Niche Modelling Challenges

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LIVING CONSERVATION

Niche modelling - What can go wrong?



Everything

Data

Analysis

Validation



Niche modelling - What can go wrong?

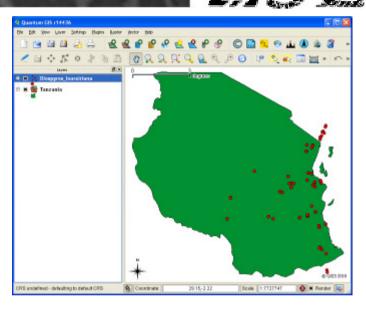


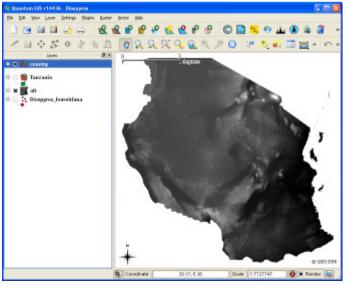
Data

- can't find enough
- using too much
- biased
- incorrect
- poor quality
- Analysis
- Validation

Common data sources

- Species distribution
 - museums / herbaria (http://data.gbif.org/)
 - literature
- Environmental data
 - Global climate grids (<u>http://www.worldclim.org/</u>)
 - Global topographic grids (strm30)
- More details this afternoon





Distribution data – can't get enough?



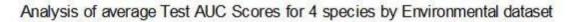
- Many Sources
 - Your own collections
 - Online museum/herbaria catalogues (GBIF)
 - Other online catalogues (some data is not accessable via GBIF)
 - -Survey data
 - Literature searches
 - Specimen digitisation

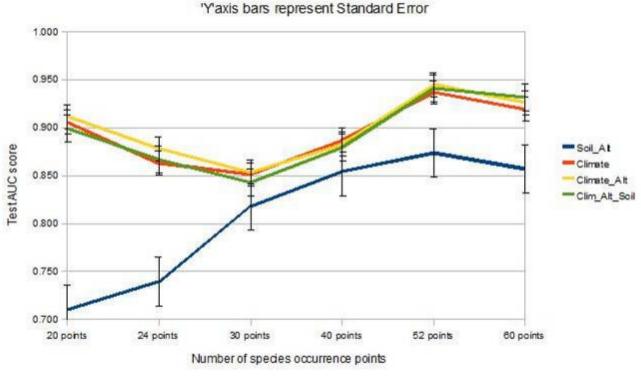


Distribution data — How many points do I need?



- Some say
 - **-**5
 - -10
 - -20
 - -50
- But it depends or your data
- You will need solid justification for modelling with only tens of points



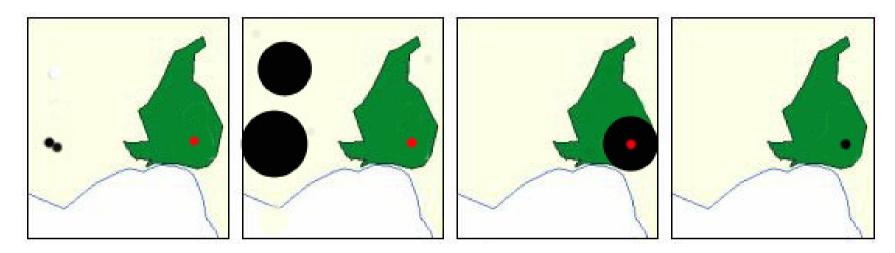


Problems with distribution data



- Sampling biases
 - regional bias
 - Look at all that UK data, its the global centre of all diversity!
 - environmental bias
 - What a lot of plants grow by road-sides
 - taxonomic bias
 - The world is full of cute furry animals
- Accuracy
 - geographic errors
 - GPS or georectification?
 - taxonomic errors
 - Who identified that specimen?

Accuracy vs Precision



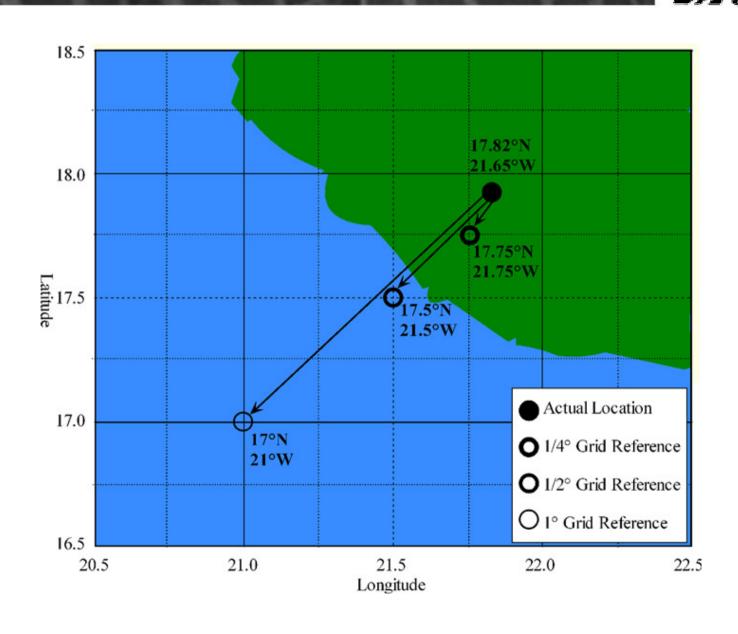
The differences between accuracy and precision in a spatial context.

The red spots show the true location, the black spots, represent the locations as reported by a collector.

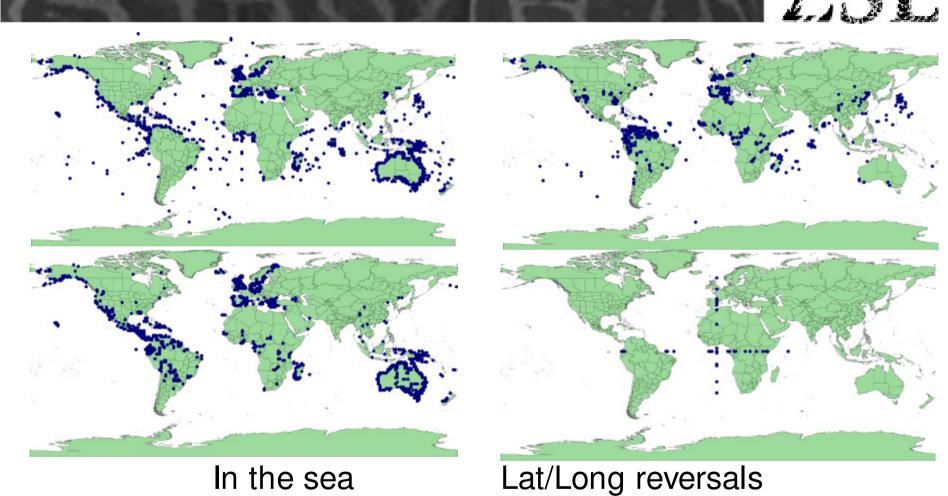
- a. High precision, low accuracy.
- b. Low precision, low accuracy showing random error.
- c. Low precision, high accuracy.
- d. High precision and high accuracy

Chapman 2005 Principles of Data Quality available to download on www.gbif.org

Good data that appear bad



Basic errors

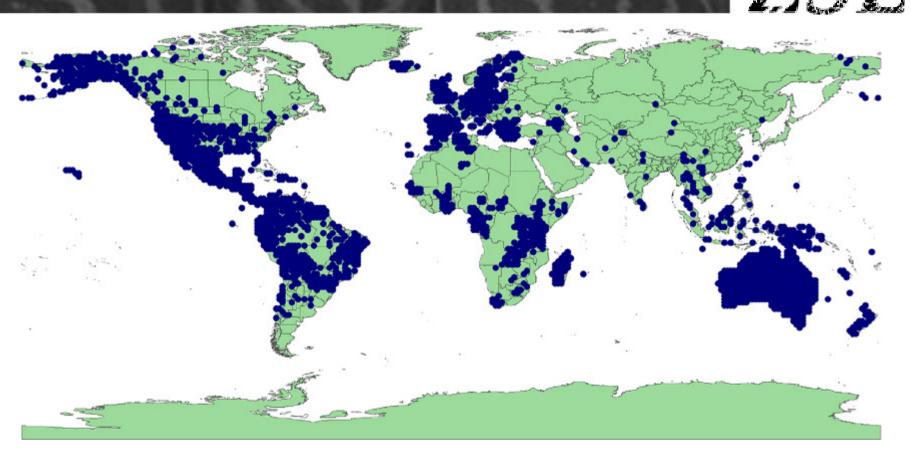


Yesson et al., (2007) How Global Is the GBIF?. PLoS ONE. 2: e1124

Lat/Long zero

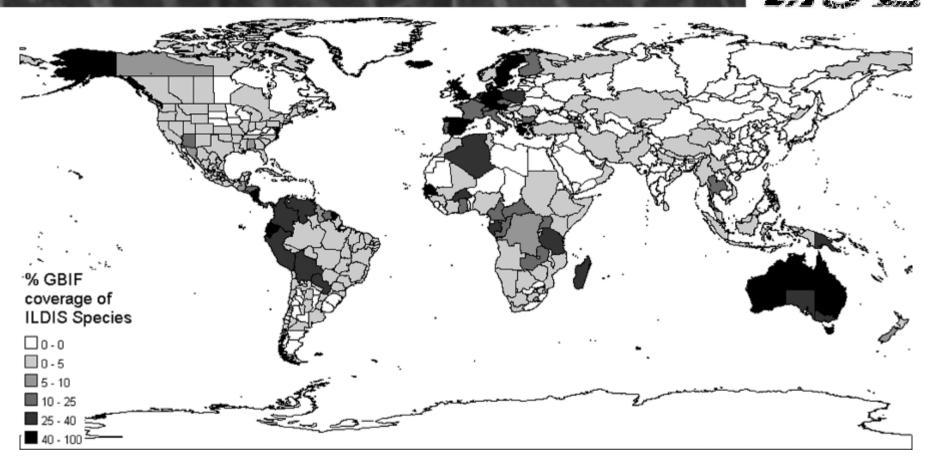
Near Valid

Geographic Coverage



Fabaceae data from GBIF showing patchy geographic coverage

Taxon Coverage



Global Legume coverage from GBIF data per TDWG level
 4 area

Other issues

- Taxonomy and checklists
- Misclassified data
 - –Synonymy
 - –Homonymy
 - -Misidentification



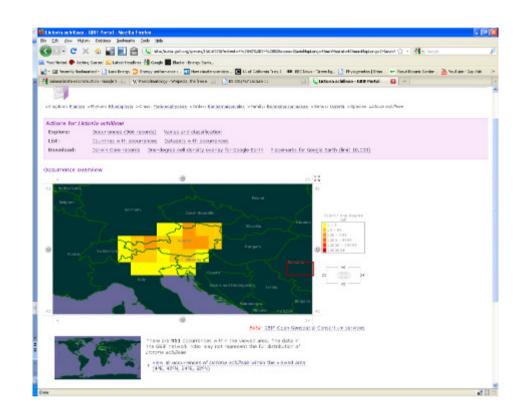
-180 90 Count / one degree cell 1:9 1:9 10:99 100:0999 100:09999 100:000+ 1:00 -90 -180 Seta: GRIF, Open Geospatial, Consortum services

This map only shows records with coordinates (28,875 records with coordinates). **Disclaimer:** Maps depict density of data registered within the GBIF network index and not necessarily true species occurrence density gradients. The data in the GBIF network index may not represent the full distribution of Ebenaceae.

Map includes data shared for all genera included in the family Ebenaceae (36 genera).

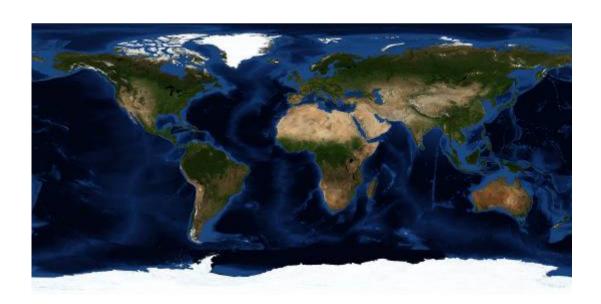
More taxonomy

- Correctly determined taxa
- Wrongly databased
- Lictoria achillae
 - -GBIF listed as Rhodophyta
 - -Source database listed as Lepidoptera!



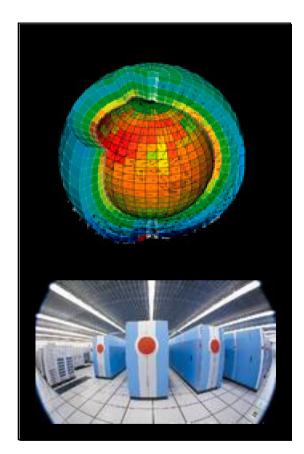
Environmental data

- Climate
- Topographic
- Classified data
- Marine



Climate data

- Modelling climate on a global scale is not trivial
- 35.86 TFLOPS
- 6.4 Mw
- 10km grid
- Resolution is improving
- Models are improving
- Computers are improving
- Global 30 arc second grids are available (http://www.worldclim.org/)



Earth Simulator (Japan)

Climate model data

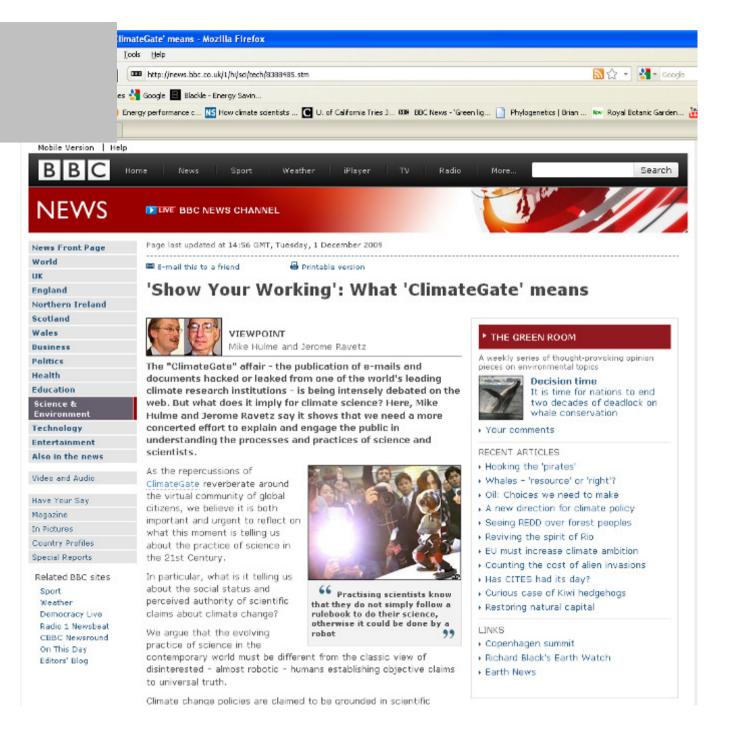
- The Intergovernmental Panel on Climate Change
- IPCC1 1990
- IPCC2 1995
- IPCC3 2001
- IPCC4 2007

 IPCC provides consensus on what scientists expect to happen

IPCC5 is on the way



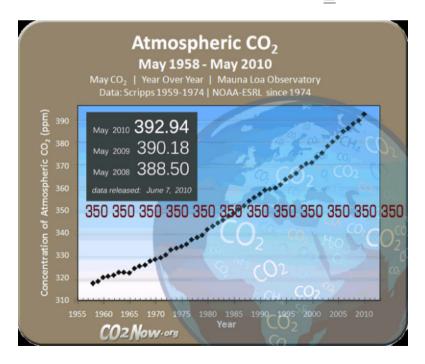
ClimateGate

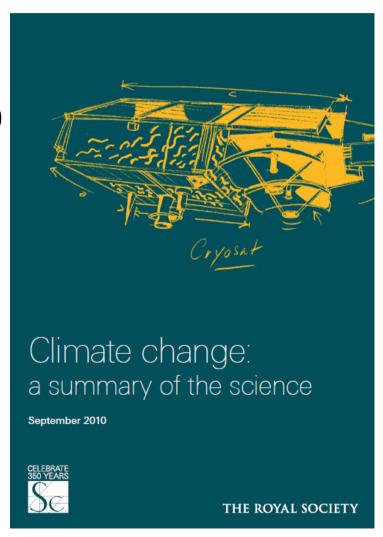


Can we rely on future climate models?

ZSL

- They are models, not predictions
- Sound basis in science
 - see royal society summary 2010
- Real observations <u>CO₂ Now</u>





Climate data continued



Good quality, high resolution, includes direct observations

Future

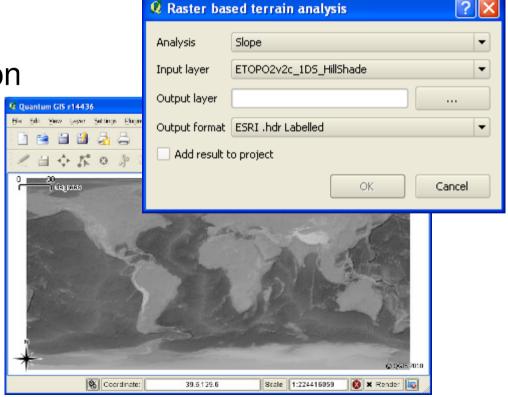
 50-100 years in the future = lots of uncertainty, low resolution, no direct observations

Past

- thousands-millions of years in the past = very uncertain, low resolution, some indirect observations
- Climate datasets are made by climatologists for climatologists

Topographic data

- Elevation/bathymetry
 - derived from satellites & local surveys
 - high resolution (1km global grids)
- Data derived from elevation
 - aspect
 - slope
 - 'roughness'
- Beware the correlation with other (climatic) data



Biome & Land use classifications



- Infrastructure
 - Roads
 - Cities/towns/villages
- Land use classifications (farmland, etc)



- Soil data
- Biomes (UN data)
- Classified data can be difficult to incorporate into models

Marine

- Bathymetry data
 - satellite & ship soundings
 - 1km grid (really?)
 - derived data (slope aspect etc)
- Ocean chemistry
 - pH, salinity, carbon
- Primary productivity
- Currents
- Temperature



 Lots of publicly accessible, global data sets, but generally low resolution

Niche modelling - What can go wrong?



Data

Analysis

- —Overfitting
- -Scale
- –Algorithm selection

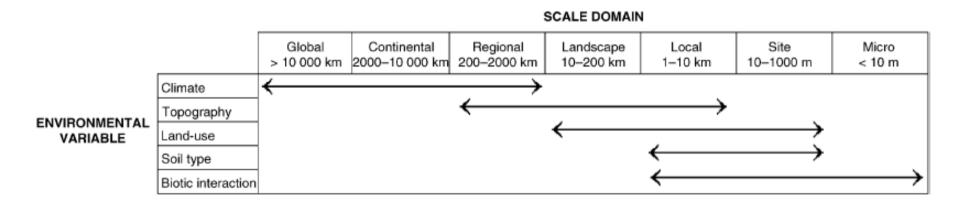
Validation

Choose your environmental layers carefully



Too many layers leads to models overfitting

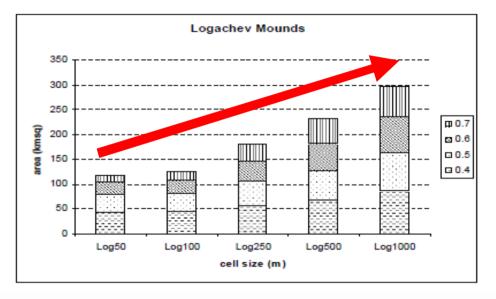
Scale is important

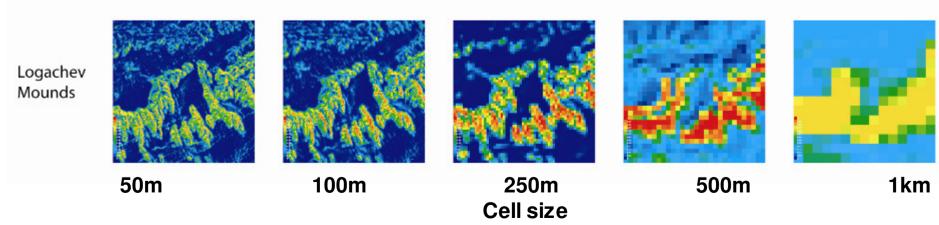


Pearson & Dawson (2003) Global Ecology & Biogeography 12: 361–371

Pixel size experiments

- Local niche model for L. pertusa
- Expectation that models will overpredict at coarser resolutions





Niche Modelling algorithms

Table 4. Modelling methods implemented.

Method	Class of model, and explanation	Data ¹	Software	Std errors?2	Contact person
BIOCLIM	envelope model	р	DIVA-GIS	no	CG, RH
BRT	boosted decision trees	pa	R, gbm package	no	JE
BRUTO	regression, a fast implementation of a gam	pa	R and Splus, mda package	yes	JE
DK-GARP	rule sets from genetic algorithms; desktop version	pa	DesktopGarp	no	ATP
DOMAIN	multivariate distance	p	DIVA-GIS	no	CG, RH
GAM	regression: generalised additive model	pa	S-Plus, GRASP add-on	ves	AG,AL,JE
GDM	generalised dissimilarity modelling;	pacomm	Specialized program not general released;	•	SF
	uses community data	A CONTRACTOR OF THE PARTY OF TH	uses Arcview and Splus		
GDM-SS	generalised dissimilarity modelling; implementation for single species	pa	as for GDM	no	SF
GLM	regression; generalised linear model	pa	S-Plus, GRASP add-on	yes	AG,AL,JE
LIVES	multivariate distance	p	Specialized program not general released	no	JLi
MARS	regression; multivariate adaptive regression splines	pa	R, mda package plus new code to handle binomial responses	yes	JE, FH
MARS- COMM	as for MARS, but implemented with community data	pacomm		yes	JE
MARS-INT	as or MARS; interactions allowed	pa	as for MARS	yes	JE
MAXENT	maximum entropy	pa	Maxent	no	SP
MAXENT-T	maximum entropy with threshold features	pa	Maxent	no	SP
OM-GARP	rule sets derived with genetic algorithms; open modeller version	pa	new version of GARP not yet available	no	ATP

Elith J, Graham CH, Anderson RP, et al. (2006)

Novel methods improve prediction of species' distributions from occurrence data. *Ecography* **29**, 129-151.

Algorithms in brief

 Simple – Poor performance -Understandable

 Complex – high performance – Black box **Bioclim**

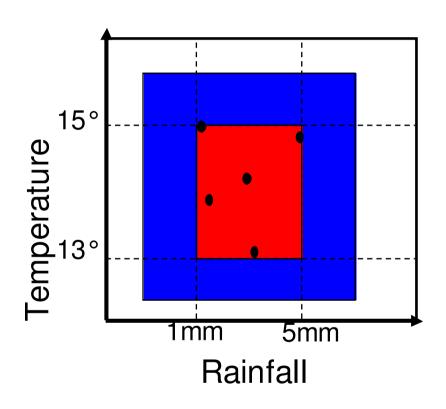
Environmental Distance CSM

GARP

Maxent

The Bioclim method (Nix 1986)

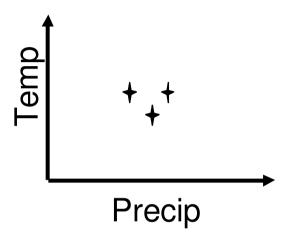
- Find Min, Max, Mean, Standard Deviation
- Core area = within 1 std.dev of mean
- Marginal = within observed range
- Overlap for multiple layers
- Methodology (Busby, 1991) has 300+ citations
- Performs poorly in comparisons with other methods

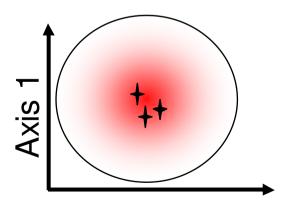


Nix, H. A. (1986) *A Biogeographic Analysis of Australian Elapid Snakes*. Australian Flora and Fauna Series Number 7: Atlas of Elapid snakes of Australia (ed. by R. Longmore), pp. 4-15. Australian Government Publishing Service, Canberra.

Distance methods

- Rescale and re-orient axes
- Account for correlation
- Some are modified PCAs
- CSM, ENFA, Environmental distance in openModeller





GARP

- GARP genetic algorithm based calculation gives probability density model based on frequency of model iterations
- Originally software in the desktop garp software
- New improved version available in openModeller
- Original methodology (Stockwell & Peters 1999) has 500+ citations
- Criticised by many as a black box

Maximum entropy

- maximum entropy algorithm uses machine learning to best identify the link between actual distribution pints and a set of given variables
- Very popular method (700+ citations for Phillips et al, 2006)
- Criticised for overfitting
- Dedicated Maxent software maintained and updated by the original developers
- ... or openModeller implementation



Phillips, S. J.; Anderson, R. P. & Schapire, R. E. (2006) Maximum entropy modeling of species geographic distributions. *Ecological Modelling*. **190:** 231-259

Niche modelling - What can go wrong?



Data

Analysis

- Validation
 - Kappa and ROC/AUC
 - Absence data



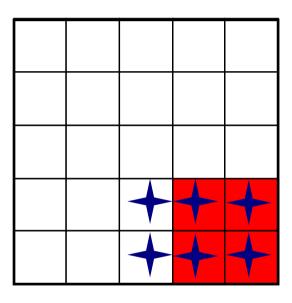
How good is a niche model?

- Niche models are based on observations.
- Models are evaluated empirically.
- Two popular approaches:
 - -Kappa
 - score for presence/absence models
 - —Area Under the Curve (AUC)
 - Score for multi-value models



Prediction errors - Underprediction

- Underprediction leads to real distribution points which are outside the predicted area
- Such points are termed false negatives
- These can be avoided by widening the area of prediction

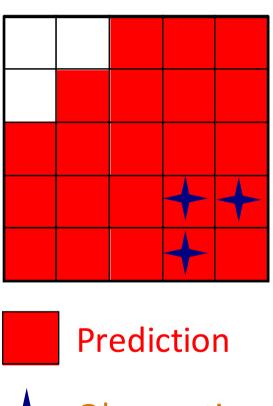






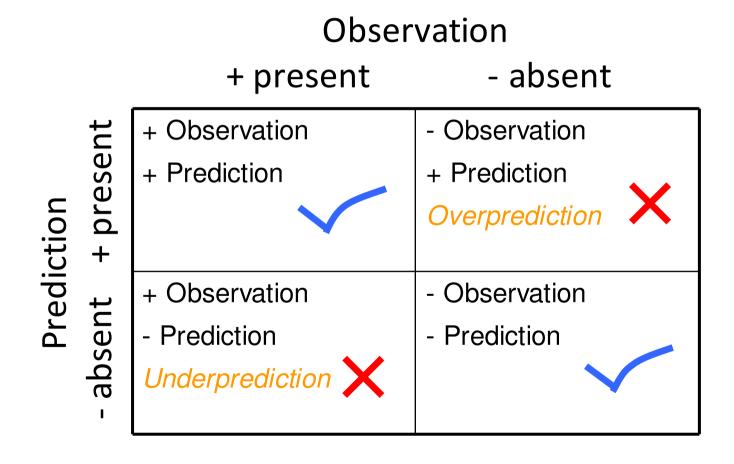
Prediction errors - Overprediction

- Overprediction is the selection of areas which do not contain your species
- Such areas are termed false positives

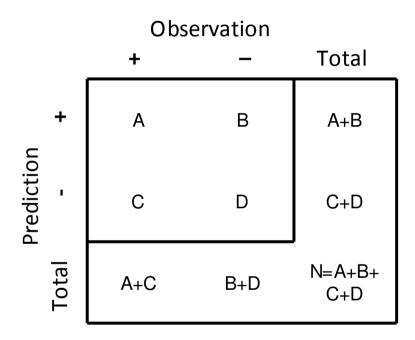




Confusion Matrix



Kappa (κ) – A single value for model accuracy



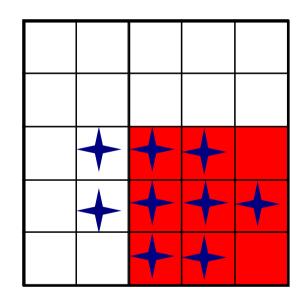
$$K = (A+D) - E/N$$

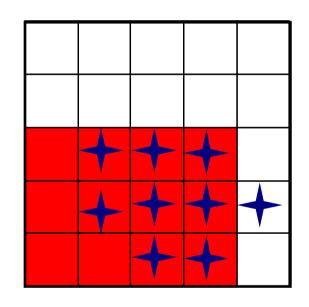
 $N - E/N$

where

$$E = (A+C)(A+B) + (B+D)(C+D)$$

Kappa (κ) - Examples





 κ =0.65 Prediction



Kappa (κ) – rule of thumb





• $0.4 < \kappa < 0.75$ is *good*

• $\kappa \ge 0.75$ is *excellent*

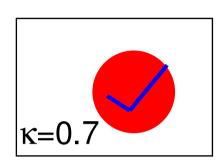


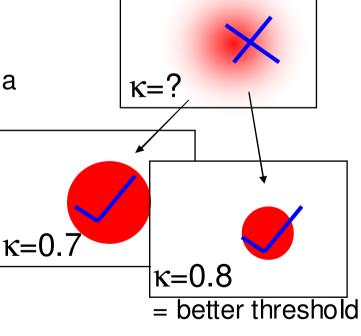
Validation for multi-value models



- Kappa assumes that models predict presence p=1 or absence p=0
- Generally models are scored to provide probability of presence 0 ≤ p ≤ 1
- Calculating kappa requires the selection of a threshold
 - -p ≤ Threshold implies absence
 - –P > Threshold implies presence

 The threshold can be chosen to maximise kappa



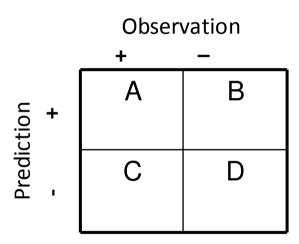


Sensitivity & Specificity



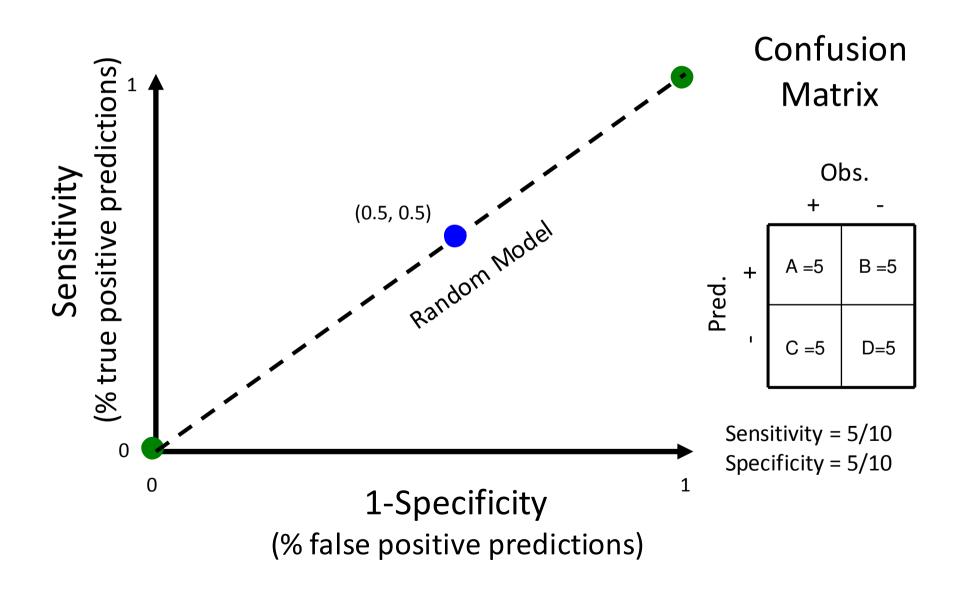
- Proportion of true positive predictions
- -Sensitivity = A / (A+C)
- Specificity
 - Proportion of false positive predictions
 - -Specificity = B / (B+D)

Plotting these values is informative

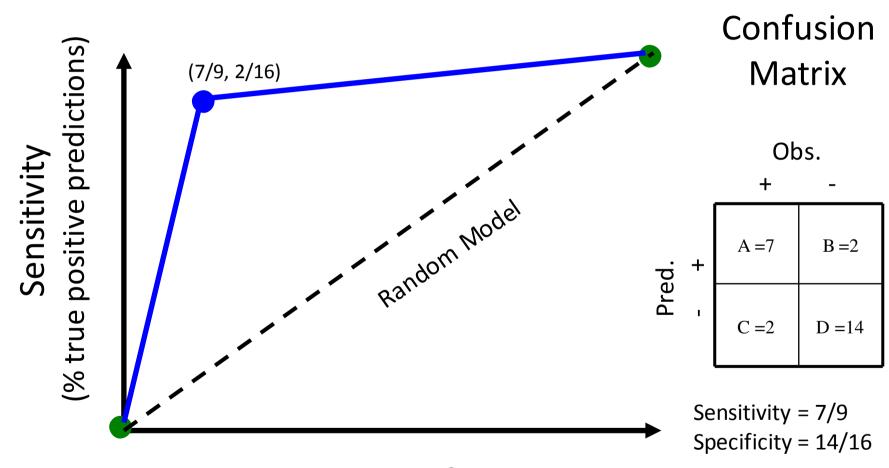


Receiver Operating Characteristic - ROC plots



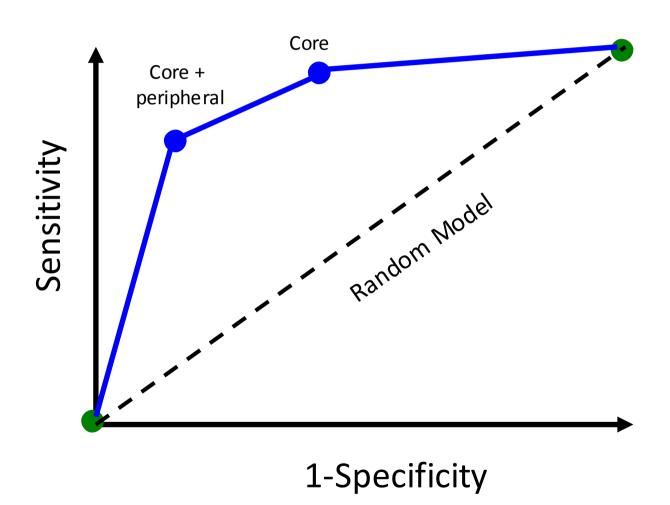


ROC plots

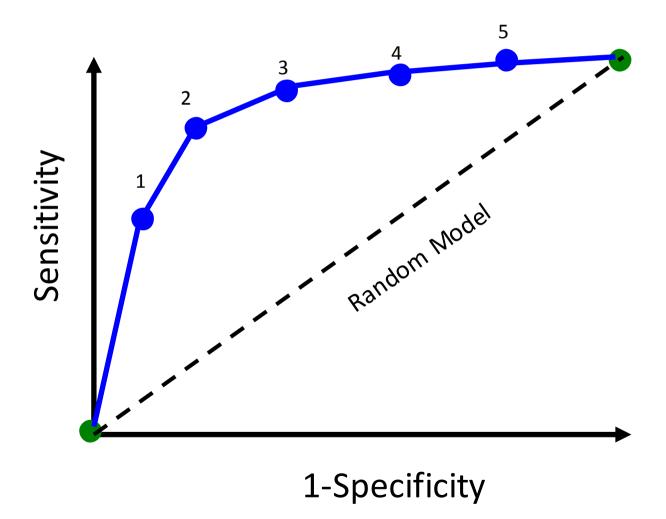


1-Specificity (% false positive predictions)

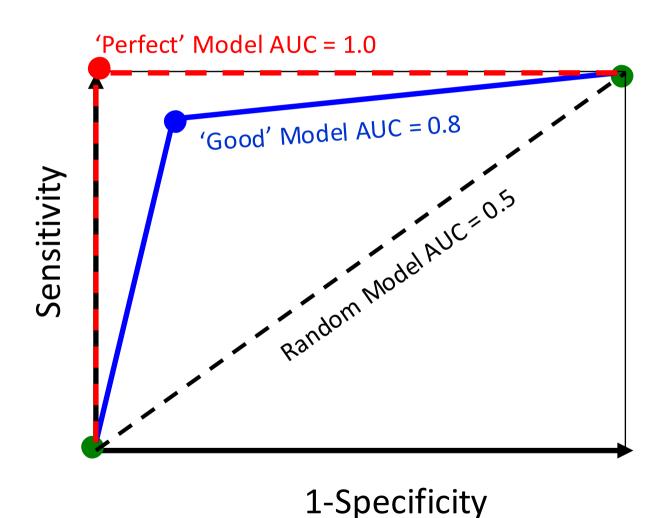
ROC plots – Bioclim models



ROC plots – multi-value models



AUC – Area under a ROC plot



AUC – rule of thumb

• AUC ≤ 0.6 *fail*



- 0.6 < AUC < 0.7 is *poor*
- 0.7 < AUC < 0.8 is *fair*



- 0.8 < AUC < 0.9 is *good*
- AUC ≥ 0.90 is *excellent*

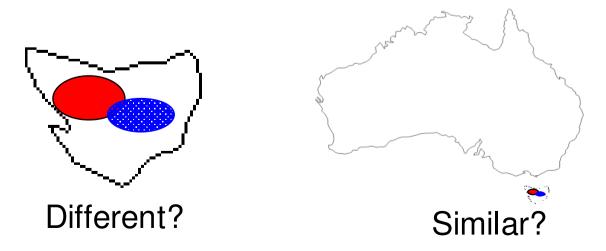


Kappa or AUC?

- Kappa can be used to determine the optimal threshold value
- ... but Kappa is dependent on the choice of threshold
- Kappa can be sensitive to absolute numbers of positives in the validation set
- AUC is independent of threshold
- AUC is generally preferred to Kappa
- But AUC is heavily criticised too, particularly where pseudo-absence data is used

Absence data

- Most model evaluation requires 'validation' data
- This should be independent of the data used to build the model
- It should include where species do and DO NOT occur
- Absence data is very difficult to obtain
- Picking the wrong background influences model evaluation



Validation in practice

- Validation data must be independent of model-building data
- Usually distribution data is randomly partitioned
 - -30% for validation
 - -70% for model building
- Validation requires absence data
 - -Usually not available
 - -Can we assume absence for areas with no presence data?
 - Pseudo absence if often used (a random selection of areas with no presence data)

References

The main reference describing validation

 Fielding, A. H. & Bell, J. F. (1997) A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation*.
 24, 38-49.

Example using validation to compare models

Elith, J., et al. (2006) Novel methods improve prediction of species' distributions from occurrence data. *Ecography*.
29, 129-151.

Problems - summary

- Garbage in Garbage out
 - Check your data quality
- Sampling biases
 - all data is biased
- Scale
- Uncertainty
- High validation scores = good model?

FAQ

- Have I got enough data?
 - No
- Model output = distribution, right?
 - No
- I ran one model with the latest algorithm, am I done?
 - No, its best to run multiple models with multiple algorithms to get a better understanding of the data
- Where can I get environmental data from?
 - … that's tricky

IFAQ (infrequently asked questions)

ZSL

- How is my data biased?
 - all data is biased, understanding how it useful
- Am I using too many environmental layers?
 - many layers cause over-fitting
- How has my choice of algorithm & parameters influenced my results?
 - try different algorithms & parameters to find out
- Can I believe the validation statistics?
 - multiple validation methodologies all with 'good' results is best

Happy modelling

- Slides, practical and data are available online
- http://www.zsl.org/science/ioz-staff-students/dr-chrisyesson/qgis-workshop-tanzania-nov-2010,1468,AR.html

