

1 **The WACMOS-ET project – Part 2: Evaluation of global**
2 **terrestrial evaporation data sets**

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1 **Abstract**

2 The WACMOS-ET project aims to advance the development of land evaporation estimates at
3 global and regional scales. Its main objective is the derivation, validation and inter-
4 comparison of a group of existing evaporation retrieval algorithms driven by a common
5 forcing data set. Three commonly used process-based evaporation methodologies are
6 evaluated: the Penman-Monteith algorithm behind the official Moderate Resolution Imaging
7 Spectroradiometer (MODIS) evaporation product (PM-MOD), the Global Land Evaporation
8 Amsterdam Model (GLEAM), and the Priestley and Taylor Jet Propulsion Laboratory model
9 (PT-JPL). The resulting global spatiotemporal variability of evaporation, the closure of
10 regional water budgets and the discrete estimation of land evaporation components or sources
11 (i.e. transpiration, interception loss and direct soil evaporation) are investigated using river
12 discharge data, independent global evaporation data sets and results from previous studies. In
13 a companion article (Part 1), Michel et al. (2015) inspect the performance of these three
14 models at local scales using measurements from eddy-covariance towers, and include in the
15 assessment the Surface Energy Balance System (SEBS) model. In agreement with Part 1, our
16 results indicate that the Priestley and Taylor products (PT-JPL and GLEAM) perform overall
17 best for most ecosystems and climate regimes. While all three evaporation products
18 adequately represent the expected average geographical patterns and seasonality, there is a
19 tendency from PM-MOD to underestimate the flux in the tropics and subtropics. Overall,
20 results from GLEAM and PT-JPL appear more realistic when compared against surface water
21 balances from 837 globally-distributed catchments, and against separate evaporation estimates
22 from ERA-Interim and the Model Tree Ensemble (MTE). Nonetheless, all products manifest
23 large dissimilarities during conditions of water stress and drought, and deficiencies in the way
24 evaporation is partitioned into its different components. This observed inter-product
25 variability, even when common forcing is used, implies caution in applying a single data set
26 for large-scale studies in isolation. A general finding that different models perform better
27 under different conditions highlights the potential for considering biome- or climate-specific
28 composites of models. Yet, the generation of a multi-product ensemble, with weighting based
29 on validation analyses and uncertainty assessments, is proposed as the best way forward in
30 our long-term goal to develop a robust observational benchmark data set of continental
31 evaporation.

1 **1 Introduction**

2 The importance of terrestrial evaporation (or '*evapotranspiration*') for hydrology, agriculture
3 and meteorology has long been recognized. As a matter of fact, most of our current
4 understanding of the physics of evaporation originated in early experiments during the past
5 two centuries (e.g. Dalton, 1802; Horton, 1919; Penman, 1948). However, it has been during
6 the last decade that the interest of the scientific community towards land evaporation has
7 increased more dramatically, following the recognition of the key role it plays in climate
8 (Wang and Dickinson, 2012; Dolman et al., 2014). Evaporation is highly sensitive to radiative
9 forcing: changes in atmospheric chemical composition affect the magnitude of the flux,
10 ensuring the propagation of anthropogenic impacts to all the components of the hydrological
11 cycle (Wild and Liepert, 2010), and altering the global availability of water resources
12 (Hagemann et al., 2014). In addition, evaporation regulates climate through a series of
13 feedbacks acting on air temperature, humidity and precipitation (Koster et al., 2006;
14 Seneviratne et al., 2010), thus affecting climate trends (Douville et al., 2013; Sheffield et al.,
15 2012) and hydro-meteorological extremes (Seneviratne et al., 2006; Teuling et al., 2013;
16 Miralles et al., 2014a). Finally, due to the link between transpiration and photosynthesis,
17 atmospheric carbon concentrations and carbon cycle feedbacks are tightly linked to terrestrial
18 evaporation (Reichstein et al., 2013). All together, evaporation stands as a crucial nexus of
19 processes and cycles in the climate system.

20 The rising interest of the climate community has coincided with an unprecedented availability
21 of global field data to scrutinize the response of evaporation to climate impacts and
22 feedbacks. However, due to the limitations in coverage of direct *in situ* measurements, the
23 scientific community have turned their eyes towards satellite remote sensing (Kalma et al.,
24 2008; Wang and Dickinson, 2012; Dolman et al., 2014). Consequently, different international
25 activities now focus on the joint advancement of remote sensing technology and evaporation
26 science, including the National Aeronautics and Space Administration (NASA) Energy and
27 Water cycle Study (NEWS, <http://nasa-news.org>), the European Union WATer and global
28 CHange (WATCH, <http://www.eu-watch.org>) project, and the Global Energy and Water-
29 cycle Experiment (GEWEX) LandFlux initiative ([https://hydrology.kaust.edu.sa/Pages/
30 GEWEX_Landflux.aspx](https://hydrology.kaust.edu.sa/Pages/GEWEX_Landflux.aspx)). Despite continuing progress in the fields of remote sensing and
31 computing science, to date, the evaporative flux cannot be directly sensed from space;
32 technology thus lags behind our physical knowledge of evaporation. Nonetheless, taking

1 advantage of this existing knowledge, different models have been proposed to combine the
2 physical variables that are linked to the evaporation process and can be observed from space
3 (e.g. radiation, temperature, soil moisture or vegetation dynamics). Such efforts have yielded
4 a number of global evaporation products in recent years (Mu et al., 2007; Zhang et al., 2010;
5 Fisher et al., 2008; Miralles et al., 2011b; Jung et al., 2010). These data sets are not to be
6 interpreted as the direct result of satellite observations, but rather as model outputs generated
7 based on satellite forcing data. The reader is directed to Su et al. (2011) or McCabe et al.
8 (2013) for recent reviews of the state of the art.

9 Despite the recent initiatives dedicated to exploring these evaporation data sets – LandFlux-
10 EVAL in particular, see Jiménez et al. (2011) and Mueller et al. (2011, 2013) – the relative
11 merits from each model at the global scale remain largely unexplored. To date, the lack of
12 inter-model consistency in the choice of forcing data has hampered the attribution of the
13 observed skill of each evaporation data set to differences in the models. Only recently, some
14 efforts have been directed to homogenising the forcing of these models to allow the
15 assessment of algorithm quality (Vinukollu et al., 2010a; Ershadi et al., 2014; Chen et al.,
16 2015; McCabe et al., 2015). In 2012, the European Space Agency (ESA) Water Cycle Multi-
17 mission Observation Strategy (WACMOS)-ET project (<http://WACMOSET.estellus.eu>)
18 started in response to the need for a thorough and consistent model inter-comparison at
19 different spatial and temporal scales. At the same time, WACMOS-ET is a direct contribution
20 to GEWEX LandFlux, sharing the long-term goal of achieving global closure of surface water
21 and energy budgets. The project objectives strive to **(a)** develop a reference input data set
22 consisting of satellite observations, reanalysis data and *in situ* measured meteorology, **(b)** run
23 a group of selected evaporation models forced by the reference input data set, and **(c)** perform
24 a cross-comparison, evaluation and validation exercise of the evaporation data sets that result
25 from running this group of models. Four algorithms that are commonly used by the research
26 community have been tested: the Surface Energy Balance Model, SEBS (Su, 2001); the
27 Penman-Monteith approach that sets the basis for the official Moderate Resolution Imaging
28 Spectroradiometer (MODIS) evaporation product, hereafter referred to as PM-MOD (Mu et
29 al. 2007, 2011, 2013); the Global Land Evaporation Amsterdam Model, GLEAM (Miralles et
30 al. 2011b); and the Priestley and Taylor model from the Jet Propulsion Laboratory, PT-JPL
31 (Fisher et al., 2008).

1 In a companion article – henceforth referred to as Part 1 – Michel et al. (2015) describe the
2 results of the local validation activities of WACMOS-ET based on *in situ* evaporation
3 measurements from eddy-covariance towers. Here, we present the global-scale inter-product
4 evaluation. After forcing the models with the reference input data set (see Sect. 2.2 for the
5 description of the forcing data), the resulting evaporation data sets are evaluated by means of:
6 **(a)** a general exploration of the global magnitude and spatiotemporal variability of the
7 estimates (Sect 3.1 and 3.2), **(b)** a comparison to other, commonly-used, evaporation data sets
8 (Sect 3.1, 3.2 and 3.3), including the Model Tree Ensemble (MTE) estimates by Jung et al.
9 (2009, 2010) and the European Centre for Medium-range Weather Forecasts (ECMWF) Re-
10 Analysis (ERA)-Interim (Dee et al., 2011), **(c)** an assessment of the skill to close the surface
11 water balance over a broad range of catchments worldwide (Sect 3.3), and **(d)** an analysis of
12 the contribution to total terrestrial evaporation from the discrete components or sources of this
13 flux, i.e. transpiration, interception loss and direct evaporation from the soil (Sect 3.4). Due to
14 the difficulties that arise from executing SEBS at the global scale (see Su et al., 2010), the
15 current work concentrates on PM-MOD, GLEAM and PT-JPL, while the local-scale analysis
16 in Part 1 also includes the SEBS model.

17 **2 Methods and data**

18 **2.1 Models or algorithms**

19 Here we present a brief description of the three models that are subjected to study in this
20 article. For more exhaustive descriptions the reader is directed to Part 1 and to the original
21 articles describing the parameterizations and algorithms from PM-MOD (Mu et al. 2007,
22 2011), GLEAM (Miralles et al., 2011b) and PT-JPL (Fisher et al., 2008). A summary of the
23 forcing requirements of PM-MOD, GLEAM and PT-JPL can be found in Table 1, together
24 with the specific product for each input variable.

25 **2.1.1 PM-MOD**

26 The Penman-Monteith model by Mu et al. (2007, 2011) is arguably the most widely-used
27 remote sensing-based global evaporation model and, in its latest version, it is also the
28 algorithm behind the official MODIS (MOD16) product (Mu et al., 2013). PM-MOD is based
29 on the Monteith (1965) adaptation of Penman (1948), thus it is relatively high-demanding in
30 terms of inputs. The parameterizations of aerodynamic and surface resistances for each

1 component of evaporation are based on extending biome-specific conductance parameters to
2 the canopy scale using vegetation phenology and meteorological data. The model applies the
3 surface resistance scheme by Cleugh et al. (2007) – which uses leaf area index as suggested
4 by Jarvis (1976) – in an extended version that considers the constraints of vapour pressure
5 deficit and minimum temperature on stomatal conductance (Mu et al., 2007). However, in
6 contrast to the majority of Penman-Monteith type of models, PM-MOD does not require soil
7 moisture or wind speed data to parameterize the surface and aerodynamic resistances. The
8 non-consideration of wind speed appears as an advantage when aiming for a fully
9 observation-driven product. Snow sublimation and open-water evaporation are not considered
10 independently from other processes. As opposed to GLEAM and PT-JPL, which do not
11 require calibration, the resistance parameters in PM-MOD have been calibrated with data
12 from a set of global eddy-covariance towers (see Mu et al., 2011).

13 2.1.2 GLEAM

14 GLEAM (www.gleam.eu) is a simple land surface model fully dedicated to deriving
15 evaporation based on satellite forcing only (Miralles et al., 2011b). It distinguishes between
16 direct soil evaporation, transpiration from short and tall vegetation, snow sublimation, open-
17 water evaporation, and interception loss from tall vegetation. The latter is independently
18 calculated based on the Gash (1979) analytical model for interception forced by observations
19 of precipitation (Miralles et al., 2010). The remaining components of evaporation are based
20 upon the formulation by Priestley and Taylor (1972), which does not require the
21 parameterization of stomatal and aerodynamic resistances, in contrast to the Penman-
22 Monteith equation. In the case of transpiration and soil evaporation, the potential evaporation
23 estimates – resulting from the application of the Priestley and Taylor approach – are
24 constrained by a multiplicative stress factor. This dynamic stress factor is calculated based on
25 the content of water in vegetation (microwave vegetation optical depth; Liu et al., 2011) and
26 root-zone (multi-layer soil model driven by observations of precipitation and updated through
27 assimilation of microwave surface soil moisture, see Martens et al., 2015). The consideration
28 of vegetation water content accounts for the effects of plant phenology, while the root-zone
29 soil moisture accounts for soil water stress. For regions covered by ice and snow, sublimation
30 is calculated using a Priestley and Taylor equation with specific parameters for ice and super-
31 cooled waters (Murphy and Koop, 2005). For the fraction of open-water at each pixel the
32 model assumes potential evaporation. GLEAM has recently been applied to look at trends in

1 the water cycle (Miralles et al., 2014b) and land-atmospheric feedbacks (Guillod et al., 2015;
2 Miralles et al., 2014a).

3 2.1.3 PT-JPL

4 The PT-JPL model by Fisher et al. (2008) uses the Priestley and Taylor (1972) approach to
5 estimate potential evaporation. Unlike GLEAM, it applies a series of eco-physiological stress
6 factors based on atmospheric moisture (vapour pressure deficit and relative humidity) and
7 vegetation indices (normalized difference vegetation index, i.e. NDVI, and soil adjusted
8 vegetation index) to constrain the atmospheric demand for water. This implies that the set of
9 forcing requirements of PT-JPL are in fact very comparable to those of PM-MOD (see Table
10 1). In order to partition land evaporation into soil evaporation, transpiration and interception
11 loss, PT-JPL first distributes the net radiation to the soil and vegetation components, and then
12 calculates the potential evaporation for soil, transpiration and interception separately. The
13 partitioning between transpiration and interception loss is done using a threshold based on
14 relative humidity. As in PM-MOD, snow sublimation and open-water evaporation are not
15 considered independently from other processes. The model has been employed in a number of
16 studies to estimate terrestrial evaporation at regional and global scales in recent years (see e.g.
17 Sahoo et al., 2011; Vinukollu et al., 2011a; Vinukollu et al., 2011b).

18 2.2 Input data

19 One of the objectives of the WACMOS-ET project has been to correct for a recurring issue in
20 inter-product evaluations of global evaporation: due to inconsistencies in the forcing data
21 behind current evaporation products, it is difficult to attribute the observed inter-product
22 disagreements to algorithm discrepancies (Jiménez et al., 2011; Mueller et al., 2013).
23 Consequently, one of the first steps in WACMOS-ET has been to compile a reference input
24 data set that has been used to run all models in a consistent manner. This consistency applies
25 to both local-scale runs (in Part 1), and regional and global runs (in the present study). On the
26 other hand, since the required input variables are not the same for all models (see Table 1) –
27 nor is the models' sensitivity to these input variables and their uncertainties – it is not possible
28 to fully attribute observed differences in performance to internal model errors. Nonetheless,
29 our efforts to homogenize forcing data in a global evaporation inter-model comparison are
30 unique, with the exception of Vinukollu et al. (2011a) that used off-the-shelf forcing data sets
31 to run earlier versions of SEBS, PT-JPL and PM-MOD. For all the details in the production of

1 the reference input data set the reader is directed to the thorough descriptions in Part 1 and the
2 supporting documents available in the project website. Nonetheless, a short summary is also
3 provided here.

4 Some of the variables considered in the reference input data set have been internally
5 generated during the project, while others were selected from the existing pool of global
6 climatic and environmental data sets. Choices regarding the spatial and temporal resolution,
7 period covered and study domain were made under the support of a large number of end users
8 surveyed via internet (see project website). The targeted grid resolution of WACMOS-ET is
9 25 km, the domain is global and the study period spans 2005–2007. A 3-hourly temporal
10 resolution maximizes the links to the work undertaken by the GEWEX LandFlux initiative to
11 produce sub-daily evaporation estimates (McCabe et al., 2015). The present Part 2 evaluates
12 the outputs after aggregating them to daily, monthly and annual scales, while the skill of the
13 models to resolve the diurnal cycle of evaporation is explored in Part 1. Although the
14 internally generated input data sets were originally derived at a relatively fine (<5 km) spatial
15 resolution, critical inputs not generated within the project were only available at 75–100 km
16 (see below). Consequently, all input data sets have been spatially resampled to match the 25
17 km targeted resolution and re-projected into a common sinusoidal grid before using them to
18 run the evaporation models.

19 Internally developed products include the fraction of photosynthetically active radiation and
20 leaf area index, which are derived to a large extent from European satellites (see Part 1). Data
21 access, product descriptions and user guidelines for these data sets are available to interested
22 parties upon request, using the project website as gateway. Whereas PM-MOD and PT-JPL
23 apply these internally generated data sets to characterize vegetation phenology, GLEAM uses
24 observations of microwave vegetation optical depth as a proxy for vegetation water content;
25 these are taken from the data set of Liu et al. (2011) based on the Advanced Microwave
26 Scanning Radiometer - Earth Observing System (AMSR)-E at 0.25° spatial resolution.

27 The remaining products comprising the reference input data set have been selected from the
28 pool of available community data sets. Surface net radiation is obtained by integrating the
29 upwelling and downwelling radiative fluxes from the NASA/GEWEX Surface Radiation
30 Budget (SRB, Release 3.1), which contains global 3-hourly averages of these fluxes on a 1°
31 resolution grid. The SRB product is based on a range of satellite data, atmospheric reanalysis
32 and data assimilation (Stackhouse et al., 2004). The meteorology (i.e. near-surface air

1 temperature, air humidity and wind speed) comes from the ERA-Interim atmospheric
2 reanalysis, provided at 3-hourly resolution (using the forecast fields) and at a spatial
3 resolution of ~ 75 km. The reason for using atmospheric reanalysis data (based on
4 observations assimilated into a weather forecast model), as opposed to direct satellite
5 observations, is that some of these variables are presently difficult to observe over continents
6 (like air temperature and humidity), if not impossible (like wind speed), and are not routinely
7 available at sub-daily time steps and over all weather conditions.

8 Despite its relevance for plant-available water and interception loss, precipitation is not a
9 direct input for most global satellite-based evaporation models. The same applies to surface
10 soil moisture, which can also be observed from space. From the WACMOS-ET models, only
11 GLEAM uses observations of precipitation and surface soil moisture as input. In the reference
12 input data set, precipitation data comes from the Climate Forecast System Reanalysis for
13 Land (CFSR-Land, Coccia and Wood. 2015), which uses the Climate Prediction Center (CPC,
14 Chen et al. 2008) and the Global Precipitation Climatology Project (GPCP, Huffman et al.
15 2001) daily data sets and applies a temporal downscaling based on the CFSR (Saha et al.
16 2010). For soil moisture, we use the satellite product of combined active-passive microwave
17 surface soil moisture by Liu et al. (2012), which blends information from scatterometers and
18 radiometers from different platforms, and was developed as part of the ESA Climate Change
19 Initiative (CCI). In addition, GLEAM also uses information on snow water equivalents that is
20 taken from the ESA GlobSnow product version 1.0 (Luoju and Pulliainen, 2010), based on
21 AMSR-E and corrected using ground-based measurements. Since GlobSnow covers the
22 Northern Hemisphere only, data from the National Snow and Ice Data Center (NSIDC) are
23 used in snow-covered regions of the Southern Hemisphere (Kelly et al., 2003). Observations
24 of soil moisture and snow water equivalents have a native resolution of 0.25° and are
25 imported in GLEAM at daily time steps.

26 **2.3 Data used for evaluation**

27 **2.3.1 Other global land evaporation products**

28 For the purpose of comparing our three WACMOS-ET products against related evaporation
29 data sets, we incorporate two additional data sets into the evaluation: the ERA-Interim
30 reanalysis evaporation (Dee et al. 2011) and the MTE product (Jung et al., 2010; Jung et al.,
31 2009). The latter is derived from satellite data and FLUXNET observations (Baldocchi et al.,

1 2001) using a machine-learning algorithm. In the model, tree ensembles are trained to predict
2 monthly eddy-covariance fluxes based on meteorological, climate and land cover data. It has a
3 monthly temporal resolution and 0.5° spatial resolution. For full details, the reader is referred
4 to Jung et al. (2009).

5 2.3.2 Catchment water balance data

6 The mass balance of a catchment implies that the space and time integration of precipitation
7 (P) minus river runoff (Q) should equal evaporation (integrated over the same space and
8 time). This requires the consideration of a long period, so changes in storage within the
9 catchment and travel time of precipitation through the landscape can be neglected (see
10 discussion in Sect. 3.3). Given that river runoff and precipitation are more easily and
11 extensively measured than evaporation, estimates of $P - Q$ based on ground measurements of
12 these two fluxes provide a convenient means to evaluate evaporation over large domains and
13 long periods (Liu et al., 2014; Miralles et al., 2011a; Vinukollu et al., 2011b; Sahoo et al.,
14 2011). Here, we use globally-distributed multi-annual river discharge data for basins larger
15 than 2500 km^2 . Discharge data and watershed boundaries are obtained from the Global
16 Runoff Data Centre (GRDC, 2013). Runoff data have been converted from cumecs into mm
17 yr^{-1} using the area of each catchment as reported by the GRDC; basins where the absolute
18 difference between the GRDC reported area and the area calculated from basin boundaries
19 exceeded 25% have been excluded from the analyses.

20 Precipitation for the target period 2005–2007 is taken from GPCP (Huffman et al., 2001) and
21 the Global Precipitation Climatology Centre (GPCC) v6 (Schneider et al., 2013). Two
22 versions of GPCC v6 are processed by applying relative gauge correction factors according to
23 Fuchs et al. (2001) and Legates and Willmott (1990) to the native GPCC products as
24 recommended by the producers. We further discard basins with (*a priori*) low-quality
25 precipitation due to the low density of rain gauges (< 0.1 per 0.5 degree latitude-longitude),
26 frequent snowfall (> 25 days per year based on CloudSat), or where cumulative values of
27 discharge exceed those of precipitation over the three-year period. Finally, radiation data from
28 the NASA Clouds and Earth's Radiant Energy System (CERES) SYN1deg product (Wielicki
29 et al., 2000) are used to exclude basins where $P - Q$ exceeds surface net radiation on average.

30 This results in a record of 837 basins from which $P - Q$ values are calculated. Figure 1
31 illustrates the location of the centroids of these catchments. Basins are then clustered in 30

1 classes based on log-transformed precipitation, net radiation, and evaporative fraction (i.e.
2 evaporation over net radiation). This is done in order to reduce noise and retain clear patterns
3 for evaluation. The clustering algorithm used is a k-means with cityblock distance, with
4 variables transformed to zero mean and unit variance. For clarity, each of the 30 classes is
5 assigned to one of four groups based on thresholds of net radiation (80 W m^{-2}) and
6 evaporative fraction (0.5) as shown in Fig. 1. The results of comparing the evaporation
7 products, integrated over the corresponding basins, to the $P - Q$ estimates are presented in
8 Sect. 3.3.

9 **3 Results and discussion**

10 **3.1 Global magnitude of terrestrial evaporation**

11 The global mean annual volume of evaporation has been intensively debated in recent years
12 (see e.g. Wang and Dickinson, 2012), with the range of reported global-averages in current
13 CMIP5 models being large (Wild et al., 2014) and observational benchmark data sets also
14 differing significantly (Mueller et al., 2013). In this section, we aim to give some context to
15 the global magnitude of evaporation that results from the WACMOS-ET analyses by
16 contrasting the results against alternative evaporation data sets and existing literature. Unless
17 otherwise noted, results come from aggregating the outputs from the 3-hourly global runs
18 based on the 25 km spatial resolution of the reference input data set for the period 2005–2007.

19 Overall, the total annual magnitude of evaporation estimated by the WACMOS-ET models
20 amounts to $54.9 \times 10^3 \text{ km}^3$ for PM-MOD, $72.9 \times 10^3 \text{ km}^3$ for GLEAM and $72.5 \times 10^3 \text{ km}^3$ for
21 PT-JPL. We further calculated $84.4 \times 10^3 \text{ km}^3$ for ERA-Interim and $68.3 \times 10^3 \text{ km}^3$ for MTE
22 based on the same 2005–2007 period. Unlike the other products, MTE does not include poles
23 and desert regions (as shown in Fig. 2); however, the contribution from these areas to the
24 global volumes is rather marginal (<5% based on our analyses). For comparison, values
25 typically found in literature based on a broad variety of methodologies and forcings are: 63.2
26 $\times 10^3 \text{ km}^3$ (Zhang et al. 2016), $65.0 \times 10^3 \text{ km}^3$ (Jung et al. 2010), $65.5 \times 10^3 \text{ km}^3$ (Oki and
27 Kanae 2006), $65.8 \times 10^3 \text{ km}^3$ (Schlosser and Gao 2010), $67.9 \times 10^3 \text{ km}^3$ (Miralles et al.
28 2011a), $71 \times 10^3 \text{ km}^3$ (Baumgartner and Reichel 1975), $73.9 \times 10^3 \text{ km}^3$ (Wang-Erlandsson et
29 al. 2014) and $74.3 \times 10^3 \text{ km}^3$ (Zhang et al., 2015). We note again that some of these studies
30 considered the poles and desert regions, while others did not. Further, the study period

1 considered in WACMOS-ET is 2005–2007, while previously reported annual averages may
2 be based on different periods.

3 In Fig. 2 the multiannual (2005–2007) mean evaporation is displayed for the different
4 products, including also MTE and ERA-Interim for comparison. All five data sets capture
5 well the expected climatic transitions, although disagreements at the regional scale are still
6 considerable (see below). Latitudinal averages are illustrated in the right panel of Fig. 2.
7 Model estimates are normally contained between the low values from PM-MOD and the high
8 values from ERA-Interim; as an exception, PM-MOD can be comparatively large in Northern
9 Hemisphere high latitudes (see Sect. 3.2). In Fig. 2, the latitudinal profiles from the
10 original/official products from PM-MOD (i.e. MOD16), GLEAM (i.e. GLEAM v1) and PT-
11 JPL (i.e. PT-Fisher) are also displayed for comparison. Note that the main differences
12 between these official products and those developed in WACMOS-ET relate to the choice of
13 forcing – see Mu et al. (2013), Miralles et al. (2011a) and Fisher et al. (2008) for the
14 particular forcing data used to generate these official data sets. In addition, models have been
15 run here at sub-daily scale (three hourly) as opposed to their original daily (PM-MOD,
16 GLEAM) or monthly (PT-JPL) temporal resolutions. While for PM-MOD and PT-JPL the
17 choice of temporal resolution and forcing in WACMOS-ET leads to overall lower values (see
18 PM-MOD in tropics), for GLEAM, values are slightly higher than in the original version (v1).

19 Inter-product differences in mean evaporation become more evident in Fig. 3, which presents
20 the anomalies for each product calculated by subtracting the average of the five-product
21 ensemble. PM-MOD displays lower averages than the multi-product ensemble mean over the
22 entire continental domain, with the exception of high latitudes, as discussed above. GLEAM
23 shows higher than average values in Europe or Amazonia, and lower in North America. This
24 pattern is somewhat shared by PT-JPL, although the two models disagree substantially in
25 water-limited regions of Africa and Australia, even if absolute mean values are low in those
26 regions (see Fig. 2). This relates to the different model representation of evaporative stress,
27 with GLEAM being based on observations of rainfall, surface soil moisture and vegetation
28 optical depth, while PT-JPL is based on air humidity, maximum air temperature and NDVI.
29 As mentioned in Sect. 2.2, it is important to note that even though we aimed to maximise
30 consistency in forcing data for PM-MOD, GLEAM and PT-JPL, their disagreement still
31 reflects a combination of algorithm structural errors and input uncertainties, given the use of a

1 distinct range of inputs for each model (Table 1) and the different model sensitivities to each
2 particular driver.

3 ERA-Interim values are often at the high end of the predictions, consistent with the results by
4 Mueller et al. (2013), more than doubling the evaporation estimated by PM-MOD on some
5 occasions (Fig. 2). MTE values, on the other hand, are lower than the inter-product average in
6 the Himalayas and in tropical forests – which may potentially relate to the lack of a separate
7 computation of interception loss and the long-lasting question of whether interception can be
8 measured with eddy-covariance instruments (see van Dijk et al., 2015) – but they agree well
9 with the mean of the multi-product ensemble in other regions (Fig. 3). A quick overview on
10 the range of uncertainty that can be expected may be obtained from the right panel of Fig. 3,
11 where the latitudinal profiles of anomalies are illustrated. Data sets appear again to be
12 confined between the low values of PM-MOD and the high values of ERA-Interim. If that
13 multi-model range is interpreted as an indication of the uncertainty, it is worth noting that it
14 often amounts to 60–80% of the mean evaporation, particularly in the subtropics. In the
15 tropics, while the relative uncertainty is lower, the inter-product range still reaches ~500 mm
16 yr⁻¹ according to the latitudinal profiles in Fig. 3. To put that volume into context, the mean
17 annual evaporation is below 500 mm yr⁻¹ for more than 50% of continental surfaces,
18 according to the inter-product ensemble mean.

19 The spatial agreement among models is further explored in Fig. 4, which presents the spatial
20 correlation for each pair of models based on their long-term global means (i.e. the maps in
21 Fig. 2). Each land pixel is an independent point in the scatter. The lowest spatial correlation
22 occurs between PM-MOD and GLEAM ($R = 0.89$), and the highest between GLEAM and PT-
23 JPL ($R = 0.94$). Although the latter may reflect the common choice of a Priestley and Taylor
24 approach to calculate potential evaporation in both models, it occurs despite their large
25 differences in input requirements (Table 1) and in the approach to derive evaporative stress
26 and interception loss (Sect. 2.1). The agreement in the mean spatial patterns between PM-
27 MOD and PT-JPL is also high in terms of correlation coefficient ($R = 0.93$), as expected from
28 their shared set of input variables (see Table 1). Nonetheless, their root mean square
29 difference is large (RMSD = 185 mm yr⁻¹) – compared to the difference between PT-JPL and
30 GLEAM (RMSD = 142 mm yr⁻¹) – which mostly reflects the overall lower values of PM-
31 MOD. These low mean values are also accompanied by a low variance, especially in mid

1 latitudes. This is illustrated in Fig. 5, which depicts the standard deviation of the monthly time
2 series at each pixel and as a function of latitude.

3 **3.2 Temporal variability of terrestrial evaporation**

4 In addition to long-term mean differences in evaporation, inter-product discrepancies in
5 temporal dynamics are certainly expected. Temporal correlations based on the (2005–2007)
6 daily time series for each pair of models are illustrated in Fig. 6a. The overall agreement in
7 temporal dynamics is larger in high latitudes, especially between GLEAM and PT-JPL. In
8 semiarid regions, product-to-product correlations are often below 0.5 and may drop below 0.2
9 (see e.g. low correlation between PM-MOD and PT-JPL in Southern Africa or Australia).
10 This occurs despite the substantial amplitude of the seasonal cycle in these transitional
11 regimes (see e.g. Fig. 5), which may, in principle, artificially increase temporal correlations.
12 Overall, Fig. 6a corroborates that, although the agreement between GLEAM and PT-JPL is
13 large, their different approach to estimating water-availability constraints on evaporation and
14 rainfall interception loss leads to significant differences for semiarid regions and tropical
15 forests.

16 Based on the monthly climatology of each model (calculated by averaging the estimates for
17 the same month of the year considering the multiannual 2005–2007 period), Fig. 6b illustrates
18 the month in which the differences between a given pair of models are the largest. In the
19 Northern Hemisphere, the product-to-product differences are at their maximum during
20 summertime, when the flux of evaporation is higher. This is particularly the case in
21 comparisons to PM-MOD, given that the seasonal evaporation peak of PM-MOD is often less
22 pronounced than for the other models (see also Figs. 5, 7, 8). In the tropics and the Southern
23 Hemisphere, maximum differences between models occur at different times of the year, but
24 often coincide with months of higher evaporative demand for water; this is the case for
25 southern Africa, the Pampas region or Australia during the Austral summer.

26 Figure 7 shows the average evaporation for boreal summer (JJA) and winter (DJF) for each
27 model based on the three-year period of study. MTE and ERA-Interim are again included for
28 comparison. As expected, the seasonal variability of evaporation follows the annual cycle of
29 radiation, except for arid and semi-arid regions that are controlled by the availability of water.
30 The lower values of PM-MOD are again highlighted. The underestimation of PM-MOD, with
31 respect to the other two models, mostly occurs in times and locations for which both

1 evaporative demand and water availability are high, thus evaporation is expected to be high as
2 well (e.g. mid-latitude summer, tropics). As discussed in Sect 3.3, this may be associated with
3 an overestimation of evaporative stress in the model. However, PM-MOD is often higher than
4 the other two models in periods and regions where radiation is severely limited, potentially
5 due to the underestimation of Priestley-Taylor type models (i.e. GLEAM and PT-JPL) when
6 radiation is not the main supply of energy for evaporation (see e.g., Parlange and Katul,
7 1992); in those conditions, the Penman-Monteith equation still considers adiabatic sources of
8 energy to drive evaporation. Once more, differences in seasonal means between GLEAM and
9 PT-JPL exist at regional scales, especially in water-limited regimes, with Australia being a
10 clear example (see also Fig. 9).

11 Nonetheless, Fig. 7 still shows a general agreement amongst the five models in their
12 representation of seasonal dynamics. This agreement becomes also apparent in Fig. 8, which
13 presents the seasonal monthly climatology of evaporation over different biome types. Except
14 for densely vegetated regions (see e.g. Southern Hemisphere tropical forests), arctic regions
15 or arid regimes (see e.g. Northern Hemisphere deserts), all models capture similar monthly
16 dynamics. This occurs despite the systematic differences in the absolute magnitudes of
17 evaporation, which become again apparent – especially between PM-MOD and ERA-Interim
18 – and may indicate limitations in the way models represent the processes governing land
19 evaporation. This highlights the importance of field-based validation activities to improve and
20 select algorithms.

21 Since the seasonality of evaporation is mostly dominated by the annual cycle of irradiance in
22 nature (especially in energy-limited regions), the skill of these models in correctly capturing
23 these seasonal dynamics relies mostly on adequately representing the sensitivity of
24 evaporation to the (common) net radiation forcing. However, if estimating average seasonal
25 dynamics in evaporation may not appear overly challenging from the modelling perspective,
26 accurately simulating anomalies (i.e. departures) relative to a seasonal expectation is far more
27 problematic. With hydro-meteorological extremes – and particularly droughts – being a target
28 application of these models, correctly reproducing the effect of surface water deficits on
29 evaporation (and *vice versa*) appears crucial. One of the most remarkable hydro-
30 meteorological extremes that coincide with the WACMOS-ET period is the Australian
31 Millennium Drought, which affected (especially) southeastern Australia, and had in 2006 one
32 of its most severe years of rainfall deficits (see van Dijk et al., 2013; Leblanc et al., 2012).

1 Figure 9a shows the daily time series of latent heat flux and net radiation for the Darling basin
2 (area contoured in Fig. 1) from the three WACMOS-ET models during 2005–2007; ERA-
3 Interim is also included for comparison. Figure 9b presents the monthly aggregates of land
4 evaporation from these models, and incorporates the estimates from MTE, precipitation from
5 GPCP v6 (with gauge correction factors from Fuchs et al., 2001) and river discharge data
6 from GRDC.

7 Given the dominant rainfall scarcity, monthly runoff volumes are very low (note the more
8 than two orders of magnitude difference between the left and right axes in Fig. 9b); the river
9 in fact dries out completely for prolonged periods. This indicates that almost the entire
10 volume of incoming rainfall is evaporated. Therefore, cumulative evaporation should
11 approximate cumulative precipitation over the multi-year period. We find, however, that in
12 the case of all models evaporation exceeds total rainfall, except for PM-MOD, in which
13 evaporation is only 66% of precipitation. In the case of MTE, the cumulative evaporation is
14 16% higher than the precipitation, while it is 21% and 29% higher for GLEAM and PT-JPL,
15 respectively, and as much as 56% higher for ERA-Interim. To some extent, this could reflect
16 the progressive soil dry out as the drought event evolves (i.e. the negative change in soil
17 storage in time), the use of irrigation, or the accessibility of groundwater for root uptake (see
18 e.g. Chen and Hu, 2004; Orellana et al., 2012), Nonetheless, there is a general tendency from
19 all models to overestimate evaporation in drier catchments, as shown in the following Sect.
20 3.3. Once more, Fig. 9 points that the estimates from the different products typically range
21 between the low values of PM-MOD and high values of ERA-Interim, and that there is a
22 general agreement on the temporal dynamics between GLEAM, PT-JPL and MTE. Yet, there
23 are clear differences in the timing of water stress and the rates of evaporation decline (see e.g.
24 summer 2006), and the inter-product disagreement at short temporal scales (Fig. 9a) is
25 considerably larger than the disagreement in mean seasonal cycles (Fig. 8).

26 **3.3 Evaluation of evaporation based on the water balance closure**

27 The skill of the different models to close the water budgets over 837 basins is investigated
28 here. As explained in Sect. 2.3.2, these analyses consist of a comparison of modelled
29 evaporation estimates from PM-MOD, GLEAM and PT-JPL (forced by the reference input
30 data set over 2005–2007) against estimates of $P - Q$. Such a comparison implies the validity
31 of a series of assumptions (see discussion below), but overall, $P - Q$ estimates remain a valid,
32 recursive means to evaluate long-term evaporation patterns (Liu et al., 2014; Miralles et al.,

1 2011a; Vinukollu et al., 2011b; Sahoo et al., 2011). Here, different criteria have been applied
2 to ensure the quality of the $P - Q$ estimates, and the remaining catchments (Fig. 1) have been
3 clustered into 30 different classes based on average precipitation and evaporative fraction (see
4 Sect. 2.3.2).

5 The skill of the three WACMOS-ET models to reproduce the general climatic patterns of
6 evaporation becomes apparent from the scatterplots in Fig. 10. All three WACMOS-ET
7 products correlate well with the observations, which implies that their long-term spatial
8 distribution of evaporation (Fig. 2) is overall realistic. The general negative bias of PM-MOD
9 becomes again discernible when compared to the $P - Q$ data, which is in agreement with the
10 results by Mu et al. (2013). In addition, there is a tendency from all models to underestimate
11 evaporation in wet regions and overestimate in dry regions – the latter was already suggested
12 by Fig. 9. While, this pattern could potentially be explained by systematic errors in $P - Q$ (see
13 discussion below on the possible sources of errors when considering $P - Q$ as a proxy for
14 evaporation), the same tendency has been found in Part 1 in comparisons against independent
15 eddy-covariance towers. Once more, it is interesting to see how the independent evaporation
16 data sets, i.e. ERA-Interim and MTE, perform in this comparison; both products correlate
17 well with the $P - Q$ estimates, although the overall higher values of ERA-Interim (and lower
18 of MTE) are again highlighted, together with the tendency to overestimate evaporation in dry
19 catchments and underestimate in wet ones, which shared by all five data sets.

20 As mentioned above, the use of $P - Q$ as a benchmark for evaporation depends on the validity
21 of several assumptions. First, the catchment needs to be watertight (no sub-surface leakage to
22 other catchments) and its geographical boundaries must be well defined. Second, the entire
23 volume of river water that is extracted for direct human use must return to the river, and it
24 shall do so upstream of the staff gauge location. Third, the lag-time between rainfall events
25 and the discharge measured at the station can be neglected when compared to the total period
26 of study. Finally, the changes in soil water storage within the catchment should be
27 insignificant compared to the cumulative volume of the three main hydrological fluxes. Here,
28 by considering long-term averages of $P - Q$, these assumptions appear to be reasonable for
29 most continental regions. However, for industrialised areas with dense population, the
30 consumption and export of water and the human regulation of the reservoir storages may
31 compromise these assumptions. Nonetheless, the largest sources of uncertainty regarding the
32 use of $P - Q$ as estimate of catchment evaporation likely come from (a) the definition of the

1 runoff-contributing area, and **(b)** errors in precipitation and discharge observations. In fact,
2 Fig. 10 shows that the choice of precipitation product can have a significant influence on the
3 results, even despite the existing inter-dependencies between the gauge-based precipitation
4 data sets tested here (Sect. 2.3.2). On the other hand, uncertainties in observations of river
5 runoff can also be significant, and come from errors in the measurements of water height, the
6 discharge data used to calibrate the rating curves, or the interpolation and extrapolation due to
7 changes in riverbed roughness, hysteresis effects, etc. (see e.g. Di Baldassarre and Montanari,
8 2009). Finally, it is important to note that model estimates correspond to the period 2005–
9 2007, while $P - Q$ estimates do not necessarily span the entire period due to limitations in the
10 availability of discharge data. This implicitly assumes that the multi-annual variability in
11 evaporation is significantly lower than its spatial climatological variability across the globe.

12 Additionally, the fit of the models to a Budyko curve (Budyko, 1974) is explored in Fig. 11 as
13 a general diagnostic for the robustness of mean evaporation estimates and their consistency
14 with the input of water and energy. Potential evaporation estimates are taken from the
15 corresponding models and precipitation from the GPCC v6 product with gauge correction
16 factors from Fuchs et al. (2001), to be consistent with Figs. 9 and 10. Overall, results are in
17 agreement with the water balance scatterplots (Fig. 10). The fraction of precipitation that is
18 evaporated (E/P) is usually lower for PM-MOD; however, this does not happen due to an
19 underestimation of the atmospheric demand for water, as the values of the ratio of potential
20 evaporation over precipitation (E_p/P) are overall comparable to those from GLEAM and PT-
21 JPL. The PM-MOD product has therefore a general tendency to overestimate the surface
22 evaporative stress (i.e. underestimate the ratio of E over E_p), which may explain the overall
23 lower estimates of evaporation found across our analyses. GLEAM and PT-JPL show a better
24 fit to the Budyko diagram, and a transition from arid to wet climates that is consistent with the
25 average fluxes of precipitation and net radiation. Nevertheless, it is worth noting that all three
26 models estimate average values of evaporation that overcome average precipitation in
27 numerous areas.

28 **3.4 Partitioning of evaporation into separate components**

29 The flux of land evaporation results from the summation of three main components or
30 sources: **(a)** transpiration (the process that describes the movement of water from the soil,
31 through the plant xylem, to the leaf and finally to the atmosphere), **(b)** interception loss (the
32 vaporization of the volume of water that is held by the surface of vegetation during rainfall),

1 and **(c)** soil evaporation (the direct vaporization of water from the topsoil). These processes
2 require separate consideration in models due to their differences in bio-physical drivers and
3 rates (Savenije, 2004; Dolman et al., 2014). In addition, two other contributors to evaporation
4 are often considered separately: the direct evaporation (sublimation) from snow- and ice-
5 covered surfaces and the vaporization from continental water bodies (or open-water
6 evaporation).

7 Transpiration is the component that has received the most attention by the scientific
8 community in recent years, due to its connection to different biogeochemical cycles. The
9 global contribution of transpiration to total average evaporation has been extensively debated
10 recently (Schlesinger and Jasechko, 2014; Wang et al., 2014). Studies have reported values
11 ranging between 35–90%, based on isotopes (Jasechko et al., 2013; Coenders-Gerrits et al.,
12 2015), sap-flow measurements (Moran et al., 2009), satellite data (Miralles et al., 2011a; Mu
13 et al., 2011; Zhang et al. 2016) or modelling (Wang-Erlandsson et al., 2014). Consequently,
14 this large range of uncertainty is also expected in the relative contribution from other
15 evaporation sources. Moreover, reducing this uncertainty appears particularly challenging due
16 to the limited amount of ground data that can be used for validation and the nature of the
17 techniques used to measure latent heat flux: most measuring devices (e.g. lysimeters, eddy-
18 covariance instruments, scintillometers) cannot distinguish amongst the different sources of
19 evaporation.

20 All three WACMOS-ET models estimate the components of evaporation separately. In the
21 case of PT-JPL and PM-MOD, the available energy is partitioned into the different land
22 covers to estimate the contribution from each of them. The approach in GLEAM is somewhat
23 different, as the flux of interception loss is calculated using a different algorithm than the one
24 used for transpiration and soil evaporation. Figure 12 illustrates the average contribution of
25 each evaporation component to the total flux as estimated by the WACMOS-ET models. In
26 the case of GLEAM (which calculates sublimation separately), the flux from snow and ice has
27 been added to the bare soil evaporation in this figure to allow visual comparison to the other
28 two products.

29 The discrepancy amongst modelled evaporation components show in Fig. 12 is large, and
30 calls for a thorough validation of the way the contribution from different sources is estimated,
31 and perhaps an in-depth revision to ensure that the conceptual definition of these components
32 is consistent from model to model. Regionally, disagreements are particularly large in

1 transitional regimes; for instance, in the climatic gradient from the Congo rainforest to the
2 savanna, the virtual totality of the flux comes from transpiration in the case of GLEAM, while
3 for PM-MOD direct soil evaporation is the dominant component. In tropical forests, the direct
4 soil evaporation can also exceed transpiration in the case of PM-MOD, while for GLEAM
5 and PT-JPL bare-soil evaporation is almost inexistent. The mean inter-model disagreement is
6 manifest in the pie diagrams in Fig. 12, with GLEAM estimating a large contribution from
7 transpiration (76%) and low from soil evaporation (14%), PM-MOD estimating little
8 transpiration (24%) and a large contribution from soil evaporation (52%), and both PM-MOD
9 and PT-JPL yielding a much larger flux of interception loss than GLEAM. Nevertheless, and
10 as discussed above, recent reviews have revealed comparable levels of uncertainty in this
11 partitioning based on a wide range of independent methods (see e.g. Schlesinger and
12 Jasechko, 2014; Wang et al., 2014).

13 While the global contribution of transpiration has received much attention in literature
14 (Jasechko et al., 2013; Coenders-Gerrits et al., 2015), the flux of interception loss has seldom
15 been explored globally (Miralles et al., 2010; Vinukollu et al., 2011b; Wang-Erlandsson et al.,
16 2014). The physical process of interception loss differs from that of transpiration on its
17 sensitivity to environmental and climatic variables: the rates and magnitude of interception
18 are dictated by the aerodynamic properties of the vegetation stand, and the occurrence and
19 characteristics of rainfall (Horton, 1919). In fact, while solar radiation is usually the main
20 supply of energy for transpiration and soil evaporation (Wild and Liepert, 2010), the source of
21 energy powering interception loss is still debated (Holwerda et al., 2011; van Dijk et al.,
22 2015). This limited process understanding, together with the scarcity of ground measurements
23 for validation, makes interception loss particularly challenging to model. Nonetheless,
24 interception has often been reported in units of percentage of incoming rainfall during the
25 restricted number of past *in situ* measuring campaigns – see e.g. Miralles et al. (2010) for a
26 non-exhaustive list of these campaigns. This makes interception measurements easy to
27 extrapolate in time and space, and it allows for a relatively straightforward validation of the
28 estimates from our three models. Therefore, Fig. 13 presents the daily time series of
29 interception loss from PM-MOD, GLEAM and PT-JPL for the average of the Amazon basin
30 (blue contour in Fig. 1), and indicates the values reported by past campaigns in Amazonia.
31 According to *in situ* measurements, all models overestimate interception loss; remarkably, in
32 the case of PM-MOD and PT-JPL there is over a two-fold overestimation of the mean flux.
33 Temporal dynamics of interception loss from the three products do not correlate well either,

1 as GLEAM tends to follow the occurrence of rainfall, while PM-MOD and PT-JPL are more
2 affected by net radiation variability, as expected from the interception algorithms (i.e. Gash's
3 model for GLEAM, Penman-Monteith for PM-MOD and Priestley and Taylor for PT-JPL).
4 Further analyses are needed to explore the skill of these (and other) models to separately
5 derive the different evaporation components or sources. Nevertheless, these preliminary
6 analyses point at the need for caution when using global estimates of transpiration, soil
7 evaporation or interception loss from a single model in isolation, as the disagreements can be
8 much larger than for total land evaporation. Up to date, the lack of *in situ* networks that
9 measure the components of evaporation independently remains an inexorable bottleneck for
10 the improvement of model estimates.

11 **4 Conclusion**

12 The ESA WACMOS-ET project started in 2012 with the goal of performing a cross-
13 comparison and validation exercise of a group of selected global observational evaporation
14 algorithms driven by a consistent set of forcing data. With the project coming to an end, this
15 article has focussed on the global and regional evaluation of the resulting evaporation data
16 sets.

17 The three main models scrutinised here were the Penman-Monteith approach from the official
18 MODIS evaporation product (Mu et al., 2007, 2011, 2013), GLEAM (Miralles et al., 2011b;
19 Martens et al., 2015) and the Priestley-Taylor JPL (Fisher et al., 2008); the SEBS model (Su,
20 2001), which was analysed at the local scale in Part 1 (revealing good performance in terms
21 of correlations but a systematic overestimation of evaporation), was not evaluated in this
22 contribution. The spatiotemporal magnitude and variability of the resulting global evaporation
23 products were compared to analogous estimates from reanalysis (ERA-Interim) and eddy-
24 covariance-based global data (MTE). The representation of evaporation dynamics during
25 droughts, the model skill to close the water balance over 837 river basins worldwide, and the
26 partitioning of evaporation into different components have also been explored.

27 Despite our efforts to create a homogeneous forcing data set to run the evaporation models,
28 the input requirements of each model are different, which implies that the resulting inter-
29 product disagreements are the result of both internal differences in the models, and
30 uncertainties in forcing and ancillary data. This prevents us from making strong claims about

1 the quality of the models. However, there is also a list of take-home messages to learn from
2 these analyses:

- 3 – In agreement with the local-scale validation in Part 1, the PM-MOD product tends to
4 underestimate evaporation (see e.g. Figs. 3, 10). This underestimation is systematic,
5 being larger in absolute terms in the tropics (where evaporation is larger), and larger in
6 relative terms in drier subtropical regions (Fig. 3). As an exception, in high latitudes
7 PM-MOD estimates are greater than those from GLEAM and PT-JPL; this may reflect
8 known deficiencies in Priestley-Taylor-based approaches over conditions of low
9 available energy (see e.g. Parlange and Katul, 1992).
- 10 – The global average magnitude of evaporation from GLEAM and PT-JPL agree well
11 with each other and with the envelope of literature values (see Figs. 2, 4). This
12 agreement extends to the average latitudinal patterns, which lay between those of PM-
13 MOD and ERA-Interim (Figs. 2, 3). In terms of temporal dynamics, there are
14 differences between GLEAM and PT-JPL in dry conditions, as expected from their
15 distinctive approach at representing evaporative stress (see Sect. 2.1). These
16 differences are pronounced in the Southern Hemisphere subtropics (Fig. 6a), reflect
17 more clearly in daily anomalies than in seasonal cycles (Fig. 8), and may exacerbate
18 during specific drought events (Fig. 9).
- 19 – The partitioning of evaporation into different components is a facet of these models
20 that has not received enough attention in previous applications. Each model has a
21 distinct way to estimate these components, and even in cases in which inter-product
22 average evaporation agrees, the separate contribution from these components may
23 fluctuate substantially (Fig. 12). As an example, differences in interception loss
24 amongst models (Fig. 13) may explain a large part of the disagreements in the
25 seasonality of evaporation over tropical forests (Fig. 8). Further exploring the skill of
26 these models at partitioning evaporation into its different sources remains a critical
27 task for the future. This is outside the scope of WACMOS-ET and it would require
28 innovative means of validation beyond traditional comparisons to eddy-covariance
29 and lysimeter data.
- 30 – On a more positive note, the analysis of the skill of different models to close the water
31 balance over particular catchments reveals that the general climatic patterns of
32 evaporation are well captured by all models (Fig. 10). While this comparison has also
33 unveiled the general underestimation by PM-MOD (and overestimation by ERA-

1 Interim), all products correlate well with the cumulative values of $P - Q$. We stress
2 however that this agreement does not indicate whether the multi-scale temporal
3 dynamics of evaporation are well captured. For a thorough validation of evaporation
4 temporal variability, we direct the readers to Part 1.

5 In summary, the activities in WACMOS-ET have demonstrated that some of the existing
6 evaporation models require an in-depth scrutiny to correct for systematic errors in their
7 estimates. This is especially the case over semi-arid regions and tropical forests. In addition,
8 even models that have demonstrated a more robust performance, like GLEAM and PT-JPL,
9 may differ substantially from one another under certain biomes and climates. Overall, our
10 results imply the need for caution in using a single model for any large-scale application in
11 isolation, especially in studies in which transpiration, soil evaporation or interception loss are
12 investigated separately.

13 As remote sensing science continues advancing, new long-term records of physical variables
14 to constrain these models are becoming available (e.g., chlorophyll fluorescence, surface soil
15 moisture). While further tools to improve evaporation models become accessible, the
16 possibility for considering biome- or climate-specific composites of flux algorithms is
17 currently being explored, given the general finding that different models may perform better
18 under certain conditions (Ershadi et al., 2014; McCabe et al., 2015). For an inter-product
19 merger to add new skill, the sensitivity of each model to its forcing should be further
20 explored, and a robust propagation of uncertainties appears essential to merge these products
21 efficiently.

22 The reader is directed to additional supporting documents available from the project website
23 at <http://WACMOS-ET.estellus.eu>.

24 **Author contributions**

25 D. G. M., C. J., M. J., D. M., A. E., M. F. M., M. H. and D. F.-P. designed the content of the
26 manuscript. D. G. M., C. J. and M. J. did the analyses. D. G. M. wrote the paper. J. B. F. and
27 Q. M. provided the computer codes of the PT-JPL and PM-MOD models, respectively. All
28 authors contributed to the accomplishment of the project, and the discussion and
29 interpretation of results.

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11

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1 **Table 1.** Inputs from the reference input data set used in each of the models. The specific
2 products chosen for each variable are also noted.

3 **Figure 1.** Climatic regimes and biomes considered in the evaluations. The background map
4 illustrates the land use classification scheme of the International Geosphere-Biosphere
5 Programme (IGBP) used in Fig. 8. The Darling basin in southeastern Australia, as considered
6 in Sect. 3.2, is contoured in red. The Amazon basin, as considered in Sect. 3.4, is marked in
7 blue, with white triangles pointing at the location of past interception loss campaigns. Dots
8 indicate the centroids of the 837 basins used in the analyses presented in Sect. 3.3.

9 **Figure 2.** Mean patterns of land evaporation. Average evaporation during 2005–2007 for PM-
10 MOD, GLEAM and PT-JPL forced by the reference input data set; the ERA-Interim
11 reanalysis and the MTE product are shown for comparison. On the right, the latitudinal
12 profiles of evaporation; the original data sets of PM-MOD, GLEAM and PT-JPL (i.e.
13 MOD16, GLEAMv1 and PT-Fisher, respectively) are also shown for comparison. We note
14 that the original PT-JPL covers until 2006 only, and therefore its latitudinal profile is based on
15 the 2005–2006 average. Due to MTE product not reporting values in polar regions and
16 deserts, those areas are excluded from the latitudinal profiles in all models.

17 **Figure 3.** Long-term anomalies of evaporation. Like Fig. 2 but based on the anomalies for
18 each product calculated as the mean of each particular product (i.e. the maps in Fig. 2) minus
19 the inter-product ensemble mean (considering the ensemble of five models). Grey areas over
20 the continents correspond to regions where MTE displays no estimates of evaporation.

21 **Figure 4.** Correlations in the average spatial patterns for each pair of models. Each point
22 represents a land pixel in Fig. 2. Pearson's correlation coefficients are listed.

23 **Figure 5.** Standard deviation of land evaporation. Based on the monthly time series for 2005–
24 2007 at each pixel for PM-MOD, GLEAM and PT-JPL forced by the reference input data set;
25 the ERA-Interim reanalysis and the MTE product are shown for comparison. The right
26 column illustrates the latitudinal profiles of these standard deviations. Due to MTE product
27 not reporting values in polar regions and deserts, those areas are excluded from the latitudinal
28 profiles in all models.

1 **Figure 6.** Temporal agreement between the models. **(a)** Temporal correlation coefficients
2 between each pair of products based on the daily (2005–2007) time series. **(b)** Month of the
3 year in which the maximum (monthly) difference occurs between a particular pair of products
4 based on their monthly climatologies.

5 **Figure 7.** Mean seasonal differences. Average evaporation for PM-MOD, GLEAM and PT-
6 JPL during boreal summer (June, July and August) and austral summer (December, January
7 and February). ERA-Interim reanalysis and MTE are considered for comparison. The three
8 years of data (2005–2007) are used in the calculation of these seasonal averages.

9 **Figure 8.** Average seasonal cycle. Monthly climatology of evaporation for each IGBP biome
10 (see Fig. 1 for the global distribution of biomes) based on the 2005–2007 period. Northern
11 Hemisphere (left) and Southern Hemisphere (right) are presented separately. In addition to the
12 PM-MOD, GLEAM and PT-JPL results, the evaporation from ERA-Interim and MTE is also
13 shown for completeness. Fluxes are displayed in mm/month.

14 **Figure 9.** Evaporation during the Australian Millennium Drought. **(a)** Daily time series of
15 evaporation from the three WACMOS-ET products for the Darling basin during 2005–2007.
16 ERA-Interim evaporation is also illustrated for comparison. **(b)** Same as **(a)** but at monthly
17 time scales, which enables to include the MTE (monthly) evaporation estimates. Precipitation
18 anomalies from GPCP v6 with gauge correction factors from Fuchs et al. (2001), and
19 discharge data from GRDC are also displayed. The contributing area is illustrated in Fig. 1.

20 **Figure 10.** Skill to close catchment water budgets. Correlations between the long-term
21 averages in evaporation from the three WACMOS-ET models and $P - Q$ estimates based on
22 observations from 837 catchments. ERA-Interim and MTE are added for the sake of
23 completeness. Three different precipitation products are considered in the calculation of $P -$
24 Q : GPCP, GPCP v6 with gauge correction factors from Fuchs et al. (2001) and GPCP v6
25 with gauge correction factors from Legates and Willmott (1990). The corresponding
26 validation statistics are noted within the scatterplots, and the range displayed for each
27 statistical inference derives from the use of the three different precipitation products.

28 **Figure 11.** Budyko diagrams for the different models. Budyko curves derived for PM-MOD,
29 GLEAM and PT-JPL. Each point represents a different land grid cell. The horizontal axis

1 presents the ratio of potential evaporation to precipitation (E_p/P) and the vertical axis presents
2 the ratio of evaporation to precipitation (E/P). Actual and potential evaporation estimates are
3 derived by each of the models, while precipitation comes from GPCP v6 with gauge
4 correction factors from Fuchs et al. (2001). Each land pixel is an independent scatter point.

5 **Figure 12.** Partitioning evaporation. Maps indicate the average (2005–2007) transpiration,
6 interception loss and bare-soil evaporation for each of the three WACMOS-ET models. Pie
7 diagrams illustrate the global average contribution to total land evaporation from each
8 component and product.

9 **Figure 13.** Interception loss in Amazonia. Daily time series of interception (mm day^{-1}) for
10 2005–2007 from the three WACMOS-ET products as averaged for the entire Amazon basin.
11 The average interception (as percentage of rainfall) from the three models is listed, together
12 with the mean (\pm one standard deviation) of past field campaigns by Lloyd (1988) (8.9%),
13 Czikowsky and Fitzjarrald (2009) (11.6%), Ubarana (1996) (11.6%), Cuartas et al. (2007)
14 (13.3%), Marin et al. (2000) (13.5%), Shuttleworth (1988) (9.1%). See Fig. 1 for the Amazon
15 catchment boundaries and the location of the field measurements.

1 **Table 1**

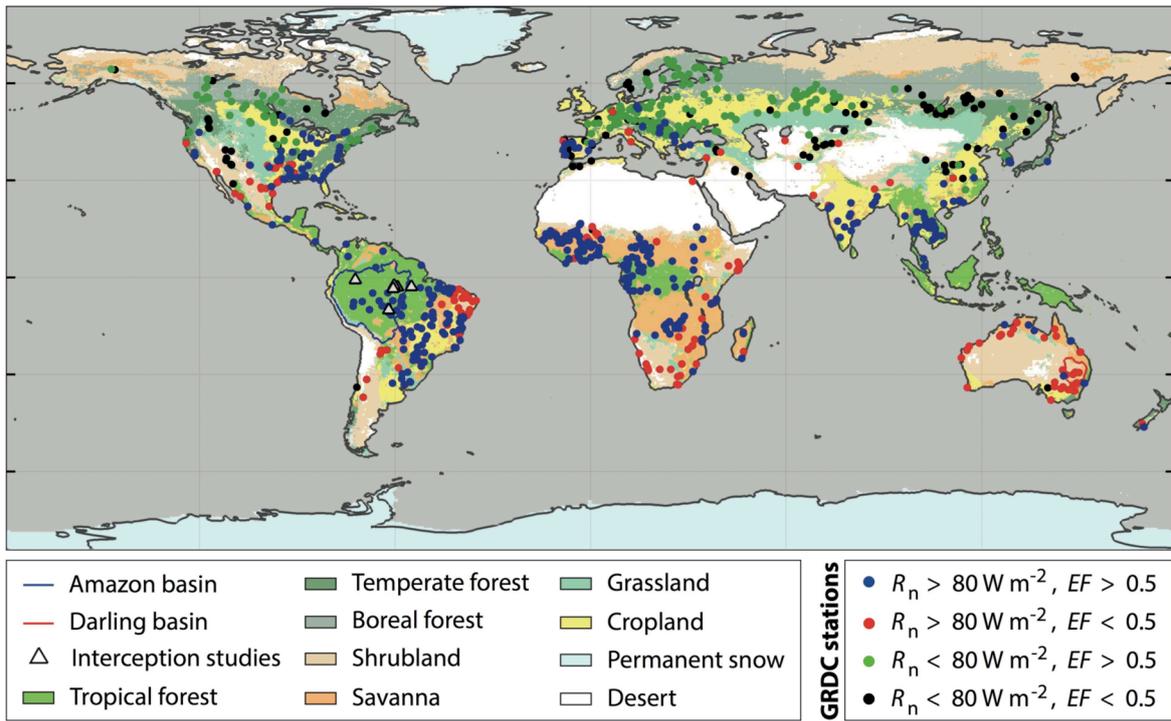
Input	Product	PM- MOD	GLEAM	PT-JPL
Radiation	SRB 3.1	✓	✓	✓
Air temperature	ERA-Interim	✓	✓	✓
Precipitation	CFSR-Land	–	✓	–
Soil moisture	CCI WACMOS	–	✓	–
Air humidity	ERA-Interim	✓	–	✓
Snow cover	GlobSnow / NSIDC	–	✓	–
Vegetation characteristics	Internally produced / vegetation optical depth from AMSR-E (see Sect. 2.2 and Part 1)	✓	✓	✓

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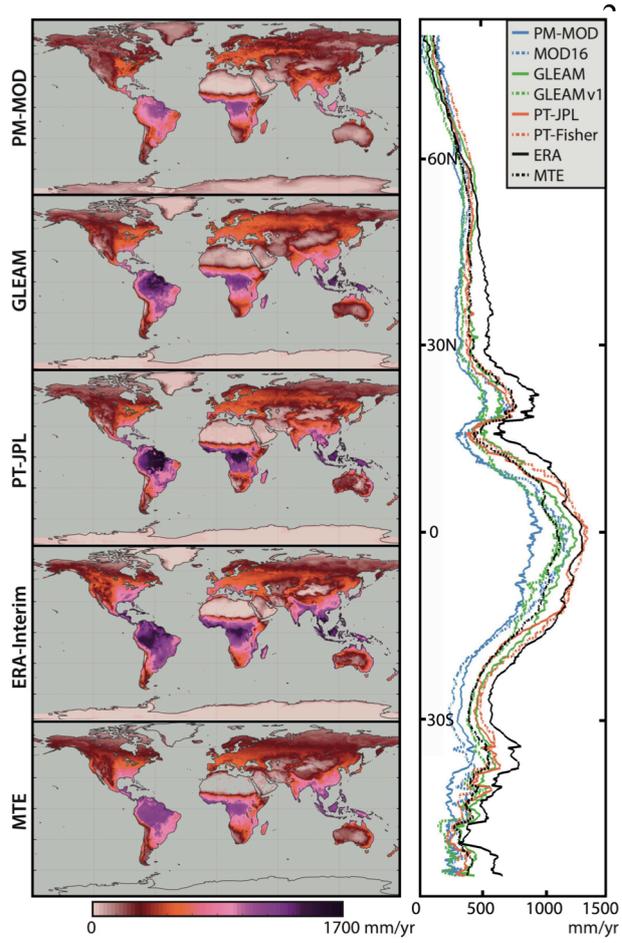
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1 **Figure 1** (*double column*)

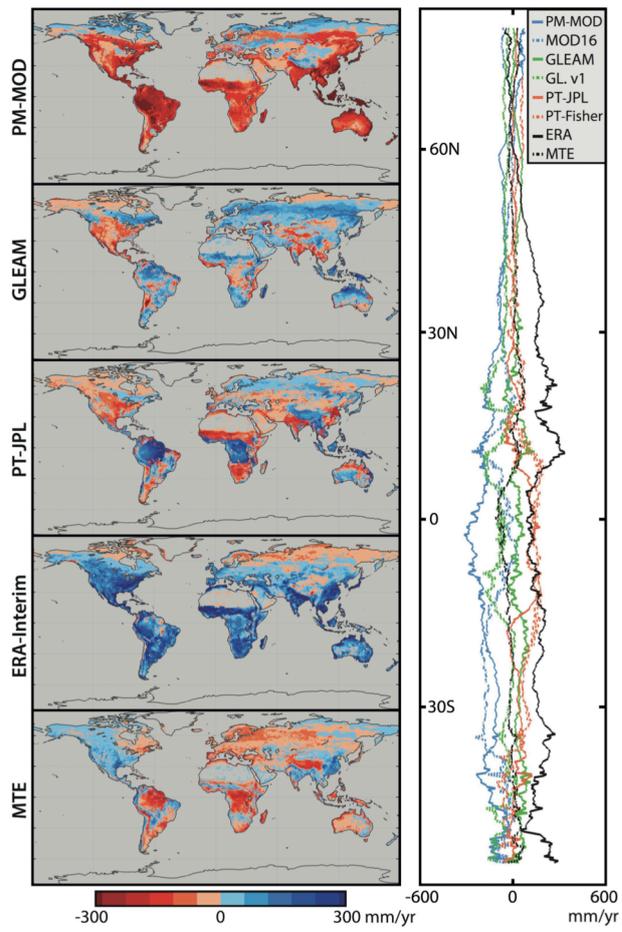
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1 **Figure 2** (single column)

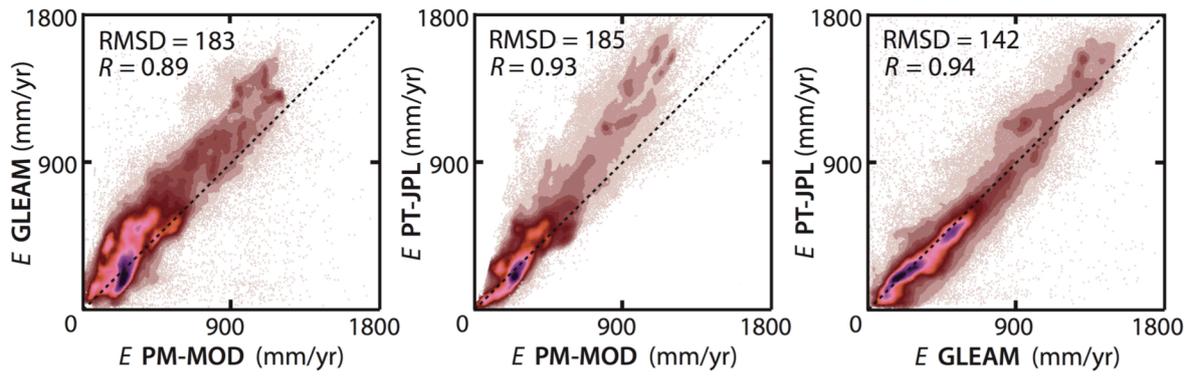


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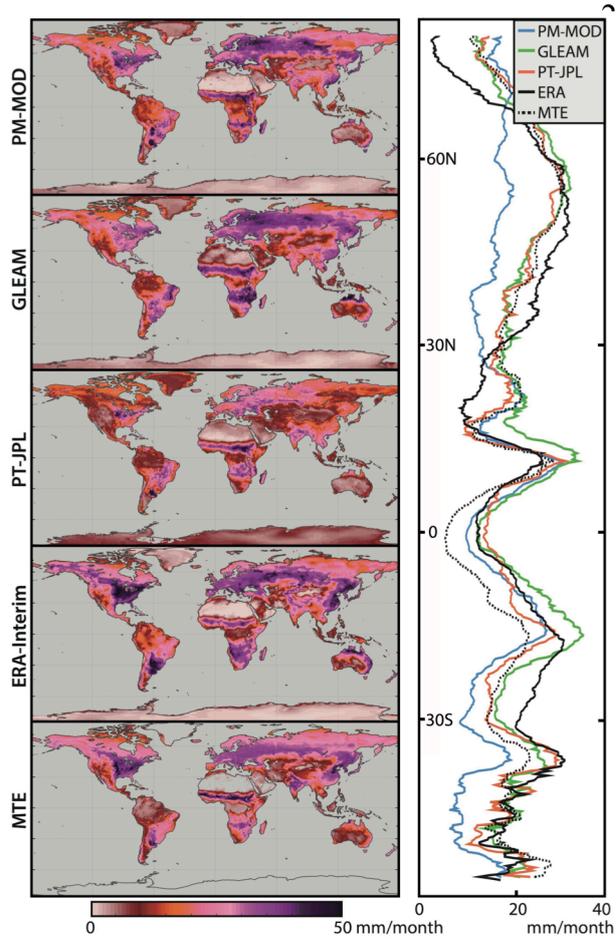
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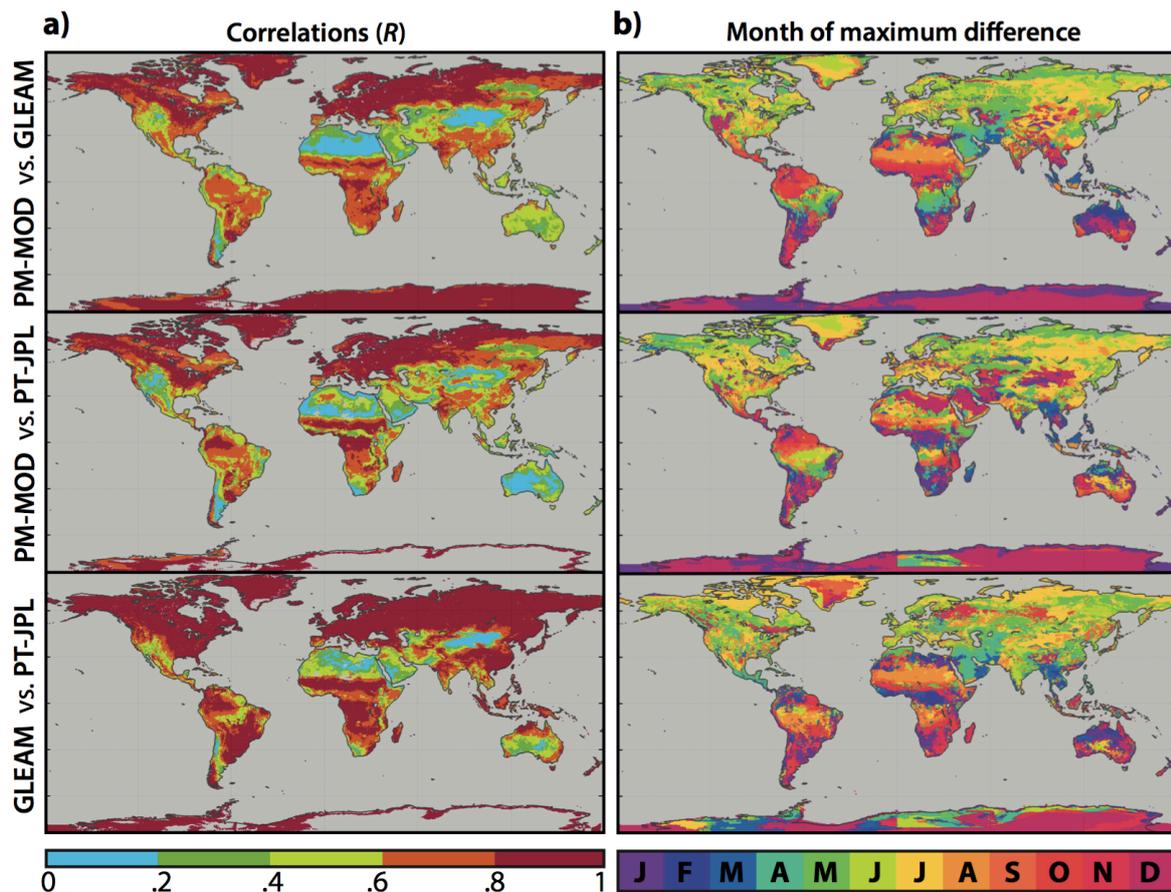


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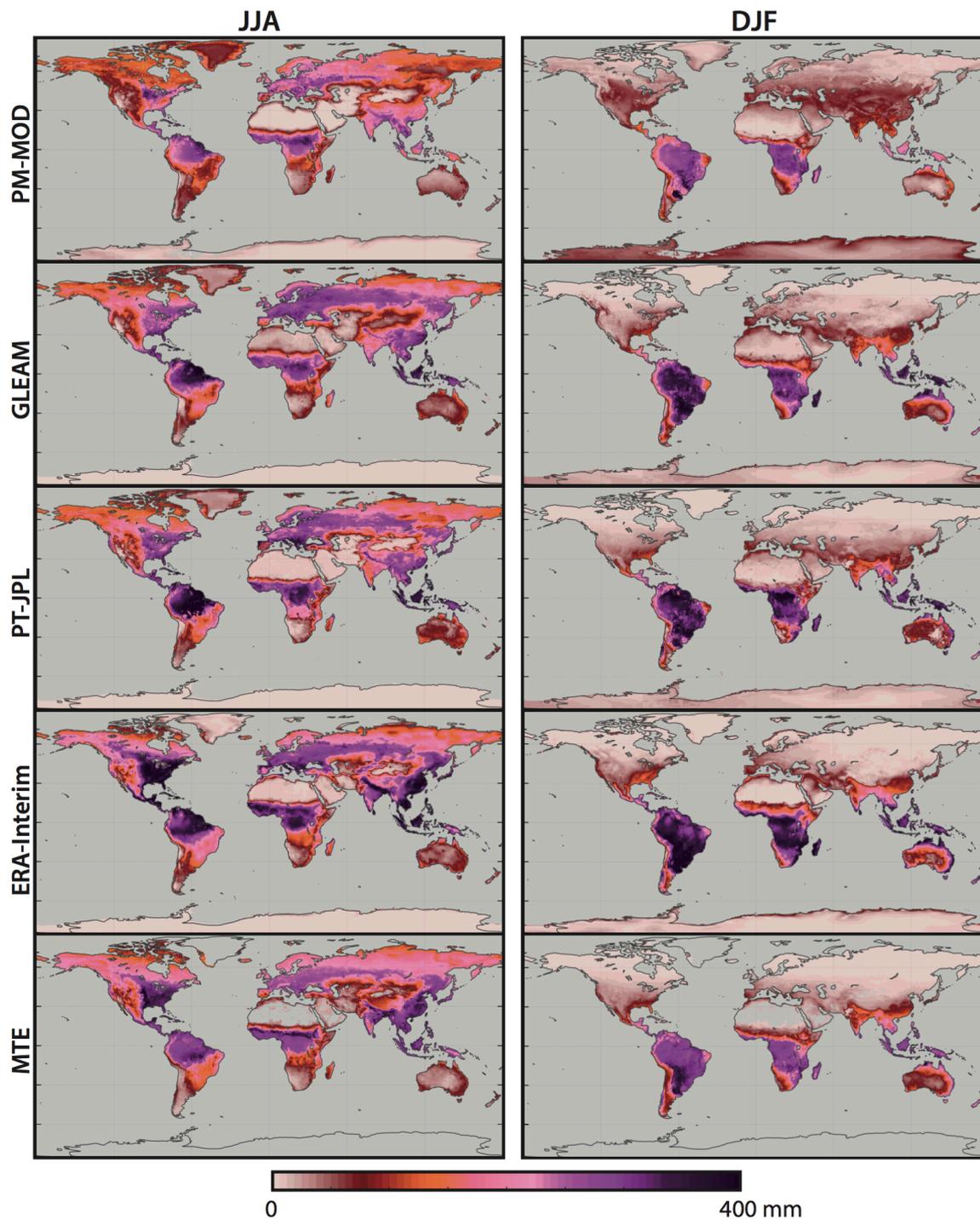
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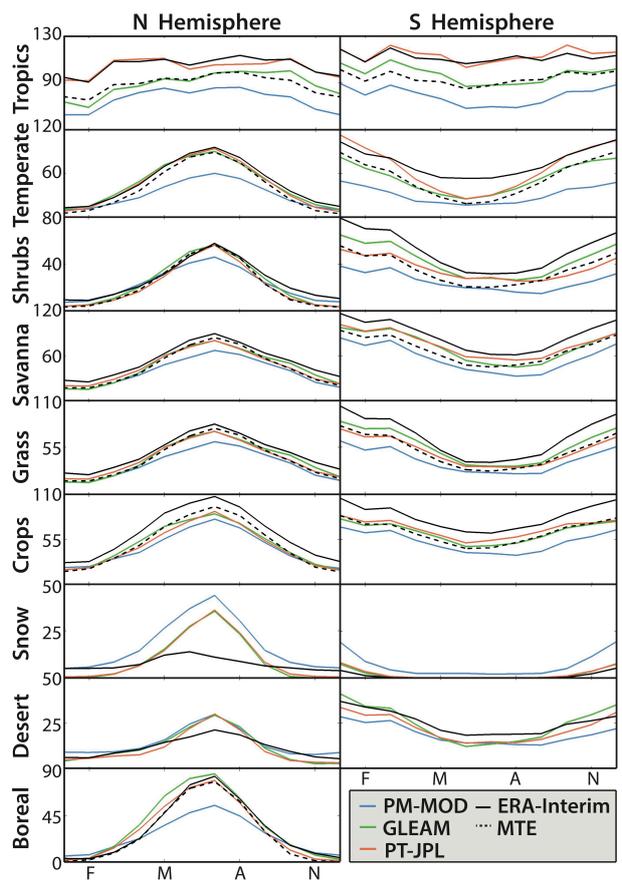
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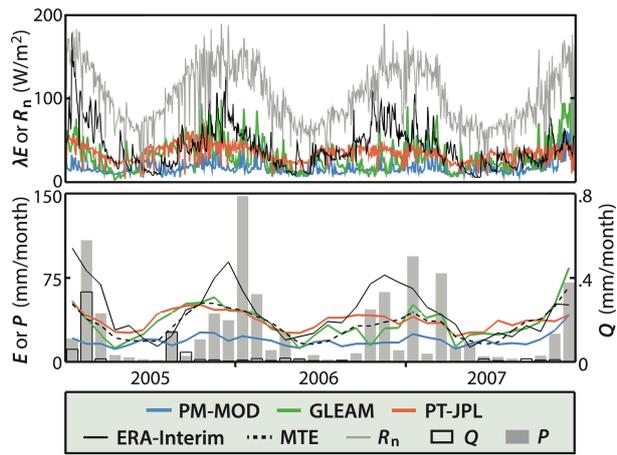
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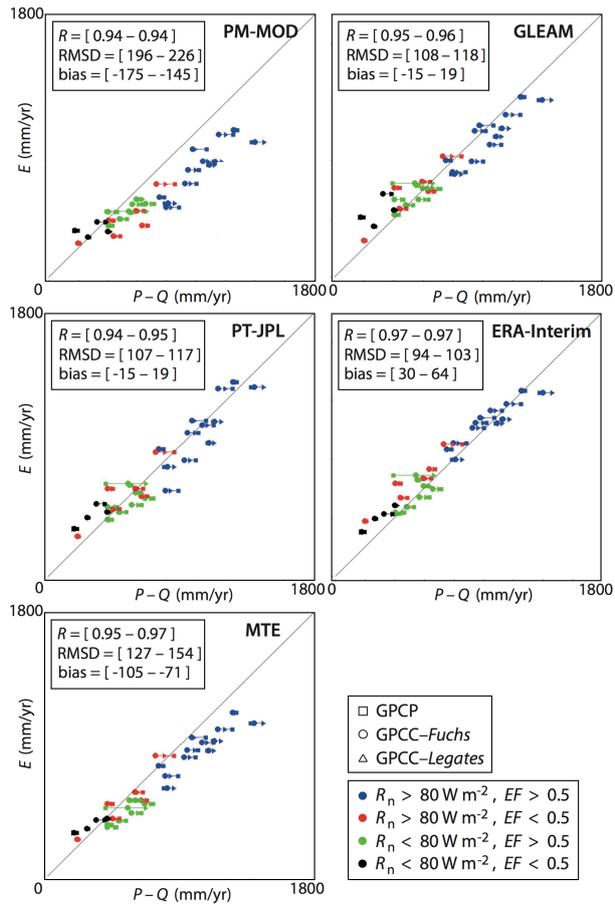


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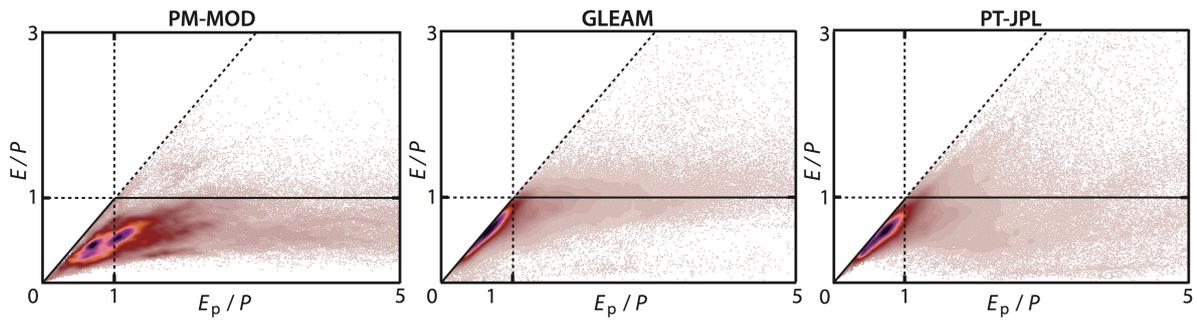
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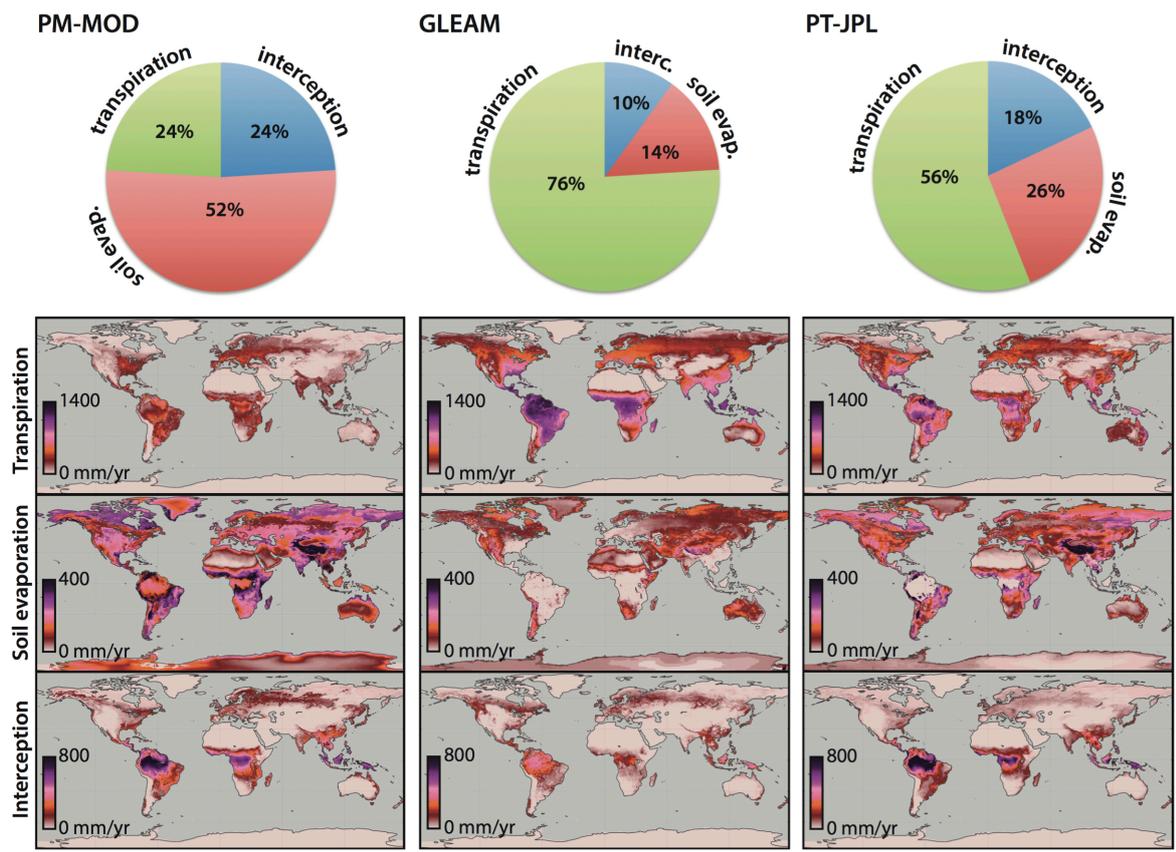
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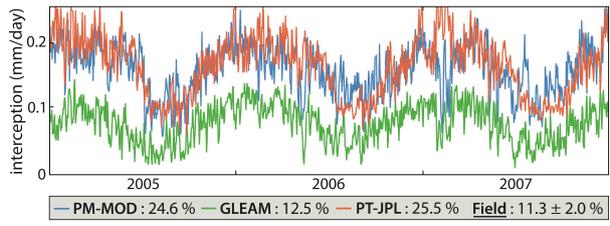
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1 **Figure 13** (*single column*)



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