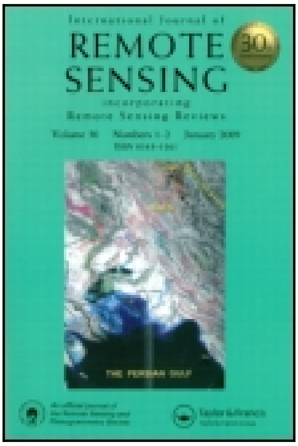

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Comparison of integrating LAS/MODIS data into a land surface model for improved estimation of surface variables through data assimilation

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Comparison of integrating LAS/MODIS data into a land surface model for improved estimation of surface variables through data assimilation

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In this article, land surface temperature (LST) and sensible heat flux (*H*) data assimilation schemes were developed separately using the ensemble Kalman filter (EnKF) and the common land model (CoLM). Surface measurements of ground temperature, *H*, and latent heat flux (LE) collected at the Yucheng (longitude: 116° 36′ E; latitude: 36° 57′ N) and Arou (longitude: 100° 27′ E; latitude: 38° 02′ N) experimental stations were compared with the predictions by assimilating different observation sources into the CoLM. The results showed that both LST and *H* data assimilation schemes could improve the estimation of ground temperature and *H*. The root mean square error (RMSE) compared between the predictions and *in situ* measurements decreased more significantly with the assimilation of values of *H* measured by a large aperture scintillometer (LAS). Assimilating Moderate Resolution Imaging Spectroradiometer (MODIS) LST only slightly improved the predictions of *H* and ground temperature. Daytime to night-time comparison results using both assimilation schemes also indicated that accurately quantifying model, prediction, and observation error would improve the efficiency of the assimilation systems. The newly developed land data assimilation schemes have proved to be a feasible and practical method to improve the predictions of heat fluxes and ground temperature from CoLM. Moreover, integrating multisource data (LAS and MODIS LST) simultaneously into the land surface model is believed to result in an efficient and robust way to improve the accuracy of model predictions from a theoretical point of view.

1. Introduction

Latent (LE) and sensible (*H*) heat fluxes are two key variables in the water and energy balance of land surface processes and in climate model forecasts (Pitman 2003). The estimation of energy partitioning into *H* and LE has attracted great attention in the fields of meteorology, oceanography, hydrology, and agriculture (Courault, Seguin, and Olioso 2005). Land surface temperature (LST) links the surface fluxes and soil water content through the energy and water balance in the soil–vegetation–atmosphere system (Corbari et al. 2010), and land surface models analyse the heat fluxes and LST

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in a physical framework. Simplification of various land surface models in simulating soil–vegetation–atmosphere, water, and energy transfer is likely to bring about some uncertainties in estimating LE and H. Data assimilation by fusing observations into the model may help reduce the uncertainties in the simulations (Crosson et al. 2002). In the data assimilation process, the uncertainties of the land surface model and observations can be fully considered, and the state variables are adjusted with the observations being assimilated. Integrating remotely sensed data into a land surface model by using a data assimilation technique has become a promising method for improving the predictions of LE and H (Boni, Entekhabi, and Castelli 2001; Caparrini, Castelli, and Entekhabi 2004).

The Ensemble Kalman filter (EnKF) (Evensen 1994) is one of the most popular data assimilation techniques due to its simple conceptual formulation and relative ease of use. The variational method is another widely applied data assimilation method (Meng et al. 2009; Tian et al. 2009).

However, until now most studies have primarily focused on the assimilation of soil moisture content (Reichle et al. 2002; Kumar et al. 2008) in the land data assimilation system to explore its influence on the heat fluxes, LE, and H. Direct assimilation of soil temperature and heat fluxes would more efficiently improve LE and H predictions. A few examples can be found for LE and H assimilations (Schuurmans et al., 2003; Pipunic, Walker, and Western 2008; Williams et al. 2009), but the synthetic observations used in the assimilation are generally derived from model emulations (Pipunic, Walker, and Western 2008). Moderate Resolution Imaging Spectroradiometer (MODIS) LST products (e.g. MOD11A1) are often assimilated to improve the prediction of land surface variables, including heat fluxes, by adjusting the parameters or the initial state variables (Huang et al. 2008; Renzullo et al. 2008; Li et al. 2009; Xu et al. 2011b), but the improvement of the model could be limited because of the low temporal resolution of LST data (Xu et al. 2011a).

A land surface model generally runs at the scale of several to tens of kilometres. In previous land data assimilations, the ground observations, such as soil water content from field experiment, represented only measurements at the point spatial scale (Zhang, Li, and Qiu 2011). The newly developed large aperture scintillometer (LAS) captures the sensible heat flux averaged over horizontal distances equivalent to the grid size of the land surface model and remote-sensing images (Kohsiek et al. 2002). However, in the past LAS data assimilation has been rarely considered in the land data assimilation. This article presents a data assimilation scheme for energy partitioning by integrating MODIS LST products and LAS-measured H into the land surface model. The assimilation results of land surface variables, including LE, H, and ground temperature, are validated with the *in situ* measurements.

2. Site description and data collection

The data measured for the assimilation experiments were collected at two locations in China: Yucheng Comprehensive Experimental Station (YC) at Yucheng City, Shandong Province, and Arou station (AR) located in Qinghai Province. Table 1 summarizes the attributes of both stations.

The involved meteorological forcing variables include atmospheric pressure, air temperature, wind speed, specific humidity, precipitation, incident solar radiation, and downward longwave radiation. These variables together with ground flux measurements, including the ground temperature, were acquired routinely every 30 min by automatic weather station at both stations.

Table 1. Attributes of the Yucheng and Arou sites.

Station name	Latitude (°N)	Longitude (°E)	Elevation (m)	Land cover	Soil type	Canopy height (m)
Yucheng	36.93	116.60	28	Crop	Sandy loam	0.78
Arou	38.04	100.46	3033	grass	Clay loam	0.2–0.3 (approximately)

MODIS (Terra and Aqua) data/products used in this study are the daily 1 km LST/emissivity (MOD11A1 for Terra, MYD11A1 for Aqua) products that can be retrieved from Land Processes Distributed Active Archive Center (https://lpdaac.usgs.gov/). MODIS/Terra data acquired at 10:30 am were used for assimilations at Yucheng, whereas at Arou, both Terra and Aqua MODIS data at daytime and night-time were applied. All of the Terra (Aqua) MODIS products required further processing with the MODIS Reprojection Tool (MRT). LASs were installed along the northeast–southwest direction to measure H in late April 2009 at Yucheng and in March 2008 at Arou. The length path between the transmitter and receiver of the LAS was 1240 m at Yucheng and 2390 m at Arou. The 30 min averaged H was derived from the post-processing of ten 30 min LAS-measured signals with the support of near-surface meteorological variables. The main land cover at the zone between transmitter and receiver is agricultural crop at Yucheng and grassland at Arou. When the vegetation flourishes and underlying surface is homogenous, H and LE flux measured by eddy covariance flux system (EC) as well as ground surface temperature observations were used to validate the prediction results with assimilation.

3. Overview of land surface model and data assimilation method

The chosen data assimilation technique is the widely applied EnKF (Evensen 1994; Li et al. 2007), and the land surface model used in this work is the common land model (CoLM) (Dai, Zeng, and Dickinson 2001). Detailed descriptions of the EnKF scheme and the CoLM have been given in a number of studies (Dai, Zeng, and Dickinson 2001; Dai et al. 2003; Evensen 2003).

3.1. EnKF method

EnKF shows superior performance compared to the Kalman filter and the extended Kalman filter (Reichle et al. 2002). EnKF can be applied in a non-linear system without calculating the tangent linear model. The core of the assimilation algorithm in this article is summarized as follows for the implementation of EnKF.

In the EnKF data assimilation system, CoLM is described according to Equation (1) as a 'black box' system:

$$\mathbf{X}_{\mathbf{t}}^{\mathbf{f}} = M(\mathbf{X}_{\mathbf{t-1}}^{\mathbf{0}}, \alpha_t, \beta_t), \tag{1}$$

where $\mathbf{X}_{\mathbf{t}}^{\mathbf{f}}$ represents the forecast CoLM state variables at time t; $M(-)$ represents the model operator; when no observation exists, $\mathbf{X}_{\mathbf{t-1}}^{\mathbf{0}} = \mathbf{X}_{\mathbf{t-1}}^{\mathbf{f}}$; when the observation (MODIS LST or LAS sensible heat flux) exists, $\mathbf{X}_{\mathbf{t-1}}^{\mathbf{0}} = \mathbf{X}_{\mathbf{t-1}}^{\mathbf{a}}$; $\mathbf{X}_{\mathbf{t}}^{\mathbf{a}}$ represents the analysed state variables at time t; α_t represents the forcing data at time t; and β_t represents the model parameters at time t.

The update of model state, i.e. the analysis field, can be computed as

$$\mathbf{X}_\mathbf{t}^\mathbf{a} = \mathbf{X}_\mathbf{t}^\mathbf{f} + \mathbf{K}_\mathbf{t}(\mathbf{Y}_t - O(\mathbf{X}_\mathbf{t}^\mathbf{f})), \tag{2}$$

where $\mathbf{X}_\mathbf{t}^\mathbf{f} = [\mathbf{X}_\mathbf{1,t}^\mathbf{f}, \mathbf{X}_\mathbf{2,t}^\mathbf{f}, \cdots, \mathbf{X}_\mathbf{N,t}^\mathbf{f}]$, with $\mathbf{X}_\mathbf{i,t}^\mathbf{f}(i = 1, 2, \ldots N)$ being the forecast state variable of the ith member at time t; N is the number of ensemble members; $\mathbf{Y}_\mathbf{t}$ is the observation at time t; O is the observation operator that projects the state vector $\mathbf{X}_\mathbf{t}^\mathbf{f}$ into the observation space (see Equation (3)); $\mathbf{K}_\mathbf{t}$ is the Kalman gain matrix at time t, which is controlled by O, $\mathbf{P}_\mathbf{t}^\mathbf{f}$, and $\mathbf{R}_\mathbf{t}$ (see Equation (4)); and $\mathbf{P}_\mathbf{t}^\mathbf{f}$ is the error covariance of the forecast model state variables (see Equation (5)). The specified settings of O, $\boldsymbol{\varepsilon}$, $\mathbf{P}_\mathbf{t}^\mathbf{f}$ are introduced in Section 4:

$$\mathbf{Y}_\mathbf{t} = O(\mathbf{X}_\mathbf{t}^\mathbf{f}) + \boldsymbol{\varepsilon}, \tag{3}$$

$$\mathbf{K}_\mathbf{t} = \mathbf{P}_\mathbf{t}^\mathbf{f} O^T (O\mathbf{P}_\mathbf{t}^\mathbf{f} O^T + \mathbf{R}_\mathbf{t})^{-1}, \tag{4}$$

$$\mathbf{P}_\mathbf{t}^\mathbf{f} = \frac{1}{N-1}\sum_{i=1}^{N} (\mathbf{X}_\mathbf{i,t}^\mathbf{f} - \overline{\mathbf{X}}_\mathbf{t}^\mathbf{f})(\mathbf{X}_\mathbf{i,t}^\mathbf{f} - \overline{\mathbf{X}}_\mathbf{t}^\mathbf{f})^T, \tag{5}$$

where $\boldsymbol{\varepsilon}$ is the observation error that conforms to a Gaussian distribution with a zero mean and a covariance matrix $\mathbf{R}_\mathbf{t}$; $\overline{\mathbf{X}}_\mathbf{t}^\mathbf{f}$ is the mean of all the ensemble members of $\mathbf{X}_\mathbf{t}^\mathbf{f}$; and the superscript '$T$' represents the transpose of the variables.

3.2. *Common land model (CoLM)*

CoLM has 10 unevenly spaced vertical soil layers and up to five snow layers (depending on snow depth). The dynamics of soil temperature is expressed with the numerical heat diffusion equation for a one-dimensional vertical column (see the following equation):

$$[c_j \Delta z_j]\frac{T_j^{t+1} - T_j^t}{\Delta t} = w[F_j^t - F_{j-1}^t] + (1-w)[F_j^{t+1} - F_{j-1}^{t+1}], \tag{6}$$

where T_j^t is the layer-averaged temperature (K) in layer j at time t; c_j and Δz_j are the volumetric soil heat capacity (J m^{-3} K^{-1}) and soil layer thickness (m) in layer j, respectively; w is the weighting coefficient in the time domain ($w = 0.5$); and F_j^t is the heat flux across the interface between layer j and $j + 1$ at time t and can be computed as follows.

For an interior interface ($j = s + 2, \cdots, m - 1$, where s and m are the number of snow layers (negative value) and maximum number of soil layers, respectively):

$$F_j^t = \lambda(z_{h,j})\frac{T_{j+1}^t - T_j^t}{z_{j+1} - z_j}, \tag{7}$$

where $\lambda(z_{h,j})$ is the thermal conductivity at the interface $z_{h,j}$ (W m^{-1} K^{-1}), and z_j is the soil depth in the layer j.

For the boundary layer and surface boundary:

$$F_m = 0,\ F_s = wF_s^t + (1-w)F_s^{t+1} = -[Q + \partial Q/\partial T_{s+1} \times (T_s^t - T_{s+1}^t)], \tag{8}$$

$$Q = R_{n,\mathrm{g}} - H_\mathrm{g} - \mathrm{LE}_\mathrm{g}, \tag{9}$$

where $R_{n,\mathrm{g}}$ is the net radiation absorbed by ground surface; H_g and LE_g represent sensible heat flux and latent heat flux at the ground surface, respectively; and Q is the net energy flux in the soil surface.

4. Results and discussion

To investigate the feasibility and the performance of the assimilation system in predicting H and LE, we performed some point-scale experiments using the *in situ* observations of LAS-measured H and MODIS LST products acquired from 1 April to 30 July 2009 at YC and from 1 March to 30 July 2008 at AR. The CoLM and assimilation system ran from January to July 2009 at YC and from January to July 2008 at AR, respectively. In this study, because of the restriction of the available observations, we mainly compare the predictions from 22 May to 2 June 2009 at YC and from 3 to 12 June 2008 at AR with ground measurements to test the assimilation schemes.

4.1. Ensemble generation

The generation of the ensembles in the EnKF data assimilation scheme is a critical issue because the ensembles embody some uncertainties in model prediction, but disturbing the forcing climate data and the initial state variables to drive the model overcomes this problem (Pauwels et al. 2007). In this work, ensembles were generated by adding random perturbations with zero mean and certain standard deviation to the spin-up initial soil temperature values (the predicted soil temperature by model after the model reached a state of statistical equilibrium under the applied forcing which maybe will take much time). The standard deviation of the random perturbation was set to 0.2 K. The initial soil moisture and temperature values originated from the ground observations.

4.2. Configuration of parameters in the assimilation scheme

Model errors related to the prediction of soil temperature in the 10 layers were specified by analysing the differences between the simulations and observations. Considering that the model errors would decrease with the assimilation, we specified model errors as smaller static values. Here, the soil temperature error induced by the model structure was limited within ± 2 K, and measurement noise was regarded as invariable. For the sensible heat flux measured by LAS, the error was assumed to be less than 10 W m^{-2} (Tang, Li, and Tang 2010); for the MODIS LST, uncertainty was less than 1 K in the range from 263 to 322 K (Wan et al. 2004). All errors described above were produced by adding a zero mean Gaussian distributed random number to the corresponding variables.

To compare the results of assimilating data from different sources, two scenarios were designed. When assimilating H, all of the calculations followed the work of Pipunic, Walker, and Western (2008) in which the observation operator does not need an explicit solution. The error of the predicted H was limited within ± 10 W m^{-2} at Yucheng and ± 15 W m^{-2} at Arou. As for the remotely sensed MODIS LST data, which are essentially a hybrid of canopy and ground temperature, the observation operator was constructed by linearly regressing ground temperature observations to MODIS LST (Huang et al. 2008). The regression formula shown in Equation (10), which was derived for the MODIS sensor passing at 10:30 am (local time), was used for Yucheng. For Arou, the three regression functions shown in Equation (11) were developed for MOD11A1 daytime and night-time data from the Terra satellite and MYD11A1 data from Aqua, respectively.

$$T_s = 0.9581T_g + 13.509, \tag{10}$$

$$T_s = \begin{cases} 1.002T_g - 11.91 & \text{MOD11A1 night} - \text{time}, 2008, \\ 1.028T_g - 2.40 & \text{MOD11A1 daytime}, 2008, \\ 1.229T_g - 69.63 & \text{MYD11A1}, 2008, \end{cases} \tag{11}$$

where T_s and T_g are the MODIS LST and ground temperature, respectively.

4.3. *Impact of the number of ensemble members*

The number of ensemble members is one of the most important parameters in EnKF data assimilation. To test the sensitivity of the predictions to the ensemble size, the root mean square error (RMSE, as shown in Equation (12)) in the comparison of the three variables (H, LE, and LST) in the data assimilation runs was intercompared for the ensemble sizes of 10, 20, 30, 50, and 100 members (Figures 1–4). The RMSE with 0 ensembles in these figures was derived from the comparison between the model prediction before assimilation and observation for reference:

$$\text{RMSE} = \left[\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2\right]^{1/2}, \tag{12}$$

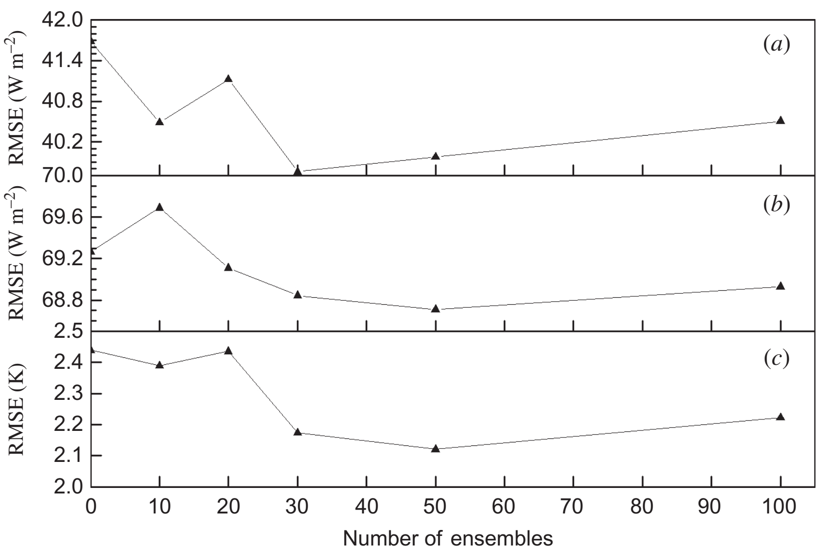

Figure 1. Impact of the ensemble size on the assimilation of MODIS LST data at Yucheng. (*a*) For sensible latent flux, (*b*) for latent heat flux, and (*c*) for ground temperature.

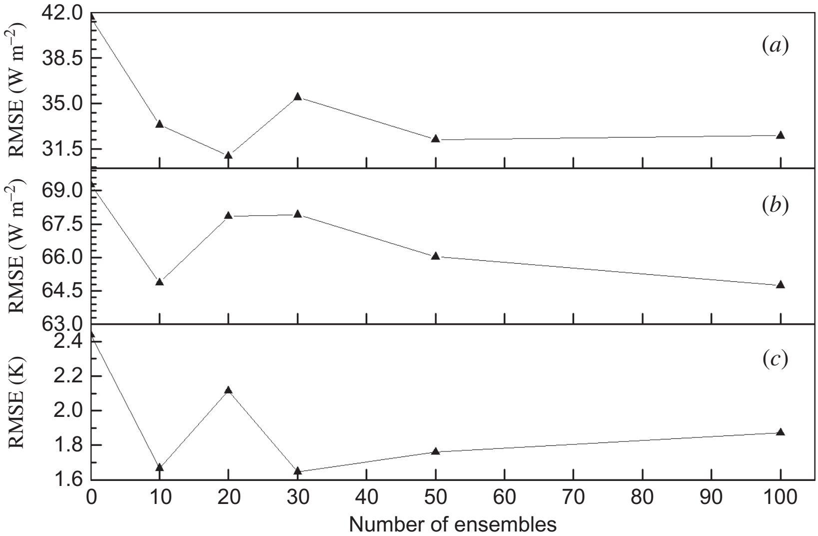

Figure 2. Impact of the ensemble size on the assimilation of LAS-measured *H* data at Yucheng. (*a*) For sensible latent flux, (*b*) for latent heat flux, and (*c*) for ground temperature.

where *n* is the number of observations, and P_i and O_i are the variables predicted by the model and the observed variables, respectively.

Obtaining a satisfactory estimate with the minimum number of ensemble members was used as the criterion for determining the ensemble size. Figure 1 shows that the RMSE was the lowest for Yucheng when the ensemble size was 30 with the assimilation of the MODIS LST data. For the assimilation of the LAS-measured *H* at Yucheng (Figure 2), the ensemble size of 10 was sufficient. A large number of ensemble members increase the computational burden (see Figure 3 for the ensemble size equal to 100). The optimal number of ensemble members for the MODIS LST data assimilation experiment at Arou was 20. Given that the decline of the RMSE was minimal for members greater than 10 with the assimilation

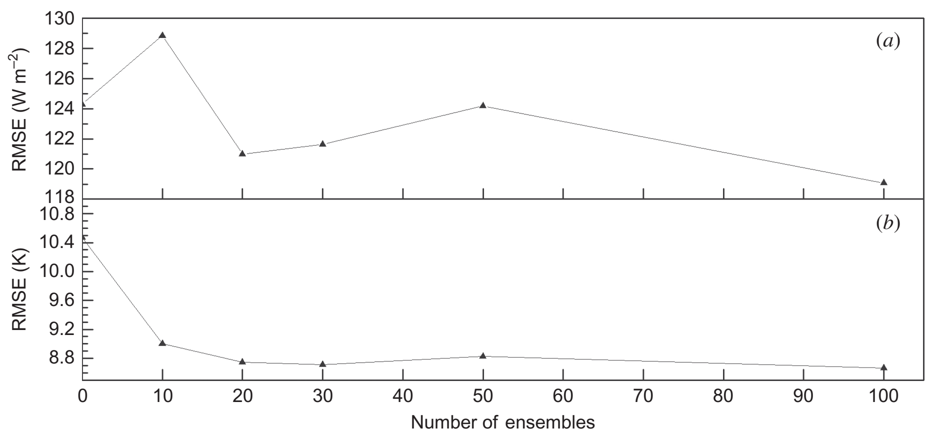

Figure 3. Impact of the ensemble size on the assimilation of MODIS LST data at Arou. (*a*) For sensible latent flux and (*b*) for ground temperature.

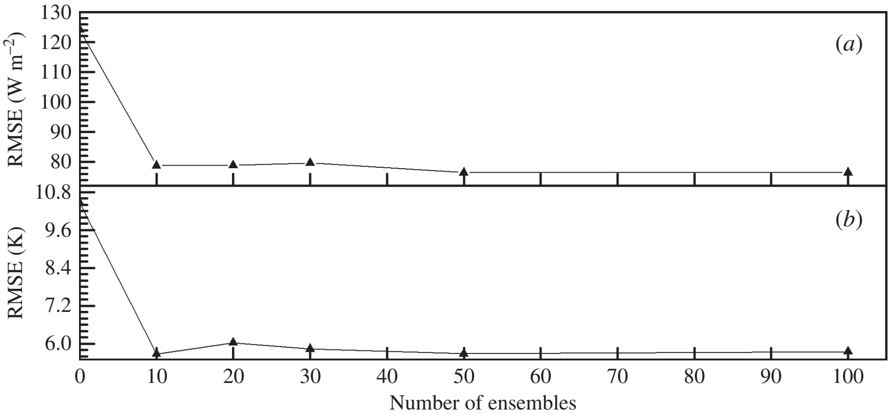

Figure 4. Impact of the ensemble size on the assimilation of LAS-measured *H* data at Arou. (*a*) For sensible latent flux and (*b*) for ground temperature.

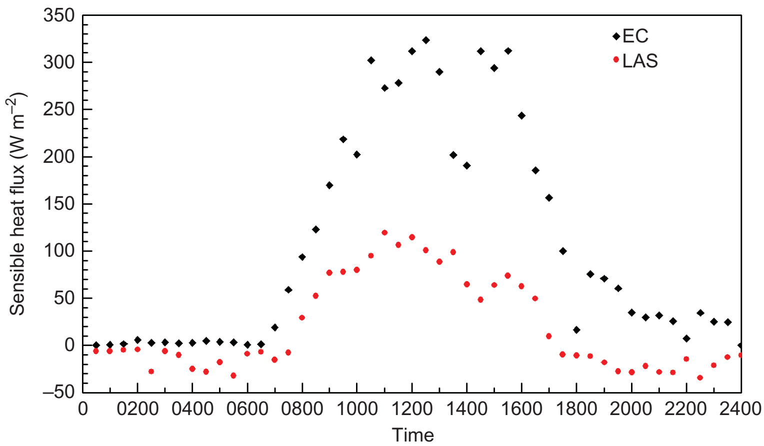

Figure 5. Comparisons of sensible heat flux measured by EC and LAS for day 175 of 2008 at Arou.

of LAS-measured *H* (Figure 4), an ensemble size of 10 was chosen for the assimilation scheme at Arou.

H and LE measured by EC were not used to validate the assimilation results at Arou because differences have been found in the sensible heat flux measured by LAS and EC (Figure 5), which may be due to the energy imbalance of EC data, the heterogeneity of the underlying surfaces, and the different footprints of LAS and EC (Liu et al. 2011). Instead, *H* measured by LAS was compared with the assimilation results at Arou.

4.4. *Comparisons of assimilating different data sources into CoLM*

Sensible heat flux obtained from LAS was assimilated into the model in a 30 min time step. MODIS LST was assimilated approximately once every 2 days at Yucheng and twice daily on average at Arou. A comparison of all the assimilation results during the 10 day period, from 24 May to 2 June at Yucheng and from 3 to 12 June at Arou, is given in Figures 6 and 7, respectively.

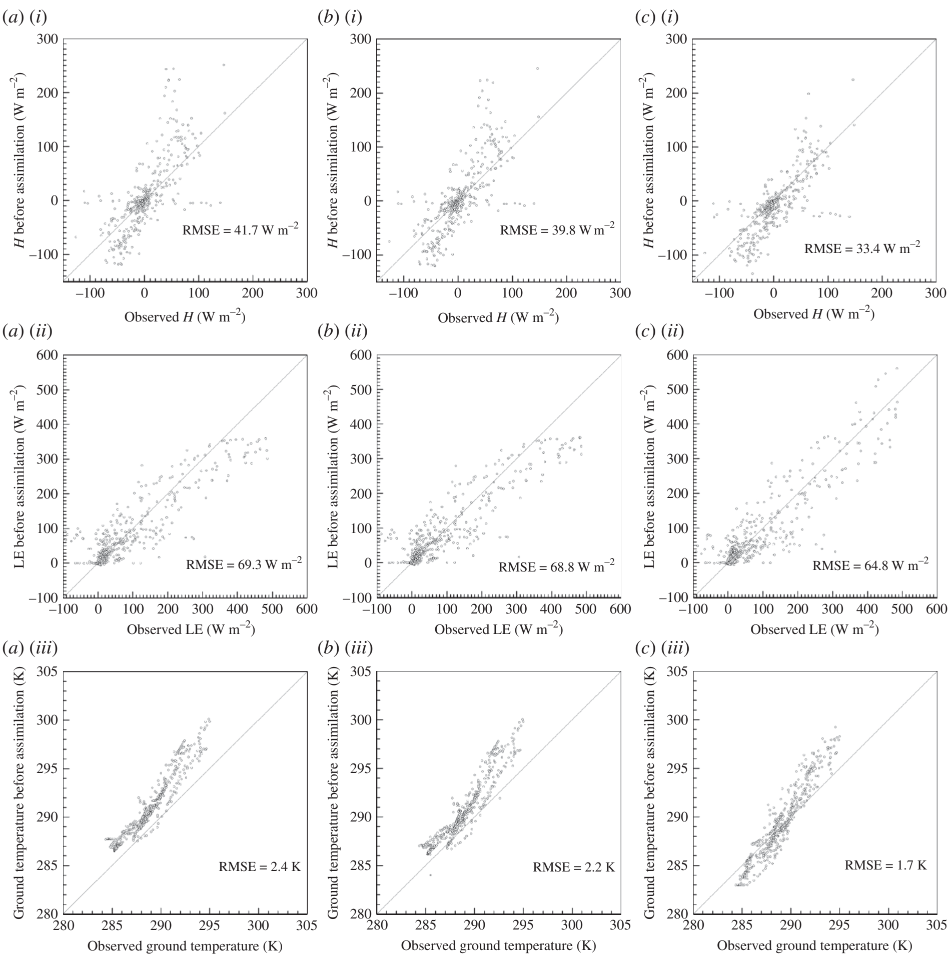

Figure 6. Comparisons of (*i*) sensible heat flux (*H*), (*ii*) latent heat flux (LE), and (*iii*) ground temperature with ground measurements at Yucheng from 24 May to 2 June 2009 (*a*) for simulation, (*b*) for assimilation of MODIS LST, and (*c*) for assimilation of LAS-measured *H*.

As shown in Figures 6 and 7, the assimilation of the two data source types could improve the estimations of *H*, LE, and ground temperature at both sites. The assimilation of LAS-measured *H* yielded better results than the assimilation of MODIS LST data, which may be due to the assimilation frequency. Additionally, the RMSE between model simulations and *in situ* measurements decreased with assimilation despite overestimating the predicted *H* and ground temperature. At Arou, there was a margin circle among the scatter plots of ground temperature: as shown in Figure 7, the margin area shrunk from (*a*) to (*c*).

4.5. Assimilation of LAS-measured H

Figure 8 shows the 10 day results for ground temperature, *H* and LE, by assimilating LAS-measured *H* at Yucheng from 24 May to 2 June 2009. As shown in this figure, the assimilation curves of the three variables were closer to the observed values than the simulation results. The predicted ground temperature was greater than the observed temperature.

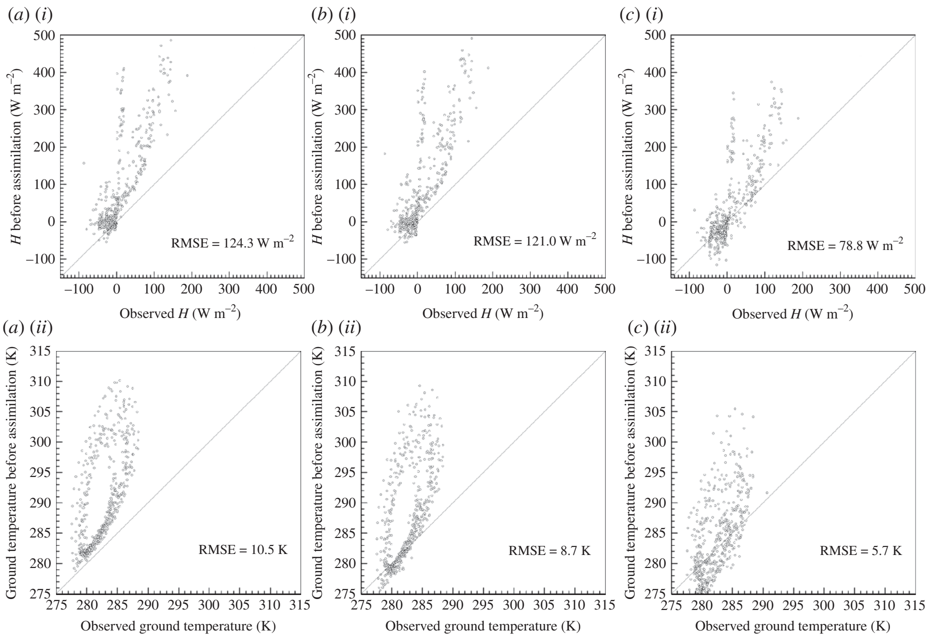

Figure 7. Comparisons of (*i*) sensible heat flux (*H*) and (*ii*) ground temperature with ground measurements at Arou from 3 to 12 June 2008 (*a*) for simulation, (*b*) for assimilation of MODIS LST, and (*c*) for assimilation of LAS-measured *H*.

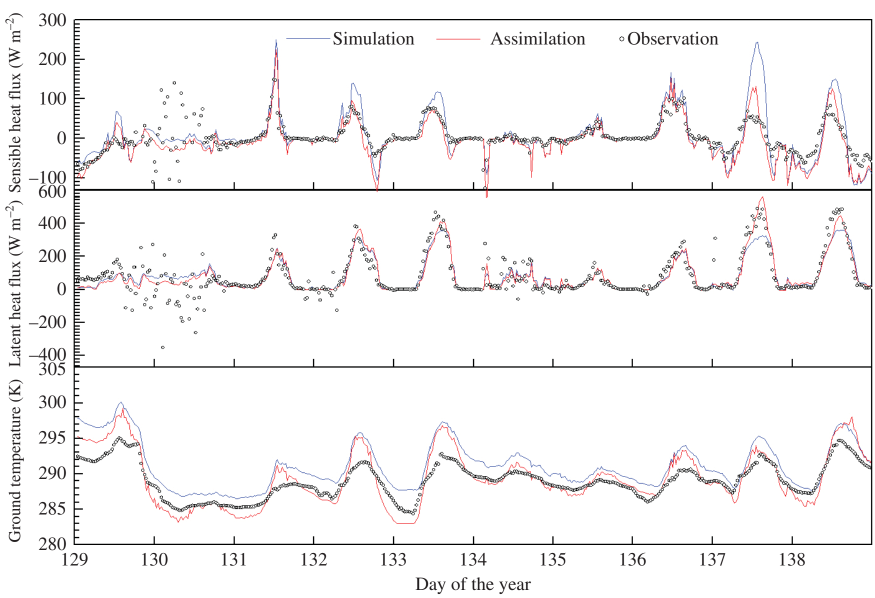

Figure 8. Comparisons of surface observations with estimates from the simulation and LAS-measured *H* data assimilation for sensible heat flux, latent heat flux, and ground temperature at Yucheng, from 24 May (Day of year = 144) to 2 June (Day of year = 153) 2009.

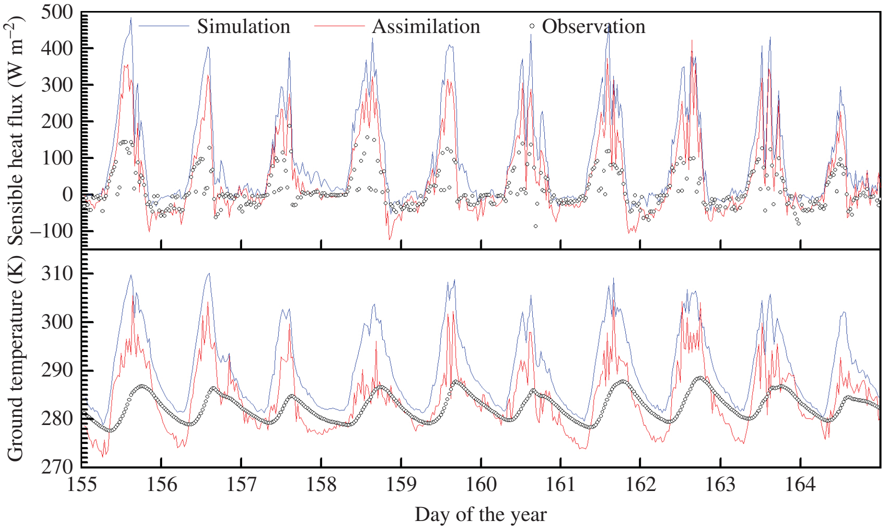

Figure 9. Comparisons of surface observations with estimates from the simulation and LAS-measured *H* data assimilation for sensible heat flux and ground temperature at Arou, from 3 (Day of year = 154) to 12 (Day of year = 163) June 2008.

After assimilation, the predicted ground temperatures were lower than the simulated results and were close to the observed temperatures except for the underestimation that occurred for the night-time temperatures on days 130–133 and 138. The underestimation in results after assimilation indicates that the model error needs to be determined dynamically according to the assimilation results in previous time periods because the initial values of state variables are real-time adjusted following the assimilation.

At Arou, the 10 day assimilation results of ground temperature and *H* by assimilating LAS-measured *H* from 3 to 12 June 2008 are given in Figure 9. Overall, the CoLM simulations have been overestimated greatly in the daytime at Arou. Improvement has been shown in the comparison of ground temperature and sensible heat flux when LAS-measured *H* and MODIS LST are assimilated. However, after assimilation, the estimation of the two variables in the night-time was lower than the model simulation results, an effect of the uniform setting of the model and the observation error for the whole day. Adjusting the model or observation error may improve results in accordance with the work of Kumar and Kaleita (2003).

4.6. Assimilation of MODIS LST

A time series of the surface variables obtained by assimilating MODIS LST products at Yucheng from 24 May to 2 June 2009 is shown in Figure 10. For Arou, the corresponding results from 3 to 12 June 2008 are shown in Figure 11. At both sites, the estimation of ground temperature has significantly improved; the assimilation results follow the *in situ* observations more closely than the simulation results. The assimilation of MODIS LST does not, however, have a large influence on the predictions of the heat flux in this scheme due to the influence of the frequency and quality of available satellite observations on the performance of the assimilation scheme and the simplification of the observation

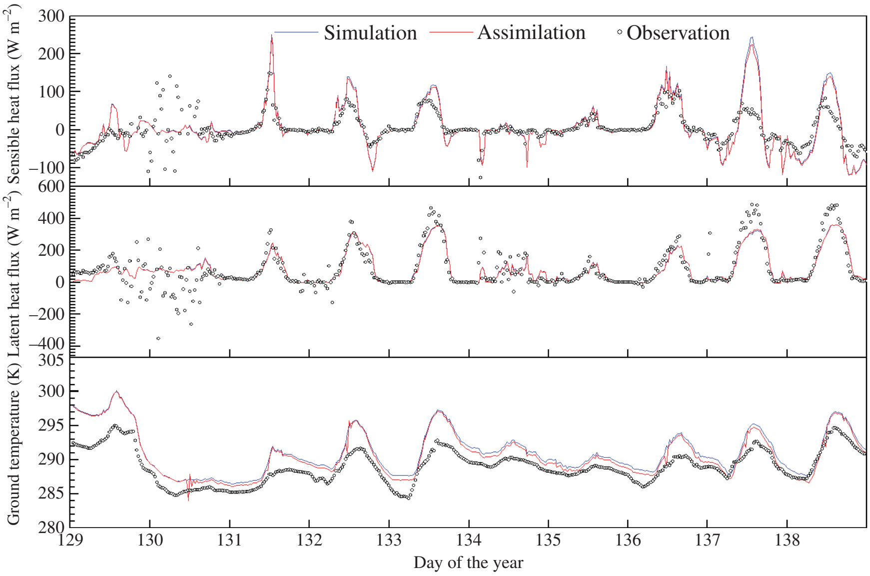

Figure 10. Comparisons of surface observations with estimates from the simulation and MODIS LST data assimilation for sensible heat flux, latent heat flux, and ground temperature at Yucheng, from 24 May (Day of year = 144) to 2 June (Day of year = 153) 2009.

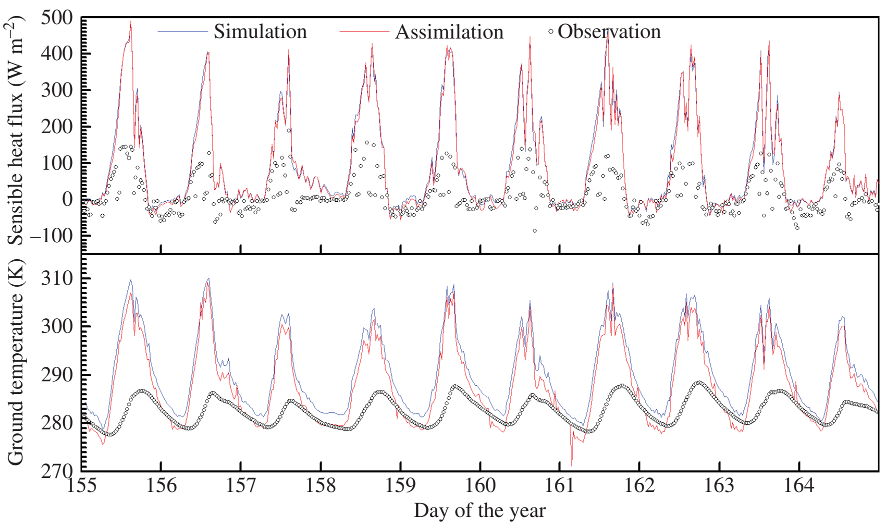

Figure 11. Comparisons of surface observations with estimates from the simulation and MODIS LST data assimilation for sensible heat flux and ground temperature at Arou, from 3 (Day of year = 154) to 12 (Day of year = 163) June 2008.

operator as a linear regression relationship between the MODIS LST and the ground temperature. Adding the soil water content to the assimilated variable will improve the estimation of H and LE because soil moisture availability influences the estimation of LE in the CoLM.

5. Conclusions

In this article, we developed a land data assimilation system to improve the predictions of soil surface temperature, sensible and latent heat fluxes. Different data sources (MODIS LST and sensible heat flux data from LAS) were assimilated into the CoLM using the EnKF technique. The data collected at two experiment stations were tested to evaluate the performance of the assimilation system. Estimations of energy partitioning and ground temperature after assimilation were compared to the model simulation results. The accuracy of the predicted ground temperature and latent and sensible heat fluxes with assimilation showed different variations. The assimilation results of *H*, LE, and ground temperature were all improved compared with the simulations when the LAS-measured *H* data were used, but only a slight improvement was found in the estimations with the assimilation of MODIS LST.

Although this study clearly demonstrates that the assimilation of *H* measured by LAS has the potential to improve the heat flux and soil temperature predictions, the results may be further improved if the errors in daytime and night-time could be solved separately. By contrast, the LAS-measured *H* assimilation influenced the model trajectory more significantly than by assimilating MODIS LST. LE cannot be improved as well as *H* with assimilation due to the model parameterization of LE. Adding the soil water content to the assimilated variable will solve this problem in future research, and it is therefore required to improve the land surface model. Additional validations at other sites are also needed. In general, assimilating remotely sensed data or LAS data into a land surface model is a practical way to improve the land surface process forecast. Furthermore, integrating multisource data (LAS, remote sensing, and ground experiments) simultaneously into the land surface model may produce better results.

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