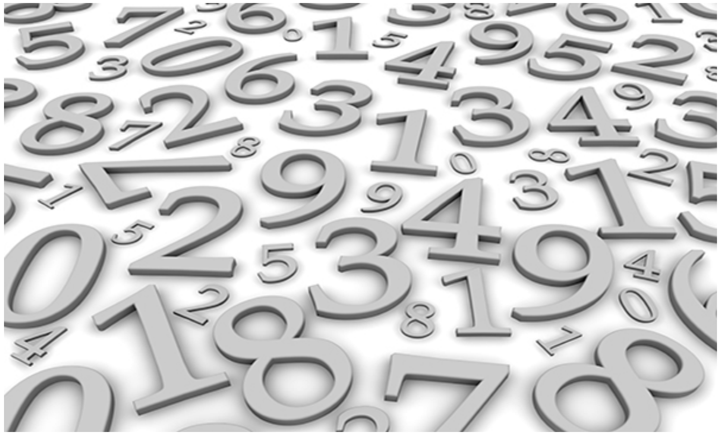
On the extinction of craft skills with numbers



the case of
"*Overall, 7.9% of species are predicted to become extinct from climate change.*"

Dr. Jeroen P. van der Sluijs

Senter for vitenskapsteori

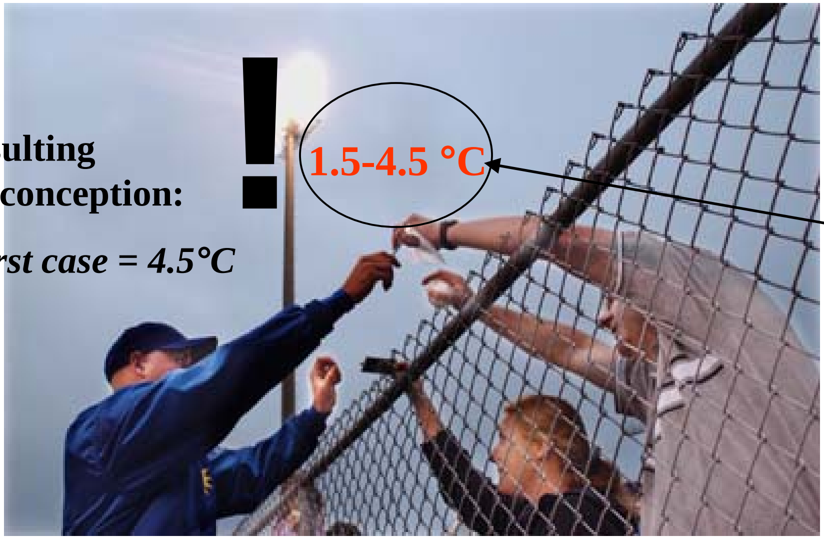
Crossing the disciplinary boundaries

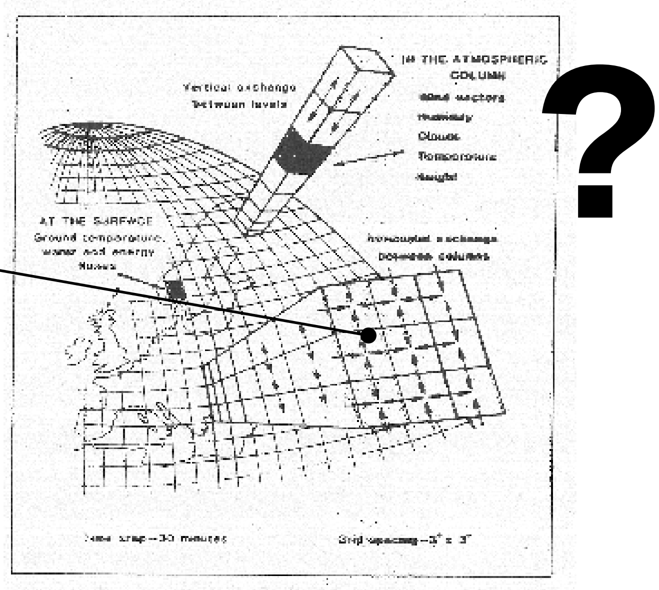
Once environmental numbers are thrown over the disciplinary fence, important caveats tend to be ignored, uncertainties compressed and numbers used at face value

e.g. **Climate Sensitivity**, see Van der Sluijs, Wynne, Shackley, 1998:

Resulting misconception:

Worst case = 4.5°C

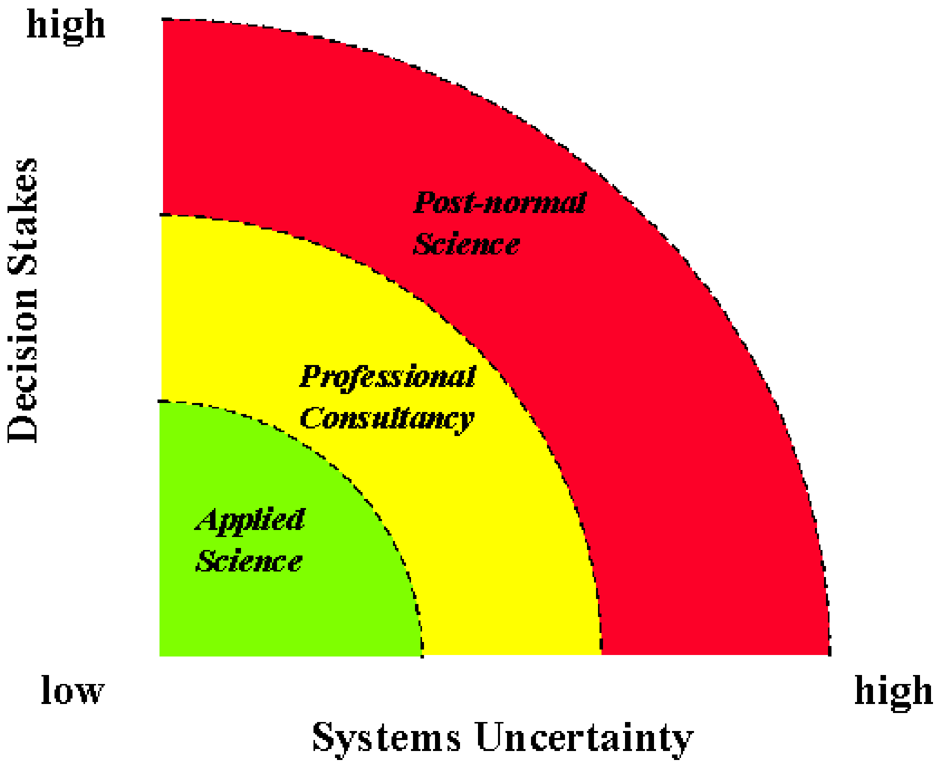




Complex - *uncertain* - risks

Typical characteristics:

- Decisions urgent
- Stakes high
- Values in dispute
- Irreducible & unquantifiable uncertainty



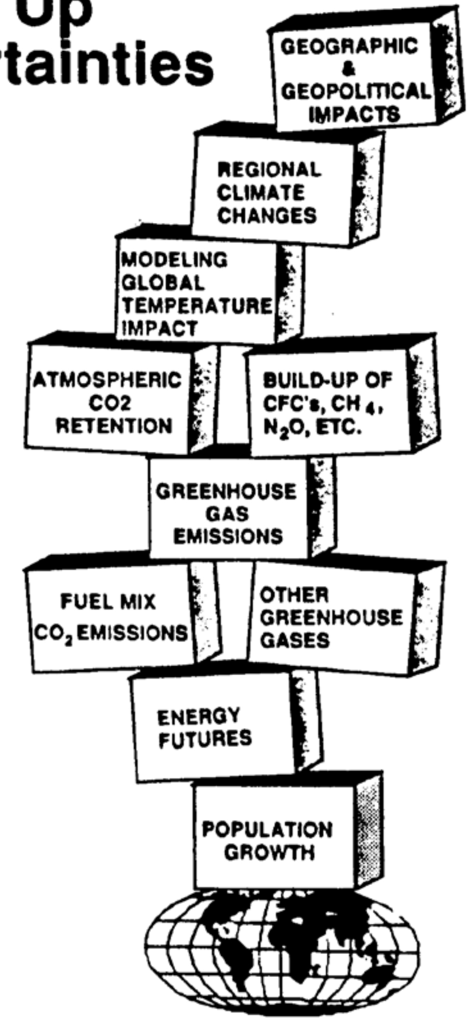
- Assessment: models, scenarios, assumptions, extrapolations
- (hidden) value loadings in problem frames, indicators chosen, assumptions made

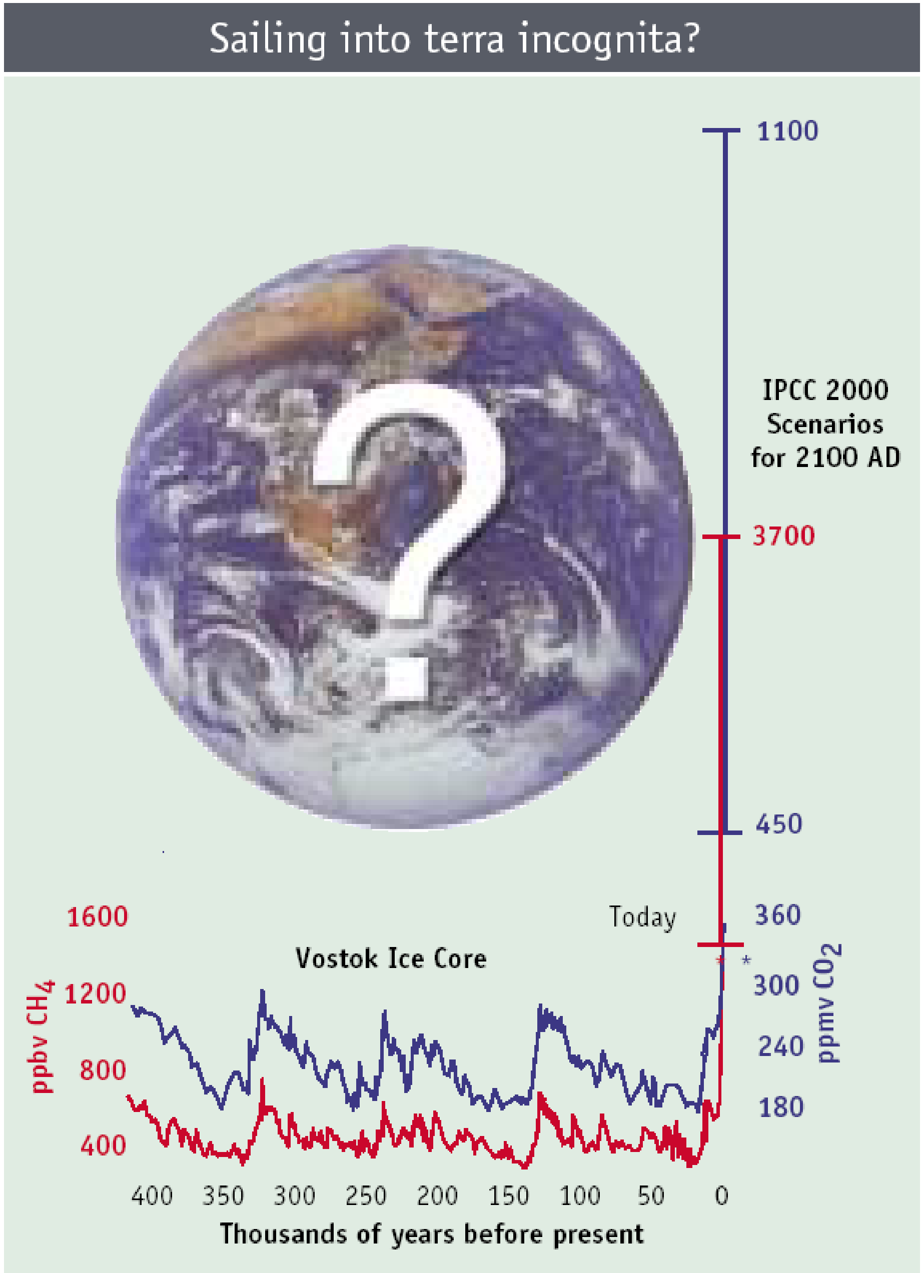
- **Knowledge Quality Assessment!**

(Funtowicz & Ravetz, 1993)
http://www.uu.nl/wetfilos/wetfil10/sprekers/Funtowicz_Ravetz_Futures_1993.pdf

GLOBAL CLIMATE CHANGE

Piling Up Uncertainties





How does science-policy interface cope with uncertainties

Two strategies dominate:

- **Overselling certainty**
  - to promote political decisions (enforced consensus), or
- **Overemphasising uncertainty**
  - to prevent political action

- Both promote decision strategies that are **not fit for meeting the challenges** posed by the uncertainties and complexities faced.

- Need for a third voice next to alarmists and skeptics: coping with uncertainty, scientific dissent & plurality in science for policy.

A practical problem:

Protecting a strategic fresh-water resource

5 scientists addressed same question:

“which parts of this area are most vulnerable to nitrate pollution and need to be protected?”

(Refsgaard, Van der Sluijs et al, 2006)

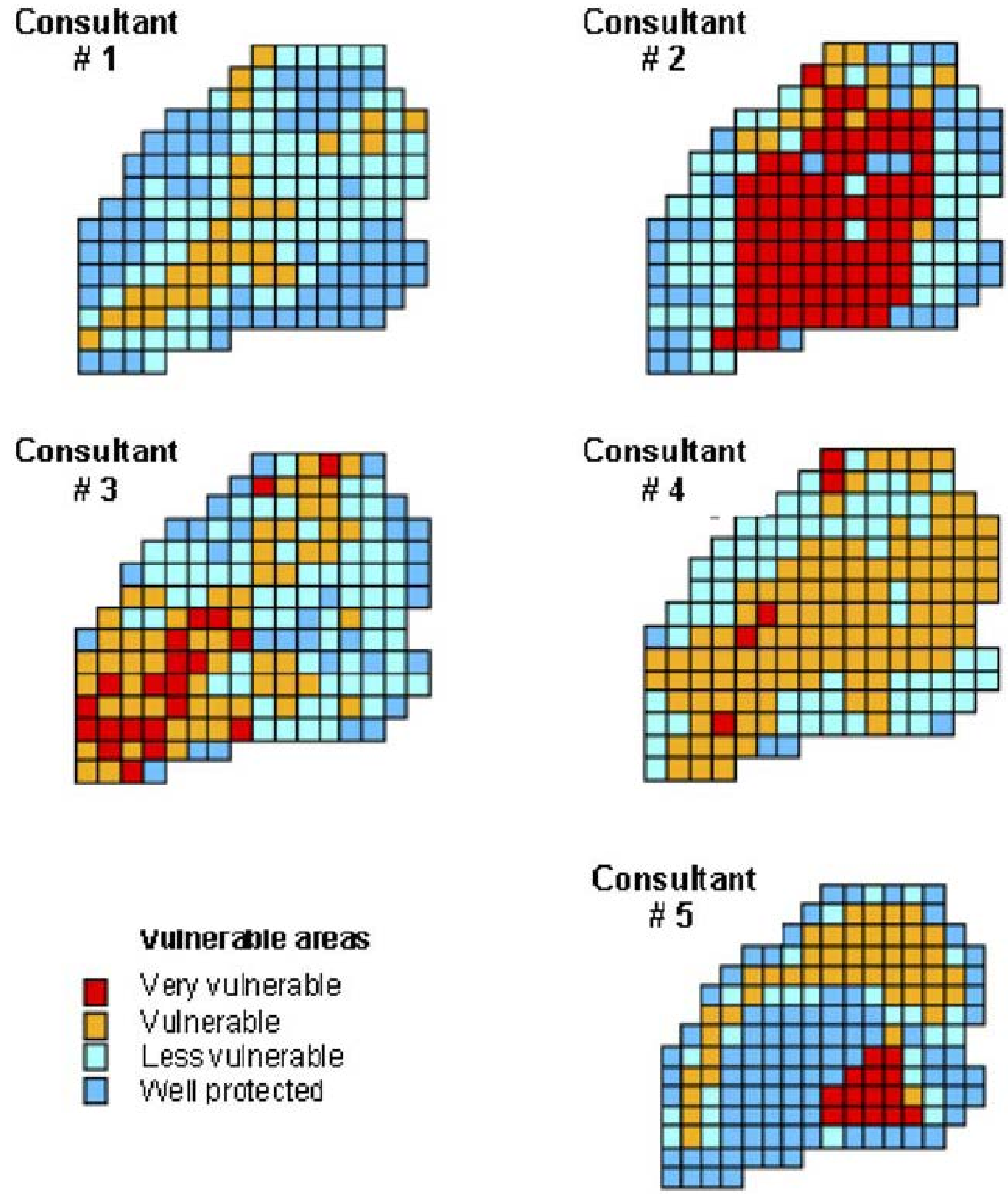


Fig. 1. Model predictions on aquifer vulnerability towards nitrate pollution for a 175 km^2 area west of Copenhagen [11].

3 framings of uncertainty

'deficit view'

- Uncertainty is provisional
- Reduce uncertainty, make ever more complex models
- *Tools:* quantification, Monte Carlo, Bayesian belief networks
  - ***Speaking truth to power***

'evidence evaluation view'

- Comparative evaluations of research results
- *Tools:* Scientific consensus building; multi disciplinary expert panels
- focus on robust findings
  - ***Speaking [consensus] to power***

'complex systems view / *post-normal* view'

- Uncertainty is intrinsic to complex systems
- Uncertainty can be result of production of knowledge
- Acknowledge that not all uncertainties can be quantified
- Openly deal with deeper dimensions of uncertainty
  (problem framing indeterminacy, ignorance, assumptions, value loadings, institutional dimensions)
- *Tools:* Knowledge Quality Assessment
  - ***Working deliberatively within imperfections***

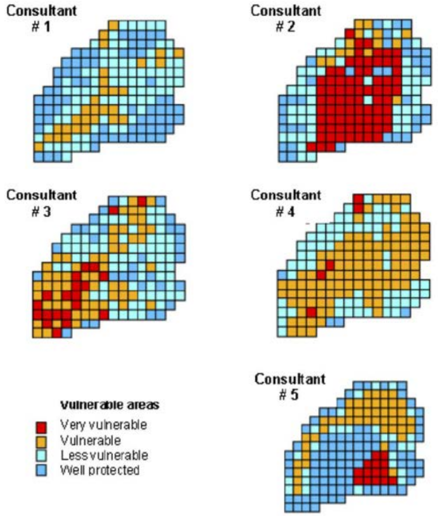


Fig. 1. Model predictions on aquifer vulnerability towards nitrate pollution for a 175 km^2 area west of Copenhagen [11].

How to act upon such uncertainty?

- **Bayesian** approach: 5 priors. Average and update likelihood of each grid-cell being red with data (but oooops, there is no data and we need decisions now)
- IPCC approach: Lock the 5 consultants up in a room and don't release them before they have **consensus**
- **Nihilist** approach: Dump the science and decide on an other basis
- **Precautionary** robustness approach: protect all grid-cells
- **Academic bureaucrat** approach: Weigh by citation index (or H-index) of consultant.
- Select the consultant that you **trust** most
- Real life approach: Select the consultant that best fits your **policy agenda**
- Post normal: explore the relevance of our ignorance: **working deliberatively within imperfections**

There are many uncertainties in our predictions particularly with regard to the timing, magnitude and regional patterns of climate change, due to our incomplete understanding of:

- sources and sinks of greenhouse gases, which affect predictions of future concentrations
- clouds, which strongly influence the magnitude of climate change
- oceans, which influence the timing and patterns of climate change
- polar ice sheets which affect predictions of sea level rise

These processes are already partially understood, and we are confident that the uncertainties can be reduced by further research However, the complexity of the system means that we cannot rule out surprises

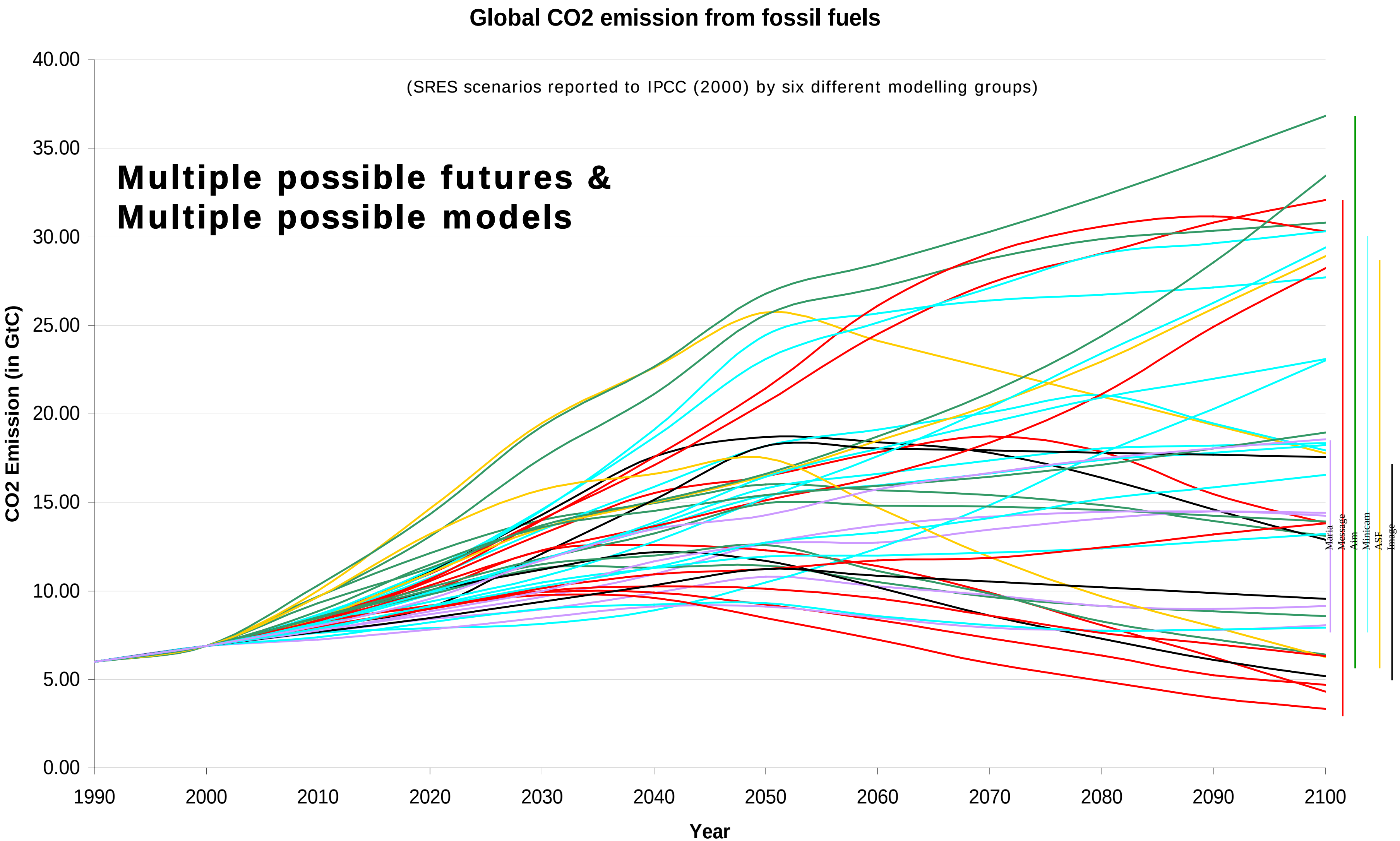
(IPCC AR1 Policy Makers Summary, 1990)
http://www.ipcc.ch/ipccreports/far/wg_I/ipcc_far_wg_I_spm.pdf

Former chairman IPCC on objective to reduce climate uncertainties:

- "*We cannot be certain that this can be achieved easily and we do know it will take time. Since a fundamentally chaotic climate system is predictable only to a certain degree, our research achievements will always remain uncertain.* ***Exploring the significance and characteristics of this uncertainty is a fundamental challenge to the scientific community.***" (Bolin, 1994)

[Prof. Bert Bolin,
15 March 1925 – 30 December 2007]
Bolin B (1994) *Ambio* 23 (1) 25-29

IPCC 10 years after *“we are confident that the uncertainties can be reduced...”*



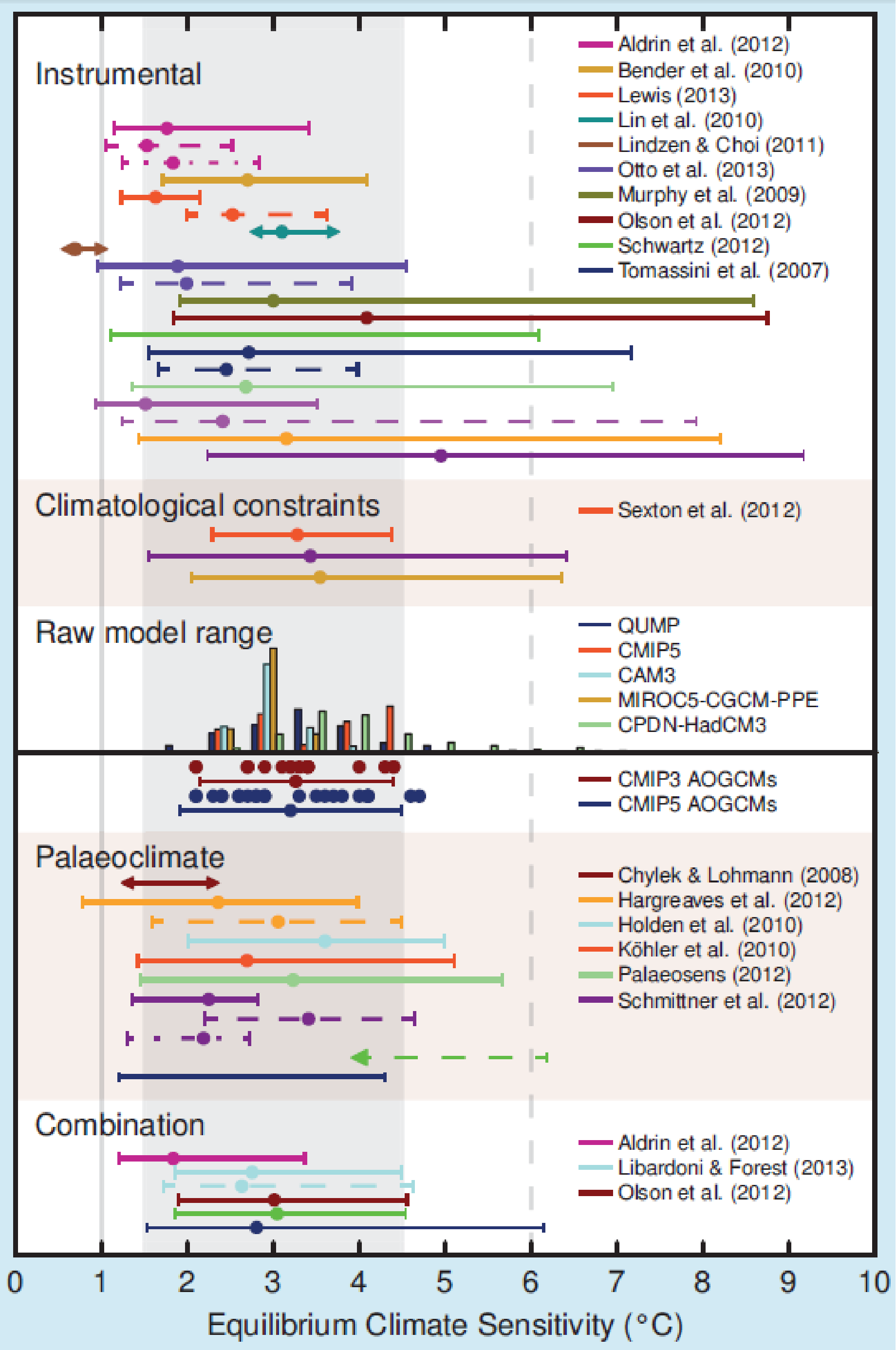
25 years after "we are confident that the uncertainties can be reduced..."

Evolution of knowledge on Climate Sensitivity over past 35 years

Assessment report	Range of GCM results (°C)	Concluded Range (°C)	Concluded best guess (°C)
NAS 1979	2-3.5	1.5-4.5	3
NAS 1983	2-3.5	1.5-4.5	3
Villach 1985	1.5-5.5	1.5-4.5	3
IPCC AR1 1990	1.9-5.2	1.5-4.5	2.5
IPCC AR2 1995	MME	1.5-4.5	2.5
IPCC AR3 2001	MME	1.5-4.5	Not given
IPCC AR4 2007	MME	2.5-4.5	3
IPCC AR5 2013	MME (0.5-9)	1.5-4.5*	Not given

*"Likely" (17-83%) range. Prior to AR4 ranges were not clearly defined.
MME = Multi Model Ensemble

(Van der Sluijs e.a. 1998, updated 2014)
http://sss.sagepub.com/content/28/2/291.short



IPCC AR5 Chapter 12

Probability density functions, distributions and ranges for equilibrium climate sensitivity

Grey shaded range:
likely 1.5°C to 4.5°C range

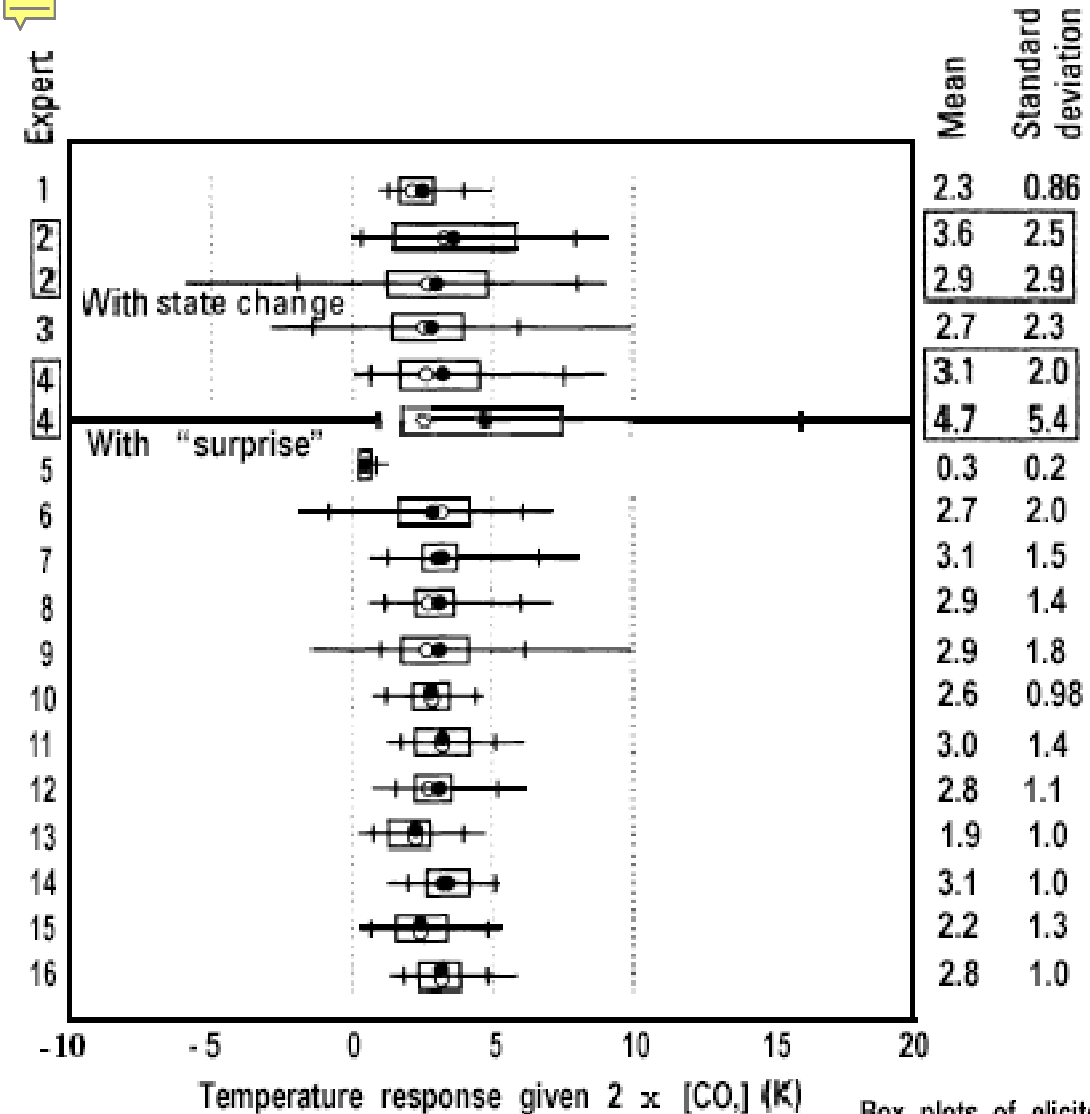
Grey solid line:
extremely unlikely less than 1°C

Grey dashed line:
very unlikely greater than 6°C.

http://www.climatechange2013.org/images/report/WG1AR5_Chapter12_FINAL.pdf

Subjective judgments by top 16 climate experts USA

(Morgan & Keith, 1995)



Box plots of elicited probability distributions of climate sensitivity, the change in globally averaged surface temperature for a 2 x [CO_2] forcing. Horizontal line denotes range from minimum to maximum assessed possible values. Vertical tick marks indicate locations of lower 5 and upper 95 percentiles. Box indicates interval spanned by 50% confidence interval. Solid dot is the mean and open dot is the median. The two columns of numbers on right side of the figure report values of mean and standard deviation of the distributions.

http://dx.doi.org/10.1021/es00010a753

Climate Change Speeds Extinctions

Species die-offs are expected to accelerate as greenhouse gases accumulate, according to a meta-analysis.

By Kerry Grens | May 3, 2015

Models have produced widely varying estimates of extinctions to come, so Urban pulled together 131 studies to generate a "global mean extinction rate." His meta-analysis found that, overall, the studies predicted 7.9 percent of species will go extinct due to climate change. That number varied depending on the severity of the warming; limiting the rise in temperatures to 2°C (35°F) wipes out 5.2 percent of species, while carrying on with current trajectories and rising 4.3°C (40°F) would kill off 16 percent of species.

http://www.the-scientist.com/?articles.view/articleNo/42877/title/Climate-Change-Speeds-Extinctions/

ECOLOGY

Extinction risks from climate change

How will climate change affect global biodiversity?

Complex threats. In addition to climate change, habitat transformation, invasive species, and pathogens also threaten amphibians like the Cascades frog, *Rana cascadae* (8, 11).

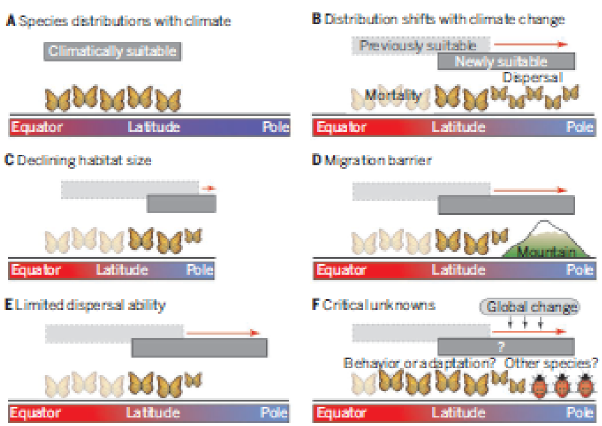
By **Janneke Hille Ris Lambers**

Biologists worry that the rapid rates of warming projected for the planet (1) will doom many species to extinction. Species could face extinction with climate change if climatically suitable habitat disappears or is made inaccessible by geographic barriers or species' inability to disperse (see the figure, panels A to E). Previous studies have provided region- or taxon-specific estimates of biodiversity loss with climate change that range from 0% to 54%, making it difficult to assess the seriousness of this problem. On page 571 of this issue, Urban (2) provides a synthetic and sobering estimate of climate change–induced biodiversity loss by applying a model-averaging approach to 131 of these studies. The result is a projection that up to one-sixth of all species may go extinct if we follow "business as usual" trajectories of carbon emissions.

By quantitatively assessing how extinction risk depends on model assumptions, Urban's study provides insight into factors that increase biodiversity loss with climate change. Surprisingly, the modeling approaches used in the studies that Urban surveyed did not have the largest effect on estimates of extinction risk, despite substantial methodological differences. Instead, the magnitude of future climate change was the most important predictor of extinction risk, with increased warming resulting in greater biodiversity loss.

What is worrying, given the current anthropogenic carbon emissions trajectory, is that biodiversity loss is predicted to accelerate with greater climate change. Geography also plays a role, with higher extinction risks projected for Australia, New Zealand, and South America—regions with high numbers of endemic species (that is, species with narrow distribution ranges) that face disappearing habitats or geographic barriers to migration (see the figure, panels C and D). Urban also found higher biodiversity loss for studies focusing on endemic species, but few differences among taxonomic groups (such as birds and amphibians). Projections of geographic and trait-based variation in extinction risk such as these are essential for targeted conservation efforts (3).

The study also highlights critical uncertainties in our understanding of how climate change drives extinction. For example, if suitable habitat disappears entirely with climate change, extinction seems inevitable. However, what if climatically suitable habitats still exist but shrink in size or quality (see the figure, panel C) (4)? Biologists believe extinction will occur before suitable habitats disappear, but they lack information on species-specific threshold habitat sizes for extinction. Similarly, what happens if species cannot reach a newly suitable habitat (see the figure, panels D and E) (5)? Biologists assume that slow-moving organisms will have trouble "keeping up"



Move, adapt, or perish. Species distributions are generally determined by climate (**A**). They track climate change (red arrows) if populations can disperse and establish in newly suitable habitats, and disappear where climate has become unsuitable (**B**). Species may face extinction if habitat sizes shrink (for example, at the poles or at mountaintops) (**C**), or if migration barriers (**D**) or limited dispersal ability (**E**) prevent them from reaching newly suitable habitat. The ability of species to adapt (or modify their behavior), species interactions, and other global change stressors represent key uncertainties (**F**) that affect our ability to predict biodiversity loss with climate change.

Department of Biology, University of Washington, Seattle, WA 98195, USA. E-mail: jhrl@uw.edu

CLIMATE CHANGE

Accelerating extinction risk from climate change

Mark C. Urban*

Current predictions of extinction risks from climate change vary widely depending on the specific assumptions and geographic and taxonomic focus of each study. I synthesized published studies in order to estimate a global mean extinction rate and determine which factors contribute the greatest uncertainty to climate change–induced extinction risks. Results suggest that extinction risks will accelerate with future global temperatures, threatening up to one in six species under current policies. Extinction risks were highest in South America, Australia, and New Zealand, and risks did not vary by taxonomic group. Realistic assumptions about extinction debt and dispersal capacity substantially increased extinction risks. We urgently need to adopt strategies that limit further climate change if we are to avoid an acceleration of global extinctions.

We critically need to know how climate change will influence species extinction rates in order to inform international policy decisions about the biological costs of failing to curb climate change and to implement specific conservation strategies to protect the most threatened species. Current predictions about extinction risks vary widely, suggesting that anywhere from 0 to 54% of species could become extinct from climate change (1–4). Studies differ in particular assumptions, methods, species, and regions and thus do not encompass the full range of our current understanding. As a result, we currently lack consistent, global estimates of species extinctions attributable to future climate change.

To provide a more comprehensive and consistent analysis of predicted extinction risks from climate change, I performed a meta-analysis of 131 published predictions (table S1). I focused on multispecies studies so as to exclude potential biases in single-species studies. I estimated the global proportion of species threatened in a Bayesian Markov chain Monte Carlo (MCMC) random-effects meta-analysis that incorporated variation among and within studies (5) and with each study weighted by sample size (6). I evaluated how extinction risk varied depending on future global temperature increases, taxonomic groups, geographic regions, endemism, modeling techniques, dispersal assumptions, and extinction thresholds. I used credible intervals (CIs) that do not overlap with zero and a deviance information criterion (DIC) greater than four to assess statistical support for factors. The majority of studies estimated correlations between current distributions and climate so as to predict suitable habitat under future climates. A smaller number of studies determined extinction risks by using process-based models of physiology or demography (15%), species-area relationships (5%), or expert opinion (4%). Species were predicted to become extinct if their range fell below a minimum threshold. An important caveat is that most of these models ignore many factors thought to be important in determining future extinction risks such as species interactions, dispersal differences, and evolution.

Overall, 7.9% of species are predicted to become extinct from climate change; (95% CIs, 6.2 and 9.8) (Fig. 1). Results were robust to model type, weighting scheme, statistical method, potential publication bias, and missing studies (fig. S1 and table S2) (6). This proportion supports an estimate from a 5-year synthesis of studies (7). Its divergence from individual studies (1–4) can be explained by their specific assumptions and taxonomic and geographic foci. These differences provide the opportunity to understand how divergent factors and assumptions influence extinction risk from climate change.

The factor that best explained variation in extinction risk was the level of future climate change. The future global extinction risk from climate change is predicted not only to increase but to accelerate as global temperatures rise (regression coefficient = 0.53; CIs, 0.46 and 0.61) (Fig. 2). Global extinction risks increase from 2.8% at present to 5.2% at the international policy target of a 2°C post-industrial rise, which most experts believe is no longer achievable (8). If the Earth warms to 3°C, the extinction risk rises to 8.5%. If we follow our current, business-as-usual trajectory [representative concentration pathway (RCP) 8.5; 4.3°C rise], climate change threatens one in six species (16%). Results were robust to alternative data transformations and were bracketed by models with liberal and conservative extinction thresholds (figs. S2 and S3 and table S3).

Regions also differed significantly in extinction risk (ΔDIC = 12.6) (Fig. 3 and table S4). North America and Europe were characterized by the lowest risks (5 and 6%, respectively), and South America (23%) and Australia and New Zealand (14%) were characterized by the highest risks. These latter regions face nonanalog climates (9) and harbor diverse assemblages of endemic species with small ranges. Extinction risks in Australia and New Zealand are further exacerbated by small land masses that limit shifts to new habitat (10). Poorly studied regions might face higher risks, but insights are limited without more research (for example, only four studies in Asia). Currently, most predictions (60%) center on North America and Europe, suggesting a need to refocus efforts toward less studied and more threatened regions.

Endemic species with smaller ranges and certain taxonomic groups such as amphibians and reptiles are predicted to face greater extinction risks (11, 12). I estimated that endemic species face a 6% greater extinction risk relative to models that include both species endemic and nonendemic to the study region (ΔDIC = 8.3). Extinction risks also rose faster with preindustrial temperature rise for models with endemic species (ΔDIC = 8.2) (fig. S4). In contrast to predictions, extinction risks did not vary significantly by taxonomic group (ΔDIC = 0.7) (Fig. 4). One explanation is that trait variation at finer taxonomic scales might play a more important role in modulating extinction risks (13). Also, typical approaches for quantifying extinction risks likely do not capture the full range of differences among taxonomic groups.

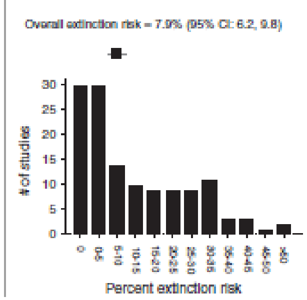


Fig. 1. Histogram of percent extinction risks from climate change for 131 studies. Percent extinction risk refers to the predicted percent of species extinctions in each study, averaged across all model assumptions. The meta-analysis estimated mean with 95% CIs is also shown.

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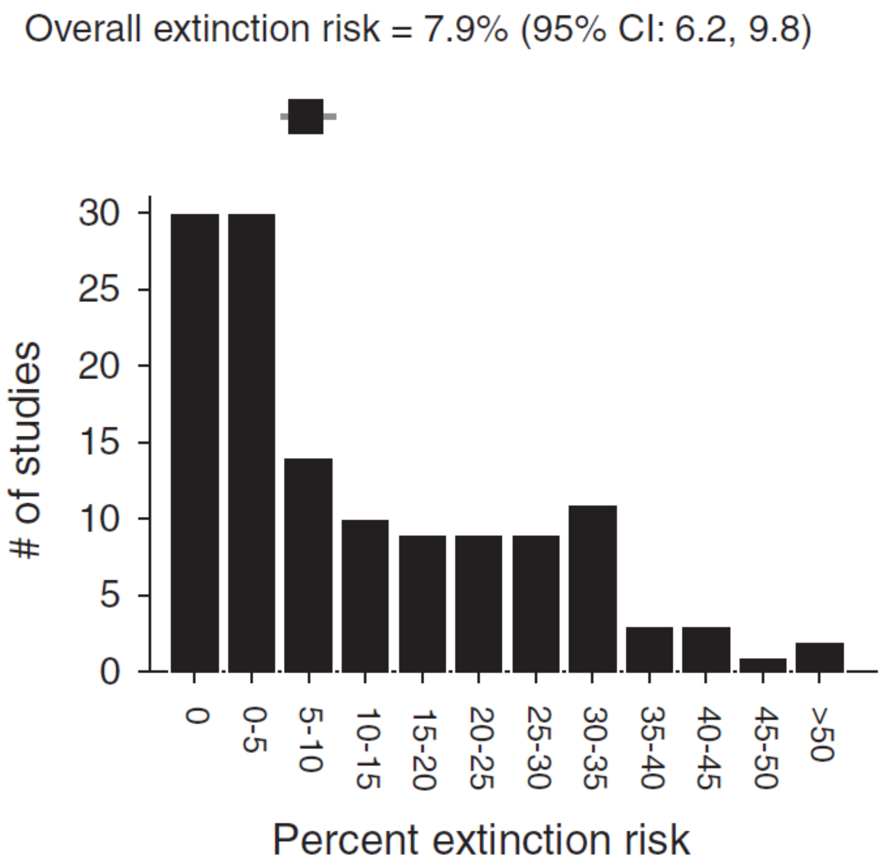
Lambers, 2015 http://dx.doi.org/10.1126/science.aab2057 Urban, 2015 http://dx.doi.org/10.1126/science.aaa4984

We critically need to know how climate change will influence species extinction rates in order to inform international policy decisions about the biological costs of failing to curb climate change and to implement specific conservation strategies to protect the most threatened species. Current predictions about extinction risks vary widely, suggesting that anywhere from 0 to 54% of species could become extinct from climate change (*1–4*). Studies differ in particular assumptions, methods, species, and regions and thus do not encompass the full range of our current understanding. As a result, we currently lack consistent, global estimates of species extinctions attributable to future climate change.

Urban, 2015 http://dx.doi.org/10.1126/science.aaa4984



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Urban, 2015 http://dx.doi.org/10.1126/science.aaa4984

NL Environmental Assessment Agency (RIVM / MNP) Guidance: Systematic reflection on uncertainty & quality in:

Foci	Key issues
Problem framing	Other problem views; interwovenness with other problems; system boundaries; role of results in policy process; relation to previous assessments
Involvement of stakeholders	Identifying stakeholders; their views and roles; controversies; mode of involvement
Selection of indicators	Adequate backing for selection; alternative indicators; support for selection in science, society, and politics
Appraisal of knowledge base	Quality required; bottlenecks in available knowledge and methods; impact of bottlenecks on quality of results
Mapping and assessing relevant uncertainties	Identification and prioritisation of key uncertainties; choice of methods to assess these; assessing robustness of conclusions
Reporting uncertainty information	Context of reporting; robustness and clarity of main messages; policy implications of uncertainty; balanced and consistent representation in progressive disclosure of uncertainty information; traceability and adequate backing

Uncertainty is more than a number

Dimensions of uncertainty:

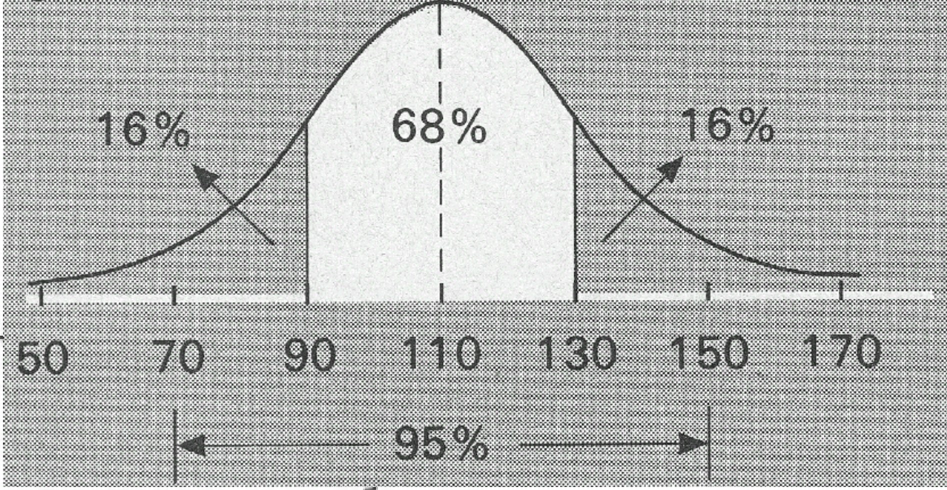
- Technical (inexactness)
- Methodological (unreliability)
- Epistemological (ignorance)
- Societal (limited social robustness)

Reliability intervals normal distributions

$\pm\,\sigma = 68\ \%$

$\pm\,2\sigma = 95\ \%$

$\pm\,3\sigma = 99.7\ \%$



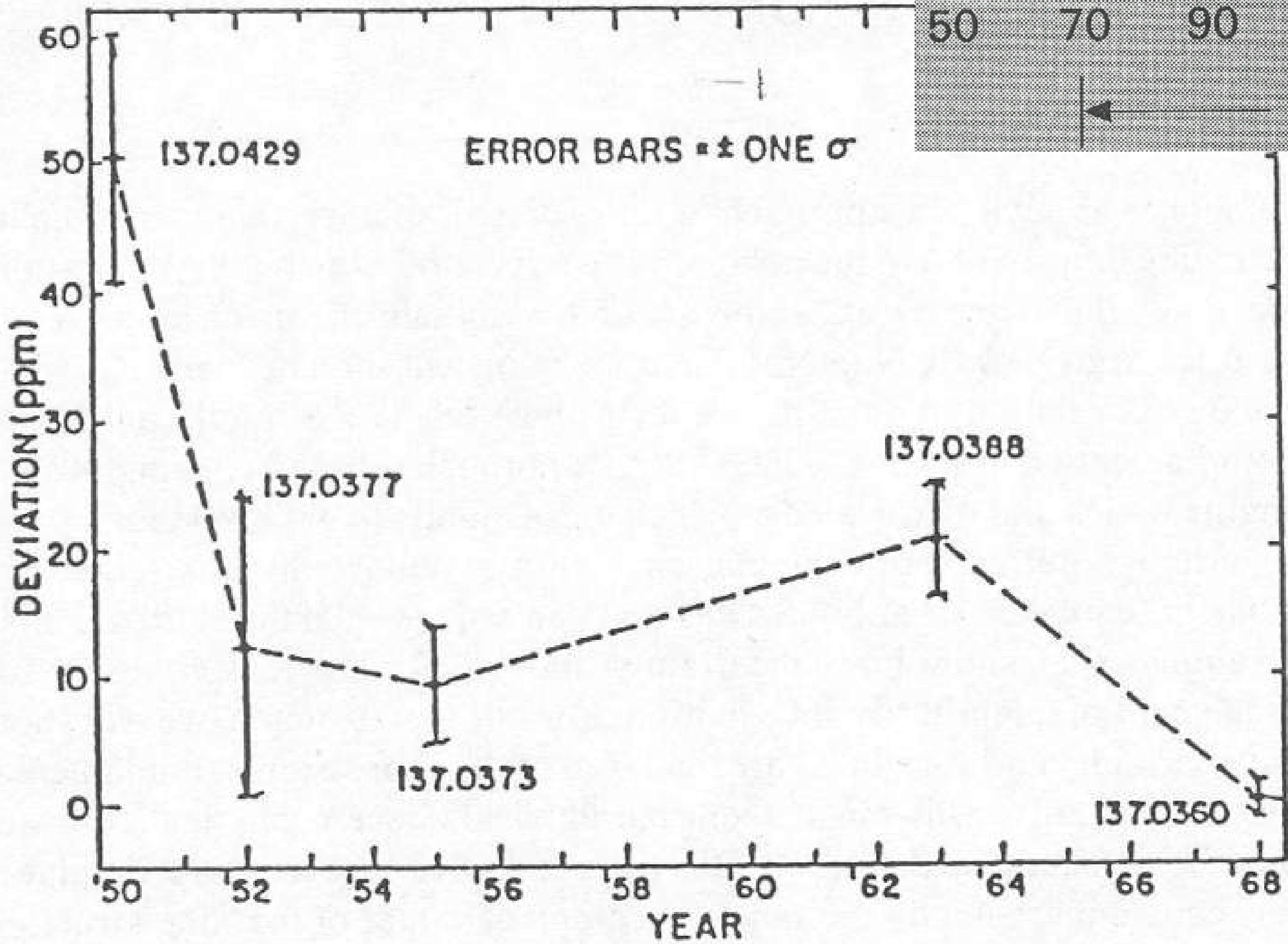
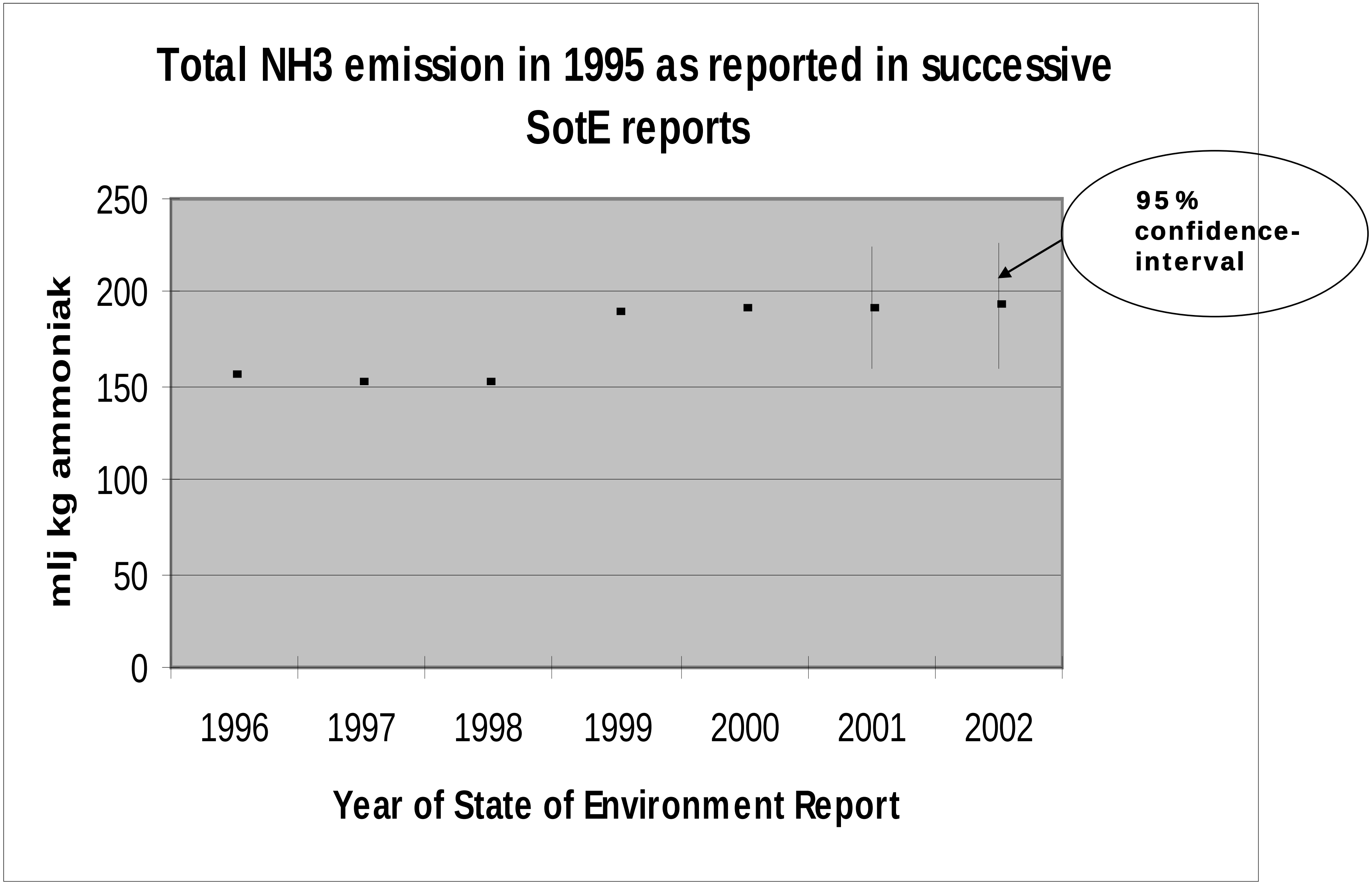


Fig. 1. Successive recommended values of the fine-structure constand α^{-1} (B. N. Taylor *et al.*, 1969, 7)


Total NH3 emission in 1995 as reported in successive SotE reports
mlj kg ammoniak
250
200
150
100
50
0
1996
1997
1998
1999
2000
2001
2002
Year of State of Environment Report
95% confidence-interval

NUSAP: Qualified Quantities

Classic scientific notational system:

- **N**umeral **U**nit **S**pread

For problems in the post-normal domain, add two qualifiers:

- **A**ssessment & **P**edigree

  "Assessment" expresses expert judgement on reliability of numeral + spread

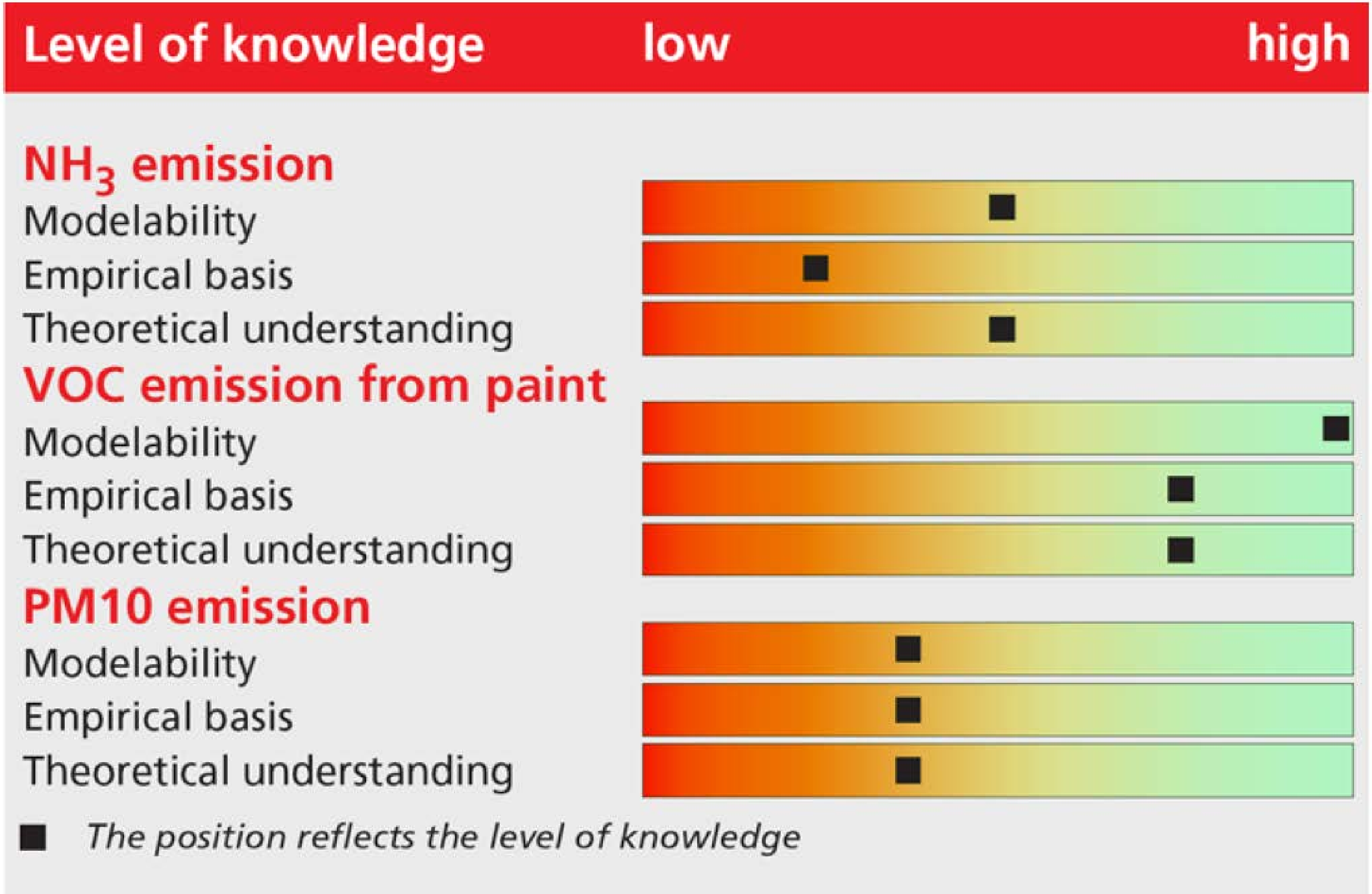
  "Pedigree" expresses multi-criteria evaluation of the strength of a number by looking at:

  - Background history by which the number was produced
  - Underpinning and scientific status of the number

Example Pedigree matrix parameter strength

Code	Proxy	Empirical	Theoretical basis	Method	Validation
4	Exact measure	Large sample direct mmts	Well established theory	Best available practice	Compared with indep. mmts of same variable
3	Good fit or measure	Small sample direct mmts	Accepted theory partial in nature	Reliable method commonly accepted	Compared with indep. mmts of closely related variable
2	Well correlated	Modeled/derived data	Partial theory limited consensus on reliability	Acceptable method limited consensus on reliability	Compared with mmts not independent
1	Weak correlation	Educated guesses / rule of thumb est	Preliminary theory	Preliminary methods unknown reliability	Weak / indirect validation
0	Not clearly related	Crude speculation	Crude speculation	No discernible rigour	No validation

Example: Air Quality



http://dx.doi.org/10.1088/1748-9326/3/2/024008

Extinction risk from climate change

nature

2004

Chris D. Thomas[1], Alison Cameron[1], Rhys E. Green[2], Michel Bakkenes[3], Linda J. Beaumont[4], Yvonne C. Collingham[5], Barend F. N. Erasmus[6], Marinez Ferreira de Siqueira[7], Alan Grainger[8], Lee Hannah[9], Lesley Hughes[4], Brian Huntley[5], Albert S. van Jaarsveld[10], Guy F. Midgley[11], Lera Miles[8*], Miguel A. Ortega-Huerta[12], A. Townsend Peterson[13], Oliver L. Phillips[8] & Stephen E. Williams[14]

Climate change over the past ~30 years has produced numerous shifts in the distributions and abundances of species[1,2] and has been implicated in one species-level extinction[3]. Using projections of species' distributions for future climate scenarios, we assess extinction risks for sample regions that cover some 20% of the Earth's terrestrial surface. Exploring three approaches in which the estimated probability of extinction shows a power-law relationship with geographical range size, we predict, on the basis of mid-range climate-warming scenarios for 2050, that 15–37% of species in our sample of regions and taxa will be 'committed to extinction'. When the average of the three methods and two dispersal scenarios is taken, minimal climate-warming scenarios produce lower projections of species committed to extinction (~18%) than mid-range (~24%) and maximum-change (~35%) scenarios. These estimates show the importance of rapid implementation of technologies to decrease greenhouse gas emissions and strategies for carbon sequestration.

Extinction risk from climate change

(Thomas *et al.*, *Nature*, 8 January 2004)

Main message of this paper:

- In 2050, 15-37% of species ‘committed to extinction’ due to climate change for a mid-range climate scenario

Extinction risks from climate change

Species-Area relationship:

- numbers of species that become extinct or threatened by habitat loss from climate change

$$S = c\,A^{z}$$

S = number of species

A = area,

c = constant

$z \approx 0.25$

Ratio of number of species that can live in a habitat of area *A* before (0) and after (t) climate change 'predicts' extinction rate:

$$\frac{S_t}{S_0} = \frac{c\,A_t^{\,z}}{c\,A_0^{\,z}} = (A_t\,/A_0)^z$$

Species committed to extinction

Climate scenario 2050	universal dispersal	no dispersal
> 2.0 °C	21–32%	38–52%
1.8–2.0 °C	15–20%	26–37%
0.8–1.7 °C	9–13%	22–31%

(Thomas et al., 2004)

Rule of thumb

Warming rate 1°C / century corresponds to:

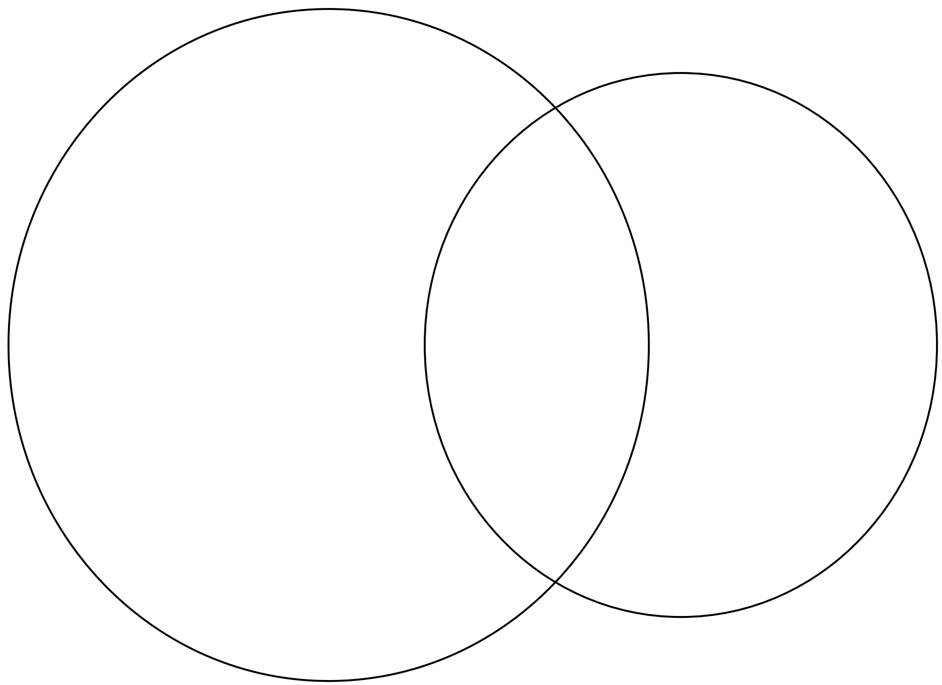
- ± 20 cm sea level rise
- ± 100 km shift of climate zone / century
- ± 150 m upward shift alpine climate zone/century

Climate tolerances of ecosystems

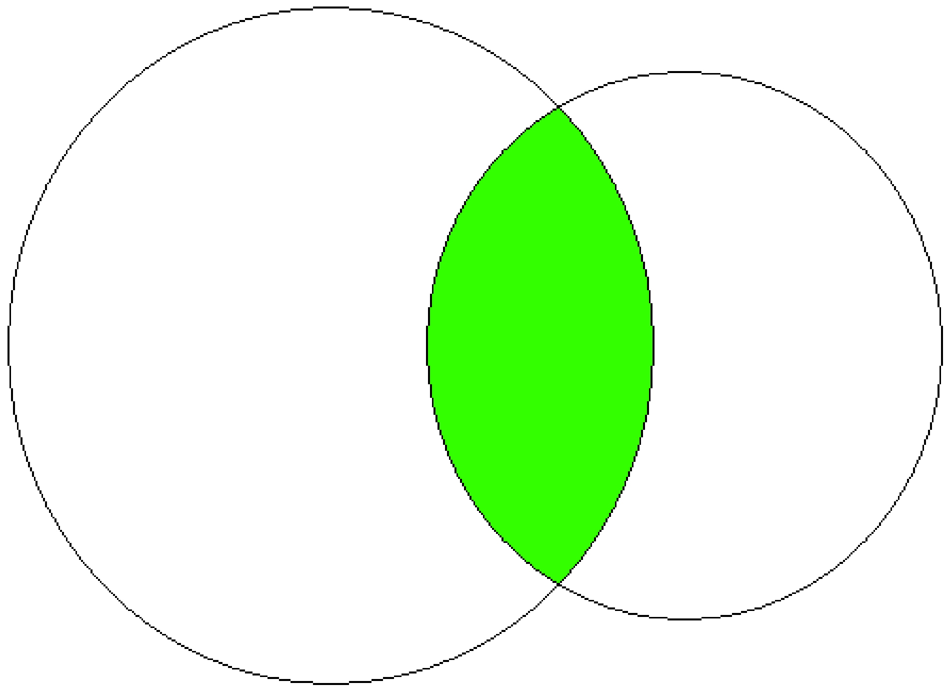
Ecosystem	Climate tolerance (°C/century)
Alpine ecosystem	0
Oak forest	0.12
Mangrove forest	0.50
Coastal wetlands	0.75
Coral reefs equator	1
Coral reefs N/S borders	5

(Hinkley, 1997)

Habitat before Climate Change **Habitat after Climate Change**

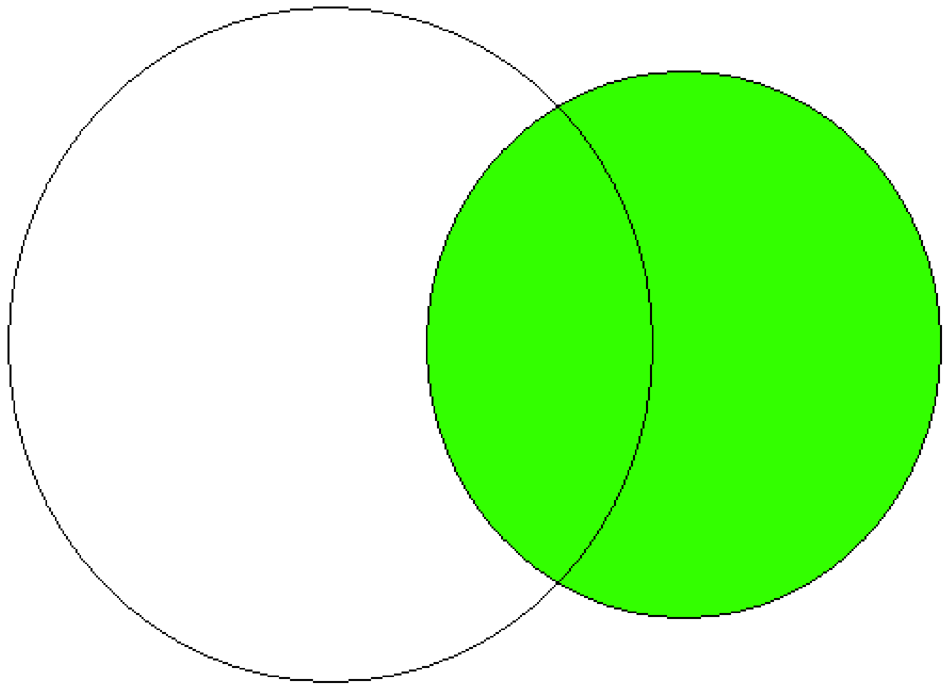


Habitat before Climate Change **Habitat after Climate Change**



Assumption: No dispersal

Habitat before Climate Change **Habitat after Climate Change**



Assumption: Full dispersal

Taxon	Region	With dispersal			No dispersal		
		Minimum expected climate change	Mid-range climate change	Maximum expected climate change	Minimum expected climate change	Mid-range climate change	Maximum expected climate change
Mammals	Mexico $n = 96$	2, 4, 5 **5**	2, 5, 7 **8**	–	9, 14, 18 **24**	10, 15, 20 **26**	–
	Queensland $n = 11$	10, 13, 15 **16**	–	48, 54, 80 **77**	–	–	–
	South Africa $n = 5$	–	24, 32, 46 **0**	–	–	28, 36, 59 **69**	–
Birds	Mexico $n = 186$	2, 2, 3 **4**	3, 3,4 **5**	–	5, 7, 8 **9**	5, 7, 8 **8**	–
	Europe $n = 34$	–	–	4, 6, 6 **7**	–	–	13, 25, 38 **48**
	Queensland $n = 13$	7, 9, 10 **12**	–	49, 54, 72 **85**	–	–	–
	South Africa $n = 5$	–	28, 29, 32 **0**	–	–	33, 35, 40 **51**	–
Frogs	Queensland $n = 23$	8, 12, 18 **13**	–	38, 47, 67 **68**	–	–	–
Reptiles	Queensland $n = 18$	7, 11, 14 **9**	–	43, 49, 64 **76**	–	–	–
	South Africa $n = 26$	–	21, 22, 27 **0**	–	–	33, 36, 45 **59**	–
Butterflies	Mexico $n = 41$	1, 3, 4 **7**	3, 4, 5 **7**	–	6, 9, 11 **13**	9, 12, 15 **19**	–
	South Africa $n = 4$	–	13, 7, 8 **0**	–	–	35, 45, 70 **78**	–
	Australia $n = 24$	5, 7, 7 **7**	13, 15, 16 **23**	21, 22, 26 **33**	9, 11, 12 **16**	18, 21, 23 **35**	29, 32, 36 **54**
Other invertebrates	South Africa $n = 10$	–	18, 15, 24 **0**	–	–	28, 46, 80 **85**	–
Plants	Amazonia $n = 9$	–	–	44, 36, 79 **69**	–	–	100, 100, 99 **87**
	Europe $n = 192$	3, 4, 5 **6**	3, 5, 6 **7**	4, 5, 6 **8**	9, 11, 14 **18**	10, 13, 16 **22**	13, 17, 21 **29**
	Cerrado $n = 163$	–	–	–	38, 39, 45 **66**	48, 48, 57 **75**	–
	South Africa Proteaceae $n = 243$	–	24, 21, 27 **38**	–	–	32, 30, 40 **52**	–
All species		9, 10, 13 **11** $n = 604$	15, 15, 20 **19** $n = 832$	21, 23, 32 **33** $n = 324$	22, 25, 31 **34** $n = 702$	26, 29, 37 **45** $n = 995$	38, 42, 52 **58** $n = 259$

Projected percentage extinction values are given, based on species–area (for $z = 0.25$) and Red Data Book (bold) approaches. The three species–area estimates are ordered in each cell with method 1 given first, followed by method 2, then method 3. Values for 'All species' are based on both these raw values and estimates interpolated for the empty (–) cells (see Methods). In each instance, n is the number of species assessed directly.

Pedigree matrix for evaluating models

Score	Supporting empirical evidence		Theoretical understanding	Representa-tion of understood underlying mechanisms	Plausibility	Colleague consensus
	Proxy	Quality and quantity				
4	Exact measures of the modelled quantities	Controlled experiments and large sample direct measurements	Well established theory	Model equations reflect high mechanistic process detail	Highly plausible	All but cranks
3	Good fits or measures of the modelled quantities	Historical/field data uncontrolled experiments small sample direct measurements	Accepted theory with partial nature (in view of the phenomenon it describes)	Model equations reflect acceptable mechanistic process detail	Reasonably plausible	All but rebels
2	Well correlated but not measuring the same thing	Modelled/derived data Indirect measurements	Accepted theory with partial nature and limited consensus on reliability	Aggregated parameterized meta model	Somewhat plausible	Competing schools
1	Weak correlation but commonalities in measure	Educated guesses indirect approx. rule of thumb estimate	Preliminary theory	Grey box model	Not very plausible	Embrionic field
0	Not correlated and not clearly related	Crude speculation	Crude speculation	Black box model	Not at all plausable	No opinion