

Cambridge Centre for Climate Science



Modelling chemistry in the atmosphere: A very brief introduction.

Alexander T. Archibald.

Department of Chemistry, University of Cambridge & NCAS Climate

5th December 2022.

www.ncas.ac.uk

Talk outline.

Brief history of modelling:

What do we mean by models?

Why do we model?

Building blocks of a model:

Writing a chemical process in a mathematical framework. Solving our mathematical problems.

• Examples :

0-D model studies.

• Evaluation:

Process based/oriented model evaluation.

• Q&A:





What is a model?

Lot's of definitions:

"A model is as a simplified representation of a complex system that enables inference of the behavior of that system."

Modelling has been going on for a long time!



| July 31, S to 9 a.m. | В. | E. | M. | D. | F. | c. | I. | S |
|-------------------------|------------|---------|---------|-------------|---------|--------|--------|------|
| Naim | 29.54 | 57 | 56 | W.S.W. | 6 | 9 | 0. | 3 |
| Aberdeen | . 29.60 | 59 | 54 | S.S.W. | 5 | 1 | b. | 3 |
| Leith | . 29.70 | 61 | 55 | W. | 3 | 5 | c. | 2 |
| Berwick | . 29.69 | 59 | 55 | W.S.W. | 4 | 4 | c. | 12 |
| Ardrossan | . 29.73 | 57 | 55 | W. | 5 | 4 | o. | 5 |
| Portrush | . 29.72 | 57 | 54 | S.W. | 2 | 2 | b. | 2 |
| Shields | . 29-80 | 59 | 54 | W.S.W. | 4 | 5 | 0. | 3 |
| Galway | . 29.83 | 65 | 62 | W. | 5 | 4 | c. | 4 |
| Scarborough . | . 20.85 | 59 | 56 | W. | 3 | 6 | c. | 2 |
| Liverpool | 29.91 | 61 | 56 | S.W. | . 2 | 8 | C. | 2 |
| Valentia | 29.87 | 62 | 60 | S.W. | 2 | 5 | 0. | 3 |
| Queenstown . | . 29.88 | 61 | 59 | W. | 3 | 5 | C. | 2 |
| Yarmouth | 30.05 | 61 | 59 | W. | 5 | 2 | c. | 13 |
| London | 30.02 | 62 | 56 | S.W. | 3 | 2 | h | 1_ |
| Dover. | 30.01 | 70 | 61 | S.W. | 3 | 7 | 0. | 2 |
| Portsmouth . | 30.01 | 61 | 59 | W. | 3 | 6 | 0. | 12 |
| Portland | 30.03 | 63 | 59 | S.W. | 3 | 2 | C. | 3 |
| Plymouth | 30.00 | 62 | 59 | W. | 5 | 1 | h. | 4 |
| Penzance | 30.04 | 61 | 60 | S.W. | 2 | 6 | C. | 3 |
| Copenhagen . | 29.94 | 64 | _ | W.S.W. | 2 | 6 | · . | 3 |
| Helder : | 29.99 | 63 | - | W.S.W. | 6 | 5 | 0 | 3 |
| Brest | 30.09 | 60 | _ | S.W. | 2 | 6 | Se. | 5 |
| Bayonne | 30.13 | 68 | _ | | _ | 9 | m | 5 |
| Lisbon | 30.18 | 70 | _ | N.N.W. | . 4 | 3 | h | 12 |
| General weat | her proba | able da | uring | next two da | ys in t | the- | | 1." |
| North-Mode | erate west | erly wi | nd ; fi | ne. | | | tige . | |
| West-Mode | rate south | -wester | rly; fi | ne. | | | | |
| South-Fresh | 1 westerly | ; fine. | | 1 | | | | |
| B. Baromete | r, correct | ed and | l redu | aced to 32 | at n | neen | sea 1 | evel |
| ach 10 feet of | vertical r | ise ca | using | about one- | hundr | edth | of an | inc |
| liminution, an | d each 1 | 0º abo | ve 32 | causing no | arly t | hree-l | hundr | edt |
| increase. E. | Exposed | thermo | meter | in shade. | M. | Mois | tened | bu |
| for evaporatio | on and d | tew-poi | int). | D. Direct | ion o | ť wi | nd (t | rue |

r., rain ; s., snow ; t., thunder. S. Sea disturbance (1 to 9).

Cloud (1 to 9). I. Initials :- b., blue sky; c., clouds (detached); f., fog; h., hail; l., lightning; m., misty (hazy); o., overcast (dull);

1st August 1861, The Times





Building the model – on paper!

Most of the interesting problems you want to study will be impossible to solve exactly – need to develop a model to represent the system.









Most chemically active molecules in the atmosphere arise from emissions (source) and the subsequent formation of intermediate species. The ultimate fate of emissions in the present-day atmosphere is oxidation. A mechanism (shown schematically above) represents this





 $A + B \rightarrow C + D$



The model we use is based on *chemical kinetics*. For every **reaction** in the **mechanism** we can write an overall **rate equation**. For each species (A, B, C etc) we can then write a **continuity equation** – an ODE which describes how the species concentration ([A], [B] etc) changes over time.





 $A + B \rightarrow C + D$



The overall rate equation can tell us if there is a **production** of a species or a **loss**.





 $A + B \rightarrow C + D$



The rate constant for a reaction is usually not constant! It usually depends on **temperature** and can also depend on pressure OR even the concentration of things like water vapour (see asad_bimol or asad trimol).





 $A + B \rightarrow C + D$



The rate constant is important as it measures how quickly a reaction will happen. If [B] is much greater than [A] then, k[B] will be roughly constant – in which case we can write:





 $A \rightarrow C + D$ $\frac{d[A]}{dt} = -k'[A]$ $k' = A \times \exp\left(\frac{-E_A}{RT}\right) \times [B]$

k' is now a pseudo-first order rate constant. It has dimensions of 1/time and so 1/k' gives us a characteristic time constant τ , for the reaction.







Time (s)

k' is now a pseudo-first order rate constant. It has dimensions of 1/time and so 1/k' gives us a characteristic time constant τ , for the reaction.





 $A \rightarrow C + D$ $\frac{d[A]}{dt} = -J[A]$ $J_{(i)} = \int_{0}^{\infty} \sigma_{(\lambda,i)} \varphi_{(\lambda,i)} F_{(\lambda)} d\lambda$

 $J_{(i)}$ is the photolysis coefficient (rate constant) for the reaction. It depends on the flux of photons (*F*), the quantum yield (ϕ) and the absorption cross-section of the molecule (σ).





The Continuity Equation



This equation is at the core of all the problems we will want to study regarding chemistry in the atmosphere. The *difficulty* lies in parameterizing the individual terms.





Emissions





National Centre for Atmospheric Science



Emissions



Garbage in garbage out!



National Centre for Atmospheric Science

Source: EC-JRC/PBL. EDGAR version 4.0. http://edgar.jrc.ec.europa.eu/, 2009





Emissions







Deposition

Atmospheric Science







Need to build up a "picture" of the chemistry of interest.

Mechanism development is just another aspect of modelling – parameterizing the millions of possible reactions to a solvable subset.







Kinetic data bases:

NATURAL ENVIRONMENT RESEARCH COUNCIL

Kinetics Database

Kinetics Database

Resources

Search

Database Search

Database Set Unit

Preferences

Feedback

Rate Our

Citation

Help

Products and Services

NIST Standard Reference Data

Search Reaction

Bibliographic



Provide archives of kinetic data and provide evaluations of kinetic data.

IUPAC home page

Heterogeneous

Related web sites

Liquids phase

Research project

Task Group on Atmospheric Chemical Kinetic Data Evaluation

| Summary tables | Gas phase | Heterogeneous on ice | Heterogeneous on mineral dust |
|----------------|-----------|----------------------|-------------------------------|

(i)
$$CH_4 + OH \Rightarrow \dots \Rightarrow CO$$
 $R_5 = k_5[CH_4][OH]$ $k_5 = 1.266 \times 10^{-7} \text{ s}^{-1} \text{ ppt}^{-1}$
(ii) $CO + OH \Rightarrow \dots$ $R_6 = k_6[CO][OH]$ $k_6 = 5.08 \times 10^{-6} \text{ s}^{-1} \text{ ppt}^{-1}$
(iii) $OH + X \Rightarrow \dots$ $R_7 = k_7[X][OH]$ $k_7[X] = 1.062 \text{ s}^{-1}$,















Methane oxidation is more complex

| species lifetime |
|------------------|
| τ ≈ 10 yrs |
| τ ≈ 1 ms |
| τ ≈ 100 s |
| τ ≈ 1 s |
| τ≈1 day |
| |
| τ≈3 months |
| τ ≈ 1 ms |
| |

Drop the very fast reactions and very short-lived species, replacing the latter with their ultimate oxidation products (e.g., HO_2 for H)





Copyrighted Material

IERICAL

The Art of Scientific Computing

THIRD EDITION

William H. Press Saul A. Teukolsku William T. Vetterling Brian P. Flannery

Copyrighted Marer M.

Let **ASAD** do the hard work for you!!

Geosci, Model Dev., 11, 3089–3108, 2018 https://doi.org/10.5194/gmd-11-3089-2018 © Author(s) 2018. This work is distributed under the Creative Commons Attribution 4.0 License. \odot

Geoscientific



Quasi-Newton methods for atmospheric chemistry simulations: implementation in UKCA UM vn10.8

Emre Esentürk^{1,2}, Nathan Luke Abraham^{1,3}, Scott Archer-Nicholls¹, Christina Mitsakou^{1,a}, Paul Griffiths^{1,3}, Alex Archibald^{1,3}, and John Pyle^{1,3}

¹Department of Chemistry, University of Cambridge, Cambridge, UK ²Mathematics Institute, University of Warwick, Coventry, UK ³National Centre for Atmospheric Science, Cambridge, UK ^acurrently at: the Centre for Radiation, Chemical Environments and Hazards, Public Health England, Chilton, UK

Correspondence: Emre Esentürk (e.esenturk.1@warwick.ac.uk)

Received: 6 February 2018 - Discussion started: 26 February 2018 Revised: 22 May 2018 - Accepted: 8 June 2018 - Published: 1 August 2018





Model types: Example 1 – the box

The 0-D box model – possibly the best way to get into modelling atmospheric chemistry

When running a box model it's common to think of it as a well mixed parcel of air. It's common to assume a fixed **temperature** and a fixed length scale (e.g. the **boundary layer height** – **NB** needed for converting emission fluxes and deposition rates).





Emissions (molecules cm⁻² s⁻¹) / "height of box" cm Deposition (cm s⁻¹) / "height of box" cm



Model types: Example 2 – many boxes

The 3-D *Eulerian* model (e.g. UM-UKCA) – possibly the most widely used modelling tool. Think of it as ~ 10⁶ box models!



ATURAL ENVIRONMENT RESEARCH COUNCIL



Resolution is a big problem. If you think about chemistry, it's highly dependent on concentration gradients!



Model types: Example 2 – many boxes

The 3-D *Eulerian* model (e.g. UM-UKCA) – possibly the most widely used modelling tool. Think of it as ~ 10⁶ box models!





Model Evaluation:

Comparing models and reality.





One of these images shows a Turner nominated art piece, which sold for £150,000.





Lets define what we mean by model evaluation to be multi component. Model evaluation includes:

Model verification – where we quantify the predictive capability of our model. Again we compare the model and observations but this is different to calibration as we will not be using the results of these comparisons to modify the model logic/parameters.

For simple models (and for code) verification may include checking the logic of the model. This is increasingly difficult for the complex models we use like UKCA.

Lets define what we mean by model evaluation to be multi component. Model evaluation includes:

Model verification – where we quantify the predictive capability of our model. Again we compare the model and observations but this is different to calibration as we will not be using the results of these comparisons to modify the model logic/parameters.

It is vital that the observational data used in model verification is distinct from the data used in calibration. NB this is not always the case or even possible.

Lets define what we mean by model evaluation to be multi component. Model evaluation includes:

Model validation – all models are wrong, some models are useful. Not to get too bogged down by philosophical argument but from a technical perspective, a valid model is one in which the scientific or conceptual output is acceptable for its purpose.

For those wanting to think more meta: Can you ever validate a model?

Lets define what we mean by model evaluation to be multi component. Model evaluation includes:

Sensitivity analysis – where the response of the model to changes in inputs/parameters is quantified. This understanding is important for:

- 1) The range of suitability of the model
- 2) Identifying "key" parameters/inputs
- 3) Understanding behavior at critical points

We will touch on perturbed parameter ensembles (PPEs – a type of sensitivity analysis) later.

Lets define what we mean by model evaluation to be multi component. Model evaluation includes: Model calibration Model verification Model validataion Sensitivity analysis

And it requires some objective measures of "goodness of fit"

How can I tell if my model is good or bad?

First, don't forget to focus on what you are comparing! Integral quantities? Hourly/high time frequency data? Other model data? What are the biases in the observational data? How are the characterized?

There are many, many, many, statistical measures that we can use and software like R and Python make it easy to abuse them.

Common Variables:

M = predicted concentration
 O = observed concentration
 X = predicted or observed concentration
 σ = standard deviation

I. Mean Bias, Mean Error, and Root Mean Square Error (ppb) Mean Bias = $\frac{1}{n} \sum_{1}^{n} (M - O)$

Mean Error =
$$\frac{1}{n} \sum_{1}^{n} |M - O|$$

Root Mean Square Error =

$$\frac{\sum_{1}^{n} (M - O)^2}{n}$$

Common Variables:

M = predicted concentration
 O = observed concentration
 X = predicted or observed concentration
 σ = standard deviation

II. Normalized Mean Bias and Error (unitless) Normalized Mean Bias =



Normalized Mean Error = $\frac{\sum_{1}^{n} |M - O|}{\sum_{1}^{n} (O)}$

Common Variables:

M = predicted concentration
 O = observed concentration
 X = predicted or observed concentration
 σ = standard deviation

III. Fractional Bias and Error (unitless) Fractional Bias =

$$\frac{1}{n} \left(\frac{\sum_{1}^{n} (M - O)}{\sum_{1}^{n} \left(\frac{(M + O)}{2} \right)} \right)$$

Fractional Error =
$$\frac{1}{n} \left(\frac{\sum_{1}^{n} |M - O|}{\sum_{1}^{n} \left(\frac{(M + O)}{2} \right)} \right)$$

Common Variables:

M = predicted concentration
 O = observed concentration
 X = predicted or observed concentration
 σ = standard deviation

IV. Correlation Coefficient (unitless) Correlation =

$$\frac{1}{(n-1)}\sum_{1}^{n}\left(\left(\frac{O-\overline{O}}{\sigma_{o}}\right)*\left(\frac{M-\overline{M}}{\sigma_{m}}\right)\right)$$

VI. Coefficient of Variation (unitless) Coefficient of Variation = $\frac{\sigma}{\overline{X}}$

Common Variables:

M = predicted concentration
 O = observed concentration
 X = predicted or observed concentration
 σ = standard deviation

IV. Correlation Coefficient (unitless) Correlation =

$$\frac{1}{(n-1)}\sum_{1}^{n}\left(\left(\frac{O-\overline{O}}{\sigma_{o}}\right)*\left(\frac{M-\overline{M}}{\sigma_{m}}\right)\right)$$

V. Coefficient of Variation (unitless) Coefficient of Variation =

 $\frac{\partial}{\overline{X}}$

VI. Index of Agreement (unitless) Index of Agreement = $1 - \left[\frac{\sum_{1}^{n} (O - M)^{2}}{\sum_{1}^{n} (|M - \overline{O}| + |O - \overline{O}|)^{2}} \right]$

Error:

Mean Absolute Error

 $ext{MAE} = rac{\sum_{i=1}^n |y_i - x_i|}{n} = rac{\sum_{i=1}^n |e_i|}{n}.$

is a straightforward measure of how far away our model simulation (y) was from our observations (x) on average. It takes the modulus of the absolute error (bias) and so is always positive.

Error:

Mean Squared Error

$$ext{MSE} = rac{1}{n}\sum_{i=1}^n (Y_i - \hat{Y_i})^2.$$

is measure of both the bias and the variance of the model. The variance is the expectation of the squared deviation of a random variable from its mean. It measures the spread from the average.

Approaches to evaluation:

The MSE is the squared difference of the modelled (mod) and observed (obs) values:

$$MSE = E(\text{mod-obs})^2 = \frac{\sum_{i=1}^{n_t} (\text{mod}_i - \text{obs}_i)^2}{n_t},$$
 (1)

where $E(\cdot)$ denotes expectation and n_t is the length of the time series. The bias is

$$bias = E (mod-obs) \tag{2}$$

i.e. bias = $\overline{\text{mod}} - \overline{\text{obs}}$. Thus, the following relationship holds:

$$MSE = var (mod-obs) + bias^2,$$
(3)

which is a well-known property of the MSE, $(var(\cdot))$ is the variance operator). By using the property of the variance for correlated fields:

$$var(mod-obs) = var(mod) + var(obs) - 2cov(mod,obs),$$
 (4)

the final formulation for the MSE components reads as follows:

$$MSE = bias^{2} + var(mod) + var(obs) - 2cov(mod,obs), \quad (5)$$

~

where the covariance term (last term on the right-hand side of Eq. 5) accounts for the degree of correlation between the modelled and observed time series. When the covariance term is zero, var(obs) is referred to as the *incompressible part of the error* and represents the lowest limit that the MSE of the model can achieve. When dealing with model evaluation, the modelled and observed time series are typically highly correlated and therefore, within the limits of the perfect match (correlation coefficient of unity), cov(mod,obs) = cov(obs,obs) = cov(mod,mod) = var(mod)= var(obs) and the MSE can be reduced to only the bias term. That implies that the development of a high-quality model needs to ensure

- a. the highest possible precision in order to maximise the cov(mod, obs) term;
- b. the highest possible accuracy, in order to minimise the bias.

Elaborating on Eq. (5), Theil (1961) derived the following:

$$MSE = (\overline{\text{mod}} - \overline{\text{obs}})^2 + (\sigma_{\text{mod}} - \sigma_{\text{obs}})^2 + 2(1 - r)\sigma_{\text{mod}}\sigma_{\text{obs}}.$$
 (6)

Solazzo et al Atmos. Chem. Phys., 16, 6263–6283, 2016

Approaches to evaluation:

mMSE is the minimum achievable Mean Square Error: mMSE = $\sigma^2_{obs}(1-r^2)$

Solazzo and Galmarini suggest: MSE = $(<mod> - <obs>)^2 + (\sigma_{mod} - r\sigma_{obs})^2 + mMSE$

As this metric allows for quantification of accuracy (bias), precision (variance) and associativity (unexplained portion through the correlation coefficient – r)



MSE of spectral components - ozone - May-September - NA - continent





Approaches to evaluation:

When the analytical decomposition of the error into bias, variance and *mMSE* is applied to the decomposition of the signals into long-term, synoptic, inter-diurnal and diurnal components, information can be gathered that helps reduce the spectrum of possible sources of errors and pinpoint the processes that are most active at a particular scale which need to be improved. The procedure is denoted here as *error apportionment* and provides an improved and more powerful capacity to identify the nature of the error and associate it with a specific part of the spectrum of the model/measurement signal. The AQMEII set of models and measurements have been used in the evaluation procedure.

Approaches to evaluation:

Spectral decomposition of modelled and observed time series

Spectral decomposition is not new and is widely used in other fields of physical science but has been used less in evaluating composition.

Courtesy of David Wade



New approaches to evaluation:

Spectral decomposition of modelled and observed time series $O_3 = LT(O_3) + SY(O_3) + DU(O_3) + ID(O_3)$

Spectral decomposition is not new and is widely used in other fields of physical science but has been used less in evaluating composition.



Approaches to evaluation:

Spectral decomposition of modelled and observed time series $O_3 = LT(O_3) + SY(O_3) + DU(O_3) + ID(O_3)$



Approaches to evaluation:



www.atmos-chem-phys.net/16/8295/2016/

Atmos. Chem. Phys., 16, 8295-8308, 2016



www.atmos-chem-phys.net/16/8295/2016/

Approaches to evaluation:

Atmos. Chem. Phys., 17, 3001-3054, 2017 www.atmos-chem-phys.net/17/3001/2017/ doi:10.5194/acp-17-3001-2017 © Author(s) 2017. CC Attribution 3.0 License. (i) (ii)

Atmospheric Chemistry and Physics

Evaluation and error apportionment of an ensemble of atmospheric chemistry transport modeling systems: multivariable temporal and spatial breakdown

Efisio Solazzo¹, Roberto Bianconi², Christian Hogrefe³, Gabriele Curci^{4,5}, Paolo Tuccella⁵, Ummugulsum Alyuz⁶, Alessandra Balzarini⁷, Rocío Baró⁸, Roberto Bellasio², Johannes Bieser⁹, Jørgen Brandt¹⁰, Jesper H. Christensen¹⁰, Augistin Colette¹¹, Xavier Francis¹², Andrea Fraser¹³, Marta Garcia Vivanco^{11,14}, Pedro Jiménez-Guerrero⁸, Ulas Im¹⁰, Astrid Manders¹⁵, Uarporn Nopmongcol¹⁶, Nutthida Kitwiroon¹⁷, Guido Pirovano⁷, Luca Pozzoli^{6,1}, Marje Prank¹⁸, Ranjeet S. Sokhi¹², Alper Unal⁶, Greg Yarwood¹⁶, and Stefano Galmarini¹



Approaches to evaluation: CO

the cause of model bias for CO is most probably attributable to the emissions and to a lesser extent the generally overestimated surface wind speed (Sect. 3.1.1). Sensitivity of the





Approaches to evaluation: NO₂

The bias is the main contributor to the NO₂ error and stems from a model underprediction of the mean observed concentration during the entire year (but, with the exception of the winter season, it is positive for WRF-CMAQ in NA and WRF-CMAQ1 in EU; Table S7). The bias is probably caused by a combination of factors, including emission estimates (e.g., underestimation of residential combustion), PBL height and vertical mixing at night (when wood com-





Approaches to evaluation: A success?

Although remarkable progress has been made since the first phase of AQMEII, both in terms of model performance and in terms of developing a more versatile and robust evaluation procedure, results of AQ model evaluation and intercomparison remain generic since they fail to associate errors with processes, or at least to narrow down the list of processes responsible for model error. AQ models are meant to be applicable to a variety of geographic (and topographic) scenarios under almost any type of weather, season, and emission conditions. For such a wide range of conditions the inherent nonlinearity among processes is difficult to disentangle, and specifically designed sensitivity runs seems to be the only viable alternative. A model evaluation strategy relying solely on the comparison of modeled vs. observed time series would never be able to quantify exactly the error induced by biogenic emissions, vertical emission profiles,

or their dependence on temperature, deposition, and vertical mixing, for example, and the analyses presented in this work are no exception. In fact, the methodology devised to carry out the evaluation activity in this study has not succeeded in determining the actual causes of model error, although it does provide much clearer indications of the processes responsible for the error with respect to conventional operational model evaluation.

www.atmos-chem-phys.net/17/3001/2017/

Atmos. Chem. Phys., 17, 3001–3054, 2017

Perturbed parameter ensembles

Atmos. Chem. Phys., 11, 12253–12273, 2011 www.atmos-chem-phys.net/11/12253/2011/ doi:10.5194/acp-11-12253-2011 © Author(s) 2011. CC Attribution 3.0 License.



Emulation of a complex global aerosol model to quantify sensitivity to uncertain parameters

L. A. Lee, K. S. Carslaw, K. J. Pringle, G. W. Mann, and D. V. Spracklen

Institute for Climate and Atmospheric Science, University of Leeds, UK

Received: 7 July 2011 – Published in Atmos. Chem. Phys. Discuss.: 19 July 2011 Revised: 11 November 2011 – Accepted: 16 November 2011 – Published: 8 December 2011



