CHAPTER 26

EVALUATING THE SPATIAL DISTRIBUTION OF EVAPORATION

WILLIAM P. KUSTAS, M. SUSAN MORAN, AND JOHN M. NORMAN

1 INTRODUCTION

Evaporation of water from soil and plant surfaces forms the connecting link between the energy balance and the water balance at Earth’s surface. This phenomenon influences the large-scale circulation of the planetary atmosphere, affects soil moisture content that in turn affects hydrologic response, and regulates the microscale carbon dioxide uptake of stomata in individual plant leaves. The vast range of scales encompassed by the process of evaporation makes it of vital environmental interest.

Over the past century, theoretical, modeling, and experimental efforts have greatly expanded our ability to evaluate water loss due to evaporation at local scales using conventional instrumentation. In recent decades, a concerted effort has been made to develop techniques for evaluating the spatial distribution of evaporation at regional and global scales. This effort has been largely focused on the use of remotely sensed information available from sensors aboard orbiting satellite platforms. The result has been a variety of methods that vary in complexity from statistical approaches to physically based analytical approaches and ultimately to numerical process models that simulate the flow of heat and water through the soil, vegetation, and atmosphere.

This chapter will present a brief discussion of the physics of evaporation, highlight conventional methods for estimating evaporation rates, and then will focus on the use of remote sensing for evaluation of the spatial distribution of evaporation at the local, regional, and global scales. Emphasis will be placed on methods for estimating evaporation at an hourly to daily time frame, which is most appropriate for atmospheric, hydrological, and agricultural applications. This work will conclude...
with a synthesis of the most important research and development issues related to the implementation of such approaches on an operational basis. Although much of the material in Sections 4 and 5 is from the work of Kustas and Norman (1996), new information and results from more recent studies are included.

2 SHORT HISTORY

Although the evaporation process has intrigued humankind for centuries, progress in understanding the physics of evaporation remained slow until the twentieth century when Bowen (1926) showed how the partitioning of available energy between the fluxes of sensible and latent heat could be determined from gradients of temperature and humidity:

\[
\dot{E} = -(R_n + G)/(1 + \beta)
\]  

where \(\dot{E}\) is the latent heat flux (W/m²), \(R_n\) is the net radiation flux at the surface (W/m²), \(G\) is the sensible heat flux conducted to the soil (W/m²), and \(\beta\) is the Bowen ratio (Table 1). The ratio of sensible heat (\(H\)) to latent heat flux density is

\[
\beta = H/\dot{E}
\]  

In Eq. (1), fluxes away from the surface are negative and those toward the surface are positive. The Bowen ratio can be derived from temperature and humidity measurements:

\[
\beta = \gamma(K_h/K_v)(\Delta T/\Delta e)
\]  

where \(\gamma\) is referred to as the psychrometric constant (2.453 MJ/kg at 20°C), \(K_h\) and \(K_v\) are the eddy transfer coefficients for sensible and latent heat, respectively, and \(\Delta T\) and \(\Delta e\) are the differences in temperature in degrees centigrade and vapor pressure in kilopascals over the same elevation difference, \(\Delta z\).

Following the work of Bowen (1926), Penman (1948) combined the thermal energy balance with certain aerodynamic aspects of evaporation and developed an

* Evaporation (\(E\)) is often represented in units of mm/day or mm/h but can also be expressed in energy units, where \(E\) is the evaporation rate (kg/s m²), \(\dot{E}\) is the heat of evaporation (J/kg), and \(\dot{E}_L\) is the latent heat flux density (W/m²). Though expressed in different units, the terms \(E\) and \(\dot{E}_L\) are interchangeable. To avoid confusion herein, the term \(E^*\) will represent evaporation rate in units of depth (mm/h or mm/d), \(E\) will represent mass flux density (kg/s m² or kg/d m²), and \(\dot{E}_L\) will represent latent heat flux density (in units of W/m² or MJ-2 d-1). For further clarification on evaluation of Eqs. (1) to (9), readers are encouraged to review Table 1, and consult the treatise by Monteith (1981) and the books by Brutsaert (1982) and Jensen et al. (1989).
### TABLE 1 Summary of Scientific and Technical Notation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>$\hat{z}$</td>
<td>Surface shortwave albedo</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Priestley–Taylor coefficient, $\tau = 1.26$ for regions with no or low advective conditions</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Bowen ratio, where $\beta = H/\lambda E$</td>
</tr>
<tr>
<td>$C_p$</td>
<td>Specific heat at constant pressure (kJ/kg°C)</td>
</tr>
<tr>
<td>$d_0$</td>
<td>Displacement height (m)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Psychrometric constant (in units of MJ/kg or kPa/°C)</td>
</tr>
<tr>
<td>$\gamma^*$</td>
<td>$\gamma(1 + r_c/r_a)$ (kPa/°C)</td>
</tr>
<tr>
<td>$\Delta T$</td>
<td>Difference in temperature (°C) over the elevation $\Delta z$</td>
</tr>
<tr>
<td>$\Delta e$</td>
<td>Difference in vapor pressure (kPa) over the elevation $\Delta z$</td>
</tr>
<tr>
<td>$\Delta z$</td>
<td>Elevation difference (m)</td>
</tr>
<tr>
<td>$\Delta$</td>
<td>Slope of the saturation vapor pressure–temperature curve (kPa/°C)</td>
</tr>
<tr>
<td>$e_z^a$</td>
<td>Saturation vapor pressure at the $z$ level above the surface (kPa)</td>
</tr>
<tr>
<td>$e_z$</td>
<td>Actual vapor pressure at the $z$ level above the surface (kPa)</td>
</tr>
<tr>
<td>$e_z^a - e_z$</td>
<td>Vapor pressure deficit (kPa)</td>
</tr>
<tr>
<td>$e'$</td>
<td>Instantaneous deviation of the partial water vapor pressure from the mean at height $z$</td>
</tr>
<tr>
<td>$E$</td>
<td>Mass flux density (kg/s/m² or kg/d/m²)</td>
</tr>
<tr>
<td>$E^*$</td>
<td>Evaporation rate in units of depth (mm/h or mm/d)</td>
</tr>
<tr>
<td>$E_F$</td>
<td>Evaporative fraction, where $E_F = -E/(-H + G)$</td>
</tr>
<tr>
<td>$e_s$</td>
<td>Surface emissivity</td>
</tr>
<tr>
<td>$f_g$</td>
<td>Fraction of green or actively transpiring vegetation</td>
</tr>
<tr>
<td>$f_G$</td>
<td>Fraction of green vegetation viewed by the radiometer</td>
</tr>
<tr>
<td>$G$</td>
<td>Soil heat flux density (W/m²)</td>
</tr>
<tr>
<td>$H$</td>
<td>Sensible heat flux density to the air (W/m²)</td>
</tr>
<tr>
<td>$H + \lambda E$</td>
<td>Turbulent fluxes (W/m²)</td>
</tr>
<tr>
<td>$H_c$</td>
<td>Sensible heat flux density from the canopy (W/m²)</td>
</tr>
<tr>
<td>$H_s$</td>
<td>Sensible heat flux density from the soil (W/m²)</td>
</tr>
<tr>
<td>$k$</td>
<td>von Karman’s constant ($\approx 0.4$)</td>
</tr>
<tr>
<td>$K_h, K_r$</td>
<td>Eddy transfer coefficients for sensible and latent heat, respectively</td>
</tr>
<tr>
<td>$\lambda E$</td>
<td>Latent heat flux density (W/m² or MJ⁻² d⁻¹)</td>
</tr>
<tr>
<td>$\lambda E_c$</td>
<td>Latent heat flux density from the canopy (W/m²)</td>
</tr>
<tr>
<td>$\lambda E_p$</td>
<td>Potential latent heat flux density (W/m²)</td>
</tr>
<tr>
<td>$N$</td>
<td>Day length (h)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Air density (kg/m³)</td>
</tr>
<tr>
<td>$\rho_{\Delta \lambda}$</td>
<td>Surface reflectance factor for the spectral range $\Delta \lambda$</td>
</tr>
<tr>
<td>$\rho_{NIR}, \rho_{Red}$</td>
<td>Surface reflectance factors in the near-infrared (NIR) and red spectrum, respectively</td>
</tr>
<tr>
<td>$P$</td>
<td>Atmospheric pressure (kPa)</td>
</tr>
<tr>
<td>$r_s$</td>
<td>Aerodynamic resistance (s/m)</td>
</tr>
<tr>
<td>$r_c$</td>
<td>Canopy resistance to vapor transport (s/m)</td>
</tr>
<tr>
<td>$r_i$</td>
<td>Resistance to heat flow in the boundary layer immediately above the soil surface (s/m)</td>
</tr>
<tr>
<td>$R_n$</td>
<td>Net radiant flux density at the surface (W/m)</td>
</tr>
<tr>
<td>$R_n + G$</td>
<td>Available energy (W/m²)</td>
</tr>
<tr>
<td>$R_{nc}$</td>
<td>Absorbed net radiant flux density by the plant canopy (W/m²)</td>
</tr>
</tbody>
</table>
TABLE I (continued)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_s$</td>
<td>Incoming shortwave solar radiant flux density (W/m²)</td>
</tr>
<tr>
<td>$R_l$</td>
<td>Incoming longwave radiant flux density (W/m²)</td>
</tr>
<tr>
<td>$R_{lu}$</td>
<td>Upwelling longwave radiant flux density, represented by $e_o \sigma T_{sh}^4$</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Stefan–Boltzman constant (5.67 x 10⁻⁸ W/m² K⁴)</td>
</tr>
<tr>
<td>$t$</td>
<td>Time starting at sunrise (h)</td>
</tr>
<tr>
<td>$T_a$</td>
<td>Air temperature (°C)</td>
</tr>
<tr>
<td>$T_{aero}$</td>
<td>Surface aerodynamic temperature (°C)</td>
</tr>
<tr>
<td>$T_c$</td>
<td>Canopy temperature (°C)</td>
</tr>
<tr>
<td>$T_{rad}$</td>
<td>Radiometric temperature measured by an infrared radiometer from a space-borne platform</td>
</tr>
<tr>
<td>$T_s$</td>
<td>Soil surface temperature (°C)</td>
</tr>
<tr>
<td>$T_{sh}$</td>
<td>Hemispherical radiometric temperature (°C or K)</td>
</tr>
<tr>
<td>$u$</td>
<td>Horizontal wind speed (m/s)</td>
</tr>
<tr>
<td>$u_*$</td>
<td>Horizontal wind speed (m/s) about 5 cm above the soil surface</td>
</tr>
<tr>
<td>$w$</td>
<td>Mean vertical wind at height $z$ (m/s)</td>
</tr>
<tr>
<td>$w'$</td>
<td>Instantaneous deviation of vertical wind speed from $w$ (m/s)</td>
</tr>
<tr>
<td>$W_f$</td>
<td>Wind function [generally, $a + b(u)$, where $u$ is the wind speed in m/s]</td>
</tr>
<tr>
<td>$\Phi_h$, $\Phi_m$</td>
<td>Stability corrections for heat and momentum, respectively</td>
</tr>
<tr>
<td>$z$</td>
<td>Height above the surface at which $u$ is measured (m)</td>
</tr>
<tr>
<td>$z_{om}$, $z_{rh}$</td>
<td>Roughness lengths for momentum and heat (m), respectively</td>
</tr>
<tr>
<td>subscript $i$</td>
<td>Instantaneous values</td>
</tr>
<tr>
<td>subscript $d$</td>
<td>Daily values</td>
</tr>
<tr>
<td>subscript $m$</td>
<td>Midday values</td>
</tr>
</tbody>
</table>

A equation for estimating evaporation that was soon adopted by hydrologists and irrigation specialists. The general form of the Penman combination equation is

$$\lambda E = -[(\Delta/\Delta + \gamma)(R_n + G) + (\gamma/(\Delta + \gamma))6.43W_f(e_o - e_z)]$$  \hspace{1cm} (4)

where $\Delta$ is the slope of the saturation vapor pressure–temperature curve (kPa/°C), $\gamma$ is the psychrometric constant (kPa/°C), $W_f$ is a wind function [generally, $a + b(u)$, where $u$ is the wind speed in m/s)], $e_o$ and $e_z$ are the saturation and actual vapor pressures at the $z$ level above the surface (kPa), and $(e_o - e_z)$ is vapor pressure deficit (kPa).

The Penman formula was recast in terms of an aerodynamic resistance and a surface resistance for application to single leaves (Penman, 1953) and vegetation canopies (Rijtema, 1965; Monteith, 1965). This result, now referred to as the Penman–Monteith equation, is probably the most universally used equation for calculating evaporation:

$$\lambda E = -[\Delta(R_n + G) + \rho C_p(e_o - e_z)/R_a]/[\Delta + \gamma^*]$$  \hspace{1cm} (5)
where $\rho$ is air density (kg/m³), $C_p$ is specific heat at constant pressure (kJ/kg°C), and the aerodynamic resistance, $r_a$ (s/m) is

$$ r_a = \left[ \ln\left(\frac{z - d_0}{z_{0m}}\right) + \ln\left(\frac{z_{0m}}{z_{0h}}\right) - \Phi_h \left[ \ln\left(\frac{z - d_0}{z_{0m}}\right) - \Phi_m \right] \right] / k^2 u $$

and $z$ is the height above the surface at which $u$ is measured (m), $d_0$ is the displacement height (m), $z_{0m}$ and $z_{0h}$ are the roughness lengths for momentum and heat (m), respectively, $\Phi_h$ and $\Phi_m$ are the stability corrections for heat and momentum, respectively, and $k$ is von Karman’s constant ($\approx 0.4$). The integral stability functions were summarized by Beljaars and Holtslag (1991) for the stable and unstable conditions. The value of $\gamma^*$ (kPa/°C) in Eq. (5) is a function of $r_a$ and the canopy resistance to vapor transport [$r_c$ (s/m)], where

$$ \gamma^* = \gamma(1 + r_c/r_a) $$

Priestley and Taylor (1972) proposed a simplified version of the Penman combination equation for computation of potential evaporation heat flux density ($\dot{E}_p$) for a surface that has minimal resistance to evaporation. Under these conditions, the aerodynamic component was ignored and the energy component was multiplied by a coefficient,

$$ \dot{E}_p = -\alpha(\Delta/(\Delta + \gamma))(R_n + G) $$

where $\alpha = 1.26$ for regions with no or low advective conditions.

Regional-scale estimates of evaporation have been made using properties of the atmospheric boundary layer (ABL). One approach applies similarity theory to humidity, temperature, and wind in the ABL (Brutsaert and Mawdsley, 1976). Another approach involves the development of simplified conservation equations for the ABL (McNaughton and Spriggs, 1986). This links the surface fluxes to temporal changes in temperature and humidity in the mixed layer. There are problems in employing either approach. The former has difficulties related to the specification of appropriate roughness parameters, especially in heterogeneous terrain, while the latter must develop parameterizations for advection and entrainment processes that commonly exist in the ABL.

3 CONVENTIONAL APPROACHES FOR MEASURING EVAPORATION

Theoretical developments such as those described in the previous section are generally dependent upon experimental data for verification. There are a variety of conventional approaches for measuring evaporation, ranging from simple to complex and having a range of accuracies and spatial scales.

Most simply, evaporation can be measured under field conditions by monitoring the change in soil water storage over a period of time. Though this can be accomplished fairly easily with a neutron soil water probe, this method does not account
for the drainage from the zone sampled or the upward movement of water from a saturated zone into the zone sampled. Discussions of the problems encountered in determining evaporation by soil sampling were presented by Robins et al. (1954) and Jensen and Wright (1978).

Weighing lysimeters are open-top tanks filled with soil in which crops are grown under natural conditions. Evaporation from the contained soil and plants is generally determined either by weighing the entire unit with a mechanical scale or with a counterbalanced scale and load cell; the reduction in the unit's weight over time equals the rate of water transfer to the atmosphere by evaporation. For accurate results, the soil conditions within the lysimeter should be the same as those without, and the lysimeter must be surrounded by the same vegetation that is growing in the lysimeter for a desired radius of about 100 m. A detailed summary of the use of lysimeters for estimation of evaporation can be found in publications by van Bavel and Myers (1962) and Howell et al. (1985).

Commercial instrumentation is available for determining evaporation using an energy balance approach (Bowen ratio) and a mass transfer method (eddy correlation). The Bowen ratio method [based on Eqs. (1) to (3)] allows values of evaporation to be obtained hourly during daylight hours. The accuracy of the method decreases with decreasing flux of water vapor, or when there is low evaporative demand (e.g., at night). A description of the Bowen ratio equipment was provided by Spittlehouse and Black (1980) and Gay and Greenberg (1985).

The eddy correlation method was proposed by Swinback (1951) based on the theoretical description of the mean vertical flux of water vapor:

\[ E = \left( \frac{0.622}{P} \right) \rho w' e' \]  

(9)

where \( P \) is atmospheric pressure (kPa), \( w' \) is the instantaneous deviation of vertical wind speed from the mean vertical wind \( w \) at height \( z \), and \( e' \) is the instantaneous deviation of the partial water vapor pressure from the mean at height \( z \). Evaluation of Eq. (9) is accomplished using vertical anemometers and vapor pressure sensors with short sampling intervals (hundredths of seconds) to determine \( w' \) and \( e' \) in short, successive periods of time (tenths of seconds). This method is amenable to field use in routine measurements for extended periods, e.g., months or years (Kanemasu et al., 1979).

Other approaches that have been used to measure evaporation rates include the inflow–outflow method for monitoring evaporation from catchments (Holmes, 1984) and portable gas assimilation chambers (Reicosky, 1981). A limitation of all the techniques described in this section is that they yield essentially point values of evaporation and, therefore, are applicable only to a homogeneous area surrounding the equipment that is exposed to the same environmental factors. An evaluation of the spatial distribution of evaporation over large heterogeneous areas would be prohibitive using these conventional point measurement techniques. There are advantages and disadvantages of these conventional methods and the remote-sensing techniques discussed in the following sections. Conventional methods yield data at one location but operate continuously over time. Techniques that utilize remotely
sensed inputs yield data for each resolution element of the sensor, thus spatially
distributed values of evaporation, but at only an instant in time.

4 APPROACHES FOR ESTIMATING EVAPORATION USING REMOTE SENSING

An alternative means of estimating the spatial distribution of evaporation is through
the use of remotely sensed images, obtained by either aircraft- or spacecraft-based
sensors. Images obtained from existing satellite sensors can cover swaths ranging
from 60 to 2050 km (at resolutions ranging from 10 m to 1 km) and include informa-
tion about surface reflectance, temperature, and general backscatter properties
(Table 2).

In this section, recent developments in the evaluation of evaporation using remo-
tely sensed images are discussed, with emphasis on several problems that must be
resolved before an operational satellite-based system for monitoring areal evapora-
tion from land surfaces can be realized. These methods have been divided into two
basic classes: (a) statistical and analytical approaches that calculate $H$ and $\lambda E$
"directly" from the remote-sensing data and (b) modeling approaches that use
remote-sensing data to "define" or serve as boundary conditions in the estimation
of $\lambda E$ and $H$.

Determination of $\lambda E$ Directly from the Remote-Sensing Data

Many approaches for determination of $\lambda E$ directly from remote-sensing data use the
surface energy balance equation as the primary boundary condition to be satisfied; that is,

$$R_n + G + H + \lambda E = 0 \quad (10)$$

where $R_n + G$ is often termed the available energy and $H + \lambda E$ are the turbulent
fluxes. Evaluation of the available energy is relatively straightforward and will be
addressed first, followed by the discussion of more complex evaluation of the turbu-
 lent fluxes $H$ and $\lambda E$.

Approaches for Determining Available Energy

A number of approaches using remote sensing have been developed for estimating
the available energy components in Eq. (10). Generally, $R_n$ is evaluated in terms of
its four radiation components (Sellers et al., 1990), namely,

$$R_n = (1 - \hat{\alpha})R_s + \varepsilon_sR_{ld} - \varepsilon_s\sigma T_{sh}^4 \quad (11)$$

where $R_s$ is the incoming shortwave solar radiation (W/m$^2$), $R_{ld}$ is the incoming
longwave radiation (W/m$^2$), $\hat{\alpha}$ is the surface shortwave albedo, $\varepsilon_s$ is the surface
<table>
<thead>
<tr>
<th>Satellite</th>
<th>Sensor</th>
<th>Reflective (μm)</th>
<th>Thermal (μm)</th>
<th>Microwave (GHz)</th>
<th>Pixel Resolution (PR)</th>
<th>Orbital Characteristics</th>
<th>Repeat Cycle</th>
<th>Time of Data Acquisition</th>
<th>Delivery time from acquisition to user ($T_d$)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GOES-8</strong> Imager</td>
<td></td>
<td>0.52–0.72</td>
<td>10.2–11.2</td>
<td></td>
<td>1 km (visible)</td>
<td>Geostationary</td>
<td>Stationary</td>
<td>Every 30 min</td>
<td>Instantaneous at ground station</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3.8–4.0</td>
<td>11.5–12.5</td>
<td></td>
<td>4 km (all others)</td>
<td></td>
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<td></td>
<td></td>
<td>6.5–7.0</td>
<td></td>
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</tr>
<tr>
<td><strong>METEOSAT</strong> VISSR</td>
<td></td>
<td>0.4–1.1</td>
<td>10.5–12.5</td>
<td></td>
<td></td>
<td>Acquired at 1 km Geostationary</td>
<td>Stationary</td>
<td>Every 30 min</td>
<td>Instantaneous at ground station</td>
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<tr>
<td></td>
<td></td>
<td>5.7–7.1</td>
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<tr>
<td><strong>NOAA-12,14</strong> Advanced Very High-Resolution Radiometer (AVHRR-2)</td>
<td></td>
<td>0.58–0.68</td>
<td>3.55–3.93</td>
<td></td>
<td>1.1 km (local area coverage)</td>
<td>Near-polar, sun-synchronous</td>
<td>12 h, every</td>
<td>19.30 (ascending) and 07.30 (descending)</td>
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<tr>
<td></td>
<td></td>
<td>0.725–1.1</td>
<td>10.5–11.5</td>
<td></td>
<td>4 km (global area coverage)</td>
<td></td>
<td>9.2 days</td>
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<tr>
<td>Landsat-5 Thematic Mapper (TM)</td>
<td></td>
<td>0.45–0.52</td>
<td>10.4–12.5</td>
<td></td>
<td>30 m (Vis-IR)</td>
<td>Near-polar, sun-synchronous</td>
<td>16 days</td>
<td>Midmorning</td>
<td>72 hours at best, generally 2 weeks to 1 month</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.52–0.60</td>
<td>120 m (thermal IR)</td>
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<td>0.63–0.69</td>
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<td>0.76–0.90</td>
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<td>1.55–1.75</td>
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<td>2.08–2.35</td>
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<tr>
<td>Landsat-7 Enhanced Thematic Mapper Plus (ETM+)</td>
<td></td>
<td>0.50–0.90</td>
<td>10.4–12.5</td>
<td></td>
<td>30 m (Vis-IR)</td>
<td>Near-polar, sun-synchronous</td>
<td>16 days</td>
<td>Midmorning</td>
<td>48 h</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.45–0.52</td>
<td>60 m (thermal, IR)</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>0.52–0.60</td>
<td>15 m</td>
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<td>0.63–0.69</td>
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<td>0.76–0.90</td>
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<td>1.55–1.75</td>
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<td>2.08–2.35</td>
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<tr>
<td>SPOT-1 to SPOT-3</td>
<td>High Resolution Visible (HRV)</td>
<td>0.30–0.75</td>
<td>10 m</td>
<td></td>
<td>Near-polar, sun-synchronous</td>
<td>26 days, and pointing capability provide shorter cycles</td>
<td>Late morning</td>
<td>48 hours at best, generally 2 weeks to 1 month</td>
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<td></td>
<td></td>
<td>0.50–0.59</td>
<td>(panchromatic)</td>
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<td></td>
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<td>0.62–0.66</td>
<td>20 m</td>
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<td></td>
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<td>0.77–0.87</td>
<td>(multispectral)</td>
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<td>Instrument</td>
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<td>Repeat Cycle</td>
<td>Acquisition Mode</td>
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<tr>
<td><strong>ERS-I to ERS-2</strong></td>
<td>Active Microwave (AM-I) Along-Track Scanning Radiometer (ATSR)</td>
<td>1.6 3.7</td>
<td>11 12</td>
<td>Near-polar, sun-synchronous</td>
<td>3 days</td>
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<td></td>
<td></td>
<td>5.3</td>
<td>1 km</td>
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<td></td>
<td>VV (optical)</td>
<td>30m (3 looks, SAR) 100m (@ radiometric resolution of 1 dB)</td>
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<tr>
<td><strong>RADARSAT</strong></td>
<td>Synthetic Aperture Radar (SAR)</td>
<td>5.3</td>
<td>11</td>
<td>Near-polar, sun-synchronous</td>
<td>24 days</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>III</td>
<td>28m (4 looks, standard product)</td>
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<tr>
<td><strong>JERS-1</strong></td>
<td>Optical Sensor (OPS)</td>
<td>0.52-0.60</td>
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<td></td>
<td>Visible and Near IR (VNIR)</td>
<td>0.63-0.69</td>
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<tr>
<td></td>
<td>Radiometer</td>
<td>0.76-0.86</td>
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<td>Short wavelength InfraRed (SWIR)</td>
<td>1.60-1.71</td>
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<td></td>
<td>Radiometer</td>
<td>2.01-2.12</td>
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<td></td>
<td>Synthetic Aperture Radar (SAR)</td>
<td>2.13-2.25</td>
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<td>2.27-2.40</td>
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<td><strong>Space IKONOS</strong></td>
<td>Imaging</td>
<td>0.45-0.90</td>
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<td>0.45-0.52</td>
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<td>1 m</td>
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<td>Inclination 1-3 days</td>
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<td>98.1 °</td>
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<td>Late morning 24-48 h</td>
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<td>(multispectral)</td>
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<td>sun-synchronous</td>
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(continued)
<table>
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<tr>
<th>Satellite</th>
<th>Sensor</th>
<th>Reflective (μm)</th>
<th>Thermal (μm)</th>
<th>Microwave (GHz)</th>
<th>Pixel Resolution (PR)</th>
<th>Orbital Characteristics</th>
<th>Repeat Cycle</th>
<th>Time of Data Acquisition</th>
<th>Delivery time from acquisition to user ($T_d$)</th>
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</thead>
<tbody>
<tr>
<td><strong>Terra</strong></td>
<td>M0D1S-N</td>
<td>0.47–2.13</td>
<td>1.60–2.43</td>
<td>3.8–14.2</td>
<td>MODIS</td>
<td>Polar orbiting, sun-synchronous</td>
<td>MODIS 1–2 days</td>
<td>10:30</td>
<td>48 h</td>
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<tr>
<td></td>
<td>MODIS</td>
<td>0.66–0.87</td>
<td>0.42–0.94</td>
<td>0.25 km (Visible, NIR)</td>
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<td></td>
<td>SNPP</td>
<td>0.47–2.13</td>
<td>1.60–2.43</td>
<td>3.8–14.2</td>
<td>MODIS</td>
<td>Polar orbiting, sun-synchronous</td>
<td>MODIS 1–2 days</td>
<td>10:30</td>
<td>48 h</td>
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<tr>
<td></td>
<td>ASTER</td>
<td>0.52–0.86</td>
<td>0.42–0.94</td>
<td>0.5 km (Vis, NIR, SWIR)</td>
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<tr>
<td></td>
<td>MISR</td>
<td>0.40–0.88</td>
<td>1.60–2.43</td>
<td>0.5 km (Vis, NIR, SWIR)</td>
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emissivity, $\sigma$ is the Stefan–Boltzmann constant ($5.67 \times 10^{-8}$ W/m$^2$ K$^4$), $T_{sh}$ is the hemispherical radiometric temperature (K) as defined by Norman and Becker (1995), so that the quantity $\varepsilon \sigma T_{sh}^4$ represents the upwelling longwave radiation flux, $R_{lu}$. The radiometric temperature measured by an infrared radiometer from a space-borne platform, $T_{rad}$, is assumed to approximate $T_{sh}$.

Both $R_s$ and $T_{rad}$ have been estimated from Geosynchronous operational environmental satellites (GOES) using empirical/statistical and physically based models (Pinker et al., 1995). On a daily basis, the estimate of $R_s$ from satellite data has an uncertainty of approximately 10%, but at shorter time scales, for example hourly, the uncertainty may be greater (probably on the order of 20 to 30%, on average), especially for partly cloudy conditions (Pinker et al., 1994). Validating $R_s$ at hourly or shorter time scales under partly cloudy skies is especially difficult due to sampling problems associated with the limited network of ground-based measurements typically available from field experiments (Pinker et al., 1994).

Satellite estimates of the contribution of the net longwave flux at the surface have been developed using sounding data (Darnell et al., 1992). The Tiros Operational Vertical Sounder (TOVS) of the National Oceanic and Atmospheric Administration (NOAA) satellites contains infrared and microwave sensors that can be used for estimating both $R_{ld}$ and $T_{rad}$. Other approaches have utilized meteorological data collected near ground level with semiempirical relationships for estimating $R_{ld}$, and then used $T_{rad}$ for calculating the upwelling longwave component (Jackson et al., 1987). Sellers et al. (1990) raise the concern that estimating the four components of $R_n$ could lead to error accumulation, especially in estimating the net longwave flux because both $R_{ld}$ and $R_{lu}$ are large components, so the difference would be small and prone to significant uncertainty. This has led some to estimate surface $R_n$ from the top of the atmosphere (TOA) $R_n$ (Pinker and Tarpley, 1988). While it has been shown that there is little correlation between surface and TOA net longwave flux (Harshvardhan et al., 1990), there is a strong correlation between $R_s$ and $R_n$ at the surface. This has lead to statistical approaches using slowly varying surface properties such as surface albedo and soil moisture with remotely sensed estimates of $R_s$ for estimating $R_n$ (Kustas et al., 1994b). Other techniques use narrow-band reflectance data and $T_{rad}$ from aircraft and satellite-based platforms for estimating the upwelling components $\Delta R_s$ and $R_{lu}$ and use meteorological data for estimating the downwelling components $R_s$ and $R_{ld}$ (e.g., Moran et al., 1989; Daughtry et al., 1990). Comparisons with ground-based observations at meteorological time scales (i.e., half-hourly to hourly) indicate that the differences are within the uncertainty in the measurements, namely 5 to 10%.

The soil heat flux ($G$) can be solved as a function of the thermal conductivity of the soil and the vertical temperature gradient. This temperature gradient cannot be measured remotely, hence numerical models solve for $G$ by having several soil layers (Campbell, 1985). This requires detailed information about soil properties. Models using routine weather data may provide satisfactory predictions of soil heat flux (e.g., Camillo, 1989). An alternative approach takes $G/R_n$ as a constant under daytime conditions that varies as a function of the amount of vegetation cover or leaf area index (LAI), which can be estimated by use of remotely sensed vegetation.
evaluating the spatial distribution of evaporation

indices (VI)* (Choudhury et al., 1994). Several studies have shown that the value of \( G/R_n \) typically ranges between 0.4 for bare soil and 0.05 for full vegetation cover (Choudhury et al., 1987). Observations (Clothier et al., 1986; Kustas et al., 1993a) indicate that a linear relationship between VI and \( G/R_n \) exists, although analytically it has been shown that the relationship should be nonlinear (Kustas et al., 1993a).

Statistical Approaches for Determination of \( \lambda E \)

Statistical methods for estimating \( \lambda E \) have mainly been developed to predict daily \( \lambda E \) using instantaneous remote-sensing observations and assumptions about the relationship between midday \( H \) and \( \lambda E \) and \( R_n + G \). One of the most widely applied approaches, using a \( T_{rad} \) observation near midday, was pioneered by Jackson et al. (1977) whereby they observed that daily differences between \( \lambda E \) and \( R_n \) could be approximated by this linear expression:

\[
R_{n,d} + \lambda E_{d} = A + B(T_{rad,d} - T_{a,d})
\]  

(12)

where the subscript \( i \) and \( d \) represent instantaneous and daily values, respectively, \( A \) and \( B \) are statistical regression coefficients, and \( T_a \) is the air temperature (°C) at about 2 m above the surface. A more general form of this expression was proposed by Seguin and Itier (1983) based on theoretical and experimental observations; namely,

\[
R_{n,d} + \lambda E_{d} = B'(T_{rad,i} - T_{a,i})^n
\]  

(13)

where \( B' \) was dependent on surface roughness and the value of \( n \) depended on stability (\( n = 1 \) for stable and 1.5 for unstable conditions). A variant of Eq. (13) was introduced by Nieuwenhuis et al. (1985) where they replaced \( T_{a,i} \) and \( R_{n,d} \) with a reference canopy temperature (\( T_c,i \)) corresponding to conditions of potential \( \lambda E \) (\( \lambda E_{d,p} \)). The linear form of Eq. (12) has been verified experimentally and theoretically (Carlson and Buffum, 1989; Lagouarde, 1991). Carlson et al. (1995) used a soil vegetation atmospheric transfer (SVAT) model to show that a systematic relationship exists between the \( B' \) and \( n \) parameters in Eq. (13) and fractional cover, which can be estimated with remotely sensed data. Theoretical and experimental work by Lagouarde and McAneney (1992) resulted in the derivation of an equation for estimating daily sensible heat flux (\( H_d \)) using \( T_{rad} \) measured around the time of the NOAA-AVHRR (advanced very high resolution radiometer) overpass (1400 local standard time) and maximum \( T_a \). The equation is similar in form to Dalton’s evaporation equation (see Brutsaert, 1982) and requires the determination of two empirical parameters relating instantaneous to daytime average values of wind speed and surface-air temperature differences. On a daily basis the above techniques appear to have an uncertainty of ±1 mm/day or 20 to 30%.

* Spectral vegetation indices (VI) are a ratio or linear combination of reflectances in the red and NIR wavebands that is particularly sensitive to vegetation amount (Jackson and Huete, 1991) or the amount of photosynthetically active plant tissue in the plant canopy (Wiegand et al., 1991).
The approaches described above attempt to extrapolate "instantaneous" remote-sensing observations of the derived fluxes to daily totals, which is required for many hydrological and agricultural applications. Interest in daily fluxes led Jackson et al. (1983) to develop a procedure using the assumption that the temporal trend in $\lambda E$ would follow the course of solar radiation during the daylight period. They showed that for a clear day the ratio of daily to midday $R_s$ ($R_{sm}$) could be approximated by an analytical expression:

$$\frac{R_{sd}}{R_{sm}} = \frac{2N}{[\pi \sin(\pi t/N)]} \tag{14}$$

where $N$ is the daylength in hours, and $t$ is the time starting at sunrise. Several studies have shown this technique can yield satisfactory estimates of $\lambda E$ using the assumed equivalence $\lambda E_d/\lambda E_m = R_{sd}/R_{sm}$ (Brutsaert and Sugita, 1992).

Experimental observations analyzed by Hall et al. (1992) suggest that the evaporative fraction $[EF = -\lambda E/(R_n + G)]$ remains fairly constant over the daytime period. With this assumption, an instantaneous estimate of the fluxes and hence $EF$ from a remote-sensing observation would have the potential to provide daily $\lambda E$ as long as one can estimate the daytime average available energy $(R_n + G)$. Several studies have found this technique can give reasonable results with differences in daily $E^*$ of less than 1 mm/d (Sugita and Brutsaert, 1991; Brutsaert and Sugita, 1992; Hall et al., 1992; Kustas et al., 1994a). The estimates of daily $\lambda E$ derived from either Eq. (14) or from assuming $EF$ is constant, however, should be adjusted for the contribution of nighttime $\lambda E$. Nighttime $\lambda E$ can be anywhere from 10 to 30% of the daily total (Owe and van de Griend, 1990). This percentage of the daily total will largely depend upon the climate and season. For temperate climates in the summer, 10 to 20% of the daily total is probably typical (Brutsaert and Sugita, 1992).

Recently, Zhang and Lemeur (1995) examined the underlying assumptions of both Eq. (14) and constant $EF$ using the Penman–Monteith equation, and compared the results to measurements from a mixed agricultural and forested region during HAPEX-MOBILHY (Hydrological Atmospheric Pilot Experiment—Modelisation du Bilan Hydrique; see, e.g., André et al., 1986) under clear skies. They found that $EF$ is fairly constant for short vegetation but may not be for forests. Furthermore, the midday values of $EF$ tended to be smaller than the daytime average and the daytime total available energy is required to use this method. Therefore they felt the approach of Jackson et al. (1983) was more suitable since it required only one instantaneous estimate of $\lambda E$ and Eq. (14) to compute daily $\lambda E$. However, Eq. (14) will only be suitable for clear-day conditions whereas Sugita and Brutsaert (1991) and Kustas et al. (1994a) found that $EF$ was reasonably constant under a wider variety of conditions.

### Analytical Approaches for Determination of $H$ and $\lambda E$

Price (1980) proposed a model for obtaining daily integrated fluxes directly by integrating Eq. (10) over a 24-h period with some simplifying assumptions. The result is an analytical expression for computing daily $\lambda E$. It requires as primary input
a 24-h max-min difference in $T_{\text{rad}}$ and daily average climate data obtained by routine weather station observations (i.e., wind speed, air temperature, and vapor pressure). This model readily lends itself to the NOAA-AVHRR series of satellites, which provide day–night pairs of radiometric surface temperature. Further refinements to the technique were made by Price (1982) resulting in a prognostic model that appears to give appropriate $\lambda E$ values when compared to local estimates using standard meteorological and pan evaporation data. However, the amplitude of the max–min difference in $T_{\text{rad}}$ is affected by more than surface soil moisture when vegetation is present and therefore it is less directly coupled to the relative magnitude of $\lambda E$ (Norman et al., 1995a).

Other methods generally compute $\lambda E$ by evaluating $R_n$, $G$, and $H$ and solving for $\lambda E$ by residual in Eq. (10). At least one radiometric surface temperature observation is required. Unfortunately, most of the approaches that are described below provide only an instantaneous estimate of the fluxes because these models require $T_{\text{rad}}$, which means that only one estimate of $\lambda E$ can be computed during the daytime except when using $T_{\text{rad}}$ observations from satellites such as GOES or METEOSAT.

With $R_n$ and $G$ estimated by the remote-sensing methods described earlier, sensible heat flux is normally computed using the following expression:

$$H = -\rho C_p \frac{(T_{\text{aero}} - T_a)}{r_a}$$

(15)

where $T_{\text{aero}}$ is the surface aerodynamic temperature ($^\circ$C) (Norman and Becker, 1995) and $T_a$ is the air temperature ($^\circ$C) either measured at screen height or the potential temperature in the mixed layer (Brutsaert and Sugita, 1991; Brutsaert et al., 1993). The resistance to heat transfer ($r_a$) is affected by windspeed, atmospheric stability, and surface roughness (Brutsaert, 1982).

Since $T_{\text{aero}}$ cannot be measured by remote sensing, it is usually replaced by $T_{\text{rad}}$. For uniform canopy cover, the difference between $T_{\text{aero}}$ and $T_{\text{rad}}$ is typically less than 2$^\circ$C (Choudhury et al., 1986; Huband and Monteith, 1986), but for partial vegetation cover the differences can reach 10$^\circ$C (Kustas, 1990). This has forced many investigators to adjust $r_a$ via empirical methods related to the scalar roughness for heat (Kustas et al., 1989; Sugita and Brutsaert, 1990; Kohsieck et al., 1993) or to use an additional resistance term (Stewart et al., 1994). However, these adjustments to Eq. (15) are not generally applicable because they have not been related to physical quantities causing differences between momentum and scalar transport (McNaughton and Van den Hurk, 1995). This is supported by Sun and Mahrt (1995) who analyzed $T_{\text{rad}}$ observations collected over heterogeneous surfaces and found that existing scalar roughness parameterizations for predicting reliable $H$ fluxes with Eq. (15) were not generally applicable. Efforts have been made to develop dual-source models (Norman et al., 1995b; Lhomme et al., 1994; Chehbouni et al., 1996) to account for differences between $T_{\text{aero}}$ and $T_{\text{rad}}$, and thus avoid the need for empirical adjustments to $r_a$. As a result, dual-source models may have broader application for heterogeneous surfaces (Kustas et al., 1996).

In dual-source modeling approaches, the energy exchange is partitioned between the soil/substrate and the vegetation. An example of a dual-source model was...
presented by Norman et al. (1995b), based on the assumption that soil surface and vegetation canopy fluxes can be taken in parallel, where

\[ H = H_c + H_s = -\varrho C_p \left\{ \left[ \frac{(T_c - T_a)}{r_a} \right] + \left[ \frac{(T_s - T_a)}{(r_a + r_s)} \right] \right\} \]  

and \( H_c \) and \( H_s \) are the sensible heat fluxes from the canopy and soil, respectively, \( r_s \) is the resistance to heat flow in the boundary layer immediately above the soil surface, and \( T_c \) and \( T_s \) are the canopy and soil temperatures, respectively. Though a dual-source approach such as that presented in Eq. (16) has the advantage over single-source approaches [represented by Eq. (15)] of accounting for different sources and sinks of energy fluxes, difficulties arise in specifying the resistances to sensible and latent heat transport from the soil and vegetation. However, relatively simple parameterizations have been proposed. For example, Norman et al. (1995b) proposed that the value of \( r_s \) be computed from the equation developed by Sauer et al. (1995)

\[ r_s = (a + bu_s)^{-1} \]  

where \( u_s \) is the wind speed (m/s) about 5 cm above the soil surface, estimated with equations of Goudriaan (1977), and \( a \approx 0.004 \) m/s and \( b \approx 0.012 \). Further, they proposed that values of \( T_c \) and \( T_s \) be derived from \( T_{rad} \) using the expression

\[ T_{rad} = \left[ f_{gr} T_c^4 + (1 - f_{gr}) T_s^4 \right]^{1/4} \]  

where \( f_{gr} \) is the fraction of green vegetation viewed by the radiometer; and that the absorbed net radiation by the plant canopy, \( R_{nc} \), be partitioned between \( H_c \) and \( \lambda E_c \) according to the Priestley–Taylor approximation (Priestley and Taylor, 1972), where

\[ R_{nc} = -H_c/[1 - 1.3f_{gr} \Delta/(\gamma + \Delta)] \]  

where \( f_{gr} \) is the fraction of green or actively transpiring vegetation.

A recent study by Zhan et al. (1996) compared several single- and dual-source models for computing \( H \) with \( T_{rad} \) over different land cover types. They showed that models containing the least empiricism to account for the differences between \( T_{rad} \) and \( T_{aero} \) gave the best results with differences less than 30%, on average. The dual-source model by Norman et al. (1995b) generally gave the smallest differences with measured \( H \) fluxes. The average difference was around 20%, which is considered the level of uncertainty in eddy correlation and Bowen ratio techniques for determining the surface fluxes in heterogeneous terrain (Nie et al., 1992).

Another approach to solve this problem relates to performing detailed simulations using microclimate and radiative transfer models that can predict the relationship between \( T_{rad} \) and \( T_{aero} \) as a function of surface conditions such as vegetation cover or LAI and surface soil moisture and solar zenith and azimuth angles (Prévot et al., 1994). Some preliminary results from the simulations indicate that LAI is a major
factor in determining the order of magnitude of the scalar roughness needed in Eq. (15) if $T_{\text{aero}}$ is replaced by $T_{\text{rad}}$. A similar result using a Lagrangian approach was obtained by McNaughton and Van de Hurk (1995) who represented the difference between momentum and scalar transport using an excess resistance term.

The analytical approaches outlined above require an estimate of $T_a$. Air temperature is not measured in many regions, and where it is measured it only represents local conditions near the site of the measurement and not at each satellite image pixel. With most current satellite observations of $T_{\text{rad}}$ at the 0.10-1-km pixel scale, significant variations in near surface meteorological conditions may exist depending on surface conditions. Methods using satellite data indicate at least $\pm 3^\circ$C uncertainty in the estimate of $T_a$ when compared to standard weather station observations (Goward et al., 1994). Zhan et al. (1996) showed that two-source models are generally more sensitive to errors in $T_{\text{rad}} - T_a$ than to most other model parameters; thus it is a major advantage for a model not to require a measurement of $T_a$. Kustas and Norman (1997) revised the Norman et al. (1995b) dual-source model for computing the turbulent fluxes without the need for $T_a$ via the use of $T_{\text{rad}}$ observations at two sensor viewing angles, $\sim 0^\circ$ and $\sim 50^\circ$ zenith angles. Such viewing angles from a satellite-based platform have been available from the along track scanning radiometer (ATSR) instrument aboard the ERS-1 satellite (Prata et al., 1990; Prata, 1993). With the ATSR data, there would be no need to extrapolate $T_a$ from a sparse network of meteorological observations to each satellite pixel, a very unreliable approach. Moreover, the model is essentially unaffected by the typical 1 to 2°C error in estimating $T_{\text{rad}}$ from satellites. With these two attributes, the model is well suited for computing regional-scale surface fluxes with an ATSR type of sensor.

Other methods avoid the need for estimating $T_a$ on a pixel-by-pixel basis by relying on air temperature in the ABL, which is much more uniform over a region (Brutsaert and Sugita, 1991; Brutsaert et al., 1993). However, the variability of evaporation is more difficult to quantify. Other approaches attempt to use remotely sensed data in the optical wavebands to define variation in meteorological conditions (Bastiaanssen et al., 1998; Gao et al., 1998). It remains to be seen how universal these relationships are for different climates.

Modeling Approaches That Use Remote-Sensing Data to Define Boundary Conditions

**Numerical Models.** Several numerical models have been developed over the past decade to simulate surface energy flux exchanges using remote sensing data (usually observations of $T_{\text{rad}}$) for updating the model parameters (Camillo et al., 1983; Carlson et al., 1981; Soer, 1980; Taconet et al., 1986). The advantage of these approaches is that the temporal trend of the fluxes can be simulated and periodically updated with the remote-sensing data. Taconet et al. (1986) show the feasibility of using this approach with AVHRR data and, more recently, included the geostationary satellite data (Meteosat) to increase the stability of the model inversion and atmospheric correction of the satellite observations (Taconet and Vidal-Madjar, 1988).
Unfortunately, these models require many input parameters related to soil and vegetation properties not readily available at regional scales. This has prompted some to simplify numerical models in order that remote sensing could potentially be used to estimate most of them (Bougeault et al., 1991). An extreme example of this is given by Brunet et al. (1991) who use an atmospheric boundary layer (ABL) model to calculate regional-scale energy fluxes with a Penman–Montieth equation for parameterizing the energy transport across the soil–vegetation–atmosphere interface. The surface resistance is the main adjustable parameter and is adjusted in order for the model to match the early afternoon infrared surface temperature observation from the NOAA–AVHRR satellite. Preliminary tests using observations under different moisture and crop conditions and surface temperatures from ground-based stations indicate the model adequately simulates the temporal trace and magnitudes of both the energy fluxes and surface temperature.

Numerical models have several advantages over the statistical and analytical approaches. First, they typically better represent the physics of energy transport in the soil–vegetation–atmosphere system. Second, with initial and boundary conditions, they can simulate the energy fluxes continuously. Yet many numerical models still require continuous weather data such as wind speed, air temperature, and vapor pressure, or in the case of atmospheric models that can simulate the near-surface weather, they require radiation data. In practice, few of these models can be used at regional scales with remote-sensing data because of the large amount of vegetation and soils information required to evaluate necessary parameters. Some success in bridging this gap has been achieved by combining a physically based robust model simulating the energy fluxes with remote-sensing data, which provides necessary information for determining key surface parameters in an operational mode (Sellers et al., 1992; Crosson et al., 1993). Two such approaches that appear to have great potential for estimating \( \dot{E} \) operationally are discussed below in some detail.

**Atmospheric Climate Models.** An important conceptual step in improving the procedure for estimating soil moisture and the surface energy balance came with the idea of using the time rate of change of \( T_{\text{rad}} \) from a geostationary satellite such as GOES with an atmospheric boundary layer model (Wetzel et al., 1984). By using time rate of change of \( T_{\text{rad}} \), one reduces the need for absolute accuracy in satellite sensing and atmospheric corrections, both major challenges. Diak (1990) improved this approach further with a method for partitioning the available energy \( (R_n + G) \) into \( H \) and \( \dot{E} \) by using the rate of rise of \( T_{\text{rad}} \) from the GOES satellite and ABL rise from the 12 Greenwich mean time (GMT) synoptic sounding to the 00 GMT sounding. The model is initialized with the 12 GMT sounding of temperature, humidity, and wind speed. Then the surface Bowen ratio (i.e., the ratio of the turbulent fluxes \( H/\dot{E} \)) and the "effective" surface roughness are varied until the predicted 12-h rise in ABL height and \( T_{\text{rad}} \) match the observations. This effective surface roughness combines the effects of the surface aerodynamic roughness, viewing angle, and fractional vegetative cover. Estimates of surface albedo and emissivity are required by the model.
Diak and Whipple (1993) further refined the model by including a procedure to account for effects of horizontal and vertical temperature advection and vertical motions above the ABL. Sensitivity of the model to the determination of the surface energy balance and to the effective roughness was performed with a case study using data from the Midwest and Great Plains areas in the continental United States. They also verified their model estimates of the surface energy balance with in situ measurements from the FIFE (First ISLSCP Field Experiment; see Sellers et al., 1988) site for 2 days. The model-derived $\lambda E$ values were within 10% of the measurements, suggesting this technique may provide reliable $\lambda E$ estimates at regional scales. Additional comparisons of 12-h averages of sensible heat flux with FIFE observations support the utility of their model (see Fig. 2 from Diak et al., 1995). They also found that temperature advection usually does not significantly impact the surface energy balance estimates given by the model on a daily basis, although for areas that are routinely affected by advection the biasing could impact longer term averages of $\lambda E$ (i.e., at climate time scales).

In a related approach, Anderson et al. (1997) recently developed and tested a two-source surface energy balance model requiring measurements of the time rate of change of surface temperature and an early morning ABL sounding. With this model, many of the problems associated with the use of radiometric surface temperature were avoided. The model accommodated the first-order dependence of the radiometric surface temperature on view angle, avoided the need for atmospheric corrections and precise emissivity evaluation, and did not require in situ measurements of air temperature. The performance of the model was evaluated with experimental data from FIFE and from a semiarid rangeland experiment (Monsoon'90; see Kustas and Goodrich, 1994). The model yielded uncertainties in flux estimates comparable to models needing in situ air temperature observations and were comparable to the uncertainties in surface energy flux measurements.

Recognizing the fact that using $T_{rad}$ requires detailed information on the characteristics of the surface and the structure of the overlying atmosphere, which is often incomplete for many regions, Diak et al. (1994) have proposed a method that employs the High Resolution Interferometer-Sounder (HIS) for estimating the turbulent heat fluxes, $H$ and $\lambda E$. The premise is that the temporal changes in the radiances observed by the HIS implicitly measure changes in the lower atmosphere, which are a measure of the absolute amount of energy added to the ABL. The HIS radiance changes were described by coefficients obtained by an eigenvalue decomposition procedure. These coefficients were in turn related to various components of the surface energy balance equation using multiple linear regression. Diak et al. (1994) provide convincing evidence that this method responds to temperature changes in the lower atmosphere as well as surface temperature changes. Consequently, this method is equivalent to the method of Diak (1990), but without requiring any ancillary data, just two remote radiance measurements. However, even when HIS becomes operational, co-located flux measurements will be required to establish a database to use the HIS technique. One possible solution is to identify sites that have sufficiently detailed surface information to permit some of the other techniques described above to be used to calibrate this procedure. In any event, the HIS tech-
nique offers tremendous potential since it can evaluate the surface energy balance relying only on remotely sensed data.

**Alternative Approach: Exploiting the VI/T\textsubscript{rad} Relation.** Numerous studies have found a significant negative correlation between the normalized difference vegetation index (NDVI) and $T_{\text{rad}}$ over a variety of surfaces (Goward et al., 1985; Hope and McDowell, 1992; Nemani and Running, 1989; Nemani et al., 1993), where

$$NDVI = \frac{\rho_{\text{NIR}} - \rho_{\text{Red}}}{\rho_{\text{NIR}} + \rho_{\text{Red}}} \quad (20)$$

and $\rho_{\text{NIR}}$ and $\rho_{\text{Red}}$ are the measured reflectance factors of the surface in the near-infrared (NIR) and red spectrum, respectively. They suggest that this relationship is related to the amount of available energy partitioned into $\lambda E$, which is driven by variation in transpiration or evaporative cooling. Hope et al. (1986) showed theoretically that with $VI$ and $T_{\text{rad}}$ one can extract canopy resistance. However, this assumes complete canopy cover, which does not usually exist in most natural land surfaces.

Nemani and Running (1989) used an ecological model for forested regions and observed a nonlinear relationship between the slope of the NDVI-$T_{\text{rad}}$ curve and the canopy resistance. Goward and Hope (1989) also proposed that the slope was a measure of the surface resistance. These approaches will be difficult to apply to most landscapes with partial canopy cover since variability in fractional cover and surface soil moisture cause significant scatter in the $VI/T_{\text{rad}}$ relationship. Furthermore, studies suggest that the relationship between surface resistance and the NDVI/$T_{\text{rad}}$ slope will vary significantly with vegetation type. Nemani et al. (1993) showed that the NDVI/$T_{\text{rad}}$ slope responded to changes in water status of forested areas, but not of the grasslands. The variability in slope for the grasslands appeared to be mainly caused by variation in fractional cover rather than in $\lambda E$. Smith and Choudhury (1991) used a coupled dual-source soil–vegetation model to show that the NDVI/$T_{\text{rad}}$ slope largely depended on whether the drying soil surface is the source of the decline in $\lambda E$ or whether it was the vegetation. They also observed that the linear relationship between NDVI and $T_{\text{rad}}$ did not exist for forests but only for agricultural and native pastures.

Others have used an energy balance model for computing spatially distributed fluxes from the variability within the NDVI-$T_{\text{rad}}$ plot from a single scene (Price, 1990). Price (1990) used NDVI to estimate the fraction of a pixel covered by vegetation. From the NDVI/$T_{\text{rad}}$ plot Price (1990) showed how one could derive bare soil and vegetation temperatures and, with enough spatial variation in surface moisture, estimate daily $\lambda E$ for the limits of full cover vegetation, dry and wet bare soils.

Following Price (1990), Carlson et al. (1990, 1994) combined an ABL model with a SVAT for mapping surface soil moisture, vegetation cover, and surface fluxes. Model simulations were run for two conditions: 100% 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 atmospheric sounding, vegetation and soil-type information) root-zone and surface soil moisture were varied, respectively, until the modeled and measured $T_{\text{rad}}$ were closely matched for both cases, and fractional vegetated cover and surface soil moisture were derived. Further refinements to this technique have been developed 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) using high-resolution aircraft-based remote-sensing measurements from a grassland ecosystem during FIFE and Monsoon'90. Approximately 90% of the variance in the fluxes was explained by the model.

In a related approach, Moran et al. (1994) defined theoretical boundaries in the $\text{SAVI}/(T_{\text{rad}} - T_a)$ two-dimensional space using the Penman–Monteith equation, where SAVI is the soil-adjusted vegetation index proposed by Huete (1988). The boundaries define a trapezoid, which has at the upper two corners unstressed and stressed 100% vegetated cover and at the lower two corners wet and dry bare soil conditions. To calculate the vertices of the trapezoid, measurements of $R_n$, vapor pressure, $T_a$, and wind speed are required as well as vegetation-specific parameters; these include maximum and minimum SAVI for the full-cover and bare soil case, maximum leaf area index, and maximum and minimum stomatal resistance. Moran et al. (1994) analyzed and discussed several of the assumptions underlying the model, especially those concerning the linearity between variations in canopy–air temperature and soil–air temperatures and transpiration and evaporation. Information about $\lambda E$ rates is derived from the location of the $\text{SAVI}/(T_{\text{rad}} - T_a)$ 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. (1990) and Price (1990). Moran et al. (1994) compared the method for estimating relative rates of $\lambda E$ with observations over agricultural fields and showed it could be used for irrigation scheduling purposes. More recently, Moran et al. (1996) showed that the technique had potential for computing $\lambda E$ over natural grassland ecosystems.

5 SYNTHESIS

In this chapter, numerous methods were reviewed for using remote sensing to estimate $\lambda E$. Based on a similar review conducted by Kustas and Norman (1996), a series of issues were identified as important for remote sensing of $\lambda E$ from measurements, modeling studies, and theoretical considerations. A slightly revised list of these issues is included here:

1. $T_{\text{rad}}$ is not equal to $T_{\text{aero}}$.
2. Most models are sensitive to errors in $T_{\text{aero}} - T_a$ and $u$, yet the measurement of $T_a$ and $u$ at the time and location of the $T_{\text{rad}}$ observation is not typically available.
3. $T_{\text{rad}}$ dependence on view angle cannot generally be neglected because differences in vegetation and soil temperatures can be significant depending on soil moisture conditions.
4. Thermal emissivity is only known approximately on the pixel scale.
5. Atmospheric corrections and satellite calibrations contribute significant errors in the measurements of $\rho_{\Delta \lambda}$ and $T_{\text{rad}}$ that are not always adequately known.
6. Remote observations are instantaneous, while integrated fluxes are desired on hourly, daily, or longer time scales.
7. Satellites with larger pixel sizes (1 to 4 km) can provide sufficiently frequent observations in time (i.e., GOES), but may have uncertainties related to the averaging over heterogeneous subpixel areas.
8. Continuous (hourly or daily) surface flux estimates are most useful, and clouds cause remote observations to be intermittent.

Kustas and Norman (1996) provided a representative list of models using remote observations to estimate $\lambda E$ and attempted to characterize which of the above eight issues each of these models addressed. None of the models address all the important issues at the present time, but several of the models address some of the important issues (1, 3, 4, and 6). Fewer models addressed the most critical issues of spatially distributed meteorological data and atmospheric correction of satellite image data (2 and 5). Related to issue 2, meteorological data acquired at a time or location other than that of the $T_{\text{rad}}$ or VI observation can cause substantial error in the estimate of $\lambda E$. Moran and Jackson (1991) reported that errors in extrapolation of $T_a$ greater than 1°C were unacceptable for estimation of $\lambda E$ using the energy balance approach. They also reported that measurements of $T_a$ measured at 2 m height over adjacent fields of bare soil and lush vegetation differed by up to 3°C at midday. Similarly disturbing results have been reported for wind speed estimation. Rahman (1996) compared a wind speed map constructed by simple interpolation of $u$ values from local weather stations with a map of wind speed derived from the Regional Atmospheric Modeling System (RAMS; Pielke et al., 1992) that accounted for topographic effects. The RAMS-derived map of $u$ was a substantial improvement over the simple interpolation because it accounted for the relatively strong winds in the passes between mountain ranges and relatively light winds in the lee of the ranges.

Related to issue 5, accounting for the attenuation of the radiances received by satellite-based sensors is not a trivial matter (Kauffman, 1989; Price, 1989). In correcting thermal-infrared data, whether using radiative transfer models or split-window techniques, the uncertainty is 1 to 3°C over land surfaces (Becker and Li, 1990; Perry and Moran, 1994). Model sensitivity to such an uncertainty in $T_{\text{rad}}$ can be significant, especially over large vegetation where errors can be ~100 W/m² for hourly to daily time scales (Norman et al., 1995a). However, the 150 W/m² uncertainty in estimating sensible heat flux from radiometric surface temperature observations suggested by Sellers et al. (1995b) is in many cases two to three times larger than errors reported by other researchers (Choudhury, 1994). All the methods reviewed in this chapter are based on the assumption that accurate remotely sensed estimates of surface reflectance, temperature, and backscatter will be readily
available. At this time, they are not. A primary challenge will be to improve the accuracy and consistency of remotely sensed information with an insight into the accuracy requirements of operational models and algorithms.

None of the models explicitly addressed the issue of subpixel averaging, often termed aggregation (issue 7). Aggregation refers to spatial averaging of some heterogeneous surface variable to obtain an effective value representative of an area. In an assessment of the state of the art in aggregation research, Michaud and Shuttleworth (1997) concluded that, over flat terrain, simple aggregation rules applied to surface properties could result in simulated values of $\lambda E$ within 10% of fluxes from models with full representation of heterogeneity. Furthermore, they concluded that aggregation rules for vegetation characteristics were relatively straightforward in the case of patch-scale heterogeneity (variability of 100 to 1000 m). However, mesoscale heterogeneity (10 to 100 km) in surface cover will need to be addressed through more complicated types of parameterization and, in mountainous terrain, the influence of topography on near-surface meteorology must be considered. In an aggregation study related to the use of remote-sensing data for energy balance evaluation, Moran et al. (1997a) found that aggregation of remotely sensed measurements in sparse canopies could be accomplished with little error (such as aggregation of $T_{\text{rad}}$ from 1 m$^2$ to 1 km$^2$) but not others (such as aggregation of $H$ to 1 km$^2$). Kustas and Humes (1996) applied the Norman et al. (1995b) dual-source model for computing basin-scale fluxes with $T_{\text{rad}}$ at 120-, 1000-, and ~8000-m pixel resolution over a semiarid rangeland landscape. They found minor changes in the fluxes aggregated from the different resolutions. Sellers et al. (1995a) investigated the impact of spatial variation in topography, vegetative cover, and soil moisture on area-averaged fluxes simulated by a SVAT model over a 2 x 15 km domain. They found simple averages of these parameters introduced minor errors in the SVAT simulations of the area-averaged fluxes. Still, other studies (Crosson et al., 1993; Sellers et al., 1992) suggest that issue 7 may be a significant problem at the 1-km scale but may average out at the 10-km scale (Norman and Divakarla, 1995).

None of the current models address the issue of continuous surface fluxes even with clouds, but studies are in progress to combine the thermal infrared remote-sensing approaches discussed in this chapter with mesoscale models and with a simplified land–atmosphere exchange model (Anderson et al., 2000). If issues 1 to 7 are addressed adequately, issue 8 will not limit remote estimation of regional $\lambda E$ fluxes.

6 CONCLUDING REMARKS

All the methods and models reviewed in this chapter have potential for operational evaluation of the spatial distribution of evaporation for agricultural and hydrological applications. Toward that goal, relatively simple methods using one-time-of-day remote sensing observations for quantifying daily ET have been applied operationally (Seguin et al., 1989, 1991). However, for many regions of Earth's land surface, meteorological data (primarily wind speed and air temperature) essential for driving
model computations are not available. 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. For air temperature, another approach is in the utilization of radiometric temperature observations from significantly different view angles in a dual-source model (Kustas and Norman, 1997). SVAT models using remote-sensing observations and linked to operational climate and hydrologic models (Ottlé and Vidal-Madjar, 1994; Gillies and Carlson, 1995; Mecikalski et al., 1999; Nouvellon et al., 2001) probably have the greatest potential for operational, regional application. This is because both the surface boundary conditions and atmospheric variables are simulated over time. For heterogenous and mountainous landscapes, further work should be focused on the development of robust aggregation techniques (e.g., Shuttleworth, 1998).

One of the greatest obstacles to the assimilation of remotely sensed information in physical models has been the inherent limitations of currently available sensors. Satellite-based sensors have the advantages of good geometric and radiometric integrity; the disadvantages include fixed spectral bands that may be inappropriate for a given application, spatial resolutions too coarse or too fine for the application, long time periods between image acquisition and delivery to user, and inadequate repeat coverage due to sensor or weather limitations. With the exception of the limitations due to weather, many of the existing limitations may be resolved with the newly launched Terra, Landsat-7, and Space Imaging satellites (Table 2).

Regarding the effects of clouds on image acquisitions, more work should be directed toward utilizing microwave remote sensing, which has some critical advantages over the use of optical data, including little atmospheric attenuation, cloud penetration, high spatial resolution, and day/night acquisitions. Microwave data have been used to derive soil moisture and other vegetation properties (Jackson et al., 1995; Moran et al., 1997b). Microwave data have also been used for estimating the partitioning of available energy into $H$ and $\iota E$, for estimating soil evaporation, and in determining soil surface temperatures (Kustas et al., 1993b; Chanzy and Kustas, 1995; Troufleau et al., 1994). More recently, the dual-source model of Norman et al. (1995b) was revised to use remotely sensed near-surface moisture from a passive microwave sensor for estimating the soil surface energy balance (Kustas et al., 1998). With remotely sensed images of near-surface soil moisture, land cover classification and LAI, the model was applied over a semiarid area in southern Arizona. Comparison of model-predicted fluxes simulated over the daytime period with ground observations showed good results, with 15% differences in evaporation estimates, on average. It is also shown that it may be possible to simulate the daytime fluxes with only a single microwave observation.

The development of methods for combining microwave and optical data with SVAT schemes will likely produce the greatest advancement in the quantification of spatially distributed evaporation. This requires collection of remote-sensing data in concert with ground observations as part of large-scale field projects conducted in different climatic regions. This is a critical part in the further development and
validation of model algorithms. Thus the conventional approaches for estimating evaporation outlined in this chapter play a key role in this effort.

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REFERENCES


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REFERENCES


Sellers, P. J., M. D. Heiser, and F. G. Hall, Relations between surface conductance and spectral vegetation indices at intermediate (100 m² to 15 km²) length scales, J. Geophys. Res., 97(D17), 19033–19059, 1992.


