EOCYTES: Evaluation of the effect of Ozone on Crop Yields and the Terrestrial carbon pool using Satellite data

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Motivation

- **Tropospheric O_3** is a secondary product of **anthropogenic emissions of NO_x, CO, CH_4**.
- **O_3 is a potent phytotoxin** – once **absorbed into the leaf via the stomata**, it reacts to form radical oxygen species, **damaging cells and inhibiting photosynthesis**. Damaged plants grow less and age faster (senescence).
- Consequences for food security (**reduction in crop yield**) climate change (**lower GPP; less CO_2 sequestered by terrestrial carbon sinks**) and air quality (**vegetation less capable of removing tropospheric O_3**)
- Despite emissions reductions in Europe & N. America, **[O_3] unlikely to fall further under most IPCC Representative Concentration Pathways (RCPs)** (Eyring et al, 2013).
- Climate changes resulting in **more droughts/heatwaves** could also result in **more high-O_3 smog episodes** (Meehl et al, 2018).

Motivation

- **Prior studies of O_3-induced vegetation damage have been limited** to fumigation experiments, long-term in-situ measurements of forests, or modelling studies – limited to mainly N. America and Europe
- **Long-term satellite datasets for O_3, meteorology, and GPP exist**, but have **not been exploited to date** to look at this problem
- **Potential for global analyses of forests** using satellite datasets to more accurately determine **carbon lost due to O_3 damage**, and **to improve modelling future vegetation feedbacks due to climate change**
- Previously, Fishman et al (2010) successfully modelled **soybean crop yield loss due to O_3** over midwestern USA **using satellite O_3 data** from the Total Ozone Mapping Spectrometer (TOMS). **Can similar functions be determined for forest GPP using newer, more advanced datasets?**

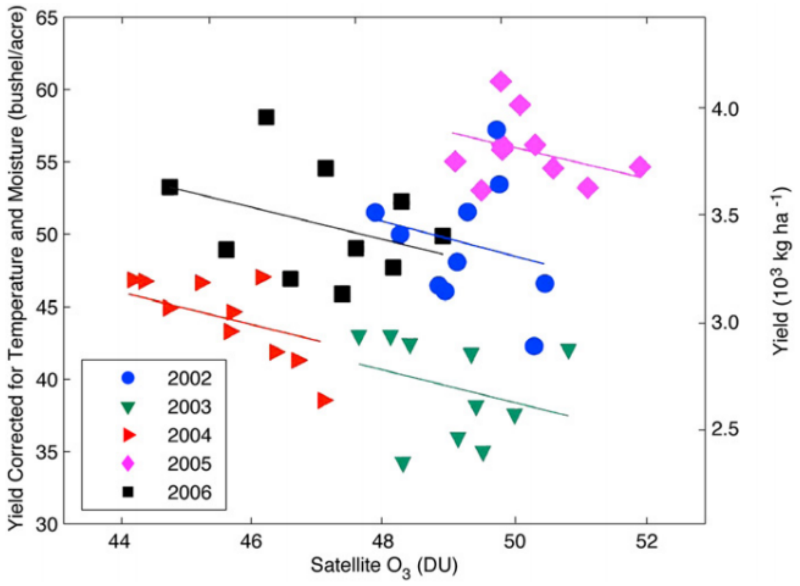


Fig. 5. Relationship between yield and satellite-derived O_3 over the southern region (37–40°N). Units for the yields on the left axis are taken directly from the USDA NASS database, which are provided in units of bushel acre^{-1}; 1 bushel acre^{-1} = 67.25 kg ha^{-1} and these units are shown on the right axis.

Fishman et al (2010)

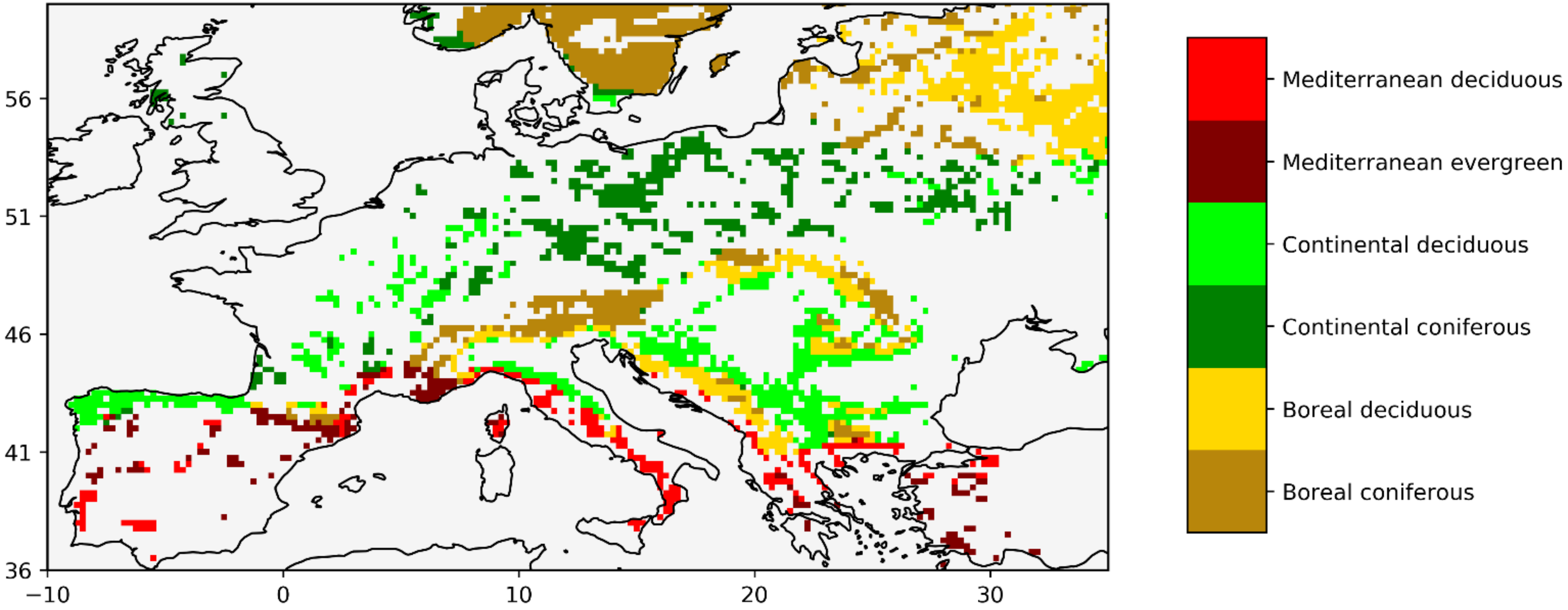
Satellite datasets

- **O_3: Copernicus Atmosphere Monitoring Service (CAMS) Reanalysis (ECMWF)**
  - 3-hourly dataset, Spatial resolution: ~80 km. Splined to give hourly data
  - **Satellite O_3 observations have poor surface sensitivity**, and their daily **temporal sampling is also hampered by cloud cover**. The **CAMS reanalysis assimilates satellite O_3 (OMI, GOME-2, SCIAMACHY) and precursor species observations (NO_2, CO, and AOD)** which have better surface sensitivity.
  - CAMS therefore offers **better spatiotemporal resolution data** with better agreement with surface measurements than raw satellite observations
- **Meteorology: ERA5 Reanalysis (ECMWF)**
  - Hourly dataset, Spatial resolution 0.25° x 0.25°
  - Direct satellite observations of photosynthesis parameters (e.g. **air temperature, vapour pressure**) are not possible. ERA5 **assimilates both satellite and surface observations** to provide long-term climate records for such variables

Satellite datasets

- **GPP: MOD17A2 (NASA, University of Montana)**
  - **Monthly resolution**, 0.05º spatial resolution
  - Derived from observations of absorbed photosynthetically active radiation (APAR) by **MODIS**
- **Land cover classification: ESA-CCI (ESA)**
  - **Annual land cover** (300 m) maps derived from multiple hyperspectral satellite missions (e.g. **AVHRR, PROBA-V**)
  - **Combined with EEA biogeographic zones** to classify vegetation according to **plant functional types** (PFTs) used in the LRTAP Mapping Manual (**Boreal coniferous, Mediterranean deciduous, etc.**)
- **Phenology (growing season): AVHRR GIMMS LAI3g (Boston University)**
  - 15-day temporal frequency and a 1/12º spatial resolution of LAI
  - **Growing season onset and offset DOY** derived from this dataset using the **4GST algorithm** discussed in Peano et al (2019)

Land cover classification example (2012)



Calculation of stomatal conductance to O_3 (g_{sto})

- Stomatal opening & gas interchange dependent on whether conditions favour photosynthesis:
  - Photosynthetically active radiation (PAR)
  - Vapour pressure deficit (VPD)
  - Soil water content (SWC)
  - Air temperature (T)
  - Growing season (phenology)

Calculation of stomatal conductance to O_3 (g_{sto})

- Jarvis model as used in **DO_3SE** (Emberson et al, 2000):

$$g_{sto} = g_{max} * f_{PAR} * f_{phen} * \max\{f_{min}, (f_T * f_{VPD} * f_{SWC})\}$$

- Maximum possible g_{sto} (g_{max}) scaled by f terms (0 – 1) based on variables calculated from ERA5 and phenology from processed LAI3g data
- f_{phen} = 1 if DOY falls within growing season, else is 0
- $f_{min:}$ Minimum possible stomatal conductance as a fraction of g_{max}
- Plant functional type specific terms (**f_{min}, g_{max}, T_{opt}, etc.**) taken from **LRTAP Mapping Manual** (UNECE, 2017)
- g_{sto} calculated for summer growing months **(April – September) during 2003 – 2015**, as [O_3] peaks during this time

Calculation of stomatal conductance to O_3 (g_{sto})

- **Temperature:** $f_T = \max\left\{f_{min}, \frac{T - T_{min}}{T_{opt} - T_{min}} \left(\frac{T_{max} - T}{T_{max} - T_{opt}}\right)^{\frac{T_{max} - T_{opt}}{T_{opt} - T_{min}}}\right\}$

- **VPD:** $f_{VPD} = \min\left\{1, \max\left(f_{min}, (1 - f_{min}) \frac{VPD_{min} - VPD}{VPD_{min} - VPD_{max}} + f_{min}\right)\right\}$

- **PAR**: $f_{PAR} = 1 - e^{-light_a PAR}$

Calculation of stomatal conductance to O_3 (g_{sto})

- **SWC** parameterisation taken from Anav et al (2018)

$$f_{SWC} = \min\left\{1, \max\left(f_{min}, \frac{SWC - WP}{FC - WP}\right)\right\}$$

- **FC**: SWC at **field capacity**
- **WP**: SWC at **wilting point**
- FC and WP taken from **ESDAC Soil Hydraulic Database** regridded to ERA5 horizontal and vertical resolution
- Tree roots are known to penetrate up to 1 m below surface, so the **mean SWC of ERA5 layers 1-3** was used

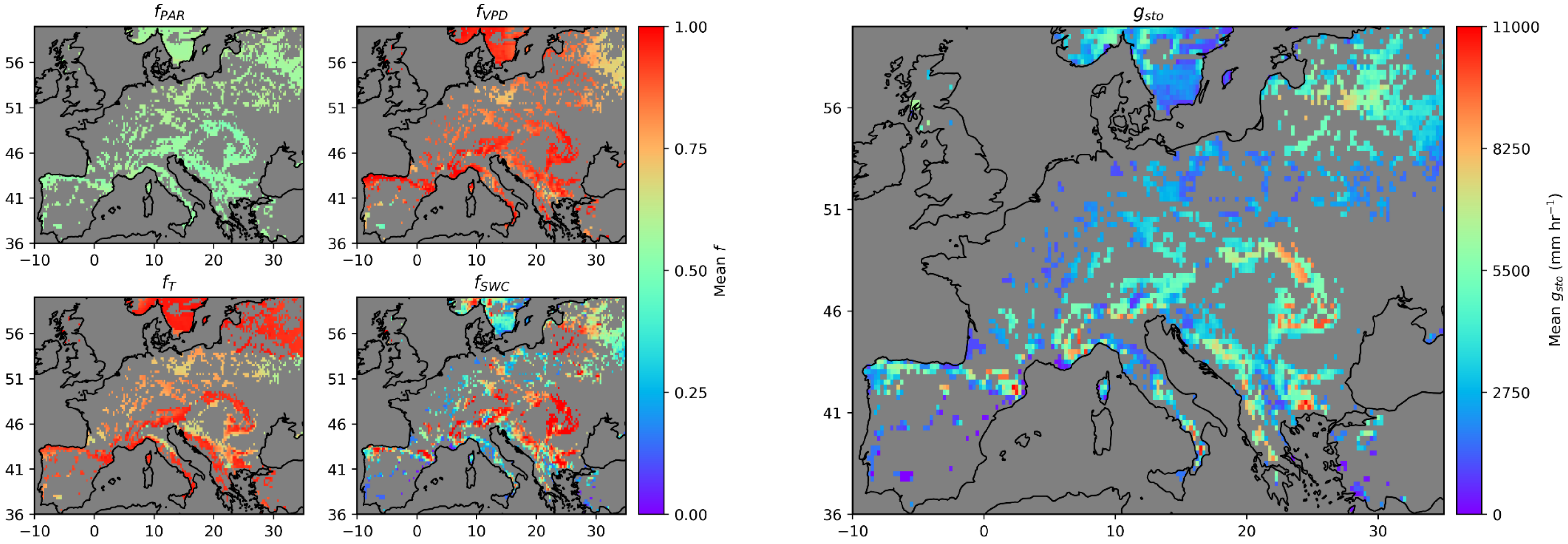
ERA5 Soil layer	ERA5 soil depth	ESDAC SHD depths binned
1	0 – 7 cm	0, 5 cm
2	7 – 28 cm	15 cm
3	28 – 100 cm	30, 60, 100 cm
4	100 – 280 cm	100, 280 cm

Calculation of stomatal conductance to O_3 (g_{sto})

Parameter	Units	Forest tree species parameterisation - POD_1SPEC					
Region *(may also be applicable in these regions)*		Boreal *(Atlantic, Steppic, Pannonian)*		Continental *(Atlantic, Steppic, Pannonian)*		Mediterranean	
Forest type		Coniferous	Broadleaf deciduous	Coniferous	Broadleaf deciduous	Broadleaf deciduous	Evergreen
Tree species		**Norway spruce**	**Birch**	**Norway spruce**	**Beech**	**Deciduous oak species**[i, ii]	**Evergreen species**[iii]
g_{max}	mmol O_3 m^{-2} PLA s^{-1}	125	240	130	155	265	195
f_{min}	fraction	0.1	0.1	0.16	0.13	0.13	0.02
light_a	-	0.006	0.0042	0.01	0.006	0.006	0.012
T_{min}	°C	0	5	0	5	0	1
T_{opt}	°C	20	20	14	16	22	23
T_{max}	°C	200[iv]	200[iv]	35	33	35	39
VPD_{max}	kPa	0.8	0.5	0.5	1.0	1.1	2.2
VPD_{min}	kPa	2.8	2.7	3.0	3.1	3.1	4.0
Leaf dimension	cm	0.8	5.0	0.8	7.0	4.2	3

LRTAP Mapping Manual (2017)

Mean O_3 g_{sto} for July 2010



Estimation of O_3-induced GPP reduction

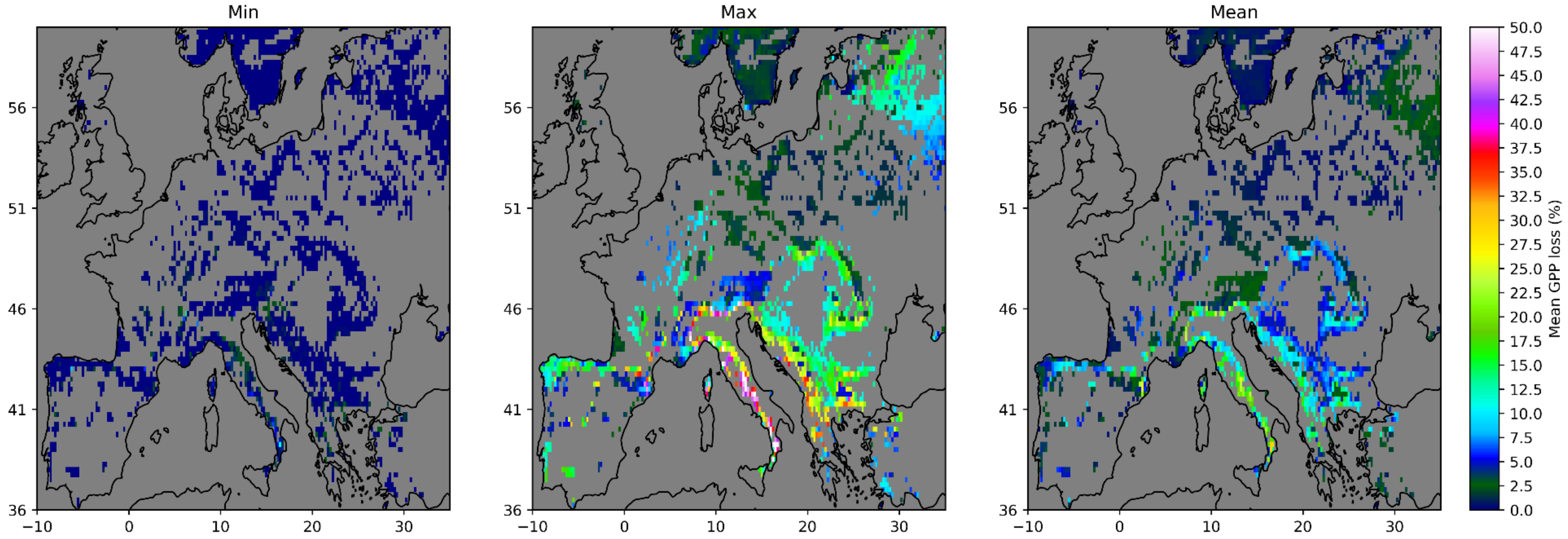
- Previously used in Anav et al (2011) and Proietti et al (2016)
- Typically $\boldsymbol{AOT40}$ ($\int(\mathbf{[O_3] - 40\ ppb})\,\boldsymbol{dt}$) is used to estimate O_3 effects on vegetation
- If $\boldsymbol{g_{sto}}\times\boldsymbol{AOT40}$ **represents O_3 uptake by vegetation**, then **change in photosynthesis (and so GPP) due to O_3** can be expressed as a dimensionless value, $\boldsymbol{I_{O_3}}$ by multiplying this with an appropriate sensitivity parameter α:

$$\boldsymbol{I_{O_3} = \alpha\times g_{sto}\times AOT40}$$

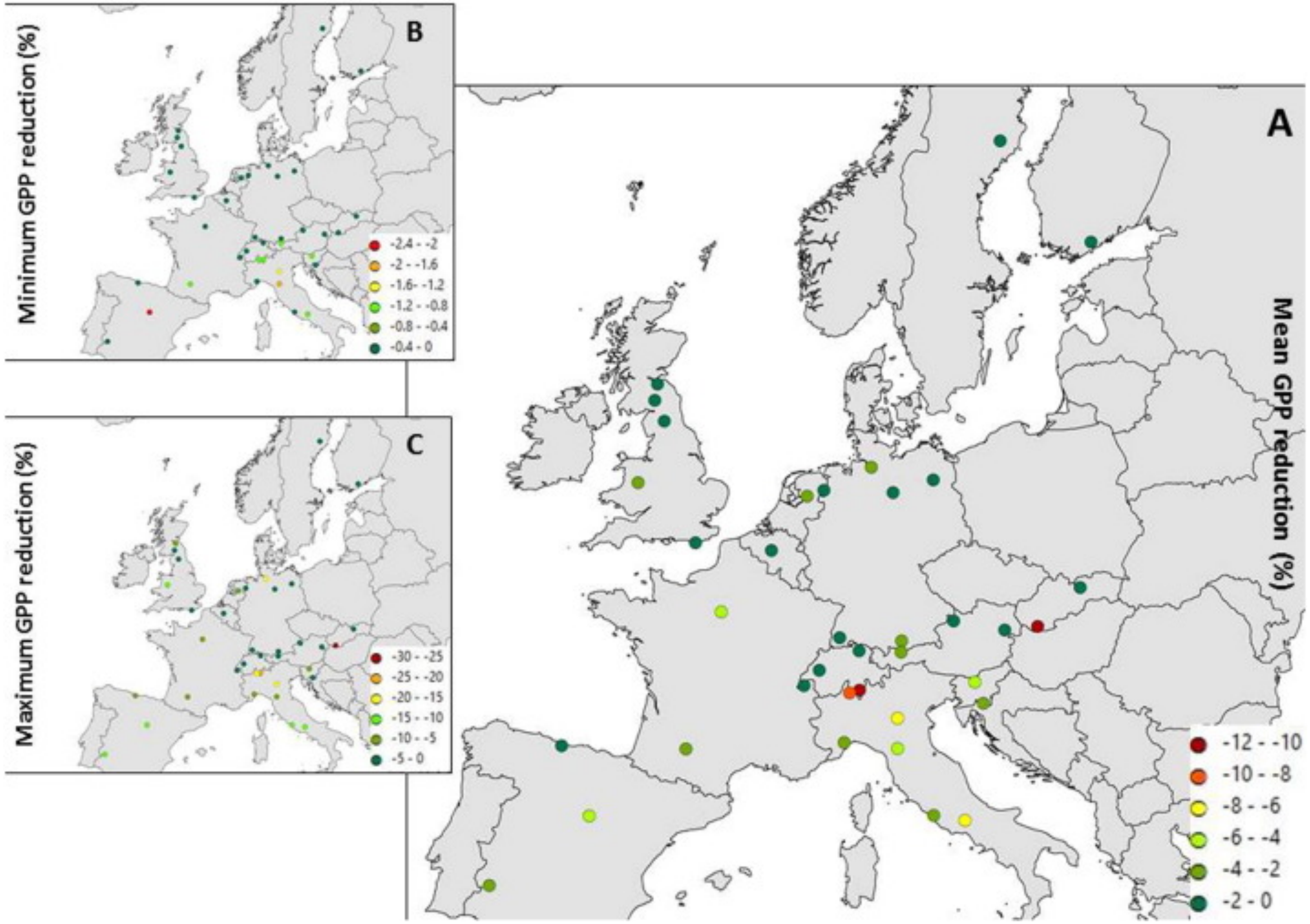
$$\text{Dimensionless} = [\text{mm}^{-1}\ \text{ppb}^{-1}] \times [\text{mm hr}^{-1}] \times [\text{ppb hr}]$$

- Values for **α** taken from **literature references**:
  - Coniferous trees: 0.7×10^{-6} (Reich, 1987)
  - Deciduous trees: 2.6×10^{-6} (Ollinger et al, 1997)
- I_{O_3} can be interpreted as the fraction of GPP in O_3-free conditions lost due to O_3 exposure

Results (monthly means)

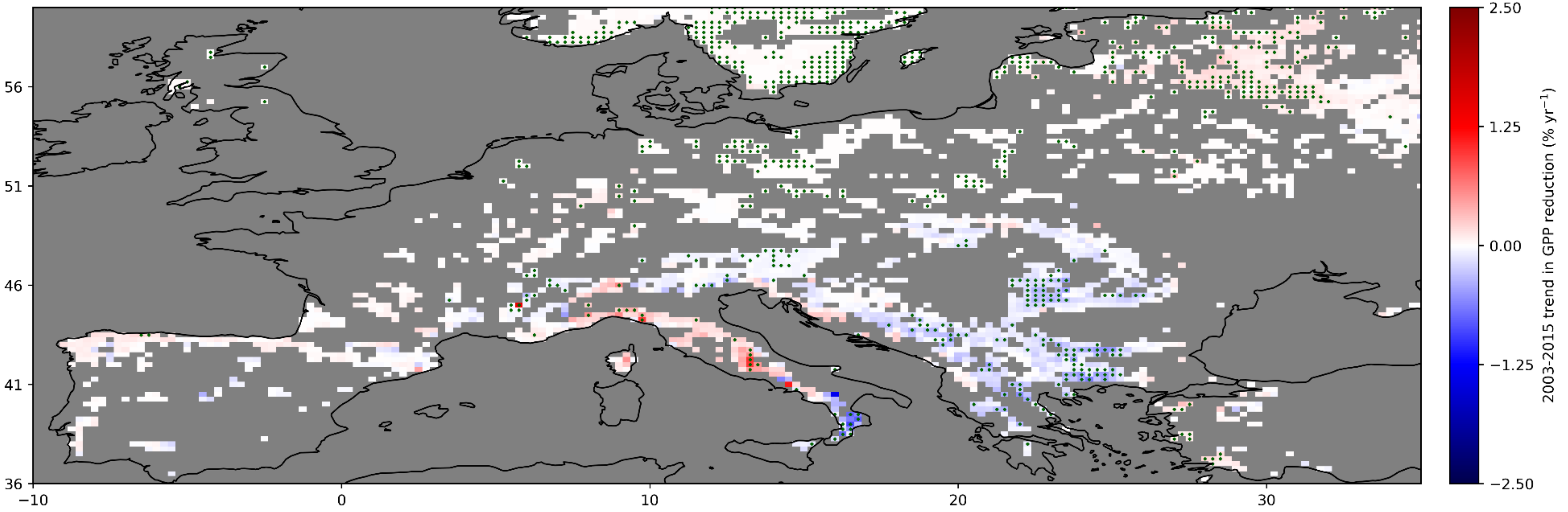


O_3-induced GPP reductions using forest in-situ O_3 measurements (Proietti et al, 2016)



- Comparable magnitudes and spatial distribution of GPP reduction estimates
- However, comparison is limited by the spatial sampling of the in-situ stations

Annual mean trend (dots: $p < 0.05$)



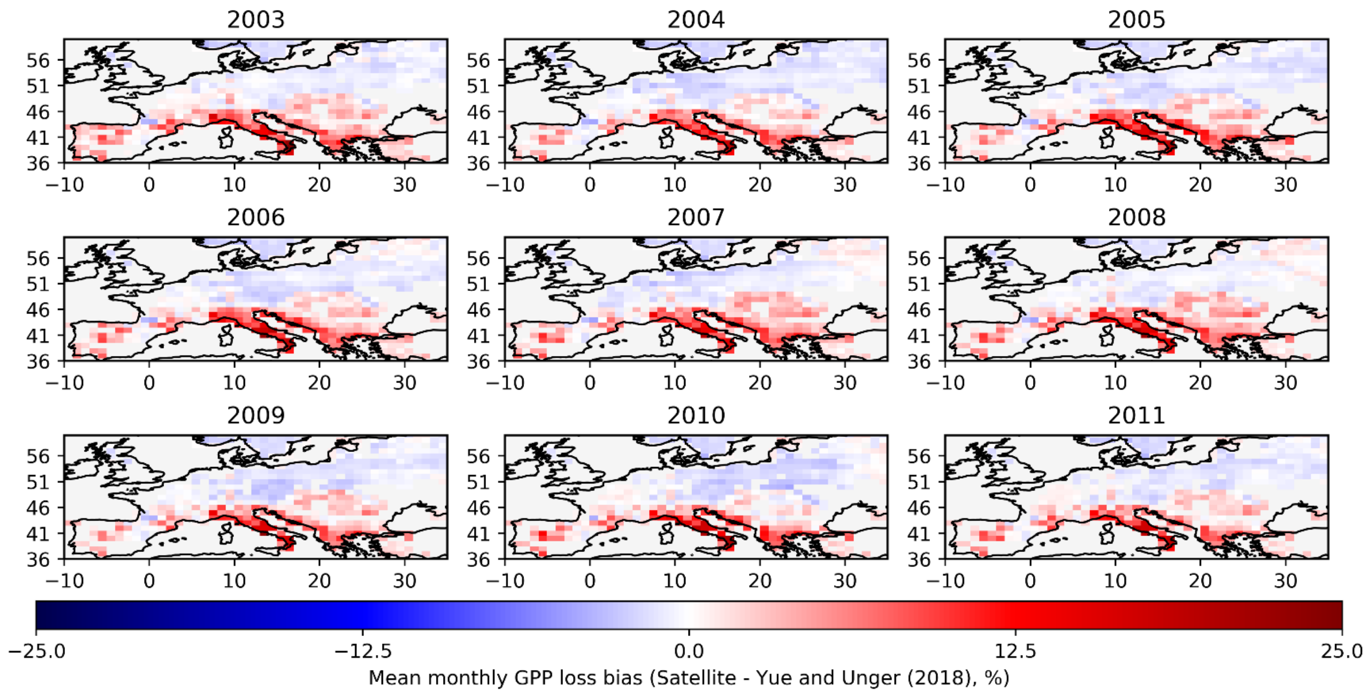
Parameter importance using Random Forest regression

- GPP reduction has **nonlinear dependence** on O_3 concentration and meteorology – **which has the largest influence?**
- Fit **Random Forest regression** model of I_{O_3} **against component parameters**.
- **"Gini importance"** (frequency parameter appears in decision trees) calculated for each parameter over different regions
- **Strong dependence on soil moisture**

	T	VPD	SWC	PAR	O_3 concentration
British Isles	16.10	6.62	19.71	4.58	**53.00**
Iberian Peninsula	15.87	4.70	29.90	**40.67**	8.86
France	11.40	21.15	**29.40**	28.66	9.39
Mid-Europe	7.98	3.27	**62.02**	4.82	21.91
Scandinavia	5.94	2.87	**58.33**	2.69	30.17
Alps	3.16	3.39	11.80	6.22	**75.42**
Mediterranean	4.43	7.26	**53.04**	30.43	4.84
Eastern Europe	15.99	10.66	18.50	6.25	**48.59**

Comparison with Yale Interactive terrestrial Biosphere (YIBs) model data

- **Yue and Unger (2018)** used YIBs model to investigate global fire and anthropogenic O_3-induced GPP reductions between 2003 – 2011.
- **O_3** concentrations modelled using **GEOS-Chem and ERA-Interim data**
- Overall good agreement…
- … but Italian and Greek GPP reductions are consistently overestimated by ~ 12%, potentially due to differences between the CAMS and GEOS-Chem O_3 concentrations

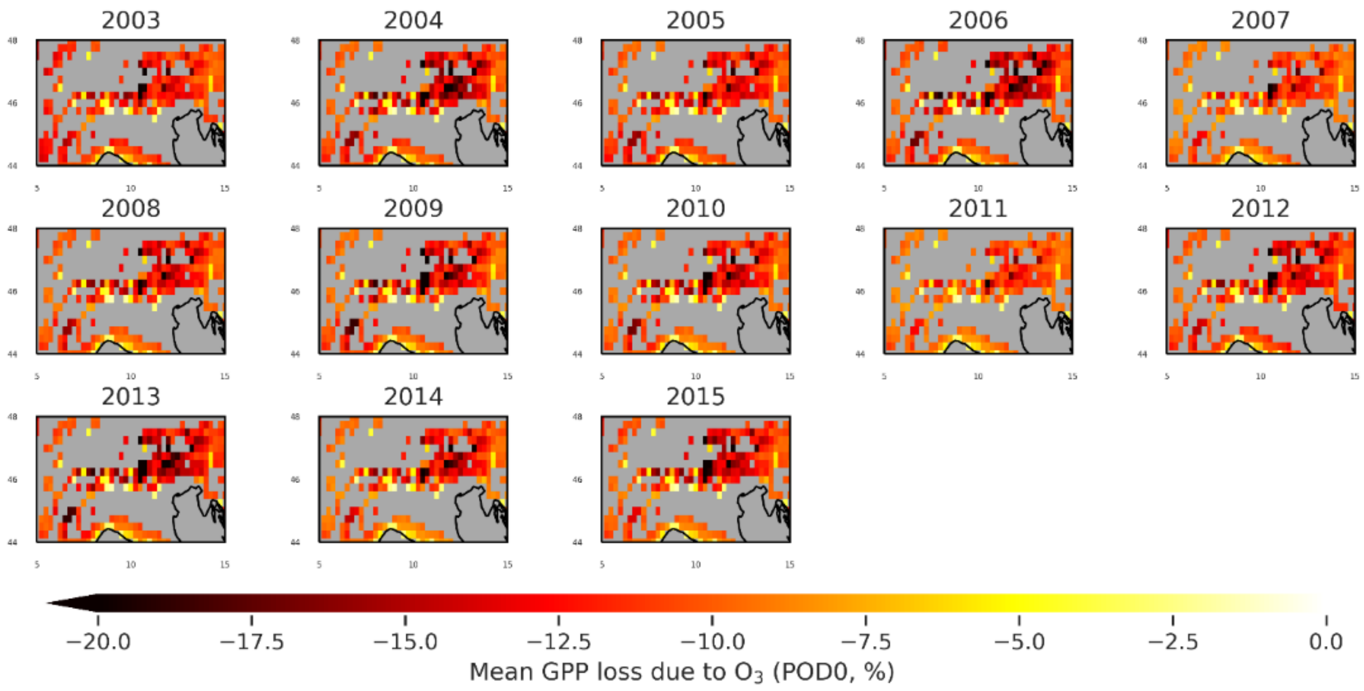


Regression modelling of GPP reductions

- Can GPP-O_3 reductions be directly inferred from satellite data?
- **MODIS GPP** is regressed against: **VPD, SWC, Temperature, PAR, and POD_0**
- **POD_0** = ($\int (g_{sto} \times [O_3]) dt$)
- **Nonlinear effects** (2nd order polynomial, two-way interaction terms, and GPP lag terms) included – **21 candidate variables**
- To minimise effect of multicollinearity, use induced smoothing LASSO (**ISLASSO**; Cilluffo et al, 2020) to perform **variable selection** and reliably **calculate p-values & standard errors**
- O_3 effect on GPP estimated by calculating $\frac{d(GPP)}{d(POD_0)}$ from model fit (**$p < 0.05$ terms only**)
- Fit models for each vegetation type using 2003-2013 data, and validate against 2014-2015 data

Case study: Alps

Parameter	Coefficient	Std err	p-value
T	85.837	13.127	0.000
T^2	-0.148	0.023	0.000
VPD	296.532	124.946	0.018
SWC	2116.363	620.532	0.001
PAR	2.257	0.272	0.000
PAR^2	-0.001	0.000	0.000
O_3	143.123	21.353	0.000
GPP (Lag 1)	0.931	0.120	0.000
T*VPD	-1.500	0.441	0.001
T*SWC	-5.861	2.145	0.006
T*O_3	-0.559	0.075	0.000
VPD*SWC	683.315	240.201	0.004
SWC*PAR	-1.398	0.454	0.002



- Validation R^2: 0.934, negative $\frac{d(GPP)}{d(POD_0)}$ caused by T*O_3 coefficient
- High O_3 concentrations caused by Po Valley emissions and high terrain blocking dispersion of air mass. Warm temperatures and low VPD also ensure high stomatal conductance for much of the summer
- GPP reductions nearing 20% consistent with Proietti et al (2016) and previous literature-based analysis. However, strong multicollinearity between variables prevents this method working as well elsewhere.

Conclusions

- **This work has demonstrated for the first time that satellite O_3, land cover, vegetation, and meteorological data can be used to estimate O_3-induced GPP reductions.** The magnitude and spatial distribution of these predicted reductions show strong similarity to prior land surface model and in-situ based analyses.
- Satellite data could potentially be used to assess O_3 damage to more remote ecosystems and better understand vegetation feedbacks in a changing climate.
- Potential overestimation over the Mediterranean requires further investigation.
- **Average monthly O_3-induced GPP reductions range between 2 – 25%**, with Italian forests reaching **~50% during severe O_3 episodes.**
- Jarvis stomatal conductance model **suggests strong dependence of GPP reductions on soil moisture** over most regions.
- **Direct estimation of GPP reductions** using **MODIS data** and **statistical modelling** may be useful for independent verification of model-based analyses. However, high multicollinearity between variables prevents this method from working well everywhere

Remaining work

- Calculate crop yield losses using literature functions
- Investigate reasons for lack of O_3 sensitivity observed over some forests with the statistical model
- Draft publications on Empirical and Statistical methods to model O_3-induced GPP reductions from satellite

References

- Eyring, V et al: Long-term ozone changes and associated climate impacts in CMIP5 simulations, J. Geophys. Res.-Atmos., 118, 5029–5060, https://doi.org/10.1002/jgrd.50316, 2013
- Meehl, G. A. et al: Future heat waves and surface ozone, Environ. Res. Lett. 13, 064004, https://doi.org/10.1088/1748-9326/aabcdc, 2018
- Fishman, J. et al: An investigation of widespread ozone damage to the soybean crop in the upper Midwest determined from ground-based and satellite measurements, Atmos. Environ., 44, 2248–2256, https://doi.org/10.1016/j.atmosenv.2010.01.015, 2010
- Emberson, L. D. et al: Modelling stomatal ozone flux across Europe, Environ. Pollut., 109, 403–413, http://doi.org/10.1016/S0269-7491(00)00043-9, 2000
- LRTAP: ICP Vegetation, Chapter 3, Mapping critical levels for vegetation: https://icpvegetation.ceh.ac.uk/get-involved/manuals/mapping-manual, 2017
- Anav, A et al: Sensitivity of stomatal conductance to soil moisture: implications for tropospheric ozone, Atmos. Chem. Phys., 18, 5747–5763, https://doi.org/10.5194/acp-18-5747-2018, 2018
- Reich, P. B.: Quantifying plant response to ozone: a unifying theory, Tree Physiol., 3, 63–91, https://doi.org/10.1093/treephys/3.1.63, 1987
- Ollinger, S. V. et al: Simulating ozone effects on forest productivity: interactions among leaf, canopy, and stand-level processes, Ecol. Appl., 7, 1237–1251, https://doi.org/10.1890/1051-0761(1997)007[1237:SOEOFP]2.0.CO;2, 1997
- Proietti, C. et al: A multi-sites analysis on the ozone effects on Gross Primary Production of European forests, Sci. Total Environ., 556, 1–11, 2016
- Anav, A. et al: Impact of tropospheric ozone on the Euro-Mediterranean vegetation, Glob. Change Biol., 17, 2342–2359, 2011
- Yue, X. and Unger, N.: Fire air pollution reduces global terrestrial productivity, Nat. Commun., 9, 5413, https://doi.org/10.1038/s41467-018-07921-4, 2018
- Cilluffo, G. et al: The Induced Smoothed lasso: A practical framework for hypothesis testing in high dimensional regression, Stat Methods Med Res., 29, 765-777, https://doi.org/10.1177%2F0962280219842890, 2020