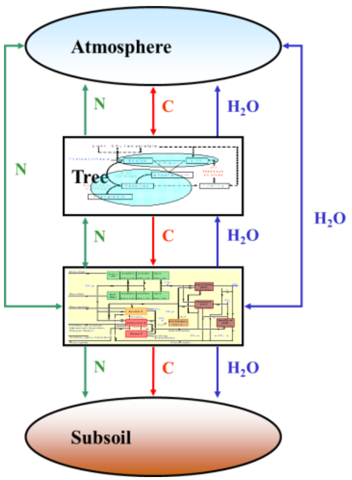
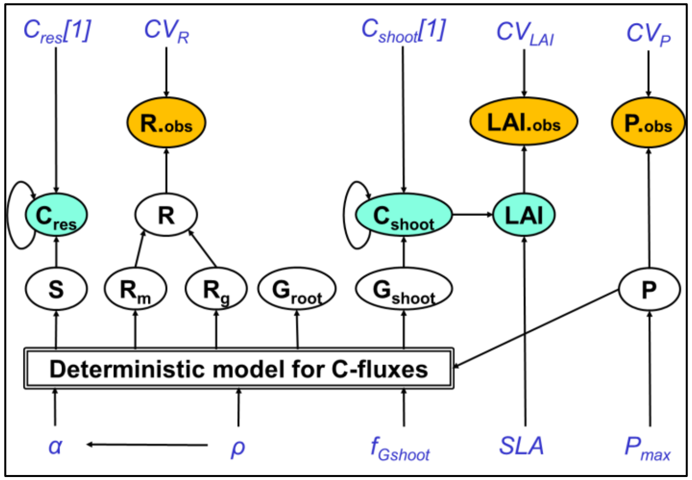
Bayesian Methods for Ecological and Environmental Modelling: COMMUNICATION





Marcel van Oijen, Lindsay Banin, David Cameron, Peter Levy, Kate Searle

CEH-Edinburgh, 2019-09-12

Contents

1. Introduction

1.1 Purpose , ToWhom-What-How, Guidelines?

- **What is the purpose of the communication?**
- **Are you co-designing a model, or is the study finished and are you reporting results?**
  - **Graphical modelling is very good for the first purpose, less so for the second**
  - **Reporting results: *To whom? What? How?***
- **Are there guidelines for visualising uncertainty?**

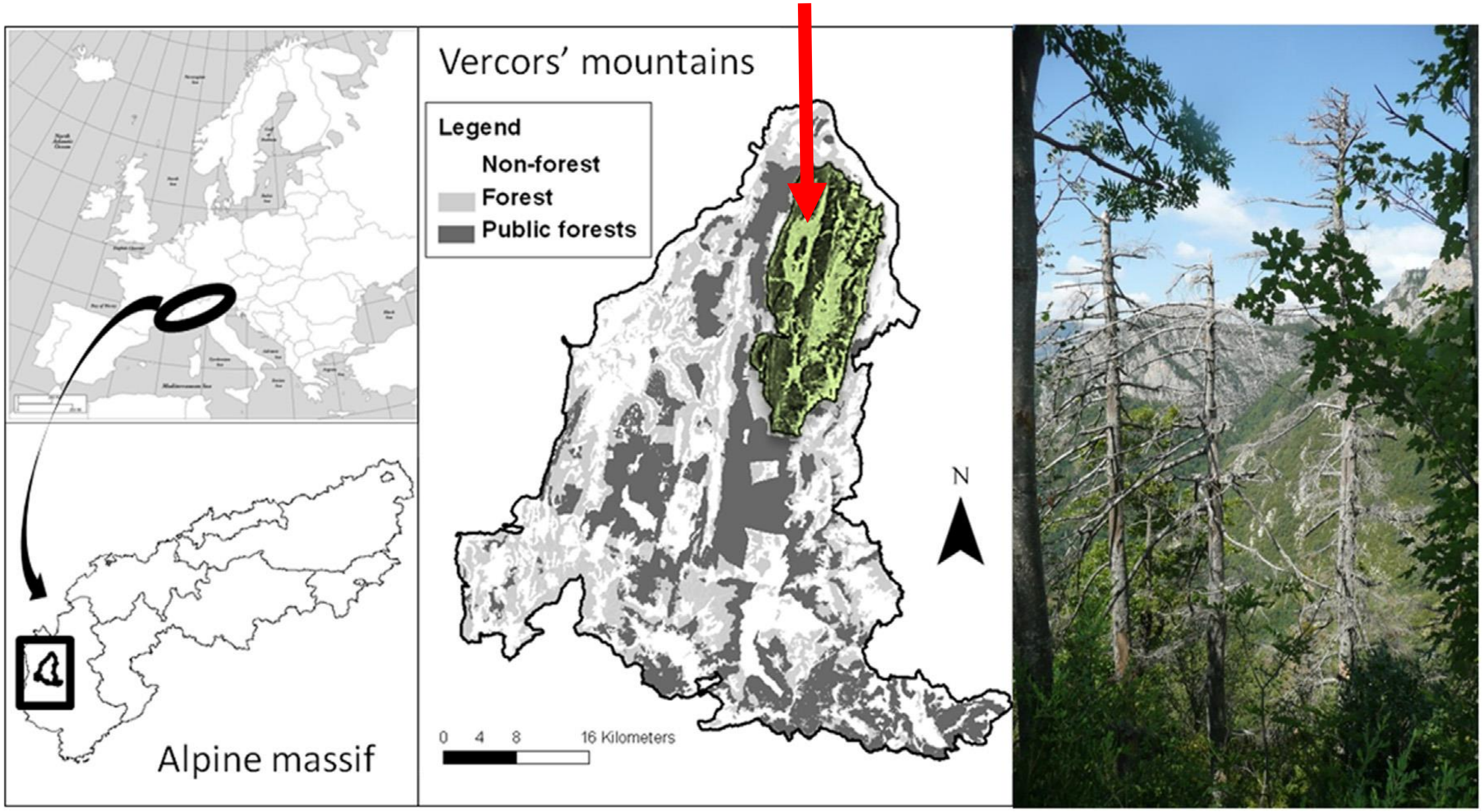
2. Co-design & graphical modelling

2.1 Decision-support

How to make LS-modelling useful for decision-making?

- ***Stimulate involvement of stakeholders***
- ***Recognise uncertainties***

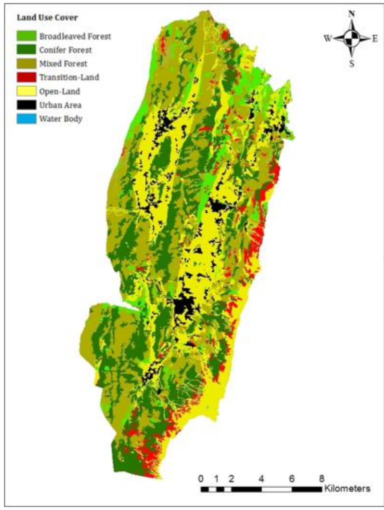
Production or conservation?

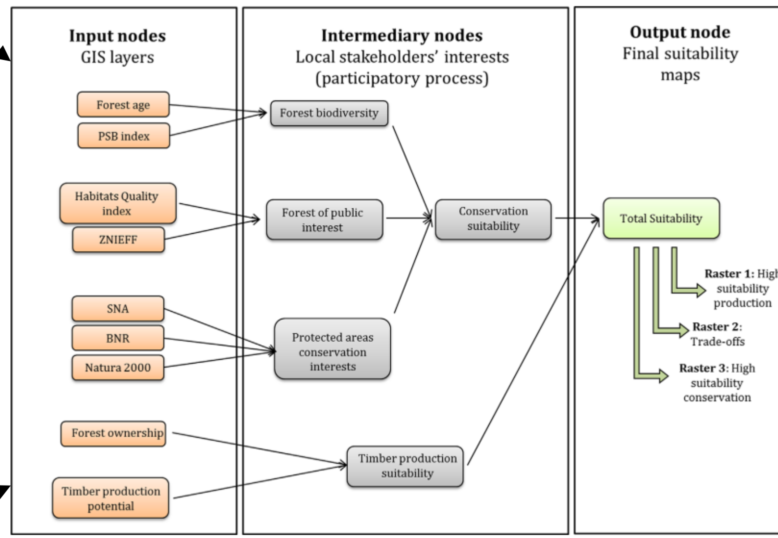


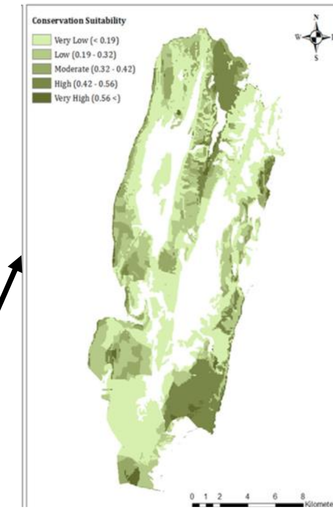
Gonzales-Redin et al. (2016)

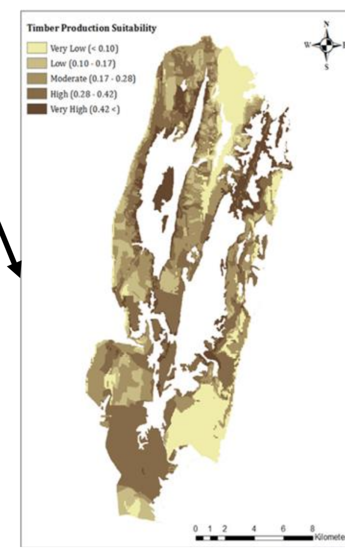
2.2 Production or conservation? GIS + BBN

GIS: inputs | **BBN: conditional probabilities** | **GIS: outputs**



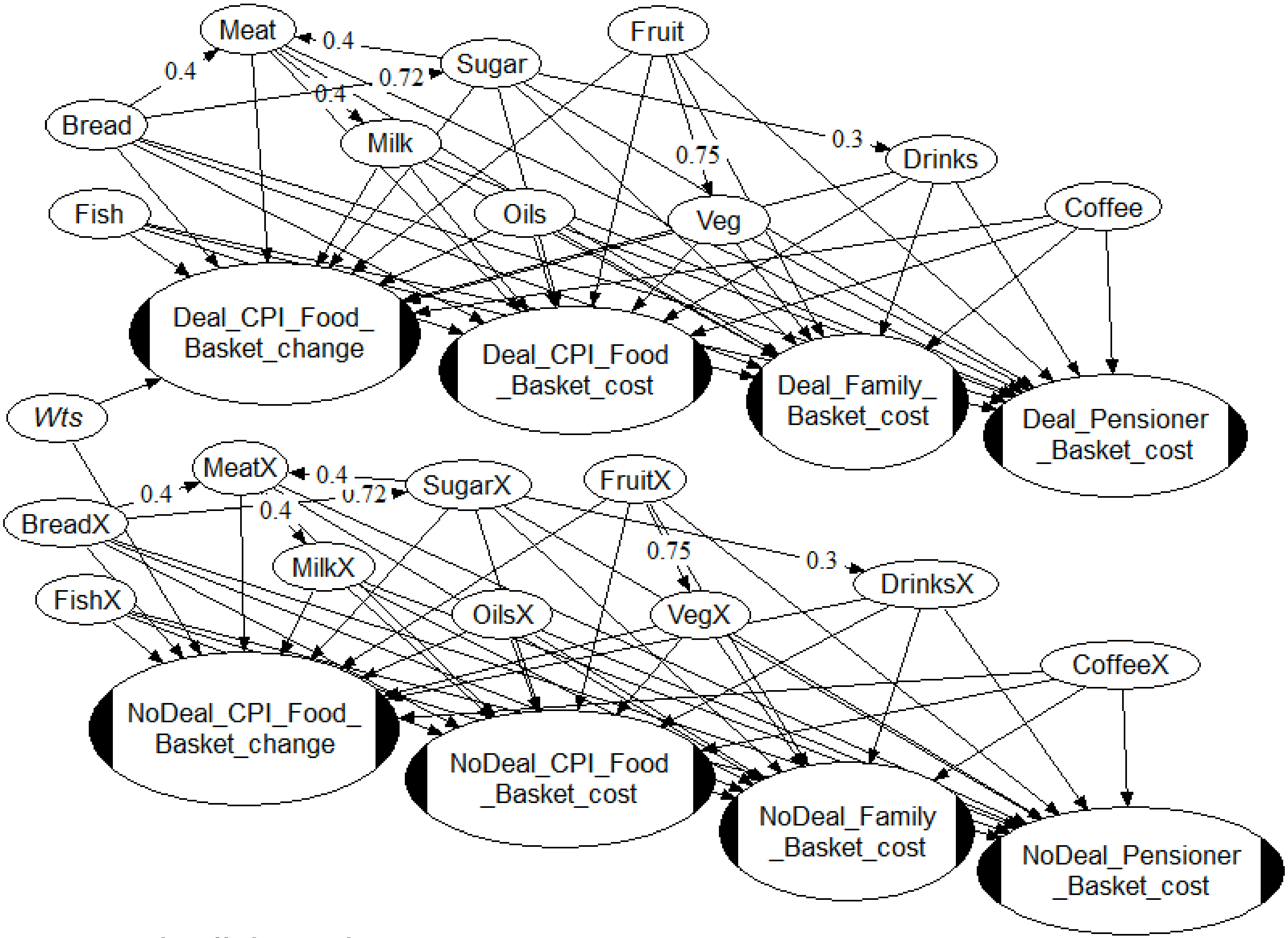






Gonzales-Redin et al. (2016)

Impacts of Brexit scenarios on UK food prices using structured expert judgement



Barons & Aspinall (2019)

3. Reporting results

3.1 Reporting: To whom? What? How

- Reporting to whom?
  - Colleagues or stakeholders? Listeners, readers (posters or papers), or app-users?
- What?
  - Main message: methodological <-> application?
  - Checklist: Reporting prior, likelihood, algorithm, software, quality test of MCMC, posterior parameter uncertainty, posterior predictive uncertainty
    - *E.g.: beta priors, Gaussian likelihoods for residuals from PBM, Metropolis, BayesianTools, Gelman-Rubin < 1.01, Posterior histograms parameters, Posterior prediction bands for output variables*
- How?
  - Text, tables, figures, interactive app

4. Visualisation of uncertainty: Guidelines

Milne et al. (2015): Communicating the uncertainty in GHG emissions

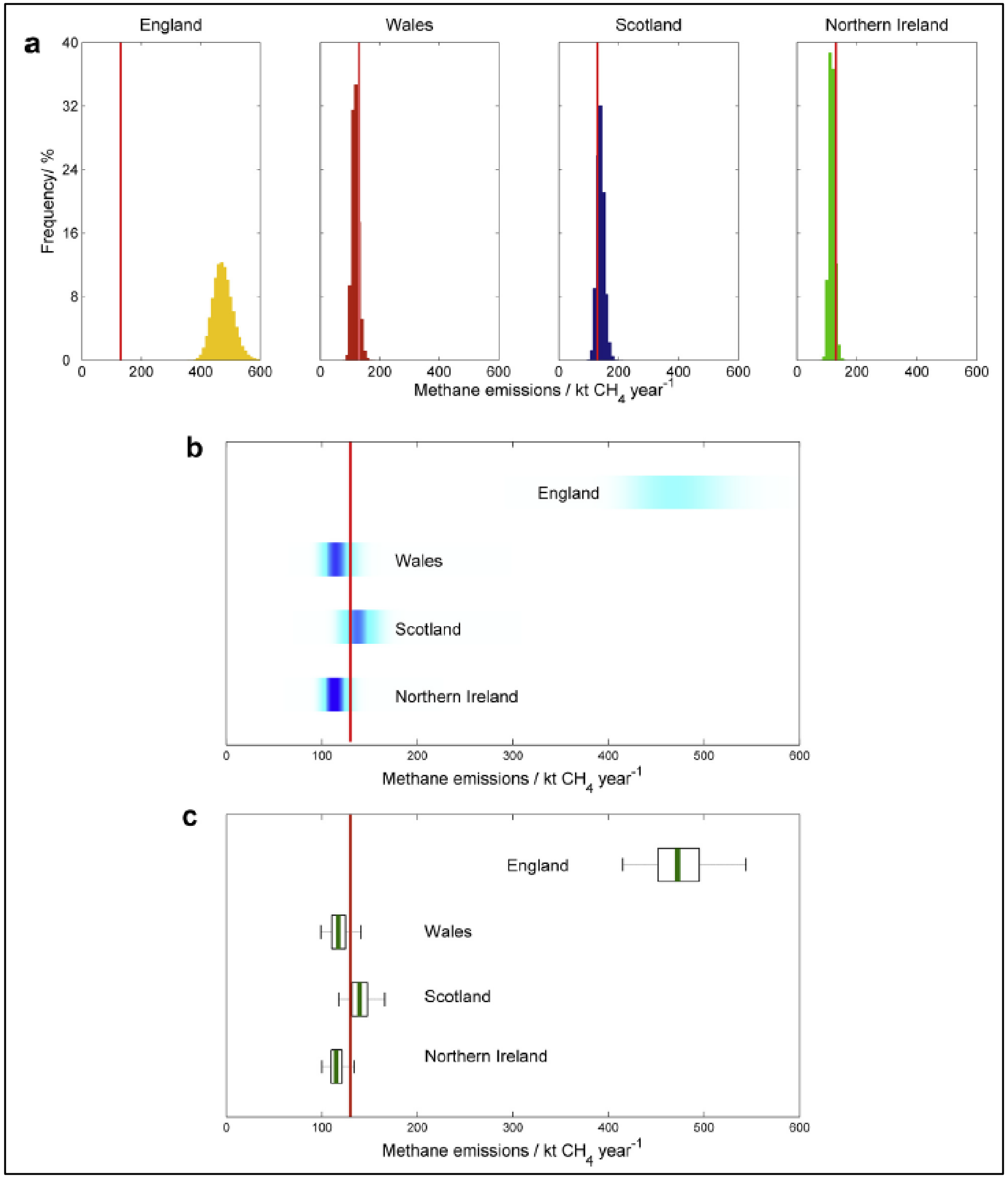
Communicating the uncertainty in estimated greenhouse gas emissions from agriculture

Alice E. Milne [a,*], Margaret J. Glendining [a], R. Murray Lark [b], Sarah A.M. Perryman Taylor Gordon [a], Andrew P. Whitmore [a] Journal of Environmental Management 160 (2015) 139–153

Histograms

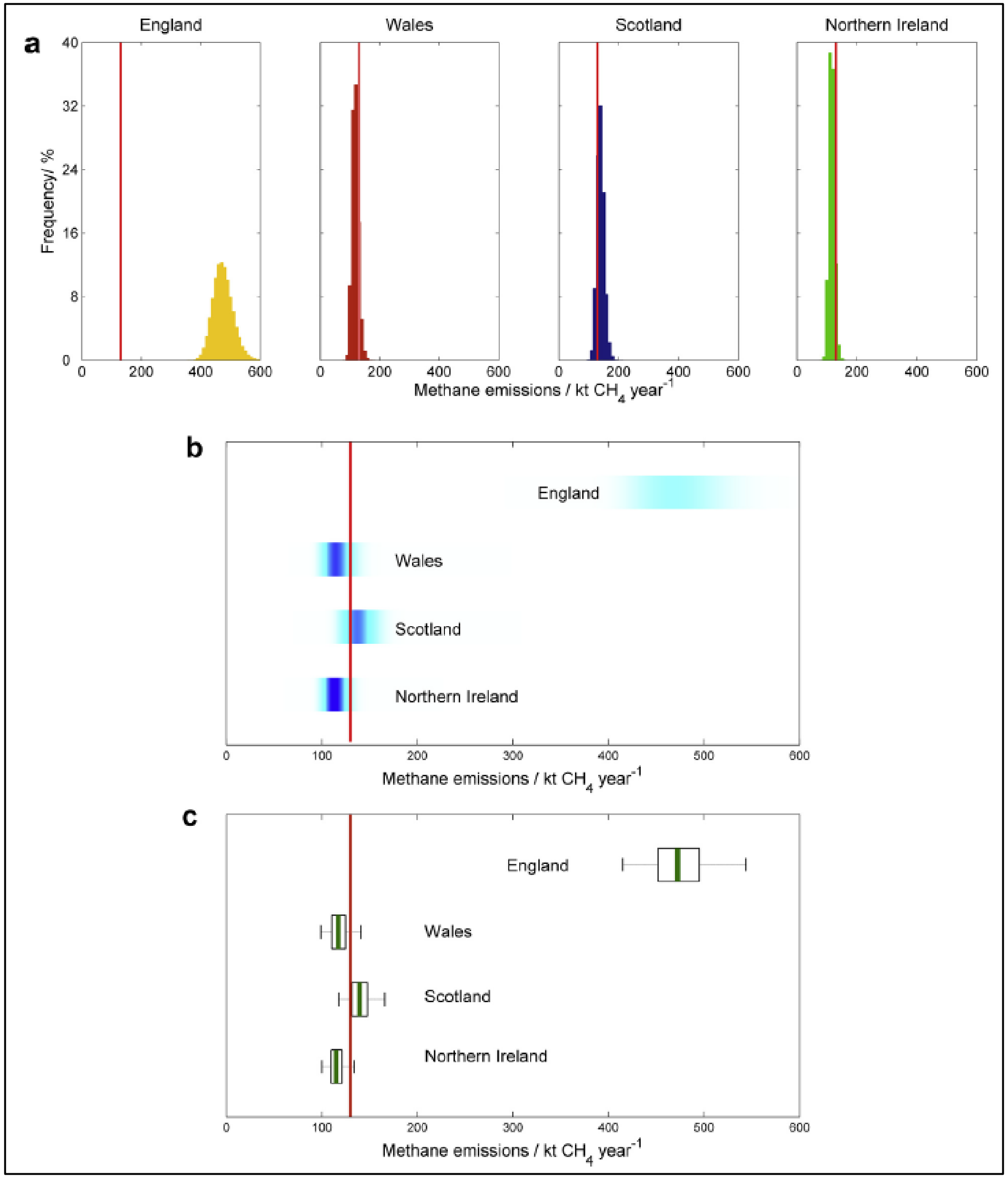
Shaded arrays

Boxplots



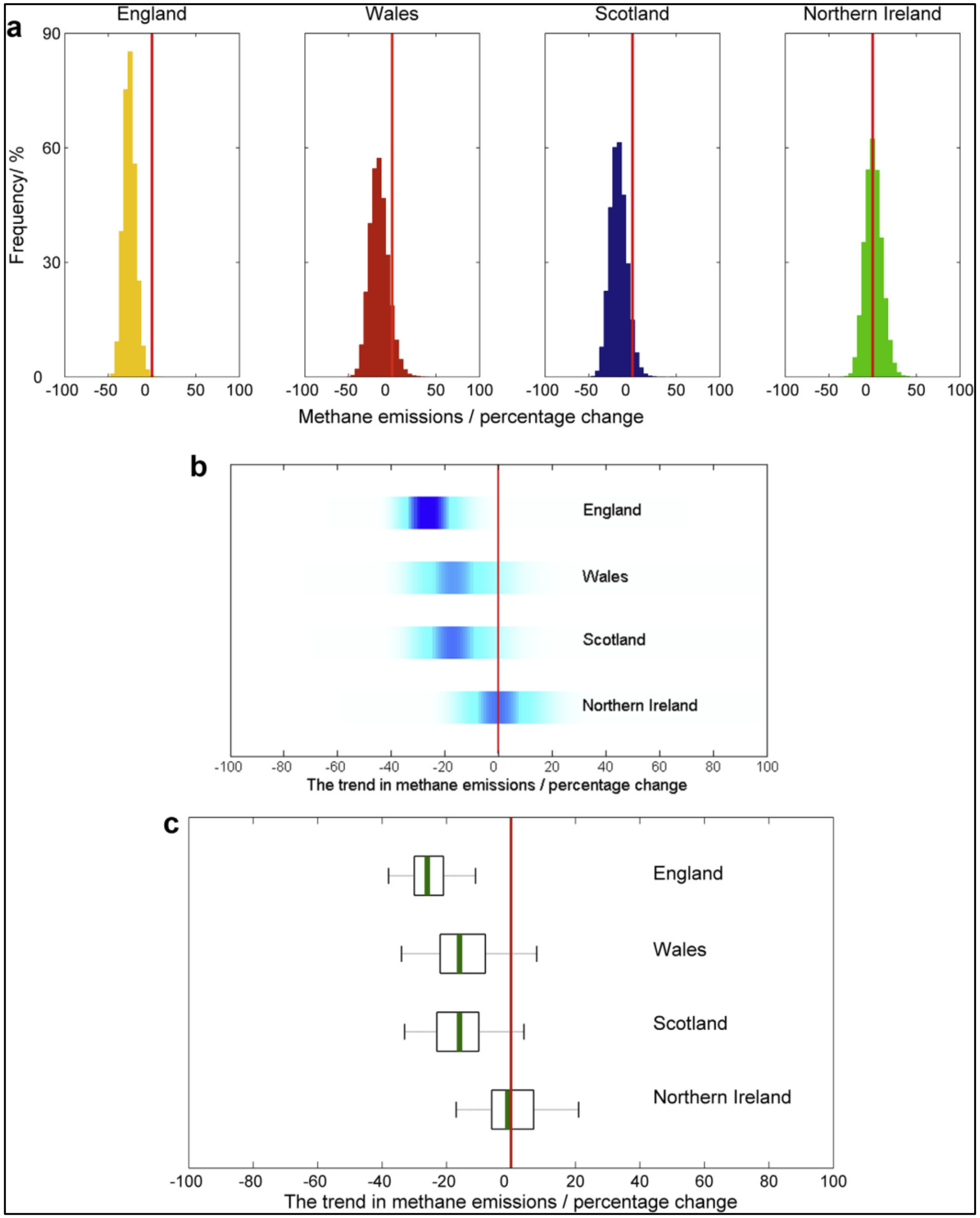
Milne et al. (2015): Communicating the uncertainty in GHG emissions

- Is it clear that the estimated emissions are most uncertain for England?

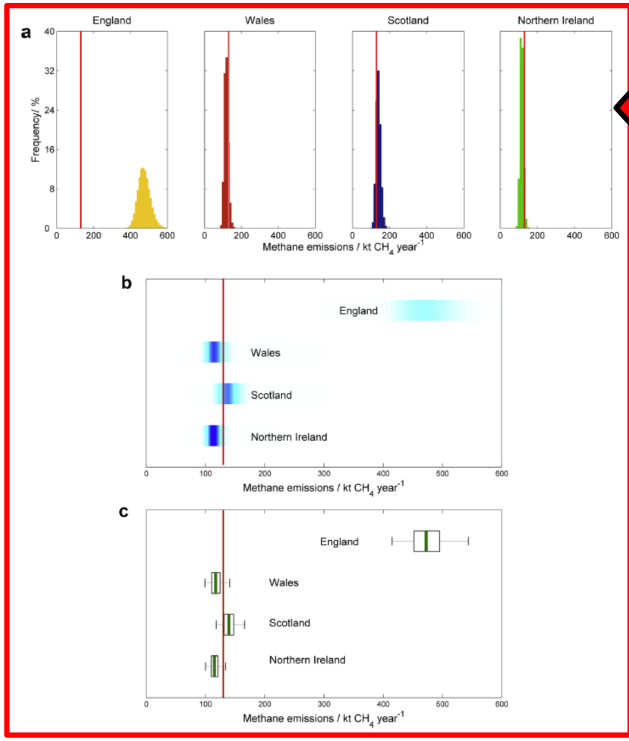


Milne et al. (2015): Communicating the uncertainty in GHG emissions

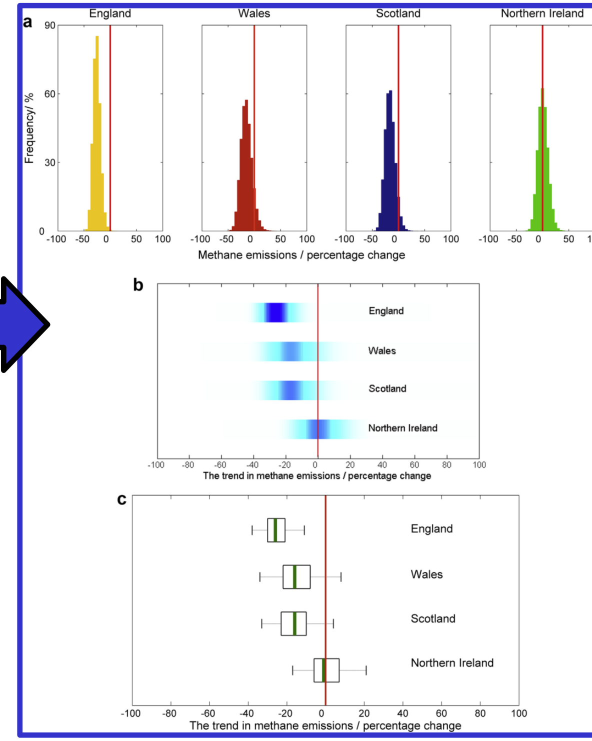
- It is more uncertain that emissions from Scotland have reduced than that emissions from England have reduced?

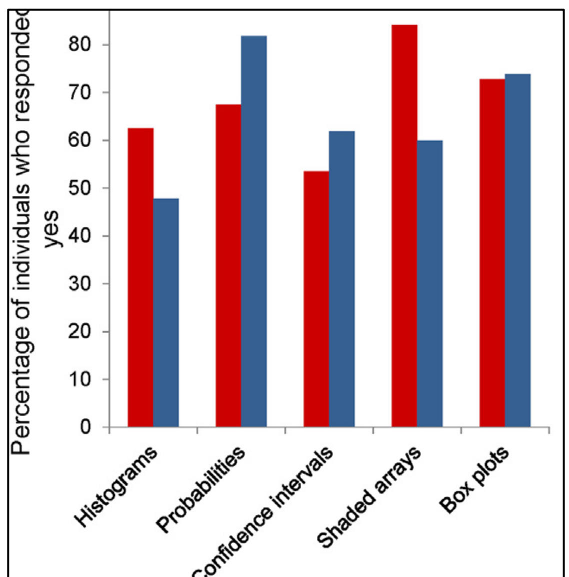


Milne et al. (2015): Communicating the uncertainty in GHG emissions



- Is it clear that the estimated emissions are most uncertain for England?
- It is more uncertain that emissions from Scotland have reduced than that emissions from England have reduced?

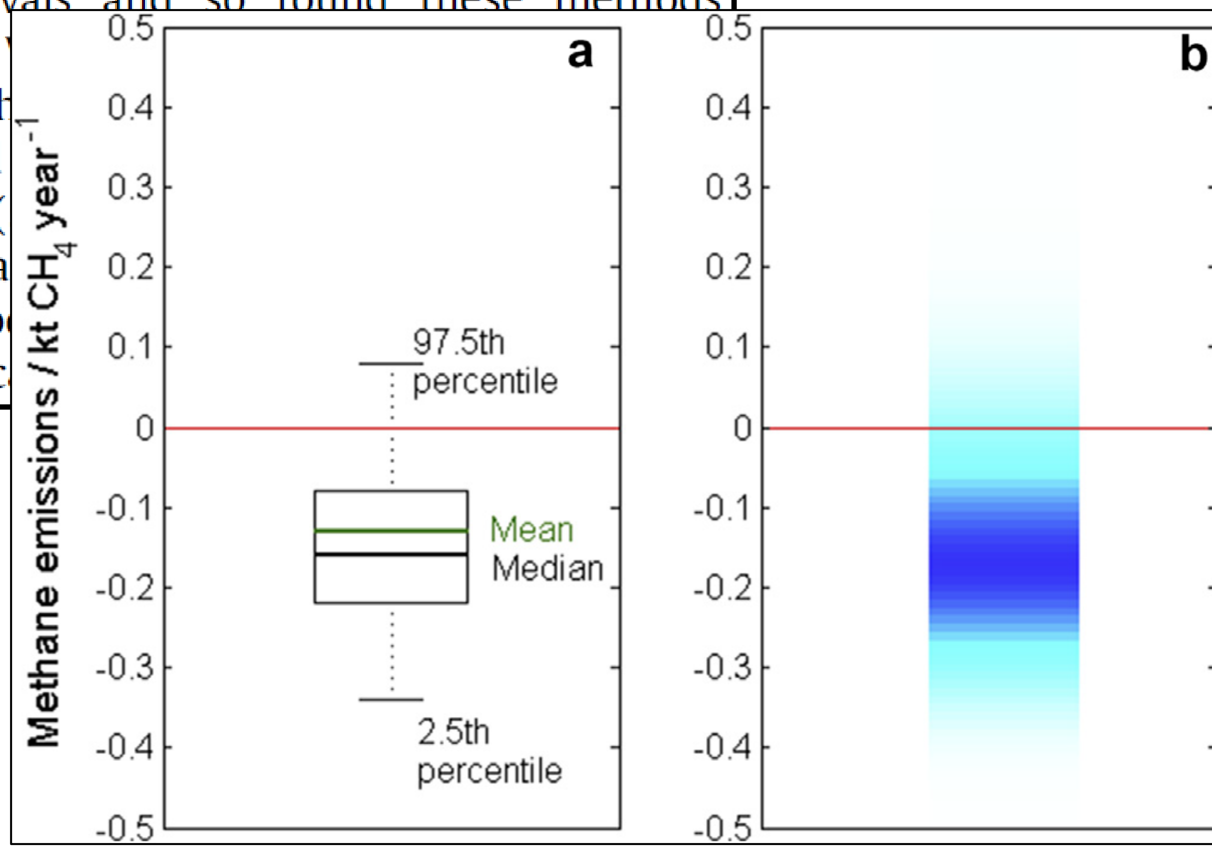




Milne et al. (2015): Communicating the uncertainty in GHG emissions

5. Conclusion and recommendation

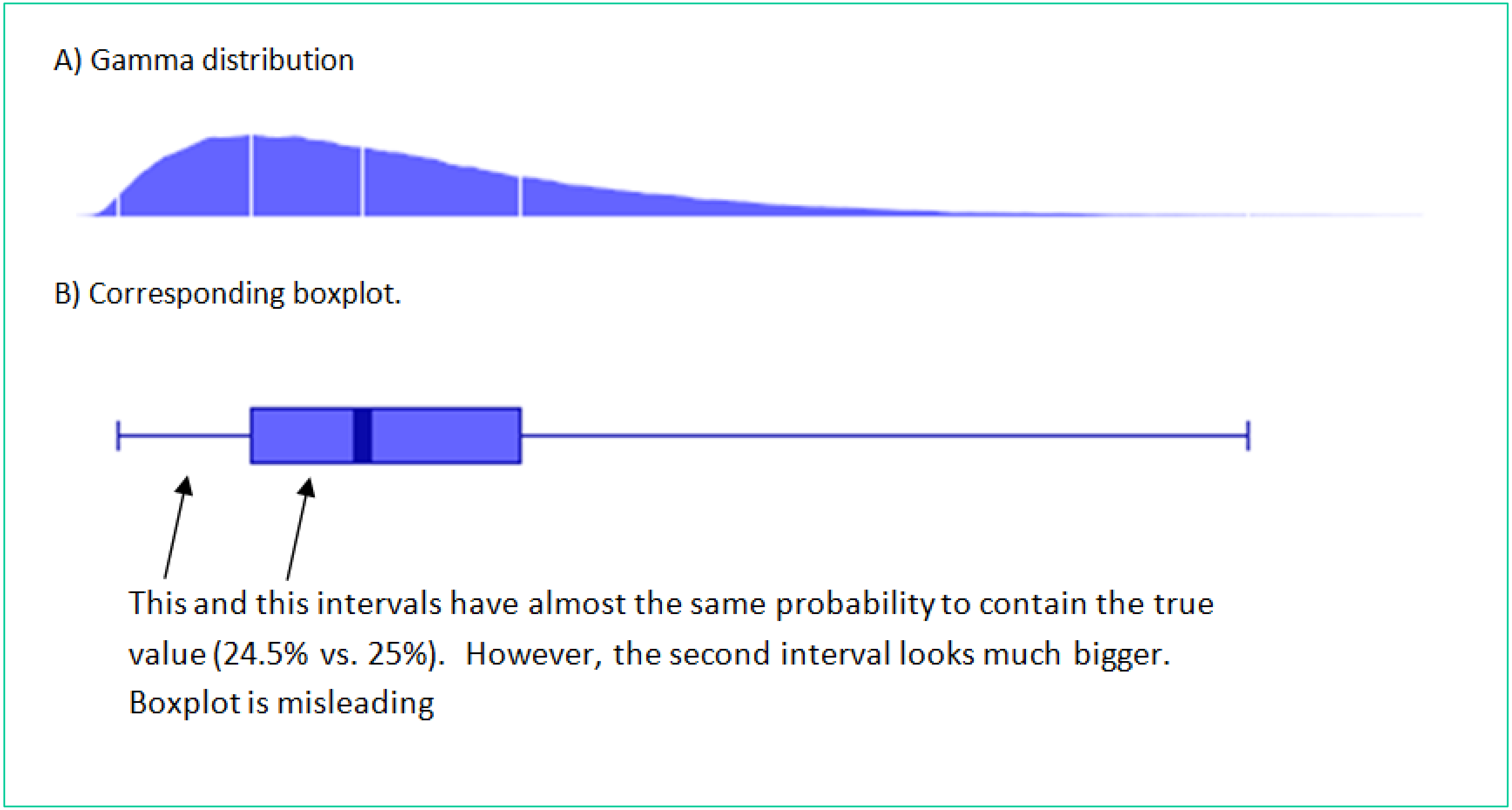
The methods chosen to communicate uncertainty in estimates of greenhouse gas emissions should be influenced by professional and mathematical background of the target audience. In our study we found that research scientists tended to be familiar with box-plots and confidence intervals and so found these methods
straightforward to interpret.
with summary statistics such
percentiles provide a sound
tainty to these individuals (
groups may not be so familia
bination of intuitive metho
shaded arrays with numeric



PRINCIPLES OF POSTERIOR VISUALIZATION (2015)

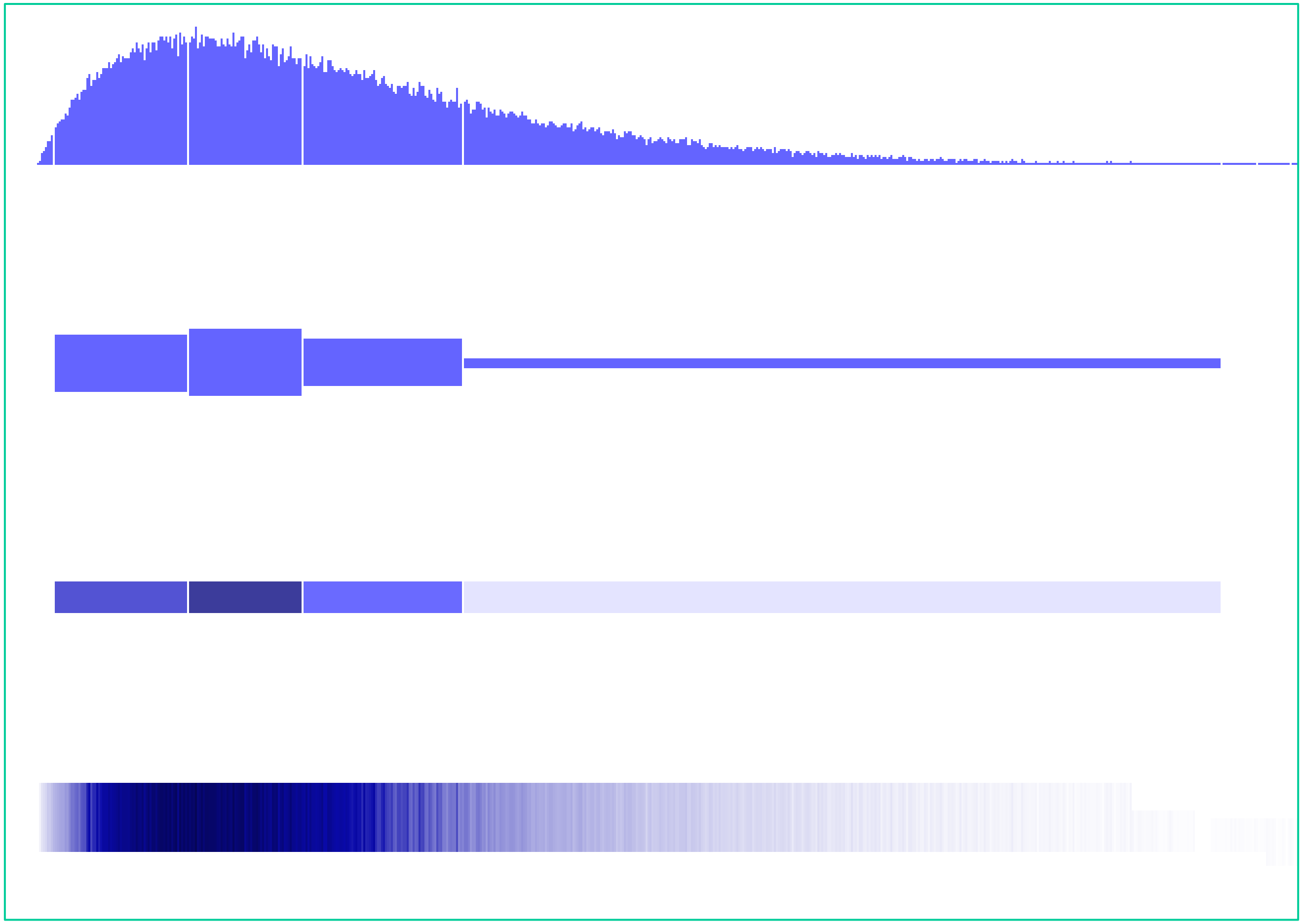
Blog by Mikhail Shubin:

https://ctg2pi.wordpress.com/2015/02/24/principles-of-posterior-visualization/



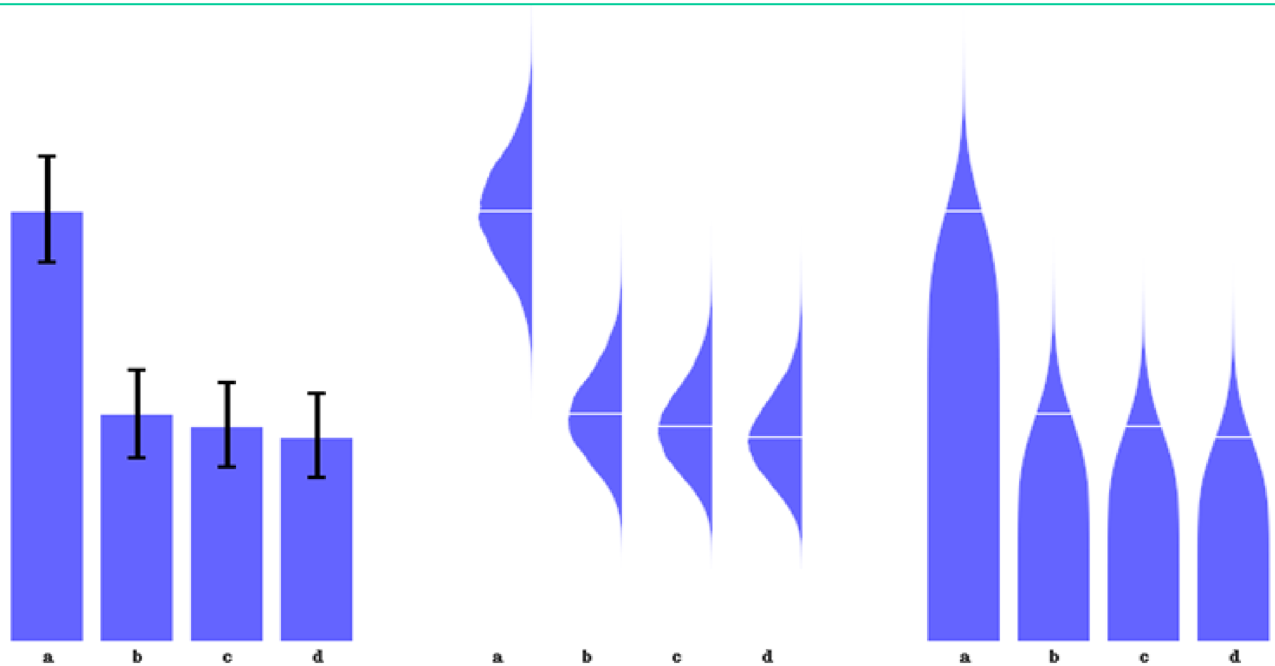
PRINCIPLES OF POSTERIOR VISUALIZATION (2015)

Principle: Equal probability = Equal ink



PRINCIPLES OF POSTERIOR VISUALIZATION (2015)

Principle: Do not overemphasize the point estimate



A)

Bars with mean estimates and whiskers representing 90% credible interval.

Mean estimates are overemphasized. This figure seems to suggest that the values are ordered: *a>b>c>d*. This is true only with probability 0.23

B)

Posterior distributions of the values with mean values highlighted.

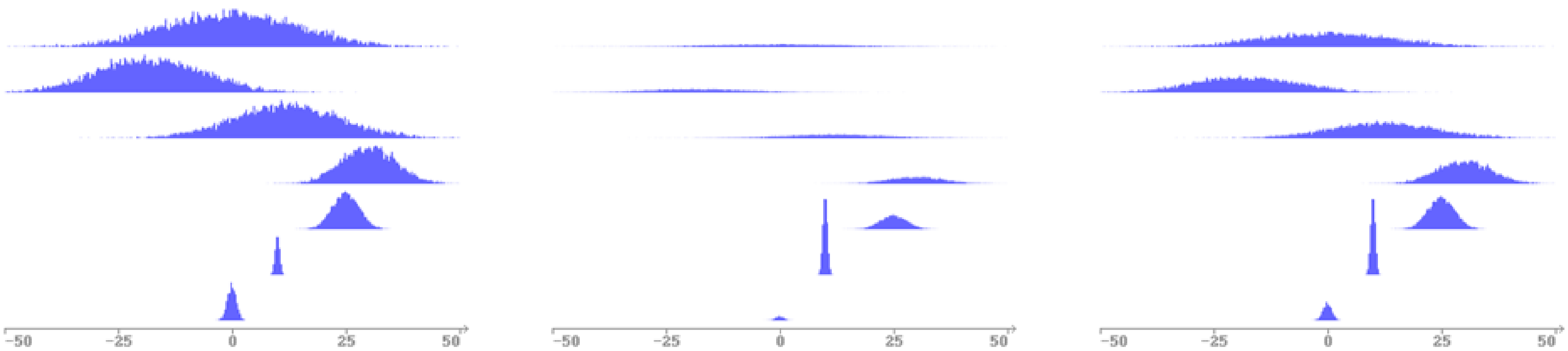
Uncertainty in the estimates and the order of values is more visible.

C)

Cumulative distributions of the posterior with mean values highlighted.

The same effect as in (B), but this figure is more similar to the original bars.

PRINCIPLES OF POSTERIOR VISUALIZATION (2015)



A)

All histograms have the same height.

Histograms of the most uncertain estimates dominate the visual space.

B)

Y-axes of all histograms have the same scale.

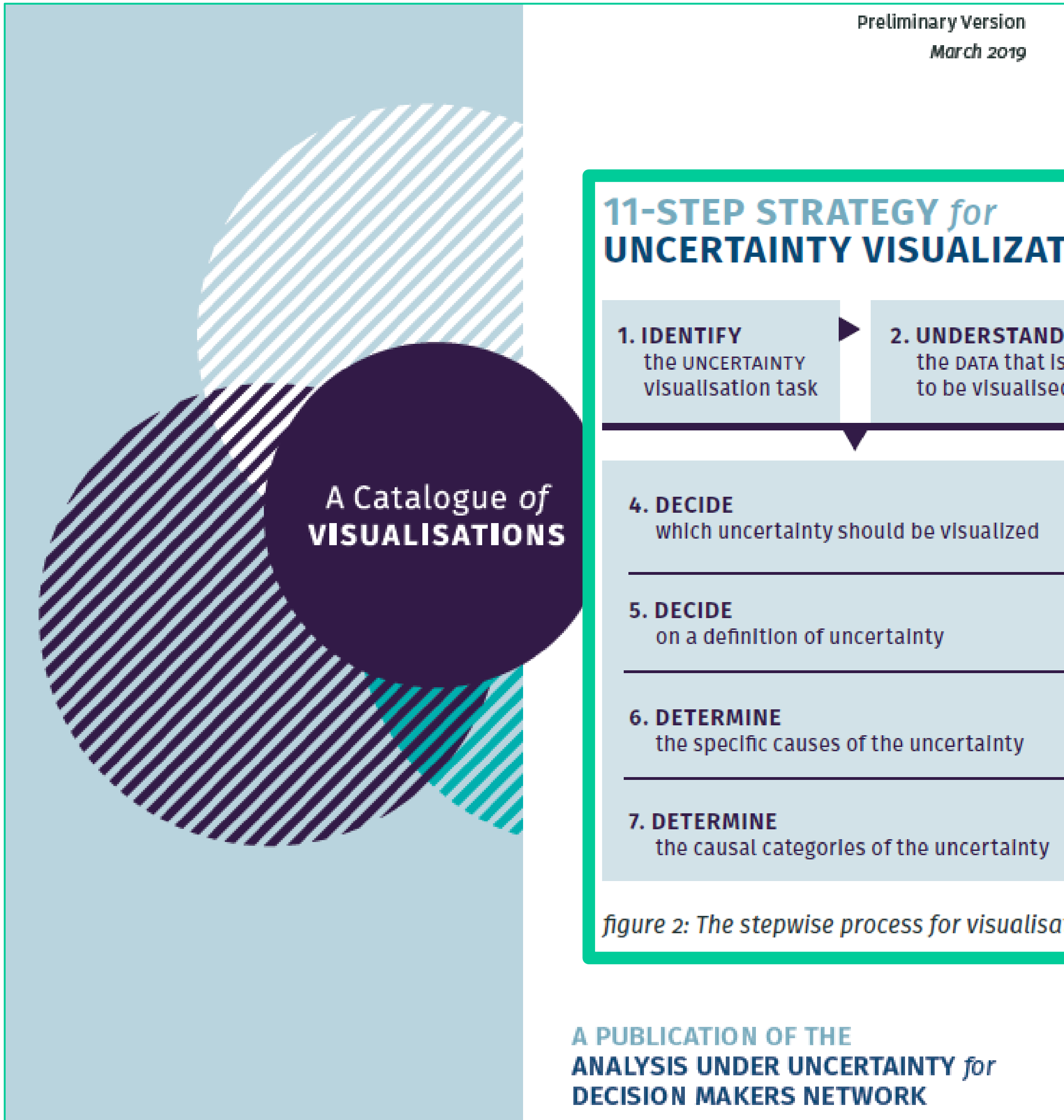
Histograms of the uncertain estimates are barely readable.

C)

The height of each histogram is proportional to the square root of its height as on Panel B.

Precise estimates are highlighted while uncertain estimates remain readable.

Kleineberg et al. (2019): Visualizing Uncertainty



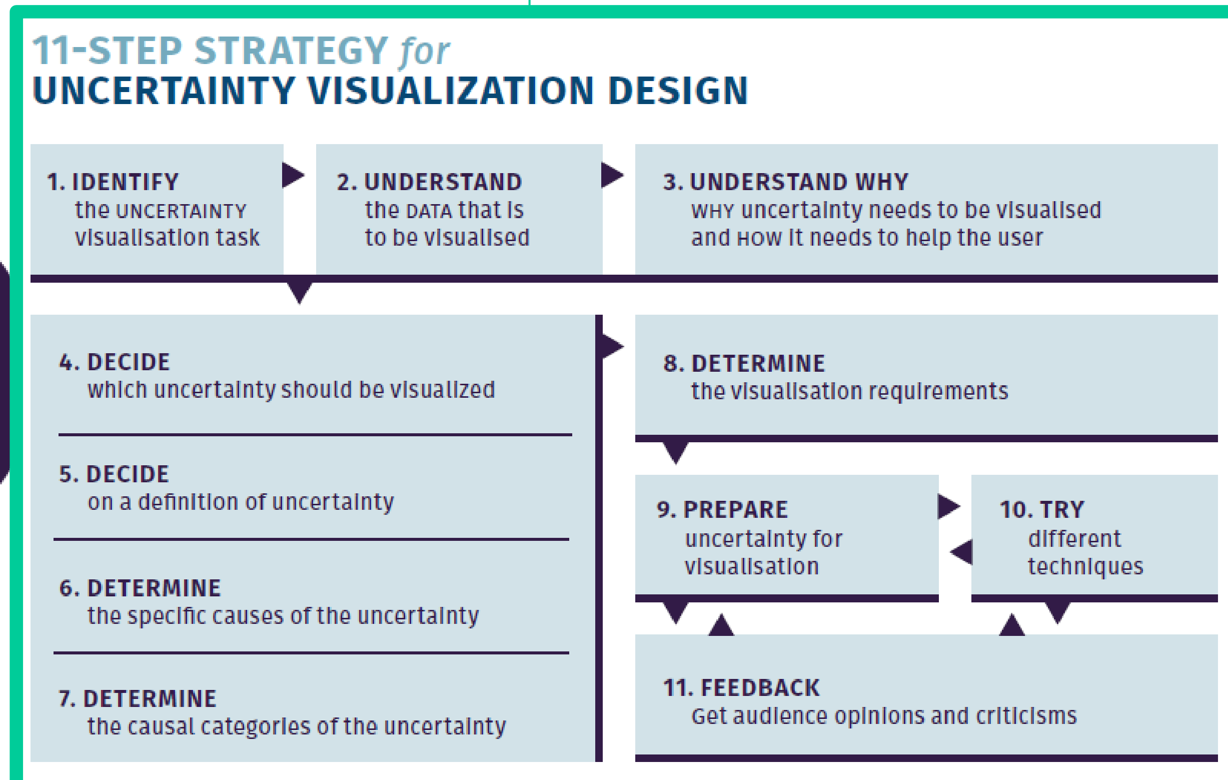
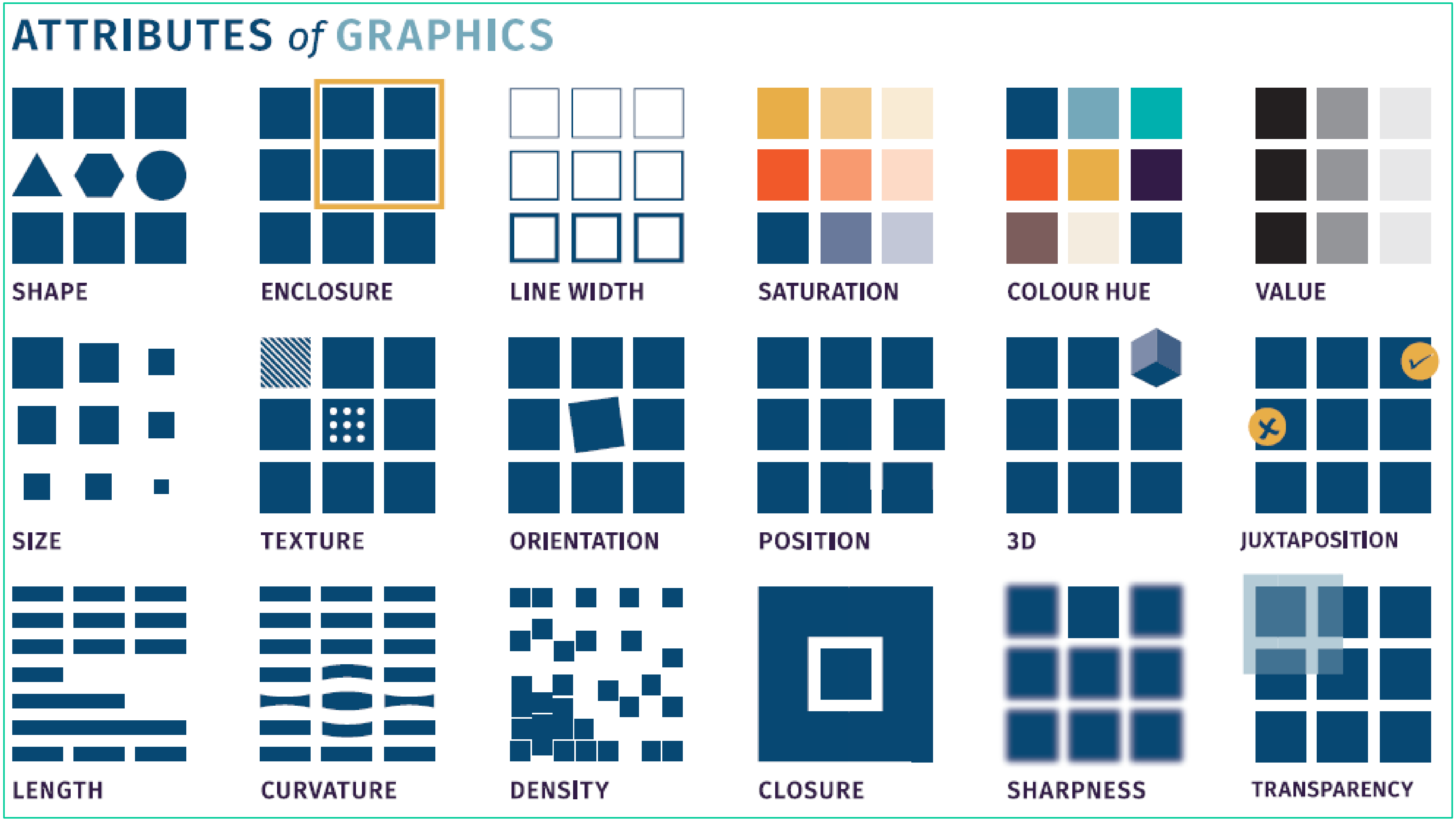


figure 2: The stepwise process for visualisation of uncertainty

Kleineberg et al. (2019): Visualizing Uncertainty



Kleineberg et al. (2019): Visualizing Uncertainty

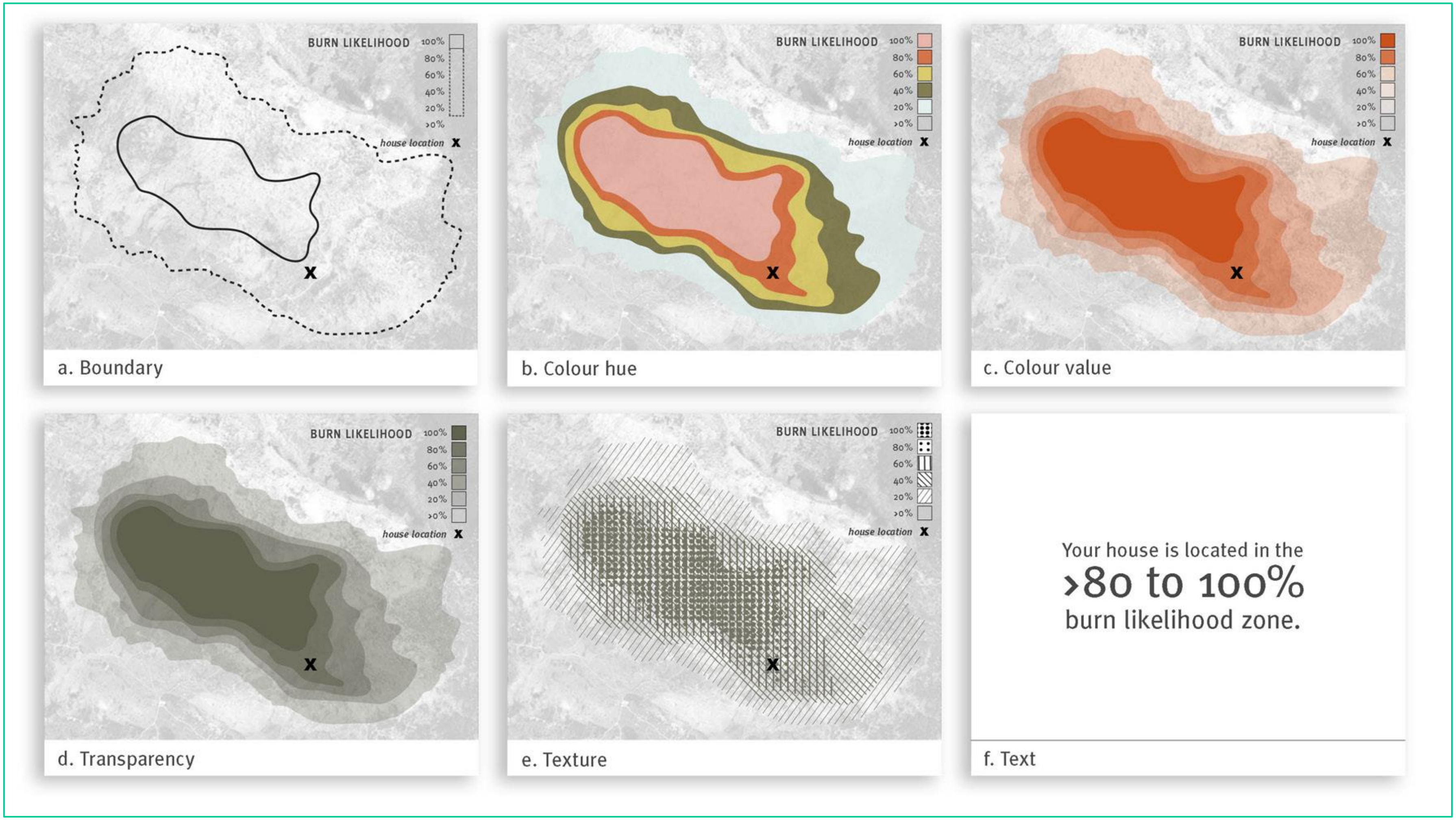
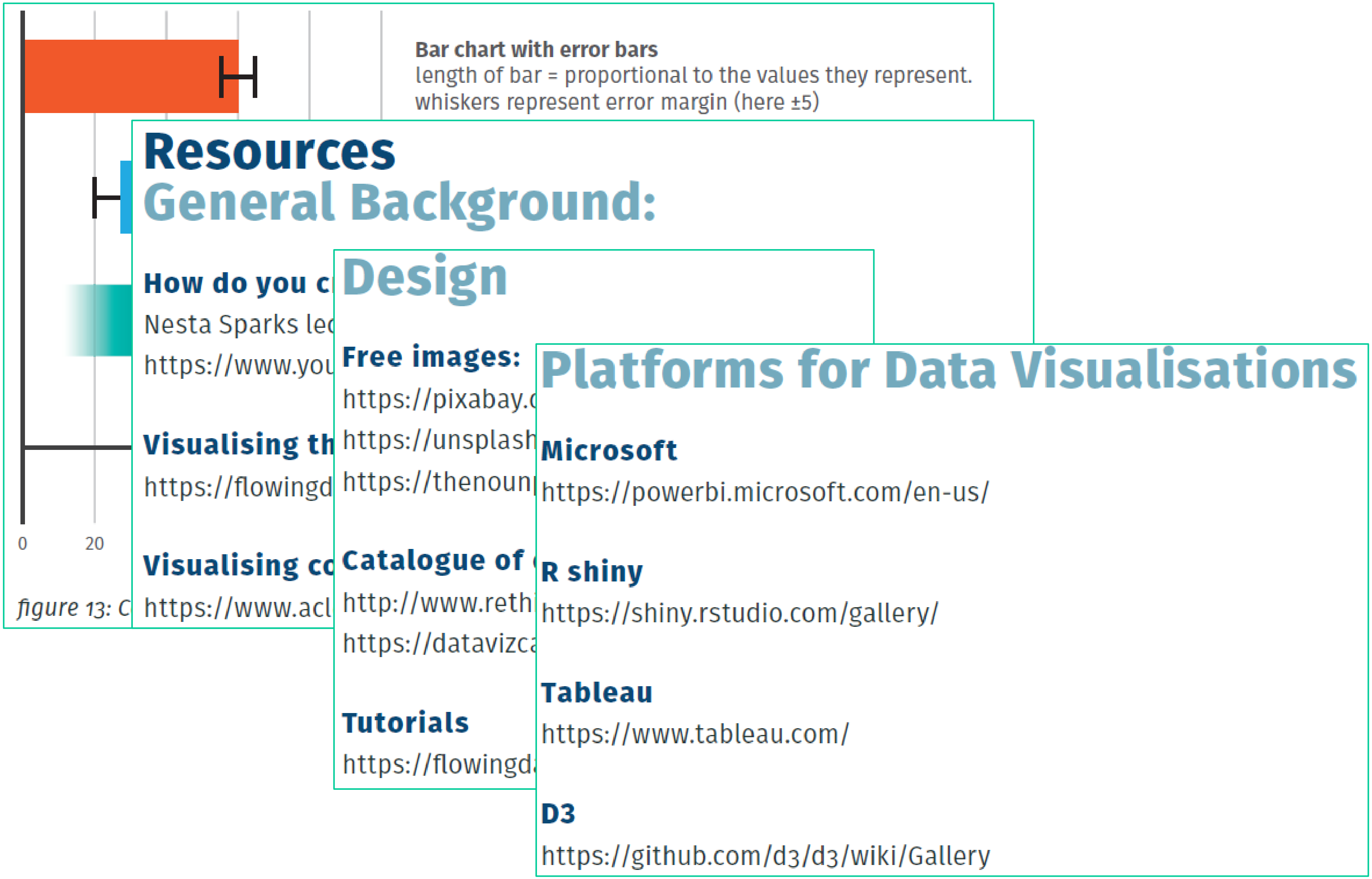


figure 8: Comparing changing different attributes to communicate uncertainty, research shows that representations involving hue(b), value(c) and transparency(d) work best.

Kleineberg et al. (2019): Visualizing Uncertainty



Kurz-Milcke et al. (2008): *Transparency in Risk Communication*

Ann. N.Y. Acad. Sci. 1128: 18–28 (2008).
doi: 10.1196/annals.1399.004

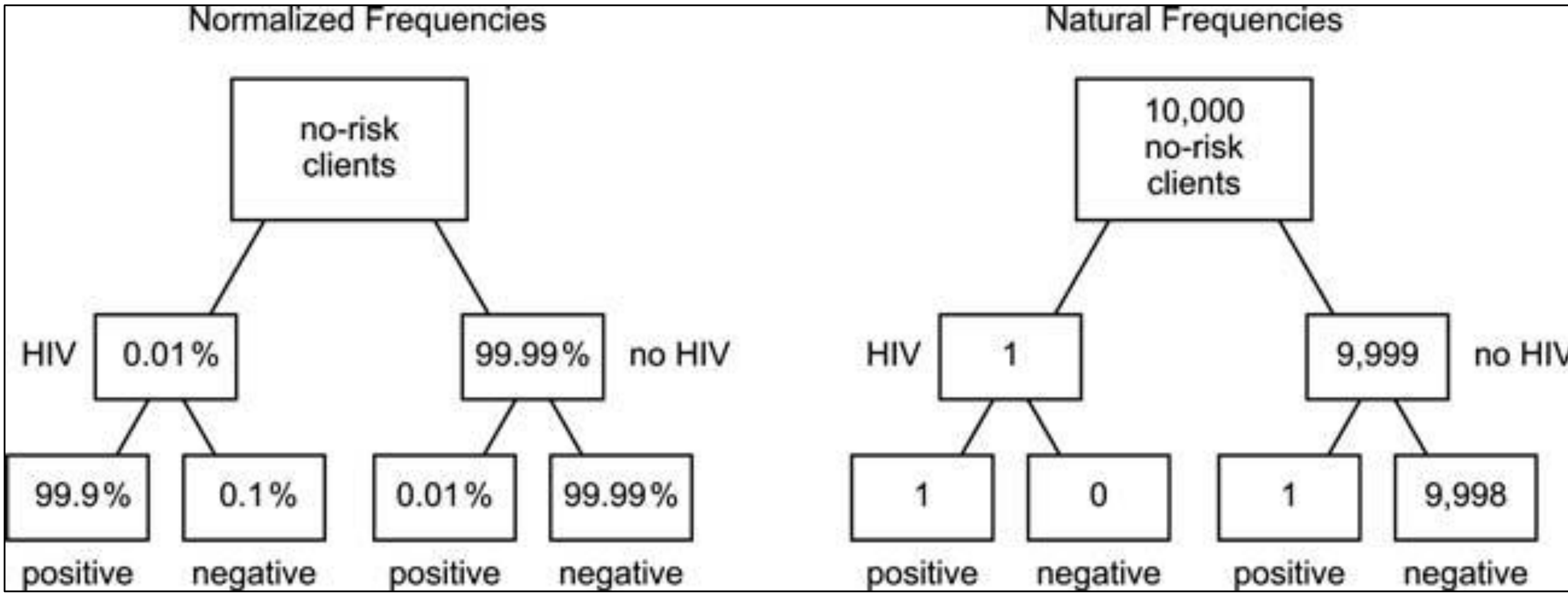
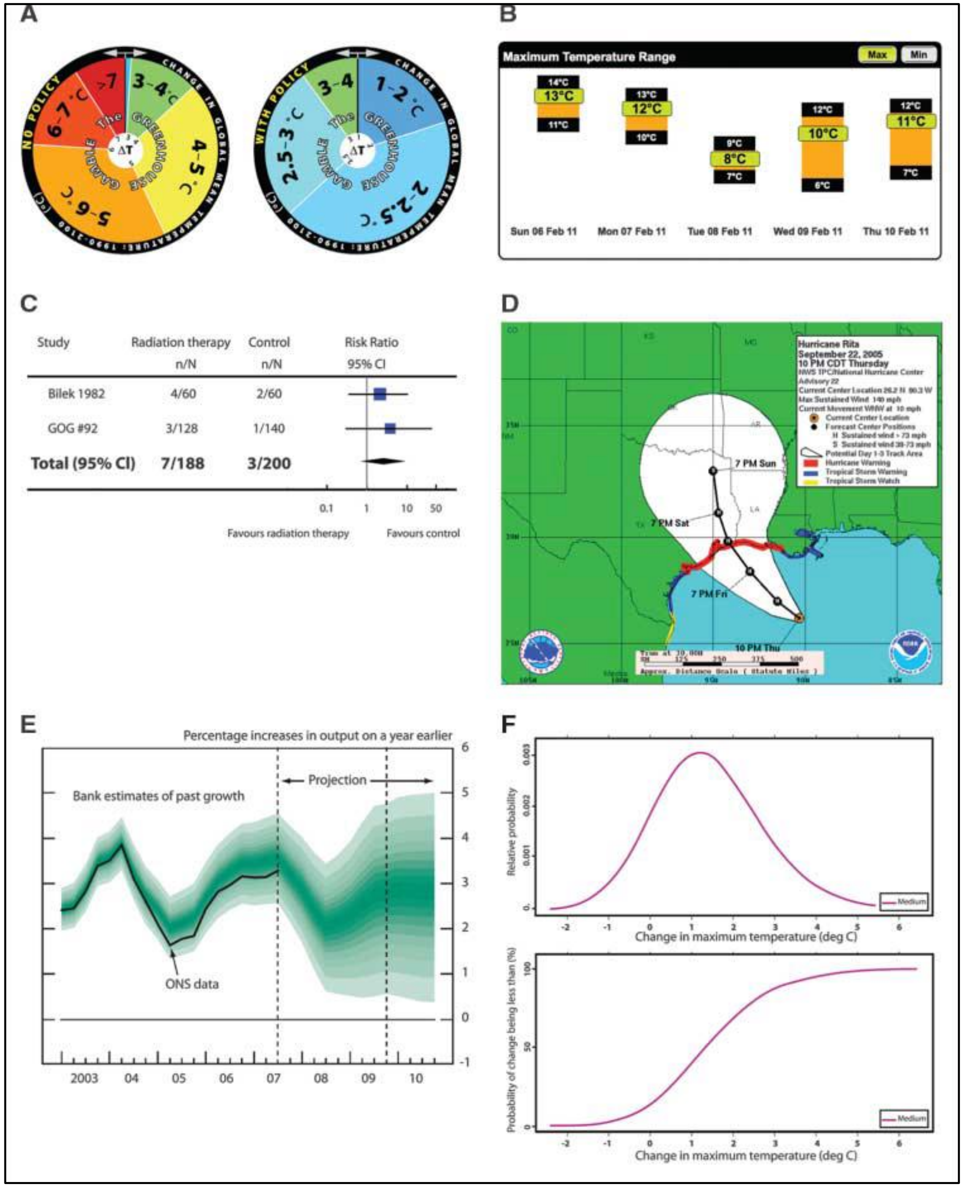


FIGURE 1. Two kinds of frequency trees for HIV testing: relative frequencies (left), which are nontransparent for many people, and natural frequencies (right), which are transparent.

Spiegelhalter et al. (2011): Visualizing uncertainty about the future

Fig. 5. Visualizations of probability distributions for continuous quantities.

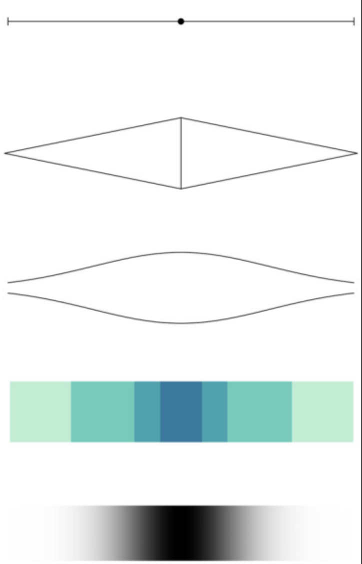


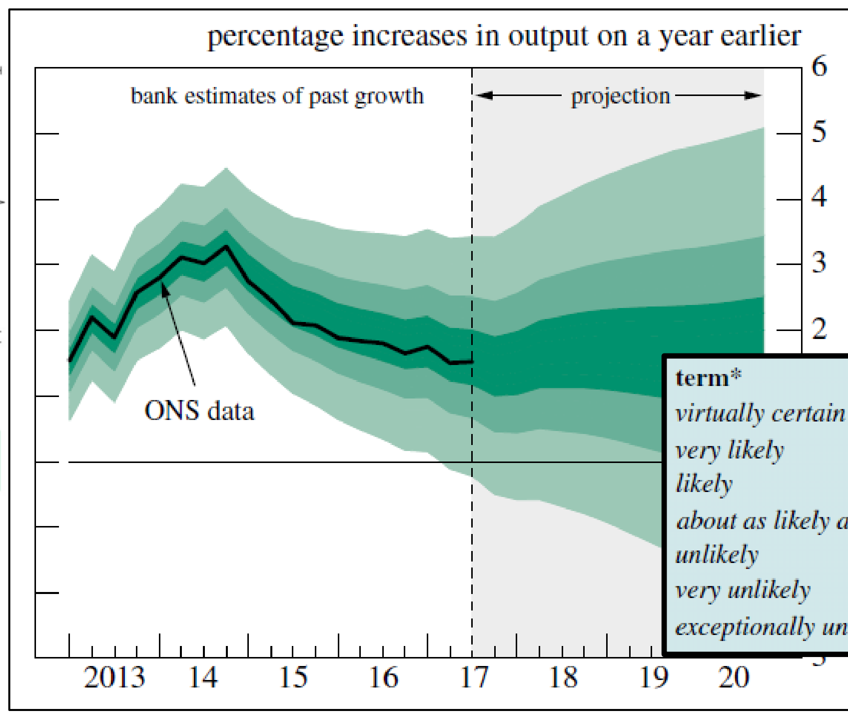
SCIENCE VOL 333 9 SEPTEMBER 2011

Van der Bles et al. (2019): Communicating unc. about facts, numbers and science

Decreasing precision

i. A full explicit probability distribution
ii. A summary of a distribution
iii. A rounded number, range or an order-of-magnitude assessment
iv. A predefined categorisation of uncertainty
v. A qualifying verbal statement
vi. A list of possibilities or scenarios
vii. Informally mentioning the existence of uncertainty
viii. No mention of uncertainty
ix. Explicit denial that uncertainty exists





R. Soc. open sci. **6**: 181870.
http://dx.doi.org/10.1098/rsos.181870

term*	likelihood of the outcome
virtually certain	99–100% probability
very likely	99–100% probability
likely	66–100% probability
about as likely as not	33–66% probability
unlikely	0–33% probability
very unlikely	0–10% probability
exceptionally unlikely	0–1% probability

Gabry et al. (2018)

Visualization in Bayesian workflow

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Aki Vehtari
Department of Computer Science, Aalto University, Espoo, Finland.
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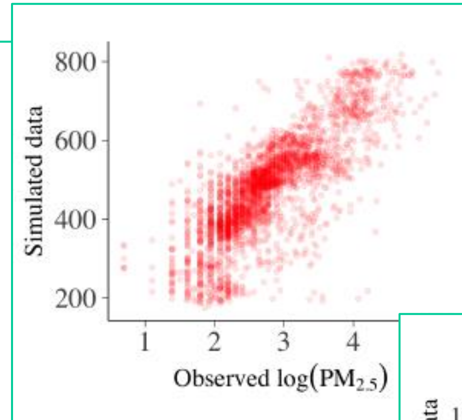
Departments of Statistics and Political Science, Columbia University, New York, USA.

Summary. Bayesian data analysis is about more than just computing a posterior distribution, and Bayesian visualization is about more than trace plots of Markov chains. Practical Bayesian data analysis, like all data analysis, is an iterative process of model building, inference, model checking and evaluation, and model expansion. Visualization is helpful in each of these stages of the Bayesian workflow and it is indispensable when drawing inferences from the types of modern, high-dimensional models that are used by applied researchers.

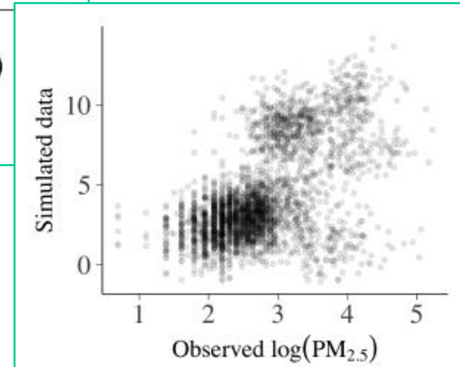
1. Introduction and running example

Visualization is a vital tool for data analysis, and its role is well established in both the exploratory and final presentation stages of a statistical workflow. In this paper, we argue that the same visualization tools should be used at all points during an analysis. We illustrate this thesis by following a single real example, estimating the global concentration of a certain type of air pollution, through all of the phases of statistical workflow: (a) Exploratory data analysis to aid in setting up an initial model; (b) Computational model checks using fake-data simulation and the prior predictive distribution; (c) Computational checks to ensure the inference algorithm works reliably, (d) Posterior predictive checks and other juxtapositions of data and predictions under the fitted model; (e) Model comparison via tools such as cross-validation.

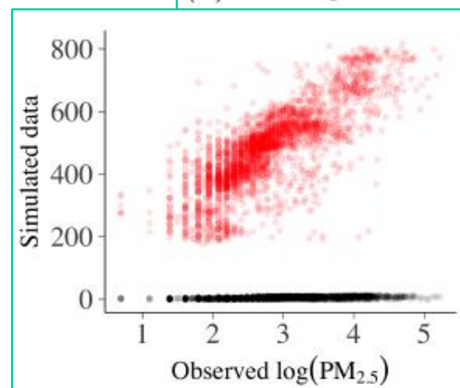
The tools developed in this paper are implemented in the `bayesplot` R package (Gabry, 2017; R Core Team, 2017), which uses `ggplot2` (Wickham, 2009) and is linked



(a) Vague priors

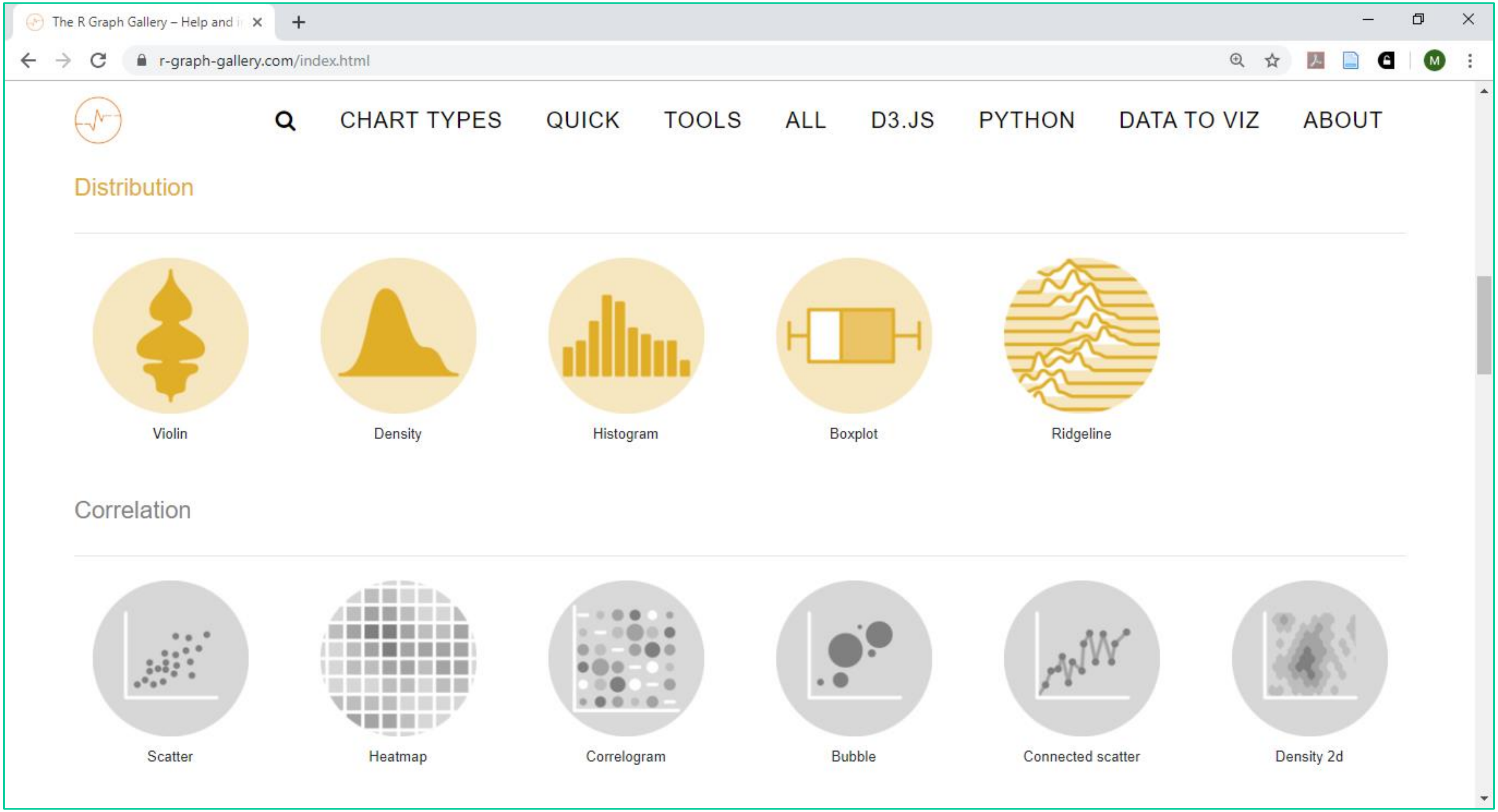


(b) Weakly informative priors



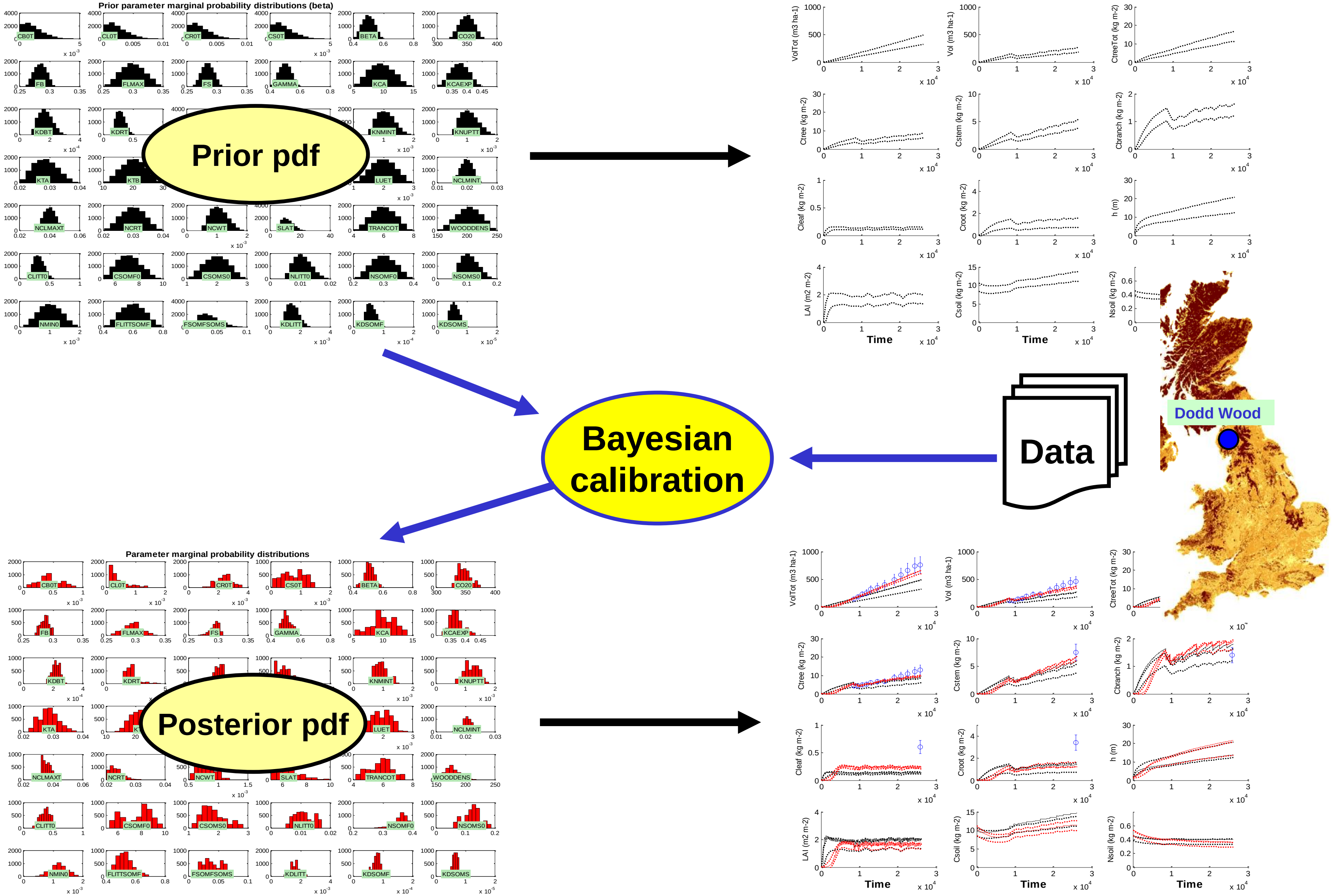
(c) Comparison

The R Graph Gallery: https://www.r-graph-gallery.com/



4. Visualisation of uncertainty: Examples CEH

3.8 Using data in Bayesian calibration of BASFOR



3.11 Parameter correlations

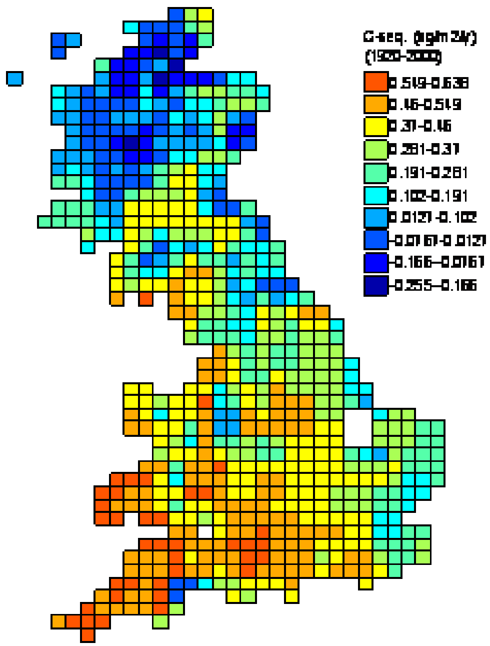
39 parameters

39 parameters

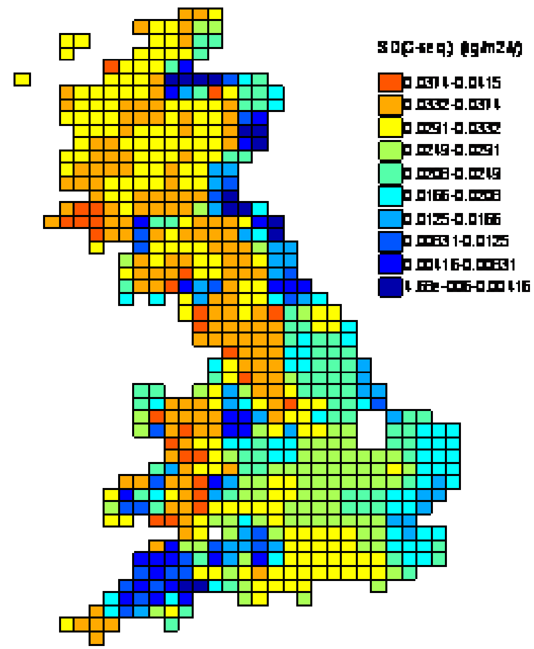
	CL0	CR0	CW0	BETA	CO20	FLMAX	FW	GAMMA	KCA	KCAEXP	KDL	KDR	KDW	KH	KHEXP	KLAIMAX	KNMIN	KNUPT	KTA	KTB	KTREE	LUE0	NLCONMIN	NLCONMAX	NRCON	NWCON	SLA	CLITT0	CSOMF0	CSOMS0	NLITT0	NSOMF0	NSOMS0
CL0	1.00	0.60	-0.67	-0.58	0.25	-0.16	0.51	0.46	0.26	0.12	0.64	0.59	0.38	-0.42	-0.07	0.71	-0.28	0.17	-0.64	-0.32	-0.58	0.23	0.55	0.52	0.12	0.50	-0.58	0.10	0.50	-0.66	-0.57	0.55	0.62
CR0	0.60	1.00	-0.49	-0.54	0.17	0.40	0.01	0.24	0.51	0.56	0.49	0.96	-0.19	-0.09	0.06	0.55	0.07	0.83	-0.60	-0.81	-0.21	-0.17	0.61	0.67	0.20	0.65	-0.54	-0.05	0.33	-0.29	0.05	0.46	0.61
CW0	-0.67	-0.49	1.00	0.91	0.24	0.45	-0.70	-0.82	-0.23	0.03	-0.74	-0.57	-0.74	0.77	-0.31	-0.98	0.76	-0.10	0.85	0.14	0.78	-0.61	-0.84	-0.91	0.51	-0.81	0.77	-0.30	-0.38	0.84	0.33	-0.88	-0.90
BETA	-0.58	-0.54	0.91	1.00	0.30	0.42	-0.78	-0.79	-0.46	-0.08	-0.79	-0.61	-0.66	0.81	0.04	-0.95	0.60	-0.32	0.94	0.17	0.61	-0.59	-0.98	-0.95	0.29	-0.94	0.84	0.01	-0.46	0.83	-0.01	-0.94	-0.96
CO20	0.25	0.17	0.24	0.30	1.00	0.05	-0.26	-0.41	-0.33	-0.28	0.11	0.09	-0.35	0.67	-0.02	-0.21	0.62	0.00	0.37	0.06	-0.22	-0.76	-0.33	-0.37	0.15	-0.19	0.57	-0.33	-0.34	-0.02	-0.28	-0.54	-0.36
FLMAX	-0.16	0.40	0.45	0.42	0.05	1.00	-0.69	-0.62	0.43	0.82	-0.56	0.25	-0.87	0.54	-0.05	-0.40	0.59	0.64	0.19	-0.81	0.74	-0.49	-0.31	-0.18	0.61	-0.33	0.06	-0.14	0.21	0.75	0.36	-0.35	-0.21
FW	0.51	0.01	-0.70	-0.78	-0.26	-0.69	1.00	0.61	0.32	-0.18	0.56	0.05	0.86	-0.83	-0.28	0.77	-0.60	-0.16	-0.75	0.26	-0.55	0.76	0.68	0.58	-0.25	0.58	-0.63	-0.17	0.54	-0.77	-0.13	0.72	0.72
GAMMA	0.46	0.24	-0.82	-0.79	-0.41	-0.62	0.61	1.00	-0.05	-0.28	0.82	0.45	0.78	-0.82	0.19	0.75	-0.81	-0.06	-0.64	0.14	-0.72	0.63	0.80	0.73	-0.46	0.78	-0.65	0.49	0.06	-0.85	-0.31	0.87	0.67
KCA	0.26	0.51	-0.23	-0.46	-0.33	0.43	0.32	-0.05	1.00	0.84	-0.01	0.38	-0.10	-0.34	-0.49	0.39	0.07	0.72	-0.68	-0.69	0.35	0.30	0.49	0.51	0.47	0.37	-0.69	-0.49	0.86	0.05	0.54	0.45	0.62
KCAEXP	0.12	0.56	0.03	-0.08	-0.28	0.82	-0.18	-0.28	0.84	1.00	-0.30	0.41	-0.48	0.00	-0.24	0.07	0.24	0.76	-0.36	-0.91	0.59	0.01	0.16	0.27	0.59	0.06	-0.48	-0.22	0.68	0.42	0.44	0.16	0.32
KDL	0.64	0.49	-0.74	-0.79	0.11	-0.56	0.56	0.82	-0.01	-0.30	1.00	0.64	0.56	-0.53	-0.03	0.73	-0.39	0.17	-0.61	0.07	-0.81	0.21	0.81	0.67	-0.25	0.88	-0.48	0.10	-0.02	-0.93	-0.25	0.70	0.63
KDR	0.59	0.96	-0.57	-0.61	0.09	0.25	0.05	0.45	0.38	0.41	0.64	1.00	-0.06	-0.20	0.12	0.59	-0.07	0.75	-0.61	-0.69	-0.34	-0.10	0.70	0.72	0.09	0.75	-0.57	0.10	0.19	-0.42	-0.01	0.57	0.63
KDW	0.38	-0.19	-0.74	-0.66	-0.35	-0.87	0.86	0.78	-0.10	-0.48	0.56	-0.06	1.00	-0.84	0.12	0.70	-0.86	-0.49	-0.54	0.49	-0.73	0.81	0.54	0.50	-0.60	0.47	-0.48	0.29	0.21	-0.81	-0.41	0.67	0.56
KH	-0.42	-0.09	0.77	0.81	0.67	0.54	-0.83	-0.82	-0.34	0.00	-0.53	-0.20	-0.84	1.00	0.07	-0.78	0.85	0.08	0.80	-0.07	0.44	-0.93	-0.77	-0.73	0.30	-0.64	0.84	-0.25	-0.52	0.68	0.12	-0.92	-0.79
KHEXP	-0.07	0.06	-0.31	0.04	-0.02	-0.05	-0.28	0.19	-0.49	-0.24	-0.03	0.12	0.12	0.07	1.00	0.14	-0.43	-0.26	0.14	0.00	-0.40	-0.01	-0.12	0.15	-0.76	-0.05	0.12	0.72	-0.37	-0.05	-0.47	-0.02	0.00
KLAIMAX	0.71	0.55	-0.98	-0.95	-0.21	-0.40	0.77	0.75	0.39	0.07	0.73	0.59	0.70	-0.78	0.14	1.00	-0.67	0.21	-0.93	-0.21	-0.70	0.60	0.88	0.93	-0.38	0.83	-0.82	0.11	0.51	-0.83	-0.22	0.89	0.96
KNMIN	-0.28	0.07	0.76	0.60	0.62	0.59	-0.60	-0.81	0.07	0.24	-0.39	-0.07	-0.86	0.85	-0.43	-0.67	1.00	0.38	0.53	-0.22	0.58	-0.86	-0.52	-0.59	0.66	-0.42	0.60	-0.63	-0.22	0.61	0.42	-0.73	-0.58
KNUPT	0.17	0.83	-0.10	-0.32	0.00	0.64	-0.16	-0.06	0.72	0.76	0.17	0.75	-0.49	0.08	-0.26	0.21	0.38	1.00	-0.43	-0.83	0.28	-0.27	0.45	0.46	0.47	0.48	-0.41	-0.38	0.33	0.10	0.58	0.26	0.41
KTA	-0.64	-0.60	0.85	0.94	0.37	0.19	-0.75	-0.64	-0.68	-0.36	-0.61	-0.61	-0.54	0.80	0.14	-0.93	0.53	-0.43	1.00	0.39	0.40	-0.64	-0.92	-0.93	0.08	-0.83	0.94	0.07	-0.71	0.66	-0.05	-0.92	-0.99
KTB	-0.32	-0.81	0.14	0.17	0.06	-0.81	0.26	0.14	-0.69	-0.91	0.07	-0.69	0.49	-0.07	0.00	-0.21	-0.22	-0.83	0.39	1.00	-0.33	0.16	-0.25	-0.39	-0.46	-0.21	0.47	0.05	-0.52	-0.25	-0.22	-0.21	-0.38
KTREE	-0.58	-0.21	0.78	0.61	-0.22	0.74	-0.55	-0.72	0.35	0.59	-0.81	-0.34	-0.73	0.44	-0.40	-0.70	0.58	0.28	0.40	-0.33	1.00	-0.26	-0.52	-0.51	0.66	-0.58	0.24	-0.32	0.15	0.91	0.60	-0.50	-0.48
LUE0	0.23	-0.17	-0.61	-0.59	-0.76	-0.49	0.76	0.63	0.30	0.01	0.21	-0.10	0.81	-0.93	-0.01	0.60	-0.86	-0.27	-0.64	0.16	-0.26	1.00	0.52	0.53	-0.33	0.35	-0.72	0.28	0.56	-0.45	-0.13	0.73	0.62
NLCONMIN	0.55	0.61	-0.84	-0.98	-0.33	-0.31	0.68	0.80	0.49	0.16	0.81	0.70	0.54	-0.77	-0.12	0.88	-0.52	0.45	-0.92	-0.25	-0.52	0.52	1.00	0.94	-0.16	0.97	-0.85	0.00	0.41	-0.77	0.10	0.95	0.92
NLCONMAX	0.52	0.67	-0.91	-0.95	-0.37	-0.18	0.58	0.73	0.51	0.27	0.67	0.72	0.50	-0.73	0.15	0.93	-0.59	0.46	-0.93	-0.39	-0.51	0.53	0.94	1.00	-0.32	0.91	-0.87	0.11	0.46	-0.67	0.05	0.92	0.96
NRCON	0.12	0.20	0.51	0.29	0.15	0.61	-0.25	-0.46	0.47	0.59	-0.25	0.09	-0.60	0.30	-0.76	-0.38	0.66	0.47	0.08	-0.46	0.66	-0.33	-0.16	-0.32	1.00	-0.22	-0.01	-0.46	0.34	0.44	0.31	-0.23	-0.21
NWCON	0.50	0.65	-0.81	-0.94	-0.19	-0.33	0.58	0.78	0.37	0.06	0.88	0.75	0.47	-0.64	-0.05	0.83	-0.42	0.48	-0.83	-0.21	-0.58	0.35	0.97	0.91	-0.22	1.00	-0.72	-0.03	0.23	-0.79	0.12	0.86	0.85
SLA	-0.58	-0.54	0.77	0.84	0.57	0.06	-0.63	-0.65	-0.69	-0.48	-0.48	-0.57	-0.48	0.84	0.12	-0.82	0.60	-0.41	0.94	0.47	0.24	-0.72	-0.85	-0.87	-0.01	-0.72	1.00	-0.13	-0.75	0.51	-0.03	-0.93	-0.92
CLITT0	0.10	-0.05	-0.30	0.01	-0.33	-0.14	-0.17	0.49	-0.49	-0.22	0.10	0.10	0.29	-0.25	0.72	0.11	-0.63	-0.38	0.07	0.05	-0.32	0.28	0.00	0.11	-0.46	-0.03	-0.13	1.00	-0.25	-0.15	-0.64	0.22	0.00
CSOMF0	0.50	0.33	-0.38	-0.46	-0.34	0.21	0.54	0.06	0.86	0.68	-0.02	0.19	0.21	-0.52	-0.37	0.51	-0.22	0.33	-0.71	-0.52	0.15	0.56	0.41	0.46	0.34	0.23	-0.75	-0.25	1.00	-0.10	0.09	0.50	0.65
CSOMS0	-0.66	-0.29	0.84	0.83	-0.02	0.75	-0.77	-0.85	0.05	0.42	-0.93	-0.42	-0.81	0.68	-0.05	-0.83	0.61	0.10	0.66	-0.25	0.91	-0.45	-0.77	-0.67	0.44	-0.79	0.51	-0.15	-0.10	1.00	0.39	-0.74	-0.68
NLITT0	-0.57	0.05	0.33	-0.01	-0.28	0.36	-0.13	-0.31	0.54	0.44	-0.25	-0.01	-0.41	0.12	-0.47	-0.22	0.42	0.58	-0.05	-0.22	0.60	-0.13	0.10	0.05	0.31	0.12	-0.03	-0.64	0.09	0.39	1.00	-0.05	0.01
NSOMF0	0.55	0.46	-0.88	-0.94	-0.54	-0.35	0.72	0.87	0.45	0.16	0.70	0.57	0.67	-0.92	-0.02	0.89	-0.73	0.26	-0.92	-0.21	-0.50	0.73	0.95	0.92	-0.23	0.86	-0.93	0.22	0.50	-0.74	-0.05	1.00	0.92
NSOMS0	0.62	0.61	-0.90	-0.96	-0.36	-0.21	0.72	0.67	0.62	0.32	0.63	0.63	0.56	-0.79	0.00	0.96	-0.58	0.41	-0.99	-0.38	-0.48	0.62	0.92	0.96	-0.21	0.85	-0.92	0.00	0.65	-0.68	0.01	0.92	1.00
NMIN0	-0.16	-0.31	-0.47	-0.41	-0.64	-0.43	0.56	0.33	0.16	-0.09	-0.06	-0.30	0.66	-0.63	0.29	0.45	-0.72	-0.33	-0.40	0.25	-0.21	0.79	0.27	0.41	-0.66	0.16	-0.39	0.14	0.33	-0.23	0.06	0.42	0.45
FLITTSOMF	0.48	0.60	-0.01	0.08	0.61	0.31	-0.43	0.03	-0.22	0.05	0.36	0.63	-0.39	0.40	0.15	-0.02	0.34	0.33	0.12	-0.39	-0.22	-0.62	0.01	-0.02	0.29	0.13	0.12	0.23	-0.28	-0.11	-0.40	-0.10	-0.10
FSOMFSOMS	-0.66	-0.28	0.86	0.83	0.08	0.55	-0.89	-0.56	-0.33	0.08	-0.58	-0.27	-0.78	0.72	-0.04	-0.91	0.61	0.04	0.81	-0.03	0.69	-0.63	-0.69	-0.72	0.41	-0.62	0.65	0.07	-0.55	0.78	0.27	-0.70	-0.83
KDLITT	0.42	0.28	-0.93	-0.89	-0.55	-0.51	0.73	0.87	0.25	-0.04	0.62	0.39	0.81	-0.91	0.26	0.90	-0.88	0.02	-0.83	-0.01	-0.63	0.80	0.84	0.88	-0.56	0.77	-0.80	0.34	0.37	-0.75	-0.16	0.92	0.87
KDSOMF	0.15	-0.43	-0.39	-0.31	-0.08	-0.70	0.75	0.19	-0.03	-0.42	0.09	-0.46	0.75	-0.46	0.03	0.41	-0.49	-0.59	-0.27	0.55	-0.45	0.60	0.12	0.14	-0.51	0.04	-0.13	-0.14	0.29	-0.43	-0.25	0.20	0.29
KDSOMS	-0.55	-0.18	0.83	0.81	0.13	0.80	-0.75	-0.92	0.12	0.47	-0.89	-0.35	-0.86	0.75	-0.12	-0.79	0.72	0.18	0.62	-0.32	0.89	-0.54	-0.76	-0.66	0.52	-0.77	0.51	-0.28	-0.03	0.98	0.39	-0.77	-0.65

3.11 Maps of (1) predictions, (2) uncertainties

C-sequestration (model output for 1920-2000)

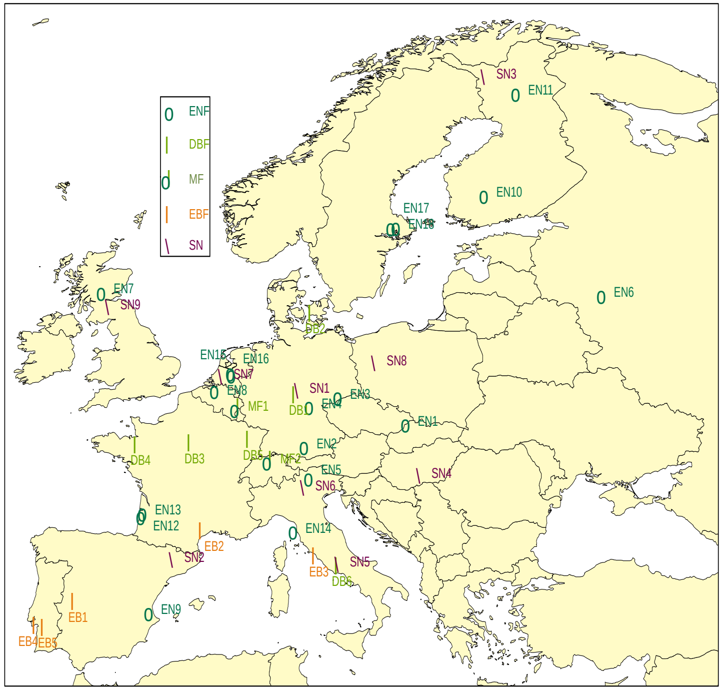


Uncertainty of C-sequestration



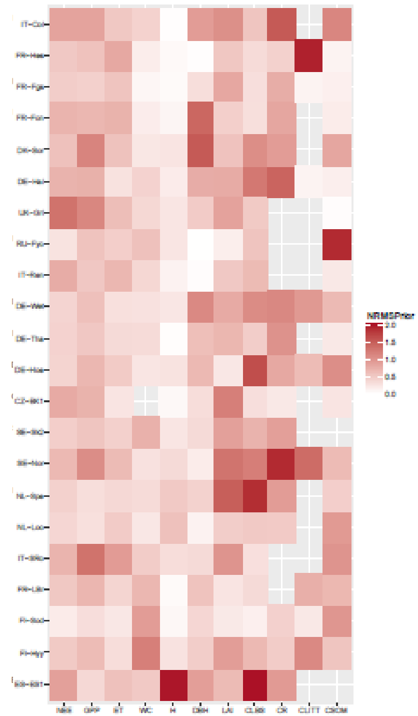
Van Oijen & Thomson (2010)
Climatic Change 103: 55-67

4.1 Site-specific vs. generic BC for European forest

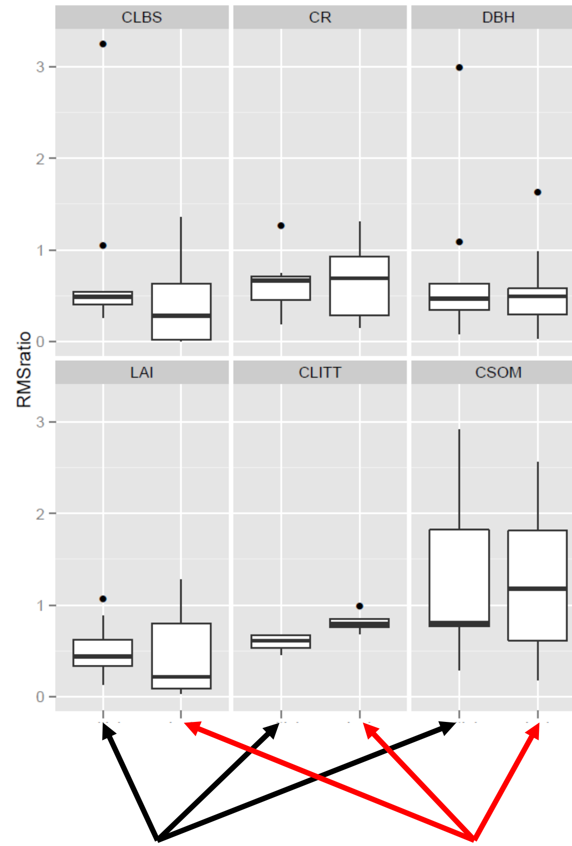


Geographical distribution of NitroEurope nitrogen deposition monitoring sites. ENF: evergreen needle leaf forest; DBF: deciduous broadleaf forest

RMS - ratio

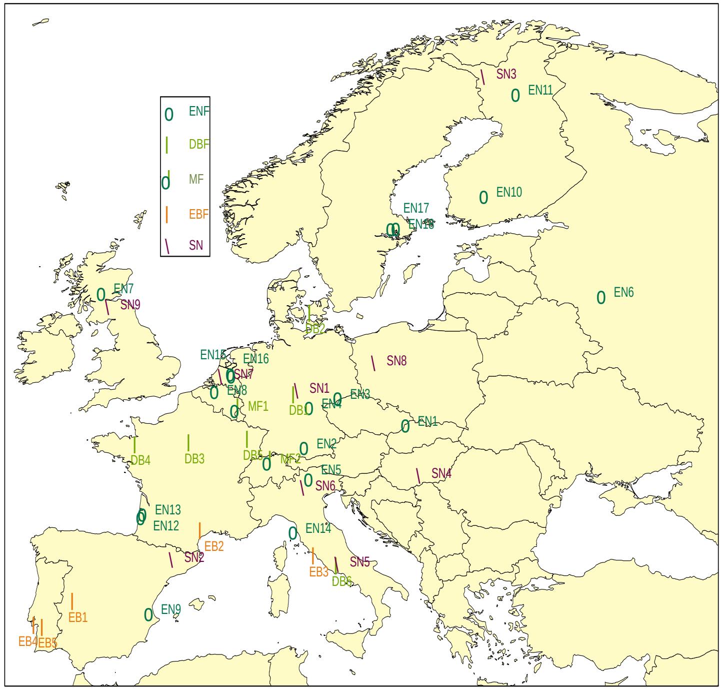


RMS - ratio



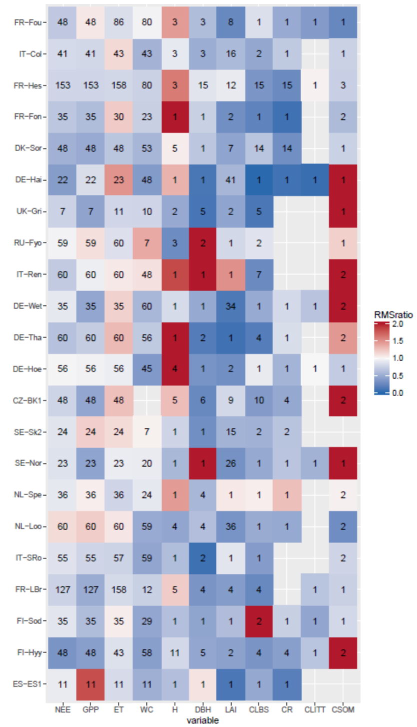
Cameron et al. (2018)

4.1 Site-specific vs. generic BC for European forest

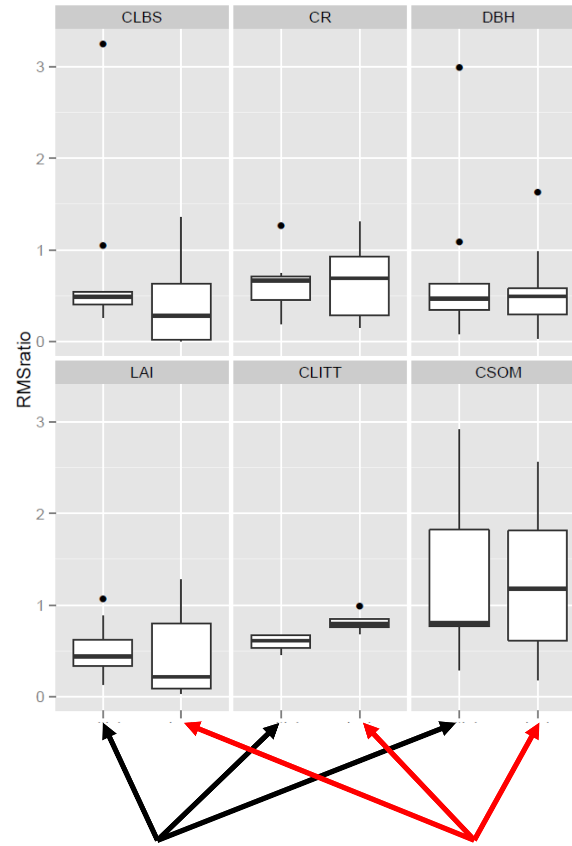


Geographical distribution of NitroEurope nitrogen deposition monitoring sites. ENF: evergreen needle leaf forest; DBF: deciduous broadleaf forest

RMS - ratio



RMS - ratio

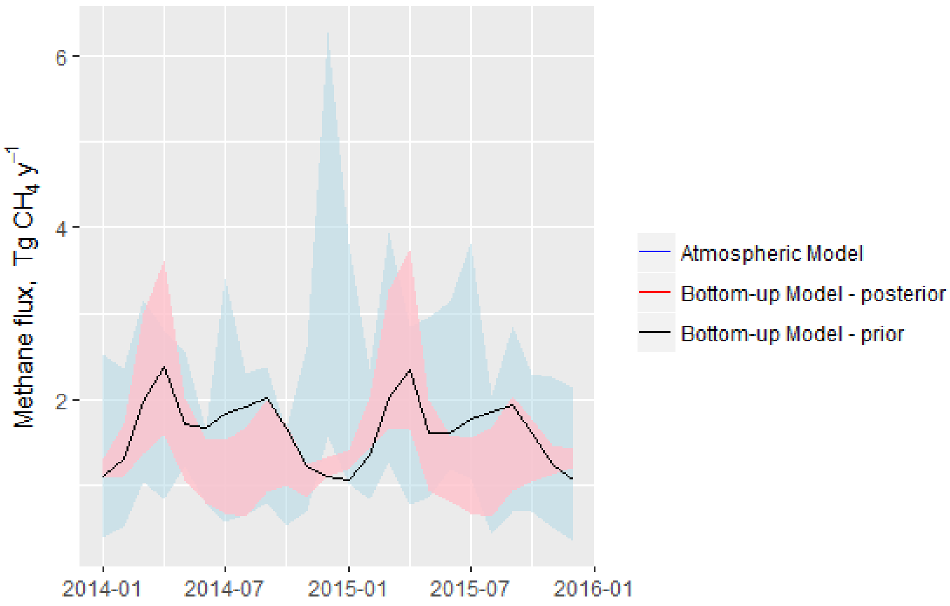


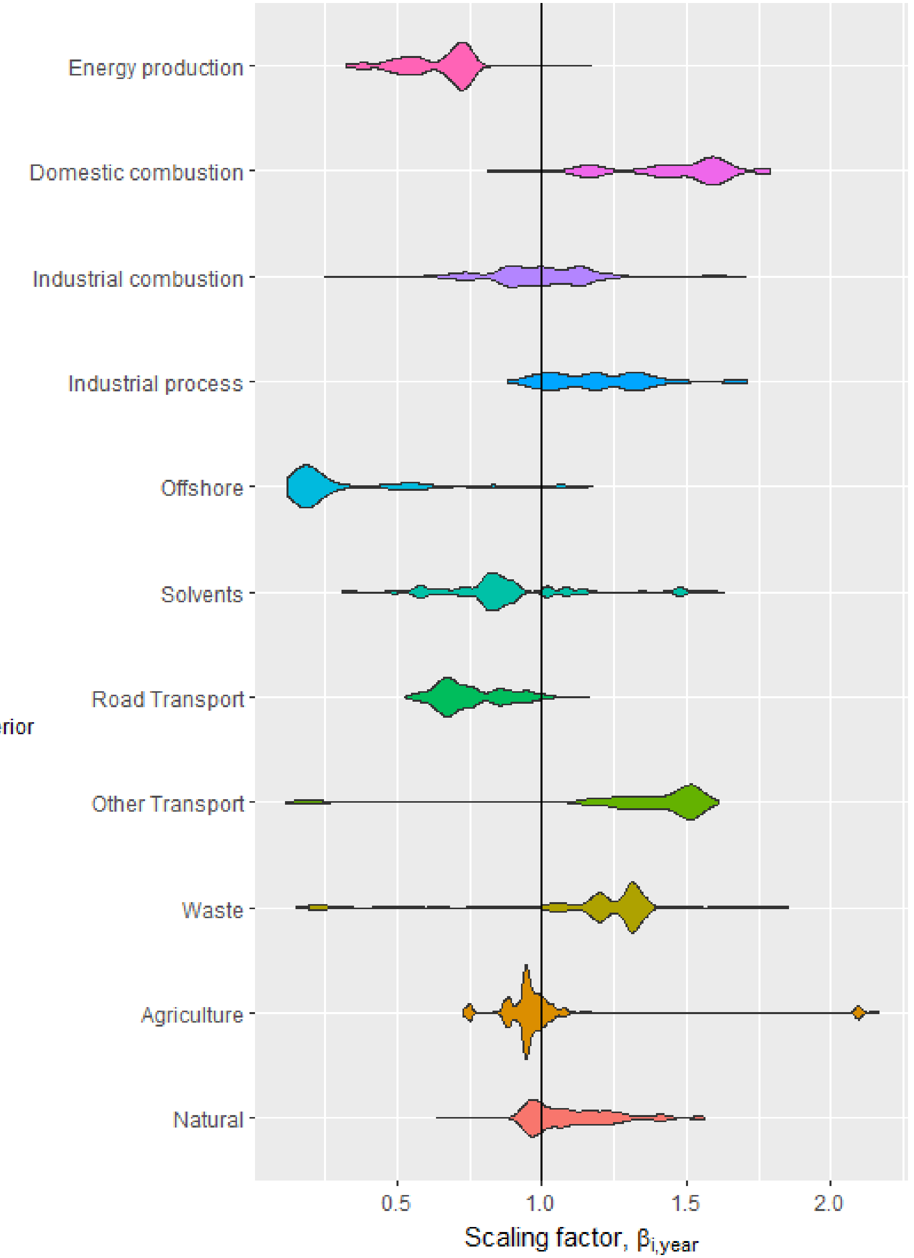
Generic BC ***Site-specific BC***

Cameron et al. (2018)

4.2 Reconciling LUC-inventory models with atmospheric inversion

- **Each emission sector has a characteristic spatial & temporal pattern**
- **Use this in a Bayesian analysis of the parameters of a "bottom-up" model (anthropogenic & biogenic)**
- **Derive sector-wise scaling factors = multipliers needed to match atmospheric model**
- **Posterior distribution for methane shown (2014-2015)**

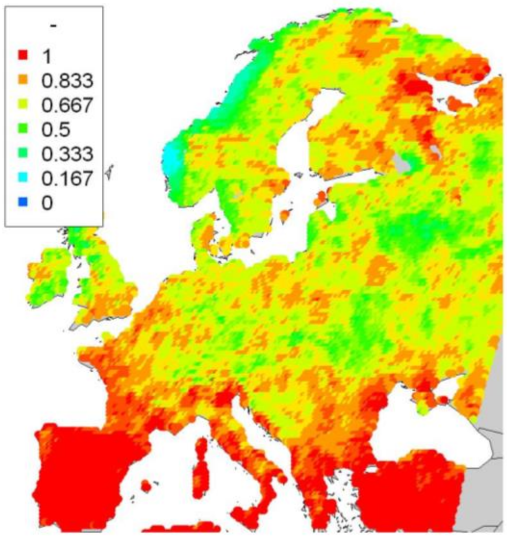




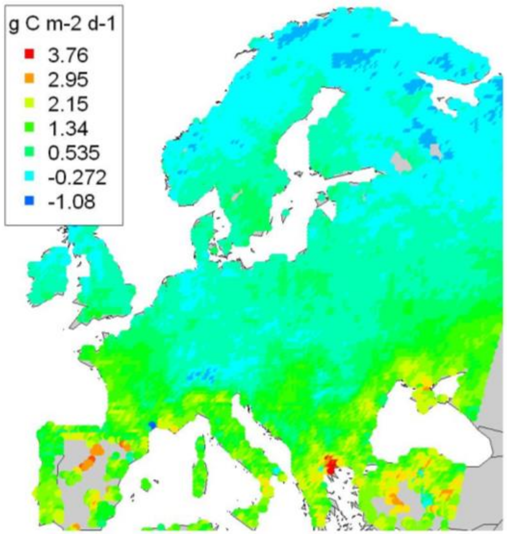
Levy et al. (in prep.)

4.5 Drought-risk analysis for NPP in 2071-2100

Probability of drought (PH)

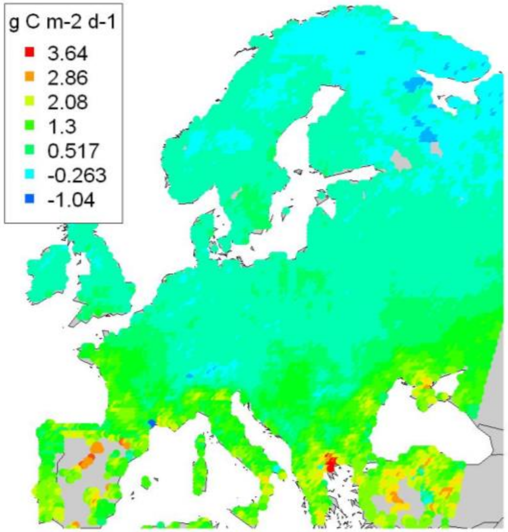


Vulnerability (V)



R = P(H) V

Risk (R)
= expectation of loss



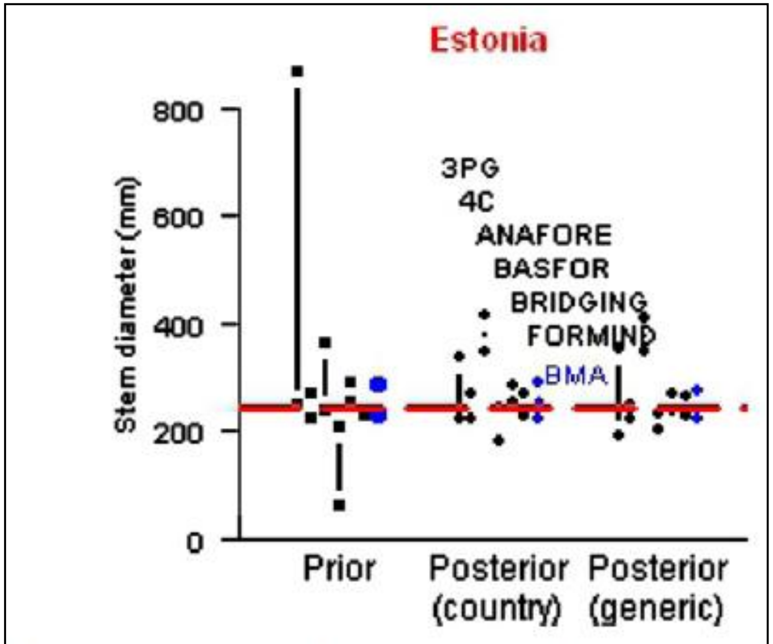
Van Oijen et al. (2013, 2014)

3.8 Bayesian calibration of process-based models

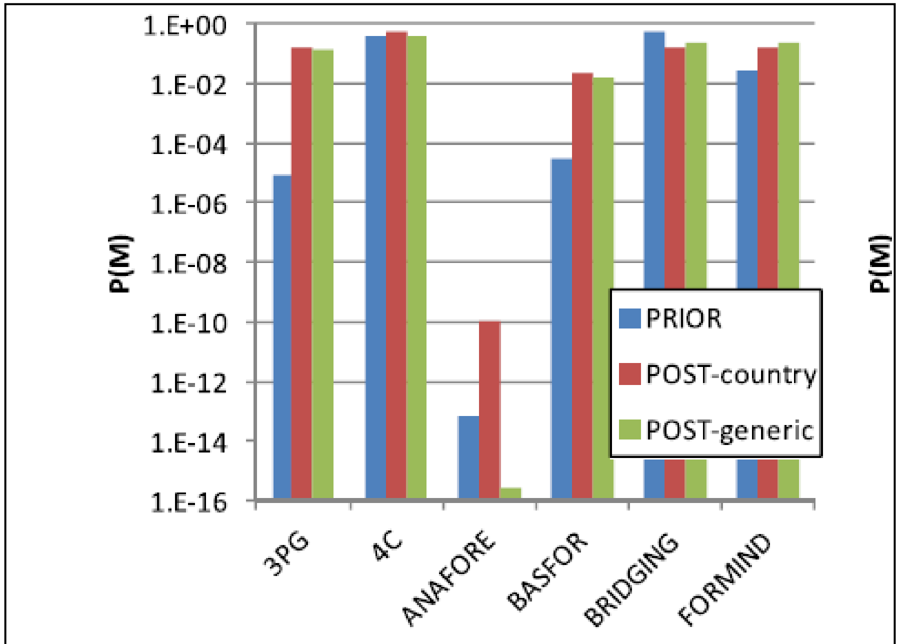
Forest Ecology and Management 289 (2013) 255–268

Bayesian calibration, comparison and averaging of six forest models, using data from Scots pine stands across Europe

M. van Oijen [a,*], C. Reyer [b], F.J. Bohn [c], D.R. Cameron [a], G. Deckmyn [d], M. Flechsig [b], S. Härkönen [e], F. Hartig [c], A. Huth [c], A. Kiviste [f], P. Lasch [b], A. Mäkelä [g], T. Mette [h], F. Minunno [i], W. Rammer [j]



Model output uncertainty for final mean stem diameter at the PSP



Prior and posterior model probabilities, derived from the integrated likelihoods

INTERMEZZO

Shiny app for BELUC

Shiny app for MU-MAP