

Review

Remote sensing and soil moisture

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Soil moisture constitutes an important contribution to the knowledge of a part of the water balance at the global, regional, and local scales. Hence, this information is widely used in hydrological applications helping to quantify the diverse components of the water balance – infiltration, surface runoff, evaporation, deep percolation, and changes in water content. Remote sensing provides researchers and the community with the possibility to monitor changes in land and ocean around the globe, especially where in-situ observations are limited or non-existent. Microwave remote sensing enables satellite to get observations day and night regardless of the lighting conditions, and at selected frequencies, microwave emissions have a good cloud penetration which proves to be an immensely advantage over the oceans, which are on average 70% covered by clouds. We can mention the recent success: 2009: ASCAT soil moisture product available in NRT, 2010: First Soil Moisture Network (ISMN) takes off 2011: International first merged multi-radiometer soil moisture product, 2012: First ECV soil moisture data set covering 1978-2010 released, 2013: Launch of Sentinel-1.

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INTRODUCTION

Soil moisture is most often described as the water in the root zone that can interact with the atmosphere through evapotranspiration and precipitation. Because soil moisture links the hydrologic cycle and the energy budget of land surfaces by regulating latent heat fluxes, accurate assessment of the spatial and temporal variation of soil moisture is important for the study, understanding, and management of surface biogeophysical processes. Given the crucial role of soil moisture in land surface processes, it should be monitored with the same accuracy and frequency as other important environmental variables. However, because in situ soil moisture measurements are generally expensive and often problematic, no large-area soil moisture networks exist to measure soil moisture at the high frequency, multiple depths, and fine spatial resolution that is required for various applications. Remote sensing of soil moisture is limited by errors introduced by soil type, landscape roughness, vegetation cover, and inadequate coverage in both space and time. Alternatively, many reliable hydrologic models are available for calculating soil moisture, but these are prone to error in both structure and parameterization. It has been suggested (Wei, 2005) that the best, operational soil moisture estimates might be obtained through a synthesis between remote-sensing data and

hydrologic modeling. Remote-sensing data, when combined with numerical simulation and other data, should provide estimates of soil moisture with higher spatial and temporal resolution and less error than either remotely sensed data or model simulations separately.

Recent successes and prospects

- 2002: First global soil moisture data set from ERS SCAT published
- 2003: NASA soil moisture product based on AMSR-E put into operations
- 2007: SMOS soil moisture data released
- 2009: ASCAT soil moisture product available in NRT
- 2010: First Soil Moisture Network (ISMN) takes off
- 2011: International first merged multi-radiometer soil moisture product
- 2012: First ECV soil moisture data set covering 1978-2010 released
- 2013: Launch of Sentinel-1
 - First operational soil moisture product at ≤ 1 km spatial resolution
- Prospects
- 2014: Launch of SMAP
 - First active/passive sensor at L-band

Soil moisture constitutes an important contribution to the knowledge of a part of the water balance at the global, regional, and local scales. Hence, this information is widely used in hydrological applications helping to quantify the diverse components of the water balance – infiltration, surface runoff, evaporation, deep percolation, and changes in water content (Davenport et al., 2005). The groundwater storage may have a direct impact on human health, and can influence agriculture activities, economy, military activities and transportation. Therefore, information about the topsoil layer is important to monitor crop conditions, and information about the moisture in deeper soil is crucial for agricultural planning and management of water resources. Additionally, low levels of soil wetness can lead to drought or wild land fire, whereas saturated soil together with precipitation may increase the risk of flooding. The knowledge of soil moisture is also of extreme importance in weather and climate forecasting.

Considering that the atmosphere has millions of degrees of freedom, weather forecasts have a limit of deterministic predictability of around 14 days. Therefore, weather prediction is considered an initial value problem and numerical weather prediction (NWP) models require accurate data about the transfer of soil moisture, energy fluxes in the boundary layer, evaporation and the partitioning of sensible heat flux and latent heat flux to accurately predict the wind circulation and cloud development. Furthermore an evaporation rate that varies strongly and consistently with soil moisture tends to lead to a higher coupling strength between atmospheres and surface (Guo et al., 2006). Specific knowledge of surface wetness patterns on a regional scale can additionally aid in the forecast of thunderstorm location, maximum and minimum temperatures and identify restricted visibility related with haze, smog and fog. Models of ecosystem and carbon cycle processes require soil moisture because it regulates both soil respiration and plant water stress, which affects stomata conductance and carbon uptake. There are also benefits for the modulation of dust generation and trace gas fluxes from earth's surface. For military defense, too, soil moisture affects everything from low level fog forecasts to the calculation of density altitude, or lift capacity of aircraft. Satellite remote sensing of soil moisture is a key factor to understand land-atmosphere coupling. Large-scale observational products using microwave radiometry are an effective method of monitoring soil moisture heterogeneity (Gao et al., 2004).

Microwave remote sensing of soil moisture

Remote sensing provides researchers and the community with the possibility to monitor changes in land and ocean around the globe, especially where in-situ observations are limited or non-existent. Microwave re-

mote sensing enables satellite to get observations day and night regardless of the lighting conditions, and at selected frequencies, microwave emissions have a good cloud penetration which proves to be an immensely advantage over the oceans, which are on average 70% covered by clouds. Microwave sensors are used for retrieval of soil moisture because they are insensitive to vegetation. The two main properties of microwave radiation are polarization and frequency.

Polarization varies with the wavelength and with the physical characteristics of the emitting or reflecting material, which in turn allows the discrimination between solid, liquid, and frozen elements on both land and ocean surfaces. Microwave remote sensing covers both active and passive forms of operation. Passive instruments (radiometers) sense the naturally emitted microwave radiation in their field of view, measuring the emanating electromagnetic radiation from the earth's surface or physical objects. The sensors require a large field of view in order to detect low level of emitted microwave radiation. The low spatial resolution is a consequence of the Rayleigh criterion, which is a diffraction limit on the resolution of sensors based on the wavelength of the radiation and the size of the observing "aperture". The smallest angle α that can be resolved is calculated as $\sin(\alpha) = 1.22 \times (\text{wavelength} / \text{aperture diameter for circular apertures})$.

Active microwave systems include imaging (radar) and non-imaging sensors (altimeters, scatterometers). This type of sensor has its own source of illumination and measures the difference between the power emitted and the power received from the target. Space borne microwave radiometry is an important technique for obtaining global estimates of parameters important to the hydrological cycle and land-surface energy coupling (surface temperature, soil moisture, vegetation). The need for frequent information of soil moisture at fine resolution scale is in fact imperative for the improvement on model outputs. Microwave are electromagnetic waves with wavelengths ranging from one meter to one millimeter, or equivalently, with frequencies between 0.3 and 300 GHz. Electromagnetic waves travel at the speed of light c , and their frequency f and wavelength λ are related by $c = f \lambda$. In order to obtain an estimation of the soil moisture, the sensor measures the soil's naturally emitted microwave radiation, and traduces that information into brightness temperature.

The quality and quantity of grapevine production is controlled by many factors, such as soil characteristics, climate, management system and the frequency of exposure to pests and diseases. Recent studies (Bramley and Proffitt, 1999; Lamb and Bramley, 2001) show that productivity within a single vineyard could vary as much as eight-fold. Precision viticulture takes advantage of remote sensing and geomatics to model this variation and estimate yield quality and quantity at the vineyard level (Bramley, 2005). Soil particularly is an

important factor in determining the productivity of vineyards. Observations show that high and low production regions within a vineyard tend to be stable over a longer time (Bramley and Proffitt, 2000), and these patterns relate to soil spatial distribution, microclimate patterns and topography variations (Lamb, 2000). Identifying zones with similar soil type helps in the planning of a vineyard, by selecting the suitable grape varieties to soil type and allocating vineyards with homogenous soil to allow easy management (Lamb et al., 2002). In addition, soil information explains the interplay between year-to-year rainfall and production.

Therefore, “considerable effort in precision viticulture research aims at measuring and mapping spatial variability in soils at the single vineyard scale” (Hall et al., 2002). Remote sensing provides high quality spatial data for vineyard management. However, it is not applied widely in viticulture (Hall et al., 2002). Optical remote sensing is used to sense changes in properties of the few millimeters of the soil surface (Kaleita et al., 2005). Alternatively, researchers apply non-contact electromagnetic survey to map soil variability within a vineyard (Bramley and Proffitt, 2000; Bramley, 2005). Measured apparent electric conductivity is used as a proxy for soil moisture content, soil texture and salinity of the soil solution (Lamb and Bramley, 2001; Lamb et al., 2005). The utility of thermal remote sensing in detecting energy and moisture fluxes at the land surface is well documented (Bennett et al., 2008; Tian et al., 2011; Wang and Bras, 2011, 1999, 2010; Wei, 2005). For the purpose of monitoring soil moisture content, the common scheme is to decouple the surface thermal properties from ambient temperature (daily temperature cycle) by calculating the thermal inertia (TI), which is a physical property that characterizes the surface resistance to ambient temperature change (Pratt and Ellyett, 1979; Price, 1977; Verhoef, 2004; Verstraeten et al., 2006). Various studies report a strong relation between soil moisture content and TI (Minacapilli et al., 2009 and 2012; Verhoef, 2004). However, the thermal inertia method is mostly conducted over bare and dry ground, to avoid complexity added by variations in evapotranspiration patterns (Maltese et al., 2013). Nevertheless, recent studies (Price, 1985 and 1977) showed that soil moisture could be estimated over partially vegetated soil if a linear relation between ground flux and surface temperature is maintained. (Verhoef, 2004) calculated TI using the surface temperature drop, during nights with clear sky and still conditions, to avoid the complex surface energy exchange that occurs during the day. The author found a significant relation between TI calculated over bare soil and volumetric soil moisture content. However, remote thermal inertia techniques were not applied to vineyards. The previous method (Van Wijk, 1963) has a potential in vineyard application, because it avoids the complex heating and evapotranspiration during the day time. However, a careful test of the method is needed to

establish the validity of this method over vegetated surfaces (Murray and Verhoef, (2007). In this study, we evaluate a technique for estimating thermal inertia using airborne thermal images acquired over a grass covered soil in a vineyard in the Niagara Region, Ontario, Canada. The technique is based on the drop of surface temperature during the night and has not been tested over grass covered soil. We further explore the functional relationships between estimated thermal inertia in the presence of grass sod (we will refer to it subsequently as TI_c) and subsurface soil properties (moisture and mechanical resistance). Finally, we provide suggestions for improving soil moisture retrieval using the nocturnal thermal inertia method.

Theoretical background

TI [$J \cdot m^{-2} \cdot K^{-1} \cdot s^{-1/2}$] of a bare soil is a physical property that describes the response of soil to an ambient temperature change:

$$TI = \sqrt{\rho c k}$$

where ρ is the soil density [$kg \cdot m^{-3}$], c is soil specific heat capacity [$J \cdot kg^{-1} \cdot K^{-1}$] and k is soil thermal conductivity [$W \cdot m^{-1} \cdot K^{-1}$]. TI can be calculated from the night cooling of land surface assuming a constant rate of surface cooling (Van Wijk, 1963 and Verhoef, 2004):

$$TI = \frac{2|\overline{R_n}| \sqrt{\Delta t}}{\Delta T \sqrt{\pi}}$$

where $|\overline{R_n}|$ [$W \cdot m^{-2}$] is the average net radiation during the night, ΔT [K] is the night temperature drop and Δt [s] is the cooling period in seconds. The common method for calculating thermal inertia depends on the periodic daily heating; in contrast, Equation (2) depends on the non-periodic cooling of the surface under still and clear sky conditions. Theoretically, if one estimated thermal inertia over the same area using both methods, the results should be similar. However, the absence of turbulent heat fluxes (*i.e.*, sensible heat flux and latent heat) during the night simplify the relation between surface temperature and ground heat flux, which cannot be guaranteed during the day (Pratt et al., 1980 and Murray and Verhoef, 2007) proposed that increasing soil saturation will result in a logistic increase of TI. The authors based their theoretical relation on a model of thermal conductivity as a function of soil saturation by Johansen (Johansen, 1975):

$$TI = K_e(TI_s - TI_d) + TI_d$$

where the subscripts, s and d , denote the saturated and air-dry conditions, respectively, and K_e is a modified Kersten number, given by:

$$K_e = \exp \left\{ \gamma \left[1 - \left[\frac{\theta}{\theta_s} \right]^{\gamma - \delta} \right] \right\}$$

where γ is a soil texture-dependent parameter, δ is a shape parameter and θ/θ_s [-] is the soil saturation ratio. Estimating soil moisture content can be done by invert-

ing Equation (3) with the Kersten number, approximated by (Minacapilli et al., 2012):

$$Ke = \frac{TI - TI_d}{TI_s - TI_d}$$

The brightness temperature, measured using a thermal infrared sensor over a grass-covered soil, is modeled as the summation of (a) the energy of the soil surface emission, which passes through the plant canopy, (b) the energy of the plant canopy emission and (c) the reflected energy of plant canopy emission by the soil surface below it, which passes through the canopy (Mo et al., 1982):

$$T_b = \varepsilon_s \zeta T_s + (1 - \omega) \cdot (1 - \zeta) \cdot T_c + (1 - \varepsilon) \cdot (1 - \omega) \cdot (1 - \zeta) \cdot T_s$$

where T_b [K] is the brightness temperature measured by the thermal infrared (TIR) sensor, T_s [K] is soil surface temperature, T_c [K] is the plant canopy temperature, ε [-] is soil surface emissivity, ω [-] is the single scattering albedo and ζ [-] is the transmissivity of the vegetation canopy. The grass canopy (leaves) temperature differs from ambient air temperature by the net radiation at both the surface of the leaf and by the temperature diffusive resistance, which is a function of leaf size and wind speed (Oke 1988). The amount of heat storage, due to photosynthesis, is negligible over a day period. If remote sensing measurements are taken on a still clear night over a grass-covered soil, it can be assumed that the grass temperature is coupled to the ambient temperature. This will result in a linear reduction of the soil surface temperature, as determined by the transmissivity of the grass canopy and the sensor viewing angle (Equation (6)). Therefore, we postulate that using Equation (2) and surface temperature measured over a grass covered soil will result in an estimated T_{Ic} , which is proportional to the true T_I of the soil below the grass. Although Equation (2) has not been applied to a grass-covered surface before, a previous field study by Kim and England reports a significant relation between T_I calculated using passive microwave and soil moisture content over a grass covered area. There is a clear trade-off between using a complex data assimilation technique and the ability to use all the available data due to the large computational burdens of performing data assimilation at fine resolutions using dense data sets. On the basis of this study, it was found that, as the complexity of the data assimilation model increases, the size of the assimilated data set needs to decrease in order to maintain computational feasibility. Complex methods have the ability to extract more useful information from assimilated data, but simpler methods use more of the data to extract similar information. This trade-off allows simpler assimilation techniques to perform almost as well as complex techniques. In general, this argument suggests the use of assimilation methods that are of moderate complexity, are sound and computationally efficient, but use as much data as possible. If the information in the data can be efficiently compressed or filtered before its use in data

assimilation, it may be more reasonable to use larger data sets in complex data assimilation strategies. Because hydrologic data assimilation requires hydrologic modeling predictions, it is limited by a similar trade-off between fine resolution and large area implementation. A statistically based assimilation may be a viable approach for use in large areas, but ultimately the trade-off between resolution and area will be determined by the application. Several supplementary observations are essential for implementation of soil moisture data assimilation, the most important being meteorological forcing. Forcing averaged over large areas may be adequate, but detailed spatial patterns of precipitation are essential. Clearly, regular, remotely sensed soil moisture observations are required, but these must be supplemented by in situ surface and root zone observations across the operational domain to specify error correlations, to calibrate parameters, and to validate the model-calculated fields. Observations of soil and vegetation characteristics are likely needed for optimal model performance, while observations of surface water and energy fluxes are valuable for validating simulation results.

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