Remote Sensing Research in Hydrometeorology

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Abstract
An overview of remote sensing research in hydrometeorology, with an emphasis on the major contributions that have been made by United States Department of Agriculture Agricultural Research Service (USDA-ARS) scientists, is provided. The major contributions are separated into deriving from remote sensing (1) hydrometeorological state variables and (2) energy fluxes, particularly evapotranspiration which includes plant water stress. For the state variables, remote sensing algorithms have been developed for estimating land surface temperatures from brightness temperature observations correcting for atmospheric and emissivity effects, estimating near-surface soil moisture from passive microwave remote sensing, determining snow cover from passive microwave data, and estimating landscape roughness, topography, vegetation height, and fractional cover from lidar distancing technology. For the hydrometeorological fluxes, including plant water stress, models estimating evapotranspiration have been developed using land surface temperature as a key boundary condition with recent schemes designed to more reliably handle partial vegetation cover conditions. These research efforts in estimating evapotranspiration with remotely sensed surface temperatures have been utilized by ARS researchers in the development of the Crop Water Stress Index and Water Deficit Index for assessing plant water stress. In addition, the development of the Thermal Kinetic Window and Crop Specific Temperatures have revealed the dynamic interactions among foliage temperature, plant species, and the physical environment. ARS researchers continue to develop new and improved remote sensing algorithms for evaluating state variables and fluxes. Moreover, they are involved in new research directions to address science questions impeding hydrometeorological research. These include investigating the utility of combining multifrequency remote sensing data for improved estimation of land surface properties, and incorporating remote sensing for evaluating the effects of landscape heterogeneity on atmospheric dynamics and mean air properties and resulting feedbacks on the land surface fluxes.

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Introduction
A major focus of remote sensing research in hydrometeorology by Agricultural Research Service (ARS) scientists has been to develop instrumentation, algorithms and models for estimating hydrometeorological states and fluxes, including plant stress/condition. The primary set of state variables include land surface temperature, near-surface soil moisture, snow cover/water equivalent and landscape roughness and vegetation cover. The hydrometeorological fluxes are primarily soil evaporation and plant transpiration or evapotranspiration, which is also related to plant stress or condition and snowmelt runoff. ARS researchers have attempted to quantify the components of the water and energy balance equation using remote sensing methods with the main purpose of estimating crop water use. This is because water availability is probably the most common limiting factor to crop growth and yield. The water balance is commonly expressed as follows:

\[
\Delta N/\Delta t = P - ET - Q \tag{1}
\]

where \(\Delta N/\Delta t\) is change in storage in the soil and/or snow layer, \(P\) is the precipitation, \(ET\) is the evapotranspiration, and \(Q\) is the runoff. The energy balance equation for most agricultural landscapes, except for tall forests, is typically written as follows:

\[
R_n - G = H + LE \tag{2}
\]

where \(R_n\) is the net radiation, \(G\) is the soil heat flux, \(H\) is the sensible heat flux, and \(LE\) is the latent heat flux, all in W m\(^{-2}\). The quantity \(R_n - G\) is commonly referred to as the available energy, and \(ET\) and \(LE\) represent the same water vapor exchange rate across the surface-atmosphere interface, except that \(ET\) is usually expressed in terms of depth of water over daily and longer time scales, namely, mm day\(^{-1}\). This paper will describe some of the major contributions of ARS scientists in providing important state variables using remote sensing and modeling schemes for estimating components of the water and energy balance. Particularly noteworthy are the methods using remote sensing pioneered by ARS scientists for assessing crop water stress. In addition, ARS scientists are making important contributions in new research directions that are emerging to address difficult problems in hydrometeorological research.

Remote Sensing of Hydrometeorological States
Land Surface Temperature
Land surface temperature is the result of the equilibrium thermodynamic state dictated by the energy balance between the atmosphere, surface, and subsurface soil and the...
efficiency by which the surface transmits radiant energy into the atmosphere (surface emissivity). The latter depends on the composition, surface roughness, and physical parameters of the surface, e.g., moisture content. In addition, the emissivity generally will vary with wavelength for natural surfaces. Thus, to make a quantitative estimate of the surface temperature, we need to separate the effects of temperature and emissivity in the observed radiance. Airborne and satellite-based radiometers measure what is commonly called a "brightness temperature" derived from the radiance reaching the sensor. This brightness temperature must be corrected for atmospheric attenuation of the surface radiance considering the impact of surface emissivity, before it can regarded as an estimate of the land surface temperature.

The relationship between land surface and brightness temperature from an aircraft- or satellite-based sensor is usually expressed in terms of the radiation balance, i.e.,

\[ L_{\text{SURF}} = L_{\text{ATM}} + \epsilon^I \frac{L_{\text{ATM}}}{H_{\text{ATM}}} \]

where \( L \) is the radiance from the \( j \)th waveband channel of the radiometer, \( L_{\text{SURF}} \) is at-sensor radiance, \( L_{\text{ATM}} \) is the surface radiance, \( L_{\text{ATM}} \) is the upwelling atmospheric radiance, and \( \epsilon^I \) is the atmospheric transmission. Values of \( L_{\text{ATM}} \) and \( \epsilon^I \) can be calculated using atmospheric radiative transfer codes, such as LOWTRAN (Kneizys et al., 1980). This permits the upwelling radiance at the surface, which yields the land surface temperature, to be computed from the following expression:

\[ L_{\text{SURF}} = \epsilon^I \frac{L_{\text{SURF}}}{H_{\text{SURF}}} + (1 - \epsilon^I) \frac{L_{\text{ATM}}}{H_{\text{ATM}}} \]

where \( \epsilon^I \) is the surface emissivity, \( L_{\text{SURF}} \) is the Planck function for the radiation from a black body, and \( L_{\text{ATM}} \) is the upwelling radiance for the \( j \)th channel of the radiometer. The value of \( L_{\text{ATM}} \) can also be determined from atmospheric radiative transfer codes. The remaining problem is to relate these radiances to the surface emissivity without direct knowledge of the land surface temperature, \( T_{\text{SURF}} \).

It was recognized early on by ARS scientists, in the application of satellite remote sensing for land surface temperature estimation, that simpler operational methods other than radiative transfer codes were needed (Price, 1983). Moreover, due to the lack of adequate atmospheric profile observations, the development of alternative approaches such as so-called "split-window" methods would be more operationally applicable (e.g., Price, 1984). These split-window methods employ two channels at slightly different wavelengths \( \lambda^I \) and \( \lambda^II \) in Equations 3 and 4 to essentially eliminate (using a few approximations) the need for estimating the atmospheric transmission and radiances. However, split-window methods are sensitive to uncertainty in the emissivities in the two channels; for example, at a brightness temperature 300 K, a difference \( \epsilon^I - \epsilon^II = 0.01 \) can yield an error in land surface temperature of -2 K (Price, 1989).

While improvements in radiative transfer codes continue, such as LOWTRAN (Kneizys et al., 1988), ARS led studies (Perry and Moran, 1994) indicate that atmospheric corrections to satellite brightness temperatures can still lead to errors in excess of 2 K, unacceptable for most hydrometeorological applications. There is continued improvement in the development of these codes for estimating atmospheric transmission, namely MODTRAN (Berk et al., 1998), but the lack of adequate atmospheric profiling data and uncertainty in the surface emissivity will continue to be limiting factors. Until recently, methods for estimating surface emissivity from remote sensing were empirical. With the launch of NASA’s Earth Observing System Platform, Terra, in December 1999, multispectral thermal-infrared data from the Advanced Spaceborne Thermal Emission Reflectance Radiometer (ASTER; Yamaguchi et al., 1998), a technique has been proposed to extract both land surface temperature and emissivity. This approach makes use of an empirical relation between the range of emissivities and the minimum value from a set of multichannel observations. It is termed Temperature Emissivity Separation or TES (Gillespie et al., 1998).

ARS scientists have evaluated TES using a prototype of ASTER, the airborne Thermal Infrared Multispectral Scanner (TIMS), over heterogeneous landscapes in West Africa and in the U.S. Southwest (Schmugge et al., 1994; Schmugge et al., 2001). In addition, using TIMS data collected in the U.S. Southern Great Plains, ARS scientists developed a technique using the spectral variation of emissivity to discriminate between bare soil fields and fields containing senescent vegetation (wheat stubble). Such a separation is not possible with visible and near-infrared data alone and is an important distinction when assessing surface energy balance using remotely sensed temperatures (French et al., 2000).

There are some inherent difficulties in the processing of thermal-infrared data that limit its utility for estimating hydrometeorological fluxes (Moran, 2000). However, research being conducted by ARS scientists has greatly enhanced the potential application of land surface temperature from satellite for ET estimation and crop water stress. Remote sensing field experiments investigating the utility of land surface temperatures for estimating ET have been lead by ARS scientists over agricultural crops in Maricopa Farms, Arizona (MAC-1-99), over grazinglands in USDA-ARS experimental watersheds in Arizona (Walnut Gulch Watershed, Monsoon ’90) and Oklahoma (Little Washita Watershed, Washita 92-94), and the USDA-ARS Jornada Experimental Range in New Mexico (ORNEX ’96-’00). ARS scientists continue to have an active role in development of algorithms to derive land surface temperatures. A recent example using ASTER satellite imagery encompassing the USDA-ARS Grazinglands Research Facility in El Reno, Oklahoma is displayed in Plate 1. The spatial distribution of land surface temperature, \( T_{\text{SURF}} \), reflects some significant differences in land-cover conditions at this time of year (September), with large areas of bare soil and wheat stubble from harvested winter wheat fields and grasslands used for cattle grazing, and with small areas of irrigated crop lands and water bodies. This type of spatially distributed information is very useful for evaluating spatial patterns of ET over large areas.

Plate 1. An image of \( T_{\text{SURF}} \) derived from ASTER over the USDA-ARS El Reno Grazinglands research facility on 04 September 2000. Spatial resolution is 90 m.
Near-Surface Soil Moisture

Passive microwave remote sensing instruments are capable of measuring the surface soil water content, and can be implemented on trucks, aircraft, and spacecraft for repetitive large-area observations. The amount of water present in a soil determines its dielectric properties. The dielectric properties, along with other physical characteristics such as surface roughness, determine the microwave signal emanating from the soil. Efforts championed by ARS scientists have been underway for some time to develop passive microwave remote sensing as a tool for measuring and mapping surface soil water content (Jackson and Schmugge, 1989). Remote sensing cannot replace ground-based methods for providing high quality profile data at a point. Its advantage is in mapping conditions at regional, continental, and even global scales.

It was recognized early on in research in this field that instruments operating at low frequencies (less than 6 GHz) provide the best soil moisture information. At low frequencies there are fewer problems with the atmosphere and vegetation, the instruments respond to a deeper soil layer, and there is a higher sensitivity to soil water content. The footprint of a passive microwave sensor will increase as frequency decreases. Current and near future satellite systems can provide only coarse resolution data (greater than 56 km). New antenna technologies under development will improve this resolution to 10 km within the next decade. The existing data interpretation algorithms for passive data are well tested for bare soil and vegetation and can be applied to a wide range of conditions (Jackson et al., 1991).

Passive microwave methods measure the natural thermal emission of the land surface using very sensitive detectors. The most useful microwave waveband in the L band, whose frequency is 1 to 2 GHz, or a wavelength of about 21 cm. A general advantage of low frequency microwave sensors is that observations are essentially unaffected by atmospheric attenuation even in the presence of clouds. In addition, these measurements are not dependent on solar illumination and can be made at any time of the day or night.

The measurement provided a brightness temperature, \( T_B \), similar to thermal-infrared observations and includes contributions from the atmosphere, reflected sky radiation, and the land surface. However, compared to the thermal-infrared wavelengths, atmospheric effects are negligible at frequencies greater than 6 GHz. Galactic and cosmic microwave radiation contribute to sky radiation and have a known small value that varies very little in the frequency range used for soil water content observations, yielding a \( T_{B,SKY} \) of about 4 K. The brightness temperature of the surface is related to its emissivity, physical temperature and contributions from the intervening atmosphere, yielding an expression similar to Equation 4.1:

\[
T_B = e \sigma T_M^4 + (1 - e) T_{B,SKY}
\]  

where \( e \) and \( T_M \) are the emissivity and physical temperature representing some effective depth in the soil surface layer (typically, a 0- to 5-cm depth in the L band) and therefore must be distinguished from the emissivity and surface temperature defined for the thermal-infrared wavelengths (Schmugge, 1980). Because the second term in Equation 5 will be on the order of 2 K, it is usually neglected, thus yielding after rearranging

\[
e = \frac{T_B}{T_M^4} - 1
\]

If \( e \) is estimated independently, emissivity can be determined. This can be done using surrogates based on satellite surface temperature, air temperature observations, or forecast model predictions. A typical range in \( e \) is about 0.9 for a dry soil to about 0.6 for a wet soil comprising the 0- to 5-cm layer (see below).

The basic reason microwave remote sensing is capable of providing soil water content information is this large dielectric difference between water and the other soil components. Because the dielectric constant is a volume property, the volumetric fraction of each component must be considered. The computation of the mixture dielectric constant (soil, air, and water) has been the subject of several studies, and there are different theories as to the exact form of the mixing equation (Schmugge, 1980; Dobson et al., 1985). A simple linear weighting function is typically used.

There are five steps involved in extracting soil water content using passive microwave remote sensing. These are normalizing microwave brightness temperature to emissivity, removing the effects of vegetation, accounting for the effects of soil surface roughness, relating the emissivity measurement to soil dielectric properties, and, finally, relating the dielectric properties to soil water content. ARS scientists have developed techniques needed in all five steps of the process.

Vegetation reduces the sensitivity of the retrieval algorithm to soil water content changes by attenuating the soil signal and by adding a microwave emission of its own to the microwave measurement. The attenuation increases as frequency increases. This is an important reason for using lower frequencies. As described in Jackson and Schmugge (1991), at lower frequencies it is possible to correct for vegetation using a vegetation water content-related parameter.

In studies reported in Jackson et al. (1982) and Jackson and Schmugge (1991), it was found that a functional relationship between the optical depth and vegetation water content, \( \psi \), could be applied. The vegetation water content can be estimated using a variety of ancillary data sources. One approach is to establish a relationship between the microwave measurement and a satellite-based vegetation index such as the Normalized Difference Vegetation Index (NDVI) as described in Jackson et al. (1990). The emissivity that results from the vegetation correction is that of the soil surface. This includes the effects of surface roughness. These effects must be removed in order to determine the soil emissivity, which is required in the inversion from microwave brightness temperature to soil moisture. One approach to removing this effect is a model described in Choudhury et al. (1979) that yields the bare smooth soil emissivity, with model parameters assigned based upon land surface type and a satellite-based vegetation index such as the Normalized Difference Vegetation Index (NDVI) as described in Jackson et al. (1990).

The contributing depth of the soil is a function of the microwave frequency or wavelength. There are well known theories describing the reflection resulting from a soil profile with uniform or varying properties (Njoku and King, 1977). The computations involve a nonlinear weighting that decays with depth. Some modeling studies have suggested that this dominant depth is a function of the frequency (one-tenth the wavelength) (Wilheit, 1979). Field experiments, many of which have been conducted by ARS scientists (Jackson and Schmugge, 1989), suggest that the contributing depth is about one-fourth the wavelength. Thus, for the L band, the effective depth is on the order of 5 cm.

A problem with passive microwave methods is spatial resolution. For a given antenna size, the footprint size increases as frequency decreases and altitude increases. For satellite designs at L band, this might result in a footprint as large as 100 km. Recent research has focused on the use of synthetic aperture thinned array radiometers which could decrease the footprint size from satellites to 10 km (Le Vine et al., 1994).
To a large degree, research and applications utilizing microwave sensors are dependent on the instruments that have been available. As the need for soil water content studies has developed, some new instruments have emerged. AMSR scientists have been and continue to be directly involved in the development of current and near future microwave sensors operating from ground, aircraft, and satellite platforms.

The advantages of ground-based systems include the small sensor footprints (a few meters in size) and the ability to control and measure the target and to collect data continuously. These systems are ideally suited to the study of the fundamental relationships between microwave observations and target variables as well as observing time-dependent hydrologic processes such as evaporation and infiltration.

Jackson et al. (1997b) describe a typical dual frequency (1.4 and 2.65 GHz single polarization) passive microwave system installed on a boom truck. This system is capable of obtaining either automatic continuous observation over a single target or moving from one target to another to collect specific data sets.

Aircraft-based microwave instruments are especially useful in studies requiring the mapping of large areas. They can also serve as prototypes of future satellite sensors. In most cases, they will offer better spatial resolution than satellite systems as well as more control over the frequency and timing of coverage. In the case of passive microwave systems, there are no appropriate satellite systems available for soil water content studies. Therefore, all large-area research has utilized aircraft sensors. In the late 1980s the L-band Push Broom Microwave Radiometer (PBMR) was used in several large area mapping experiments involving NASA and USDA-ARS scientists (Schmugge et al., 1992). During the 1990s, much of this work has been replaced by the L-band and S-band Advanced Microwave Scanning Radiometer (AMSR). AMSR is an L-band horizontally polarized instrument that can provide image products. It also is a prototype for a new synthetic aperture antenna technology that can solve the high altitude-spatial resolution problem described earlier (Le Vine et al., 1994).

Satellite-based sensors offer the advantages of large-area mapping and long-term repetitive coverage. Revisit time can be a critical problem in studies involving rapidly changing conditions such as surface soil water content. With very high revisit times it is possible to obtain near-daily coverage with a polar orbiting satellite. For most satellites, especially if constant viewing angle is important, the revisit time can be much longer. Optimizing the time and frequency of coverage is a critical problem for soil water content studies. Currently, all passive microwave sensors on satellite platforms operate at high frequencies (greater than 7 GHz). A more recent option is the multiple frequency Advanced Microwave Scanning Radiometer (AMSR) satellite systems that will include a 6.9-GHz channel. AMSR holds great promise for estimating soil water content in regions of low levels of vegetation. AMSR is not the optimal solution to mapping soil water content but it is the best possibility in the near term. Based on the published results and supporting theory (Wang, 1985; Choudhury and Golus, 1988; Cosh et al., 1992; Alsdorf et al., 1995; Njoku and Li, 1999), this instrument should be able to provide soil water content information in regions of low vegetation cover, less than 1 kg m\(^{-2}\) vegetation water content. Research programs are underway to develop and implement space-based systems with a 1.4-GHz channel which would provide improved global soil moisture information.

Research on microwave remote sensing of soil water content has historically focused on establishing accurate retrieval algorithms. The ability to apply this understanding to large heterogeneous areas on a regular basis has been the focus of much of the recent field experimentation involving AMSR scientists. Washita ’92 was a large-scale study of remote sensing and hydrology conducted by NASA and USDA-ARS using ESTAR over the USDA-ARS Little Washita Watershed facility in southwest Oklahoma (Jackson et al., 1995). Data collection during the experiment included passive and active microwave observations. Data were collected over a nine day period in June, 1992. The watershed was saturated with a great deal of standing water at the outset of the study. During the experiment there was no rainfall and surface soil water content observations exhibited a drydown pattern over the period. Surface soil water content observations were made at sites distributed over the area. Significant variations in the level and rate of change in surface soil water content were noted over areas dominated by different soil textures. Passive microwave observations were made on eight days. The ESTAR data were processed to produce brightness temperature maps of a 740-km\(^2\) area on each of the eight days. Using the soil water content algorithm developed by AMSR scientists (Jackson et al.,1995), these data were converted to soil water content images. Gray-scale images for each day are shown in Figure 1. These data exhibited significant spatial and temporal patterns. Spatial patterns were clearly associated with soil textures and temporal patterns with drainage and evaporative processes. Relationships between the ground-sampled soil water content and the brightness temperatures were consistent with previous results.

More recently, ESTAR collected data over a much larger domain, mapping an area about 40 km east-west and about 260 km north-south as part of the 1997 Southern Great Plains Experiment (SGPE) which encompassed the USDA-ARS Little Washita Watershed, USDA-ARS Grazing-lands Research Facility, and Department of Energy Atmospheric Radiation Measurement (ARM) Cloud and Radiation Test Bed (CART) Central Facility. SGPE was designed to conduct to extended surface soil moisture retrieval algorithms based on passive microwave observations to coarser resolutions, larger regions with more diverse conditions, and longer time periods. The ESTAR instrument was used for daily mapping of surface soil moisture over one month period from mid-June to mid-July. Results showed that the soil moisture retrieval algorithm performed the same as in previous investigations (e.g., Washita ’92) demonstrating consistency of both the retrieval and the instrument. Snow Cover and Water Equivalent

The occurrence of precipitation in the form of snow as opposed to rain typically causes a change in how a drainage basin responds to the input of water. The reason for the modified hydrological response is that snow is held in cold storage on a basin for an extended period of time before it enters the runoff process. There is such a vast difference in the physical properties of snow and other natural surfaces that the occurrence of snow on a drainage basin can cause significant changes in the energy and water budgets. As an example, the relatively high albedo of snow reflects a much higher percentage of incoming solar shortwave radiation than snow-free surfaces (80 percent for relatively new snow as opposed to roughly 15 percent for snow-free vegetation) which may cover up to 50 percent of the land surface in the northern hemisphere (Foster and Rango, 1982) and up to 44 percent of the world’s land areas at any one time. Snow cover and the equivalent
amount of water volume stored supplies at least one-third of the water that is used for irrigation and the growth of crops worldwide (Steppuhn, 1981). In high mountain snowmelt basins of the Rocky Mountains, as much as 75 percent of the total annual precipitation is in the form of snow (Storr, 1967), and 90 percent of the annual runoff is from snowmelt (Goodell, 1966).

Despite the various problems mentioned, visible aircraft and satellite imagery have been found to be very useful for monitoring both the buildup of snow cover in a drainage basin and, even more importantly, the disappearance of the snow covered area in the spring. This disappearance or depletion of the snow cover is important to monitor for snowmelt runoff forecasting purposes. It has been recommended by ARS researchers that the optimum frequency of observation of the snow cover during depletion would be once a week (Rango, 1985). Depending on the remote sensing data used, it could be very difficult to obtain this frequency. Certain snowmelt-runoff applications have been possible with as few as two to three observations during the entire snowmelt season (Rango, 1985).

Snow on the Earth’s surface is, in simple terms, an accumulation of ice crystals or grains, resulting in a snowpack which over an area may cover the ground either completely or partly. The physical characteristics of the snowpack determine its microwave properties; microwave radiation emitted from the underlying ground is scattered in many different directions by the snow grains within the snow layer, resulting in a microwave emission at the top of the snow surface being less than the ground emission. Properties affecting microwave response from a snowpack include snow depth, snow water equivalent (SWE), and snow state (wet/dry). Because the number of scatterers within a snowpack is proportional to the thickness and density, SWE can be related to the brightness temperature of the observed scene (Hallikainen and Jolma, 1986); deeper snowpacks generally result in lower brightness temperatures.

The general approach used to derive SWE and snow depth from passive microwave satellite data relates back to those presented by Rango et al. (1979) and Kunzi et al. (1982) using empirical approaches and Chang et al., (1987) using a theoretical basis from radiative transfer calculations to estimate snow depth from Scanning Multispectral Microwave Radiometer (SMMR) data. As discussed in Rott (1993), the most generally applied algorithms for deriving depth or snow water equivalent (SWE) are based on the generalized relation given in Equation 7.1:

\[ SWE = \frac{A}{H_1} \frac{TB(f_1)}{(f_2)} \left(1 - f_2\right) \] in mm, for SWE < 1 mm.

where A and B are the offset and slope of the regression of the brightness temperature difference between a high scattering channel (f_2, commonly 19 GHz) and a low scattering one (f_1, commonly 18 or 19 GHz) of vertical or horizontal polarization. No single global algorithm will estimate snow depth or water equivalent under all snowpack and land-cover conditions. The coefficients are generally determined...
for different climate and land covered regions and for different snow-cover conditions; algorithms used in regions other than those for which they were developed and tested usually provide inaccurate estimates of snow cover. Also, accurate retrieval of information on snow extent, depth, and water equivalent requires dry snow conditions, because the presence of liquid water within the snowpack drastically alters the emissivity of the snow, resulting in brightness temperatures significantly higher than if that snowpack were dry. Therefore, an early morning overpass (local time) is the preferred orbit for retrieval of snow-cover information to minimize wet snow conditions. It is also recognized that knowledge of snowpack state is useful for hydrological applications. Regular monitoring allows detection of the onset of melt or wet snow conditions (Goodison and Walker, 1995).

Passive microwave data provide several advantages not offered by other satellite sensors. Studies have shown that passive microwave data offer the potential to extract meaningful snow-cover information, such as SWE, depth, extent, and snow state. SSM/I is a part of an operational satellite system, providing daily coverage of most snow areas, with multiple passes at high latitudes, hence allowing the study of diurnal variability. The technique has generally all-weather capability (although affected by precipitation at 85 GHz), and can provide data during darkness. The data are available in near real time, and hence can be used for hydrological forecasting. There are limitations and challenges in using microwave data for deriving snow-cover information for hydrology. The coarse resolution of passive microwave satellite sensors such as SMMR and SSM/I (about 25km) is more suited to regional and large basin studies, although Rango et al. (1998) did find that reasonable SWE estimates could be made for basins of less than 10,000 km2.

Another challenge is to incorporate the effect of changing snowpack conditions on the microwave response. Seasonal aging, or metamorphism, results in a change in the grain size and shape, and this will affect the microwave emission from the snowpack. In very cold regions, depth hoar characterized by its large crystal structure enhances the scattering effect on the microwave radiation, resulting in lower surface emission and producing an overestimate of SWE or snow depth (Hill, 1987; Armstrong et al., 1993). The increase in brightness temperature associated with wet snow conditions currently prevents the quantitative determination of depth or water equivalent because algorithms will tend to produce zero values under these conditions. The best way to view the seasonal variability in microwave emission from the snowpack is to compile a time series of satellite data spanning the entire season, which can then be related to changes in the pack over the season (Walker et al., 1995).

In Canada, a federal government program (Climate Research Branch, Atmospheric Environment Service) has been ongoing since the early 1980s to develop, validate, and apply passive microwave satellite data to determine snow extent, snow water equivalent, and snowpack state (wet/dry) in Canadian regions for near-real-time and operational use in hydrological and climatological applications. Goodison and Walker (1995) provide a summary of the program, its algorithm research and development, and future thrusts. For the prairie region a snow water equivalent algorithm was empirically derived using airborne microwave radiometer data (Goodison et al., 1988), and was tested and validated using Nimbus-7 SMMR and DMSP SSM/I satellite data (Goodison, 1989). After ten winter seasons in operation, the Canadian prairie SWE mapping program has successfully demonstrated a useful application of SSM/I-derived snow-cover information for operational hydrological analyses. It is also a cooperative program in that user feedback has served to enhance the validation and the refinement of the SSM/I SWE algorithm (Goodison and Walker, 1995). One enhancement has been the development of a wet snow indicator (Walker and Goodison, 1993), which overcomes a major limitation of the passive microwave technique by providing the capability to discriminate wet snow areas from snow-free areas and hence a more accurate retrieval of snow extent during melting conditions.

Because area snow-cover extent data have been available since the 1960s, various investigators have found many useful applications. A team of scientists from a variety of U.S. government agencies developed plans in the early 1980s for operational snow mapping by the U.S. National Weather Service (NWS) for hydrological purposes. In 1986, NWS adopted these plans and proceeded to develop operational remote sensing products, mostly for snow hydrology. The most widely distributed products of the NWS National Operational Hydrologic Remote Sensing Center (NOHRSIC) are periodic river basin snow cover extent maps from NOAA-AVHRR and the Geostationary Operational Environmental Satellite (GOES). Digital maps for about 4000 basins in North America are produced about once per week and are used by a large group of users including the NWS River Forecast Centers and individual water authorities.

Very few hydrological models have been developed to be compatible with remote sensing data. One of the few models that was developed requiring direct remote sensing input is the Snowmelt Runoff Model (SRM), involving ARS researchers (Martinec et al., 1998). The SRM requires remote sensing measurements of the snow covered area in a basin. Although aircraft observations can be used, satellite-derived snow cover extent is the most common. The SRM employs the degree day approach to melting the snow cover in a basin (Martinec et al., 1998). To date, this version of the SRM has been tested on over 80 basins in 25 countries worldwide. Spain is also using NOAA-AVHRR snow-cover data for the forecasting of snowmelt runoff volume during the spring and summer months in the Pyrenees. Development of subpixel analysis techniques (Gomez-Landesa and Rango, 1998) has allowed snow-cover mapping on basins as small as 10 km2 using the AVHRR data. This approach could make NOAA-AVHRR data more widely useful for hydrological applications after it is tested in different geographic regions. Gomez-Landesa and Rango (1998) applied NOAA-AVHRR snow-cover data as input to the Snowmelt Runoff Model (SRM) for use in forecasting the seasonal snowmelt runoff volume in the Pyrenees to assist in planning hydropower production. More recently, Gomez-Landesa and Rango (2000) compared snow-cover mapping of NOAA-AVHRR with the higher resolution (250-m pixel) data from the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA’s Terra satellite platform. Figure 2 shows the NOAA-AVHRR and MODIS-derived snow-cover for the Noguera Ribagorzana Basin (572.9 km2) in the Central Pyrenees of Spain on 07 April 2000. The different gray levels correspond to different percents of snow cover in each NOAA-AVHRR and MODIS pixel. The correlation between AVHRR and MODIS snow maps were on the order of 0.8 to 0.9 with good agreement between the snow distribution with altitude obtained from both instruments. The agreement was good even in very small basins with an area of about 8.3 km2.  

Landscape Roughness and Vegetation Cover

Roughness refers to the unevenness of the Earth’s surface due to natural processes (i.e., topography, vegetation,
erosion) or human activities (i.e., buildings, power lines, forest clearings). Roughness affects transport of hydrometeorological fluxes between the land surface and atmosphere as well as below the surface, i.e., infiltration and water movement. Roughness is often separated into different complexities related to its effects on land surface-atmosphere dynamics. The complexities are (1) vegetation and urban roughness where the horizontal scale is relatively small, (2) transition roughness between landscape patches (i.e., plowed field next to a forest), and (3) topographic roughness due to changing landscape elevations. These complexities and scales have different effects on wind, heat, and water movement and are difficult to measure in the field at large scales. Lidar, synthetic aperture radar (SAR), digital elevation models (DEM), and photogrammetry are among the remote sensing techniques that have been used to measure landscape surface roughness properties over large areas.

The need for accurate and rapid measurements and assessments of land surface terrain features to estimate the effects of land surface roughness on hydrometeorological processes led to the application of lidar distancing technology by ARS scientists using an aircraft-based platform (Ritchie and Jackson, 1989; Ritchie 1996). Satellite platforms have also been employed (Harding et al., 1994).

The first applications of the airborne lidar altimeter were to measure topography (Link, 1969) and sea ice roughness (Robin, 1966). Lidar altimeters can measure long topographic profiles quickly and efficiently. An example of a topographic profile is shown in Figure 3 using approximately 45 seconds of profiling lidar altimeter data collected in the USDA-ARS Reynolds Creek Experimental Watershed. The length of this profile is 3.5 km and was part of a 10-km profile. The inset in Figure 3 shows the data at full resolution, making the vegetation canopy visible in greater detail. Topographic, transitional, and canopy roughness can be determined from this profile. Ease and speed of data collection would allow measurement of several profiles with a minimum of extra survey cost. Rango et al. (2000) used scanning lidar data to study morphological characteristics of shrub coppice dunes in the USDA-ARS Jornada Experimental Range situated within the Chihuahuan desert. They calculated dune distribution, area, and volume from the scanning laser data. Lidar measurements provide spatial data necessary to understand the effects of topography at all scales on roughness patterns of the landscape.

Detailed measurements of microtopography over distances of 1 to 2 meters to understand the development and patterns of surface roughness using a profiling airborne lidar altimeter for a bare agricultural field is shown in Figure 4 (upper profile). This profile shows the surface micro-roughness superimposed on the overall topography measured with a lidar altimeter. A moving average filter was
used to remove random and system noise (McCuen and Snyder, 1986) and is shown with the lower profile in Figure 3. Microroughness of soil and vegetation has been shown to influence rill development, germination, water retention, infiltration, evaporation, runoff, and soil erosion by water and wind (Zobeck and Onstad, 1987). Lidar altimeter measurements of microroughness of the landscape surface can be used to understand and calculate the effects of roughness on evaporation, soil moisture, runoff, and soil erosion at field and landscape scales.

Entrenched erosional features need to be quantified to estimate their effects on water movement and soil loss across the landscape. Measurements of these features can be difficult and time consuming using ground-based techniques. Measurement of large erosional landscape features can be made rapidly using airborne lidar data (Ritchie et al., 1994). The shape and roughness of gullies and stream channels can be defined (see Figure 5). The lower dotted line in Figure 5 represents the maximum stage of this stream channel cross section, but other stages could be represented and used to calculate the carrying capacity at different channel and floodplain stages. Data on stream bottom roughness can also be used to estimate resistance to flow of the stream. Channel and flood plain cross sections and roughness allow better estimates of channel and flood plain carrying capacity and resistance to flow. Data on channel, gully, and flood plain size, roughness, and degradation can help in the design, development, and placement of physical structures to control and calculate flows.

Vegetation canopies are an important part of landscape roughness that are difficult to measure by conventional techniques. Airborne lidar measurements provided accurate measurements of canopy top roughness (Figure 6a), heights (Figure 6b), and cover (Ritchie et al., 1992; Ritchie et al., 1993; Weltz et al., 1994). Scanning lasers (Rango et al., 2000) can provide a three-dimensional view of canopy structure needed to understand canopy roughness. Lidar measurements of vegetation properties were made at eight locations in the USDA-ARS Walnut Gulch Experimental Watershed in Arizona (Weltz et al., 1994) and used in an algorithm for estimating effective aerodynamic roughness, an important parameter in ET models (Meneti and Ritchie, 1994). These remote estimates agreed with aerodynamic roughness calculated from micrometeorological methods using tower-based measurements (Kustas et al., 1994). Fractals calculated for lidar data have also been used as a way to separate roughness (Pachepsky et al., 1997; Pachepsky and Ritchie, 1998; Ritchie et al., 2001) due to topography and vegetation and to show seasonal patterns in roughness. This type of information from lidar should provide more accurate parameter estimation for models computing hydrometeorological fluxes.

**Remote Sensing of Hydrometeorological Fluxes**

**Evapotranspiration**

One of the more common ways in estimating ET is to rearrange Equation 2, solving for the latent heat flux, LE, as a residual in the energy balance equation for the land surface: i.e.,

\[
LE = R_n - G - H
\]

Figure 4. A bare soil profile measured in an agricultural field. The lower profile was derived from the upper profile (raw data) using an 11-measurement moving average filter.

Figure 5. A lidar altimeter measured stream cross section. Lower dashed line represents the stream cross section and upper dashed line represents the flood plain cross section.

Figure 6. A forest canopy (a) and tree heights (b) measured using an airborne lidar altimeter.
where $R_N$ is the net radiation, $G$ is the soil heat flux, and $H$ is the sensible heat flux, all usually in W m$^{-2}$. The quantity $R_N - G$ is commonly called the "available energy." Remote sensing methods for estimating these components are described in Kustas and Norman (1996). Typically with reliable estimates of solar radiation, differences between remote sensing estimates and observed $R_N - G$ are within 10 percent.

The largest uncertainty in estimating $LE$ comes from computing $z_{OH}$, the so-called "aerodynamic" surface resistance, and $R_{EX}$ is the so-called "excess resistance," which addresses the fact that momentum and heat transport from the roughness elements differ (Bristow, 1982). The radiometric temperature observations, $T_d(\theta)$, at some viewing angle $\theta$, are converted from satellite brightness temperatures and are an estimate of the land surface temperature, $T_{MS}$. Thus, Equations 8 and 9 offer the possibility of mapping surface heat fluxes on a regional scale if $R_N$ and $R_{EX}$ can be estimated appropriately. $R_{EX}$ has been related to the ratio of roughness lengths for momentum, $z_{OM}$, and heat, $z_{OH}$, and the friction velocity $u'_*$. Having the form (e.g., Stewart et al., 1994)

$$ R_{EX} = k^{-1} \ln(z_{OM}/z_{OH}) w^{-1} $$

(10)

where $k = 0.4$ is von Karman's constant. This definition addresses the fact that momentum and heat transport from the roughness elements differ, but is just one of several that have been developed (e.g., Stewart et al., 1994; Muñoz and Van den Hurk, 1995). There have been numerous efforts in recent years to apply Equation 10 and hence determine the behavior of $R_{EX}$ or $z_{OM}/z_{OH}$ for different surfaces, but no universal relationship exists (Kustas and Norman, 1995). Large spatial and temporal variations in the magnitude of $z_{OM}/z_{OH}$ have been found. Nevertheless, solving for $LE$ with the approach summarized in Equations 8, 9, and 10 is still widely applied. It is important to recognize that the fact satellite observations are essentially "instantaneous" or merely "snap shots" of the surface conditions. For many practical applications, LE estimates at longer time scales, i.e., daily values, are needed. This was the impetus for an empirical scheme for estimating daily $LE$, $LE_D$, pioneered by AIS scientists (Jackson et al., 1977) using observations of $T_d(\theta)$ and $T_{MS}$ near midday or maximum heating, i.e.,

$$ LE_D = R_{LE} - R_{TA}(\theta) - R_{TR}(\theta) $$

(11)

where the subscripts $D$ and $LE$ represent "instantaneous" and daily values, respectively. The coefficients $D$ and $LE$ have been related to physical properties of the land surface and atmosphere, namely, $\varepsilon_{TS}$ and stability, respectively (Seguin and Rieze, 1983). Both theoretical and experimental studies have evaluated Equation 11, lending further support for its usability as a simple technique for estimating $LE$ (Carlson and Buffam, 1989; Lagouarde, 1991; Carlson et al., 1995). In fact, studies have applied Equation 11 to meteorological satellites for longer term regional ET monitoring in the Sahelian regions and for France (Seguin et al., 1989; Seguin et al., 1991).

However, a major drawback with these approaches summarized above is that there is no distinction made between soil and vegetation canopy components. Hence, vegetation water use or stress cannot be assessed. Furthermore, as evidence from many previous studies, both the resistances in Equation 9 and consequently the parameterization in Equation 11 are not uniquely defined by surface roughness parameters. In addition to experimental evidence (e.g., Vining and Blad, 1992; Verhoef et al., 1997), Kustas et al. (2003), using a complex soil-vegetation-atmosphere-transfer (SVAT) model (Copip, Norman and Campbell, 1983), have shown the lack of a unique relationship between $T_d(\theta)$ and the so-called "aerodynamic" surface temperature, $T_d$. $T_d$ is the temperature satisfying Equation 9 with traditional expressions for the resistances; see Norman and Becker (1995).

An alternative approach recently proposed considers the soil and vegetation contribution to the total or composite heat fluxes and soil and vegetation temperatures to the radiometric temperature measurements in a so-called "Two-Source" Modeling (TSM) scheme (Norman et al., 1995). This allows for Equation 9 to be recast into the following expression

$$ H = \rho C_P[(T_d(\theta) - T_d(\theta)] $$

(12)

where $R_{EX}$ is the radiometric-convective resistance given by Norman et al. (1995), i.e.,

$$ R_{EX} = (T_d(\theta) - T_d(\theta))/R_{LE}(\theta) $$

(13)

$T_d$ is the canopy temperature, $T_d$ is the soil temperature, and $R_{LE}$ is the soil resistance to heat transfer. An estimate of leaf area index or fractional vegetation cover, $f_c$, is used to estimate $T_d$ and $T_d$ from $T_d(\theta)$, i.e.,

$$ T_d(\theta) \sim f_c(T_{MS}(\theta) - 1 - f_c) $$

(14)

where $f_c(\theta)$ is the fractional vegetation cover at radiometer viewing angle $\theta$, and $R_{LE}$ is computed from a relatively simple formulation predicting wind speed near the soil surface (Norman et al., 1995). With some additional formulations for estimating canopy transpiration, and the dual requirement of energy and radiative balance of the soil and vegetation components, closure in the set of equations is achieved. Through model validation studies, revisions to the original two-source formulations have been made (Kustas and Norman, 1999; Kustas et al., 2003).

Earlier studies recognized the need to consider fractional vegetation cover on ET using information provided in the Vegetation Index-radiometric temperature, VI-$(T_d(\theta))$ space (Price, 1990). Price (1990) used an energy balance model for computing spatially distributed fluxes from the variability within the Normalized Difference Vegetation Index NDVI-$T_d(\theta)$ space from a single satellite scene. Price (1990) used NDVI to estimate the fraction of a pixel covered by vegetation and showed how one could derive bare soil and vegetation temperatures and, with enough spatial variation in surface moisture, estimate daily ET for the limits of full cover vegetation, dry and bare soils.

Following Price (1990), Carlson et al. (1990; 1994) combined an Atmospheric Boundary Layer (ABL) model with a SVAT for mapping surface soil moisture, vegetation cover, and surface fluxes. Model simulations are run for two conditions: 180 percent vegetative cover with the maximum NDVI being known a priori, and with bare soil conditions knowing the minimum NDVI. Using ancillary data (including a morning sounding, vegetation, and soil type information) root-zone and surface soil moisture are varied, respectively, until the modeled and measured $T_d(\theta)$ are closely matched for both cases so that fractional vegetation cover and surface soil moisture are derived. Further refinements to this technique have been developed.
opened by Gillies and Carlson (1995) for potential incorporation into climate models. Comparisons between modeled-derived fluxes and observations have been made recently by Gillies et al. (1997), indicating that approximately 90 percent of the variance in the fluxes were captured by the model.

In a related approach, Moran et al. (1994) defined theoretical boundaries in Vi(TA(u)-TR) space using the Penman-Monteith equation in order to extend the application of the crop water stress index to partial vegetation cover (see below). The boundaries define a trapezoid, which has at the upper two corners unstressed and stressed 100 percent vegetation cover and at the lower corners dry bare soil and dry bare soil conditions (Figure 7). In order to calculate the vertices of the trapezoid, measurements of RH, vapor pressure, TA, and wind speed are required as well as vegetation specific parameters; these include maximum and minimum VT for the full-cover and bare soil case, maximum leaf area index, and maximum and minimum stomatal resistance. Moran et al. (1994) analyze and discuss several of the assumptions underlying the model, especially those concerning the linearly between variables in canopy-air temperature and soil-air temperatures and transpiration and evaporation. Information about ET rates are derived from the location of the Vi(TA(u)-TR) measurements within the date and time-specific trapezoid. This approach permits the technique to be used for both heterogeneous and uniform areas and thus does not require having a range of NDVI and surface temperature in the scene of interest as required by Carlson et al. (1996) and Price (1996). Moran et al. (1994) have compared the method for estimating relative rates of ET with observations over agricultural fields and showed it could be used for irrigation scheduling purposes. More recently, Moran et al. (1996) have shown the technique has potential for computing ET over natural grassland ecosystems.

All these modeling schemes however, are susceptible to errors in the radiometric temperature observations and most require screen level meteorological inputs (primarily wind speed, u, and air temperature, TA, observations) which at regional scales suffer from errors of representativeness. Approaches using remotely sensed data for estimating the variation of these quantities are being developed and tested (Bastiaanssen et al., 1998; Gao et al., 1998). How reliable the algorithms are for different climatic regimes needs to be evaluated.

A modeling framework has recently been developed involving ARS scientists to addressed these limitations (Anderson et al., 1997; Mecikalski et al., 1998) through an energy closure scheme, Atmospheric-Land-EXchange. Inverse (ALEXI) which employs the TSM approach (Norman et al., 1995) to also address the non-uniqueness of the radiometric-aerosol temperature relationship. At this stage, the use of the ABL, a quantity sensitive to heat flux input to the lower atmosphere, and coupling this growth to the temporal changes in surface radiometric temperature from the Geosynchronous Operational Environmental Satellite (GOES). Using temporal changes of brightness temperatures, errors in the conversion to radiometric surface temperatures are significantly mitigated. The use of an energy balance method involving the temporal-change of the height of the ABL moderates errors that arise in schemes that utilize the surface-air temperature gradient for estimating the heat fluxes because the ALEXI model derives local air temperature at an interface height of approximately 50 m.

Another much simpler scheme co-developed by ARS researchers, which also uses the TSM framework, employs the time rate of change in radiometric temperature and air temperature observations from a nearby weather station in a simple formulation for computing regional heat fluxes, called the Dual-Temperature-Difference (DTD) approach (Norman et al., 2000). Although this technique requires air temperature observations, it can use a time difference in air temperature, errors caused by using local shelter level observations for representing a region are still reduced. Moreover, the scheme is simple; thus, it is computationally efficient and does not require atmospheric sounding data for initialization. Preliminary comparisons of regional scale ET output over the central United States between DTD and the more computational intensive and complex ALEXI scheme show good agreement in the patterns (Kustas et al., 2001).

An example of application of the TSM approach for estimating daily ET is illustrated in Plate 2 for the September 2000 ASTER image of T6(θ) and NDVI computed from the ASTER red and near-infrared reflectance data (Plate 2a). Many of the low ET rates are from fields that are either bare soil or contain wheat stubble from the summer winter wheat harvest, which generally have the highest T6(θ) and 0 < NDVI < 0.1. Higher ET rates come from grassland sites (NDVI > 0.2) with the highest rates over irrigated crop fields and riparian areas along streams where NDVI > 0.4 and water bodies where NDVI ≤ 0 (Plate 2a).

Crop Water Stress

Crop water stress is one of the most common problems in agricultural production because soil water deficits occur at some time during the growing season. Development of methods that accurately assess the level of stress and the impact on crop yield would provide more realistic assessment of crop water stress. Of the suite of techniques available, leaf or foliage temperature has been considered one of the more reliable because it is directly related to energy exchanges in the plant. One of the first discussions of the potential usefulness of plant temperature was made by Tanner (1963). This was followed by research by Wingard and Namkon (1966) and Ehler et al. (1978) demonstrating...
that leaf temperature was related to plant moisture status. These two groups used thermocouples and infrared thermometers attached to leaves to obtain leaf temperatures. Development of portable infrared thermometers that could accurately measure foliage temperature prompted the further development of the relationships between foliage temperature and plant water stress.

Over the past 25 years there has been considerable progress in the development and application of foliage temperature as a tool for quantifying plant water stress. There are a variety of terms that have appeared in the literature to describe the relationship between plant water status and foliage temperature. These terms include Stress-Degree-Day, Crop Water Stress Index (CWSI), Non-water Stressed Baselines, and Crop Post-heading Growth Rates (Idso, 1982). These derivations have formed the basis for many of the current applications of CWSI to show how foliage-air temperature differences, \( T_c - T_a \), to the available energy, \( R_h - G \), the vapor pressure deficit, \( VPD \), and aerodynamic and canopy resistances, \( R_a \) and \( R_c \), respectively:

\[
T_c - T_a = \left( \frac{R_h - G}{\rho L_v} \right) \left( \frac{\gamma (1 + R_h/R_c)}{\Delta + \gamma (1 + R_h/R_c)} \right) VPD
\]

where \( \Delta \) is the slope of the saturation vapor pressure-air temperature curve, \( \gamma \) is the psychrometric constant, and the vapor pressure deficit \( VPD = \sigma \Delta - \phi \), which is the difference between saturated and actual vapor pressure at \( T_c \), respectively. By taking the ratio of actual transpiration to the potential rate \( T_{\text{pot}} \) where \( R_h = R_c \), a simple ratio of resistance expression is derived: i.e.,

\[
\frac{T_{\text{pot}}}{T_c} = \frac{1}{1 + R_c R_h / (1 + R_c R_h)}
\]

To solve Equation 17, a value of \( R_c R_h \) is obtained by rearranging Equation 15 and assuming \( G \) is negligible for a full-cover canopy; hence,

\[
\frac{R_c}{R_a} = \frac{\gamma (1 + R_h/R_c)}{\gamma (1 + R_h/R_c)} \frac{\left[ (T_c - T_a) / (\Delta + \gamma) \right]}{VPD}
\]

and \( R_c/R_h \) is substituted into Equation 17 to obtain the CWSI as a function of the canopy-air temperature difference.

Though Jackson et al. (1981) provided a thorough theoretical approach for computation of CWSI, the concept is more universally applied using a semi-empirical variation proposed by Idso et al. (1981) based on the “non-water-stressed baseline.” This baseline is defined by the relation between \( T_c - T_a \) and \( VPD \) under non-limiting soil moisture conditions, i.e., when the plant water is evaporating at the potential rate. Such non-water-stressed baselines have been determined for many different crops, including aquatic crops and grain crops, for both pre-heading and post-heading growth rates (Idso, 1982). These derivations have formed the basis for many of the current applications of foliage temperature to assessment of crop water stress. Hatfield et al. (1987) showed that there were differences among 50 cotton (Gossypium hirsutum L.) strains in their slope of the non-water stressed baseline, suggesting that genetic variation exists between soil water deficits and foliage temperature responses.

The commercial applicability of CWSI is evidenced by the commercial production of a handheld instrument designed to measure CWSI, several commercial imaging companies that are providing CWSI to farmers, and the multitude of examples of application of this theory with airborne and satellite-based thermal sensors combined with ground-based meteorological information (see the review by Moran and Jackson (1991)).
Application of CWSI with satellite- or aircraft-based measurements of surface temperature is generally restricted to full-canopy conditions so that the surface temperature sensed is equal to canopy temperature. To deal with partial plant cover conditions, Moran et al. (1994) developed a Water Deficit Index (WDI) which combined measurements of reflectance with land surface temperature measurements as expressed by:

\[
\text{WDI} = 1 - \frac{\text{ET}\text{P}}{\text{ET}} = (\text{\(\theta_{\text{max}}\) - \(\theta_{\text{min}}\)) - (\text{\(\theta_{\text{ref}}\) - \(\theta_{\text{norm}}\))}
\]

where the subscript OBS is the observed surface-air temperature difference, and subscripts MAX and MIN refer to maximum and minimum observed surface temperature differences, respectively. The WDI is operationally equivalent to the CWSI for full-cover canopies, where \(\theta = \theta_c\). Graphically, WDI is equal to the ratio of distances AC/AB in the trapezoidal shape presented in Figure 7, where WDI = 0.0 for well-watered conditions and WDI = 1.0 for maximum stress conditions. That is, the left edge of the Vegetation Index/Temperature (VIT) trapezoid corresponds to \(\theta = \theta_c\), \(\theta_{\text{ref}}\) values for surfaces evaporating at the potential rate; the right edge corresponds to \(\theta = \theta_c\), \(\theta_{\text{norm}}\) values for surfaces in which no ET is occurring.

Another promising approach for operational application is the use of remotely sensed crop coefficients (the ratio of actual crop evaporation to that of a reference crop) for estimation of actual, site-specific crop evaporation rate from readily available meteorological information (e.g., Bausch, 1993). This approach requires only a measure of NDVI and is simply an improvement of an approach already accepted and in use by farmers to manage crops, where such improvements include increases in accuracy of the evaporation estimate obtained, with useful changes, the ability to work within-field and between-field variations. Variations of foliage temperatures within fields have been used to indicate the onset of crop water stress. Hearman and Duke (1978) found that foliage temperatures of corn (Zea mays L.) that were 1.5°C above air temperature could be used reliably to schedule irrigations. Hatfield et al. (1984) evaluated the variability patterns in grain sorghum (Sorghum bicolor (L.) Moench.) and found that, when the standard deviation of foliage temperature was less than 0.7°C, the soil water extraction was less than 50 percent of the available soil water in the 1.5-m depth. The variance of foliage temperature increased linearly with soil water extraction above 50 percent of the available soil water. Bryant and Moran (1999) used a different approach to quantify variation of foliage temperature in fields and proposed a histogram-derived Crop Water Stress Index. They derived an index based on the deviation of the shape of a histogram of foliage temperature compared to the shape of histogram generated from the mean and variance of thermal image data. To account for differences in the mean foliage temperature, they normalized the frequency of foliage temperatures. They stated that a recently irrigated field would have a histogram close to the normal distribution while a stressed field would deviate from this pattern. This approach is an extension of the variability work conducted with handheld infrared thermometers to the use of thermal images across a field.

In the past 15 years the development of the Thermal Kinetic Window and Crop Specific Temperatures have revealed the dynamic interactions among foliage temperature, soil temperature, and the physical environment. Wanjura and Upchurch (2006) showed that they could effectively use foliage temperatures to manage irrigation on corn and cotton and increase the efficiency of water use on these crops. This concept was based on the development of Crop Specific Temperatures that were defined from original observations by Burke et al. (1988) to show that leaf temperatures of different species achieved an optimal range during the day. Research by Mahan and Upchurch (1986) and Upchurch and Mahan (1988) revealed that plants operated under a narrow range of leaf temperatures during the day that was imposed by the amount of energy received on the leaf and the species that dictated the stomatal conductance or rate of water loss. Hatfield and Burke (1993) found that plants (cotton, cucumber, Cucumis sativa L.; and bell pepper, Capsicum frutescens L.) had different foliage temperatures throughout the day and that these temperatures were specific to a given species. This research prompted the examination of the response of leaf temperature as being a dynamic balance between the leaf characteristics, species, and energy balance.

Concluding Remarks

Agricultural Research Service scientists will continue to play a major role in remote sensing research in hydrometeorology. Algorithm and model development with existing new remote sensing technologies for assessing hydrometeorological state variables and fluxes is considered critical because this is the only technology available that can ultimately provide the capability to monitor crop development and yield using stress indicators and plant water use over a range of spatial scales, from field, farm, and watershed, up to regional scales. To attain this goal, ARS scientists are making important contributions in some of the new research directions to address science questions important hydrometeorological research.

One area is in developing a framework for combining multifrequency remote sensing information, from the visible to microwave wavelengths, for more reliable estimation of vegetation and soil properties and states. There is empirical and theoretical evidence that synthetic aperture radar (SAR) backscatter in combination with optical data (i.e., visible through thermal-infrared wavelengths) may provide useful information about crop water stress (Moran et al., 1997). At high frequencies (about 13 GHz), field experiments have shown that the radar signal was particularly sensitive to soil moisture, though this sensitivity decreased with increasing vegetation cover. At lower frequencies (about 5 GHz), many studies have shown that the radar signal is very sensitive to soil moisture, though this sensitivity decreased with increasing vegetation cover. In a related approach, remotely sensed near-surface moisture from a passive microwave sensor has been used in combination with optical data for estimating the soil and vegetation energy balance (Kustas et al., 1998). The model has been applied over a semiarid area in southern Arizona (Kustas et al., 1998), and in the Southern Great Plains in Oklahoma (Kustas et al., 1999). Comparison of model-computed ET with ground- and aircraft-based observations showed good results, with discrepancies between modeled and observed ET averaging about 15 percent. It is also shown that it may be possible to simulate the daytime fluxes with only a single microwave observation.

Another important area related to scaling up from field to regional scales is the effects of landscape heterogeneity on atmospheric dynamics and mean air properties and resulting feedbacks on the land surface fluxes. This can be captured in a modeling framework using Large Eddy Simulation (LES). LES models simulate the space and time dynamics of all turbulence scales and interactions with the land surface using a numerical solution of the Navier-Stokes equations (e.g., Albertson and Parlange, 1999). However, most studies to date addressing land surface heterogeneity
using L&S have described surface boundary conditions as predefined fluxes with arbitrary variability or with spatial variability defined to match the surface flux fields estimated from experimental data at a particular site. The questions of how the surface heterogeneity affects ABL heterogeneity, and how the surface and air properties in turn affect the flux fields that develop over a region with heterogeneous surface properties are left unanswered in most LES studies.

The LES-remote sensing model recently developed by Albertson et al. (2001) couples remotely sensed surface temperature and soil moisture fields to dynamic ABL variables using the TSM scheme described earlier. Hence, separate and explicit contributions from soil and vegetation (i.e., two sources) to mass and energy exchanges are included. This is a model of active lines of research: the use of remotely sensed land surface properties to study water and energy fluxes, and the use of LES to study the impacts of surface variability on ABL processes. This LES-remote sensing model can run over about a 10-km² domain at relatively high spatial resolution (about 100 m) with remotely sensed vegetation cover, surface soil moisture, and temperature defining surface heterogeneities governing atmospheric exchanges/interactions with the land surface. Typically, land-atmosphere are either driven by a network of surface meteorological observations, or use energy conservation principles applied to ABL dynamics to deduce air temperature (Anderson et al., 1997). However, neither approach considers the resulting impact/feedback of surface heterogeneity on atmospheric turbulence and the resulting spatial features of the mean air properties, particularly at the patch or local scale. The predictions from the LES-remote sensing modeling scheme will provide a benchmark for assessing the impact of a range of surface heterogeneity features on land-atmosphere predictions neglecting such coupling.

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