Article

A Comparison of SSEBop-Model-Based Evapotranspiration with Eight Evapotranspiration Products in the Yellow River Basin, China

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Received: 16 July 2020; Accepted: 3 August 2020; Published: 6 August 2020

Abstract: Accurate evapotranspiration (ET) estimation is important in understanding the hydrological cycle and improving water resource management. The operational simplified surface energy balance (SSEBop) model can be set up quickly for the routine monitoring of ET. Several studies have suggested that the SSEBop model, which can simulate ET, has performed inconsistently across the United States. There are few detailed studies on the evaluation of ET simulated by SSEBop in other regions. To explore the potential and application scope of the SSEBop model, more evaluation of the ET simulated by SSEBop is clearly needed. We calculated the SSEBop-model-based ET ($ET_{SSEBopYRB}$) with land surface temperature product of MOD11A2 and climate variables as inputs for the Yellow River Basin (YRB), China. We also compared the $ET_{SSEBopYRB}$ with eight coarse resolution ET products, including China ET_{MTE} , produced using the upscaling energy flux method; China ET_{CR} , which is generated using the non-linear complementary relationship model; three global products based on the Penman–Monteith logic (ET_{PMLv2} , ET_{MODIS} , and ET_{BESS}), two global ET products based on the surface energy balance (ET_{SEBS} , $ET_{SSEBopGlo}$), and integrated ET products based on the Bayesian model averaging method (ET_{GLASS}), using the annual ET data derived from the water balance method (WB-ET) for fourteen catchments. We found that $ET_{SSEBopYRB}$ and the other eight ET products were able to explain 23 to 52% of the variability in the water balance ET for fourteen small catchments in the YRB. $ET_{SSEBopYRB}$ had a better agreement with WB-ET than ET_{SEBS} , ET_{MODIS} , ET_{CR} , and ET_{GLASS} , with lower RMSE (88.3 mm yr^{−1} vs. 121.7 mm yr^{−1}), higher R² (0.49 vs. 0.43), and lower absolute RPE (−3.3% vs. −19.9%) values for the years 2003–2015. We also found that the uncertainties of the spatial patterns of the average annual ET values and the ET trends were still large for different ET products. Third, we found that the free global ET product derived from the SSEBop model ($ET_{SSEBopGlo}$) highly underestimated the annual total ET trend for the YRB. The poor performance of the land surface temperature product of MOD11A2 in 2015 caused the large $ET_{SSEBopYRB}$ uncertainty at eight-day and monthly scales. Further evaluation of ET based on the SSEBop model for site measurements is needed.

Keywords: evapotranspiration; operational simplified surface energy balance model; Yellow River Basin

1. Introduction

Evapotranspiration (ET) is an essential water flux that connects the soil, vegetation, and atmosphere. The estimation of ET helps us understand the hydrological cycle, improve water resource management [1], and enhance decision support [2], especially in water-limited areas, where water resource competition among agriculture, the social economy, and the environment is more intense [3,4].

Although it is difficult to accurately calculate ET due to the spatial heterogeneity and complex processes involved at regional and global scales [5], there are many methods for estimating ET, which can be categorized into seven main groups: (1) field observations; (2) coupled-process models [6]; (3) remote sensing [7,8]; (4) the meteorologically-based complementary relationship methods [9]; (5) water-balance-based methods [10]; (6) empirical formulae [11]; and (7) machine learning [12]. Surface energy balance algorithms based on remote sensing images are widely used to estimate ET [13–16]. The operational simplified surface energy balance (SSEBop) model was specifically designed to monitor long-term ET using minimum remote sensing and weather inputs, and has clear advantages over other thermal ET models in terms of operational uses [17]. Although the designation of SSEBop as a surface energy balance model has been criticized due to not resolving the full surface energy balance components [17], it has been successfully used to estimate wheat ET [18], soybean ET [19], and sorghum ET [20], separating blue and green water resources of the coterminous United States (CONUS) [21]; water stress [22]; and long-term regional ET estimates in the whole CONUS [8], the southwestern United States [23], the Midwestern United States [24], the Colorado River Basin of the United States [25], the Nile Basin of Africa [26,27], the Mara Basin of East Africa [28], the arid region of Chile [29], and Ethiopia [30], Landsat images and moderate-resolution imaging spectroradiometer (MODIS) datasets as inputs.

Extensive evaluation of ET estimates is necessary before they are used in various applications [31]. A comprehensive evaluation of SSEBop and MODIS ET over the CONUS indicated that SSEBop showed better performance for grassland and forest classes and effectively reproduced the basin-scale ET response [31]. Singh et al. (2013) estimated the Colorado River Basin ET by applying Landsat images and SSEBop, finding that the SSEBop model captured the annual ET variability well at the site level and sub-basin level [25]. Other research has also reported that the SSEBop model performed well over the CONUS, with an R^2 of 0.86 between the estimated ET and the ET of 42 flux tower sites from 2001 to 2007 [32]. In the Midwestern United States, the validation of estimated ET by SSEBop using Landsat images captured the spatial and temporal variations in ET, with a low root mean square error and high R^2 . However, SSEBop was consistently the worst-performing model among SEBAL, METRIC, S-SEBI, SEBS, and SSEBop, and it overestimated ET at all sites when estimating humid southeastern United States ET by Landsat imaging from 2000 to 2010 [33], indicating its limited applicability in the southeastern US. A sensitivity research of SSEBop ET in the CONUS demonstrated that the SSEBop model was most sensitive to the land surface temperature, reference ET, differential temperature, and maximum ET scalar [32]. Therefore, the accuracy of the ET derived from the SSEBop model varies from place to place depending on the accuracy of the input parameters, including climate data and calibration data [30], indicating that the magnitude and annual trend of ET are still uncertain [34]. The validation and application of SSEBop have been concentrated on the CONUS. There is a clear need to evaluate ET derived from SSEBop in other regions, such as China and Europe, to reduce uncertainty in terms of the regional ET variation and to prioritize studies of the water cycle, land-atmosphere interactions, and water management [35,36].

The estimation of ET in arid and semiarid areas in China has attracted increasing attention [15,37–41]. For example, Yang et al. (2012) applied the surface energy balance algorithm for land (SEBAL) model in the Hetao area to examine the spatial and temporal patterns of ET [15]. Feng et al. (2012) constructed a semiempirical monthly ET model in the Loess Plateau region using watershed streamflow data [39]. Xu et al. (2018) used the water balance method to estimate the ET of the upper reaches of the Yellow River Basin from 1960 to 2014 [40]. Bai et al. (2019) investigated the ET

trends from 2000 to 2016 and related them to interannual climatic variability and vegetation greening in the Yangtze River Basin by using the process-based vegetation interface processes ecohydrological model [38]. Yuan et al. (2018) used the common land model to estimate the Xinjiang ET under two representative concentration pathway scenarios during the period of 2021–2050 [41]. Xiong et al. (2019) adopted the three-temperature model to estimate the ET in a heterogeneous oasis in northwestern China, and the mean absolute percent error values of the ET ranged from 9% to 25% over different landscapes [37]. The validation of ET derived from SSEBop in the semiarid basin of the Yellow River Basin (YRB) of China has not been done. A series of ecological restoration projects (e.g., Grain to Green Program) have been implemented since 2000 in the YRB, which have altered the hydrological cycle [42]. The long-term accurate estimation of ET in the YRB will help the government evaluate the results of the ecological restoration projects, assess the water resource carrying capacity, and adjust the future ecological recovery strategy.

Therefore, the main objective of this study is to evaluate the SSEBop model in the YRB (hereafter $ET_{SSEBopYRB}$). The $ET_{SSEBopYRB}$ will be evaluated using water balance ET across the YRB. In addition, we compare the SSEBop ET performance against eight widely used coarse resolution ET products (500 m $\sim$ 0.1°). Finally, the uncertainty of $ET_{SSEBopYRB}$ is discussed from the perspective of the model input, model parameters, and validation method. This research is expected to reduce regional ET uncertainty.

2. Materials and Methods

2.1. Study Area

The Yellow River is the main source of water in northwestern and northern China. The YRB, a semiarid basin, is located between 95°E–119°E and 32°N–42°N, covering an area of approximately $7.95 \times 10^5 \text{ km}^2$ (Figure 1). The annual precipitation ranges from 140 mm yr^{-1} in the north to 1100 mm yr^{-1} in the east of the YRB, with an average value of 495.6 mm yr^{-1} . Precipitation is concentrated in the summer months. The irrigation agriculture is developed, and there are four major irrigation areas along the Yellow River. In the midstream of the region, the ecological environment is fragile and land degradation is severe [43]. A series of ecological restoration projects have been implemented, such as nature reserves, the Three-North Shelterbelt, and the Grain to Green Program, of which the area covered by the Grain to Green Program is the largest among all of the ecological restoration programs [44].

Figure 1. Study area: location, elevation, meteorological stations, and hydrological stations.

2.2. Data Sources

2.2.1. MODIS Data

Sixteen-day interval normalized vegetation index (NDVI) images (MOD13A2 and MYD13A2 version 6 (V6) products) and 8-day interval land surface temperature (LST) images (MOD11A2 and MYD11A2 version 6 (V6) products) with a spatial resolution of 1 km covering the whole YRB were downloaded from the Level-1 and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC) website (<https://ladsweb.modaps.eosdis.nasa.gov/>). MOD11A2 and MOD13A2 were produced from the Aqua satellite images during the years 2003–2015, while MYD11A2 and MYD13A2 were produced from Terra satellite images during the years 2003–2015. To simplify processing, we defaulted the 16-day NDVI values in MOD13A2 and MYD13A2, which occur in the median day. Over the short time period, there are small changes in NDVI. “Day of year VI pixel” provides the date of the NDVI value, which appears within 16 days. Therefore, we can avoid large errors by setting the date when the 16-day interval NDVI value appears in the middle, and do not use “day of year VI pixel”. “Quality reliability of VI pixel” provides the quality of the pixel. In time series, we first used the Savitzky–Golay filtering to process the 23-period NDVI to obtain a new NDVI time series. For the new NDVI time series, we replaced the pixel values of the corresponding positions in the new time series with the high-quality pixel values of the original time series. The time resolution doubling algorithm [45] was used to fuse MOD13A2 and MYD13A2 during the years 2003–2015 to produce 8-day interval NDVI products. The missing values in MOD11A2 and MYD11A2 were filled by the adaptive window method [46], which constructs the relationship between the valid LST and NDVI, temperature, and elevation ($LST \sim NDVI + Temperature + elevation$), and uses the relationship to calculate the no data values in LST.

2.2.2. Meteorological Data

Daily meteorological data, including the atmospheric pressure (pa), temperature (°C) at a height of 2m (maximum temperature (°C), minimum temperature (°C) and mean temperature (°C)), wind speed ($m s^{-1}$) at a height of 10 m, sunshine hours (hour), and relative humidity (%) from 2003 to 2015, were collected from the website of the National Meteorological Administration of China (<http://data.cma.cn>). The daily meteorological data were subjected to a good quality control via the website of the National Meteorological Administration of China. The quality control method includes: (1) valid range check; (2) extreme inspection of stations; (3) internal consistency check between the timing value, daily average value, and daily extreme value; (4) time consistency check; and (5) spatial consistency check. The total meteorological station number of sites is 163, distributed inside and around the YRB (Figure 1). The daily weather data were aggregated into an 8-day interval weather dataset using an averaging method. Combining climatologic and topographic data, the point climate data were interpolated at a 1-km resolution covering the whole YRB, using the thin-plate smoothing spline method provided in the ANUSPLIN 3.1 program [47–49]. The interpolated climate raster were used to calculate reference evapotranspiration by the Penman-Monteith equation [50].

2.2.3. ET Products

Given the scale of the basins in this paper, eight ET products with spatial resolutions higher than 0.1° (listed in Table 1) were collected to compare with $ET_{SSEBopYRB}$. The algorithms used to produce eight ET products cover the mainstream ET estimation methods. The information about the time period, spatial resolution, data source, and spatial coverage of each ET product is listed in Table 1. Since the common time period for the ET products selected in this paper was 2003–2015, we took 2003–2015 as the time period for ET evaluation.

Table 1. Basic information about each evapotranspiration (ET) product.

Name	Time Period	Method	Resolution	Data Source
ET _{MTE}	1982–2015	Upscaling	0.1°/month	Li et al. 2018
ET _{CR}	1982–2015	CR	0.1°/month	http://www.tpedatabase.cn
ET _{MODIS}	2001–2019	RS-PM	500 m/8 days	https://modis.gsfc.nasa.gov/data/dataproduct/mod16.php
ET _{SSEBopGlo}	2003–2019	SEB	1 km/month	https://earlywarning.usgs.gov/
ET _{BESS}	2001–2015	RS-PM	1 km/8 days	http://environment.snu.ac.kr/
ET _{SEBS}	2001–2016	SEB	0.05°/day	http://www.tpedatabase.cn
ET _{GLASS}	2001–2015	BMA	0.05°/8 days	http://www.geodata.cn
ET _{PMLV2}	2002–2018	RS-PM	0.05°/8 days	http://www.tpdac.ac.cn/

Note: MTE = model tree ensemble. BESS = breathing earth system simulator. SEBS = surface energy balance system. GLASS = Global Land-Surface Satellite. PMLV2 = Penman–Monteith –Leuning model version 2. SEB = surface energy balance. CR = complementary relationship. RS = remote sensing. PM = Penman–Monteith equation. BMA = Bayesian model average. ET = evapotranspiration.

The ET_{MTE} is a china ET product that is produced by the upscaling method of a model tree ensemble with four kinds of data inputs: (1) remote sensing data of NDVI 3 g; (2) the eddy covariance technique observing ET data at 36 sites covering forest, shrub-land, grassland, wetland, and cropland; (3) the climate data for surface air temperature, precipitation, incoming solar radiation, and relative humidity; and (4) the vegetation distribution map [34]. The validation results showed that this product can capture ET well for nine different vegetation types. Compared with the global data-driven ET product [12], this product is less uncertain in China due to the use of more China flux tower data.

The ET_{CR} is the China ET product that is estimated using the calibration-free nonlinear complementary relationship (CR) model, with climate variables (air and dew-point temperatures at a height of 2 m, wind speed at a height of 10 m, downward shortwave and downward longwave solar radiation) and remote sensing data (monthly land surface temperature, longwave broadband emissivity, and land surface albedo from MODIS) inputs [51]. Validation results from the 13 eddy covariance measurements and water-balance-derived ET for 10 major river basins showed that this product was reliable in China [51].

The ET_{MODIS} is the global ET product that is based on the Penman–Monteith equation [52]. It is composed of information for the vegetation transpiration, soil evaporation, and evaporation from the wet canopy surface. The data inputs of ET_{MODIS} are land cover (MOD12Q1), FPAR/Leaf area index (MOD15A2H), albedo (MOD43C1), and global Modern-Era Retrospective Analysis for Research and Applications (MERRA) meteorological data provided by the NASA Global Modeling and Assimilation Office (GMAO). This product has been applied in many regions [2,53]. Some studies have reported the shortcomings of ET_{MODIS}, such as underestimating the ET of farmland [31,54].

The ET_{BESS} is the global ET product that is produced using the simplified process-based model of the breathing earth system simulator (BESS), which can couple atmosphere and canopy radiative transfers, photosynthesis, and ET. The BESS adopts a quadratic form of the Penman–Monteith (PM) equation to calculate the two-leaf canopy latent heat flux [6]. Seven MODIS atmosphere (collection 6 MOD04_L2 aerosol, MOD06_L2 cloud, and MOD07_L2 atmosphere profile) and land (collection 5 MCD12Q1, MOD11A1, MOD06_L2, MCD15A2, and MCD43B3) products, four other satellite datasets, four reanalysis datasets, and three ancillary datasets were the input data for ET_{BESS}. At the site scale, ET_{BESS} agreed with FLUXNET observations, with $R^2 = 0.67$, and captured the majority of the seasonal variability [55].

ET_{PMLV2} is the global ET product that is based on the Penman–Monteith –Leuning model version 2. The main focus of the PM-based method is the accurate estimation of surface conductance (Gs), which describes the canopy–soil conductance to the water flux. Leuning et al. (2008) [56] and Zhang et al. (2010) [57] developed the biophysical model for Gs to account for canopy physiological processes and soil evaporation (resulting in PMLv1). Gan et al. (2018) [58] coupled vegetation transpiration

with gross primary productivity using a biophysical canopy conductance (G_c) model in the PML model (resulting in PMLv2). Zhang et al. applied the PMLv2 model [59] at the global scale with 0.25° resolution and 3-h Global Land Data Assimilation System (GLDAS-2.1 meteorological data, monthly atmospheric (CO_2) concentration, LAI (MCD15A3H), albedo (MCD43A3), and surface emissivity data (MOD11A2) inputs. The ET_{PMLV2} method is well-calibrated against 8-day EC ET at 95 widely distributed flux towers for ten plant functional types [59].

Two global ET products based on the surface energy balance method were released by Senay et al. (2013) [17] and Chen et al. (2019) [60]. The former is based on the SSEBop model (hereafter $ET_{SSEBopGlo}$) with the inputs of model-assimilated weather datasets and MODIS thermal images, while the latter is based on the surface energy balance system (hereafter ET_{SEBS}) with a column canopy–air turbulent diffusion method [60].

Considering that a single process-based algorithm cannot characterize global ET well, the Bayesian model averaging method was used to merge five process-based algorithms (hereafter ET_{GLASS}), including the MODIS latent heat flux product algorithm, the revised remote-sensing-based PM LE algorithm [61], the Priestley–Taylor-based LE algorithm [62], the modified satellite-based Priestley–Taylor LE algorithm [63], and the semiempirical Penman LE algorithm [64], to reduce the ET estimate uncertainty [65]. The production process of ET_{GLASS} is based on the Global Land-Surface Satellite (GLASS) data.

2.2.4. Regional Database for ET Model Evaluation

Annual ET evaluation data from 2003 to 2015 were derived from the water balance approach (annual ET is the difference in annual precipitation and annual streamflow, ignoring the soil water storage change). Because the streamflow of the fourteen catchments (Figure 1) is dominated by surface runoff, annual changes of soil water and groundwater are not likely to be large [39]. Therefore, ignoring the soil water storage change does not cause large water balance ET uncertainty in these catchments. Water balance ET (hereafter WB-ET) is an ordinary practice and a reliable method used to estimate basin-scale ET when streamflow and precipitation are accessible [10]. The annual streamflow of each hydrological site came from the Chinese Annual Hydrographic Yearbook of the Yellow River Basin (<http://www.mwr.gov.cn/>). The information on the 14 hydrological sites (total 182 samples) used for ET evaluation is listed in Table 2. The spatial distribution of the sites and the watershed extent are shown in Figure 1. The watershed boundaries are from previous studies [39,66]. The annual precipitation dataset was produced using ANUSPLIN3.1 to interpolate 507 precipitation points within and around the YRB (Figure A4). In addition, we also collected three other precipitation datasets, including Tropical Rainfall Measuring Mission satellite precipitation data (TRMM3b42), which were derived from remote sensing satellite [67], reanalysis data of Climatic Research Unit (CRU) [68], as well as the precipitation product of the China meteorological forcing dataset (CMFD) [69], in order to analyze the uncertainty of WB-ET.

Table 2. Hydrological characteristics of catchments for model validation.

Hydrological Station	Station Location	Catchment Area (km ²)	Annual Runoff (10 ⁸ m ³)	Annual Precipitation (mm)
DaNing	110.71 E, 36.46 N	4186	0.84	514
DingJiaGou	110.25 E, 37.55 N	41948	6.70	339
GanGuYi	109.8 E, 36.7 N	5857	1.51	482
GaoJiaChuan	110.48 E, 35.56 N	4955	2.14	378
GaoShiYa	111.13 E, 38.93 N	1260	0.18	399
Hejing	110.8 E, 35.56 N	39186	5.07	486
HuangFu	111.08 E, 39.28 N	3230	0.36	375
ShenJiaWan	110.48 E, 38.03 N	1138	0.33	405
SuiDe	110.23 E, 37.5 N	3861	1.07	416
WenJiaChuan	110.75 E, 38.43 N	8621	2.17	373
YanChuan	110.18 E, 36.8 N	2095	0.98	458
ZhangJiaShan	108.6 E, 34.63 N	43106	10.32	484
ZhuangTou	109.83 E, 35.03 N	25645	0.21	519

2.3. Methods

2.3.1. Framework of the Assessment of $ET_{SSEBopYRB}$

Figure 2 shows the framework for evaluating $ET_{SSEBopYRB}$, which includes the input and output of the SSEBop model, evaluation of $ET_{SSEBopYRB}$ with water balance ET, comparison between $ET_{SSEBopYRB}$ and available eight ET products, and the uncertainty analysis of $ET_{SSEBopYRB}$.

Figure 2. The framework of the assessment of $ET_{SSEBopYRB}$ in the YRB during the years 2003–2015.

2.3.2. SSEBop Model

In previous surface energy balance methods (e.g., SEBAL), the ET is the residual of the energy balance terms ($\lambda ET = R_n - H - G$, where H is the sensible heat ($\text{MJ m}^{-2} \text{ day}^{-1}$), G is the soil heat ($\text{MJ m}^{-2} \text{ day}^{-1}$), R_n is the net radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$), and λ is the latent heat of evaporation of water). Among the four variables, the calculation process of H is complicated and especially depends on the setting of cold pixels and hot pixels. The SSEBop model assumes that the surface energy balance process is mostly driven by the available net radiation (R_n), and a decline in ET due to water stress and other factors can be quantified by differences in land surface temperature [8]. SSEBop directly estimates pixel-based ET by multiplying the ET fraction (ET_f) and reference ET (ET_o).

$$ET_a = ET_f \times k_{mas} \times ET_o \quad (1)$$

where k_{max} is a coefficient that scales the grass reference ET into the level of a maximum ET experienced by an aerodynamically rougher crop; ET_o is the grass reference ET (mm day^{-1}), which is calculated using the revised PM equation in YRB [50,70].

$$ET_o = \left[0.408 \Delta (R_n - G) + \gamma \frac{900}{T_{em} + 273} u_2 VPD \right] / [\Delta + \gamma (1 + 0.34 u_2)] \quad (2)$$

where Δ is the slope of the vapor pressure curve ($\text{kPa } ^\circ\text{C}^{-1}$), γ is the psychrometric constant ($\text{kPa } ^\circ\text{C}^{-1}$), T_{em} is the mean daily air temperature ($^\circ\text{C}$) at a height of 2 m, u_2 is the wind speed

at a height of 2 m (m s^{-1}), and VPD is the water vapor pressure difference (kPa). ET_f is calculated as follows:

$$ET_f = [(T_h - T_s) / (T_h - T_c)] \quad (3)$$

where T_s is the eight-day average satellite-observed LST of the pixel (K), T_h is the estimated T_s at the idealized reference “hot-dry” limit of the same pixel for the same time period, and T_c is the estimated T_s at the idealized “cold-wet” limit of the same pixel. The minimum ET_f is set to 0.09, the maximum ET_f is 1.05, and the ET_f exceeding 1.3 is considered to be a pixel with cloud pollution and is set to “no data”. The “no data” is filled through temporal interpolation [17]:

$$T_c = c \times T_a \quad (4)$$

$$c = (T_{s_cold} / T_a) \quad (5)$$

where T_a is the eight-day average near-surface maximum air temperature (K), c is a correction factor that relates T_a to T_{s_cold} ; T_{s_cold} is the eight-day average LST on a well-watered, fully transpiring vegetation surface; T_{s_cold} is obtained on all pixels where NDVI is greater than or equal to 0.8. If no pixels in an image in a certain period meet the NDVI conditions, the c value of that image is the median value of the effective c value within one year:

$$T_h = T_c + dT \quad (6)$$

where dT is a predefined temperature difference (K) between T_h and T_c for each pixel. The minimum value of dT is recommended as 6 K, which can reduce the ET uncertainty in cold climates [17]:

$$dT = (R_{n,cs} \times r_{ah}) / (\rho_a \times C_p) \quad (7)$$

where r_{ah} is the aerodynamic resistance to heat flow from a hypothetical bare and dry surface (110 s m^{-1}), ρ_a is the air density (kg m^{-3}), C_p is the specific heat of the air at constant pressure ($\sim 1.013 \text{ kJ kg}^{-1} \text{ K}^{-1}$), and $R_{n,cs}$ is the clear-sky net radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$), which is estimated using the series of equations in [50]:

$$R_{n,cs} = R_{ns} - R_{nl} \quad (8)$$

$$R_{ns} = (1 - \alpha) \times R_s \quad (9)$$

$$R_s = (0.75 + 2 \times 10^{-5} \times z) R_a \quad (10)$$

$$R_{nl} = \sigma \times \left(\frac{T_{max}^4 + T_{min}^4}{2} \right) \times (0.34 - 0.14 \sqrt{ea}) \quad (11)$$

where R_{ns} and R_{nl} are the clear sky net shortwave radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$) and clear sky longwave radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$); α is the surface albedo, which is set to 0.23 in this study; R_s and R_a are the clear sky incoming solar radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$) and extraterrestrial radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$); z is the elevation (m); σ is the Stefan–Boltzmann constant ($4.9039 \times 10^{-9} \text{ MJ K}^{-4} \text{ m}^{-2} \text{ day}^{-1}$). T_{max} and T_{min} are the air maximum and minimum temperatures (K), and ea is the actual vapor pressure (kPa). More details about R_a and ea can be found in [50].

The difference between the SSEBop model and other energy balance models is that it predefines a differential temperature (dT) as two extreme limiting surface temperatures—a cold temperature (T_c) for little or no sensible heat flux and hot temperature (T_h) for little or no latent heat flux, eliminating the subjectivity that could be introduced during manual hot and cold reference selection. More detailed information about the calculation process for SSEBop can be found in [8,17]. This study mainly used MOD11A2 and climate datasets to drive the SSEBop model to estimate the ET of the YRB.

2.3.3. Trend Analysis

We conducted linear regression based on the least squares method to detect the trend for annual ET. The regression coefficient was used as the annual ET change rate:

$$b = \frac{\sum_{i=1}^{13} (ET_i - \overline{ET})(y_i - \bar{y})}{\sum_{i=1}^{13} (ET_{yi} - \overline{ET})^2} \quad (12)$$

where i is the sequential year range (2003–2015), ET_i is the annual ET in the year y_i , and $\overline{ET}$ and $\bar{y}$ are the mean values. A positive or negative value predicts an increased or decreased rate of annual water yield. If the regression coefficient passes through the significance test (F test, $p < 0.05$), it shows a significant ascending or descending trend [71,72].

2.3.4. Performance of Estimated ET

Commonly used hydrological model evaluation metrics such as the coefficient of determination (R^2), root mean square error (RMSE), and relative percent error (RPE) [13] are used in this paper. The formula of RPE is as follows:

$$RPE = [(X - Y) / Y] \times 100 \quad (13)$$

where X is the simulated ET and Y is the observed ET. The closer the RPE (%) is to 0, the smaller the difference between the average of the observed and simulated values.

3. Results

3.1. Evaluation of SSEBopYRB-ET on a Basin Scale

$ET_{SSEBopYRB}$'s estimated annual ET performance for 14 small watersheds was lower than $ET_{SSEBopGlo}$ from the RMSE (88.30 mm yr⁻¹ vs. 82.59 mm yr⁻¹) and R^2 (0.49 vs. 0.52) values (Figure 3). $ET_{SSEBopGlo}$ overestimated 3.01% of the annual WB-ET, while $ET_{SSEBopYRB}$ underestimated 3.38% of the annual WB-ET. Compared with the ET_{SEBS} , ET_{MODIS} , ET_{CR} , and ET_{GLASS} , $ET_{SSEBopYRB}$ had better performance when estimating the annual WB-ET, with a higher R^2 , lower RMSE, and lower absolute RPE. ET_{MODIS} , ET_{SEBS} , and ET_{CR} highly underestimated the annual WB-ET, with RPE values of -19.97%, -28.73%, and -26.54%, respectively, while ET_{GLASS} highly overestimated annual WB-ET (44.59%). As a widely used product, ET_{MODIS} could only explain 37% of the annual WB-ET variability and had a much higher RMSE (121.75 mm yr⁻¹ vs. 88.30 mm yr⁻¹) than $ET_{SSEBopYRB}$. ET_{MTE} and ET_{PMLV2} had lower RMSE values than $ET_{SSEBopYRB}$, but had smaller R^2 and higher absolute RPE values than $ET_{SSEBopYRB}$. ET_{BESS} had a lower RMSE (79.01 mm yr⁻¹ vs. 88.30 mm yr⁻¹) than $ET_{SSEBopYRB}$, but ET_{BESS} underestimated 11.62% of the annual WB-ET.

Figure 3. Evaluation of the annual ET at fourteen small catchment sites in $ET_{SSEBopYRB}$ and evaluation of eight other ET products during 2003–2015. The blue line is the fitted line and the black line is the 1:1 line.

We also evaluated $ET_{SSEBopYRB}$ and the other eight ET products from the perspective of the multiyear average ET using the multiyear average WB-ET on 14 small watersheds (total 14 samples). The result showed that $ET_{SSEBopYRB}$ performed better than six (ET_{SEBS} , $ET_{SSEBopGlo}$, ET_{GLASS} , ET_{CR} , ET_{MODIS} , and ET_{MTE}) out of the eight ET products (Table 3). The R^2 , RMSE, and RPE values for $ET_{SSEBopYRB}$ were 0.85, 60.09 mm yr⁻¹, and -3.38%, respectively, indicating that there is good agreement between $ET_{SSEBopYRB}$ and WB-ET on a multiyear scale. The R^2 of $ET_{SSEBopYRB}$ was slightly lower than that of ET_{BESS} (0.87 vs. 0.85), but the RPE for ET_{BESS} was higher than for $ET_{SSEBopYRB}$. Although the RMSE for ET_{PMLv2} was lower than $ET_{SSEBopYRB}$, ET_{PMLv2} could only explain 69% of the WB-ET variability, which was lower than $ET_{SSEBopYRB}$.

Table 3. Evaluation of average annual ET during the years 2003–2015.

ET Product	R ²	RMSE (mm yr ^{−1})	RPE (%)
ET _{SEBS}	0.95	125.32	−28.73
ET _{BESS}	0.87	54.02	−11.62
ET _{SSEBopYRB}	0.85	60.09	−3.38
ET _{SSEBopGlo}	0.84	63.25	3.01
ET _{GLASS}	0.79	224.73	44.59
ET _{CR}	0.70	120.38	−26.54
ET _{PMLv2}	0.69	44.00	5.28
ET _{MODIS}	0.65	105.45	−19.97
ET _{MTE}	0.17	58.31	−4.11

3.2. Spatial Pattern Comparison between ET_{SSEBopYRB} and Other ET Products

The spatial pattern of the average annual ET_{SSEBopYRB} during 2003–2015 in YRB exhibited a notable high value in the east and low value in the west (Figure 4), which is similar to the findings for ET_{SSEBopGlo}. The main difference between ET_{SSEBopYRB} and the other seven ET products was concentrated on the upper YRB and irrigated farmland. In the upper YRB, the mean annual ET estimated by ET_{SSEBopYRB} and ET_{SSEBopGlo} ranged from 200 to 300 mm yr^{−1}, while the estimated mean annual ET of the other seven ET products was higher than that of ET_{SSEBopYRB}. For example, ET_{MODIS} ranged from 600 to 700 mm yr^{−1}, while the ET_{CR} ranged from 400 to 600 mm yr^{−1} in the upper YRB (Figure 4). In the irrigated farmland located in the north (Figure A1), the mean annual ET values for ET_{SSEBopYRB}, ET_{SSEBopGlo}, and ET_{GLASS} ranged from 500 to 700 mm yr^{−1}, while the mean annual ET values estimated by the other six ET products ranged from 200 to 500 mm yr^{−1}.

Figure 4. Spatial patterns of the average annual ET comparisons between ET_{SSEBopYRB} and other ET products in the YRB during the years 2003–2015. The white areas represent missing values for the corresponding ET product.

Averaged over all vegetated areas (all land cover types except the barren type reported in Figure A1), the YRB mean annual ET_{SSEBopYRB} weighted by area during the years 2003–2015 was

$369.26 \pm 29.72 \text{ mm yr}^{-1}$, which included $84.04\% \pm 8.27\%$ of the mean annual precipitation (Figure 5). This result was slightly higher than those of ET_{SEBS} and ET_{CR} and slightly lower than those of $ET_{SSEBopGlo}$ ($375.63 \text{ mm yr}^{-1}$) and ET_{BESS} ($395.32 \text{ mm yr}^{-1}$). The mean annual ET estimates for the YRB in the ET_{MTE} , ET_{PMLV2} , and ET_{GLASS} were higher than that in the $ET_{SSEBopYRB}$ and larger than the mean annual precipitation. Considering that the main land type in the YRB is grassland (Figure A1), it is impossible for the average annual average ET to exceed the average annual precipitation. On a multiyear scale (e.g., 13 years), ignoring changes in groundwater in the YRB, the average annual ET of YRB derived from the water balance method using the run-off data from the Water Resources Bulletin of the YRB (<http://www.yrcc.gov.cn/>) is 375.86 mm. Therefore, ET_{MTE} , ET_{PMLV2} , and ET_{GLASS} highly overestimated the mean annual ET of the YRB, while the annual average ET of YRB estimated by $ET_{SSEBopYRB}$ was reasonable.

Figure 5. Mean annual ET values for nine ET products and the ratios of the mean annual ET to mean annual precipitation (ET/precipitation) during the years 2003–2015 over the YRB.

3.3. Trend Comparison between $ET_{SSEBopYRB}$ and other ET Products

Figure 6 shows that the annual ET trend in the YRB estimated by $ET_{SSEBopYRB}$ shows an increasing trend in most areas (75.24%), of which the increase in the central part is more obvious, while the increase in the western part is lower. In the western YRB, the annual ET values in $ET_{SSEBopYRB}$ and ET_{SEBS} mainly decreased, which is different from $ET_{SSEBopYRB}$. In the irrigated farmland located in the north of the YRB, the annual ET in $ET_{SSEBopYRB}$ decreased, while the annual ET for other ET products increased. In the central parts of the YRB where the NDVI increased significantly (Figure A2), all ET products showed that the annual ET increased. In the south of the YRB, the annual ET for $ET_{SSEBopYRB}$ decreased, which was similar to $ET_{SSEBopGlo}$, ET_{CR} , and ET_{GLASS} and different from ET_{MODIS} , ET_{PMLV2} , and ET_{BESS} .

Figure 6. Annual ET trend comparison of $ET_{SSEBopYRB}$ and other ET products in the YRB during the years 2003–2015. The ET slope is the change rate of the annual ET, which is calculated using Equation (12).

Overall, the annual ET of the YRB simulated by $ET_{SSEBopYRB}$ during 2003–2015 showed a significantly increased trend with a slope of 4.34 mm yr^{-1} , which was lower than the annual ET trends from ET_{MODIS} and ET_{PMLV2} and higher than the annual ET trends from the other six ET products (Table 4). The annual rate for ET change for the whole YRB estimated by $ET_{SSEBopGlo}$ was only 0.92 mm yr^{-1} , which was much lower than that of the $ET_{SSEBopYRB}$. The reason for the different trends between $ET_{SSEBopGlo}$ and $ET_{SSEBopYRB}$ is that the forcing climate data are different. The annual ET trend type for $ET_{SSEBopYRB}$ is mainly a non-significant increase with a proportion of 62.50%, while the annual ET trend type for $ET_{SSEBopGlo}$ is mainly a non-significant increase (44.02%) and non-significant decrease (40.83%).

Table 4. Annual ET trend statistics for the whole YRB during the years 2003–2015.

ET Product	ET Slope (mm yr^{-1})	Significant Increase (%)	Significant Decrease (%)	Non-Significant Increase (%)	Non-Significant Decrease (%)
ET_{MODIS}	6.61 *	58.16	0.72	37.90	3.21
ET_{PMLV2}	5.16 *	53.50	0.36	43.53	2.60
$ET_{SSEBopYRB}$	4.34 *	12.74	1.16	62.50	23.60
ET_{MTE}	3.35 *	35.28	1.19	45.47	18.07
ET_{GLASS}	1.78	16.88	5.83	55.19	22.10
ET_{BEES}	1.59	22.21	4.43	45.67	27.69
ET_{CR}	1.24	12.00	1.19	50.38	36.43
$ET_{SSEBopGlo}$	0.92	9.30	5.85	44.02	40.83
ET_{SEBS}	-1.05	2.63	11.03	31.07	55.26

Note: * means the p -value is below 0.05.

4. Discussion

The annual total ET trend in the YRB showed a significant increase for $ET_{SSEBopYRB}$ but no significant change for $ET_{SSEBopGlo}$. When researchers directly apply the free global ET product

simulated by SSEBop, especially the ET trend analysis, validation should be done if possible. In cases of flux data unavailability, the water balance method could be used or ET products could be compared with global ET products in their research area. Some researchers directly applied this product to analyze the relationships between ET variability and vegetation dynamics without validating the reliability of the product in the Nile Basin, Africa [26,27]. To further improve the estimation of ET, the uncertainty of $ET_{SSEBopYRB}$ in this research area should be discussed.

4.1. The Effect of Potential ET Estimation on ET Uncertainty

The reference ET is one of the most sensitive factors in the SSEBop model [32]. In this paper, we use the PM formula [50] to calculate the reference ET with the eight-day average pressure, sunshine hours, wind speed, relative humidity, minimum temperature, maximum temperature, and mean temperature as inputs. The optimal interpolation method for each climate variable is different [73], but each climate variable was interpolated using the same thin-plate spline function interpolation method, which may cause reference errors and affect the ET. Because the reference ET is strongly related to the pan evaporation [50], the small observed pan evaporation in the station within the YRB from 2003 to 2015 was used to evaluate the reference ET. The results showed that the correlation coefficient of the eight-day average reference ET and small pan evaporation ranged from 0.86 to 0.95 (Figure 7), which indicated a strong relationship between the reference ET and the small pan evaporation. In the earlier research, three different methods, including the standard global PM formula [50], revised PM formula in China [74], and the revised PM formula in the YRB [70], were used to calculate the reference ET in the YRB. The difference between the three methods focuses on the radiation term. The difference in the annual reference ET of the YRB simulated by the three methods is very small (Figure A3). Therefore, the uncertainty of the reference ET in this research cannot cause the large ET uncertainty simulated by the SSEBop model in the YRB from 2003 to 2015.

Figure 7. Evaluation of the reference ET simulated by the PM formula. The blue line is the fitted line.

4.2. Influence of the Land Surface Temperature Product on ET Uncertainty

The errors of LST images (MOD11A2) are generally within ± 1 K in most areas, especially in the areas that have complicated biophysical conditions, or arid or semiarid climatic conditions, which contain errors of up to ± 5 K [75]. The YRB is a typical arid and semiarid river basin, which results in large uncertainty in the LST. An uncertainty assessment of the SSEBop model implemented in the United States showed that an error of LST within a range of 0.35% (i.e., ± 1 K) can lead to an ET error in the range of 20% [32]. We used the observed LST data from 94 meteorological stations evenly distributed across the YRB (Figure A6) and air temperature to evaluate MOD11A2 and MYD11A2 during the years 2003–2015.

The 8-day average satellite LST, including MYD11A2 and MOD11A2, in the YRB can explain 92–96% of the 8-day average site LST during the years 2003–2014, except 2015 (Figure 8). The LST curve for MOD11A2 was abnormal in 2015, however MYD11A2 was not. The abnormal 8-day average MOD11A2 LST curves in 2015 were different from the eight-day LST curves in 2000–2014 throughout the YRB and on the meteorological observation sites, while the eight-day average observed LST curve and eight-day average observed air mean temperature curve were normal in 2015 (Figure 8). We assumed that the above phenomenon was due to the large missing values in MOD11A2 in 2015. However, after performing statistical analysis of the missing MOD11A2 ratio for the whole YRB and meteorological observation sites, we found that our assumption was wrong, because the missing ratio in 2015 was the same as the missing ratio during the years 2003–2014 (Figure A7). We concluded that the MOD11A2 product could not characterize the YRB's eight-day average LST variability in 2015.

Figure 8. Evaluation of the 8-day average land surface temperatures for MODIS during the years 2003–2015. The text in the upper right corner of each figure indicates the coefficient of determination of the linear model between the 8-day average satellite LST and the 8-day average observed LST values. r^2_{mod} is the R^2 between sites LST and MOD11A2 LST. r^2_{myd} is the R^2 between sites LST and MYD11A2 LST.

Obviously, abnormal LST decreases the accuracy of the ET_f and then decreases the accuracy of ET according to the principles of the SSEBop model. We also ran the SSEBop model with the MYD11A2

input to calculate the 8-day interval ET in the YRB during the years 2003–2015. Figure A8 shows that the eight-day average YRB ET_f derived from MYD11A2 (hereafter $ET_{f_{MYD}}$) and the eight-day average YRB ET_f from MOD11A2 (hereafter $ET_{f_{MOD}}$) were inconsistent for days 137–153 and days 297–337 in 2015. The abnormal LST of MOD11A2 in 2015 occurs during days 137–153 and days 169–217. Although there were abnormal MOD11A2 LST values for days 169–217, the $ET_{f_{MOD}}$ value was normal and the same as $ET_{f_{MYD}}$, which is related to the ET_f temporal interpolation method. The ET_f temporal interpolation method had no effect on days 169–217 in 2015. Correspondingly, the intrayear change of the average YRB ET derived from MYD11A2 (hereafter $ET_{SSEBopYRB, MYD}$) was very close to the $ET_{SSEBopYRB}$, which was derived from MOD11A2 during the years 2003–2014, except for 2015 at the 8-day scale and monthly scale (Figures A9 and A10). This is closely related with the intrayear change of the eight-day ET_f . The abnormal $ET_{SSEBopYRB}$ value in 2015 occurred on days 137–153 at the eight-day scale and in May at the monthly scale. The 8-day LST abnormal data for MOD11A2 had a weak influence on the YRB annual ET (Figure A11). Therefore, abnormal eight-day LST data have a great influence on the intravariability of ET, but have a small influence on the interannual variability.

It should be noted that due to the scale mismatch between in situ measurements and satellite-based observations, it is relatively difficult to obtain true values for pixels, especially for terrestrial regions that are typically heterogeneous and non-isothermal terrestrial regions [76]. Figure A7 shows that the average missing LST value ratio (average of 46 ratios of missing LST values per year) in each image varies from 2.22% to 5.04% during the years 2003–2015. However, the missing LST ratio for some of the dates is as high as 25% or more (Figure A7). The filling method for the LST missing value causes different errors [46]. This paper adopted the adaptive window method, which considers the relationship between high-quality pixel LST values and influencing factors (e.g., elevation, NDVI, and air temperature) to fill the missing values [77].

4.3. Influence of Precipitation Products on ET Uncertainty

This paper used the difference between annual precipitation and run-off (WB-ET) as the annual evaluation data for $ET_{SSEBopYRB}$. The uncertainty of the precipitation and run-off was approximately 10% for the water-balanced ET method [78]. Compared to the YRB precipitation site interpolation involved in previous studies [39,79], the annual precipitation was interpolated using more rain gauge stations ($N = 507$ vs. $N = 134$) (Figure A4). With more site distributions, the annual precipitation uncertainty caused by the different interpolation methods, the thin-plate spline function, ordinary kriging, and inverse distance weight was small (Figure A5). Cross validation results indicated that interpolated precipitation using the three methods accounted for $84.1\% \pm 1.7\%$ of the annual precipitation observed at the sites (Figure A5). The unexplained 15% may be due to the complexity of the land surface in the YRB, which greatly increases the interpolation difficulty.

There are also some free global coarse resolution precipitation products, such as TRMM3b42 derived from remote sensing satellites [67] and reanalysis data of CRU [68], while the Chinese precipitation product from the China meteorological forcing dataset (CMFD) integrates ground observations, satellite data, and reanalysis data [80]. $ET_{SSEBopYRB}$ can explain 38%, 47%, 50%, and 49% of the WB-ET based on the CMFD, CRU, TRMM3b42, and the interpolation of the annual precipitation, respectively, during the years 2003–2015. In the \ RMSE and RPE indices, there were lower RMSE and lower RPE values for WB-ET based on interpolation than for WB-ET based on the other three precipitation products (Figure 9). Therefore, the WB-ET used for evaluation will have a great impact on the evaluation results because of the differences in annual precipitation data.

Figure 9. Evaluation of $ET_{SSEBopYRB}$ using water balance ET derived from four precipitation products during the years 2003–2015. The dotted line is the 1:1 line and the blue line is the fitted line between observed values.

4.4. Influence of Model Parameters on ET Uncertainty

The model parameters of coefficient k_{max} involving the magnitude of the estimated ET are additional sensitive and critical factors in the SSEBop model [32]. The coefficient k_{max} factor was recommended to be set at 1.2 in the original research [8]. Later, Chen et al. (2016) recommended that the coefficient k_{max} range should be from 0.95 to 1.2, and that it was acceptable to take the coefficient k_{max} as 1.1, since its maximum error of 15% leads to an ET uncertainty of approximately 15% [32]. Senay et al. (2018) highly emphasized the correction of this factor in the applied research region using the WB-ET or site observation ET [17]. In this research, through the correction using WB-ET in 2003–2014, the coefficient k_{max} was set as 1.218 (Figure 10). When the coefficient k_{max} was 1.2168, the RMSE (88.98 mm yr^{-1}) between the WB-ET and $ET_{SSEBopYRB}$ (the LST input is MOD11A1) during the years 2003–2014 was lower than the other k_{max} setting, while the RPE (-4.49%) for $ET_{SSEBopYRB}$ was small.

Figure 10. RMSE and RPE differences between WB-ET and $ET_{SSEBopYRB}$ for different k_{max} settings. The WB-ET was derived from the fourteen catchments reported in Figure 1.

4.5. Influence of the Basin Size on ET Uncertainty

The fourteen basins have different basin sizes, varying from 1138 km² to 43,106 km², which may influence the evaluation results. According to whether a watershed's area is larger or smaller than 10,000 km², the 14 small watersheds were divided into two groups. The evaluation of the large basins (Figure A12) showed that the nine ET products could only explain 22–63% of the ET variability. For all ET products except ET_{MTE} , the simulated ET could explain higher ET variability than if all fourteen basins were included, especially for ET_{SEBS} (0.43 vs. 0.59), ET_{CR} (0.41 vs. 0.54), ET_{GLASS} (0.40 vs. 0.54), and ET_{PMLv2} (0.41 vs. 0.62). The improvements of R^2 values for $ET_{SSEBopYRB}$ (0.49 vs. 0.51) and $ET_{SSEBopGlo}$ were relatively small (0.52 vs. 0.57). RMSE values also changed, especially for ET_{MODIS} and ET_{GLASS} . ET_{MODIS} and ET_{GLASS} in the five large area basins had much lower (121.75 mm yr⁻¹ vs. 84.50 mm yr⁻¹) and higher (232.12 mm yr⁻¹ vs. 307.35 mm yr⁻¹) RMSE values, respectively, than that for all fourteen basins. The increases in RMSE values for $ET_{SSEBopYRB}$ (88.30 mm yr⁻¹ vs. 96.65 mm yr⁻¹) and $ET_{SSEBopGlo}$ (82.59 mm yr⁻¹ vs. 84.66 mm yr⁻¹) were small. In terms of the RPE, the changes for $ET_{SSEBopYRB}$ and $ET_{SSEBopGlo}$ were low, but were high in ET_{MODIS} (−19.97% vs. −5.83%). Therefore, the basin size did not have a great impact on the evaluation of $ET_{SSEBopYRB}$ and $ET_{SSEBopGlo}$, but did have a noticeable influence on the evaluation of ET_{MODIS} .

4.6. Difference between $ET_{SSEBopYRB}$ and Eight Other ET Products

The results section showed the differences between the $ET_{SSEBopYRB}$ and the eight other ET products in capturing the annual ET for fourteen small catchments (Figure 3, Table 3), estimating the average annual ET in YRB (Figure 4), and simulating the ET trend for the YRB (Figure 5, Table 4).

$ET_{SSEBopYRB}$ and $ET_{SSEBopGlo}$ are both driven by the SSEBop model, however with different input datasets. A scatter plot based on the pixel values of the mean annual ET values shows that the R^2 is as high as 0.84 and the root mean square difference (RMSD) is as low as 24.04 mm yr⁻¹ (Figure A13). The small differences in the spatial distribution of the mean annual ET for the YRB during the years 2003–2015 are related to the same forcing data as MOD11A2 being used, the same methods (PM equation) being used to calculate the reference ET, and the same method (temporal interpolation)

being used to interpolate the no data value for ET_f . The differences in the ET trends for the YRB are mainly due to the differences in the reference ET trends. The meteorological data used to calculate the reference ET for $ET_{SSEBopGlo}$ are derived from GLDAS, while the meteorological data used for $ET_{SSEBopYRB}$ were interpolated using regional dense station data.

The differences between $ET_{SSEBopYRB}$ and the other seven ET products are not just driven by model physics, but also forcing data. The forcing datasets for each ET product are described in Section 2.2.3. Eight-day MODIS LST and 16-day NDVI values are the main inputs used to quantify the land surface conditions in $ET_{SSEBopYRB}$. The ET products that had similar remote sensing input data to $ET_{SSEBopYRB}$ were ET_{SEBS} , ET_{CR} , ET_{BESS} , ET_{MTE} , and ET_{GLASS} . The daily MODIS LST, eight-day MODIS LST, and monthly MODIS LST were the important inputs for ET_{SEBS} , ET_{BESS} , and ET_{CR} , respectively. ET_{MTE} and ET_{GLASS} used GIMMS NDVI and MODIS NDVI to represent land surface conditions, respectively. The ET products that had different remote sensing input data for $ET_{SSEBopYRB}$ were ET_{MODIS} and ET_{PMLv2} . ET_{MODIS} and ET_{PMLv2} used the eight-day MODIS LAI and FPAR data to characterize the land surface conditions. There was a correlation between NDVI and LAI-FPAR.

In terms of the meteorological forcing data, many ET products (e.g., ET_{MODIS}) rely upon global reanalysis data, which have their limitations. For example, Modern Era Retrospective Analysis for Research and Applications- meteorological data provided by the NASA Global Modeling and Assimilation Office, which has a spatial resolution of $1/2^\circ \times 2/3^\circ$, uses the same meteorological data as in ET_{MODIS} and ET_{GLASS} . ET_{BESS} adopts National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) reanalysis data, while ET_{PMLv2} adopts the 0.25° resolution and 3-h GLDAS-2.1 data. ET_{CR} and ET_{MTE} both use the 0.1° CMFD data as the meteorological forcing data. The trend differences among these various climate datasets in the YRB affect the estimated ET trend.

5. Conclusions

We conducted a comparison of ET values derived from the SSEBop model using the water balance ET values in a highly spatially heterogeneous river basin (the YRB) and reached the following conclusions for the years 2003–2015:

- (1) $ET_{SSEBopYRB}$ and the other eight ET products were able to explain 23 to 52% of the variability in WB-ET for fourteen small catchments in YRB. $ET_{SSEBopYRB}$ had better agreement with WB-ET than ET_{SEBS} , ET_{MODIS} , ET_{CR} , and ET_{GLASS} , with lower RMSE (88.3 mm yr^{-1} vs. 121.7 mm yr^{-1}), higher R^2 (0.49 vs. 0.43), and lower absolute RPE (-3.3% vs. -19.9%) values;
- (2) The free global ET product derived from the SSEBop model highly underestimated the annual total ET trend for the YRB. More validation regarding this product is required in other regions using site measurements (e.g., eddy covariance flux tower measurements);
- (3) The abnormal data in the land surface temperature products of MOD11A2 for 2015 limited the performance of the SSEBop model at the eight-day and monthly scales. Future studies will explore the use of MYD11A2;
- (4) At the basin scale, the uncertainties of the ET trends and spatial patterns are still large for different ET products. We need to further reduce the ET uncertainty to better serve water resource management and ecological restoration project construction purposes.

Author Contributions: Conceptualization, L.Y. and X.W.; methodology, L.Y., X.W. and Y.C.; validation, L.Y., X.F.; formal analysis, L.Y. and X.W.; resources, B.F.; data curation, L.Y.; writing—original draft preparation, L.Y. and X.W.; writing—review and editing, L.Y.; visualization, L.Y. and X.F.; supervision, B.F.; project administration, X.W.; funding acquisition, X.W., X.F. and B.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Second Tibetan Plateau Scientific Expedition and Research Program (2019QZKK0405), the Strategic Priority Research Program of the Chinese Academy of Sciences (XDA2002040201), and the National Key R&D Program of China (2018YFC0507301). The APC was funded by 2019QZKK0405, XDA2002040201 and 2018YFC0507301.

Acknowledgments: Special thanks are given to the two anonymous reviewers for their valuable comments.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Data Availability: ET data based on the SSEBop model on the YRB are available. Readers can contact the corresponding author for data. Other datasets are publicly available.

Appendix A

Figure A1. Spatial distribution of the (a) land type and (b) rainfed, irrigated, and paddy cropland during 2003–2015. Data regarding rainfed, irrigated, and paddy cropland distribution are from Salmon et al. (2015). Data regarding the spatial distribution of land type are from the MODIS land use/land type product of MCD12Q1 version 6 (V6), which can be download from <https://ladsweb.modaps.eosdis.nasa.gov>. We classified 17 categories into eight broad categories.

Figure A2. Annual NDVI trends in the YRB during the years 2003–2015. NDVI slope is the change rate of the annual NDVI, which is calculated using Equation (12).

Figure A3. Differences among three annual YRB average reference ET products calculated using three methods. China PM is the revised PM in China, YRB PM is the revised PM in the YRB, and standard PM is the original PM from Food and Agriculture Organization Irrigation and Drainage Paper No. 56 [50].

Figure A4. Spatial distribution of rain gauges during the years 2003–2015 in the YRB.

Figure A5. Evaluation of the interpolation method during the years 2003–2015. OK is the ordinary kriging method. TPS is the thin-plate spline function. IDW is the inverse distance weight method.

Figure A6. The spatial distribution of the land surface temperature observation sites during the years 2003–2015.

Figure A7. The ratio of the missing values in the YRB sites during the years 2003–2015. In the original files of MODIS land surface temperature product of MOD11A2 and MYD11A2, some of the pixel values are filling values, which are not within the valid range. In other words, these values are missing values. The ratio of missing values is the ratio of the area containing all missing value pixels to the total area of the YRB.

Figure A8. Eight-day ET_f derived from the MOD11A1 and MYD11A1 in the whole YRB during the years 2003–2015.

Figure A9. Eight-day ET derived from the MOD11A1 and MYD11A1 over the whole YRB during the years 2003–2015.

Figure A10. Monthly ET derived from the MOD11A1 and MYD11A1 in the whole YRB during the years 2003–2015.

Figure A11. Annual ET derived from MOD11A1 and MYD11A1 over the whole YRB during the years 2003–2015.

Figure A12. Evaluation of the annual ET for five small catchments (area >10000 km²) in ET_{SSEBopYRB} and evaluation of eight other ET products during 2003–2015. The blue line is the fitted line and the black line is the 1:1 line.

Figure A13. Pixel-based average annual ET comparison between $ET_{SSEBopYRB}$ and $ET_{SSEBopGlo}$ in YRB during the years 2003–2015. RMSD is the root mean square difference ($RMS_{ET_{SSEBopGlo}} - RMS_{ET_{SSEBopYRB}}$).

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