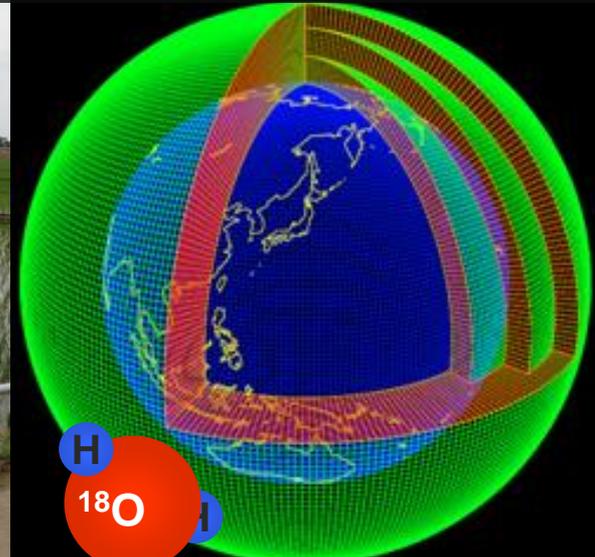


Transpiration accounts for two thirds of global terrestrial evaporation



Zhongwang Wei

魏忠旺

2016/08/04

Xuhui Lee LAB

About me (Graduated from Univ. of Tokyo)

My research topic:

1. Observations

- ❖ Lake surface fluxes observation (Lake Kasumigaura, Japan, 2010~2016)
- ❖ Land surface fluxes and Isotopic observation (Paddy field, Mase, Japan, 2013~2016)

2. Modeling

- Water vapor isotopic simulations based on Isotope-incorporated Global Spectral Model (IsoGSM)
- Precipitation isotope data assimilation in Thai: using data assimilation system based on a local transform ensemble Kalman filter (LETKF) and the Isotope-incorporated Regional Spectral Model (IsoRSM)
- **Isotopic LES simulation and deuterium excess of water vapor in the atmospheric boundary layer**

3. Remote sensing

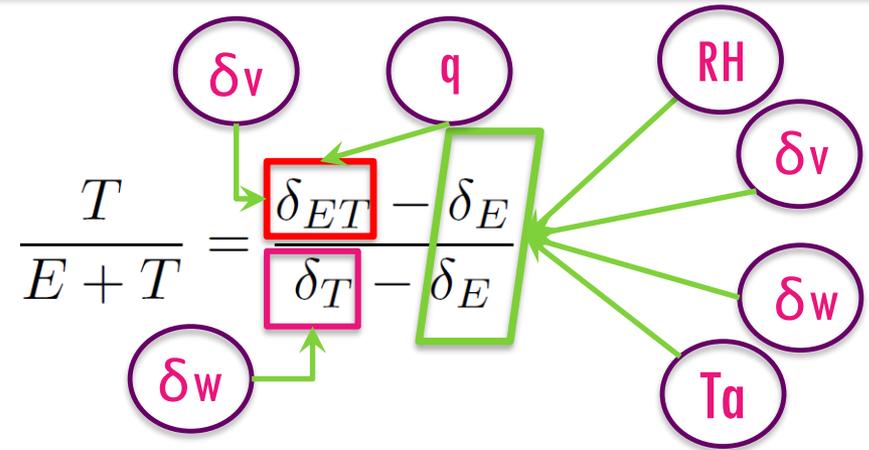
- ❑ Global ET partitioning based on remote sensing data, land surface model and field observation

ET partitioning: Field scale

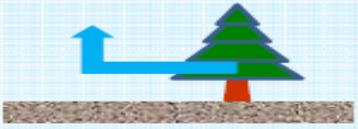
Isotope approach

$$\begin{cases} ET = E + T \\ ET\delta_{ET} = E\delta_E + T\delta_T \end{cases}$$

v: water vapor, w: surface water,
 δ : isotope ratio, q: vapor mixing ratio



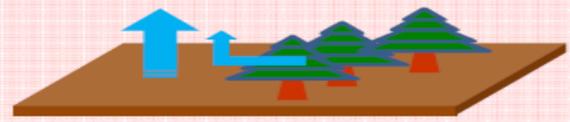
Transpiration δ_T



Evaporation δ_E



ET δ_{ET}



Non-isotope approach

$$\frac{T}{ET} = \frac{T}{E + T}$$

Observation and/or simulation

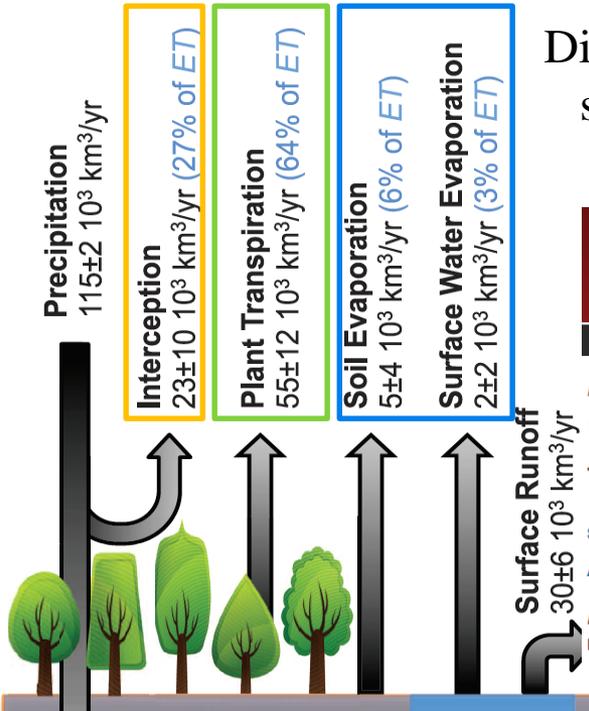
$$\frac{T}{ET} = \frac{uWUE_a}{uWUE_p}$$

Flux-variance similarity partitioning method

- 1. Stable isotopes in Terrestrial water fluxes partitioning**
- 2. Remote sensing based ET partitioning**
- 3. Land surface model based ET partitioning**
- 4. lateral ground flow based partitioning**

Stable isotopes in Terrestrial water fluxes partitioning— global scale

Different from Evapotranspiration, no reliable dataset of transpiration, soil evaporation and interception is available. Isotopes can help to solve these questions



nature International weekly journal of science

nature International weekly journal of science

NATURE | LETTER
Jasechko et al. (2013), nature
Terrestrial water fluxes dominated by transpiration
 Scott Jasechko, Zachary D. Sharp, John J. Gibson, S. Jean Birks, Yi Yi & Peter J. Fawcett
 Affiliations | Contributions | Corresponding author
 Nature 496, 347–350 (18 April 2013) | doi:10.1038/nature11983
 Received 06 September 2012 | Accepted 04 February 2013 | Published online 03 April 2013

NATURE | BRIEF COMMUNICATION ARISING
Coenders-Gerrits et al. (2014), nature
Uncertainties in transpiration estimates
 A. M. J. Coenders-Gerrits, R. J. van der Ent, T. A. Bogaard, L. Wang-Erlandsson, M. Hrachowitz & H. H. G. Savenije
 Affiliations | Contributions | Corresponding author
 Nature 506, E1–E2 (13 February 2014) | doi:10.1038/nature12925
 Published online 12 February 2014
 Brief Communication Arising (February, 2014)
 Letter (April, 2013)

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Science The World's Leading Journal of Original Scientific Research, Global News, and Commentary.

Science 10 July 2015: Vol. 349 no. 6244 pp. 175–177
 DOI: 10.1126/science.aaa5931

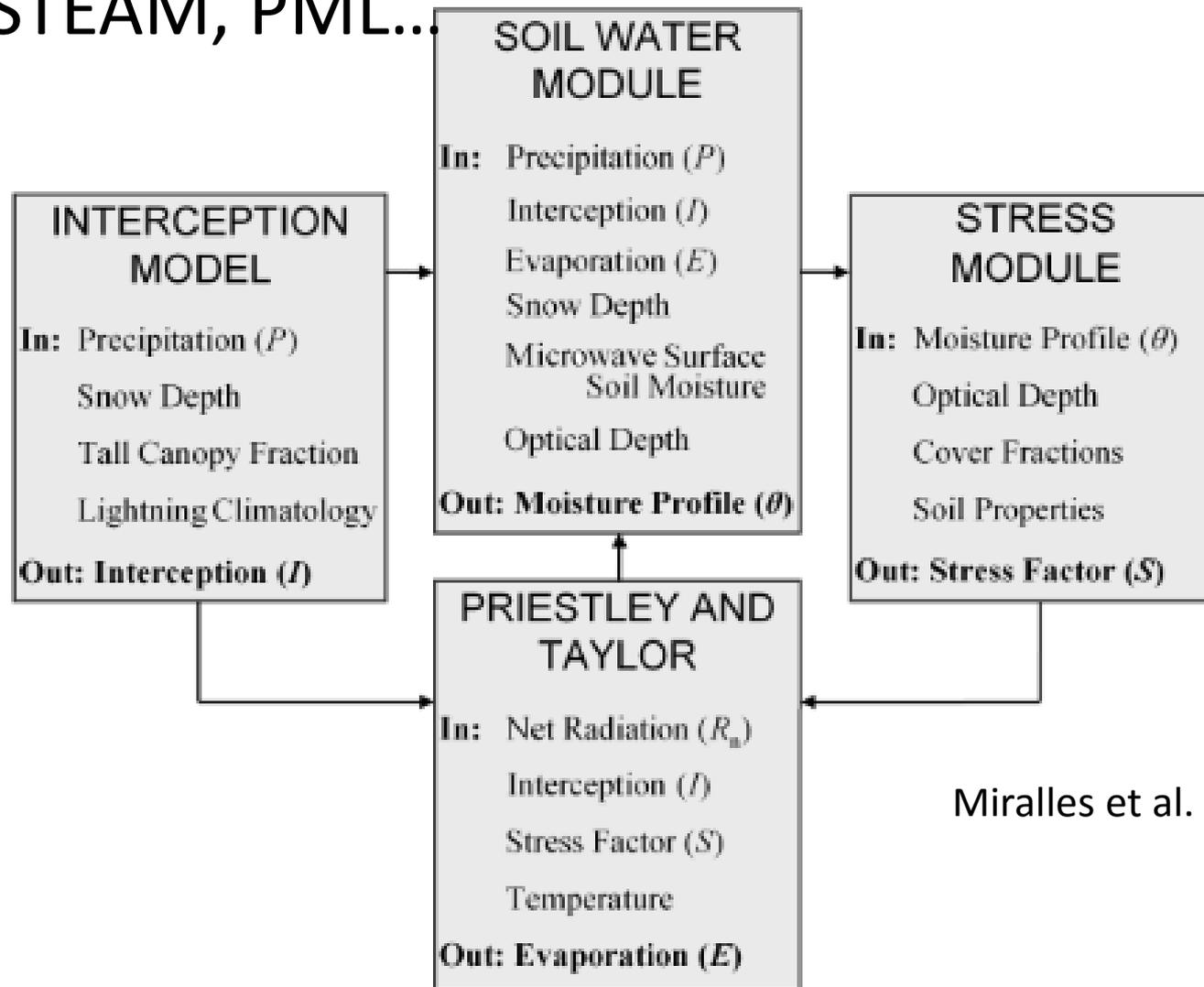
Hydrologic connectivity constrains partitioning of global terrestrial water fluxes
 Stephen P. Good^{1,2,3,4}, David Noone³, Gabriel Bowen^{1,4}

precipitation Runoff interception

$$T = \frac{P(\delta P - \delta E) - Q(\delta Q - \delta E) - I(\delta I - \delta E)}{\delta T - \delta E}$$

Remote sensing based ET partitioning

GLEAM, STEAM, PML...



Miralles et al. (2016)

Fig. 1. Schematic overview of GLEAM (adapted from Miralles et al., 2011).

Land surface model based ET partitioning

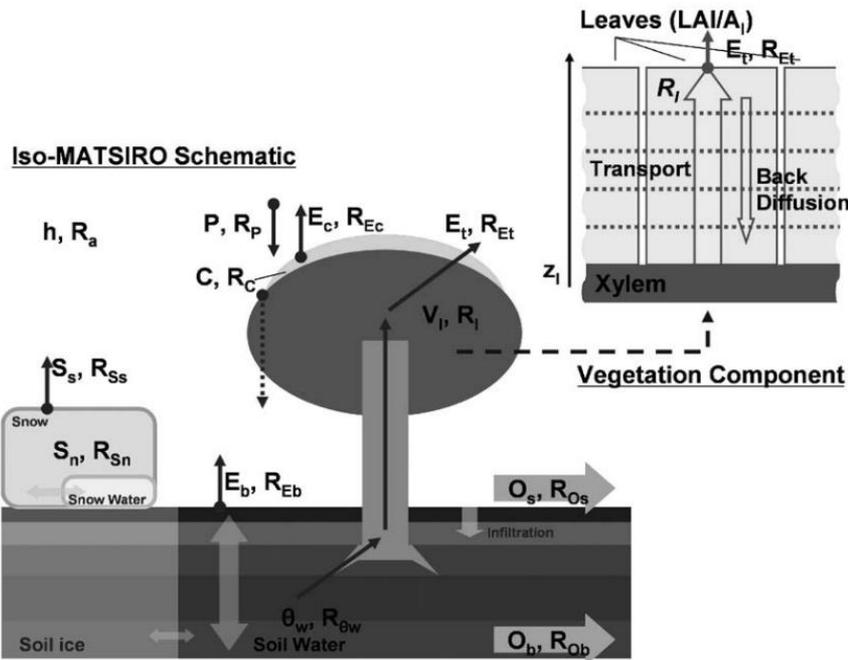
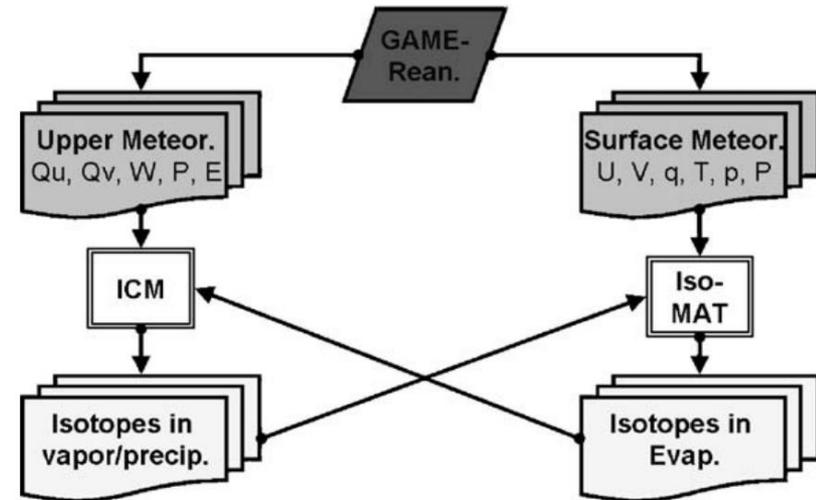


Fig. 1. Schematic representation of Iso-MATSIRO.

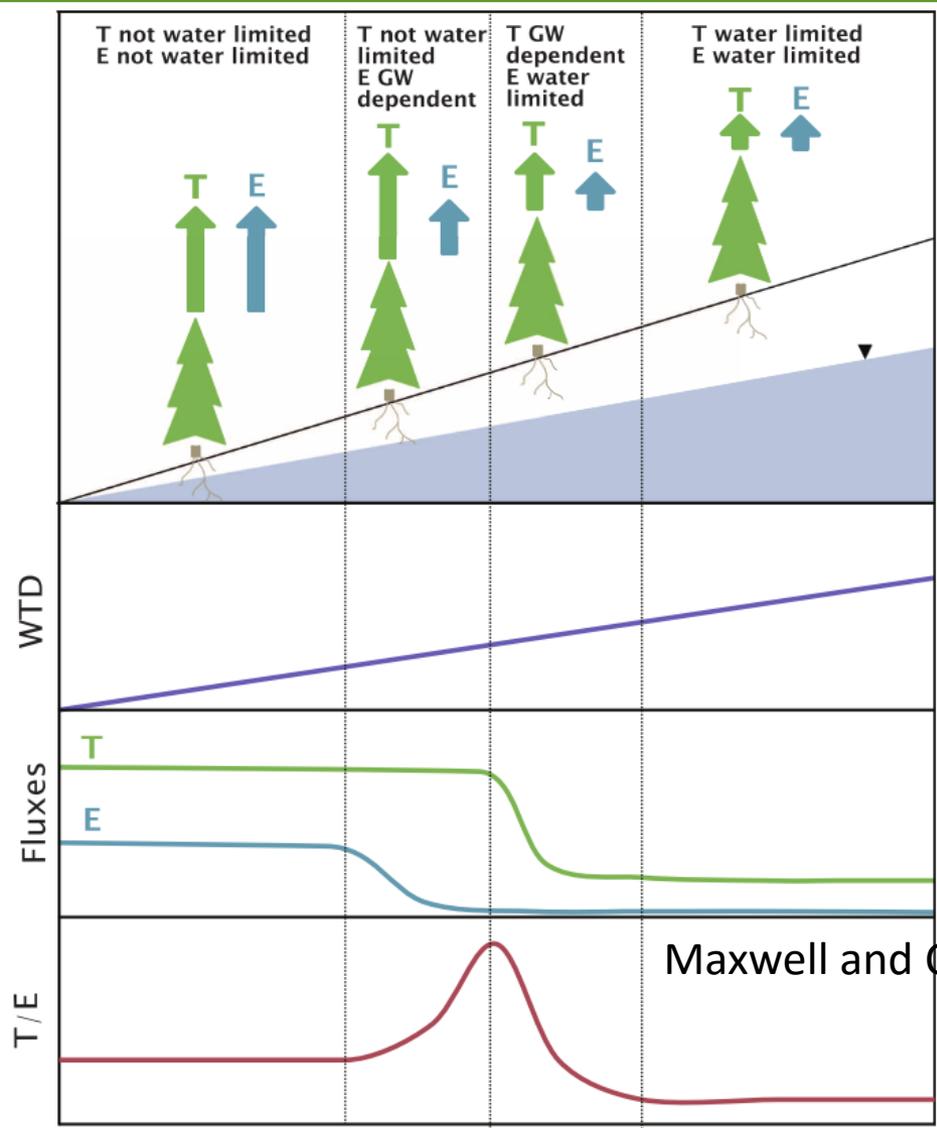


Yoshimura et al. (2006)

Fig. 7. Schematic representation of Iso-MATSIRO and ICM coupling.

Typical cases: Global Climate Models (e.g. CMIP5 family)

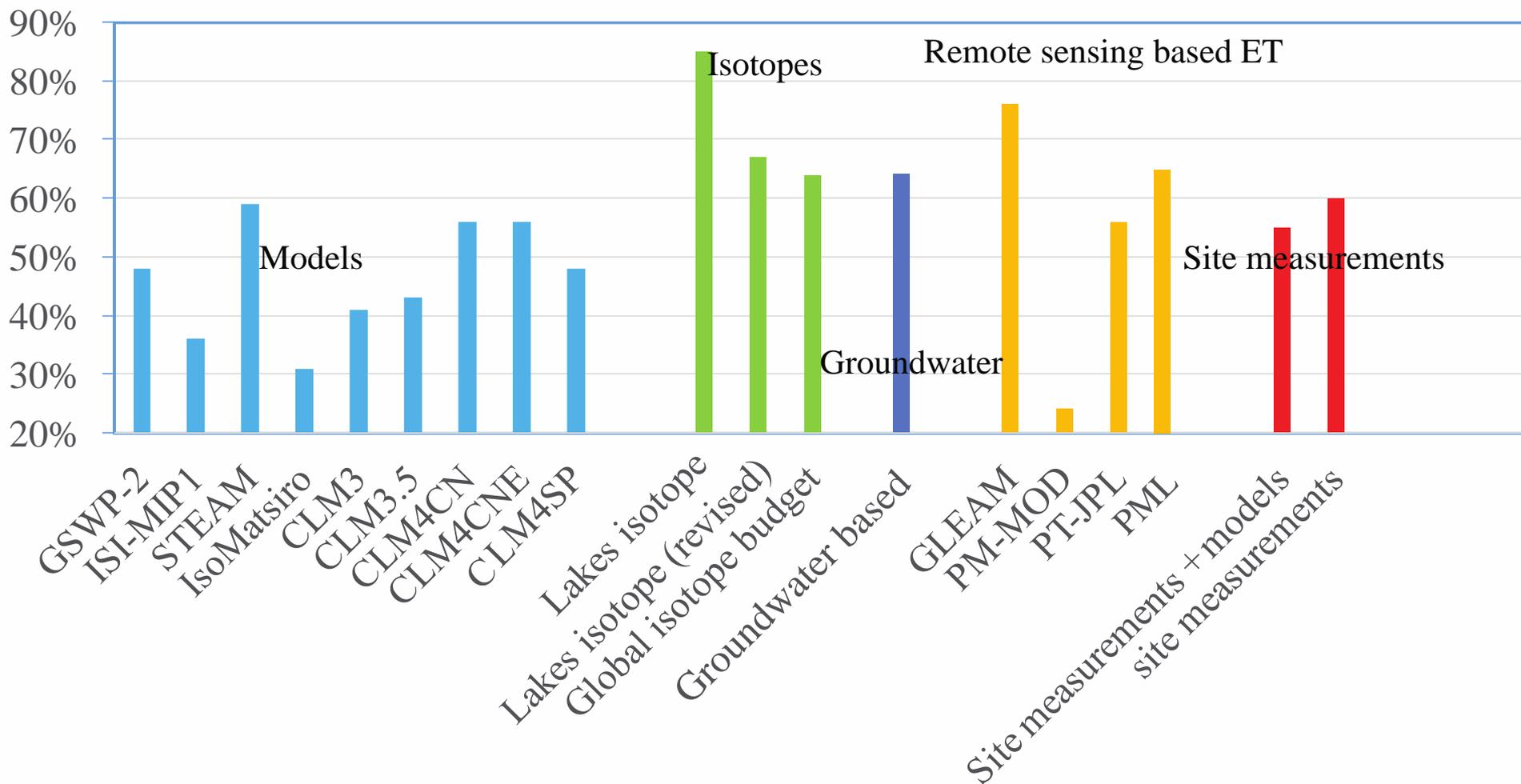
Groundwater based ET partitioning



Maxwell and Condon (2016) Science

The relationship between groundwater depth and land-energy fluxes

global scale T/ET uncertainty



$$T/ET = T/(I+E+T)$$

The uncertainties in these global ET partitioning studies are significant

This topic is getting hotter and hotter

Teuling et al. :Contrasting response of European forest and grassland energy exchange to heatwaves, [Nature Geoscience](#), 2010.

Jasechko et al.: Terrestrial water fluxes dominated by transpiration, [Nature](#), 2013.

Coenders-Gerrits et al.: Uncertainties in transpiration estimates, [Nature](#), 2014.

Wang et al.: Global synthesis of vegetation control on evapotranspiration partitioning, [GRL](#), 2014.

Sutanto et al.: HESS Opinions "A perspective on isotope versus non-isotope approaches to determine the contribution of transpiration to total evaporation", [HESS](#), 2014.

Schlaepfer et al.: Terrestrial water fluxes dominated by transpiration: Comment, [Ecosphere](#), 2014.

Schlesinger and Jasechko: Transpiration in the global water cycle, [Agric. For. Meteorol.](#), 2014.

Kool et al.: A review of approaches for evapotranspiration partitioning, [Agric. For. Meteorol.](#), 2014.

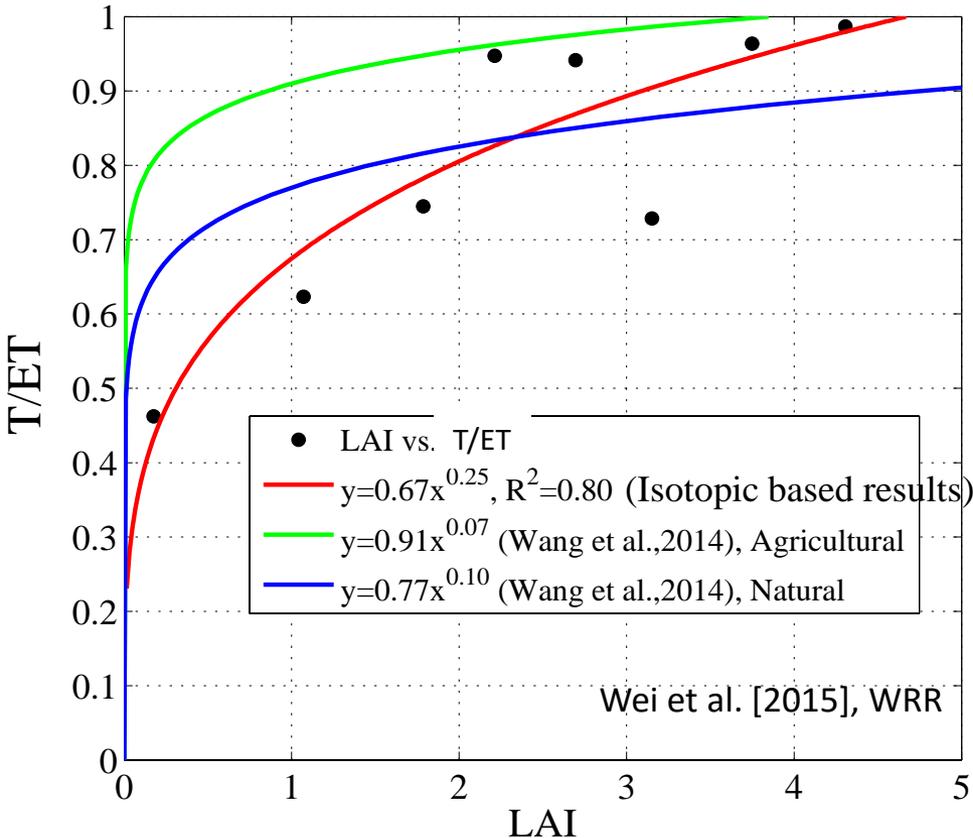
Zhou et al. :The effect of vapor pressure deficit on water use efficiency at the subdaily time scale, [GRL](#), 2014

[Good et al.](#): Hydrologic connectivity constrains partitioning of global terrestrial water fluxes, [Science](#), 2015

[Zhou et al.](#) Partitioning evapotranspiration based on the concept of underlying water use efficiency, [WRR](#), 2016

Maxwell and Condon: Connections between groundwater flow and transpiration partitioning, [Science](#), 2016

Factor controlling dry canopy T/ET



1. Our results generally agree with the global scale nonlinear relationships in Wang et al. (2014) but tend to have a slightly lower proportion of transpiration under low-LAI conditions.

2. Vegetation plays a major role in driving the contribution of E and T.

This suggests that LAI could be used to partition ET in spatial studies, as LAI can be easily obtained through both in situ observations and remote sensing techniques.

T estimation based on LAI regression

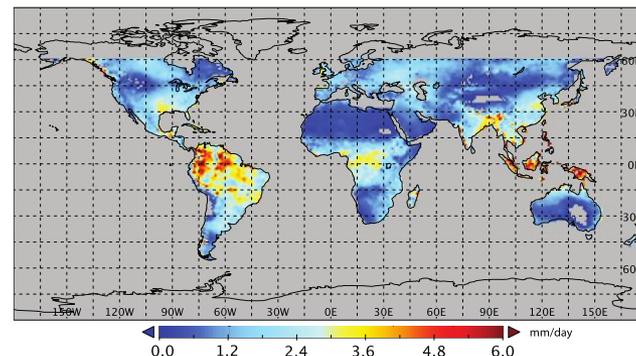
In each grid (1-degree) T is estimated by:

Land Cover ET dataset

$$T = \sum_{i=1}^n (ET - I) * Fv_i * f(LAI)_i$$

Interception dataset

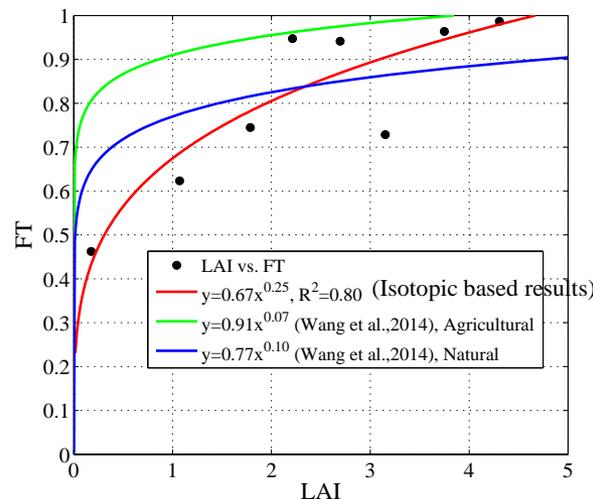
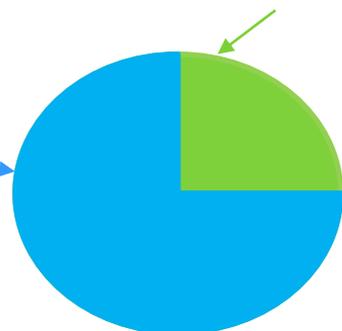
LAI regression for different vegetation types?



ISLSCP II MODIS IGBP Land Cover

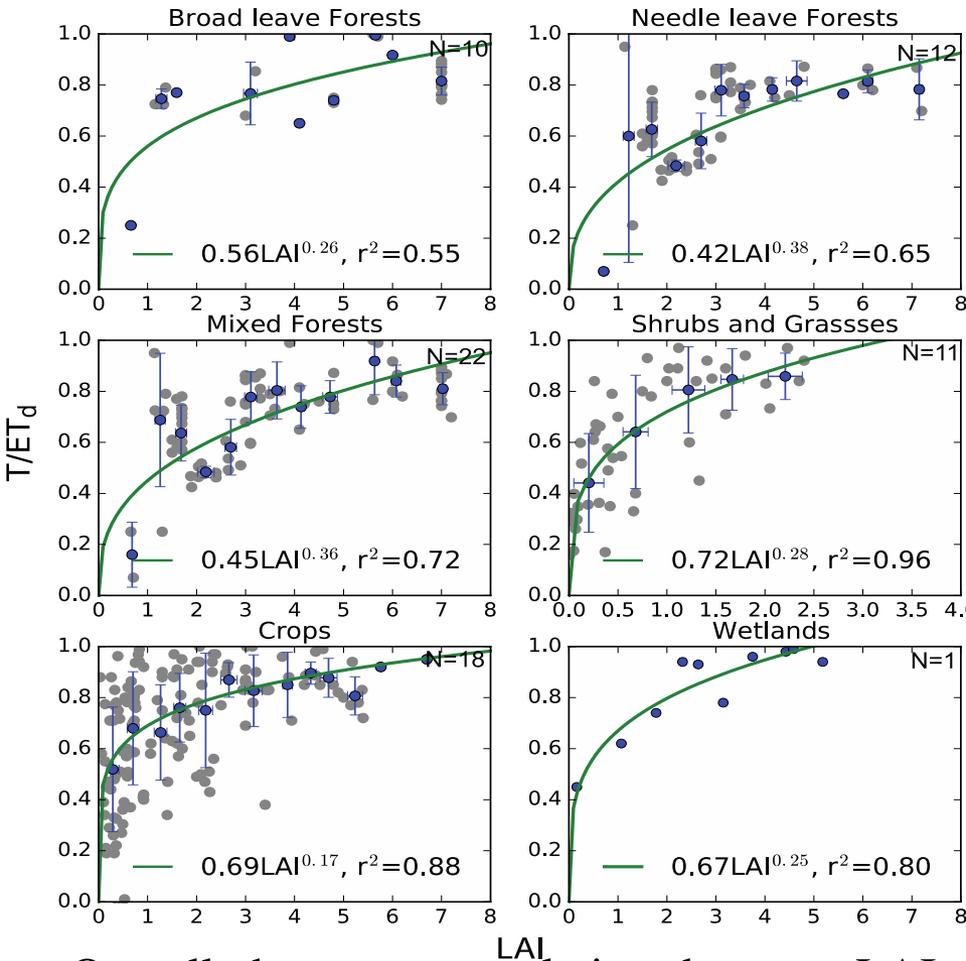
25% forest
Then $Fv_i=0.25$

75% grass
then $Fv_i=0.75$



Global synthesis of vegetation control on dry canopy ET partitioning

We conducted a study to establish a quantitative relationship between ET partitioning and LAI. Article searches in ISI Web of Science and Google Scholar and retrieved the references cited in papers (51 papers) were conducted.



Vegetation Class	LAI regression	R ²	T/ET _d (LAI=1)	T/ET _d (LAI=3)	T/ET _d (LAI=6)
Broad leaf forests	$0.56LAI^{0.26}$	0.55	0.56	0.75	0.89
Needle leaf forests	$0.42LAI^{0.38}$	0.65	0.42	0.64	0.82
Mixed forests	$0.45LAI^{0.36}$	0.72	0.45	0.67	0.86
Shrubs and Grasses	$0.72LAI^{0.28}$	0.96	0.72	0.97	1.0
Crops	$0.69LAI^{0.17}$	0.88	0.69	0.83	0.94
Wetlands	$0.67LAI^{0.25}$	0.80	0.67	0.88	1.0

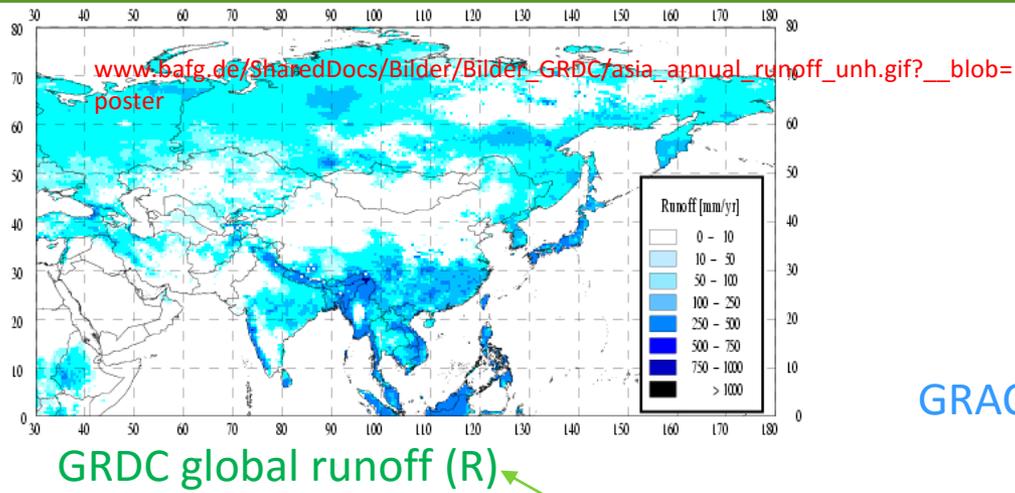
Overall, the strong correlations between LAI and T/ET_d obtained from the different datasets suggest that LAI can be considered the first-order factor affecting ET partitioning

T estimation based on GRACE derived ET and LAI regression

$$T = \sum_{i=1}^n (ET - I) * Fv_i * f(LAI)_i$$

<i>DATESET</i>	<i>ET estimation</i>	<i>Dynamic inputs</i>
<i>CLM4.5SP</i>	<i>LSM</i>	<i>Transient land cover and land use change:LUHa.v1 [Hurt et al. (2006)] Surface datasets based on MODIS products (LAI, SAI, and vegetation height): CRUNCEP (CRU+NCEP) atmospheric reanalysis data</i>
<i>GLEAM V3a</i>	<i>Priestley-Taylor</i>	<i>Radiation: CERES SYN1deg [Wielicki et al., (1996)] Precipitation: CMORPH v1[Joyce et al.(2004)] Air Temperature: AIRS v7 [Braverman et al. (2012)] Soil moisture: WACMOS-CCI [Liu et al. (2012)] Vegetation Optical Depth: LPRM-NASA [Liu et al.(2013)] Snow water equivalent: GlobSnow [Luojus&Pulliainen (2010)]</i>
<i>GRACE based ET</i>	<i>Water balance</i>	<i>Global GMAO meteorological data at 1.00°×1.25° resolution. Global 1-km Collection 4 MODIS land cover type 2 (MOD12Q1) (Friedl et al., 2002) Global 1-km MODIS Collection 5 FPAR/LAI (MOD15A2) (Myneni et al., 2002) Global 0.05-degree CMG MODIS albedo (the 10th band of the White-Sky Albedo from MOD43C1) (Jin et al., 2003; Salomon et al., 2006; Schaaf et al., 2002).</i>

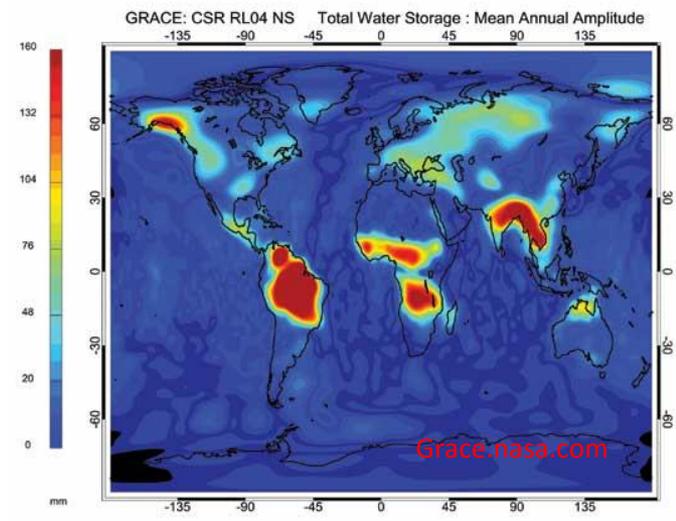
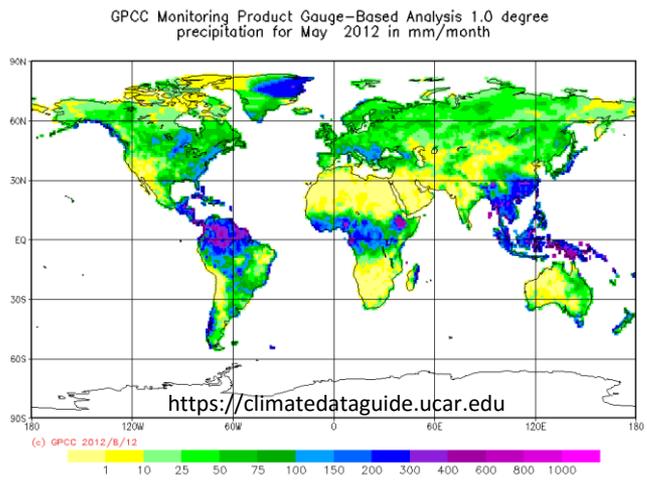
GRACE based ET calculation



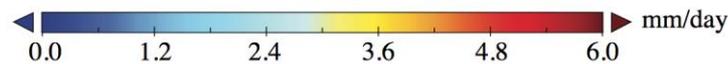
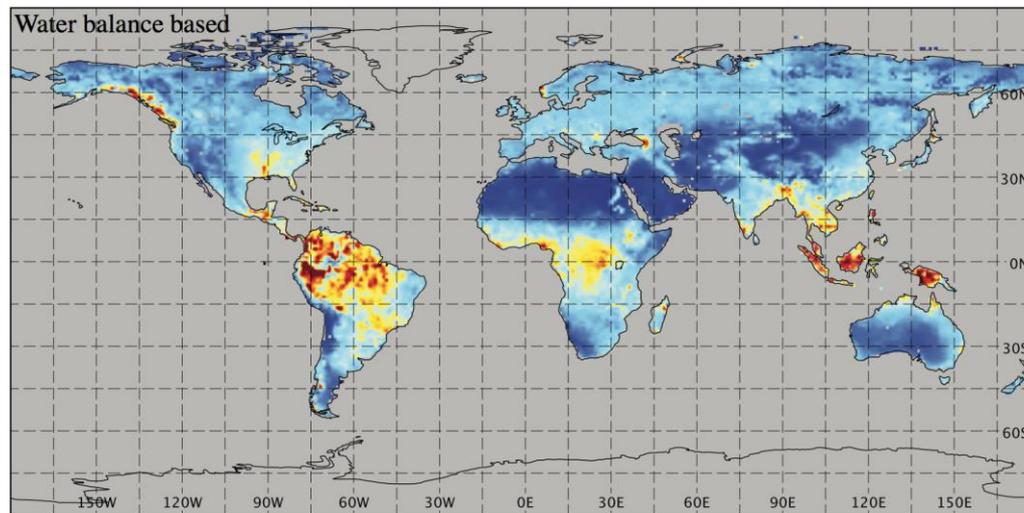
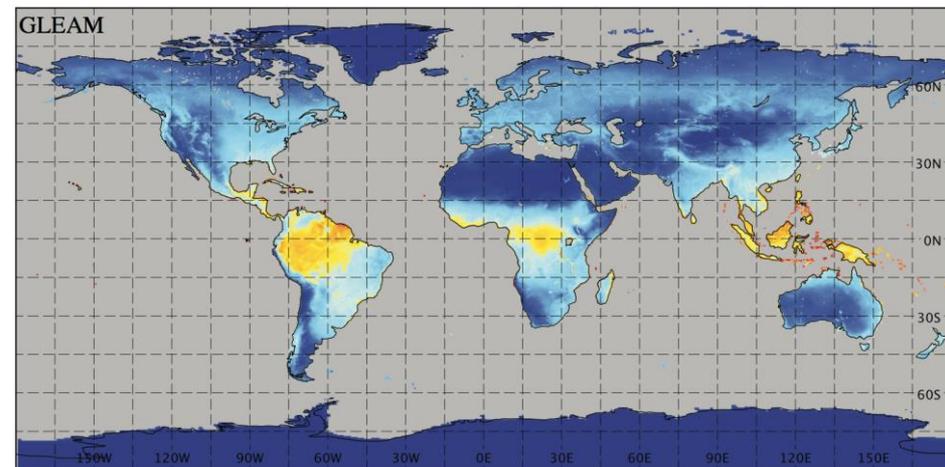
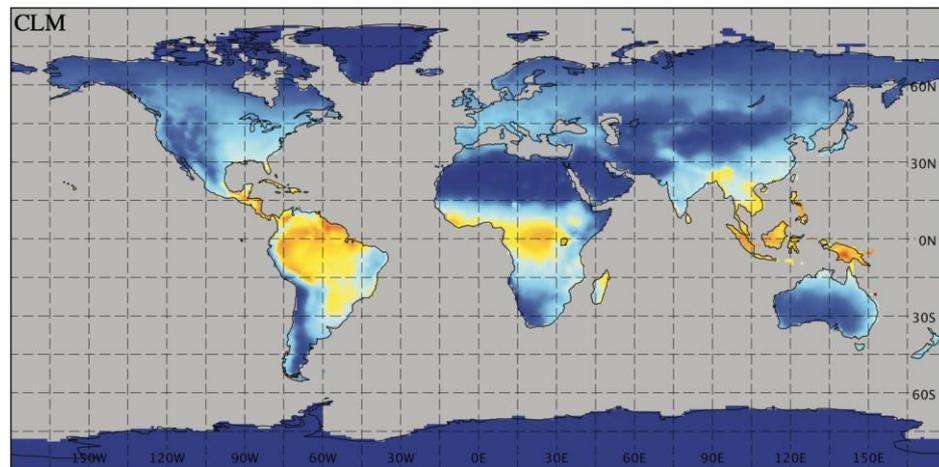
GRACE terrestrial water storage change (TWSC)

$$ET = P - R - TWSC$$

GPCC precipitation (P)



Comparison of different ET products



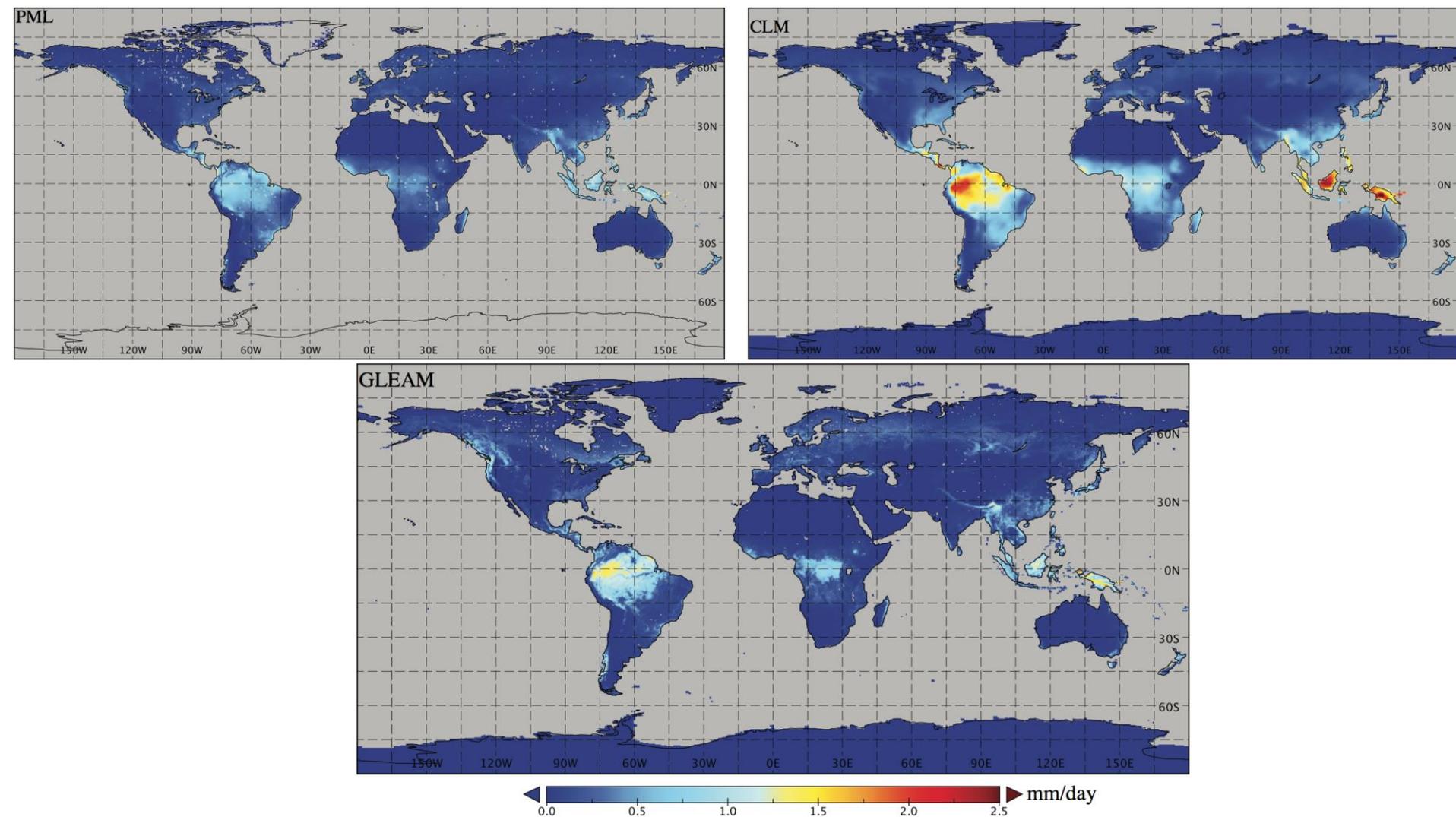
Global patterns of annual mean ET estimated from GLEAM, CLM and water balance approach based on GRACE reveal a high convergence

Comparison of different I products

$$T = \sum_{i=1}^n (ET - I) * Fv_i * f(LAI)_i$$

<i>DATESET</i>	<i>I estimation</i>	<i>Dynamic inputs</i>
<i>CLM4.5SP</i>	a simple model based on the observed P, LAI, and stem area index (SAI)	<i>CRUNCEP (CRU+NCEP) atmospheric reanalysis data</i>
<i>GLEAM V3a</i>	Gash's analytical model based on observed	<i>Precipitation: CMORPH v1 [Joyce et al.(2004)] Air Temperature: AIRS v7 [Braverman et al. (2012)] Soil moisture: WACMOS-CCI [Liu et al. (2012)] Vegetation Optical Depth: LPRM-NASA [Liu et al.(2013)] Snow water equivalents: GlobSnow [Luojus&Pulliainen (2010)]</i>
<i>PML</i>	adapted version of the widely adopted Gash rainfall interception model	<i>Princeton Global Forcing (PGF) data^{14,15} and the WATCH Forcing Data ERA-Interim (WFDEI) meteorological forcing data</i>

Comparison of different I products

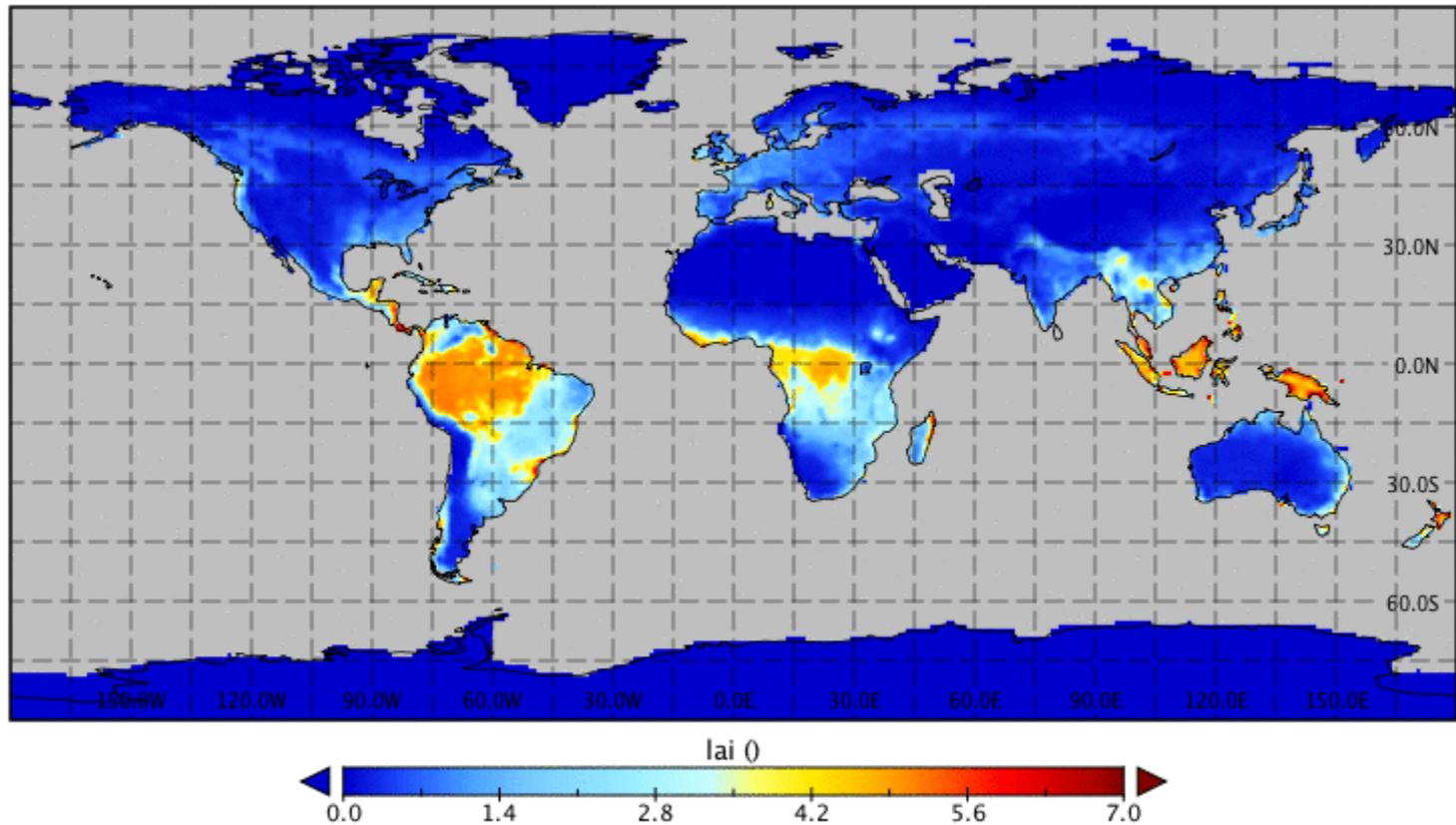


Although ET derived from CLM is generally consistent with that of GLEAM and Penman-Monteith-Leuning (PML) model6, a significantly lower I is found in GLEAM and PML, at about 11% and 10% of I/ET at the global scale, compare to that of the CLM value of 20%.

Seasonal variation of LAI

$$T = \sum_{i=1}^n (ET - I) * Fv_i * f(LAI)_i$$

Time: 2010-01-01 00:00:00

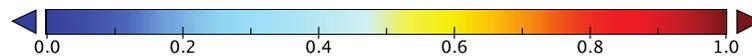
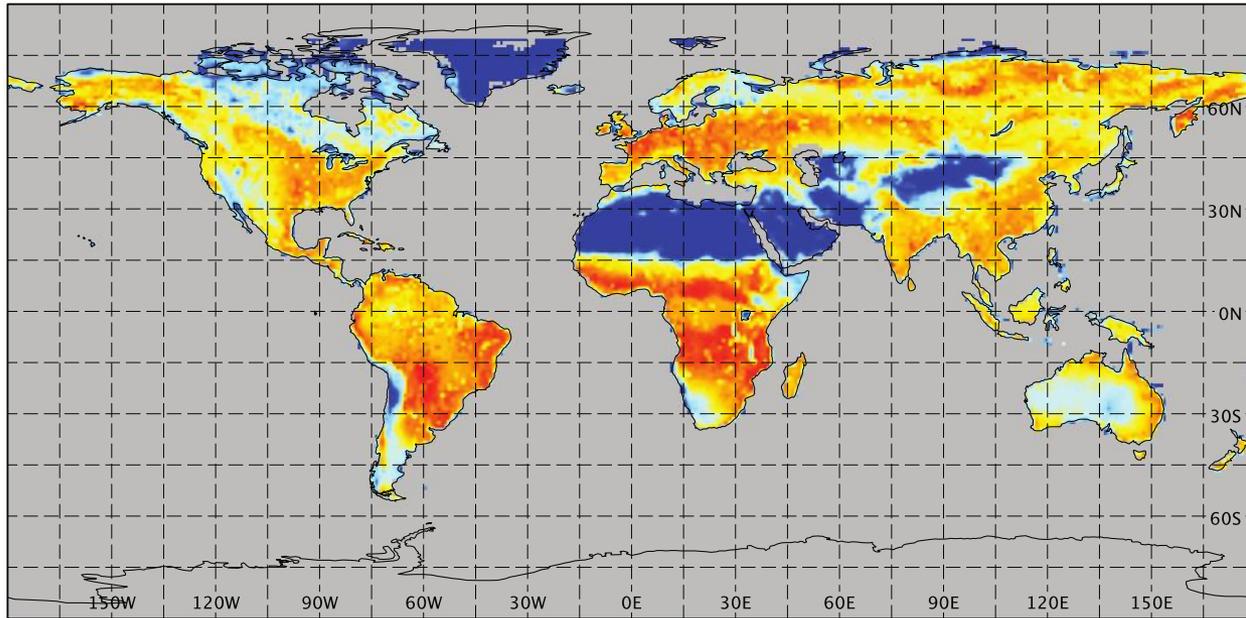


Estimated T/ET ratios using different sources of ET and I

$$\frac{T}{ET} = \frac{1}{ET} \sum_{i=1}^n (ET - I) * Fv_i * f(LAI)_i$$

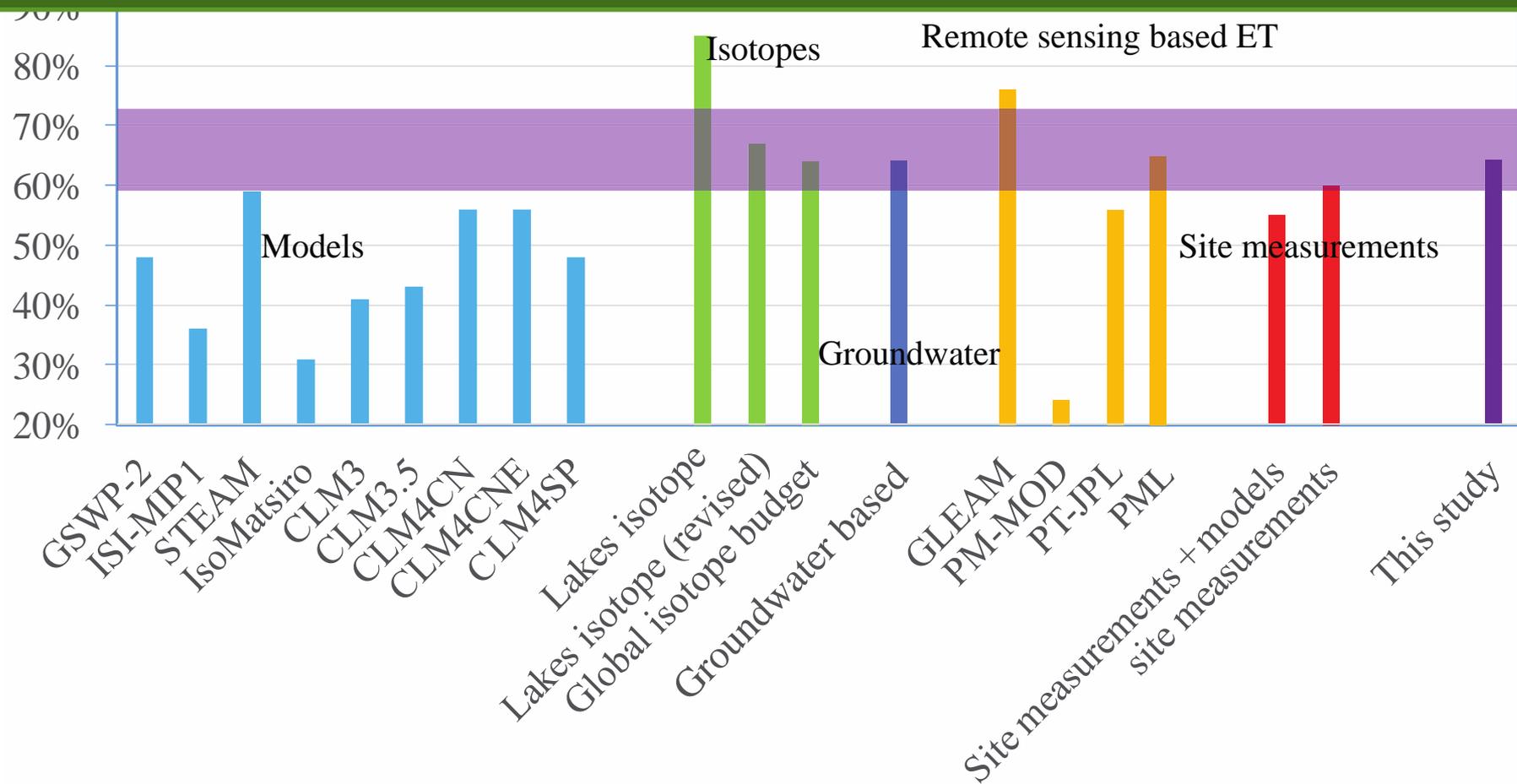
ET	I	T/ET
GRACE-based water balance	CLM	61.2%
GRACE-based water balance	GLEAM	66.8%
GRACE-based water balance	PML	66.7%
CLM	CLM	59.5%
CLM	GLEAM	67.1%
CLM	PML	68.8%
GLEAM	CLM	60.1%
GLEAM	GLEAM	65.2%
GLEAM	PML	73.9%

Ensemble mean of global distribution of T/ET using different sources of ET and I.



Vegetation class	Zhou et al. ²	Wang-Erlandsson et al. ⁶¹	Miralles et al. ⁶²	Schlesinger and Jasechko et al. ⁶	This study
Crops	0.62-0.69	0.72	0.92		0.70
Shrubs and Grasses	0.6	0.58-0.70	0.72-0.90	0.47-0.62	0.68
Needle leaf forests	0.56	0.50-0.52	0.7	0.55-0.65	0.50
Broad leaf forests	0.52	0.54-0.64	0.79	0.7	0.64
Mixed forests		0.57			0.56
Wetlands		0.31-0.37			0.33

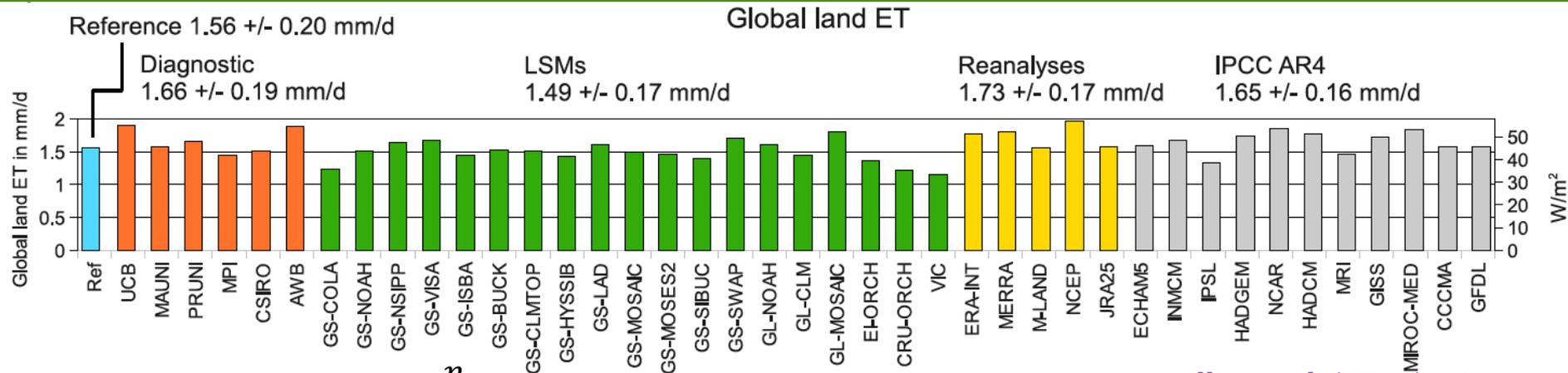
Comparison of T/ET estimated by different methods.



Because the approaches were developed from independent theory, the agreement that transpiration accounts for two thirds of global terrestrial evaporation suggests we need more interception research going forward in order to bring data-driven T/ET estimates together. Based on our approach, the total annual magnitude of transpiration, amounts to $42.5 \cdot 10^3 \text{ km}^3$ of $65.5 \cdot 10^3 \text{ km}^3$ ET for Global scale

Was ET well estimated ?

To some extent: **Yes.**

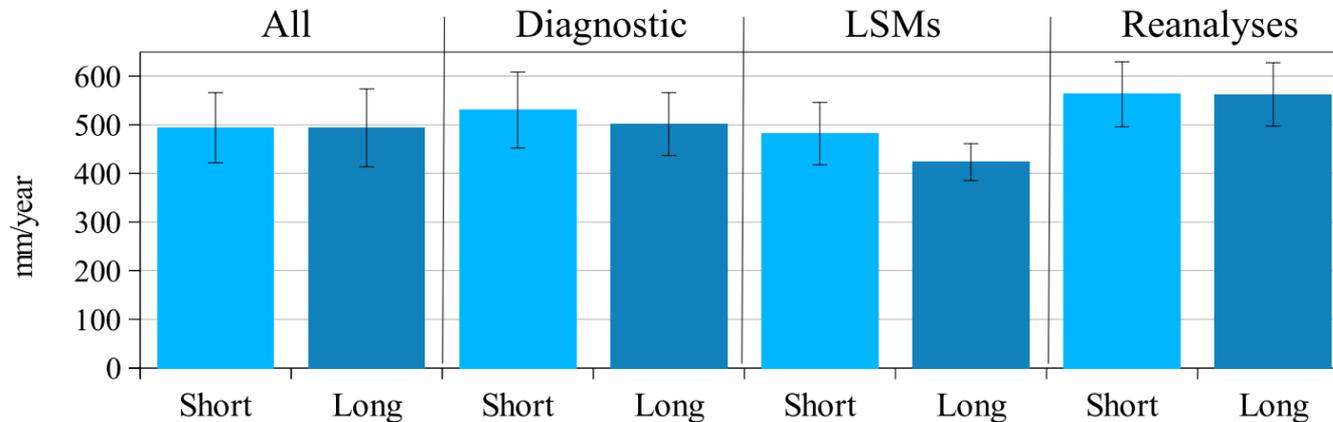


Mueller et al. (2011) GRL

$$\frac{T}{ET} = \frac{1}{ET} \sum_{i=1}^n (ET - I) * Fv_i * f(LAI)_i$$

Global mean land ET of merged products

Median and interquartile range of products based on:



Mueller et al. (2013) HESS

The reason
is that

.....

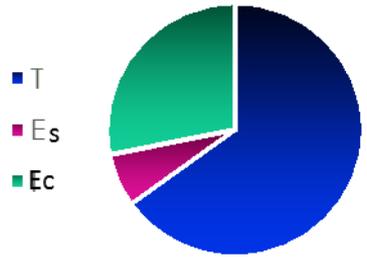
Method	I/(E+T+I)	T/(E+T+I)	T/(E+T)	Scale	Source
Land surface models					
GSWP-2	16%	48%	57%	Global	Dirmeyer et al. (2006); BAMS
ISI-MIP1	27%	36%	49%	Global	Calculated from ISI-MIP1 models
STEAM	21%	59%	74%	Global	Wang-Erlandsson et al. (2015); EDS
IsoMatsiro	36%	31%	49%	Global	Yoshimura et al. (2006); GPC
LCM3	17%	41%	49%	Global	Lawrence et al. (2007); J Hydrometeor
LCM3.5	18%	43%	52%	Global	Lawrence et al. (2011); JAMES
LCM4CN ^b	21%	56%	70%	Global	Lawrence et al. (2011); JAMES
LCM4CNE ^c	22%	56%	71%	Global	Lawrence et al. (2011); JAMES
Isotope					
Lakes isotope	10% ^d	85%	94%	Catchment	Jasechko et al. (2013); Nature
Lakes isotope	29% ^e	67%	94%	Catchment	Coenders-Gerrits et al. (2014); Nature
Global isotope budget	27% ^e	64%	88%	Global	Good et al. (2015); Science
Satellite					
MOD16	24%	24%	32%	Global	Mu et al. (2011); RSE
LCM4SP ^a	20%	48%	60%	Global	Lawrence et al. (2011); JAMES
GLEAM	11%	80%	89%	Global	Miralles et al. (2011); HESS
Site measurement					
Isotope+hydrometric+model			61%	Site averaged	Schlesinger and Jasechko et al. (2014); AFM
Isotope+hydrometric			60%	Site averaged	Wang et al. (2014); GRL
Other					
Groundwater		64%		global	
LAI regression ^f	14%	65%	76%	Global	This study

Uncertainties in isotope-based global T/ET partitioning

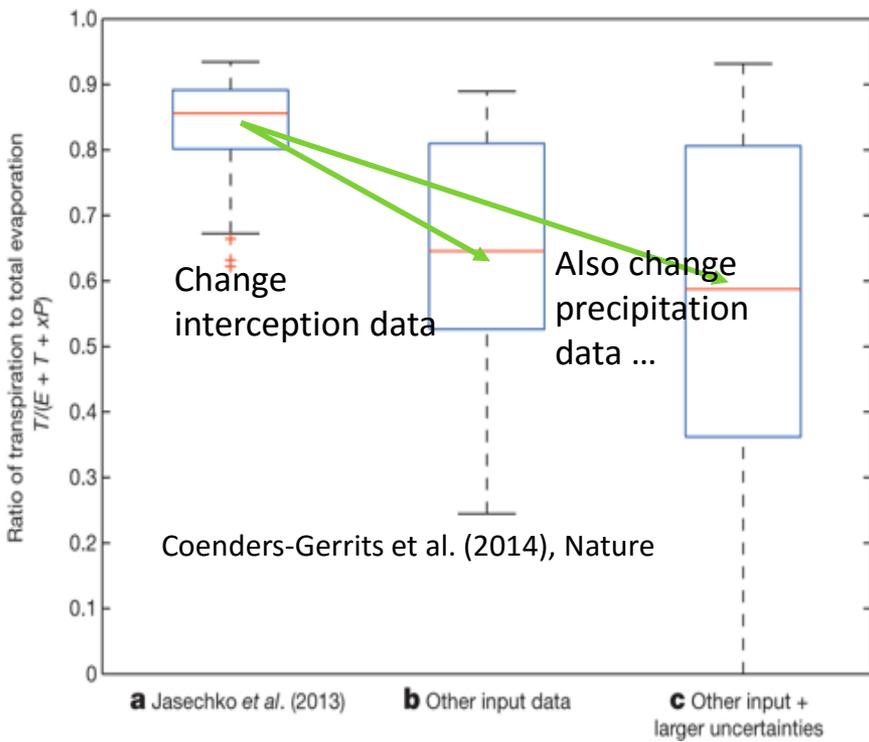
Jasechko et al. (2013) Nature



Coenders-Gerrits et al. (2014) Nature



Good et al. (2015) Science



precipitation Runoff interception

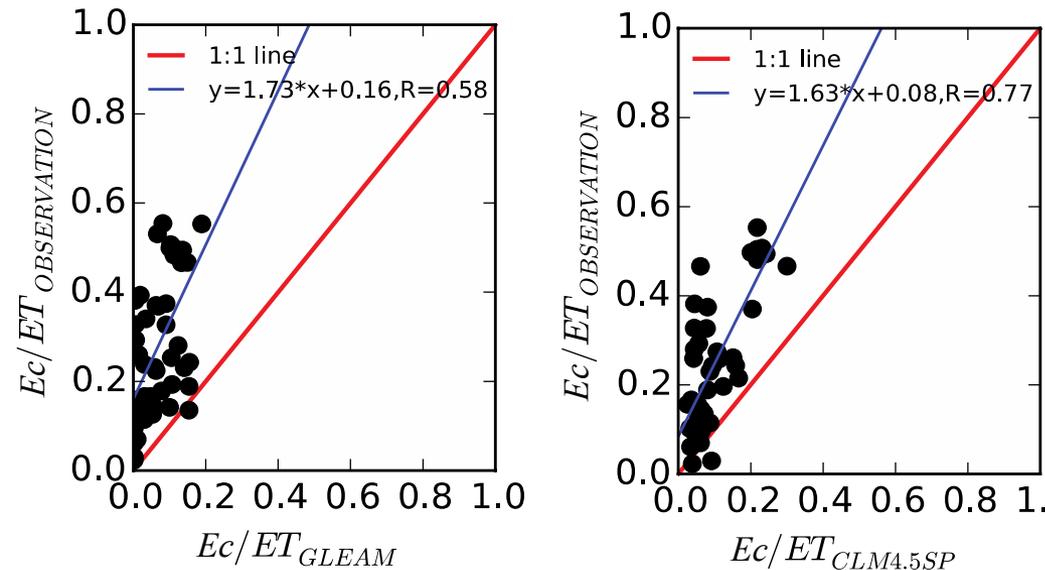
$$T = \frac{P(\delta P - \delta E) - Q(\delta Q - \delta E) - I(\delta I - \delta E)}{\delta T - \delta E}$$

For global scale, T/ET is sensitive to bulk flux estimates (such as precipitation and interception amount)

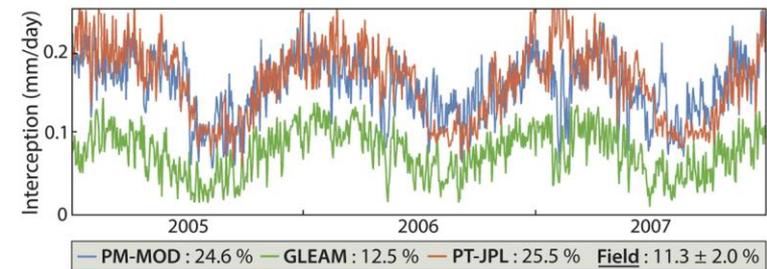
Uncertainty

$$\frac{T}{ET} = \frac{1}{ET} \sum_{i=1}^n (ET - I) * Fv_i * f(LAI)_i$$

We reviewed the published studies (15 individual long term ET partitioning measurement studies) that measured at least two of the three components in an attempt to compare with global simulation.



The I is significantly underestimated!



Miralles et al. (2016)

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

Conclusions

1. The T/ET was represented quite well as a function of a 0.5-bin averaged LAI, implying that vegetation plays a major role in driving the contribution of T/ET.
2. Based on global synthesis of LAI control on ET partitioning and different ET products, the T/ET ratio was reported to be 65%. It was significantly smaller than that reported in isotopic approaches.
3. A further study about interception is also required because canopy interception loss at various regions of the globe has been scarcely reported in the literature.

Thank you for your listening !