Computing Surface Fluxes from Mesonet Data

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ABSTRACT

By using air–vegetation–soil layer coupled model equations as weak constraints, a variational method is developed to compute sensible and latent heat fluxes from conventional observations obtained at meteorological surface stations. This method also retrieves the top soil layer water content (daytime only) and the surface skin temperature as by-products. The method is applied to Oklahoma Mesonet data collected in the summer of 1995. Fluxes computed for selected Mesonet stations are verified against those obtained by the surface energy and radiation balance system at Atmospheric Radiation Measurement (ARM) Cloud and Radiation Testbed (CART) sites closest to the selected Mesonet stations. The retrieved values of soil water content are also compared with the direct measurements at the closest ARM CART stations. With data provided by the dense Mesonet, the method is shown to be useful in deriving the mesoscale distributions and temporal variabilities of surface fluxes, soil water content, and skin temperature. The method is unique in that it provides an additional means to derive flux fields directly from conventional surface observations.

1. Introduction

Numerical simulations have shown that mesoscale inhomogeneities in land surface characteristics can have strong impacts on mesoscale variabilities of surface fluxes of sensible and latent heat and thus affect mesoscale weather and climate in many important ways (McCumber and Pielke 1981; Ockouchi et al. 1984; Pielke et al. 1991). Many researchers have derived surface flux fields of sensible and latent heat through running a land surface model forced by observations (Pinty et al. 1989; Zhong and Doran 1995). However, observational verifications of model-simulated mesoscale variabilities of surface fluxes of sensible and latent heat have been difficult due to lack of “qualified” observational data. A dense network of surface stations, such as the Oklahoma Mesonet, can cover a sufficiently large mesoscale area, but data collected by such a network are mostly conventional and not qualified for the existing Bowen ratio energy balance (BREB) method (Fritschen and Simpson 1989) and the profile method (Panofsky and Dutton 1984). These existing methods, including their extensions (André et al. 1986; Doran 1992; Sellers et al. 1992; Xu and Qiu 1997), require accurate measurements of temperature and humidity differences between different atmospheric levels in order to obtain reliable estimates of surface heat fluxes.

Recently, an air–soil layer coupled scheme was developed by Xu et al. (1999). Unlike the above existing methods, this coupled scheme can give reliable estimates of surface heat fluxes without using temperature and humidity differences between two vertical atmospheric levels, but it requires measurements of soil water content, which are not available in general at conventional surface stations. On the other hand, measurements of soil temperature are available at most conventional surface stations but not used by the previous coupled scheme. The conventional soil temperature data can be used in the formula of Al Naksha-band and Kohnke (1965) to compute the soil heat flux. The conventional observations of cloud coverage and downward solar radiative flux are also available but not used by the previous coupled scheme. These conventional observations can be used to estimate the net radiative flux (together with the retrieved skin temperature and other conventional surface observations). With these additional physical constraints, the previous
The air–soil layer coupled scheme can be upgraded into a new variational method to compute fluxes from conventional surface measurements, such as those at the Oklahoma Mesonet stations. The new method will not require input soil water data. Instead, it will retrieve the soil water content. The detailed approach is presented in this paper.

The paper is organized as follows. Data and weather conditions are described in section 2. The model equations and the variational formulation are presented in section 3. The results of the new method tested with Oklahoma Mesonet data with the computed fluxes verified against those obtained at the nearly collocated Atmospheric Radiation Measurement (ARM) Cloud and Radiation Testbed (CART) stations are given in section 4a, while the results from the data sensitivity experiments are described in section 4b. In section 5, the method is applied to the entire area of the Oklahoma Mesonet to examine the mesoscale variabilities of surface fluxes, skin temperature, and soil water content. Conclusions follow in section 6.

2. Description of data

The input data used for the new method developed in this study were conventional measurements collected by the Oklahoma Mesonet during 11–18 June 1995. Unconventional measurements collected by the Surface Bowen Ratio Energy Balance System (SERBS) at 10 ARM CART stations within the area covered by the Oklahoma Mesonet will be used as input data for the BREB method (Fritschen and Simpson 1989). Fluxes computed by the BREB method from the SERBS data will be used to verify those computed by the new method from the Oklahoma Mesonet data. Detailed descriptions of the ARM CART facilities and SERBS can be found in Stokes and Schwartz (1994). The Oklahoma Mesonet stations and ARM CART stations are distributed across 180 000 km² of the entire state of Oklahoma, and the average spacing is about 40 km with at least one station in each county (see Fig. 1). The terrain is relatively flat and about 200–400 m MSL. The land surface is covered primarily by short vegetation, such as grasses and crops. The specification of soil texture type for each Mesonet station is obtained from the U.S. Department of Agriculture.

At each Mesonet station, meteorological sensors are mounted on a 10-m measurement tower, which also supports datalogger, radio transceiver, and battery power. There are two types of Mesonet stations: basic and enhanced. The basic stations measure eight core parameters: air pressure at 0.75 m, wind speed and direction at 10.0 m, air temperature and humidity at 1.5 m, solar radiation at 1.8 m, soil temperature at −10 cm, and rainfall at 0.6 m. The enhanced stations measure not only the eight core parameters but also wind speed at 2.0 m, air temperature at 9.0 m, soil temperature at −5 and −30 cm, and leaf wetness at 1.0 m. All of these measurements are averaged over 5-min intervals and then relayed (every 15 min) to the processing center. As will be seen in the next section, the new method requires wind and temperature measurements at two levels, so we shall only use data collected from the enhanced stations (about a half of the Mesonet stations). The method will use nearly all above listed measurements, except for rainfall, leaf wetness, and soil temperature at the two supplemental levels: −5 and −30 cm.

Cloud types and amounts have been routinely observed for four quadrants (NE, SE, SW, and NW) of the overhead sky at the ARM CART central facility (CF). This type of cloud data is not available at the Oklahoma Mesonet stations but is needed for the new method to compute the net longwave radiative flux. As proxies, the cloud data collected at the ARM CART CF are used to estimate the cloud coverage averaged over the entire Mesonet area, and then (together with the air temperature and surface skin temperature) to compute the net longwave radiative flux at each station. As we shall see in this paper, this approximation is acceptable for the daytime when the solar radiative flux is much larger than the net longwave radiative flux. Errors caused by this approximation in the computed heat fluxes remain about the same from daytime to nighttime, but the relative errors can become very large as the heat fluxes themselves become very small during the nighttime. As far as daily variations are concerned, the above approximation seems to be acceptable, and it has not caused any serious problem in this study (as shown in section 4).

The weather during 11–18 June 1995 is characterized by typical dry summer days of Oklahoma. Two days (8–9 June) prior this period, some Mesonet stations experienced severe thunderstorms, with recorded rainfall
ranging from 1 to 40 mm. During the night of 10 June, localized rainfalls were recorded up to 15 mm in 6 h at some Mesonet stations. On 11 June, just before the dry period, localized rainfalls were recorded again at some Mesonet stations (see Fig. 7c). Although the weather was relatively calm with no severe thunderstorm and heavy rainfall after 11 June, the retrieved soil wetness shows persistent mesoscale patterns through the entire period of 11–18 June (see section 5).

3. Model equations and method of solution

a. Model equations

The model equations used in this paper for the near-surface atmospheric layer are the same as those in Xu and Qiu (1997) and Xu et al. (1999), but the similarity laws of horizontal wind speed and temperature are applied to two measurement levels separately. This gives the following four independent measures for the residual differences between the model’s estimates and observations:

\[ \delta T_1 = T_c - T_1 + \frac{\kappa}{u_w} \left[ \ln \left( \frac{z_{0m}}{z_{0w}} \right) - \psi_u \left( \frac{z_{1m}}{L} \right) + \psi_s \left( \frac{z_{0m}}{L} \right) \right] - T_1, \] (1)

\[ \delta u_2 = \frac{u_w}{\kappa} \left[ \ln \left( \frac{z_{2m}}{z_{0m}} \right) - \psi_u \left( \frac{z_{2m}}{L} \right) + \psi_s \left( \frac{z_{0m}}{L} \right) \right] - u_2, \] (2)

\[ \delta T_3 = T_s - T_3 + \frac{\kappa}{u_w} \left[ \ln \left( \frac{z_{0m}}{z_{0w}} \right) - \psi_u \left( \frac{z_{1m}}{L} \right) + \psi_s \left( \frac{z_{0m}}{L} \right) \right] - T_3, \] (3)

and

\[ \delta u_4 = \frac{u_w}{\kappa} \left[ \ln \left( \frac{z_{4m}}{z_{0m}} \right) - \psi_u \left( \frac{z_{4m}}{L} \right) + \psi_s \left( \frac{z_{0m}}{L} \right) \right] - u_4, \] (4)

where \( u_w \) is the friction velocity; \( T_{1m} \) is the temperature scale; \( \nu_2, \nu_3, \nu_4 \) are the observed wind speed and temperature at the heights of \( z_2 = 1.5 \text{ m}, \ z_3 = 2.0 \text{ m}, \ z_4 = 9.0 \text{ m}, \) and \( z_4 = 10.0 \text{ m}, \) respectively; \( T_c \) is the surface skin temperature; \( z_{0w} = 0.01 \text{ m} \) for grass land and \( 0.1z_{0w} \) used in this paper are the roughness lengths for momentum and heat, respectively; \( L = u_w^2(T_1 + T_3)/\kappa g T_w \) is the Obukhov length; and \( \psi_u \) and \( \psi_s \) are the stability functions in (6)–(9) of Xu and Qiu (1997) based on Paulson (1970), Dyer and Hicks (1970), Hicks (1976), Holtslag and DeBruin (1988), and Beljaars and Holtslag (1991). Here \( g \) is the gravitational acceleration and \( \kappa \) is the von Kármán constant.

The surface evaporation of water vapor can be estimated by the Penman–Monteith equation (Monteith 1973) with a single-level measurement of air humidity. The residual error in the latent heat flux estimated by this equation can be denoted by

\[ \delta E_s = \frac{s(R_s + R_l + G)r_s + \rho C_p(q_s - q)}{(\gamma + s)r_a + r_c} - \lambda E, \] (5)

where \( R_s \), \( R_l \), and \( G \) are the net solar radiative flux, net longwave flux, and soil heat flux, respectively; \( q \) and \( q_s \) are the specific humidity and saturation specific humidity at the measurement level; \( s = \partial q / \partial T \); \( r_s \) and \( r_c \) are the aerodynamic and canopy resistances to heat and moisture fluxes, respectively; \( \rho \) is the air density; \( C_p \) is the specific heat; \( \lambda \) is the latent heat of evaporation; \( \gamma = C_p/\lambda \); and \( \lambda E \) is the latent heat flux. The aerodynamic resistance \( r_s \) can be determined from the similarity profile in (3)–(4) and the resulting formula is the same as in (6) of Xu et al. (1999). The canopy resistance \( r_c \) is a bulk measure of moisture flux resistance for radiation from canopy leaf stomata to the air around them. According to Deardorff (1978), Sellers et al. (1986), and Noilhan and Planton (1989), \( r_c \) can be parameterized as a function of the leaf area index (LAI), visible solar radiation received by leaves, air humidity and temperature around leaves, and soil water content. The detailed formulations are given by (12)–(14) of Xu et al. (1999), following Dickinson (1984) and Noilhan and Planton (1989).

The net solar radiative flux in (5) is obtained by

\[ R_s = R_s^i (1 - \alpha_s), \] (6)

where \( R_s^i \) is the observed downward solar radiative flux, \( \alpha_s \) is the albedo, and \( \alpha_s = 0.21 \) is assumed for grasses and crops. The net longwave radiative flux is estimated by (Paltridge and Platt 1976)

\[ R_l = -\sigma(e_s T_s^4 - e_a T_s^4) + 0.3\sigma N_c T_s^4, \] (7)

where \( \sigma \) is the Boltzmann constant; \( T_s \) is the surface skin temperature, and \( T_s \) is the observed temperature at level \( z_1 \) as in (1); \( N_c \) is the observed cloud coverage; \( T_s \) is the cloud base temperature derived, by using the standard atmospheric lapse rate, from the estimated cloud base height based on the observed cloud type; \( e_s \) is the ground surface infrared emissivity; and \( e_a \) is the clear-sky infrared emissivity. In this paper, \( e_s = 0.95 \) is used for grass land, and \( e_a \) is computed by (Idso 1980)

\[ e_a = 0.7 + 5.95e^{-5} \exp(1500/T_s). \] (8)

where \( e \) is the water vapor pressure computed from the observed air pressure (at 0.75 m) and humidity (at 1.5 m).

The soil heat flux is computed by

\[ G = -D \frac{T_s - T_s^d}{d}, \] (9)

where \( T_s \) is the observed soil temperature at depth \( d \) (=10 cm) and \( D \) is the soil heat conductivity. According to Al Nakshabandi and Kohnke (1965), \( D \) can be expressed as a function of soil water potential \( \psi_c \)
In this expression, $D$ depends on soil water content ($w$) and soil texture through the soil water potential defined by

$$
\psi = \psi_0 \left( \frac{w}{w_s} \right)^{-b},
$$

(11)

where $\psi_0$ is the saturated soil water potential, $w_s$ is the saturated soil water content, $w$ is the soil water content (in m$^3$ m$^{-3}$), and $b$ is a constant. As in (14) of Xu et al. (1999), these three parameters depend on soil texture, and their values are estimated in this paper based on Table 2 of Clapp and Hornberger (1978). In this paper, the soil water content $w$ is an unknown variable that needs to be retrieved. This retrieved variable represents the average value of the total available water content per volume in the top soil layer (0–10 cm).

Finally, the residual error in the surface energy balance equation can be denoted by

$$
\delta E_s = R_s + R_l + G - H - \lambda E,
$$

(12)

where the sensible and latent heat fluxes are computed, respectively, by

$$
H = -\rho C_p u_q T_s,
$$

(13)

and

$$
\lambda E = -\rho \lambda u_q q_s,
$$

(14)

where $q_s$ is the humidity scale. Ideally, the residual error should be zero in (12). However, since the terms on the right-hand side of (12) are measured or calculated with some errors, the sum of these errors is represented by the residual error on the left-hand side of (12).

b. Variational formulation

In the above air–vegetation–soil layer coupled model, only the net solar radiative flux $R_s$ is directly obtained from observations. The remaining four flux components in (12) should be computed from (7), (9), (13), and (14), while the five basic unknown variables ($u_q$, $T_s$, $q_s$, $T_i$, $w$) need to be retrieved from the available observations under the weak constraints of (1)–(5) and (12), respectively. The weights in (15) should be inversely proportional to the variances of their respectively associated residual terms. The weights used in this paper are $\alpha_1 = 1.0$ K$^{-1}$, $\alpha_2 = 10$ m$^{-1}$ s, and $\alpha_3 = 1.0$ m$^2$ W$^{-1}$. Without knowing the residual error statistics, these values are purely empirical and cannot be precise. Fortunately, the computations are found to be not very sensitive to the weights in the vicinity (within the same orders of magnitudes) of these selected values.

The quasi-Newton algorithm is used to minimize the cost function $J$ in (15). The algorithm procedures consist of the following iterative steps.

1. Set zero initial guesses for ($u_q$, $q_s$, $w$) and 0°C (273 K) initial guesses for ($T_s$, $T_i$).

2. Calculate all the intermediate parameters (Monin–Obukhov height $L$, longwave radiative flux, soil heat flux, sensible and latent heat fluxes, resistances $r$ and $r_i$), and then compute $\delta u_q$ and $\delta T_i$ from (1)–(4), $\delta E_s$ from (5), $\delta E$ from (12), and the cost function from (15).

3. Compute the five gradient components of the cost function with respect to ($u_q$, $T_s$, $q_s$, $T_i$, $w$) from (A1)–(A5) in the appendix.

4. If the convergence criterion is satisfied ($|\nabla J| \leq 10^{-4}$), then ($u_q$, $T_s$, $q_s$, $T_i$, $w$) reach the estimated values at the minimum of the cost function; otherwise, determine a search direction based on the gradients and the search directions of previous iterations.

5. Determine the search step size and find the minimum of $J$ along the search direction, obtain the new estimates of ($u_q$, $T_s$, $q_s$, $T_i$, $w$) and return to step 2.

Here, the soil moisture can be retrieved from the current method only for the daytime. During the nighttime, since there is no solar radiation, the canopy resistance reaches the maximum value and becomes independent of soil moisture. Thus, it is not necessary to know soil moisture for the flux computations, and only four parameters ($u_q$, $T_s$, $q_s$, $T_i$) are retrieved for the nighttime.

4. Tests with Mesonet data and sensitivity experiments

a. Tests with Mesonet data and verifications with ARM data

To test the method and verify the computed fluxes, data are selected from three pairs of nearly collocated Mesonet and ARM stations (see the small boxes numbered from 1 to 3 in Fig. 1): 1) Mesonet 38 and ARM 12 (about 200 m away from each other), 2) Mesonet 9 and ARM 22 (about 5 km apart), and 3) Mesonet 27 and ARM 26 (within 10 km from each other). For each
Fig. 2. Sensible heat fluxes at the three pairs of stations (from number 1 to 3 as marked in Fig. 1): (a) Mesonet 38 and ARM 12, (b) Mesonet 9 and ARM 22, (c) Mesonet 27 and ARM 26.

pair of stations, the soil texture and vegetation coverage are similar, so surface heat fluxes should be nearly the same. As described in section 2, data collected at these three (enhanced) Mesonet stations during 11–18 June 1995 are suitable for the tests, and the computed fluxes and retrieved soil wetness can be verified against direct measurements of net radiation, soil heat flux, and soil wetness (by SERBS) and direct estimates of sensible and latent heat fluxes (by the BREB method) at the nearly collocated ARM stations. The computed sensible and latent heat fluxes at the Mesonet stations are plotted in Figs. 2 and 3 in comparison with those obtained at the ARM stations. Note that the estimated fluxes at the ARM stations contain spurious spikes that were caused by the well-known computational instability of the BREB method when the Bowen ratio became very close to $-1$. The current method as well as our previous methods (Xu and Qiu 1997; and Xu et al. 1999) have no such computational instability problem. Clearly, the computed sensible and latent heat fluxes at the Mesonet stations are very close to the estimated fluxes (not including the spurious spikes) at the ARM stations.

The retrieved soil water contents at the Mesonet stations are plotted in Fig. 4 in comparison with the direct measurements (−5-cm depth) at the ARM stations. The comparison is very good for the second pair, that is, Mesonet 9 and ARM 22 in Fig. 4b. For the other two pairs, the retrieved soil water contents show significant daily variations that are not seen in the measurements at the ARM stations. These variations could manifest retrieval errors, and these errors could be caused mainly by the reduced sensitivity of the canopy resistance to the variation of soil moisture. According to (12)–(13) of Xu et al. (1999), the canopy resistance becomes independent of the soil moisture when any of the following three conditions is satisfied. 1) The soil is too wet and thus the canopy resistance becomes unstressed. 2) There is no solar radiation (in the nighttime). 3) The soil is too dry and thus the canopy resistance reaches the maximum value. Under any of these conditions, the flux computations become independent of soil moisture. Because of this, the current method cannot and does not need to retrieve the nighttime soil moisture. By setting the canopy resistance to its maximum value the current method can compute the nighttime fluxes, but the computed nighttime fluxes may contain large relative errors (because the fluxes themselves become very small during the nighttime, as shown in Figs. 2–3).

With the current method, the retrieved soil water content should be most reliable between 1000 and 1600 LT for a clear or lightly cloudy summer day. The soil water content retrieved from sunrise to 1000 LT or from 1600

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LT to sunset may not be reliable. This may explain the spurious daily variations of the retrieved soil water content in Figs. 4a–c. Besides, each pair of the ARM and Mesonet stations are not exactly collocated. The possible inhomogeneity and difference in their true soil properties between the ARM and Mesonet stations might also be responsible for some of the differences between the retrieved soil water content and the direct measurement compared in Figs. 4a–c.

The rms error of the computed surface energy balance based on (12) can be defined by

$$ \| \delta E_r \| = \left( \frac{1}{N} \sum_{n} \delta E_r^2 \right)^{1/2}, $$

where \( N (= 96 \times 8) \) is the total number of time levels of data sampling for the eight days. For the fluxes computed at the three Mesonet stations, the averaged rms error is \( \| \delta E_r \| = 11 \text{ W m}^{-2} \). This value is slightly smaller than the rms error (15 W m\(^{-2}\)) showed by Xu and Qiu (1997) for the previous variational method applied to the ARM data.

### b. Sensitivities to data errors

To examine the sensitivities of the computed fluxes to observational errors in the input data obtained at the conventional Mesonet stations, random errors are added to the input data. These random errors are generated artificially by the computer with uniform probability distributions over given ranges. Since the errors are generated independently for different variables and different measurement heights, the vertical gradients of wind speed and air temperature also contain random errors. The rms errors for the computed sensible and latent heat fluxes can be evaluated, respectively, by

$$ \sigma_H = \left( \frac{1}{N} \sum [(H' - H)^2] \right)^{1/2} \quad \text{and} $$

$$ \sigma_E = \left( \frac{1}{N} \sum [(\lambda E' - \lambda E)^2] \right)^{1/2}, $$

where \( H' \) and \( \lambda E' \) denote the sensible and latent heat fluxes computed with the data contaminated by random errors. As plotted in Fig. 5a, \( \sigma_H \) is more sensitive to errors in wind speed and air temperature than errors in other input parameters (such as air humidity, ground temperature, cloud amount, and solar radiation). When errors in wind speed are in the range of \( \pm 0.2 \text{ m s}^{-1} \) or errors in air temperature in the range of \( \pm 0.1^\circ \text{C} \), \( \sigma_H \) is about 20 W m\(^{-2}\). However, \( \sigma_E \) increases significantly when wind speed errors are beyond the range of \( \pm 0.3 \text{ m s}^{-1} \), or air temperature errors are beyond the range.
of ±0.15°C. Similar situations are seen for $\sigma_s$ in Fig. 5b. As shown in Table 1, for the Mesonet data, wind speed errors are in the range of ±2% of the reading (normally ≤10 m s$^{-1}$). This causes $\sigma_H$ and $\sigma_E$ close to 20 (W m$^{-2}$), which is about 10% of the fluxes in the daytime. The air temperature errors are in the range of ±0.4°C, and this causes $\sigma_H$ and $\sigma_E$ to be around 30 (W m$^{-2}$), which is about 15% of the fluxes in the daytime. The soil temperature errors can be as large as ±0.5°C, but this does not cause $\sigma_H$ and $\sigma_E$ to be more than 20 W m$^{-2}$. Errors in cloud amount can be ±25%, and this also does not cause $\sigma_H$ and $\sigma_E$ to be more than 20 W m$^{-2}$.

In general, errors in different input parameters are not correlated, so $\sigma_H$ (or $\sigma_E$) caused by all the errors in the Mesonet data should be smaller or much smaller than the sum of $\sigma_H$ (or $\sigma_E$) caused by errors in each individual parameter listed in Table 1. With random errors generated independently for each input parameter listed in Table 1, the rms errors caused by the combined effect of all the input parameter errors are found to be $\sigma_H = 40.5$ W m$^{-2}$ and $\sigma_E = 39.9$ W m$^{-2}$. The relative rms errors are about 15%–20% for the daytime but can be as large as 100% for the nighttime. Thus, the method is applicable to the Mesonet data for the daytime but becomes unreliable for the nighttime. As seen in Table 1, errors in the vertical difference of wind speed and air temperature can be as large as ±4% of reading and ±0.7°C, respectively. With these large errors, the current method still can work reasonably well. The reason is that the method does not use the vertical gradients of wind speed and air temperature and thus is insensitive to errors in these gradients.

5. Mesoscale variabilities of surface fluxes

In this section, the new method is applied to data collected at 50 enhanced stations in the Oklahoma Mesonet to study the mesoscale variabilities of surface fluxes.
es, skin temperature, and soil water content over the entire state of Oklahoma during 11–18 June 1995.

a. Daytime distributions of surface fluxes

The distributions of the computed surface fluxes need to be examined together with the distributions of retrieved soil water content (0–10-cm soil layer). As explained earlier, soil wetness cannot be precisely retrieved for the nighttime, so we only examine the daytime results. Distributions of the retrieved soil water content, sensible and latent heat fluxes, and skin temperature are shown in the four panels, Figs. 6a–d, respectively, for three time levels (3.5 h apart) from 0900 to 1600 LT on 11 June (the first day of the 7-day period). The three plots of soil water content in the top panel show mesoscale patterns with three distinct high centers in north and southwest of Oklahoma state, while relatively low values are seen in the central west and south-
east of the state. The highs are twice as large as the lows, indicating that the soil wetness distribution was nonuniform for that day.

Factors causing the spatial variations in the soil water content could include local precipitation, soil texture inhomogeneity, and difference in water vapor evaporation affected by differences in soil types and vegetation covers. The distribution of soil water content could also be affected by the rainfalls that occurred before that day, but the relationship between rainfalls and soil wetness is beyond the interest of this study. Our discussion will be focused on the relationships between the soil wetness and surface fluxes.

In Figs. 6a–c note that the sensible and latent heat...
fluxes are spatially correlated with the soil water content. The high latent heat flux centers are nearly collocated with the wet centers, while the sensible heat flux is relatively high in the dry areas. These correlated features can be explained by the evaporation process and energy balance near the surface. Under the steady income of solar radiation, one flux component becomes larger, the other must become smaller. Over the wet land, strong evaporation forced by the solar radiation leads to a large amount of latent heat flux. Over the dry land, evaporation is severely limited by the dry soil–vegetation system, so the sensible heat flux is increased to balance the incoming solar radiation. The enhanced sensible heat flux can produce strong thermal turbulence. Direct observations of boundary layer turbulence were not available for these seven days, but other observational studies have indicated that air over the dry land can be much more turbulent than over the wet land (Doran 1992). Our results indicate that the soil wetness inhomogeneity could be mostly responsible for the spatial variations of the surface fluxes, while the latter could further enhance the turbulence (mainly large eddies) and even produce mesoscale circulations.

During the day the solar radiation varied dramatically, from 0 at sunset to the maximum at noon, and then to 0 at sunset, but the distribution of soil water content changed very little as shown in Fig. 6a. Clearly, the daytime temporal variations of the surface fluxes (Figs. 6a–c) were driven mainly by the variation of solar radiation. When the solar radiation was weak (at 0900), both latent and sensible heat flux were smaller. Later in the day (1230 and 1600), their distributions remained nearly the same. In general, solar radiation at the ground can be reduced greatly and/or locally by dense cloud covers and, through this, the cloud distribution can significantly affect the distributions of the surface fluxes. This, however, is not the case for the results in Fig. 6 because the sky was mostly clear and there was no storm over the entire Oklahoma Mesonet area for that day.

b. Surface skin temperature and soil moisture

With our new method, the surface skin temperature is also retrieved. As shown in Fig. 6d, the retrieved skin temperature is spatially correlated with the soil water content and surface fluxes. The skin temperature is relatively low in the wet areas mainly due to the enhanced evaporation. The skin temperature is relatively high in the dry areas because evaporation is limited by the dry soil resistance.

We have examined the spatial variations of the four retrieved fields (sensible and latent heat fluxes, skin temperature, and soil moisture) and their relationships. These retrieved fields and their relationships provide improved understandings of the physical processes that could not be directly seen from the observational data (Figs. 7a,b). It is well understandable that the soil temperature and soil heat flux can affect each other interactively. As the soil heat flux is regulated by the soil conductivity and the latter is strongly affected by the soil water content, the soil heat flux and soil temperature can be indirectly affected by the soil water content. The soil water content also partially determines the surface evaporation process, especially when the soil is wet. As the surface evaporation absorbs large amounts of heat over wet soil, it cools the ground and the near-surface air. In this way, the soil water content affects the skin temperature and near-surface air temperature.

Since the soil temperature measurements are used as input data to compute the surface fluxes, it is interesting to examine how the computed fluxes are affected by the observed soil temperature in comparison with the observed air temperature. As shown in Fig. 7a, the high and low centers of soil temperature are roughly collocated with those of surface fluxes in Figs. 6b,c, but no obvious spatial correlation is seen between the air temperature and surface fluxes (Fig. 7b). The surface skin temperature in Fig. 6d shows strong spatial variations, but the near-surface air temperature (Fig. 7b) does not. In general, the air temperature is affected more by the advection and mixing processes than by the soil heat flux, so the air temperature distribution should be much smoother than the soil temperature distribution, as shown in Figs. 7a,b. This explains why the surface fluxes are correlated better with the soil temperature in their mesoscale patterns than with the air temperature.

The skin temperature depends not only on the conditions in the soil layer but also on the conditions in the air layer (including air temperature, solar radiation, albedo, surface vegetation cover, etc.). Because of this, it is difficult to directly compare the retrieved skin temperature distributions with the observed soil temperature distributions at −5 cm. On the other hand, rainfall can be a good indicator for the soil water content. The observed rainfall distributions are plotted for every 6 h in Fig. 7c. The impacts of the rainfalls that occurred during the night of 10 June and the early morning of 11 June are clearly reflected in the retrieved soil water content distributions in Fig. 6a.

c. Day-to-day variations

Using the sequential data collected at the Oklahoma Mesonet, the day-to-day variations of surface fluxes, soil water content, and surface skin temperature can be examined closely. For simplicity, only noontime distributions are plotted in Figs. 8a–d for three consecutive days, from 14 June 1995 to 16 June 1997. During these days, there was no significant rainfall, so the soil water content maintained roughly the same day-to-day distribution and decreased slowly (mainly due to evaporation) during these days. The variations in cloud coverage, air temperature, and wind speed could be the major factors causing the small and yet
notable day-to-day variations in the distributions of the surface fluxes and skin temperature. Although there was not much day-to-day variation in the soil water content, the spatial variations of soil water content seemed to have dominant and persistent influences on the distributions of surface fluxes and skin temperature during these days.

6. Conclusions

In this paper, the previous air–soil layer coupled scheme (Xu et al. 1999) is upgraded into a new variational method. In this new method, the conventional soil temperature data are used to compute the soil heat flux [see (9)] together with the air–vegetation–soil layer coupled model, the soil water content in the top soil layer (0–10 cm) is retrieved together with the surface skin temperature, and the net longwave radiative flux is estimated from the retrieved skin temperature and other conventional surface observations. Because the new method does not require input measurements of soil heat flux and soil moisture, it can be applied to conventional surface stations. The method is unique in that it provides an additional means to derive flux fields directly from conventional surface observations without running a land surface model forced by observations.

The new method is tested with Oklahoma Mesonet data and the computed fluxes are verified against those obtained at ARM CART stations nearly collocated with the selected Mesonet stations. Since the standard deviations of wind and temperature are not conventional measurements (though required by the previous method in order to estimate the effective roughness length and to compute the nonlocal fluxes), the new method computes only the local fluxes with a prescribed surface roughness length. The soil water content is not available from the conventional surface data but can be retrieved together with the surface skin temperature by the new
method by using conventional surface measurements (including soil temperature).

Because soil temperature data are used together with the vegetation–soil layer coupled model, and because wind speed and air temperature data at different vertical levels are used independently [see (1)–(4)] and not in forms of their vertical gradients, the new method is expected to be not sensitive to measurement errors (Table 1). This general property is verified by the sensitivity experiments presented in section 4b. The current method retrieves the soil moisture only for the daytime. During the nighttime, the canopy resistance reaches the maximum value (in response to the disappearance of solar radiation) and becomes independent of soil moisture [see (12)–(13) of Xu et al. 1999]. Thus, the current method cannot and does not need to retrieve the night-

Fig. 8. As in Figs. 6a–d, but for midday distributions on three consecutive days.
time soil moisture when it is used to compute the nighttime fluxes. The computed nighttime fluxes, however, may contain large relative errors due to their nearly diminished values (Figs. 2–3). In general, the computed fluxes are accurate and reliable only for the daytime when the sky is clear or lightly cloudy. The method becomes unreliable under heavy cloudiness.

The method is applied to data collected at 50 enhanced stations in the Oklahoma Mesonet to study the mesoscale variabilities of surface fluxes, skin temperature, and soil water content over the entire state of Oklahoma during 11–18 June 1995. It is found that the soil water content was spatially correlated with the surface fluxes and surface skin temperature. Over the wet areas, the latent heat flux was relatively large and the sensible heat flux was large with relatively high surface skin temperature. Over the dry areas, the latent heat flux was relatively small, but the sensible heat flux was relatively low, and the latent heat flux was relatively large and the sensible heat flux was large with relatively high surface skin temperature. These relationships can be interpreted physically in terms of the interactions between the soil processes and atmospheric processes near the ground, and these processes and their interaction are largely captured by the coupled air–vegetation–soil layer model used for the variational method in this paper.

The current method uses the cloud data collected at the ARM CART CFF, as proxies, to estimate the cloud coverage averaged over the entire Oklahoma Mesonet area and to compute the net longwave radiative flux at each station. This approximation may be improved if accurate cloud information can be derived from satellite data. Furthermore, the air–vegetation–soil layer model used in this paper is a diagnostic model that does not consider the time variation of soil moisture. To consider soil moisture change in time, the model needs to be further upgraded to include a prognostic equation for the soil moisture. The related problems are under our investigation. In the last two years, the Oklahoma Mesonet has installed heat dissipation sensors to measure soil water potential profiles (at depths of 5, 25, 60, and 75 cm below the ground) at 60 of 115 sites, which provides excellent opportunities for further testing and improving our methods for future real-time applications.

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APPENDIX
Formulations for the Gradient Components

By using the chain rule of differentiation, the gradient components of the cost function \( J \) defined in (15) with respect to \((u_a, T_u, q_a, T_r, w)\) can be derived as follows.

\[
\frac{\partial J}{\partial u_a} = \alpha_1 \left( \frac{\partial \bar{T}_1}{\partial u_a} + \frac{\partial \bar{T}_s}{\partial u_a} \right) + \alpha_2 \left( \frac{\partial \bar{u}_s}{\partial u_a} + \frac{\partial \bar{u}_4}{\partial u_a} \right) + \alpha_3 \left( \frac{\partial \bar{E}_q}{\partial u_a} + \frac{\partial \bar{E}_E}{\partial u_a} \right),
\]

\[
\frac{\partial J}{\partial T_u} = \alpha_1 \left( \frac{\partial \bar{T}_1}{\partial T_u} + \frac{\partial \bar{T}_s}{\partial T_u} \right) + \alpha_2 \left( \frac{\partial \bar{T}_s}{\partial T_u} + \frac{\partial \bar{T}_4}{\partial T_u} \right) + \alpha_3 \left( \frac{\partial \bar{E}_q}{\partial T_u} + \frac{\partial \bar{E}_E}{\partial T_u} \right),
\]

\[
\frac{\partial J}{\partial q_a} = \alpha_3 \left( \frac{\partial \bar{E}_q}{\partial q_a} + \frac{\partial \bar{E}_E}{\partial q_a} \right),
\]

\[
\frac{\partial J}{\partial T_r} = \alpha_2 \left( \frac{\partial \bar{T}_s}{\partial T_r} + \frac{\partial \bar{T}_4}{\partial T_r} \right) + \alpha_3 \left( \frac{\partial \bar{E}_q}{\partial T_r} + \frac{\partial \bar{E}_E}{\partial T_r} \right),
\]

and

\[
\frac{\partial J}{\partial w} = \alpha_3 \left( \frac{\partial \bar{E}_q}{\partial w} + \frac{\partial \bar{E}_E}{\partial w} \right).
\]

Here, the gradient terms \( \partial \bar{T}_1/\partial u_a, \partial \bar{T}_2/\partial u_a, \partial \bar{T}_s/\partial u_a, \partial \bar{T}_4/\partial u_a, \partial \bar{u}_s/\partial u_a, \partial \bar{u}_4/\partial u_a, \partial \bar{E}_q/\partial q_a, \) and \( \partial \bar{E}_E/\partial q_a \) are similar to those used in the appendix of Xu and Qiu (1997). It is easy to see \( \partial \bar{T}_1/\partial T_u = 1 \) from (1) and (3); \( \partial \bar{E}_q/\partial q_a = \rho C_w u_a \) from (5) and (14); \( \partial \bar{E}_E/\partial T_u = \rho C_w u_a \) and \( \partial \bar{E}_E/\partial q_a = \rho \lambda u_a \) from (12)–(14); \( \partial \bar{E}_E/\partial T_r = -4 \sigma \epsilon_0 T_r^4 - D(\psi)/d \) from (7), (9), and (12); and \( \partial \bar{E}_E/\partial T_r = -\sigma r_a [4 \sigma \epsilon_0 T_r^4 + D(\psi)/d]/[(s + \gamma) r_a + r_a] \) from (5), (7), and (9). It is also easy to obtain the detailed formula (omitted here) for \( \partial \bar{E}_E/\partial w = \partial G/\partial w \) from (9)–(12).

The remaining gradient terms in (A1)–(A5) can be derived from (5), (12)–(14) in this paper and (11) in Xu et al. (1999). The derived formulas are given as follows.
\[
\frac{\partial \delta E_t}{\partial u_\theta} = \rho \lambda q_\theta + \frac{s(R_u + R_i + G)}{(s + \gamma) r_\theta + r_e} \frac{\partial r_u}{\partial u_\theta} + \frac{sr_e(R_u + R_i + G) + \rho C_p(q_u - q)}{[(s + \gamma) r_u + r_e]^2} (s + \gamma) \frac{\partial r_e}{\partial u_\theta},
\]

\[
\frac{\partial r_u}{\partial u_\theta} = \frac{1}{\kappa u_\theta} \left[ -\frac{\partial \psi_\theta(z/L)}{\partial u_\theta} + \psi_\theta \left( \frac{z}{L} \right) \right] - \frac{1}{\kappa u_\theta} \left[ \ln \left( \frac{z_{0_\theta}}{L} \right) - \psi_\theta \left( \frac{z}{L} \right) + \psi_\theta \left( \frac{z_{0_\theta}}{L} \right) \right].
\]

\[
\frac{\partial \delta E_t}{\partial T_\theta} = \frac{s(R_u + R_i + G)}{(s + \gamma) r_\theta + r_e} \frac{\partial r_u}{\partial T_\theta} + \frac{sr_e(R_u + R_i + G) + \rho C_p(q_u - q)}{[(s + \gamma) r_u + r_e]^2} (s + \gamma) \frac{\partial r_e}{\partial T_\theta},
\]

\[
\frac{\partial r_u}{\partial T_\theta} = \frac{1}{\kappa u_\theta} \left[ -\frac{\partial \psi_\theta(z/L)}{\partial T_\theta} + \psi_\theta \left( \frac{z}{L} \right) \right],
\]

where the detailed formulas for \([\partial \psi_\theta(z/L)]/\partial u_\theta\) and \([\partial \psi_\theta(z/L)]/\partial T_\theta\) in \((A7)\) and \([\partial \psi_\theta(z/L)]/\partial u_\theta\) and \([\partial \psi_\theta(z/L)]/\partial T_\theta\) in \((A10)\) can be found in the appendix of Xu and Qiu (1997).

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