Quantitative Landscape Ecology
-
recent challenges & developments

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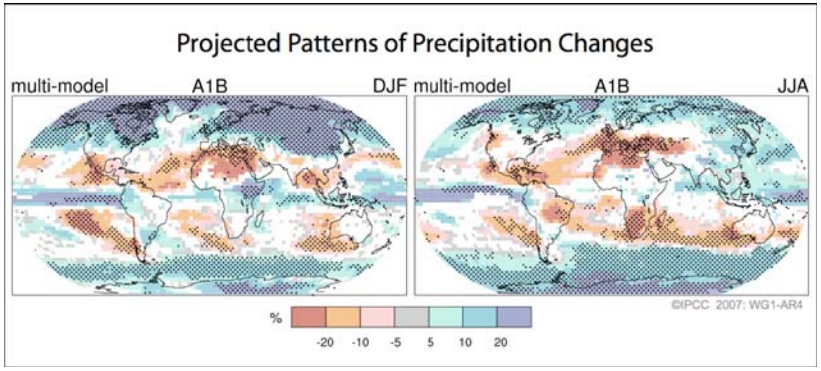
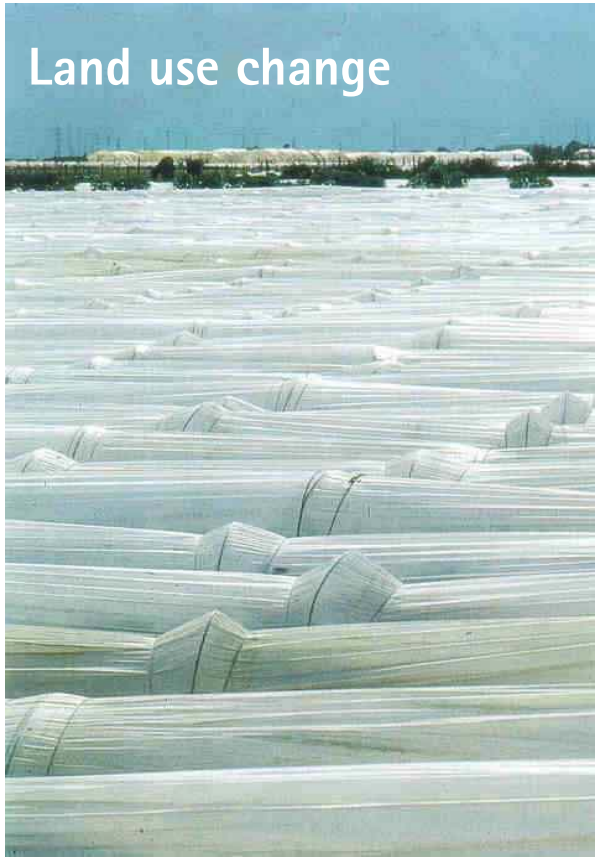
Berlin
12-14. Okt 2011

Motivation



Understanding the drivers of species distributions and predicting the effects of environmental change on species are pivotal prerequisites for understanding and predicting future changes in biodiversity, ecosystem functioning and services.



Need to predict..
Need to model...

VIEWPOINT

Ecological Forecasts: An Emerging Imperative

James S. Clark,[1]* Steven R. Carpenter,[2] Mary Barber,[3] Scott Collins,[4] Andy Dobson,[5] Jonathan A. Foley,[6] David M. Lodge,[7] Mercedes Pascual,[8] Roger Pielke Jr.,[9] William Pizer,[10] Cathy Pringle,[11] Walter V. Reid,[12] Kenneth A. Rose,[13] Osvaldo Sala,[14] William H. Schlesinger,[15] Diana H. Wall,[16] David Wear[17]

Planning and decision-making can be improved by access to reliable forecasts of ecosystem state, ecosystem services, and natural capital. Availability of new data sets, together with progress in computation and statistics, will increase our ability to forecast ecosystem change. An agenda that would lead toward a capacity to produce, evaluate, and communicate forecasts of critical ecosystem services requires a process that engages scientists and decision-makers. Interdisciplinary linkages are necessary because of the climate and societal controls on ecosystems, the feedbacks involving social change, and the decision-making relevance of forecasts.

for which uncertainty can be reduced to the point where a forecast reports a useful amount of information. Information content is affected by all sources of stochasticity.

[1]Department of Biology, Duke University, Durham, NC 27708 USA. [2]University of Wisconsin Center for Limnology, Madison, WI 53706, USA. [3]Ecological Society of America, 1707 H Street NW, Suite 400, Washington, DC 20006, USA. [4]Division of Biology,

Clark JS et al. 2001. Ecological forecasts: An emerging imperative. Science 293: 657-660.

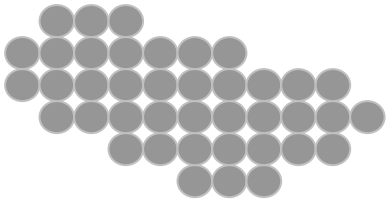
Key research questions

Where do we find which species?

Why? Underlying mechanisms?

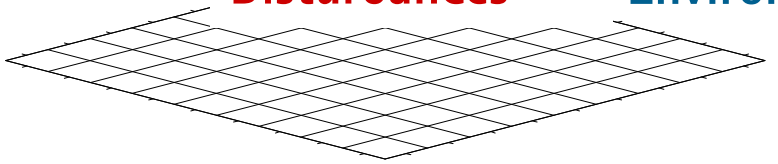
How are these distributional patterns affected by environmental change?

Does this has an effect on the functioning of ecosystems?



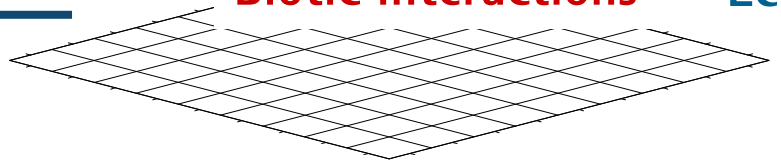
Potential species pool

Resources
Limiting factors
Disturbances

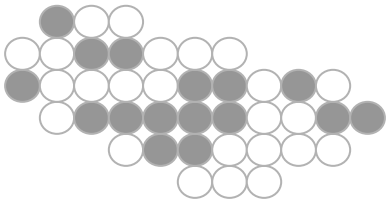


Environmental filter

Patch area, connectivity
Dispersal limitation
Biotic interactions



Ecological filter



Realised community

Understanding the relationship between patterns, processes, and functions in dynamic landscapes

Schröder B, 2008. Species in dynamic landscapes: Patterns, processes, and functions.

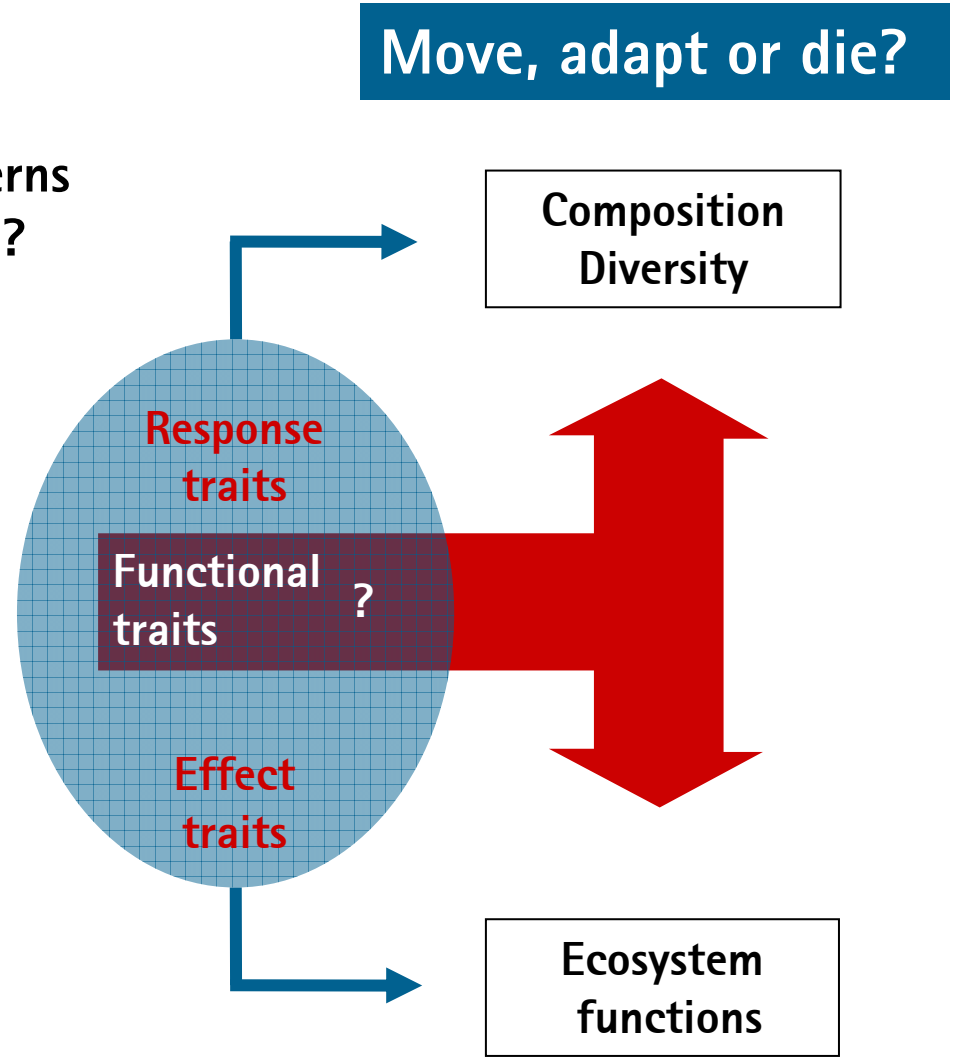
Key research questions

...

How are these distributional patterns affected by environmental change?

How does this affect ecosystem functioning?

Land use and cover change x Climate change x Biotic interactions



Aitken SN et al. 2008. Adaptation, migration or extirpation: climate change outcomes for tree populations. Evol Appl 1: 95–111.

Key research questions

...

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How does this affect ecosystem functioning?

Land use and cover change
x Climate change
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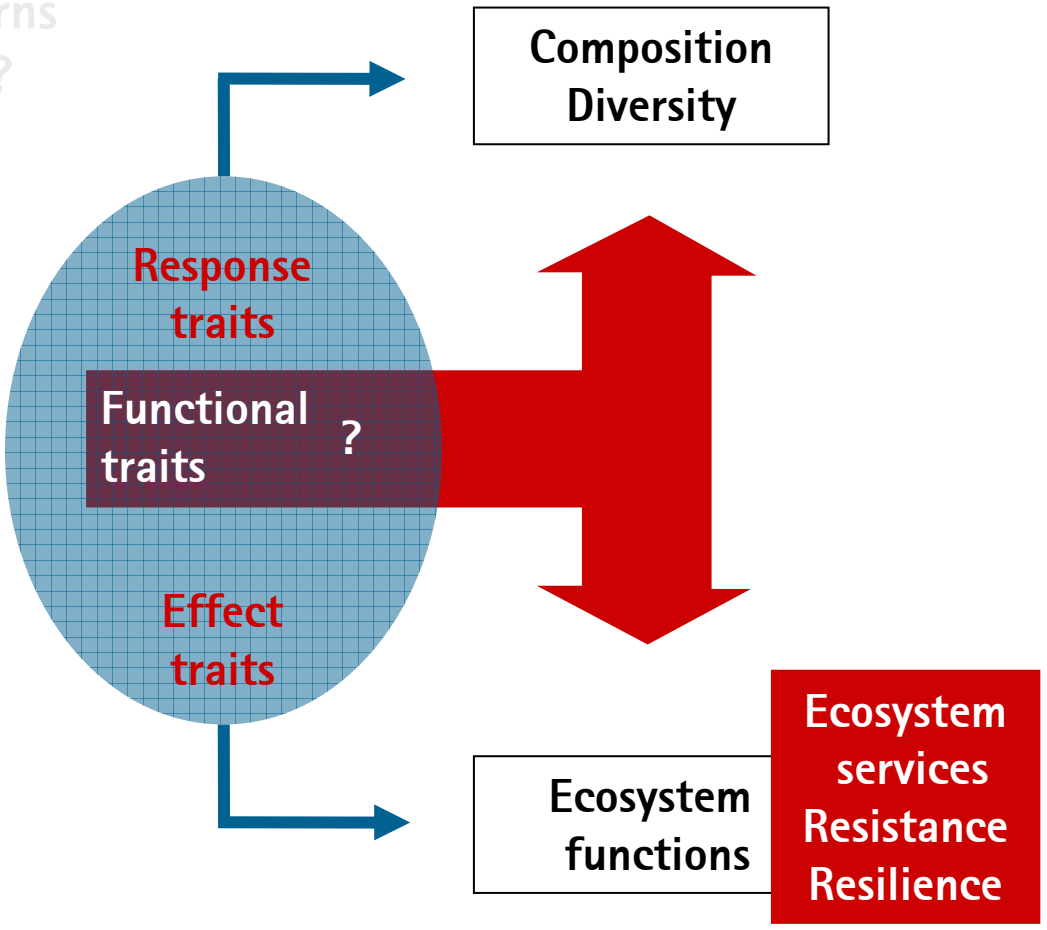


Approaches

Phenomenological models

- pattern detection & description
- simple parameterisation
- very many species, diversity
- multiple scales

- ... but no implementation of

Process-based models

- process description
- laborious parameterisation
- only for single species (or funct. groups)
- often small scales

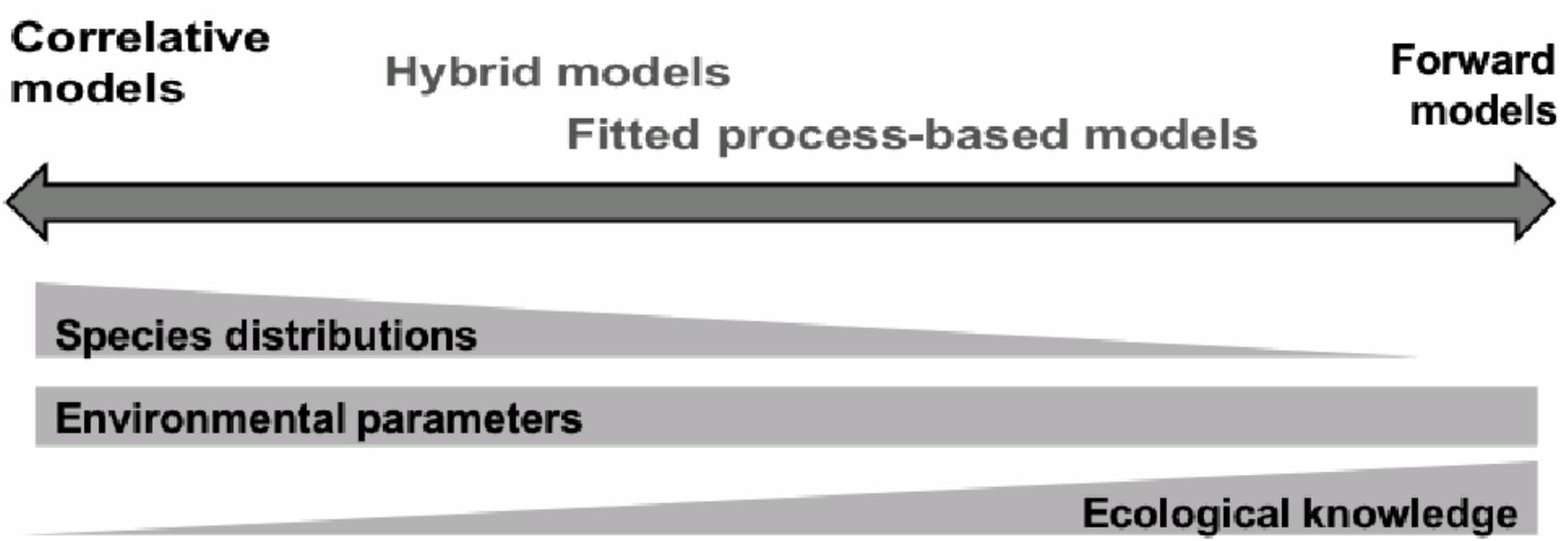
- ... but explicit implementation of

  - processes:
    - dispersal
    - adaptation
    - biotic interactions
  - feedback mechanisms
  - transient dynamics

e.g. species distribution models SDMs / Environmental niche models

e.g. population models (IBMs, etc.) DGVMs; DRMs

Rather a continuum... ?



Dormann, C. F., S. J. Schymanski, J. S. Cabral, I. Chuine, C. H. Graham, F. Hartig, M. Kearney, X. Morin, C. Römermann, B. Schröder, and A. Singer. accepted. Correlation and process in species distribution models: bridging a dichotomy. Journal of Biogeography.

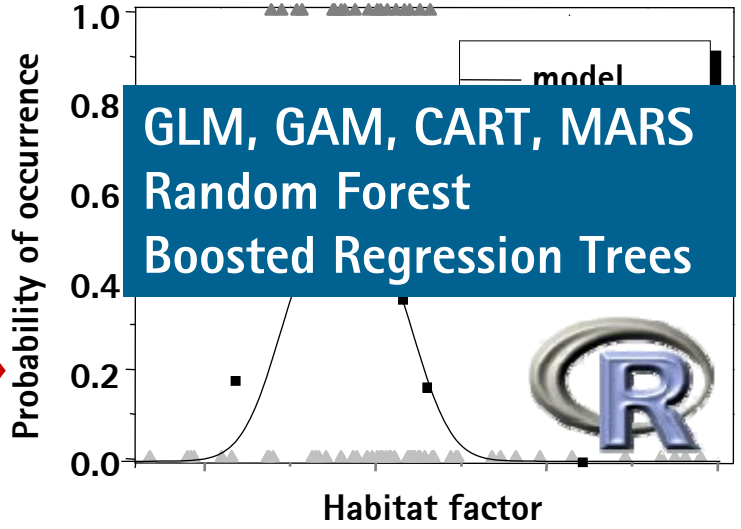
KEY METHOD

Species distribution modelling | SDM – principle

Environmental Niche Modelling, Habitat modeling

Hypotheses regarding species-habitat relationships

Statistics



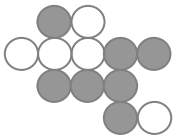
&

Presence-absence data

Prediction

Explanation

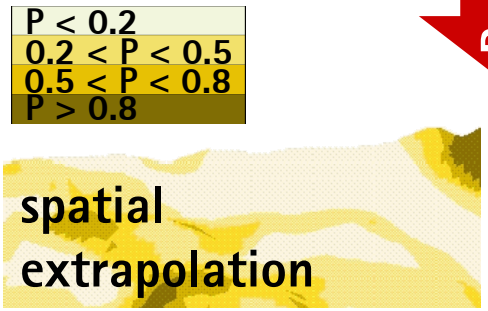
	Habitat factors
Relevance	soil attributes
	disturbance frequency
	patch isolation
	land use



&

Independent data

Validation



Challenges (Araújo & Guisan 2006)

Model selection and predictor contribution

hierarchical and variance partitioning

new techniques: shrinkage, multi-model inference, boosted trees

Parameterisation and diagnostics

violation of assumptions, influential observations,

independency and autocorrelation, level of complexity

Model evaluation

improved assessment of errors and uncertainties

validation

Integration with Ecological Theory

niche concepts, biotic interactions, hierarchy & scale

source-sink dynamics, dispersal limitations, functional groups

... 5 years later?

Araújo, M. B. and Guisan, A., 2006. Five (or so) challenges for species distribution modelling. J. Biogeog. 33: 1677-1688.

CHALLENGES

Outline

Model selection and predictor contribution

- hierarchical and variance partitioning
- new techniques: shrinkage, multi-model inference, boosted trees

Parameterisation and diagnostics

- violation of assumptions, influential observations,
- independency and autocorrelation, level of complexity

Model evaluation

- improved assessment of errors and uncertainties
- validation

Integration with Ecological Theory

- niche concepts, biotic interactions, hierarchy & scale
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Araújo, M. B. and Guisan, A., 2006. Five (or so) challenges for species distribution modelling. J. Biogeog. 33: 1677-1688.

- New techniques
- Model selection
- Predictor contribution

- Multicollinearity
- Spatial autocorrelation
- Non-stationarity

1 Parameterisation Statistical obstacles

State-of-the-Art

Species Distribution Models: Ecological Explanation and Prediction Across Space and Time

Jane Elith[1] and John R. Leathwick[2]

[1]School of Botany, The University of Melbourne, Victoria 3010, Australia;
email: j.elith@unimelb.edu.au

[2]National Institute of Water and Atmospheric Research, Hamilton, New Zealand;
email: j.leathwick@niwa.co.nz

Elith, J., and J. R. Leathwick. 2009. Species distribution models: Ecological explanation and prediction across space and time. Annual Review of Ecology, Evolution, and Systematics 40:677-697.

State-of-the-Art

Journal of Animal Ecology

British Ecological Society

Journal of Animal Ecology 2008, 77, 802–813 doi: 10.1111/j.1365-2656.2008.01390.x

A working guide to boosted regression trees

J. Elith[1]*, J. R. Leathwick[2] and T. Hastie[3]

[1]School of Botany, The University of Melbourne, Parkville, Victoria, Australia 3010; [2]National Institute of Water and Atmospheric Research, PO Box 11115, Hamilton, New Zealand; and [3]Department of Statistics, Stanford University, CA, USA

Summary

1. Ecologists use statistical models for both explanation and prediction, and need techniques that are flexible enough to express typical features of their data, such as nonlinearities and interactions.
2. This study provides a working guide to boosted regression trees (BRT), an ensemble method for fitting statistical models that differs fundamentally from conventional techniques that aim to fit a single parsimonious model. Boosted regression trees combine the strengths of two algorithms: regression trees (models that relate a response to their predictors by recursive binary splits) and

dismo

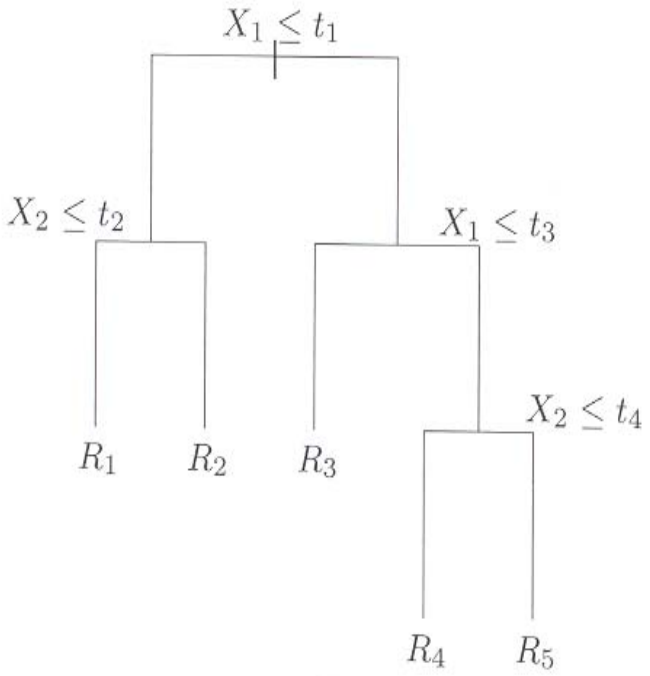
Elith, J., J. R. Leathwick, and T. Hastie. 2008. A working guide to boosted regression trees. Journal of Animal Ecology 77:802–813.

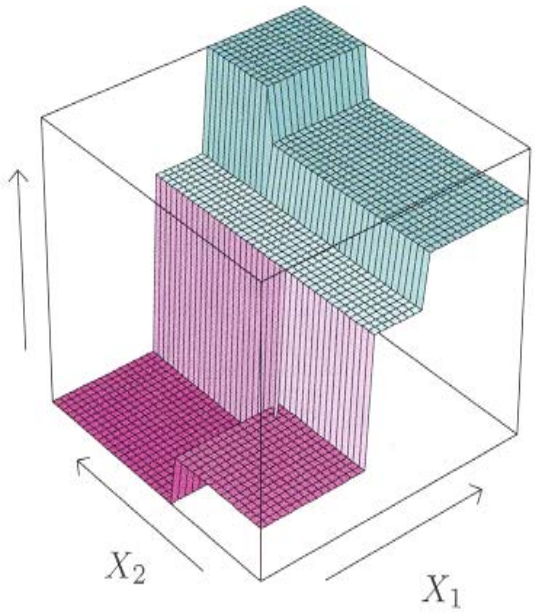
Boosted regression trees | Stochastic gradient boosting

Combination of

A Classification and regression trees | CART

- powerful (variable selection, dealing with interactions)
- but inaccurate





Hastie, T., Tibshirani, R., Friedman, J.H., 2001. The elements of statistical learning, Springer, New York.

METHODS

Boosted regression trees | Stochastic gradient boosting

Combination of

A Classification and regression trees | CART

- powerful (variable selection, dealing with interactions)
- but inaccurate

B Boosting algorithm

- idea: many rough rules of thumb instead of one single highly accurate rule
- ensemble prediction method
- sequential, i.e. penalized forward stage-wise
  (adding trees, "reweighting data" by fitting on residuals)

- avoid overfitting via crossvalidation
- avoid overfitting via simplification, i.e. backward stepwise elimination
- one of the best performing methods in recent model comparison (Elith et al.)

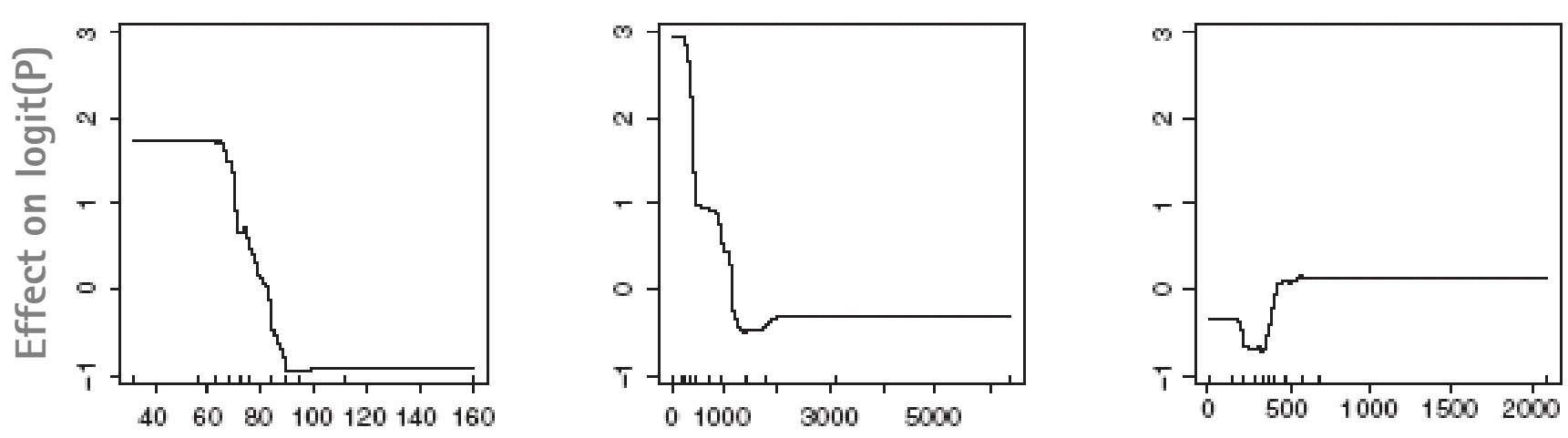
Random forests: similar idea; bagging = bootstrap aggregation of CARTs

Elith, Graham et al. 2006 Ecography, Elith, Leathwick, Tibshirani J Animal Ecol 2008

METHODS

Opening the Black Box – response curves, contributions

Response curves (partial dependency plots) BRT



Vegetation height [cm] — **Contribution: 31.5 %**

Distance to next occurrence [m] — **29.2 %**

Prey [g] — **8.5 %**

Aquatic warbler

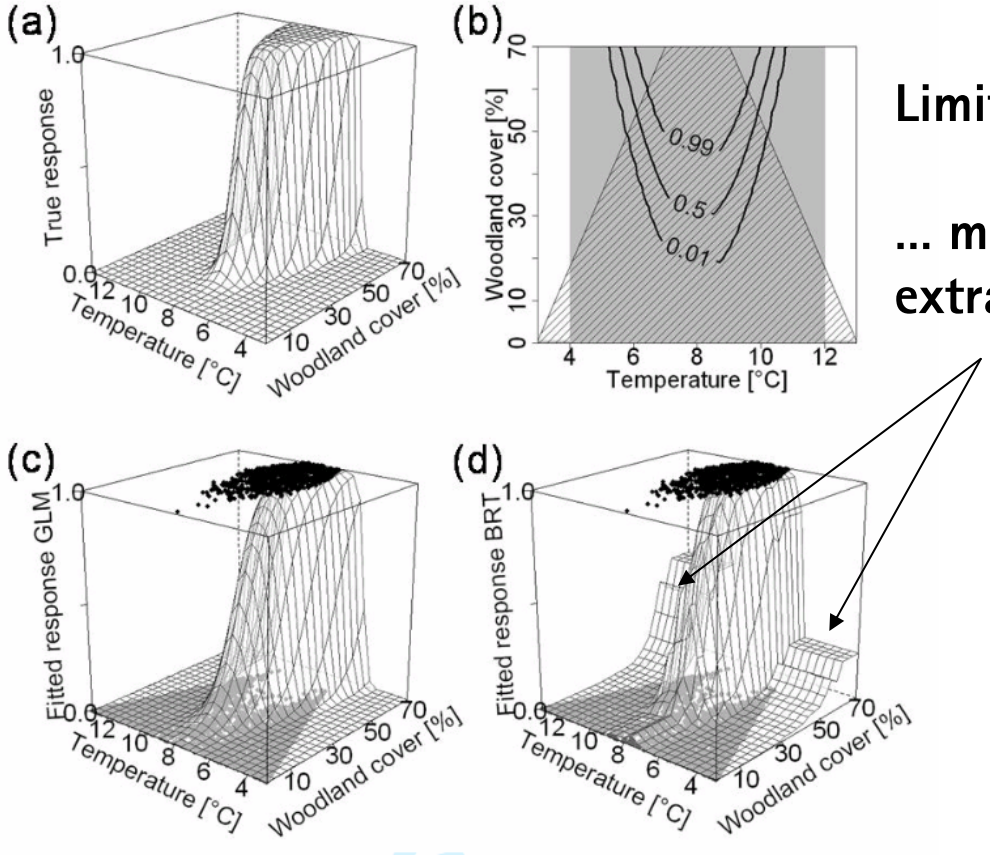
R^2_N = 0.76
AUC = 0.98

Lower Oder Valley National Park, Pomerania
+ Poland
+ Lithuania + Belarus

Tanneberger F, Flade M, Preiksa Z, Schröder B, 2010. Habitat selection of the globally threatened Aquatic Warbler at the western margin of the breeding range: Implications for management. Ibis 152: 347-358.

METHODS

A new tool: Inflated response curves



Limited data coverage & truncated niches

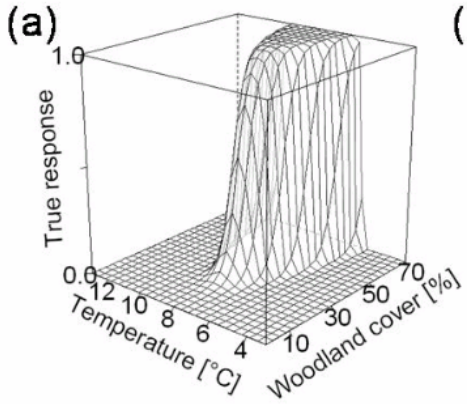
... may yield unrealistic fits and spurious extrapolation to novel environments!

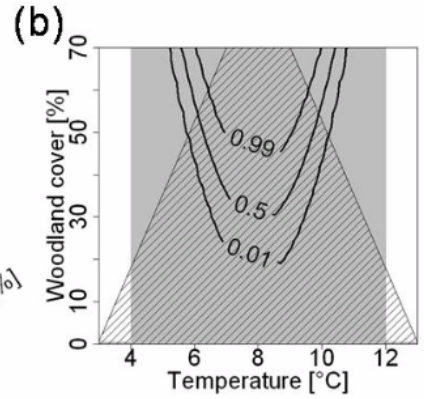
UPGradE

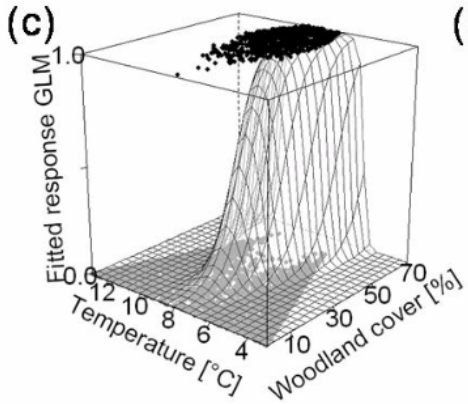
Zurell, D., J. Elith, and B. Schröder. accepted.
Why range predictions differ: on the importance of understanding niche and data dimensions. Diversity and Distributions.

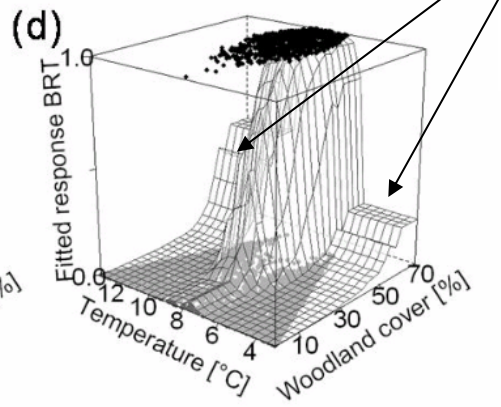
METHODS

A new tool: Inflated response curves







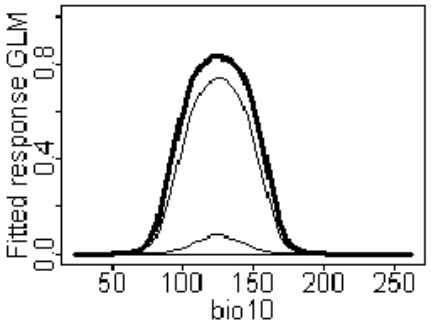


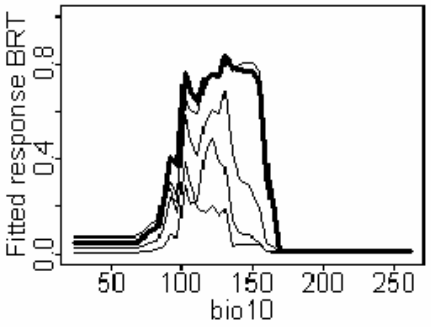
Limited data coverage & truncated niches

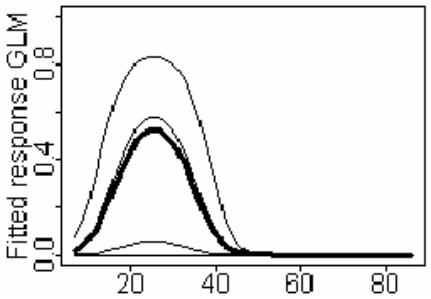
... may yield unrealistic fits and spurious extrapolation to novel environments!

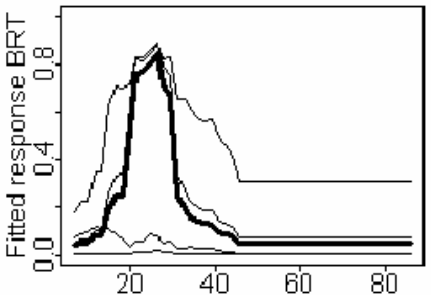
black : mean effect, i.e. conventional

grey : effect of full range (min, max, median, quantiles) of other predictor









Inflated response curves
... allow a visual examination of extrapolation behaviour

Damaris Zurell

Universität Potsdam

zalf

Zurell, D., J. Elith, and B. Schröder. accepted.
Why range predictions differ: on the importance of understanding niche and data dimensions. Diversity and Distributions.

Torsten Hothorn

LMU

Thomas Kneib

CARL VON OSSIETZKY universität OLDENBURG

Universität Potsdam

zalf

Red kite

`mboost`

Unified framework

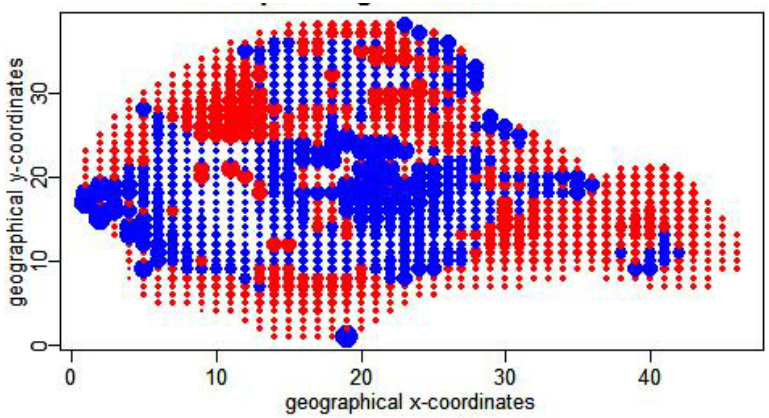
- boosted regression trees/environment
- non-stationarity
- spatial autocorrelation
- spatiotemporal variability

OBSTACLES

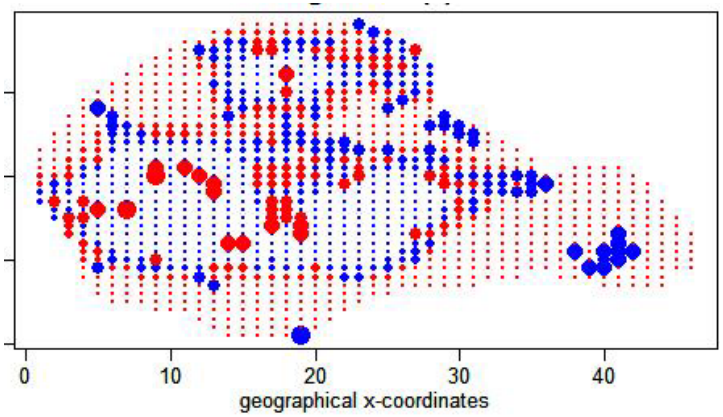
Spatial autocorrelation

- … confounds the analysis of species distribution data, since it
  - violates the assumption of iid errors
  - inflates Type I errors
  - may invert the slope of relationships from non-spatial analyses
- Need to account for spatial autocorrelation
- Need to correct parameter estimates

Non-spatial model



Spatial model



Kühn, I. (2007) Incorporating spatial autocorrelation may invert observed patterns. Diversity & Distributions, 13, 66-69.
Dormann et al. (2007) Methods to account for spatial autocorrelation in the analysis of species distributional data. Ecography 30, 609–628.

OBSTACLES

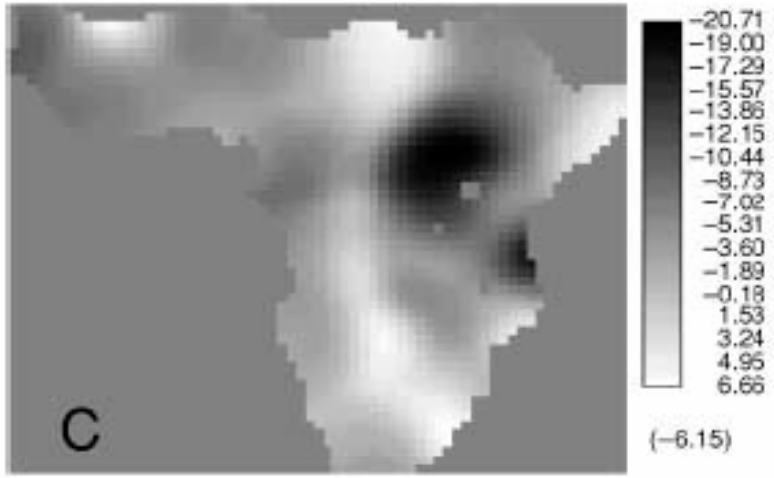
Non-stationarity

- **Does the statistical model remain constant over the extent of a study?**

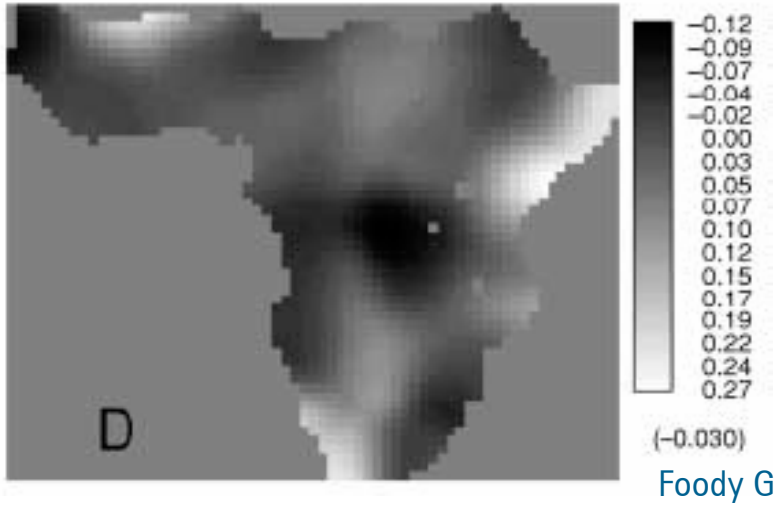
- **common approach (among others): geographically-weighted regression**
- **regression parameters vary in space**
- **no consideration of autocorrelation**
- **only linear regression functions**
- **no prediction for new areas possible**

Avian species richness ~ mean annual temp + total annual precip + max. NDVI
spatially varying slope for...

... mean annual temperature



... total annual precipitation



Foody GEB 2004

Austin (2007) Species distribution models and ecological theory Ecol Model 200, 1-19.

UNIFIED FRAMEWORK

Approach

Aim : Estimating a model for the unobserved heterogeneity caused by spatiotemporal autocorrelation or non-stationarity

Decomposition into global & local components

- **global : only environmental effects**
- **local : spatiotemporal autocorrelation & non-stationarity effects**

$$f(\mathbf{x}, s, t) = \underbrace{f_{\text{env}}(\mathbf{x})}_{\text{global}} + \underbrace{f_{\text{ns}}(\mathbf{x}, s) + f_{\text{s}}(s) + f_{\text{st}}(s, t)}_{\text{local}}$$

Total Variability	~	Environment	Non-stationary env. effects	Spatial auto-correlation	Spatio-temporal variability

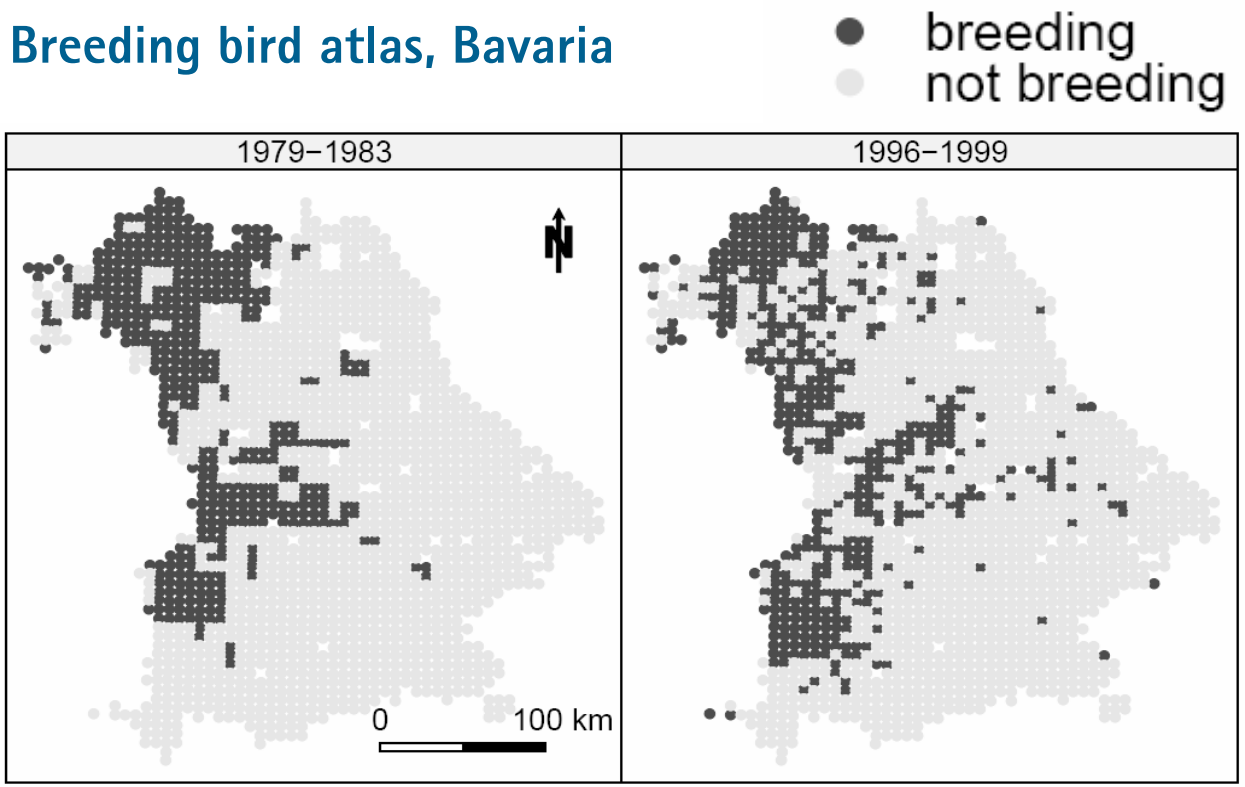
Hothorn T, Müller J, Schröder B, Kneib T, Brandl R, 2011.
Decomposing environmental, spatial, and spatiotemporal components of species distributions. Ecol Monogr 81: 329-347.

UNIFIED FRAMEWORK

Decomposition of environmental, spatial and spatiotemporal components of distributions patterns

Red kite

Breeding bird atlas, Bavaria



36 numeric + 7 binary predictors taken from

- CORINE land cover
- FRAGSTATS
- WorldClim

5 numeric + 2 binary predictors entered the model...

Hothorn T, Müller J, Schröder B, Kneib T, Brandl R, 2011. Decomposing environmental, spatial, and spatiotemporal components of species distributions. Ecol Monogr 81: 329-347.

UNIFIED FRAMEWORK

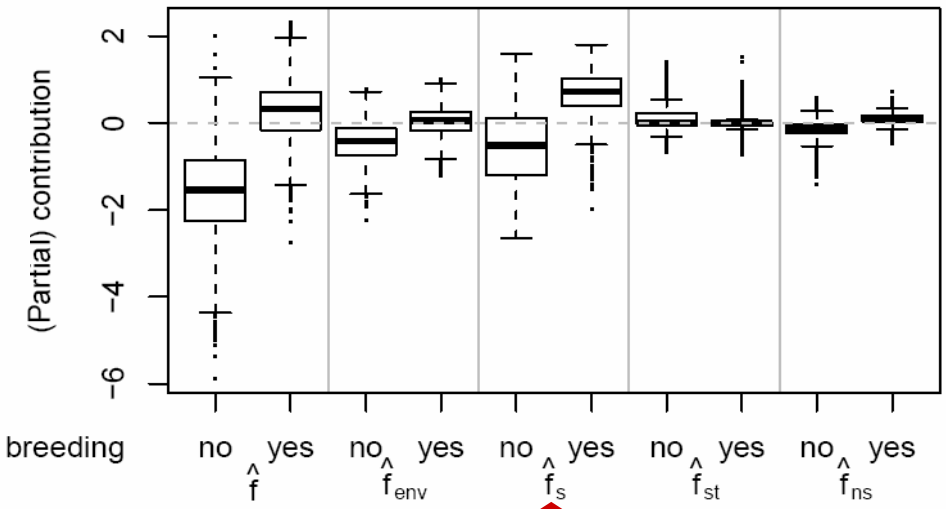
Decomposition of environmental, spatial and spatiotemporal components of distributions patterns

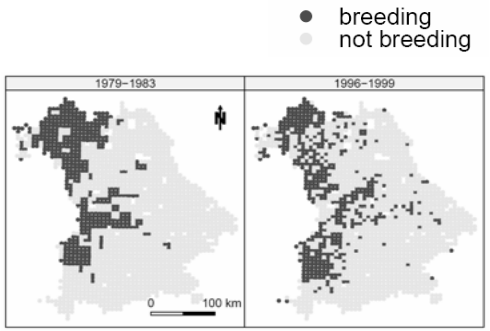
Unified framework basing on boosted regression trees

$$f(\mathbf{x}, s, t) = \underbrace{f_{\text{env}}(\mathbf{x})}_{\text{global}} + \underbrace{f_{\text{ns}}(\mathbf{x}, s) + f_{\text{s}}(s) + f_{\text{st}}(s, t)}_{\text{local}}$$

Total variability	~	Environ-ment	non-stationary env. effects	spatial auto-correlation	spatio-temporal variability

Red kite in Bavaria





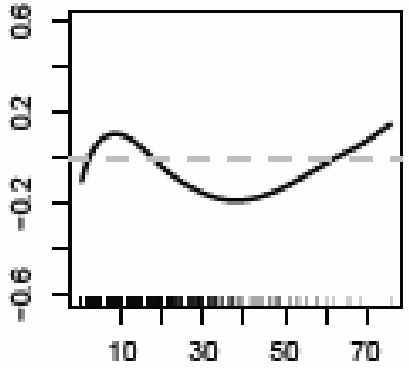
- CORINE
- FRAGSTATS
- WorldClim

7 predictors

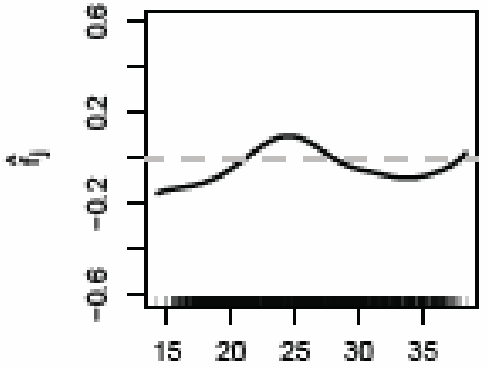
Hothorn T, Müller J, Schröder B, Kneib T, Brandl R, 2011. Decomposing environmental, spatial, and spatiotemporal components of species distributions. Ecol Monogr 81: 329-347.

UNIFIED FRAMEWORK

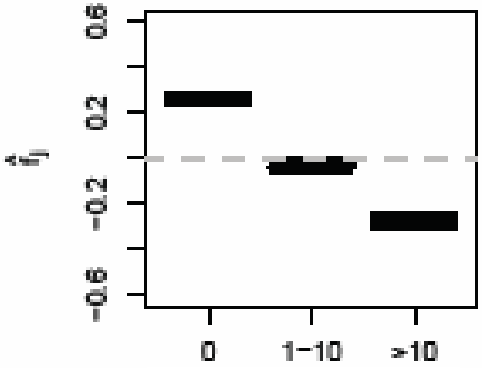
Partial effects – environmental component f_{env}



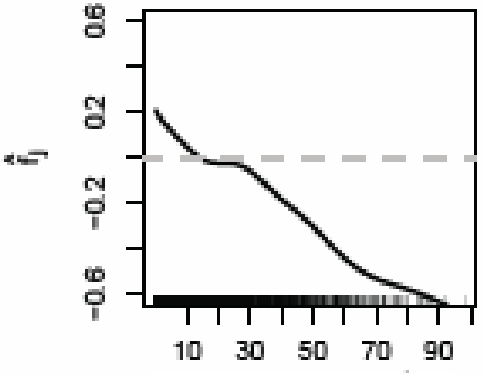
Mixed forests [%]



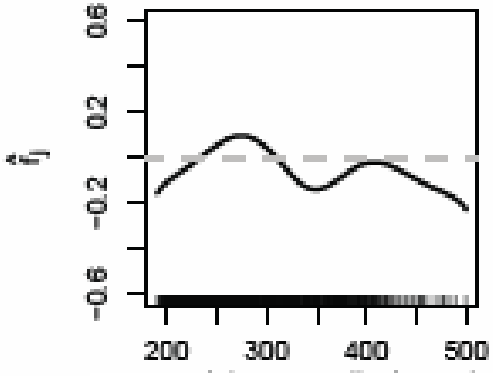
Precipitation seasonality [CV]



Cities & villages [%]



Coniferous forests [%]



Precipitation of wettest quarter [mm]

Hothorn T, Müller J, Schröder B, Kneib T, Brandl R, 2011.
Decomposing environmental, spatial, and spatiotemporal components of species distributions. Ecol Monogr 81: 329-347.

RESULTS

Predictions for Baden-Württemberg based on f_{env}

Observed
Predicted

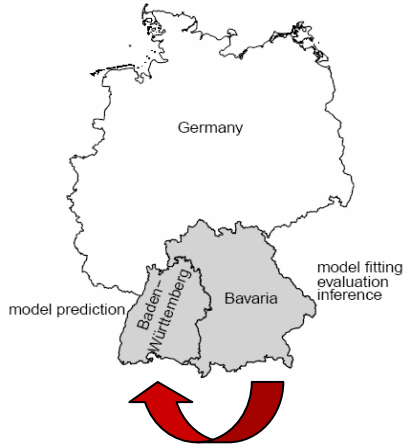
- (−, +)
- (−, −)
- (+, +)
- (+, −)

low

high predicted occurrence probability

+ breeding
- non-breeding

... due to large effect of spatial component f_s



- Niche concepts, niche conservatism vs. niche dynamics
- Dispersal (limitation)
- Biotic interactions
- Population dynamics
- Link to traits, functional groups
- Towards mechanistic niche modelling – DRM

- Consideration of plasticity & evolutionary dynamics
- Link to ecosystem function / ecosystem services
- Link to economics

2

Ecological theory
Integration of processes

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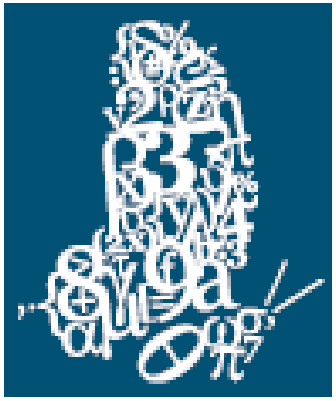


How much process detail do we need?

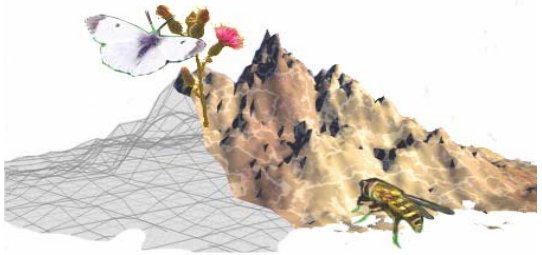
INTEGRATION

Virtual ecologist approach

Virtual world

Dynamic Model

Effects of transient dynamics and ecological processes on SDM prediction accuracy



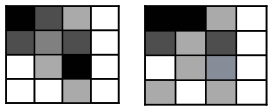
Virtual, tri-trophic host-parasitoid system, virtual landscape

Scenarios

Sampling by virtual ecologist

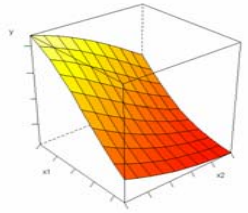
„Real" distribution

Training data



Pattern comparison

Extrapolation



SDM

Importance of dispersal & population dynamics & interactions!

Damaris Zurell

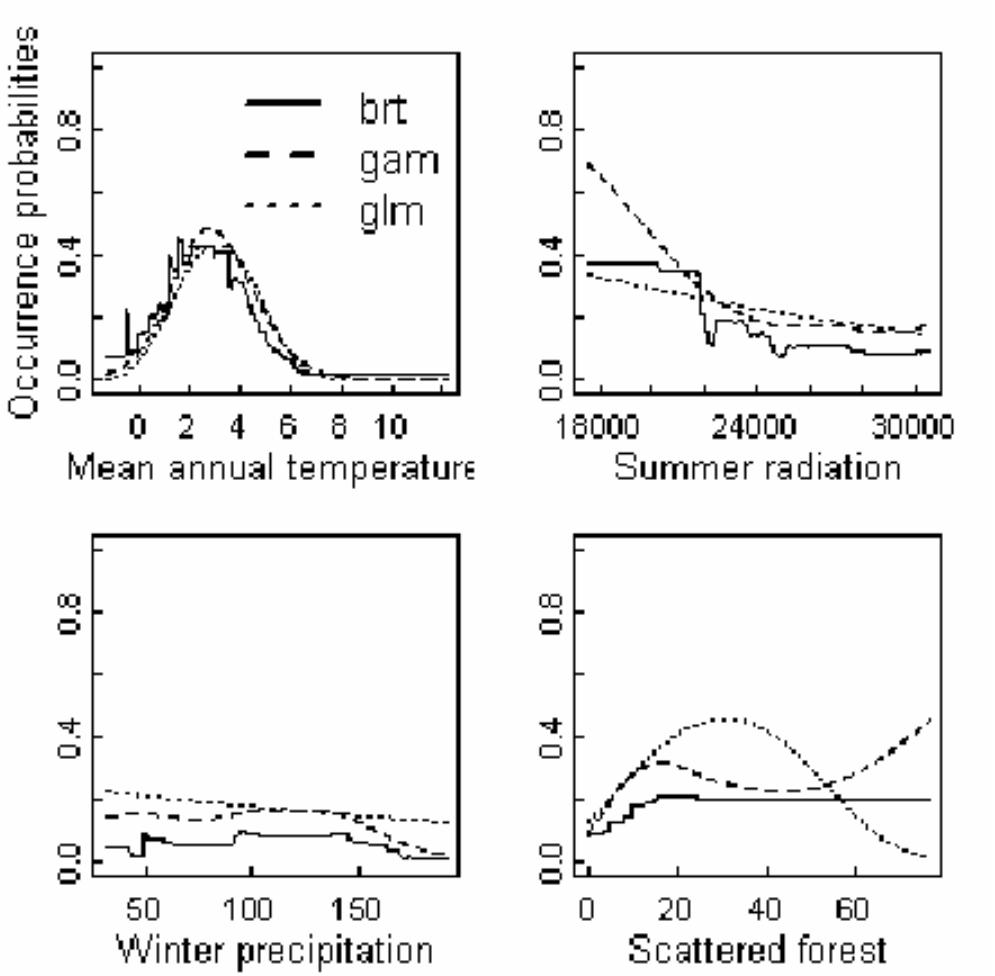
Zurell D, Jeltsch F, Dormann CF, Schröder B 2009 Static species distribution models in dynamically changing systems: How good can predictions really be? Ecography 32: 733-744

Zurell D et al. 2010 The virtual ecologist approach: simulating data and observers. Oikos 119: 622-635

INTEGRATION

Integrating SDM & process-based models (IBM)

1. GLM, GAM, BRT
2. Habitat suitability map -> map of carrying capacity



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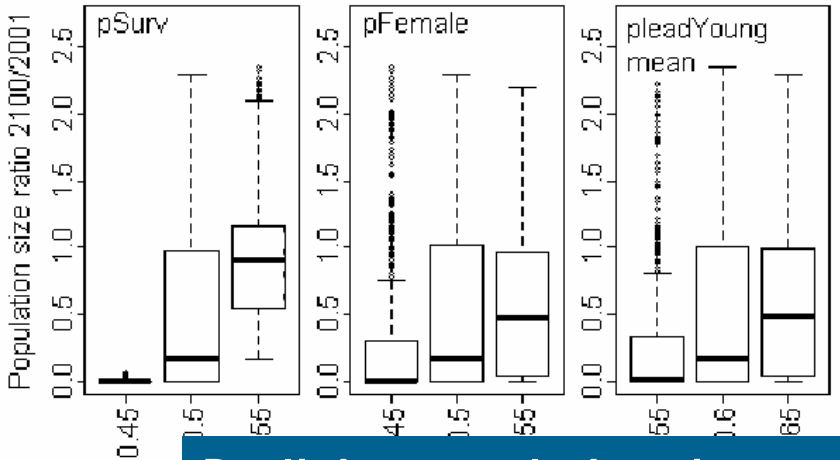
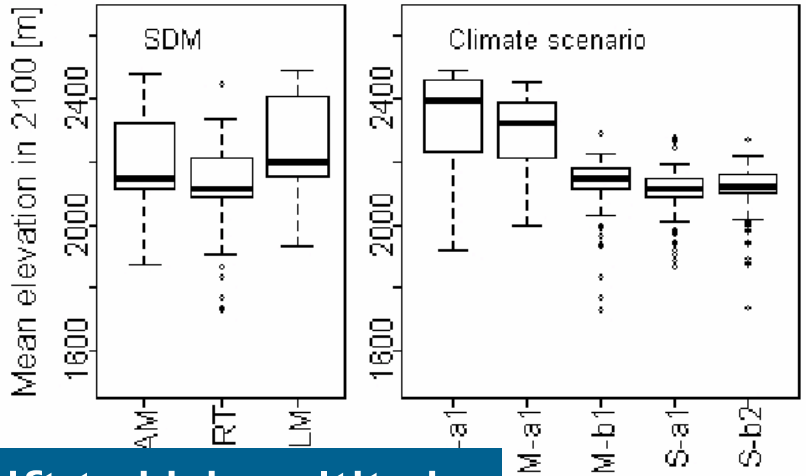
Zurell D, Grimm V, Rossmanith E, Zbinden N, Zimmermann NE, Schröder B, 2011
Uncertainty in predictions of range dynamics: Black Grouse climbing the Swiss Alps Ecography in press

INTEGRATION

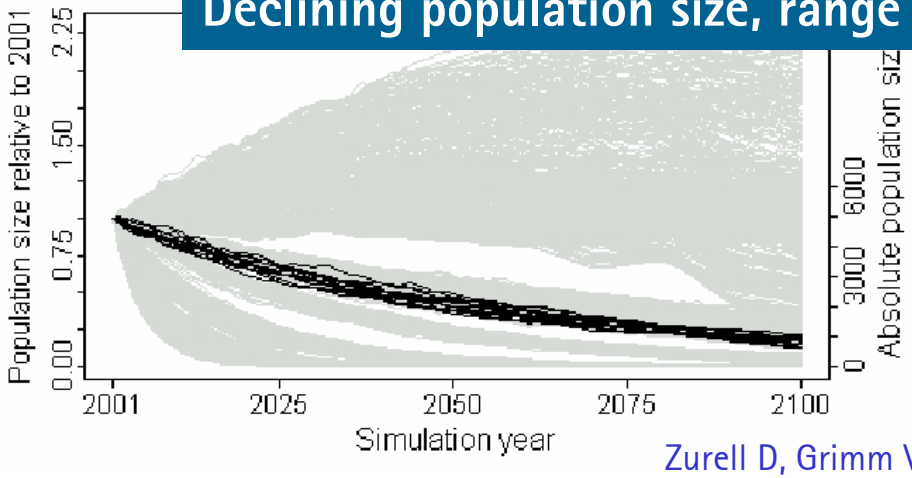
Integrating SDM & process-based models (IBM)

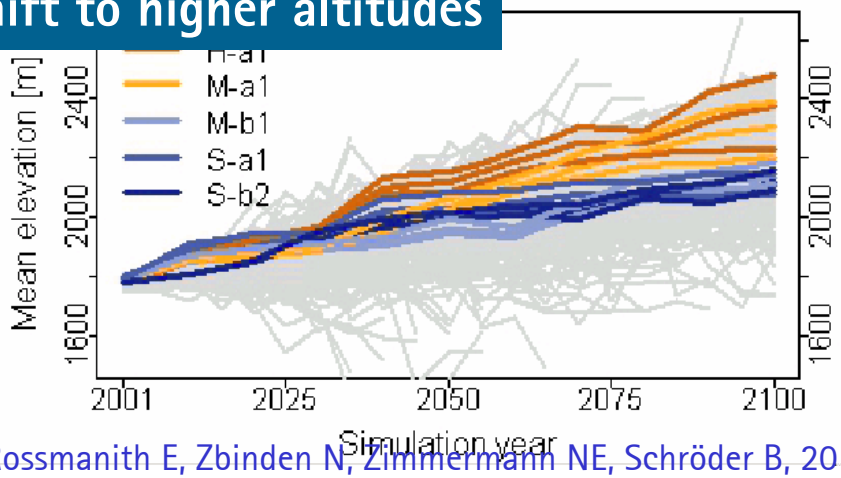
1. GLM, GAM, BRT
2. Habitat suitability map -> map of carrying capacity
3. IBM (birth, death, dispersal), sensitivity analysis
4. Prediction of abundance, range shifts





Declining population size, range shift to higher altitudes

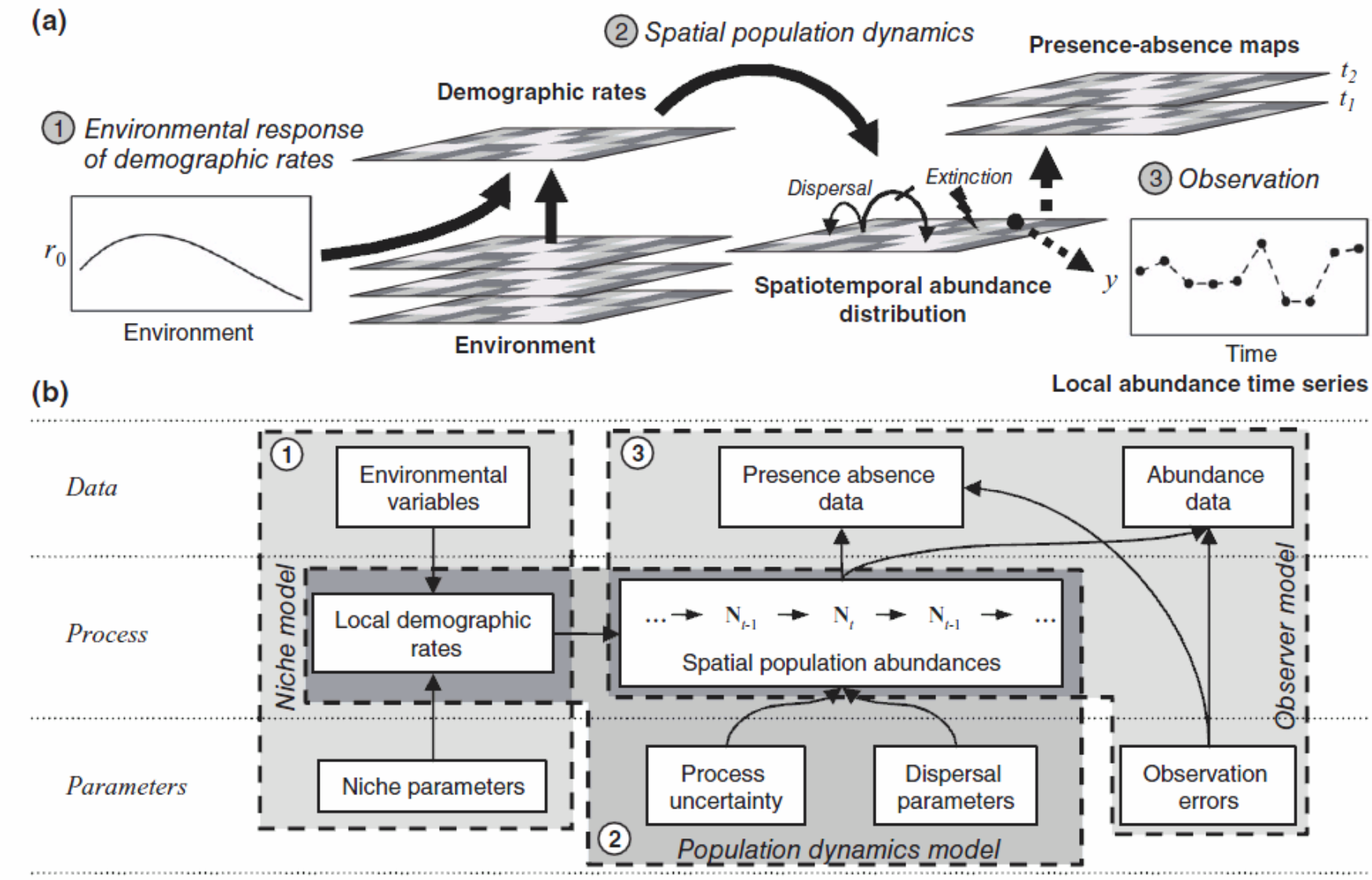




Zurell D, Grimm V, Rossmanith E, Zbinden N, Zimmermann NE, Schröder B, 2011
Uncertainty in predictions of range dynamics: Black Grouse climbing the Swiss Alps Ecography in press

RANGE DYNAMICS

Dynamic range models – Hierarchical Bayesian Models



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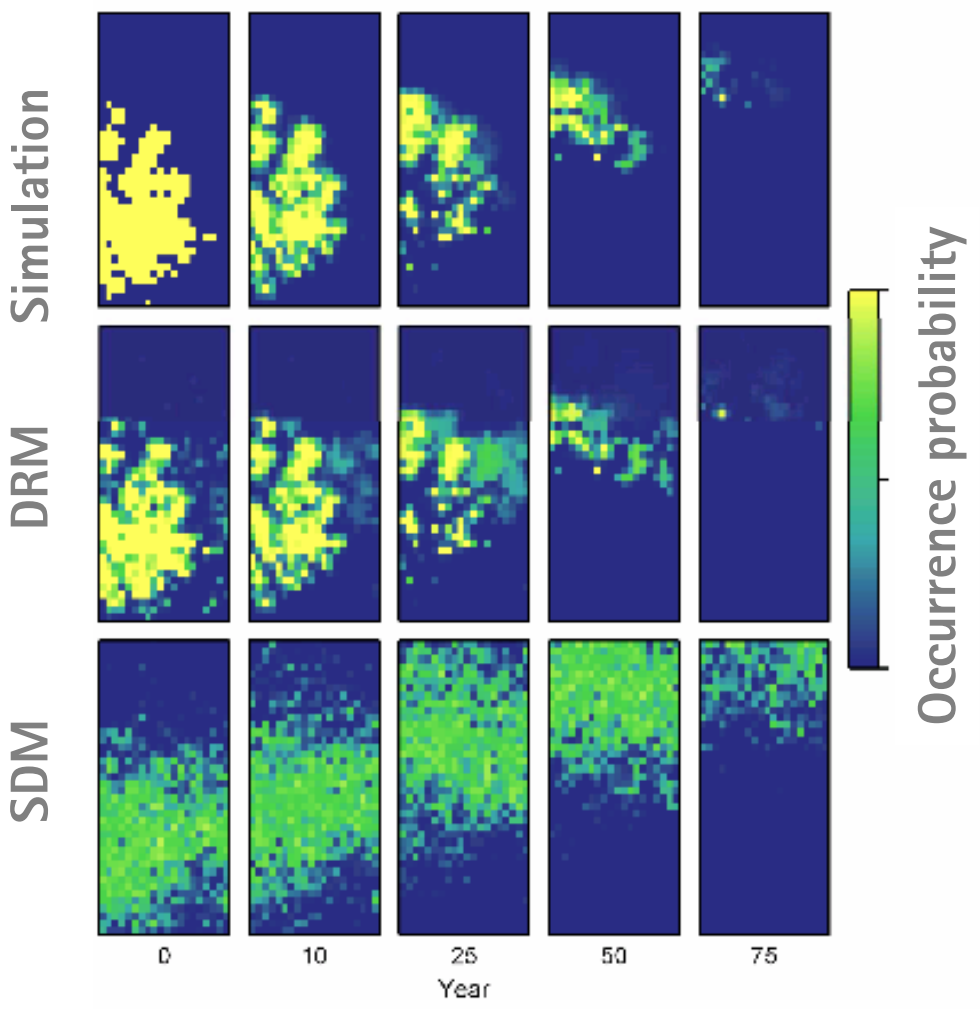
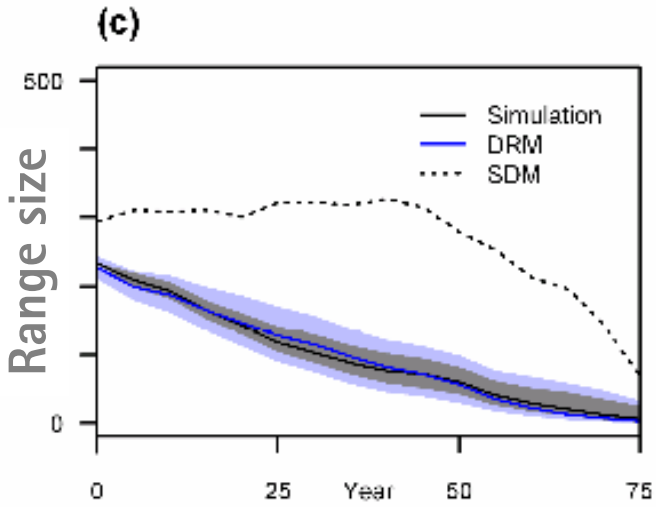
Pagel, J. & Schurr, F. M. (2011) Forecasting species ranges by statistical estimation of ecological niches and spatial population dynamics. Global Ecology and Biogeography, in press doi: 10.1111/j.1466-8238.2011.00663.x.

RANGE DYNAMICS

Dynamic range models



Excellent performance in virtual ecologist approach.



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Schurr, F. M., J. Pagel, J. S. Cabral, J. Groeneveld, O. Bykova, R. O'Hara, F. Hartig, D. W. Kissling, H. P. Linder, G. P. Midgley, B. Schröder, A. Singer, and N. E. Zimmermann. submitted. How to understand species niches and range dynamics: a demographic research agenda for biogeography. Journal of Biogeography.

DISCUSSION

Distribution modelling?

Despite all criticsm:
SDMs = still widely used for

- Understanding species-environment / diversity-environment relationships
- Generation of hypotheses
- Extrapolation and projection in space & time (assuming niche conservatism)
- Detection of niche shifts

Need to model as thoughtful as possible:

- Use best available methods
- Analyse multicollinearity
- Check for residual spatial autocorrelation and non-stationarity
- Consider scale dependency & process relevance of predictors
- Validate
- Provide uncertainty analysis
- Check interpretability of response curves & interaction terms
- Consider key processes & biotic interactions

CONCLUSIONS

Towards a mechanistic approach

Approaches to integrate processes into SDMs

- using process-related predictors
  e.g. presence of competitor, prey ~ biotic interactions
  e.g. habitat connectivity ~ dispersal limitation
- **Combination with process-based models, e.g. hybrid models**
- **Dynamic Range Models (Schurr, Pagel)**

New methods - most promising: Hierarchical Bayesian models – open new avenues towards demographic biogeography.

Need to integrate demographic processes as "first principles" of population biology

Need to link to species traits, ecosystem functions and services...
... and to embed into decision theory

Universität Potsdam

zalf


Thanks to all collaborators and funding institutions
Thank you...