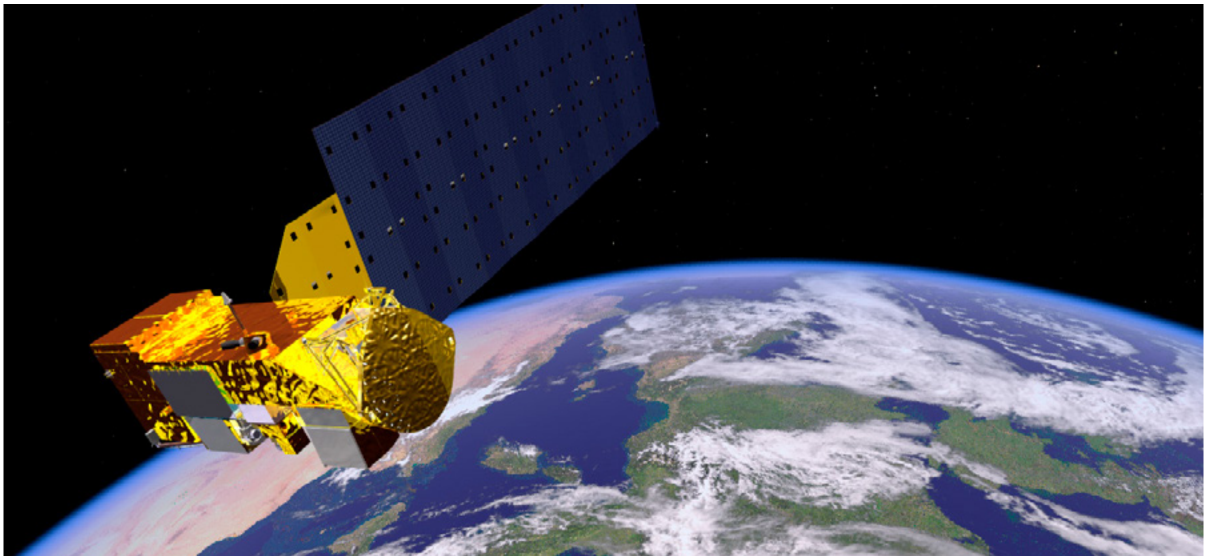


An artist's rendering of the Aqua satellite containing AMSR-E. Credit: NASA

CHAPTER 3

MODELING & REMOTE SENSING

3.1 INTRODUCTION

Soil moisture is fundamental to land surface hydrology in many ways. Importantly, it strongly influences the partitioning of precipitation into either runoff or infiltration. Both of these hydrological variables are very important and play critical roles in the transport of water at the land/atmosphere boundary, including providing water for vegetation, and recharge to the ground water table. The surface runoff constitutes the water in the streams, rivers, and other surface water bodies. Infiltrated water is the source for evapotranspiration, which in turn reduces soil moisture and allows more soil water to infiltrate.

In situ soil moisture monitoring networks are important in establishing a baseline for observations. However, for some applications in hydrology, ecology, weather, agriculture and climate, spatially continuous observations are needed. Recent work has demonstrated that spatially continuous soil moisture maps can be produced using data from in situ networks combined with digital soil maps and radar precipitation estimates (Ochsner et al., 2019). However, satellite remote sensing and modeling are two methods by which spatially continuous soil moisture estimates have been more commonly produced.

In this chapter, we review the various methods associated with modeling and satellite remote sensing. In the area of modeling, most hydrological models are intrinsically linked to atmospheric circulation models. Precipitation is input to these models using various sources of observations – rain gages, ground-based radars or satellite sensors. Models estimate various quantities, for example – soil moisture, latent heat flux and streamflow. These variables are also observed using in situ or satellite sensors. Data assimilation is the technique that uses these observations and reconciles their differences with the model simulations and then updates the model states. In this way the model has been "course-corrected" after the assimilation. A model that uses data assimilation typically produces a better estimate of the land surface states compared to a model that does not use data assimilation. There are numerous well-calibrated hydrological models with data assimilation modules that estimate the water and energy balance of the land surface at various temporal and spatial scales (Han et al., 2012; Houser et al., 1998).

Since the 1970s, scientists have leveraged the water sensitivity of microwave frequencies to sense soil moisture. The evolution of microwave sensors has come a long way from tower- and truck-mounted sensors of the 1970s and 1980s, to aircraft sensors and finally satellite sensors. Lower microwave frequencies such as the L band (1 to 2 GHz) are optimal for monitoring of soil moisture as they are less impacted by the water contained in the vegetation canopy. Both passive (radiometer) and active (radar) sensors have been used. Today, there are numerous satellite sensors that offer global soil moisture estimates at different times of the day from space, but the sensing depth is in the near surface, approximately 5 cm. The assimilation of microwave-based soil moisture data with hydrologic models is the key to offering the most accurate representation of the soil moisture across space and time to date. Both models and satellite estimates are calibrated and validated using in situ networks and field experiment observations of soil moisture. Together, these diverse data inputs help us integrate point observations with spatial representation of soil moisture for more reliable applications in hydrology, ecology, weather, agriculture, and climate.

3.2 LAND SURFACE MODELS

Interest in regional and global soil moisture datasets has increased rapidly over the past several decades. One well-established method that permits routine monitoring of soil moisture is applying a land surface water, or water and energy balance, approach. Land Surface Models (LSM) represent a compilation of physically- and statistically-based empirical equations that simulate the flow of water and energy within the soil–vegetation–atmosphere transfer continuum and model water and energy exchange at the land surface–atmosphere interface. The water balance approach applied by LSMs calculates a change in soil water storage (ΔS) as the difference between incoming (i.e., precipitation) and outgoing (i.e., evaporation, runoff and deep ground water storage) fluxes of water (Maidment 1992; Pitman 2003; Singh 2017).

LSMs differ widely with regards to their physical complexity, assumptions and forcing requirements. Chow et al. (1988) subdivides hydrologic models in two broad categories: physical and abstract. The physical models represent the system on a reduced scale, while the abstract models represent the link between the system variables using mathematical equations, where the variables may be probabilistic or random depending on the spatial and temporal behavior of the specific variables. Singh (2017) offers a comprehensive description of some of the available water balance models. Depending on physical complexity, assumptions, number of hydrologic processes captured by the model, and model response or grid unit, the available models can be categorized as a: 1) a simple bucket model, or bucket with a bottom hole model; 2) a simple water balance model; 3) the Soil and Water Assessment Tool (SWAT); and 4) more complex grid-based hydrologic models, (i.e., the Variable Infiltration Capacity model (VIC), the Noah model, the Noah-Multi Physics (Noah-MP) model, the Community Land Model (CLM), and the Catchment Land Surface Model (CLSM)). See Table 3.1 (*next page*) for a general overview of the most commonly used models.

The bucket hydrologic model represents the simplest viable soil water balance model. It typically assumes a single soil layer configuration and one-dimensional water flow, while ignoring the impact of vegetation and energy fluxes. Once the maximum water holding capacity of the soil layer is reached, the extra water added to the system through precipitation is discarded as runoff. The bucket with a bottom-hole model adds upward and downward movement of water through the bottom of the surface layer. The simple water balance model improves the representation of runoff and incorporates additional capabilities that simulate snow accumulation and snow melt. SWAT, VIC, Noah, CLM, and CLSM are examples of more complex models. SWAT was developed as an agricultural water management tool that incorporates numerous models that simulate the complex soil–water–vegetation interactions and processes as well as crop yield and biomass accumulation (Arnold et al., 2012). SWAT is run at a watershed/sub-watershed scale, where each basin can be further subdivided to hydrologic response units based on dominant land, soil type and management practice. VIC, Noah, CLM, and CLSM are multilayer models run at a grid/sub-grid scale that solve for both the water and energy balance and simulate sub-grid heterogeneity in detail. Most models in this tier offer multiple options to simulate

Table 3.1: Overview of Hydrologic Land Surface Models

LSM Model	Basic Characteristics
Bucket with a bottom-hole model Two-layer Palmer model	• One layer • One-way movement of water • Excess water from precipitation is modelled as runoff
Bucket with a bottom-hole model • Two-layer Palmer model	• Multiple layers • Upward and downward movement of water
Simple water balance model	• Improved runoff representation • Snow-related components
Soil and Water Assessment Tool (SWAT)	• Water management tool • Tools that model numerous hydrologic processes and account for various hydrologic components (i.e., irrigation, snowmelt, evapotranspiration, etc.) • Allows the simulation of agricultural yield and biomass
Complex Hydrologic models • Variable Infiltration Capacity Model (VIC) • Community Land Model (CLM) • Catchment Land Surface Model (CLSM) • Noah model (Noah) • Noah-Multi Physics Model (Noah-MP)	• All hydrologic processes are modelled separately within the soil and snow layers • Solves for both the water and energy balance • Multiple soil, canopy and snow layers • Multiple options to model the various hydrologic components

the land, canopy, and snow layers separately (Liang et al., 1996; Lohmann et al. 1998a, 1998b; Koster et al. 2000; Liang, Xie, and Huang 2003; Ek et al. 2003; Mitchell 2005; Niu et al. 2011).

Model-based soil moisture datasets are easily accessible, and provide temporal continuity (e.g., no missing data compared with in situ observations) and continuous spatial distribution. However, models still have several key limitations including limited spatial resolution, which is typically defined by the (often coarse) resolution of the meteorological forcing parameters used to run the models. In addition, LSM performance and accuracy are highly susceptible to the quality of the forcing data, where some of the key forcing datasets necessary to run an LSM include precipitation, temperature, net radiation, humidity, and wind. However, all of these meteorological inputs can now be acquired at a global scale using satellite-based technologies. The large availability of routinely delivered forcing data, along with the long-term trend in computational power, has substantially reduced obstacles for operational, large-scale monitoring of soil moisture using LSMs. For example, Phase-2 of the North American Land Data Assimilation System (NLDAS-2) routinely produces and distributes 0.125-degree resolution North American soil moisture maps[11] with a data latency of approximately 3–4 days. NLDAS-2 soil moisture data have been widely used to support drought monitoring by, for example, the U.S. Drought Monitor (Xia et al., 2014). Such models can be additionally constrained by assimilation of surface soil moisture data available from satellites as noted previously. For a review of regional and global land data assimilation systems, see Xia et al. (2019).

3.3 SATELLITE SOIL MOISTURE

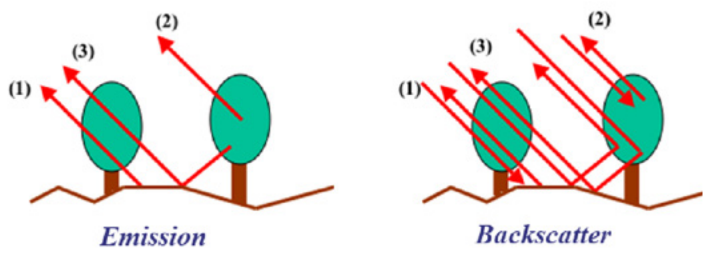
Remote sensors are designed to operate at specific regions of the electromagnetic spectrum according to their intended application. Sensors intended for surface observations operate at frequencies where attenuation and emission by atmospheric gases is low. Sensors intended for global soil moisture sensing must also operate where attenuation by vegetation is low, which implies sensing at low microwave frequencies since vegetation attenuation decreases as frequency decreases. Attenuation by clouds and rain is also lower at lower frequencies. The sensitivity of microwave radiation to soil moisture is governed by the dielectric constant of water, which is greatest at frequencies less than about 5–7 GHz. For the above reasons, satellite soil moisture sensors are designed to operate at microwave frequencies below ~10 GHz (X-band), and preferably close to ~1 GHz (L-band) for highest

[11] *https://www.emc.ncep.noaa.gov/mmb/nldas/drought/*

accuracy. At frequencies below about 1 GHz, Faraday rotation by the ionosphere becomes a significant problem and there is increased threat from radio frequency interference (RFI) from man-made emitting sources. A final consideration is that wavelengths longer than L-band would present limitations in spatial resolution of the instrument (coarser resolution) because the resolving power of the instrument is related to the ratio of the antenna size (linear dimension) to the wavelength, and large antennae are expensive to deploy in space. Table 3.2 (*page 28*) lists current microwave remote sensing satellites.

Microwave remote sensors can either be passive (receive energy only) or active (transmit and receive energy). Passive remote sensors (radiometers) measure thermally emitted radiation from a medium to determine the emissivity of the surface. The intensity of emitted radiation depends on the dielectric properties, which for the near surface soil layer is a function of the amount of moisture present, and the temperature of the target medium. Active remote sensors (or radars) provide their own illumination source, sending out a transmitted wave and measuring the received reflection back from the target to determine its backscatter cross-section. Radars that employ synthetic aperture processing are known as synthetic aperture radars or SARs. SARs provide higher spatial resolution, allowing finer scale features of the surface to be observed.

Measurements of emissivity and backscatter cross-section (sometimes simply called backscatter) provide complementary information on the soil moisture, roughness and vegetation characteristics of the land surface. Radiometers measures the power of the received radiation, while radars measure both the amplitude and phase of the received signal relative to the transmitted signal. Emission (radiometer) and backscatter (radar) equations are used to model the interactions



$$T^t_{Bp} = T^s_{Bp} L_p + T^v_{Bp} + T^{sv}_{Bp} \qquad \text{(Emission)}$$

$$\sigma^t_{pq} = \sigma^s_{pq} L^2_{pq} + \sigma^v_{pq} + \sigma^{sv}_{pq} \qquad \text{(Backscatter)}$$

Figure 3.1: Illustration of the passive emission of brightness temperature (TB) and the backscatter measurement technique from remote sensing.

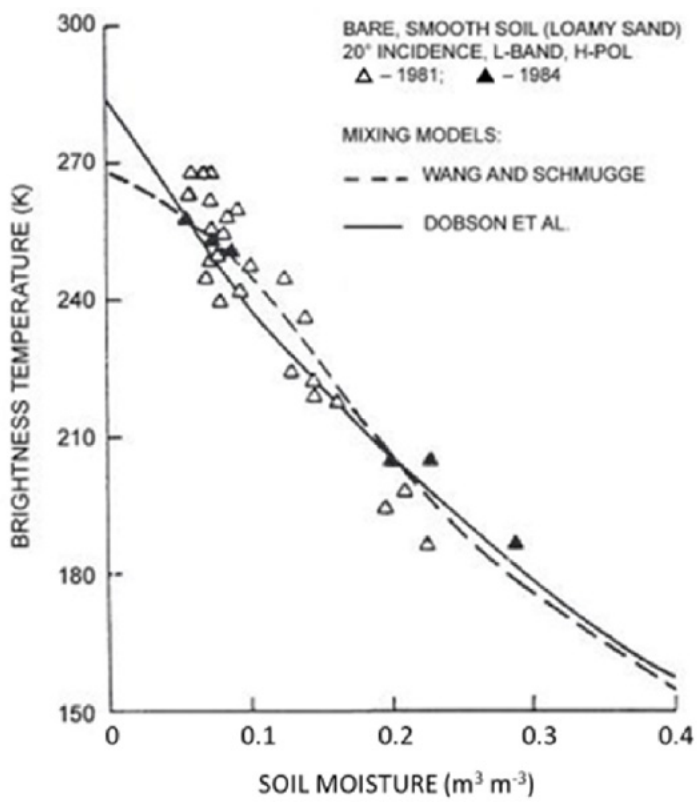


Figure 3.2: L-band brightness temperature response for a bare, smooth soil surface as a function of soil moisture. Soil moisture can range from close to 0.02 $m^3\ m^{-3}$ (very dry), to about 0.40 $m^3\ m^{-3}$ (near saturation for the soil studied). As soil moisture increases the brightness temperature decreases, changing by about 100 K over the full range of soil moisture. Current microwave radiometers have a precision of about 1 K. Details of theoretical modeling and experimental verification for radiometer and radar measurements of vegetation-covered soils can be found in the literature (e.g., Fung et al., 1986; SMAP Handbook, SMAP ATBD, SMOS ATBD).

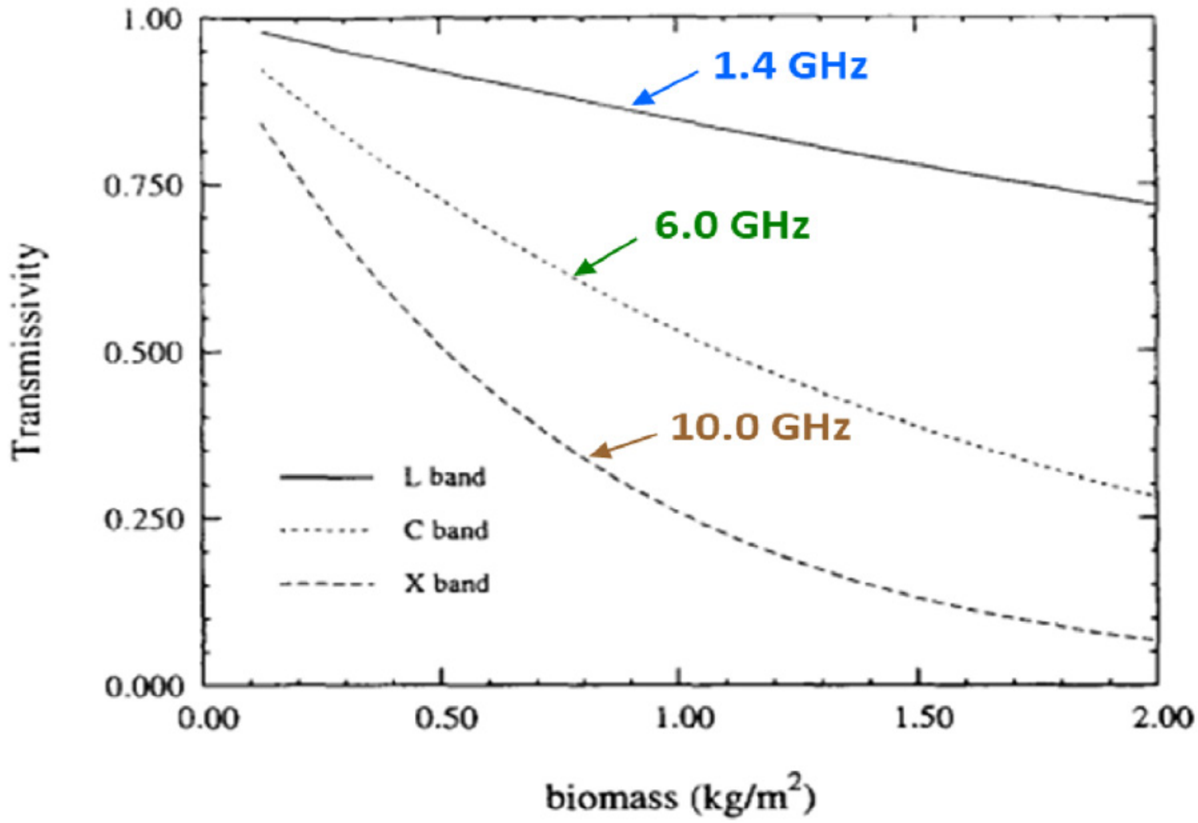


Figure 3.3: The sensitivity of microwave transmission to vegetation biomass.

between microwaves and the vegetation and soil for a typical vegetation-covered landscape. The radiometer measures the emitted radiation intensity or brightness temperature (TB in units of kelvin) and the radar measures the backscatter of the transmitted signal (σ in units of dB).

Each equation models three components of the radiation–surface interaction. Emissions that reach the radiometer come from: 1) the soil directly; 2) the vegetation directly; and 3) from the vegetation after scattering off the soil. Similarly, backscattering interactions from the radar signal come from: 1) the soil; 2) the vegetation; and 3) the vegetation–soil or the soil–vegetation. The radar interactions are more complex because the scattering interactions are more dependent (than emission) on the relative sizes and orientations of the vegetation components. The backscatter signal is also more sensitive (than emission) to the roughness of the soil, the mm-scale variations in soil surface height. The theoretical modeling and experimental verification of the three terms in each of the equations is therefore more complex and difficult for the radar than for the radiometer. Relationships between brightness temperature and volumetric soil moisture are illustrated in Figure 3.2 (*previous page*).

Within the microwave portion of the electromagnetic spectrum, emission from soil at L-band frequencies can be measured through greater amounts of vegetation than emission at higher frequencies. Figure 3.3 (*above*) shows microwave transmissivity as a function of increasing biomass at L-band (1.4 GHz), C-band (6 GHz) and X-band (10 GHz), based upon modeling. The results show that L-band has a significant advantage over the C- and X-band provided by satellite instruments such as the Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) and WindSat. Satellite sensors utilizing L-band frequencies, such as NASA's Soil Moisture Active Passive (SMAP) and the ESA's Soil Moisture Ocean Salinity (SMOS), are able to estimate soil moisture globally over the widest possible vegetation conditions. Another advantage of measuring soil moisture at L-band is that the microwave emission originates from deeper in the soil (typically 2 to 5 cm), whereas C- and X-band

Table 3.2: The soil moisture products developed using different microwave satellites. Sun synchronous orbits are described as ascending (asc) or descending (desc).

	Mission duration	SM Spatial Coverage	Temporal Revisit	Orbit	Product Resolution
AMSR-E	2002–2011	Global land	2-3 days	(1:30 pm asc / 1:30 am desc)	25 km
GCOM-W (AMSR2)	2012–Present	Global land	2-3 days	(1:30 pm asc / 1:30 am desc)	25 km
WindSat (DoD)	2004–Present	Global land	2-3 days	Sun synch (6:00 am asc/ 6:00 desc)	25 km
ASCAT	2009–Present	Global land	2-3 days	Sun synch (9:30pm asc / 9:30am desc)	12.5 km/25 km
SMOS (ESA)	2009–Present	Global land	2-3 days	Sun-synch (6am asc / 6pm desc)	25 km
Aquarius	2011–2015	Global land	8 days	Sun-synch (6pm asc / 6 am desc)	100 km
SMAP (NASA)	2015–Present	Global land	2-3 days	Sun-synch (6am desc / 6pm asc)	3 km/9 km/36 km
CYGNSS	2017–Present	Mid-latitudes	Week-Month	Varying overpass time	1-3 km
NISAR	Launch date: Sep. 2022	Global	12 days	6 am /6 pm	200 m

emissions originate from the top 1 cm or less of the soil. The same benefits of longer wavelengths hold for radars. Consequently, the SMOS and SMAP radars also operate within the L-band, and the backscatter observed by SMAP is sensitive to water at a frequency of 1.41 GHz, and the radar operates at adjustable frequencies in approximately the top 5 cm of the soil small range near 1.26 GHz.

A summary of commonly used satellite-based products observation systems and their product resolution are listed in Table 3.2 (*above*). A review of various in situ and satellite-based soil moisture platforms and related issues can be found in Mohanty et al. (2017).

3.4 CALIBRATION AND VALIDATION METHODOLOGY

3.4.1 Validation and Scaling

There is little doubt that satellite observations provide important information regarding the space and time variation of soil moisture. However, the only way to determine the actual value of satellite data is through validation, which can be strictly defined as "… the quantitative determination of the space and time statistical structure of uncertainty." Validation is absolutely necessary before satellite remote sensing can be effectively used to enhance our understanding of the terrestrial water cycle and make predictions: We first need to know the quality of the satellite observations. Validation is simply not possible without acceptably accurate data from in situ soil moisture networks.

There are two main difficulties associated with the validation of remotely-sensed soil moisture observations. First, the resolution limitation imposed by a satellite antenna means that satellite soil moisture observations are spatial averages. The scale mismatch between in situ soil moisture sensors and a satellite sensor can be 10 orders of magnitude (10's of cm^2 versus 100's of km^2). Second, the signal measured (emitted or scattered microwave radiation) is strongly related to soil moisture, but not solely determined by soil moisture. Soil and vegetation temperature, soil texture, soil organic content, the small-scale and large-scale topography of the soil surface, the amount and type of vegetation, and atmospheric conditions also contribute.

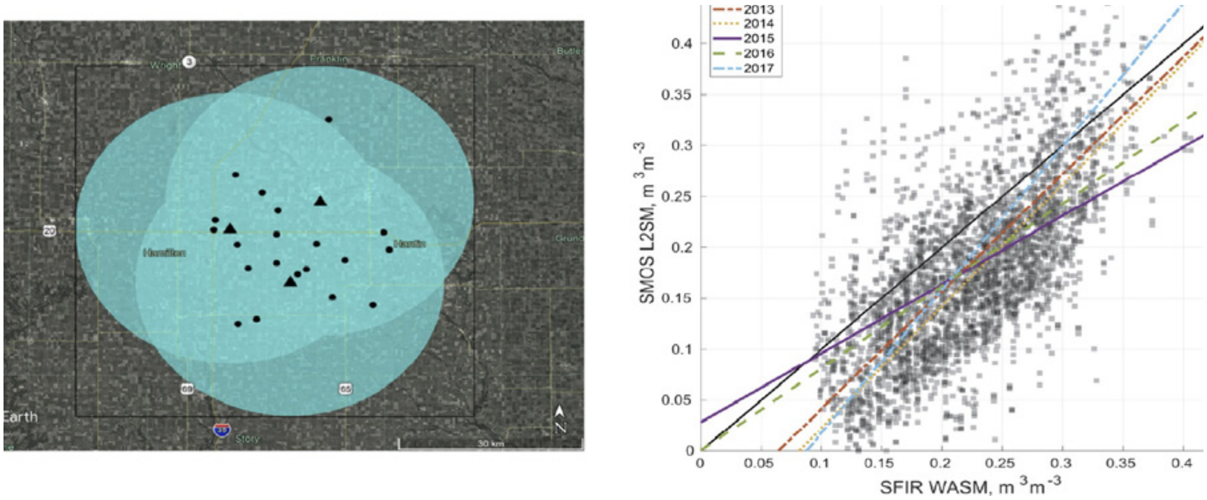


Figure 3.4: (*Left*) The South Fork Iowa River (SFIR) network in central Iowa, an in situ soil moisture network used for validation of satellite soil moisture observations. The black dots mark the locations of the 20 network stations. The black triangles mark the centers of the three Soil Moisture and Ocean Salinity (SMOS) satellite pixels that best match the network. The cyan circles (50 km in diameter) illustrate the approximate area influencing each SMOS pixel. (*Right*) Validation of the SMOS Level 2 soil moisture product in central Iowa, which here is defined as the average soil moisture for these three SMOS pixels (SMOS L2SM) regressed against the SFIR network weighted-average soil moisture (WASM). From Walker et al. (2018).

The first difficulty requires the establishment of a standard for the main quantity of interest (soil moisture) that is valid at the satellite scale. Soil moisture networks are currently the only practical way to upscale, or translate, in situ soil moisture measurements to the scale observed by a satellite. Consequently, network soil moisture is used as "the truth" in satellite validation. The second difficulty (which is, fundamentally, the nature of remote sensing) must be addressed through the use of models and either some type of measurement or estimation of all or at least the most important biogeophysical quantities also affecting the remotely sensed observation. This information can be used to formulate and adjust the models and to explain the validation statistics.

Satellite validation sites have been used by NASA (as well as other international space agencies), often in cooperation with other federal agencies like the USDA who have interest in satellite data. For example, several validation sites built around soil moisture networks were created for NASA's Soil Moisture Active Passive (SMAP) soil moisture satellite (Entekhabi et al., 2010). These sites have been used to generate the data needed to calculate statistics such as bias (the mean difference between the satellite soil moisture product and the soil moisture derived from the network) and noise (normally some form of the root mean squared difference or RMSD) in order to determine whether SMAP is meeting its mission goals (Chan et al., 2016; Colliander et al., 2017).

Ideally, validation sites should be located in all biomes of interest so that the best estimate of overall satellite performance can be found. Walker et al. (2018) evaluated another soil moisture satellite, the European Space Agency's Soil Moisture and Ocean Salinity (SMOS) (Kerr et al., 2010), in the U.S. Corn Belt, a large region of extensive row cropping, using a SMAP Core Validation Site established in the watershed of the South Fork Iowa River in central Iowa by the USDA. A map of the South Fork Iowa River (SFIR) soil moisture network in relation to the three SMOS pixels that best match the extent of the network is shown in Figure 3.4 (*above*). Also shown in Figure 3.4 is a comparison between the SMOS soil moisture product (SMOS L2SM) and soil moisture derived from the SFIR soil moisture network (SFIR WASM). This is the classic validation result. Ideally, points in this figure would line up around the black 1:1 line. In this case, it can be seen that SMOS soil moisture values tend to be smaller (drier) than values from the network. Rather than a simple average of the in situ soil moisture measured at each of the 20 SFIR network stations, the network soil moisture in this example is a weighted average,

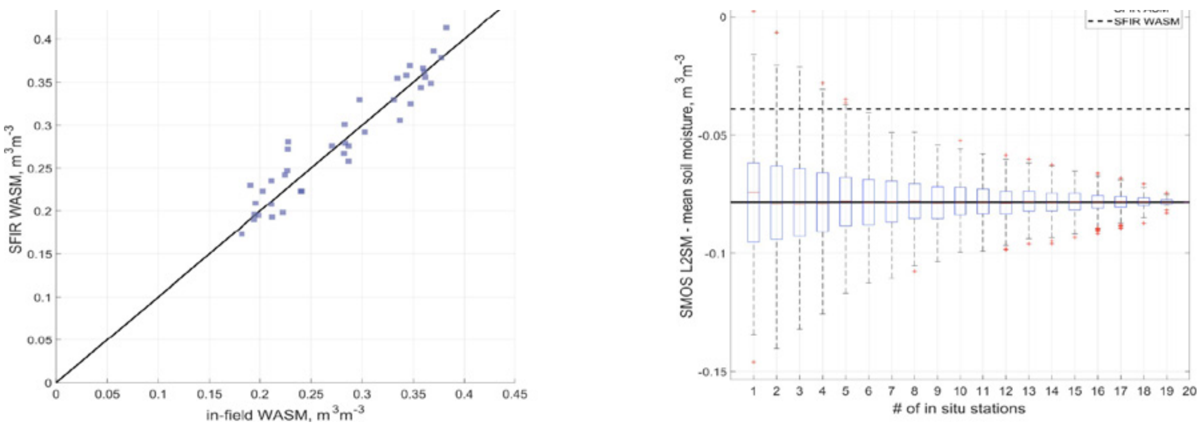


Figure 3.5: (*Left*) South Fork Iowa River (SFIR) network weighted-average soil moisture from 5 cm installed sensors under grass on edges of fields (SFIR WASM) versus in-field soil moisture under row crops measured during a 2014 campaign (in-field WASM). There was essentially no bias between in-field and out-of-field measurements, but there was some noise. (*Right*) the difference between SMOS satellite soil moisture (SMOS L2SM) and SFIR network soil moisture as a function of the number of network stations used to compute a simple average (SFIR average soil moisture or ASM). Also shown is the difference between SMOS L2SM and all 20 stations weighted according pixel area represented (SFIR WASM). Even as few as about five stations clearly indicate SMOS soil moisture is less (drier) than network soil moisture. (Source: Walker et al. (2018))

where stations farther away from neighboring stations receive a larger weight since they represent a larger area of the satellite pixel (weights calculated using a Voronoi diagram, also called Thiessen polygons). This type of scaling function may be appropriate for pixels in which precipitation is the largest source of variability. Scaling functions can also be adjusted using additional in situ measurements obtained during time-limited field campaigns. This can be done using geostatistical techniques (Kathuria et al., 2019) and identifying dominant geophysical factors, i.e. soil, topography and vegetation (Cosh et al., 2004; Gaur and Mohanty, 2013, 2016, 2019).

There are many things to consider when designing a soil moisture network suitable for use in satellite validation. One aspect is representativeness: Do the in situ sensors observe the same quantity of soil moisture as the satellite? In reality, satellites “see” the first few cm of the soil surface, while in situ sensors buried at, for example, 5 cm for long-term robustness observe a different soil layer centered around that depth. These two layers act differently hydrologically: the shallower layer observed by satellites is more dynamic, reacting more dramatically to precipitation events and dry periods. While this circumstance is unavoidable (satellites will always observe from the top-down, and in situ sensors at some depth) these two layers can still share similar statistics (Rondinelli et al., 2015). Hence, soil moisture networks are integral for a remote sensing program.

Another practical matter is the physical location of network stations. In order to have continuous, long-term measurements, in situ sensors must be buried where they will not be disturbed. This location may not be the same as where the soil moisture measurement is desired. Can such compromises be managed? Walker et al. (2018) examined this situation in the Corn Belt. Field operations such as tillage, planting, and harvest make it impossible to install soil moisture sensors directly in fields. Instead, SFIR stations have been installed on the edge of fields, so that in situ sensors are under grass and not the dominant vegetation of the region, row crops. However, this approach leads to a question of whether or not these out-of-field sensors still measure the soil moisture of interest. A field campaign in 2014, during which in-field soil moisture measurements were compared to the SFIR network measurements, found that essentially no bias (but some noise) is introduced into the validation. This result is shown in Figure 3.5 (*above*). From this single study, it appears that these compromises can be managed if fields are rain fed rather than irrigated. In areas where fields are predominantly irrigated (large areas of California, the Great Plains, Mid-South, and Intermountain West) satellite observations of field soil moisture would not be expected to correlate well with data from stations outside of the irrigated area.

Finally, it is necessary to determine if it is realistic to use a limited number of in situ soil moisture measurements (each representing 10's of cm^2) to represent an entire satellite pixel (100's of km^2). The spatial scale of soil moisture can be defined in terms of the spacing, extent, and support of component measurements. Spacing is the distance between measurements or model grid points, extent is the overall coverage or total distance spanned by the measurements, and support is the area integrated by each measurement (Western and Blo¨schl, 1999). The ideal case is small spacing, adequate extent to match the scale of interest, and small support. In situ soil moisture sensors provide small support, and validation networks are designed to span the extent of a satellite footprint. But since this area is so large, necessity dictates that spacing will not be ideal. Further complicating this matter is the fact that stations must normally be located on private land. It is often difficult to identify hosts and make long-term arrangements. In the case of the SFIR, these constraints resulted in 20 network stations.

3.4.2 Data Assimilation

In situ-based soil moisture measurements as well as remote sensing- and model-based estimates are not perfect and do not always directly meet user requirements in terms of their precision, resolution, temporal and spatial coverage, and observation depth (Reichle, 2008). For example, satellite-based retrievals provide an estimate of the soil moisture conditions for only the top 1–5 cm of the soil profile. Many applications require knowledge of the root-zone soil moisture, which cannot be observed directly using remote sensing but could be well simulated by a model informed by forcing data and constrained by data assimilation, some of which data could be derived from remote sensing. The quality of the forcing data plays major role in the accuracy of the model estimates. For example, erroneous precipitation events are directly transferred through model simulations and commonly result in incorrect model soil moisture estimates – especially in data-poor regions of the world (Bolten and Crow 2012; Dong et al. 2019). Data assimilation (DA) offers the opportunity to mitigate these limitations. Data assimilation is a technique for updating a continuously running model with incomplete and uncertain information acquired from observations. Ideally, this updating should be based on a complete statistical understanding of errors present in both the model and the observations (McLaughlin 1995; Reichle et al. 2004; Reichle 2008; Crow and Reichle 2008; Park and Xu 2009). Direct insertion, optimal interpolation, nudging, Kalman Filter, 3D/4D variational assimilation are all methods that are potentially suitable for land data assimilation (Reichle 2008). Of these, the Ensemble Kalman Filter (EnKF) is generally considered one of the most widely applied data assimilation approaches in hydrology (Evensen 2003). EnKF is a sequential, Monte Carlo–based method that uses a Monte Carlo forecast ensemble to compute the error covariance of the satellite data and the modelled estimates at the time of the update. Therefore, it has two steps: a forecast, where the ensemble is propagated forward in time, and an update step, where the update is performed based on the so called Kalman gain (Reichle, McLaughlin, and Entekhabi 2002). The latter is a function of the forecast error covariance sampled prior to the update from the Monte Carlo ensemble. Essentially, the Kalman gain is a weighing matrix that assigns specific weights to the model and the observations estimates, which reflects our confidence in the model physics and forcing data, and the accuracy of the satellite retrieval algorithm. The Kalman gain also provides a statistical basis for translating updates between observed and unobserved states (e.g., surface soil moisture to root-zone soil moisture).

McLaughlin (1995) summarized that hydrologic data assimilation is "not yet well established." However, substantial progress has been made in the past two decades such that data assimilation methodologies, initially borrowed from the oceanography and atmospheric sciences, have been well-adapted to meet the unique dynamics and requirements of land-based systems. These system have been extensively tested, and the benefits of incorporating satellite-based observations into spatially distributed hydrologic models are well-demonstrated (de Wit and van Diepen 2007; Crow and Ryu 2009; Crow and Van den Berg 2010; Bolten and Crow 2012; Crow, Kumar, and Bolten 2012; Han et al. 2014; Mladenova et al. 2019).

There currently exist multiple land DA systems that operationally ingest remote-sensed soil moisture retrievals (or the satellite brightness temperature observations that underlie these retrievals) to update LSMs and produce a global analysis of surface and root-zone soil moisture (see, e.g., Reichle, De Lannoy, Liu, Ardizzone, et al. 2017; Reichle, De Lannoy, Liu, Koster, et al. 2017; Mladenova et al. 2019). Important advances have also been made towards the development of systems that simultaneously assimilate both satellite- and ground-based soil moisture observations into a unified analysis (Gruber, Crow, and Dorigo 2018).

3.5 APPLICATIONS

Remote sensing and hydrological modeling are important tools in the study of both hydrological extremes such as drought and flooding, as well as general weather phenomena. Here are some examples of the distinctive application of these tools:

1. In recent years, floods associated with hurricanes (for example, Hurricane Harvey in Texas in 2017 and Hurricane Florence in South Carolina in 2018) have caused huge disasters. The mapping of these and similar floods using airborne (JPL AIRSAR), and satellite radars (Sentinel), and visible and near infrared (Moderate Resolution Imaging Spectroradiometer – MODIS) have been carried out (Oddo and Bolten, 2019
2. In the case of droughts (and their associated wildfires), the State of California stands out. These droughts have been studied using numerous models (Land Information System, LIS) and observations using satellite sensors.
3. The launch of the Global Precipitation Measurement (GPM) mission in February 2014 and the Soil Moisture Active Passive (SMAP) mission in January 2015 present a big step forward in global monitoring of precipitation and soil moisture. In addition, we have sensors that monitor vegetation, surface temperature and evapotranspiration (MODIS) and the continuation of the Gravity Recovery and Climate Experiment (GRACE) with GRACE-FO (Follow On) that estimates changes in surface and subsurface water storage which together provide a larger picture of the land surface hydrological state. The levels of water in lakes and rivers can be monitored with the SWOT (Surface Water and Ocean Topography) that will be launched in 2021. The NISAR (NASA ISRO Synthetic Aperture Radar) will be launched in 2022 and can monitor the land surface using L and S band SAR (soil moisture).

3.6 FUTURE DIRECTIONS

With rapid advances in computer modeling and observing systems, and the wider adoption of cloud computing technologies, floods, droughts and other weather phenomena are analyzed and forecast with greater precision today than ever before. Land surface models (especially over the continental United States) can map the hydrological cycle at kilometer and sub-kilometer scales. In the case of smaller areas, there is even higher spatial resolution of simulation and the only limiting factor is the resolution of input data. In situ sensors are automated and the data directly relayed to the internet for many hydrological variables such as precipitation, soil moisture, surface temperature and heat fluxes. In addition, satellite remote sensing has advanced to providing twice a day repeat observations at kilometer to 10-kilometer spatial scales.

With remote sensing, we have already mentioned the SWOT and NISAR, two satellite missions that monitor the hydrological state of the land surface. In addition, there are numerous other measurements, for example CyGNSS (Cyclone Global Navigation Satellite System) that was originally launched to monitor cyclones can be used to infer soil moisture on the land surface. Another breakthrough is the downscaling of soil moisture retrieved from L-band brightness temperature to 1 km using MODIS NDVI (Normalized Difference Vegetation Index) and surface temperature and lookup tables (Colliander et al., 2017; Piles et al., 2011). Still, the key to further adopting these technologies and reducing the uncertainty of the aforementioned hydrological models and remote sensing platforms is the development of a robust strategy for characterizing and integrating soil moisture information collected by the National Coordinated Soil Moisture Monitoring Network.