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# Applications of microwave remote sensing of soil moisture for agricultural applications

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**Abstract**

Agricultural irrigation is the largest (80%) user of freshwater resources. With increasing freshwater demand, it is important to make optimal use of water resources with improved agricultural productivity through objective and accurate information provided by remote sensing. This paper reviews the potential of applications of microwave remote sensing of soil moisture and vegetation for agricultural application. Microwave remote sensing can be used to estimate soil moisture on the basis of large contrast that exists between the dielectric constant values for dry and wet soils. Temporal monitoring of water availability at soil root zone during growth periods of crop could prevent water stress and improve the productivity. At field scales, the high resolution soil moisture data can be better used for irrigation scheduling through precision agriculture. At larger scales, low resolution soil moisture data as alternative to vegetation index can be used to monitor and predict crop yield. Because microwaves penetrate cloud, microwave remote sensing could be a good alternative to VIS/IR hyperspectral data for monitoring vegetation distribution, health and water needs for agricultural applications.

*Keywords*: Soil moisture; Microwave remote sensing; Agriculture.

## 1. Introduction

Agricultural irrigation has a major impact on water resources management as it accounts for more than 80% of total water withdrawn [1-3]. The global extent of irrigated area has expanded during the last 30 years by 1.6% per year [4] leading to a significant increase in freshwater consumption and therefore to water resource degradation and depletion. Further, the emerging concern over climate and land use change impact on agriculture needs accurate monitoring of crop yield production. Precise use of fresh water resources for irrigation is required for implementation of sustainable water management policies and to monitor high yields in a changing climate and rising water demands. Soil moisture, water content in the root zone, and vegetation indices are critical parameters for crop yield forecasting, irrigation management, and issuing early warning of droughts.

Soil moisture data with high spatial and temporal resolution over the agricultural growing season have potential for rational planning of irrigation management and increased crop yields. Temporal monitoring of soil moisture at different growth stages of crop could prevent water stress and improve the crop yield [5]. Soil moisture characteristics influence the availability of nitrogen and water to the crop during the growing season, strongly affecting the availability of soil nitrogen during periods of low water availability [6]. On the other hand, excessive irrigation leads to leaching of fertilizer (N and P), inducing groundwater pollution and soil degradation [7]. Using knowledge of soil moisture to manage insects and plant disease [8] is a potential application that needs more research. Information on spatial distribution of soil moisture over the field will allow pesticides to be applied selectively to achieve economic and environmental benefits.

Currently, various crop monitoring schemes are used to retrieve crop yield information from visible/near IR remote sensing data. These schemes could be improved with the addition of microwave based soil moisture information to achieve greater efficiency. Many studies carried out during past three decades have successfully demonstrated the use of active and passive microwave remote sensing techniques to obtain spatial and temporal estimates of soil moisture mapping over large regions [9-12]. In the case of passive microwave system, the radiometric emission measure as a brightness temperature decreases with the increasing soil moisture. However, in the case of active microwave system, the stronger radar backscatter signals are observed at higher soil moisture [13].

The spatial heterogeneity soil moisture and precipitation make it difficult to estimate soil moisture at relevant scales from field soil moisture measurements. Lacking accurate information, farmers/managers often leave irrigation systems

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running to ensure that water is available to driest area. This leads to wasteful water application to wet area damaging crop growth and development. Field soil moisture measurements are limited to a small fraction of the total area because of the expense and logistical constraints. While field measurement using gravimetric sampling, calibrated neutron attenuation, or timedomain reflectometry (TDR) technique may be quantitatively accurate, it poorly represents the spatial and temporal distribution of soil moisture as a function of variable soil surface characteristics.

Microwave remote sensing systems have shown great potential in spatial soil moisture estimation for crop yield fluctuation forecasting at regional and global scale. Spaceborne active microwave sensors, synthetic aperture radar (SAR), are able to provide high spatial resolution (up to 10 m), but have low temporal resolution and are more sensitive to surface characteristics than passive microwave sensors. However, passive microwave sensors (radiometers) provide low spatial resolutions (20 to 50 km) with a higher temporal resolution (12 to 24 hrs). The low resolution information of soil moisture and vegetation anomalies at global scale is critical for large-scale crop yield monitoring and forecasting, which is needed, for example for food crisis management. High spatial resolution data from active microwave sensors have larger application in the agricultural field through precision farming, where crop growth and production is highly dependent on available surface soil moisture at small scales [5, 14]. Also high resolution imagery can be very useful in assessing water fees and establishing an equitable access to water resources.

Table 1 gives list of active and passive sensors that have operated in space for at least a year. It also lists some Short lived satellite sensors such as SEASAT, SIR-A/B have also played a role in proof of concept studies. Active microwave SAR sensors at C-band (4.0–8.0 GHz) and L-band (1.0-2.0 GHz) frequencies are commonly used for soil moisture estimation [15]. Fig.2, shows high resolution (30m pixel size) active microwave SAR data from RADARSAT-1 satellite for Southern Great Plains of Oklahoma State. Recently launched sensors have quad-polarized capabilities to acquire multiple co-polarized and cross-polarized images simultaneously. Current passive microwave sensors like AMSR-E (Advanced Microwave Scanning Radiometer), WindSAT and SMOS (Soil Moisture and Ocean Salinity) are capable of providing a global coverage soil moisture product with coarse spatial resolutions (a few 10s km) over lightly vegetated areas. In vegetated area, these sensors are sensitive to variations in vegetation properties in a relatively thick layer of the canopy. Fig.2 shows the global soil moisture product for February 2008 from AMSR-E sensors. The greatest advantage of the microwave sensors is its ability to observe the earth's surface under all weather conditions. Hydrological experiment and observation campaigns such as FIFE 87-89, MANSOON 90, OXSOME 90, MACHYDRO 90, HAPEX 90-92, WASHITA 92, SGP 97 and 99, SMOSREX'01-06, SMEX 02, SMEX 03, SMEX 04, AgriSAR 2006, and SMAPVEX 08, have explored the potential of microwave remote sensing for estimation of soil moisture and other hydrological parameters [9, 16-19].

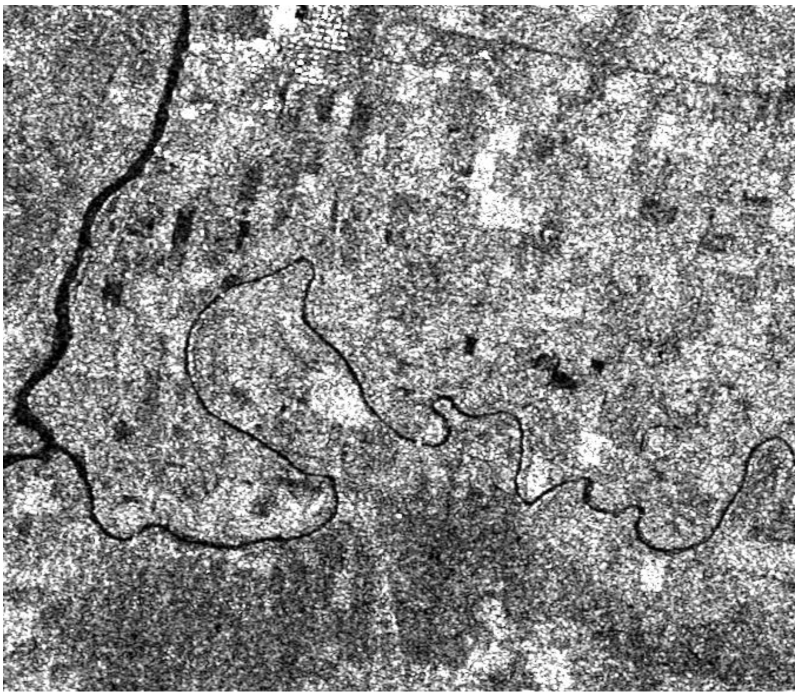

Fig.1 Active microwave remote sensing (RADARSAT-1) based high resolution backscatter data for Oklahoma, USA

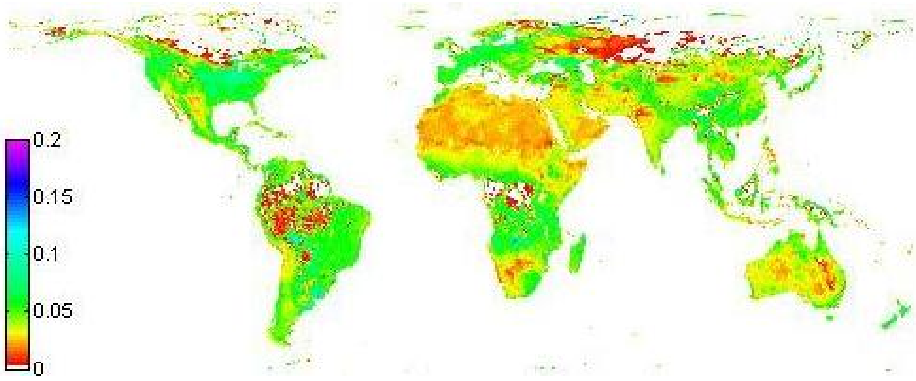


Fig.2 Passive microwave remote sensing (AMSR-E) based global soil moisture product for month February, 2008

Table 1 Details of C and L band Microwave Sensors have one objective to used for soil moisture retrieval

| Sensors | Period | Band | Polarization | Type |
|---|---|---|---|---|
| SEASAT-SAR | Jun-Oct 1978 | L | HH | Active |
| ERS-1 | 1991 - 2000 | C | VV | Active |
| JERS-1 | 1992 - 1998 | L | HH | Active |
| SIR-C/X-SAR | Apr-Oct 1994 | L, C+ | VV,HH,HV | Active |
| ERS-2 | 1995 - 2003 | L | VV | Active |
| RADARSAT-1 | 1995 - | C | HH | Active |
| RADARSAT-2 | 2007 - | C | Quad | Active |
| ENVISAT (ASAR) | 2002 - 2010 | C | VV,HH,HV, VH | Active |
| AMSR-E | 2002 | C+ | V, H | Passive |
| WindSAT | 2003 | C+ | V, H | Passive |
| PALSAR | 2005 - | L | Quad | Active |
| METOP-ASCAT | 2007 - | C | VV | Active |
| RISAT | 2009 - | C | Quad | Active |
| SMOS | 2009 - | L | V, H | Passive |
| SAOCom (1A-1B) | 2011 - | L | Quad | Active |
| Sentinel-1 (GMES) | 2011 - | C | Quad | Active |
| SMAP | 2013 - | L | HH, HV, VV / V, H | Active/Passive |

* C+ Satellite has high frequency sensors including C band.

The objective of this paper is to review the potential of active and passive microwave remote sensing application in the agriculture. Soil moisture retrieval methodologies using active and passive microwave remote sensing as well as applications for vegetation monitoring and agriculture management are discussed.

## 2. Microwave remote sensing

Soil moisture response to microwave remote sensing system from ground surface is influenced by parameters such as land cover, vegetation density and soil texture; which make the retrieval process more complex. A large number of studies have been carried out to investigate the relationship between emission and backscatter and soil moisture and vegetation parameters for different study areas.

### 2.1 Parameters affecting soil moisture retrieval

#### 2.1.1 Frequency or wavelength

The frequency of incident radiation has a direct relationship with the penetration depth in the surface. The L and C bandwidths are the most commonly used wavelengths for soil moisture estimation. The longer wavelengths (L-band) penetrate deeper in the soil surface and/or vegetation canopy. L-band SAR sensor is able to penetrate leaves and small branches and can interact with tree trunks and branches as well as the soil surface. In sparse vegetation, L band interacts more with underlying surface rather than vegetation, reducing its sensitivity to vegetation [20, 21].

#### 2.1.2 Incidence angle

The sensitivity of microwave sensor to soil moisture decreases when the incidence angle increases [22]. At higher incidence angle, the vegetation intercepts more of the signal and attenuates it. The energy backscattered by vegetation reduces the contribution of soil to the total backscattering [22, 23]. The optimal soil moisture can be derived using low incidence angle because it is optimized for sensing soil properties and minimizes the effect of vegetation and surface roughness on backscatter or emission signals [13].

#### 2.1.3 Polarization

Active and passive microwave systems are capable of measuring the backscattering and emission response from the surface using different polarization configurations. Active sensors can measure backscatter as co-polarized (HH and VV) and cross-polarized (HV and VH). Passive sensors measure the emission in V or H polarization. These polarization configurations are used to retrieve more accurate information from different layers of the target surface. These polarizations can have different penetration depths for the same frequency and the soil surface characteristics and the ratio of response between polarizations is valuable for inferring soil and vegetation properties [10, 13].

### 2.1.4 Surface roughness

The surface roughness is a measure of the irregularities of the surface geometry which has a significant effect on the variation of radar backscattering amount. The degree of roughness or smoothness of a surface depends on the wavelength of the incidence energy. Higher surface roughness increases the backscattering by increasing the total emitting surface. In SAR images water bodies have dark tone (low backscatter) except where the water is rough due to wind stress or current. This difference between the respective properties of land and water can be very useful for such applications as flood extent measurement or coastal zones erosion also this sensitivity can yield information on canopy structure [13].

### 2.1.5 Soil texture

The reliance of the dielectric constant on soil texture is a function of variation of water retention by soil particles. The sensitivity of soil texture to dielectric constant is lower in dry soil, and higher in wet soil conditions [24]. Different soil textures have distinct patterns of soil moisture content and soil drainage [25]. Soil texture is closely related to dynamics of soil moisture spatial and temporal distribution. In general, precipitation is responsible for soil moisture variability at a larger scale and soil texture controls this variability at a smaller scale [26].

### 2.1.6 Topography

The local incidence angle due to variation in topography modifies the backscattering from the soil surface. The surface facing the sensor produces higher radar backscatter due to its geometry. However, a surface facing in the opposite direction to the sensor produces a limited or no backscatter for similar surface soil moisture conditions [20, 27]. For passive microwave, topography roughness has lesser impact on the signal because of the larger sensor footprint.

### 2.1.7 Observation depth

The penetration of microwave energy into the ground depends on the dielectric constant of the upper layer, frequency and radar polarization. A longer wavelength beam penetrates deeper into the soil medium provides information from the deeper soil layer. The penetration depth is also influenced by soil moisture; the penetration depth decreases with increased soil moisture content. VV polarization penetrates deeper in the soil surface than HH polarization for similar soil moisture content [13].

### 2.1.8 Vegetation characteristics

Vegetation cover is the most important factor that influences the retrieval of soil moisture from microwave remote sensing. The degree of its influence on the retrieval of soil moisture depends upon physical and structural properties of vegetation cover. Various vegetation indices have been developed based on multi-spectral measurements from remote sensing satellites, to study quantitative and qualitative status of the vegetation. NDVI values are related to the optical properties of vegetation and are mainly sensitive to leaf chlorophyll content.

Vegetation optical depth is directly related to the vegetation water content and vegetation constant (b parameter). However, vegetation water content cannot be derived directly from remotely sensed data. NDVI in particular is used as a surrogate measure of vegetation water content for microwave surface soil moisture retrieval [28]. A quadratic relationship between the ground-based vegetation water content measurement and remotely sensed NDVI values was used to specify the regional based vegetation water content for the SGP97 mission. The relationship between vegetation water content and remotely sensed NDVI was established by optimizing a polynomial function [9]. It was found [29] that the vegetation water content and canopy heights are directly correlated with leaf area index. In another study, it was found [30] that leaf area index and vegetation optical depth are more correlated for green vegetation compared to mulch and standing biomass. Current research focuses on using these vegetation characteristics to improve estimates of the vegetation impact on soil moisture retrieval.

## 2.2 Passive microwave remote sensing of Soil moisture

The principle of passive microwave remote sensing is based on the thermal radiation measurement from the land surface, and depends on physical temperature and the surface emissivity. The passive sensors measure the natural thermal emission of the land surface at microwave wavelength. The total backscatter and emission signals have relatively significant levels of three contributions (vegetation, soil surface, and interaction between soil and vegetation emission) from vegetated surface. The microwave brightness temperature of the land surface as a function of the thermodynamic temperature of the soil/vegetation and surface emissivity [31, 32] is given by:

$$T_B = \varepsilon_{soil} \cdot T_{soil} \cdot e^{-\tau/\cos\theta} + (1-\omega) \cdot T_{veg} \cdot (1-e^{-\tau/\cos\theta})$$
$$+ (1-\varepsilon_{soil}) \cdot (1-\omega) \cdot T_{veg} (1-e^{-\tau/\cos\theta}) \cdot e^{-\tau/\cos\theta} \quad (1)$$

where, $\varepsilon_{soil}$ is the soil emissivity, ω is the single-scattering albedo within the canopy, τ is the optical depth of the vegetation canopy, θ is the look angle from nadir, $T_{soil}$ is the soil temperature, and $T_{veg}$ is the vegetation temperature. The soil emissivity calculated from the Fresnel equations, is a function of the soil dielectric constant.

Under the vegetation cover, the observed brightness temperature is a composite of the soil and vegetation. The microwave emission of soil surface will be reduced by vegetation cover, which also adds microwave emission of its own to the measurement. The vegetation effect on microwave emission is described as a “cloud” which can absorb and re-emit radiation. At C and L band the scattering effect is minimal so that in a vegetated agricultural field, only radiation from canopy will be observed. In that case, the emission from vegetation canopy is function of vegetation structure (v), polarization (p) and frequency (f). The microwave emission of vegetation is function of vegetation optical depth. The vegetation water content contributes to the microwave emission of the surface and also attenuates the emission of the soil [9, 33].

### 2.3 Active microwave remote sensing of soil moisture

A number of studies have been carried out to investigate the relationship between radar backscattering and soil moisture for different study areas. Various theoretical [34], empirical models [20, 35, 36] and non-parametric based model [37] have been developed to retrieve the soil moisture from active microwave data.

The theoretical models are based on the science of diffraction of electromagnetic waves with the observed surface, to predict the backscattering coefficient for a given configuration (frequency, polarization and incidence angle) and surface characteristics (dielectric properties and surface roughness). Developed in [34] is an Integral Equation Model (IEM) based on a radiative transfer model for bare soil surfaces. The IEM model has been used by many researchers [38-44] to retrieve soil moisture and/or surface roughness and to validate data obtained from field studies. Simplified in [36] is the complex IEM to infer soil moisture and surface roughness over bare and short vegetated fields.

An empirical model [35] was proposed for co-polarized and cross-polarized backscatter to relate soil moisture to dielectric constant. Used in [20] is a ground-based scatterometer data of [35] to generate an empirical model for co-polarized SAR system. The Dubois model claims best results with sparsely vegetated area (NDVI < 0.4). The use of the Dubois model for sparsely vegetated area, showed better correlation between backscatter from C-band than from L-band [45]. A detailed comparison between these empirical models can be found in [46]. These empirical models have used field experiments to validate their results, but many of them are applicable only to similar radar parameters and surface conditions present at the time of the experiments.

The theoretical and empirical models discussed above are complex in nature and require many inputs that are not always available. Many researchers used a linear regression model to simplify the complex relationship between radar backscattering and soil moisture [27, 47-57]. It was proposed in [58] that the Normalized Backscatter Soil Moisture Index (NBMI) was proposed where the ratio of backscatter values from two different days was used as explanatory variable in a simple linear regression model to estimate soil moisture.

The synergistic use of microwave and hyper-spectral sensors allows a better understanding of the interactions of the SAR signal with soil and plant surfaces [59, 60]. The synergistic model developed by Proposed in [61] is a temporal differential backscatter coefficient as a function of NDVI for used in soil moisture estimation. The synergistic use of the two active microwave instruments (SAR and wind scatterometer) on the ERS satellites has been used for [44] soil moisture estimation over bare soil areas at a larger scale. Non-parametric models, such as neural networks and fuzzy logic have been shown to have potential in soil moisture retrieval [37, 41, 42, 62-64]. The advantage of neural network and fuzzy logic is that all surface parameters included and trained in neural network acts as an empirical mapping relation between radar backscatter and land surface parameters [15].

The major challenge to the above theoretical and empirical models is the modeling backscatter behavior under the vegetation canopy. In addition, the variability and heterogeneity that exist within a larger footprint of passive microwave sensors make the retrieval process complex [65]. The incorporation of vegetation parameters in the above models introduces large number of variables and makes their inversion more difficult. A simple approach in the form a semi-empirical *water-cloud* model (WCM) was developed in [66] based on a first-order solution of a radiative transfer model chosen for simplicity in radar data inversion and adequacy to represent plants with leaf dimensions smaller than the sensor wavelength. In the WCM, the canopy is represented as a cloud, uniformly distributed above the soil surface where multiple scattering between canopy and soil can be neglected. The canopy is represented by bulk variables such as leaf area index or vegetation water content. The cloud density is assumed to be proportional to the volumetric water content of the canopy.

The total backscatter from a vegetated soil surface consists of three types of contributions: backscatter from bare soil surface ($\sigma^0_{soil}$), direct backscatter of the vegetation layer ($\sigma^0_{canopy}$) and multiple backscattering ($\sigma^0_{soil+canopy}$) involving the vegetation canopy and ground surfaces [10, 66] is given by:

$$\sigma^0 = \sigma^0_{canopy} + \sigma^0_{soil+canopy} + \tau^2 * \sigma^0_{soil} \tag{2}$$

where $\tau^2 = e^{(-2B*M_v*Wc)}$
and backscatter from canopy is given by:

$$\sigma^0_{canopy} = A*M_v*\cos\theta\left(1-\tau^2\right) \tag{3}$$

where $\tau^2$ is the two-way vegetation transmissivity, $M_v$ is the volumetric soil moisture content, $W_c$ is the vegetation water content in kg/m$^2$ and θ is the radar incidence angle. The vegetation related parameters (A and B) are determined from experimental observations, representing the vegetation scattering and the vegetation attenuation, respectively. Further, WCM is modified [68] by introducing a vegetation correlation length, α, and neglecting soil-vegetation interaction.

## 3. Microwave remote sensing applications

Inference of vegetation distribution and characteristics from remote sensing has usually been based on the difference between vegetation reflectance in the red and near-infrared channels (which yields the Normalized Difference Vegetation Index, NDVI [69]. Some other channels such as the shortwave infrared and thermal infrared have been also used, yielding other indices of vegetation status. For example, the Normalized Difference Infrared Index (NDII) is a widely employed measure of vegetation water status based on near and shortwave infrared channels. Compared with VIS/IR remote sensing, microwave remote sensing has the advantage of not requiring cloud-free conditions and also has unique applications such as the ability to directly sense soil moisture. While the relatively coarse spatial resolution (several km) of satellite passive microwave instruments makes them most useful for regional and global studies, active microwave instruments such as synthetic aperture radar (SAR) offer spatial resolution similar to that of high-resolution visible and infrared satellite imaging (tens of m) and are suitable for field-scale monitoring and precision agriculture applications. Combining information from different microwave bands and from microwave and visible/infrared bands offers particularly promising avenues for maximizing the usefulness of available and upcoming remote sensing modalities.

### 3.1 Vegetation density and condition

Using Nimbus SMMR data at 37 GHz, Defined in [70] is a microwave difference polarization index (MDPI) from the difference in brightness temperatures between vertical and horizontal polarization, an indicator of vegetation water content. They showed that MDPI offers a measure of vegetation density comparable to NDVI, and is more sensitive than NDVI in sparsely vegetated semiarid areas such as the Sahel. It was shown [71] hat MDPI and NDVI sensitivity 'cross over' at NDVI ≈ 0.13. Justice et al. (1989) analyzed MDPI versus NDVI seasonality across biomes in South America and Africa, finding that unlike NDVI, MDPI did not show consistent seasonal cycle in areas with dense vegetation (forests and shrublands) but only in areas with sparse, seasonal vegetation (steppe).

Used in [72] is a somewhat more sophisticated processing approach, applying a physics-based radiative transfer model to simultaneously retrieve surface temperature, vegetation water content, and soil moisture from nighttime Nimbus SMMR data at 6.6 and 37 GHz over Illinois, finding a good correspondence with in situ soil moisture measurements and that the inferred vegetation water content did correlate well with NDVI, although with less pronounced seasonality. New microwave vegetation indices [73] were derived from C and X band brightness temperatures that are suitable for use with Aqua AMSR-E data, finding a high correlation between this and NDVI over sparsely vegetated Tibet and Mongolia.

Active microwave technology can yield vegetation properties with high spatial resolution. Experimental results obtained in a pine plantation (Landes forest, France) show that L- and especially P-band SAR is useful for retrieving forest biomass, but this appears to require calibration for each forest type [74]. A linear relationship was shown [20] between the cross-polarization ratios for L-band data and NDVI over the range 0.2 < NDVI < 0.6 in an Oklahoma grassland. Presented in [75] is a review of efforts to quantify biomass using spaceborne and airborne SAR.

### 3.2 Crop yield monitoring and forecasting

Apart from soil moisture application, active microwave remote sensing (RADARSAT, C-band SAR) has been successfully used to map inter-annual variation in rice planted area in India at low cost and weeks in advance of harvest [76]. Similarly, C-band SAR on ENVISAT has been assimilated into an agricultural model coupled with a representation of microwave radiative transfer (WCM) to predict rice yield in east-central China at 30-m spatial resolution

[77]. It was found [78] that ERS SAR images could be used to determine the of sugar beet in fields in England with about equal skill compared to an NDVI-like vegetation index from high-resolution (SPOT) satellite imagery. Discussions were made [79] for assimilating the soil moisture product from AMSR-E on the Aqua satellite into a global agricultural model to improve seasonal yield predictions, finding in a preliminary assessment that soil moisture from AMSR-E improves the quality of the modeled soil moisture compared to basing the modeled soil moisture solely on precipitation datasets.

### 3.3 Vegetation water content

Microwave wavelengths are sensitive to vegetation water content (VWC) [31]; with multiple microwave channels, it is possible to retrieve both soil moisture and VWC. Early studies showed that microwave polarization difference temperatures at 37 GHz were highly correlated to NDVI in arid and semi-arid regions and related to variations in leaf water content [70, 80].

In areas with substantial vegetation cover, vegetation water content can be retrieved using multiple microwave channels with different sensitivity to soil vs. vegetation layers. The sensitivity of MDPI at the X-band to plant water content has been used to improve the retrieval of the soil moisture in vegetated fields from C-band data in an airborne campaign [80]. NDII is a measure of leaf water content based on infrared remote sensing, but is only sensitive to water close to leaf surfaces. In a study of corn and soybean canopies in Iowa, VWC and NDII have been shown to be closely related, but in a crop-specific manner; used together, they may offer more information about crop water status than either alone [82].

### 3.4 Irrigated area delineation

Remote sensing information on irrigated area is useful for studies of global food production and land and freshwater use as well as for more concrete purposes such as planning and evaluation of water projects [83]. A predefined threshold has been usually applied to derived indices of vegetation density and water content such as NDVI, NDWI, and VHI to differentiate between irrigated and non-irrigated areas [84-86]. More recently supervised and unsupervised classification techniques have been proposed for mapping irrigated areas [87, 88]. Supervised classification techniques make use of training samples to cluster the image pixels into predefined classes. Unsupervised classification techniques, on the other hand, do not require a set of predefined clusters nor a training sample. They can automatically differentiate between multiple classes using the appropriate statistical methods and are effective for defining irrigated area where there is a large contrast between it and natural vegetation, such as summer persistence of green vegetation in Mediterranean environments [4].

Microwave remote sensing can complement information from visible and infrared bands in determining irrigated area because it senses the irrigation directly as higher soil water content, rather than indirectly as higher vegetation density, water content, and evapotranspiration rate, and because it is insensitive to cloud cover. It was shown [89] that an airborne L-band microwave radiometer could be used to map irrigated fields in northern Texas. It was further. found [90] that microwave sensing (the Spaceborne ERS-2 C-band SAR and an airborne P-band scatterometer) was better able than visible and near infrared spectra to quantify variations in soil moisture over mostly bare, sandy desert soil in southern Israel. Good correlations were also found [91] between microwave backscatter from the RADARSAT-1 satellite (C-band SAR) and soil moisture early in the growing season in a mainly agricultural landscape in Navarre, Spain.

### 3.5 Effect on fertilizer application

It was demonstrated [6] that plant responses to growing-season rainfall and N fertilizer application are both sensitively dependent on the soil's water holding capacity, which governs its uptake and release of both water and bio-available N. Measurements of the spatial variability in soil moisture over field scales, as enabled by SAR, can elucidate the response of soil moisture to precipitation as modulated by variation in soil composition and textures, and used to estimate variables such as soil water capacity that are relevant to the response of yield to N application. This could offer opportunities for yield enhancement and cost reduction by targeting both water and N application to where they can do the most good.

### 3.6 Irrigation scheduling

Irrigation scheduling by the water balance approach is based on estimating the soil water content. The determination of irrigation water need is important for promoting efficient water use, with large economic and environmental impacts. Precision agriculture requires high spatial resolution to resolve individual fields and local topographic variations; to attain this resolution from space requires active microwave instrumentation like SAR. Microwave wavelengths, however, are only sensitive to soil moisture in the uppermost soil layers (of the same order as the wavelength) and are less sensitive to soil moisture under dense vegetation. One approach for guiding real-time irrigation would be to estimate root-zone soil moisture indirectly from the vegetation water content inferred from C or X band microwave remote sensing [92], which can be combined with L-band direct information about soil moisture near the surface for a more comprehensive retrieval of the moisture condition of both soil and vegetation [62, 93, 94].

Another approach along the same lines combines Ku with C band scattering [95]. Writing from a watershed management perspective [96], it was advocated to use a model of soil water transport to infer the soil moisture vertical profile from near-surface soil moisture measured at high resolution by spaceborne SAR. Microwave remote sensing could also be combined with visible and infrared observations to facilitate fuller understanding of crop and water dynamics. It was shown [97] that combining thermal infrared surface brightness temperature from AVHRR on NOAA-18, which is an indicator of the evapotranspiration rate, with microwave observations from AMSR-E on the Aqua satellite results in substantially better soil moisture estimates over heterogeneous landscapes in southeastern Australia than either modality alone.

## 4. Summary

Microwave remote sensing techniques have shown great potential in agricultural applications such as crop yield forecasting, irrigation management, and issuing early warning of droughts. Substantial progress has been made in terms of vegetation classification and monitoring from hyperspectral visible/infrared remote sensing. However, considering the limitation of hyperspectral remote sensing under cloud cover, its combination with microwave based techniques for routine measurement of soil moisture and vegetation characteristics has great future potential for agriculturist and hydrologist. Agricultural irrigation has not routinely considered in-situ or remote sensing based soil moisture data in its many operational decisions. However, considering the potential discussed in the paper, microwave remote sensing can play critical role in improving agricultural production.

Research needs toward this goal are extensive and include the calibration and validation of vegetation and soil moisture retrieval methodologies corresponding to current (SMOS, AMSR-E) and future (SMAP) soil moisture missions as well as a better theoretical understanding of microwave radiative transfer particularly in dense vegetation. Some of these issues are being investigated using ground based L-band radiometry to understand the vegetation effect through temporal monitoring of brightness temperature for complete growth cycle of wheat, corn, and soybean [98].

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