Evaluation of a satellite-derived model parameterized by three soil moisture constraints to estimate terrestrial latent heat flux in the Heihe River basin of Northwest China

Yunjun Yao a, Yuhu Zhang b,*, Qiang Liu c, Shaomin Liu d, Kun Jia a, Xiaotong Zhang a, Ziwei Xu d, Tongren Xu d, Jiquan Chen e, Joshua B. Fisher f

a State Key Laboratory of Remote Sensing Science, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
b College of Resource Environment and Tourism, Capital Normal University, Beijing 100048, China
c College of Global Change and Earth System Science, Beijing Normal University, Beijing 100875, China
d State Key Laboratory of Earth Surface Processes and Resource Ecology, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China
e CGCEO/Geography, Michigan State University, East Lansing, MI 48823, USA
f Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Dr., Pasadena, CA 91109, USA

HIGHLIGHTS

• A satellite-derived hybrid LE model was developed from MODIS and reanalysis data.
• Three SM constraints schemes exhibited some LE modeling differences.
• Different SM constraint schemes could impact the regional LE simulation.

GRAPHICAL ABSTRACT


ARTICLE INFO

Article history:
Received 24 March 2019
Received in revised form 2 August 2019
Accepted 4 August 2019
Available online 6 August 2019

Editor: Ashantha Goonetilleke

Keywords:
Terrestrial latent heat flux
MODIS

ABSTRACT

Satellite-derived terrestrial latent heat flux (LE) models are useful tools to understand regional surface energy and water cycle processes for terrestrial ecosystems in the Heihe River basin (HRB) of Northwest China. This study developed a satellite-derived hybrid LE model parameterized by three soil moisture (SM) constraints: SM, relative humidity (RH), and diurnal air temperature range (DT); and assessed model performance and sensitivity. We used MODerate Resolution Imaging Spectroradiometer (MODIS) and eddy covariance (EC) data from 12 EC flux tower sites across the HRB. The hybrid model was trained using observed LE over 2012/2013–2014, and validated using observed LE for 2015 and leave-one-out cross-validation. The results show that the three SM constraints schemes exhibited some modeling differences at the flux tower site scale. LE estimation using SM achieved the highest correlation ($R^2 = 0.87, p < 0.01$) and lowest root mean square error (RMSE = 20.1 W/m²) compared to schemes using RH or DT schemes. We then produced regional daily LE
1. Introduction

Terrestrial latent heat flux (LE) plays an important role in exchanges of water, energy and carbon cycles in the terrestrial ecosystem (Wang and Dickinson, 2012). Terrestrial LE has noticeably shifted for many regional LE estimation models, due to climatic change and human activities, which influences regional water cycles, vegetation growth, and climate change feedback, particularly in arid and semiarid regions (Fisher et al., 2017; Liu et al., 2018a; Zhou et al., 2018). Therefore, accurate regional LE quantification in arid and semiarid regions is crucial for water resource management, ecosystem conservation, and adaptation strategies to climate change.

The Heihe River basin (HRB) is a typical oasis-desert arid region, particularly susceptible to surface energy and water cycle process changes due to increased agricultural irrigation, population expansion, and economic development (Liu et al., 2018a; Song et al., 2018; McVicar and Jupp, 2002; Mu et al., 2007; Wang and Dickinson, 2012; Yao et al., 2013; Priestley and Taylor, 1972). The Chinese scientific community has monitored terrestrial LE and eco-hydrological processes in the HRB, as part of the Heihe Plan launched by the National Natural Science Foundation of China (NSFC), including the watershed allied telemetry experimental research (WATER) and Heihe watershed allied telemetry experimental research (HiWATER) programs (Li et al., 2009a, 2009b; Li et al., 2013; Liu et al., 2018a; Cheng et al., 2014). Although these experiments provide accurate point measurements using eddy covariance (EC) methods, they may not represent large areas due to terrestrial ecosystem heterogeneity and dynamic heat transfer processes (Baldocchi et al., 2001; Twine et al., 2000; Wang et al., 2007).

Remote sensing has greatly improved regional scale soil and vegetation dynamics observations linked to terrestrial LE over heterogeneous ecosystems. Many satellite-derived LE products are available, including the MODe-rate-resolution Imaging Spectroradiometer (MODIS) LE (MOD16) (Mu et al., 2011; Yao et al., 2014; Jung et al., 2010; Zhang et al., 2010). Although MOD16 has relatively high spatial (1 km) and temporal (8-day) resolution, validations have indicated that it retains significant uncertainties for most EC flux tower sites and LE values for the HRB are omitted (Hu et al., 2015a; Yao et al., 2017a; Mu et al., 2011; Xiong et al., 2015).

Various satellite-derived methods have been developed to estimate regional terrestrial LE, including empirical methods (Jackson et al., 1977; Jung et al., 2011; Nagler et al., 2005; Yang et al., 2006; Yao et al., 2015), physical models (e.g. surface energy balance (SEB) models, Penman-Monteith (PM) logic, Priestley-Taylor (PT) approach) (Norman et al., 1995; Anderson et al., 2008; Cleugh et al., 2007; Mu et al., 2011; Zhang et al., 2010; Fisher et al., 2008; Yao et al., 2017b; Miralles et al., 2011), data assimilation models (Pipunic et al., 2008; Xu et al., 2011a, 2011b), and distributed hydrology and land surface models based on satellite and meteorological data (Overgaard et al., 2006; Xie et al., 2015). Comprehensive reviews of the models development and validation accuracies are provided elsewhere (Kalma et al., 2008; Li et al., 2009a, 2009b; Wang and Dickinson, 2012; Ershadi et al., 2014; Polhamsus et al., 2012; Badgley et al., 2015). However, not all models are equally good, providing a range of LE estimates at site and regional scales. For example, Wang and Dickinson (2012) reported that globally averaged LE estimates varied from 24.1 W/m² to 42.0 W/m² from 17 models. Similarly Ershadi et al. (2014) compared four models for various land cover types and showed that no single model was consistently best across all biomes. Model results were verified with low confidence at regional and site scales due to three main limitations: (1) surface landscape and terrestrial ecosystem process heterogeneity, (2) physiological parameter calibrations in the model, and (3) inadequate validation against ground measurements (Baldocchi et al., 1996; Yuan et al., 2010).

Satellite derived hybrid LE models may have the best potential to adequately simulate LE over a wide range of soil moisture (SM) content and land cover type, because they combine physical models and calibrated coefficients using ground observations from different ecosystems. For example, Wang et al. (2007) proposed a simple hybrid method to estimate terrestrial LE by relating ground-measured LE to net radiation (LE/Rn) from the US Atmospheric Radiation Measurement (ARM) to normalized difference vegetation index (NDVI) and air temperature (Ta). This method was consistent with the PT equation while incorporating vegetation influence on LE. However, the proposed method ignored SM impact on LE and overestimated LE during severe drought conditions. Subsequently Wang and Liang (2008) took into account the influence of SM on LE by incorporating diurnal Ta, range (DT), and Ta and air temperature deficits (VPD) to parameterize SM effects on LE in a satellite-derived hybrid algorithm. Purdy et al. (2018) used SM from the Soil Moisture Active Passive Mission (SMAP) with the PT-JPL model (PT model provided by the Jet Propulsion Laboratory, USA), and demonstrated improved performance for semi-arid ecosystems. However, performance for satellite-derived hybrid LE models parameterized by different SM constraints remains unclear, particularly for the HRB, which incorporates large barren or sparsely vegetated areas. Thus, effects from employing surface SM, RH, and DT to characterize SM constraints for hybrid LE model performance require further evaluation for HRB.

In this study, we developed a satellite derived hybrid LE model parameterized by SM, RH, and DT soil moisture constraints in HRB, and assessed model performance. The objectives of this study are threefold: (1) to develop a satellite-derived hybrid LE model based on site-specific flux tower and MODIS data for HRB, and validate the model using eddy flux data in temporal and spatial domains; (2) to assess performance for the hybrid LE model parameterized by SM, RH, and DT constraints; and (3) to examine regional LE patterns using SM, RH, and DT constraints for 2013–2015.

2. Materials and methods

2.1. Research area

HRB is located on the northern slopes of the Qilian Mountains between 37.7°–42.7°N and 97.1°–102.0°E, covering a land area of approximately 143, 200 km² (Fig. 1). HRB is the second largest inland river basin in arid Northern China, with the Heihe River originating in the Qilian Mountains (Liu et al., 2018a, 2018b). The river stream flows through the Hexi Corridor of Gansu Province and arrives at two terminal lakes in the Western Inner Mongolia Plateau desert (Xiong et al., 2015). Study area elevation decreases from 2000 to 5000 m upstream, 1000–3000 m midstream, and 800–1700 m to downstream, covering several biomes. Major land cover types in the upstream region are glacier (snow/ice, SIN), alpine meadow (grassland, GRA) and Qinghai spruce (evergreen needleleaf forest, ENF); midstream includes maize (cropland, CRO), and piedmont desert (barren lands, BAR); and downstream includes mixed forests (MIF), terminal lake (water body, WAT),
Regional scale $R_n$ was obtained following the method by Wang and Liang (2009). This model estimates the $R_n$ from the surface albedo,
daily $R_n$, $T_{\text{min}}$, $DT$, $NDVI$ and $RH$. Wang and Liang (2009) reported that the method used in their study to estimate $R_n$ for 22 US sites yielded 19% relative error.

2.3. Remote sensing method

2.3.1. Satellite-derived hybrid LE model logic

We proposed a satellite-derived hybrid LE model based on the Wang and Liang (2008) model:

$$LE = R_n (k_0 + k_1 T_e + k_2 NDVI + k_3 f_s),$$

(1)

where $k_i (i = 0, \ldots, 3)$ is the empirical coefficient, which can be calibrated using ground-measurements and satellite data; and $f_s$ is the SM constraint. In the Wang and Liang (2008) model, $f_s$ refers exclusively to DT, whereas in the current study, $f_s$ can refer to SM, RH, or DT because these variables reflect surface SM stress in different regions (Fisher et al., 2008; Wang and Liang, 2008; Wang et al., 2010; Yan and Shugart, 2010). Fig. S1 shows the hybrid LE model design, and empirical model coefficients were determined using surface meteorology and satellite data.

This satellite-derived hybrid LE model, characterized with $LE/R_n$, is a classical soil moisture and energy-limited LE regime (Seneviratne et al., 2010). In the energy-limited LE regime, corresponding to $SM >$ threshold or critical value, $LE/R_n$ is independent of SM content and $f_s$ (SM, RH, or DT). This hybrid LE model varies less for SM saturated conditions and does not impact LE variability. In contrast, below the critical value, SM content provides a first-order constraint on $LE/R_n$ in the soil moisture-limited LE regime. Incorporating $f_s$ into the algorithm to estimate LE under insufficient-water conditions considers the effects of surface SM stress on terrestrial LE because $f_s$ varies greatly for water-deficient surfaces, which strongly constrains $LE/R_n$ variability and feedbacks to the atmosphere.

A satellite-derived hybrid LE model offers several advantages over complicated physical LE models, including providing easy routine and long term LE mapping because it only requires $R_n$, $T_e$, $NDVI$, and $f_s$, avoiding computational complexities of aerodynamic and surface resistance (Gao and Dirmeyer, 2006; McVicar et al., 2012; Yao et al., 2015); and reducing errors from forcing data by avoiding the use of the land surface temperature and $T_e$ differences (Wang and Dickinson, 2012).

2.3.2. Model calibration and validation

We calibrated empirical coefficients for Eq. (1) using site specific MODIS and EC ground measured data. We split site level EC and MODIS datasets from the 12 flux tower sites into training (2012–2013) and test (2015) datasets using the holdout method, providing 5113 and 2605 sample datasets, respectively. We evaluated model performance using root mean squared error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_{io} - x_{ip})^2},$$

(2)

where $x_{io}$ is the daily simulated LE, $x_{ip}$ is the daily observed LE, $N$ is the number of samples. We then estimated RMSE and seasonal variations between estimated and observed LE.

We also assessed the proposed model performance in the spatial domain using leave one out cross-validation (Xiao et al., 2010), i.e., data from a single site was used for validation, after data from the remaining sites provided Eq. (1) calibration coefficients. Because calibration and validation data were from different sites that were generally several kilometers from each other, and spatial autocorrelation between sites was negligible, calibration and validation data were considered to be independent. The leave one out cross-validation was separately conducted for each site.

2.3.3. Regional LE estimation

As discussed above, since land cover types for the 12 EC flux tower sites included alpine meadow, cropland, Gobi, desert, wetlands, forests, and mixed cover (including vegetation and bare soil); and the locations differed from each other, ground-measured datasets were reasonable representative of typical HRB ecosystems and climate types. Thus, the proposed model developed from the 12 sites could be extrapolated to regional LE estimation across the HRB. We used the proposed model to estimate daily terrestrial LE for each 1 × 1 km cell across HRB for 2013–2015 using MODIS, ESA CCI SM, and WRF gridded meteorological data. Monthly estimated LE was calculated by averaging daily estimated LE. We examined regional LE patterns for 2013–2015 to compare model performance.

3. Results

3.1. Sensitivity of environmental regulators to LE

Data collected from 2012/2013–2014 were analyzed at 12 flux tower sites to identify environmental regulators from terrestrial LE variation. Table S2 summarizes the correlation coefficients between LE and surface $R_n$, $T_e$, $RH$, $DT$, $SM$, $NDVI$ and $P$ at the 12 sites. For all flux tower sites, $R_n$ exhibited the highest correlation coefficient ($r$) with LE ($0.50 \leq r \leq 0.91$), with correlation coefficients between LE and $T_e$ second highest ($0.46 \leq r \leq 0.84$), indicating $R_n$ and $T_e$ were the most essential controlling parameters to estimate terrestrial LE. $NDVI$ and SM were also highly correlated to LE with correlation coefficients between LE and $NDVI$ (and SM) for most flux tower sites ($0.5$ and $0.4$). Therefore, $NDVI$ and SM are also important parameters for determining terrestrial LE. In contrast, correlation coefficients between $RH$ (and $DT$) and LE were relatively low because seasonal variation differ between $RH$ (and $DT$) and LE. Cumulative $P$ over 15 days was also highly correlated with LE for most flux tower sites ($0.35 \leq r \leq 0.65$) due to time lags between LE change and $P$ occurrence for consecutive time periods.

Normalized terrestrial LE ($LE/R_n$) can also be used to develop LE models due to their near-linear relationship (Wang et al., 2007; Wang and Liang, 2008). Table 1 shows $LE/R_n$ correlation coefficients with related parameters. For most flux tower sites, ground measured $LE/R_n$ showed highest correlations with $NDVI$ ($0.14 \leq r \leq 0.81$) and SM ($0.05 \leq r \leq 0.83$), with $T_e$ ($0.12 \leq r \leq 0.80$), cumulated $P$ over 15 days ($0.15 \leq r \leq 0.53$), RH ($0.02 \leq r \leq 0.67$), and DT ($-0.45 \leq r \leq -0.01$) subsequently. Although SM was weakly positive correlated to $LE/R_n$ at three sites (Mixed forest, Populus forest and Barren-land), the high correlations between SM and $LE/R_n$ at most sites indicated that SM influence on LE was larger than for near-surface meteorological conditions ($RH$ and $DT$) in the HRB. Overall, after $NDVI$, SM had high potential capacity for...
determining \( LE/R_n \) variations across various land cover and environmental status types. \( SM \) was positively correlated with \( LE/R_n \) everywhere, and had the largest overall correlation for almost all flux tower sites, whereas \( DT \) was negatively correlated with \( LE/R_n \) everywhere, and had the lowest overall correlation (Table 1).

However, the correlations differed greatly between tower sites. For example, \( LE/R_n \) showed strong correlation with \( RH \) at two desert sites (Huazhazi and Shenshawo), suggesting that \( RH \) may capture the water stress for \( LE \) estimation on bare land (desert), whereas \( RH \) and \( LE/R_n \) were only weakly correlated at the two forests sites (Mixed forest and Populus forest), suggesting that \( RH \) may not successfully characterize \( LE \) at forest sites.

3.2. Model evaluation using three soil moisture constraints

3.2.1. Model evaluation based on the holdout method

Fig. 2 shows performance for the hybrid \( LE \) model parameterized by \( SM \), \( RH \), and \( DT \) using the training dataset (2012/2013–2014) collected at the 12 flux tower sites, covering a wide range of land cover types. The \( SM \) constrained schemes exhibited \( LE \) model differences at the flux tower site scale. \( LE \) estimation using \( SM \) (\( LE_{-SM} \)) achieved the highest \( R^2 = 0.87 \) \((p < 0.01)\) and lowest \( RMSE = 20.1 \text{ W/m}^2 \) compared with \( LE \) estimation using \( RH \) (\( LE_{-RH} \)) and \( DT \) (\( LE_{-DT} \)); with \( LE_{-DT} \) achieving the lowest \( R^2 = 0.81 \) \((p < 0.01)\) and largest \( RMSE = 22.1 \text{ W/m}^2 \). Hybrid \( LE \) models using different \( SM \) constraint schemes

---

**Fig. 2.** Scatterplots of observed daily \( LE \) versus estimated daily \( LE \) for 2015. The estimated \( LE \) was calculated using the coefficients for Eq. (1) for 2012/2013–2014. a) \( LE_{-SM} \); b) \( LE_{-RH} \) and c) \( LE_{-DT} \).
performances for the test dataset (2015) were similar to the training dataset (Fig. 2), although RMSE and $R^2$ were slightly poorer [22.1 W/m² and 0.81 ($p < 0.01$), 25.3 W/m² and 0.76 ($p < 0.01$), and 26.7 W/m² and 0.72 ($p < 0.01$) for $LE_{SM}$, $LE_{RH}$, and $LE_{DT}$, respectively]. Validation tests showed that $LE_{SM}$ decreased RMSE by $>3.2$ W/m², and increased $R^2$ by $>0.05$ ($p < 0.01$) compared with $LE_{RH}$ and $LE_{DT}$.

Fig. 3 compares $LE$ estimates using the SM constraint schemes with observed $LE$ for each flux tower site for 2015. The estimates captured most $LE$ seasonal features through 2015, aside from exceptionally high $LE$ for some sites, e.g., Mixed forest and Populus forest sites. Model performance between the SM constraint schemes also varied with site. The schemes all exhibited large overestimation for Barren land and large underestimation for the Sidaqiao site; with other forest and cropland sites only showing moderate underestimation over June to August. In contrast, the Shenshawo site underestimation occurred for winter 2015 and Barren land overestimation occurred in other periods. $LE_{SM}$ produced the closest seasonal $LE$ variations to ground observed values compared with $LE_{RH}$ and $LE_{DT}$ for most flux tower sites.

Fig. 4 shows the superior capacity of the proposed model to predict $LE$ spatial variation by comparing estimated and measured site average daily $LE$ for 2015 at the 12 flux tower sites. The proposed models estimated $LE$ reasonably ($R^2 = 0.75, 0.62, \text{ and } 0.55$; and RMSE = 14.3, 18.4, and 19.3 W/m², respectively) although they all greatly underestimated $LE$ at Sidaqiao. $LE_{SM}$ achieved the highest accuracy according to $LE$ spatial variation validation. Therefore, regional $LE$
simulation may be acceptable by adjusting Eq. (1) coefficients to local conditions with relatively sparse ground observations.

### 3.2.2. Model evaluation using leave-one-out cross-validation

We then validated the models in the spatial domain using leave one out cross-validation. Fig. 5 shows that all proposed models (LE_SM, LE_RH, and LE_DT) estimated LE fairly well, though model performance varied with site and biome type. Generally, higher performance was achieved for GRA (meadow) and CRO (maize) ecosystems than MIF, DBF (Populus forest), and SHR (Tamarix chinensis). Overall, LE_SM exhibited slightly better performance compared to ground measurements than LE_RH and LE_DT at most flux tower sites, achieving approximately 7.8% higher $R^2$ ($p < 0.01$), and 8.2% smaller RMSE. Fig. S3 shows the proposed model had a good ability to estimate LE spatial variation. Site averaged LE_SM estimates for different biome LEs at the 12 sites achieved superior RMSE = 6.8 W/m² and $R^2 = 0.89$ ($p < 0.01$), compared with LE_RH (RMSE = 10.5 W/m², $R^2 = 0.77$, $p < 0.01$) and LE_DT (RMSE = 10.9 W/m², $R^2 = 0.73$, $p < 0.01$). SM constraints in the hybrid LE model generally improved model performance compared with RH and DT constraints for most flux tower sites and landcover types.

Temporal and spatial domain validation verified that the performance of our proposed model using three SM constraints schemes was particularly encouraging, across ecosystem types, structures, and management practices. The model used EC flux tower data, and included typical HRB ecosystems and climate types. Thus, the proposed hybrid model has potential to upscale flux tower LE data to regional scale across HRB.

### 3.3. Regional LE estimation using three soil moisture constraints

#### 3.3.1. Regional implementation of the LE model

We implemented the satellite-derived hybrid LE model in the HRB to further demonstrate its robustness. We recalibrated Eq. (1) coefficients using the MODIS products, ground measured meteorological variables, and LE data collected at all 12 flux tower sites. Table 2 lists Eq. (1) parameters for all biomes by linear regression based on MODIS derived NDVI, ground measured $T_a$, and RH, and DT, and SM. Because of the different land cover types and locations of the 12 EC flux tower sites, we found the models sufficiently representative to estimate regional LE across the HRB.

Fig. 6 compares daily estimated LE derived from tower specific meteorology and ground measured LE at all 12 flux tower sites, with RMSE = 21.1, 23.1, and 24.2 W/m²; and $R^2 = 0.85, 0.80, and 0.78$ (all $p < 0.01$) for LE_SM, LE_RH and LE_DT, respectively. Monthly estimated LE showed good correlation to ground measured LE at all 12 flux tower sites, with RMSE = 15.8 W/m², 18.5 W/m², and 19.9 W/m²; and $R^2 = 0.89, 0.84$, and 0.81 at the 99% level of confidence, respectively. Similar outcomes were found for estimated daily and monthly LE derived from WRF re-analysis, MODIS, and ESA CCI SM data (Fig. S3). Thus, estimated LE from the proposed approach could be applied to estimate regional terrestrial LE across HRB for 2013–2015.

#### 3.3.2. Seasonal and annual LE patterns

Daily LE estimates from the proposed approach were highly constrained by eddy flux data, and provided spatially and temporally continuous LE across HRB, allowing seasonal and annual LE patterns to be investigated. Fig. 7 shows multyear (2013–2015) mean seasonality for LE_SM, LE_RH and LE_DT model estimates. LE exhibited large spatial variability and strong seasonal fluctuations reflecting controlling effects from climate conditions. In the spring months (March–May), LE in the upstream and midstream area was higher than downstream as temperature gradually increased and vegetation growth commenced. In the summer months (June–August), LE peaked due to favorable temperature and SM conditions, with summer precipitation accounting for approximately 80% of annual precipitation. In the fall months (September–November), LE substantially decreased relative to summer as temperature dropped and vegetation began to senesce. Spatial patterns and LE magnitude were similar to spring. In the winter months (December–February), LE values were lowest since the low temperature caused little or no photosynthesis as the vegetation was dormant.

Fig. S4 shows seasonal terrestrial LE spatial differences across the HRB ($\Delta LE_{SM} = LE_SM - LE_RH$, $\Delta LE_{DT} = LE_SM - LE_DT$, and $\Delta LE_{RH} = LE_RH - LE_DT$). Relative to LE_RH and LE_DT, LE_SM yielded lower seasonal terrestrial LE across almost all HRB regions; whereas LE_RH
Fig. 5. Leave one out cross-validation for estimated daily LE models.
Fig. 5 (continued).
exhibited higher seasonal terrestrial LE than LE DT across almost all HRB regions from summer to winter, but lower than LE DT during spring.

Fig. S5 shows calculated annual LE SM, LE RH, and LE DT for 2013–2015 from daily LE estimates, and subsequent average annual LE over the period. Total LE for LE SM, LE RH, and LE DT is 25.1 W/m², 29.6 W/m², and 30.3 W/m² for HRB over 2013–2015, respectively. Annual LE showed considerable spatial variation with large spatial gradient from south (upstream) to north (downstream), i.e., LE decreased along a gradient starting in the southern mountains, where vegetation coverage was abundant, through to sparse vegetation across the northern region, which is largely semiarid climate (Xiong et al., 2015). Therefore, LE variation was consistent with regional climate and vegetation distributions.

Fig. S6 compares estimated annual LE from the proposed models for 2013–2015 across HRB. LE SM exhibited lower annual terrestrial LE for almost all regions compared with LE RH and LE DT; whereas LE RH had higher annual LE than LE DT for most upstream and downstream regions but lower LE across most midstream regions. The LE DT model exhibited particularly low performance for water limited regions (desert regions).
4. Discussion

4.1. Model performance for different biomes

Previous studies have shown that satellite-derived hybrid $LE$ models can achieve comparable accuracy to more complicated models (Jiménez et al., 2011; Kalma et al., 2008; Mueller et al., 2011; Wang and Dickinson, 2012; Yao et al., 2018) and, the model simplicity also allows regional application. However, the proposed hybrid $LE$ models parameterized by $SM$, $RH$, and $DT$ differed over various biomes and conditions. For example, all the proposed hybrid $LE$ models achieved high performance at Arou, Daman, Dashalong, and Zhangye sites, which may be partially attributed to the model successfully capturing seasonal $LE$ variation reflected by the strong NDVI seasonality for grass (meadow) and crops (Yebra et al., 2013). Vinukollu et al. (2011) and Ershadi et al. (2014) showed superior PT model performance, similar to satellite-derived hybrid $LE$ models, for 12 EC towers located in grasslands and croplands over a three-year period using monthly averages of hourly data. However, significant bias was identified for the growing season (summer). In contrast, the proposed hybrid $LE$ models achieved relatively low performance for most forest sites because rising groundwater levels due to the ecological water diversion project (EWDP) induced $LE$...
changes and the models did not consider groundwater effects on LE (Zhou et al., 2018). Vegetation transpiration can extract groundwater from the rooting zone down to tens of meters or more when available soil water is low (Wang and Dickinson, 2012). For example, LE for the forested area (in the middle of the study region), which had high groundwater level, was higher than that in lower areas where vegetation degradation was associated with artificial canals (Hu et al., 2015b).

Generally, LE_SM models achieved superior statistical agreement to observation compared with LE_RH and LE_DT models, which had relatively close agreement. However, LE_SM achieved lower accuracy compared with both LE_RH and LE_DT for Mixed forest and Populus forest sites, because SM was not the main LE controlling factor. Previous studies have shown that RH was more closely related to evaporation fraction (EF) than SM for several biome (Yan and Shugart, 2010). García et al. (2013) also found that SM was the most sensitive constraint for energy driven LE models, contributing 22% to estimated LE uncertainty.

Satellite derived hybrid LE model bias was likely due to the following reasons. First, EC measurements have approximately 5–20% error (Foken, 2008; Glenn et al., 2008) and gap filling from half hourly data to daily means also adds approximately 5% error (Hui et al., 2004). EC measurements also have energy imbalances and we corrected LE using the Twine et al. (2000) method in this study; but, errors due to these effects remain unclear (Shuttleworth, 2007). Second, MODIS NDVI and tower footprints were not matched, hence vegetation signals at flux towers could significantly differ from those within the MODIS footprint (Xiao et al., 2010). Third, cloud cover caused significant missing daily NDVI, hence 16 day NDVI may not always represent valid average environmental conditions and fluxes over the period, causing LE underestimation or overestimation (Xiao et al., 2008). Finally, independent variables included in the model did not consider potentially significant other factors, e.g. wind speed or CO2 levels, which could potentially reduce LE estimation errors by 5–10% (Idso and Braelz, 1984; McVicar et al., 2012).

4.2. Regulators impacts on model performance

Available energy, air temperature, and moisture demand were been considered as the three most important regulators controlling LE. The satellite-derived hybrid LE models correlated strongly with $R_{n}$ because it represents the energy available to drive surface evaporation and vegetation transpiration, which varies with spatiotemporal LE variation in terrestrial ecosystems (Wang and Dickinson, 2012). However, $R_{n}$ exerts greater influence on energy limited water yielding than water limited catchments (McVicar et al., 2012). Air temperature ($T_{a}$) is another key factor in determining LE for most ecosystems, particularly in alpine regions. Previous studies have shown that transpiration shows significant linear correlation with $T_{a}$ in desert riparian forest and other extreme arid regions (Si et al., 2007). The present study confirmed high correlation between $LE$ and $T_{a}$ in HRR. Additionally, we used NDVI to develop the hybrid models because it can characterize spatial vegetation moisture variability. LE is significantly modulated by available water and vegetation canopy characteristics characterized by NDVI for unsaturated soil and vegetation surfaces with limited water supply (Fisher et al., 2008; Wang and Liang, 2008; Wang et al., 2010). Therefore, the hybrid LE models improved LE simulation accuracy by integrating satellite-derived vegetation parameters (NDVI).

Three variables (SM, RH, and DT) were used to parameterize SM constraints for the hybrid LE models. For hybrid model parameterized by SM, SM is directly used to optimize SM constraints. The SM in this study from ground observation covered 0–5 cm and ESA CCI SM generally covers layer depth as 0.5–2 cm, but SM from deeper soil layers contributed to water energy processes, which may be another reason for underestimated the Mixed forest and DBF (Populus forest). Previous studies have shown explicit SM functions from different soil layers to be useful in parameterizing LE moisture controls (Jin et al., 2011; Brutsaert, 2005; Chen and Dudhia, 2001; Miralles et al., 2011). However, they cannot be applied when SM from different soil layers is unavailable. The proposed hybrid LE models parameterized by different SM constraints were complementary to other complicated approaches.

The proposed hybrid model used RH to characterize SM constraint based on the complementary Bouchet (1963) hypothesis, where surface moisture status was linked to and reflected atmospheric evaporative demands (Fisher et al., 2008; Yao et al., 2015; Yan and Shugart, 2010). Similarly, the hybrid models parameterized by DT used simplified apparent thermal inertia (ATI) characterized by temperature change, because ATI reflects surface SM variation (Zhang et al., 2003). However, RH and DT used in the hybrid models include uncertainties for optimizing SM constraints. First, they only account for effects due to air moisture concentration and atmospheric evaporation demand, ignoring surface SM supply impacts. Second, they are not good indicators for SM spatial heterogeneity across the landscape (Yao et al., 2017a). Therefore, SM constraint noise (SM, RH, or DT) will reduce hybrid LE model performance due to the complicated relationship between SM and soil evaporation. Future research will consider other biophysical variable influences on SM constraints for different biomes.

4.3. Regional LE estimation differences using different soil moisture constraints

Spatial differences among LE_SM, LE_RH, and LE_DT were much greater than those for regional mean values. The large discrepancies may be attributed to differences in water constraint parameterization for the model. Fig. S7 shows an example spatial distribution for interpolated daily SM derived from the ESA CCI dataset, with RH and DT derived from reanalysis data for June 2013–2015 at 1 km spatial resolution. SM, RH, and DT had similar spatial distribution patterns reflecting surface moisture variations, although spatial distributions in Northwestern HRB exhibited small differences. Different SM constraint parameterizations could impact the simulation by partitioning surface energy flux differently (Robock et al., 2003; Wang and Liang, 2008).

Aside from SM constraint effects on LE, biases and discrepancies in regional LE estimates among LE_SM, LE_RH, and LE_DT could be attributed to the following reasons. First, ESA CCI SM biases may influence hybrid LE model accuracy, which would lead to estimated LE discrepancies among LE_SM, LE_RH, and LE_DT. For example, we found ESA CCI SM underestimated SM compared to ground measurements at Arou site (Fig. S8) (Wang et al., 2018). Thus, ESA CCI SM product biases could have introduced substantial uncertainties into LE estimates. Second, although all gridded products were interpolated to 1 km at the regional scale, error propagation through averaging and interpolation could have affected biases and discrepancies in different LE estimates. For example, three downscaling methods (bilinear interpolation, Kriging interpolation, and Bayesian maximum entropy) for interpolating ESA CCI SM data with 0.25° spatial resolution to 1 km resolution generate 12%, 13%, and 15% LE estimation error, respectively. Finally, the regional $R_{n}$ algorithm derived from gridded data could also introduced LE estimation errors and discrepancies in regional LE estimates among LE_SM, LE_RH, and LE_DT. The algorithm considers NDVI and RH influences, which are also included in the satellite derived hybrid LE models. Thus, RH effects on LE are greater than both DT and SM. Further work is required to compare and explain differences between hybrid model estimate LE and other LE products.

5. Conclusion

The goal of this study was to develop a suitable satellite-derived hybrid LE model to estimate terrestrial LE in the Heihe River Basin of Northwest China, and to assess model performance and sensitivity parameterized by three soil moisture constraints: SM, RH and DT. The hybrid LE model was trained using observed LE over 2012/2013–2014, and validated using observed LE for 2015 and leave-one-out cross-
validation. We also estimated regional LE in HRR using the resulting LE_SM, LE_RH, and LE_DT models. Validation results showed LE model differences across the 12 selected flux tower sites, incorporating different land cover types. From the three SM constraint schemes investigated, LE_SM achieved the highest accuracy in terms of spatial variation compared with LE_RH and LE_DT. A satellite-derived hybrid model using three SM constraints may be the most feasible approach to estimate terrestrial LE for different biomes, since SM, RH, and DT could potentially determine LE/R, variants for various land cover types. Regional LE estimation showed large spatial variability for LE estimates along with strong seasonal and annual variations, reflecting climate conditions and vegetation distributions controlling effects. The large discrepancies may be attributed to differences in water content parameterization within the models. To refine a satellite-derived hybrid model by coupling empirical models and process-based models for improving regional terrestrial LE, further work is required to compare and explain differences between hybrid model derived-LE and other LE products.

Declaration of competing interest

The authors declare they have no conflicts of interest.

Acknowledgements

We thank Dr. Xinhong Xie from Faculty of Geographical Science, Beijing Normal University, China for their suggestions to improve this manuscript. We also thank International Science Editing (http://www.internationalscienceediting.com) for editing this manuscript. We also thank International Science Editing (http://www.internationalscienceediting.com) for editing this manuscript. We gratefully acknowledge Kun Yang Institute of Tibetan Plateau Research, Chinese Academy of Sciences, and Bo Jiang from Beijing Normal University for providing gridded meteorological and satellite data. The forced dataset used in this study was developed by Data Assimilation and Modeling Center for Tibetan Multi-spheres, Institute of Tibetan Plateau Research, Chinese Academy of Sciences and this data set is provided by Environmental & Ecological Science Data Center for West China, National Natural Science Foundation of China. Eddy covariance ground-measurements of surface heat fluxes and corresponding meteorological data across HRR were provided by WATER and HIWATER experiments (http://www.heihedata.org/data). We would like to address our appreciation for the PI’s and staff that are working on these sites. This work was partially supported by the Strategic Priority Research Program of the Chinese Academy of Sciences (No. XDA20100101), the Natural Science Fund of China (No. 41671331) and the National Key Research and Development Program of China (No. 2016YFA0601002 and No. 2017YFC0406002). JBF contributed to this paper from the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration. California Institute of Technology. Government sponsorship acknowledged. JBF was supported in part by the NASA SUSMAP program.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2019.133787.

References
