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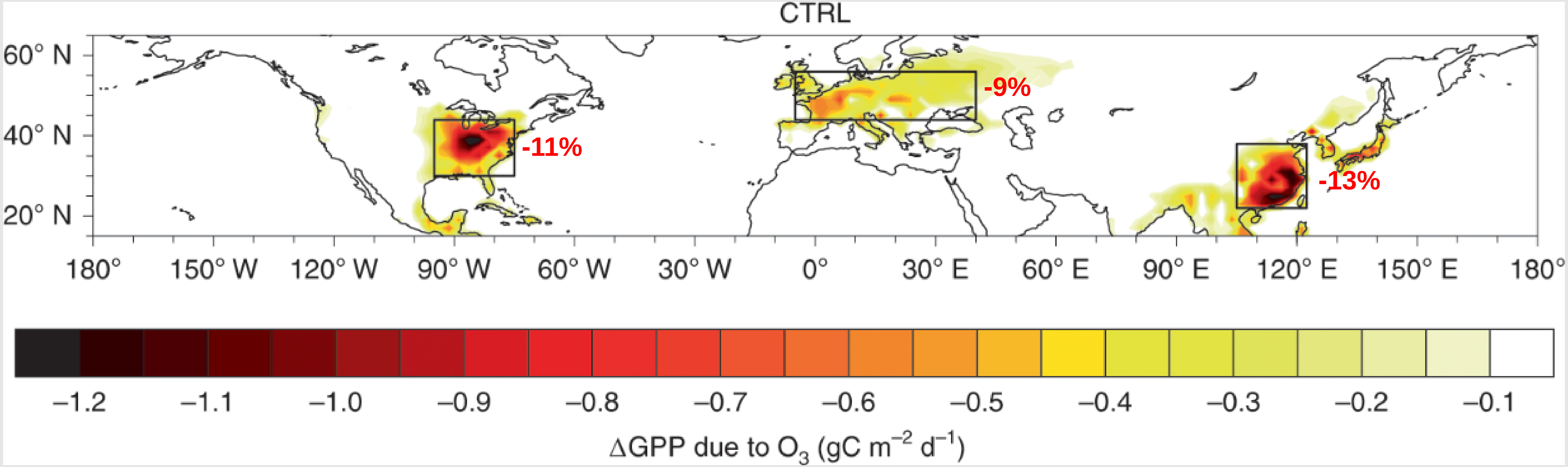
Estimating the effect of tropospheric O_3 on GPP over European forests using satellite data

Jasdeep Singh Anand (UoL), **Alessandro Anav** (ENEA, Italy), **Marcello Vitale** (Sapienza Uni. Of Rome, Italy), **Daniele Peano** (Euro-Mediterranean Center on Climate Change, Italy), **Nadine Unger** (University of Exeter), **Xu Yue** (NUIST, China)

Impact of O_3 on the land carbon sink



Unger et al, 2020

Can satellite data help?

Advantages:

- **Continuous measurements** approaching 20+ years for many variables
- Often **single instruments** used to cover entire planet – **inter-calibration unnecessary**
- Superior **spatio-temporal coverage** compared to in-situ measurements
- **Simultaneous observation** of many **different variables** possible from a single instrument

Disadvantages:

- Dependent on unobstructed view of the surface – **cloud cover means no observation**
- Passive methods rely on sunlight – **no night-time observations** possible
- Many datasets are of **daily measurements only** – hourly observations impossible outside of specialist geostationary missions (e.g. temperature)
- Some variables not possible to observe directly without **model assimilation** into a model (e.g. GPP, air temperature)

Necessary variables

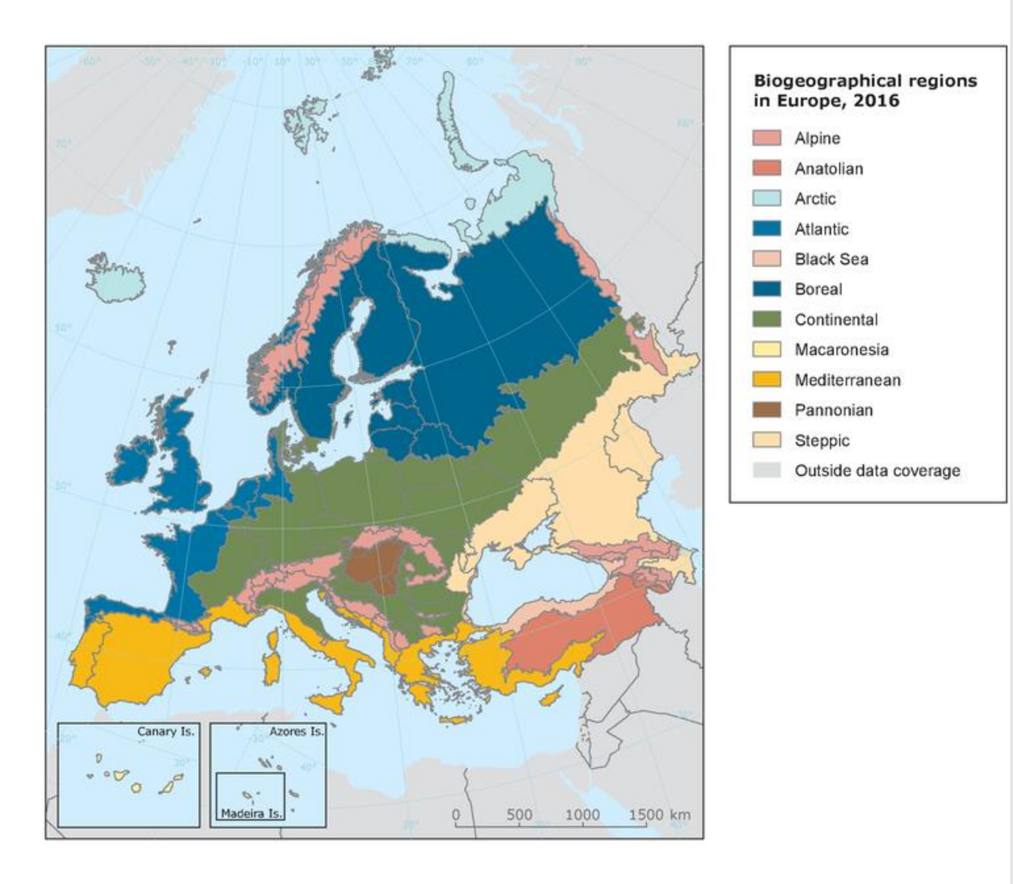
- **Stomatal conductance to O_3 (g_{sto})** is calculated using the Jarvis (1979) model, which requires the following variables:
  - **Vegetation type**
  - Photosynthetically active radiation (***PAR***)
  - Vapour pressure deficit (***VPD***)
  - Soil water content (***SWC***)
  - Air temperature (***T***)
  - Phenology (**growing season start/end**)
- **O_3 exposure** is usually calculated as accumulated exposure over 40 ppb (***AOT40***), so *hourly* data is needed

Vegetation type: ESA-CCI Land Cover

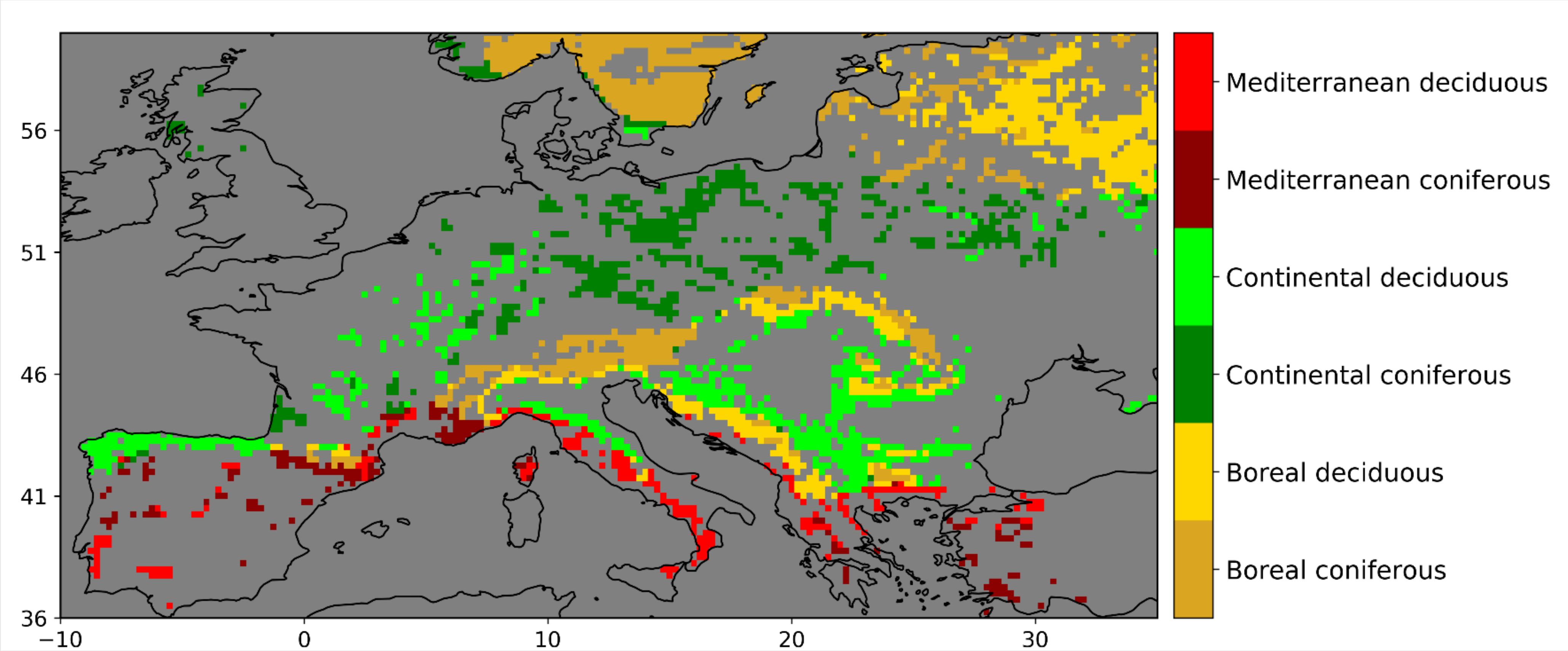
- Available from: http://maps.elie.ucl.ac.be/CCI/viewer/
- **Annual** land cover class from **1992-2019;** derived from imaging satellites (e.g. AVHRR, PROBA-V)
- **300 m resolution**

Vegetation type: EEA Biogeographical Regions

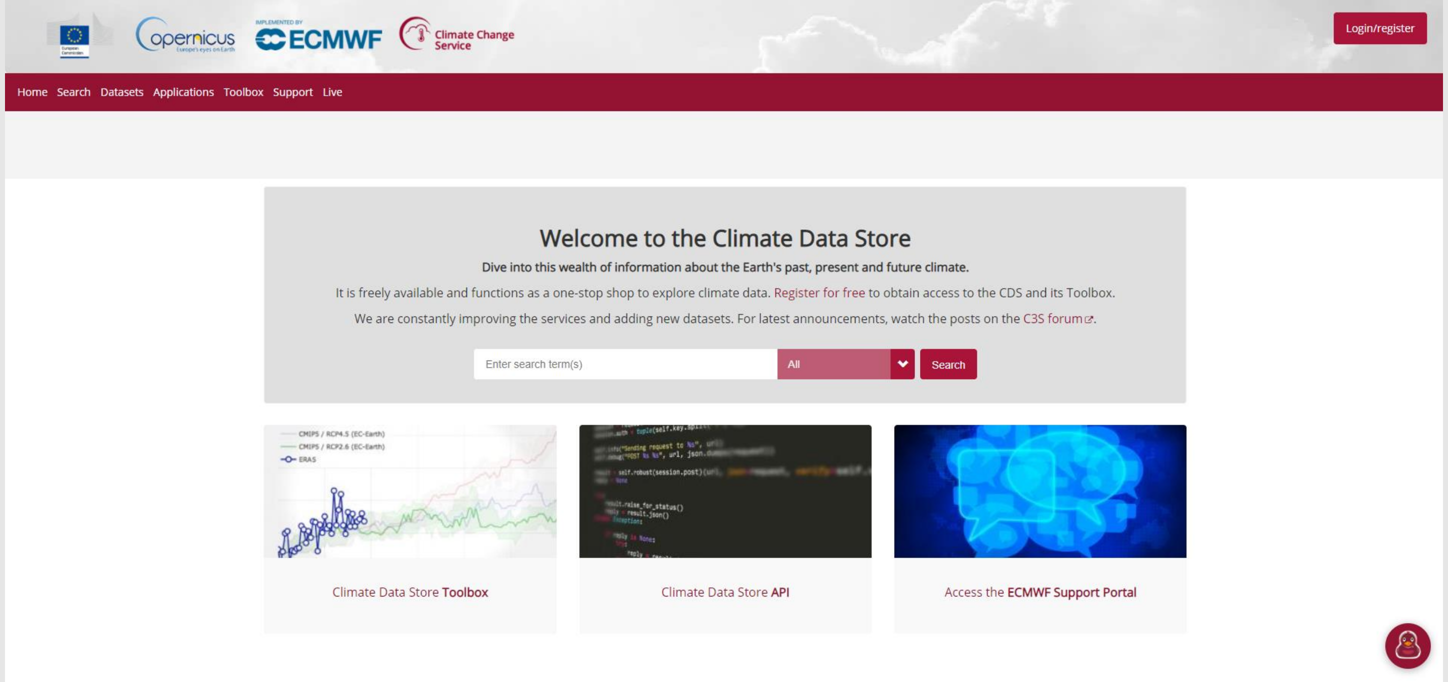
- Available from:
- https://www.eea.europa.eu/data-and-maps/data/biogeographical-regions-europe-3
- Climate/vegetation zones
- **Vector** dataset



ESA-CCI + EEA data (2012) = DO_3SE classes



SWC, PAR, T, VPD: ECMWF ERA5 reanalysis



- Available from: https://cds.climate.copernicus.eu/
- **Hourly** climate data from **1979-today;** assimilated in-situ and satellite data
- **0.25° resolution; SWC available from 0 – 2 m soil depth (Only < 1 m validated)**

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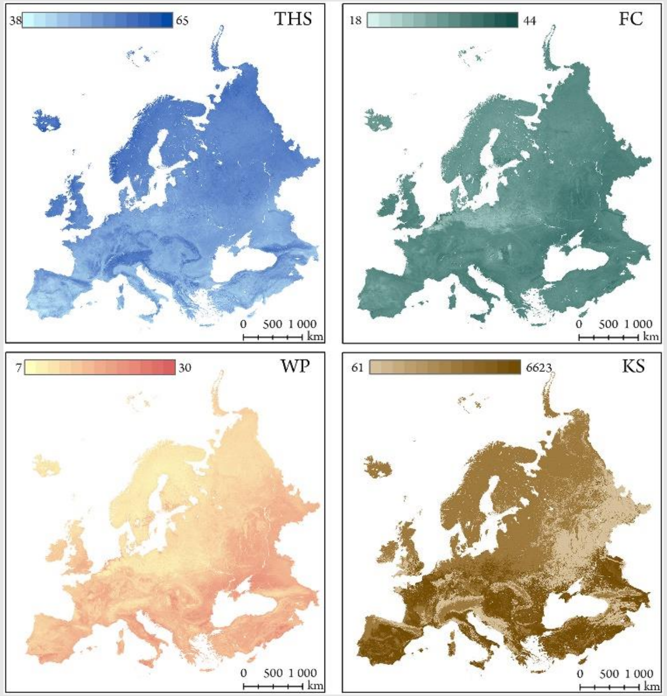
SWC: ESDAC EU-SoilHydroGrids Database

Parameterising SWC on g_{sto} requires knowledge of soil:

- **WP**: Wilting point
- **FP**: Field capacity



Tóth et al, 2017

ERA5 soil layer	ERA5 soil depth	ESDAC EU-SHG 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

- Available from: https://esdac.jrc.ec.europa.eu/content/3d-soil-hydraulic-database-europe-1-km-and-250-m-resolution
- **WP and FP given at 0, 5, 15, 30, 60, 100, and 200 cm – necessary to bin these to ERA-5 soil levels**
- **1 km or 250 m resolution**

Phenology (growing season): AVHRR GIMMS LAI3g

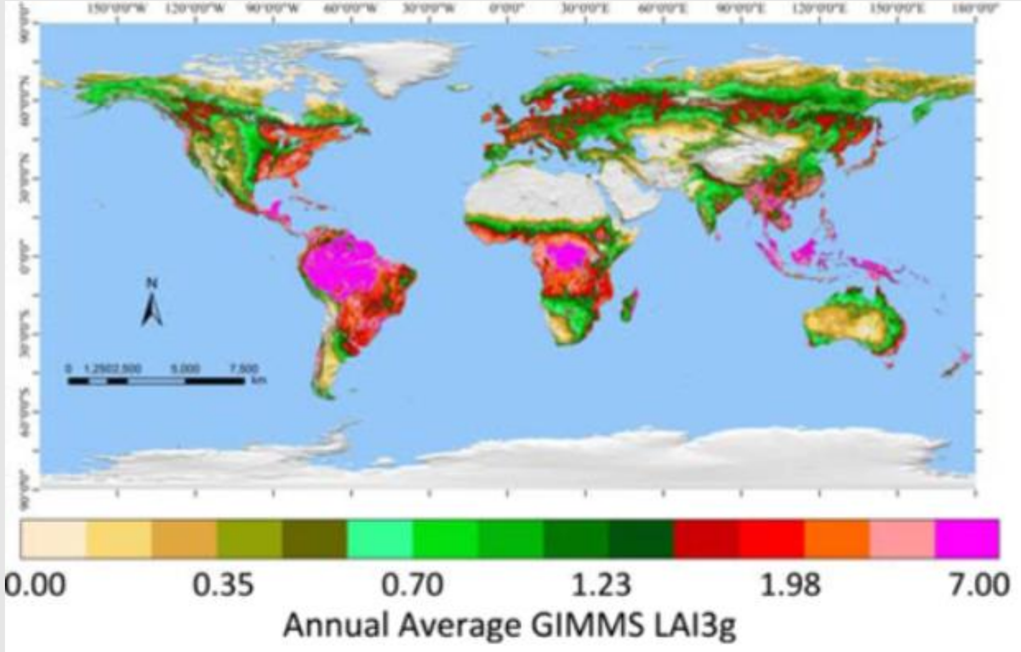
- **Leaf Area Index (LAI)** from AVHRR satellite available from:

http://cliveg.bu.edu/modismisr/lai3g-fpar3g.html

- **15-day data** from **1981-today**
- Growing season start/end DOY calculated using **4GST algorithm** (Peano et al, 2019):

https://github.com/daniele-peano/4GST

- **1/12° resolution**



Zhu et al, 2013

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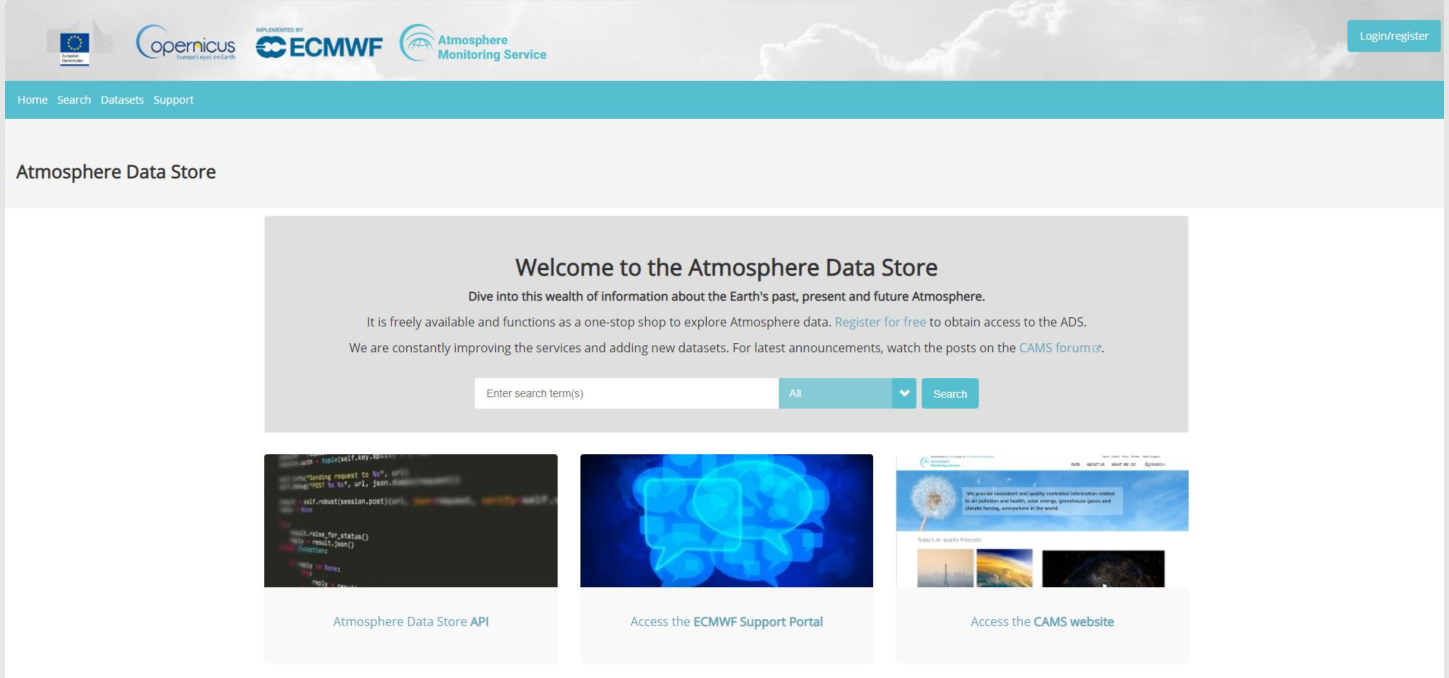
O_3: ECMWF CAMS reanalysis



- Available from: https://ads.atmosphere.copernicus.eu/
- **3-hourly** climate data from **2003-today;** assimilated satellite O_3, NO_2, CO, and aerosols
- **0.25° resolution**

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

- Jarvis model as used in **DO_3SE** (Büker et al, 2015):

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

- 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**: $f_{PAR} = 1 - e^{-light_a PAR}$
- **SWC**: $f_{SWC} = \min\left\{1, \max\left(f_{min}, \frac{SWC-WP}{FC-WP}\right)\right\}$

WP, FC taken from ESDAC database, mean of SWC of 0 – 1 m used (Anav et al, 2018)

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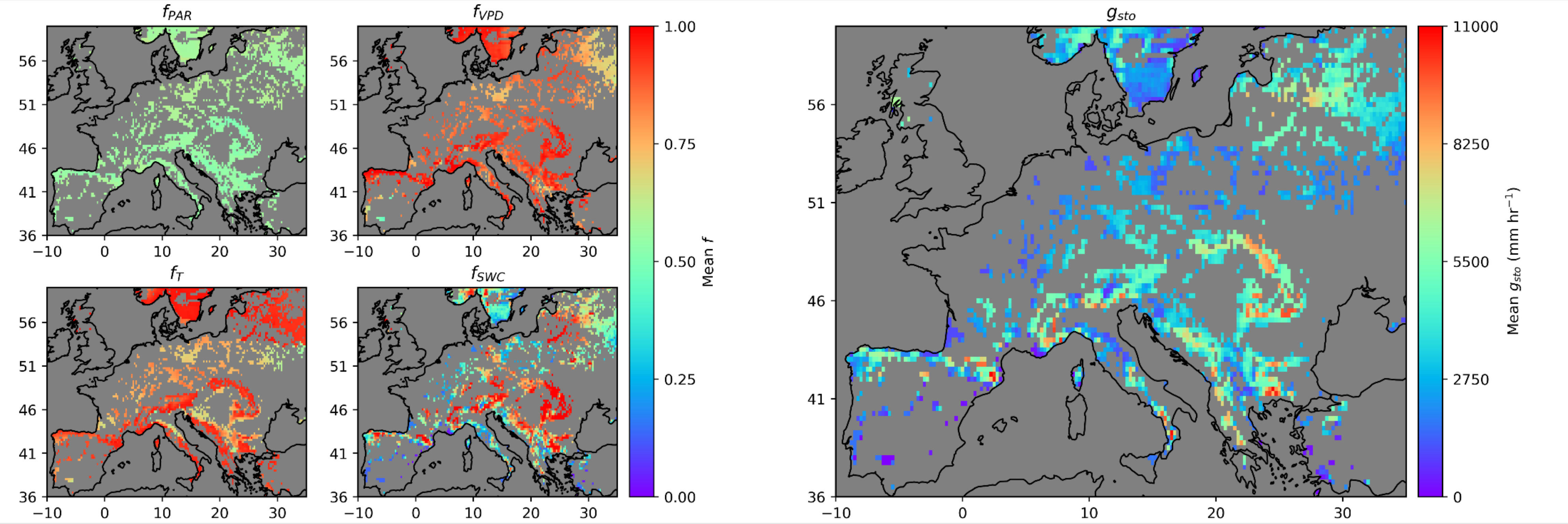
Mean O_3 g_{sto} for July 2010



Estimating O_3-induced GPP reductions

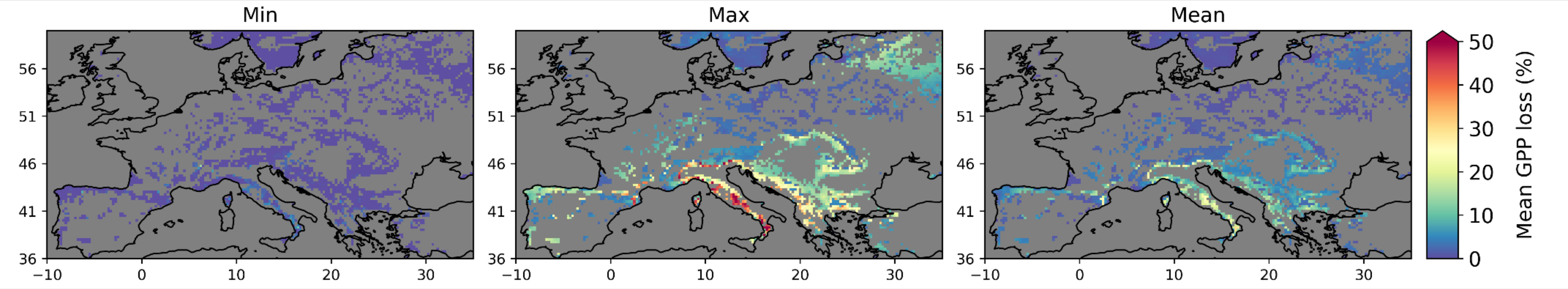
- Previously used in Anav et al (2011) and Proietti et al (2016)
- Typically $\boldsymbol{AOT40}$ **($\int$([O_3] – 40 ppb)** $\boldsymbol{dt}$**)** is used to estimate O_3 effects on vegetation
- If $\boldsymbol{g_{sto}} \times \boldsymbol{AOT40}$ **represents O_3 uptake by vegetation**, then **change 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:

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

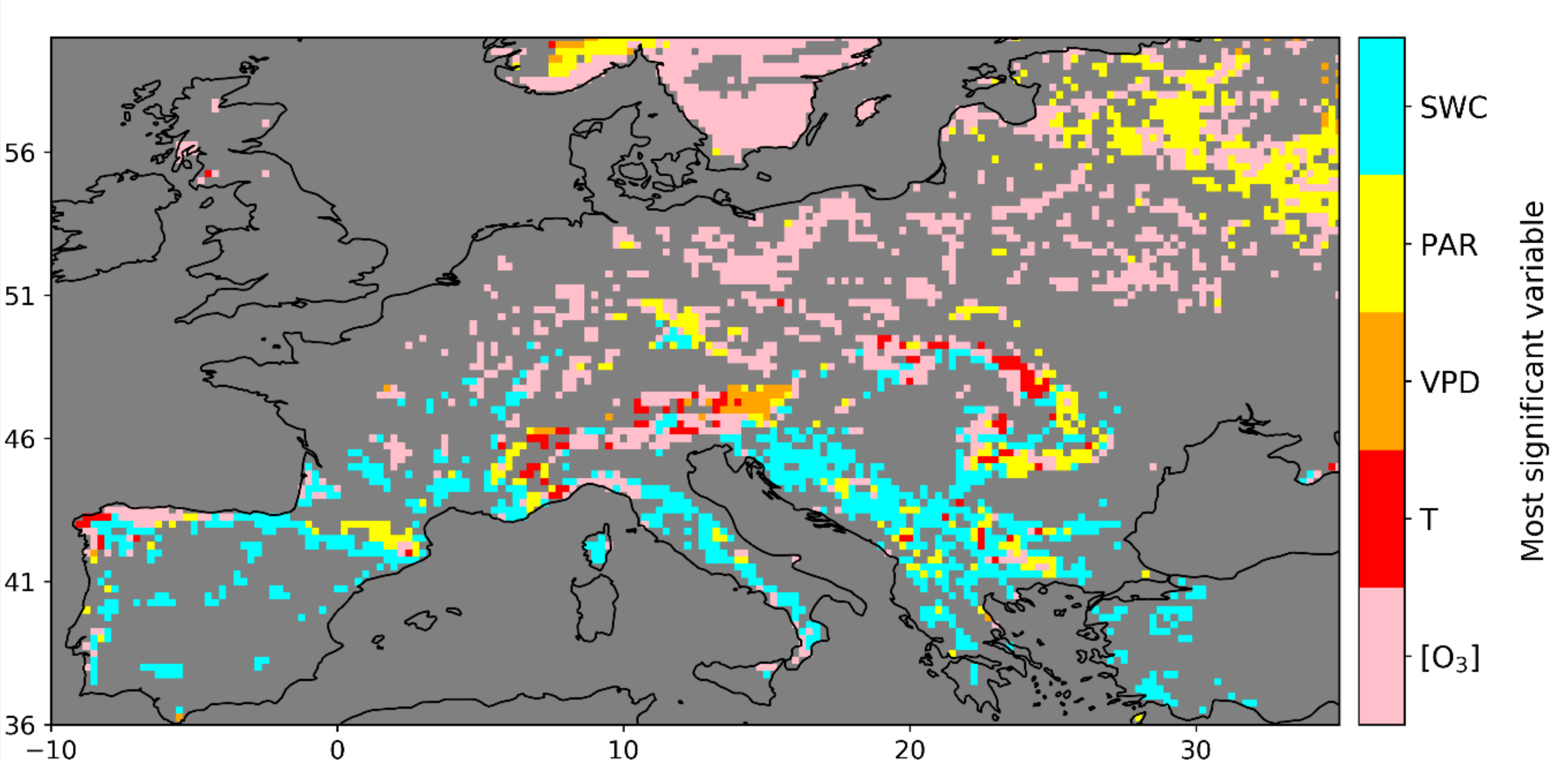
Dimensionless = [mm^{-1} ppb^{-1}] × [mm hr^{-1}] × [ppb hr]

- 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

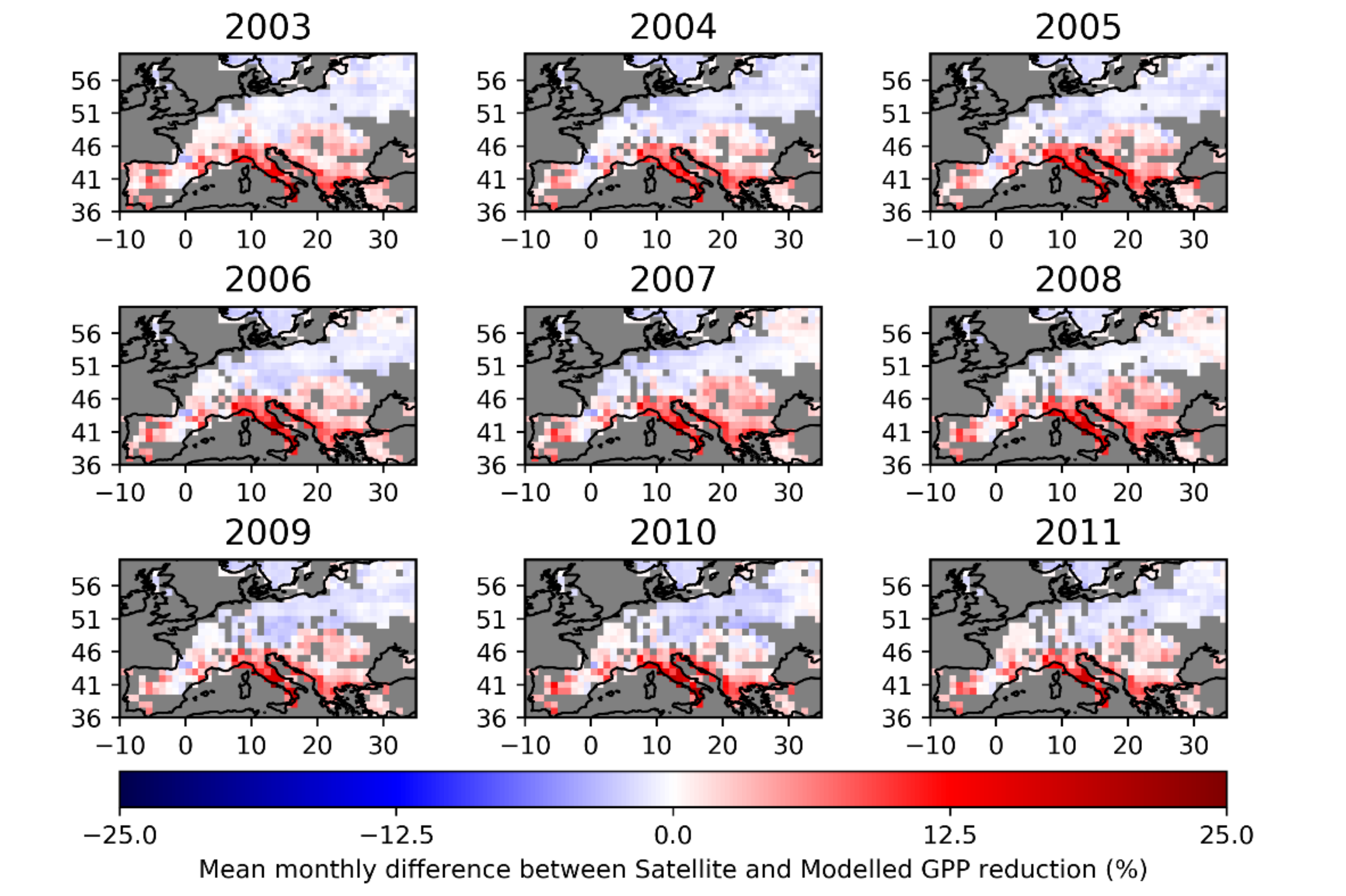
Results (monthly means)



Random forest analysis



Comparison with GPP losses simulated by YIBs (Low O_3 sensitivity – see Sitch et al 2007)



Model data from Yue and Unger (2018)

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** $(\int(g_{sto} \times [O_3])dt)$
- **Nonlinear effects** (2nd order polynomial, two-way interaction terms, and GPP lag terms) included – **21 candidate variables**
- 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 with 2003-2013 data, and validate against 2014-2015 data

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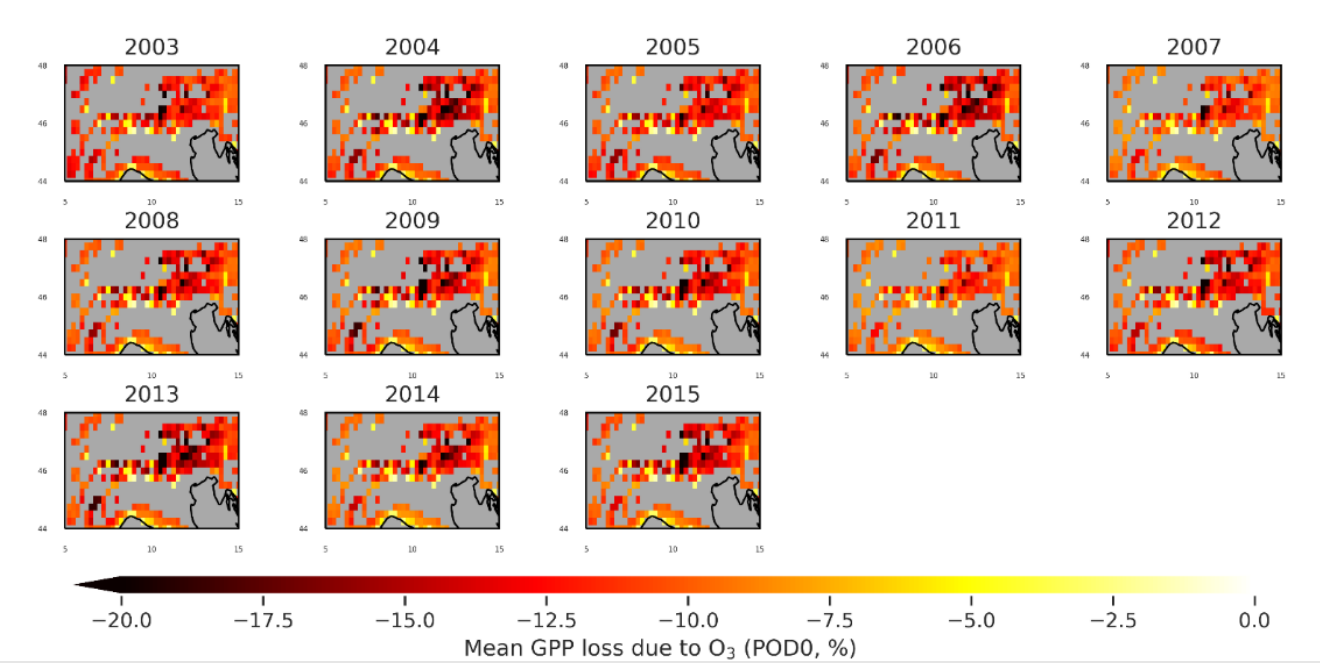
Case study: Alps

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
$PAR*O_3$	0.019	0.011	0.084



- 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

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, **but more work is needed**.

Outstanding questions

- The risk of droughts are likely to increase in the future, and O_3 concentrations are likely to at least remain at current levels under most climate change scenarios – **What would the effect of O_3 *and* drought stress on European forest GPP be?** Several possibilities:
    - **Drought causes stomatal closure**, so while GPP would fall due to drought, **O_3 deposition would be minimised**
    - *HOWEVER*, O_3 exposure causes "**stomatal sluggishness**" in some species – the stomata loses the ability to close under drought stress, **increasing transpiration and early death**
    - At the same time, **drought-induced stomatal closure increases O_3 concentrations**, as less O_3 is absorbed by vegetation
- **At high [O_3], photosynthesis and stomatal conductance decouples** (i.e. $\text{GPP} \not\propto g_{sto}$) – the model may be overestimating the effect of Mediterranean high O_3 episodes – but how do we account for this?
- Could **machine learning** models trained on these + other satellite datasets (e.g. canopy height) provide a better predictive model?

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Thank you!

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Questions?

Email: jsa13@le.ac.uk

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