Constraining Gaseous Dry Deposition with In-situ Flux Observations

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Parameterizing gaseous dry deposition in CTMs

Current Theory:
- \( r_s = f(PFT, Rad, LAI, Water, T, CO_2) \)
- \( r_{ns} \): very messy

In GEOS-Chem:
- \( r_s = f_1(PFT, Rad, LAI) f_2(T) \)
- \( r_{ns} = f(PFT, Rad, LAI, T) \), practically land-type specific constants with some scaling to LAI
Not exhaustive, but representative of current available approaches:

1) W98: GEOS-Chem parameterization

2) W98_BB: Replacing $r_s$ of W98 by Ball-Berry (BB) photosynthesis-stomatal conductance ($A_n-g_s$) module (Collatz et al., 1992)

3) Z03: The Zhang et al. (2003) parameterization. $R_s$ further includes effect of water. $R_{ns}$ includes effects of canopy wetness and canopy-to-soil transfer

4) Z03_BB: Replacing $r_s$ of Z03 by BB $A_n-g_s$ module

- 30-years offline run with MERRA2
- Combine with 1-year GC sensitivity simulation
- Explore impact of $v_d$ parameterization on modelled surface $O_3$
Choice of $r_c$ parametrization affect modelled O$_3$

**July ΔO$_3$**

- Tropics/Mediterranean: All alternative schemes have lower $v_d$ in dry season.
- India/China: Wet soil in Summer $\rightarrow$ higher $v_d$ from BB

**December ΔO$_3$**

- Indochina: W98 may not capture observed $v_d$ drop in dry season
- ΔO$_3$ Up to 8 ppbv

**July σ$_{O3}$ (proxy of interannual variability)**

- σ$_{O3}$ Up to 3 ppbv
- W98 (GC) is very sensitive to LAI
- Important to have temporally consistent LAI

Wong et al., (2019), Submitted to ACPD
If $\nu_d$ parameterization matters CTMs...

Constrain it!

But how?
What observations do we have?

**Pros:**
- Species-specific
- Measure of total deposition

**Cons:**
- Spatiotemporally sparse
- No standard archive for relevant micromet/rad/soil data

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**Direct trace gas flux (e.g. Munger et al., 1996):**

**Pros:**
- Nearly complete micromet/rad data
- Excellent global coverage
- \( r_s \) relates directly to \( O_3 \) uptake/damage
- Information for other species (e.g. \( NO_2, NH_3 \))

**Cons:**
- Does not directly fit to total \( \nu_d \)

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**SynFlux \( r_s \) derived from FLUXNET (Ducker et al., 2018):**

**Pros:**
- Co-located measurements help gauge if better \( r_s \) leads to better \( \nu_d \)!
Does $R_s$ observation improve daytime $\nu_d$ of $O_3$?

<table>
<thead>
<tr>
<th></th>
<th>Harvard Forest Hourly (N = 4179)</th>
<th>Daily (N = 341)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$W$</td>
<td>$W_{\text{SynFlux}}$</td>
</tr>
<tr>
<td>$R$</td>
<td>0.30</td>
<td>0.50</td>
</tr>
<tr>
<td>Error Frac</td>
<td>0.50</td>
<td>0.38</td>
</tr>
<tr>
<td>Bias Frac</td>
<td>0.24</td>
<td>0.02</td>
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</tbody>
</table>

- $W$: Wesely (1989) model
- $W_{\text{SynFlux}}$: $W$ with $R_s$ replaced by “observation” from SynFlux

**SynFlux $R_s$ improves $\nu_d$ at hourly and daily timescale over HF and Hyytiala**

**But...**
1) SynFlux is not available everywhere
2) Even within a site, SynFlux has lots of time gap

How may SynFlux help model $R_s$?

Wong et al., in prep
Data-driven approach of modelling $R_s$ is viable

Machine learning (ML) can reproduce SynFlux hourly $g_s$ over HF and Hyytiala

Harvard Forest Hourly (N = 11797)

<table>
<thead>
<tr>
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<th>W</th>
<th>W_SynFlux</th>
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<tbody>
<tr>
<td>$R$</td>
<td>0.34</td>
<td>0.47</td>
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<tr>
<td>Error Frac</td>
<td>0.49</td>
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<tr>
<td>Bias Frac</td>
<td>-0.06</td>
<td>-0.05</td>
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Daily (N = 886)

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<tr>
<td>$R$</td>
<td>0.32</td>
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<tr>
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<td>0.39</td>
<td>0.27</td>
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<tr>
<td>Bias Frac</td>
<td>-0.21</td>
<td>-0.01</td>
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</table>

ML $R_s$ improves $v_d$ over HF and Hyytiala

Can we do this in global scale?

- Possible, + Remote sensing, climate indices
- Across biomes, $R^2 = 0.5 – 0.75$, Error ~ 30%
- Implement back to GC potentially improve gaseous dry deposition and stomatal $O_3$ uptake simulation
- Speed and software engineering can be concerns (Silva et al., 2019)

Wong et al., in prep
Conclusion

Choice of $v_d$ parameterization have significant impact on modelled mean and IAV of surface $O_3$

$R_s$ constrained by observation can potentially improve modelling of total and stomatal $O_3$ deposition

Machine learning provides an easy way to model $R_s$ with high quality

Other more “transparent” (e.g. optimizing parameters of existing $R_s$ models) will also be explored
## Model performance

### Random Forest of All SynFlux data points

<table>
<thead>
<tr>
<th>Variable</th>
<th>MF</th>
<th>ENF</th>
<th>GRA</th>
<th>WSA</th>
<th>SAV</th>
<th>EBF</th>
<th>WET</th>
<th>DBF</th>
<th>OSH</th>
<th>CRO</th>
<th>CSH</th>
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<tbody>
<tr>
<td>Fractional Error</td>
<td>0.317</td>
<td>0.331</td>
<td>0.290</td>
<td>0.310</td>
<td>0.265</td>
<td>0.270</td>
<td>0.262</td>
<td>0.266</td>
<td>0.317</td>
<td>0.312</td>
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<tr>
<td>R²</td>
<td>0.532</td>
<td>0.499</td>
<td>0.687</td>
<td>0.674</td>
<td>0.610</td>
<td>0.749</td>
<td>0.686</td>
<td>0.649</td>
<td>0.610</td>
<td>0.624</td>
<td>0.670</td>
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</table>

### Variable Importance

![Variable Importance Heatmap](image-url)
### Seasonal mean daytime $v_d$ performance

<table>
<thead>
<tr>
<th></th>
<th>NMBF</th>
<th>NMAEF</th>
<th>W98</th>
<th>Z03</th>
<th>W89_BB</th>
<th>Z03_BB</th>
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<tbody>
<tr>
<td>Dec</td>
<td>NMBF</td>
<td>0.134</td>
<td>-0.367</td>
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<tr>
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<td>NMAEF</td>
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<tr>
<td></td>
<td>Con</td>
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<td>-0.217</td>
<td>-0.252</td>
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<td>NMAEF</td>
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<td>0.455</td>
<td>0.483</td>
<td>0.399</td>
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<tr>
<td></td>
<td>Tro</td>
<td>0.080</td>
<td>-0.808</td>
<td>-0.086</td>
<td>-0.438</td>
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<tr>
<td></td>
<td>NMAEF</td>
<td>0.423</td>
<td>0.831</td>
<td>0.404</td>
<td>0.569</td>
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</tr>
<tr>
<td></td>
<td>Gra</td>
<td>0.276</td>
<td>0.015</td>
<td>0.175</td>
<td>0.097</td>
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<tr>
<td></td>
<td>NMAEF</td>
<td>0.392</td>
<td>0.479</td>
<td>0.307</td>
<td>0.318</td>
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<tr>
<td></td>
<td>Cro</td>
<td>0.297</td>
<td>0.360</td>
<td>0.241</td>
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<tr>
<td></td>
<td>NMAEF</td>
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<td>0.541</td>
<td>0.474</td>
<td>0.570</td>
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