Transpiration accounts for two thirds of global terrestrial evaporation

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2016/08/04
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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**

\[
ET = E + T \\
ET \delta_{ET} = E \delta_E + T \delta_T
\]

$v$: water vapor, $w$: surface water, $\delta$: isotope ratio, $q$: vapor mixing ratio

\[
\frac{T}{E + T} = \frac{\delta_{ET} - \delta_E}{\delta_T - \delta_E}
\]

**Non-isotope approach**

\[
\frac{T}{ET} = \frac{u \text{WUE}_a}{u \text{WUE}_p}
\]

Observation and/or simulation

Flux-variance similarity partitioning method
ET partitioning: Global scale

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

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

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

Fig. 1. Schematic representation of Iso-MATSIRO.

Yoshimura et al. (2006)

Fig. 7. Schematic representation of Iso-MATSIRO and ICM coupling.
Groundwater based ET partitioning

Maxwell and Condon (2016) Science

The relationship between groundwater depth and land-energy fluxes
The uncertainties in these global ET partitioning studies are significant.
This topic is getting hotter and hotter


Zhou et al.: The effect of vapor pressure deficit on water use efficiency at the subdaily time scale, *GRL*, 2014


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.

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.
**T estimation based on LAI regression**

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

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

**Land Cover**

- **ISLSCP II MODIS IGBP Land Cover**
  - 25% forest
    - Then $Fv_i = 0.25$
  - 75% grass
    - Then $Fv_i = 0.75$

**ET dataset**

**Interception dataset**

**LAI regression for different vegetation types?**

![LAI vs. FT](attachment:image.png)
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.

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

\[ T = \sum_{i=1}^{n} (ET - I) \times Fv_i \times f(LAI)_i \]

<table>
<thead>
<tr>
<th>DATESET</th>
<th>ET estimation</th>
<th>Dynamic inputs</th>
</tr>
</thead>
</table>
| CLM4.5SP        | LSM           | Transient land cover and land use change: LUHa.v1 [Hurtt et al. (2006)]
|                 |               | Surface datasets based on MODIS products (LAI, SAI, and vegetation height):
|                 |               | CRUNCEP (CRU+NCEP) atmospheric reanalysis data                                |
| GLEAM V3a       | Priestley-Taylor | 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 equivalents: GlobSnow [Luojus & Pulliainen (2010)]                 |
| GRACE based ET  | Water balance | 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].         |
GRACE based ET calculation

\[ ET = P - R - TWSC \]

GRDC global runoff (R)

GPCC precipitation (P)

GRACE terrestrial water storage change (TWSC)

GRDC global runoff (R)
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

\[ T = \sum_{i=1}^{n} (ET - I) \times Fv_i \times f(LAI)_i \]

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

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

\[ T = \sum_{i=1}^{n} (ET - I) \times Fv_i \times f(LAI)_i \]
Estimated T/ET ratios using different sources of ET and I

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

<table>
<thead>
<tr>
<th>ET</th>
<th>I</th>
<th>T/ET</th>
</tr>
</thead>
<tbody>
<tr>
<td>GRACE-based water balance</td>
<td>CLM</td>
<td>61.2%</td>
</tr>
<tr>
<td>GRACE-based water balance</td>
<td>GLEAM</td>
<td>66.8%</td>
</tr>
<tr>
<td>GRACE-based water balance</td>
<td>PML</td>
<td>66.7%</td>
</tr>
<tr>
<td>CLM</td>
<td>CLM</td>
<td>59.5%</td>
</tr>
<tr>
<td>CLM</td>
<td>GLEAM</td>
<td>67.1%</td>
</tr>
<tr>
<td>CLM</td>
<td>PML</td>
<td>68.8%</td>
</tr>
<tr>
<td>GLEAM</td>
<td>CLM</td>
<td>60.1%</td>
</tr>
<tr>
<td>GLEAM</td>
<td>GLEAM</td>
<td>65.2%</td>
</tr>
<tr>
<td>GLEAM</td>
<td>PML</td>
<td>73.9%</td>
</tr>
</tbody>
</table>
Ensemble mean of global distribution of T/ET using different sources of ET and I.

<table>
<thead>
<tr>
<th>Vegetation class</th>
<th>Zhou et al\textsuperscript{2}</th>
<th>Wang-Erlandsson et al.\textsuperscript{61}</th>
<th>Miralles et al\textsuperscript{62}</th>
<th>Schlesinger and Jasechko et al.\textsuperscript{6}</th>
<th>This study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crops</td>
<td>0.62-0.69</td>
<td>0.72</td>
<td>0.92</td>
<td></td>
<td>0.70</td>
</tr>
<tr>
<td>Shrubs and Grasses</td>
<td>0.6</td>
<td>0.58-0.70</td>
<td>0.72-0.90</td>
<td>0.47-0.62</td>
<td>0.68</td>
</tr>
<tr>
<td>Needle leave forests</td>
<td>0.56</td>
<td>0.50-0.52</td>
<td>0.7</td>
<td>0.55-0.65</td>
<td>0.50</td>
</tr>
<tr>
<td>Broad leave forests</td>
<td>0.52</td>
<td>0.54-0.64</td>
<td>0.79</td>
<td>0.7</td>
<td>0.64</td>
</tr>
<tr>
<td>Mixed forests</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.56</td>
</tr>
<tr>
<td>Wetlands</td>
<td>0.31-0.37</td>
<td></td>
<td></td>
<td></td>
<td>0.33</td>
</tr>
</tbody>
</table>
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 $42.5 \times 10^3$ km$^3$ of $65.5 \times 10^3$ km$^3$ ET for Global scale.
Was ET well estimated?

To some extent: Yes.

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

Global mean land ET of merged products

Median and interquartile range of products based on:

### Reference 1.56 +/- 0.20 mm/d

- Diagnostic: 1.66 +/- 0.19 mm/d
- LSMs: 1.49 +/- 0.17 mm/d
- Reanalyses: 1.73 +/- 0.17 mm/d
- IPCC AR4: 1.65 +/- 0.16 mm/d

Mueller et al. (2011) GRL

The reason is that

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

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

\[ T = \frac{P(\delta P - \delta E) - Q(\delta Q - \delta E) - I(\delta I - \delta E)}{\delta T - \delta E} \]
I uncertainty

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

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!

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 %), Cuertas 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!