

S1 Supplementary Figures

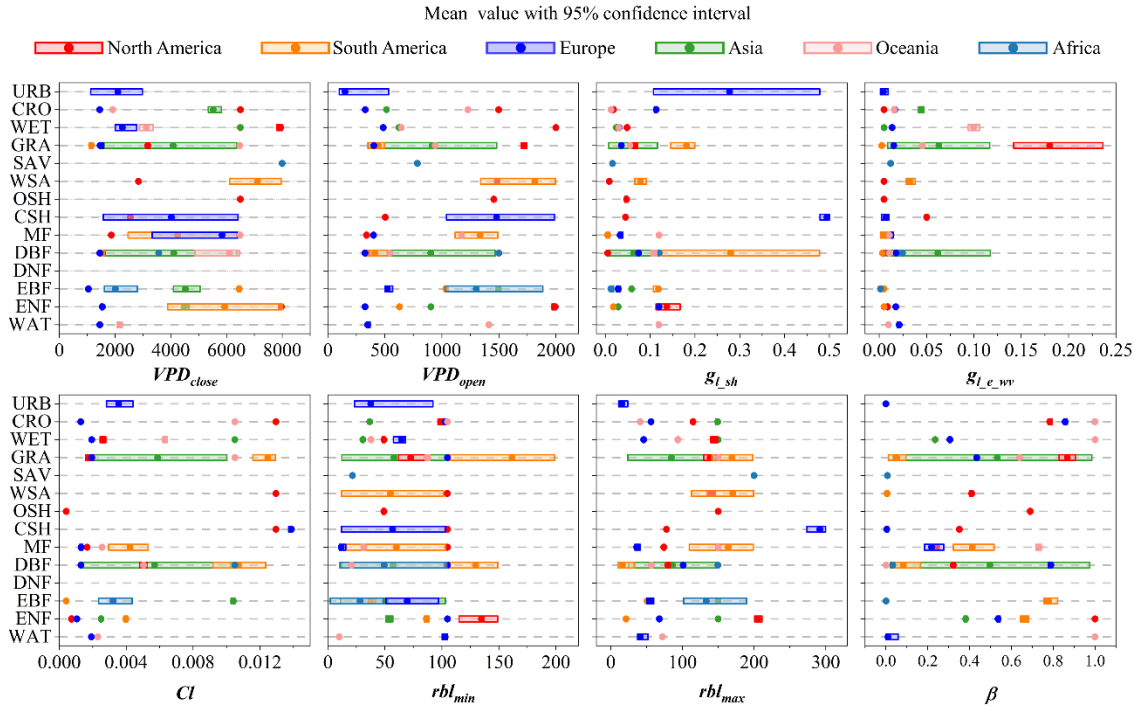


Fig. S1. Posterior distributions of the eight key parameters of the MOD16 models inferred from FLUXNET data.

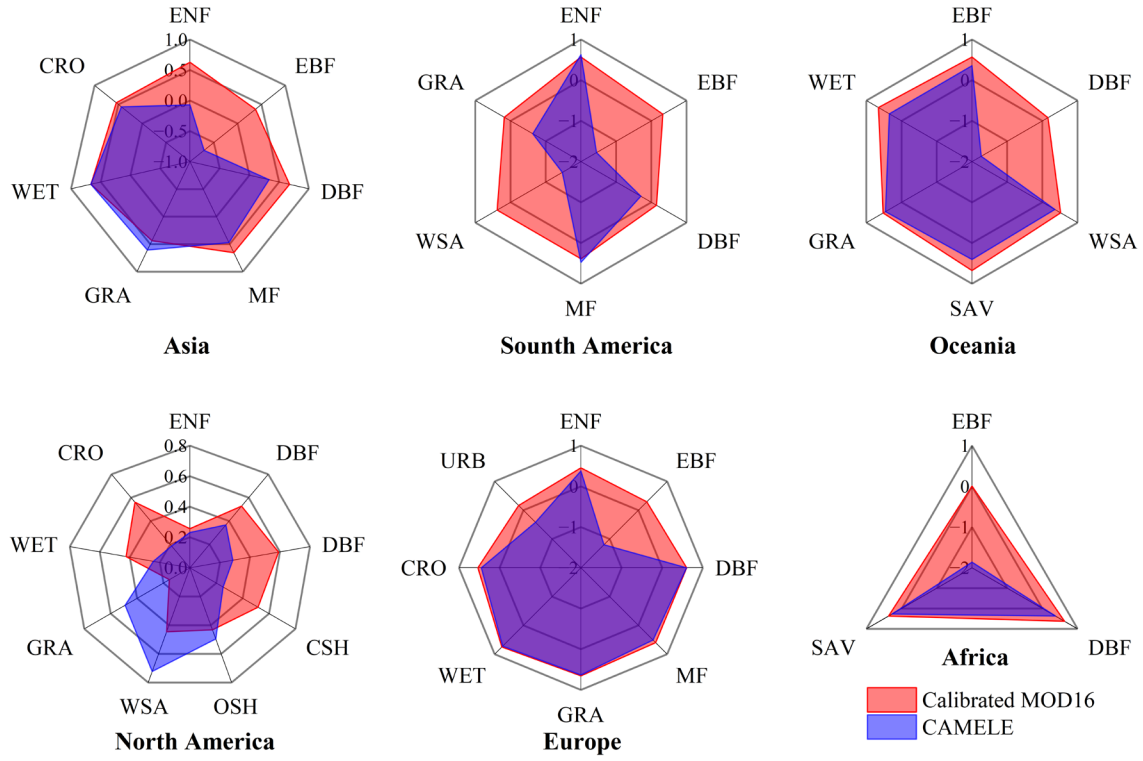


Fig. S2. Nash–Sutcliffe efficiency (NSE) of ET simulated by the calibrated MOD16 model and the CAMELE dataset against FLUXNET-observed ET across IGBP land-cover types and continents.

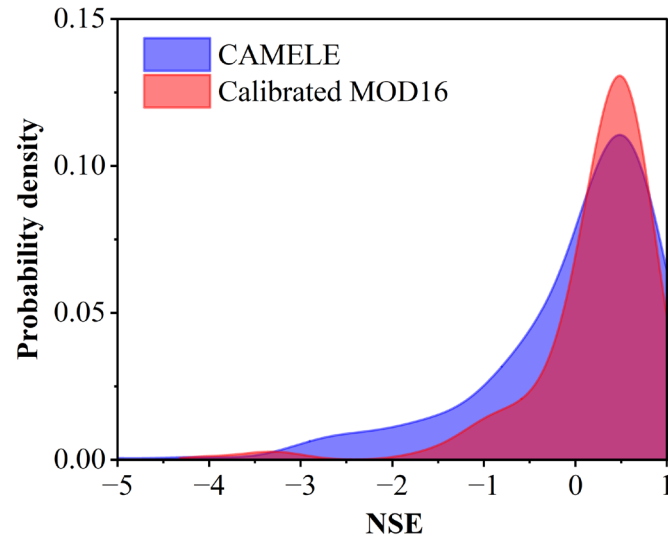


Fig. S3. Distribution of Nash–Sutcliffe efficiency (NSE) values for ET simulated by the calibrated MOD16 model and the CAMELE dataset against observed ET at 206 FLUXNET sites.

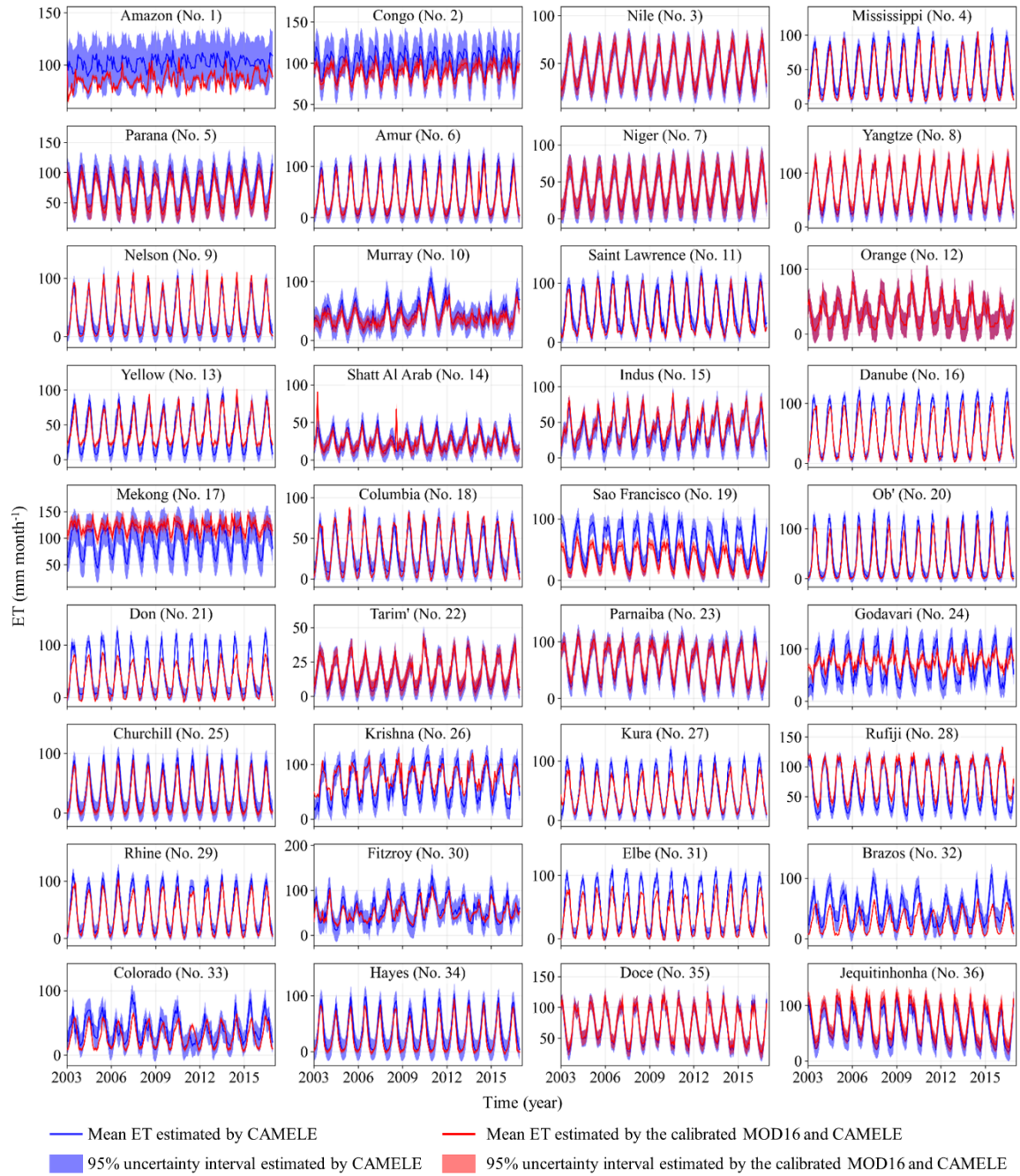


Fig. S4. Comparison of basin-scale ET estimates from CAMELE alone and from the calibrated MOD16-CAMELE fusion scheme.

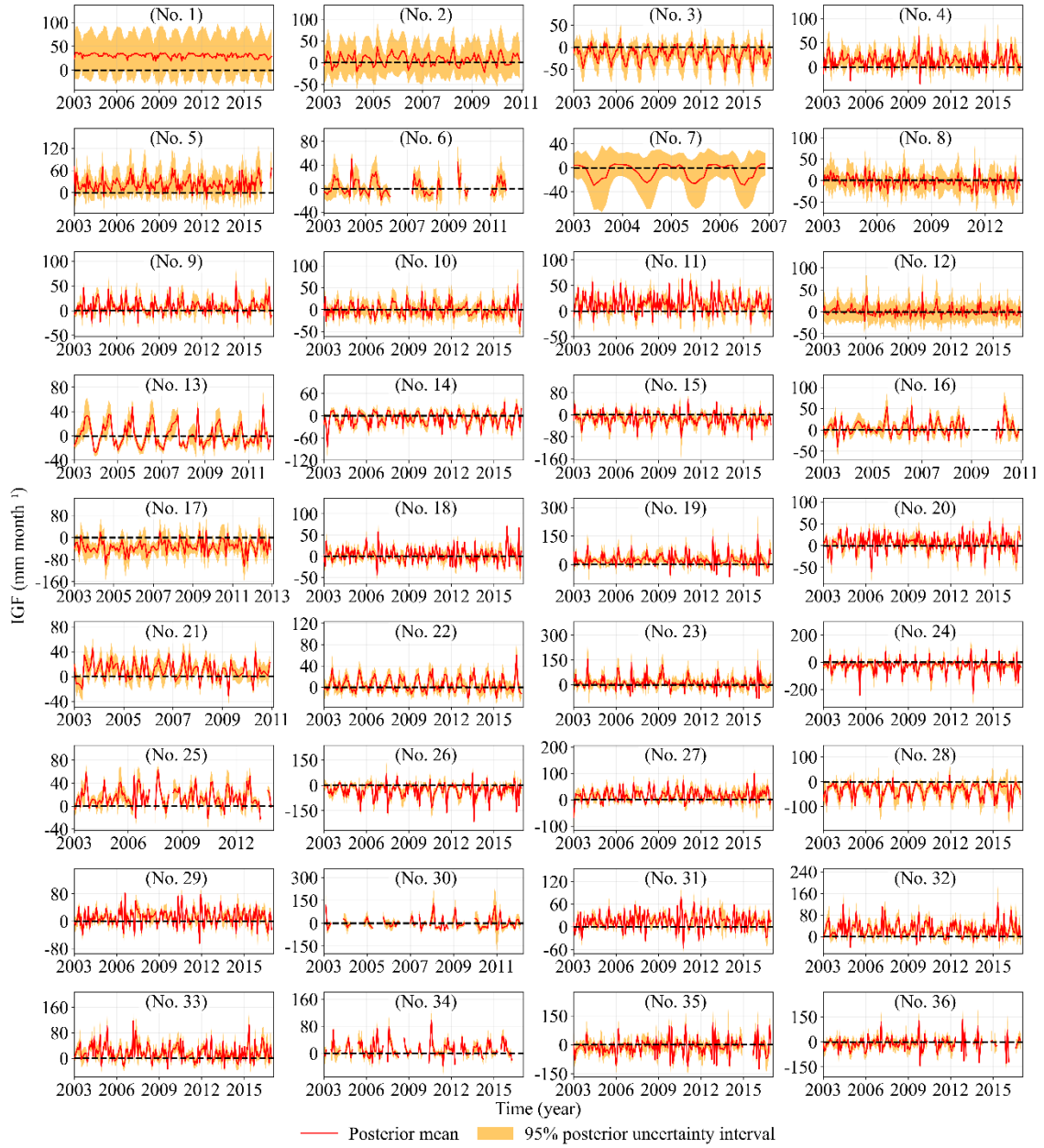


Fig. S5. Monthly IGF time series for 36 basins estimated using the additive GPR-based IGF model.

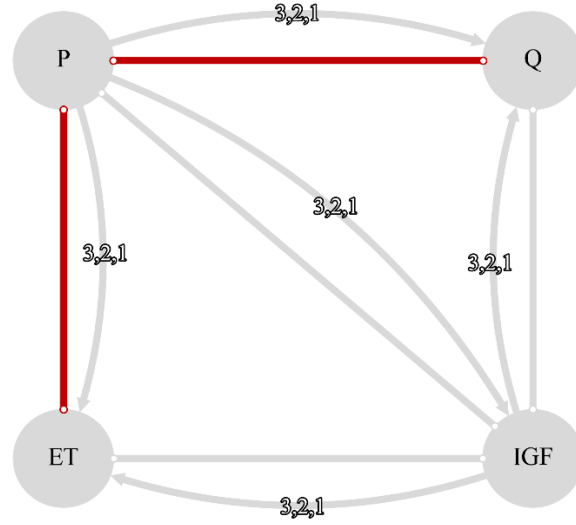


Fig. S6. Prior structural assumptions for causal relationships among precipitation (P), streamflow (Q), evapotranspiration (ET), and inter-basin groundwater flow (IGF). Red edges denote predefined causal links with explicit mechanistic support; grey edges denote candidate causal links allowed a priori. Numbers on the curved edges indicate the lag times considered for each causal effect (lags = 1, 2, and 3 months).

S2 Supplementary Tables

Table S1. Streamflow data sources for the 36 study basins, including the Global River Flow and Continental Discharge Dataset (NCAR), the Global Runoff Data Centre (GRDC), the Global Flood Awareness System (GloFAS) reanalysis product and published literature.

Basin	Station	Lon (°)	Lat (°)	Reference
Amazon	Obidos	-55.51	-1.95	NCAR
Congo	Kinshasa	15.30	-4.30	NCAR
Nile	-	30.43	31.34	GloFAS
Mississippi	Vicksburg	-90.91	32.31	NCAR
Parana	Timbues	-60.71	-32.67	NCAR
Amur	Komsomolsk	137.00	50.53	NCAR
Niger	Lokoja	6.77	7.80	NCAR
Yangtze	Hankou	118.32	31.10	Wang et al., 2020
Nelson	-	-92.75	56.94	GRDC
Murray	-	138.87	-35.55	Heimhuber et al., 2019
Saint Lawrence	Cornwall	-74.79	45.01	GRDC
Orange	Vioolsdrift	17.63	-28.78	NCAR
Yellow	Lijin	118.25	37.49	Yuan et al., 2016
Shatt Al Arab	-	48.46	29.95	GloFAS
Indus	-	67.64	24.04	GloFAS
Danube	Ceatal Izma	28.73	45.22	GloFAS
Mekong	Kratie	106.02	12.49	Fok et al., 2021
Columbia	Beaver Army Terminal	-123.18	46.18	GRDC
Sao Francisco	Traipu	-36.99	-9.98	GRDC
Ob'	Kolpashevo	82.88	58.30	GRDC
Don	Razdorskaya	40.65	47.54	GRDC
Tarim'	Alar	80.27	41.13	Yu et al., 2023
Parnaiba	Porto Formo	-42.37	-3.46	NCAR
Godavari	-	82.24	16.72	GloFAS
Churchill	Red Hea	-94.62	58.12	NCAR
Krishna	-	80.84	15.76	GloFAS
Kura	Surra	48.53	40.07	GRDC
Rufiji	-	39.25	-7.95	GloFAS
Rhine	Lobith	6.11	51.85	NCAR
Fitzroy	The Gap	150.10	-23.10	NCAR
Elbe	Wittenberge	11.76	53.00	NCAR
Brazos	Richmond	-95.76	29.58	NCAR
Colorado	Wharton	-96.10	29.31	NCAR
Hayes	Gods Ri	-92.78	56.43	NCAR
Doce	Linhares	-40.06	-19.41	NCAR
Jequitinhonha	Itapebi	-39.52	-15.95	NCAR

Table S2. Nash–Sutcliffe efficiency of IGF with data errors simulated by the additive GPR model against estimates derived from the water-balance equation (Eq. (3)).

No.	Basin	Calibration NSE	Validation NSE
1	Amazon	0.5572	0.5703
2	Congo	0.9384	0.9585
3	Nile	0.9909	0.9855
4	Mississippi	0.9939	0.9936
5	Parana	0.9848	0.9884
6	Amur	0.9835	0.9800
7	Niger	0.6268	0.7847
8	Yangtze	0.9627	0.9640
9	Nelson	0.9960	0.9924
10	Murray	0.9976	0.9881
11	Saint Lawrence	0.9992	0.9992
12	Orange	0.9626	0.9716
13	Yellow	0.9983	0.9980
14	Shatt Al Arab	0.9965	0.9984
15	Indus	0.9905	0.9949
16	Danube	0.9915	0.9962
17	Mekong	0.9654	0.9754
18	Columbia	0.9960	0.9968
19	Sao Francisco	0.9824	0.9799
20	Ob'	0.9968	0.9983
21	Don	0.9959	0.9951
22	Tarim'	0.9981	0.9835
23	Parnaiba	0.9775	0.9984
24	Godavari	0.9960	0.9955
25	Churchill	0.9983	0.9989
26	Krishna	0.9980	0.9987
27	Kura	0.9990	0.9987
28	Rufiji	0.9939	0.9931
29	Rhine	0.9983	0.9988
30	Fitzroy	0.9923	0.9258
31	Elbe	0.9989	0.9995
32	Brazos	0.9986	0.9971
33	Colorado	0.9985	0.9989
34	Hayes	0.9966	0.9990
35	Doce	0.9977	0.9889
36	Jequitinhonha	0.9978	0.9925

S3 Supplementary Methods

S3.1 Construction of the MOD16 model

Inputs to the MOD16 model include meteorological forcing data and surface vegetation data. Meteorological inputs were derived from the ERA5-Land reanalysis dataset (Muñoz Sabater, 2019) (spatial resolution: 0.25°, temporal resolution: hourly), including surface pressure, surface temperature, air temperature at 2 m, dew point temperature at 2 m, and downward shortwave radiation. Daily broadband albedo was sourced from the MODIS MCD43C3 product (Schaaf and Wang, 2015), with a spatial resolution of 0.05° and daily temporal resolution. Surface vegetation data, including leaf area index (LAI) and fraction of absorbed photosynthetically active radiation (FAPAR), were obtained from the Global Land Surface Satellite (GLASS) products GLASS01J01 and GLASS09J01 (Liang et al., 2013; Liang et al., 2014; Liang et al., 2021), both with spatial resolutions of 0.25° and daily temporal resolutions. Additionally, land cover classification was based on the MODIS MCD12C1 product (Friedl and Sulla-Menashe, 2015), which provides annual International Geosphere-Biosphere Programme (IGBP) classifications at a 0.05° resolution.

The spatial resolution of ERA5-Land, GLASS, and MODIS data was unified at 0.25°, with daily temporal resolution. Since the MOD16 model calculates ET separately for daytime and nighttime conditions, hourly ERA5-Land meteorological data were aggregated into daily daytime and nighttime datasets based on whether downward shortwave radiation exceeded zero. These aggregated datasets included solar radiation, temperature, surface pressure, surface vegetation, and relative humidity (RH), serving as input variables for MOD16. Relative humidity was computed from air temperature and dew point temperature using the following equation:

$$RH = 100 \times \frac{6.11 \times 10^{\frac{7.5 \times T_d}{T_d + 237.3}}}{6.11 \times 10^{\frac{7.5 \times T}{T + 237.3}}} \quad (S1)$$

where RH is relative humidity (%), T_d is the dew point temperature (°C), and T is the air temperature (°C).

Supplementary References

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