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Yang Hong, Yu Zhang, Sadiq Ibrahim Khan

Soil Moisture Estimation Using Active and Passive Remote Sensing Techniques

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Ming Pan, Xing Yuan, Hui Lu, Xiaodong Li, Guanghua Qin
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3 Soil Moisture Estimation Using Active and Passive Remote Sensing Techniques

Ming Pan, Xing Yuan, Hui Lu, Xiaodong Li, and Guanghua Qin

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3.1 INTRODUCTION

Soil moisture is a key land surface state variable for its important role in regulating the energy and moisture fluxes between the atmosphere and land surface. It is an important boundary condition for the atmosphere and imposes a strong control on the water and energy exchanges between the land and atmosphere through regulating the evapotranspiration flux (Koster and Suarez, 1992). Better knowledge of soil moisture greatly contributes to our understanding of land surface processes (Albertson and Parlange, 1999; Cahill et al., 1999). Because the land surface soil moisture has a longer memory than the dynamic processes in the atmosphere, better quantification of land surface soil moisture status has the potential to improve numerical weather
forecasts at both short-term and seasonal scales (Koster and Suarez, 2001), especially in the warm season when land–atmosphere interactions are greatest. Operational large-scale soil moisture observational products would likely enhance the accuracy of numerical weather prediction products, hydrologic flood forecasting, agricultural drought monitoring as well as water cycle research related to climate studies. Soil moisture information is also of great value in agriculture and water resources management, especially for drought management (Sheffield and Wood, 2007; Mo, 2008).

Therefore, efforts have been made in developing soil moisture observational networks (Robock et al., 2000) and evaluating soil moisture as modeled by land surface schemes (Schaake et al., 2004) and climate models (Luo and Wood, 2008). However, soil moisture is highly variable across a range of temporal and spatial scales (Crow and Wood, 1999; Pan et al., 2009), making it difficult to either model or measure. *In situ* measurement of soil moisture is carried out by networks of ground sensors, for example, the Natural Resource Conservation Service’s (NRCS) Soil Climate Analysis Network (SCAN) and the National Oceanic and Atmospheric Administration’s (NOAA) United States Climate Reference Network (USCRN) (Bell et al., 2013; Diamond et al., 2013), both of which use a frequency domain reflectometer (Seyfried et al., 2005) to measure soil moisture content at different depths. More recently, more coherent efforts have been made to implement *in situ* networks across the conterminous United States (Jackson et al., 2012b). Still, ground networks are generally very expensive and cannot offer large-scale coverage with reasonable density (Robock et al., 2000). Therefore, space-borne remote sensing provides an important global alternative to the limited *in situ* observations of soil moisture (Owe et al., 2008).

### 3.2 ESTIMATING SOIL MOISTURE CONTENT FROM MICROWAVE SENSORS

The underpinnings of space-borne soil moisture remote sensing come from the fact that changes in surface soil moisture content lead to changes in the surface emissivity and backscattering properties in microwave frequencies. Therefore, passive satellite sensors (radiometers) can detect soil moisture variations by measuring the brightness temperature (Njoku, 1977) and active sensors (radars) can detect soil moisture variations by measuring the backscatter returned to a satellite sensor (Dobson and Ulaby, 1986). Simply speaking, wetter soil looks cooler in the eyes of the radiometer relative to its physical temperature and appears brighter on a radar scan. However, vegetation also emits and backscatters microwave signals, and dense vegetation (e.g., forests) can significantly attenuate or overwhelm the soil moisture signals especially at short wavelengths, making it hard or impossible to retrieve soil moisture information. Heavy rain clouds also add noise to the retrieval process and retrievals over active raining areas are less reliable. Also, microwave signals can only penetrate a thin layer of soil, about 1/10 to half of the wavelength, so the remotely sensed soil moisture is representative of a shallow surface layer. Longer wavelengths result in a deeper penetration and so far 1.4 GHz (L-band; 1–5 cm penetration) is the longest wavelength in use due to technical limitations and tradeoffs in antenna size, orbital geometry (including the implications for revisit time), and other factors.
Nevertheless, the global coverage and long-term availability of remote sensing products makes them an extremely valuable source of observations for large-scale analysis in applications such as model validation, drought analysis, and climate studies.

3.2.1 Radiative Transfer Process from Ground to Space and Passive Remote Sensing

Passive measurements in microwave frequencies can be used for monitoring surface moisture conditions for a number of reasons. First, as the soil water content increases, the dielectric conductivity of the wet soil decreases, resulting in reduced surface emission (or brightness temperature). The lower the frequency, the higher is the sensitivity to soil moisture. Second, atmospheric emissions are minimal at many microwave frequencies such that land surface emission can penetrate through the atmosphere and thin clouds with little atmospheric attenuation (Ulaby et al., 1982). Research has been done to establish the physical relationship between soil moisture and other surface conditions and the brightness temperature measured in space. Such a physical relationship is usually parameterized into a radiative transfer model (RTM). An RTM calculates the brightness temperature measured at the top of atmosphere (TOA) given the conditions of soil (temperature, wetness, texture, etc.), vegetation (thickness, structure, temperature, etc.), and atmosphere (temperature, pressure, humidity, etc.). Usually, the RTM is the basis for retrieving surface soil moisture from satellite measurements.

Figure 3.1 shows the radiative transfer process over a vegetated soil surface. $T_s$ and $T_v$ are the physical temperature of the soil and vegetation, $T_{b,a}^{\uparrow}$ and $T_{b,a}^{\downarrow}$ are the up- and downward brightness temperature of the atmosphere, $\Gamma_v = \exp(-\tau_v)$ and $\Gamma_a = \exp(-\tau_a)$.
\[ \Gamma_a = \exp(-\tau_a) \] are the transmissivity of the vegetation layer and atmosphere (\( \tau_v \) and \( \tau_a \) are the optical depth of the vegetation and atmosphere), \( \varepsilon_s \) and \( \omega_v \) are the emissivity of the wet soil and single scattering albedo of the vegetation layer, and \( T_{b, \text{c}} \) is the brightness temperature of the cosmic background.

The figure shows that the emission reaching TOA consists of six components: (1) soil emission, (2) direct vegetation emission, (3) reflected vegetation emission, (4) reflected cosmic emission, (5) reflected atmospheric emission, and (6) upward atmospheric emission. Not all these six components are important and almost all RTM schemes will do some simplifications, for example, the cosmic and atmospheric contributions are constants and these constants are usually determined through calibrations (Drusch et al., 2001) and only the soil and vegetation emissions need to be parameterized. And the brightness temperature at TOA is

\[
T_b = \varepsilon_s T_t \Gamma_v \Gamma_a + T_v (1 - \omega_v) (1 - \Gamma_v) (1 + (1 - \varepsilon_s) \Gamma_v) \Gamma_a + \text{constant}
\]

An important goal of an RTM is to parameterize the relationship between moisture content \( \theta \) and wet soil emissivity \( \varepsilon_s \), together with other soil and vegetation parameters, such that once the surface moisture/temperature is known, the brightness temperature at TOA can be calculated. To this end, some researchers use very detailed physical models that include dielectric property of wet soil (Wang and Schmugge, 1980; Dobson et al., 1985) and soil polarization mixing (Choudhury et al., 1979; Wang and Choudhury, 1981), while others simply lump everything (emissivity, soil roughness, etc.) into one effective emissivity parameter (de Jeu et al., 2008; Pan et al., 2014). For the vegetation properties, they can be treated as a simple function of the leaf area index and vegetation type (Kirdyashev et al., 1979), or in most cases, estimated simultaneously with soil moisture from measurements of multiple polarizations and/or multiple frequencies.

The bare soil is considered a special case of vegetation surface where the vegetation is completely transparent; however, the water surface needs to be treated differently as the water body has a dramatically lower emissivity.

Once the radiative transfer process is parameterized, the retrieval of soil moisture from satellite measurements is simply a reverse estimation problem. This could be done by inverting the RTM using a root-finding algorithm, for example, the land surface microwave emission model (LSMEM) approach (Drusch et al., 2001; Gao et al., 2004, 2006), the retrieval products by the United States Department of Agriculture (USDA) (Jackson, 1993; Jackson et al., 1999; Jackson and Hsu, 2001) and the L-band Microwave Emission of the Biosphere (L-MEB) model (Wigneron et al., 2007) used for SMOS soil moisture retrievals at the European Centre for Medium Range Weather Forecasts. This approach usually solves for one unknown (soil moisture) given the brightness temperature from a single channel/polarization and the inversion is algorithmically simple. But it requires many physical parameters, some of which we lack any accurate knowledge of, for example, the emission/optical properties of the soil surface and vegetation cover in target frequency.

The alternative to parameter-intensive approaches is to solve for more parameters altogether. The initial production of the official National Aeronautics and Space
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Administration (NASA) Advanced Microwave Scanning Radiometer (AMSR-E) soil moisture product (Njoku et al., 2003) takes a multichannel and multipolarization approach (Njoku and Li, 1999) where the vegetation properties and soil moisture (as well as the surface temperature) are solved simultaneously. Later this approach was revised such that the combined vegetation-roughness effect is modeled as a function of the microwave polarization difference index (MPDI) and the soil moisture is estimated as a deviation relative to a reference dry moisture condition (Njoku and Chan, 2006). The land parameter retrieval model (LPRM) (Owe et al., 2001) provides another alternative based on the concept of the MPDI and it solves for the soil moisture and other parameters through an iterative optimization procedure (de Jeu et al., 2008). The improved LSMEM approach (Pan et al., 2014) also falls into this category. Figure 3.2 gives an example of soil moisture retrievals (Pan et al., 2014) and the comparison against in situ observations over two sites in the United States. These time series clearly show that the passive microwave estimates can very well capture the dynamics of daily soil moisture variations.

3.2.2 RADAR BACKSCATTER AND ACTIVE REMOTE SENSING

A very strong limitation of the passive sensors arises from the fact that all the signals the radiometer can receive come from the natural emission of the target (soil). Such natural microwave emission is quite weak by itself, thus the sensor antenna has to have a very large effective aperture to achieve a reasonable spatial resolution and noise-to-signal ratio. Or otherwise the satellite has to fly lower, that is, to measure at a closer distance to the target. However, both the large antenna and low orbit can

FIGURE 3.2 Soil moisture retrieval (LSMEM) time series versus ground observations from the SMEX03 campaign over two areas in (a) Little River, GA, and (b) Little Washita, OK.
dramatically add to the manufacture and operation cost and bring compromises on other aspects such as swath width, revisit time, service life, and so on. The most practical design of a passive sensor (e.g., with an unfolding antenna reflector or synthetic aperture design) and orbit configuration can achieve the ground spatial resolution of several tens of kilometers. To further improve the resolution, active sensors are needed. The active sensor, also known as radar, sends a well-focused microwave beam to the target through a transmitter pretty much like shining a flash light on the target when we need to see it in the dark. As the radar beam hits the target (soil and vegetation), part of the energy is scattered back and measured by the radar (see Figure 3.3). The wetter the soil or vegetation is, the brighter it looks on the radar screen. Because the radar shines a bright beam onto the surface, the returned signals are much stronger than a passive sensor and a significantly higher spatial resolution can be achieved (several kilometers).

The relationship between backscatter signals and soil/vegetation water has also been studied for a long time (Ulaby et al., 1982). The basic theory is that the radar backscatter intensity depends on the soil moisture content (linearly) and other factors such as vegetation water content and viewing angles. At the same time, the viewing angle dependence of backscatter is not caused by soil moisture but vegetation, and this allows the vegetation effect to be removed by analyzing the angular behavior of the backscatter. After soil moisture dynamics are extracted from the backscatter data, the time series can then be normalized to a predefined range (e.g., zero to saturation). One typical example is various versions of the WAter Retrieval Package (WARP) algorithm, for example, WARP4 and WARP5 (Naeimi et al., 2009). As different radars have different sets of viewing angles and sampling patterns (e.g., real aperture vs. synthetic aperture), the retrieval (Dobson and Ulaby, 1986; Wagner
et al., 1999) and the algorithm may vary slightly with the specific design of the radar (Naeimi et al., 2009; Entekhabi et al., 2010).

3.3 SATELLITE MISSIONS AND MICROWAVE SENSORS

Even though the research about estimating surface soil moisture from microwave sensors started decades ago (Njoku, 1977; Wang and Schmugge, 1980; Ulaby et al., 1982), there have not been any “dedicated” satellite missions for soil moisture observations until very recently, that is, the launch of the European Space Agency (ESA) Soil Moisture and Ocean Salinity (SMOS) mission on November 2, 2009. Prior to SMOS, nevertheless, many other satellite missions do carry microwave sensors (radiometers and radars). These microwave sensors are deployed primarily for measuring other parameters such as cloud activities, precipitation, water vapor, sea wind, and so on, and the science community has been utilizing these “opportunistic” sensors for soil moisture retrievals. Sensors not specifically designed/built for soil moisture observing purposes may not carry the best channels or optimally configured for soil moisture detections, but very successful efforts have been made by various researchers to derive soil moisture datasets from those sensors.

3.3.1 Passive Sensors

A number of microwave sensors (generally dedicated to purposes other than soil moisture measurement) have been utilized to estimate soil moisture, from the early Scanning Multichannel Microwave Radiometer (SMMR) sensor on board Nimbus (launched in 1978) to the most recent and fully dedicated Soil Moisture Active and Passive (SMAP) mission (Entekhabi et al., 2010) launched January 31, 2015 (see Table 3.1).

3.3.2 Active Sensors

The number of active sensors is much smaller than the passive sensors because the latter usually serve more purposes than the former. Soil moisture retrievals have been made primarily upon only three active sensors, the scatterometers on board the European Remote Sensing satellites (ERS-1 and ERS-2) and the METeorological OPerational satellite (METOP). The ERS-1 and ERS-2 satellites carry a 5.3 GHz scatterometer (SCAT) and METOP carries an improved version of the instrument, the Advanced Scatterometer (ASCAT). The third active sensor flies on board the SMAP mission, a 1.4 GHz synthetic aperture radar.

3.4 SOIL MOISTURE RETRIEVAL PRODUCTS

Prior to SMAP and SMOS, most satellite-based soil moisture estimation was via passive sensors of opportunity, with wavelengths shorter than are desirable for soil moisture sensing. Many studies have therefore been devoted to understanding the radiative transfer processes that link the soil moisture to the brightness temperature measured by space-borne sensors, and these studies have led to a number of soil moisture retrieval algorithms. Therefore, quite a large number of soil moisture
retrieval products, both operational and experimental, have been created based on different satellite sensors and by many institutions.

Among satellite (as contrasted with airborne) sensors, the AMSR-E is one of the most frequently used for its relatively long service time, modest radio frequency interference in its 10.7 GHz channel, and public availability. The official NASA AMSR-E product (Njoku and Li, 1999), the LPRM (Owe et al., 2001; de Jeu et al., 2008), and the modified LSMEM-based AMSR-E retrievals (Pan et al., 2014) are produced by solving for the vegetation/other parameters separately from multiple polarizations or simultaneously with soil moisture through an iterative scheme. The USDA (Jackson and Hsu, 2001) also offers an AMSR-E retrieval product where a different approach is taken to use predefined vegetation parameters and to treat the soil moisture as the only unknown. The original version of AMSR-E-based LSMEM retrieval product (Gao et al., 2006) also takes a similar approach as the USDA product. See Figure 3.4 for the sample retrieval maps from four different products.

The LPRM model has also been used to retrieve soil moisture from other sensors such as Nimbus 7 SMMR, DMSP SSM/I, TRMM TMI (Liu et al., 2012), and AMSR2 (Parinussa et al., 2015). The USDA algorithm and LSMEM algorithm have

### TABLE 3.1

<table>
<thead>
<tr>
<th>Sensor and Platform</th>
<th>Channel</th>
<th>Resolution (km)</th>
<th>Revisit</th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scanning Multichannel Microwave Radiometer (SMMR), Nimbus-7</td>
<td>Multiple, from 6.6 GHz (4.5 cm)</td>
<td>140</td>
<td>Daily</td>
<td>1978–1987</td>
</tr>
<tr>
<td>Microwave Imager/Sounder (MIS), WindSat</td>
<td>Multiple, from 6.8 GHz (4.4 cm)</td>
<td>25</td>
<td>Daily</td>
<td>2003–present</td>
</tr>
<tr>
<td>TRMM Microwave Imager (TMI), TRMM</td>
<td>Multiple, from 10.7 GHz (2.8 cm)</td>
<td>25 (resampled)</td>
<td>Daily</td>
<td>1997–present</td>
</tr>
<tr>
<td>Special Sensor Microwave Imager (SSM/I), DSMP</td>
<td>Multiple, from 19.4 GHz (1.5 cm)</td>
<td>25</td>
<td>Daily</td>
<td>1987–present</td>
</tr>
<tr>
<td>Advanced Microwave Scanning Radiometer (AMSR-E), EOS-Aqua</td>
<td>Multiple, from 6.9 GHz (4.3 cm)</td>
<td>25 (resampled)</td>
<td>Daily</td>
<td>2002–2011</td>
</tr>
<tr>
<td>Soil Moisture and Ocean Salinity (SMOS), SMOS</td>
<td>1.4 GHz (21 cm)</td>
<td>~35</td>
<td>2–3 days</td>
<td>2009–present</td>
</tr>
<tr>
<td>Advanced Microwave Scanning Radiometer 2 (AMSR-2), GCOM-W</td>
<td>Multiple, from 6.9 GHz (4.3 cm)</td>
<td>25 (resampled)</td>
<td>Daily</td>
<td>2012–present</td>
</tr>
<tr>
<td>Soil Moisture Active and Passive (SMAP), SMAP</td>
<td>1.4 GHz (21 cm)</td>
<td>3, 9, 36</td>
<td>2–3 days</td>
<td>2015–present</td>
</tr>
</tbody>
</table>
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Also been applied to TRMM TMI (Jackson and Hsu, 2001; Gao et al., 2006). For the L-band sensor on board SMOS, the L-MEB model (Wigneron et al., 2007) is used to create the standard SMOS soil moisture product (Kerr et al., 2012). The Japan Aerospace Exploration Agency (JAXA) maintains an AMSR2-based soil moisture retrieval product (Fujii et al., 2009) that uses a similar algorithm for retrieving soil moisture from ASMR-E after some intercalibration between the two sensors (Imaoka et al., 2010).

With SMOS and SMAP products available to the community (see Figure 3.5 for an example of an early SMAP product), the community is beginning to have global soil moisture measurements (albeit of near-surface conditions) that have been targeted to hydrologic users. The designs of these missions are bringing about tremendous advances in the quality of retrieval products. Both SMOS and SMAP carry a radiometer operating at 1.4 GHz, the longest practical wavelength for soil penetration. The SMOS radiometer uses synthetic aperture techniques to achieve large equivalent antenna size and makes measurements at a range of incident angles. The SMAP radiometer has a large (6 m) space-deployed reflector antenna and a fixed angle design that enhances the spatial resolution of its passive product to 36 km. However, a key advance of SMAP is its Synthetic Aperture Radar that provides the ability effectively to disaggregate the passive retrievals to an unprecedentedly high resolution (~3 km). The two missions bring the soil moisture remote sensing to a dramatically higher level and have motivated increased attention to soil moisture.

**FIGURE 3.4** Soil moisture retrievals on September 6, 2010, from four products: SMOS, AMSR-E/LSMEM, AMSR-E/LPRM, and AMSR-E/NASA.
product development. Unfortunately, the radar on board the SMAP satellite stopped functioning as of July 7, 2015, though all other operations of SMAP (including the passive sensor) continued normally.

Besides the soil moisture retrieval products from individual sensors, various global long-term remotely sensed soil moisture data sets have been established by blending estimates from different sensors. Examples are the Soil Moisture Essential Climate Variable (ECV) (Liu et al., 2012) produced under the ESA, Climate Change Initiative (CCI), and the Soil Moisture Operational Products System (SMOPS) produced by the NOAA’s Satellite and Information Service (NESDIS). The ESA Soil Moisture ECV products (separated into active-only, passive-only, and combined) include and/or will include SMMR, TMI, SSM/I, AMSR-E, WindSat, SMOS, SCAT, ASCAT, and SMAP sensors. Data homogenizations are performed to make it more convenient for long-term global scale analysis. SMOPS currently blends WindSat, ASCAT, and SMOS.

### 3.5 VALIDATION, UNCERTAINTY ASSESSMENT, AND IMITATIONS OF MICROWAVE SOIL MOISTURE ESTIMATES

For both the passive and active remote sensing of soil moisture, the major noise to the soil moisture signals comes from the vegetation overlying on top of the soil surface. In the case of passive sensors, the vegetation layer can considerably attenuate the soil emission and the vegetation’s own emission also adds noise to the soil signals reaching the satellite. In the case of the active sensors, the vegetation layer generates significant backscatter on hit by the radar beam. Depending on specific conditions, for example, number of channels/polarizations available and vegetation layer thickness, the noise may or may not be effectively filtered out. Both types of soil moisture retrievals will suffer over heavily vegetated areas and snow-covered areas as well.
As many studies confirm the breakdown of the quality of soil moisture retrievals over thicker vegetation (Wagner et al., 2007; Draper et al., 2009; Jackson et al., 2012a), there hasn’t been an “absolute” threshold above which the soil moisture retrievals are considered impossible to too unreliable (Pan et al., 2014). Figure 3.6 shows the seasonal variations of vegetation water content (kg/m²) over the globe and usually the vegetation is considered “thick” when this number is greater than 1–2 kg/m².

The validation of soil moisture retrievals are normally performed against in situ observations. As discussed earlier, such in situ observations are not readily available over most parts of the world. Some areas such as the United States may have more monitoring site available, for example, the SCAN and USCRN (Bell et al., 2013; Diamond et al., 2013). There are also dense sensor networks at local experimental sites, such as the Soil Moisture In Situ Sensor Testbed, USDA experimental watersheds at Little Washita, Little River, Reynolds Creek, and Walnut Gulch. These sites provide an excellent source of data for scaling analysis. More recently, the COSmic-ray Soil Moisture Observing System (COSMOS) (Zreda et al., 2012) started to offer a measurement footprint size of tens to hundreds of meters and sensing depth of tens of centimeters (Zreda et al., 2008; Franz et al., 2012). The measurements at COSMOS pivot site reach ~30 m resolution (Franz et al., personal communications). Figure 3.7 shows the ground validation of two AMSR-E retrieval products over SCAN sites the contiguous United States region.
FIGURE 3.7  Pearson correlation between satellite soil moisture retrievals and SCAN in situ observations (June 2002 to September 2011): (a) AMSR-E/LSMEM ascending, (b) AMSR-E/LSMEM descending, (c) AMSR-E/LPRM ascending, and (d) AMSR-E/LPRM descending.
The soil moisture retrievals can also be validated against land surface model (LSM) simulations forced with observed meteorological fields. LSM simulations offer a gapless coverage and a reasonable temporal dynamics, even though they often suffer from biases and errors in parameters and input forcing data. Another type of alternative error assessment approach relies on pure statistical manipulations. For example, the triple collocation method (Scipal et al., 2008; Dorigo et al., 2010; Zwieback et al., 2012; Pan et al., 2015) and data assimilation (DA) (Crow et al., 2005). The triple collocation method makes a strong assumption on the error behavior of the soil moisture products to assess, for example, independent errors across products (Scipal et al., 2008), and thus the assessment conclusion can strongly depend on the validity of such assumptions. The DA method (Crow et al., 2005; Pan et al., 2012) tries to measure how much the remote sensing soil moisture can help correcting LSM model errors due to poor-quality precipitation forcing.

The design error level of retrievals is usually 0.02–0.05 (volumetric) (Entekhabi et al., 2010) and in situ validations normally support such goals under favorable conditions. As we can see from Figure 3.7, the errors do vary a lot from place to place and the uncertainty level can be quite high over difficult areas.

3.6 APPLICATIONS

Given the relatively large uncertainties in satellite soil moisture retrievals, these datasets are often used in an aggregated way (in time and space) for long-term analysis in climate and hydrologic applications (Liu et al., 2011). For example, drought analysis over crop growing season has been performed using the ECV soil moisture dataset (Yuan et al., 2015).

DA techniques (McLaughlin, 2002; Reichle et al., 2007; Reichle, 2008; Crow et al., 2009) have been a popular choice when we work with uncertain data. Numerous efforts have been made to assimilate satellite soil moisture retrievals into an LSM. Researchers have been assimilating retrievals from all sensors, from the X-band TRMM/TMI, AMSR-E (Pan and Wood, 2009; Pan et al., 2009; De Lannoy et al., 2012; Sahoo et al., 2013; Reichle et al., 2014; Lu et al., 2015) to L-band SMOS (Wanders et al., 2014; Han et al., 2015; Lievens et al., 2015). Some efforts try to use multiple satellites at the same time (Wanders et al., 2015). The goal of these DA studies is usually to improve the model predictions of soil moisture, soil temperature, evapotranspiration, runoff and streamflow, and even the input precipitation forcing (Crow et al., 2011; Wanders et al., 2015).

A lot of different algorithms are used in those DA studies such as simple nudging, variational methods (Reichle et al., 2000, 2001), various types of ensemble Kalman filters (EnKF) (Reichle et al., 2002) and smoothers, and sequential Monte Carlo methods (primarily particle filters) (Kitagawa, 1996; Arulampalam et al., 2002). Among those DA methods, the Kalman filter (Kalman, 1960) and its ensemble variants are the most popular, for example, the EnKF (Evensen, 1994), multiscale EnKF (Zhou et al., 2008), constrained ensemble filter (Pan and Wood, 2006), weakly constrained EnKF (Yilmaz et al., 2012), correlation localized EnKF, scented Kalman filter, and so on.

The Kalman filter works like a tracking system where the LSM derives the trajectory of soil moisture states and the state gets adjusted toward the observation every time the observation is available (Figure 3.8). Essentially, a filter tries to optimally
merge/blend the information from a dynamic model (e.g., LSM) and the observations together based on error levels in each source of information. Such practice is also called data fusion, and in the case of filtering, such fusion is performed recursively in time to ensure that the state estimates are optimal given all the observations up to the current model time step. When the dynamic model and its errors are simple, that is, a linear system with Gaussian errors, a deterministic filter (e.g., Kalman filter and extended Kalman filter) may be used. However, the terrestrial hydrologic dynamics is inherently nonlinear with non-Gaussian errors, and an ensemble or particle version of the filter is normally used. The use of an ensemble of model replicates helps the filter to quantify the model errors and determine much adjustment should be applied to the model states. Both the ensemble filters and particle filters use Monte Carlo samples to quantify the model uncertainty and the replicates in ensemble filters are not weighted while they are weighted in particle filters.

3.7 SUMMARY

Soil moisture content in the top thin layer of the surface can be estimated from both passive (radiometer) and active (radar) sensors on board satellites. The greatest advantage of satellite sensors is their global coverage, and the technical limitations such as wavelength, antenna size, orbit height, and swath width have resulted in a relatively coarse spatial resolution of the measurements. Passive sensors usually

![Figure 3.8](image-url)
have a footprint size of 30–50 km and active sensors can resolve down to several kilometers. The depth of soil moisture detection is also limited to about 0.01–0.1 m given the wavelength being used. Noise in the soil moisture retrievals comes primarily from the vegetation cover and also from surface water bodies, snow cover, and atmospheric-source emissions such as storm clouds.

A series of passive and active microwave sensors have been utilized by the community since the late 1970s to estimate soil moisture and a large number of retrieval products have been created. These retrieval products have been validated against in situ observations, LSM and other model simulations, and through statistical techniques. Validation and assessment studies have found very reasonable performance of the retrievals under favorable conditions, although the uncertainties become large over heavily vegetated as well as snow-covered areas. Long-term global satellite records of soil moisture have been used for in various different studies such as climate and drought analysis. With new satellite missions dedicated to soil moisture observations, we envision a more active and fruitful research into the satellite remote sensing of soil moisture as well as its applications to a wider range of problems in Earth science.

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