Figure S1. Model validation accuracy for nine PFTs: **(a)** CRO, **(b)** DBF, **(c)** SH, **(d)** EBF, **(e)** GRA, **(f)** MF, **(g)** ENF, and **(h)** WET.
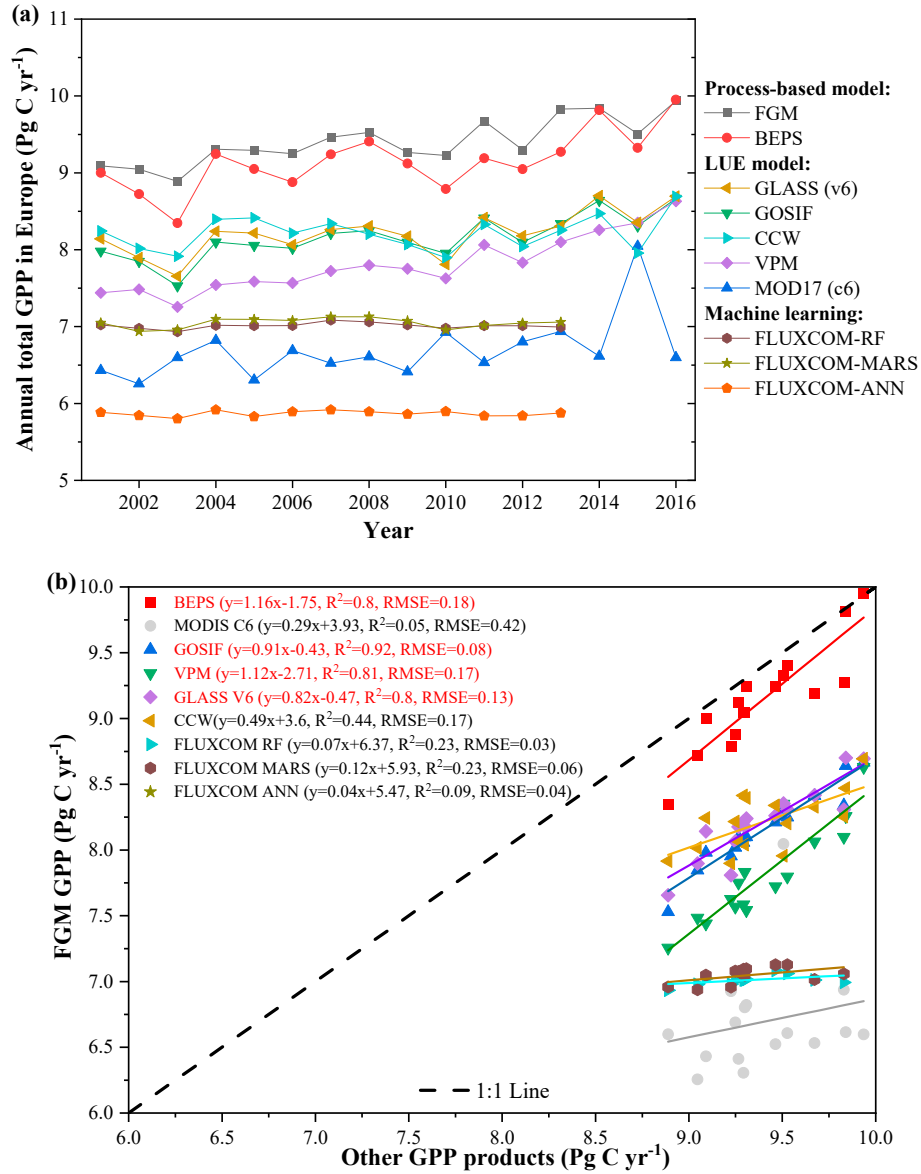
Figure S2. Inter-comparison of **(a)** interannual dynamics in GPP estimated by FGM and other methods, including one empirical model, four light use efficiency (LUE) models, three machining learning methods, and one process-based biophysical model. **(b)** Scatter plots between the FGM GPP and other GPP products. As listed in Table S2, the GOSIF GPP product was derived from the empirical relationships between GPP and SIF (Li and Xiao 2019; Xiao et al. 2019). The CCW (Zhang et al. 2016), MOD17 (Running et al. 2004), VPM (Zhang et al. 2017), and GLASS (Yuan et al. 2010; Yuan et al. 2007) products are estimated based on LUE models. FLUXCOM GPP products are estimated by three machine learning approaches, including an artificial neural network (ANN), the multivariate adaptive regression splines method (MARS), and the random forest method (RF) (Jung et al. 2020; Tramontana et al. 2016). In addition, one process model-based GPP product (i.e., BEPS) is also included (Chen et al. 2019a; He et al. 2021; Liu et al. 2014).

Table S1. Accuracy of model calibration and validation and the calibrated g_1 for nine plant functional types (PFTs).

PFTs	g_1[1]	Sites for Calibration	Sites for Validation
CSH	1.14	US-KS2	RU-Vrk
CRO	10	DE-Geb, DE-Seh, IT-BCi, IT-Cas	BE-Lon, DE-Kli, FR-Gri
DBF	1.66	DE-Lnf, FR-Fon, IT-Col	DE-Hai, IT-Ro1, IT-Ro2
ENF	0.62	CZ-BK1, RU-Fyo, IT-ren, NL-Loo	CH-Dav, DE-Obe, DE-Tha, IT-Lav
EBF	0.62	FR-Pue	IT-Cpz
GRA	1.14	CZ-BK2, CH-Cha, CH-Oe1, IT-Tor	IT-MBo, DE-Gri , CH-Fru
MF	0.62	CH-Lae, BE-Bra	BE-Vie
OSH	10	ES-LgS	ES-Lgs
WET	0.62	DE-Spw, DE-Zrk, CZ-Wet	DE-Akm, DE-SfN

[1] Abbreviations: closed shrublands (CSH), croplands (CRO), deciduous broadleaf forest (DBF), evergreen needleleaf forest (ENF), evergreen broadleaf forest (EBF), grasslands (GRA), mixed forest (MF), open shrublands (OSH), and wetland (WET).

Table S2. Information of nine GPP products for intercomparison.

GPP	Spatial resolution	Model	Time period	Website	Reference
GOSIF	0.05°	Empirical model	2001-2016	https://globalecology.unh.edu//data/GOSIF.html	(Li and Xiao 2019; Li et al. 2018)
BEPS	0.073°	Process-based model	2001-2016	http://www.nesdc.org.cn/sdo/detail?id=612f42ee7e28172cbed3d809	(Chen et al. 2019a; He et al. 2021; Liu et al. 2014; Xiao et al. 2019)
GLASS (v6)	500 m	LUE model	2001-2016	http://www.glass.umd.edu/GPP/MODIS/500m/	(Yuan et al. 2010; Yuan et al. 2007)
MODIS (c6)	500 m	LUE model	2001-2016	https://lpdaac.usgs.gov/products/mod17a2hv006/	(Running et al. 2004)
VPM	500 m	LUE model	2001-2016	https://figshare.com/collections/A_global_moderate_resolution_dataset_of_gross_primary_production_of_vegetation_for_2000-2016/3789814	(Zhang et al. 2017)
CCW	0.05°	LUE model	2001-2015	https://osf.io/mnptv/?view_only=77e57939fe474ae88f356ec64c573c45	(Zhang et al. 2016)
FLUXCOM	0.5°	LUE model	2001-2016	http://www.fluxcom.org/CF-Download/	(Jung et al. 2020; Tramontana et al. 2016)

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