Towards fast machine learning parameterizations of stratospheric ozone in climate change simulations

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@NowackPeer

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What I would have talked about...(roughly)

Hypothesis

It matters how ozone is represented in climate model simulations.

Interactive atmospheric chemistry schemes to-the-rescue?

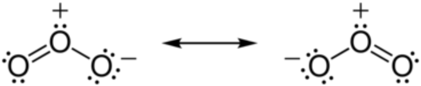
A good but typically computationally expensive option.

A suggestion for an alternative

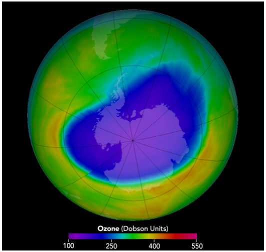
Machine learning parameterizations of stratospheric ozone.

Throughout my slides, I mention and link to some relevant studies (you can hover over citations and click to be re-directed).

Recap: ozone - a multifunctional molecule

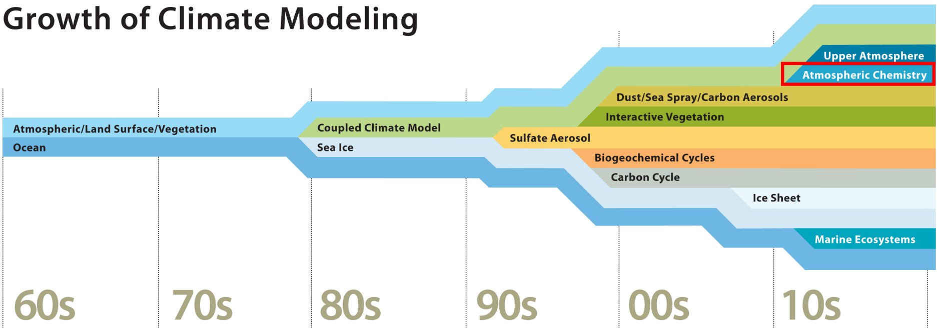


- Ozone layer is key to life on Earth.
- Greenhouse gas.
- Air pollutant in the troposphere.



NASA: ozone hole above Antarctica

The evolution of climate modelling



www2.ucar.edu

- Many climate models still do <u>not</u> include atmospheric chemistry schemes.
- Often there is no well-defined way to represent ozone otherwise.
- Key issue: atmospheric chemistry can slow down models substantially.

What if your model does not include ozone chemistry?

A standard go-to solution is to simply use an ozone field from observations, or other chemistry-climate model simulations.

This can be an effective **non-interactive** set-up for historical and RCP-type scenarios for which standardized **ozone climatologies** have been provided, see e.g. Cionni et al. (2011).

For many other forcing scenarios, including paleo-climate or abrupt-4xCO_2 forcings, such ozone climatologies are typically not provided $\rightarrow$ ozone is often prescribed in highly unrealistic ways, especially in the stratosphere and upper troposphere.

Example set-up for an interactive chemistry-climate model

Atmosphere

Unified Model @ UMv7.3
3.75° lon x 2.5° lat resolution
60 vertical levels $\leq$ 84km

Atmospheric Chemistry

CheS chemistry model
(Chemistry for the Stratosphere)
159 rxns / 41 species

HadGEM3 AO-UKCA Configuration

Ocean

NEMO model
2° lon x 2° lat resolution
31 vertical levels $\geq$ 5km max. depth

Sea-Ice

CICE model
2° lon x 2° lat resolution
5 different ice categories

A global climate model coupled to an interactive stratospheric chemistry scheme

See also Hewitt et al., *Geosci. Model Dev.*, 4(2):223-253, 2011 and `www.ukca.ac.uk`

Example for a non-interactive climate model configuration

Atmosphere

Unified Model @ UMv7.3
3.75° lon x 2.5° lat resolution
60 vertical levels $\leq$ 84km

Fixed ozone climatology

Ozone varies seasonally, but **not** with internal variability or forcing

HadGEM3
AO-~~UKCA~~
Configuration

Ocean

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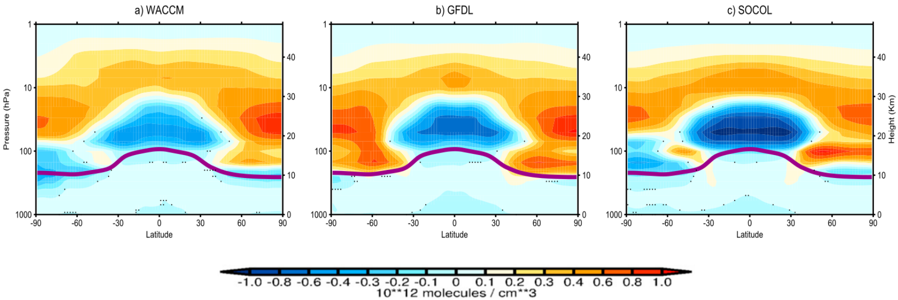
A global climate model ~~coupled to an interactive stratospheric chemistry scheme~~

See also Hewitt et al., *Geosci. Model Dev.*, 4(2):223-253, 2011 and www.ukca.ac.uk

The representation of ozone matters (I)



The implicit assumption of ‘constant’ ozone in many simulations is not correct, see above changes in ozone in abrupt-4xCO_2 scenarios for three chemistry-climate models; cf. Chiodo & Polvani (2019):

Ozone ↓ in the tropical upper troposphere/lower stratosphere (UTLS) and ↑ elsewhere. Changes in ozone, in turn, can feedback on stratospheric water vapour, cirrus clouds, the jet streams etc.

The representation of ozone matters (II)

For example in 4xCO_2 and solar forcing simulations

- effects on global and regional warming

(e.g. Li et al. *Clim. Dyn.* 2013, Dietmueller et al. *JGR* 2014, Nowack et al. *NCC* 2014/*JGR* 2018, Muthers et al. *GMD* 2014, Chiodo & Polvani *J. Clim.* 2016)

- effects on atmospheric dynamics

(e.g. Haigh *Science* 1996, Rind et al. *JGR* 2014, Chiodo & Polvani *GRL* 2017, Muthers et al. *ESD* 2016, Nowack et al. *GRL* 2017, Silverman et al. *ACP* 2018)

and paleo-climate simulations

- reduced temperature biases

(e.g. Heinemann *MPI* 2009, Noda *JGR* 2017 and 2018)

Can we implement a faster ozone parameterization?

LETTER

Using machine learning to build temperature-based ozone parameterizations for climate sensitivity simulations

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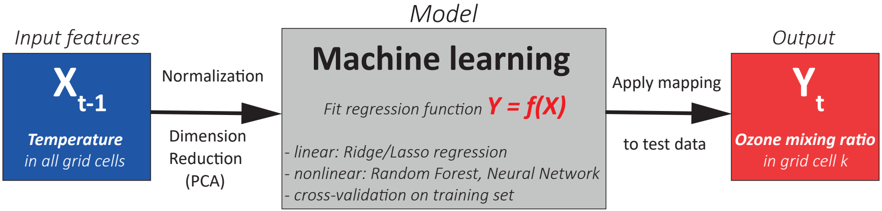
Supplementary material for this article is available online

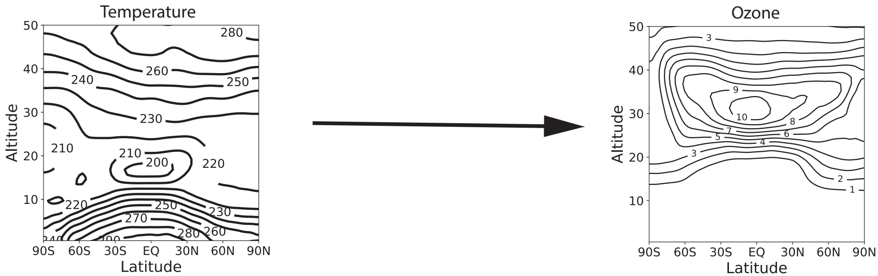
Abstract

A number of studies have demonstrated the importance of ozone in climate change simulations, for example concerning global warming projections and atmospheric dynamics. However, fully interactive atmospheric chemistry schemes needed for calculating changes in ozone are computationally expensive. Climate modelers therefore often use climatological ozone fields, which are typically neither consistent with the actual climate state simulated by each model nor with the specific climate change scenario. This limitation applies in particular to standard modeling experiments such as

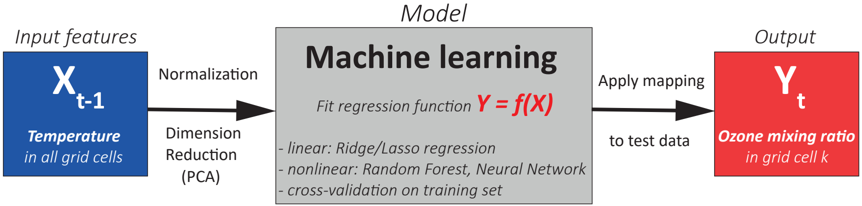
ERL 2018

The machine learning parameterization shows potential





The machine learning parameterization shows potential



Ridge regression cost function:

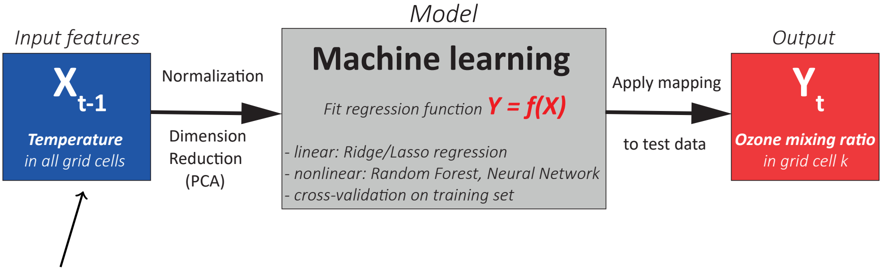
$$J_{\text{Ridge,k}} = \sum_{t=1}^{N} \left(Y_k^{(t)} - \sum_{j=1}^{p} c_{kj} X_j^{(t-1)} \right)^2 + \lambda \sum_{j=1}^{p} c_{kj}^2$$

X = 1000 temperature modes of variability $\equiv$ inputs

Y = Ozone mass mixing ratios in each grid cell

c_{kj}, λ = coefficients (subject to optimization), regularization parameter

The machine learning parameterization shows potential



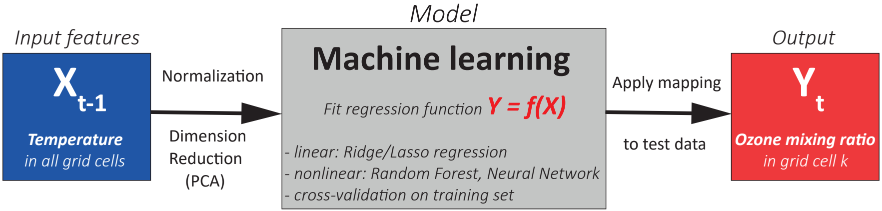
Why temperature?

Forcing scenarios such as piControl/4xCO_2: factors driving changes in ozone are directly or indirectly correlated with temperature (circulation, sunlight, water vapour, catalytic reactions...)

An extension to scenarios with CFCs etc appears feasible.

Nowack et al. *ERL* (2018)

The machine learning parameterization shows potential



Simple and effective:

Predicts ozone as a self-learned function of the climate state.

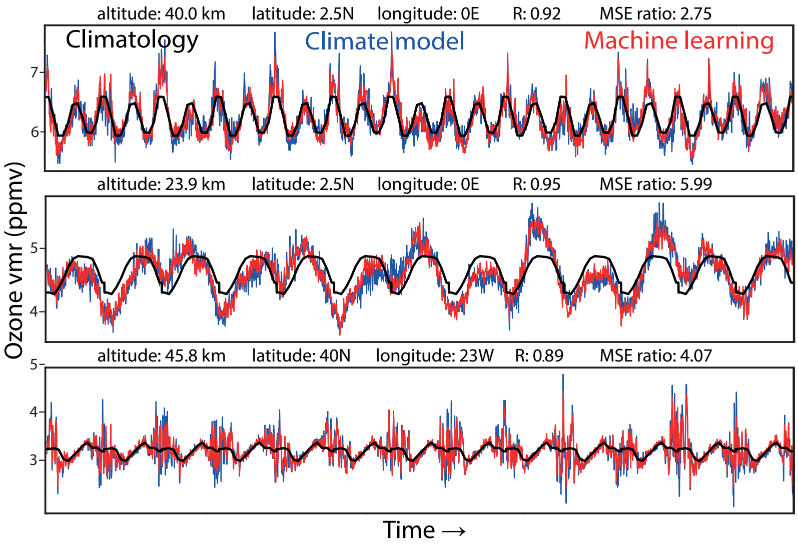
Replaces both tracer transport and chemical reaction system.

Requires little training data from expensive simulations (<10 years).

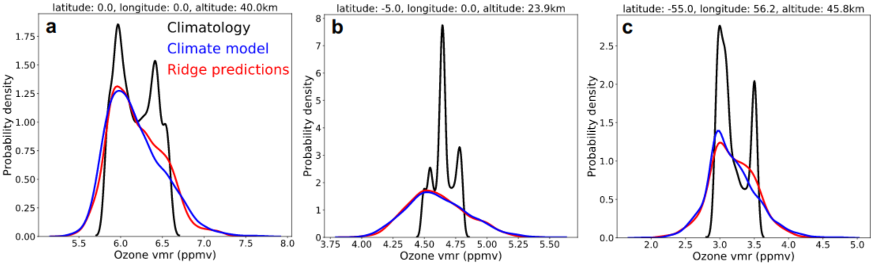
Ridge regression performs well under extrapolation $\rightarrow$ climate change.

Nowack et al. *ERL* (2018)

Parameterization for pre-industrial run: internal variability (I)



Parameterization for pre-industrial run: internal variability (II)

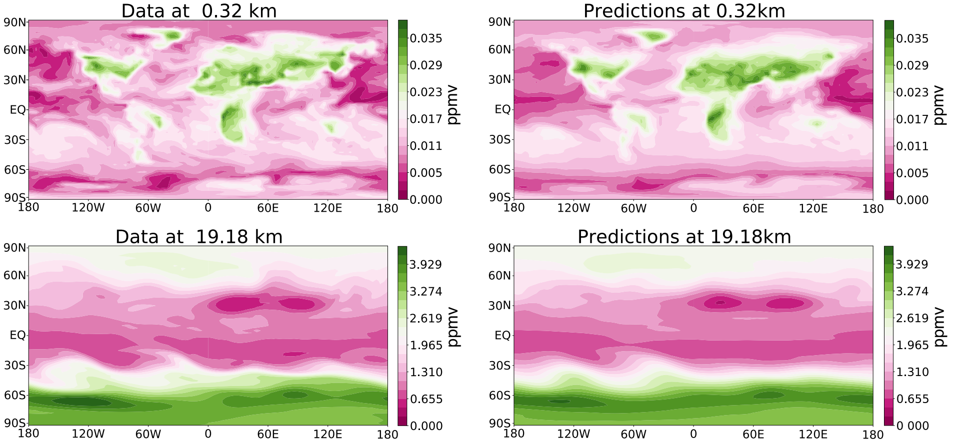


Kernel density estimates for ozone mixing ratios in three grid cells.

Comparison of the **fixed climatological distributions** to **interactive chemistry** and the **machine learning predictions**.

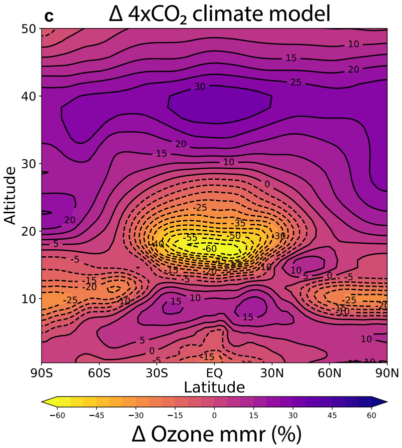
See also Nowack, Ong et al. Climate Informatics (2019).

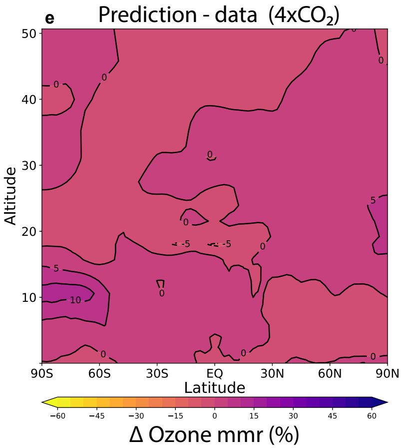
The ML regression also reproduces the spatial structure well



At a given time snapshot t_i

The same applies to changes in ozone under $4xCO_2$

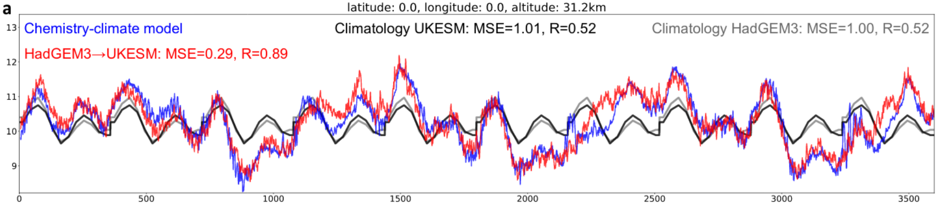




Left: interactively modelled %-changes in ozone under $4xCO_2$. Right: the machine learning model predicts those changes to within 5% almost everywhere.

Model transferability: HadGEM3 to UKESM

see Nowack, Ong et al. (2019)



1) Re-center temperature field

2) Use new X_{scaled} as input

3) Gives $Y_{\text{HadGEM-consistent}}$

4) Define: $Y_{\text{HadGEM-consistent}} = \overline{Y}_{\text{HadGEM}} + + Y'$

5) Substitute climatologies: $Y_{\text{UKESM-consistent}} = \overline{Y}_{\text{UKESM}} + Y'$

Works already with 5 years of UKESM data (see linked publication).

Take-home messages

- Stratospheric ozone is an important factor in climate modelling.
- This is not reflected in many current climate model configurations.
- A machine learning parameterization could pose an effective alternative for including ozone in simulations.
- Lessons learned could be useful for other parameterization schemes (ocean, cloud/convection, carbon cycle).

Next steps

- Fully coupled implementation in UKESM1. The initial version appears to be stable over long timescales.
- Comparison to other computationally cheaper modelling alternatives such as linearized chemistry schemes; cf. Meraner et al. (2020).
- Method development: other algorithms/other inputs.