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

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LIVING PLANET FELLOWSHIP

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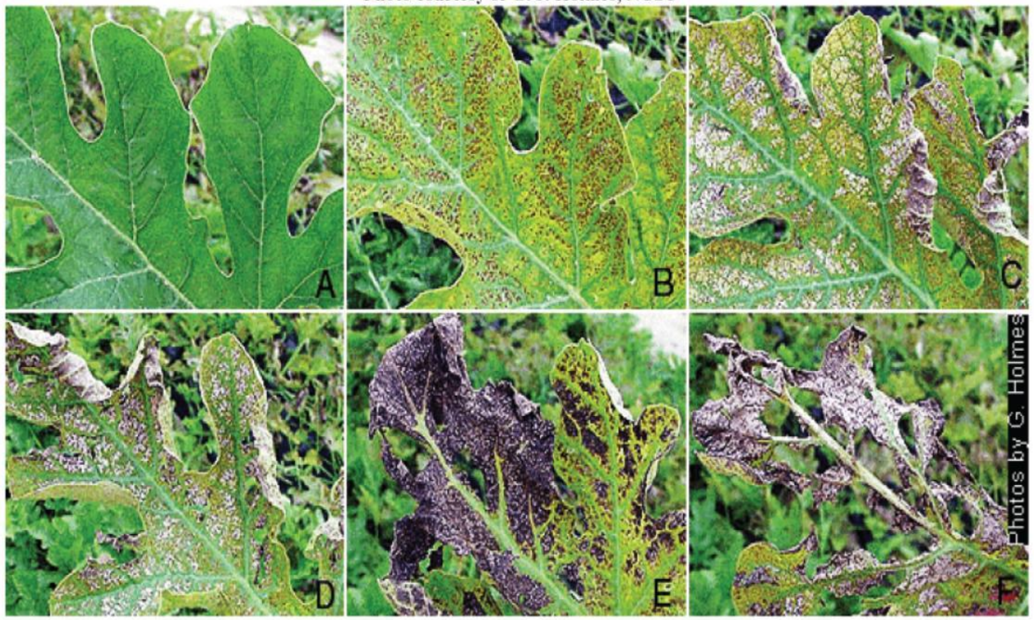
Introduction

- 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, which damage the cells and inhibits photosynthesis. Damaged plants grow less and age faster.
- Consequences for agriculture (**crop yield loss**) and climate change (**lower GPP; less CO_2 sequestered** by terrestrial carbon sinks)
- Despite emissions reductions in Europe & N. America, **[O_3] unlikely to fall further under most IPCC RCPs** (Eyring et al, 2013).
- Climate changes resulting in **more droughts/heatwaves** could also result in **greater high-O_3 episodes** (Meehl et al, 2018).

Fig. 2 Progression of ozone damage (A=none to F=severe) on watermelon foliage.
Photo courtesy of G. J. Holmes, NCSU



Brust, 2009

Research motivation

- **Prior studies of O_3-induced vegetation damage have been limited** to fumigation experiments, long-term time series analyses of forests, or modelling studies – limited to mainly N. America and Europe
- **Long-term satellite datasets for O_3, ambient conditions (e.g. temperature), and GPP/NPP exist**, but have **not been exploited to date** to look at this problem
- **Potential for global analyses** using satellite datasets to more accurately determine **cumulative crop yield & carbon lost due to O_3 damage**, and **to improve modelling future losses due to climate change**
- Good correlation of TOMS O_3 data and soybean crop yield over midwestern USA observed by Fishman et al (2010). Can a similar relationship be determined using newer, advanced data?

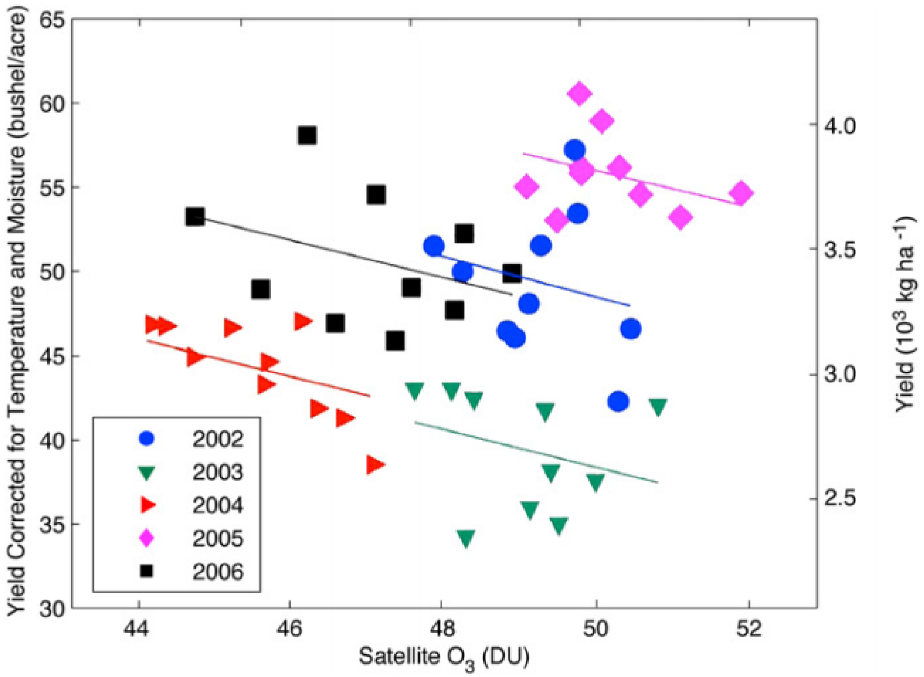


Fig. 5. Relationship between yield and satellite-derived O_3 over the southern region (37–40°N). Units for the yields on the left axis are taken directly from the USDA NASS database, which are provided in units of bushel acre^{-1}; 1 bushel acre^{-1} = 67.25 kg ha^{-1} and these units are shown on the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

Fishman et al, Atmos. Env., 2010

Scientific objectives and progress

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- **Compare satellite O_3 datasets (tropospheric columns or vertical profiles) with surface concentration in-situ data** – which satellite dataset best represents near-surface concentrations? ☑
- Develop an **empirical or statistical model of satellite-derived GPP as a function of [O_3] from satellite data.** Investigate spatiotemporal variation and compare against in-situ observations (e.g. FLUXnet) ☑
- **Compare results with models fitted to other satellite datasets of photosynthetic activity (e.g. SIF).** Are these results consistent with the GPP model? ☐
- Run a **land surface model** (e.g. JULES, ORCHIDEE) **using satellite datasets** to compare with and provide context to empirical models ☐
- Use models to **predict GPP and/or crop yield losses under future climate scenarios** using UK Earth System Modelling (UKESM) data ☐

Surface validation of satellite O_3 datasets

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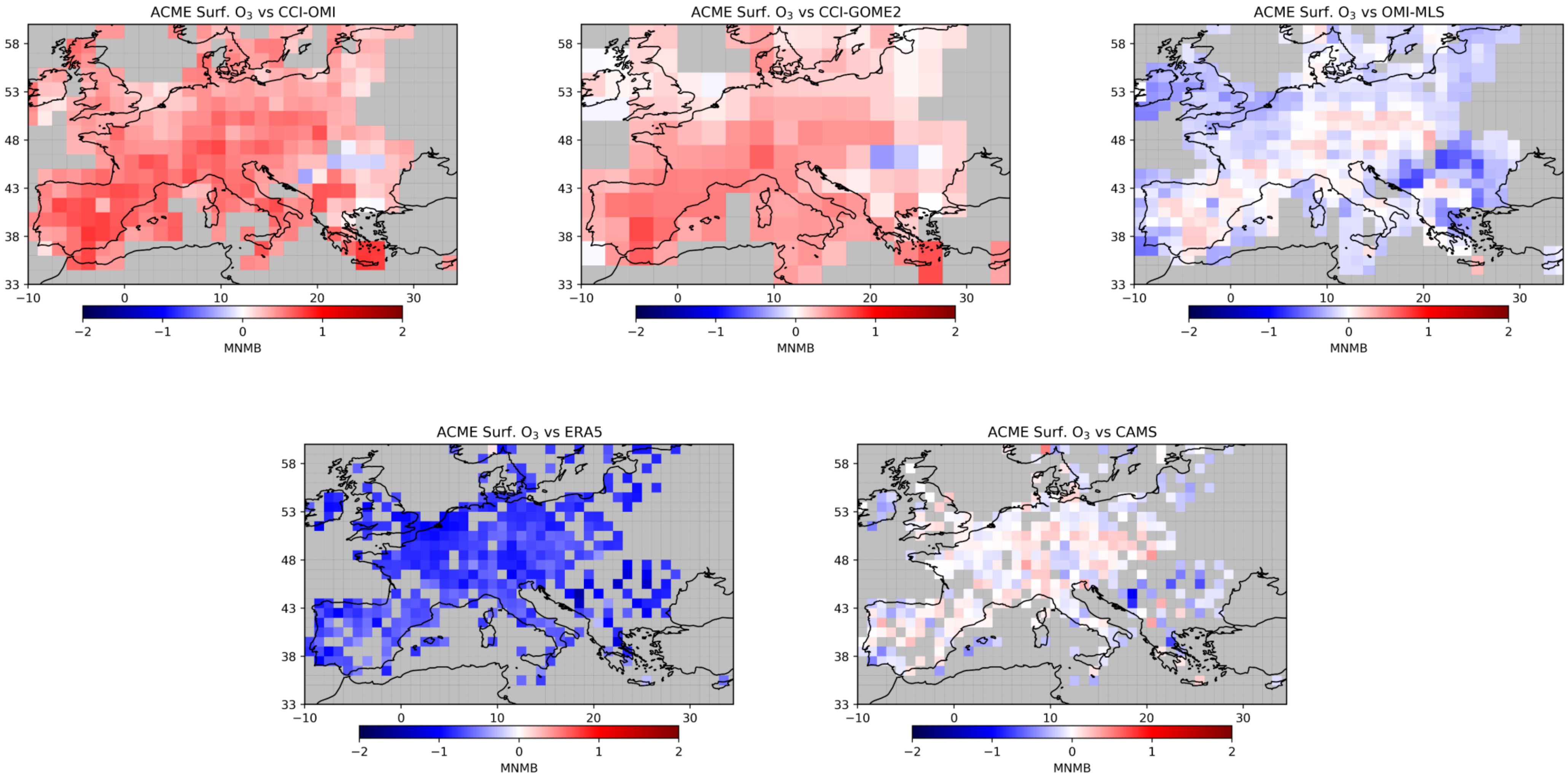
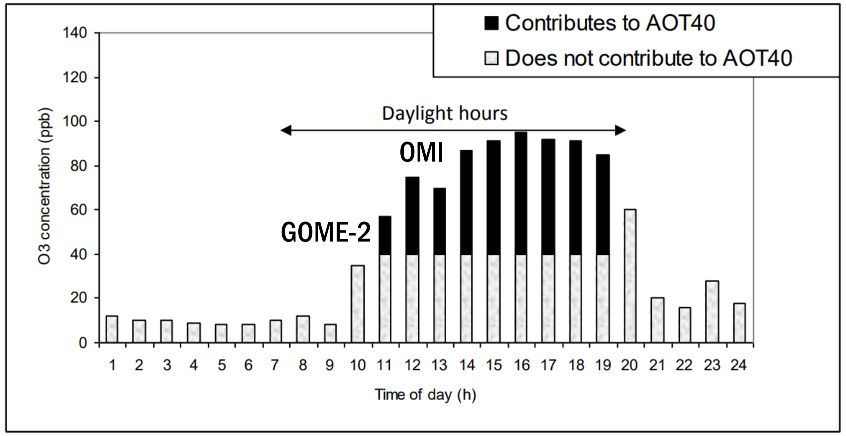
- **Perform comparison over Europe** – high density of **background surface measurements.** Sofen et al (2016) **gridded mean monthly [O_3] between 1990 – 2013** to a **1° x 1° grid**
- Only concerned with O_3 during **growing season: April – September** (also less cloud cover)
- Comparisons using **Level 3 data only** – recommended post-retrieval screening and spatial gridding already applied.
- Where available, **compare lowest profile layer directly with surface data.** No averaging kernel applied
- Datasets:
  - **OMI** (ESA-CCI, profile, 1.5° x 1.5°)
  - **GOME-2** (ESA-CCI, profile, 2.5° x 2.5°)
  - **OMI-MLS** (NASA, tropospheric column, 1.0° x 1.25°)
  - **ERA-5 analysis** (ECMWF, profile, 0.25° x 0.25°, assimilates satellite O_3 only)
  - **CAMS reanalysis** (ECMWF, profile, 1.0° x 1.0°, assimilates satellite O_3 , NO_2, CO, and AOD)
- Overlap period with all surface & satellite data: **2010 – 2013**

Satellite O_3 datasets have mostly poor surface sensitivity



Satellite datasets cannot be used for exposure statistics – Use CAMS



CLRTAP, 2017

$$\mathbf{AOT40} = \int_{08:00}^{20:00} \max([O_3] - 40.0\ \text{ppb}, 0)\ dt$$

- **O_3 exposure is a cumulative effect**, so averages are usually not used. Instead, statistics like Accumulated O_3 over Threshold of 40 ppb (AOT40) are calculated from in-situ data
- **Prior modelling/in-situ studies have all used AOT40 computed from hourly data** – need to do the same to compare results with prior efforts or land surface models
- **Monthly averages in L3 satellite data or analyses correlate very poorly with in-situ AOT40 values – CAMS reanalysis data will instead be used for the remainder of this work.**

Statistical GPP-O_3 model

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- **CAMS reanalysis data range: 2003 – 2018**
- The only **satellite-based global GPP dataset** in that covers this period is **MODIS MOD17A2**: monthly, 0.05° x 0.05° resolution, **2000 – 2015**
- Fit model for **2003 – 2015 monthly (April – September) data over Europe.** Regrid all datasets to CAMS spatial resolution
- From literature review of in-situ experiments, the following variables are known to influence GPP:

CAMS
  - **O_3** (AOT40)

ERA-5
  - **Air temperature**
  - **Vapour pressure deficit** (VPD, derived from air & dew-point temperature)
  - **Photosynthetically Active Radiation** (PAR)
  - **Soil moisture**

- Note: ERA-5 uses assimilated in-situ and satellite data to produce these variables

Attempt 1: Spatial Panel Model (SPM)

- **Assume that GPP is a linear function of AOT40, temperature, etc.**
- **Additional paramters** (e.g. Plant phenotype) assumed to vary with location, but cannot be modelled using available data – assume they can be **represented as a fitted intercept**
- **Data will vary with both space and time** («longitudinal data»). Ordinary Least Squares (OLS) will give biased/inaccurate results, as variance may not be the same across all grid cells
- **Spatial autocorrelation** will also bias results
- Try accounting for these by using **spatial panel data regression.**
  - Group data in **2 dimensions: time & grid cell**, and fit a linear model simultaneously across both
  - Additional terms fitted to both function and error to account for spatial autocorrelation
  - Treat **grid cell location as fixed effect** – each grid cell will have the same coefficients, but a **unique intercept** representing location-specific effects.
- Expecting **O_3 coefficient** to be **negative and statistically significant.** Model coefficients could then be compared by fitting the same model to in-situ FLUXNET data

Fit SPM over different subdomains

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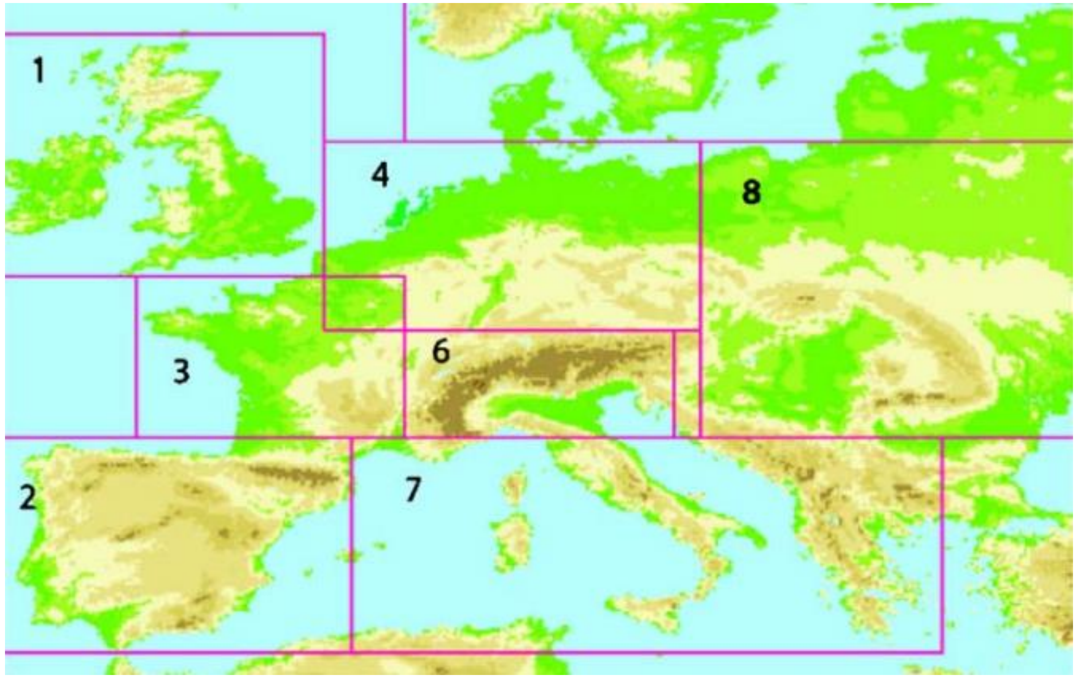

Area	West	East	South	North
1 (BI) British Isles	-10	2	50	59
2 (IP) Iberian Peninsula	-10	3	36	44
3 (FR) France	-5	5	44	50
4 (ME) Mid-Europe	2	16	48	55
5 (SC) Scandinavia	5	30	55	70
6 (AL) Alps	5	15	44	48
7 (MD) Mediterranean	3	25	36	44
8 (EA) Eastern Europe	16	30	44	55

Christensen and Christensen, Clim. Change, 2007

Vegetation response will vary according to climate and species. Fitting the SPM for different regions may yield information about regional responses

(Note: No MODIS GPP data was available North of 60°)

SPM results

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Region	GPP-O_3 coefficient ($g\ C\ m^{-2}\ ppb{\cdot}hr^{-1}$)	$p < 0.05$?
British Isles	-1.71×10^{-3}	Yes
Iberian Peninsula	-1.63×10^{-3}	Yes
France	4.44×10^{-4}	No
Mid-Europe	1.19×10^{-3}	Yes
Scandinavia	-5.88×10^{-4}	Yes
Alps	4.70×10^{-4}	No
Mediterranean	-9.76×10^{-4}	Yes
Eastern Europe	-6.44×10^{-4}	Yes

- **Unknown factors affecting model performance** over central Europe, even though AOT40 is high over most regions.
- Cannot diagnose issues using this model alone. **Spatial variation in the fit coefficients** must be investigated to assess possible causes.

Attempt 2: Geographically Weighted Regression (GWR)

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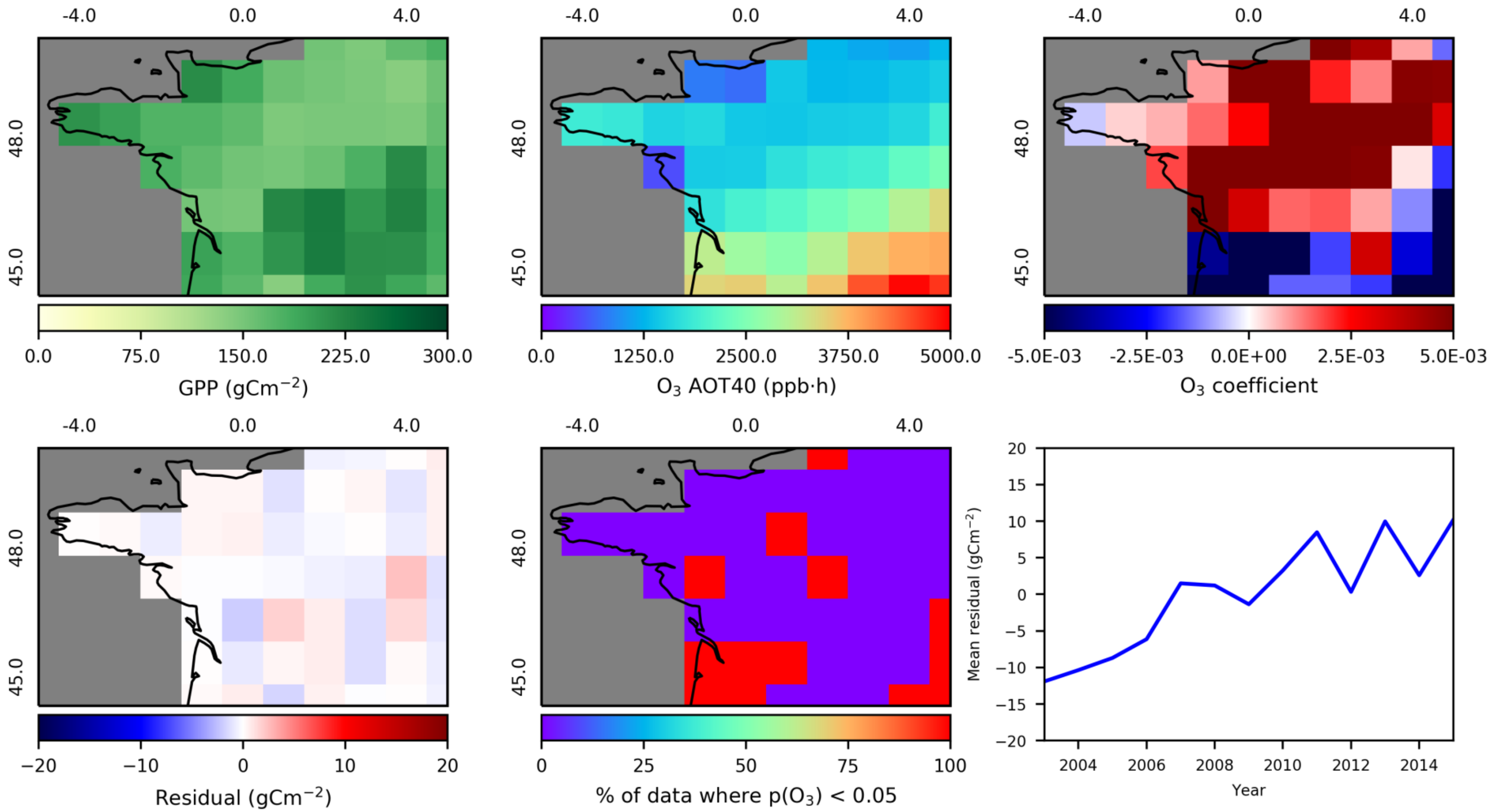
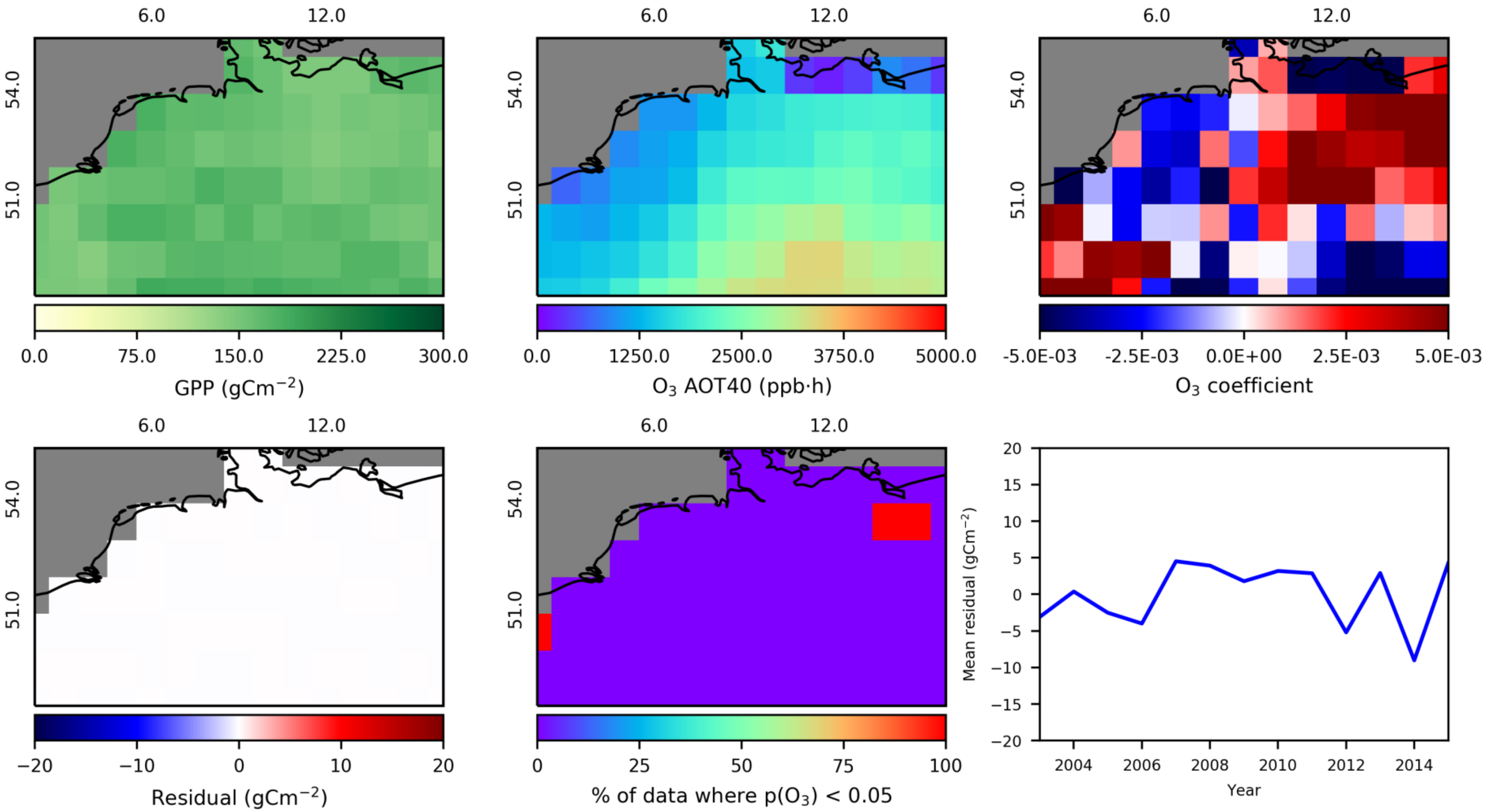
- GWR assumes a linear relationship between GPP and O_3, temperature, etc., but also **allows local variations in the fit coefficients and intercepts**.
- **Coefficient estimates are weighted by a kernel based on distance** between grid cells.
  - **Gaussian distance-decay-based weighting function** assumed
  - Optimal **bandwidth found through cross-validation**
- Run GWR fit for each subdomain as before – do specific regions produce anomalous results?
- Does the model residual change over time? Further investigation may need a geographically AND temporally weighted regression (GTWR) model

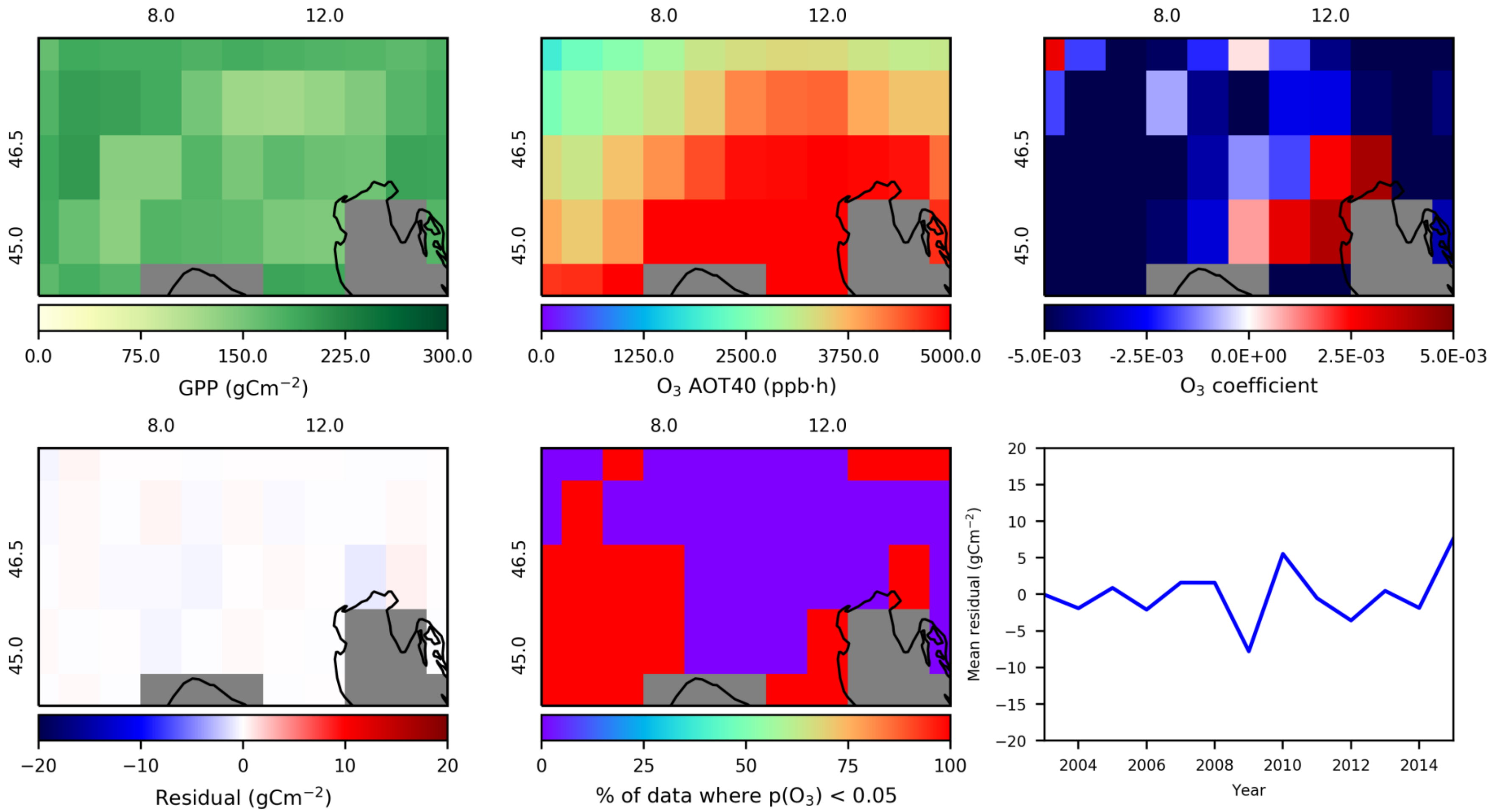
GWR fit: France



GWR fit: Mid-Europe



GWR fit: Alps



8.0
12.0
46.5
45.0
0.0 75.0 150.0 225.0 300.0
GPP (gCm^{-2})
O$_3$ AOT40 (ppb·h)
0.0 1250.0 2500.0 3750.0 5000.0
-5.0E-03 -2.5E-03 0.0E+00 2.5E-03 5.0E-03
O$_3$ coefficient
−20 −10 0 10 20
Residual (gCm^{-2})
0 25 50 75 100
% of data where p(O$_3$) < 0.05
Mean residual (gCm^{-2})
2004 2006 2008 2010 2012 2014
Year

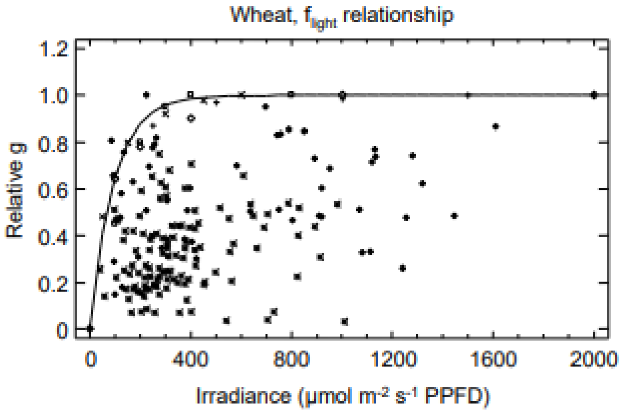
Theoretical GPP loss – estimating stomatal conductance

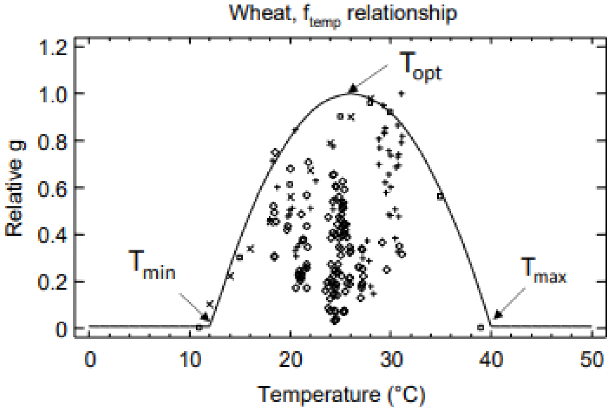
- Vegetation O_3 **dose also depends on flux entering the leaf**, which is determined by **stomatal conductance** (g_{sto})
- Under the Jarvis (1979) model g_{sto} can be calculated from ERA-5 data using:

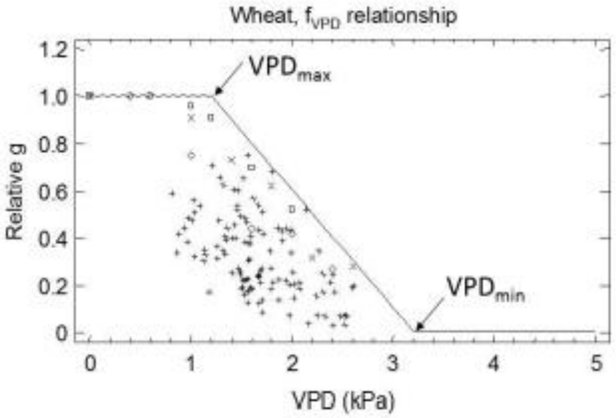
$$g_{sto} = g_{max} * f_{PAR} * \max\{f_{min}, (f_{temp} * f_{VPD} * f_{Soil\_water\_content})\}$$

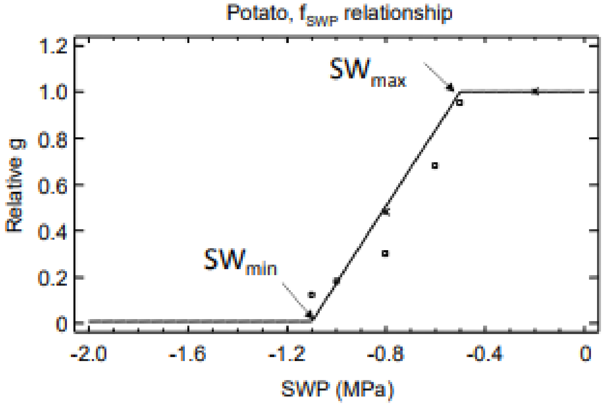
- g_{max} (g_{sto} measured under ideal conditions) is reduced by weighting functions (0–1), where f_{min}: minimum possible reduction in g_{sto} estimated from fumigation data
- g_{max} and weighting functions are parameterised depending on vegetation type (grass, crop, and forest) and climate (Mediterranean and Rest of Europe)

Examples of weighting functions









CLRTAP, 2017

Estimating theoretical GPP loss

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- Instantaneous loss of GPP due to O_3 exposure (I_{O3}) compared to O_3-free conditions can be calculated from CAMS AOT40 using:

$$I_{O3} = \alpha g_{sto} \mathrm{AOT40}$$

- α = Reduction in plant growth due to O_3:
  - Crops: 3.9×10^{-6} mm^{-1} ppb^{-1} (Reich, Tree Physiology, 1987)
  - Other vegetation: 2.6×10^{-6} mm^{-1} ppb^{-1} (Ollinger et al, Ecological Applications, 1997)
- Separate values of I_{O3} were calculated for grass, forest, and crops
- ESA-CCI Land Cover annual data was used to compute a weighted mean I_{O3} based on fractional vegetation coverage in each CAMS 1° x 1° grid cell
- Result can be compared with output from land surface models (e.g. JULES/ORCHIDEE)

Proietti et al, Sci. of the Tot. Env., 2016

Theoretical GPP loss due to O_3 (2003 – 2015)

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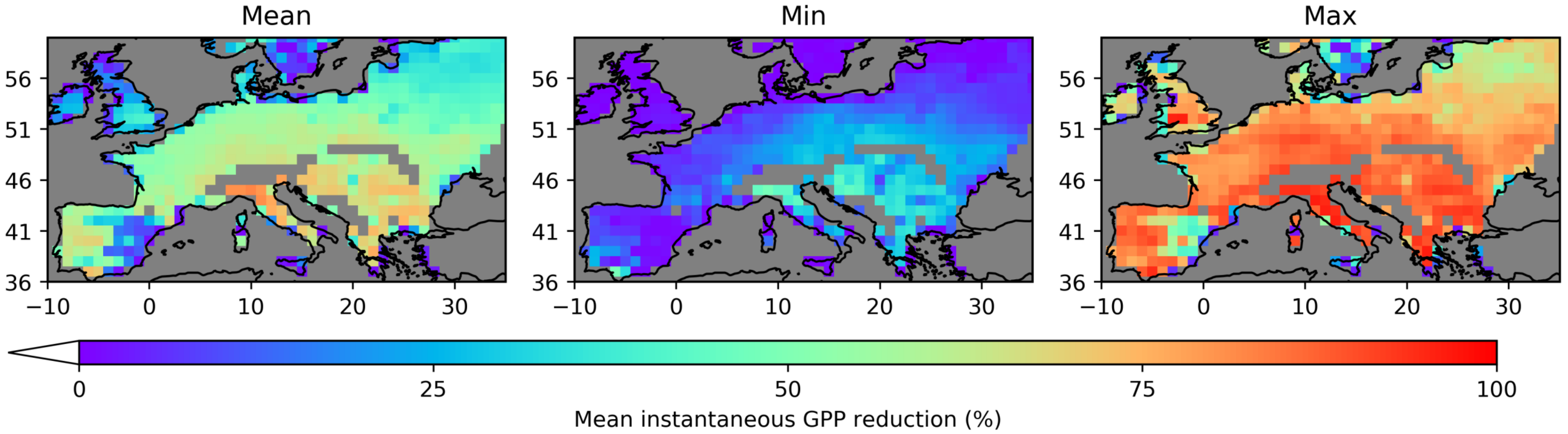
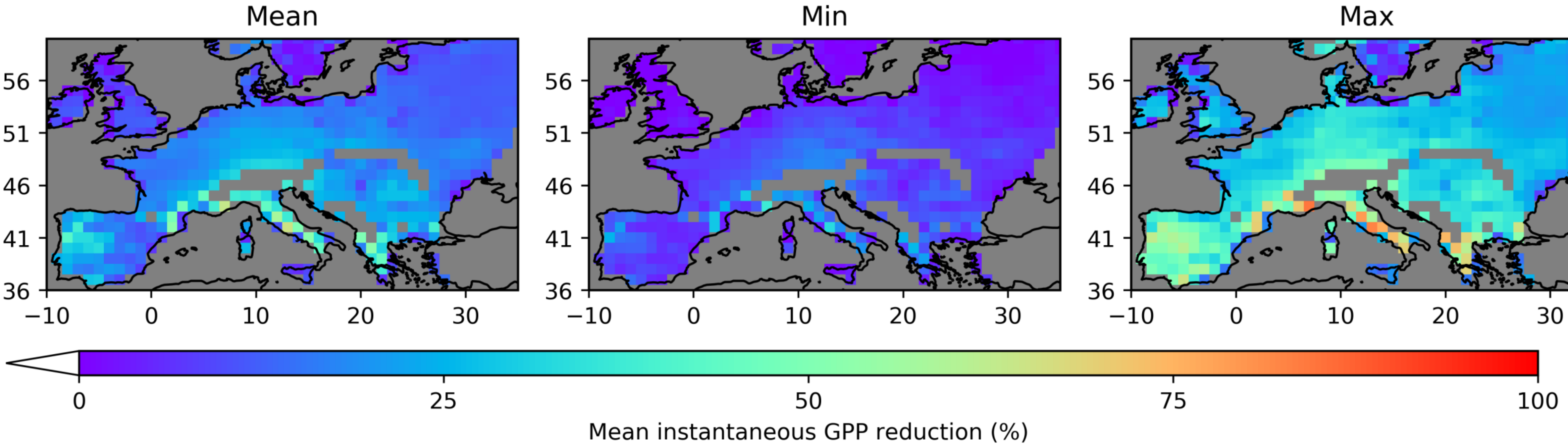
Crops



Theoretical GPP loss due to O_3 (2003 – 2015)

Forest



Theoretical GPP loss due to O_3 (2003 – 2015)

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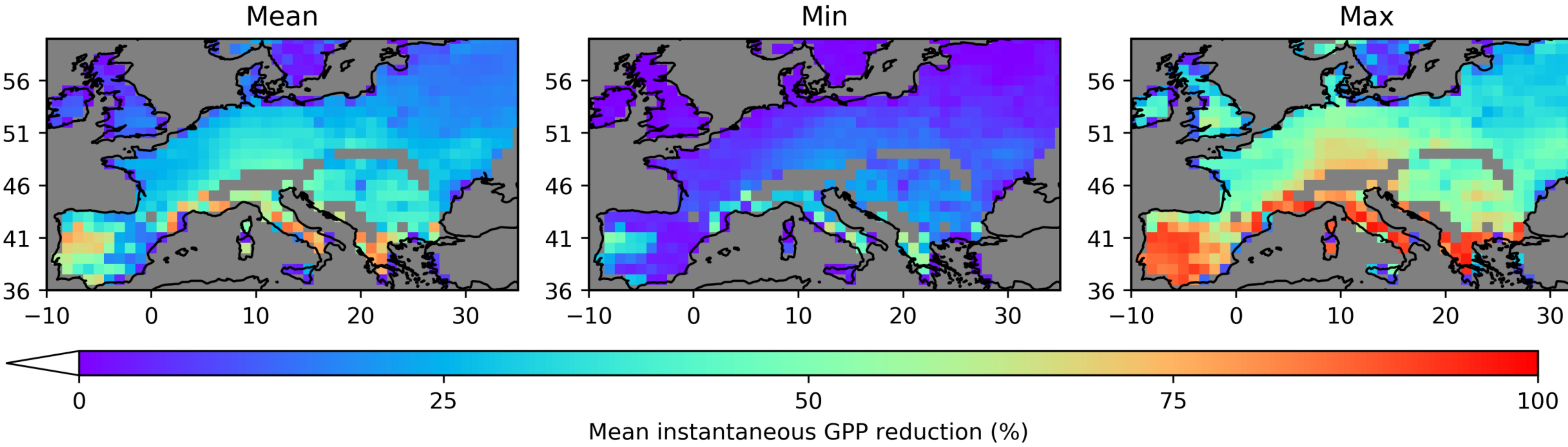
Grass



Theoretical GPP loss due to O_3 (2003 – 2015)

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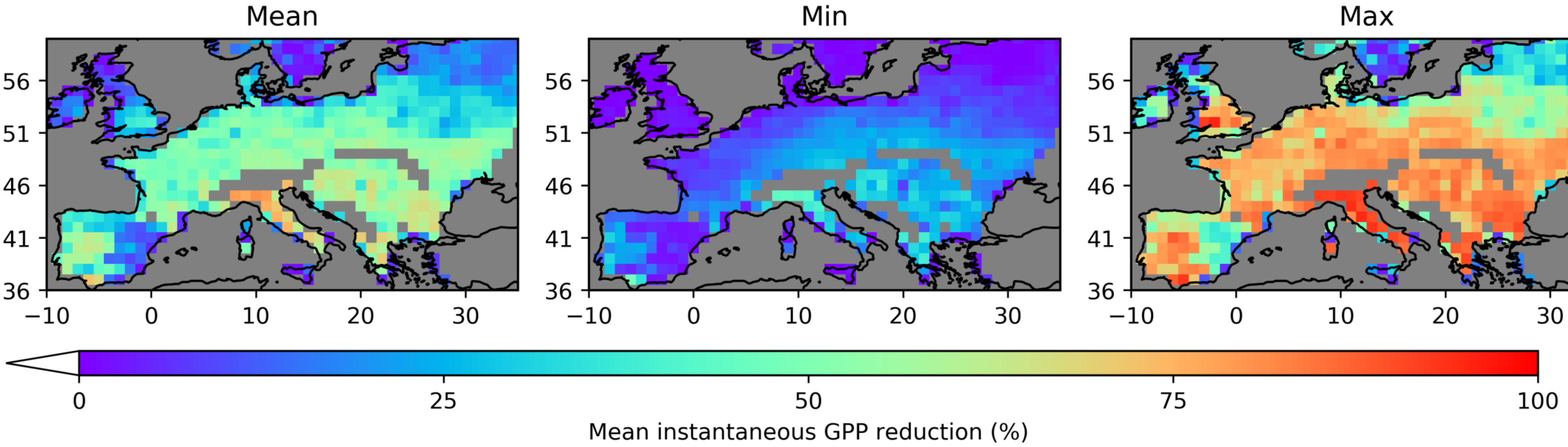
Weighted mean



Theoretical GPP loss due to O_3 (2003 – 2015)

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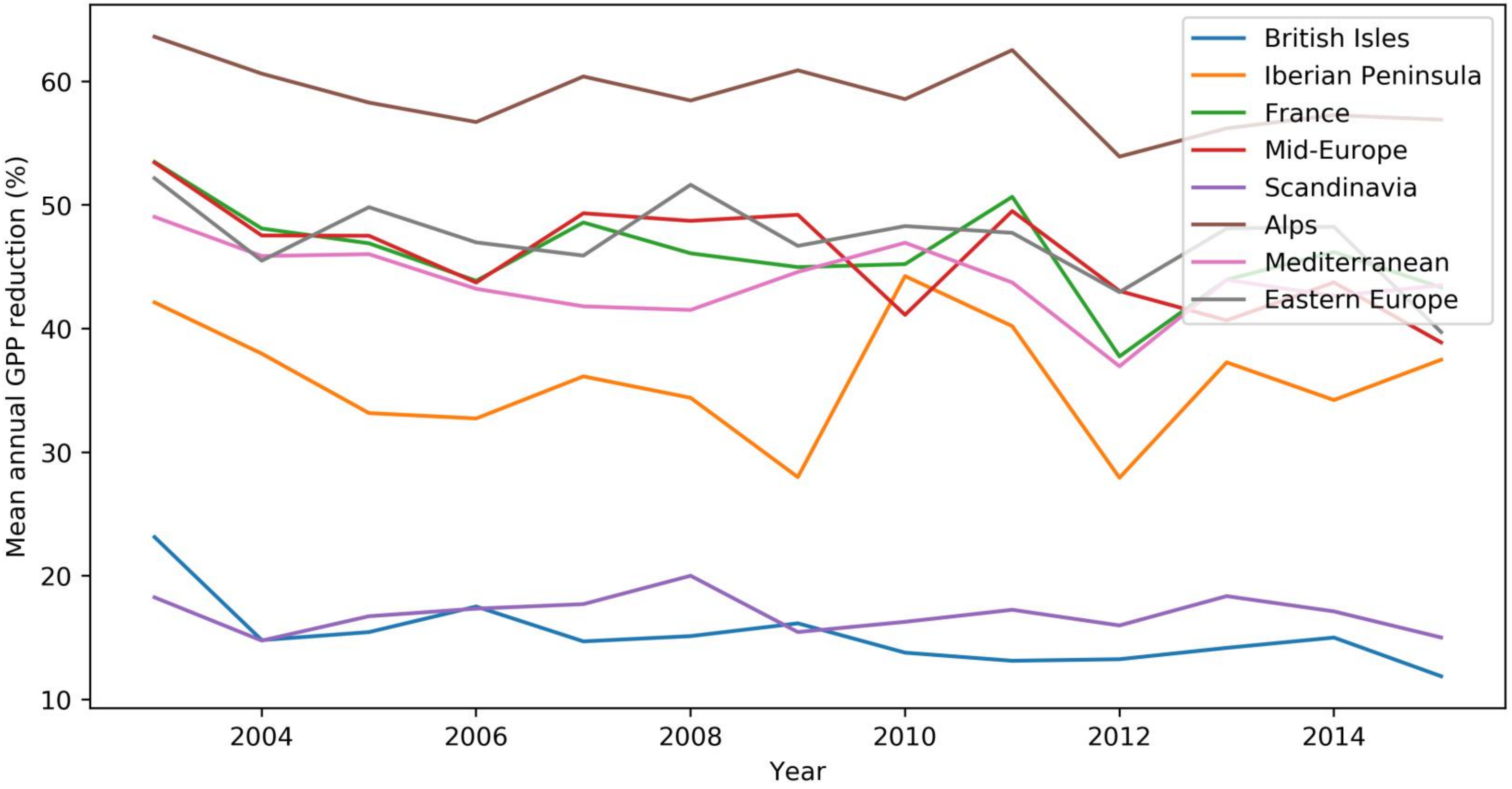

Next steps (I)

- **Statistical modelling:**
  - Investigate why linear model fails for some regions – may need to introduce polynomial terms or two-way interactions (e.g. Temperature*AOT40) to account for this
  - Experiment with calculating and using Phytotoxic O_3 Dose (POD) instead of AOT40, along with using SIF instead of GPP to fit model against
  - Compare fitted models against FLUXNET data
- **g_{sto}-based model:**
  - Meet with Env. Biology group @ Sapienza University of Rome on Wednesday to discuss results and possible improvements to methods
  - Compare results against ORCHIDEE runs (Sapienza) for verification. Use ERA-5/CAMS data as model input
  - Calculate GPP loss from ORCHIDEE, CAMS-based model and compare with FLUXNET data

Next steps (II)

- Repeat prior analyses with crop-yield data and verify against ORCHIDEE runs
- Using ORCHIDEE and UKESM data, predict likely crop & GPP loss caused by likely O_3 exposure by 2100 over Europe
- Potentially fit and verify models in other areas (e.g. USA, China)
- **Publications:**
  - Co-authored paper with Sapienza group comparing statistical and theoretical model with ORCHIDEE and FLUXNET over Europe
  - Paper modelling O_3-induced losses over other chronically polluted regions (e.g. S. Africa)
  - Potential paper investigating future crop and carbon sink losses
- **Conferences:**
  - Quadrennial Ozone Symposium (S. Korea), October 2020
  - AGU (USA), December 2020