Can we trust remote sensing ET products over Africa?

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Abstract. Evapotranspiration (ET) is one of the most important components in the water cycle. However, there are relatively few direct measurements of available ET (e.g. using flux towers). Nevertheless, various disciplines ranging from hydrology to agricultural and climate sciences require information on the spatial and temporal distribution of ET at regional and global scales. Due to the limited data availability, attention has turned toward satellite based products to fill observational gaps. Various remote sensing (RS) and other data products have been developed, providing a large range of ET estimations. Across Africa only a limited number of flux towers are available which are insufficient for systematic evaluation of RS derived and other available ET products. Thus, in this study, we conduct a methodological evaluation of nine existing RS derived and other ET products in order to evaluate their reliability at the basin scale. A general water balance (WB) approach is used, where ET is equal to precipitation minus discharge for long-term averages. Firstly, ET products are compared with WB inferred ET (ET_{WB}) for basins without long-term trends present. The ET products and calculated ET_{WB} are then evaluated against the Budyko equation, used as a reference condition. The spatial characteristics of the ET products are finally assessed through the analysis of selected land cover elements, forests, irrigated areas and water bodies, across Africa. Additionally, a cluster analysis is conducted to identify similarities between individual ET products. The results show that CMRSET, SSEBop and WaPOR rank highest in terms of estimation of long-term average mean ET across basins with low biases and good spatial variability across Africa. GLEAM consistently ranks the lowest in most evaluation criteria however, has the longest available time period. Each product shows specific advantages and disadvantages. Depending on the study under question at least one product should be suitable for a particular requirement. Care should be taken to bear in mind that many products suffer from a large bias. Based on the evaluation criteria in this study the three highest ranked products, CMRSET, SSEBop and WaPOR would suit many user needs due to low biases and good spatial variability across Africa.

1 Introduction

Evapotranspiration (ET) or the water vapor flux is an important component in the water cycle and is widely studied due to its implications in hydrology to agricultural and climate sciences (Trambauer et al., 2014). Growing attention has been given to estimating ET fluxes at regional and global scales for a wide variety of reasons, for example, understanding the partitioning of energy and water at the earths surface and their feedbacks; how the different external drivers of ET vary regionally and; understanding the impacts of potential changes on the hydrological cycle under a changing climate, to name a few (Teuling et al., 2009; Vinukollu et al., 2011a; Mu et al., 2011). However, the estimation of ET at large scales has always been a difficult task due to direct measurement of ET being possible only at point locations, for example using flux towers (Trambauer et al., 2014). Obtaining ET observations from flux towers is challenging due to the high costs of implementation and maintenance and often studies rely on openly accessible data especially for regions in Asia, South America and Africa. Worldwide flux tower data can be openly accessed through FLUXNET [1], however there is limited coverage in many regions (Figure 1 (left panel)). For the entire African continent, for example, there are only six FLUXNET sites (Figure 1 (right panel)) with available ET data. Due to the limited data availability of in situ measurements a method of evaluating ET estimations using data other than point observations is required.

Recent advances in satellite based ET products provide promising data to fill these observational gaps (Alkema et al., 2011; Miralles et al., 2016; Guerschman et al., 2009; Zheng et al., 2016; Mu et al., 2007, 2011; Jung et al., 2011; Senay et al., 2013). ET cannot be directly measured by satellite based measurements, but can be derived from physical variables that can be observed from space, such as latent heat flux and surface heat flux using the surface energy balance. In addition, due to passing frequencies and cloud interference, interpolations in time are required. Keeping this in mind, remote sensing derived ET cannot be interpreted as direct satellite observations but as model outputs based on satellite forcing data (Miralles et al., 2016). Therefore, large-scale estimations of ET are most commonly products of remote sensing based models, hydrological models and land-surface models (Trambauer et al., 2014). More recently, ET products have also been developed using Machine Learning (ML) approaches such as Model Tree Ensemble (MTE) or Artificial Neural Networks (ANN) combined with observed flux tower data or model outputs used as training sets (Tramontana et al., 2016; Jiménez et al., 2011; Jung et al., 2017; Alemohammad et al., 2017).

Satellite observations often give useful information on the spatial variability, however many products tend to suffer from a large bias. With this range of approaches to estimate ET, large differences are observed among the products and therefore, evaluation is required. Keeping in mind limited availability of in situ measurements for evaluation, an alternate approach is to consider the water balance closure at the river basin scale. Only few studies exist comparing different satelite based and gridded ET products at the global and continental scales using this approach among others. In their study, Miralles et al. (2016) evaluated four commonly used and tested algorithms (the Surface Energy Balance System (SEBS): (Su, 2002), the Moderate Resolution Imaging Spectroradiometer (MOD16): (Mu et al., 2007, 2011), the Global Land Evaporation Amsterdam Model

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[1]FLUXNET is a global network of micrometeorological flux measurement sites that measure the exchange of CO2, water vapor and energy between the biosphere and the atmosphere (Baldocchi et al., 2001)

(GLEAM): (Miralles et al., 2011) and the Priestly-Taylor Jet Propulsion Laboratory model (PT-JPL): (Fisher et al., 2008)) to derive ET using a range of methods including water balance closure across a broad range of catchments worldwide. They found that GLEAM and PT-JPL appear more realistic when compared with 837 globally distributed catchments, however find that all products show large dissimilarities in conditions of water stress and drought conditions (Miralles et al., 2016). Another

5   global evaluation of three process-based models (SEBS, Penman-Montieth algorithm (PM-Mu): (Mu et al., 2007; Penman, 1948; Montieth, 1965) and Priestly-Taylor based approach (PT-Fi): (Priestley and Taylor, 1972; Fisher et al., 2008)) in their estimation of ET was conducted by Vinukollu et al. (2011a) using the water balance approach at twenty six major basins worldwide along with other methods. A Root Mean Square Difference (RMSD) of 118 to 194 mm/year and bias of -132 to 53 mm/year were found between the estimated annual ET and water balance approximations. The LandFlux initiative, supported

10   by GEWEX (http://www.gewex.org/) is a framework aiming to evaluate and compare several global ET data sets (Mueller et al., 2011; Jiménez et al., 2011). With these aims, global merged bench-marking ET products were derived (Mueller et al., 2013a) using 40 datasets over a seven year period (1989-1995) and 14 datasets over a seventeen year period (1989-2005) to be used for evaluation. At the continental scale a study by Trambauer et al. (2014) compared ET estimates derived using a continental hydrological model (PCR-GLOBWB: (Van Beek and Bierkens, 2009) with other independently computed ET products (the

15   European Center for Medium-range Weather Forecasts (ECMWF) Re-Analysis (ERA)-Interim: (Dee et al., 2011), ERA-Land: (Balsamo et al., 2015), MOD16, GLEAM and three other versions of the PCR-GLOBWB model) using visual inspection and statistical methods. By sub-diving the continent into climatic regions, they found that the annual anomalies of ET for each of the products with respect to the multi-product mean was highest in ERA-Interim. GLEAM was in most cases lower than the multi-product mean while PCR-GLOBWB was close to the multi-product mean in nearly all cases.

20   To our knowledge, there are no existing studies focusing solely and entirely on the African continent that use the water balance approach for evaluating existing ET products. The water budget of a catchment implies that precipitation (P) minus river discharge (Q) equals evapotranspiration (ET_{WB}) when considering a long time period so that the change in water storage (soil moisture, lakes, deltas) can be neglected (Miralles et al., 2016, 2011; Vinukollu et al., 2011b). Using this general water balance to infer ET_{WB}, it is possible to gain understanding of the magnitude of ET within a given basin and hence to estimate

25   biases in ET estimation by the different products at the catchment scale. Unfortunately, the period of observation for measured discharge for certain basins is limited or do not overlap with existing ET products and thus different time periods need to be used.

      Therefore, this study focuses on evaluating nine existing, mostly open access, ET products (ET_{RS}) using a water balance approach over Africa. The products being analysed are CSIRO's Moderate resolution imaging spectroradiometer Reflectance Scaling Evapotranspiration (CMRSET): (Guerschman et al., 2009), ETMonitor: (Zheng et al., 2016), GLEAM, LandFlux-

30   EVAL, MOD16, FLUXNET Model Tree Ensemble (MTE): (Jung et al., 2011), the operational Simplified Surface Energy Balance model (SSEBop): (Senay et al., 2013), the Food and Agriculture Organisation's (FAO) portal to monitor **Wa**ter **P**roductivity through **O**pen access of **R**emotely sensed derived data (WaPOR): (FAO, 2018) and the Water, Energy and Carbon Cycle with Artificial Neural Networks (WECANN): (Alemohammad et al., 2017). The evaluation of the products will be con-

35   ducted using a) a comparison of their performance against calculated ET_{WB}, b) a robustness check of their performance against

the Budyko curve (Budyko, 1974) which provides a reference condition for the water balance assuming it correctly partitions P into Q and c) a spatial variability assessment using specific land cover elements (forests, water bodies and irrigated areas).

2 Data and Methods

2.1 Data

2.1.1 Evapotranspiration products

The derived ET products being evaluated in this study include CMRSET, ETMonitor, GLEAM, LandFlux-EVAL, MOD16, MTE, SSEBop, WaPOR and WECANN. Overall there are large differences between the products which results in certain advantages and disadvantages between products. All products have a global spatial coverage (advantage) except for WaPOR (disadvantage). All products are openly accessible (advantage) except for ETMonitor (disadvantage). GLEAM and ETMonitor have a daily, CMRSET has an 8-daily and WaPOR has dekadal temporal resolution (advantage) over other products which have monthly or yearly resolutions (disadvantage). Most products are still ongoing (advantage) except for ETMonitor, LandFlux-EVAL and MTE (disadvantage). GLEAM, MTE and LandFlux-EVAL have data available prior to 1990 (advantage) with all other product data available after 1999 (disadvantage). CMRSET and WaPOR have the highest resolutions (($0.0022 ° \times 0.0022°$)) (possible advantage), LandFlux-EVAL and WECANN have the lowest resolutions ($1 ° \times 1°$) (possible disadvantage) with all other products ranging in between. Table 1 summarises the different features mentioned and whether these are possible advantages or disadvantages. These different ET products give a good sample of the available data sets to choose from.

All products have been projected and gridded on a $0.0022 ° \times 0.0022°$ geographic grid and averaged at yearly temporal resolution for the purposes of this study. Table 2 summarizes the characteristics of the products being used. For details and access on each of the products please refer to the references and access section in Table 2.

2.1.2 Precipitation products

The precipitation products used in this study are the EartH2Observe (E2OBS), WATCH forcing data methodology applied to ERA-Interim Reanalysis (WFDEI), ERA-Interim data Merged and Bias-corrected (EWEMBI), the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) and the Multi-Source Weighted Ensemble Precipitation (MSWEP). Precipitation products were averaged at yearly temporal resolution for the purposes of this study. Table 3 summarizes the characteristics of the products being used. For details and access on each of the products please refer to the references and access section in Table 3. The ensemble of the three P products were used for all calculations requiring P.

2.1.3 Discharge data

Discharge data was obtained from the Global Runoff Data Centre (GRDC) and the Vrije Universiteit Brussels (VUB) Department of Hydrology and Hydraulic Engineering (HYDR). Table 4 summarizes the characteristics of the data being used. For details and access on each of the products please refer to the references and access section in Table 4.

2.1.4 Reference potential evapotranspiration data

Three global reference Potential Evapotranspiration (PET) data products developed by Deltares (Sperna Weiland et al., 2015) are used based on the Hargreaves (Har) (Hargreaves and Samani, 1985), Penman-Montieth (P-M) (Montieth, 1965; Penman, 1948) and Priestly-Taylor (P-T) (Priestley and Taylor, 1972) approaches. Table 5 summarizes the characteristics of the products being used. For details and access on each of the products please refer to the references and access section in Table 5. The ensemble of the three PET products were used for all calcuations requiring PET.

2.2 Methods

A methodology to evaluate ET product estimations is presented next:

1. Comparison between catchment water balance evapotranspiration (ET_{WB}) and ET products

2. Evaluation of ET_{WB} and ET product estimations using the Budyko curve (ET_{Budyko}) as a reference

3. Assessment of spatial variability using land cover elements

4. Assessment of similarity using a cluster analysis

2.2.1 Catchment water balance evapotranspiration (ET_{WB})

Due to the limited availability of direct observations of ET across Africa, we infer ET estimates at the river basin level using the water balance approach assuming a negligible change in storage (discussed further in Section 5) for long time periods:

$$ET_{WB} = P - Q \tag{1}$$

ET_{WB} was calculated for 27 major river basins across Africa based on discharge data (GRDC and HYDR VUB) quality and availability at the outlets of 54 major basins (Fig. 2). Catchment or basin areas were taken from the 'Major River Basins of the World' (MRBW) shapefile (World Bank, 2017). Discharge was converted from cubic meters per second to millimeters per year using the above mentioned catchment areas for all years of data availability for each basin. Since direct observations of precipitation from gauges were not used, precipitation was taken as the average of the three data products, EWEMBI, CHIRPS and MSWEP. Basin average precipitation was calculated for the years 1979-2016 according to the MRBW shapefile boundaries recording the basin mean. The performance of the precipitation products in estimating P for each of the basins were compared. Long-term ET_{WB} was calculated by using the long-term average discharge and precipitation data for each catchment. The MRBW shapefile area did not differ greatly with the drainage area reported by the GRDC except in two cases. Here we found the ET_{WB} calculated using the two areas only differed by 2.5 percent and 3.3 percent and thus kept these basins in the analyses.

One problem that arises when using the water balance approach is that the period of observation for measured discharge is limited or does not overlap with existing ET products in certain cases. For this reason, long-term averages of ET_{WB} were used where no major trends were present in order to justify the evaluation using different time periods (discussed further in

Section 5). The Mann-Kendall (MK) (Mann, 1945; Kendall, 1948) test was used to identify whether a monotonic upward or downward trend is present in the calculated ET_{WB} estimates. The MK test is non-parametric (distribution free) and best used as an exploratory analysis to identify where changes are significant or of large magnitude (Matzke et al., 2014) and should only be used where seasonal trends are not present. Considering annual averages are used in this study, the MK test was deemed appropriate.

In order to conduct our comparisons using the calculated ET_{WB}, all ET products being evaluated were projected to WGS 84, EPSG:4326 on a $0.0022° \times 0.0022°$ grid. This resolution represented the highest spatial resolution of the products being analysed. Products were resampled to the highest resolution in order to obtain the best approximation of basin areas when overlaid with basin boundary shapefiles. Only negligible differences were found between calculation of ET_{WB} using products with original resolution compared with ET_{WB} calculated using resampled products. The nearest neighbours' interpolation method was used for any resampling required from course to high resolution to limit the loss of any information. The estimations were then combined to give a single map for each product of the long-term average ET_{RS} across Africa. The time periods averaged for each product can be found in Table 2. Basin average ET_{RS} was calculated according to the MRBW shapefile boundaries and the basin mean was recorded. The Root Mean Square Error (RMSE), the basin area weighted RMSE ($RMSE_{aw}$), the correlation coefficient (r), bias and basin area weighted bias ($bias_{aw}$) between ET_{WB} versus ET_{RS} for all basins were calculated. Basin area weighting was considered when calculating bias and RMSE due to a large difference in basin areas. Therefore, basins with larger areas had more weight in the basin area weighted statistics than basins with smaller areas. Correlations were calculated based on long-term averages across all basins.

The ranking of the ET products are based on their performance on RMSE, $RMSE_{aw}$, r, bias and $bias_{aw}$.

2.2.2 Evaluation using the Budyko curve

The Budyko equation partitions precipitation into streamflow and ET_{Budyko} by describing the relationship between mean annual ET and the long-term average water and energy balance at catchment scales (Sposito, 2017) as seen in Fig. 3. Budyko (1974) developed this approach for the physics of catchment ET by postulating on the phase transformation of green water to vapor and thus that ET reflects not only the partitioning of water but also radiant energy at the vadoze zone and atmosphere interface (Sposito, 2017; Gerrits et al., 2009) following equation 2.

$$\left[\frac{PET}{P} tanh(\frac{1}{\frac{PET}{P}})(1 - exp^{-\frac{PET}{P}}) \right]^{0.5} \tag{2}$$

The Budyko curve provides a reference condition for the water balance assuming it correctly describes the partitioning of P into Q, which can be used to see how well the ET products and calculated ET_{WB} perform in estimating ET. For each of the basins under study, we calculated ET/P and PET/P and plotted these against the Budyko curve. Average PET estimates from the three products using the Hargreaves, P-M and P-T approaches were used by taking the basin mean PET according to the MRBW shapefile boundaries. The performance of the reference potential evapotranspiration products in estimating PET for each of the basins were compared. P was taken as the average of EWEMBI, CHIRPS and MSWEP precipitation products. The bias was found between the calculated ET_{WB} and ET_{RS} with the calculated ET_{Budyko}.

The ranking of the ET$_{RS}$ from each product are based on the performance of their average bias across all basins with that of the calculated ET$_{Budyko}$.

2.2.3 Spatial variability assessment

Three types of land cover elements were evaluated in this study, irrigated areas, water bodies and forested areas. A map with Areas Equipped for Irrigation actually irrigated (AEIai) by FAO and Rheinische Friedrich-Wilhelms-University (Siebert et al., 2013), a map of Water Bodies obtained from the Global Reservoir and Dam (WB_{GRanD}) database (Lehner et al., 2011) and a map of 2013 Intact Forest Landscapes (IFL) were used to evaluate how well the ET products identified spatial characteristics. Two steps were used. Firstly the ET products were evaluated visually. Using different scales and identified land cover elements (Figure 4) the ET products were evaluated on how well each type of land cover element was detected. Secondly, a quantitative assessment was conducted for forested areas and water bodies. A quantitative assessment of irrigated areas was not conducted due to not being able to find a suitable reference condition for such large pixels and long-term temporal scales. For water bodies ET should be more or less equal to the PET. Therefore, the long-term annual average ET$_{RS}$ and PET across water bodies was calculated by recording the mean according to the boundary provided by the WB_{GRanD} map. The mean ET$_{RS}$ for water bodies for each ET product was then compared with the PET mean for water bodies by calculating the bias.

For forested areas, the average ET was taken from literature where estimations for the Congo forest, the forested area being evaluated, were between 1200-1500 mm/year (Otto et al., 2013; Reynolds et al., 1988). Therefore a value of 1350 mm/year as a reference for ET across the evaluated forested area was taken. Mean values of ET for the forested area were found using the IFL shapefile and recorded for each ET product. The bias between the reference ET as reported in literature and calculated mean ET for forested areas for each product was found and recorded.

Ranking was conducted in two stages. Firstly on the performance of ET products to characterise the three land cover element types through visual inspection. And secondly based on the bias of each of the ET products in relation to the used reference for water bodies and forested area.

2.2.4 Assessment of similarity

Lastly, a cluster analysis was performed, using the method followed by Wartenburger et al. (2018) on the ET products to find the overall level of similarity between the individual products in terms of spatial variability and magnitude. The aggregated long-term average maps for all products were used whereby the pairwise Euclidean distance between each data set for each pixel was calculated and evaluated. Each of the maps used were resampled to $0.0096° \times 0.0096°$ for computation efficiency.

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3 Results

3.1 Catchment water balance

3.1.1 Comparison of precipitation and potential evapotranspiration products

Precipitation and PET were taken as the average of three products. Here we compare the results of the different P and PET products for the basins being analysed. We see that the three precipitation products show little differences in their estimations of long-term average P across the basins. No large outliers can be seen (Figure 5). The comparison of the three PET products showed larger differences in their estimations of long-term average PET across the basins (Figure 6). One significant outlier can be seen for Bandama basin where the Hargreaves PET product has a much lower PET estimation than the Priestly-Taylor product. However, as no reference PET was available for Banadama or any of the other basins we kept all basins within the analyses and still used the average of all three products.

3.1.2 Basins used in the analyses

Figure 7 (left) shows the long-term average ET_{WB} estimates for the 27 basins with available discharge and precipitation data. The spread of the ET across the basins seems to be consistent with the African climate, where basins in the semi-arid to arid northern and southern parts of Africa show lower ET than the more centrally located basins known to be more tropical.

The MK test was then conducted on the 27 basins with calculated ET_{WB} to test for trends. In order for the MK test to be accurate a minimum of ten data points should be used which were not available for all basins. For these basins the MK test was conducted on the collected P and Q data used to calculate ET. For the results from the MK test please see Table 6 in Appendix A. After conducting the MK test on the 27 basins for major trends in the calculated ET_{WB} and/or the precipitation and discharge data, 20 basins remained without a monotonic trend being present (Fig. 7). The spread of the remaining 20 basins still gives good spatial coverage for analysis across the African continent.

3.1.3 Catchment water balance comparison

Table 7 shows the calculated statistics for the comparison of the long-term average ET_{WB} versus ET_{RS} across the average of all basins. Three products, CMRSET, SSEBop and WaPOR, clearly stand out in terms of showing low biases ranging from 3-46 mm/year. The remainder of the products have relatively large biases ranging from 115-313 mm/year. CMRSET and WaPOR are the only two products that overestimate ET with respect to calculated ET_{WB} while all other products underestimate ET when looking at the average bias across all basins. All products show a high RMSE, with CMRSET, SSEBop and WaPOR showing the lowest RMSE and $RMSE_{aw}$. The $RMSE_{aw}$ for most products exceeds 300 mm/year. There is a significant positive correlation for all products ranging from 0.89-0.97 with GLEAM and LandFlux-EVAL showing the strongest relationships with ET_{WB} across the different basins.

Delving deeper into the biases (Fig. 8) we can identify certain basins where most products have large biases, namely Awash, Groot, Niger, Olifant and the Upper Blue Nile. The only pattern that may be seen here with the location of the basins is that they

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are found in the semi-arid northern and southern regions of Africa. The majority of the products underestimate basin-average ET across most basins except for CMRSET and WaPOR where ET is mostly overestimated. While the ET is equally over and underestimated by SSEBop across the different basins.

3.2 Evaluation using the Budyko curve

Figure 9 shows the ability of each ET product to capture ET according to the Budyko curve. The ET_{WB} follows the Budyko curve well, where we see that for each of the basins, the calculated ET_{WB} falls very close to the Budyko curve. The calculated ET for most of the ET products and also for the majority of basins falls under the curve showing a tendency for products to underestimate basin ET as previously observed. Conversely, a clear tendency by the CMRSET product of overestimating basin ET can be seen. What is interesting to note here is that some ET products exceed either the water limit and/or the energy limit in their calculation of ET in certain basins. This implies water is being lost, for example through the groundwater system when the energy limit is exceeded or there is an additional input of water beyond precipitation if the water limit is exceeded. SSEBop, WECANN and CMRSET exceed the water limit in more basins relative to other products, however their ET estimations are not necessarily further from ET estimations using the Budyko approach as given by equation 2. This is confirmed in table 8 where CMRSET and SSEBop along with WaPOR have the lowest biases when compared with ET_{Budyko} after ET_{WB}.

3.3 Spatial variability assessment

Figure 10 shows ET across Africa for all ET products with the specific land cover elements (forest, irrigated areas and water bodies) highlighted. Two different scales are used in order to be able to visually compare the products according to spatial variability rather than magnitude of ET. For products where large biases were found, a scale of 0-1200 mm/year was used and for the remaining products a scale of 0-1800 mm/year was used. Visually, all products capture the forested area. Irrigated areas are also captured well by most products. GLEAM and LandFlux-EVAL do not capture the majority of selected irrigated areas. CMRSET, ETMonitor, SSEBop and WaPOR capture most of the selected irrigated areas while the remaining products capture a few. GLEAM, LandFlux-EVAL, MOD16, MTE and WECANN only estimate land ET and thus do not have ET across water bodies. The remaining products capture the water bodies well, with CMRSET and ETMonitor showing larger differences in their estimations of ET across water bodies than the surrounding areas over SSEBop and WaPOR. A ranking based on visual inspection of how well each ET product captures the selected land cover element can be found in Table 9.

Figures 11 and 12 show the bias between the mean ET across the forests and water bodies estimated by the ET products and the reference ET used for each element. All ET products capture ET across the selected forested area, however some perform better than others at describing the magnitude. CMRSET, SSEBop and WaPOR have very low biases with respect to the reference found in literature, while MOD16 and WECANN have the largest biases. All products underestimate ET across the forested area with respect to the used reference. The four products which estimate ET across water bodies, show relatively low biases with the reference PET. CMRSET overestimates ET while ETMonitor, SSEBop and WaPOR underestimate ET on average across water bodies. The lowest bias for water bodies is found in ETMonitor.

3.4 Product similarity assessment

Two groupings or clusters are observed when looking at the similarity between individual products (Fig. 13). We see one cluster formed with three products, CMRSET, SSEBop and WaPOR, with SSEBop and WaPOR being slightly more similar than with CMRSET. And a second cluster with the remaining products. Within the second cluster, LandFlux-EVAL and WECANN show the highest level of similarity which also coincides with having the same spatial resolution.

3.5 Ranking of products

Table 9 shows the ranking of the ET products based on the different assessment criteria. First we look at the ranking for statistics of the catchment water balance. In terms of bias and bias$_{aw}$ CMRSET, SSEBop and WaPOR are consistently ranked the highest while GLEAM is ranked the lowest. When looking at the RMSE and RMSE$_{aw}$ the same three products along with LandFlux-EVAL are ranked the top four while again GLEAM is ranked lowest. For correlation GLEAM and LandFlux-EVAL rank highest while SSEBop is ranked the lowest. Overall for comparison of calculated ET$_{WB}$ and ET calculated by the products, CMRSET, LandFlux-EVAL, SSEBop and WaPOR rank the highest while GLEAM and MOD16 rank the lowest. Second we look at the comparison with the reference condition of the Budyko curve. Here, the same ranking pattern can be seen, with CMRSET, LandFlux-EVAL, SSEBop and WaPOR ranking highest and GLEAM and MOD16 ranking the lowest. Thirdly we look at the spatial variability rankings. For spatial variability with visual inspection, CMRSET, ETMonitor, SSEBop and WaPOR rank the highest and LandFlux-EVAL and WECANN rank the lowest. For spatial variability with quantitative inspection we see that the same four products, CMRSET, ETMonitor, SSEBop and WaPOR rank the highest with GLEAM and WECANN ranking the lowest. Overall for spatial variability, CMRSET, ETMonitor, SSEBop and WaPOR rank highest while GLEAM and WECANN rank the lowest. The final ranking was conducted with and without visual inspection. The top four products, CMRSET, LandFlux-EVAL, SSEBop and WaPOR, do not vary in the two ranking schemes. GLEAM is also ranked lowest in both ranking schemes. Interesting to note is that ETMonitor ranks higher when including visual inspection while WECANN ranks higher when excluding visual inspection.

4 Discussion

We make two assumptions in this paper regarding the methodology applied for evaluating the selected ET products. The first assumption is that if no trends are present in long-term average ET$_{WB}$ across a basin, then long-term average ET$_{WB}$ across basins can be compared with different time periods. This is true if long-term trends in global ET are not visibly present. However, Jung et al. (2010) claim that there have been declining trends in global ET estimates in the recent past along with the last major El Niño event in 1998 with largest regional contributions to the declining trend in Australia and Southern Africa. The exact opposite effect is reported by Zhang et al. (2016) which claims significant increases in global land ET trends especially in Australia and Southern Africa. Other studies also focus on investigating trends in long-term ET and do not come to a consensus as to the cause or direction of the trend (Miralles et al., 2014; Douville et al., 2013; Jung et al., 2010; Zhang et al., 2016). With

this in mind, it is difficult to assume there is long-term global trend in one direction or the other. For this first assumption to hold, we must also address the possibility that regardless of whether there are no trends present, the mean ET from one period may be different from another period due to precipitation variability. In this case we analysed four basins for which the calculated ET_{WB} estimations had a period sufficient enough to cover the time period of the range of ET products being

5   evaluated. For the four basins, ET_{WB} was calculated for each of the different time periods of the ET products. We then found the bias from the the calculated long-term average ET_{WB}. From Table 10 we see that the percentage differences relative to total basin long-term average ET ranges from 0 to a maximum of 7.4 percent for the four basins evaluated and all ET products. Thus, considering the lack of consensus of the direction of a long-term global trend in ET and very low differences in precipitation variability, in this study our assumption holds that if no significant trend can be found in annual long-term ET estimates then

10   different time periods can be used due to lack of overlapping data.

The second assumption is that the water balance can be simplified to equation 1 where for long-term average estimates the change in storage is negligible. Many studies make this assumption for long-term averages and basin scale averages (Du et al., 2016; Taniguchi et al., 2003; Wang and Alimohammadi, 2012; Carter, 2001; Budyko, 1974). However a recent study by Rodell et al. (2018) quantified trends in terrestrial water storage using the Gravity Recovery and Climate Experiment (GRACE) data

15   for the period 2002- 2016. The largest annual trend found in this study is 20 mm per year and for the African continent can be found across sections of the Congo, Zambezi, Okavango, Cunene, Save and Rufiji basins. Of these basins Okavango, Cunene and Save are not used in this study and thus are not affected. Assuming a contribution of the largest trend in storage for the other basins this represents a maximum of 2.3 percent of the long-term annual average mean basin ET. Therefore we assumed negligible change in storage for our calculations.

20   The comparison between the RS products was carried out at the highest spatial resolution of the different products which is $0.0022° \times 0.0022°$. As we are resampling from coarse resolution to higher resolution, the nearest neighbor method employed for completing the resampling is sufficient, as the magnitude and spatial characteristics will not be altered or lost (Porwal and Katiyar, 2014; Gurjar and Padmanabhan, 2005). It must also be kept in mind that the initial spatial resolution and the temporal period under comparison are not the same for each product and this may effect the ranking that we are considering. However,

25   considering there are different resolution products available, this is an important feature in considering the ranking of products in terms of accuracy in order to make an educated decision on which product to use. Also many of the products do not estimate ET across water bodies and this may therefore explain the large biases in certain products when comparing ET estimations with the ET_{WB} estimations. Another aspect to bear in mind, is that WaPOR, ETMonitor and WECANN have less than 10 years in total coverage in order to calculate their long-term average.

30   Evaluation of the spatial characteristics is completed using two steps, the comparison of land cover elements with reference estimates and visual interpretation. There are two issues involved in this spatial comparison. Firstly, the evaluation is taking place based on products originating with different resolutions. Thus, the view that higher resolution products may outperform the coarser resolution products, which is generally the case. However, we can also see that coarser resolution products, namely LandFlux-EVAL and in certain cases MTE and WECANN, outperform the higher resolution product GLEAM. Thus higher

35   resolution products do not always outperform lower resolutions as can be seen. The spatial resolution of the ET estimates used

may also be a critical element in determining which product is of use for the user. Secondly, the visual interpretation can be viewed as quite arbitrary and subjective according to the evaluator's eye. However, by using land cover elements that are large and easy to visualize, such as forested areas, irrigated areas and water bodies, the relative subjectivity can be reduced.

We used the assumption that where there is ample water ET equals PET (McMahon et al., 2013) and thus applied this assumption for evaluating our ET products for water bodies. The assumption holds quite well for the products that estimate ET over water. There are several reasons why it is difficult to find a quantitative reference for irrigated areas at such large magnitudes. Firstly, it is difficult to assume there is no mixing and only irrigated areas are found in pixels of a minimum of 250m x 250m. Secondly, an irrigated area of a particular size is often in reality growing more than one crop which is difficult to measure or map. A reference that could be used in subsequent studies would be to use water productivity (biomass/water consumed (ET)) for comparison.

The overall ranking for each product was based on the average ranking of the different comparative elements. An overall ranking was performed including the visual inspection of the land cover elements, however was also performed without, due to the subjectivity of the analyst doing the visual inspection. This does not affect the ranking of the top four or the lowest ranked product but changes the order of the products ranked in the middle. WaPOR, CMRSET, SSEBop and LandFlux-EVAL are consistently ranked 1, 2, 3 and 4 respectively. CMRSET and WaPOR rank first when including a visual inspection however only WaPOR ranks first without. The lowest ranked product is GLEAM in both cases. WECANN ranks higher without visual inspection from positions 8 to 6 and ETMonitor ranks lower without visual inspection going from position 5 to 7.

Looking at the overall level of similarity between the products in Fig. 5 we can see that for the cluster between CMRSET, SSEBop and WaPOR all products use MODIS as an input. SSEBop and WaPOR both use the P-M method for the calculation of ET, while CMRSET uses the P-T method. ETMonitor and MOD16 also use MODIS as an input with MOD16 using the P-M method for ET calculation and ETMonitor using both Shuttleworth-Wallace and the P-M method, however both are found in the second cluster. The remaining products within the second cluster use different inputs and different ET estimation methods. Thus, no patterns can be inferred through the cluster analysis by looking at the input or ET calculation method. What is clear is that the first cluster contains the products which have the highest spatial resolutions and which overall rank the best in terms of ET estimation based on the evaluation criteria.

In terms of consistency in results with previous studies conducted on some of the products under evaluation we see similar tendencies. According to Miralles et al. (2016) GLEAM, MOD16 and other products in their study show divergences in conditions of water stress and drought. Considering large parts of Africa are potentially under water stress due to the semi-arid and arid climate (IPCC, 2019; World Bank, 2018), this can explain the low ranking of GLEAM and MOD16 in this study. The RMSE and biases found in our study for Africa are comparable with those found by Vinukollu et al. (2011b) at the global scale, however comparing different products to that of this study. The range is higher in this study for Africa than the range found at the global scale. In their study, Trambauer et al. (2014) found GLEAM to underestimate ET in terms of their multi-product mean. This is again consistent with our finding where biases in GLEAM showed large underestimations across the basins in Africa with respected to the calculated ET_{WB}. We used the LandFlux-EVAL benchmark product as an ensemble product without calculating the multi-product mean of the products being used in this study, as it was developed using a large range

of ET products. LandFlux-EVAL, with the coarsest spatial resolution, ranked fourth in the final ranking only outranked by the products with the three highest spatial resolutions in this study, CMRSET, SSEBop and WaPOR. Therefore, LandFlux-EVAL performs well overall regardless of it's coarse resolution and is interesting due to being an ensemble product. Therefore, continuation or commencement of a similar initiative to develop a benchmark product using a range of ET data sets including high resolution products ranked within this study may improve the ensemble product for future use.

It is also important to note that the overall ranking is interesting for global or large scale regional modellers however, for catchment studies a detailed look into their basin(s) of interest and local elements should also be considered. For example, if we look at the basin level bias and area weighted bias (Fig 8) for three of the large basins in Africa, the Congo, the Nile and the Niger basins, the following products have the lowest biases in the specified order: for the Congo basin, SSEBop, CMRSET and WaPOR; for the Nile basin, MTE, SSEBop and CMRSET; and for the Niger basin, WaPOR, SSEBop and MOD16. This shows that a detailed look into the local characteristics of a particular basin is required before selecting a product for use. Due to the limited overlap between discharge data and ET estimations by the products, temporal evaluations were not possible. It would also be interesting and valuable to see which products capture temporal trends which may also effect the choice of a product.

5   Conclusions

This study focuses on the question of whether or not we can trust remote sensing and other ET products over Africa. By trying to overcome the problem of the lack of data for validation and evaluation purposes the methodology used can identify which products perform well in terms of biases and spatial characteristics. Using observations of discharge and observation based precipitation products to infer long-term average mean ET estimates at the basin scale and overcoming the lack of overlapping data for comparison by using different time periods for calculation of our long-term averages, different ET products were evaluated. According to the comparison of the ET_{WB} with ET_{Budyko}, we see that ET_{WB} follows the Budyko curve and has an overall low bias across the basins. This indicates the calculated ET_{WB} is a sound reference condition to use for analyses. Based on the different elements being analysed CMRSET, WaPOR and SSEBop capture the magnitude of ET showing small biases in the long-term average mean ET across basins. The same products also capture the spatial distribution of the ET patterns well along with ETMonitor. Apart from the visual inspection, the ensemble product LandFlux-EVAL consistently ranks fourth or higher acting as a bridge between the products with the highest spatial resolutions and others. The high correlation statistics indicate good spatial distribution in all products, especially GLEAM and LandFlux-EVAL which rank the highest. However, nearly all products show relatively large biases in ET estimations, except CMRSET, SSEBop and WaPOR. It is difficult to come to a concrete judgement as to the reasons behind the differences between the ET products. A big difference between the top three ranked products and the others is the high spatial resolution as well as the estimation of ET as a whole rather than only land ET in most other cases. However, no pattern can be found between the product ranking and the forcing or ET calculation methods. There are also certain advantages and disadvantages of the products outside of the evaluation criteria which are important to name. Although GLEAM is ranked lowest overall, the product has the longest temporal coverage

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starting from 1980 and is on-going. LandFlux-EVAL and MTE also have early starting years however only go up to 2005 and 2012, respectively. ETMonitor is also no longer being extended and is not openly accessible or available for use. WaPOR is only available for Africa and not globally compared to all other products. Therefore, if we answer our question of whether to trust remote sensing estimates of ET across Africa, the answer is not black and white. Yes, in general we can trust the products under evaluation in this study. CMRSET, WaPOR and SSEBop show low biases in estimations and a good spatial distribution of ET patterns. Each of these products have relatively high resolutions and both CMRSET and SSEBop are global products. Depending on the study under question, whether an early and long time period is needed, whether a higher or lower resolution is required, whether looking at the global or regional scale or whether looking only at land evapotranspiration, a different product may be more suited than another. However, a large consideration to be kept in mind for Africa, is that the three highest ranked products, CMRSET, SSEBop and WaPOR have low biases and perform well in spatial variability and will suit most needs within a given study. However, for catchment scale studies within Africa a detailed look into the characteristics of the basin should be considered along with the overall ranking.

Appendix A: Appendix A

References

Alemohammad, S. H., Fang, B., Konings, A. G., Aires, F., Green, J. K., Kolassa, J., Miralles, D., Prigent, C., and Gentine, P.: Water, Energy, and Carbon with Artificial Neural Networks (WECANN): a statistically based estimate of global surface turbulent fluxes and gross primary productivity using solar-induced fluorescence, Biogeosciences, 14, 4101–4124, https://doi.org/10.5194/bg-14-4101-2017, https://doi.org/10.5194/bg-14-4101-2017, 2017.

Alkema, L., Raftery, A. E., Gerland, P., Clark, S. J., and Pelletier, F.: Estimating the Total Fertility Rate from Multiple Imperfect Data Sources and Assessing its Uncertainty, Center for Statistics and the Social Sciences, University of Washington, 50, 1–19, https://doi.org/10.1029/2011RG000373.1.INTRODUCTION, http://www.csss.washington.edu/Papers/wp89.pdf, 2011.

Bai, P. and Liu, X.: Intercomparison and evaluation of three global high-resolution evapotranspiration products across China, Journal of Hydrology, 566, 743–755, https://doi.org/10.1016/j.jhydrol.2018.09.065, https://linkinghub.elsevier.com/retrieve/pii/S0022169418307595, 2018.

Baldocchi, D., Falge, E., Gu, L., Olson, R., Hollinger, D., Run-ning, S., Anthoni, P., Bernhofer, C., Davis, K., Evans, R., Fuentes, J., Goldstein, A., Katul, G., Law, B., Lee, X., Malhi, Y., Meyers, T., Munger, W., Oechel, W., Paw, K. T., Pilegaard, K., Schmid, H. P., Valentini, R., Verma, S., Vesala, T., Wil-son, K., and Wofsy, S.: FLUXNET: A New Tool to Study the Temporal and Spatial Variability of Ecosystem–Scale Carbon Dioxide, Water Vapor, and Energy Flux Densities, Bulletin of the American Meteorological Society, 82, 2415–2434, 2001.

Balsamo, G., Albergel, C., Beljaars, A., Boussetta, S., Brun, E., Cloke, H., Dee, D., Dutra, E., Muñoz-Sabater, J., Pappenberger, F., De Rosnay, P., Stockdale, T., and Vitart, F.: ERA-Interim/Land: a global land surface reanalysis data set, Hydrol. Earth Syst. Sci, 19, 389–407, https://doi.org/10.5194/hess-19-389-2015, www.hydrol-earth-syst-sci.net/19/389/2015/, 2015.

Budyko, M. I.: Climate and life, Academic Press, New York, english edn., 1974.

Calton, B., Schellekens, J., and Martinez-De La Torre, A.: Water Resource Reanalysis v1: Data Access and Model Verification Results., https://doi.org/10.5281/zenodo.57760, 2016.

Carter, J. M.: Hydrologic Budgets Methods for Estimating Basin Yield and Recharge, Tech. rep., 2001.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., M. A. Balmased, G. B., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimb, L., Vitart, F., and J. N. Thépautaan: The ERA-Interim reanalysis: configuration and performance ofthe data assimilation system., Royal Meteorology Society, 137, 553–597, 2011.

Douville, H., Ribes, A., Decharme, B., Alkama, R., and Sheffield, J.: Anthropogenic influence on multidecadal changes in reconstructed global evapotranspiration, Nature Climate Change, 3, 2013.

Du, C., Sun, F., Yu, J., Liu, X., and Chen, Y.: New interpretation of the role of water balance in an extended Budyko hypothesis in arid regions, Hydrology and Earth System Sciences, 20, 393–409, https://doi.org/10.5194/hess-20-393-2016, 2016.

FAO: WaPOR Database Methodology:Level 1 Data using remote sensing in support of solutions to reduce agricultural water productivity gaps, Tech. rep., FAO, Rome, http://www.fao.org/3/I7315EN/i7315en.pdf, 2018.

Fisher, J. B., Tu, K. P., and Baldocchi, D. D.: Global estimates of the land–atmosphere water flux based on monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites, Remote Sensing of Environment, 112, 901–919, https://doi.org/10.1016/j.rse.2007.06.025, https://linkinghub.elsevier.com/retrieve/pii/S0034425707003938, 2008.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J.: The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes, Scientific Data, 2, 1–21, https://doi.org/10.1038/sdata.2015.66, 2015.

Gerrits, A. M., Savenije, H. H., Veling, E. J., and Pfister, L.: Analytical derivation of the Budyko curve based on rainfall characteristics and a simple evaporation model, Water Resources Research, 45, 1–15, https://doi.org/10.1029/2008WR007308, 2009.

Google: Distribution of flux towers across Africa, https://fluxnet.fluxdata.org/sites/site-list-and-pages/?view=map.

Guerschman, J. P., Van Dijk, A. I., Mattersdorf, G., Beringer, J., Hutley, L. B., Leuning, R., Pipunic, R. C., and Sherman, B. S.: Scaling of potential evapotranspiration with MODIS data reproduces flux observations and catchment water balance observations across Australia, Journal of Hydrology, 369, 107–119, https://doi.org/10.1016/j.jhydrol.2009.02.013, http://dx.doi.org/10.1016/j.jhydrol.2009.02.013, 2009.

Gurjar, S. B. and Padmanabhan, N.: Study of various resampling techniques for high-resolution remote sensing imagery, Journal of the Indian Society of Remote Sensing, 33, 113–120, https://doi.org/10.1007/BF02989999, 2005.

Hargreaves, G. and Samani, Z.: Reference crop evapotranspiration from temperature, Applied engineering in agriculture, 1, 96–99, 1985.

Huffman, G. J., Adler, R. F., Bolvin, D. T., Gu, G., Nelkin, E. J., Bowman, K. P., Hong, Y., Stocker, E. F., and Wolff, D. B.: The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales, https://doi.org/10.1175/JHM560.1, https://pdfs.semanticscholar.org/3516/25f66dfe426c0515d216d34da8fd9b7b2d09.pdf?{_}ga= 2.230540574.326887509.1566376018-571311706.1562918336, 2007.

IPCC, I. P. o. C. C.: IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, Tech. rep., Intergovernmental Panel on Climate Change, https://www.ipcc.ch/site/assets/uploads/2019/08/Fullreport-1.pdf, 2019.

JAXA: The Global Satellite Mapping of Precipitation (GSMaP) project, https://sharaku.eorc.jaxa.jp/GSMaP{_}crest/, 2009.

Jiménez, C., Prigent, C., Mueller, B., Seneviratne, S. I., McCabe, M. F., Wood, E. F., Rossow, W. B., Balsamo, G., Betts, A. K., Dirmeyer, P. A., Fisher, J. B., Jung, M., Kanamitsu, M., Reichle, R. H., Reichstein, M., Rodell, M., Sheffield, J., Tu, K., and Wang, K.: Global intercomparison of 12 land surface heat flux estimates, Journal of Geophysical Research Atmospheres, 116, 1–27, https://doi.org/10.1029/2010JD014545, 2011.

Jung, H. C., Getirana, A., Policelli, F., McNally, A., Arsenault, K. R., Kumar, S., Tadesse, T., and Peters-Lidard, C. D.: Upper Blue Nile basin water budget from a multi-model perspective, Journal of Hydrology, 555, 535–546, https://doi.org/10.1016/j.jhydrol.2017.10.040, https://doi.org/10.1016/j.jhydrol.2017.10.040, 2017.

Jung, M., Reichstein, M., Ciais, P., Seneviratne, S. I., Sheffield, J., Goulden, M. L., Bonan, G., Cescatti, A., Chen, J., De Jeu, R., Dolman, A. J., Eugster, W., Gerten, D., Gianelle, D., Gobron, N., Heinke, J., Kimball, J., Law, B. E., Montagnani, L., Mu, Q., Mueller, B., Oleson, K., Papale, D., Richardson, A. D., Roupsard, O., Running, S., Tomelleri, E., Viovy, N., Weber, U., Williams, C., Wood, E., Zaehle, S., and Zhang, K.: Recent decline in the global land evapotranspiration trend due to limited moisture supply, Nature, 467, 951–954, https://doi.org/10.1038/nature09396, 2010.

Jung, M., Reichstein, M., Margolis, H. A., Cescatti, A., Richardson, A. D., Arain, M. A., Arneth, A., Bernhofer, C., Bonal, D., Chen, J., Gianelle, D., Gobron, N., Kiely, G., Kutsch, W., Lasslop, G., Law, B. E., Lindroth, A., Merbold, L., Montagnani, L., Moors, E. J., Papale, D., Sottocornola, M., Vaccari, F., and Williams, C.: Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations, Journal of Geophysical Research: Biogeosciences, 116, 1–16, https://doi.org/10.1029/2010JG001566, 2011.

Kendall, M.: Rank correlation methods, Griffin, Oxford, England, 1948.

Lange, S.: EartH2Observe, WFDEI and ERA-Interim data Merged and Bias-corrected for ISIMIP (EWEMBI). V. 1.1, http://doi.org/10.5880/pik.2019.004, 2019.

Lehner, B., Liermann, C. R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., Döll, P., Endejan, M., and Frenken, K.: Global Reservoir and Dam (GRanD) database, Tech. Rep. March, https://doi.org/10.1128/JCM.01792-10, http://www.gwsp.org/products/grand-database.html, 2011.

Mann, H.: Non-parametric tests against trend, Econometrica, 13, 163–171, 1945.

Martens, B., Miralles, D. G., Lievens, H., Van Der Schalie, R., De Jeu, R. A. M., Fernández-Prieto, D., Beck, H. E., Dorigo, W. A., and Verhoest, N. E. C.: GLEAM v3: satellite-based land evaporation and root-zone soil moisture, Geosci. Model Dev, 10, 1903–1925, https://doi.org/10.5194/gmd-10-1903-2017, www.geosci-model-dev.net/10/1903/2017/, 2017.

Matzke, B. D., Wilson, J. E., Newburn, L., Dowson, S. T., Hathaway, J. E., Sego, L. H., Bramer, L. M., and Pulsipher, B. A.: Mann-Kendall Test For Monotonic Trend, Tech. rep., Pacific Northwest National Laboratory, Richland, Washington, 2014.

McMahon, T. A., Peel, M. C., Lowe, L., Srikanthan, R., and McVicar, T. R.: Estimating actual , potential , reference crop and pan evaporation using standard meteorological data : a pragmatic synthesis, Hydrol. Earth Syst. Sci, 17, 1331–1363, https://doi.org/10.5194/hess-17-1331-2013, 2013.

Miralles, D. G., Holmes, T. R. H., De Jeu, R. A. M., Gash, J. H., Meesters, A. G. C. A., and Dolman, A. J.: Hydrology and Earth System Sciences Global land-surface evaporation estimated from satellite-based observations, Hydrol. Earth Syst. Sci, 15, 453–469, https://doi.org/10.5194/hess-15-453-2011, www.hydrol-earth-syst-sci.net/15/453/2011/, 2011.

Miralles, D. G., Van Den Berg, M. J., Gash, J. H., Parinussa, R. M., De Jeu, R. A. M., Beck, H. E., Holmes, T. R. H., Jiménez, C., Verhoest, N. E. C., Dorigo, W. A., Teuling, A. J., and Johannes Dolman, A.: El Niño-La Niña cycle and recent trends in continental evaporation, Nature Climate Change, 4, 122–126, https://doi.org/10.1038/nclimate2068, http://dx.doi.org/10.1038/nclimate2068, 2014.

Miralles, D. G., Jiménez, C., Jung, M., Michel, D., Ershadi, A., Mccabe, M. F., Hirschi, M., Martens, B., Dolman, A. J., Fisher, J. B., Mu, Q., Seneviratne, S. I., Wood, E. F., and Fernández-Prieto, D.: The WACMOS-ET project-Part 2: Evaluation of global terrestrial evaporation data sets, Hydrol. Earth Syst. Sci, 20, 823–842, https://doi.org/10.5194/hess-20-823-2016, www.hydrol-earth-syst-sci.net/20/823/2016/, 2016.

Montieth, L. J.: State and movement of water in living organisms, in: 19th Symposium of Evaporation and the Environment, Cambridge University Press, Swansea, London, 1965.

Mu, Q., Heinsch, F. A., Zhao, M., and Running, S. W.: Development of a global evapotranspiration algorithm based on MODIS and global meteorology data, Remote Sensing of Environment, 111, 519–536, https://doi.org/10.1016/j.rse.2006.07.007, www.elsevier.com/locate/rse, 2007.

Mu, Q., Heinsch, F. A., Zhao, M., and Running, S. W.: Improvements to a MODIS global terrestrial evapotranspiration algorith, Remote Sensing of Environment, 115, 1781–1800, https://doi.org/10.1016/j.rse.2007.04.015, http://www.taiga.net/wolfcreek/Proceed-, 2011.

Mueller, B., Seneviratne, S. I., Jimenez, C., Corti, T., Hirschi, M., Balsamo, G., Ciais, P., Dirmeyer, P., Fisher, J. B., Guo, Z., Jung, M., Maignan, F., McCabe, M. F., Reichle, R., Reichstein, M., Rodell, M., Sheffield, J., Teuling, A. J., Wang, K., Wood, E. F., and Zhang, Y.: Evaluation of global observations-based evapotranspiration datasets and IPCC AR4 simulations, Geophysical Research Letters, 38, 1–7, https://doi.org/10.1029/2010GL046230, 2011.

Mueller, B., Hirschi, M., Jimenez, C., Ciais, P., Dirmeyer, P. A., Dolman, A. J., Fisher, J. B., Jung, M., Ludwig, F., Maignan, F., Miralles, D. G., Mccabe, M. F., Reichstein, M., Sheffield, J., Wang, K., Wood, E. F., Zhang, Y., and Seneviratne, S. I.: Benchmark products for

land evapotranspiration: LandFlux-EVAL multi-data set synthesis, Hydrol. Earth Syst. Sci, 17, 3707–3720, https://doi.org/10.5194/hess-17-3707-2013, www.hydrol-earth-syst-sci.net/17/3707/2013/, 2013a.

Mueller, B., Hirschi, M., Jimenez, C., Ciais, P., Dirmeyer, P. A., Dolman, A. J., Fisher, J. B., Jung, M., Ludwig, F., Maignan, F., Miralles, D. G., Mccabe, M. F., Reichstein, M., Sheffield, J., Wang, K., Wood, E. F., Zhang, Y., and Seneviratne, S. I.: Benchmark products for land evapotranspiration: LandFlux-EVAL multi-data set synthesis, Hydrol. Earth Syst. Sci, 17, 3707–3720, https://doi.org/10.5194/hess-17-3707-2013, www.hydrol-earth-syst-sci.net/17/3707/2013/, 2013b.

NCAR: CMORPH (CPC MORPHING TECHNIQUE): HIGH RESOLUTION PRECIPITATION (60S-60N), https://climatedataguide.ucar.edu/climate-data/cmorph-cpc-morphing-technique-high-resolution-precipitation-60s-60n, 2017.

Otto, F. E. L., Jones, R. G., Halladay, K., and Allen, M. R.: Attribution of changes in precipitation patterns in African rainforests, Phil Trans R Soc B, 368, 20120 299, https://doi.org/10.1098/rstb.2012.0299, http://dx.doi.org/10.1098/rstb.2012.0299http://dx.doi.org/10.1098/rstb.2012.0299orviahttp://rstb.royalsocietypublishing.org., 2013.

Penman, H. L.: Natural Evaporation from Open Water, Bare Soil and Grass, Tech. Rep. 1032, 1948.

Porwal, S. and Katiyar, S. K.: Performance evaluation of various resampling techniques on IRS imagery, 2014 7th International Conference on Contemporary Computing, IC3 2014, pp. 489–494, https://doi.org/10.1109/IC3.2014.6897222, 2014.

Priestley, B. and Taylor, R.: On the assessment of surface heat flux and exporation using large-scale parameters, Monthly Weather Review, 100, 81–92, 1972.

Reynolds, E. R. C., Thompson, F. B., and United Nations University.: Forests, climate, and hydrology : regional impacts, United Nations University, http://archive.unu.edu/unupress/unupbooks/80635e/80635E00.htm{#}Contents, 1988.

Rodell, M., Famiglietti, J. S., Wiese, D. N., Reager, J. T., Beaudoing, H. K., Landerer, F. W., and Lo, M.-H.: Emerging trends in global freshwater availability, Nature, https://doi.org/10.1038/s41586-018-0123-1, https://doi.org/10.1038/s41586-018-0123-1, 2018.

Senay, G. B., Bohms, S., Singh, R. K., Gowda, P. H., Velpuri, N. M., Alemu, H., and Verdin, J. P.: Operational Evapotranspiration Mapping Using Remote Sensing and Weather Datasets: A New Parameterization for the SSEB Approach, Journal of the American Water Resources Association, 49, 577–591, https://doi.org/10.1111/jawr.12057, 2013.

Siebert, S., Henrich, V., Frenken, K., and Burke, J.: Global Map of Irrigation Areas version 5, 2013.

Sperna Weiland, F., Lopez, P., van Dijk, A., and Schellekens, J.: Global high-resolution reference potential evaporation, 21st International Congress on Modelling and Simulation, pp. 2548–2554, 2015.

Sposito, G.: Understanding the budyko equation, Water (Switzerland), 9, 1–14, https://doi.org/10.3390/w9040236, 2017.

Su, Z.: The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes, Tech. Rep. 1, https://www.hydrol-earth-syst-sci.net/6/85/2002/hess-6-85-2002.pdf, 2002.

Taniguchi, M., Burnett, W., Cable, J., and Turnerd, J.: Assessment methodologies for submarine groundwater discharge, Land and Marine Hydrogeology, pp. 1–23, 2003.

Teuling, A. J., Hirschi, M., Ohmura, A., Wild, M., Reichstein, M., Ciais, P., Buchmann, N., Ammann, C., Montagnani, L., Richardson, A. D., Wohlfahrt, G., and Seneviratne, S. I.: A regional perspective on trends in continental evaporation, Geophysical Research Letters, 36, 1–5, https://doi.org/10.1029/2008GL036584, 2009.

Trambauer, P., Dutra, E., Maskey, S., Werner, M., Pappenberger, F., Van Beek, L. P. H., and Uhlenbrook, S.: Comparison of different evaporation estimates over the African continent, Hydrol. Earth Syst. Sci, 18, 193–212, https://doi.org/10.5194/hess-18-193-2014, www.hydrol-earth-syst-sci.net/18/193/2014/, 2014.

Tramontana, G., Jung, M., Schwalm, C. R., Ichii, K., Camps-Valls, G., Ráduly, B., Reichstein, M., Arain, M. A., Cescatti, A., Kiely, G., Merbold, L., Serrano-Ortiz, P., Sickert, S., Wolf, S., and Papale, D.: Predicting carbon dioxide and energy fluxes across global FLUXNET sites with regression algorithms, Biogeosciences, 13, 4291–4313, https://doi.org/10.5194/bg-13-4291-2016, www.biogeosciences.net/13/4291/2016/, 2016.

5 Van Beek, L. R. and Bierkens, M. F. P.: The Global Hydrological Model PCR-GLOBWB: Conceptualization, Parameterization and Verification Report, Tech. rep., Utrecht University, Faculty of Earth Sciences, Department of Geography, Utrecht, Netherlands, http://vanbeek.geo.uu.nl/suppinfo/vanbeekbierkens2009.pdf, 2009.

Vinukollu, R. K., Meynadier, R., Sheffield, J., and Wood, E. F.: Multi-model, multi-sensor estimates of global evapotranspiration: climatology, uncertainties and trends, Hydrological Processes, 25, 3993–4010, https://doi.org/10.1002/hyp.8393, 2011a.

10 Vinukollu, R. K., Wood, E. F., Ferguson, C. R., and Fisher, J. B.: Global estimates of evapotranspiration for climate studies using multi-sensor remote sensing data: Evaluation of three process-based approaches, https://doi.org/10.1016/j.rse.2010.11.006, http://www.wmo.ch/pages/, 2011b.

Wang, D. and Alimohammadi, N.: Responses of annual runoff, evaporation, and storage change to climate variability at the watershed scale, Water Resources Research, 48, https://doi.org/10.1029/2011WR011444, 2012.

15 Wartenburger, R., Seneviratne, S. I., Hirschi, M., Chang, J., Ciais, P., Deryng, D., Elliott, J., Folberth, C., Gosling, S. N., Gudmundsson, L., Henrot, A.-J., Hickler, T., Ito, A., Khabarov, N., Kim, H., Leng, G., Liu, J., Liu, X., Masaki, Y., Morfopoulos, C., Muller, C., Schmied, H., Nishina, K., Orth, R., Pokhrel, Y., Pugh, T., Satoh, Y., Schaphoff, S., Schmid, E., Sheffield, J., Stacke, T., Steinkamp, J., Tang, Q., Thiery, W., Wada, Y., Wang, X., Weedon, G., Yang, H., and Zhou, T.: Evapotranspiration simulations in ISIMIP2a-Evaluation of spatio-temporal characteristics with a comprehensive ensemble of independent datasets, Environmental Research Letters, 13, https://doi.org/10.1088/1748-

20 9326/aac4bb, https://doi.org/10.1088/1748-9326/aac4bb, 2018.

Weedon, G. P., Balsamo, G., Bellouin, N., Gomes, S., Best, M. J., and Viterbo, P.: The WFDEI meteorological forcing data set: WATCH ForcingData methodology applied to ERA-Interim reanalysis data, Water Resource Research, 50, 7505–7514, https://doi.org/doi:10.1002/2014WR015638, 2014.

World Bank: Major River Basins Of The World, https://datacatalog.worldbank.org/dataset/major-river-basins-world, 2017.

25 World Bank: Beyond Scarcity Water Security in the Middle East and North Africa, MENA Development Report:, Washington DC, https://doi.org/10.1192/bjp.111.479.1009-a, https://openknowledge.worldbank.org/handle/10986/27659, 2018.

Zhang, Y., Peña-Arancibia, J. L., Mcvicar, T. R., Chiew, F. H. S., Vaze, J., Liu, C., Lu, X., Zheng, H., Wang, Y., Liu, Y. Y., Miralles, D. G., and Pan, M.: Multi-decadal trends in global terrestrial evapotranspiration and its components OPEN, Scientific Reports, 6, https://doi.org/10.1038/srep19124, www.nature.com/scientificreports/, 2016.

30 Zheng, C., Jia, L., Hu, G., Lu, J., Wang, K., and Li, Z.: Global evapotranspiration derived by ETMonitor model based on earth observations, International Geoscience and Remote Sensing Symposium (IGARSS), 2016-Novem, 222–225, https://doi.org/10.1109/IGARSS.2016.7729049, 2016.

Basin	Variable	Data Availability	Trend	hypothesis	p-value	z-value	no. of samples
Awash	ET	1990-2004	no trend	false	0.2496	-1.1514	14
	P	1979-2016					38
	Q	1990-2004	MK test not conducted, no trend found in ET				15
Bandama	ET	1979-1996	no trend	false	0.7619	-0.3030	18
	P	1979-2016					38
	Q	1970-1996	MK test not conducted, no trend found in ET				27
Blue Nile	ET	not enough ET data points to conduct MK test on calculated ET					4

	P	1979-2016	no trend	false	0.6875	-0.4023	38
	Q	1900-1982	decreasing	true	0.0009	-3.3271	83
Buzi	ET	not enough ET data points to conduct MK test on calculated ET					5
	P	1979-2016	no trend	false	0.4210	-0.8046	38
	Q	1957-1983	no trend	false	1.0	0.0	23
Cavally	ET	1979-1996	no trend	false	0.54449	-0.6060	18
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1970-1996					27
Congo	ET	1979-2010	no trend	false	0.0830	-1.7336	31
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1903-2010					108
Cunene	ET	1980-2015	increasing	true	0.0003	3.5823	36
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1980-2015					36
Gambia	ET	not enough ET data points to conduct MK test on calculated ET					5
	P	1979-2016	no trend	false	0.2579	1.1315	38
	Q	1979, 1981-82, 1984,1988	no trend	false	0.8065	0.2449	5
Groot	ET	1979-2015	no trend	false	0.1697	1.3733	37
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1964-2014					51
Kamoe	ET	1979-1996	no trend	false	0.3633	-0.9091	18
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1970-1996					27
Lake Chad	ET	not enough ET data points to conduct MK test on calculated ET					4
	P	1979-2016	increasing	true	0.0194	2.3384	38
	Q	1983-1986	no trend	false	0.3081	-1.0190	4
Maputo	ET	not enough ET data points to conduct MK test on calculated ET					5
	P	1979-2016	no trend	false	0.3393	-0.9555	38
	Q	1953-1983	no trend	false	0.1261	-1.5297	31
Mono	ET	1979-2007	no trend	false	0.5115	-0.6565	29
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1944-2007					64
Niger	ET	1979-2006	no trend	false	0.6214	0.4939	28
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1970-2006					37
Nile	ET	not enough ET data points to conduct MK test on calculated ET					6
	P	1979-2016	no trend	false	0.2909	1.0560	38
	Q	1912-1984	no trend	false	0.0693	1.8164	56
Okavango	ET	1979-2014	increasing	true	0.0127	2.4926	36
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1950-2014					65
Olifant	ET	1979-2014	no trend	false	0.9457	0.0681	36
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1927-2014					88
Orange	ET	1979-2016	no trend	false	0.6691	0.4274	38
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1936-2014					79
Queme	ET	1979-80, 1982-84, 1990-2005, 2007	no trend	false	0.3377	0.9587	22
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1948-2007					60
Rufiji	ET	not enough ET data points to conduct MK test on calculated ET					0
	P	1979-2016	no trend	False	0.6508	-0.4526	38
	Q	1954-1978	no trend	False	0.9741	-0.0324	20
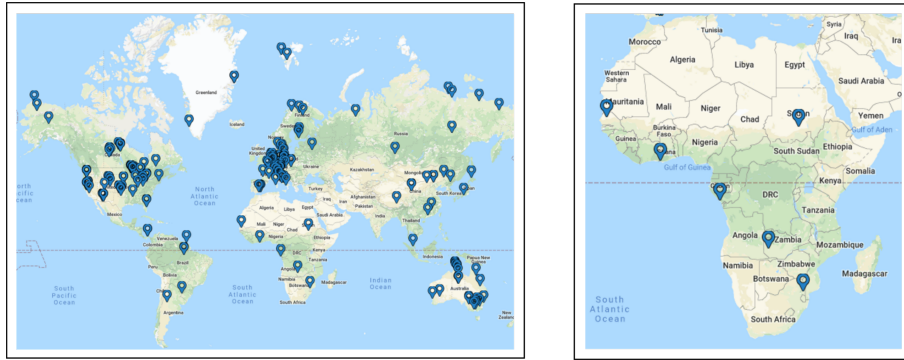
Figure 1. (left) distribution of flux towers worldwide. (right) distribution of flux towers across Africa (Google)

Sassandra	ET	1979-1996	no trend	false	0.8796	0.1515	18
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1970-1996					27
Save	ET	not enough ET data points to conduct MK test on calculated ET					3
	P	1979-2016	no trend	False	0.8801	0.1509	38
	Q	1968-1981	increasing	True	0.0118	2.5183	14
Senegal	ET	1979-1989	no trend	false	0.2129	1.2456	11
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1979-1989					11
Tana	ET	not enough ET data points to conduct MK test on calculated ET					0
	P	1979-2016	decreasing	True	0.0006	-3.4447	38
	Q	1975-1978	no trend	False	0.7341	-0.3397	4
Upper Blue Nile	ET	not enough ET data points to conduct MK test on calculated ET					8
	P	1979-2016	no trend	False	0.6875	-0.4023	38
	Q	1961-1983	no trend	False	0.1339	-1.4988	26
Void	ET	not enough ET data points to conduct MK test on calculated ET					3
	P	1979-2016	no trend	False	0.1251	-1.5338	38
	Q	1979-1981	increasing	True	0.0483	1.9748	7
Zambezi	ET	1979-1990	no trend	false	0.5371	0.6172	12
	P	1979-2016	MK test not conducted, no trend found in ET				38
	Q	1960-1990					31

Table 1. Characteristics of evapotranspiration products

Feature	Global Spatial Coverage	Openly Accessible	Dekaadal or higher temporal resolution	Product ongoing	Available from 1990 or earlier	highest resolution	Lowest resolution
Possible advantage or disadvantage	Advantage in general. Possible disadvantage in losing features if coarse resolution.	Advantage as accessible for everyone	Advantage as captures more temporal features	Advantage as can still be accessed for the present	Advantage as available for a longer time period	Possible advantage as may capture more features	Possible disadvantage as may capture fewer features
CMRSET	Yes	Yes	Yes	Yes	No	Yes	No
ETMonitor	Yes	No	Yes	No	No	No	No
GLEAM	Yes	Yes	Yes	Yes	Yes	No	No
LandFlux-EVAL	Yes	Yes	No	No	Yes	No	Yes
MOD16	Yes	Yes	No	Yes	No	No	No
MTE	Yes	Yes	No	No	Yes	No	No
SSEBop	Yes	Yes	No	Yes	No	No	No
WaPOR	No	Yes	Yes	Yes	No	Yes	No
WECANN	Yes	Yes	No	Yes	No	No	Yes
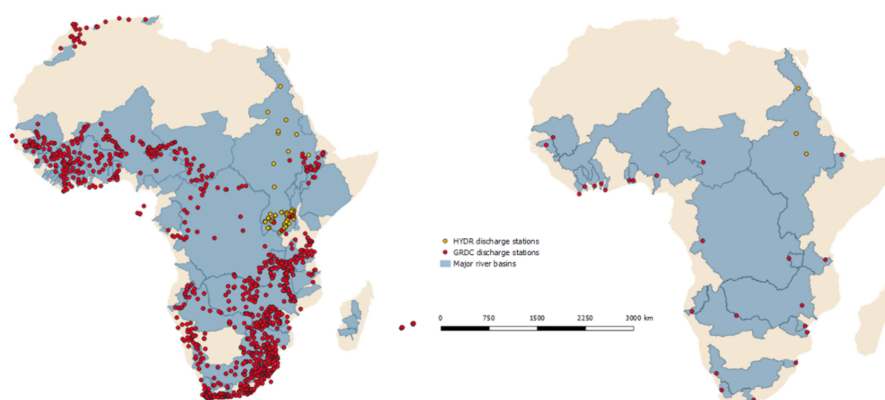
Figure 2. (left) All major basins in Africa and all available discharge stations; (right) Major basins in Africa with available discharge data at outlet

Table 2. Characteristics of remotely sensed ET products

Product	Temporal Coverage	Spatial Coverage	Temporal Resolution	Spatial Resolution	Estimation Approach	Input Data Source	Reference
CMRSET (v20140423)	2000-2013	Global	8-daily	$0.0022° \times 0.0022°$	P-T Equation, relationship between EVI and GVMI	MODIS	(Guerschman et al., 2009)
Access: http://remote-sensing.nci.org.au/u39/public/html/wirada/index.shtml							
ETMonitor	2008-2013	Global	daily	$0.005° \times 0.005°$	P-M, Gash model, Shuttleworth-Wallace	MODIS	Zheng et al. (2016)
Access: email first author in reference							
GLEAM (v3.2a)	1980-2016	Global	Daily	$0.25° \times 0.25°$	P-T Equation, soil stress factor	AMSR-E, LPRM, TRMM	Martens et al. (2017); Miralles et al. (2011)
Access: www.gleam.eu							
LandFlux-EVAL	1989-2005	Global	Monthly	$1° \times 1°$	Ensemble Approach	See reference	Mueller et al. (2013b)
Access: https://iac.ethz.ch/group/land-climate-dynamics/research/landflux-eval.html							
MOD16 (vA3)	2000-2014	Global	Monthly	$0.0083° \times 0.0083°$	P-M Equation, surface conductance model	MODIS	Mu et al. (2011, 2007)
Access: https://modis.gsfc.nasa.gov/data/dataprod/mod16.php							
MTE (vMay12)	1982-2012	Global	Monthly	$0.5° \times 0.5°$	MTE approach, training using in-situ observations, flux tower data	Eddy Covariance, in-situ	Jung et al. (2011)
Access: https://climatedataguide.ucar.edu/climate-data/fluxnet-mte-multi-tree-ensemble							
SSEBop (v4)	2003-2017	Global	Monthly	$0.0096° \times 0.0096°$	P-M Equation, ET fractions from T_s estimates	MODIS	Senay et al. (2013)
Access: https://earlywarning.usgs.gov/fews/search							
WaPOR (v1.1)	2009-2017	Africa	Dekadal	$0.0022° \times 0.0022°$	P-M Equation, calculates E, T and I separately	MODIS, GEOS-5/MERRA	FAO (2018)
Access: https://wapor.apps.fao.org/home/1							
WECANN (v1.0)	2007-2015	Global	Monthly	$1° \times 1°$	ANN approach, training using observations and model based LE	GOME-2	Alemohammad et al. (2017)
Access: https://avdc.gsfc.nasa.gov/pub/data/project/WECANN/							

Table 3. Characteristics of precipitation products

Product	Temporal Coverage	Spatial Coverage	Temporal Resolution	Spatial Resolution	Input Data Source	Reference
EWEMBI (v1.1)	1979-2016	Global	daily	$0.5° \times 0.5°$	ERA-Interim, WFDEI: (Weedon et al., 2014), E2OBS: (Calton et al., 2016)	(Lange, 2019)
	Access: http://doi.org/10.5880/pik.2019.004					
CHIRPS (v2.0)	1981-2019	quasi-Global	daily	$0.05° \times 0.05°$	in situ precipitation gauges, TRMM: (Huffman et al., 2007), CMORPH: (NCAR, 2017)	Funk et al. (2015)
	Access: https://chc.ucsb.edu/data/chirps					
MSWEP (v2.2)	1979-2017	Global	3-hourly	$0.1° \times 0.1°$	in situ precipitation gauges, CMORPH, TRMM, GSMaP: (JAXA, 2009), IRA-Interim	Bai and Liu (2018)
	Access: http://www.gloh2o.org/					

Table 4. Characteristics of discharge data

Product	Temporal Coverage	Spatial Coverage	Temporal Resolution	Spatial Resolution	Input Data Source	Reference
GRDC (v1.1)	1806-2019	Global	daily	point data	in situ discharge gauges	
	Access: https://www.bafg.de/GRDC/EN/Home/					
HYDR-VUB	1932-2018	Global	daily	point data	in situ discharge gauges	
	Access: on request to http://www.hydr.vub.ac.be/					

Table 5. Characteristics of potential evapotranspiration products

Product	Temporal Coverage	Spatial Coverage	Temporal Resolution	Spatial Resolution	Input Data Source		Reference
Hargreaves	1979-2012	Global	daily	$0.05° \times 0.05°$	WFDEI, DEM	SRTM	(Sperna Weiland et al., 2015)
	Access: https://wci.earth2observe.eu/						
Penman-Montieth	1979-2012	Global	daily	$0.05° \times 0.05°$	WFDEI, DEM	SRTM	(Sperna Weiland et al., 2015)
	Access: https://wci.earth2observe.eu/						
Priestly-Taylor	1979-2012	Global	daily	$0.05° \times 0.05°$	WFDEI, DEM	SRTM	(Sperna Weiland et al., 2015)
	Access: https://wci.earth2observe.eu/						

Table 7. Calculated statistics, bias, bias_{aw}, RMSE, RMSE_{aw} and r, for the comparison of the long-term annual average ET_{WB} versus ET_{RS}

	CMRSET	ETMonitor	GLEAM	LandFlux-EVAL	MOD16	MTE	SSEBop	WaPOR	WECANN
bias	-19	156	254	115	131	146	12	-3	139
bias_{aw}	-18	237	313	148	266	183	30	-46	223
RMSE	113	211	273	152	199	184	163	104	189
RMSE_{aw}	187	502	594	304	590	424	123	165	520
r	0.94	0.91	0.97	0.97	0.91	0.95	0.89	0.96	0.95

Table 8. Bias between the ET_{Budyko} and, ET_{WB} and ET_{RS}

mm/year	ET_{WB}	CMRSET	ETMonitor	GLEAM	LandFlux-EVAL	MOD16	MTE	SSEBop	WaPOR	WECANN
bias	42	101	202	284	152	185	177	140	86	180

Table 9. Ranking of the RS products based on the different evaluation steps of the proposed methodology

	CMRSET	ETMonitor	GLEAM	LandFlux-EVAL	MOD16	MTE	SSEBop	WaPOR	WECANN
Catchment water balance ranking (CWB)									
bias	3	8	9	4	5	7	2	1	6
$bias_{aw}$	1	7	9	4	8	5	2	3	6
RMSE	2	8	9	3	7	5	4	1	6
$RMSE_{aw}$	3	6	9	4	8	5	1	2	7
r	6	7	1	1	7	4	9	3	4
Overall CWB ranking	2	8	9	3	7	5	4	1	6
Budyko ranking									
Budyko	2	8	9	4	7	5	3	1	6
Spatial variability ranking									
Visual Inspection (VI) - land cover elements									
Forest	2	2	6	8	1	7	2	2	9
Irrigated Area	1	4	8	9	5	6	3	2	7
Water Bodies	1	1	n/a	n/a	n/a	n/a	3	3	n/a
Overall VI spatial ranking	1	2	7	9	5	6	4	3	8
Quantitative Inspection (QI) - land cover elements									
Forest	1	6	7	4	8	5	3	2	8
Water Bodies	2	1	n/a	n/a	n/a	n/a	3	4	n/a
Overall QI spatial ranking	1	4	9	5	7	6	2	2	7
Overall spatial ranking	1	3	8	7	5	6	3	2	9
Final ranking									
With visual inspection	1	5	9	4	7	6	3	1	8
Without visual inspection	2	7	9	4	8	5	3	1	6

Table 10. Differences in mean WB ET estimations for varying RS product periods

|	Total	CMRSET	ETMonitor	GLEAM	Period MOD16	MTE	SSEBop	WaPOR	WECANN	Average
Congo										
	1979-2010	2000-2010	2008-2010	1980-2010	2000-2010	1982-2010	2003-2010	2009-2010	2007-2010	
ET mm/year	1186	1203	1159	1196	1203	1194	1194	1168	1193	1189
Bias mm/year		17	27	10	17	8	8	18	7	14
% bias		1.4	2.3	0.8	1.4	0.7	0.7	1.5	0.6	1.2
Groot										
	1979-2015	2000-2013	2008-2013	1980-2015	2000-2014	1982-2012	2003-2015	2009-2015	2007-2015	
ET mm/year	373	390	381	377	390	371	387	396	392	386
Bias mm/year		17	8	4	17	2	14	23	19	13
% bias		4.4	2.1	1.1	4.4	0.5	3.6	5.8	4.9	3.4
Olifant										
	1979-2014	2000-2013	2008-2013	1980-2014	2000-2014	1982-2012	2003-2014	2009-2014	2007-2014	
ET mm/year	278	279	293	284	278	286	272	275	296	283
Bias mm/year		1	15	6	0	8	6	3	18	7
% bias		0.4	5.1	2.1	0.0	2.8	2.2	1.1	6.1	2.5
Orange										
	1979-2015	2000-2013	2008-2013	1980-2015	2000-2014	1982-2012	2003-2015	2009-2015	2007-2015	
ET mm/year	349	377	376	356	374	362	351	350	351	362
Bias mm/year		28	27	7	25	13	2	1	2	13
% bias		7.4	7.2	2.0	6.7	3.6	0.6	0.3	0.6	3.6
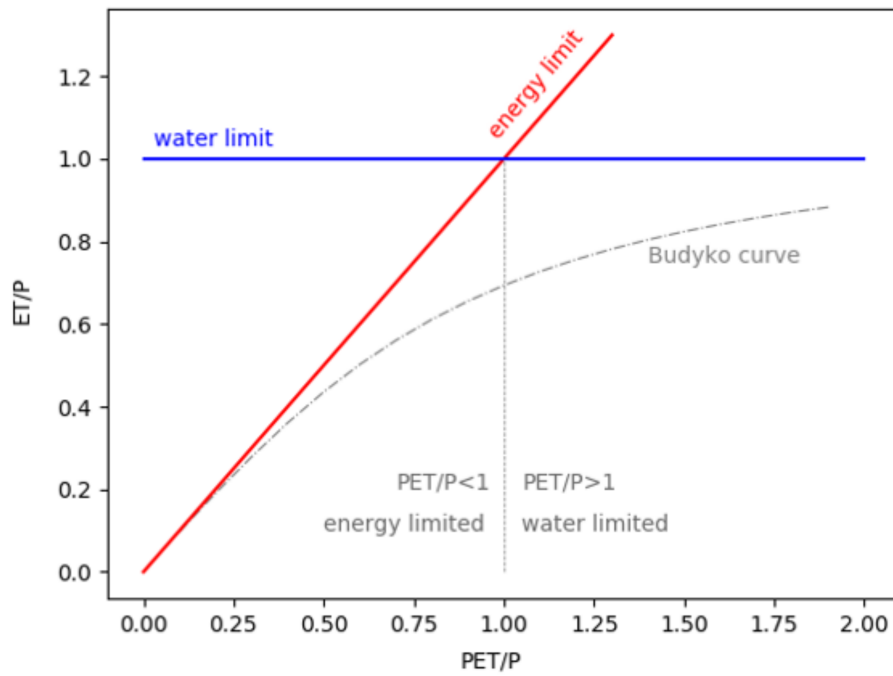
Figure 3. Budyko curve showing the energy limit and water limit
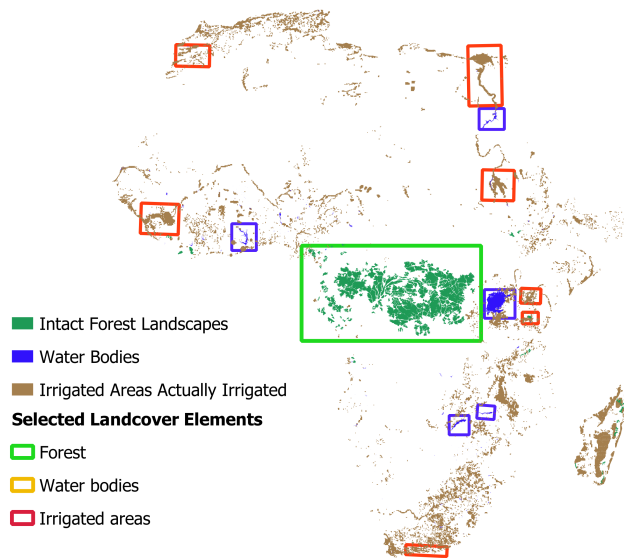
Figure 4. IFL, WB GRanD and AEIai land cover element maps and areas selected for visual inspection
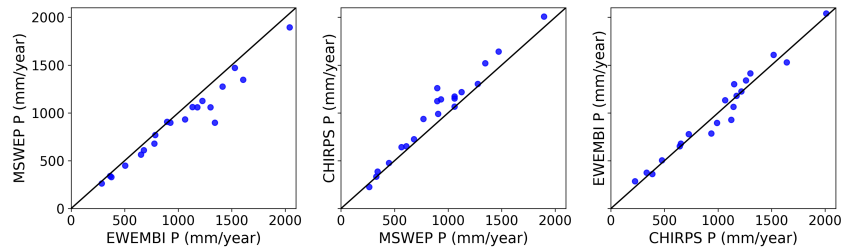
Figure 5. Comparison of the EWEMBI, MSWEP and CHIRPS precipitation products on their prediction of mean P across the basins

Figure 6. Comparison of the P-M, P-T and Hargreaves potential evapotranspiration products on their prediction of mean PET across the basins

Figure 7. (right) ET_{WB} estimation for 28 major basins in Africa using P-Q (left) Final basins being analysed after analyses to discount basins with trends in ET_{WB}, P and/or Q.

Bias

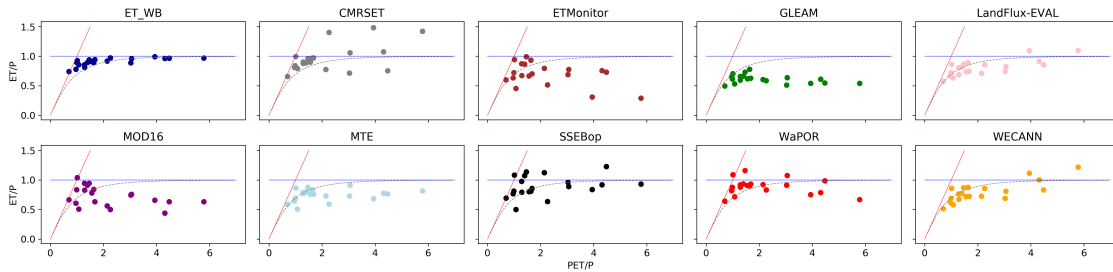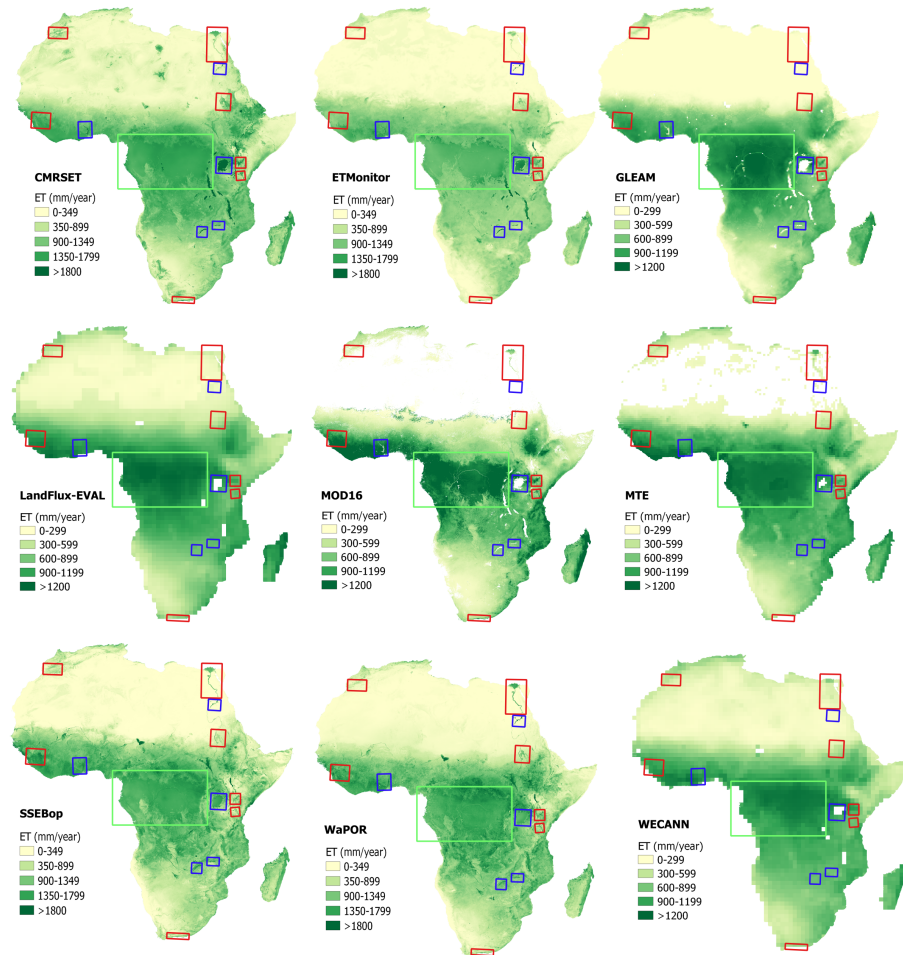|	CMRSET	ETMonitor	GLEAM	LandFlux-EVAL	MOD16	MTE	SSEBop	WaPOR	WECANN
Awash	-315.7	331.3	280.3	83.3	342.3	276.3	243.3	101.3	83.3
Bandama	-78.5	-18.5	261.5	71.5	-129.5	77.5	-178.5	-187.5	78.5
Buzi	-110.1	155.9	243.9	137.9	-24.1	42.9	13.9	-87.1	153.9
Cavally	168.4	280.4	481.4	323.4	147.4	302.4	92.4	196.4	447.4
Congo	-50.0	221.0	195.0	169.0	268.0	205.0	17.0	-61.0	243.0
Gambia	132.9	114.9	292.9	192.9	332.9	175.9	-193.1	-3.1	178.9
Groot	-169.9	237.1	156.1	-34.9	116.1	107.1	53.1	83.1	-42.9
Komoe	-17.9	-55.9	229.1	80.1	-4.9	69.1	-213.9	-236.9	77.1
Maputo	-63.4	-35.4	93.6	0.6	41.6	47.6	68.6	-9.4	13.6
Mono	-25.3	-20.3	235.7	57.7	-103.3	79.7	-142.3	-72.3	109.7
Niger	113.0	129.0	244.0	93.0	93.0	103.0	-46.0	-16.0	129.0
Nile	-61.6	112.4	199.4	83.4	124.4	29.4	43.4	-73.6	92.4
Olifant	-117.2	174.8	109.8	-33.2	86.8	39.8	9.8	77.8	-64.2
Orange	-41.2	74.8	126.8	17.8	189.8	67.8	15.8	63.8	-14.2
Queme	7.2	31.2	262.2	88.2	-21.8	107.2	-202.8	-46.8	141.2
Rufiji	5.4	251.4	303.4	180.4	134.4	153.4	110.4	3.4	198.4
Sassandra	81.7	259.7	418.7	255.7	88.7	305.7	121.7	25.7	303.7
Senegal	101.8	111.8	199.8	51.8	158.8	95.8	-124.2	-9.2	63.8
Upper Blue Nile	83.5	533.5	431.5	292.5	464.5	463.5	473.5	183.5	365.5
Zambezi	-29.1	237.9	308.9	193.9	304.9	179.9	83.9	11.9	218.9
Average	-19.3	156.4	253.7	115.3	130.5	146.5	12.3	-2.8	138.9

Area Weighted Bias

|	CMRSET	ETMonitor	GLEAM	LandFlux-EVAL	MOD16	MTE	SSEBop	WaPOR	WECANN
Awash	-65.3	68.5	57.9	34.7	70.8	57.1	50.3	20.9	17.2
Bandama	-11.7	-2.8	39.0	-3.3	-19.3	11.6	-26.6	-27.9	11.7
Buzi	-7.2	10.2	15.9	3.2	-1.6	2.8	0.9	-5.7	10.0
Cavally	11.2	18.7	32.0	17.6	9.8	20.1	6.1	13.1	29.8
Congo	-415.5	1837.2	1621.1	1078.7	2227.9	1704.2	141.4	-506.9	2020.1
Gambia	20.9	18.0	46.0	20.3	52.3	27.6	-30.3	-0.5	28.1
Groot	-12.9	18.0	11.8	5.1	8.8	8.1	4.0	6.3	-3.3
Komoe	-3.1	-9.8	40.3	-3.4	-0.9	12.2	-37.6	-41.7	13.6
Maputo	-4.4	-2.4	6.5	1.4	2.9	3.3	4.7	-0.6	0.9
Mono	-1.7	-1.3	15.6	0.5	-6.8	5.3	-9.4	-4.8	7.3
Niger	560.4	639.8	1210.2	464.3	461.2	510.8	-228.4	-79.6	639.8
Nile	-425.5	775.6	1376.2	402.0	858.5	202.7	299.3	-508.4	637.6
Olifant	-12.4	18.5	11.6	4.2	9.2	4.2	1.0	8.2	-6.8
Orange	-57.6	104.5	177.2	84.4	265.2	94.7	22.1	89.2	-19.8
Queme	0.9	3.9	32.4	4.3	-2.7	13.2	-25.0	-5.8	17.4
Rufiji	2.5	115.6	139.5	66.7	61.8	70.6	50.8	1.6	91.2
Sassandra	12.8	40.6	65.4	31.4	13.9	47.8	19.0	4.0	47.4
Senegal	99.9	109.7	196.0	73.4	155.8	94.0	-121.9	-9.1	62.6
Upper Blue Nile	37.5	239.8	194.0	168.5	208.8	208.3	212.8	82.5	164.3
Zambezi	-90.7	741.9	963.3	513.5	950.8	561.0	261.7	37.2	682.6
Average	-18.1	237.2	312.6	148.4	266.3	183.0	29.7	-46.4	222.6

Figure 8. Bias and basin area weighted bias between the long-term annual average calculated ET_{WB} and ET_{RS} for all basins and the average of the 20 basins


Figure 9. Evaluation of the calculated ET_{WB} and ET_{RS} from products using the Budyko curve calculated using average P and PET from three products

Figure 10. Spatial assessment across Africa of each ET product based on selected land cover elements, forest, irrigated areas and water bodies. Red boxes indicate irrigated areas, blue boxes indicate water bodies and green boxes indicate forested areas
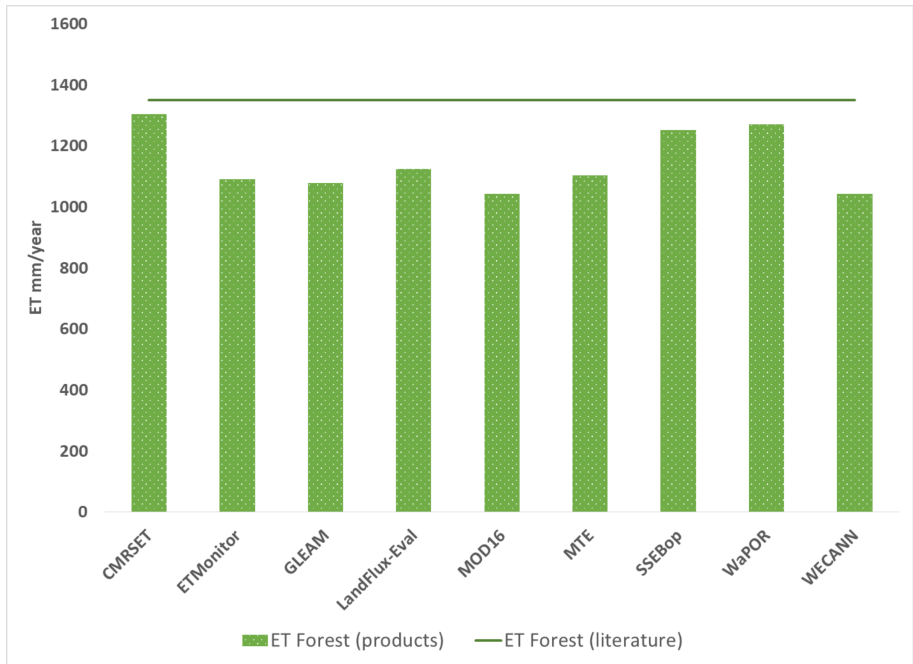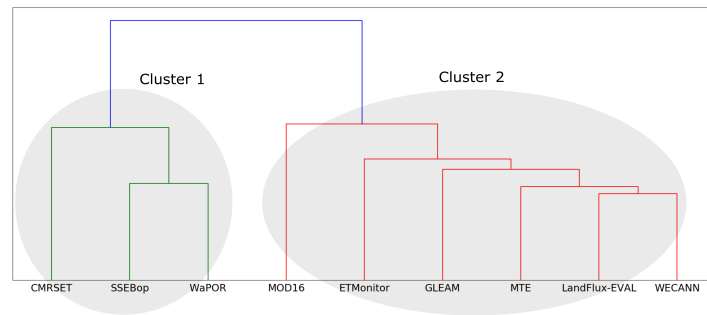
Figure 11. Comparison of mean ET across the selected forested area for each product versus mean ET found from literature
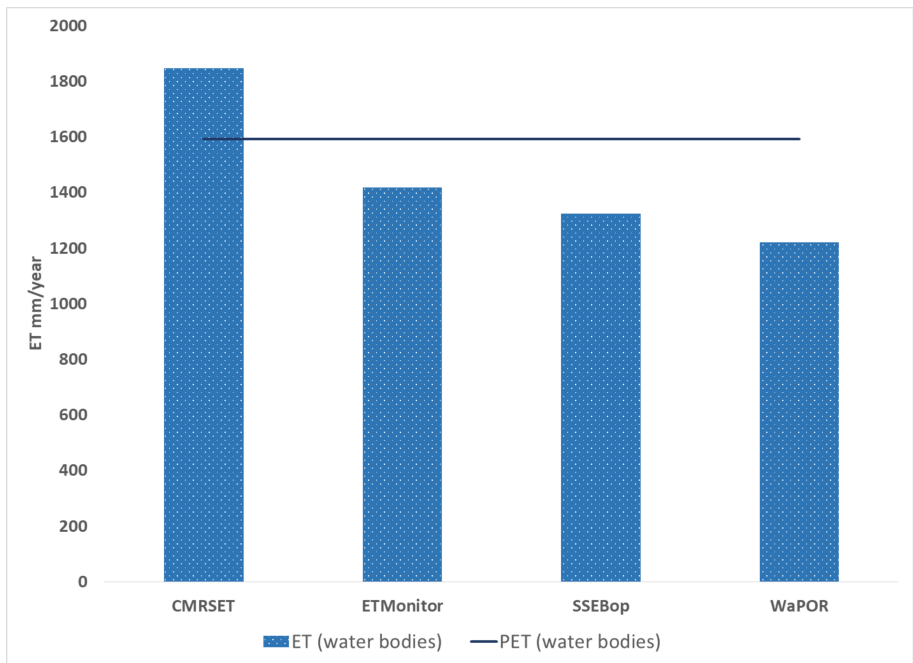
Figure 12. Comparison of mean ET across water bodies estimated by each ET product and PET using the average of three PET products

Figure 13. Cluster analysis based on the pairwise Euclidean distance between each pixel for each ET product to assess overall similarity between data sets