al. [131] reported that the band wavelengths of 520 nm to 550 nm and 695 nm to 705 nm are closely related to the chlorophyll content in all of the leaf species. A similar range of absorption features has also been mentioned by Delagido et al. [29] and Daughtry et al. [132], for whom chlorophyll concentrations are related to the wavelengths of 643 nm to 795 nm and 550 nm and 715 nm, respectively. Based on these results, it can be concluded that leaf chlorophyll has strong absorption in the VIS and NIR domains.

3.4. Vegetation Water Content

VWC quantification through remote sensing generally assesses several vegetation physiological indicators, such as stomatal conductance, leaf water potential, canopy water content, leaf equivalent water thickness, live fuel moisture content, and relative water content [133]. Basically, optical and microwave remote sensing are the two common approaches which are utilized in VWC measurement (Table 3). Besides them, the use of thermal remote sensing was also explored by several studies.

Optical remote sensing can be considered as the conventional approach to measure VWC. The volume of water in vegetation commonly has strong absorption features in the NIR and SWIR spectral regions, thus allowing us to quantify VWC [130,134,135]. For example, Ullah et al. [134] mentioned that spectral reflectances of 1397 nm and 1600 nm are related to LWC, while Jin et al. [135] identified 75 wavelengths related to LWC, with a range from 926 nm to 1940 nm. The use of NIR or SWIR solely is not suitable to retrieve VWC, particularly at the leaf level (LWC); thus their combination is required [136]. Therefore, different vegetation indices based on spectral reflectance have been utilized to assess VWC, such as the normalized difference infrared index (NDII), the normalized difference vegetation index (NDVI), the normalized difference water index (NDWI), and the canopy temperature [137]. Among these indices, NDWI that employs NIR and SWIR provides a better estimate of VWC, as reported by previous studies [138,139].

Recently, active microwave remote sensing or radar have been carried out by a number of studies to retrieve VWC. One radar-based vegetation index to monitor crop properties, named the radar vegetation index (RVI) was developed and applied for VWC measurement [140–142]. This index represents a simple function of radar backscattered from all polarizations, including co- and cross-polarization [142]. RVI is not only applied to assess VWC, but also the vegetation greenness and LAI. Technically, the reduction of VWC will be reflected by the decreasing RVI from the L-, C-, and X-bands [141]. The L-band has been found to have better accuracy for VWC retrieval compared to the C- and X-bands due to its better penetration [141,143].

One of the limitations of RVI is the sensitivity of radar measurement to soil scattering (moisture and roughness). Therefore, the revised RVIs named RVII and RVIII were proposed by Szigarski et al. [144] to reduce the effect of soil moisture and roughness. Besides RVI and RVII, other radar-based vegetation indices were also developed to improve their performance in VWC measurement, e.g., the polarimetric radar vegetation index (PRVI) that exploits the polarization degree and the cross-polarized backscattering coefficient [145], and the dual polarimetric radar vegetation index (DpRVI) [146]. The latter index utilizes the normalized dominant eigenvalue and the degree of polarization instead of polarization backscatter intensities [146].

Several findings showed that thermal infrared (TIR) remote sensing can be utilized to retrieve VWC, particularly at the leaf level. Despite its potential, the use of TIR in VWC has not been heavily exploited due to several reasons. The relationship between VWC and spectral features in the TIR domain is relatively weak compared to the NIR and SWIR regions [147]. Regarding the spaceborne platform, the number of TIR satellites is still limited to a few satellites—for instance MODIS, Landsat-8 and Sentinel-3—thus limiting its use at a larger scale [148]. An additional issue restricting the use of TIR satellites in VWC studies is the scaling process from the leaf to the canopy level [149].

Table 3. A number of remote sensing platforms and sensor types in crop development monitoring.

Applications	Platforms	Sensor Types	References
Crop chlorophyll content	PROBA	Optical	[29,150]
	UAV	Optical-Thermal	[24]
	UAV	Optical	[122,151]
LAI	Sentinel-2	Optical	[30]
	Compact Airborne Spectrographic Imager	Optical	[121]
	UAV	Optical	[122,151]
VWC	Sentinel-2	Optical	[152]
	Lansat 5, ASTER, and AWiFS	Optical	[153]
	MODIS	Optical	[139]
	Sentinel-1	Microwave	[146]
	SMAP	Microwave	[142]

4. Geophysical Acquisitions

Potential agricultural geophysical applications are widespread, varying from soil structure characterization to SM assessment. Geophysical acquisitions are regarded as non-invasive, non-destructive, rapid, and cost-effective methods that are frequently used for soil investigation. Those methods would allow the user to investigate all of the sub-surface soil without disturbing the structure and dynamic of the soil [154]. In addition, the geophysical survey can map large spatial and temporal domains, bridging the gap between remote sensing observations and point-based measurements. Moreover, information derived from the geophysical survey could also be utilized to calibrate or validate remote sensing measurement.

Basically, resistivity, EMI, and GPR are the most common geophysical methods employed for agricultural applications [155]. Soil properties and state variables such as porosity, density, clay content, SM, and salinity are the typical parameters observed through a geophysical survey [156]. Besides them, magnetometry, self-potential, and seismic methods are three promising geophysical methods that can be applied for the same purpose in the future [155]. However, the interpretation phase in geophysics poses a challenge for the

user due to its ambiguity. Therefore, the combination of different available geophysical methods and the integration of the final geophysical model with other parameters such as geochemical and remote sensing in datalogs are usually applied to minimize uncertainties and improve the final geophysical solution. Table 4 provides an overview of different applications of geophysical methods used to assess the soil water availability and dynamic in the vadose zone.

4.1. Soil Characteristics

Subsurface soil characterization is considered to be a prerequisite step of agricultural management. Several soil parameters—such as soil texture and structure—that might govern the distribution of water irrigation can be potentially monitored using geophysics-based assessment. Some geophysical methods like resistivity and seismic assessment are expected to have strong soil texture and structure signatures.

The feasibility of electrical resistivity (ER) to identify a tilled soil structure in the agricultural area has been examined by several studies. ER is known to be sensitive to bulk density, where increasing bulk density due to soil compaction corresponds to a reduction of porosity, air and pore water volume, an increase of clay fraction, and subsequently the decrease of the soil ER [157–160]. However, the degree of compaction cannot be directly measured by ER [161]. As an extension of ER, electrical resistivity tomography (ERT) can develop a high resolution of the 3D subsurface soil structure that enables a user to investigate soil facies based on the seasonal soil water content period [162,163]. Other applications of ERT for soil characterization include, but are not limited to, soil compaction [164], the soil–rock interface [165], and soil organic matter (SOM) delineation [166–171].

The soil's apparent electrical conductivity (ECa), measured by EMI, can indirectly indicate several soil properties that influence agricultural productivity [172,173]. In the irrigated landscape, EMI is becoming one of the frequently used approaches to map the subsurface due to its high mobility. Subsurface soil characterization through EMI can be acquired faster than other instruments, as the induction principle of EMI does not require direct contact with the ground surface [174]. Confounding geophysical interpretation might appear as a combination of various soil properties, which could affect ECa. Some approaches have been proposed and established in order to overcome this issue, involving simple statistical correlations and wavelet analysis [172]. Soil texture assessment through EMI generally focuses on the clay content, rather than sand and silt compositions [175–178], while soil structure evaluation typically pays more attention to reduced permeability due to soil compaction [179,180].

While ERT and EMI offer a general spatial pattern of the soil, GPR has the ability to provide detailed information on soil stratigraphy [181]. The antenna frequencies should be appropriately selected based on the aim of acquisition and field conditions [182]. In the agricultural field, one of the exciting aspects of the GPR applications is soil structure monitoring based on dielectric permittivity, as this would affect water movement within the vadose zone [183–185]. Another application for soil characterization assessment required in agricultural studies is compacted layer assessment [186,187]. Basically, the effectiveness of GPR in soil assessment is related to the soil condition. For example, the implementation of GPR in soil dominated by clay is difficult due to the strong absorption of radar waves.

Even though the use of seismic assessment in soil studies is still rare, the sensitivity of the shallow seismic method offers better soil mechanical measurements such as compacted layers and aggregation than other geophysical techniques [156,188]. This method analyses the propagation velocity of the seismic wave, which is affected by material properties. Soil compaction will result in an increase of bulk density; subsequently, the velocity of the seismic wave will increase as well [159]. Several studies have also identified a significant difference in seismic wave velocities representing compact and loose soil [189,190].

4.2. Soil Water Availability and Dynamic

High-resolution SM mapping in 2D and 3D models commonly employs resistivity [191–194], EMI [195–197] and GPR [196,198,199]. These geophysical techniques might

overcome the scale gap between point-scale SM sensors, such as time-domain reflectometry (TDR) sensors and remote sensing observation [17,200]. Moreover, information on SM derived by the geophysical technique is generally used as a basis to characterize the spatiotemporality of RWU [16].

ERT is one of the most appropriate methods to monitor the spatiotemporal resolution of SM at the field scale by measuring the bulk soil electrical conductivity. It is widely known that the variability of soil electrical resistivity is highly affected by the soil water content [158,191], allowing a user to determine SM variabilities. In order to convert the bulk soil electrical conductivity into the soil water content, the in situ calibration of ERT acquisition at a specific horizon is required [14]. The coverage of subsurface information given from electrical resistivity measurement depends on the space between the electrodes inserted into the soil for the measurements [193]. The spatial distribution of SM can be presented as 2D, 3D, or 4D tomograms [201]. ERT can also provide simultaneous data acquired from different depths and locations in order to improve the 4D spatiotemporal variability of SM [193]. Besides SM, the application of ERT for the assessment of RWU is also highlighted by numerous studies in order to monitor the impact of different irrigation schemes [202] and the extent of plant roots [14,203].

SM measurements by the EMI method are typically based on the strong relationship between the soil water distribution and ECa [204]. Different agricultural treatments like fertilizer applications might result in a complex relationship between SM and ECa [205]. EMI was initially used for soil salinity assessment before expanding to various applications [195]. In saline soil, soluble salt is the major physicochemical property influencing the apparent soil electrical conductivity; therefore, the interpretation is often straightforward [172]. In an area with a low salt concentration, ECa is mostly highly affected by SM variations [196,206,207].

Another method used to estimate SM is a GPR. SM is the dominant factor affecting the wave attenuation and velocity of GPR's electromagnetic signal, thus influencing the soil dielectric constant [199]. GPR has a disadvantage compared to ERT, as its performance decreases in electrically conductive media like fine-textured soil such as clay [14]. The GPR-derived soil dielectric constant can then be converted to volumetric SM using a technique called Topp's empirical relationship [208]. In the past decade, the development of multichannel GPR measurement became promising for SM observation [200]. This could allow the user to obtain a high-resolution measurement of the reflector depth and SM with less effort. Nowadays, the combination of GPR and EMI in an integrated inverse modeling scheme to obtain multi-layered media has been widely adopted, as shown by Mogadhas et al. [204] and Barca et al. [196].

Table 4. Various geophysical methods to characterize the soil water availability and dynamic in the vadose zone.

Geophysical Methods	Applications	References
ERT	Deliniation of soil facies	[162,163]
	SOM investigation	[166]
	Soil compaction assessment	[164]
	Monitoring SM variabilities	[14,163,191–193]
	RWU characterization for monitoring the impact of different irrigation schemes	[202]
	RWU characterization to assess the extent of root plant	[14,203]
EMI	Clay layer investigation	[175–177]
	Soil compaction assessment	[179,180]
	Monitoring SM variabilities	[196,197,206]
GPR	Soil structure monitoring	[183–185]
	Soil compaction assessment	[186,187]
	Monitoring SM variabilities	[196,199,200,209,210]
Seismic	Soil compaction assessment	[189,190]

5. Irrigation Modellings to Support Precision Agriculture

During the past decade, the domain of agricultural modeling has progressively evolved. Instead of focusing solely on the increase in farm productivity, agricultural modeling has expanded its application to recent challenges such as greenhouse gas emissions, food and water security, climate change mitigation, and carbon sequestration [211]. From the context of precision agriculture, agricultural modeling would overcome the insufficient on-farm dataset required in space and time to enhance farm management decisions. In general, crop yield, soil, the availability of natural resources, and the effects of human practices are the necessary information to understand the complex behaviour of an agricultural system [212]. Based on Jones et al. [212], the spatiotemporal scope of agricultural modeling varies depending on the problems that are being addressed by farmers, researchers, or decision-makers. It is widely known that the larger the scale, the more demanding the required data [213]. A brief overview of various applications of agricultural modeling is provided in Table 5.

Coupled Hydrologic–Crop Modelling

The rising concern for water and food security has elevated the need for coupled hydrological and crop-growth modeling [214]. Hydrological simulation refers to the numerical representation of soil water distribution in the soil-plant-atmosphere continuum. Most hydrological models are based on the Richards equation and the convection–dispersion equation in order to simulate water flow and solute movement in granular media [215]. Various hydrological models with different characteristics have been developed for this purpose, including SUTRA [216] TOUGH [217], UNSAT-1 [218], UNSAT-2 [219], SATURN [220], 3DFEMWATER [221], SVAT [222,223], SWAP [224,225], SWAT [226,227], and HYDRUS [215,228,229]. Among them, HYDRUS is the most frequently used model to simulate 1D, 2D and 3D hydrological movement in the unsaturated and saturated zones. According to Arnold et al. [230], six essential parameters should be considered and implemented in order to build a reliable hydrological model: computation efficiency, high spatial resolution, data input availability, continuity, the ability to simulate land-management scenarios, and the ability to provide reasonable results.

Crop growth models are mainly employed to simulate biophysical processes and to predict crop yield, which is affected by soil, weather, crop varieties, and cultivation practices, including irrigation and fertilizer application [231–233]. Commonly, crop growth is simulated based on mathematical expressions that describe the flow and conversion processes of water, nitrogen, and carbon [234]. Numerous models based on various concepts and underlying theories have been developed and successfully utilized over the years, such as DAISY [235,236], DSSAT [234,237], DSSAT-CERES [238,239], SUCROS [240], and WOFOST [241,242]. In addition, the integration of hydrological and crop growth models with other parameters, such as remote sensing data, could provide the improved, real-time calibration of model parameters [36].

The coupling of hydrological and crop modeling under spatial and temporal variations is essential in complex agricultural systems, despite being at an early stage of development [214]. Without the coupling of the two models, the accuracy of the crop growth might be decreased due to the oversimplification of the processes involved [243]. Recently, this approach was proposed by Mc Nider et al. [244], Pauwels et al. [231], Sheila et al. [234], Vaghefi et al. [245], Zhang et al. [243], and Zhou et al. [246]. Several challenges can surface during the process of coupling two models, such as the model simulation and application, methodology, and model hypothesis [243]. In order to select the appropriate methodology, a lot of factors should be considered, such as the scale, basin characteristics, availability of the dataset, method requirements, time constraints, and required accuracy [214].

Table 5. Overview of different applications of hydrologic, crop, and coupled models for agricultural practices.

Models		Applications	References
Hydrologic	Crop		
HYDRUS 1D	-	Nitrate accumulation and leaching simulation	[247]
HYDRUS 2D	-	Soil and plant water simulation under different irrigation systems	[228]
SWAT	-	The effect of climate change on hydrology and crop yield simulation	[226]
SWAT	-	Simulation of streamflow, total suspended nutrient, and sediment	[227]
SWAP	-	Field water cycle simulation under deficit irrigation	[224]
-	DSSAT	Simulation of crop yield under practice of conservation agriculture	[237]
-	DSSAT	Simulation of crop response to fertilizer microdosing	[239]
WaSSI	GidDSSAT	Estimation the impact of irrigation withdrawal on hydrologic flow	[244]
HYDRUS 1D	DSSAT	Soil water dynamic, crop growth and yield simulation	[234]
JULES	SUCROS	Dynamic crop growth simulation	[240]
SVAT	DAISY	Simulation of crop production and nitrate leaching	[236]
VIC	EPIC	Improvement discharge, SM and evapotranspiration simulation	[243]
HYDRUS 1D	WOFOST	Optimizing irrigation water and predicting crop yield	[246]
SWAT	MODSIM	Crop water productivity simulation	[245]

6. Precision Agriculture and Future Challenges concerning Proper Irrigation

Optical (Vis, NIR, SWIR), thermal, active, and passive microwave remote sensing have been proven to be viable approaches to support precision irrigation, from the local to the global scale. Despite providing high-resolution images, the ability of optical satellite acquisition is constrained by atmospheric conditions and solar illumination. Microwave remote sensing has the potential to complement the conventional remote sensing technique in irrigation monitoring. The primary advantage of microwave remote sensing is the ability to penetrate clouds, and that it can be acquired at any time (day and night). However, the characterization of vegetation properties due to irrigation practices and obtaining radar observation for a range of system configurations is still a challenging issue [141]. Even though each sensor (optical, microwave, and thermal) has its own limitation in agricultural monitoring, they are complementary to each other; thus, they can be integrated together for better results. Among remote sensing technologies, UAV might also offer low-cost

alternatives for agricultural monitoring, especially for small farms where the resolution is large enough to observe the variabilities of the soil and plant properties.

The lack of quantitative subsurface soil spatial data is known to be a major constraint for the development of hydrological models. This gap can be overcome by the utilization of geophysics-based measurement. The geophysical survey offers soil characterization in the vadose zone in a rapid, reliable, and cost-effective way. This approach offers spatially extensive and high-resolution information that helps the user to understand complex pictures of hydrological states and fluxes in the subsoil. The non-uniqueness of the signal response that results in misleading interpretation and uncertainty are some challenges that should be addressed for future studies. The high resolution of ERT acquisition is still restricted to a shallow depth due to the requirement of electrode spacing increments, limiting its potential for larger surveys [248]. On the other hand, despite its mobility, the vertical resolution of soil characterization acquired by EMI is low in many studies, and can be improved by applying new EMI instruments with multiple coil separations and orientations [173]. Combining various geophysical techniques might reduce the ambiguity of interpretation and improve the resolution [156].

In addition, agricultural modeling would overcome the insufficient on-farm dataset required in space and time to enhance farm management. Water states and fluxes inside soil and irrigation water demand can be reflected by hydrological and crop models, respectively. The coupling of crop and hydrological models would improve the accuracy of the model, and could help the decision-maker to predict crop yields based on the irrigation input and scheme. The upscaling process from the field scale to the regional scale offers the better understanding required by decision-maker to manage valuable resources and optimize crop productivity. However, this process needs extensive information representing the physical, chemical, and biological heterogeneities of the study areas. Moreover, the scarcity of the ground-based datasets used for calibration could limit the accuracy of the model. The uncertainty could come not only from the data input but also from the modeling approach applied. Therefore, the chosen data input along with the modeling approach is a critical step to obtain the modeling objectives. The development of a simple generic model that can be applied at various scales and is easy to integrate with other datasets due to its flexibility would help the user, particularly in an agricultural study [249].

7. Conclusions

This paper aims to assist farmers or decision-makers in better understanding the potential of recent advances in agricultural studies in the optimization of irrigation water use. The tremendous progress of remote sensing, geophysics, and modeling applications in agricultural studies have established them as advanced techniques which complement each other. The integration of remote sensing, geophysical surveys, and agrohydrological modeling will probably become a standard approach in agricultural practice in the future. Their applications to monitor variables in the soil-plant-atmosphere continuum include, but are not limited to, the soil texture, soil structure, soil compaction, SM, RWU, ET, crop chlorophyll, LAI, and VWC. The regular monitoring of these variables is necessary for the improvement of irrigation water use efficiency and the projection of the end-of-season crop yield as part of precision agriculture.

At the decision level, the delineation of the farm zone based on information retrieved from remote sensing, geophysics, and modeling could help farmers to manage valuable resources and optimize crop productivity by supplying the actual water requirement needed by the soil and plant [210,250]. Future advancements are expected to improve data processing techniques and reduce the acquisition cost; thus, the more significant benefits of remote sensing, geophysics and modeling for agricultural applications can be achieved. As the concept of precision agriculture is directly linked to the spatial and temporal variabilities of soil and plant properties, understanding these parameters would provide a solid foundation for farm development in order to achieve the ultimate goal of optimal agricultural management.

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