Annual Journal of Hydraulic Engineering, JSCE, Vol.53, 2009, February

SIMULATING SURFACE ENERGY FLUX AND SOIL MOISTURE AT THE WENJIANG PBL SITE USING THE LAND DATA ASSIMILATION SYSTEM OF THE UNIVERSITY OF TOKYO

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This paper reports an application of a Land Data Assimilation System (LDAS) to the Wenjiang site located near Chengdu, China, for the period from January to March, 2008. The LDAS was first driven by in-situ observed micrometeorological data. Simulated energy fluxes were compared to hourly direct measurements and simulated soil moisture content was compared to the in-situ soil moisture observations at a depth of 4 cm. The results show that the LDAS well simulated those variables and thus validated the capability of LDAS. To check the possibility of applying LDAS globally and simulating surface energy and water budget worldwide, two sets of model output data were used as the driving data of the LDAS: the Japan Meteorology Agency (JMA) Model Output Local Time Series (MOLTS), and the Modified JMA MOLTS. The LDAS performance was not so good when driven by the original JMA MOLTS data, but improved after we used modified MOLTS data with some simple linear regression equations. This result demonstrated the feasibility of reliably simulating land surface fluxes with a LDAS driven by model outputs.

Key Words: *Land Data Assimilation System, Energy Fluxes, Soil Moisture, Field Experiments*

1. INTRODUCTION

Land surface processes through which exchanges of water, energy and carbon between the land surface and the atmosphere are realized, remarkably affect weather and climate. Climate simulations are especially sensitive to the diurnal and seasonal cycles of the surface energy balance[1)]. Land surface energy budgets are also very important in hydrological and ecological modeling. The energy flux can be measured at a patch scale with some special instruments such as triaxial sonic anemometers, krypton hygrometers and fine-wire thermocouples. It also can be estimated at a regional scale from satellite observations when infrared images and ancillary data are available. Land surface models (LSMs) are developed to predict temporal and spatial patterns of land surface variables[2,3)], but the quality of the predictions are usually not so good because of model initialization, parameter and forcing errors, and inadequate model physics and/or resolution[4,5)].

The Land Data Assimilation System (LDAS), developed by merging observation information (from ground-based stations, satellites and so on) into dynamic models (i.e. LSMs), is expected to provide high quality surface energy and water flux estimates with adequate coverage and resolution. In this study, we applied an LDAS developed at the University of Tokyo (LDASUT) [6)] for the Wenjiang site of a JICA project where a PBL tower had been built. The objectives of this study are: (1) to evaluate LDASUT in a vegetated land surface using in-situ observations, and (2) to check the feasibility of estimating areal land surface energy and water fluxes reliably using LDASUT driven by spatially-distributed forcing data. In this study, LDASUT was driven by Japan Meteorology Agency (JMA) Model Output Local Time Series (MOLTS) data and simulation results were compared with direct measurements.

In the following section, we briefly describe the materials and methods used in this study, including the experimental site and introduce the LDASUT. The simulation results of LDASUT driven by in-situ data are described in section 3. In section 4, the LDASUT was first driven by MOLTS data, and then by modified MOTLS data to improve the quality of the simulation. Finally, we finish this paper with some conclusions.

2. MATERIALS AND METHODS

2.1 Experimental site description

The Wenjiang site is located on a flat farm field approximately 19 km west of Chendu city of Sichuan province, China. The site has an elevation of 530 m and is centered at 30°44'N latitude, 103°52'E longitude. It is near the edge of Tibetan Plateau and in the water vapor corridor of the Asian monsoon. A PBL tower, established by a JICA project, was built in this site in Feb. 2007. Observations at the PBL tower include wind speed and direction at four levels, air temperature and humidity, turbulences, fluxes of energy and CO2, soil moisture and temperature profiles, soil heat flux, solar and atmospheric radiation, and precipitation.

2.2 LDASUT

In this study, the land surface energy and water budget was simulated using the LDASUT[6]. This system consists of a LSM to calculate surface fluxes and soil moisture, a radiative transfer model (RTM) to estimate microwave brightness temperature, and an optimization scheme to search for optimal values of soil moisture through minimizing the difference between modeled and observed brightness temperature.

The LSM is a Simple Biosphere model (SiB2)[2]. The RTM used in the LDASUT has two components: volume scattering and surface scattering parts[7]. The volume scattering part simulates the radiative transfer process inside the soil layer by a 4-stream based RTM in which the multiply scattering effects of a dry soil medium is calculated by the dense media radiative transfer model (DMRT)[8]. The surface scattering part simulates the surface scattering effects at the land-atmosphere interface by the Advanced Integral Equation Method (AIEM)[9]. The minimization scheme is a shuffled complex evolution method.

The initial parameters of LDASUT are obtained from a global data set; for example, the leaf area index (LAI) from Moderate Resolution Imaging Spectroradiometer (MODIS) data; and the soil and vegetation parameters from The International Satellite Land Surface Climatology Project (ISLSCP). The satellite observation data is from the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) brightness temperature data. The meteorological driving data of the LDASUT can be either weather model outputs or in-situ observation.

2.3 Statistical analysis of the simulation results

The simulation results (M_i) of the LDASUT are compared against the in-situ field measurements (O_i), on the basis of three statistical analyses:

$$MBE = \sum_{i=1}^{n}(M_i - O_i)/n \tag{1}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}(M_i - O_i)^2/n} \tag{2}$$

$$NSEE = \sqrt{\sum_{i=1}^{n}(M_i - O_i)^2 / \sum_{i=1}^{n}(O_i)^2} \tag{3}$$

where n is the total hourly observation points; MBE is the mean bias error; RMSE is the Root Mean Square Error; and NSEE is the Normalized Standard Error of the Estimation, denoting an estimation of relative uncertainty.

3. SIMULATION DRIVEN BY IN-SITU DATA

As the first step in this study , we performed season long runs from Jan. to Mar. 2008 (90 days) with PBL observation as the forcing data of the LDASUT. Agriculture/C3 grassland in the standard SiB2 parameters for vegetation was used for the simulation. The default soil parameters (texture, thermal and hydraulic properties) were derived from the ISLSCP Initiative II soil data. This simulation is called “PBL”.

To avoid anomalous results, data are rejected when (i) latent heat flux was less than -20 W/m^2 or (ii) the residual energy was less than -100 W/m^2. After data filtering, we retained 1990 data sets from the original 2160 data sets.

3.1 Surface Energy Budget

Figure 1 shows the monthly mean diurnal changes of net radiation (hereinafter referred to as Rn), latent heat flux (lE), sensible heat flux (Hs), and soil heat flux (G), from the top to the bottom row, respectively. The open cycle represents the direct measurements and the solid line represents the results of ‘PBL’.

From figure 1a, it is clear that ‘PBL’ simulated Rn with high accuracy for both the peak and diurnal patterns. This was because in-situ observed downward radiation was used as forcing data and

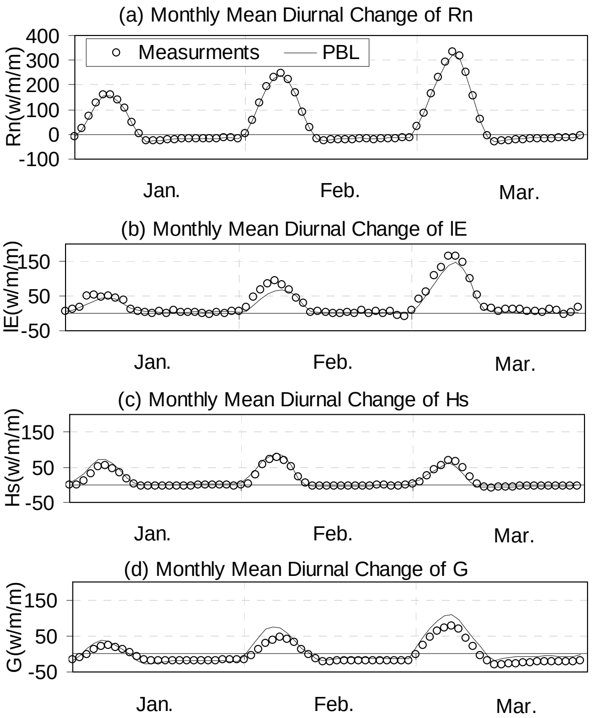

Fig. 1 Comparison of monthly mean diurnal change of (a) Rn, (b) lE, (c) Hs and (d) G of 'PBL' against direct measurement.

SiB2 calculates Rn from the four components of radiation budgets. As shown in figure 1 b-d, it is obvious that 'PBL' captured the temporal variation characteristics of lE, Hs and G.

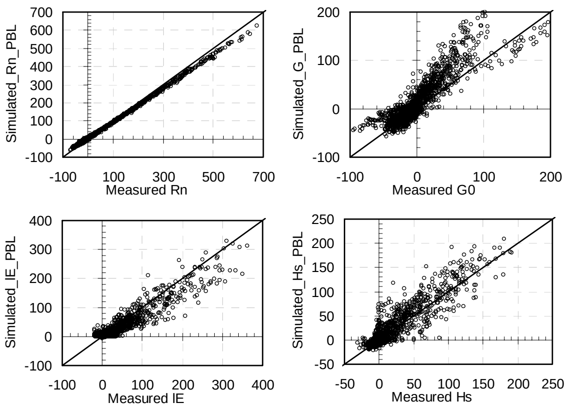

Fig. 2 Scatterplots of Rn, lE, Hs and G of 'PBL' against direct measurements.

Figure 2 shows scatterplots of simulated Rn, G, lE, and Hs, against direct measurements. The squared correlation coefficients are 0.99, 0.80, 0.89 and 0.85.

As shown in table 1, 'PBL' slightly overestimated G and underestimated lE, while it well estimated Rn. The overestimation of G may be to the result of measurement errors of soil heat flux and the underestimation of energy storage in the upper soil layer above the heat flux plate where the heterogeneity increased as crop roots developed. The discrepancies in lE may be partly to the result of instrument errors. According to Mauder et al.[10], the accuracy of sensible heat flux measurement is

Table. 1 Statistic analysis of energy components of 'PBL'

	MBE	RMSE	NSEE
Rn (W/m^2)	-1.3	12.5	9%
lE (W/m^2)	-5.9	19.6	32%
Hs (W/m^2)	2.8	14.3	41%
G (W/m^2)	11.0	22.9	65%

around 10-30 W/m^2, and 20-40 W/m^2 for latent heat flux. Moreover, considering the fact that 'PBL' simulation and in-situ observation have different scales, and the fact that the residual energy (Re) of direct measurement (*Re=Rn-lE-Hs-G*, shown in table 2) is comparable to the largest RMSE of energy components, the quality of surface energy budget simulation of 'PBL' is acceptable. The capability of LDASUT to simulate land surface fluxes reliably is then validated.

Table. 2 Three months averaged energy components (unit: W/m^2)

	Rn	lE	Hs	G	Re
Measurements	91	55	23	-6	19
PBL	89	44	30	16	0

3.2 Surface temperature and upward long-wave radiation

Temperature is a very important prognostic state variable on the land surface. LDASUT is able to provide vegetation, ground surface and deep soil temperatures. Unfortunately, the infrared thermometer used at the Wenjiang site was broken during the study period and so we do not have direct ground surface temperature measurements. According to the Stefan-Boltzmann law, upward long-wave radiation (ULR) is a good surrogate of land surface temperature. We therefore compared the simulated ULR with the direct measurements.

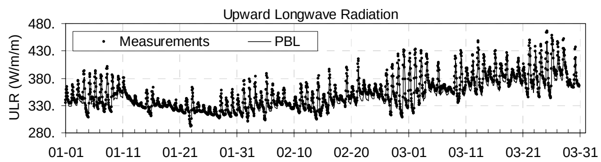

Fig. 3 Comparison of hourly long-wave radiation of 'PBL' against direct measurements.

Figure 3 shows a comparison of hourly ULR. It is apparent that 'PBL' generated consistent temporal variations of ULR. The squared correlation coefficient was 0.88; MBE -4.1 W/m^2; RMSE 11.8 W/m^2 and NSEE 3%.

3.3 Soil Water Content

Figure 4 shows a time series of the volumetric soil moisture content observed at 4 cm depth (thin line) and those generated by 'PBL' (thick line). In-situ observed precipitation is also plotted. We found that the observed soil moisture did not change much during this period, ranging from 0.23 to 0.33. 'PBL' predicted the moisture peak in good agreement with direct measurements, for both the occurring time and values. The gaps between 'PBL' soil moisture and observed ones get larger in the drying processes. This is partly due because in-situ soil moisture is measured at a depth of 4 cm, which is generally deeper than the penetration depth of AMSR-E. The scale difference of the AMSR-E observations and in-situ ones also contribute to such discrepancies. Generally and statistically, 'PBL' estimated soil moisture with high quality, considering that MBE is -0.02; RMSE is 0.02 and NSEE is 9%.

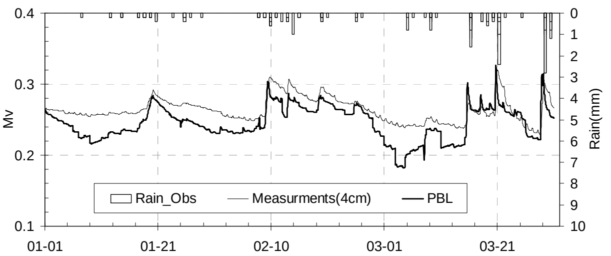

Fig. 4 Comparing simulated soil moisture content with direct measurements

4. SIMULATION DRIVEN BY MODEL OUTPUT

From an analysis of the 'PBL' simulation in section 3, it is clear that LDASUT can correctly simulate the surface energy and water budget when it is driven by in-situ observed forcing data. In climate studies and numerical weather predictions, the spatial distribution information of energy and water fluxes is very essential. To simulate land surface fluxes at a regional or global scale, spatially-distributed meteorological forcing data are needed. Such forcing data were only available from model outputs, and, as mentioned in section 1, JMA MOLTS data was selected in this study. Same as the "PBL" simulation, a simulation was conducted by using the original MOLTS as meteorological forcing data and is called "M_O".

4.1 Surface Energy Budget of 'M_O'

Table 3 shows the statistical results of the energy fluxes of 'M_O'. It is clear that the quality of 'M_O' is much worse than that of 'PBL'. The MBE of Rn is larger than 5 W/m^2, which is the accuracy of solar radiation measurement. The NSEE of Hs and G are larger than 100%. Therefore, the quality of 'M_O' is not acceptable and we can not directly apply MOLTS data as forcing data for LDASUT.

Table. 3 Statistic analysis of radiation components of 'M_O'

	MBE	RMSE	NSEE
Rn (W/m^2)	14.1	75.5	56%
lE (W/m^2)	7.4	32.6	53%
Hs (W/m^2)	2.1	35.4	101%
G (W/m^2)	13.9	41.6	118%

4.2 Modification to MOLTS data

To ascertain the reason why 'M_O' performance is not so good, we compared MOLTS forcing data with in-situ observations.

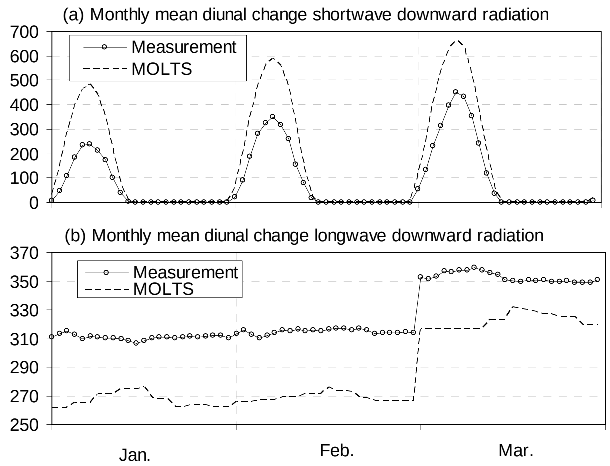

Fig. 5 Monthly mean diurnal changes in down ward radiation of MOLTS and in-situ PBL observation

From an analysis of monthly mean diurnal radiation (see Fig. 5a), it is clear that the peak of the downward short wave radiation of MOLTS was much bigger than that of in-situ observations, while the downward long-wave radiation of MOLTS was around 20W/m^2 smaller than that of PBL observations(Fig. 5b).

The pressure of MOLTS was slightly larger (mean 959.7 hPa) than that of PBL observation (mean 956.9hPa). The mean air temperature of MOLTS was 280.8K, almost the same as that of PBL observation, 280.5K.

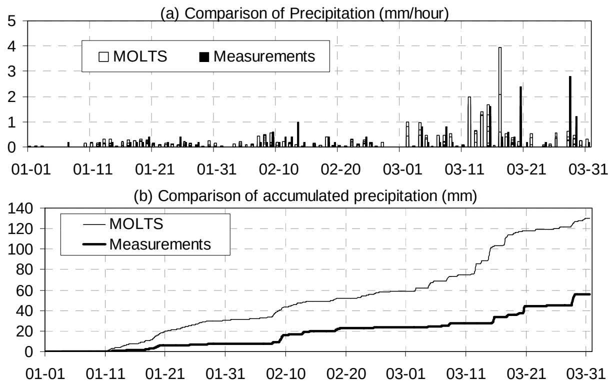

Fig. 6 Hourly precipitation and accumulated values of MOLTS and in-situ observation

There are some obvious differences between MOTLS precipitation data and PBL observation (see Fig. 6). MOLTS gave a larger precipitation than PBL observation. The accumulated precipitation of MOLTS in this period was 130.3 mm, while that of PBL observation was just 56.0 mm. Fortunately, as demonstrated by Yang et al.[6], LDASUT is able to partly overcome such biases in input precipitation data, because it directly assimilates AMSR-E brightness data to correct the soil moisture states.

Through a comparison of MOLTS forcing data and in-situ observed data, it was clear that the large overestimation in MOLTS downward radiation is the main reason that 'M_O' failed to correctly simulate the land surface energy budget. To mitigate such an obvious overestimation, we modified the JMA MOLTS downward shortwave radiation data by using linear equations acquired from the regression analysis of the monthly mean diurnal cycle data. Analogously, the MOLTS downward long-wave radiation data was modified using a linear regression equation of all three month data. The correction equations are as follows:

$$RSW\_C = \max[0, (RSW\_O - 15.21)/1.6435] \quad (4)$$

$$RLW\_C = (RLW\_O + 25.877)/0.9557 \quad (5)$$

where RSW is the downward short wave radiation, RLW is the downward long-wave radiation, $\_C$ means the modified value, and $\_O$ means the original value.

After applying equations 4 and 5 to all downward radiation MOLTS data, a new data set, modified MOLTS, was created. Analogously, the simulation driven by the modified MOLTS data is called "M_C.

4.3 Results of 'M_O' and 'M_C'

As shown in table 4, comparing table 3, it is clear that 'M_C' estimates surface energy fluxes better than 'M_O'; as all items in table 4 are smaller than those in table 3. This means that the performance of LDASUT is improved using the modified MOLTS instead of the original MOLTS.

Table. 4 Statistical analysis of radiation components of 'M_C'

	MBE	RMSE	NSEE
Rn (W/m^2)	-2.4	61.5	46%
lE (W/m^2)	2.5	31.0	50%
Hs (W/m^2)	-9.9	26.2	75%
G (W/m^2)	13.6	30.4	86%

Figure 7 shows the monthly mean diurnal changes of the surface energy components. Comparing 'M_O' (dash line) and 'M_C' (solid line) against the direct measurements (open cycles), it is clear that 'M_C' generally produced better results than 'M_O'. This means the performance of the energy budget simulation can be improved through a simple linear modification. With considering measurement accuracy and scale problems, the quality of "M_C" is reasonable for the big domain simulations.

Figure 8 shows a comparison of the monthly mean diurnal changes of ULR. It is clear that 'M_O' underestimated ULR at night time, with a MBE of -7.2 W/m^2; while 'M_C' estimated ULR with better accuracy, with a MBE of -4.4 W/m^2.

Figure 9 shows a time series of the hourly soil moisture of 'M_O' (dash line), 'M_C' (thick line) and in-situ observation (thin line). The results of 'M_O' and 'M_C' are acceptable, because the strength of LDASUT, which optimized soil parameters and assimilating soil moisture. But sometimes 'M_O' and 'M_C' did not follow the

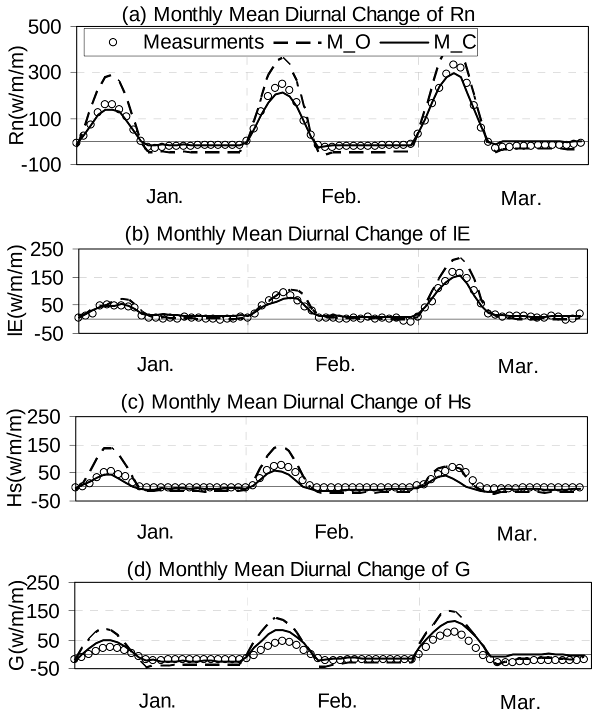

Fig. 7 Comparison of monthly mean diurnal change of (a) Rn, (b) lE, (c) Hs and (d) G of 'M_O' and 'M_C' against direct measurement.

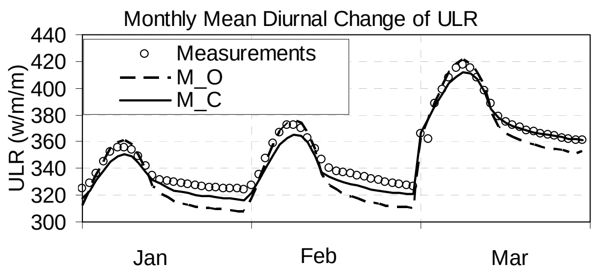

Fig. 8 Comparison of monthly mean diurnal change of ULR of 'M_O' and 'M_C' against direct measurement.

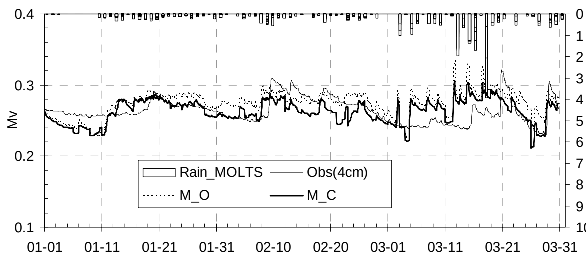

Fig. 9 Comparing simulated soil moisture content with direct measurements tendency of the direct measurements. This is partly to the result of the big difference between MOLTS precipitation and the observed one, as shown in figure 6. Statistically, 'M_O' estimates soil moisture with a MBE of 0.02, a RMSE of 0.02 and NSEE of 8%, while those of 'M_C' are -0.01, 0.02 and 7%, respectively.

By comparing M_O and M_C results with in-situ measurements, the advantages of modified MOLTS were verified. Thus the possibility of generating reliable spatial distribution of land surface fluxes with LDASUT driven by modified MOLTS data can be confirmed.

5. CONCLUSIONS

LDAS is expected to provide accurate temporal and spatial continuous land surface variables that will promote research in fields such as climate change, weather forecasting, and hydrological modeling. In this study, the LDASUT was firstly driven by in-situ observation data to validate its capability to estimate land surface fluxes (PBL). Then, to check the feasibility to estimate the spatial pattern of land surface fluxes with using LDASUT and model output forcing data, LDASUT was driven by two model output data sets: the original MOLTS (M_O) and a modified MOLTS (M_C). Simulation results of Rn, lE, Hs, G, ULR and soil moisture content were compared against the direct measurements.

Our results show that the simulation results of 'PBL' generally well agreed with the direct measurement, and the differences between in-situ observation and simulation are generally smaller than instrumental observation errors. Therefore, we validated that LDASUT can reliably simulate land surface fluxes.

The discrepancies between the simulated fluxes of 'M_O' and the direct measurements are appreciable; while 'M_C', a simple modification from 'M_O' using linear regression equations, estimated those fluxes with improved accuracy. Because of the unique feature of the LDASUT to optimize soil parameters and then assimilate soil moisture, the simulated soil moisture of 'M_O' and 'M_C' were good quality. From these encouraging results, it is possible to reliably estimate land surface variables using the LDAS driven by model outputs. It is especially important for running the GCM and for studies in remote areas where in-situ micrometeorological observation is not available.

We also found that the quality of the lE and G simulations was not as good as that of Rn. This could be the result of instrumental errors, different scales of the LDASUT and in-situ observation, the heterogeneity problem in the calculation of energy storage, and the model deficiencies in the structure and parameters. Further efforts are needed in both experimental and model research.

ACKNOWLEDGMENTS:

This study was carried out as part of a JICA project; for which the authors express their great gratitude. We also thank our local colleagues at the Wenjiang site and JMA for providing necessary data set.

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(Received September 30, 2008)