Constraining Gaseous Dry Deposition with In-situ Flux Observations

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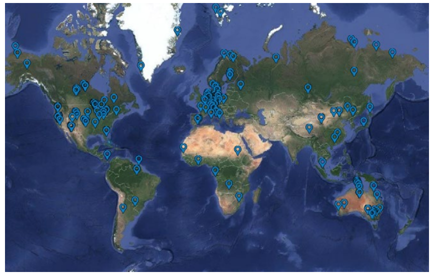
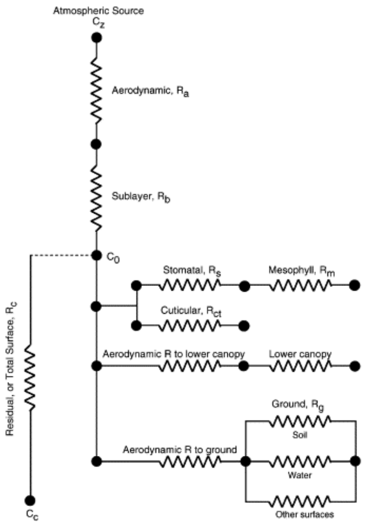
Flux Observation

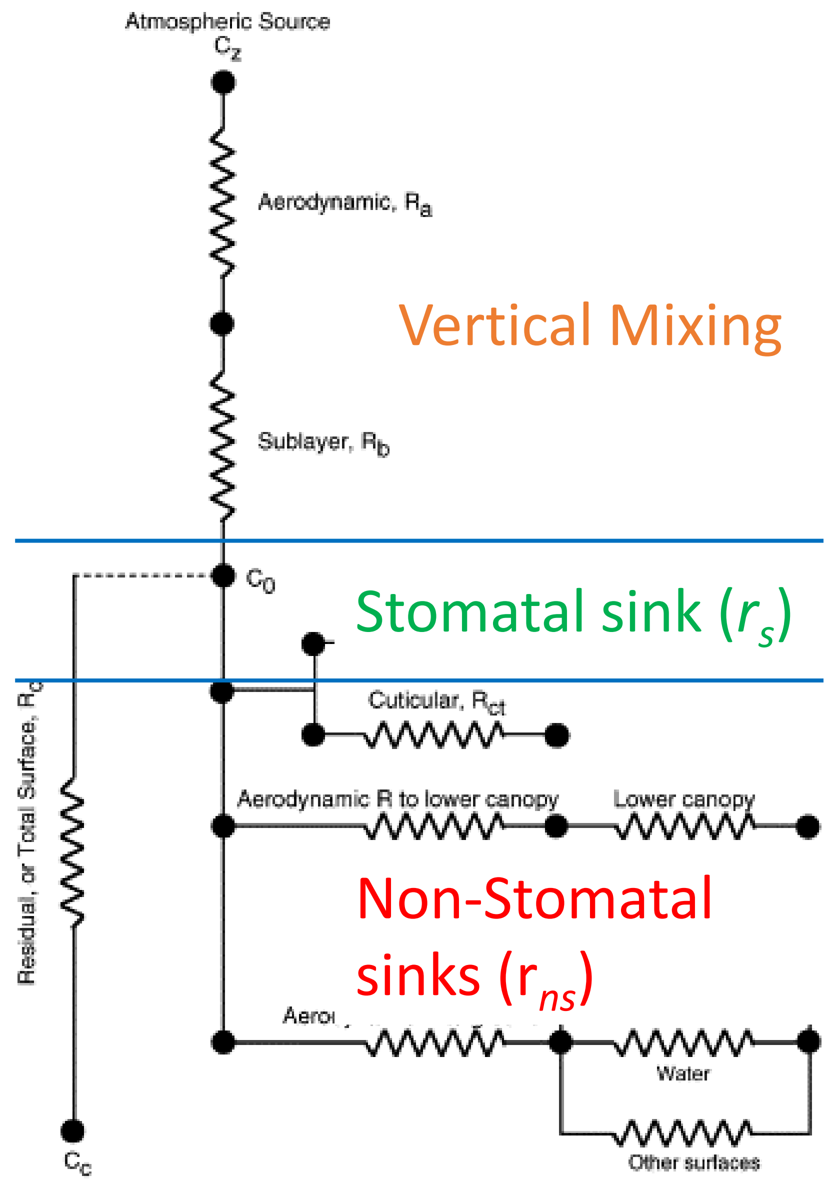
Global Network



GEOS-Chem



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

Other types r_s and r_{ns} parameterizations applicable ***in global model***

Not exhaustive, but representative of current available approaches:

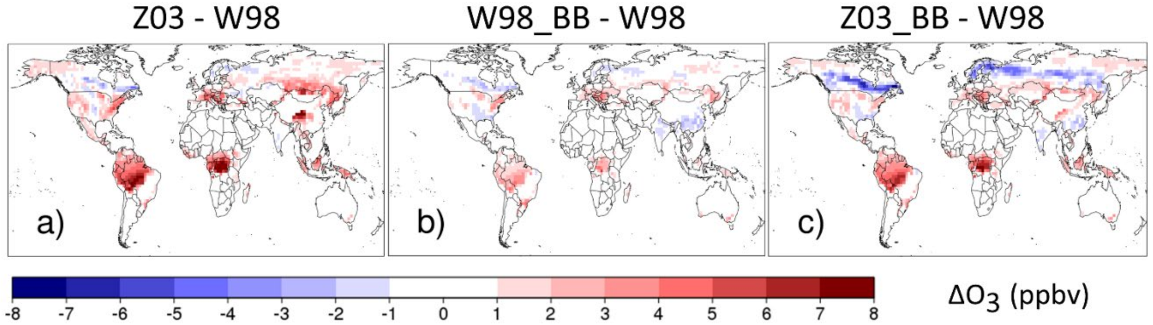
1) W98: GEOS-Chem parameterization
2) W98_BB: Replacing r_s of W98 by Ball-Berry (BB) photosynthesis-stomatal conductance (A_n-g_s) module (Collatz et al., 1992)
3) Z03: The Zhang et al. (2003) parameterization. R_s further includes effect of water. R_{ns} includes effects of canopy wetness and canopy-to-soil 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

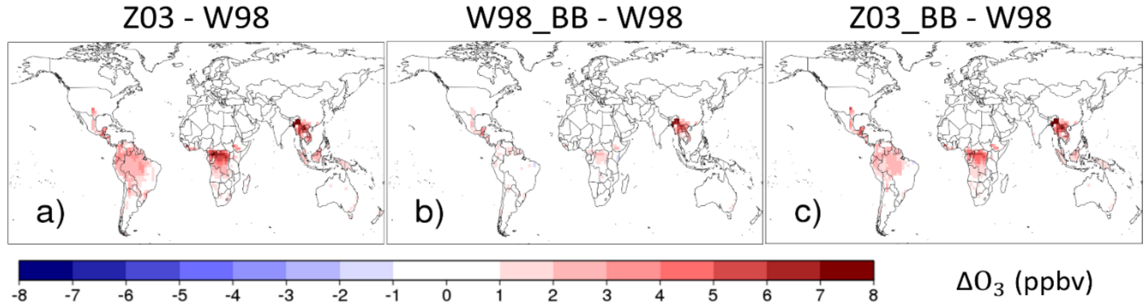
Wong et al., (2019), Submitted to ACPD

Choice of r_c parametrization affect modelled O_3

July ΔO_3



December ΔO_3



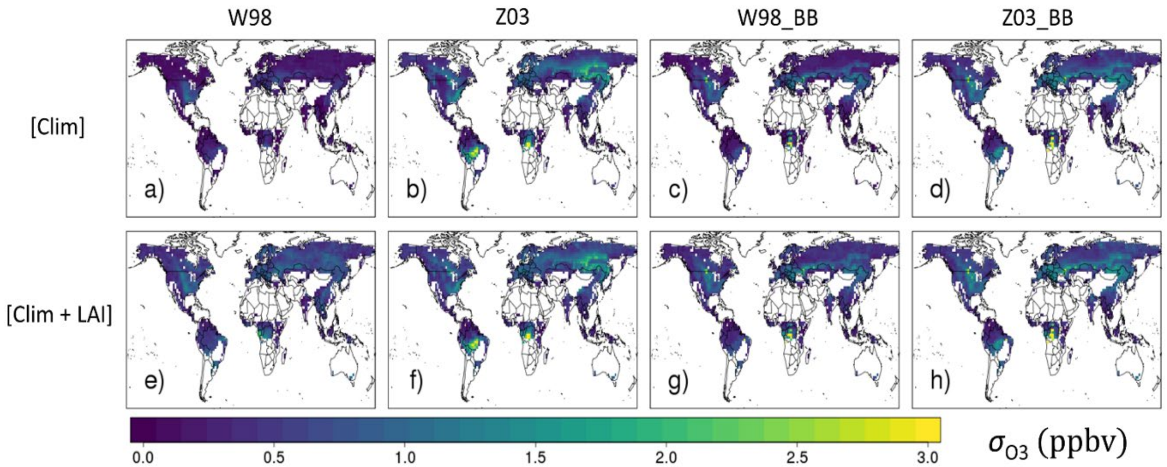
- **σ_{O3}** Up to 3 ppbv
- W98 (GC) is very sensitive to LAI
- Important to have temporally consistent LAI

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

Wong et al., (2019), Submitted to ACPD

- 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)



If v_d parameterization matters CTMs…

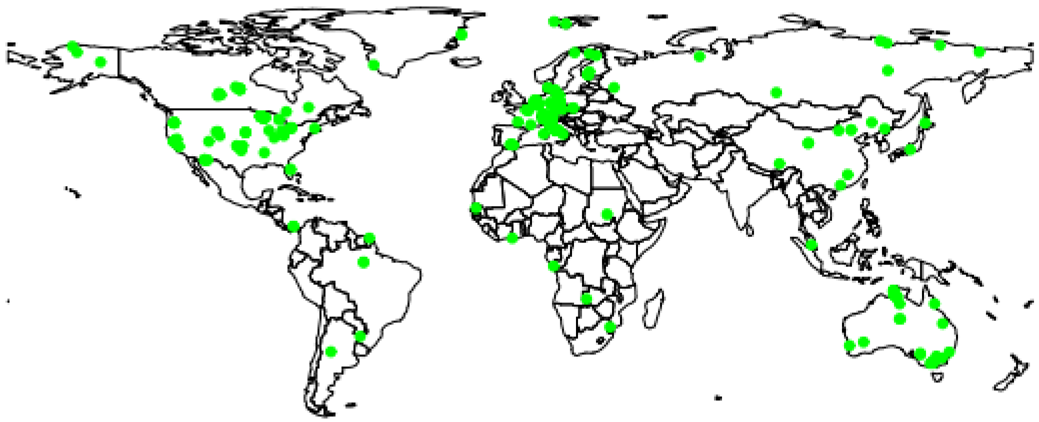
Constrain it!

But how?

What observations do we have?

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

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



Co-located measurements help gauge if better r_s leads to better v_d!

Pros:
- Species-specific
- Measure of total deposition

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

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 v_d

Wong et al., in prep

Does R_s observation improve daytime v_d of O_3?

Harvard Forest Hourly (N = 4179)			Daily (N = 341)	
	W	W_SynFlux	W	W_SynFlux
R	0.30	0.50	0.21	0.53
Error Frac	0.50	0.38	0.39	0.24
Bias Frac	0.24	0.02	0.30	0.03

- W: Wesely (1989) model
- W_SynFlux: W with R_s replaced by "observation" from SynFlux

SynFlux R_s improves v_d at hourly and daily timescale over HF and Hyytiala

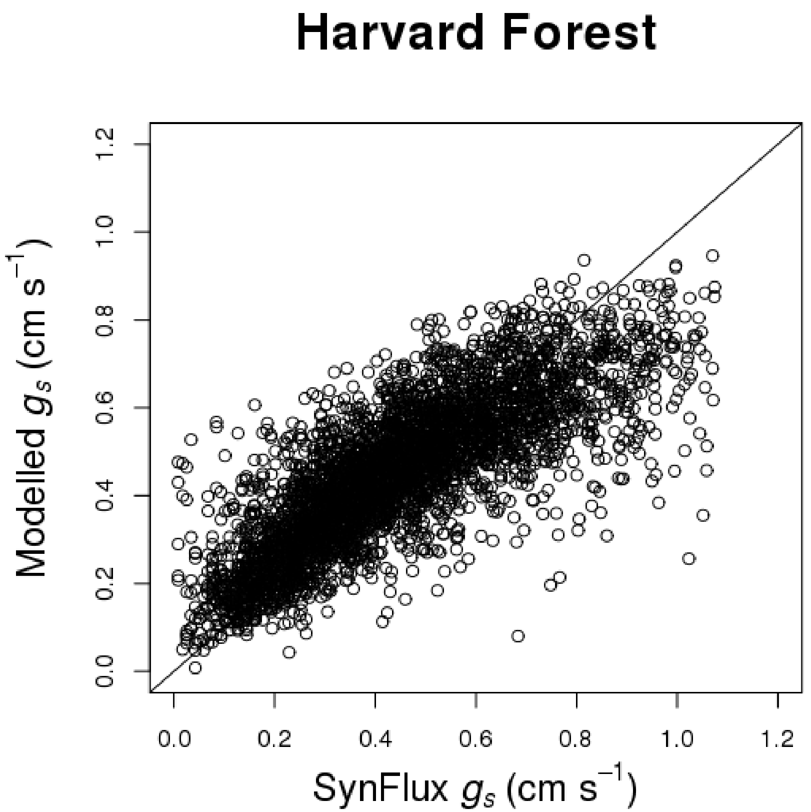
But…

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



Harvard Forest Hourly (N = 11797) Daily (N = 886)

	Hourly W	Hourly W_SynFlux	Daily W	Daily W_SynFlux
R	0.34	0.47	0.32	0.51
Error Frac	0.49	0.44	0.39	0.27
Bias Frac	-0.06	-0.05	-0.21	-0.01

ML R_s improves v_d over HF and Hyytiala

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

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

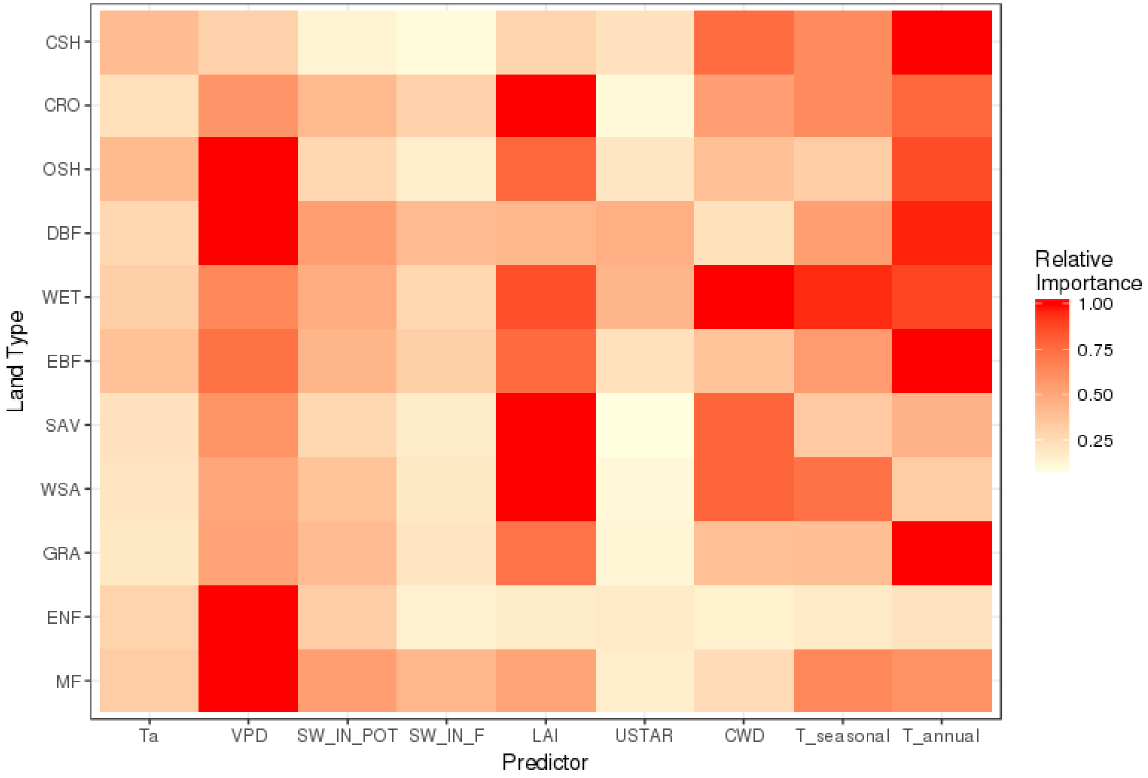
Other more "transparent" (e.g. optimizing parameters of existing R_s models) will also be explored

Model performance

Random Forest of All SynFlux data points

	MF	ENF	GRA	WSA	SAV	EBF	WET	DBF	OSH	CRO	CSH
Fractional Error	0.317	0.331	0.290	0.310	0.265	0.270	0.262	0.266	0.317	0.312	0.254
R^2	0.532	0.499	0.687	0.674	0.610	0.749	0.686	0.649	0.610	0.624	0.670

Variable Importance



Seasonal mean daytime v_d performance

		W98	Z03	W89_BB	Z03_BB
Dec (N=8)	NMBF	0.134	-0.367	-0.287	-0.142
	NMAEF	0.322	0.369	0.305	0.215
Con (N=16)	NMBF	-0.362	-0.217	-0.252	-0.025
	NMAEF	0.448	0.455	0.483	0.399
Tro (N=5)	NMBF	0.080	-0.808	-0.086	-0.438
	NMAEF	0.423	0.831	0.404	0.569
Gra (N=10)	NMBF	0.276	0.015	0.175	0.097
	NMAEF	0.392	0.479	0.307	0.318
Cro (N=11)	NMBF	0.297	0.360	0.241	0.282
	NMAEF	0.473	0.541	0.474	0.570