Determining Soil Moisture from Geosynchronous Satellite Infrared Data: A Feasibility Study

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ABSTRACT

In the absence of a current capability for global routine daily soil moisture observation, an infrared technique using existing instrumentation is sought. Numerical modeling results are reported from a pilot study, the purpose of which was to develop such a technique and to determine the quality and reliability of soil moisture information which it can produce.

In order to determine which physical parameters observable from GOES are most sensitive to soil moisture and which are less prone to interference by seasonal changes, atmospheric effects, vegetation cover, etc., a detailed one-dimensional boundary layer–surface–soil model was employed. The model is described briefly. Results of sensitivity tests are presented which show that the mid-morning differential of surface temperature with respect to absorbed solar radiation is optimally sensitive to soil moisture. A case study comparing model results with GOES infrared data confirms the sensitivity of this parameter to soil moisture and also establishes the applicability of the model to predicting area-averaged surface temperature changes.

A series of model runs were then used to develop a simulated surface temperature dataset from which a soil moisture algorithm was developed. This algorithm uses only GOES observations to separate the soil moisture signal from the interfering effects on the surface temperature. It is shown that soil moisture can be most accurately estimated by this method in dry or marginal agricultural areas where drought is a frequent threat. Sources of error, including the effects of advection and clouds, are examined and methods of minimizing errors are discussed.

1. Introduction and background

A variety of techniques are available to the observer interested in the near-surface and root zone water content of the soil. Many of these techniques are summarized by Schmugge et al. (1980). Practical methods applicable to remote sensing of vegetation covered surfaces are limited to two basic wavelength bands: the thermal infrared and the microwave. Each of these has its special advantages and disadvantages, which often work in a manner that allows the two observations to complement one another. Microwave techniques, which rely on the large effect that water content has on the dielectric constant of soil, have the advantage of a wide dynamic range in the signal between wet and dry soils. They also enable the observer to take measurements through nonprecipitating clouds. On the other hand, the thermal infrared observation of soil moisture has the advantage of requiring a vastly more modest sensing system. It is, therefore, possible to use sensors on existing satellites at geosynchronous altitudes to continuously monitor soil moisture with the same horizontal resolution that is planned for a possible future 21 cm microwave antenna of 10 m diameter to be flown on a low-earth orbiter (400–800 km). When that system is in place, the thermal IR data will remain useful for comparison and to fill temporal gaps in the microwave coverage where skies are clear.

Until recently, remote sensing experiments with thermal infrared techniques have been limited to study of a single parameter, the diurnal temperature range. This is, to some extent, a result of the historical development of the approach. The soil moisture estimation studies grew out of efforts by geologists to detect surface rock types through their thermal inertia. Watson et al. (1971) developed an early method to estimate thermal inertia from the diurnal temperature range. Their method used a surface energy balance model to separate the unwanted effects of the atmosphere and of surface properties from the effects of thermal inertia on the daytime maximum and nocturnal minimum temperatures. This is the basic method which is still in use today. Pohn et al. (1974) successfully applied the model to satellite observations from Nimbus 3 HRIR and Nimbus 4 THR. It was immediately realized that soil moisture has a major effect on the thermal inertia of porous soils. Idso et al. (1976b) took advantage of this fact. They used a rudimentary atmospheric correction model to estimate soil moisture in bare soil directly from the diurnal temperature range.

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1 Also, General Software Corporation, Landover, MD 20785.
Later, Carlson et al. (1981) used a more sophisticated model to estimate both thermal inertia and soil moisture availability from the diurnal temperature range. At about the same time, similar modeling work was underway in Europe, where Rosema et al. (1978) developed an algorithm for estimating thermal inertia and surface relative humidity. Both of these models require considerable in situ meteorological data as model input. Price (1980) developed a theoretical expression for estimating the diurnal heat capacity (related to thermal inertia and thus to soil moisture) under bare soil conditions. None of the above models take into consideration the effects of vegetation on the soil moisture–surface temperature relationship. Vegetation cover was avoided because it was felt to obscure any relationship that might exist. However, in a recent in situ study of irrigated wheat, Jackson (1982) concluded that useful qualitative root zone soil moisture information can be obtained from vegetation canopy temperature measurements where the soil is completely obscured.

Throughout the development of these techniques, the desire for maximum surface resolution limited studies to the best available IR sensors aboard low-earth orbiting satellites, particularly sun-synchronous polar orbiters which view the same area twice daily near the times of maximum and minimum temperature. Use of geosynchronous satellites was not considered. Therefore, until recently, the possibility of examining other features of the diurnal surface temperature wave was not explored. In an early feasibility study, Vieillefosse and Favard (1978) suggested some methods and pointed to some problems in using geosynchronous satellites to estimate thermal inertia and related properties over vegetation free areas of North Africa. Recently, Polansky (1982) and Carlson et al. (1984) have applied the model of Carlson et al. (1981) to GOES data with some success. They used up to three GOES scenes daily which are widely separated in time to provide maximum sensitivity to a moisture related parameter and to thermal inertia. Carlson et al. (1984) found good correlation between their derived moisture parameter and an antecedent precipitation index for 12 cases in 1978 and 1980 over Kansas. Their “man-in-the-loop” algorithm combines initial surface and sounding data with satellite temperatures to produce a matrix of (usually 16) model runs from which a regression is developed. This regression is unique to the area and time under study. It assumes horizontal homogeneity of the atmospheric conditions within the study area and is used to produce maps of relative moisture availability, thermal inertia, and the fluxes of sensible and latent heat. Although the particular model used has some shortcomings to be discussed below, this type of technique is well suited to local- and regional-scale studies on a case study basis where the 5–10 min interactive program does not need to be run repeatedly. The work reported below is an attempt to develop a technique applicable to global- or continental-scale inference of root zone soil moisture under vegetated surfaces for use as input to numerical models, climatological, agricultural and hydrological datasets and global habitability studies.

This study involves examination of the excellent time resolution of the diurnal surface temperature wave to identify signatures in that wave that are sensitive to soil moisture. An algorithm is developed to remove the effects of horizontal variations in vegetation biomass and roughness, wind speed and other surface and atmospheric properties which affect the soil moisture signal. The model predictions are also compared with GOES surface temperature observations in a case study.

2. Selection of the GOES observable parameter

In order to determine which of the GOES observable physical parameters are most sensitive to soil moisture and which are least prone to interference by seasonal changes, atmospheric effects, vegetation cover, etc., a numerical model was employed. The model is an updated version of the boundary layer–earth’s surface model of Wetzel (1978). In this section we will briefly describe the model, then present results from sensitivity tests which led to the selection of an optimum parameter.

a. Model description

The model used is a one-dimensional parameterization of the atmospheric boundary layer over land. The predicted atmospheric variables are turbulent-layer mean horizontal wind components, virtual potential temperature and mixing ratio of water vapor:

$$\frac{\partial u_m}{\partial t} = \frac{w'u'_s - w'u'_l}{z_i} + f(v_m - v_{gm})$$

(1)

$$\frac{\partial v_m}{\partial t} = \frac{w'v'_s - w'v'_l}{z_i} - f(u_m - u_{gm})$$

(2)

$$\frac{\partial \theta_m}{\partial t} = \frac{w'\theta'_s - w'\theta'_l}{z_i} + R,$$

(3)

$$\frac{\partial q_m}{\partial t} = \frac{w'q'_s - w'q'_l}{z_i},$$

(4)

where $u_s$ and $v_s$ are the geostrophic wind components and $R$ represents radiative sources and sinks of heat due to longwave radiation flux divergence and absorption of shortwave radiation by water vapor. The first term on the right side of Eqs. (1)–(4) is the vertically averaged turbulent flux divergence. Subscripts $s$ and $l$ refer to the surface and the top of the turbulent layer, respectively, and $z_i$ is the depth of the turbulent layer, given by a bulk Richardson number equation (Wetzel, 1982) under stable conditions and by a solution to the jump model equations (Wetzel, 1983a) under unstable conditions. The fluxes of all quantities are set to zero
at \( z_i \) during the stable regime, implying no entrainment into the turbulent layer. The entrainment of virtual potential temperature in the unstable case is given by Wetzel (1983a), where it is assumed that the unstable entrainment process is dominated by buoyant processes. This is generally a good assumption except under conditions of near-neutral stability or large vertical wind shear (e.g., Zeman and Tennekes, 1977). Under this assumption, the entrainment of momentum and moisture is computed in a bulk sense, dependent on the rate of growth of \( z_i \) and the difference between the free-air value above \( z_i \) and the mean turbulent layer value. The surface fluxes of all quantities are given by the flux-profile relationships of Businger et al. (1971) as integrated by Paulson (1970).

At the air–earth interface, the model incorporates a surface energy budget equation, prognostic in surface temperature, which is derived by applying the first and second laws of thermodynamics to a vegetation layer of finite thickness. The layer is assumed to contain all vegetation, litter and rubble which is not well linked to the soil and thus acts to store surface heat and to moderate the fluctuations of surface temperature. It is assumed to extend from a point in the soil where it is compact enough so that heat is transferred primarily by conduction, up to some height near the foliage canopy top where the air is adequately free to transport heat primarily by convection. Neglecting the small amount of work done by the small quantity of air within the vegetation layer, the first and second laws of thermodynamics are combined into the general statement

\[
de = \Sigma dQ, \tag{5}
\]

where \( de \) is the change of internal specific energy of the system and \( dQ \) are the various forms of reversible equivalent energy entering or leaving the system. For a horizontal slab, the latter may be expressed in terms of fluxes of energy per unit area across one surface of the slab, i.e.,

\[
dQ = F dt/m, \tag{6}
\]

where \( F \) is a generic flux in units of energy per unit area per unit time, \( dt \) is an increment of time, and \( m \) is the mass per unit area of the slab. We treat \( m \) as the total mass (hereafter called biomass) of loose material at the surface, including vegetation, litter and rubble, that is poorly linked conductively to the soil. Neglecting magnetic, atomic and other meteorologically constant forms of energy, we may write

\[
de = cdT_s, \tag{7}
\]

where \( c \) is the specific heat of the material within the vegetation layer and \( T_s \) is its average temperature. The surface energy budget equation results from combining Eqs. (5)–(7) giving

\[
mc \frac{dT_s}{dt} = R - G - H - E. \tag{8}
\]

Rutter (1975) quotes observed total biomass values ranging from approximately 0.6 g cm\(^{-2}\) for agricultural crops, 0.9 for grassland, to between 3 and 5 g cm\(^{-2}\) for mature forests. Since much of the mass of vegetation is simply water, we assign the value of the specific heat of liquid water to \( c \). The terms on the right side of (8) represent the net radiation flux through the top of the layer \( (R) \), the exchange of heat with the soil \( (G) \), and the sensible \( (H) \) and latent heat \( (E) \) transfer between the vegetation layer and the atmosphere. The radiation flux is divided into shortwave and longwave components. The former is computed from standard geometric considerations taking into account clouds, atmospheric transmission, surface albedo and surface slope (Allen, 1963). The latter is also computed in a standard manner including a full radiation computation for the atmosphere using the empirical functions of Sasamori (1968). The heat flux into the ground is calculated explicitly using 15 equally spaced layers between the bottom of the vegetation layer where \( T = T_s \) and 30 cm depth where \( T \) is assumed constant. The sensible and latent heat fluxes are calculated from the stability dependent surface layer profile functions of Businger et al. (1971) by assuming that conditions at the top of the vegetation layer may be represented by \( T_s \) and by \( q_s \), the surface mixing ratio. The latter is computed from the empirical equation

\[
q_s = q_a + \left( \frac{W_j}{W_i} \right)^2 \frac{E_{ref}}{E} [q_{sat}(T_s) - q_a], \tag{9}
\]

where \( q_a \) and \( q_{sat} \) are the observed atmospheric and saturation mixing ratios, and \( W/W_i \) is the bulk fractional available soil moisture content, where \( W_i \) is the field capacity extractable water content of the root zone and \( W \) is defined so that \( W = 0 \) at the wilting point. The parameter \( E_{ref} \) is a reference evapotranspiration rate which is dependent on the vegetation cover characteristics of the area in question. In the experiments presented below, \( E_{ref} \) is set at 200 W m\(^{-2}\). The derivation of Eq. (9) and a further explanation of the significance of \( E_{ref} \) are given in the Appendix.

Equations (8) and (9) are both well suited for remote sensing applications. The mean vegetation layer temperature \( T_s \) is a mass weighted average of sunlit and shaded leaves, stems, thatch and exposed soil. To the extent that the fractional mass of an object correlates with its fractional cross-sectional area exposed to the remote sensor (probably a good assumption only for fairly sparse vegetation—up to and including grasslands with scattered bushes and trees), the model predicted surface temperature should closely approximate the observed. The fact that the observations are also horizontally averaged by the remote sensor further supports the generalized approach to the prediction of surface temperature. The footprint of the GOES infrared sensor covers about 100 km\(^2\). Such a large area necessarily contains a diversity of surface cover in-
cluding many species of vegetation, each with its own thermal, transpiration and radiation characteristics. The only adequate practical way to represent such a heterogeneous unit is with a very simple generalized vegetation parameterization. Thus, the thermal and radiative characteristics are represented by $T_s$ and $m$ and the transpiration properties are parameterized using Eq. (9).

The model described above may be compared with a large number of existing atmospheric boundary layer and land surface parameterizations used in three-dimensional numerical prediction models, in boundary layer studies and in remote sensing research. These models can be divided into two basic categories. The first involves those whose upper boundary terminates at the top of the surface layer or at shelter level (Halstead et al., 1957; Watson et al., 1971; Nickerson and Smiley, 1975; Rosema et al., 1978; Price, 1980; Soer, 1980; Itier and Riou, 1982). Among the models in this category, some incorporate very detailed representations of the flow of moisture and water vapor in the soil (Camillo et al., 1983) and through vegetation (Fe
derer, 1979). These models require continuous input of surface meteorological data which are not uniformly available on a global basis. The other category of model, however, may use available data or generate data where necessary, because they contain or are coupled to a complete atmospheric boundary layer model and often to a fully three-dimensional numerical weather prediction model (Estoque, 1963; Manabe, 1969; Sasaki, 1970; Atwater, 1972; Deardorff, 1972, 1974, 1977, 1978; Bhumralkar, 1975; Pielke and Mahrrer, 1975; Benoit, 1976; Gannon, 1977; Carlson and Boland, 1978; Blackadar, 1979; McCumber and Pielke, 1981; Zhang and Anthes, 1982; also see International Council of Scientific Unions and World Meteorological Organization, 1981). Of the latter, only the model of Carlson and Boland (1978) has been tested extensively in, and applied specifically to, the estimation of soil moisture, evapotranspiration and related surface properties by remote sensing. A comparison of the present model formulation with that of Carlson and Boland reveals several important advantages of the present model which especially apply to the estimation of soil moisture:

1) The moisture availability parameter $M$ is a specified constant in the Carlson–Boland model. The relationship of soil moisture to $M$ when used to predict actual evapotranspiration depends on atmospheric conditions and the physiology of the vegetation (see the Appendix; also Carlson, 1983; Carlson et al., 1984). The applicability of the Carlson-Boland model to diagnosing actual soil water content is therefore dependent on the interpretation of their diagnosed $M$. Although $M$ may be directly used as input to prediction models with compatible surface parameterizations, it is of uncertain value to hydrology, agriculture and climatic interests. The present model is diagnostic in $W$, the bulk root zone soil water content. Comparisons have been made between the model and observations which include measurements of the soil water profile (Wetzel, 1978). These tests verify the intended direct relationship of $W$ to soil moisture.

2) The soil thermal inertia $P$ is a specified constant in the Carlson–Boland model. It is assumed to be independent of the specified soil moisture. Thermal inertia, however, is a function of soil conductivity, density and heat capacity, all of which have a strong direct relationship to soil water content. The algorithm used by Carlson et al. (1981) employs the model output to diagnose $M$ and $P$ from observed surface temperatures. This algorithm continues to assume that $P$ is independent of soil moisture. In the present model, thermal inertia is assumed to vary with soil moisture.

3) Except for the roughness length parameter $z_0$, the Carlson–Boland model neglects the effects of vegetation. Horizontal variations in roughness are not considered in their soil moisture retrieval algorithm.

b. Sensitivity tests

A large number of runs were made using this model, in which the diurnal march of $T_s$ was computed under a variety of conditions. Individual parameters such as surface albedo, biomass, soil moisture, emissivity, wind speed, etc. were varied systematically, one at a time through the extreme range of their expected values. Results of some of these runs are presented in Fig. 1 and may be compared with similar tests of the model of Carlson and Boland (1978). For each series of tests, the surface temperature is plotted as a function of time and also as a function of the flux of shortwave radiation absorbed by the surface $S$ in a manner similar to Vielefeso and Favard (1978). The latter plot takes the form of a tilted truncated ellipse whose tilt and eccentricity depend primarily on the rate at which energy is removed from the surface by the soil and atmosphere. The identical “standard” case curve appears in each section of the figure as the intermediate curve. From inspection of Fig. 1a it is clear that there are a number of potential signatures sensitive to soil moisture. These include the slopes of the curves at various times of the day, the diurnal temperature range, the lag time of the peak temperature behind local solar noon and the integral area beneath the curves. It is also clear from the remaining figures, however, that many of these same signatures are affected by a number of other parameters as well. The surface geostrophic wind affects pre-dawn surface temperatures more than any other parameter, but also has a strong effect on daytime temperatures. The roughness height which appears as a parameter in the surface layer flux–profile equations, has little effect at night, but strongly influences the rate of rise of temperature after sunrise, as well as the peak surface temperature that is reached. Experiments with the bio-
mass parameter show that low values, up to and including the equivalent of agricultural crops, have a relatively small effect on surface temperature, but when more dense vegetation is present, the damping of the temperature wave becomes significant. It should be noted however that total biomass and roughness height are generally correlated with each other. A sparsely vegetated desert surface with biomass of 0.1 g cm\(^{-2}\) is likely to have a roughness much closer to 0.1 cm than to 10 cm, as is assumed in the run shown in Fig. 1d. Rougher, rocky desert surfaces will have larger biomass values, as defined, because much of the loose surface rubble is poorly linked conductively to the soil. Fig. 1e shows that the thermal inertia at a fixed 50% soil moisture has a somewhat smaller effect on the march of surface temperature and is more important at night than during the day. This is in agreement with the findings of Carlson and Boland (1978). The assigned value of the fixed temperature at 30 cm depth in the soil has little effect on the relative trends of surface temperature throughout the day, although the actual temperature is uniformly altered. The surface albedo has quite a large effect on the peak temperature reached during the day. However, one notes on the \(T_s\) versus \(S\) figure that the morning and afternoon slopes of these curves are not significantly changed by changes in albedo. This is also true of parameters which affect the geometry of the surface with respect to the sun, such as the surface slope, the season and the latitude of the site (not shown). For the purposes of a global- or continental-scale observational program, it is important to be able to account for the effects of varying geometry in a simple way. By inferring \(S\) from the GOES visible channel data and by using a slope parameter \(dT_s/dS\), Fig. 1 shows that this goal is substantially realized.

The effect of surface longwave emissivity on the surface temperature is small and is not shown. The emissivity generally varies within a very narrow range for natural surfaces (Sellers, 1965) and is therefore relatively unimportant to the march of actual surface temperature. However, the effect on the remotely sensed apparent surface temperature can be large under some circumstances. When emissivity is less than 1, the surface will radiate at a lower apparent temperature and at the same time it will reflect downward radiation emitted by the atmosphere, primarily by water vapor. If the effective temperature of the reflected downward radiation is significantly different from the true surface temperature, as it can be at high altitude sites where little atmospheric water vapor is present, or at extreme desert sites where the surface can be much warmer than the air, serious error may result. However, in the

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**Fig. 1.** Results of model sensitivity tests in which each variable was varied individually about a standard case. Unless otherwise indicated, central curve in each panel represents the standard case.
more prevalent moderate situations, this error is generally less than the sensitivity of the GOES radiometer.

Finally, Fig. 1j shows the results of tests in which the stability of the atmosphere above the boundary layer is varied. When a strong temperature inversion is present, boundary layer heating during the day is restricted to a shallower layer. This requires the reservoirs of heat in the surface and adjacent air to reach higher temperatures than the standard case. When the atmosphere is neutral (no lapse of potential temperature with height), a much narrower day–night temperature range results and the surface temperature peak is reached earlier in the day. However, in the $T_v$ versus $S$ plot, we see that the slopes of these curves are all quite similar for most of the day.

Table 1 summarizes the results shown in Fig. 1 by displaying the net variation produced by each individual parameter on a selection of potential soil moisture signatures. The numbers listed represent the combined percentages of variation produced by extreme values of the parameter above and below the standard case. For example, the effects of soil moisture produce a 90% total variation on the mid-morning slope $dT_v/dS$ of the temperature curve. This number represents the fact that a completely dry soil produced a morning slope 58% larger than the standard case and the morning slope over saturated soil was 32% smaller than the standard. Examination of Table 1 reveals an apparent natural division between the first four parameters, which have a large effect on all the potential soil moisture signatures, and the remaining eight which generally have a smaller effect. The soil moisture signal is strongest in the mid-morning slope signature. A strong signal also appears in the area integral of the $T_v$ versus time curves and in the maximum–minimum temperature difference. Signatures which have weaker soil moisture signals include the change in $dT_v/dt$ at sunrise, the late afternoon value of $dT_v/dS$, and the lag time of the surface temperature behind solar noon. The morning slope parameter also has the smallest overall variation due to the last eight parameters in Table 1. The three more important parameters (wind speed, roughness and biomass) have a uniformly large effect on all the potential signatures and would, therefore, have to be taken into account in any chosen soil moisture algorithm. In addition, the effect of thermal inertia on the morning slope may be too large to neglect; however, a normalization procedure described later which is intended to remove the effects of surface cover variations should also eliminate most of this variation.

As a result of the analysis of these model runs, it is concluded that the morning slope parameter appears to have the clearest soil moisture signal. Additional considerations which led to the choice of this parameter over the area integral and diurnal range are as follows:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mid-morning slope (0800–1000 LST)</th>
<th>Integral area of diurnal curve above minimum temperature</th>
<th>Diurnal temperature range</th>
<th>Change in morning slope (1 h before and after sunrise)</th>
<th>Late afternoon slope (2 h before sunset to sunset)</th>
<th>Lag time of maximum temperature behind noon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil moisture (50% ± 50%)</td>
<td>90</td>
<td>82</td>
<td>72</td>
<td>53</td>
<td>26</td>
<td>25</td>
</tr>
<tr>
<td>Wind speed (1–7–25 m s&lt;sup&gt;−1&lt;/sup&gt;)</td>
<td>75</td>
<td>79</td>
<td>75</td>
<td>112</td>
<td>92</td>
<td>9*</td>
</tr>
<tr>
<td>Roughness length (0.1–10–150 cm)</td>
<td>73</td>
<td>54</td>
<td>60</td>
<td>65</td>
<td>103</td>
<td>21</td>
</tr>
<tr>
<td>Biomass [0.08–0.8–8.0 g (H&lt;sub&gt;2&lt;/sub&gt;O equiv.) cm&lt;sup&gt;−2&lt;/sup&gt;]</td>
<td>83</td>
<td>54</td>
<td>43</td>
<td>124</td>
<td>82</td>
<td>84*</td>
</tr>
<tr>
<td>Thermal inertia at fixed soil moisture (0.028 ± 0.02 cal cm&lt;sup&gt;−3&lt;/sup&gt; K&lt;sup&gt;−1&lt;/sup&gt; s&lt;sup&gt;−1/2&lt;/sup&gt;)</td>
<td>36</td>
<td>23</td>
<td>22</td>
<td>12*</td>
<td>18</td>
<td>8</td>
</tr>
<tr>
<td>Deep soil temperature (285 ± 30 K)</td>
<td>21</td>
<td>2</td>
<td>8</td>
<td>35</td>
<td>37</td>
<td>1</td>
</tr>
<tr>
<td>Surface albedo (0.25 ± 0.20)</td>
<td>18</td>
<td>37</td>
<td>34</td>
<td>59</td>
<td>34</td>
<td>10</td>
</tr>
<tr>
<td>Latitude (40° ± 25°)</td>
<td>18</td>
<td>48</td>
<td>43</td>
<td>47*</td>
<td>41*</td>
<td>10</td>
</tr>
<tr>
<td>North–south slope (0 ± 15%)</td>
<td>16</td>
<td>18</td>
<td>15</td>
<td>35</td>
<td>13</td>
<td>2*</td>
</tr>
<tr>
<td>Surface emissivity (0.9 ± 0.1)</td>
<td>14</td>
<td>3*</td>
<td>2</td>
<td>24</td>
<td>18</td>
<td>6</td>
</tr>
<tr>
<td>East–west slope (0 ± 15%)</td>
<td>14*</td>
<td>4</td>
<td>4</td>
<td>88*</td>
<td>22</td>
<td>31</td>
</tr>
<tr>
<td>Season (21 June–21 March–21 Dec)</td>
<td>8</td>
<td>97</td>
<td>61</td>
<td>41*</td>
<td>26</td>
<td>17</td>
</tr>
</tbody>
</table>
1) The amount of data required to determine the morning slope is minimal compared to the area integral parameter. The former requires a minimum of only two measurements per day, the latter at least four to six.

2) The two measurements required to determine the morning slope are only a few hours apart, compared to six to ten hours for the diurnal range. This leaves less time for large-scale changes in atmospheric conditions to occur. Also, since Fig. 1 shows that the morning slope remains quite constant for a number of hours, the exact times of measurement are not important, allowing flexibility to avoid clouds, instrument problems, etc. The time window for measurement of the diurnal range parameter is not only narrower, but may vary with season, latitude and even from day to day.

3) The mid-morning time period is meteorologically uniquely well suited for the observation of soil moisture effects on surface temperature. The boundary layer is well mixed, so that the topographic effects which dominate the surface temperature signal overnight are removed. However, the boundary layer is still shallow and still separated from the free atmosphere by the elevated remnants of the nocturnal inversion. This isolation means that some of the larger-scale effects of the atmosphere which affect the surface temperature, such as temperature advection, are minimized. Also, in most land areas of the world, except where coastal cold water fog is frequent, mid-morning is climatologically the most cloud-free time of day.

4) Finally, mid-morning is the time of day in which the simplest physical relationship exists between soil moisture and surface temperature. Lack of evaporative demand overnight, and through the early morning as dew evaporates, allows the vertical profile of moisture within the soil to reach its most uniform distribution by mid-morning. Thus, a simple direct proportionality between the slab or root-zone average soil moisture and the rate of removal of latent heat is most closely realized during the first hours after the dew has evaporated.

3. A comparison of the model with observations

In order to assess the ability of the model to predict surface temperatures as seen by GOES, a case study using satellite data was examined. The case also served the purpose of verifying the model's prediction that the mid-morning slope parameter is highly sensitive to soil moisture. The day chosen was 28 July 1978, which has also been examined by Polansky (1982). This was a day in which a wide variation of soil moisture existed across the eastern half of Kansas and Nebraska. It was also selected because the skies were clear, the wind was very uniform across the area of interest and no significant advection was occurring. Therefore, the effects of vegetation and soil moisture should dominate the variations in surface temperature on this day.

The GOES infrared data were processed on the NASA/Goddard Space Flight Center's Atmospheric and Oceanographic Information Processing System (AOIPS) to produce accurately registered maps of the change in apparent surface temperature between 0800 and 1000 local time on 28 July. Soil moisture data were computed in the form of an antecedent precipitation index (API) from more than 400 NOAA climatological network raingage stations in the area. The API for day $i$ is calculated from

$$ (\text{API})_i = R_i + k(\text{API})_{i-1}, $$

where $R$ is the 24 h total precipitation and $k$ is a recession coefficient specified to be 0.935 in June and 0.92 in July. All stations were initialized with an API of zero on 1 June. The API is considered the best "ground truth" estimate of area-averaged soil moisture available on a routine basis over large areas (Blanchard et al., 1981; Choudhury and Blanchard, 1983).

Maps of the GOES morning temperature change and the API are presented in Figs. 2a and 2b respectively. It is clear from comparison of these figures that

![Figure 2](image_url)

**Fig. 2.** Surface observations from Kansas and Nebraska on 28 July 1978. (a) GOES 2 h temperature change (K). Stippled areas are cloud covered. Cross hatching marks areas with two-hour temperature change greater than 8 K (right hatching) and less than 5 K (left hatching). (b) Antecedent precipitation index analysis (mm) from raingage stations. Features labeled with capital letters are examples of patterns which appear in both figures.
the GOES data display some sensitivity to soil moisture. Some specific features which appear on both maps are labeled. Points A and D in north central Kansas mark narrow tongues of wet and dry soil respectively which are well reflected in the surface temperature data. The region of wettest soil, point B, in southeastern Nebraska—an area in which nearly 200 mm of rain fell on 22–23 July—also has the smallest 2 h temperature change. Point C marks a region of sharp gradients in both the API and temperature change parameter. An extensive area of irrigated farmland along the Platte River in Nebraska (Schickedanz, 1976), within which the API has no significance, appears to be a relatively wet surface based on the GOES data.

The effects of vegetation can also be seen in these figures if one notes that near the western edge of the figures, a given value of API systematically corresponds to larger temperature changes than along the eastern edge. In general, vegetation density, or biomass, varies with longitude over the High Plains, in response to the gradient of climatological mean precipitation. In fact, there is a distinct dividing line near 97°W longitude (through point C, Fig. 2) which separates cropland primarily planted in corn to the east and winter wheat to the west. This line appears clearly in Fig. 3 which displays a meridionally averaged relative green leaf biomass index in the state of Kansas during mid-July 1982. The data are a combination of two channels from the TIROS-N AVHRR using the model of Tucker (1979) and are not to be confused with the parameter $m$ in Eq. (6). In late July, the wheat has been harvested and index values appear relatively high, while the index in corn is near its minimum level at this time of year.

As a quantitative test of the model's performance, the data in Fig. 2 were divided into a corn region (east of 97°W) and a wheat region (west of 97°30'W). All of Nebraska west of 97°W and north of 41°N was excluded due to the effects of irrigation or the possible influence of clouds (Fig. 2a). In each region, a series of model runs were made in which the atmospheric conditions over Kansas on this day were simulated. All model initial conditions were kept the same except for the soil moisture, biomass and roughness length. For the corn region simulation, the biomass was set at 0.85 g cm$^{-2}$ and the roughness length at 12 cm. In the wheat region, values were 0.3 g cm$^{-2}$ and 0.5 cm respectively. The model predicted response of the mid-morning temperature change parameter to soil moisture was then compared to that of the GOES observations. Results for the two regions are presented in Figs. 4a and b. The modeled root zone soil moisture and the observed API were assumed to be linearly related as follows:

$$\frac{W}{W_s} = \frac{1}{0.85} \left( \frac{\text{API}}{W_s} - 0.15 \right).$$

A field capacity of 10 cm was assumed for both API and $W$ (Thornthwaite, 1948; Penman, 1949) and the wilting point ($W = 0$) occurs at an API of 1.5 cm. Plotted on Fig. 4 are the data from all the raingage stations in each area. The solid line represents a linear regression fit between the GOES data and API on a logarithmic scale. Correlation coefficients of −0.86 and −0.80 were found for the corn and wheat regions respectively. This level of correlation indicates that useful soil moisture data is indeed obtainable from the observations. Model results are plotted as circles on the figures. The agreement is very good between the model predictions and the regression fit to the observations. The results suggest that the model is correctly simulating the area-averaged surface temperature changes as seen by GOES. It is of course possible to “tune” the model by adjusting the biomass, roughness and the parameters in the API = $W/W_s$ relationship. It is nevertheless encouraging that the values which best agree with the observations also bear the best possible physical resemblance to true soil and vegetation conditions in Kansas on this day. It is also important to note that the model accurately predicts the logarithmic nature of the API-temperature change relationship and properly simulates the change in slope of that relationship with changing vegetation density. Carlson et al. (1984) also found a log-linear relationship between $M$ and API in the 12 cases they studied. Finally, we should note that field studies with homogeneous vegetation often show that evapotranspiration remains near potential rates until some critical moisture level is reached, whereupon it drops rapidly to small values. Considering this observation, one may question the value of the temperature change parameter for inferring soil moisture over vegetated surfaces. However, the data in Fig. 4 show that there is, in the GOES observations, a gradual transition in the temperature change.

Fig. 3. Meridionally averaged mean and standard deviation of green leaf biomass index for the state of Kansas (37°–40°N). Numbers are relative units, smaller values correspond to greater biomass. Data are a combination of two channels from TIROS-N AVHRR using the method of Tucker (1979).
between dry and wet soil. We attribute this to the heterogeneous nature of the $10 \times 10$ km GOES pixel, which reflects the average of many types of vegetation with different evapotranspiration properties.

4. Separation of the soil moisture signal

In the case study presented above, the effects of wind and vegetation were easily separated from the soil moisture signal by selecting an area of uniform wind and homogeneous vegetation. In general, however, it is necessary to develop a routine procedure to remove these effects from the signal before the soil moisture information can be extracted. The variability caused by the remaining “less important” parameters at the bottom of Table 1 and by other effects such as advection, is neglected for the moment. When considering large heterogeneous surface units, we will make the further assumption of perfect correlation between biomass and roughness length. Under this assumption, the two parameters are considered as one quantity, indicative of the bulk properties of the heterogeneous vegetation canopy. We first discuss methods of accounting for wind and vegetation effects under the assumptions stated, and then we address some of the additional problems which must be considered when applying the algorithm to satellite observations.

a. The basic approach

Assuming that ideal conditions exist, or that observations can be satisfactorily preprocessed, we will consider a morning slope signature which responds only to the three primary parameters: soil moisture, wind and surface cover. It then follows that two quantities in addition to $dT_s/dS$ must be observed. Ideally, these measurements should also be made from the GOES platform and should be optimally sensitive to wind and vegetation, as $dT_s/dS$ is to soil moisture. Table 1 suggests two possible signatures which are considerably more sensitive to wind than to soil moisture. These are the change in morning slope at sunrise, when the presence of any dew masks the soil moisture signal, and the late afternoon slope. One of these can therefore be used as a second observable. We have selected the early morning change of slope with time $d^2T_s/dt^2$ for use in the analysis which follows. The geostrophic wind generally varies slowly with time and is not subject to the large diurnal cycle that the measured surface wind speed is, so the requirement that the geostrophic wind be constant between the sunrise and mid-morning observations should usually be met to good approximation. In place of a third independent observable quantity, one sensitive to surface properties, we will normalize the other two parameters, $dT_s/dS$ and $d^2T_s/dt^2$, by their values taken at fixed soil moisture and wind speed. The normalization procedure is possible because surface cover is static in time relative to the meteorological and hydrological phenomena of interest. One may therefore “pre-observe” the pertinent surface properties and store them for later reference. This approach is necessary when using GOES data since it is not possible to obtain a satisfactory independent measure of vegetation characteristics from
datasets consisting of model results and/or observations, the functional relationships can be established (e.g., by regression) between $A$ and $B$ and the variables $V_g$ and $W/W_s$. Assuming that these functions are tractable, and that $A$ and $B$ are sufficiently independent, the geostrophic wind speed can be eliminated between the two equations, leaving an expression relating $W/W_s$ to the observables $A$ and $B$.

To demonstrate and test the procedure outlined above, a series of 125 model runs were made, representing five surface cover and environmental conditions in five different soil moisture classes and five values of geostrophic wind. This dataset was analyzed to produce simulated values of $A$ and $B$. The results for $B$ are presented in Fig. 5. Similar results for $A$ are not shown. At each point on the $V_g - W/W_s$ plane, five values are plotted, representing the five separate surface and environmental conditions simulated. Details of the initial conditions are given in Table 2. Although there is some scatter in the normalized quantity $B$, particularly at the extremities of the figure, it is generally concluded that the normalization process substantially removes the effects of variations in surface properties as simulated.

After experimentation with various forms, multiple linear regression fits to the five run mean values of $A$ and $B$ were selected as follows:

$$A = c_1 + c_2 V + c_3 D^2, \quad R^2 = 0.98,$$

$$B = c_4 + c_5 V + c_6 \left(D^2 \left(1 + \frac{1}{V}\right)\right), \quad R^2 = 0.96,$$

where $D$ is the soil moisture deficit, $(1 - W/W_s)$, and $V = \ln V_g$. The constants $c_i$ represent coefficients produced by the regression. These equations are chosen only as examples. A large number of tractable regression solutions exist for this simulated dataset. The final

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TABLE 2. Initial conditions used in model tests of the normalization approach; sounding column refers to atmospheric temperature and humidity soundings for mean midlatitude spring and midlatitude summer conditions adapted from McClatchey et al. (1972).

<table>
<thead>
<tr>
<th>Run set</th>
<th>Sounding</th>
<th>Biomass (g cm$^{-2}$)</th>
<th>Roughness length (cm)</th>
<th>Typical vegetation represented</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Spring</td>
<td>0.3</td>
<td>0.5</td>
<td>Semi-arid short grass, pasture, desert</td>
</tr>
<tr>
<td>2</td>
<td>Spring</td>
<td>0.8</td>
<td>10.0</td>
<td>Tall grass, mature agricultural crops</td>
</tr>
<tr>
<td>3</td>
<td>Summer</td>
<td>0.3</td>
<td>0.5</td>
<td>Semi-arid short grass, pasture, desert</td>
</tr>
<tr>
<td>4</td>
<td>Summer</td>
<td>0.6</td>
<td>5.0</td>
<td>Small crops, thick short grass</td>
</tr>
<tr>
<td>5</td>
<td>Summer</td>
<td>1.2</td>
<td>50.0</td>
<td>Mixed crops and trees, savannah</td>
</tr>
</tbody>
</table>
selection of a regression should, of course, be based on an extensive body of actual observations. Eqs. (12) and (13) are combined to eliminate V, and the resulting expression is rearranged to yield an expression for $W/W_s$ in terms of the GOES observed quantities A and B. One then observes A and B using a predetermined library of reference values and computes $W/W_s$ from the rearranged equation.

If A and B are sufficiently independent functions of wind speed and soil moisture, that is if A is a strong function of wind and only weakly dependent on soil moisture, and if B is the reverse, then the resulting inference of soil moisture can be highly accurate. In reality the two functions are somewhat more parallel, particularly under conditions of wet soil with dense vegetation cover. In this case, any errors in measurement of A or B can be magnified in the resulting soil moisture estimate. Illustration of this effect is presented in Fig. 6, on which the solution of Eqs. (12) and (13) is plotted. Two sample estimates of soil moisture are illustrated, in which it is assumed that an error of 0.1 units occurs in the measurement of A and B. In example (1), A and B are both small. This corresponds to densely vegetated surfaces with wet soil and relatively high wind speeds. These are conditions under which the range of the surface temperature signal, and therefore the signal-to-noise ratio, is the smallest. The resulting error in the estimate of soil moisture, represented by the shaded area in Fig. 6, can be quite large. In this case it can be greater than 30%. On the other hand, the error is much smaller in example (2) where $A$ and $B$ are large. This corresponds to desert, semiarid or marginal agricultural surfaces under dry soil conditions. It is fortuitous that the estimate of soil moisture is most accurate under these circumstances, since the monitoring of drought and crop failure are important applications of the information.

In summary, separation of the soil moisture signal from the two primary interfering effects, surface cover and wind, may be accomplished by observing a second GOES variable which is sensitive to wind and by normalizing both variables for surface cover effects. The resulting algorithm is least sensitive to measurement errors of A and B in dry, semi-arid regions where the surface temperature response is largest. In the following section, we discuss some of the major sources for error in the measurement of A and B and we suggest procedures for circumventing or overcoming these problems. Because the errors demonstrated by Fig. 6 are potentially large, it is probably practical to expect to distinguish only a handful of soil moisture classes by this method rather than a firm value of $W/W_s$. Thus, the actual soil moisture value obtained from the algorithm is best interpreted not as a quantitative estimate but as an indicator of a soil moisture category (e.g., dry, widespread moisture deficit, scattered moisture deficit, or moist).

b. Sources of error

Because this approach is an inference rather than a direct measurement of soil moisture, the potential for

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**Fig. 6.** Plot of the solution of a model derived algorithm relating soil moisture to the two normalized GOES observable parameters A and B. Cylinders represent examples discussed in the text, in which an error of 0.1 units is assumed in the measurement of A and B. Shaded regions mark the intersection of the cylinders with the solution surface.
error in the result is relatively large. Therefore, the errors must be carefully managed and controlled in order to optimize the final product. In this section we examine the major sources of error, in some cases using further model tests, and we discuss some strategies for controlling these errors.

1) INSTRUMENT ERRORS

The errors in detection of the apparent surface temperature by the GOES infrared sensor are of several types. These include errors due to instrument accuracy, precision, resolution and ground registration. The accuracy of the instrument can be divided further into the absolute accuracy (calibration) and relative accuracy (repeatability of the measurement). For the algorithm described above, only the relative accuracy is of consequence since all the quantities to be used involve only surface temperature changes. Experience with the data has shown that the repeatability of measurement is quite good. The random errors are found to be small compared to the precision to which the data are reported. The GOES IR radiances are converted to digital counts which limit the precision to about ½ K. This value, therefore, appears to be a satisfactory figure for the expected random error of a single measurement. By averaging over larger areas, and/or several independent samplings of the same point, one can attain improved accuracy at the expense of spatial or temporal resolution. Thus for applications such as the initialization of global circulation models where grid spacing may be several hundred kilometers, instrument errors present no problem. Without horizontal or temporal averaging, the ½ K random error can produce errors in the measurement of A and B on the order of 0.1 units or larger (see Fig. 6). Because A and B are not linear functions of soil moisture, there may be some resolution-dependent bias when taking large-area averages. The importance of this error is difficult to assess, however since large fluctuations in soil moisture can occur over very short distances (Bell et al., 1980). Therefore, virtually any practical remote measurement will contain important unresolved fluctuations in soil moisture.

In areas where large horizontal contrast in surface temperature exists, the registration errors can be important. Using the available orbit and attitude information, navigation solutions can be obtained which locate the data to within one pixel (10 km) of its true ground location. Once again horizontal averaging can reduce the relative magnitude of these errors.

2) ATMOSPHERIC ATTENUATION

Interference of the surface signal by the intervening atmosphere is primarily produced by water vapor in the infrared window channel and by aerosols in the visible channel (clouds will be discussed separately). The measurement of the absorbed shortwave radiation S, using the GOES window channel, has not been addressed in this paper because suitable techniques for this purpose have been discussed elsewhere (Gautier, 1982). Similarly in the infrared, a variety of techniques exist for retrieving true surface temperatures from available observations (Idso et al., 1976a; Zandlo et al., 1982).

3) LOW-LEVEL ADOPTION

The effect of thermal advection on changes in surface temperature was explored using a set of model runs in which uniform atmospheric temperature tendencies were imposed just before sunrise. Results are presented in Fig. 7. Under warm advection and shallow cold advection conditions, the mid-morning temperature change varied only a few tenths of a degree per hour from the non-advective case. Only under deep cold advection was the parameter seriously affected. Under these conditions, the temperature change depends on the strength of the advection. Since it is difficult to quantitatively assess the magnitude of cold advection at the surface from observations, it would be quite difficult to formulate a correction. In some cases dry, cloud free cold frontal boundaries can be identified in IR imagery by a sharp, horizontally coherent change in surface temperature (J. J. Gurka, 1979; unpublished manuscript). In these cases, the differences between pre-frontal and post-frontal surface temperature changes can provide some quantitative information on the advection. However it is suggested that the sign of the temperature advection above the PBL be monitored and whenever significant cold advection is present, the data be rejected.

4) THE EFFECT OF CLOUDS

Aside from the obvious effects of clouds over the area of interest during the time of observation, clouds preceding the time of observation can modify the surface temperature response as well. Several model runs were made to test this effect as a function of duration of cloud over the surface and the time which the cloud dissipated. The imposed cloud was assumed to attenuate 60% of the shortwave radiation and to act as a blackbody to longwave radiation. Results of this study are summarized in Fig. 8. Only runs where the cloud was terminated at 1000 and at 1200 are shown. Clouds which terminate early enough to allow observation of the mid-morning temperature change, have very little effect on the surface temperature response to subsequent solar heating since relatively little solar radiation is available before 0800 to be reflected by clouds. This trend is apparent in Fig. 8, which shows that the more total solar radiation blocked by the cloud, the greater the recovery time to steady state (where temperature changes are the same as those in the completely clear case) and the larger the disparity between the steady state and the clear case. The recovery curve of the
surface temperature following the return of sunshine contains soil moisture information analogous to the morning temperature change parameter. If adequate time and spatial resolution were available, this information could be found useful in special cases.

Pre-dawn cloud cover can affect the evolution of the nocturnal surface inversion through which the morning boundary layer must grow, but the resulting effects on surface temperature changes could not be explored with the present model. Experience with GOES data has shown that this effect is negligible. In general, it is found that if one rejects all GOES IR data within 20–40 km of a cloud at any observation time, the resulting computed temperature changes are not noticeably contaminated.

5) MISCELLANEOUS ERRORS

There are a variety of error sources which cannot be directly addressed without further observational data. We will list and discuss some of these in a general sense. First, there are the effects of the “lesser” variables listed in Table 1. The effects of thermal inertia are accounted for by the normalization process since the reference values account for all time-invariant properties of the surface. The other variables have been shown by the model to be quite small in their effect. However if observations show this to be incorrect, these variables may need to be considered in future analyses. Second, there are the effects of variables not tested by the model. These primarily include a variety of vegetation and soil parameters which the normalization process should obviate. There are also a group of atmospheric effects including the effects of nonhomo-
geneity on the surface layer turbulent structure, boundary layer phenomena, convective cloud density currents, etc., which have not been considered. Finally, there are the errors incurred by the assumptions used in modeling the variables that were included. For example, it is assumed that the roughness length \( z_0 \) is the same value for sensible heat and water vapor exchange as it is for momentum. This is not always the case (e.g., Garratt, 1978), although it may be more accurate when considering large heterogeneous areas. A number of vegetation properties which vary over short time periods in response to soil moisture may cause ambiguity in interpreting the surface temperature data. These effects include the growth of deeper roots in response to depletion of root zone moisture and the recovery time of several days which a plant requires following water stress (Bielorai and Hopmans, 1975; Jackson, 1982). An additional potentially important effect not considered by the model is the enhanced evaporation of intercepted precipitation immediately after a rainfall. Evaporation rates may be higher under these conditions than they are with saturated soil but dry external leaf surfaces (Federer, 1979).

Also, the use of the geostrophic wind rather than the actual anemometer level wind may be questioned, particularly over broad regions of sloping terrain where heating-induced buoyant horizontal accelerations may be important. There are two reasons why the geostrophic wind is used. First, continuous horizontal coverage of this variable is available. In data sparse regions, model extrapolations in time and space can provide useful pressure gradient information far from any station. Second, in order to obtain representative point measurements of mean wind speed in the unstable morning boundary layer, an averaging time of several hours is required (Wynngaard et al., 1974). Thus the reported “ instantaneous” observations can be highly misleading even under ideal conditions where all anemometers are similarly exposed, free of obstructions and at the same height above a flat grassy surface.

6) ERRORS IN THE REFERENCE VALUE

All the errors involved in obtaining the morning slope and sunrise slope change parameters also apply, of course, to the measured reference value. In addition, for the latter there is uncertainty in estimating the fixed values of soil moisture and geostrophic wind speed at which the reference value must be measured. Since the error in the values of \( A \) and \( B \) is the product of the error in the observed and reference values, the latter must be kept to a minimum. This can be done by averaging large numbers of reference values at every point. Each time the soil moisture and wind conditions are correct, the slope and slope change parameters are computed and averaged into the preexisting library of reference values. In this way, the error of the mean is steadily reduced as more data are gathered. A potentially serious source of error with this approach is the sudden or gradual broad-scale (significant in an area of 100 km\(^2\)) change in land use which could render the historical data useless. Another important problem which requires further study is the seasonal difference in vegetation cover. It may be found necessary to store several different reference values depending on the season of the year.

7) REDUCING ERROR BY HYBRID METHODS

The approach described above is capable of diagnosing soil moisture on an individual day without knowledge of the hydrologic history of the soil. Therefore, the estimates from one day to the next are entirely independent of one another. This is important, since cloud cover often interrupts the collection of the infrared data. In reality however, in the absence of precipitation, the daily depletion of soil moisture by evapotranspiration, percolation, etc. is dependent on the preexisting level of soil wetness. The drying of the soil is in fact a prognostic initial value problem. One can make use of this fact by employing a simple hydrologic model to put certain constraints or bounds on the soil moisture estimate based on the previous day's values. Such a model could be no more complex than an exponential decay of \( W \) or simple empirical relationship containing the observed precipitation and pan evaporation. Or it could be as detailed as the model used in this study, containing an explicit prognostic equation for soil moisture. Additional inputs from independent measurement techniques, such as microwave and ground truth data, could further refine the final estimate. When observations are missing for any reason, model results would be useful in filling the data gaps. As described above, the errors in the infrared inference of soil moisture are many. It may behoove us to combine every available source of data into the final estimate in order to minimize these errors.

5. Summary

An algorithm for inferring soil moisture from geosynchronous satellite infrared data is developed using a one-dimensional model of the atmospheric boundary layer, earth’s surface and soil. The model employs a surface energy budget equation designed to predict area-averaged surface temperature as seen by GOES. Evapotranspiration and soil heat flux are formulated as functions of the bulk fractional soil moisture in the root zone. Vegetation is treated in a generalized manner applicable to large heterogeneous surface units. Complete atmospheric surface layer and boundary layer parameterizations for temperature, water vapor, momentum and their fluxes are included.

A series of sensitivity tests were run using the model to identify signatures in the diurnal surface temperature wave which are optimally sensitive to soil moisture. The results led to selection of the mid-morning dif-
The differential of surface temperature with respect to absorbed shortwave radiation as the soil moisture parameter. The change in the slope of the temperature curve with time at sunrise was identified as a parameter especially sensitive to wind speed.

An example is presented comparing GOES observations of the mid-morning temperature change in Kansas and Nebraska with model computations of the same parameter and with an in situ estimate of soil moisture, the antecedent precipitation index. It is shown that this parameter is sensitive to soil moisture as predicted by the model. For this case, the model is shown to quantitatively predict the GOES observed temperature changes with accuracy.

Further model tests were performed to develop an algorithm for separating the soil moisture information from the interfering effects of wind and vegetation in the mid-morning slope parameter. The algorithm makes use of the wind sensitive sunrise slope change parameter and a normalization procedure to account for variations in surface cover. The normalization requires “pre-observation” of reference values of the mid-morning and sunrise parameters taken at fixed known values of soil moisture and wind speed. Based on these model results, the algorithm is shown to infer soil moisture most accurately in arid or marginal agricultural areas when the soil is dry. This will allow close monitoring of potential drought and crop failure in areas prone to these conditions.

Finally we discuss the sources of error involved in obtaining soil moisture information by this method. The effects of advection and cloud cover are explored using further model tests. Other errors are discussed and methods of ameliorating their effects are proposed.

Acknowledgment. We would especially like to thank Dr. C. J. Tucker who graciously provided the data for Fig. 3.

APPENDIX

The Model Soil Moisture–Evapotranspiration Relationship

Nappo (1975) tested two expressions for surface mixing ratio $q_s$:

$$ q_s = q_a + M(q_{sat} - q_a), \quad (A1) $$

$$ q_s = h q_{sat}, \quad (A2) $$

where $M$ is a moisture availability and $h$ is a surface relative humidity. He found each equation to work well under a limited range of conditions. We make use of an Ohm’s law analog for evapotranspiration and a physical interpretation of $M$ and $h$ in order to combine (A1) and (A2) to produce Eq. (9). Extensive tests have shown that (9) reproduces observed evapotranspiration rates under conditions ranging from midsummer moist to winter desert surfaces.

The expression for the current in the Ohm’s law analog is the evaporation rate

$$ E = f(q_s - q_a), \quad (A3) $$

where $f$ represents an arbitrary turbulent intensity term. The potential term may be expressed by combining (A1) and (A3) with the straightforward physical interpretation that $M$ represents the fraction of the otherwise dry surface that is covered with freely evaporating “pools”, i.e.,

$$ E_p = f M(q_{sat} - q_a), \quad (A4) $$

where $E_p$ is a potential evaporation rate. If each wet or dry surface “pool” is linked by an idealized root to a corresponding full or empty unit reservoir of soil water, then we may interpret $M$ to be the bulk fractional root zone available soil water content, $M = w/\bar{w}$.

Finally, Eq. (A2) gives us an expression for resistance. If we allow $h < 1$ when the soil is saturated, it is clear that $1/h$ represents a resistance to evapotranspiration. Physically we conceptualize $h$ by replacing the open “pools” of water at the surface with “wicks” representing leaves and porous surfaces of finite resistance. For a given wick there is some threshold rate of evaporation at which the capillary flow through the wick cannot replace the water as it is removed. At this threshold the end of the wick dries and the relative humidity averaged over the entire wick surface begins to drop. For a unit of heterogeneous surface this threshold evaporation rate, which we will call $E_{ref}$, is dependent on the overall wick surface area [i.e., a leaf area index (LAI) or other ratio of evaporating surface to total surface] and on the average wick resistance. Since the former may vary by several orders of magnitude while the latter, averaged over many species of plants and different non-vegetated surfaces, exhibits relatively little variability from place to place, it is believed that $E_{ref}$ is primarily dependent on LAI and may therefore lend itself to measurement by remote sensing, such as by the method of Tucker (1979). Also, $E_{ref}$ has an advantage over the Penman-Monteith canopy resistance parameter in that it is not dependent on atmospheric demand or soil wetness and is therefore much less variable in time.

Returning to the interpretation of $h$, for wicks tapping wet soil reservoirs, the relative humidity is inversely proportional to the evaporation rate since as the rate of removal of water from the wick increases, more of its surface becomes dry. Naturally the dry soil reservoirs, as in the interpretation of $M$, contribute nothing to the moisture in the air. Therefore we write

$$ h = M \frac{E_{ref}}{E} = \frac{w}{\bar{w}} \frac{E_{ref}}{E}, \quad \frac{E_{ref}}{E} \leq 1. \quad (A5) $$

We now substitute Eqs. (A3), (A4) and (A5) into Ohm’s law which states that potential equals current times resistance; the result is Eq. (9).
Equation (9) has been tested in the context of the boundary layer model described above. It is found that specifying values of $E_{\text{ref}}$ greater than approximately 100 W m$^{-2}$ allows the model to quantitatively duplicate observed evapotranspiration rates for vegetated surfaces. Smaller values should be appropriate for bare soil surfaces. By initializing the model with values of $x_0$, $E_{\text{ref}}$ and $m$ appropriate for various types of vegetation, and varying $W/W_s$ from dry to wet, the normalized daily evapotranspiration curves shown in Fig. (A1) were produced. The quantity $E_{\text{sat}}$ is the total 24-h computed evaporation for wet soil. The behavior of the curves is qualitatively very similar to observational studies reported in the literature (see Wetzel, 1983b). In the extreme cases shown, the wind speed, albedo and atmospheric mixing ratio were also varied to demonstrate the flexibility of this model in reproducing the variability of evapotranspiration curves quoted in the literature. Finally, the curve in which $W_s$ is doubled is included to demonstrate the importance of properly measuring or specifying the root zone depth.

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