Development and Evaluation of a Coupled Photosynthesis-Based Gas Exchange Evapotranspiration Model (GEM) for Mesoscale Weather Forecasting Applications

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(Manuscript received 7 December 2006, in final form 13 May 2008)

ABSTRACT

Current land surface schemes used for mesoscale weather forecast models use the Jarvis-type stomatal resistance formulations for representing the vegetation transpiration processes. The Jarvis scheme, however, despite its robustness, needs significant tuning of the hypothetical minimum-stomatal resistance term to simulate surface energy balances. In this study, the authors show that the Jarvis-type stomatal resistance/transpiration model can be efficiently replaced in a coupled land–atmosphere model with a photosynthesis-based scheme and still achieve dynamically consistent results. To demonstrate this transformative potential, the authors developed and coupled a photosynthesis, gas exchange–based surface evapotranspiration model (GEM) as a land surface scheme for mesoscale weather forecasting model applications. The GEM was dynamically coupled with a prognostic soil moisture–soil temperature model and an atmospheric boundary layer (ABL) model. This coupled system was then validated over different natural surfaces including temperate C4 vegetation (prairie grass and corn field) and C3 vegetation (soybean, fallow, and hardwood forest) under contrasting surface conditions (such as different soil moisture and leaf area index). Results indicated that the coupled model was able to realistically simulate the surface fluxes and the boundary layer characteristics over different landscapes. The surface energy fluxes, particularly for latent heat, are typically within 10%–20% of the observations without any tuning of the biophysical–vegetation characteristics, and the response to the changes in the surface characteristics is consistent with observations and theory. This result shows that photosynthesis-based transpiration/stomatal resistance models such as GEM, despite various complexities, can be applied for mesoscale weather forecasting applications. Future efforts for understanding the different scaling parameterizations and for correcting errors for low soil moisture and/or wilting vegetation conditions are necessary to improve model performance. Results from this study suggest that the GEM approach using the photosynthesis-based soil vegetation atmosphere transfer (SVAT) scheme is thus superior to the Jarvis-based approaches. Currently GEM is being implemented within the Noah land surface model for the community Weather Research and Forecasting (WRF) Advanced Research Version Modeling System (ARW) and the NCAR high-resolution land data assimilation system (HRLDAS), and validation is under way.

* The National Center for Atmospheric Research is sponsored by the National Science Foundation.

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DOI: 10.1175/2008JAMC1662.1

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1. Introduction

Land surface processes (LSPs) and their interactions with the atmosphere are critical at different scales (Pielke et al. 2002; Feddema et al. 2005; Holt et al. 2006; Pielke and Niyogi 2009). Hence, LSPs need to be modeled as a continuum involving coupled feedback between different biospheric and hydrometeorological components. LSPs are modeled through soil–vegetation–atmosphere transfer (SVAT) schemes in which the stomatal response is the key to developing realistic biosphere–atmosphere interactions [see Niyogi and Raman (1997) for a review].

In the 1970s, most LSP parameterizations were diagnostic with an emphasis on the bare ground processes (e.g., Blackadar 1976). The soil–vegetation scheme proposed by Jarvis (1976) and Deardorff (1978) represents the “second generation” of the SVAT models. The Jarvis-type evapotranspirative schemes are relatively simple and dependent on meteorological variables such as air temperature and incident radiation. With several empirical modifications, the Jarvis schemes (Jarvis 1976) continue to be adopted to estimate latent heat fluxes and the surface energy balance in atmospheric models (Noilhan and Planton 1989; Chen et al. 1996; Chen and Dudhia 2001; Ek et al. 2003). However, as discussed in Niyogi et al. (1998), these second-generation SVAT schemes do not rigorously account for the coupled vegetation–atmosphere interactions and boundary layer feedback processes important to various environmental applications (Niyogi and Raman 2001). These limitations are addressed in the CO2-based physiological or “third generation” land surface models (LSM; Sellers et al. 1996; Pitman 2003) that consider evapotranspiration an inevitable cost during photosynthesis (Cowan 1982).

The third-generation SVATs are relatively complex schemes that consider photosynthesis (carbon assimilation) and biochemical responses and are explicitly coupled with the atmosphere and the surface to estimate carbon, water vapor, and energy exchange (Farquhar et al. 1980; Collatz et al. 1991, 1992; Anderson et al. 2000; see also Niyogi and Raman 1997). These schemes generally have been applied in leaf/canopy scale models (e.g., Baldocchi 1992), or in global/regional climate studies (Sellers et al. 1996; Calvet et al. 1998; Cox et al. 1999; Dai et al. 2003). Mesoscale or weather forecast models continue to be predominantly Jarvis-based (e.g., Chen and Dudhia 2001; Ek et al. 2003), but several reasons support the adoption of the photosyn thesis schemes over the Jarvis-type approaches.

First, for the estimate of stomatal resistance ($R_s$), the Jarvis approach relies on the prescription of so-called minimum stomatal resistance ($R_{s,\text{min}}$). However, the $R_{s,\text{min}}$ prescription not only varies with vegetation type, but also varies with the seasons (Schulze et al. 1994; Alfieri et al. 2008). Second, as shown in Alapaty et al. (1997a) and Cooter and Schwede (2000), $R_{s,\text{min}}$ errors impact surface hydrology and boundary layer simulations. These photosynthesis-based relations, though not causal, are based on gas exchange parameters that can be measured in the laboratory or in field studies (Ball et al. 1987). The gas exchange parameters seem to be robust and show phenological similarities without any significant seasonal or other environmental modulation in the basal values (Collatz et al. 1991). Third, with the current advances in remote sensing technology, a number of high-resolution land use–land cover and vegetation phenology datasets now can facilitate applications of photosynthesis-based models (Masson et al. 2003). Additionally, the photosynthesis-based schemes are more interactive and can thus better replicate the stomatal resistance variations under a variety of environmental changes (Niyogi et al. 1998).

In this study, we show first that the photosynthesis-based gas exchange transpiration model (GEM), despite various complexities, can be efficiently coupled to boundary layer and mesoscale models, and is preferable over the Jarvis scheme. In section 2, we describe the photosynthesis-based gas exchange evapotranspiration model (GEM) formulations. In section 3 we describe the coupling of the GEM with a prognostic soil moisture/soil temperature scheme and an atmospheric/PBL model; we also describe the development of initial conditions for the different model evaluation case studies. Results from the coupled model, for nine different cases, are then discussed in section 4. The conclusions from this study are summarized in section 5.

2. Model description

The photosynthesis-based gas exchange evapotranspiration model that we developed was integrated within a prognostic soil moisture and soil temperature prediction model similar to the one developed by Noilhan and Planton (1989) and Alapaty et al. (1997a). A brief summary of the model components is presented below. The equations and the parameterization schemes are described in the appendixes.

A core component of GEM is the stomatal resistance scheme. A number of stomatal models that link plant physiological or ecological processes have been reported in the literature. Previously we evaluated these stomatal models (Niyogi and Raman 1997; Niyogi et al. 1998) using direct observations and concluded that different approaches yield similar stomatal resistance estimates. We also found that the relative humidity–based...
stomatal resistance approach, such as the one originally developed by Ball et al. (1987), and subsequently modified by Leuning (1990), can be efficiently applied to atmospheric models. This is because of the linear main effect and interaction terms for relative humidity and stomatal resistance that aids scaling. Hence in the GEM, we use the Ball et al. (1987) relative humidity–based approach (also known as the Ball–Berry model) as a stomatal resistance (conductance) model:

\[
\frac{1}{R_s} = g_s = m A_n h_s + b.
\] (1)

In the above equation, \(R_s\) and \(g_s\) are the stomatal resistance and stomatal conductance terms; \(A_n\) is the net CO\(_2\) assimilation or the photosynthesis rate; \(h_s\) is the relative humidity at the leaf surface; \(C_s\) is the CO\(_2\) concentration at the leaf surface; and the terms \(m\) and \(b\) are linear coefficients based on gas exchange considerations (Ball et al. 1987), which are predominantly a function of vegetation type and photosynthesis pathway (Sellers et al. 1996). The Ball–Berry stomatal model is relatively complex because it requires a number of submodels for calculating the photosynthesis rate (e.g., information on variables such as CO\(_2\) concentrations at leaf surface and intercellular space), which are described in appendix A.

In the GEM, the estimation of the different parameters required to solve the Ball–Berry model [Eq. (1)], particularly the carbon assimilation \((A_n)\) term, mainly follows the Collatz et al. (1991, 1992) scheme. Also, the coupling between the \(h_s\) and \(C_s\) is achieved in solving for the photosynthesis rate estimation, following Sellers et al. (1996). The stomatal resistance calculations are interactively linked with soil variables such as soil temperature and soil moisture as well as with the atmospheric components such as wind, radiation, pressure, temperature, and humidity. The photosynthesis-based stomatal resistance model is linked to a Noilhan and Planton (1989) type prognostic soil moisture–soil temperature (SMST) scheme with two soil depths (0.1 and 1 m) and one canopy layer. Noting that the model will be typically applied at mesoscale model grids with ~10-km horizontal spacing, a number of simplifying assumptions have been made in the interest of computational efficiency. These include using surface temperature from the SMST scheme (which accounts for the fractional vegetation cover) in place of an explicit canopy temperature calculation as well as the consideration of big-leaf scaling instead of the multilayer canopy model. Recently, the GEM has been coupled within the Noah land surface model with four soil layers, and similar formulations can be used (cf. Kumar et al. 2007, 2008). The SMST scheme is coupled as a surface energy balance scheme to an atmospheric boundary layer model as described in Alapaty et al. (1997a). To couple the models, the GEM \(R_s\) output is linked with the surface energy balance model that is coupled to the atmospheric boundary layer model. In other words, the Jarvis-type stomatal resistance is replaced with the GEM-based estimates. All three schemes, the GEM, the soil model, and the PBL model, are interactive at every time step (~30 s).

3. Data and numerical simulations

The coupled SVAT scheme discussed above is primarily developed for land surface models that can be coupled to mesoscale numerical weather forecast models. Since the scheme is being adopted in a 3D modeling framework such as the Noah Model within the Weather Research and Forecasting (WRF) Model (e.g., Kumar et al. 2008), a number of tests were necessary to evaluate the model’s ability to reproduce important features related to surface boundary conditions, such as surface energy fluxes. In this study, we provide an overview of the model development and report on tests over different land covers by comparing the modeled and observed surface energy fluxes under contrasting micrometeorological conditions. These land covers were selected based on the following criteria: (i) test of two different photosynthesis submodels for the C3 and C4 pathways, (ii) tests over grasslands, agricultural crops, and forests (the most common vegetation types), (iii) availability of soil moisture and plant biophysical data, and (iv) our experience working with the site scientists and the datasets, which reduced uncertainties in defining the model initial conditions.

The study sites included (i) a temperate prairie grassland with a mixture of C4 vegetation, (ii) a C4 corn crop field, (iii) a C3 soybean crop field, (iv) a mixed C3 natural fallow field, and (v) a mixed C3 forest area. For all the sites, except the fallow field (for which only one day of data was readily available), two case studies were performed under different soil moisture and/or vegetation characteristic conditions, a total of nine scenarios. The soil–vegetation model also requires the initial condition to be externally specified. The values of the surface variables used to simulate this case are shown in Table 1. We recognize that the single-day coupled simulations provide only an initial analysis of the model performance. A longer simulation in an offline mode is currently under way by coupling the GEM formulation within the Noah land surface model as part of the National Center for Atmospheric Research (NCAR) high-resolution land data assimilation system, and the initial results are consistent with those reported here (cf. Kumar et al. 2007, 2008).
For the prairie grassland case [First International Satellite Land Surface Climatology Project (ISLSCP) Field Experiment (FIFE1 and FIFE2 data)], Alapaty et al. (1997a,b) developed a thermodynamically consistent, calibrated SVAT input for a Jarvis-based scheme following Noilhan and Planton (1989). The corresponding model results were validated using previously published results and field observations; the calibrated results were within 10%–20% of the observations (which in themselves had equivalent scatter). Hence, we will use the model output for this case as a surrogate for variables such as stomatal resistance, which are not directly observed for most field studies. The different cases are discussed in the following sections.

We defined the FIFE (Sellers et al. 1992) site as dense, temperate C4 grassland in Kansas. The FIFE site covers a region of 15 km × 15 km near Manhattan, Kansas (Polley et al. 1992; Niyogi and Raman 1997). We discuss the case for intensive field campaigns (IFCs) as the “golden days 1 and 2”: 7 June and 11 July 1987. Various researchers have extensively tested the golden days, and a reference input dataset is available [see, e.g., Sellers et al. (1992), and a series of papers included in that issue, as well as Alapaty et al. (1997a,b), Bosilovich and Sun (1995), and Niyogi and Raman (1997)]. Numerical simulations were performed for a period of 12 h starting at 1200 UTC (0700 LT) for both cases.

The second evaluation case was performed for a homogeneous C4 crop canopy (corn). Two case studies were selected: CORN-FULL (a fully grown stage with relatively low soil moisture) and CORN-OLD (the drying crop stage with relatively higher soil moisture). Following the two evaluations over C4 vegetation, additional case studies were undertaken over C3 vegetation. The first two of these were over a soybean canopy in an agricultural field: SOY-FULL (a fully grown soybean crop) and SOY-OLD (older, drying soybean crop). Of these two case studies, the soil moisture availability was high for the SOY-FULL case, and was low for the SOY-OLD case. Details regarding these field observations can be found in Meyers et al. (1998).

### Table 1. Initial values of surface parameters used in the numerical simulations (Pleim and Xiu 1995; Alapaty et al. 1997a,b; Calvet et al. 1998; Meyers et al. 1998; Finkelstein et al. 2000).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>FIFE1</th>
<th>FIFE2</th>
<th>MUREX</th>
<th>CORN-FULL</th>
<th>CORN-OLD</th>
<th>SOY-FULL</th>
<th>SOY-OLD</th>
<th>FOREST-WET</th>
<th>FOREST-DRY</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAI</td>
<td>1.9</td>
<td>2.8</td>
<td>1.36</td>
<td>3.1</td>
<td>2.8</td>
<td>6</td>
<td>3</td>
<td>3.6</td>
<td>1.95</td>
</tr>
<tr>
<td>Vegetation cover (Veg)</td>
<td>0.95</td>
<td>0.99</td>
<td>0.95</td>
<td>0.95</td>
<td>0.95</td>
<td>0.95</td>
<td>0.95</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>Soil texture*</td>
<td>Silty-clay loam</td>
<td>Silty-clay loam</td>
<td>Silty-clay loam</td>
<td>Silty-clay loam</td>
<td>Silty-clay loam</td>
<td>Silty-clay loam</td>
<td>Silty-clay loam</td>
<td>Silty-clay loam</td>
<td>Silty-clay loam</td>
</tr>
<tr>
<td>Top 10-cm soil layer moisture ($W_{g1}$) (m$^3$ m$^{-2}$)$^*$</td>
<td>0.23</td>
<td>0.27</td>
<td>0.32</td>
<td>0.2</td>
<td>0.35</td>
<td>0.33</td>
<td>0.29</td>
<td>0.24</td>
<td>0.2</td>
</tr>
<tr>
<td>Deep soil moisture ($W_{g2}$) (m$^3$ m$^{-2}$)$^*$</td>
<td>0.25</td>
<td>0.255</td>
<td>0.33</td>
<td>0.17</td>
<td>0.35</td>
<td>0.35</td>
<td>0.27</td>
<td>0.24</td>
<td>0.2</td>
</tr>
<tr>
<td>Surface roughness ($z_0$) (m)</td>
<td>0.045</td>
<td>0.065</td>
<td>1.0</td>
<td>0.28</td>
<td>0.28</td>
<td>0.088</td>
<td>0.088</td>
<td>2.4</td>
<td>2.4</td>
</tr>
<tr>
<td>Surface albedo</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2*</td>
<td>0.2</td>
<td>0.21</td>
<td>0.2</td>
<td>0.4</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Top 10-cm soil layer temperature ($T_{g1}$) (K)</td>
<td>289.15</td>
<td>296.0</td>
<td>292.0</td>
<td>298</td>
<td>295</td>
<td>298</td>
<td>291</td>
<td>292.0</td>
<td>292.0</td>
</tr>
<tr>
<td>Deep soil temperature ($T_{g2}$) (K)</td>
<td>293.35</td>
<td>297.0</td>
<td>295.0</td>
<td>298.0</td>
<td>295.0</td>
<td>298.0</td>
<td>286.0</td>
<td>295.0</td>
<td>295.0</td>
</tr>
<tr>
<td>Ambient CO$_2$ concentration (Pa)$^*$</td>
<td>34.0</td>
<td>34.0</td>
<td>34.0</td>
<td>34.0</td>
<td>34.0</td>
<td>34.0</td>
<td>34.0</td>
<td>34.0</td>
<td>34.0</td>
</tr>
<tr>
<td>Vegetation type*</td>
<td>C4, grass</td>
<td>C4, grass</td>
<td>C3, fallow</td>
<td>C3, crop</td>
<td>C3, crop</td>
<td>C3, crop</td>
<td>C3, crop</td>
<td>C3, mixed needle leaf trees</td>
<td>C3, mixed needle leaf trees</td>
</tr>
<tr>
<td>$m$, b (mol m$^{-2}$ s$^{-1}$)$^*$</td>
<td>4, 0.04</td>
<td>4, 0.04</td>
<td>9, 0.01</td>
<td>9, 0.01</td>
<td>9, 0.01</td>
<td>9, 0.01</td>
<td>9, 0.01</td>
<td>9, 0.01</td>
<td></td>
</tr>
</tbody>
</table>

* Parameter input values were not directly observed and were developed through discussions with the site scientists or were cited from literature review.
simulated: FOREST-WET (high soil moisture period) and FOREST-DRY (low soil moisture period). The corresponding input surface data are shown in Table 1.

In the case studies, the evaluation parameters are the surface heat fluxes. Evaluating fluxes, instead of individual evapotranspiration components, is sufficient and appropriate considering GEM is intended to be used as a surface energy balance scheme in the land surface models. The sensible (SHF) and latent heat fluxes (LHF) were measured using an eddy covariance technique and were quality assured by site investigators. In addition to the fluxes, we also compared the model results with the best estimates of stomatal resistance ($R_s$) for the FIFE case, and the observations of photosynthesis rates ($A_m$) for the Monitoring the Usable Soil Reservoir Experimentally (MUREX) case (Calvet et al. 1999). These two parameters, $R_s$ and $A_m$, are key variables in GEM.

For all of the cases, with the exception of the FIFE, on-site sounding data were not available. In the 1D model, meteorological sounding data were used to initialize the ABL model with representative wind and thermodynamic structure and to provide external boundary conditions for winds. The observed sounding data were also useful for evaluating the model-simulated boundary layer variables. Hence, when direct on-site observations were not available, archived analysis-based upper-air data were obtained corresponding to the study’s time and location. These sounding products were obtained through the National Oceanic and Atmospheric Administration (NOAA) Realtime Environmental Analysis and Display System site (http://www.arl.noaa.gov/ready.html) and the University of Wyoming (http://www.das.uwyo.edu). The sounding data were then processed for geostrophic winds and interpolated to the model sigma levels. These vertically integrated soundings were then temporally interpolated to generate hourly data over the numerical simulation locations (Alapaty et al. 2001). These processed data were used for initialization and developing boundary conditions for the atmospheric model.

4. Results and discussion

The simulation results over the different landscapes are presented in this section. The results are presented first for the C4 vegetation and then for the C3 vegetation.

a. Simulation over C4 vegetation

In this section, the model results from the FIFE cases over temperate grassland and over a corn field are discussed. Both the vegetation canopies showed a C4 photosynthesis pathway.

1) FIFE1

This case corresponded to the FIFE golden day 1 (Sellers et al. 1992) on 6 June 1987. During this period, the vegetation was in its “greening up” phase with moderate to low soil moisture availability. Figures 1a–c show the observed and the predicted net radiation ($R_n$), latent heat fluxes, and sensible heat flux for this case. Though the modeled net radiation flux estimates were not directly linked with the transpiration model, the agreement of these estimates with the observations provided confidence in the specified initial conditions of the biophysical parameters such as albedo, emissivity, and soil texture (Table 1). The simulations closely followed the observed $R_n$ generally within 20 W m$^{-2}$, until early evening. After 1600 LT the observations were larger than the model-estimated values by about 30–40 W m$^{-2}$. The model-predicted latent and sensible surface heat fluxes are also in good agreement with observations. The latent heat fluxes, in particular, are generally within about 20 W m$^{-2}$ of the observations. For most of the day, the model-predicted values were slightly lower than the observations and the afternoon and early evening predictions were about 25 W m$^{-2}$ higher. As expected for the vegetated field with freely transpiring...
surface, the SHF values are lower than the LHF. The SHF values show some scatter in the morning, and reach a peak of about 130 W m$^{-2}$ at the beginning of the day. The simulated values were within about 20 W m$^{-2}$ until the afternoon, and then they were within about 35 W m$^{-2}$ into the later part of the day. The modeled SHF values are underestimated in the morning and evening and overpredicted in the afternoon. This could be due to vegetation stress in the afternoon leading to lower-than-observed LHF (in the latter part of the day) and uncertainty in the input conditions. Overall, the coupled scheme simulated the surface energy fluxes fairly well, with values within 10% of the observations.

In addition to the surface fluxes, observed soundings are available for FIFE. We evaluated the model-simulated vertical virtual potential temperature profiles against the observations. As shown by Alapaty et al. (1997a), surface fluxes can impact the entire boundary layer structure, which corroborates the importance of this study of GEM coupled to an atmospheric boundary layer model. The vertical distribution of the virtual potential temperature ($\theta_v$) and the resulting PBL height variation provides an overall view of the mean thermodynamic structure of the boundary layer. Figure 2 shows a summary of the observed and model-predicted boundary layer heights. The observed boundary layer deepened over the day with the 0700, 1000, 1300, and 1600 LT values corresponding to about 250, 1000, 1300, and 1400 m, respectively. The evolution of the observed and the model-simulated $\theta_v$ profiles (not shown) also shows good agreement with each other. At 0700 LT, the observations indicated a shallow (~250 m) stable boundary layer. This profile was used as the model initial condition. After model integration, around 1000 LT, the PBL was weakly unstable with mean temperatures in the mixed layer around 299 K. At 1300 LT, the boundary layer evolved further with a mixed layer $\theta_v$ value around 302 K. The boundary layer was warmer in the 1600 LT profile with a surface value of 305 K. The simulated $\theta_v$ values were similar to the observations, though lower by about 1 K in the PBL. The $\theta_v$ values and the boundary layer depth are often closely linked with the surface heat fluxes, since the atmospheric eddy size increases with higher sensible heating, thereby deepening the boundary layer. If more validation data had been available, the relationship between the errors in $\theta_v$ and errors in the SHF could have been verified. In general, the model simulations are fairly similar to the observations.

2) FIFE2

The FIFE2 case corresponds to the FIFE golden day 2 on 11 July 1987 (Sellers et al. 1992). As compared with FIFE1, FIFE2 corresponds to modestly higher initial soil moisture availability (0.27 as compared with 0.25 m$^3$ m$^{-3}$ in the top 10-cm soil layer). The vegetation is also at its peak green with a higher LAI than in FIFE1 (2.8 as compared with 1.9). Similar to the FIFE1 case, this day corresponds to clear-sky conditions with nearly advection-free meteorological conditions for the initial part of the day. However, after 1500 LT, overcast-sky conditions were recorded; in the absence of explicit large-scale advection, the 1D model results are ideally comparable with observations only until 1500 LT.

Figures 3a–c show the temporal variations in the observed and simulated net radiation and surface sensible and latent heat fluxes. The simulated SHF and LHF values are also within 10%–20% of the observations and are within the range of uncertainty in the model formulations and the measurements (LeMone et al. 2007). The model appears to reproduce the observations in terms of the temporal evolution as well as the measured quantities for the temperate prairie grassland. Also, for this case, the model performance is relatively better than FIFE1. This could be due to a number of factors including a denser and more homogeneous vegetation canopy, as well as modestly higher soil moisture availability (see also Colello et al. 1998). This aspect of better model performance under higher soil moisture availability
is seen as a general conclusion for the different cases discussed ahead.

The model-estimated and observed boundary layer heights are plotted in Fig. 4. The observed and model-predicted $\theta_e$ profiles also agree well (not shown). The model evolution of the PBL height and potential temperature are consistent with the good performance of the ABL model over the FIFE region reported by Alapaty et al. (1997a). Thus the coupling of GEM within the LSM appears to be dynamically consistent within the coupled SVAT model that was initially tested and calibrated using a Jarvis-type vegetation representation by Alapaty et al. (1997a) and Niyogi et al. (1999).

3) CORN-HIGH

This case corresponds to a period when the corn crop was at its peak with an LAI around 3 (Meyers et al. 1998). The soil moisture availability was moderate to low. The model was initialized at 0200 LT 24 August 1994 and integrated for a period of 48 h. The observed and the model-simulated net radiation and the sensible and latent heat fluxes are shown in Figs. 5a–c. The model errors are on average within 20% of the observations, with the spikes showing larger differences. It is interesting to note that the model is able to simulate the day-to-day variations in the energy fluxes noted in the observations. The model shows much more negative net radiation at night than seen in the observations. This nighttime net radiation error is a known problem with the SVAT scheme used in Alapaty et al. (2001). Sensitivity runs (not shown) suggest that the error may be mainly due to the prescribed albedo and emissivity values. In the current version, both albedo and emissivity are independent of soil moisture and are one of the modifications we plan to incorporate in a follow-up study for integration within the Noah model (Idso et al. 1975; Ek et al. 2003; LeMone et al. 2008). Also, we do not know the possible impact of correcting the observations to account for the energy balance closure (Wilson et al. 2002).
4) CORN-OLD

This case study for 15–16 September 1994 simulated the atmosphere over the same crop field simulated in the CORN-FULL case. In this case, the corn was aged and drying primarily because of senescence. The LAI was about half of the CORN-FULL case, but the soil moisture availability was much higher. This created a confounding between the wilting vegetation that generally resists transpiration with age (Niyogi et al. 1997) and the high-soil moisture availability that induces higher-water vapor exchange through the stoma. Figures 6a–c show the temporal variations in the observed and the model-predicted $R_n$, SHF, and LHF. Largely due to scattered (subgrid) clouds over the study domain, the observed net radiation values show significant variability particularly in the late afternoon and early evenings for both days. The error in $R_n$ introduces some inherent limitations in simulating SHF and LHF values. Generally, the effect of the $R_n$ overprediction will be more on the SHF than the LHF model predictions. Although the LHF values depend on $R_n$, the error results because these values were calculated explicitly through the GEM-based SVAT scheme, and the SHF prediction is a function of the air and land surface temperature differential. Thus, the simulated LHF was lower than the observations by about 10%, while the sensible heat fluxes were generally overestimated by about 20%. Despite these differences and considering the difficulties of simulating this case with limited site-specific input data, the overall coupled model performance was quite satisfactory for the C4 vegetation. Interestingly, even though the vegetation was wilting, the overall model performance appears to be comparable with the CORN-FULL case, possibly due to the high soil moisture availability.

b. Simulation over C3 vegetation

This section discusses the numerical simulations and evaluation results over three different C3 vegetation
types: a soybean crop, a fallow field, and a hardwood forest.

1) SOY-FULL

During this case, the soybean crop was at its peak green with LAI around 6 and high soil moisture availability (Meyers et al. 1998). The model was initialized at 0600 LT 6 August 1995 and integrated for a 48-h period with the surface conditions shown in Table 1. Figures 7a–c show the observed and the modeled radiation fluxes. The $R_n$ observations showed significant variability due to intermittent cloud cover. The afternoon peak for the 2 days was around 350 W m$^{-2}$ for $R_n$, which the model captured well. However, the observed and modeled $R_n$ values differed by about 50 W m$^{-2}$ for any individual hour. The maximum LHF and SHF values measured approximately 150 and 100 W m$^{-2}$, respectively. Though the simulations did not show the variability seen in the open canopy, the gross features including day-to-day variability were captured. Results also indicate that short-term errors can occur for such a modeling case when vegetation is wilting and soil moisture availability is low.

2) SOY-OLD

This case study was performed over the same soybean crop as discussed above, but for a period about 5 weeks later than the peak green, and the vegetation was aged and partly wilting (Meyers et al. 1998). The model simulations involved a 48-h period starting from 0600 LT 12 September 1995. Figures 8a–c show the observed and the modeled radiation fluxes. The $R_n$ observations showed significant variability due to intermittent cloud cover. The afternoon peak for the 2 days was around 350 W m$^{-2}$ for $R_n$, which the model captured well. However, the observed and modeled $R_n$ values differed by about 50 W m$^{-2}$ for any individual hour. The maximum LHF and SHF values measured approximately 150 and 100 W m$^{-2}$, respectively. Though the simulations did not show the variability seen in the open canopy, the gross features including day-to-day variability were captured. Results also indicate that short-term errors can occur for such a modeling case when vegetation is wilting and soil moisture availability is low.

3) MUREX

This case studied the land–atmosphere interaction over a C3 fallow field on an agricultural site near Toulouse,
France, on 4 September 1997 (Calvet et al. 1999). Two grass species, Brachypodium sp. and Potentilla reptans, dominated the domain with a vegetation cover of 0.95 and an LAI of 2.5. The soil texture was silty-loam with surface albedo and emissivity values of 0.21 and 0.97. The model was integrated from 0000 LT 4 September 1997 for a period of 24 h. Figures 9a–c show the observed and the model-predicted radiative fluxes for the MUREX case. For the \( R_n \), observations showed a positive value between 0600 and 1700 LT with a noontime peak around 600 W m\(^{-2}\). The simulated \( R_n \) values followed the observations closely, though the midday values were underestimated by \( \approx 50 \) W m\(^{-2}\). This underestimation could have been due to a number of possible interactions, and our analysis suggests that the uncertainty in the albedo observations (by ±0.04) and heterogeneity in the fallow field were the main reasons for the differences in the model results (cf. Calvet et al. 1999). Barring this underestimation, the model-simulated values were within 10% of the observations.

Also, as shown in Fig. 9b, the simulated LHF is in agreement with the observations. This agreement held true especially from the afternoon through to the end of the simulation. This general agreement could be largely attributed to the availability of site-specific vegetation and surface characteristics (Dang et al. 1998). For the earlier part of the day, the SHF values were underpredicted, and the observations showed an unusual peak in SHF at 0900 LT. Corresponding to this underprediction in the mornings, the modeled SHF outcome was higher than the observations by about 40 W m\(^{-2}\) at midday. After 1500 LT, the simulated values followed the observations. The errors in the net radiation estimation could also have offset the SHF values.

c. Simulation over C3 forest

1) FOREST-WET

The FOREST-WET and the FOREST-DRY cases validated the GEM-based SVAT over a C3 woody canopy in a forested area. The measurements were made over the Sandflats, a mixed forest of the Adirondack Mountain region of New York (Finkelstein et al. 2000). The site was instrumented with a 36-m tower, and the energy fluxes were measured at a height of approximately 10 m above the average tree cover using a sonic anemometer and an infrared gas analyzer. The vegetation canopy showed complex, inhomogeneous variations. Details regarding the instrumentation, the data quality control, and the seasonal changes in the site characteristics can be found in Finkelstein et al. (2000); the surface features are shown in Table 1. The model was initialized at 0000 LT 24 July 1998, using an Eta Model–based sounding centered over the study site. A complete diurnal cycle was simulated.

Figures 10a–c show the observed and model-simulated radiative flux. The large variations in the observed net radiation values are possibly due to the presence of scattered (subgrid scale) clouds and an undetermined forest energy storage term (McCaughey 1985). In the GEM, we adopted a big-leaf approach and did not consider multiple canopy layers (Meyers et al. 1998) or biomass energy storage (Gu et al. 2007), thus the variations due to within-canopy processes cannot be reproduced. The simulated net radiation values showed much of the features seen in the observed \( R_n \), such as the peak value of 700 W m\(^{-2}\), although the observed variability in the midday values was absent.

Regarding the LHF and SHF, the observations showed variability that is not apparent in the \( R_n \) data and may be indicative of large within-canopy or surface storage flux. The fluxes varied by about 150 W m\(^{-2}\) between subsequent hourly readings. The LHF values were...
more variable than the relatively smooth $R_n$ and SHF curves. The SHF values showed a smooth rise and peak around 150 W m$^{-2}$ and then decreased to negative values after 1700 LT. The observations showed variability until noon and then peaked at about 200 W m$^{-2}$ for a short period after fluctuating close to 0 and 100. Thus for this case, the SHF values were generally overpredicted. The model performance for this simulation was less satisfactory than it was for the grass and crops, though the general features were well simulated in terms of the evapotranspiration-based exchanges.

2) FOREST-DRY

The FOREST-DRY simulations were performed over the same forest canopy except the surface conditions were relatively drier. The model was initialized at 0000 LT 10 October 1998 and integrated for a period of 24 h. Figures 11a–c show the observed and modeled net radiation, latent heat fluxes, and sensible heat fluxes, respectively. The simulated values followed the net radiation observations until sunrise, after which the observed and simulated $R_n$ values show noticeable differences. The peak $R_n$ prediction was approximately 120 W m$^{-2}$, and was consistent with observations, but the timings varied. There was also an overprediction in the simulated LHF. Even though the short-term variability was not captured, the model did perform well in simulating the case-to-case variability with generally lower LHF values for the FOREST-DRY case as compared with the FOREST-WET case.

Considering the variability in the observations and the difficulty associated with simulating the energy balance in patchy forest canopies, the model performance was modest. The results also suggest that the simplified scaling approach used in the land surface model could be applied for most mesoscale applications; however, for tall canopies, this approach could lead to
larger uncertainties in the evapotranspiration and energy flux outcome. The scaling approach and the surface energy storage term for forested landscapes (Gu et al. 2007) need to be evaluated in a future study.

Recently, Kumar et al. (2007, 2008) and A. Kumar et al. (2008, unpublished manuscript) tested the GEM scheme within the NCAR high-resolution land data assimilation system with the Noah land surface model to simulate a month-long surface energy balance and soil moisture/soil temperature time series over the eastern half of the United States. The model results were compared with AmeriFlux observations (Baldocchi et al. 2001). Many of the validation sites were over forested landscapes and a very good agreement was seen, particularly over Morgan Forest in southern Indiana, Walker Branch in Tennessee, Duke Forest site in North Carolina, and Park Falls site in Wisconsin. Therefore, even though we obtained relatively modest results in this study with the 1D coupled modeling study for the FOREST-WET and FOREST-DRY cases, the viability of the GEM-based $R_s$ and energy balance or soil fields can be considered good even over forest site.

d. GEM-predicted stomatal resistances

Based on the various field evaluations, we conclude that the default values used in the GEM-based coupled SVAT model were able to simulate the surface energy balance and the boundary layer feedback over different natural surfaces reasonably well (at least within the range of uncertainty associated with a coupled column model). An important variable that GEM simulates for the SVAT and that forms the basis for replacing the Jarvis-type transpiration model is stomatal resistance ($R_s$) [and carbon assimilation rate ($A_n$)]. Field measurements of $R_s$ and $A_n$ were available for the MUREX case. The MUREX observations and the corresponding model results are shown in Figs. 12a.b. Although there are apparent differences in the outcome, the variations are realistic considering the heterogeneity in the natural landscape as well as the intraspecies variations in the two dominant fallow grasses ($Brachypodium$ sp. and $Potentilla reptans$) found on the observational site (Calvet et al. 1999). As discussed in Dang et al. (1998) and Colello et al. (1998), the performance of the $g_r$-$A_n$ models cannot be compared with every plant species that a particular vegetation type represents in a land surface model. Thus, from this perspective, similarity of the observed and modeled $g_r$-$A_n$ terms is satisfactory.

To put the results in perspective, we evaluated the model response when the traditional minimum stomatal resistance ($R_{s,\min}$) based Jarvis scheme was used instead of the GEM. For this testing we used the same surface conditions as used for GEM (shown in Table 1), except with the Jarvis-type model (Alapaty et al. 1997a). Note that the critical variable in adopting the Jarvis scheme is the specification of $R_{s,\min}$. The vegetation type over the MUREX study area (natural fallow landscape) can be classified under a number of land use categories in a land surface model, such as the one adopted in the Noah land surface model (Ek et al. 2003). Considering the U.S. Geological Survey (USGS) land use category, one could prescribe the fallow landscape as grasslands with shrubs ($R_{s,\min} = 150$ s m$^{-2}$) or even possibly as an agricultural area ($R_{s,\min} = 40$ s m$^{-2}$). Other possibilities include considering the landscape as grassland ($R_{s,\min} = 40$ s m$^{-2}$), mixed shrub or grasslands ($R_{s,\min} = 170$ s m$^{-2}$), or shrubland ($R_{s,\min} = 300$ s m$^{-2}$). As discussed before, the $R_{s,\min}$ assignment is an arbitrary parameter used only in the models, and thus compiled from the literature and modeling studies, and does not have a measurement-based reference. Further, considering the broad definitions of each of the land use categories, no
guiding principle exists for choosing one land use category over the other. Hence, corresponding to these different realistically possible vegetation-type assignments for the fallow surface, we prescribed three corresponding \( R_s, \min \) values—40, 150, and 300 s m\(^{-2}\)—and compared the model outcome for stomatal resistance \( (R_s) \) temporal changes.

Figure 13 shows the observed and modeled stomatal resistances over the fallow site. As discussed earlier, the GEM-based \( R_s \) values were close to the observations for the two dominant species over the study domain. The Jarvis-type outcome was of the same order of magnitude but showed a large dependence on the \( R_s, \min \) assignment. The model performance depends on, and to a large extent can be tuned to, the prescribed value of minimum stomatal resistance (Niyogi and Raman 1997). Consequently, results for \( R_s, \min = 40 \) s m\(^{-1}\) do yield stomatal resistance values relatively closer to the observed (though underpredicted), as compared with the high \( R_s \) values yielded by the other two \( R_s, \min \) assignments. Thus, as shown in Alfieri et al. (2008), one could in practice tune the \( R_s, \min \) value (in this particular case, increase it slightly) to achieve a good stomatal resistance variation from the Jarvis scheme. [Regarding the MUREX study referred to here, Calvet et al. (1998) used \( R_s, \min = 50 \) s m\(^{-1}\) in one of their simulations and obtained fairly good agreement between the modeled and observed values.]

Changes in the \( R_s, \min \) values affected the modeled LHF. Higher stomatal resistance resulted in lower latent heat fluxes (Fig. 14). The modeled LHF values during the afternoon ranged from about 150 to 350 W m\(^{-2}\) for the fallow land, while the observations showed values around 300 W m\(^{-2}\). Consistent with the earlier discussion, the GEM results were in close agreement with the LHF, and also with the \( R_s, \min = 40 \) case results.

In addition to these direct observations available during MUREX, a number of studies such as Pleim and Xiu (1995) and Alapaty et al. (1997a,b) have calibrated the Jarvis-type Noilhan–Planton scheme (principally the \( R_s, \min \) values) for integrated field campaigns. As discussed for the MUREX case study earlier, the Jarvis-type \( R_s \) time series can be considered a surrogate for observed values if the \( R_s, \min \) is calibrated with other surface observations. Hence, we used the simulated stomatal resistance time series using the Jarvis scheme for the two FIFE cases: FIFE1 and FIFE2 following Alapaty et al. (1997a), to compare the GEM-predicted \( R_s \) values for the two cases. Figures 15a,b show the stomatal resistance variations from the two schemes over the FIFE region. In general, the \( R_s \) values are similar, as expected because of the close agreement between the observed and GEM-predicted surface energy fluxes shown earlier (Figs. 1, 3). The GEM predictions showed a somewhat larger \( R_s \) than the calibrated values, but the differences were relatively small (as revealed from comparisons with observed profiles and surface energy fluxes). Thus the photosynthesis/gas exchange–based evapotranspiration approach to estimating stomatal resistances (net carbon assimilation) as part of coupled surface–atmosphere models was shown in this study to be robust and effective.

5. Conclusions

In the majority of mesoscale weather forecast models, the Jarvis-type scheme is employed for simulating
vegetation feedback in a land surface model. We showed that the Jarvis scheme, despite its robustness, needs significant tuning to simulate surface energy balances over different natural surfaces (Alfieri et al. 2008). Recent advances in vegetation models have developed explicit relations for modeling photosynthesis and stomatal conductance, and subsequently the variations in surface evapotranspiration. These photosynthesis or carbon assimilation–based stomatal models have been successfully employed at the leaf scale and in climate studies. In this study, we showed that a photosynthesis-based stomatal resistance model despite its complexity can efficiently replace the Jarvis scheme for coupled mesoscale land–atmosphere models. To show this, we developed and coupled a gas exchange–based surface evapotranspiration model (GEM) as a land surface/SVAT scheme designed for mesoscale applications.

The GEM was dynamically coupled with a prognostic soil moisture, soil temperature model, and a PBL model. This coupled system was then validated with nine case studies over five different natural surfaces: a C4 prairie grass, a C4 corn field, a C3 soybean field, a C3 fallow site, and a C3 hardwood forest site. For each of the five surfaces except the fallow site, two case studies were performed under contrasting surface conditions (such as different soil moisture and LAI). The model simulations were compared with actual field measurements of surface sensible and latent heat fluxes. For some of the case studies, measurements of vertical boundary layer profiles, or direct measurements of stomatal resistance and photosynthesis rates were available and were compared with the GEM-based, coupled SVAT model output.

The model was able to simulate the different surface as well as boundary layer characteristics quite successfully. The surface energy fluxes in general, and the average latent heat fluxes in particular, were within 10%–20% of the observations without any tuning of the biophysical–vegetation characteristics. The model was also able to satisfactorily simulate the day-to-day variations in the heat fluxes. The model response to the changes in the surface characteristics was consistent with observations and theory.

A number of features can be further developed in the parameterization. For example, in this study the big-leaf approach was adopted, which could have caused significant errors for tall canopies, particularly when a large storage flux may be involved. A future study could be undertaken redesigning the coupling with a detailed sun–shade scaling and a multilayer modeling approach, particularly for tall canopies. Additionally, the photosynthesis-based model performance was relatively poor under low–soil moisture conditions. It should be mentioned that for grass and homogeneous crop canopies, the big-leaf approach was satisfactory, particularly under high–soil moisture conditions or when the vegetation was not aged or stressed.

The case studies provide two significant conclusions: (i) the inclusion of a new photosynthesis-based vegetation scheme did not deteriorate the overall performance of the coupled model, and (ii) inclusion of the new photosynthesis transpiration scheme and the generally good results obtained without any significant tuning of the physiological variables in the vegetation model validated the robust coupling between GEM and the ABL. Results thus suggest that the photosynthesis-based SVAT approaches are superior to Jarvis-based approaches and can be applied to regional environmental models. Also, the GEM has been successfully coupled with the Noah land surface model within the
Coupled Ocean–Atmospheric Modeling System (Niyogi et al. 2006; Holt et al. 2006) and the Weather Research and Forecasting system (Kumar et al. 2008; Chang et al. 2009); the results for the coupled 3D simulations as well as the seasonal to longer-term offline simulations show the GEM capable of the reproduction of a realistic land surface response (Kumar et al. 2008; A. Kumar et al. 2008, unpublished manuscript).

Acknowledgments. This study benefited in part from the following grants: NSF-ATM 0233780 (Dr. S. Nelson), NASA-THP NNG04GI84G and NNG06GH17G (Dr. J. Entin), NASA-IDS NNG04GL61G (Drs. J. Entin and G. Gutman), NASA Land Use Landcover Change Program (Dr. G. Gutman), USDA NRICGP on Water Resources (subcontract though Tufts University Dr. S. Islam), and the NOAA Joint Center for Satellite Data Assimilation NA06NES4400013 (Dr. K. Mitchell). We also acknowledge the support from the NCAR Water Cycle Across Scale Program at The Institute for Integrative and Multidisciplinary Earth Studies. We also appreciate detailed comments and suggestions from three reviewers.

APPENDIX A

The Photosynthesis/Carbon Assimilation Model

In the GEM, we couple the photosynthesis/carbon assimilation model developed by Collatz et al. (1991, 1992) with the Ball–Berry model [Eq. (1) in the main text]. Photosynthesis is calculated for three potentially limiting factors: (i) efficiency of the photosynthetic enzyme system or Rubisco limitation ($w_c$); (ii) amount of photosynthetically active radiation (PAR) absorbed by the leaf chlorophyll or light limitation ($w_e$); and (iii) capacity of the C3 vegetation to utilize the photosynthesis products, or the phosphoenolpyruvate (PEP)–carboxylase limitation in the C4 vegetation ($w_s$).

Each of the limiting carbon assimilation rates (mol m$^{-2}$ s$^{-1}$) is calculated as follows: for C3 vegetation,

$$w_c = V_m \left( \frac{C_i - \Gamma^*}{C_i + K_c (1 + O_2 / K_{o2})} \right),$$

(A1a)

$$w_e = \text{PAR}(1 - \omega_P) \left[ (C_i - \Gamma^*) - (C_i + 2\Gamma^*) \right],$$

(A1b)

$$w_s = 0.5 V_m,$$

(A1c)

and for C4 vegetation,

$$w_c = V_m,$$

(A2a)

$$w_e = \text{PAR}(1 - \omega_P),$$

(A2b)

$$w_s = 20000 V_m (C_i / P).$$

(A2c)

In the above calculations, $\varepsilon$ is the quantum efficiency for carbon dioxide uptake (0.08 mol mol$^{-1}$ for C3, and 0.05 mol mol$^{-1}$ for C4 vegetation), $C_i$ is the CO$_2$ concentration in the leaf intercellular spaces, and $\omega_P$ is the leaf-scattering coefficient for PAR ($\sim 0.1$ and 0.2; Sellers et al. 1996). In the mesoscale modeling perspective, PAR is often taken as 55%-70% of the net radiation (Noilhan and Planton 1989) and $P$ is the surface pressure (Pa) obtained from the atmospheric model. Additionally, $V_m$ is the maximum catalytic Rubisco capacity for the leaf, which is a leaf chloroplast–based physiological entity providing the nutrient state of the biota through Rubisco storage or nitrogen content (Wilson et al. 2000a). The $V_m$ maximum value ($V_{\text{max}}$, $3 \times 10^{-5}$ mol m$^{-2}$ s$^{-1}$ for C4 plants and 2 or 3 times as much for C3 plants) is modulated principally as a function of temperature and soil moisture as

$$V_m = V_{\text{max}} f(T) f(w_2) 21^{0.5},$$

(A3)

The temperature dependence follows Sellers et al. (1996) as

$$f(T) = \frac{2^{Q_{10}} \left\{ 1 + \exp \left[ 0.3(S_2 - T_s) \right] \right\}}{1 + \exp \left[ 0.3(T_s - S_2) \right]},$$

(A4)

where $S_2$ and $S_4$ are high and low temperature vegetation stress factors (around 310 and 280 K, respectively) as a function of vegetation type. The $Q_{10}$ term is the temperature dependency taken as 0.1($T_s - 298$)., where $T_s$ (K) is the surface or canopy temperature (see also Paw U 1987). The modulation of the effect of $V_m$ by soil moisture is calculated following Calvet et al. (1998) as

$$f(w_2) = \frac{w_2 - w_{\text{wilt}}}{w_{fc} - w_{\text{wilt}}},$$

(A5)

In the above equation, $w_{\text{wilt}}$ and $w_{fc}$ are the root-level soil moisture wilting and field capacity values, prescribed as a function of soil texture (see Clapp and Hornberger 1978; Maier-Maercker 1998). Both the surface temperature and soil moisture values are prognosticated using the soil model. Additionally, for the carbon assimilation equations, $\Gamma^*$ is the CO$_2$ compensation point (Pa) and is calculated following Collatz et al. (1991) as

$$\Gamma^* = 0.5(O_2 / S),$$

(A6)
where $O_2$ is oxygen availability in the leaf cells [20 900 Pa from Sellers et al. (1996)] and $S$ is the Rubisco specificity for CO$_2$ relative to O$_2$, calculated as

$$S = 2600 \times 0.57^{O_2_{10}}. \tag{A7}$$

In Eq. (A1a), two constants, $K_c$ and $K_o$, are the Michaelis–Menten constant for CO$_2$ (Pa) and the oxygen inhibition constant (Pa), respectively, which are calculated as (Sellers et al. 1996)

$$K_c = 30 \times 2.1^{O_2_{10}} \quad \text{and} \quad K_o = 30 \times 3000 \times 1.2^{O_2_{10}}. \tag{A8}, (A9}$$

To solve Eqs. (A1a)–(A1c) and (A2a)–(A2c), $C_i$ is needed. This result is obtained through an iterative solution with an initial estimate of $C_i$ (as a fraction of $C_a$; see Anderson et al. 2000), net assimilation ($A_n$), and stomatal conductance ($g_s$).

Knowing the three limiting assimilation rates, the minimum value is considered as the estimate of gross carbon assimilation rate ($A_g$) (Farquhar et al. 1980). However, as discussed in Collatz et al. (1991, 1992), the gross assimilation rate is dependent on all three limiting rates. First, a minimum assimilation rate ($w_p$) is estimated assuming a coupling coefficient ($\beta_1$) between the Rubisco-limited ($w_c$) and light-limited rate ($w_s$) of carbon assimilation. The gross carbon assimilation rate ($A_g$) is then the minimum of $w_p$ and CO$_2$-limited rate ($w_c$). Then, a coupling coefficient ($\beta_2$) is assumed between the $w_p$ and CO$_2$-limited transition. These coupling coefficients are assigned values between 0.8 and 0.99 for the $w_p$ and $A_g$ estimation, respectively (Collatz et al. 1991, 1992). For obtaining the solutions, a set of quadratic equations are solved for the limiting rates by taking the smaller root for each:

$$\beta_1 w_p^2 - w_p(w_c + w_s) + w_c w_s = 0 \quad \text{and} \quad \beta_2 A_g^2 - A_g(w_p + w_s) + w_p w_s = 0. \tag{A10}$$

By calculating the gross carbon assimilation rate ($A_g$), the net assimilation or photosynthesis rate $A_n$ is estimated by deducting the loss due to leaf respiration rate ($R_d$). In GEM, we adopt an approach initially presented by Goudriaan et al. (1985) and developed further by Jacobs (1994) and Calvet et al. (1998). Accordingly, respiration is estimated as (van Heemst 1988)

$$R_d = A_m/9.0, \tag{A11}$$

where $A_m$ is the maximum assimilation rate, estimated as

$$A_m = A_{m,\max}\{1 - \exp[-g_m(C_i - \Gamma^*)/A_{m,\max}]\}. \tag{A12a}$$

In the above, $A_{m,\max} = 9.8 \times 10^{-5}$ mol m$^{-2}$ s$^{-1}$ for C3 and $7.48 \times 10^{-5}$ mol m$^{-2}$ s$^{-1}$ for C4 vegetation (Jacobs 1994). Also, $g_m$ is the mesophyll conductance, which is based on the modulation of a potentially maximum value ($g_{mp}$) as a function of the photosynthesis pathway:

$$g_m = g_{mp}\left[2^{O_2_{10}}\left(1 + \exp\left[0.3(T_c - S_2)\right]\right)\left(1 + \exp\left[0.3(S_4 - T_a)\right]\right)\left(w_c - w_{vint}\right)\right]. \tag{A12b}$$

Typically $g_{mp}$ is $7 \times 10^{-3}$ m s$^{-1}$ for C3 and $17.5 \times 10^{-3}$ m s$^{-1}$ for C4 plants (Jacobs 1994). Knowing these variables, the photosynthesis rate $A_n$ (mol m$^{-2}$ s$^{-1}$) is estimated as

$$A_n = A_g - R_d. \tag{A13}$$

Three variables are still needed to solve the $g_e/A_n$ equations: CO$_2$ concentrations at the leaf surface ($C_i$), relative humidity at the leaf surface ($r_h$) for the Ball–Berry model [Eq. (1)], and the CO$_2$ concentration in the intercellular spaces ($C_s$) for the Collatz $A_n$ model [Eqs. (A1a)–(A1c), Eqs. (A2a)–(A2c)]. Thus, additional coupling terms are needed to link ambient CO$_2$ concentrations ($C_a$) with leaf-level CO$_2$. This coupling is achieved through a leaf boundary layer model discussed in appendix B.

**APPENDIX B**

**Leaf Boundary Layer Scheme for the Stomatal Conductance/Photosynthesis Model**

The leaf boundary layer conductance ($g_{bl}$) modulates the interaction between the leaf surface and the ambient environment. In some models to reduce computational time (such as SiB2; Sellers et al. 1996), the $g_{bl}$ term is maintained at a constant value such as 0.04 mol m$^{-2}$ s$^{-1}$. However, our intent in adopting a physiologically intensive stomatal parameterization is to facilitate more dynamic interactions between the vegetation, soil moisture, and meteorological variations (that exist in the nature, but not captured by diagnostic schemes). Hence, in the GEM we assume an interactive representation of the leaf-scale boundary layer through a variable $g_{bl}$ as discussed in Nikolov et al. (1995) and Su et al. (1996). Two sets of empirical equations can be adopted for estimating $g_{bl}$: one for forced convection ($g_{blc}$) and the other for free convective ($g_{blf}$) conditions. Accordingly,
where $T_a$ is the ambient air temperature (K), $u$ is the wind speed (m s$^{-1}$), $d$ is leaf length scale [m; with default values for needle-shaped leaves and width for broad leaves following Nikolov et al. (1995)], $P$ is the ambient pressure (Pa), and $c$ is the transfer coefficient [equal to $4.322 \times 10^{-2}$ for broad leaves and $1.2035 \times 10^{-2}$ for conifers, following Nikolov et al. (1995)].

For the free convection boundary layer, the equation is

$$g_{btc} = c T_a^{0.56} \left( (T_a + 120) \frac{u}{dP} \right)^{0.5}, \quad (B1)$$

where $T_a$ is the ambient air temperature (K), $u$ is the wind speed (m s$^{-1}$), $d$ is leaf length scale [m; with default values for needle-shaped leaves and width for broad leaves following Nikolov et al. (1995)], $P$ is the ambient pressure (Pa), and $c$ is the transfer coefficient [equal to $4.322 \times 10^{-2}$ for broad leaves and $1.2035 \times 10^{-2}$ for conifers, following Nikolov et al. (1995)].

For closure, using the approach adopted by Collatz et al. (1991), $C_i$ is then estimated again as

$$C_i = C_s - \frac{\eta A_n P}{g_s}. \quad (B4)$$

For CO$_2$ the value of $\eta$ is 1.6. The above equations are solved in an iterative mode until a convergence is achieved ($A_n$ values typically within 1% in the consecutive iterations).
The converged $A_n$ and $g_c$ values need to be further adjusted for changes in the environmental conditions (Makela et al. 1996; Wilson et al. 2000b), and the unstressed values are scaled by a moisture stress factor $S_m$ (Anderson et al. 2000) as

$$ S_m = 1 - \left\{ \left[ \left( \frac{w_2 - w_{\text{wilt}}}{w_{fc} - w_{\text{wilt}}} \right) \left( 0.03^{-\frac{1}{B}} - 1.5^{-\frac{1}{B}} \right) + 1.5^{-\frac{1}{B}} \right] \right\}^{-\frac{1}{B}}. \quad (B5) $$

Here, $w_{\text{wilt}}$, $w_{fc}$, and $B$ are the wilting soil moisture, field capacity soil moisture, and the slope of the soil moisture retention curve, and can be considered to be soil texture-dependent “constants” (Noilhan and Planton 1989). Also, $w_2$ is the deep soil moisture content, which is dynamically obtained from the prognostic soil moisture–soil temperature scheme.

Another correction is required to account for the lag in the leaf response and changes in the ambient conditions. Carbon assimilation may require up to a minute to achieve a quasi-steady state, whereas stomatal response may require several minutes (~10 min). In the GEM, we adopt the exponential time response of Su et al. (1996), based on the observations of Jones (1998). Accordingly, the temporal stomatal response $g_s(t)$ for the steady-state stomatal conductance $g_s$ is introduced based on the stomatal conductance value for the prior time step $g_s(t - 1)$ as

$$ g_s(t) = g_s(t - 1) + [g_s - g_s(t - 1)]\left[ 1 - \exp\left[ -k(\Delta t/\tau) \right] \right]. \quad (B6) $$

We use the same transient response time $\tau$ as in Su et al. (1996; i.e., 20 s) and $k$ is taken as 3 to adjust for the numerical time step ($\Delta t$) in the PBL model.

The leaf-scale quantities obtained from the leaf model are scaled to the canopy using relations developed by Sellers et al. (1996), and the simplifications adopted by Calvet et al. (1998). From an atmospheric modeling perspective, the stomatal conductance terms ($g_s$) can be scaled with a prescribed leaf area index as

$$ G_s = \sum (g_s LAI). \quad (B7) $$

The linkage between the different model components is shown in Fig. B1.

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