Estimation of the Minimum Canopy Resistance for Croplands and Grasslands Using Data from the 2002 International H_2O Project

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ABSTRACT

Vegetated surfaces, such as grasslands and croplands, constitute a significant portion of the earth’s surface and play an important role in land–atmosphere exchange processes. This study focuses on one important parameter used in describing the exchange of moisture from vegetated surfaces: the minimum canopy resistance ($r_{cmin}$). This parameter is used in the Jarvis canopy resistance scheme that is incorporated into the Noah and many other land surface models. By using an inverted form of the Jarvis scheme, $r_{cmin}$ is determined from observational data collected during the 2002 International H_2O Project (IHOP_2002). The results indicate that $r_{cmin}$ is highly variable both site to site and over diurnal and longer time scales. The mean value at the grassland sites in this study is 96 s m$^{-1}$ while the mean value for the cropland (winter wheat) sites is one-fourth that value at 24 s m$^{-1}$. The mean $r_{cmin}$ for all the sites is 72 s m$^{-1}$ with a standard deviation of 39 s m$^{-1}$. This variability is due to both the empirical nature of the Jarvis scheme and a combination of changing environmental conditions, such as plant physiology and plant species composition, that are not explicitly considered by the scheme. This variability in $r_{cmin}$ has important implications for land surface modeling where $r_{cmin}$ is often parameterized as a constant. For example, the Noah land surface model parameterizes $r_{cmin}$ for the grasslands and croplands types in this study as 40 s m$^{-1}$. Tests with the coupled Weather Research and Forecasting (WRF)–Noah model indicate that the using the modified values of $r_{cmin}$ from this study improves the estimates of latent heat flux; the difference between the observed and modeled moisture flux decreased by 50% or more. While land surface models that estimate transpiration using Jarvis-type relationships may be improved by revising the $r_{cmin}$ values for grasslands and croplands, updating the $r_{cmin}$ will not fully account for the variability in $r_{cmin}$ observed in this study. As such, it may be necessary to replace the Jarvis scheme currently used in many land surface and numerical weather prediction models with a physiologically based estimate of the canopy resistance.

1. Introduction

Grasslands and croplands constitute approximately 40% of the earth’s terrestrial surface (Foley et al. 2005).

Due to the ubiquitous nature of these landscapes, they play an important role in land–atmosphere exchange processes and subsequent atmospheric phenomena (Burba and Verma 2005). For example, the distribution of grasslands and croplands has been linked to the differential partitioning of the surface energy balance and thus the evolution of the convective boundary layer (Alapaty et al. 1997; McPherson and Stensrud 2005;
LeMone et al. (2007b) and the development of local circulation patterns (Raddatz 2007). These ecosystems have also been tied to precipitation recycling (Wever et al. 2002; Raddatz 2005; Wang et al. 2006) and the onset of convective storms (Pielke 2001; Hanesiak et al. 2004; Pielke et al. 2007). Additionally, these ecosystems act as important loci for carbon and energy exchange and thus may play an important role in global climate change (Scurlock and Hall 1998; Novak et al. 2004; Li et al. 2005; FedDemma et al. 2005).

As with all vegetated surfaces, the influence of grasslands and croplands on environmental processes is largely a function of their physical and physiological characteristics (Sellers et al. 1996). However, as discussed by Niyogi and Raman (1997), the key to understanding and modeling the interactions of vegetation with its environment is an accurate depiction of stomatal mechanisms. This is because stomatal mechanisms directly control the exchange of water and trace gases, such as carbon dioxide, between the vegetation and the atmosphere (Wong et al. 1979). In turn, these exchange processes directly influence the partition of the available energy between the sensible and latent heat fluxes (Lhomme et al. 1998) and indirectly control the subsequent atmospheric, hydrologic, and environmental processes driven by these energy fluxes (Niyogi et al. 1998).

The exchange of water vapor between the land surface and atmosphere is often characterized analogously to Ohm’s law. In brief, the amount of moisture transported to the atmosphere is expressed as a function of the atmosphere’s ability to uptake moisture and the resistance of the surface to the exchange of moisture between the surface and the atmosphere (Blanken 2002). Depending on the surface and environmental conditions, the surface resistance ($r_s$) can vary significantly with both time and location (Alves and Pereira 2000; Alfieri et al. 2007); for example, one estimate of $r_s$ for grassland and cropland ecosystems ranges from 25 to more than 1000 s m$^{-1}$ (Amer and Hatfield 2004).

Further, as discussed by Shuttleworth and Wallace (1985), the total moisture flux can be separated into the flux due to evaporation from the soil and transpiration from the vegetation. A unique resistance is associated with each of these moisture transfer pathways. While the resistance associated with soil evaporation can be estimated from the ambient environmental conditions, determining the resistance associated with vegetation is more difficult because transpiration is a function of both environmental factors and plant physiology.

Many methods have been developed to estimate transpiration and canopy resistance ($r_c$) including the statistically based Jarvis scheme (Jarvis 1976; Stewart 1988), the physiologically based Ball–Berry scheme (Ball et al. 1987; Collatz et al. 1991), the carbon- and water-use efficiency-based approach of Choudhury (1994), and the hydrodynamically based Buckley scheme (Buckley et al. 2003). For land surface modeling and numerical weather prediction, however, the Jarvis scheme continues to be the most widely used method for estimating canopy resistance. For example, the Jarvis scheme is used by the Noah land surface model (Noah LSM), which is one of the land surface models used in the North American Land Data Assimilation System (NLDAS; Mitchell et al. 2004), and is a core component of the Weather Research and Forecasting model (WRF) and the High-Resolution Land Data Assimilation System (HRLDAS; Chen et al. 2007).

The Jarvis scheme determines $r_c$ as the product of some minimum canopy resistance ($r_{cmin}$) and a number of empirically based functions that characterize plant stress due to a limited number of environmental conditions. In the Jarvis scheme, $r_{cmin}$ represents the resistance of unstressed vegetation under optimal conditions and is typically considered to be constant. However, as pointed out by Schulze et al. (1994) and Rhonda et al. (2001), $r_{cmin}$ is both time and site specific. Due to their empirical nature, the environmental stress functions are highly simplified and do not consider many of the factors controlling $r_c$ that vary from plant to plant. Examples of these factors include plant species, phenology, photosynthetic pathway, local climatology, nutrient availability, and life history.

The limitations of the Jarvis scheme can impact not only the estimates of $r_c$ and transpiration, but also all subsequent land–atmosphere and meteorological processes. The objective of this study is to better understand the limitations of the Jarvis scheme—particularly within the context of variability in the $r_{cmin}$ parameter—and its impacts on the representation of land–atmosphere exchange processes in land surface and numerical weather prediction models. The results of this study are expected to enhance not only model representations of moisture exchange with the atmosphere, but also improve model representations of the surface energy balance, soil moisture content, and surface temperature (Niyogi et al. 1999). Ultimately, this is expected to lead to better representations of such atmospheric phenomena as the evolution of the surface boundary layer and the development of convective storms (Holt et al. 2006).

The next section of this paper provides an overview of the research domain in the southern Great Plains and the data used in this study from the International H$_2$O Project 2002 (IHOP 2002; Weckworth et al. 2004;
It also discusses the methods that were used to estimate the resistances. Section 3 describes the results of this study including a comparison of the resistance values derived from the observations and those used to parameterize Noah LSM. Section 4 provides a discussion of the results and the conclusions that can be drawn from this study.

2. Methods

a. Research domain

While a complete description of the field program and the surface data used in this study can be found elsewhere (e.g., Weckworth et al. 2004; LeMone et al. 2007a), a brief summary of IHOP_2002 is provided here. IHOP_2002 was a multiagency field campaign conducted from 13 May to 25 June 2002 in the southern Great Plains of the United States. Specifically, the study domain included portions of Kansas, Oklahoma, and Texas (Fig. 1), and incorporated a broad range of environmental conditions. For example, a strong west–east precipitation gradient existed across the domain with the western one-third of the domain experiencing severe drought and the eastern portion of the domain, which was located in the Walnut River watershed, experiencing a water surplus. The elevation decreased by nearly 500 m from approximately 850 m in the western portion of the domain to approximately 400 m in the east. The research domain also represented a broad range of land cover types from bare ground and cropland (primarily winter wheat) to grassland and sagebrush rangeland.

b. Data

Surface data including meteorological, radiometric, and energy flux data were collected at 10 surface sites distributed across the IHOP_2002 domain (Table 1). Each of these sites represented a combination of land-use and environmental conditions typical of the surrounding region. As such, the sites included sparse to fully vegetated land cover and dry to wet moisture conditions.

<table>
<thead>
<tr>
<th>Site</th>
<th>Location</th>
<th>Lat (°N)</th>
<th>Lon (°W)</th>
<th>Elevation (m)</th>
<th>Environmental conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Booker, TX</td>
<td>36.4728</td>
<td>100.6179</td>
<td>872</td>
<td>Fallow; persistent drought</td>
</tr>
<tr>
<td>2</td>
<td>Elmwood, OK</td>
<td>36.6221</td>
<td>100.6270</td>
<td>859</td>
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<tr>
<td>3</td>
<td>Beaver, OK</td>
<td>36.8610</td>
<td>100.5945</td>
<td>780</td>
<td>Sand–sagebrush; persistent drought</td>
</tr>
<tr>
<td>4</td>
<td>Zenda, KS</td>
<td>37.3579</td>
<td>98.2447</td>
<td>509</td>
<td>Pasture; intermediate precipitation</td>
</tr>
<tr>
<td>5</td>
<td>Spivey, KS</td>
<td>37.3781</td>
<td>98.1636</td>
<td>506</td>
<td>Winter wheat; intermediate precipitation</td>
</tr>
<tr>
<td>6</td>
<td>Conway Springs, KS</td>
<td>37.3545</td>
<td>97.6533</td>
<td>417</td>
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</tr>
<tr>
<td>7</td>
<td>New Salem, KS</td>
<td>37.3132</td>
<td>96.9387</td>
<td>382</td>
<td>Pasture; water surplus</td>
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<tr>
<td>8</td>
<td>Atlanta, KS</td>
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<td>96.7656</td>
<td>430</td>
<td>Grassland; water surplus</td>
</tr>
<tr>
<td>9</td>
<td>Grenola, KS</td>
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<td>96.5671</td>
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<td>Pasture; water surplus</td>
</tr>
<tr>
<td>10</td>
<td>Beaver, OK</td>
<td>36.8701</td>
<td>100.6180</td>
<td>785</td>
<td>Heavily grazed pasture; persistent drought</td>
</tr>
</tbody>
</table>
The meteorological data collected at the surface sites included air temperature, mixing ratio, wind speed, precipitation, and turbulent fluxes (latent and sensible heat fluxes) measured using the eddy covariance method. All of these variables were measured at a height of 2 m AGL. Site measurements also included both radiometric data, such as incident solar radiation, net radiation, and photosynthetically active radiation, and soil data including the soil heat flux, volumetric soil moisture content, and soil temperature. The soil data were measured at a depth of 0.05 m. The meteorological and soil data were collected as 5-min block averages that were postprocessed using a standard suite of corrections and aggregated to 30-min block averages. Finally, surface conditions were periodically (approximately every 10 days) characterized using measures of the normalized difference vegetation index, greenness fraction, and leaf area index.

While the analyses in this study were conducted using data from all of the vegetated IHOP_2002 sites, this paper focuses primarily on three representative sites (Fig. 2): site 2 (sparse grassland), site 6 (winter wheat), and site 9 (grassland).

c. Estimation of the bulk surface resistance \( (r_{sfc}) \)

Estimates of the bulk surface resistance \( (r_{sfc}) \), which represents the resistance to moisture exchange of the land surface as a whole including both vegetated and bare soil regions, were calculated using an inverted form of the Penman–Monteith (P–M) equation (Monteith 1965). The P–M equation incorporates the radiative and micrometeorological factors that drive evapotranspiration in an Ohm’s law analog. By rearranging the P–M equation, \( r_{sfc} \) (s m\(^{-1}\)) can be calculated as follows:

\[
r_{sfc} = \frac{r_a \Delta(\Delta R_n - G) - \lambda E(\Delta + \gamma) + \rho c_p D}{\gamma \Delta E},
\]

where \( r_a \) is the aerodynamic resistance (s m\(^{-1}\)), \( \Delta \) is the slope of the saturation vapor pressure–air temperature curve (Pa K\(^{-1}\)), \( R_n \) is the net radiation (W m\(^{-2}\)), \( G \) is the soil heat flux (W m\(^{-2}\)), \( \Delta E \) is the latent heat flux (W m\(^{-2}\)), \( \gamma \) is the psychrometric constant (Pa K\(^{-1}\)), \( \rho \) is the air density (kg m\(^{-3}\)), \( c_p \) is the specific heat (J kg\(^{-1}\) K\(^{-1}\)), and \( D \) is the vapor pressure deficit (Pa), the difference between the saturation vapor pressure and the actual vapor pressure. The aerodynamic resistance was estimated as

\[
r_a = \frac{U}{u_*^2},
\]

where \( U \) is the horizontal wind speed and \( u_* \) is the friction velocity (Blanken et al. 1997; Alfieri et al. 2007).

d. Conversion of surface resistance to canopy resistance \( (r_c) \)

The technique used to convert \( r_{sfc} \) to \( r_c \), which has been used successfully by Hatfield and Allen (1996) and Amer and Hatfield (2004) among others, was developed as an extension of the work by Ben Mehrez et al. (1992) using data collected over croplands. This method scales \( r_{sfc} \) as a function of leaf area index (LAI) to estimate \( r_c \) (s m\(^{-1}\)) as follows:

\[
r_c = \frac{0.3 \text{LAI} + 1.2}{\text{LAI}} r_{sfc},
\]

where LAI is defined as the one-sided leaf area per unit area of the land surface.

This technique begins with the assumption that \( r_c \) for a vegetated surface is equal to the ratio of the stomatal resistance and the effective LAI (Noilhan and Planton 1989; Pinty et al. 1989). The effective LAI accounts for the sheltering impacts of shading and reduced airflow in

![Fig. 2. The IHOP_2002 surface sites including sites (a) 2, (b) 6, and (c) 9, which are the focus of this study.](image-url)
the interior of the canopy (Amer and Hatfield 2004). The technique for estimating the effective LAI was tested successfully over both fully and partially vegetated surfaces with an LAI and vegetation height as low as 0.20 m² m⁻² and 20 cm, respectively (Ben Mehrez et al. 1992). These values are similar to the sparsely vegetated sites in the western portion of the IHOP_2002 domain. Using this technique, however, does assume that \( r_{sfc} \) is a function of vegetation cover; in other terms, transpiration is the primary pathway of moisture exchange between the surface and atmosphere. To conform to this assumption, the data were parsed to eliminate those periods when transpiration was negligible or other moisture sources contributed significantly to the exchange process as is discussed in section 3a below.

e. Determination of the minimum canopy resistance (r_{cmin})

The empirical approach of Jarvis (1976) determines \( r_c \) as the product of a number of noninteracting environmental stress functions. Each of these stress functions represents a statistical and often nonlinear relationship between the canopy resistance and one or as many as five ambient conditions including incident solar radiation, humidity, air temperature, leaf water potential, and carbon dioxide concentration. The impact of carbon dioxide is often neglected under the assumption that its concentration is nearly constant during the day (Niyogi and Raman 1997) while leaf water potential is often replaced by more readily obtainable soil measurements such as soil moisture content (Lhomme 2001). Additional factors, such as nutrient availability and plant phenology, history, and distribution, also play a role in regulating \( r_c \), but they are not considered as a part of the Jarvis scheme (Alves and Pereira 2000).

For this study, four environmental stress functions as described by Noilhan and Planton (1989) were used. This formulation of the Jarvis scheme is the same as used by the Noah LSM (Ek et al. 2003) and is employed here for consistency when comparing the values of \( r_{cmin} \) derived from observations with those used to parameterize the land surface model. The first of the empirical stress functions characterizes the role of solar radiation in driving transpiration and is defined as

\[
F_1 = \frac{f + \frac{r_{cmin}}{r_{cmax}}}{f + 1},
\]

with

\[
f = 0.55 \frac{K_{\downarrow}}{K_{dmb} \text{LAI}},
\]

where \( r_{cmax} \) is a constant (5000 s m⁻¹) representing the maximum canopy resistance (Noilhan and Planton 1989), \( K_{dmb} \) is a scaling parameter taken as a constant of 100 W m⁻². The second environmental stress function, which characterizes the influence of the soil moisture content, is defined as

\[
F_2 = \frac{\theta - \theta_w}{\theta_{ref} - \theta_w},
\]

where \( \theta \) is the observed soil moisture content, \( \theta_w \) is the wilting point soil moisture content, and \( \theta_{ref} \) is the reference soil moisture content. Both \( \theta_w \) and \( \theta_{ref} \) are taken as constants specific to a given soil texture; the values are taken from Chen and Dudhia (2001) so that these constants, like all of the others used in the calculations of the stress functions, are consistent with the Noah LSM. The third environmental stress factor representing the influence of \( D \) in controlling transpiration is defined as

\[
F_3 = 1 - gD,
\]

where \( g \) is a vegetation-specific constant. The value used here for \( g \) is taken from the Noah LSM (0.1914 kPa⁻¹) and is consistent with the range of values from 0.14 to 0.25 kPa⁻¹ used elsewhere (e.g., Stewart and Gay 1989; Noilhan and Planton 1989; Kim and Verma 1991; Niyogi and Raman 1997). The final empirical environmental stress function represents the influence of air temperature (\( T_a \)) on transpiration as

\[
F_4 = [1 - 1.6 \times 10^{-3}(298.0 - T_a)^2]^{4}.
\]

From these environmental stress factors, \( r_c \) is calculated as

\[
r_c = \frac{r_{cmin}}{\text{LAI}} \sum_{i=1}^{4} \frac{1}{F_i},
\]

which can be expanded and rearranged to estimate \( r_{cmin} \) as

\[
r_{cmin} = \frac{r_{cmax} f_c LAIF_2 F_3 F_4}{r_{cmax} (f + 1) - r_{cmax} LAIF_2 F_3 F_4}.
\]

The stress functions are empirical in nature and replete with simplifying assumptions. For example, the environmental stress function associated with the influence of air temperature \( (F_4) \) assumes all vegetation photosynthesizes most efficiently at an optimum temperature of 298 K. Yet, as is well known for grasslands and croplands, this temperature varies from plant to plant depending on species, photosynthetic pathway, local climatology, and life history (Charles-Edwards et al. 1971; Kubien and Sage 2004; Carmo-Silva et al. 2007). Another example is the assumption that photo-
synthetically active radiation (PAR) is about 55% of \( K_{\downarrow} \); depending on the atmospheric conditions, such as cloud cover and aerosol content, the fraction of \( K_{\downarrow} \) constituting PAR can vary by as much as 25% (Pinker et al. 2003). Furthermore, \( r_{\text{min}} \) is a function of factors beyond incident solar radiation, moisture availability, humidity, and air temperature; these factors include ambient carbon dioxide concentration, plant species, plant phenology, and nutrient availability (Farquhar and Sharkey 1982; Schulze et al. 1994; Kelliher et al. 1995; Niyogi et al. 1999), which are not considered as a part of the Jarvis scheme.

The overall process for calculating \( r_{\text{min}} \) begins with the estimate of \( r_{\text{sfc}} \) from Eq. (1). Next, \( r_c \) was calculated using this estimate of \( r_{\text{sfc}} \) and the observed LAI with Eq. (3). Finally, using this value of \( r_c \) and the observed LAI, along with the values of \( f, F_1, F_2, F_3, \) and \( F_4 \) calculated using Eqs. (4)–(7), \( r_{\text{min}} \) was calculated using Eq. (10).

3. Results

Consistent with other studies (e.g., Alves and Pereira 2000; Amer and Hatfield 2004; Alfieri et al. 2007), the values of \( r_{\text{sfc}}, r_c, \) and \( r_{\text{min}} \) varied significantly with both time and location depending on environmental conditions. For example, site 9, which was located in the Walnut River watershed in southeastern Kansas, had \( r_{\text{min}} \) values ranging from 54 to 152 s m\(^{-1}\) with an average value of 105 s m\(^{-1}\). In contrast, site 6, which is located in central Kansas, had an average \( r_{\text{min}} \) of 24 s m\(^{-1}\), and site 2, which was located in the panhandle of Oklahoma, had an average \( r_{\text{min}} \) of 95 s m\(^{-1}\). In all cases, \( r_{\text{min}} \) derived from the observations using the method outlined above differed significantly from the constant values used in the Noah LSM.

a. Episodic variability of bulk surface resistance \((r_{\text{sfc}})\)

For the study period, \( r_{\text{sfc}} \) exhibited a clear temporal pattern (e.g., Fig. 3) linking a decrease in \( r_{\text{sfc}} \) with \( \theta \) and, ultimately, to rainfall. Sixty-two of the 106 precipitation events recorded at all of the IHOP_2002 surface sites resulted in a decrease in \( r_{\text{sfc}} \) by at least 50% within 12 h after the precipitation event. An additional 24 of the 106 precipitation events occurred within 2 days of the previous precipitation event when \( r_{\text{sfc}} \) was already low; thus, little additional effect would be expected.

The increased soil moisture after a rain event implies a greater supply of water for both soil evaporation and reduced plant water stress; in turn, these conditions would result in lower soil and canopy resistances. Also,
rainfall intercepted by plant foliage would contribute to the total moisture exchange while effectively acting as open water; thus, there would be only negligible resistance from the surface to the evaporation of the intercepted moisture.

The decrease in $r_{scf}$ after rain events is more pronounced in the western one-third of the IHOP_2002 domain, where it was observed after 76% of the precipitation events, as compared to the eastern one-third of the domain, where this pattern was observed after only 46% of the precipitation events. In the central one-third of the domain the pattern relating precipitation events and increasing $r_{scf}$ was observed after 58% of the precipitation events. The spatial trend relating precipitation events to decreasing $r_{scf}$ may be due to the shorter time interval between precipitation events in the east of the IHOP_2002 domain as compared to the drought-stricken western one-third of the field campaign’s domain. The number of precipitation events that occurred within 3 days of the previous event increased from 12% to 27% and to 24% for the western, central, and eastern portions of the IHOP_2002 domain, respectively. The pattern may also be due, in part, to the east to west trend to sparser vegetation; soil evaporation is more sensitive to changes in soil moisture than transpiration (LeMone et al. 2007b).

Based on these results of this analysis, it was necessary that all subsequent analyses be limited to data collected at least 24 h after a rain event so that the effects of evaporation from either water intercepted by the foliage or standing on the surface could be eliminated. Similarly, data collected within 8 h of when the air temperature was within 2 K of the dewpoint temperature were omitted to minimize the potential of dewfall impacting the $r_{cmin}$ calculations (Kim et al. 2006). Additionally, nighttime periods were ignored, as were periods when the vegetation was dormant or, in the case of crops, had been harvested. Also, periods when the energy budget did not close to within 25% were eliminated. The remaining sensible and latent heat flux data were adjusted to force closure of the surface energy budget while maintaining a constant Bowen ratio (Blanken et al. 1997; Twine et al. 2000). Finally, in an effort to eliminate outliers, the data were trimmed to retain only the central 95% of the data. The resulting sample for each site was between 100 and 500 data points. (sites 7 and 10, which were represented by less than 100 half-hourly data points, were not included in further analyses.) By eliminating these data points, it is anticipated that the confounding factors unrelated to the vegetation are minimized prior to the back-calculation of $r_{cmin}$.

b. Estimates of minimum canopy resistance ($r_{cmin}$)

Contrary to the assumptions made in the land surface models, the estimates of $r_{cmin}$ indicate that it is highly variable both from site to site and over time (Fig. 4). The mean value of $r_{cmin}$ varied from 24 s m$^{-1}$ at the winter wheat sites (sites 5 and 6) to 107 s m$^{-1}$ at site 8 (Table 2). The mean of the grassland sites was 96 s m$^{-1}$. The mean $r_{cmin}$ values for all of the IHOP_2002 surface sites averages to 72 s m$^{-1}$; this value is nearly twice the 40 s m$^{-1}$ commonly used in models, such as Noah LSM, for grassland and cropland landscapes. Additionally, the range of $r_{cmin}$ at any given site varied from as little as 31 s m$^{-1}$ to 206 s m$^{-1}$ at sites 5 and 2, respectively, with the grassland sites having greater variability. For the cropland sites (sites 5 and 6) the range in $r_{cmin}$ averaged 40 s m$^{-1}$ while the range in grassland sites (sites 2, 4, 8, and 9) averaged 140 s m$^{-1}$. In terms of standard deviation, the variability in $r_{cmin}$ at a given surface site ranged from 8 s m$^{-1}$ at site 5 to 41 s m$^{-1}$ at site 2 with a mean standard deviation in $r_{cmin}$ for all the vegetated surface sites of 24 s m$^{-1}$. Histograms of $r_{cmin}$ (Fig. 5) show the distributions of the resistances typically have a single well-defined maximum.

c. Monte Carlo simulations

To further understand the sensitivity of the Jarvis scheme to environmental conditions, a series of Monte Carlo simulations was conducted for each of the IHOP_2002 sites. The aim was to broadly assess whether the variability in $r_{cmin}$ was due to changing environmental conditions or the inherent limitations of the Jarvis scheme. The four environmental stress functions ($K_{↓}$, $θ$, $D$, and $T_a$) used in the Jarvis scheme were perturbed one at a time in the simulations. Additionally, LAI was perturbed in a fifth simulation because it appears in the calculation of $r_c$, $r_{cmin}$, and $f$. The simulations consisted of 1000 iterations in which each point in the time series was varied randomly by as much as 10% about the observed value. That is, the random value was selected from a uniform distribution of values ranging from 90% of the observed value to 110% of the observed value. For example, if the observed value of $K_{↓}$ was 1000 W m$^{-2}$, the range of values used in the Monte Carlo simulation would be uniformly distributed across a range from 900 to 1100 W m$^{-2}$. The range of values used with Monte Carlo simulations of $T_a$ was based on the temperature expressed on the Celsius scale instead of the Kelvin scale; this ensured the values of $T_a$ used in the simulations would fall within a physically reasonable range. The environmental stress functions, $r_c$, and $r_{cmin}$ were then recalculated.

The maximum deviation and mean maximum devia-
tion were used to evaluate the Monte Carlo simulations. Figure 6 shows an idealized case with the maximum deviation defined as the greatest difference between the simulated \( r_{\text{c min}} \) and the value derived from observations for any half-hourly period in any of the 1000 iterations of a simulation. Similarly, the mean maximum deviation is the average of the maximum deviation for each half-hourly period in any of the 1000 iterations of a simulation.

The Monte Carlo simulations demonstrated little sensitivity to changes in either LAI or \( K_{\downarrow} \) at any of the IHOP_2002 sites (Table 3). The simulated \( r_{\text{c min}} \) differed by less than 2% compared to the values derived from the observations. The sensitivity was somewhat greater to perturbations of \( D \); variations in \( D \) by as much as 10% resulted in changes in \( r_{\text{c min}} \) of no more than between 3.9% and 5.5% depending on the site. The maximum deviation was by no more than 13%. The strongest sensitivity, however, was to changes in \( \theta \) and, particularly in the western portion of the IHOP_2002 domain, \( T_{\sigma} \). In the case of \( \theta \), the maximum deviation between the simulated \( r_{\text{c min}} \) and the value derived from observations was between 21.9% and 38.7% with the mean of the maximum deviation ranging from 15.7% to 23.2%. In the case of \( T_{\sigma} \), the mean maximum deviation of \( r_{\text{c min}} \) ranged from as little as 5.4% at site 9 to as much as 15% at site 2. While this variability is significant, it is less than the variability seen in the \( r_{\text{c min}} \) derived from the observations. This suggests that the variability in \( r_{\text{c min}} \) is due to factors other than the uncertainty in the observational data.

The Monte Carlo simulations also suggest differences in sensitivity based on location or vegetation type. For example, although the sensitivity is still modest, the

<table>
<thead>
<tr>
<th>Site</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>Range</th>
<th>Std dev</th>
<th>Noah default</th>
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FIG. 5. Histograms showing the count of minimum canopy resistance ($r_{c_{\text{min}}}$) values across the range of observed values for sites (a) 2, (b) 6, and (c) 9.

FIG. 6. An idealization of a Monte Carlo simulation showing the maximum deviation and the mean maximum deviation.
Table 3. A summary of the results of the Monte Carlo simulations showing the sensitivity of the $r_{\text{min}}$ estimate to variations in LAI, $K^\downarrow$, $\theta$, $D$, and $T_\alpha$ for each of the IHOP_2002 surface sites.

<table>
<thead>
<tr>
<th>Site</th>
<th>Max dev (s m$^{-1}$) (%)</th>
<th>Mean max dev</th>
<th>F$_1$ variations in $K^\downarrow$</th>
<th>Site</th>
<th>Max dev (s m$^{-1}$) (%)</th>
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<table>
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<th>$F_3$ variations in $D$</th>
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<table>
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<tr>
<th>$F_4$ variations in $T_\alpha$</th>
<th>Site</th>
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<th>Mean max dev</th>
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</table>

sites in the eastern portion of the study domain tended to be somewhat more sensitive to perturbations in $K^\downarrow$ than those in the western portion of the domain. The western sites were generally more sensitive to variations in $T_\alpha$ than the eastern ones. Both of these results are reasonable given that the eastern portion of the IHOP_2002 domain tended to be cooler, wetter, and had a lower $K^\downarrow$ on average as compared to the western portion of the domain. The results also show that the cropped sites, which were located in south-central Kansas, tended to be more sensitive to changes in $\theta$ than the grassland sites. This may be due to an interaction effect related to the higher LAI of crops as compared to grasslands (Niyogi et al. 1999).

These results are reinforced by analyses of the distribution of the environmental stress functions (Fig. 7). For example, at site 2, the environmental stress function associated with $K^\downarrow$, $F_1$, was consistently near one. Indeed, $F_1$ ranged only between 0.83 and 0.99 with an average value of 0.97 at site 2. In contrast, while $F_1$ remained high at site 9, it extended over a broader range from 0.40 to 0.96 with an average value of 0.78. In the case of the environmental stress function associated with $T_\alpha$, $F_3$, the distribution was much broader. At site 2 it ranged from 0.40 to 1.0 and at site 9 it ranged from 0.3 to 1.0. However, the distribution of $F_4$ was strongly skewed to the left at site 9 (skewness = −2.20) such that 84% of the data points had a value greater than 0.80 and 56% of the data had a value greater than 0.90.

**d. Estimates of minimum canopy resistance ($r_{\text{min}}$) with HRLDAS soil moisture data**

Given the strong influence of $\theta$ on the $r_{\text{min}}$ calculation, additional analyses were conducted using the $\theta$ output from the HRLDAS model (Chen et al. 2007). This allowed the $\theta$ over the entire rooting depth to be considered. It also allows for the impact of using the observed $\theta$ measured at a depth of 5 cm as a proxy for the $\theta$ of the full rooting depth to be assessed.

While a complete description can be found elsewhere (e.g., Chen et al. 2007), HRLDAS is a land data assimilation system built around the Noah land surface model primarily developed to assimilate a range of in situ and remotely sensed observations and to provide initial conditions for the WRF model. The surface characteristics such as land use–land cover, and soil texture used in HRLDAS, are the same as those used in the Noah model (Chen and Dudhia 2001). The initial soil conditions were from the Eta Data Assimilation System (EDAS; Rogers et al. 1995) and the spinup time was 18 months. HRLDAS was run in an uncoupled mode and forced using data from a number of sources. Air temperature, wind speed, humidity, atmospheric pressure, and downwelling longwave radiation were obtained from the 3-hourly analysis from the EDAS. Downwelling shortwave (solar) radiation was from the Global Energy and Water Cycle Experiment (GEWEX) Continental Scale International Project (GCIP) analysis archived at the University of Maryland (Pinkert et al. 2003). The precipitation forcing data is from National Centers for Environmental Prediction (NCEP) stage IV rainfall analysis (Fulton et al. 1998).

Comparisons of the first-layer HRLDAS data, which represent the uppermost 10 cm of soil, to the point observations suggested a bias in the HRLDAS output. For example, the HRLDAS data for site 9 underestimates $\theta$ by nearly 10%. The HRLDAS data for site 2 overestimated $\theta$ by approximately 25% on average while the HRLDAS data for site 6 overestimated $\theta$ by 46%. The uncertainty in soil texture, the point versus grid average values, and the uncertainty in measurements contribute to this bias. To minimize this bias, the HRLDAS data for each soil layer were rescaled as

$$\tilde{\theta}_i = \theta_i - \overline{\theta}_i - \frac{\overline{\theta}_i - \theta_i}{\theta_k},$$

where $\tilde{\theta}_i$ is the rescaled HRLDAS soil moisture for the $i$th soil layer, $\theta_i$ is the HRLDAS data for the $i$th soil...
layer, $\overline{\theta}_1$ is the mean HRLDAS soil moisture for the first layer, and $\overline{\theta}$ is the mean observed soil moisture. This rescaling allowed the first-layer HRLDAS $\theta$ to be adjusted so that it had the same mean value as the observational data. It also allowed the deeper HRLDAS soil layers, which lacked observational data, to be rescaled proportionately. A weighted-average $\theta$ was determined as the average of the rescaled HRLDAS data for each soil layer in the rooting depth weighted by the thickness of the soil layer. Figure 8 shows this $\theta$ along with the observed $\theta$ and a weighted-average $\theta$ using unmodified HRLDAS data.

The $r_{\text{min}}$ values tended to be slightly lower when the rescaled HRLDAS data were used in lieu of the observed $\theta$. Typically, this decrease was between 3 and 8 s m$^{-1}$ with the exception being site 8 where $r_{\text{min}}$ increased by 4 s m$^{-1}$ (Table 4). However, the variability in $r_{\text{min}}$ remained. Indeed, in some cases the standard deviation of $r_{\text{min}}$ increased (Fig. 9). For example, in the case of site 2, the standard deviation increased by approximately 12% from 41 to 46 s m$^{-1}$. This suggests that the variability in $r_{\text{min}}$ is not tied to the use of the observational $\theta$ as proxy for $\theta$ over the full rooting depth but to other factors including the empirical nature of the Jarvis scheme and the changes in plant physiology and species composition at the surface sites.

e. Coupled WRF–Noah model simulations

In a further effort to show the impacts of the parameterization of $r_{\text{min}}$, a series of simulations were conducted over the IHOP_2002 domain for 31 May 2002 using the Noah LSM coupled with WRF version V2.2 (further information is available online at http://www.mmm.ucar.edu/wrf/users/wrfv2/). The model was run using a nested grid (Fig. 10) with the outer domain having a grid resolution of 9 km and an inner domain having a resolution of 3 km. The initial and boundary conditions for the atmospheric and soil fields are derived from 6-hourly NCEP Global Final Analysis (FNL) data and the WRF Preprocessing System (WPS).

The model microphysics were configured using the WRF single-moment six-class scheme (Hong et al. 2004). The convective scheme was the Betts–Miller–Janjić (BJM) convection scheme (Betts 1986; Betts and Miller 1986; Janjić 1994, 2000). The planetary boundary layer formulation followed the Yonsei University (YSU) scheme, which is nonlocal-$K$ theory based and
allows for explicit entrainment in the unstable mixing layer (Hong et al. 2006). Radiation was calculated using the Rapid Radiative Transfer Model (RRTM; Mlawer et al. 1997) for longwave radiation and the Dudhia (1989) scheme for shortwave radiation.

Two of the model simulations were conducted for sites 2 and 9, respectively, while the third simulation represented the mixed grassland of the Ameriflux site in the Walnut River watershed near Smileyburg, Kansas. The control run used the default parameterization for $r_{\text{cmin}}$ (40 s m$^{-1}$) while the experimental run used the higher value of $r_{\text{cmin}}$ for grasslands derived from the observational data (rounded to 100 s m$^{-1}$).

At site 2, both coupled model simulations tended to overestimate the turbulent heat fluxes (Fig. 11). The experimental run, nonetheless, did yield a modeled $\lambda E$ much closer to the observations, particularly during the day. When only daytime values were considered, the mean difference between the observed and model flux using the higher value of $r_{\text{cmin}}$ was 4 W m$^{-2}$ as compared to 42 W m$^{-2}$ for the control run. When the full diurnal cycle was considered, the mean differences were 1 and 18 W m$^{-2}$ for the experimental and control run, respectively. The impact of increasing $r_{\text{cmin}}$ on the model representation of $H$ was less apparent in the coupled model run. At site 2, the decrease in $\lambda E$ was matched by a compensating increase in $H$. The experimental run overestimated $H$ during the daytime period by 35 W m$^{-2}$ on average as compared to 12 W m$^{-2}$ for the control runs.

A similar analysis of $T_a$ and humidity, expressed as a mixing ratio ($q; \text{g Kg}^{-1}$), at site 2 shows that the experimental run provided better estimates of these vari-
The control run underestimated $T_a$ by 1.1 K on average while the experimental run underestimated $T_a$ by 0.6 K on average for the daytime period. When the full diurnal period is considered, the experimental run overestimated $T_a$ by 0.7 K on average while the control run overestimated $T_a$ by 0.4 K on average. In the case of $q$, the experimental run overestimated $q$ by 2.1 and 1.8 g Kg$^{-1}$ for the daytime and full diurnal periods, respectively. In comparison, the control run overestimated $q$ by 2.8 and 2.2 g Kg$^{-1}$ for the daytime and full diurnal periods, respectively.

The model runs at site 9 (Fig. 12) yielded similar results. The mean differences between the observed and modeled $\lambda E$ equaled 16 and 28 W m$^{-2}$ for the experimental and control runs, respectively, when only the daytime period is considered. The mean differences between the observed and modeled $\lambda E$ were 9 and 16 W m$^{-2}$ for the experimental and control runs, respectively, for the full diurnal period. In this case, the representation of $H$ was also improved. For the daytime period, the mean differences between the observed and modeled $H$ were 7 and 36 W m$^{-2}$ for the experimental and control runs, respectively. For the full diurnal period, the differences were 6 and 19 W m$^{-2}$, respectively, for the experimental and control runs. For the daytime period, the mean differences between the observed and modeled $T_a$ were 0.1 and 0.7 K for the experimental and control runs, respectively, while for the diurnal period, these differences were 0.4 and 0.7 K for the experimental and control runs, respectively. The experimental run tended to overestimate $q$ by 0.2 g Kg$^{-1}$ on
average during the daytime period while it underestimated $q$ by 0.1 g Kg$^{-1}$ when the full diurnal period was considered. The control run underestimated $q$ by 0.6 and 0.5 g Kg$^{-1}$, respectively, for the daytime and full diurnal periods.

At the Smileyburg Ameriflux site (not shown), $\lambda E$ was substantially greater than at the IHOP_2002 sites, and the difference between the observed and modeled $\lambda E$ increased commensurately. For the daytime period, the differences were 30 and 91 W m$^{-2}$ for the experi-
mental and control runs, respectively. For the full diurnal period, the differences in the observed and model $\lambda E$ were 12 and 32 W m$^{-2}$, respectively. In the case of $H$, the observed fluxes were overestimated by 57 and 29 W m$^{-2}$, respectively, for the experimental and control runs during the daytime period. For the full diurnal period, the observed $H$ were overestimated by 31 and 18 W m$^{-2}$, respectively, for the experimental and control runs.

4. Conclusions

From the results of this study, several conclusions may be drawn. First among these is that the 40 s m$^{-1}$ value for $r_{\text{min}}$ used in the Noah LSM is a significant underestimate of $r_{\text{min}}$ for the IHOP_2002 domain and by extrapolation for the grassland and croplands over the southern Great Plains. Our results indicate a value of 96 s m$^{-1}$ for the grasslands and 24 s m$^{-1}$ for the crops.
and grassland land-use types used in the Noah LSM. However, using this set value neglects both the site-to-site and temporal variability associated with \( r_{\text{min}} \). This, in turn, can impact model estimates of the moisture exchange and, thus, other related processes such as the partitioning of the surface energy budget. This conclusion is in agreement with Schulze et al. (1994) and Rhonda et al. (2001), who point out that \( r_{\text{min}} \) is both time and site specific, and Alapaty et al. (1997) and Cooter and Schwede (2000), who show that errors in estimates of \( r_{\text{min}} \) propagate into model simulations of atmospheric and hydrologic processes.

The analysis also suggests that variations in \( r_{\text{min}} \) are due to both the empirical nature of the Jarvis scheme, which represents some environmental factors only imperfectly and other factors, such as plant physiological, not at all. The site-to-site variability, along with the variability evident in the time series, would suggest that local conditions, such as species composition and plant phenology, are important controls on \( r_{\text{min}} \). The results also show that \( \theta \), in particular, has a dominant control on \( r_{\text{min}} \); as such, accurate estimates of \( \theta \) are prerequisites for determining \( r_{\text{min}} \) using the Jarvis scheme.

Given the variability in \( r_{\text{min}} \) and its impacts on the estimation of the moisture flux and numerous subsequent atmospheric, hydrologic, and environmental processes, the analysis suggests one means of improving the Noah LSM would be to develop a time-varying value of \( r_{\text{min}} \) that incorporates the effects of changing environmental and plant characteristics by improving the empirical stress functions used by the scheme or by adding additional terms to the Jarvis scheme. While the best method of accomplishing this is unclear, such a modification of the Noah LSM would most likely include dynamic vegetation growth and many additional data inputs. However, the value of the Jarvis scheme lies in its simplicity and the fact that it provides useful results with a minimum of inputs. Therefore, it would be more prudent to forego such modifications and instead replace the Jarvis scheme with a process-based version of the Noah LSM to yield better estimates of \( r_{\text{min}} \); one such model that is currently available is the Noah LSM coupled with the physiologically based Gas Exchange Evapotranspiration Model (GEM; Niyogi et al. 2006, 2008; Holt et al. 2006). Similar studies should be conducted with other land surface models that also utilize the Jarvis scheme to estimate \( r_{\text{min}} \).

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REFERENCES


