

Reducing uncertainty in projections of species range shift from climate change



Miguel B. Araújo

In collaboration with Richard Pearson, Wilfried Thuiller, and others...



ALARM project - Assessing Large-scale Environmental Risks with Tested Methods

Extinction risk from climate change

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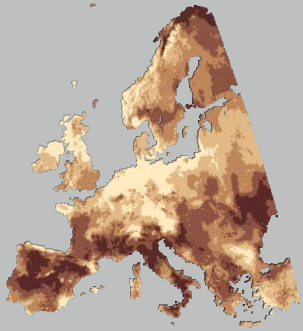
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Climate change over the past ~30 years has produced numerous shifts in the distributions and abundances of species^{1,2} and has been implicated in one species-level extinction³. Using projections of species' distributions for future climate scenarios, 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-

areas^{7–12}. This 'climate envelope' represents the conditions under which populations of a species currently persist in the face of competitors and natural enemies. Future distributions are estimated by assuming that current envelopes are retained and can be projected for future climate scenarios^{7–12}. We assume that a species either has no limits to dispersal such that its future distribution becomes the entire area projected by the climate envelope model or that it is incapable of dispersal, in which case the new distribution is the overlap between current and future potential distributions (for example, species with little dispersal or that inhabit fragmented landscapes)¹¹. Reality for most species is likely to fall between these extremes.

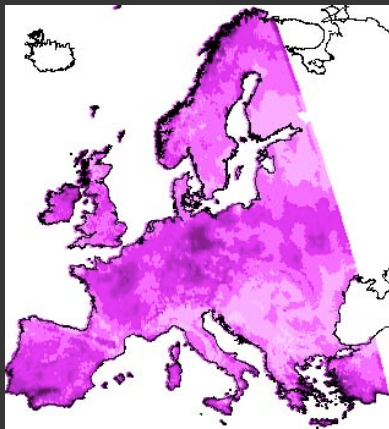
We explore three methods to estimate extinction, based on the species–area relationship, which is a well-established empirical power-law relationship describing how the number of species relates to area ($S = cA^z$, where S is the number of species, A is area, and c and z are constants)¹³. This relationship predicts adequately the numbers of species that become extinct or threatened when the area available to them is reduced by habitat destruction^{14,15}. Extinctions arising from area reductions should apply regardless of whether the cause of distribution loss is habitat destruction or climatic unsuitability.

Because climate change can affect the distributional area of each species independently, classical community-level approaches need to be modified (see Methods). In method 1 we use changes in the summed distribution areas of all species. This is consistent with the traditional species–area approach: on average, the destruction of half of a habitat results in the loss of half of the distribution area summed across all species restricted to that habitat. However, this analysis tends to be weighted towards species with large distributional areas. To address this, in method 2 we use the average proportional loss of the distribution area of each species to estimate the fraction of species predicted to become extinct. This approach is faithful to the species–area relationship because halving the habitat area leads on average to the proportional loss of half the distribution of each species. Method 3 considers the extinction risk of each species in turn. In classical applications of the species–area approach, the fraction of species predicted to become extinct is equivalent to the mean probability of extinction per species. Thus, in method 3 we estimate the extinction risk of each species separately by substituting its area loss in the species–area relationship, before averaging across species (see Methods). Our conclusions are not dependent on which of these methods is used. We use $z = 0.25$ in the species–area relationship throughout, given its previous success in predicting proportions of threatened species^{14,15}, but our qualitative conclusions are not dependent on choice of z (Supplementary Information). As there are gaps in the data (not all dispersal/climate scenarios were available for each region), a logit–linear model is fitted to the extinction risk data to produce estimates for missing values in the extinction risk table (Table 1). Balanced estimates of extinction risk, averaged across all data sets, can then be calculated for each scenario.

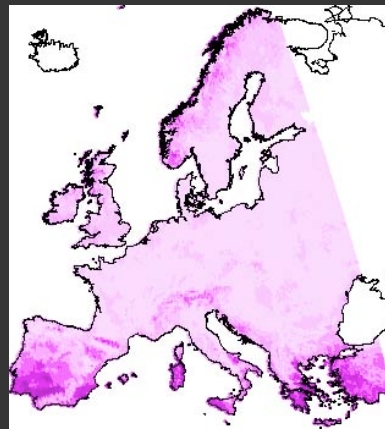


Measuring sources of uncertainty

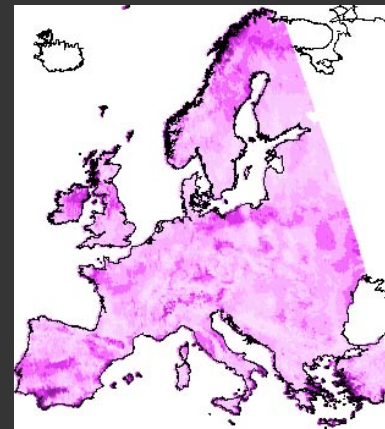
European plant species



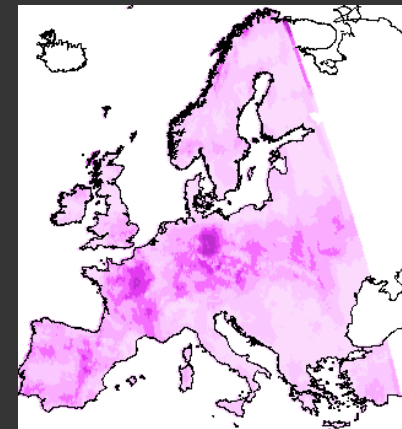
Combined variability



Modelling technique



Probability threshold



Climate scenario

PCA axis 1 = Agreement among projections (52% variance)

PCA axes 2 and 3 = Disagreement among projections (44% variance)

90% of the disagreement is explained by model and choice of threshold

Would inter-model variability be important?

European plant species

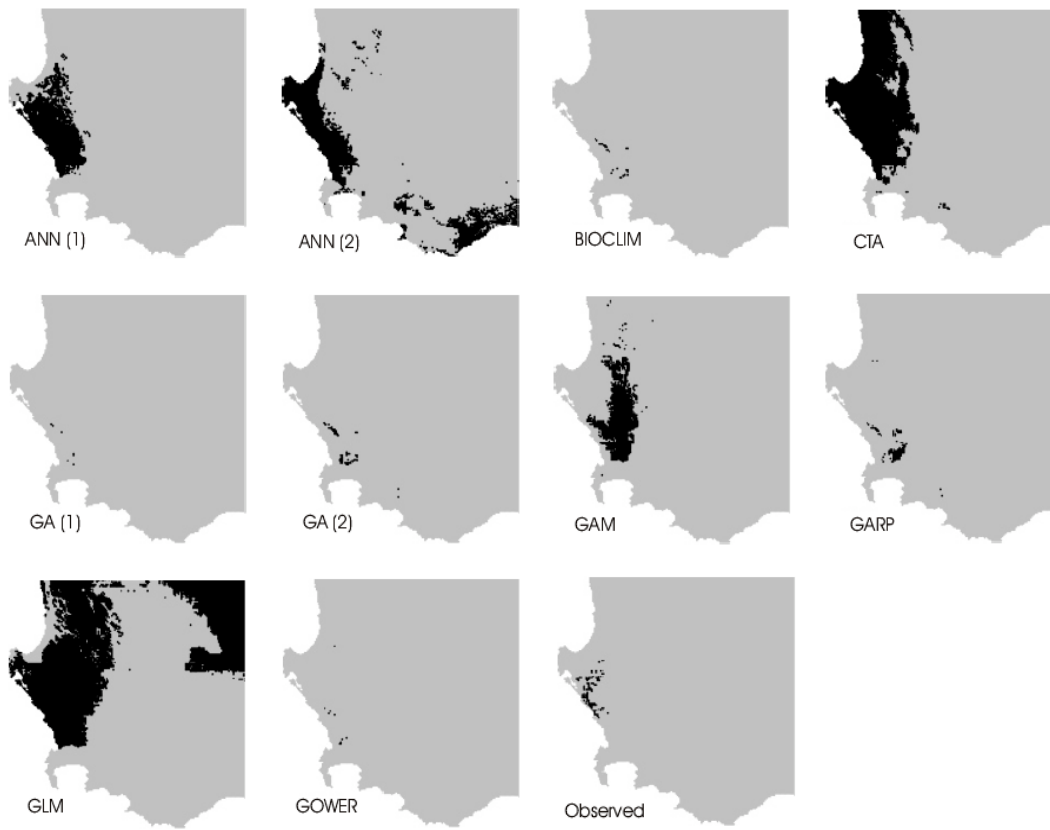
	Universal dispersal	No dispersal
Minimum CC	0.9 – 6	2 – 15.1
Mid-range CC	0 – 6.5	2.9 – 16.3
Maximum CC	1.1 – 7.8	2.3 – 18.2

Estimated proportion of plant species 'committed' to extinction by 2050

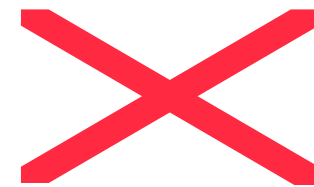
Variability of model predictions

Cape Proteaceae

C. Leucosperna tomentosum



1 2 3 4 5 6 7 8 9



1. ANN1 (SPECIES)
2. ANN2 (SPLUS)
3. BIOCLIM
4. CTA
5. GA
6. GAM
7. GARP
8. GLM
9. DOMAIN

Pearson, Thuiller, Araújo, et al. In review

Validation

Sometimes used to mean evaluation

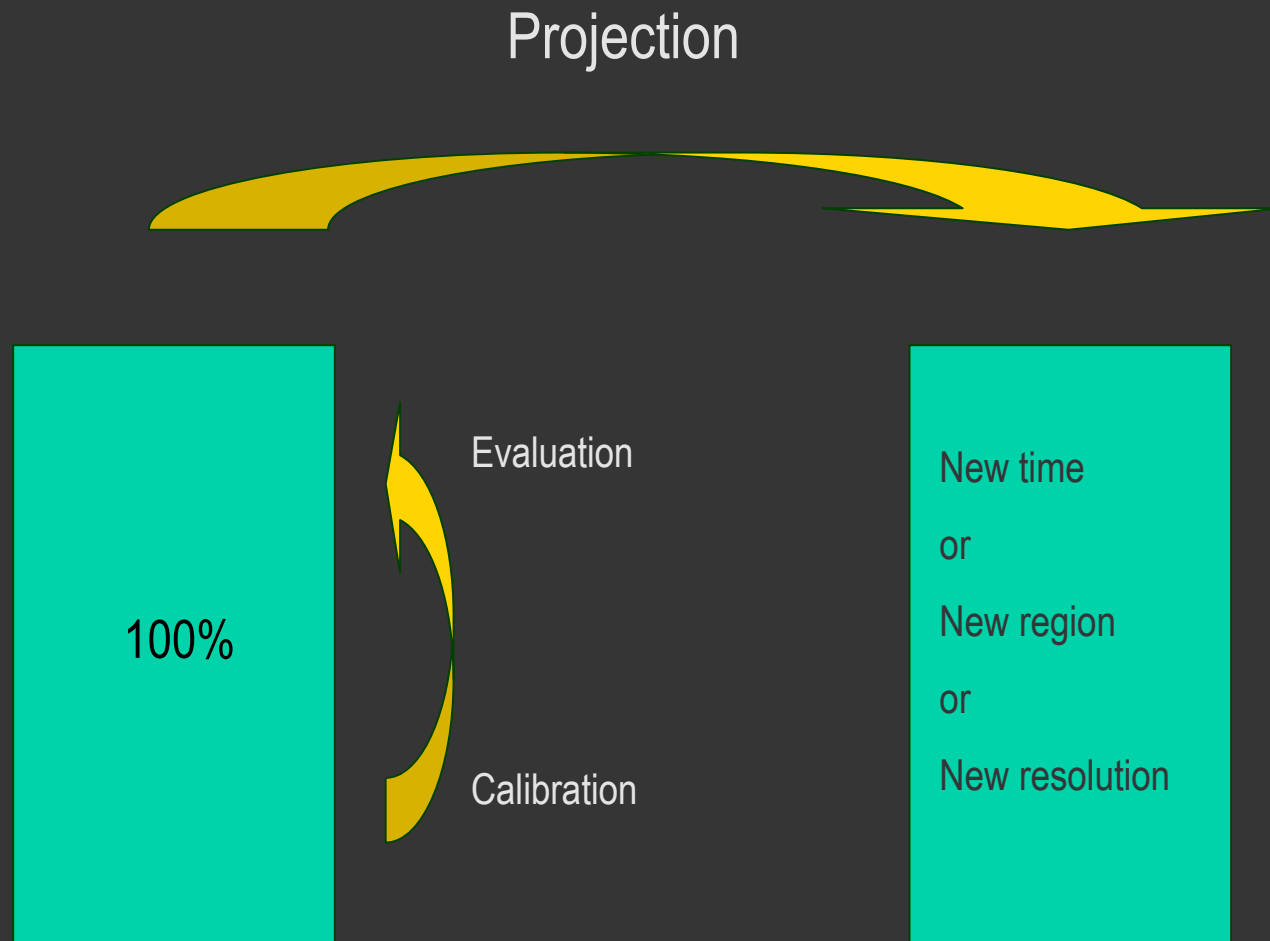
Validation

Scientific acceptance that major processes are formulated correctly and the model achieves intended purpose and objectives

Validation carries the idea of legitimacy

Strategies for evaluation (resubstitution)

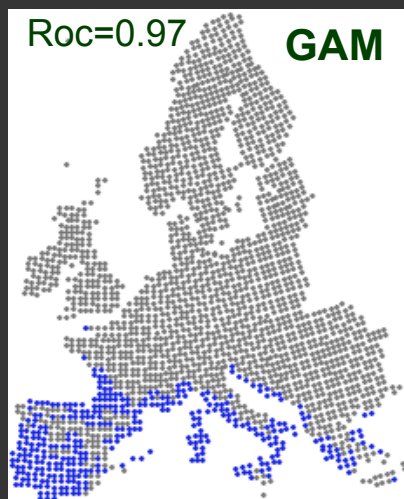
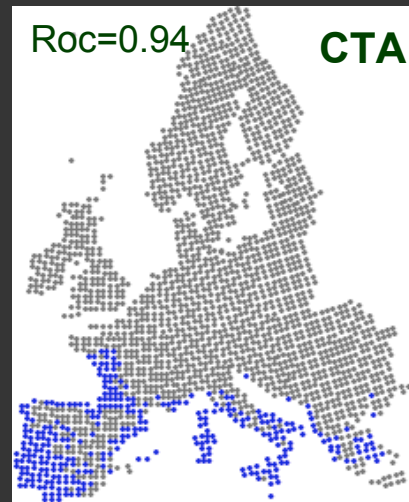
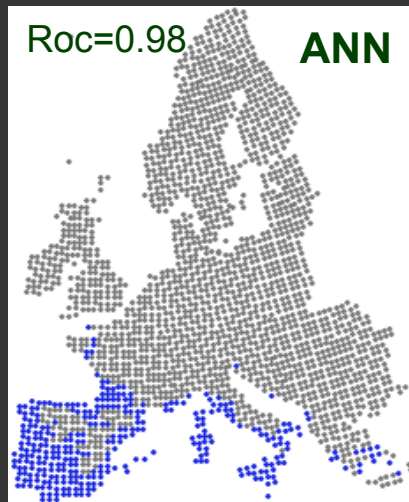
e.g. Huntley et al. 1995, Sykes et al. 1996



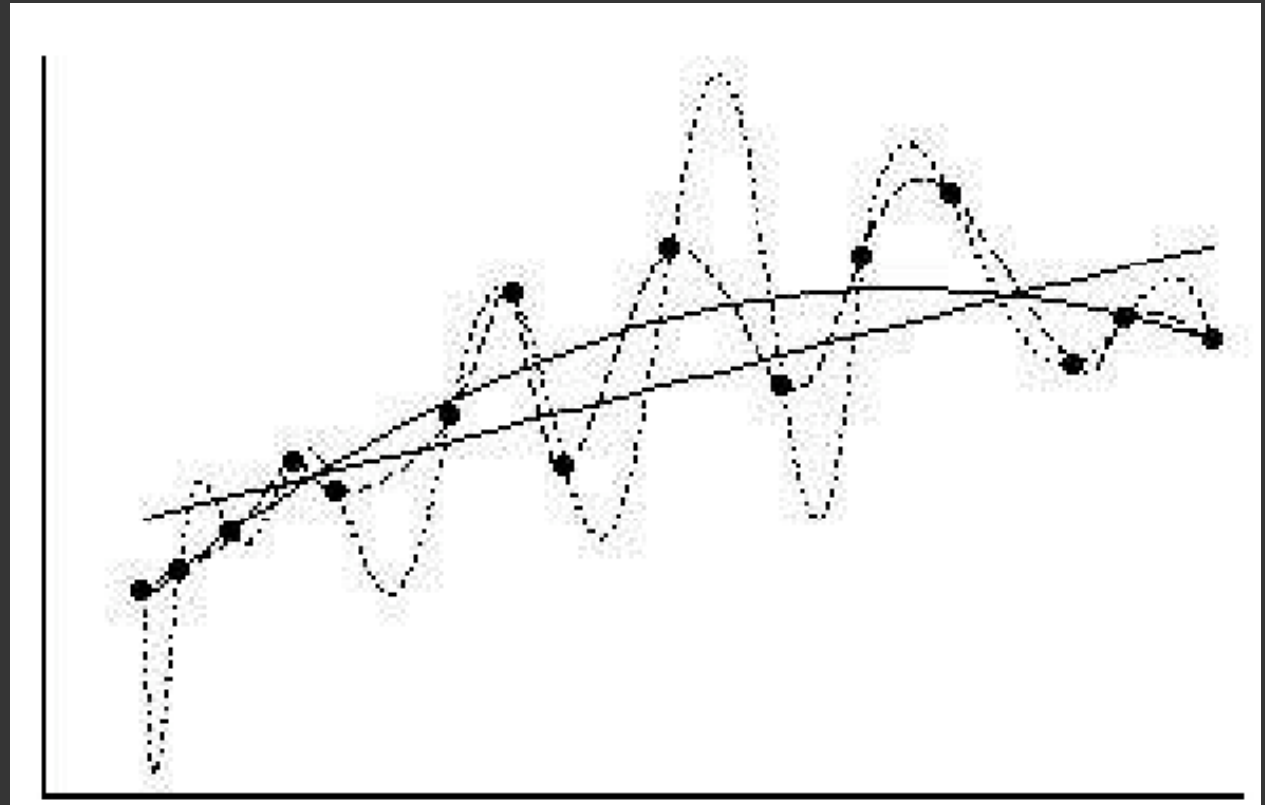


Example of cork oak

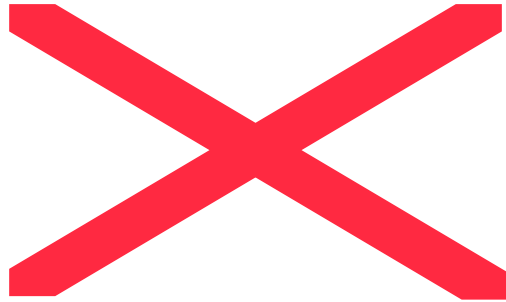
Projecting current distributions



Problems of interpolation



Model performance across different methods



Study area: Portugal

Resolution: 10 km grid squares

44 herptile species

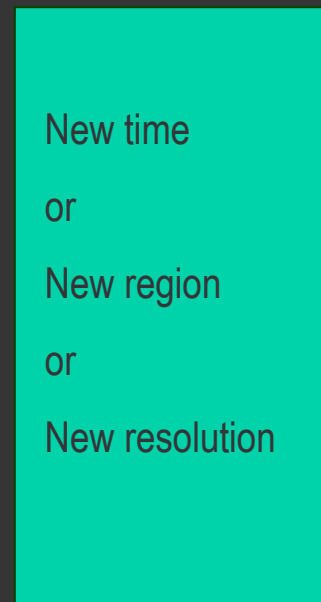
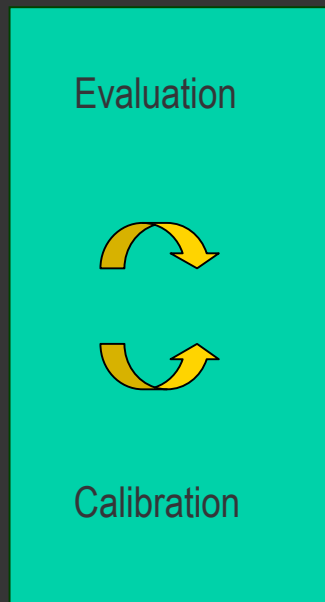
16 climatic and land-use variables

Models using non-linear complex response curves provide generally better fits to the data

Strategies for evaluation (permutation)

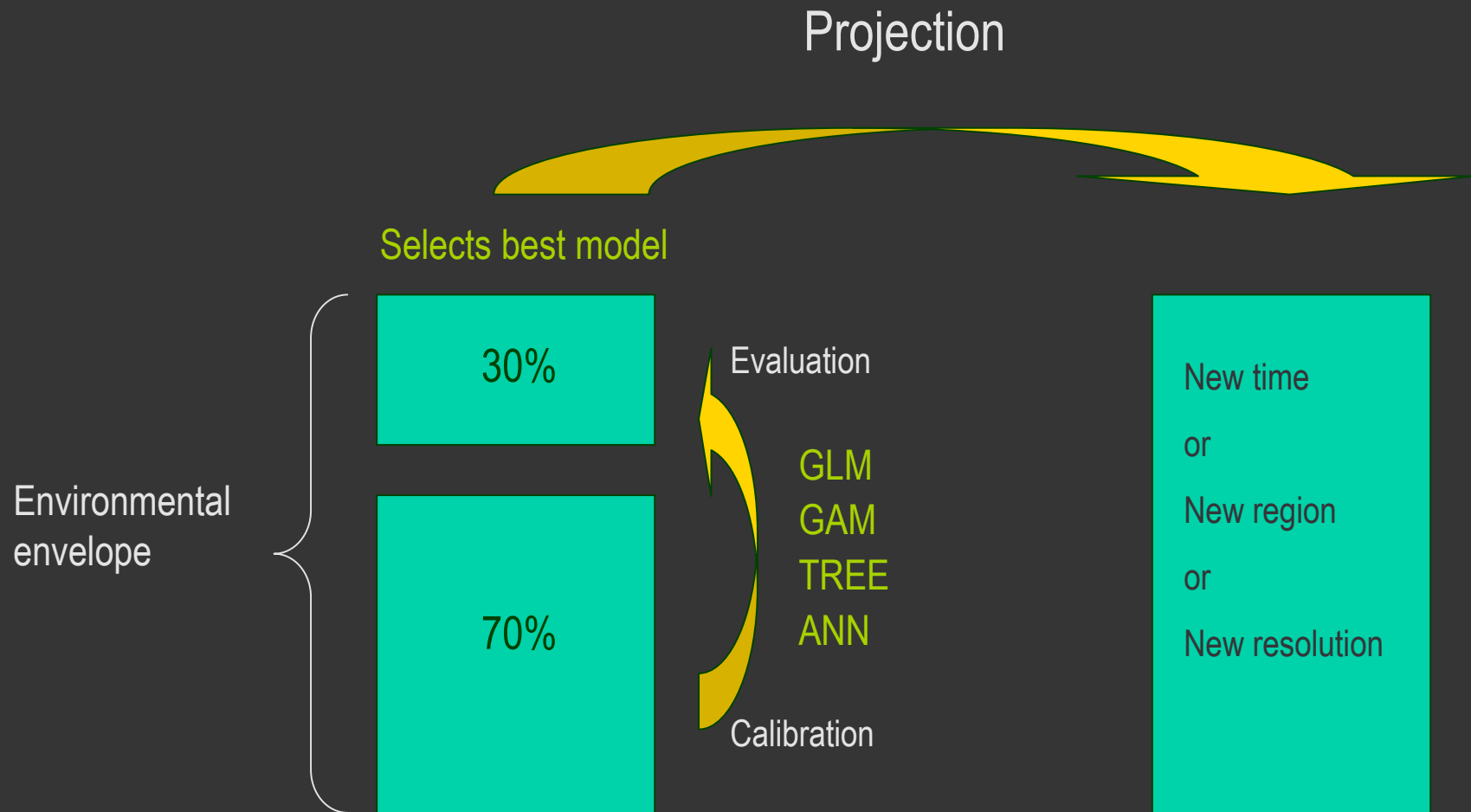
e.g. Peterson et al. 2000

Projection



Strategies for evaluation (data splitting)

e.g. Thuiller 2003

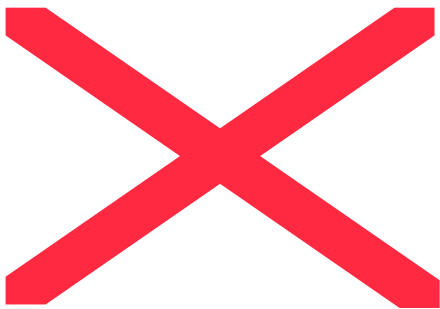


Problems with data splitting

Araújo et al. 2005 Global Change Biology

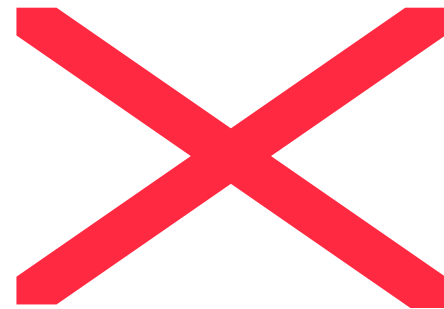
Calibration 70% t1

Validation 30% t1



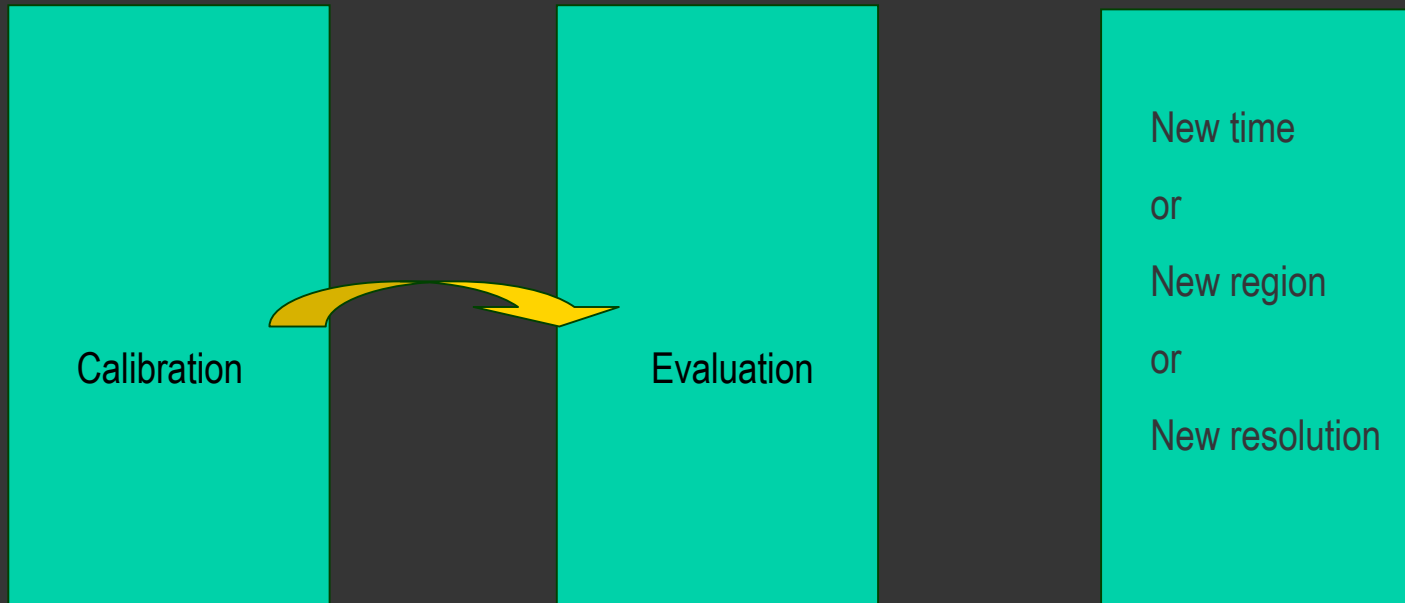
Calibration t1

Validation t2



Strategies for evaluation (independent)


Projection



Standard practices for model evaluation

From a review of species-climate-change impact studies

Number of studies		Desirability
Resubstitution	14	
Permutation	2	
Data splitting	10	
Independent	1	



Some argue that validation is impossible

The “dying-mother problem”

“If it rains tomorrow, I will stay home and revise this paper. The next day it rains, but you find that I am not home. You conclude that my original statement was false. But in fact it was my intention to stay home and work on my paper. The formulation was a true statement of my intent. Later, you find that I left the house because my mother died, and you realise that my original formulation was not false, but incomplete. It did not allow for the possibility of extenuating circumstances”.



“In combining the results of these two methods, one can obtain a result whose probability law of error will be more rapidly decreasing”

Pierre Laplace (1818)



“As if someone were to buy several copies of the morning newspaper to assure himself that what it said was true”

Ludwig Wittgenstein (1889-1951)

>200 papers reviewed!!!

Combining forecasts: A review and annotated bibliography

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College of Business Administration, University of Oregon, Eugene, OR 97403-1208, USA

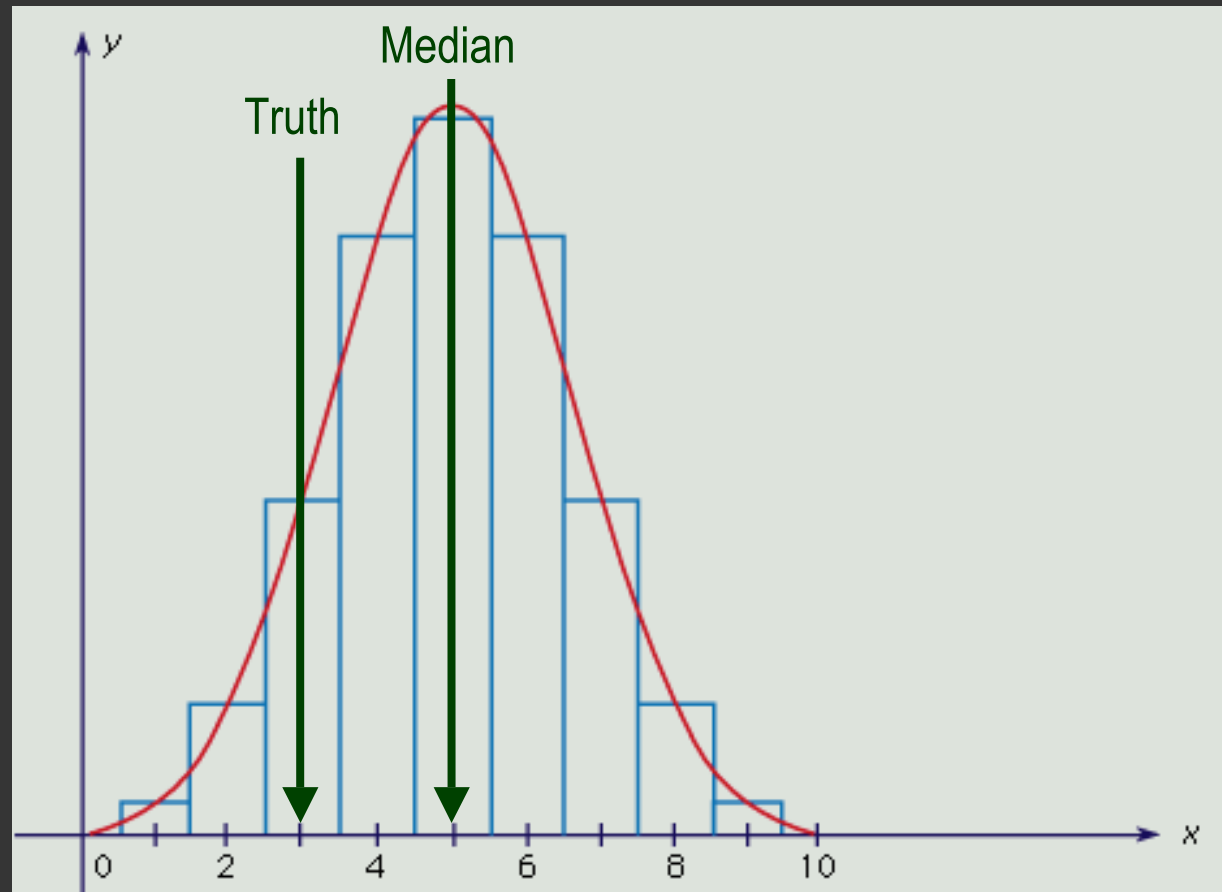
Abstract: Considerable literature has accumulated over the years regarding the combination of forecasts. The primary conclusion of this line of research is that forecast accuracy can be substantially improved through the combination of multiple individual forecasts. Furthermore, simple combination methods often work reasonably well relative to more complex combinations. This paper provides a review and annotated bibliography of that literature, including contributions from the forecasting, psychology, statistics, and management science literatures. The objectives are to provide a guide to the literature for students and researchers and to help researchers locate contributions in specific areas, both theoretical and applied. Suggestions for future research directions include (1) examination of simple combining approaches to determine reasons for their robustness, (2) development of alternative uses of multiple forecasts in order to make better use of the information they contain, (3) use of combined forecasts as benchmarks for forecast evaluation, and (4) study of subjective combination procedures. Finally, combining forecasts should become part of the mainstream of forecasting practice. In order to achieve this, practitioners should be encouraged to combine forecasts, and software to produce combined forecasts easily should be made available.

Keywords: Forecast combination, Composite models, Forecast aggregation, Consensus, Forecast synthesis.

Approaches for combining ensembles of forecasts

- Bounding box
 - range of uncertainties
- Consensus forecasting
 - central tendency of forecasts
- Probabilistic forecasting
 - central tendency + assumption of PDF
- Intermediate forecasting techniques
 - central tendencies in different sections of the frequency distribution of forecasts

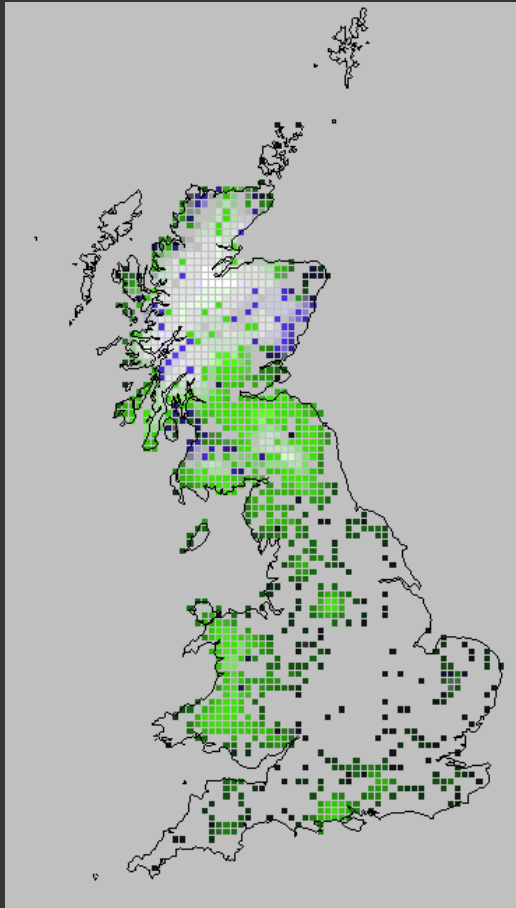
What's special about the mean?



Probability distribution function of an ensemble of model projections

Testing the usefulness of consensus forecasting

With distributions for 166 British bird species



Siskin *Carduelis spinus*
1968-1972 and 1995-1999

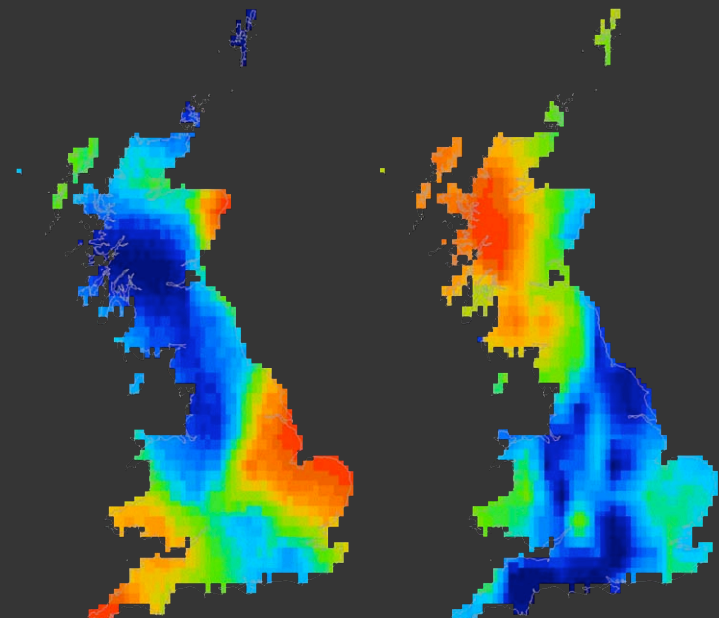
Stable

Contraction

Expansion

“Northern margins of southerly species with expanding ranges shifted northwards, and the northern species that declined shifted southwards”.

Thomas & Lennon, *Nature*, 1999



Delta temperature

Delta precipitation

Model simulations

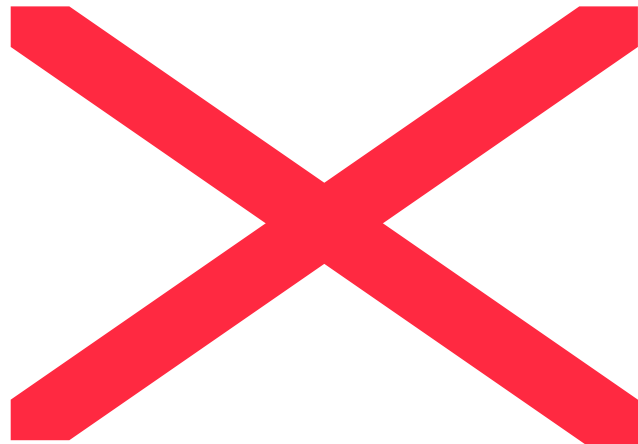
with 116 British breeding birds

4 modelling techniques (ANN, GAM, GLM, CTA) x
2 rules for transforming probabilities (Kappa, AUC) x
2 parameterisations (70%, 100% data in time t_1) x
= 16 predictions for every species

1856 model simulations

90% of species predicted to both expand and contract

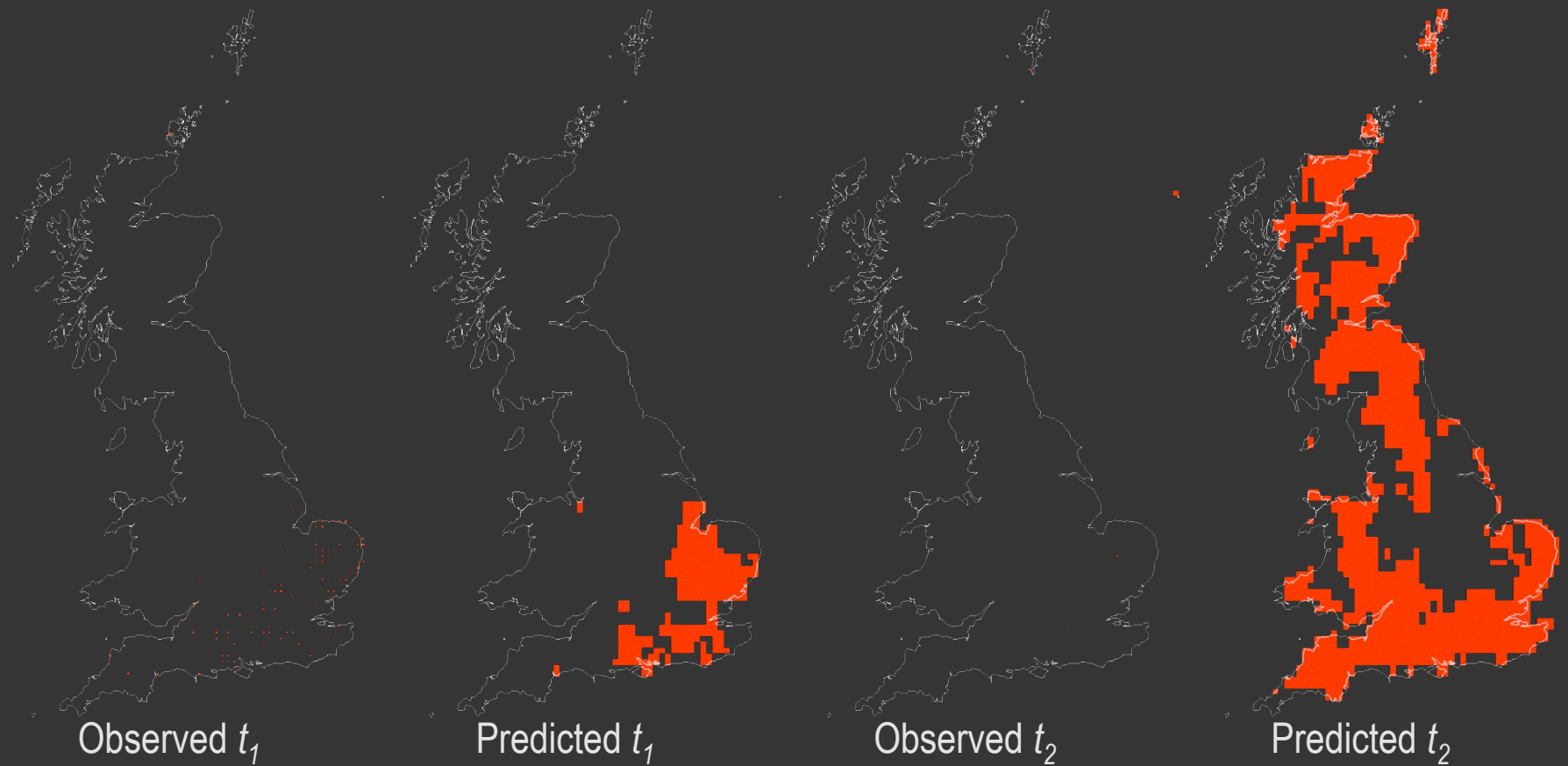
pared



10% of species had consistent predictions in all models

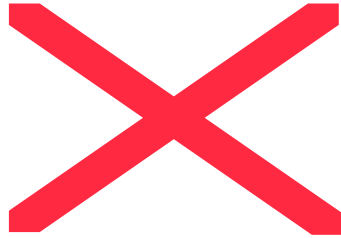
But 50% were wrong

Example of Red-backed shrike *Lanius collurio*

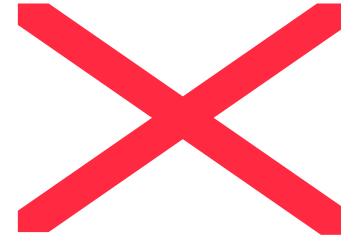


Araújo, et al. 2005 *Global Ecology and Biogeography*

ANN



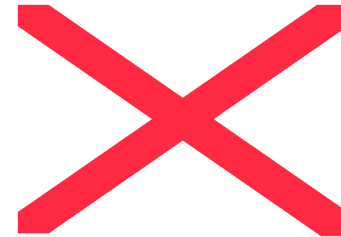
GAM



CTA



GLM



53% of species has consistent
predictions in all models

Consensual models

Methods using all data and the kappa statistic

Reduction of uncertainty by consensus

Predicted: Observed:	Contracted	Did not contract
Species contracted	TRUE POSITIVES All: 50% (LQ=31%; UQ=69%)	FALSE NEGATIVES All: 50% (LQ=31%; UQ=69%)
Species did not contract	FALSE POSITIVES All: 44% (LQ=12%; UQ=56%)	TRUE NEGATIVES All: 56% (LQ=44%; UQ=88%)

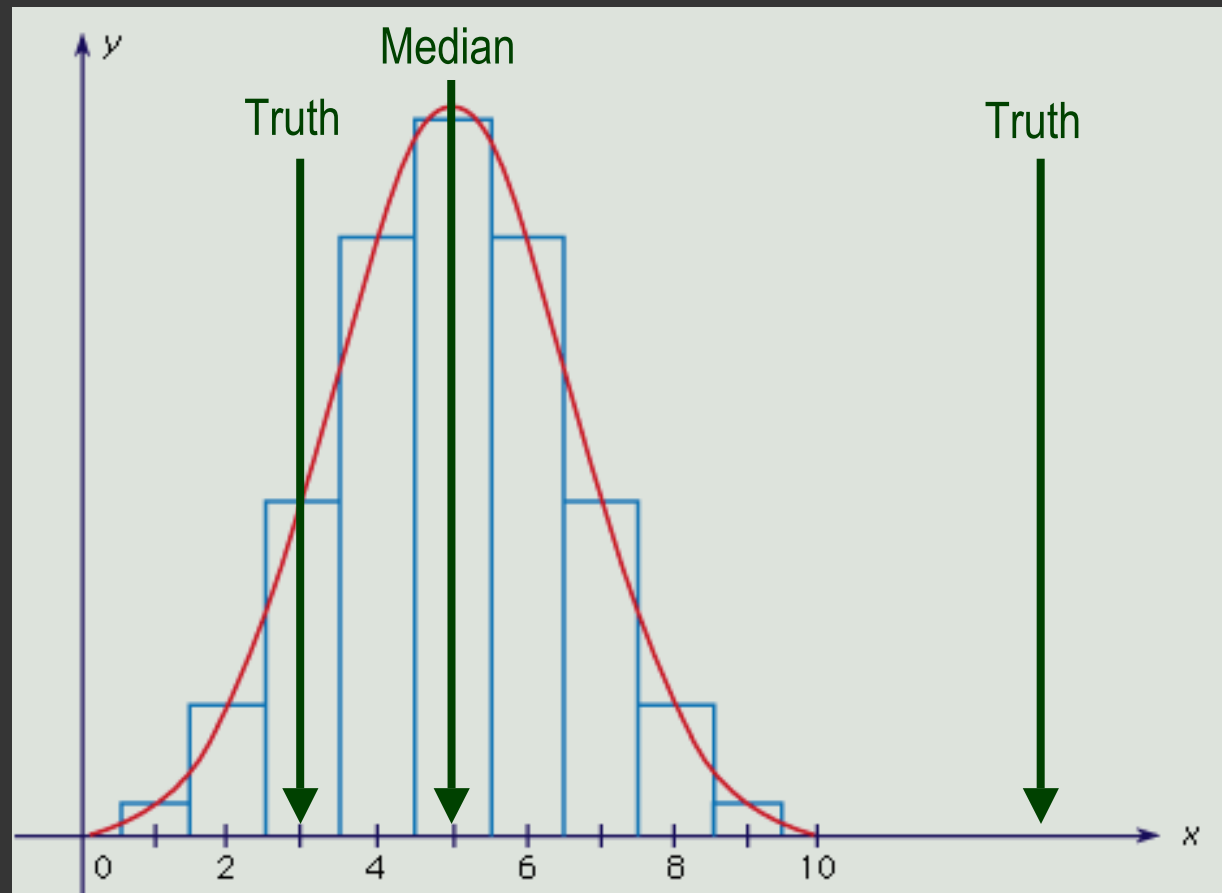
Reduction of uncertainty by consensus

Predicted: Observed:	Contracted	Did not contract
Species contracted	TRUE POSITIVES All: 50% (LQ=31%; UQ=69%) Consensus 1: 75% (LQ=50%; UQ=100%)	FALSE NEGATIVES All: 50% (LQ=31%; UQ=69%) Consensus 1: 25% (LQ=0%; UQ=50%)
Species did not contract	FALSE POSITIVES All: 44% (LQ=12%; UQ=56%) Consensus 1: 12% (LQ=0%; UQ=50%)	TRUE NEGATIVES All: 56% (LQ=44%; UQ=88%) Consensus 1: 88% (LQ=50%; UQ=100%)

Reduction of uncertainty by consensus

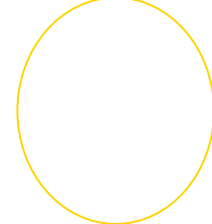
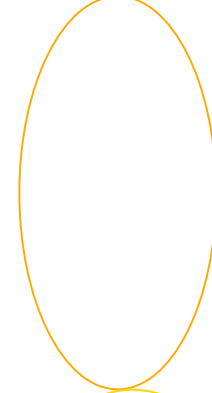
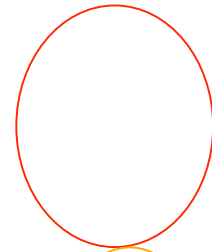
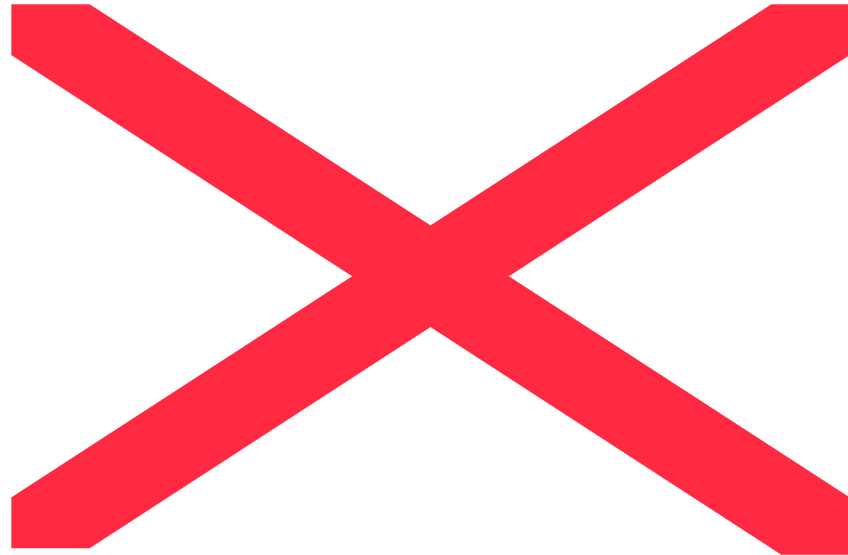
Predicted: Observed:	Contracted	Did not contract
Species contracted	TRUE POSITIVES All: 50% (LQ=31%; UQ=69%) Consensus 1: 75% (LQ=50%; UQ=100%) Consensus 2: 100% (LQ=100%; UQ=100%)	FALSE NEGATIVES All: 50% (LQ=31%; UQ=69%) Consensus 1: 25% (LQ=0%; UQ=50%) Consensus 2: 0% (LQ=0%; UQ=0%)
Species did not contract	FALSE POSITIVES All: 44% (LQ=12%; UQ=56%) Consensus 1: 12% (LQ=0%; UQ=50%) Consensus 2: 0% (LQ=0%; UQ=0%)	TRUE NEGATIVES All: 56% (LQ=44%; UQ=88%) Consensus 1: 88% (LQ=50%; UQ=100%) Consensus 2: 100% (LQ=100%; UQ=100%)

But can we always trust the mean?



Intermediate forecasting techniques

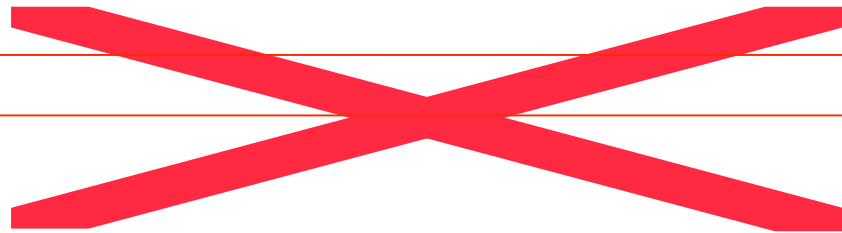
for combining forecasts



Consensus

Assessment of risk among European herptiles

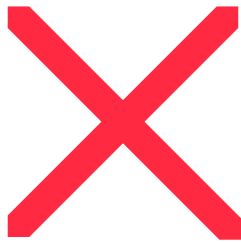
Taking uncertainty into account



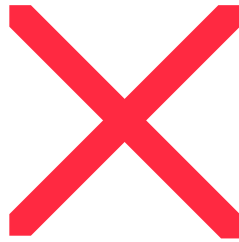
Mapping of risk among European herptiles

Taking uncertainty into account

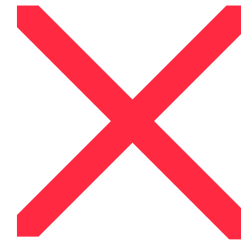
Cluster 1



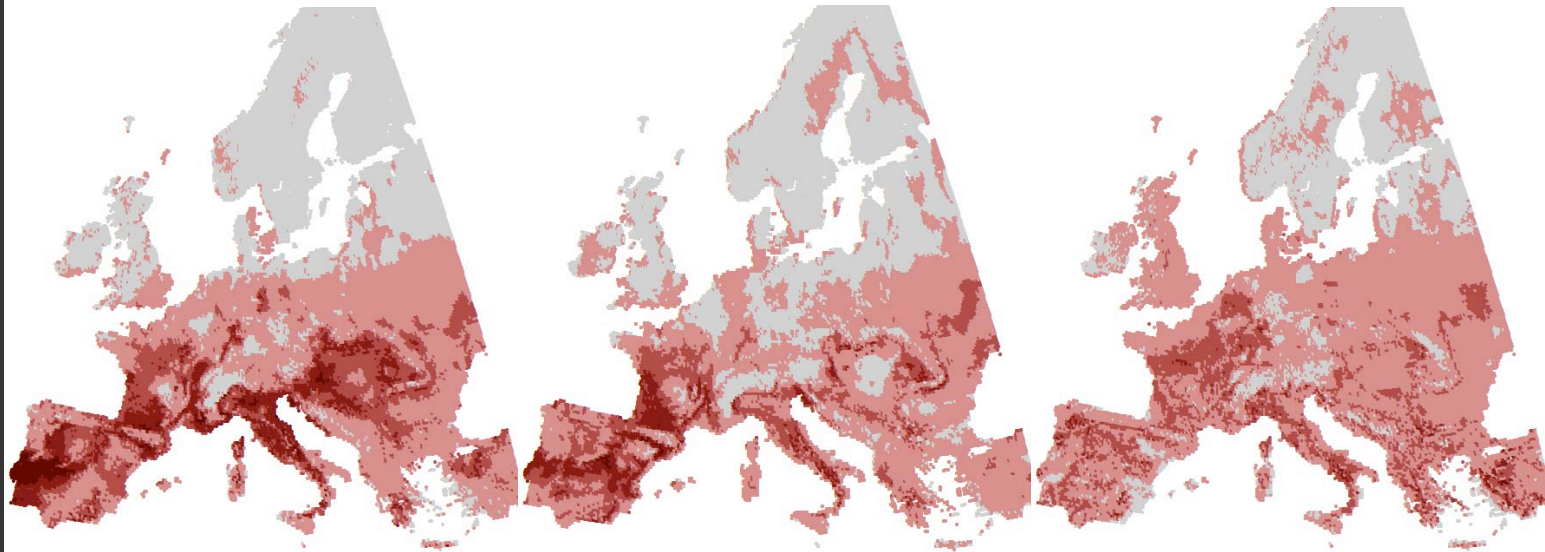
Cluster 2



Cluster 3



Geographical
distribution of
winners and
losers



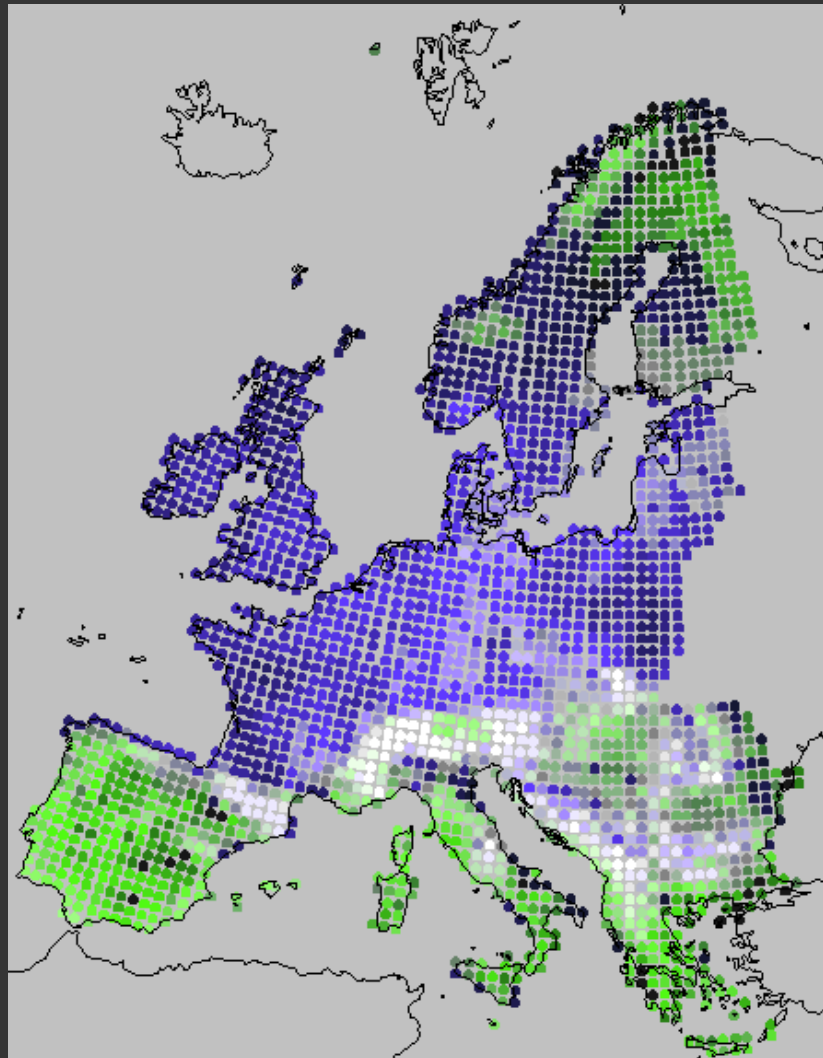
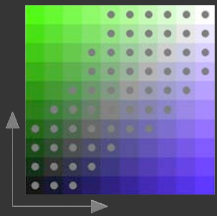
Species loss
per grid cell

*Araújo, Thuiller
and Pearson
2006 Journal of
Biogeography*

Forthcoming developments

- Explore different approaches to ensemble forecasting
(potentially exciting bridges with the climate community and the ENSEMBLES project)
- Investigate ways of improving the performance of individual bioclimate models
(improving existing modelling techniques and potentially devising new techniques, understanding the consequences of different rules for the identification of thresholds, learning how to deal with spatial autocorrelation)

Extinction risk in conservation planning



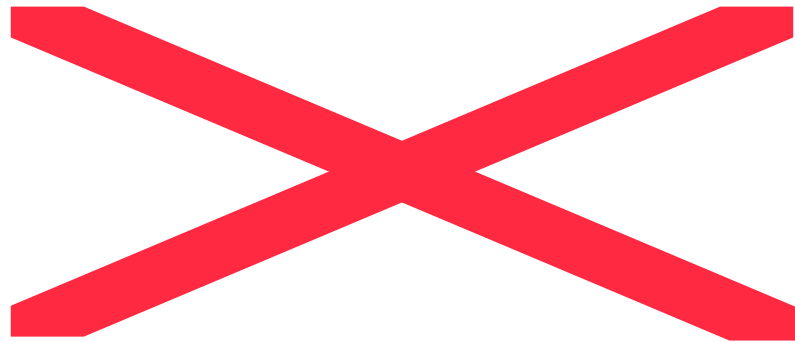
Low risk

High risk

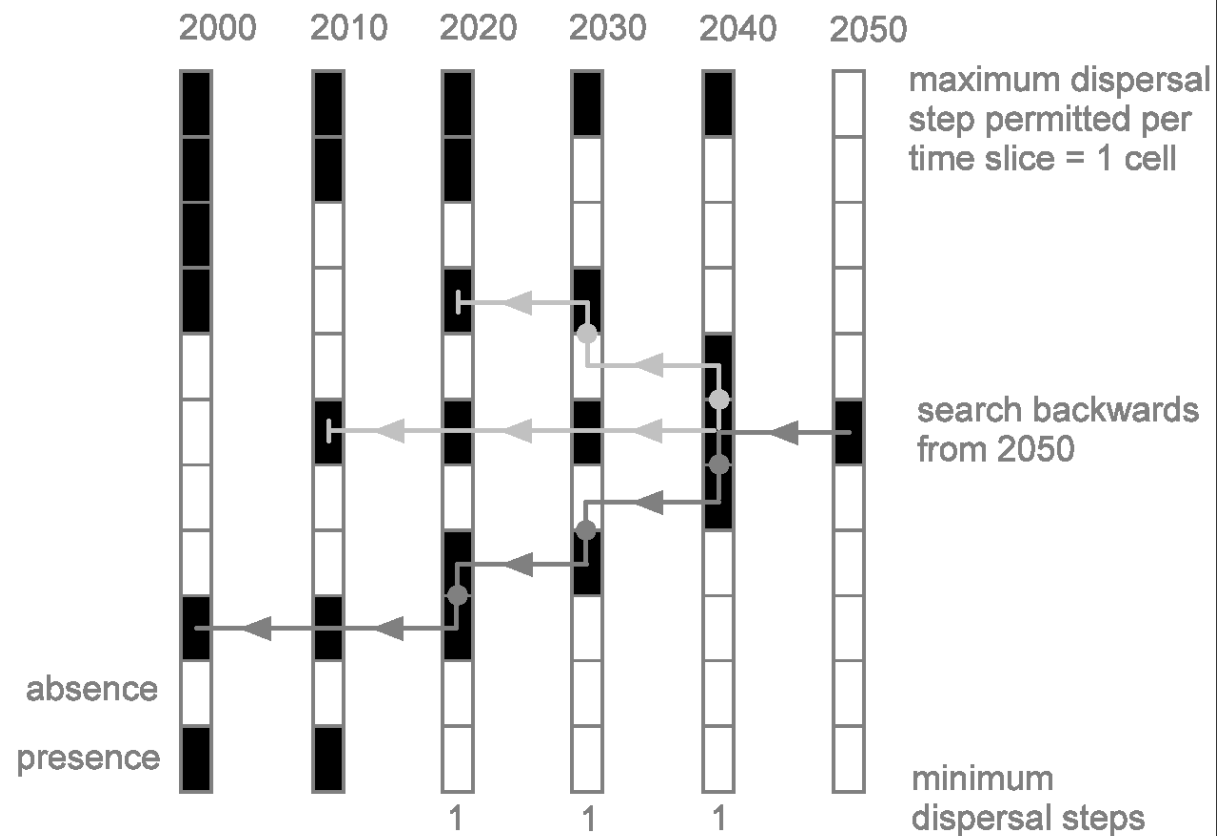
High/low risk

Araújo, et al. 2004 Global Change Biology

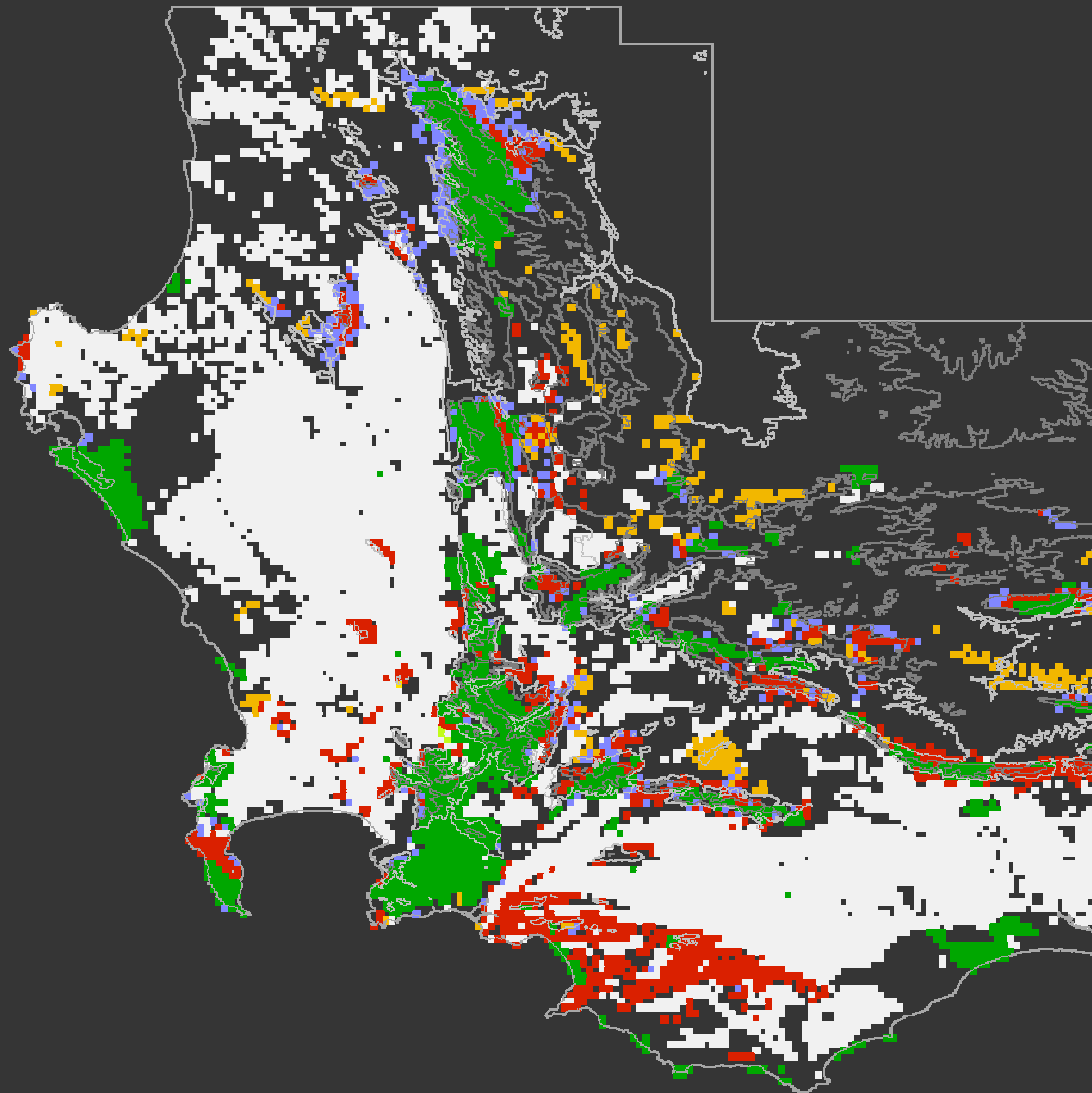
Effectiveness of reserve-selection with climate change



Identifying minimum-dispersal corridors



Selecting new reserves and corridors



Protected areas

New irreplaceable
areas

Contiguous flexible
areas

Other flexible areas

Williams et al. 2005 Conservation Biology