UPSCALING N₂O EMISSIONS FROM PLOT TO REGION

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Soil N₂O fluxes are highly variable in space and time







Skiba et al, Biogeosciences, 10, 1231-1241, 2013 Jones et al, Biogeosciences, 14, 2069-2088, 2017



Emissi	on factor				
[% of N applied]					
2007	6.5				
2008	3.7				
2009	1.6				
1					





To reduce the uncertainty of N₂O flux measurements

- Gapfilling of static chambers
- Gapfilling of eddy covariance
- N₂O from urine patches
- Upscaling to the UK
 - Comparing bottom up Tier 1 model with atmospheric concentrations





Improve chamber flux calculations

Easter Bush Farm, 20 fields, 4 seasons, dynamic closed chamber + QCL





- N₂O flux is spatially heterogeneous and chamber measurements observe a log-normal spatial distribution in all conditions
- Bayesian statistics works with probabilities, combing prior knowledge with new data
 - (Created model based on best goodness of fit Log NH4-N +NO3-N+ pH+ Soil C+ Soil N+Soil T + WFPS%)
- Using Markov chain Monte Carlo simulations we can use log-normal data to estimate means and confidence intervals



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Cowan et al 2017 Agro. Ecosys. Environ. 243



Nitrous oxide emission sources from a mixed livestock farm

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Arithmetic vs Bayesian flux calculation

Mean N₂O flux values with 95% C.I.'s estimated for each source category per season using three different methods of calculation (units in µg N₂O-N m⁻² h⁻¹).

Source categories	Season	n	Naive	95% C.I.		Bayesian Method	95% C.I.	
			Mean Flux	Lower	Upper	Mean Flux	Lower	Upper
Arable	Autumn	19	6	-25	36	3	0	6
	Winter	18	6	-7	19	7	4	13
	Spring	24	64	-75	203	65	41	101
	Summer	36	102	-326	530	81	51	128
Cattle	Autumn	23	99	-757	954	11	4	21
	Winter	29	0	-4	4	0	-1	1
	Spring	29	57	-104	217	46	29	72
	Summer	11	14	0	28	14	10	19
Sheep	Autumn	26	46	-273	365	21	9	42
-	Winter	0	NA	NA	NA	NA	NA	NA
	Spring	54	160	-770	1090	60	43	83
	Summer	112	111	-752	973	55	41	73

Bayesian method provides a robust approach to calculate uncertainty for low frequency flux measurements (i.e. chamber systems)





Cowan et al 2017 Agro. Ecosys. Environ. 243:929-102

Generalised additive mixed models for EC data



GAM is a smoothing technique, with little predictive power, GAM provides an appropriate tool for inputing the missing observations in the context of eddy covariance data.

Generalized Additive Mixed Model

Input data: Air T, Soil T, Rainfall, Wind speed, Wind direction (30 min), days since fertilisation







Cowan et al, submitted, 2019

Eddy covariance N₂O fluxes





Cowan, Levy et al submitted, 2019



GAM method for eddy covariance fluxes



The GAM method is used to interpolate measurement data and estimate 95 % C.I.s in cumulative flux estimates (shaded).

Fertilizer = ammonium nitrate

Cowan, Levy et al, submitted, 2019





Generalised additive mixed models for EC data









Daily mean WFPS% & N₂O Flux at Easter Bush, Cowan et al, in preparation

COMPARING PLOT AND FIELD SCALE N₂O FLUXES



Static chamber ~0.1 m² 1 h Daily-weekly Lots of gaps **High uncertainty**



Eddy covariance ~100 m² >10Hz 'Continuous' Less gaps Lower uncertainty



Levy et al, European J. Soil Sci. 68, 2017



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NOVEL USE OF UAV TO IMPROVE FIELD SCALE ESTIMATES OF N_2O FLUXES FROM GRAZED GRASSLANDS





12% of field is covered in urine patches Contribution to N_2O emissions Urine 47%, N fertiliser 53%

> frontiers in Sustainable Food Systems

ORIGINAL RESEARCH published: 25 April 2018 doi: 10.3389/fsufs.2018.00010

Juliette Maire (Walsh Fellowship PhD student with CEH, SRUC, Edin. Uni., Teagasc), Frontiers in Sustainable Food systems Vol 2 article 10



Identifying Urine Patches on Intensively Managed Grassland Using Aerial Imagery Captured From Remotely Piloted Aircraft Systems

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Comparing N₂O emissions inventories with atmospheric concentration measurements

- Global Atmospheric Watch stations
- Tall Towers
- National disaggregated N₂O emission inventory (5 km²)



















Comparing national scale N₂O emission inventories using bottom-up and top down methods



A NEW CONCEPT FOR NATIONAL CH₄ & N₂O REPORTING



<u>Change to</u>

Develop inventory using spatially resolved atmospheric concentrations plus atmospheric transport model and constrain with bottom up Tier 1



Benefits of greater emphasis on Top Down

- Inverse model can monitor actual changes in emissions i.e. detect mitigation
- Emissions can be constrained in countries lacking in activity data
- Cheaper than verification with labour intensive chamber systems
- Use chambers only for emission hotspot areas, or developing mitigation

A. Leip, U. Skiba, A. Vermeulen, R.L. Thompson Atmos. Environ. 174 (2018) 237-240





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www.ghgplatform.org.uk









