Improvement Test for the Canopy Interception Parameterization Scheme in the Community Land Model

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Abstract

The Qian atmospheric forcing dataset is used to drive version 4.5 of the Community Land Model (CLM4.5) in off-line simulation tests. Based on the Global Land Evaporation Amsterdam Model (GLEAM) data, we attempt to ameliorate the canopy interception parameterization scheme in CLM4.5 by improving the empirical parameter and the physical structure. Considering that different plant functional types (PFTs) have different capacities to intercept rainfall is denoted as SEN1, and accounting for the influence of wind speed on canopy interception on the basis of SEN1 is denoted as SEN2. SEN1 shows obvious improvement in the simulated evaporation of intercepted water from vegetation canopy (Ec), not only greatly reduces the positive bias of the model to simulate Ec, especially in the equatorial region, but also significantly reduces the root mean square error (RMSE). SEN2 further improves the simulation of Ec by lowering the RMSE and increasing consistency with GLEAM data. In addition, the percentages of Ec over total evapotranspiration in both SEN1 and SEN2 are more reasonable and much closer to GLEAM data than that in CLM4.5.

(Citation: Yang, M., R. Zuo, X. Li, and L. Wang, 2019: Improvement test for the canopy interception parameterization scheme in the Community Land Model. *SOLA*, **15**, 166–171, doi: 10.2151/sola.2019-030.)

1. Introduction

The canopy is the most direct and active interfacial layer between vegetation and the atmosphere. It participates in the ecosystem water cycle through shading, intercepting rainfall and transpiration. Rainfall interception is the first step of rainfall redistribution and has an important ecological and hydrological significance. Rainfall that hits the surface of plants is temporarily retained, and eventually evaporates into the atmosphere, drops down, or flows down along branches and trunks (Muzylo et al. 2009; Nanko et al. 2011).

Intercepted water from the vegetation canopy is an important part of the water cycle (Massman 1983; Keim and Skaugset 2004), modifying the land-atmosphere moisture and energy balance (Zeng et al. 2000). The process of canopy interception can slow the time when rainfall reaches the surface, which can affect the spatial distribution of rainfall reaching the ground to varying degrees by runoff and soil infiltration, making the rainfall become fully absorbed by the understory and the soil layer. In addition, the time scale of the response of intercepted water from the vegetation canopy is less than that for soil evaporation and vegetation transpiration, and can rapidly respond to atmospheric rainfall and accelerated the regional water cycle (Savenije 2004; Lawrence et al. 2007). As a carrier of latent heat flux and an important component of land surface evapotranspiration (Wang and Dickinson 2012), the evaporation of intercepted water from the vegetation canopy (Ec) transports water and energy to the atmosphere, affecting atmospheric dynamics and thermal processes (Seneviratne et al. 2006). Based on the Community Land Model (CLM) version

4 (CLM4), Yin and Chen (2013) investigated the potential impact of Ec on global land surface water and energy balance through comparative analysis of experiments with and without Ec. It was found that global total soil moisture, surface runoff and subsurface runoff increased and evapotranspiration decreased without considering Ec. In addition, an overestimated Ec means that much of the atmospheric demand for evaporation is satisfied by Ec, thereby limiting transpiration and photosynthesis (Wang and Eltahir 2000), resulting in underestimated gross primary production (GPP) (Lawrence et al. 2007, 2009), drier soil and degraded vegetation when coupled to a dynamic global vegetation model (DGVM) (Bonan and Levis 2006).

Since the first attempt to conceptually model the Ec by Horton (1919), the Ec has gradually gained the attention of researchers in hydrology, meteorology, forestry and other related disciplines. Subsequently, the physical-based interception models (such as Rutter model (Rutter 1972), Liu model (Liu 2010) and Gash model (Gash 1979), etc.) have made great progress (Muzylo et al. 2009). For example, based on sound physical fundamentals, Rutter et al. (1972) established an interception model that can be used to calculate the Ec of a certain known vegetation type by inputting rainfall and some meteorological variables controlling evaporation. This model has been verified by comparisons with observed data of some forest or specific vegetation types (Wallace and Mcjannet 2008). Although these models are verified with some vegetation types, they have not been popularized and applied to large-scale studies (Kozak et al. 2007). Ec is highly spatially and temporally variable (Klaassen et al. 1998; Dunkerley 2000). The physical-based interception models are more suitable to deal with a certain vegetation type by inputting meteorological variables obtained by site observation, while land surface models calculate the Ec of all plant functional types (PFTs) within a grid box a few hundred kilometres wide (Zeng et al. 2000; Fan et al. 2019).

Comparatively, land surface models, which are favourable tools for studying surface hydrology, have been widely used in Ec studies on the regional or global scale. However, Wang and Wang (2007) found that the Community Land Model version 3 (CLM3) significantly overestimated the annual rainfall interception ratio for tropical areas. In contrast, de Kauwe et al. (2013) reported that CLM4 underestimated rainfall interception for temperate forest and tree plantation sites. Yang et al. (2018) evaluated the capability of version 4.5 of the Community Land Model (CLM4.5) to simulate global Ec, and found that there was still a large simulation bias. Improving the capability of the model to simulate the Ec is a prerequisite to further explore the influence of canopy interception on water and energy circulation and to understand the role of vegetation in the land-atmosphere system. Fortunately, some scholars have improved the canopy interception scheme in the CLM. For example, Lawrence et al. (2007) changed the value of an empirical parameter α in the interception coefficient from 1 to 0.25, which made the simulation of Ec, vegetation transpiration and evapotranspiration on a global scale more reasonable. Data from 15 flux network (FLUXNET) sites are used by Stöckli et al. (2008) to identify and improve model deficiencies. Starting from the leaf area index (LAI) and stem area index (SAI), Yin (2013) selected the logistic curve commonly used in ecology to improve the calculation of Ec in CLM4.0, to reduce the overall simulation biases. Reconciling the interception scheme with realistic precipitation forcing, Fan et al. (2019) produced more accurate Ec and transpiration for both PFTs, which in turn improved simulated

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evapotranspiration and energy partitioning. However, previous improvements did not consider the influence of meteorological factors, such as wind speed, on canopy interception, and we believe that the value of empirical parameters α still needs to be improved.

The recent release of global land surface evaporation data GLEAM (Global Land Evaporation Amsterdam Model) (Miralles et al. 2010; Martens et al. 2017) makes it possible to better evaluate and improve the canopy interception scheme in the land surface model CLM4.5. In view of this, we aim to improve the original canopy interception parameterization scheme and the simulation ability of the model. In the following text, Section 2 includes a brief description about the data and the methods used in this study. Section 3 presents the improved results. The conclusion and discussion are given in Section 4.

2. Data and methods

The Qian dataset (Qian et al. 2006), which combines the National Center for Environmental Prediction (NCEP) reanalysis data with observation-based analyses of monthly rainfall, surface air temperature, and surface downward solar radiation, was used as the atmospheric forcing data. This dataset was extensively applied to the improvement and evaluation of the land surface model (Liu et al. 2009; Bonan et al. 2011). The Community Land Model is one of the most widely used land surface models in the world, and integrates the advantages of several land surface models, such as the Biosphere-Atmosphere Transfer Scheme (BATS), the 1994 version of the land surface model of the Chinese Academy of Sciences Institute of Atmospheric Physics (IAP94), and Bonan's Land Surface Model (LSM), which has become one of the most developed and promising land surface models in the world. CLM4.5 performed off-line simulations for the years between 1952 and 2002 using the satellite phenology option, where the years 1952–1982 were used for the spin-up. The distribution of PFTs was based on remote sensing data and the LAI and SAI for vegetation was based on satellite phenology data that accounts for monthly variation and provided by the Moderate Resolution Imaging Spectroradiometer (MODIS).

The E_c from GLEAM is a set of global evaporation data that includes intercepted water from the vegetation canopy with high reliability based on multi-satellite observation data proposed by Miralles et al. (2010). GLEAM is derived from the revised version of Gash's analytical model (Valente et al. 1997) driven by the 3-hourly Multi-Source Weighted-Ensemble Precipitation (MSWEP) (Beck et al. 2017), satellite remotely sensed data of canopy fraction and lightning frequency which is used to distinguish between the rainfall rates of convective and frontal precipitation. In addition, GLEAM compare well with field observations of rainfall interception (Miralles et al. 2010) and the flux network (FLUXNET) of tower (Michel et al. 2016). Davies-Barnard et al. (2014) used GLEAM to evaluate the canopy interception scheme in the Met Office Hadley Centre climate model, version 3 (HadCM3). Miralles et al. (2016) found that GLEAM has higher reliability than other land surface evaporation dataset. Considering the high reliability of GLEAM, the years between 1983 and 2002 for E_c from GLEAM were used as observation data in our research.

The original canopy interception parameterization scheme in CLM4.5 is expressed as follows:

$$\text{fpi} = \alpha \{1 - \exp[-0.5(L + S)]\} \quad (1)$$

$$Q = \text{fpi} \times (q_{\text{rain}} + q_{\text{sno}}) \quad (2)$$

where fpi represents the interception coefficient; α is the empirical parameter; L is the leaf area index and S is the stem area index;

Table 1. The “best” empirical parameters for five dominant PFTs.

PFT Name	“Best” Empirical Parameter
C3 dry land crops	0.12
C4 grassland	0.08
north deciduous broad-leaved shrubs	0.15
tropical evergreen broad-leaved forests	0.18
northern evergreen coniferous forests	0.2

Q is the intercepted water; q_{rain} and q_{sno} represent the amount of rainfall and snowfall per unit time, respectively.

Bonan et al. (2011) pointed out that there are two main ideas to improve the physics parameterization scheme of the land surface model, namely, the improvement of the empirical parameters and the improvement of the physical structure. Reasonable estimation of the empirical parameters in land surface model is the premise to guarantee the reliability of the simulation results. The empirical parameter α in the interception coefficient used in CLM3.0 and the previous versions was set as a fixed value of 1. Some scholars found that the model seriously overestimated E_c , resulting in dry soil, small surface runoff and low vegetation transpiration. This affects the intensity of land-atmosphere coupling, and if coupled with dynamic vegetation, it would lead to forest degradation into grasslands in some regions (Bonan and Levis 2006). Lawrence et al. (2007) changed the value of α from 1 to 0.25, which made the simulation results more reasonable. However, considering that different PFTs must have different capacities to intercept rainfall, the empirical parameter α should not be set as a fixed value for each PFT. Thus, we think that the value of this empirical parameter can still be improved. Therefore, the “best” α of the five dominant PFTs (see Table 1) is identified through 15 sensitivity tests (see Table 2), and this improvement work is marked as SEN1 (It should be noted that there are 16 PFTs in CLM4.5, except for five dominant PFTs in Table 1, the α of other PFTs keep the original value 0.25).

Moreover, it can be seen from the original canopy interception parameterization scheme in CLM4.5 that only rainfall, LAI and SAI were considered in the calculations. As a result, for a certain PFT, intercepted water increases linearly with rainfall, which is inconsistent with reality, especially in the case of heavy or long-term rainfall where the bias is larger. In addition, this scheme does not take into account the influence of meteorological factors, such as wind speed and rain intensity. For example, wind may affect canopy interception by shaking branches (Gash 1979; Massman 1983; Zeng et al. 2000; Muzyllo et al. 2009). By investigating the parameterization schemes of canopy interception in more than 10 other land surface modes, including SiB, BATS, Mosaic, VIC, Noah-MP, SWAT, RUC, LSM, PX and Noah, we found that none of these models considered the effect of rainfall intensity, and only the Noah-MP model considered the effect of wind speed on canopy interception. On the basis of SEN1, this paper refers to the calculation scheme in Noah-MP to introduce the influence of wind speed on canopy interception into CLM4.5 (see formula (3), u and v represent zonal and meridional wind speeds at 10 meters above the surface, respectively), which is denoted as SEN2.

$$Q = \text{fpi} \times (q_{\text{rain}} + q_{\text{sno}}) \times \exp\left(-\frac{u^2 + v^2}{10}\right) \quad (3)$$

3. Results

In Fig. 1, the spatial pattern of seasonality for global E_c is given from the simulation results of SEN2 and GLEAM data. From the GLEAM data shown in Figs. 1a, 1b, 1c, and 1d, global

Table 2. The value of empirical parameters in 15 sensitivity tests.

α	0.5	0.45	0.4	0.35	0.3	0.28	0.25	0.22	0.2	0.18	0.15	0.12	0.1	0.08	0.05
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Fig. 1. Spatial distribution of global Ec (units: mm): (a–e) GLEAM data and (f–j) simulations by SEN2.

Ec clearly exhibits zonal distribution characteristics and obvious seasonal variation. The seasonal variation in the spatial pattern of global Ec is mainly determined by the seasonal variation in the spatial pattern of rainfall and the sum of LAI and SAI (Yang et al. 2018). As observed from Figs. 1e, 1f, 1g, and 1h, the simulation results of SEN2 on global Ec are basically consistent with the GLEAM data.

To clearly see the improvement, Fig. 2 shows the differences

among the GLEAM data, SEN2 and CLM4.5. As observed from Figs. 2a, 2b, 2c, and 2d, the simulated Ec in SEN2 in January is relatively large in the Southern Hemisphere compared with the GLEAM data, but relatively small in the Northern Hemisphere, especially in southeast China, Europe, southeast America and southwest Canada. The simulation bias in April is mainly positive, principally distributed in the low latitudes of the two hemispheres, and the negative bias is near 50°N. In July, the simulation result of

Fig. 2. Spatial distribution of global Ec (units: mm): (a–e) difference between SEN2 and GLEAM, (f–j) difference between CLM4.5 and GLEAM, and (k–o) difference between SEN2 and CLM4.5.

SEN2 on global Ec is significantly larger than that of the GLEAM data, and generally shows a positive bias, especially in regions in the Northern Hemisphere, such as central Africa, southern Asia and the eastern United States. However, a positive bias occurs in October and is primarily near the equator, while the negative bias is mainly at the middle and high latitudes of the Northern Hemisphere. It can be seen in Figs. 2i, 2j, 2k, and 2l that the simulated Ec in SEN2 near the equator is much smaller compared with that in CLM4.5, which largely reduces the positive bias in CLM4.5 (see Figs. 2e, 2f, 2g, and 2h). Furthermore, the simulated Ec in SEN2 in July at the middle and high latitudes of the Northern Hemisphere, southern Asia and eastern North America is relatively small compared with CLM4.5 (see Fig. 2k) and reduced the positive bias of CLM4.5 in these regions, making the simulation results of SEN2 on global Ec in July significantly improved compared with CLM4.5.

Table 3 shows the root mean square errors (RMSEs), means and spatial correlation coefficients of the simulation results of the

CLM4.5, SEN1, SEN2 and GLEAM data. Table 3 demonstrates that CLM4.5 seriously overestimates global Ec, especially in July. Simulation biases of Ec in CLM4.5 in January, April, July, October and annual mean account for 90%, 104%, 131%, 33% and 88% of the means in the GLEAM data, respectively. After changing the empirical parameters in the interception coefficient, the biases of SEN1 accounted for only 15%, 30%, 48%, 19% and 16% respectively. It can be seen that, relative to CLM4.5, SEN1 significantly reduces the biases of the means of global Ec in CLM4.5. Moreover, the RMSEs in SEN1 are also obviously reduced compared with those in CLM4.5. The spatial correlation coefficients for the simulated results of CLM4.5 and the GLEAM data are 0.75, 0.86, 0.77, 0.64 and 0.80, respectively. In contrast, the results in SEN1 are 0.73, 0.86, 0.77, 0.62 and 0.79, respectively.

After considering the impacts of wind speed, the simulated means of global Ec in SEN2 are slightly reduced compared with those in SEN1, especially in July which shows a decrease of

Table 3. RMSEs, means and spatial correlation coefficients (SCC) for globally Ec in the months of January, April, July and October, as well as annual mean.

	RMSE (units: mm)			Mean (units: mm)				SCC		
	CLM4.5	SEN1	SEN2	CLM4.5	SEN1	SEN2	GLEAM	CLM4.5	SEN1	SEN2
January	8.6	5.2	4.9	3.8	2.3	2.2	2.0	0.75	0.73	0.75
April	7.2	3.7	3.5	4.7	3.0	2.9	2.3	0.86	0.86	0.87
July	8.5	4.7	4.2	6.7	4.3	4.0	2.9	0.77	0.77	0.79
October	7.8	5.2	5.0	3.6	2.2	2.1	2.7	0.64	0.62	0.64
Annual mean	6.4	3.6	3.3	4.7	2.9	2.8	2.5	0.80	0.79	0.81

Table 4. The proportion of Ec in evapotranspiration (ET).

	CLM4.5	SEN1	SEN2	GLEAM
Ec/ET	19%	13%	12%	10%

0.3 mm. Except for October, the simulation results for the mean of Ec in SEN2 are closer to the GLEAM data with a little improvement compared with that in SEN1. In addition, it is satisfactory that the RMSEs in SEN2 are also smaller than those in SEN1 for all seasons and the annual mean. It can be seen that despite the spatial correlation coefficients of January and October in SEN2 being the same as in CLM4.5, the simulation results of April, July and the annual average are slightly improved compared with CLM4.5.

As for the percentage of annual mean Ec over total evapotranspiration, it can be learned from Table 4 that the proportions of Ec in evapotranspiration in CLM4.5, SEN1, SEN2 and GLEAM are 19%, 13%, 12% and 10%, respectively, indicating that the distribution ratio of evapotranspiration in SEN1 and SEN2 are more accurate than that in CLM4.5.

4. Conclusion and discussion

This research uses the Qian dataset as atmospheric forcing data and the GLEAM data as observational data to improve the canopy interception parameterization scheme in the land surface model, CLM4.5. The improvement is divided into two parts. One is to modify the empirical parameter in the interception coefficient by considering that different PFTs have different capacities to intercept rainfall, which is denoted as SEN1. The second part is to account for the influence of wind speed on canopy interception based on SEN1, which is denoted as SEN2. By comparing the improvement tests with the control test and the GLEAM data, the improvement effects were investigated, and the main conclusions are as follows:

Considering that the capability to intercept rainfall varies from PFT to PFT, the simulated Ec in SEN1 has an obvious improvement effect, which not only greatly reduces the positive bias of the model to simulate Ec, especially in the equatorial region, but also significantly reduces the RMSEs. After considering the influence of wind speed on canopy interception on the basis of SEN1, the simulation biases of Ec in SEN2 are further reduced, the means are closer to the GLEAM data, and the RMSEs are also further reduced. In addition, the percentages of Ec over total evapotranspiration in both SEN1 and SEN2 are more accurate than that in CLM4.5.

Although this article has made some improvements on the original canopy interception parameterization scheme in the land surface model CLM4.5, there are still some deficiencies. For example, we changed the empirical parameters in the interception coefficient using 15 sensitivity tests, which can only roughly determine the respective empirical parameters of different PFTs and is not extremely accurate. In addition, there are 17 PFTs in the model; however, the empirical parameters of only the five dominant PFTs are estimated in this research.

To consider the influence of wind on canopy interception, we

referred to another land surface model, Noah-MP, and constructed the impact of wind speed on canopy interception in the form of an exponential, but the parameter is highly empirical. Although some improvement aims have been achieved, there is a lack of theoretical demonstration. Therefore, to better account for the influence of wind speed on canopy interception in the model, one should refer to more analytical models of canopy interception with a solid physical basis, like the wind-driven rainfall model put forward by Herwitz and Slye (1995).

GLEAM actually is a set of algorithms that separately estimate the different components of evapotranspiration. Based on observation and satellite remote sensing data, Ec in GLEAM is calculated using a Gash analytical model (Valente et al. 1997) which has a much stronger universality and continuity and distinguished from other physical-based interception models. In spite of a diverse mix of forests with a single set of parameters (Miralles et al. 2010), the Ec in GLEAM has been validated in a large number of site observations and the physical process is detailed enough to calculate the Ec from canopy and trunks separately rather than together as CLM does. Although the canopy interception scheme in CLM is simpler than GLEAM, one of the great advantages of CLM is to calculate the Ec of different PFTs at one grid point. CLM can become a more popular and promising tool to study the large-scale and global Ec if more detailed physical processes are considered.

Many studies have pointed out that rain intensity has an important impact on canopy interception (Massman1983; Zeng et al. 2000; Murakami 2007). Limited to the time step of integration in the land surface model, the rain intensity in the model is often underestimated, especially for short-term heavy rainfall. Thus, accounting for the role of rain intensity and making the simulation results closer to the observational data is the work we need to do next. In addition, the interaction between canopy leaves and rainfall influences the energy of raindrops by weakening the intensity of rainfall hitting the ground, reducing the lash of rainfall on the soil, and therefore influencing the soil erosion process (Brandt 1988), which may be a reflection of the potential significance in our future work.

Acknowledgements

Three anonymous reviewers provided careful comments on the submitted manuscript, which helped improve this article. The first author thanks Miao Li for her encouragement. This research was supported by National Natural Science Foundation of China (41475071).

Edited by: M. Huang

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