Comparison of SMOS vegetation optical thickness data with the proposed SMAP algorithm

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Comparison of SMOS vegetation optical thickness data with the proposed SMAP algorithm

by

Jason Carl Patton

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Agricultural Meteorology

Program of Study Committee:

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Iowa State University
Ames, Iowa
2014

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ABSTRACT

Soil moisture is an important hydrologic variable due to its influence on plant growth and the surface energy budget. Most current soil moisture networks measure soil moisture at single points; these point measurements of soil moisture may not relate to the soil moisture of the larger, surrounding areas. Crop models and weather and climate models, which are sensitive to soil moisture, could be improved by having accurate soil moisture data that is relevant at scales larger than a point. Microwave C-band and X-band sensing satellites have attempted to retrieve soil moisture at relevant, large spatial scales needed for models, but these satellites are limited in their sensing depth, sensitivity to vegetation, and sensitivity to scattering by precipitation. Two recent satellite missions, the European Space Agency’s Soil Moisture and Ocean Salinity (SMOS) mission and NASA’s Soil Moisture Active Passive (SMAP) mission, retrieve soil moisture from L-band measurements of radiation, which improve upon the limitations of previous satellites.

The retrieval of soil moisture from microwave satellite measurements requires knowledge of the vegetation optical thickness ($\tau$), which is related to the vegetation water content (VWC). The multi-incidence angular design of SMOS provides its retrieval algorithm the advantage of retrieving soil moisture and $\tau$ simultaneously. SMAP will measure at a single incidence angle and will require an ancillary source of $\tau$ data. The current plan is for SMAP to use a climatology of normalized difference vegetation index (NDVI) data to generate a $\tau$ climatology. This dissertation analyzed this SMAP $\tau$ climatology by first validating SMOS $\tau$ and then by comparing SMOS $\tau$ to SMAP $\tau$.

The validation of SMOS $\tau$ was done by comparing SMOS $\tau$ during the growing season to crop yield estimates for each Iowa county. The result was that larger values of SMOS $\tau$ were correlated with larger crop yields, which suggested that SMOS $\tau$ is related to the growth of vegetation. SMOS $\tau$ was also found to be noisy and to behave strangely outside of the growing
season. The strange behavior was hypothesized to be related to land management activities, such as tillage.

SMOS $\tau$ was also used to estimate values of the $b$ parameter at the satellite scale. The $b$ parameter is the link between VWC and $\tau$. Previous measurements of $b$ were done at single, homogeneous field sites. The estimates of $b$ in this dissertation were made over Iowa by using allometric relationships in concert with the $\tau$-yield relationship found in the initial validation of SMOS. The resulting $b$ values were lower than the field-scale estimates but of the same order of magnitude.

A SMAP $\tau$ climatology was generated from NDVI using a method similar to the method described in official SMAP documents. When compared to SMOS $\tau$, SMAP $\tau$ was close in the timing of peak $\tau$, but the magnitude of SMAP $\tau$ was larger than SMOS $\tau$ by up to about 33% during the growing season. SMAP $\tau$ should be larger than SMOS $\tau$ because SMAP accounts for vegetation scattering while SMOS does not. By incorporating the $b$ values found from SMOS, much closer agreements in the magnitudes of SMOS and SMAP $\tau$ were found. However, this method of incorporating satellite estimates of $b$ is not applicable due to the requirement of having full years of SMOS $\tau$ and crop yield data.

The main hypothesis of this dissertation was that SMAP $\tau$ will differ from SMOS $\tau$ significantly enough that retrieved values of soil moisture by the two satellites for the same conditions would differ by more than 0.04 m$^3$ m$^{-3}$, which is the accuracy goal for both satellite missions. Using the average peak values of $\tau$ over the growing season, an example soil moisture retrieval was performed for the two satellites. The resulting soil moistures differed by 0.017 m$^3$ m$^{-3}$.
CHAPTER 1. INTRODUCTION

Soil moisture is a crucial hydrologic variable because of its impact on (at least) three processes that affect human welfare: the growth of crops, the movement of water and water contaminants above and through soil, and the partitioning of energy at the land surface. Yet in-situ measurements of soil moisture are rare and usually irrelevant at spatial scales at which modeling and decision making related to these processes is done. Two soil moisture satellite missions propose to provide soil moisture measurements at more relevant spatial scales: the European Space Agency’s (ESA) Soil Moisture Ocean Salinity (SMOS) mission and the National Aeronautics and Space Administration’s (NASA) Soil Moisture Active Passive (SMAP) mission. In addition to soil moisture, these satellites are sensitive to the amount of water held in vegetation. A major difference between SMOS and SMAP is SMOS can simultaneously retrieve soil moisture and a measure of vegetation water while SMAP will use an independent vegetation water data source. This dissertation aims to validate SMOS’s measure of vegetation water (called vegetation optical thickness $\tau$), compare SMOS $\tau$ to SMAP’s ancillary data, and suggest how SMAP’s ancillary data may be improved.

1.1 Soil Moisture and Agriculture

Plants require water for many purposes, including but not limited to:

- enabling plant cells to have sufficient turgidity;
- supplying hydrogen during photosynthesis to create carbohydrates; and
- meeting evaporative demands (i.e. transpiring) to keep leaves from overheating.

If not enough water is available to meet all of these requirements, a plant will undergo water stress and will compensate by reducing the growth of leaves and, if stress continues, by closing
stomata on existing leaves to limit the amount of water lost through photosynthesis and transpiration (Hsiao, 1973). The limitations water stressed plants place on photosynthesis, both “now” by reducing stomatal conductance and “later” by reducing leaf growth, have a clear negative effect on plant productivity. Crop growers, modelers, and forecasters, therefore, have a strong interest in knowing when crops could face water stress.

A plant’s water reservoir is defined by the soil moisture in the root zone of the soil profile that is not tightly bound to soil particles. One way to quantify this reservoir is through the plant available water fraction, $A_w$ (Campbell and Norman, 1998, chap. 9):

$$A_w = \frac{\theta - \theta_{pwp}}{\theta_{fc} - \theta_{pwp}},$$

where $\theta$ is the volumetric soil moisture, $\theta_{fc}$ is the field capacity (i.e. the value of soil moisture a freely-drained soil will attain after being saturated), and $\theta_{pwp}$ is the permanent wilting point (i.e. the value of soil moisture at which water is tightly bound to soil) averaged throughout the root zone.

$A_w$ can be used to estimate water stress factors, e.g. Campbell and Norman (1998, chap. 9) propose a limitation on a plant’s rate of water uptake, $U_p$:

$$U_p = 1 - (1 + 1.3A_w)^{-b}$$

(where $b$ is the exponent of the soil water retention curve presented in Campbell and Norman, 1998, chap. 9). A similar, common model of water stress used in some crop models (e.g. Agro-IBIS, Kucharik, 2003) is the Feddes function (Feddes et al., 1976), which linearly adjusts rates of potential photosynthesis based on threshold values ($\theta_1$, $\theta_2$) of root zone soil moisture.

$$F = \text{Feddes function} = \begin{cases} 
0 & \text{if } \theta \leq \theta_1 \\
\frac{\theta - \theta_1}{\theta_2 - \theta_1} & \text{if } \theta_1 < \theta \leq \theta_2 \\
1 & \text{if } \theta_2 \leq \theta 
\end{cases}$$

$F$ is multiplied by the potential rate of photosynthesis to estimate the water stressed photosynthesis rate. Similar thresholds may be defined at the upper bounds of volumetric soil moisture values to account for oxygen stress. The above equations may also be written in forms that use soil water potential.
These formulations of crop stress can be used to constrain photosynthesis in crop models, however, they require either:

1. measurements of root zone soil moisture at spatial and temporal scales relevant to the models, or

2. coupled soil physics and plant uptake models that use meteorological data (precipitation, temperature, etc.) to simulate the movement, storage, and uptake of water in and out of the root zone.

Because soil moisture is highly variable in space, in-situ measurements of root zone soil moisture at spatial scales larger than a single point (horizontal diameter on the order of centimeters) are rare. Similarly, validations of soil physics models have mostly been done in laboratories and/or at single points.

If we wish to use crop models and/or validate their soil models at spatial scales larger than single points (e.g. for a county or the U.S. Corn Belt), what soil moisture data can we use? Furthermore, there are regions of the world where neither meteorological nor soil moisture data needed to drive and validate crop and soil models are available or are of good quality. Can any crop modeling be done in these regions? Remotely sensed soil moisture may be able to provide the information needed to run, constrain, and/or validate crop models used at larger spatial scales and/or over data sparse regions.

1.2 Soil Moisture and Weather and Climate

A simple land surface energy balance can be written:

\[ R_n = H + \lambda E + G, \]  

(1.1)

where \( R_n \) is the net radiation absorbed by the surface, \( H \) is the sensible heat flux from the surface, \( \lambda E \) is the latent heat flux from the surface, and \( G \) is heat flux in to the surface. \( R_n \) can be broken down further:

\[ R_n = (1 - \alpha)S - L_n, \]
where $\alpha$ is the albedo (i.e. shortwave reflectivity) of the surface, $S$ is the total solar radiation incident on the surface, and $L_n$ is the net longwave (i.e. infrared) radiation emitted by the surface. Surface fluxes of energy (and water) determine the properties of the planetary boundary layer (e.g. potential temperature, mixing ratio; Stull, 1988, chap. 7) and thus must be known to realistically model weather and climate (Sellers et al., 1997; Pielke, 2001).

Every term in the energy balance equation (Equation 1.1) is affected by soil moisture. Surface soil moisture affects $R_n$ by modifying the albedo of the soil (Ångström, 1925); wet soils absorb more solar radiation than dry soils. For example, Campbell and Norman (1998, chap. 11) report albedos of 0.13–0.18 for dry soils, while wet soils have albedos of 0.08–0.10. Similarly, the albedos of leaves change with water content. Stressed, low water content leaves generally reflect more sunlight than non-stressed leaves (Zygelbaum et al., 2009).

$G$ is also dependent upon the surface soil moisture status. Heat flow in soil can be modeled using a simple flux-gradient model (i.e. Fourier’s law; Stull, 1988, chap. 7):

$$G = -k \frac{\partial T}{\partial z},$$

where $k$ is the thermal conductivity of the soil and $\partial T/\partial z$ is the temperature gradient. $k$ is heavily dependent on soil moisture as the thermal conductivity of air is different than water. For example, Campbell and Norman (1998, chap. 8) report:

$$k_{\text{water}} = 0.56 + 0.0018 T \text{ W m}^{-1} \text{ K}^{-1}$$

$$k_{\text{air}}(101 \text{ kPa}) = 0.024 + 0.00007 T \text{ W m}^{-1} \text{ K}^{-1},$$

where $T$ is temperature. The total soil $k$ is determined by considering the solid, air, and water fractions of a soil volume.

Finally, soil moisture determines the partitioning of the remaining energy balance terms, $H$ and $\lambda E$, by constraining evapotranspiration ($E$ in $\lambda E$). The Penman-Monteith equation (Monteith, 1965) is often used to estimate evapotranspiration over plant canopies. However, canopy vapor conductance, a required variable, is usually estimated in the equation from a reference condition where plants were not water stressed. Therefore, the Penman-Monteith equation usually provides an upper-end estimate of evapotranspiration. As mentioned in the
previous section, one way plants respond to water stress is by closing stomata (Hsiao, 1973), which reduces the canopy vapor conductance, and so reduces evapotranspiration. If $E$ (and, therefore, $\lambda E$) is reduced, then more of the “leftover” energy ($R_n - G$) in the energy balance must go to $H$:

$$R_n - G = \lambda E + H.$$ 

A number of studies have indeed identified a strong sensitivity of weather and climate to soil moisture, both in models and in observations (Betts et al., 1996; Sellers et al., 1997; Pielke, 2001; Koster et al., 2004; Seneviratne et al., 2010). This sensitivity is somewhat problematic as, again, in-situ soil moisture measurements relevant at the large spatial scales ($\geq 1$ km) used in weather and climate modeling are rare. To initialize soil moisture, these models traditionally relied on output from other models (e.g. the Global Land Data Assimilation System, Rodell et al., 2004), which, again, lacks validation at large spatial scales. Satellite measurements of soil moisture could play, and for some models, are playing, a vital role in improving the initialization and validation of soil moisture in weather and climate models.

### 1.3 In-situ Measurements of Soil Moisture

Traditional methods of in-situ soil moisture sampling include manual measurement of field-moist and dried soil (i.e. gravimetric sampling), measurement of subsurface neutron thermalization (e.g. using neutron probes), and measurement of soil electrical properties. Most soil moisture networks use the latter method, and deploy probes that are sensitive to changes in the relative permittivity ($\varepsilon_r$, i.e. dielectric constant) of the soil. These probes sense changes in soil moisture because the $\varepsilon_r$ of water ($\varepsilon_{r,\text{water}} \approx 80$) is significantly different than that of soil particles ($\varepsilon_{r,\text{soil, dry}} \approx 3.5$).

Relative permittivity-based soil moisture sensors work in one of two ways. In the first method, they measure the travel time of an electrical pulse along two metal rods (which form a “transmission line”) buried in the soil. The time it takes for the pulse to travel down, reflect, and travel back is determined by the relative permittivity of the soil. In the second method, the sensors directly measure the electrical properties of the soil that is contained within a
volume adjacent to the sensor. Most soil moisture networks use these types of sensors because they are relatively safe (neutron probes must use a radioactive source), are cheap (compared to manual labor), and are easily automated (measurements can be taken at time intervals of a few seconds). The volume of soil measured by a soil moisture sensor is usually on the order of cubic centimeters to cubic decimeters. For example, the latest Campbell Scientific sensors, the CS650 and CS655, have rods that are 12 or 30 cm long and have a sensing radius of about 1.5 cm (Campbell Scientific, 2014; Baker and Lascano, 1989).

Soil moisture networks are typically composed of sparse stations that each measure soil moisture, often at multiple depths, at a single location. For example, the Oklahoma Mesonet has 120 sites spread over an area of 181,195 km², which equates to an average distance between stations of about 39 km. (The Oklahoma Mesonet is considered a fairly dense soil moisture network compared to most state-run networks [Vinnikov et al., 1999].) However, soil moisture is known to exhibit large variability at many different spatial scales. Soil moisture at one location may be very different from soil moisture at another point meters away due to differences in soil or landcover properties, or even just small changes in elevation. For example, Bramer et al. (2013) made 350 measurements of surface soil moisture per day within a 7 by 9 m bare soil plot and found ranges in volumetric soil moisture as large as 0.15 m³ m⁻³ and standard deviations as large as 0.03 m³ m⁻³. Similarly, a measurement of soil moisture at one point may be very different than the average soil moisture of a field or an area the size of a weather model grid cell. For example, Jacobs et al. (2004) made 91–140 measurements of surface soil moisture per day in four fields with dimensions approximately 800 by 800 m and found that the mean difference between a single point measure of soil moisture and field average soil moisture could be as large as about 75%. However, Jacobs et al. (2004) also found “time-stable” points within their fields that gave consistently good estimates of the field average soil moisture.

Time-stable points may be a feature of most fields or watersheds (Grayson and Western, 1998). However, there is no evidence that current sparse networks are making measurements at time-stable locations. Often, as is the case with the Oklahoma Mesonet, measurements are done in reference landcovers (e.g. mown grass) that have properties (e.g. rooting depths, plant water usages) that are not representative of the surrounding landscape. This lack of representation
would suggest that these locations may not estimate large-scale average soil moisture with any sort of time-stability.

1.4 Satellite Remote Sensing of Soil Moisture

Soil moisture sensing satellites are needed to measure soil moisture at larger spatial scales. Specifically:

Remote sensing satellite missions that measure microwave radiation at frequencies low enough (wavelengths large enough) to “see through” dense vegetation and that have orbits that enable global measurements at high enough temporal and spatial resolutions are needed to supply a better source of soil moisture data for climate, weather, and crop model assimilation and validation.

Two soil moisture satellite missions propose to fill this need: ESA SMOS (Kerr et al., 2010) and NASA SMAP (Entekhabi et al., 2010).

Prior to SMOS and SMAP, microwave sensors on other satellite missions have been exploited to estimate soil moisture at large spatial scales. These satellites, not developed specifically to measure soil moisture, have sensors that measure in the C–band \((f = frequency = 6.9 \text{ GHz}, \lambda = \text{wavelength} = 4.3 \text{ cm})\) or X–band \((f = 10.7 \text{ GHz}, \lambda = 2.8 \text{ cm})\) of the microwave region of the electromagnetic spectrum. For example, the National Environmental Satellite, Data, and Information Service’s Soil Moisture Operational Products System (SMOPS) originally retrieved its baseline soil moisture data using X–band measurements from the Advanced Microwave Scanning Radiometer-EOS (AMSR-E) instrument on the Aqua satellite (Zhan et al., 2012). After a malfunction of the AMSR-E instrument in October, 2011, SMOPS changed its data source to X–band data from the WindSat instrument on the Coriolis satellite (Zhan et al., 2012). The retrieval of soil moisture from C–band and X–band instruments is limited in three ways:

1. sensing depth of soil moisture is limited to about two tenths of a wavelength (Newton et al., 1982; Schmugge, 1983), so retrievals are limited to the upper 0.5–1 cm of soil;
2. scattering by vegetation canopies significantly decreases the quality of soil moisture retrievals when vegetation water contents exceed 1.5 kg m$^{-2}$ (Njoku et al., 2003); and

3. scattering by precipitating clouds reduces data availability (Njoku et al., 2003).

SMOS, the Soil Moisture and Ocean Salinity mission, is the European Space Agency’s first soil moisture satellite mission (Kerr et al., 2010). It was launched November 2, 2009. A mission goal is to provide global maps of surface soil moisture and ocean salinity at spatial and temporal resolutions relevant to weather and climate modeling. SMOS contains a passive, interferometric radiometer, the Microwave Imaging Radiometer using Aperture Synthesis (MIRAS), that measures L–band (1.41 GHz) microwave radiation using 69 Light-weight Cost Effective Front-end antennas spaced 18 cm apart and arranged in a Y-shaped pattern. MIRAS is fully polarimetric, i.e. it measures all four Stokes parameters that describe the polarization of radiation. SMOS has a sun-synchronous, polar orbit at an altitude of 758 km and takes measurements at around 6 AM and 6 PM local solar time. The measurement repeat cycle is every three days at the Equator (more often poleward), while the exact repeat cycle of a single orbit is every 149 days. SMOS’s measurements are hexagonal star-like 2D images (or swaths) of brightness temperatures (a measure of spectral radiance, will be defined in the next section) at multiple incidence angles (0–55°). The swaths have a width of around 600 km and a pixel resolution that averages around 43 km. Consecutive swaths overlap, leading to near-simultaneous measurements of brightness temperature at multiple incidence angles for overlapping pixels. The brightness temperature data is subset to a 15 km Icosahedron Snyder Equal Area grid (ISEA 4H9) and provided in the Level 1C (L1C) data product.

SMAP, the Soil Moisture Active Passive mission, is NASA’s first soil moisture satellite mission (Entekhabi et al., 2010). The current planned launch date for SMAP is November 5, 2014. Similar to SMOS, a SMAP mission goal is to provide global maps of soil moisture and soil freeze-thaw state at spatial and temporal resolutions relevant to weather and climate modeling. SMAP will have both a passive, L–band (1.41 GHz) radiometer and active, L–band (1.26 GHz) radar. The radiometer is fully polarimetric. Both instruments are fed by a 6 m diameter parabolic reflector that focuses radiation into a feedhorn. Also similar to SMOS, SMAP will
have a sun-synchronous, polar orbit at an altitude of 685 km and will take measurements at around 6 AM and 6 PM local solar time. The measurement repeat cycle will be every three days at the Equator (more often poleward). The SMAP radiometer will measure brightness temperatures at a single 40° incidence angle and with a pixel resolution of around 36 km. The reflector will rotate at 14.6 rpm to generate a swath with a width of 1000 km. The passive-only brightness temperature data will be subset to a 36 km Equal-Area Scalable Earth Grid (EASE-Grid 2.0) and provided in the Level 1C TB data product.

Recalling the limitations of C–band and X–band satellites with respect to sensing depth, vegetation scattering, and precipitation scattering, these limitations are either removed or improved upon in SMOS and SMAP because they measure radiation at lower frequencies/higher wavelengths of L–band. The sensing depth of SMOS and SMAP is around 3–5 cm. The satellites are sensitive to soil moisture under more heavily vegetated surfaces, up to vegetation water contents of about 6 kg m$^{-2}$ (Hornbuckle and England, 2004). With exceptions in only extreme cases (e.g. hail), clouds and precipitation do not cause significant scattering at L–band.

1.4.1 Retrieval of Soil Moisture: Theory

Similar to in-situ soil moisture sensors, the main principle behind SMOS and SMAP is that water has a very different relative permittivity ($\varepsilon_{r,\text{water}} \approx 80$) than dry soil ($\varepsilon_{r,\text{soil, dry}} \approx 3.5$). The relative permittivity of soil will vary with water content, which varies the index of refraction ($n_{\text{soil}} = \sqrt{\varepsilon_{r,\text{soil}}}$) of the soil, which varies the reflectivity ($R_{\text{soil}}^h$) of the soil:

$$R_{\text{soil}}^h = \left| \frac{n_{\text{air}} \mu_i - n_{\text{soil}} \mu_t}{n_{\text{air}} \mu_i + n_{\text{soil}} \mu_t} \right|^2,$$

$$R_{\text{soil}}^v = \left| \frac{n_{\text{soil}} \mu_i - n_{\text{air}} \mu_t}{n_{\text{soil}} \mu_i + n_{\text{air}} \mu_t} \right|^2,$$

where $\mu_i$ and $\mu_t$ are the cosines of the incidence and transmission angles and $h$ and $v$ denote horizontal and vertical polarization. Varying the reflectivity of the soil varies the emissivity ($e_{\text{soil}}^p$) of the soil ($e_{\text{soil}}^p = 1 - R_{\text{soil}}^p$). Finally, varying the emissivity varies the brightness temperature ($T_B^p$) of the soil:

$$T_B^p = e_{\text{soil}}^p \ T_{\text{soil}},$$

(1.2)
where $T_{\text{soil}}$ is the temperature of the soil, assumed to be isothermal across the emitting depth. $T_B$ is a measure of spectral radiance, and is often used in microwave remote sensing because of intuitive units (kelvin), values (between 0 K and the absolute temperature of a surface, scaled by the emissivity of the surface), and because it represents the spectral radiance emitted by a blackbody at the temperature.

SMOS and SMAP both measure $T_B$ and use a zeroth-order emission model, often referred to as the $\tau$-$\omega$ model (Equation 1.3, Wigneron et al., 2007), with a dielectric mixing model (e.g. Mironov et al., 2009) to retrieve soil moisture. The $\tau$-$\omega$ model builds upon Equation 1.2 by adding the attenuation and emission effects of vegetation, through which the radiation emitted by soil must travel to reach the satellite:

$$T_B^p = T_{\text{soil}} (1 - R_{\text{soil}}^p) e^{-\tau/\mu} + (1 - e^{-\tau/\mu}) (1 - \omega) T_{\text{veg}}$$

$$+ (1 - e^{-\tau/\mu}) (1 - \omega) T_{\text{veg}} R_{\text{soil}}^p e^{-\tau/\mu}.$$  

Interpreting the $\tau$-$\omega$ model from top to bottom, the brightness temperature ($T_B^p$) of a vegetated surface is:

1. the brightness temperature of the soil ($T_{\text{soil}} [1 - R_{\text{soil}}^p]$) attenuated through the canopy ($e^{-\tau/\mu}$), where the attenuation depends upon the vegetation optical thickness ($\tau$, also commonly referred to as the vegetation opacity or vegetation optical depth) and cosine of the incidence angle ($\mu$); plus

2. the contribution from the vegetation, which is dependent upon $\tau$, $\mu$, and the vegetation single scattering albedo ($\omega$); plus

3. the contribution from the vegetation reflected off the soil surface.

As vegetation increases, $\tau$ increases, simultaneously attenuating more of the soil’s contribution to $T_B$ and adding more of the vegetation’s contribution to $T_B$; $\tau$ “masks” the soil moisture signal, and must be accounted for to retrieve $e_{\text{soil}} (= 1 - R_{\text{soil}})$ from measured $T_B$. $\tau$ has been found to vary linearly with vegetation water content (VWC), the mass of water held in
vegetation per unit area, with the conversion factor $b$ (Jackson and Schmugge, 1991):

$$\tau = b \times \text{VWC}. \quad (1.4)$$

As a check of Equation 1.3, if there is no vegetation ($\tau = 0$), then the $\tau$-$\omega$ model is reduced to Equation 1.2. Some common simplifications of Equation 1.3 are to assume $T_{\text{soil}} = T_{\text{veg}}$, which is likely true at 6 AM and 6 PM local solar time, and to assume $\omega$ is zero.

### 1.4.2 Retrieval of Soil Moisture: Practice

SMOS and SMAP differ in their actual retrieval methods due to one major difference between their instrument designs. SMOS’s design enables the measurement of multiple pairs of $T_B$ and $\mu$ at the same place and at (nearly) the same time (see Figure 1.1 for a diagram). This allows SMOS to retrieve $R_{\text{soil}}$ and $\tau$ simultaneously through error minimization of Equation 1.3 (Mahmoodi, 2011).

SMAP’s design only allows measurement at a single incidence angle (see Figure 1.2 for a diagram), and so, for the baseline single channel algorithm (SCA) which will use only $T_B^h$ ($T_B^v$ is ignored), $\tau$ must be provided through an ancillary data source (O’Neill et al., 2012) in order to retrieve $R_{\text{soil}}$ from Equation 1.3. SMAP’s current plan is to use a global climatology of Normalized Difference Vegetation Index (NDVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) project to generate a global climatology of vegetation water content, and then to generate a global climatology of $\tau$ (using Equation 1.4). More details of this method are described in Chapter 4. SMAP’s method of estimating $\tau$ relies on several assumptions:

- NDVI reliably tracks changes in VWC;
- VWC does not have significant interannual variability;
- $b$ parameters from field studies can be applied to satellite pixels;
- $b$ does not have significant interannual variability; and (therefore)
- $\tau$ does not have significant interannual variability.
Figure 1.1: SMOS makes multiple measurements of brightness temperature for each pixel (e.g. the oval), each measurement differing in its incidence angle.
Figure 1.2: SMAP makes a single measurement of brightness temperature for each pixel (e.g. the oval) at a single incidence angle of $40^\circ$. 
1.5 Motivation and Hypothesis

Global, large spatial scale measurements of soil moisture are needed for better predictions by, and validations of, agricultural, weather, and climate models. SMOS and SMAP may be able to provide these needed measurements. However, SMAP requires an ancillary source of \( \tau \) data to retrieve soil moisture. The sensitivity of L–band measurements of \( T_B \) to \( \tau \) (see, e.g., Figure 2.4) cannot be ignored, and so this ancillary source should be validated. SMOS’s retrievals of \( \tau \) provide one of the only, if not the only, global datasets of \( \tau \) at L–band. If shown to be reasonable, SMOS \( \tau \) could be used to validate SMAP’s \( \tau \) climatology and the assumptions made in the climatology’s development.

This dissertation aims to:

1. validate SMOS \( \tau \) using large-scale measurements of vegetation;
2. use SMOS \( \tau \) to estimate a key parameter, \( b \), at the satellite (\( \approx 40 \) km) scale; and
3. compare SMOS \( \tau \) to the SMAP \( \tau \) climatology.

My overall hypothesis is that the difference between SMAP’s climatology of \( \tau \) and SMOS \( \tau \) during the peak of the growing season in Iowa will lead to retrievals of volumetric soil moisture that differ by more than 0.04 \( \text{m}^3 \text{m}^{-3} \). This value is significant as it is the accuracy benchmark for both satellite missions.

1.6 Dissertation Organization

Chapter 2 is modified from a paper published in *IEEE Geoscience and Remote Sensing Letters*. For this paper, I was the lead author; I led the analysis and primarily wrote the Observations, Analysis, and Conclusion sections. My co-author, Brian Hornbuckle, assisted with the analysis and primarily wrote the Introduction section. Modifications were made to the paper to fit the format and citation style of this dissertation. Works cited are included in the bibliography at the end of the dissertation.

The remaining chapters that make up the body of this dissertation, Chapters 3 and 4, are standard dissertation chapters with methods and results first published here.
CHAPTER 2. INITIAL VALIDATION OF SMOS VEGETATION OPTICAL THICKNESS IN IOWA

Modified from a paper published in *IEEE Geoscience and Remote Sensing Letters*

Jason Patton and Brian Hornbuckle

2.1 Introduction

The European Space Agency’s Soil Moisture and Ocean Salinity (SMOS) satellite mission began observing Earth’s surface with an L–band radiometer shortly after its launch in November, 2009 (*Kerr et al.*, 2010). One goal of the mission was to monitor the water content of soil at the land–atmosphere interface in order to better understand the global water cycle. SMOS employed microwave radiometry to achieve this goal because in the microwave region of the electromagnetic spectrum the dielectric constant of liquid water is much larger than dry soil (*De Loor*, 1956) and hence the brightness temperature of Earth’s surface is a function of soil moisture.

Besides having a large dielectric constant, liquid water is also lossy at microwave frequencies. Consequently, vegetation, which also contains liquid water, both scatters and attenuates microwave radiation emitted by the soil. Taking into account these considerations, SMOS is sensitive to the water content of the first few centimeters of the soil surface with a spatial resolution of 40 to 50 km. There is useful sensitivity to soil moisture at L–band throughout the year in many parts of the world including agricultural regions where crops such as wheat, soybean, cotton, and maize are grown (*Hornbuckle and England*, 2004).

The STAR antenna technology employed by the MIRAS instrument on the SMOS satellite makes it possible to measure the brightness temperature at multiple incidence angles relative to
Earth’s surface. At each incidence angle the influence of soil moisture and vegetation changes. Because of this unique design, SMOS delivers two products: soil moisture and vegetation optical thickness ($\tau$). $\tau$ is a measure of the attenuation of soil brightness due to vegetation. The SMOS retrieval algorithm considers the data collected at multiple incidence angles and uses them along with a microwave model to best estimate both the value of soil moisture and $\tau$ within the satellite footprint.

The water content of row crops varies over the growing season (Hornbuckle and England, 2005). Ground–based experiments have shown that $\tau$ is directly proportional to the amount of liquid water contained within vegetation tissue (Jackson and Schmugge, 1991). This amount of water is normally quantified using the water column density, defined as the mass of water contained within vegetation tissue per ground area. According to Kirchoff’s law of thermal radiation, the absorption of radiation that causes attenuation leads to the emission of radiation. Emission from the vegetation itself can be a large fraction of the brightness temperature. The water column density of crops increases as crops progress through the vegetative (growth) stages and it reaches a peak after the beginning of the reproductive stages. Considering that most agricultural areas are essentially bare (no vegetation) before and shortly after planting, the signal produced by growing vegetation will be quite large and SMOS should be sensitive to the growth of crops. The relationship between $\tau$ and crop growth could be used to develop new satellite crop monitoring products which are less prone to signal saturation than currently available visible and near-infrared based products, but a validation of $\tau$ in agricultural regions is needed first.

The U.S. Corn Belt is a 400,000 km$^2$ region dominated by row–crop (maize and soybean) agriculture. In this region, the vegetation water column density can vary by more than 6 kg m$^{-2}$ during the six–month (May–October) growing season.

We hypothesize that changes in vegetation optical thickness produced by SMOS in the U.S. Corn Belt are related to the growth of crops.

We will test our hypothesis by examining the SMOS $\tau$ product from the 2010 growing season over the state of Iowa, a primary Corn Belt state. Iowa is an ideal location for testing the
Figure 2.1: SMOS optical thickness in Kossuth County, Iowa, in 2010. Standard deviations of moving average (vertical bars) are plotted bi-monthly.

Sensitivity of \( \tau \) to crop growth as the state is largely devoted to crops. For instance, in 77 of the 99 counties that partition Iowa, the areal coverage of maize and/or soybeans is at least 50%.

2.2 Observations

SMOS \( \tau \) data (reprocessed, v.4.0.0) from 2010 was collected for each ISEA4h9 grid point in Iowa and from each overpass that covered any part of Iowa. For each of the 99 counties in Iowa (where the area of each county is between 1000–2500 km\(^2\)), county mean \( \tau \) was computed by averaging the data from every grid point whose center fell inside the county. Because of the high-frequency noise in the \( \tau \) data (see Figure 2.1, for example), 21-observation moving
averages were computed. The value of 21 observations was chosen as the averaging period based on visual inspection, with preference towards a smooth enough signal to determine growing season minimum and maximum $\tau$. The minima were found during the months of May and June, the period of crop emergence, and the maxima during July through September, the period of crop maturity. The change in optical thickness ($\Delta \tau$) for each county was then computed by taking the difference between the minimum and maximum.

Kossuth County, located in north–central Iowa along the state border with Minnesota, is an example of a particularly heavily cultivated county. In Kossuth County, 87% of its 2,500 km$^2$ area is covered by maize and soybean fields. An example of its 2010 $\tau$ signal can be seen in Figure 2.1. The period between the minimum and maximum average $\tau$ is highlighted in Region III. The senescent and harvest period can be seen in Region IV with its expected decline in $\tau$. There are other interesting and unexpected patterns to the $\tau$ data highlighted in Regions I, II, and V which will be discussed later.

County maize and soybean yield data for 2010 were collected from USDA NASS, converted to a mass basis, and averaged together based on the areal fractions of each crop grown. Other crops besides maize and soybean are rarely grown in Iowa and were not considered here. The relationship between county yields ($Y$) and $\Delta \tau$ is shown in Figure 2.2. An initial linear regression was computed and had a non-zero intercept. This intercept did not vary significantly from zero (i.e. 0 kg m$^{-2}$ was included in the 95% confidence interval) and a non-zero intercept did not make physical sense, so a second regression was computed with a zero intercept forced. While the regression could be suspect due to the high concentration of points centered near $\Delta \tau = 0.20$ and $Y = 0.8$ kg m$^{-2}$, there appears to be a clear relationship between $\Delta \tau$ and $Y$. Using the regression and $\Delta \tau$ as a predictor of $Y$ gives a root mean squared error of 0.096 kg m$^{-2}$ and a coefficient of determination ($R^2$) of 0.575.

### 2.3 Analysis

While the relationship between $\Delta \tau$ over the growing season and crop yields in Figure 2.2 seems to be clear, there are some inconsistencies with the SMOS $\tau$ data that may currently present a challenge to providing a yield–prediction product. One example is the change in
Figure 2.2: 2010 crop yields ($Y$) compared with change in optical thickness ($\Delta \tau$) for each county in Iowa.
SMOS $\tau$ outside of the growing season (Regions I, II, and V of Figure 2.1), which do not appear to be realistic at first glance. There ought to be no significant vegetation growing in the periods highlighted in Regions I and V as they are outside of the growing season, and so, similarly, $\tau$ should not be increasing. $\tau$ should stay steady at or near a minimum value when no vegetation is growing. Similarly, in Region II, since there is no vegetation being removed or senescing, there is no reason to expect a decline in $\tau$. These patterns also appear in other heavily cultivated counties in Iowa while they are dampened in counties with more forest and/or urban coverage.

We hypothesize that these changes outside of the growing season are caused by changes in the micro–topography of the soil surface (soil surface roughness) caused by field operations. For example in Region I, when preparations for crop planting are done in the spring, agricultural machinery must move across farm fields and the soil roughness increases. In the fall following harvest (Region V), the common practice on Iowa farms is to till the soil in order to improve its hydraulic conductivity and promote evaporation near the surface so that the soil surface is drier and machinery can enter fields in the spring to plant as early as possible. In between these two types of field operations (Regions II, III, and IV), soil roughness decreases with rainfall (Zobeck and Onstad, 1987).

The microwave model used by the SMOS mission to interpret L–band brightness temperatures, $T_B$, is (Wigneron et al., 2007):

$$T_B = T_{\text{soil}} (1 - R_{\text{soil}}) e^{-\tau/\mu} + (1 - e^{-\tau/\mu}) (1 - \omega)T_{\text{veg}} + (1 - e^{-\tau/\mu}) (1 - \omega)T_{\text{veg}} R_{\text{soil}} e^{-\tau/\mu}$$

where: $T_{\text{soil}}$ is the temperature of the soil; $R_{\text{soil}}$ is the soil surface reflectivity (a function of soil moisture and soil roughness) (Mironov et al., 2009); $\tau$ is the vegetation optical thickness; $\mu = \cos \theta$; $\theta$ is the incidence angle; $\omega$ is the single–scattering albedo, which simulates the effect of scattering within the vegetation; and $T_{\text{veg}}$ is the temperature of the vegetation. The model considers three components of the overall brightness temperature: the brightness emitted by the soil that is attenuated as it passes through the vegetation; emission from the vegetation
Figure 2.3: The relationship between changes in optical thickness and changes in the roughness parameter from initial values of $\tau = 0.1$ and $h = 0.1$ required to keep the same brightness temperature at varying incidence angles and polarizations. Computed using Equation 2.1 and Mironov et al. (2009) with $\omega = 0$, $T = 300$ K, volumetric soil moisture of 0.26 $m^3 \, m^{-3}$, and a soil texture clay content of 30%.
itself; and emission from the vegetation that is scattered by the soil surface and attenuated as it passes back through the vegetation canopy.

When $\tau$ increases (more vegetation is present), $T_B$ also increases. The same overall effect happens when the soil surface roughness increases (as when the soil is tilled or plowed): $R_{\text{soil}}$ decreases as the soil surface roughness increases and $T_B$ increases. Hence we believe that changes in soil surface roughness due to plowing are causing the observed increase in $\tau$ since the current SMOS algorithm does not take any changes in soil surface roughness into account (Mahmoodi, 2011, personal communication, J.–P. Wigneron). If the effect of soil surface roughness on the soil surface specular reflectivity, $R$, is to exponentially decrease the reflectivity, $R_{\text{soil}} = Re^{-h\mu^N}$, where $h$ is a general soil roughness parameter (Choudhury et al., 1979) and $N$ is a polarization dependent parameter that accounts for the combined effect of incidence angle and roughness (Mahmoodi, 2011); if $T_{\text{soil}} \approx T_{\text{veg}} = T$; if $\omega = 0$ (the assumption made by SMOS); if $h$ is increased by $h + \Delta h$; and if $\tau$ is increased by $\tau + \Delta \tau$, then using Equation 2.1 it can be shown that:

$$\Delta T_{B\tau} = TR e^{-h\mu^N} e^{-2\tau/\mu} \left[ 1 - e^{-2\Delta \tau/\mu} \right]$$

(2.2)

and that:

$$\Delta T_{Bh} = TR e^{-2\tau/\mu} e^{-h\mu^N} \left[ 1 - e^{-\Delta h\mu^N} \right]$$

(2.3)

where: $\Delta T_{B\tau}$ and $\Delta T_{Bh}$ are changes in brightness temperature caused by changes in $\tau$ and soil surface roughness, respectively; and $\Delta h$ is a change in the soil roughness parameter. When $\Delta T_{B\tau} = \Delta T_{Bh}$, symmetry between Equations 2.2 and 2.3 requires that $h\mu^N = 2\tau/\mu$. Hence

$$\Delta h = \frac{2}{\mu^{1+N}} \Delta \tau$$

(2.4)

which indicates that a change in soil roughness $\Delta h$ can cause the same change in brightness temperature $\Delta T_B$ as a change in $\Delta \tau$ scaled by $2/\mu^{1+N}$. This relationship is shown in Figure 2.3 for $\omega = 0$; for h-pol and v-pol $N$ values of $N_h = 2$ and $N_v = 0$, as these values of $N$ are used in the current SMOS L2 algorithm (personal communication, J.–P. Wigneron); for an initial $h = 0.1$, as this value of $h$ is the constant value assumed in the SMOS L2 algorithm (personal communication, J.–P. Wigneron); and for an initial $\tau = 0.1$, which represents the “base $\tau$” or minimum moving average $\tau$ seen throughout the year. Because $N_h = 2$, the effect of $\Delta h$ on
$T_B$ is small compared to $\Delta \tau$ at large incidence angles for h-pol. However, SMOS retrieves $\tau$ and soil moisture using $T_B$ from multiple angles and both polarizations, and so changes in the “true” roughness parameter will still have an effect on retrieved $\tau$.

The increase in $\tau$ seen in Region V of Figure 2.1 may be attributed to an increase in soil roughness. Following harvest (late September/early October in 2010), most farmers in Iowa will run a chisel plow over their fields to till the soil and to incorporate some of the crop residue (the litter leftover following harvest) into the soil. In some cases, farmers will also employ disking to bury more residue. Soil roughness, on average, will be around 23 mm to 18 mm following chisel plow and disking activities (Zobeck and Onstad, 1987). Similarly, the soil roughness immediately after harvest and before any additional field work could be estimated using the value for soil managed under no-till (i.e. crop residue is left on the soil surface), which is 7 mm. A relationship between soil surface roughness, defined as the standard deviation of elevation ($SD$, in mm), and $h$ has been found (Wigneron et al., 2011, with correction supplied via personal communication with J.-P. Wigneron), where

\[
h = \left( \frac{0.9437 \cdot SD}{0.8865 \cdot SD + 2.2913} \right)^6.
\]  

(2.5)

An initial $SD = 7$ mm and final $SD = 20$ mm gives $\Delta h = 0.48$. Using Equation 2.4 with $N_h = 2$ and $N_v = 0$ and a central incidence angle of $\theta = 40^\circ$, this could be interpreted as a range of possible $\Delta \tau$ values of 0.11 to 0.18. The actual $\Delta \tau$ seen in Region V of Figure 2.1 is around 0.15.

Similarly, there is a decrease in $\tau$ in Region II of Figure 2.1 that may be attributed to a decrease in soil roughness. Prior to planting and, subsequently, the emergence of vegetation, most soils in Iowa are again disturbed by field activities. In order to provide a better seedbed, farmers will run a field cultivator or harrow over the soil to break up clods left over from fall tillage. The average value for soil roughness following these spring management activities is 15 mm (Zobeck and Onstad, 1987). The major changes to soil roughness after these activities occur are caused by rainfall. The average decrease in soil roughness has been found to be (Zobeck and Onstad, 1987)

\[
SD/SD_0 = 0.89 \exp(-0.026 \cdot P)
\]  

(2.6)
where \( P \) is cumulative rainfall in cm and \( SD_0 \) is the initial roughness value. The total rainfall in Algona, Iowa (located within Kossuth County) over the period highlighted in Region II was 16.3 cm, which gives \( SD/SD_0 = 0.58 \). Assuming \( SD_0 = 15 \) mm, the final roughness value in Region II of Figure 2.1 was approximately 8.7 mm. Using Equations 2.5, 2.4, \( N_h = 2, N_v = 0, \) and \( \theta = 40^\circ \) to compute the \( \Delta \tau \) interpretation gives a \( \Delta \tau \) range of \(-0.14\) to \(-0.08\). The actual \( \Delta \tau \) seen in Region II is around \(-0.12\).

While soil roughness ought to be decreasing in Regions III and IV, the presence of vegetation overwhelms the \( \tau \) signal. Additionally, interception of rainfall by the vegetation canopy reduces the rate of change in soil roughness.

The high–frequency noise in the SMOS \( \tau \) product is another challenge and likely has a more complicated explanation. We hypothesize that the high–frequency noise is caused by either a short–coming in a key data set used in the current algorithm; and/or anthropogenic microwave emissions (radio frequency interference, or RFI). The SMOS algorithm solves a cost function to find the best estimates of both soil moisture and \( \tau \). If recent observations of \( \tau \) are available, they are used as an initial guess in the algorithm. If recent observations are not available, either because of additive noise from RFI that has corrupted the data, or because of some other error in the data stream, then an initial estimate of \( \tau \) is used from another database. It is conceivable that the high–frequency variations in \( \tau \) could be caused by the periodic use of poor initial estimates. RFI has been detected in SMOS brightness temperature in the U.S. Midwest, and more often in the ascending (6 AM) than the descending (6 PM) passes (Johnson and Aksoy, 2011). However, differences in evening and morning \( \tau \) observations can also be caused by real changes in vegetation water content that occur overnight (Rowlandson et al., 2012).

The exact effect of the roughness “confusion” on SMOS soil moisture retrieval is unknown. Because of the lack of soil moisture measurement sites in Iowa adequately equipped to validate a SMOS pixel, we cannot estimate what biases may or may not exist in the SMOS L2 soil moisture data for the times where it appears SMOS is overestimating \( \tau \) and underestimating \( h \). However, we can demonstrate the differing effect of changes in \( \tau \) and changes in \( h \) on the brightness temperature sensitivity to changes in soil moisture. We have plotted simulated \( T_B \) sensitivity for the post-harvest (Region V in Figure 2.1) peak in Kossuth County using SMOS’s
Figure 2.4: Brightness temperature sensitivity to changes in soil moisture following harvest in Kossuth County computed using Equation 2.1, Mironov et al. (2009), and what SMOS “believes” for values of $\tau$ and $h$ (solid line) and using reasonable estimates of the “true” $\tau$ and $h$ (dashed line). The sensitivities were computed between volumetric soil moisture values of 0.2 and 0.3 m$^3$ m$^{-3}$ with $T = 300$ K and soil texture clay content of 30%.
values of $\tau$ and $h$ (0.25 and 0.1, respectively) and our best estimate of the “true” values of $\tau$ and $h$ (0.10 and 0.6) in Figure 2.4. For large incidence angles, the h-pol $T_B$ sensitivity may actually be higher than what SMOS “believes” while for small incidence angles, the v-pol $T_B$ sensitivity may be lower than what SMOS “believes.” The total effect on soil moisture retrieval will depend the particular range of incidence angles SMOS has measured. The number and range of incidence angles can vary pixel to pixel depending on where each pixel is located within a SMOS measurement swath.

2.4 Conclusions

Although noisy, SMOS vegetation optical thickness contains useful information regarding the growth of vegetation. While short–term changes in $\tau$ are not reliable, long–term changes in $\tau$ during the growing season are related to crop yield. We found a positive linear relationship between changes in $\tau$ and yields with a RMSE of 0.096 kg m$^{-2}$. Changes in $\tau$ that are not caused by vegetation may be explained by farming practices, specifically operations that change the roughness of the soil surface such as tillage of the soil and planting activities. By estimating changes in soil roughness in a county in Iowa, we were able to use a relationship between $\tau$ and roughness to estimate the changes in $\tau$ that SMOS’s roughness-constant algorithm retrieved. More work is necessary, perhaps using the SMOS retrieval algorithm itself, to confirm that roughness effects explain the changes in $\tau$ outside of the growing season. The effect of the $\tau$ retrieval error on soil moisture retrieval is hard to quantify because it depends on the incidence angles that SMOS measures $T_B$ at, which can vary pixel to pixel.

Thus far, the SMOS mission has been focused on providing a reliable soil moisture product, and improvements to the $\tau$ product have been of secondary importance. As the value of L–band as a source of vegetation information is realized, this attitude may change. NASA’s L–band Soil Moisture Active Passive (SMAP) mission (Entekhabi et al., 2010) will rely on third–party sources of vegetation and/or optical thickness data. More reliable SMOS data could be used as validation of these sources.

Finally, remote sensing scientists for many years have desired a satellite product that can be used to directly monitor the growth of vegetation. Several visible and near–infrared products
(such as leaf area index and normalized difference vegetation index) are available, but they are only sensitive to exposed leaves and could therefore fail at higher levels of vegetation that can be reached in agricultural crops. The SMOS $\tau$ product has the potential to become a better satellite product for monitoring agricultural crops throughout the growing season. However, further analysis as more years of SMOS data become available is needed to assess the ability of the $\tau$ product to track interannual variability in yields and other important crop properties.
CHAPTER 3. ESTIMATION OF THE B PARAMETER FROM SMOS

3.1 Introduction

When measuring brightness temperatures from satellites, water in vegetation “masks” soil $T_B$ by simultaneously attenuating the soil-emitted radiation while adding its own outgoing and reflected radiation. This effect of vegetation can be accounted for with the $\tau$-$\omega$ model (Equation 1.3), through the vegetation optical thickness parameter. $\tau$ can be related to VWC through the $b$ parameter (Equation 1.4).

Values of the $b$ parameter have been measured at single field sites using tower-based or airplane-based radiometers (Jackson and Schmugge, 1991). $b$ has been shown to vary with landcover type. Different values have been found for different crop types and even for different studies of the same crop type. For example, at L-band, Jackson and Schmugge (1991) report $b = 0.102$ to $0.133$ for maize and $b = 0.086$ to $0.087$ for soybean. These literature values of $b$ assume zero single scattering albedo ($\omega = 0$), which is also assumed in ESA’s Soil Moisture and Ocean Salinity soil moisture retrieval algorithm. Despite the variation between crop types and between field sites, a single value of $b = 0.110$ is proposed for use in NASA’s Soil Moisture Active Passive soil moisture retrieval algorithm for all crop landcover types (O’Neill et al., 2012). However, SMAP is also assuming a small single scattering albedo, $\omega = 0.05$, which means a direct comparison to literature and SMOS-derived values of $b$ cannot be made. Looking at the $\tau$-$\omega$ model (Equation 1.3), a non-zero $\omega$ implies that, for the same measured brightness temperature, $\tau$ should be larger than if one were to assume $\omega = 0$. Therefore, larger values of $b$ should be used when vegetation scattering is taken in to account in a soil moisture retrieval.

SMOS and SMAP both have pixel resolutions of around 40 km and so are sensitive to $\tau$ over large, sometimes heterogeneous areas. If one can determine $b$ for these heterogeneous
areas, then SMOS \( \tau \) data may be used to produce maps of VWC, which could be useful in validating SMAP’s proposed technique for estimating VWC from a climatology of Normalized Difference Vegetation Index (O’Neill et al., 2012). Moreover, one could test to see if SMAP is using reasonable values of \( b \) in their retrieval algorithm, though again, the effect of different vegetation scattering assumptions may need to be taken into account.

In this chapter, I propose an innovative method for estimating satellite-scale values of the \( b \)-parameter using SMOS \( \tau \) data and county crop yield estimates. I expect that our estimates of \( b \) will be most reliable during years of normal precipitation; in 2012, drought in the U.S. Corn Belt may have caused a key parameter, the “harvest index,” to be lower than the constant value assumed by this method. My hypothesis is that the values of \( b \) that I derive for Iowa from SMOS in 2010 and 2011 using the proposed method will fall between values of \( b \) in literature for maize and soybean, the two major crops grown in Iowa.

### 3.2 Methods

Iowa counties are similar in area to SMOS pixel footprints. I took advantage of this similarity by pairing SMOS pixels with each Iowa county in order to do comparisons with data that is only available aggregated to the county level (e.g. county crop yield estimates). A geographical information system database was used to determine the centroid of each Iowa county. Then, a nearest neighbor approach was used to find the centers of the three closest SMOS pixels to each county centroid.

I extracted SMOS \( \tau \) data (version 5.0.1 or later) for 2010–2012 for each of the matching SMOS pixels and kept only retrievals that included both \( \tau \) and soil moisture (i.e. SMOS \( \tau \) “retrievals” that were based only on ancillary vegetation data were not considered). Because data gaps could cause problems in data smoothing routines, I compared each pixel’s length of \( \tau \) record to its two neighbors. If the lengths differed by less than 10\%, I chose the most central SMOS pixel to represent a county, otherwise I used the pixel with the longest record (fewest gaps).

The resulting SMOS pixels can be seen in Figure 3.1. While the shape and size of some counties cause some of the chosen SMOS footprints to “bleed” in to other counties, each pixel
Figure 3.1: The 99 SMOS pixels paired with each Iowa county. Satellite footprints are approximated by 43 km diameter circles. Actual footprints vary in size; 43 km is a general average of SMOS footprint sizes.

represents a majority of its represented county. It should be noted that the properties of the SMOS satellite and the way that raw SMOS swaths are sampled by the upstream data processors lead to SMOS pixel footprints overlapping each other. Some overlapping pixels can be seen in Figure 3.1, which is an expected result.

Because SMOS $\tau$ data is riddled with nonphysical, high frequency noise (Patton and Hornbuckle, 2013), the data need to be smoothed. In the previous chapter, I used a moving average to smooth $\tau$. I sought the help of the Agriculture Experiment Station Consulting Group in the Department of Statistics at Iowa State University to see if my method could be improved. A graduate student, Daniel Fortin, answered my request and presented the possibility of using functional data analysis (FDA). FDA works from the assumption that a process should be smooth and continuous and can be represented by a function (or superposition of functions).
Fitting a Fourier series to data would be a FDA-like example. In my case, $\tau$ ought to fit the assumptions needed for FDA as vegetation, at the satellite scale, should not vary disjointedly one day to the next. Using the R FDA package (Ramsay et al., 2013), I smoothed the $\tau$ data using FDA with a Fourier basis, which uses a superposition of sines and cosines to describe the data (also similar to a Fourier series), and a roughness penalty ($\lambda$) that forces a minimization of the 2nd derivative of the fit function based on the magnitude of $\lambda$. I allowed the periods of the fit sine and cosine functions to vary between 12 hours and 365 days.

I chose $\lambda = 10,000$ (the green line in Figure 3.2) based on visual inspection of the data. This value of $\lambda$ allowed the fitting function to not react strongly to the high frequency noise, as was the case for $\lambda = 1,000$, and to not greatly reduce the amplitude of the $\tau$ signal, as was the case for $\lambda = 100,000$. A comparison of FDA (with Fourier basis and $\lambda = 10,000$) to a moving average method can be seen in Figure 3.3. For “well-behaved” data sets that have noise patterns that follow a typical autoregressive model, there are ways to analytically fix $\lambda$. However, SMOS $\tau$ is not well-behaved; autocorrelation of the noise (Figure 3.4) shows that there seems to be a periodicity to the noise (with the period being roughly 18 days) and the covariance of the noise does not drop off, even after 90 days. The exact repeat cycle of a SMOS swath is 149 days. While 149 is prime, 18 is a factor of 144, so perhaps the noise is a function of where a pixel falls in the satellite’s swath. The position of a pixel within the swath determines how many and which incidence angles are available for parameter retrieval, and it is known that there are biases in $T_B$ within a SMOS swath. More investigation is needed in to the high frequency noise, and perhaps a newer version (6+) of SMOS data, reported to fix some of the $T_B$ biases found in SMOS swaths, will reduce the noise seen in SMOS $\tau$.

Examples of FDA smoothed SMOS $\tau$ data for multiple counties and years that spanning different crop areal fractions and meteorological conditions are shown in Figure 3.5. Most smoothed $\tau$ timeseries follow the expected pattern of $\tau$ rising and falling over the growing season (June–October), which is mostly related to the growth and senescence of cropland vegetation. Other vegetation in a pixel can also affect $\tau$, but I assume these effects are minimal given the large areal crop fractions in most Iowa counties (Figure 3.6). Differences in timing of the growth and decay periods are likely related to differences in planting dates. I computed
Figure 3.2: Comparison of SMOS $\tau$ smoothed by functional data analysis under three different roughness penalties.

Figure 3.3: Comparison of SMOS $\tau$ smoothed by FDA versus by a moving average.
the growing season change in optical thickness \((\Delta \tau)\) for each county and each year from the smoothed \(\tau\) timeseries. I define \(\Delta \tau\) as the difference between the minimum \(\tau\) from the beginning of the growing season (May–June) and the maximum \(\tau\) from the peak of the growing season (July–September). For example, Kossuth County in 2010 (see Figure 3.5), had a minimum value of \(\tau\) of about 0.1 in mid-June and a maximum value of about 0.3 in mid-August, so \(\Delta \tau \approx 0.3 - 0.1 \approx 0.2\). (the actual value was \(\Delta \tau = 0.19\)).

Representative in-situ measurements of vegetation water content (VWC) in Iowa can not be feasibly obtained at the county/SMOS satellite scale. However, crop yield estimates are provided every year on a county basis. I collected yield estimates for maize (grain) and soybean for each county in Iowa for the years 2010–2012 from the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) \((USDA\ NASS, 2013)\). Estimates of yield (or, ultimately, plant dry mass) may be related to VWC, and so may be compared with \(\tau\) (and/or \(\Delta \tau\)). Yield estimates are provided in units of bu ac\(^{-1}\) (where bushels are a measure of volume), whereas for deriving VWC, units of kg m\(^{-2}\) (mass of yield per area) are needed. I
Figure 3.5: Raw and smoothed SMOS $\tau$ from five different county-year pairs.
converted the yield data to a mass basis using standard conversions (e.g. Prince et al., 2001):

\[
1 \text{ bu maize grain} = 25.4 \text{ kg maize grain}\n\]

\[
1 \text{ bu soybean} = 27.2 \text{ kg soybean}\n\]

The yield estimates also assume some residual moisture content. The moisture content needs to be factored out as dry mass will be used later to estimate water mass. Following Prince et al. (2001), I multiplied maize and soybean yield data by 0.871 and 0.920, respectively, to remove the water fraction and obtain the actual dry mass grain yield estimates that will be compared with \(\Delta \tau\). For example, Kossuth County in 2010 had a maize yield estimate of 184 bu ac\(^{-1}\). I convert that to a dry maize yield estimate \((Y_m)\) of:

\[
Y_m = \frac{184 \text{ bu maize}}{1 \text{ ac}} \times \frac{25.4 \text{ kg maize}}{1 \text{ bu maize}} \times \frac{1 \text{ ac}}{4046.86 \text{ m}^2} \times \frac{0.871 \text{ kg dry maize}}{\text{kg maize}} = 1.01 \text{ kg dry maize m}^{-2}.\n\]

Finally, to arrive at a total county dry yield estimate weighted by the area covered by maize and soybean croplands in each county, I computed the fractional area for each crop and county using the USDA NASS Cropland Data Layer (CDL) (Boryan et al., 2011) from 2010–2012. For example, if a county were 40 km\(^2\) in total area and, in 2010, contained 20 km\(^2\) of maize and 10 km\(^2\) of soybean, the fractional area for each crop in that county in 2010 would be 0.50 and 0.25, respectively. The average total cropland (maize and soybean) fractional area over the three years is shown in Figure 3.6. A county’s total dry yield estimate for a year was then computed by multiplying each crop dry mass yield estimate by the crop’s areal fraction, then summing up the results for both crops. For example, Kossuth County in 2010 had maize and soybean dry yield estimates of 1.01 and 0.310 kg m\(^{-2}\), respectively, and maize and soybean areal fractions of 0.4867 and 0.3769, respectively. The total dry mass yield estimate \((Y)\) for Kossuth in 2010 was:

\[
Y = (1.01 \text{ kg maize m}^{-2}) (0.4867) + (0.310 \text{ kg soybean m}^{-2}) (0.3769) = 0.608 \text{ kg crop m}^{-2}.\n\]

The \(Y\) for each county were grouped by year and compared with \(\Delta \tau\) (Figure 3.7). The results are similar to those in the previous chapter as larger \(\Delta \tau\) were related to larger \(Y\). I generated linear fits through the origin such that:

\[
Y = m \Delta \tau,\n\]

\[(3.1)\]
where $m$ is the slope of the fit line. The results (e.g. from 2010) are not exactly the same as in the previous chapter, with the differences due to the new methods for smoothing $\tau$ and deriving county total dry mass yield estimates. Regressions including axis intercepts (e.g. $Y = m\Delta\tau + b$) were also done and did fit the data better (i.e. better $R^2$ and RMSE). However, the intercept parameters did not have a clear physical interpretation. For every year, a value of $\Delta\tau = 0$ would give negative $Y$, which is impossible.

The value of $m$ from Equation 3.1 for each year can be used to estimate values of the $b$ parameter through a chain of empirical microwave remote sensing and allometric vegetation relationships:

**harvest index**, $h_i$ the ratio of dry yield to maximum dry plant mass ($m_{d,max}$):

$$h_i = \frac{Y}{m_{d,max}}.$$  \hspace{1cm}(3.2)

**maximum gravimetric vegetation water content**, $\theta_{gv,max}$
Figure 3.7: Relationship between crop yields and $\Delta \tau$ for Iowa counties.
the ratio of maximum vegetation water content (VWC\textsubscript{max}) to \(m_{d,max}\):

\[
\theta_{gv,max} = \frac{VWC_{max}}{m_{d,max}}.
\] (3.3)

**the \(b\) parameter** the ratio of VWC to \(\tau\):

\[
b = \frac{\tau}{VWC},
\]

which also holds for \(\Delta\tau\) and VWC\textsubscript{max}:

\[
b = \frac{\Delta\tau}{VWC_{max}},
\] (3.4)

assuming that \(\Delta VWC = VWC_{max}\) (i.e. changes in \(\tau\) over the growing season are only due to changes in crop VWC) and that \(b\) is constant.

By combining and rearranging Equations 3.1, 3.2, 3.3, and 3.4, it can be shown:

\[
b = \frac{h_i}{m \theta_{gv,max}}.
\] (3.5)

Equation 3.5 has to be modified in order to represent the combined effect of maize and soybean. The areal fractions of each crop for each county and each year computed from the USDA NASS CDL (Boryan et al., 2011) are used once again. However, the maize and soybean fractions are normalized to the total crop areal fraction. For example, if a county were 50% maize and 25% soybean, the normalized crop fractions (\(f\)) would be:

\[
f(\text{maize}) = \frac{0.5}{0.5 + 0.25} = 0.67,
\]

\[
f(\text{soybean}) = \frac{0.25}{0.5 + 0.25} = 0.33.
\]

Once \(f\) were computed for each county, year, and crop, I can calculate \(b\) as:

\[
b(\text{county,year}) = \frac{1}{m(\text{year})} \sum_{\text{crops}} f(\text{county,year,crop}) \frac{h_i(\text{crop})}{\theta_{gv,max}(\text{crop})}.
\] (3.6)

I used values of \(h_i\) from Prince et al. (2001):

\[
h_i(\text{maize}) = 0.53,
\]

\[
h_i(\text{soybean}) = 0.42.
\]
For maize and soybean, these values of $h_i$ can usually be considered constant. Crops that are stressed may exhibit lower values of $h_i$, however (Prince et al., 2001).

$\theta_{gv,max}$ is a parameter that, to the best of my knowledge, has not been reported in previous literature. I defined $\theta_{gv,max}$ in Equation 3.3 as the ratio of $VWC_{max}$ to $m_{d,max}$. This definition may seem peculiar as $VWC_{max}$ and $m_{d,max}$ usually represent two different phenological stages in crop growth; however, these two variables link what SMOS “sees” to what yield estimators measure. SMOS $\tau$ should be maximized when VWC is at a maximum, while crop yields are estimated when dry mass is close to a maximum.

To estimate $\theta_{gv,max}$ for maize and soybean, I used crop dry mass and total mass measured in Nebraska (personal communication, A. Suyker) and Iowa (personal communication, M. Boyer and R. Elmore). These data include different management treatments (e.g. irrigation, cultivar) and weather conditions. Per the definition of $\theta_{gv,max}$, for each set of mass data over a growing season, I found the maximum value of water mass (total mass − dry mass) and dry mass, then took the ratio of water mass to dry mass. The values I found are:

$\theta_{gv,max}(\text{maize}) = 2.621 \pm 0.1251 \frac{\text{kg water}}{\text{kg dry}}$,

$\theta_{gv,max}(\text{soybean}) = 2.735 \pm 0.2298 \frac{\text{kg water}}{\text{kg dry}}$,

where the uncertainties represent 95% confidence intervals that assume $\theta_{gv,max}$ estimates follow a Student’s $t$-distribution. The individual estimates of $\theta_{gv,max}$ used to generate these values are summarized in Figure 3.8. The data needed to estimate $\theta_{gv,max}$ are difficult to collect; only seven points of data (all from Nebraska [personal communication, A. Suyker]) were available for estimating $\theta_{gv,max}(\text{soybean})$. More maize and soybean data would be welcome to revise the values and to potentially narrow the uncertainties.

Most maize and soybean biomass research has been focused on dry matter or carbon content only. Therefore, these are the first known reported values of this $\theta_{gv,max}$ parameter that links the maximum dry matter content of the crops to the maximum VWC. Similar to reported research, most crop and/or land surface models’ predictions of plant biomass are reported in terms of dry plant matter or carbon content. Given the difficulties in measuring VWC at the satellite scale, it would be beneficial if one could use a crop or land surface model to estimate
VWC at this scale.

I mentored an honors meteorology undergraduate student, Eswar Iyer, on a project where we sought to estimate $\theta_{gv}(GDD)$ for maize. This variable is the ratio of VWC to dry biomass at any accumulated thermal time (i.e. growing degree day, GDD), beginning at planting. (Note that, as defined here, the maximum value of $\theta_{gv}(GDD)$ is not the same as $\theta_{gv,max}$, see Equation 3.3.) We computed dry biomass, VWC (i.e. water biomass), and $\theta_{gv}$ for each day available from irrigated maize biomass data that was measured about every 10 days in Mead, Nebraska from 2003–2011 (personal communication, A. Suyker). We found the accumulated GDDs for each day that biomass measurements were made ($GDD_i$) by accumulating GDDs starting at the stated planting date (Equation 3.7).

$$GDD_i = GDD_{i-1} + \max \left( \frac{\max (T_{max}, 30 \degree C) + \min (T_{min}, 10 \degree C)}{2} - 10 \degree C, 0 \degree C \right). \quad (3.7)$$

The standard base temperature of 10 °C and ceiling temperature of 30 °C were used. The maximum and minimum temperatures ($T_{max}$ and $T_{min}$) were taken from the nearest National Weather Service Cooperative Observer Network station that had a observation record spanning 2003–2011, which was the Ashland No. 2 station.

Plots of dry biomass, water biomass, and $\theta_{gv}$ against GDDs (in °C) are shown in Fig-
Figure 3.9: Individual measurements of dry and wet biomass and $\theta_{gv}$ plotted against accumulated GDDs, along with a two-part model of $\theta_{gv}$ (Equation 3.8).
Irrigated (i.e. non-water stressed) maize appears to reach a maximum VWC at around 1000 GDD. This is roughly equivalent to the “blister stage” in maize, often abbreviated as R2. Dry biomass monotonically increases throughout the growing season except towards the end of the season when the crop is senescent and may lose some mass. The result of the two biomass timeseries is that θ_{gv} increases almost linearly until around 450 GDD, then decreases exponentially. 450 GDD is around the V10 stage of maize growth, when the crop has produced 10 leaves. V10 is a transition stage; maize increases its rate of leaf production at V10, which may explain the change in the behavior of θ_{gv} from increase to decline.

We present a model for θ_{gv} non-stressed maize in Figure 3.9. It is a two-part model, capturing the rise in θ_{gv} with a linear function and the fall in θ_{gv} with an exponential decay:

\[
θ_{gv}(\text{GDD}) = \begin{cases} 
5.685 + 0.004953 \times \text{GDD} & \text{for } \text{GDD} < 450 ^\circ C \\
21.55 \exp(-0.0009818 \times \text{GDD}) & \text{for } \text{GDD} \geq 450 ^\circ C.
\end{cases}
\] (3.8)

The linear part of the model has a root mean squared error (RMSE) of 0.9 kg-water kg-dry^{-1} while the exponential decay portion has an RMSE of 0.5 kg-water kg-dry^{-1}.

While preliminary, this model could be used to convert crop model predictions of dry maize biomass to VWC. Some further work could be beneficial in this endeavor, such as normalizing the time variable to represent particular growth stages, which would allow the model to be applied across different maize cultivars, and also incorporating rain-fed maize data, which may have reduced θ_{gv} in times of water stress.

### 3.3 Results

My estimates of b, averaged over counties and grouped by year, are summarized in Table 3.1. The variability in b year-to-year seems large, but given the methodology and the interannual variability seen in m (Figure 3.7), this result is not completely unexpected.

These estimates of the b parameter are similar in magnitude to the field study estimates in Jackson and Schmugge (1991), which reported b in maize of 0.102, 0.113, and 0.133 and b in soybean of 0.086 and 0.087. Considering that Iowa is covered by more maize than soybean, though, the statewide mean estimates of b for 2010 and 2011 are lower than expected. Without
prior knowledge of $\tau$ and $m$ in 2012, because of drought conditions that affected crop growth that year, I would have expected 2012 to have the lowest estimate of $b$. Yet my estimate for 2012, for which I used the same $h_i$ as the other years even though stressed crops are known to have lower $h_i$, was highest and closest to field-based measurements of $b$ in maize. All three statewide mean estimates also fall below SMAP’s all croplands $b$ value of 0.110 that will be used in SMAP’s baseline soil moisture retrieval algorithm, though again, SMAP’s assumption of $\omega = 0.05$ could mean a larger value of $b$ is necessary to correctly estimate $\tau$.

Given all of the assumptions that go in to these estimates of $b$, an estimate of the uncertainty of these estimates is warranted. I simulated 1,000,000 estimations of $b$ for a hypothetical Iowa county with median maize (41%) and soybean (23%) areal fractions. I sampled $h_i$ from uniform distributions. For maize, the distribution ranged from 0.45 to 0.6 based on values reported in Boomsma et al. (2009) for stressed and non-stressed plants. For soybean, I assumed a similar range around the constant I used in estimating $b$, 0.3 to 0.55. $m$ was sampled from a uniform distribution ranging from the minimum and maximum of the values I have reported, 1.74 to 2.71. $\theta_{gv,max}$ was sampled from Student’s $t$-distributions based on the mean, variance, and number of observations used to estimate $\theta_{gv,max}$ for each crop.

The resulting distribution is right-skewed with a mean $b$ of 0.086 and with a standard deviation of 0.017 (Figure 3.10). This is a large uncertainty but not unexpectedly large given that a conservative range of $h_i$ values and that the first known estimates of $\theta_{gv,max}$ were used. Again, the need for more estimates of $\theta_{gv}$ and $\theta_{gv,max}$ is emphasized.
Figure 3.10: Histogram of estimates of the $b$ parameter spanning plausible ranges of $h_i$, $m$, and $\theta_{gv,max}$.

3.4 Conclusions

I have presented the first satellite-scale estimates of the $b$ parameter that links $\tau$ and VWC. The estimates are similar in magnitude to published values of $b$ for maize and soybean. While the estimates for 2010 and 2011 appear to be low, there is considerable uncertainty in the estimates, with standard error of around 20%.

The most interesting result is that my estimates of $b$ had interannual variability. My estimate of $b$ for 2010 was 35% lower than my estimate for 2012. It is not clear what exactly would cause the year to year variability, but my hypothesis would be that the variability is related to differences in weather and farming practices. For example, according to the USDA’s weekly crop reports, the lag time between when half of Iowa’s maize crop was planted and half of the soybean crop was planted varied between 10 and 21 days in 2010–2012. The crops also matured at different rates. Maize took 81 days to reach tassel stage (i.e. VT) in 2010, while only taking 69 days in 2012. Differences in the alignment of the two crops’ growing seasons
and differences in growth rates year to year may affect the slope of the \( \tau \)-yield relationship, though it is somewhat unclear whether the effect is real (i.e. \( \Delta \tau \) is and ought to be larger when crops mature more quickly) or artificially induced (i.e. through the smoothing method and associated parameters used).

My method for deriving \( b \) at the satellite scale could be improved by better measurement or modeling of the allometric relationships used. I have presented some of the first estimates of \( \theta_{gv} \), which relates plant dry matter to VWC, but more measurements are needed to improve the estimated value and understand its uncertainty. Harvest index can vary, especially when crops are stressed. Crop models that simulate water stress could provide better estimates of harvest index in drought years, especially compared to assuming a constant value across all years, which I have done. Perhaps most importantly, reducing the noise in SMOS \( \tau \) retrievals would help us see and understand more clearly year to year variation in \( \tau \) and, therefore, the relationship between \( \tau \) and crop yields.

Finally, SMOS’s retrieval algorithm could be improved by taking vegetation scattering into account. Scattering cannot be ignored in maize canopies at L-band (Hornbuckle et al., 2003); maize fields can make up the majority of SMOS pixels in Iowa. Compared to current retrievals, this improvement would cause retrievals of \( \tau \) to be larger with crop growth, suggesting that \( b \) values should also be larger. For example, using \( \omega(\text{maize}) = 0.03 \) and \( \omega(\text{soybean}) = 0.05 \), one study found \( b \) to be about 10% and 20% larger, respectively (Jackson and O’Neill, 1990).
CHAPTER 4. COMPARISON OF SMOS AND SMAP OPTICAL THICKNESS

4.1 Introduction

A major objective of NASA’s Soil Moisture Active Passive satellite mission is to produce measurements of surface volumetric soil moisture at a spatial resolution of 10 km by using its high resolution (3 km) L–band radar to downscale soil moisture retrievals from its lower resolution (36 km) L–band radiometer. In order for SMAP to be successful at its objective, the low resolution, passive soil moisture products must have high accuracy; the mission goal is for a maximum soil moisture error of 0.04 cm$^3$ cm$^{-3}$.

The current baseline algorithm for SMAP soil moisture retrieval is the single channel algorithm (SCA). For each pixel, SCA will use only a single measurement of horizontally polarized brightness temperature to solve for the soil reflectivity in the $\tau$-$\omega$ model (Equation 1.3). SCA requires that all parameters neither retrieved nor measured (i.e. $\tau$, $\omega$, $T_{\text{soil}}$) be supplied by an ancillary data source. The proposed method for supplying $\tau$ to SMAP is to create a climatology of normalized difference vegetation index values from the Moderate Resolution Imaging Spectroradiometer, convert the NDVI climatology to vegetation water content, then convert VWC to $\tau$.

In order to ensure that SMAP will meet its soil moisture retrieval goals, I will compare SMAP’s proposed NDVI climatology-derived $\tau$ method (which I will refer to as “SMAP $\tau$”) against SMOS $\tau$ retrievals. This comparison will be used to test two hypotheses:

1. SMAP $\tau$ will produce estimates of $\tau$ that are low compared to SMOS $\tau$ during the peak of the growing season, and

2. SMAP $\tau$ will peak earlier in the growing season than SMOS $\tau$. 
My reasoning for these hypotheses is that, because NDVI is an optical/infrared measurement that only sees the “skin” of most objects, NDVI may saturate early in the growing season as vegetation canopies close. This saturation would cause NDVI to reach a maximum and stop tracking changes in vegetation water some time before the ($\tau$) peak of the growing season. I will test these hypotheses by looking at 30 co-located and densely cultivated SMAP and SMOS pixels in Iowa.

4.2 Methods

Once it has been launched, SMAP brightness temperature data will be sampled and soil moisture retrievals performed at grid spacings similar to the footprint size of each product and locations defined by the Equal-Area Scalable Earth Grid (EASE-Grid) version 2.0. The location of SMAP’s 36 km passive-only pixel centroids for pixel footprints that fall completely within Iowa are shown in Figure 4.1. SMOS pixel centroids, which are more dense, are also plotted for reference.

Similar to what was done with counties in the previous chapter, I estimated the areal fraction of each SMAP pixel in Iowa that is covered by maize and soybean. SMAP passive-only pixel footprints were estimated by applying a buffer of 18 km to each pixel centroid, then the areal crop fractions were estimated for each pixel using the 2012 USDA NASS CDL (Boryan et al., 2011). For comparing SMAP’s method of deriving $\tau$ with SMOS’s retrievals of $\tau$, I selected the 30 most cultivated pixels (Figure 4.2). These pixels should minimize effects from urban areas and forested areas; urban areas (uncertain electrical properties of surface) and forests (too large VWC for 0th order $\tau$-$\omega$ model) can be problematic for soil moisture and $\tau$ retrievals. The 30 pixels ranged in areal crop fractions from 75–85%.

Corresponding SMOS pixels were found by taking the nearest neighbor to each SMAP pixel. The distance between SMAP and SMOS pixel centroids ranged between 1–9 km, and overlap was considerable (Figure 4.2). For each of these pixels, I extracted retrieved SMOS $\tau$ from the latest version (5.5.1) of the SMOS soil moisture product. Using the method from the previous chapter, the $\tau$ data were smoothed using FDA (see e.g. Figure 3.3).

I gathered MODIS Aqua and Terra 16 day 1 km vegetation indices products from 2003-
Figure 4.1: Centroid locations of all of the SMAP (●) and SMOS (∗) pixels that fit entirely inside Iowa.
Figure 4.2: The 30 SMAP pixel footprints (outlined circles) that contain the largest areal fractions of crops, and co-located SMOS pixels (gray-filled circles). The pixels labeled with a number will be referenced in following figures.
2013 for the two MODIS tiles that have data that intersect Iowa. The tiled data for each date were stitched together, subset over Iowa, and reprojected to a common geometric format (Universal Transverse Mercator zone 15N). For every 1 km pixel, the 16 day vegetation indices products provide the best available measurement (i.e. lowest cloud cover, no sunglint, etc.) of NDVI over the 16 day period and the day of year within the 16 day period when the NDVI measurement was made.

To develop the MODIS NDVI climatology for each of the 30 SMAP pixels, I found the mean NDVI and mean day of year (of NDVI measurements) inside each SMAP pixel footprint for each 16 day MODIS product. I used FDA to smooth the resulting mean NDVI and mean day of year data to generate a daily climatology of NDVI for each pixel (Figure 4.3). Days with NDVI values below 1.75 were ignored for likely being influenced by snow. This method for deriving the NDVI climatology used for generating SMAP $\tau$ data does differ from the official SMAP method (O’Neill et al., 2012) in a few ways, as the official method:

- uses NDVI data only from the Terra satellite,
- uses data from years 2000–2010,
- reprojects data onto a geographic (i.e. latitude/longitude-based) projection (0.01° resolution),
- uses data quality flags to discard data,
- generates the NDVI climatology for every 10 days during the year, and
- does not aggregate to SMAP pixel scale.

However, despite all of these differences, my results compare well to examples given in O’Neill et al. (2012). For example, the NDVI climatology for the SMAP pixel located in central Iowa (#3) (Figure 4.3) compares almost exactly with an example given for Walnut Creek, Iowa in O’Neill et al. (2012) (Figure 4.4).

For the next step, I computed the VWC climatologies for each of the 30 SMAP pixels using the following equation from the official SMAP document on vegetation water content (Chan
Figure 4.3: NDVI climatologies for five SMAP pixels.
Figure 4.4: NDVI climatology for Walnut Creek, Iowa. Reproduced from O’Neill et al. (2012).
\[ VWC = (1.9134 \text{ NDVI}^2 - 0.3215 \text{ NDVI}) + \text{stem factor} \times \frac{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}}{1 - \text{NDVI}_{\text{min}}}. \]  

\text{(4.1)}

The first half of the equation estimates the water content of leaves while the other half estimates the water content of stems. For cropland, the stem factor is 3.50 (Chan et al., 2013). The equation is simplified by assuming \( \text{NDVI}_{\text{min}} = 0.1 \), and, for crops, the daily climatological value of NDVI is used in place of \( \text{NDVI}_{\text{max}} \). The results for five SMAP pixels can be seen in Figure 4.5. Note that for all of the SMAP pixels, the VWC climatologies remained below 5 kg m\(^{-2}\) for the entire timeseries. The SMAP mission’s accuracy requirements only hold for areas where VWC \( \leq 5 \text{ kg m}^{-2} \).

Finally, to get values of SMAP \( \tau \), following O’Neill et al. (2012), I used Equation 1.4, which relates \( \tau \) and VWC, with the current proposed value of \( b \) for all croplands, \( b = 0.110 \). Results for five SMAP pixels can be seen in Figure 4.6. I also plotted the SMAP \( \tau \) climatology for each of the five pixels against the smoothed SMOS \( \tau \) timeseries from 2010–2013 in Figures 4.7, 4.8, and 4.9.

### 4.3 Results

The SMAP \( \tau \) timeseries have a reasonable phenology (Figure 4.6): the timeseries increase in late May/early June, close to the time that crops in Iowa begin to emerge; they reach a peak in early August (August 7 or 8, on average), which coincides with crops beginning their reproductive stages; and, finally, they decay until early to mid October, when crops are maturing, senescing, and harvested. However, the SMOS \( \tau \) timeseries show that there can be a significant variability year to year in the exact timing of each of these stages. For example, for the SMOS and SMAP pixels in the northern part of Iowa (Figure 4.7), SMAP \( \tau \) matches well in peak timing for 2010, 2011, and 2013, but in 2012, SMOS \( \tau \) peaked at the end of July, which precedes the SMAP \( \tau \) prediction by about 15–20 days. In general, SMOS \( \tau \) peaked early in 2012 across the 30 pixels (Table 4.1). But averaged across all years, SMAP \( \tau \) reasonably
Figure 4.5: VWC climatologies for five SMAP pixels.
Figure 4.6: $\tau$ climatologies for five SMAP pixels.
Figure 4.7: Comparison of SMAP and SMOS $\tau$ for pixels in northwest Iowa (1) and north central Iowa (2).
Figure 4.8: Comparison of SMAP and SMOS $\tau$ for pixels in central Iowa (3) and east central Iowa (4).
predicts the timing of the peak of the growing season, only off by 2.5 days from the average of the SMOS data.

In terms of magnitude, SMAP τ generally rises too quickly (and, sometimes, too early) in the first half of the growing season, and reaches a peak of τ that is, on average, 0.1 units greater than the peak of the smoothed SMOS τ (Table 4.1). SMOS τ does come close to SMAP τ peak values in 2012, though, and considering the noise in SMOS’s τ data, the peak values between 2012 SMOS τ and SMAP τ may not be significantly different. But since the timing

Table 4.1: Mean maximum τ and corresponding day of year of maximum τ averaged across all 30 pixels.

<table>
<thead>
<tr>
<th>Mission</th>
<th>Year</th>
<th>τ_{max}</th>
<th>Day of Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>SMOS</td>
<td>2010</td>
<td>0.3119</td>
<td>222.5</td>
</tr>
<tr>
<td></td>
<td>2011</td>
<td>0.3533</td>
<td>227.7</td>
</tr>
<tr>
<td></td>
<td>2012</td>
<td>0.3701</td>
<td>206.5</td>
</tr>
<tr>
<td></td>
<td>2013</td>
<td>0.3414</td>
<td>231.6</td>
</tr>
<tr>
<td>SMOS Climo</td>
<td>0.3442</td>
<td></td>
<td>222.1</td>
</tr>
<tr>
<td>SMAP Climo</td>
<td>0.4512</td>
<td></td>
<td>219.5</td>
</tr>
</tbody>
</table>
between the peaks are most different in 2012, some of the largest differences between SMOS $\tau$ and SMAP $\tau$ can be found late in the 2012 growing season.

There are many viable reasons for why SMOS $\tau$ and SMAP $\tau$ are different. Estimation of VWC at large scales is difficult and requires the use of empirical models that may have only been tested over a single location or a single time period. Other issues involving estimation of VWC are discussed in Chan et al. (2013).

Another possibility is that SMAP’s estimates of VWC from a NDVI climatologies are “good”, but the value of $b$ that is being used is too large or varies from year to year. Recalling Chapter 3 where I presented results from a method of determining $b$ at the satellite scale from SMOS, I found a mean value of $b$ for all of Iowa to be 0.065 in 2010, 0.085 in 2011, and 0.100 in 2012. Adjusting Equation 1.4 ($\tau = b \times \text{VWC}$) to use these $b$ values in these years with the VWC climatology computed from NDVI and recomputing the SMAP $\tau$ “climatology” (which is no longer the same every year), I find that the peak values are much more similar (Figures 4.10, 4.11, and 4.12), though, of course, there is no improvement in timing.

While it is not feasible to adjust for $b$ every year in real time using this method, as it requires estimates of crop yields and SMOS $\Delta \tau$, which are only available at the end of the year, these results encourage more inquiry in to the $b$ parameter. For static values, though, the data presented here suggest that a $b$ parameter value of 0.110 may be too high for the particular case of the croplands of Iowa. However, SMAP’s soil moisture retrieval algorithm differs from SMOS’s in one important way: SMAP will consider non-zero single scattering albedos. For all croplands, SMAP’s current method will use $\omega = 0.05$. A non-zero value of $\omega$ means that higher values of $\tau$ (and, therefore, $b$) are needed to correctly model the contribution of vegetation in the $\tau$-$\omega$ model. For example, Jackson and O’Neill (1990) used $\omega = 0.05$ and $\omega = 0$ to retrieve $b$ values in a tower-based study over a soybean field. They found that $b$ was 20% larger for the case where $\omega = 0.05$. Still, there is a wide range in $\tau$ peak magnitude from year to year in SMOS (which assumes $\omega = 0$), and the difference in SMOS-derived and SMAP-constant $b$ was as large as 40% in 2010.
Figure 4.10: Comparison of $b$-adjusted SMAP and SMOS $\tau$ for pixels in northwest Iowa (1) and north central Iowa (2).
Figure 4.11: Comparison of $b$-adjusted SMAP and SMOS $\tau$ for pixels in central Iowa (3) and east central Iowa (4).
4.4 Conclusion

I hypothesized that the saturation of NDVI would cause NDVI climatology-derived estimates of $\tau$ over croplands to be low compared to SMOS $\tau$. However, we found that, using SMAP’s proposed method for deriving $\tau$ from an NDVI climatology, that $\tau$ is actually overestimated compared to SMOS $\tau$ during the peak of the growing season. The overestimation of peak $\tau$ can be partially explained by SMAP assuming a non-zero $\omega$, however, there is still variability that can not be explained by SMOS and SMAP’s different assumptions about scattering. Allowing the $b$-parameter to vary from year-to-year based on my estimates from the previous chapter reduced SMAP $\tau$ and brought it more in line with values of SMOS $\tau$ during the growing season. I also hypothesized that SMAP $\tau$ would peak earlier in the growing season than SMOS $\tau$. On average, SMAP $\tau$ peaks earlier, but only by about 2.5 days. However, when considering the annual timeseries of SMOS $\tau$ data, there can be large differences in timing of peak $\tau$. In one case, the peak in SMAP $\tau$ occurred 19 days after the peak in 2012 SMOS $\tau$.

Given these results, what is the impact on SMAP soil moisture retrievals? Over the last
Figure 4.13: Brightness temperature sensitivity curves for SMOS and SMAP given their average maximum $\tau$ values over the growing season. Dotted lines show an example single channel algorithm retrieval for $T_B = 265.6$ K.

Four years, the average peak value of SMOS $\tau$ in the 30 most agricultural pixels during the growing season was 0.3442 (Table 4.1). The average peak value of SMAP $\tau$ for these pixels is 0.4512. According to SMOS $\tau$, the mean day of year of the peak in $\tau$ is August 11. Using the Iowa Environmental Mesonet Climodat (Herzmann, 2014), the closest long-term weather station to the central Iowa SMAP pixel (pixel #3) was located in Humboldt, Iowa. Low temperatures usually occur around the time of morning SMOS/SMAP overpass, at 6 AM. The average low temperature for August 11 in Humboldt, Iowa is 58°F (14°C, 287 K). The only August 11 morning SMOS overpass available for central Iowa occurred in 2011, when SMOS measured $T_B(\theta = 40°) = 265.6$ K. Assuming a typical roughness parameter, $h = 0.1$, and a typical Iowa soil clay content of 30%, using the $\tau$-$\omega$ model (Equation 1.3) with Mironov et al. (2009), I retrieved the volumetric soil moisture that corresponded to the measured brightness temperature given the two satellites’ average values of $\tau$ (Figure 4.13). For SMOS, the retrieved soil moisture is $0.098 \text{ m}^3 \text{ m}^{-3}$, while for SMAP it is $0.081 \text{ m}^3 \text{ m}^{-3}$, a difference of $0.017 \text{ m}^3 \text{ m}^{-3}$. 
As the difference in retrieved soil moisture is less than 0.04 m$^3$ m$^{-3}$, this is evidence against my hypothesis that SMOS and SMAP retrieved soil moisture at the peak of the growing season would diverge by more than the mission accuracy requirement. However, given that the lines in Figure 4.13 diverge as soil moisture increases, this example may not hold true in all cases, particularly for wetter soils (i.e. lower brightness temperatures). For example, if $T_B^h = 240$ K, the differences in retrieved soil moisture would be around 0.05 m$^3$ m$^{-3}$.

Even though it was not a focus of this study, there are also major differences between SMOS $\tau$ and SMAP $\tau$ outside of the growing season. These differences in $\tau$, which can be even larger than the differences at the peak of the growing season, are likely caused by changes in soil roughness due to tillage practices and/or the presence of residue on most fields in Iowa (Patton and Hornbuckle, 2013). The NDVI climatology does not track changes in soil roughness, and so $\tau$ drops to near zero outside of the growing season. More study is needed to predict the impact on soil moisture retrieval accuracy of adjusting or not adjusting $\tau$ and/or roughness parameters in the SMAP retrieval algorithms to account for these changes in roughness.
CHAPTER 5. SUMMARY AND DISCUSSION

The goals of this dissertation were to:

1. validate SMOS $\tau$ using large-scale measurements of vegetation,

2. use SMOS $\tau$ to estimate a key parameter, $b$, at the satellite scale, and

3. compare SMOS $\tau$ to the SMAP $\tau$ climatology.

For the first goal, in Chapter 2, I compared SMOS $\tau$ over a growing season in Iowa to county crop yield estimates, finding that higher yielding counties correlated with higher values of $\tau$. This correlation was the expected result, so my conclusion was that SMOS $\tau$ is related to the growth of vegetation during the growing season, even though it is noisy and has strange behavior outside of the growing season. I hypothesized and gave some evidence that SMOS $\tau$’s behavior outside of the growing season may be due to changes in soil roughness, and gave an example of how physical roughing of the soil due to tillage could cause a rise in $\tau$.

For the second goal, in Chapter 3, I developed a method of estimating the $b$ parameter from SMOS for counties in Iowa by using the $\tau$-yield relationship found in Chapter 2. By exploiting a chain of allometric relationships, I showed that, theoretically, $b$ could be estimated combining the slope of the $\tau$-yield relationship with the harvest index and the ratio of maximum vegetation water content to maximum dry vegetation mass. Initially, my results from this method seemed poor, as I found values of $b$ that were lower than expected based on published values of $b$ from field campaigns. However, applying my estimates of $b$ to the computation of SMAP $\tau$ in Chapter 4 brought SMAP $\tau$ in closer alignment with SMOS $\tau$.

For the third goal, in Chapter 4, I followed NASA SMAP’s method (though with slight variations) to develop NDVI climatologies for 30 co-located SMAP and SMOS pixels in Iowa.
Continuing with SMAP’s method, I used the NDVI climatologies to compute VWC climatologies, and then used SMAP’s proposed value of the $b$ parameter for croplands to produce a $\tau$ climatology for each pixel. SMAP $\tau$ was larger than SMOS $\tau$ during the peak of the growing season by about 33%. The average timing of the peak in SMOS and SMAP $\tau$ was close, differing, when averaging over all years of SMOS data, by only 2.5 days.

Returning back to the hypothesis I gave in Chapter 1:

the difference between SMAP’s climatology of $\tau$ and SMOS $\tau$ during the peak of the growing season in Iowa will lead to retrievals of volumetric soil moisture that differ by more than 0.04 m$^3$ m$^{-3}$,

I took the results from Table 4.1 and did an example soil moisture retrieval (Figure 4.13), to test this hypothesis. The soil moisture retrieved for the two satellites in this example differs by less than 0.04 m$^3$ m$^{-3}$, which gives some evidence to reject my hypothesis and to suggest that SMAP will meet its mission requirements in the peak of the growing season. However, the example is for a case of dry soils; wetter soils would result in a larger difference in retrieved soil moisture by the two satellites.

More research could and should be done regarding SMOS and SMAP vegetation optical thickness and estimating the $b$ parameter that links optical thickness and vegetation water content. Past soil moisture and vegetation water content remote sensing calibration and validation (cal/val) experiments in the U.S. Corn Belt (e.g. SMEX02, Jackson et al., 2004) have focused only on the early part of single growing seasons. The research presented in this dissertation shows that, according to SMOS retrievals in Iowa,

1. $\tau$ exhibits significant interannual variability in its timing and magnitude,

2. $\tau$ and/or soil roughness varies outside of the growing season, and

3. $b$ may vary year to year.

These results suggest that future microwave remote sensing studies (e.g. SMOS and SMAP cal/val experiments) would benefit by establishing long term experiments over agricultural sites that observe $T_B$, soil moisture, and VWC and derive $\tau$ and $b$ (and possibly $h$ and other
roughness-related parameters) over multiple growing seasons and over different soil and residue management practices outside of growing seasons. These studies would help to parameterize SMAP retrievals in the U.S. Corn Belt and similar regions around the world that largely cultivate maize. These regions have large intra-annual (0 to 6 kg m$^{-2}$) changes in VWC during the growing season, may have large changes in roughness and/or $\tau$ outside of the growing season due to tillage and residue management, and may have large interannual changes in $\tau$. Finally, more research could be done with respect to SMOS retrievals by looking at potential angular/polarization dependencies of $\tau$, $b$, and $\omega$. SMOS, through its full polarization and multi-angular measurements, has the capability of including these dependencies in its retrieval algorithm, however the current assumption is that these effects are small at the satellite-scale and not worth accounting for at the expense of extra computations.
BIBLIOGRAPHY


Mahmoodi, A. (2011), Algorithm Theoretical Basis Document (ATBD) for the SMOS Level 2 Soil Moisture Processor Development Continuation Project.


