Species distributions: where a species is found

How have they changed?
How will they change?

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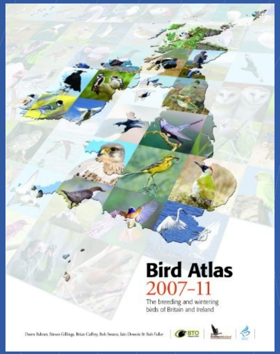
1. Learning from the past: How have species distributions changed?

- What information do we need to document climate driven range shifts?
- What is the evidence for climate driven range shifts?
  - Do we observe shifts in the hypothesized direction?
  - How are different taxa and environments impacted?
- Which other anthropogenic influences are causing shifts in species distributions?

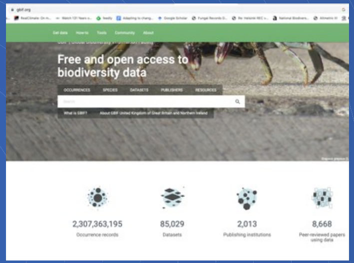
What information do we need?

Temporally replicated (i.e. many years) data from across a species' range

- Occurrence

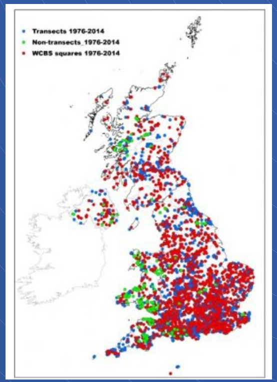


Atlas data (presence/absence), where atlases have been produced at different times



GBIF (presence only)—the Global Biodiversity Information Facility

- Abundance

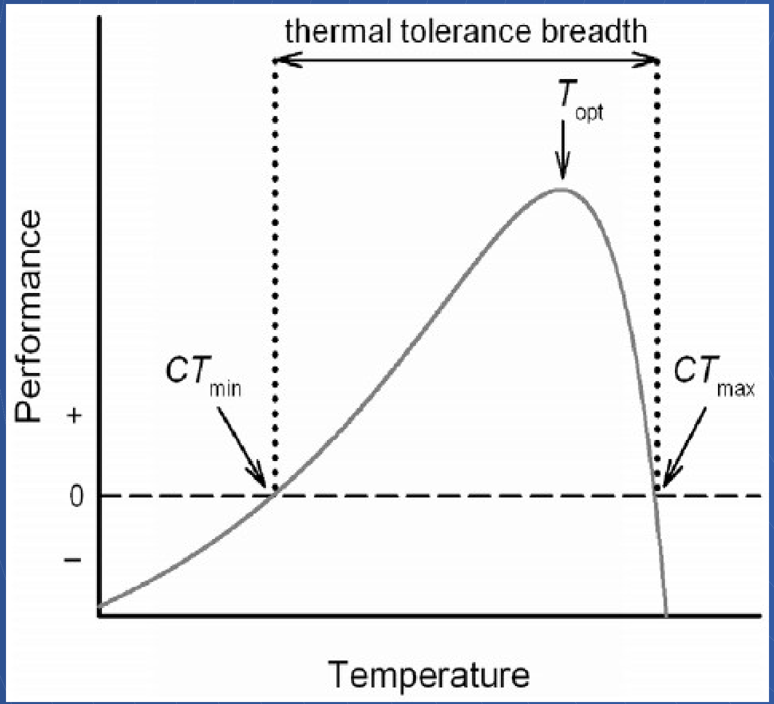


UK butterfly monitoring scheme. Repeat transects walked on particular dates each year

BTO
Looking out for birds

Breeding bird survey monitors the population changes of 118 breeding bird species across the UK

Predicting distribution shifts under warming

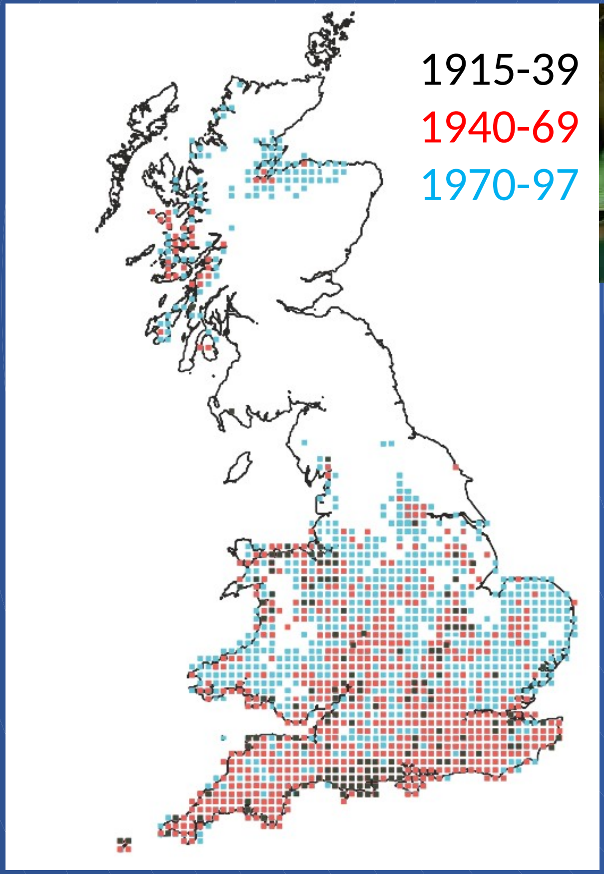


Polewards shifts

Upslope shifts

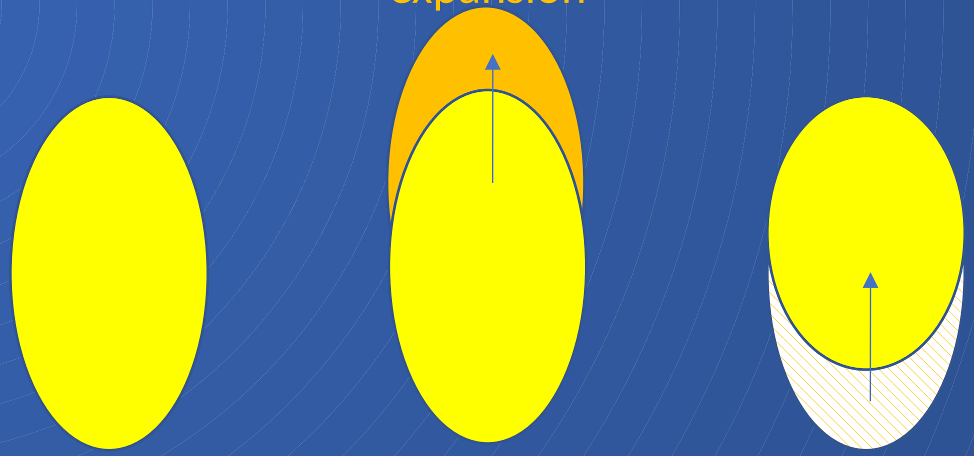
Greater depth shifts

Poleward shifts:
butterflies in Europe



Speckled wood
Pararge aegeria

A cross-species analysis of butterfly species with their southern or northern range limits in Europe.



Parmesan et al. 1999 Nature 399: 579

Poleward shifts:
butterflies in Europe

Poleward (leading edge) expansion

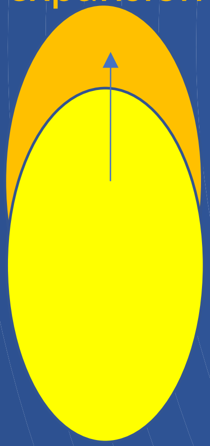
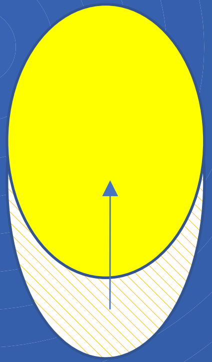


Table 1 Northern boundary assessment

Family/subfamily*	Extended northwards	Stable	Retracted southwards
Papilionidae	*Parnassius apollo* *Parnassius mnemosyne*		
Pieridae	*Anthocaris cardamines* *Aporia crataegi*	*Gonepteryx rhamni*	
Lycaenidae	*Agrodiaetus amanda* *Everes argiades*† *Glaucopsyche alexis* *Heodes tityrus* *Quercusia quercus* *Strymonidia pruni* *Hamearis lucina* (Riodininae)	*Celastrina argiolus* *Cyaniris semiargus* *Heodes alciphron* *Heodes virgaureae* *Plebejus argus* *Strymonidia w-album* *Thecla betulae*	
Nymphalinae	*Apatura iris* *Araschnia levana* *Argynnis paphia* *Argynnis niobe* *Clossiana dia* *Brenthis daphne* *Inachis io*† *Limenitis camilla* *Limenitis populi* *Polygonum c-album*	*Argynnis adippe* *Brenthis ino* *Clossiana selene* *Melitaea cinxia*	*Apatura ilia*
Satyrinae	*Aphantopus hyperantus* *Coenonympha glycerion* *Hipparchia semele* *Lasiommata megera* *Lopinga achine* *Maniola jurtina* *Melanargia galathea* *Pararge aegeria* *Pyronia tithonus*	*Coenonympha arcania* *Erebia aethiops* *Lasiommata maera*	
Hesperiidae	*Erynnis tages* *Ochlodes venatus* *Thymelicus lineola* *Thymelicus sylvestris*	*Carterocephalus palaemon* *Thymelicus acteon*	

Data are from one or more countries: Great Britain, Sweden, Finland and Estonia.
* Taxonomy for all species are from ref. 19.
† Highly mobile species included because the distance of boundary change is much greater than individual dispersal distances.



Trailing edge contraction

Table 2 Southern boundary assessment

Family/subfamily	Retracted northwards	Stable	Extended southwards
Papilionidae	*Parnassius apollo* *Parnassius mnemosyne*		
Pieridae		*Aporia crataegi*	
Lycaenidae	*Everes argiades* *Glaucopsyche alexis* *Heodes tityrus* *Hamearis lucina* (Riodininae)	*Agrodiaetus amanda* *Celastrina argiolus* *Cupido minimus* *Heodes alciphron* *Heodes virgaureae* *Quercusia quercus* *Strymonidia w-album* *Thecla betulae*	
Nymphalinae	*Clossiana dia* *Clossiana selene*	*Apatura ilia* *Apatura iris* *Argynnis adippe* *Argynnis paphia* *Brenthis daphne* *Clossiana euphrosyne* *Limenitis camilla* *Limenitis populi* *Limenitis reducta* *Polygonum c-album**	*Brenthis ino* *Araschnia levana*
Satyrinae	*Aphantopus hyperantus* *Minois dryas*	*Coenonympha arcania* *Lasiommata maera* *Maniola jurtina* *Melanargia galathea* *Neohipparchia statilinus* *Pyronia tithonus*	
Hesperiidae		*Carterocephalus palaemon* *Thymelicus acteon*† *Thymelicus sylvestris*	

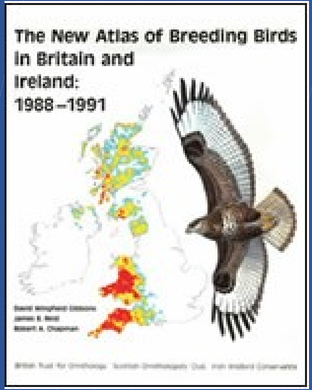
Data are from one or more countries: France, Catalonia (Spain), Morocco, Algeria and Tunisia.

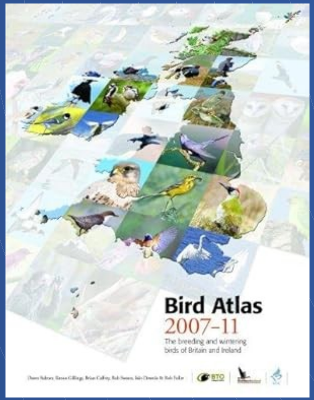
Of 52 species, the northern boundary has
shifted northwards for 65%
Stable for 34%
Shifted southwards for 2%

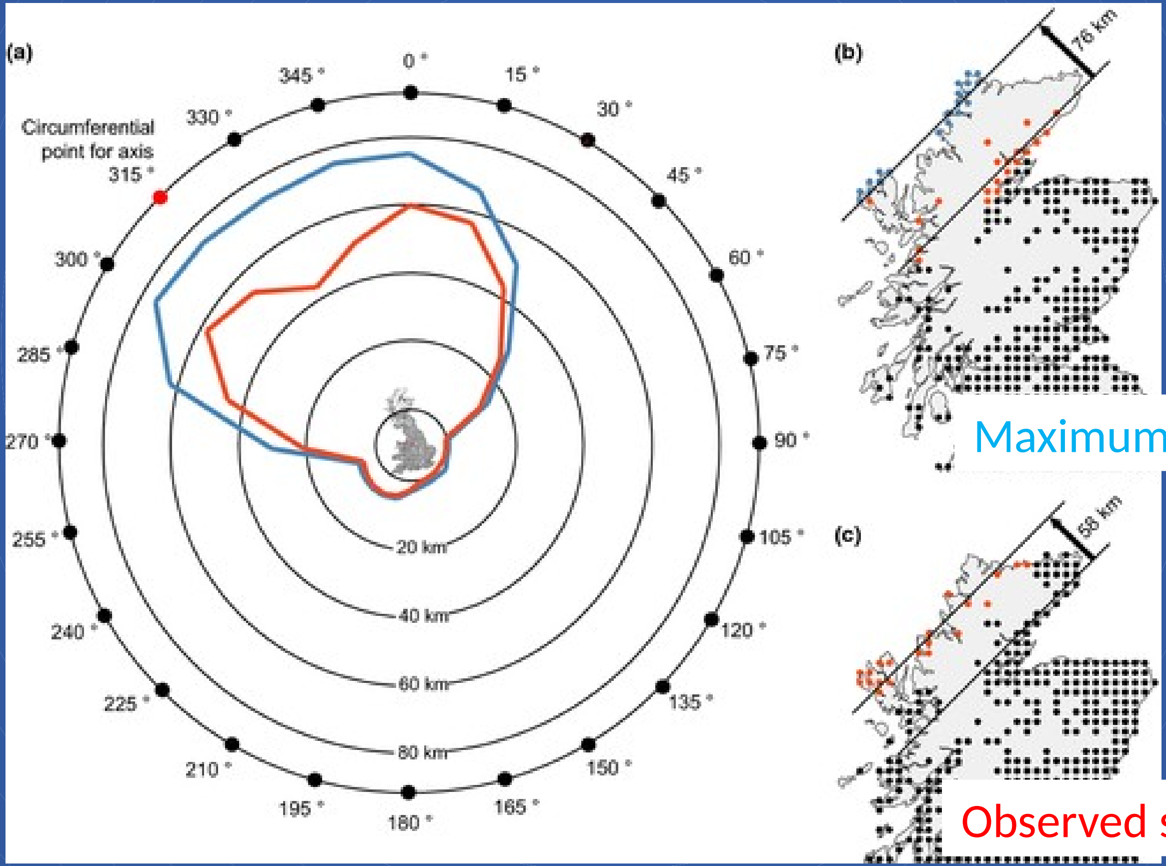
Of 40 species the southern range boundary has
Contracted northwards for 22%
Stable for 72%. Extended southwards for 5%

Parmesan et al. 1999 Nature 399: 579

Poleward shifts:
Birds in the UK – identifying directionality





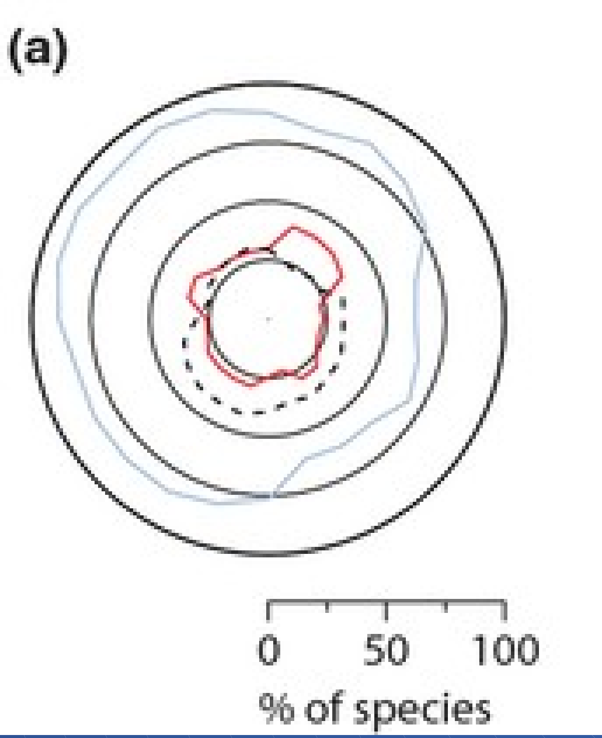


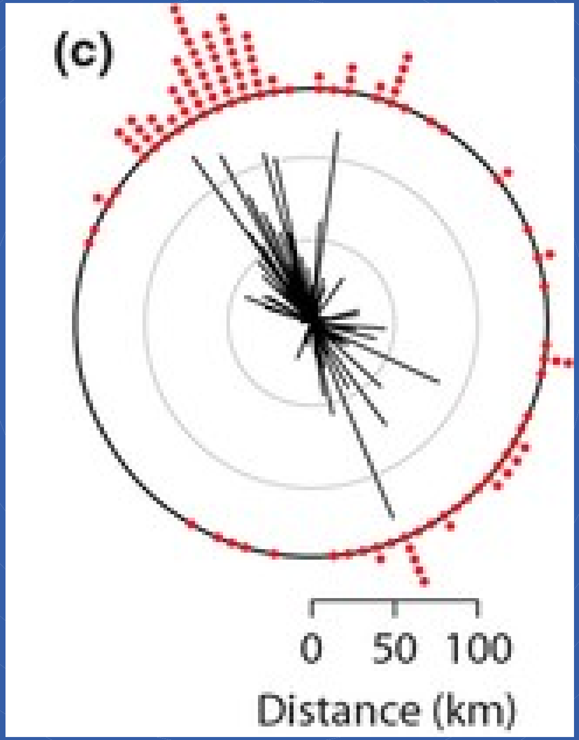
Maximum potential shift

Observed shift

Gillings et al. (2015) Global Change Biology 21: 2155

Poleward shifts:
Birds in the UK: Identifying directionality

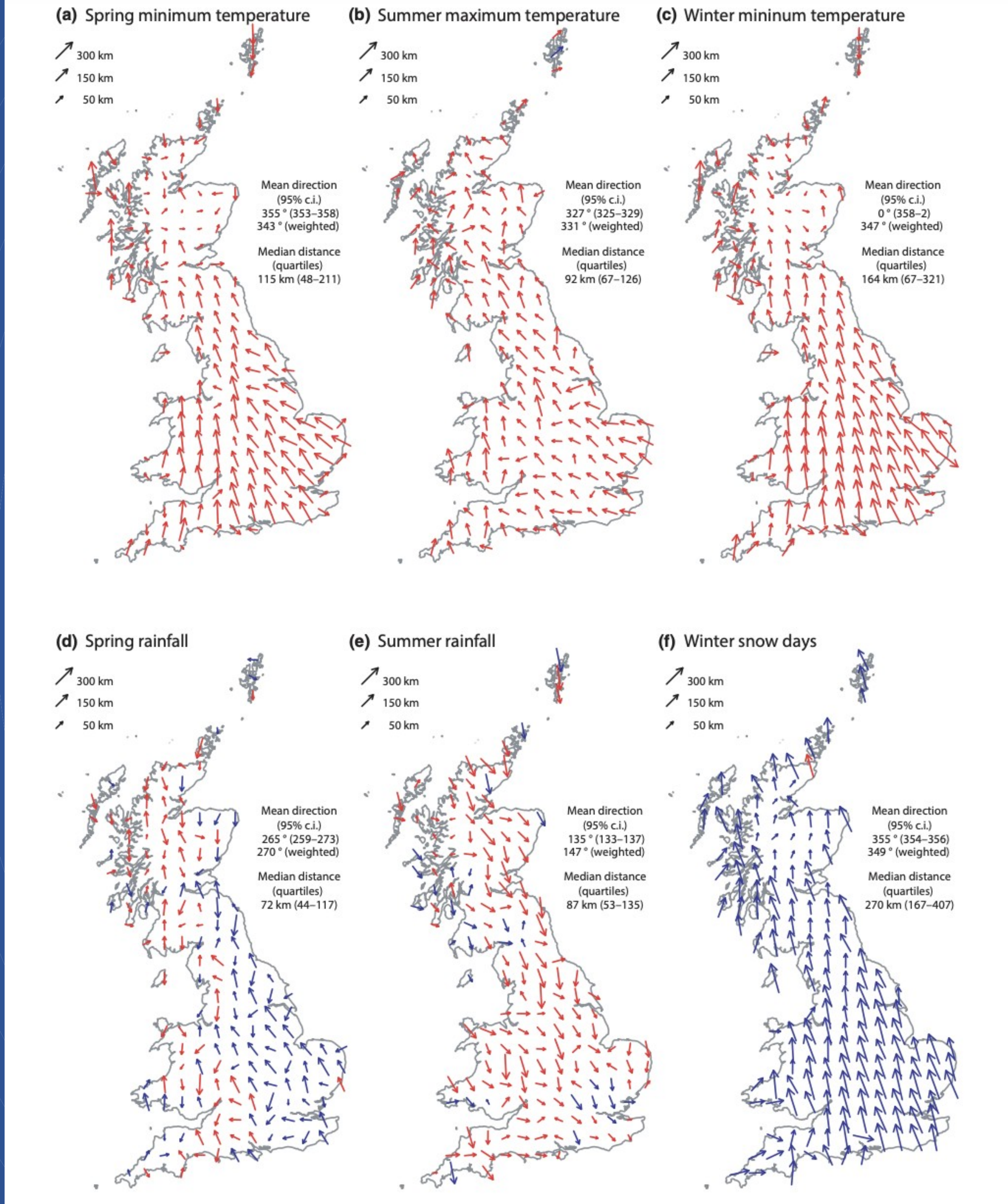




Red line = range extensions
Dashed black line = range contractions

- Widespread evidence for poleward expansion and southern limit range contractions
- Centroids of ranges tending to move north

Gillings et al. (2015) Global Change Biology 21: 2155



Vectors of how far you'd need to move to maintain historic climate conditions

This is related to the idea of *climate velocity* that we'll come back to

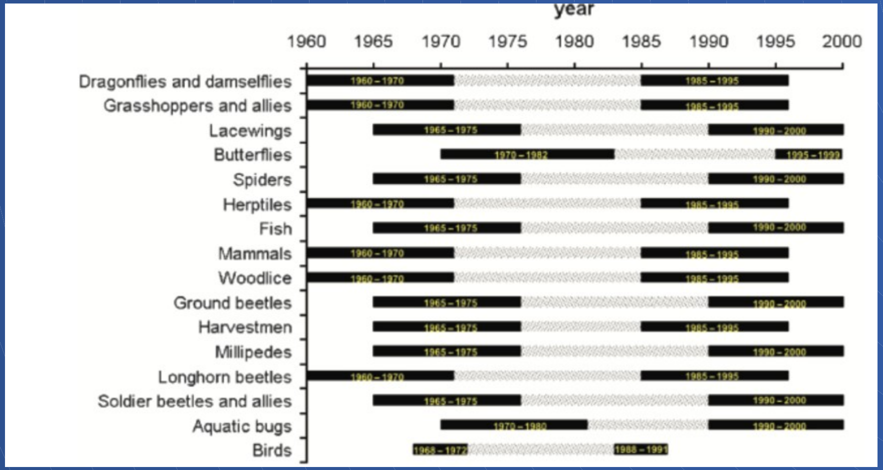
Gillings et al. (2015) Global Change Biology 21: 2155

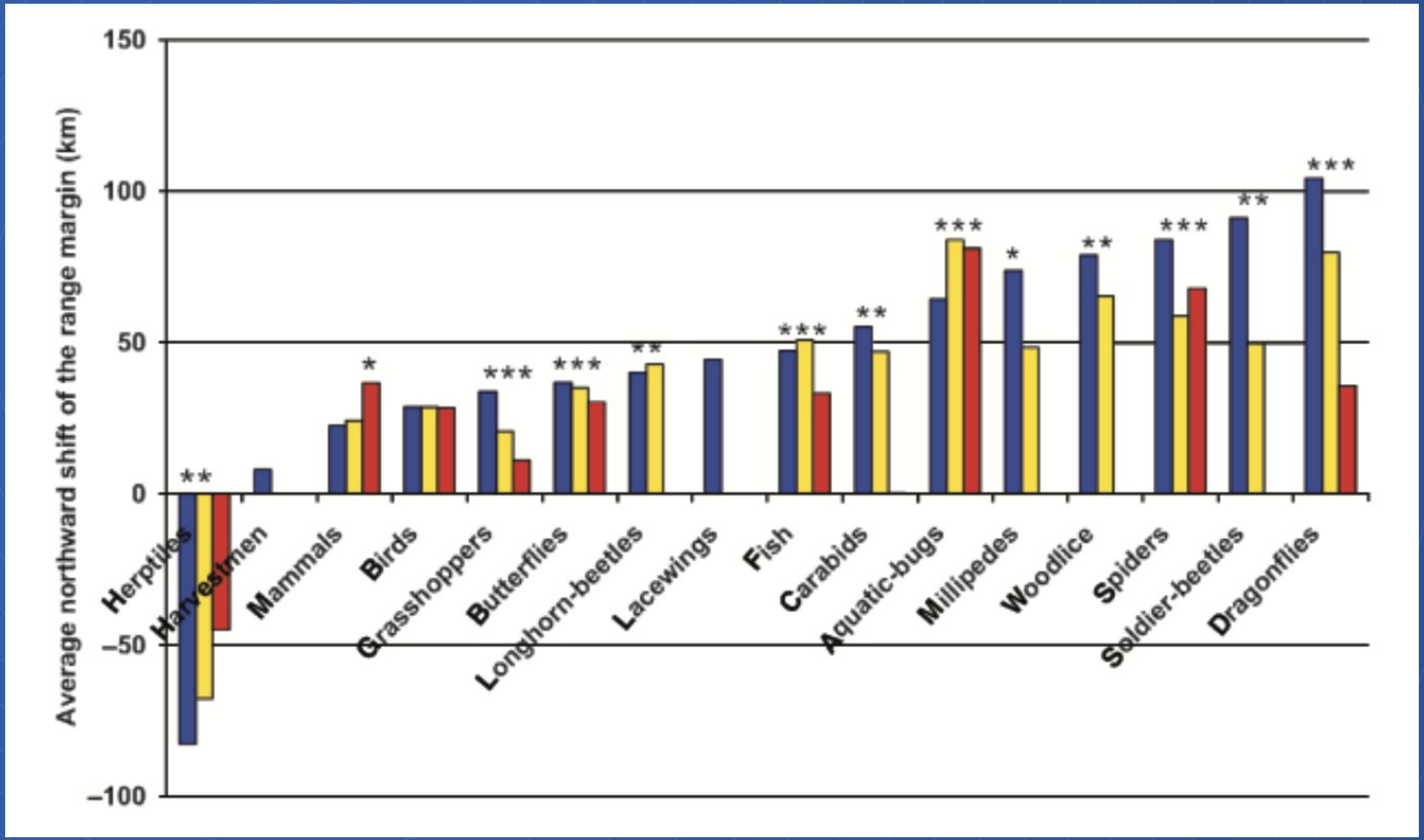
Poleward shifts:

Taxon comparison focused on northern margin in UK

329 species

25-year time period

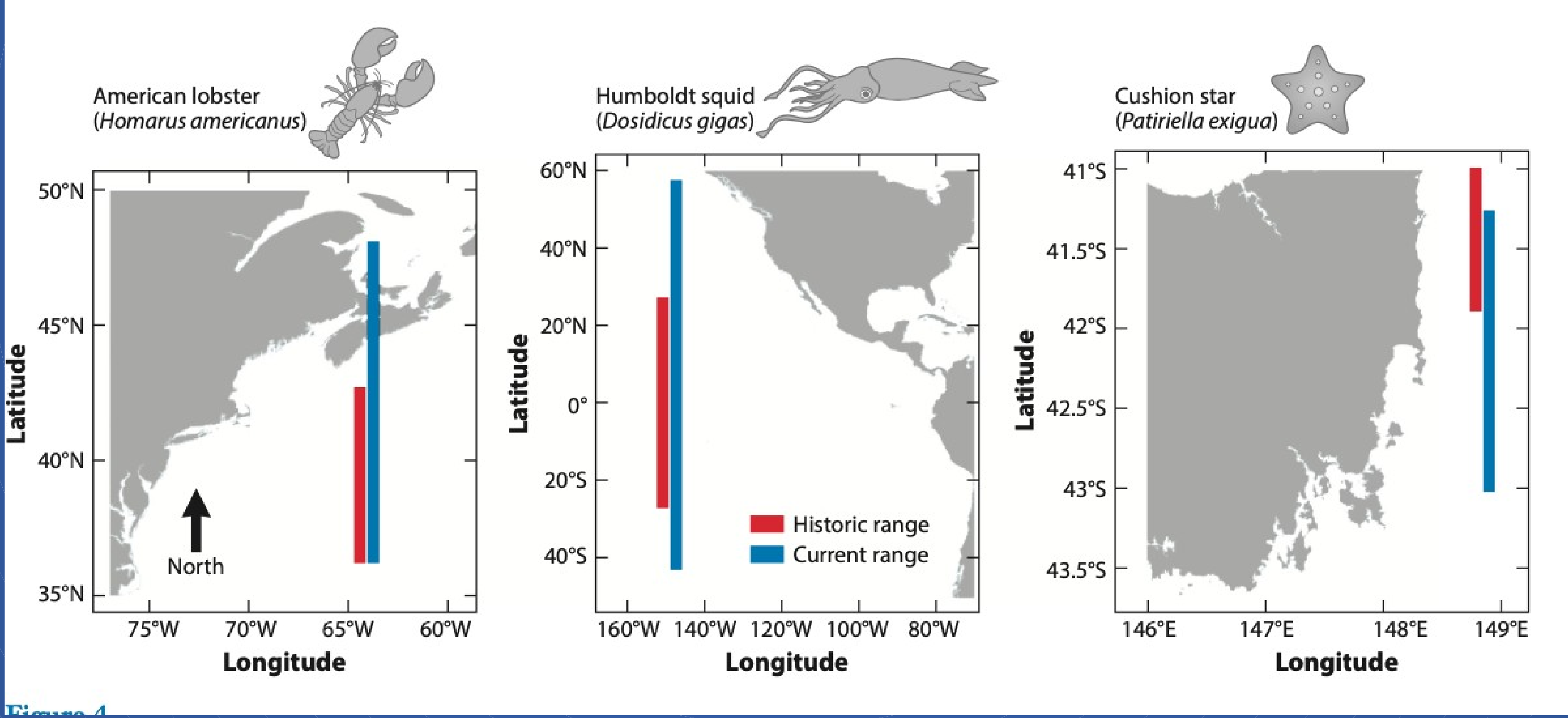




Hickling et al. 2006 Global Change Biology 12: 450

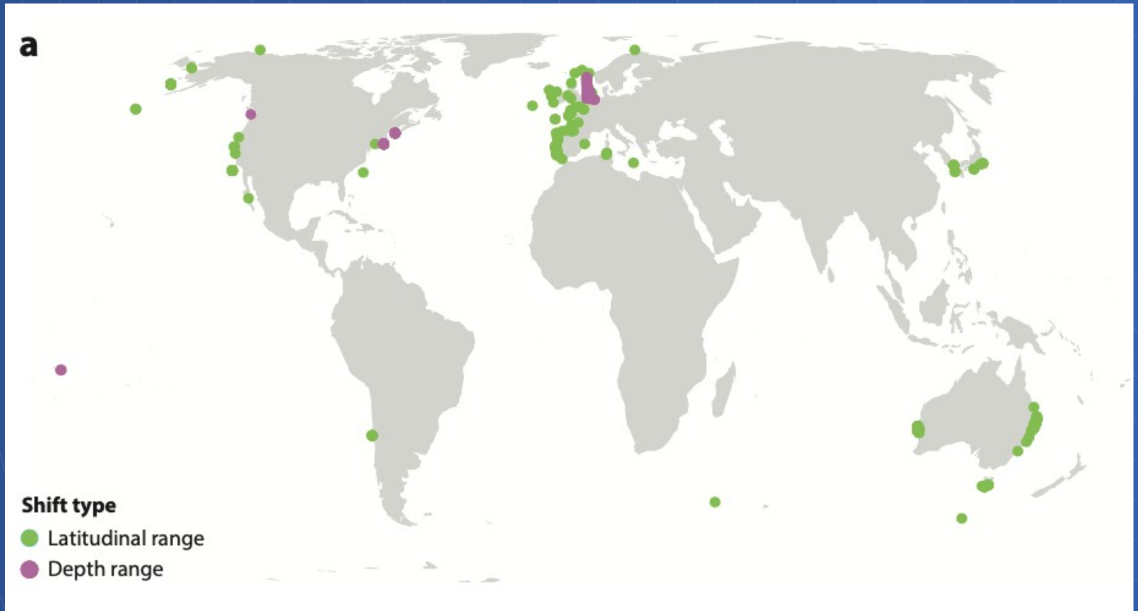
Poleward shifts:
marine taxa

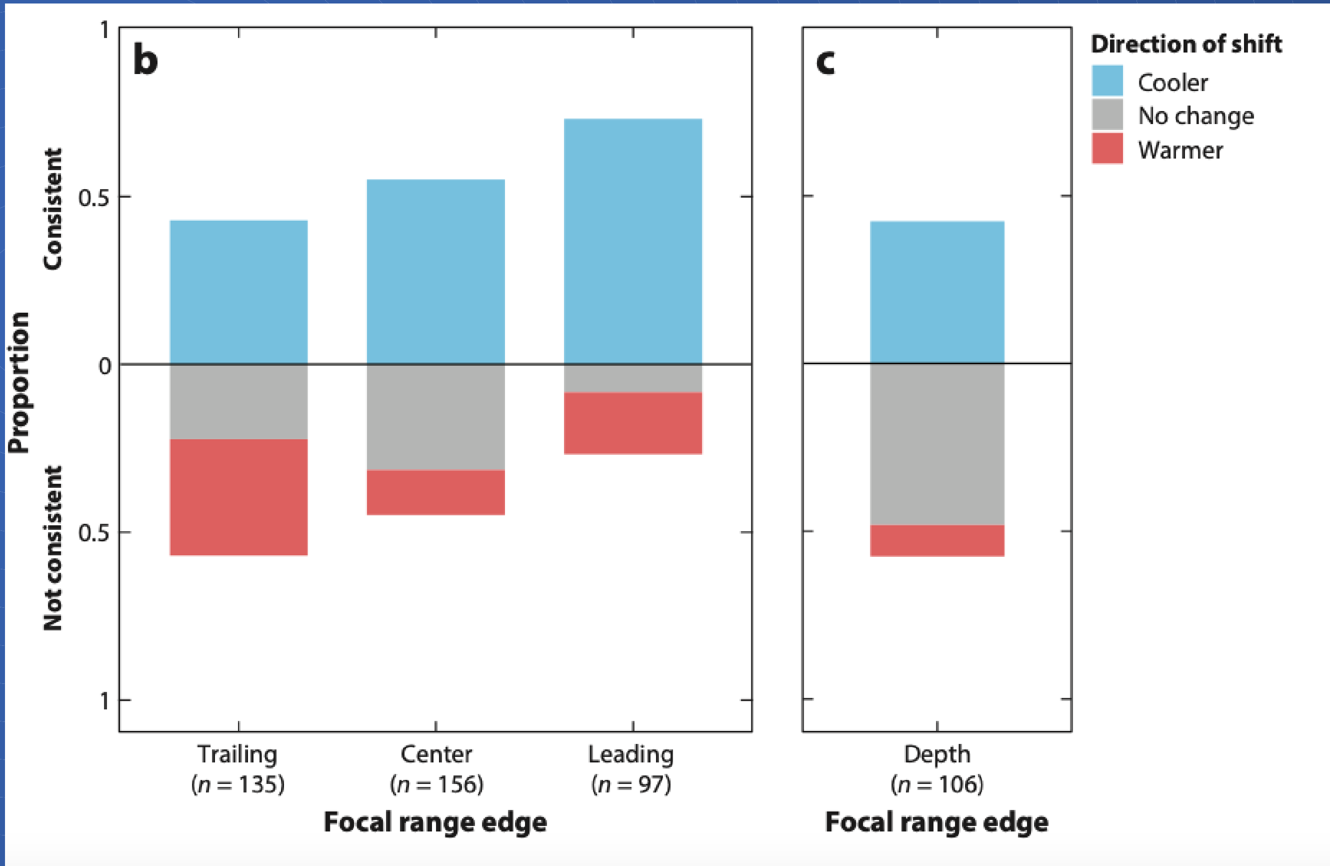
> 80% of global warming absorbed by oceans.
Surface layers of ocean have warmed at 1/3 rate of terrestrial systems



Pinsky et al. 2020 Annual Review of Marine Science 12: 153

Polewards and deeper:
Shifts for marine taxa





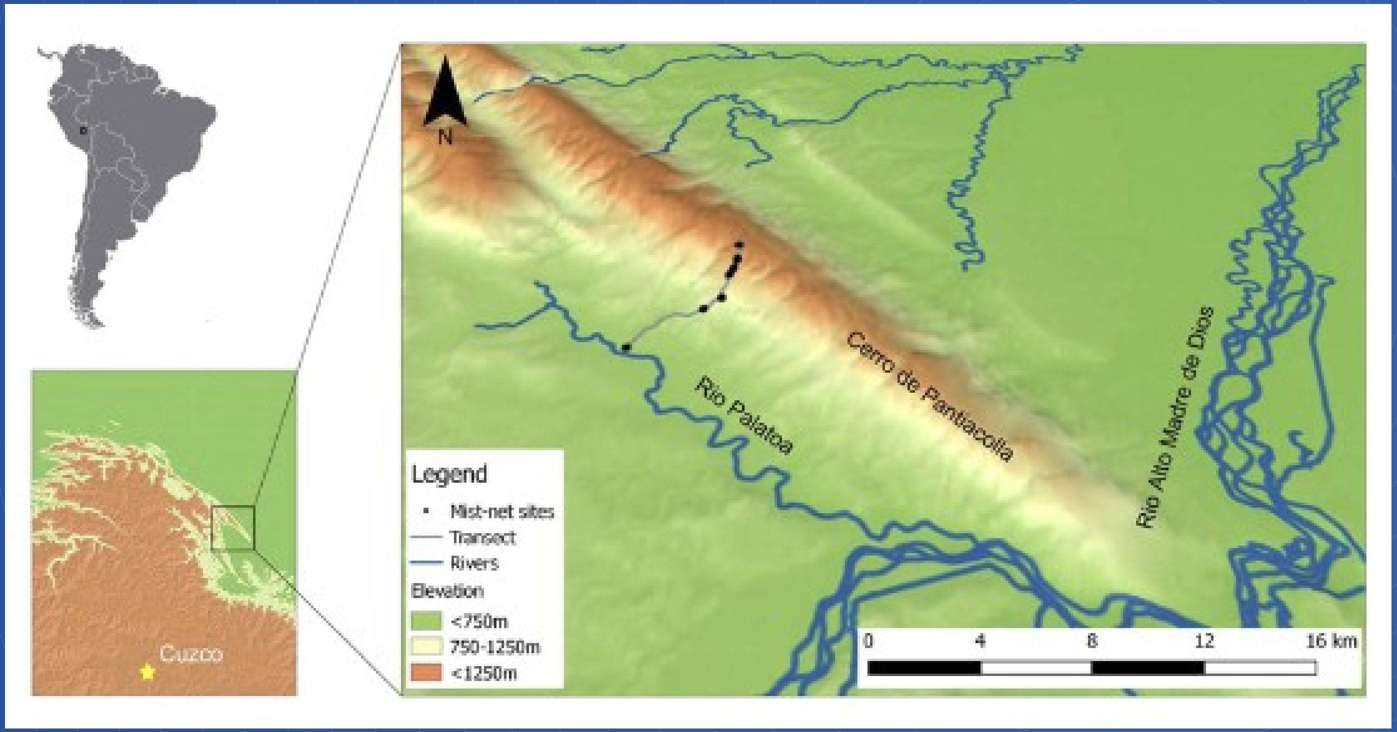
Pinsky et al. 2020 Annual Review of Marine Science 12: 153

Upslope shifts:
Birds in the Andes

River to ridge-top 8km transect from 470m to 1415m. Forest unaffected by humans.

Survey 1: 1985

Survey 2: 2017 (following same protocol). Temperature had increased by ~0.4C

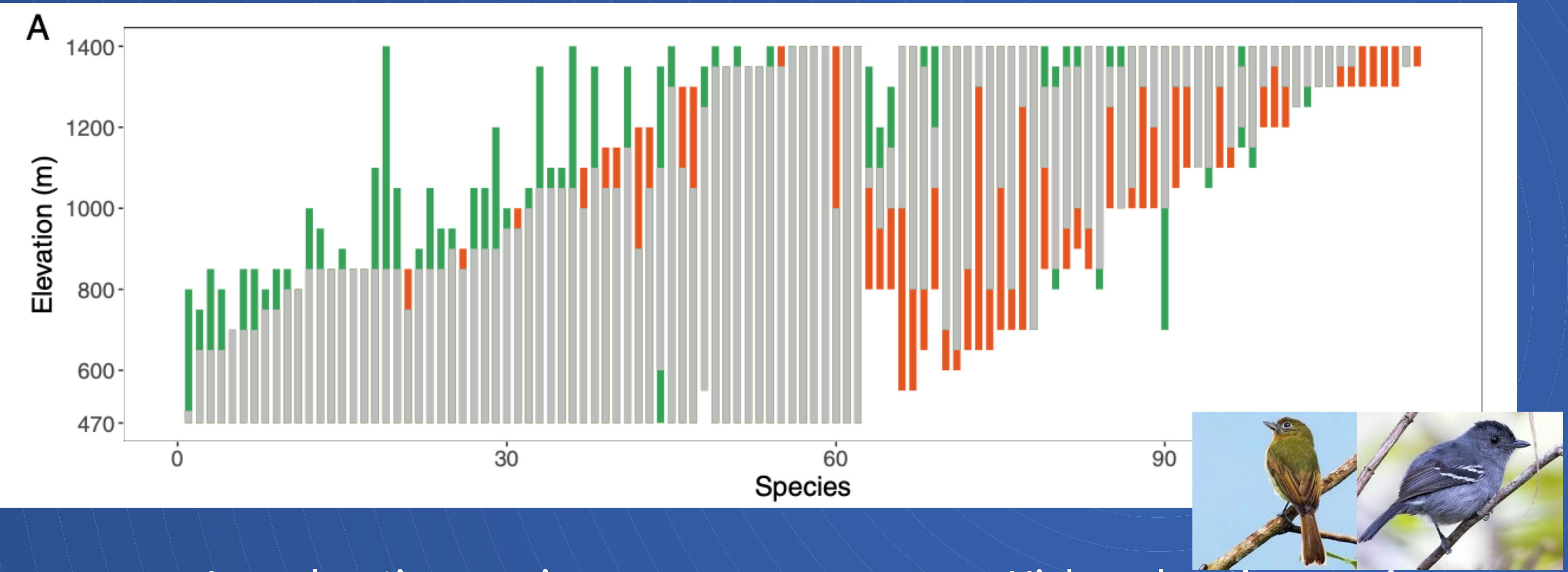


Pantiocolla in southeastern Peru

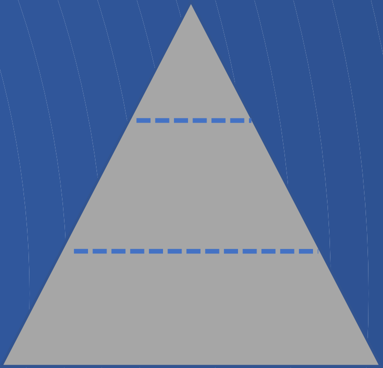
Authors calculates uphill movement should have been ~76m to track constant climate*

Freeman et al. 2018 PNAS 115: 11982

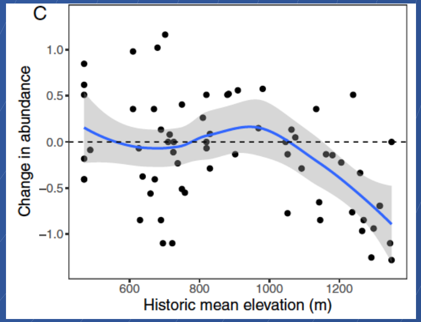
Upslope shifts:
“the escalator to extinction”



Declining area with increasing elevation bands



So species contracting upwards are left with much less area and are becoming less abundant



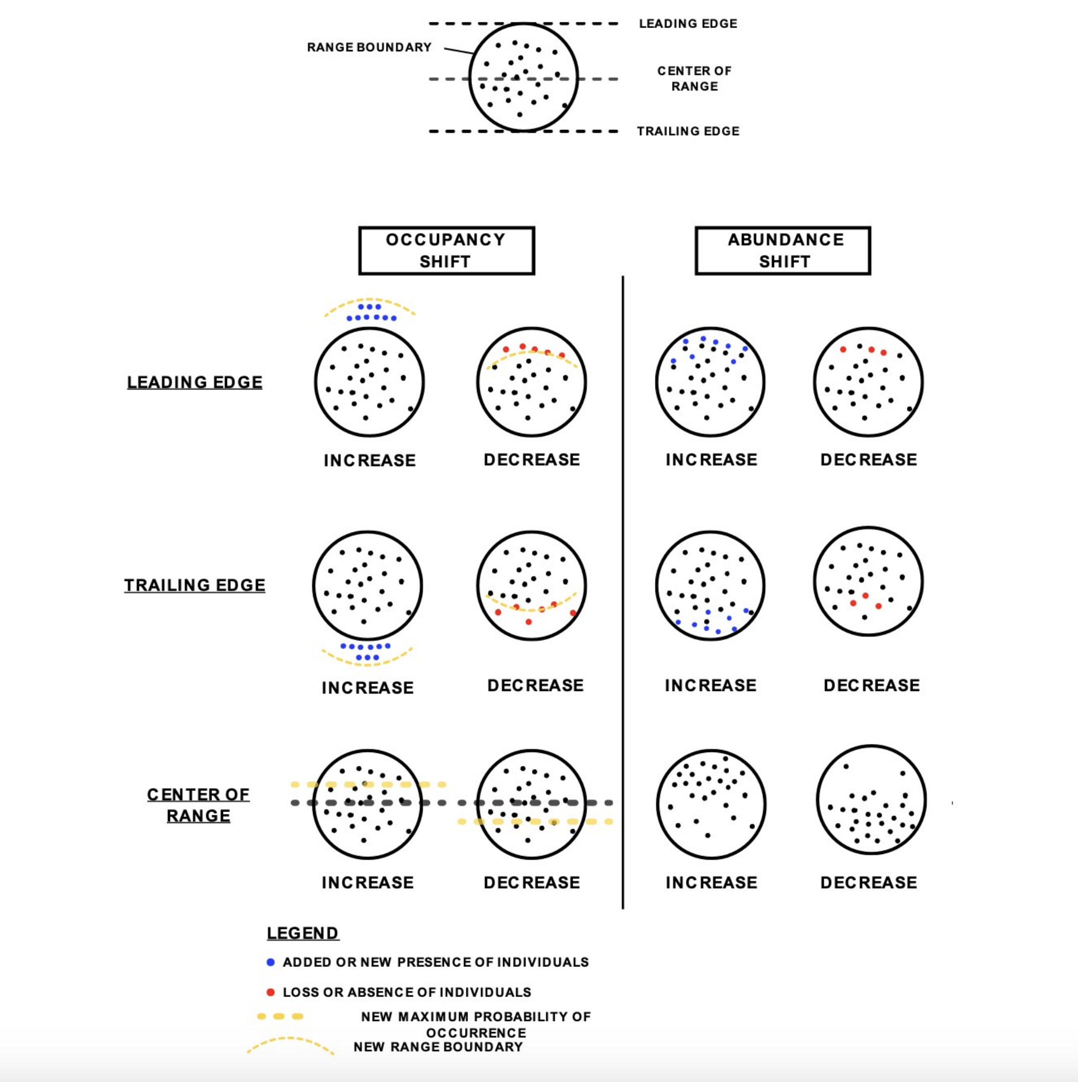
Low elevation species expanding uphill
= Winners

Higher elevation species contracting uphill
= Losers

Average upslope shift was ~48m (lagging behind the shift required to maintain temp = 76m)

Freeman et al. 2018 PNAS 115: 11982

Synthesis: What's going on overall?

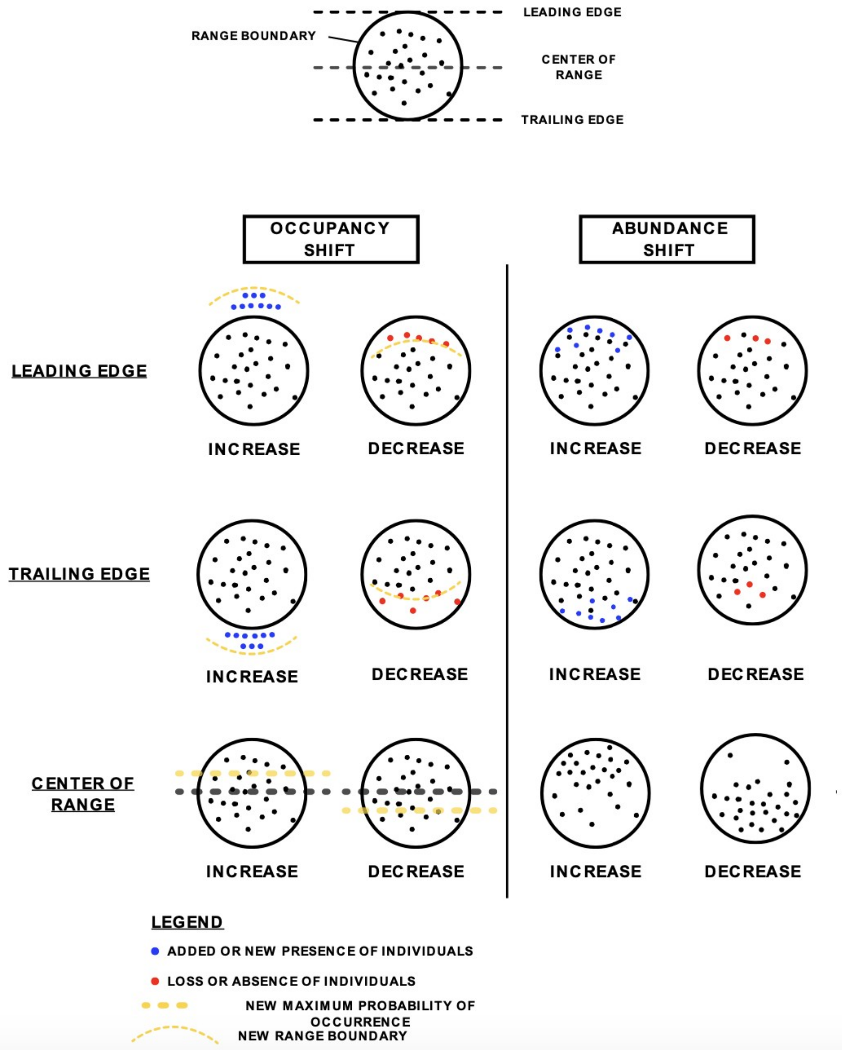


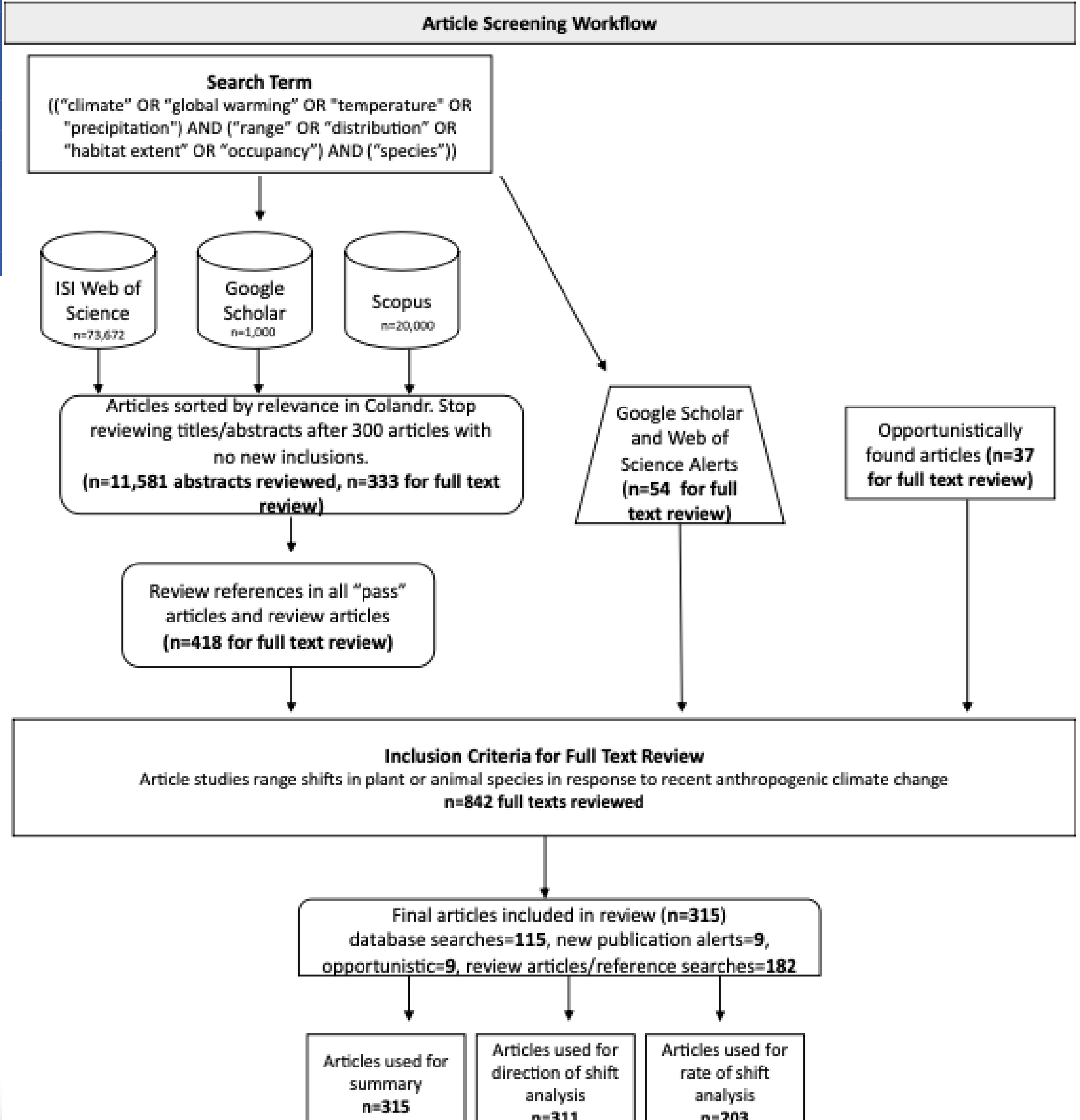
A systematic review considering:

- Latitudinal shifts
- Elevational shifts
- Depth shifts

Rubenstein et al. (2023)
https://environmentalevidencejournal.biomedcentral.com/articles/10.1186/s13750-023-00296-0

Synthesis: What's going on overall?



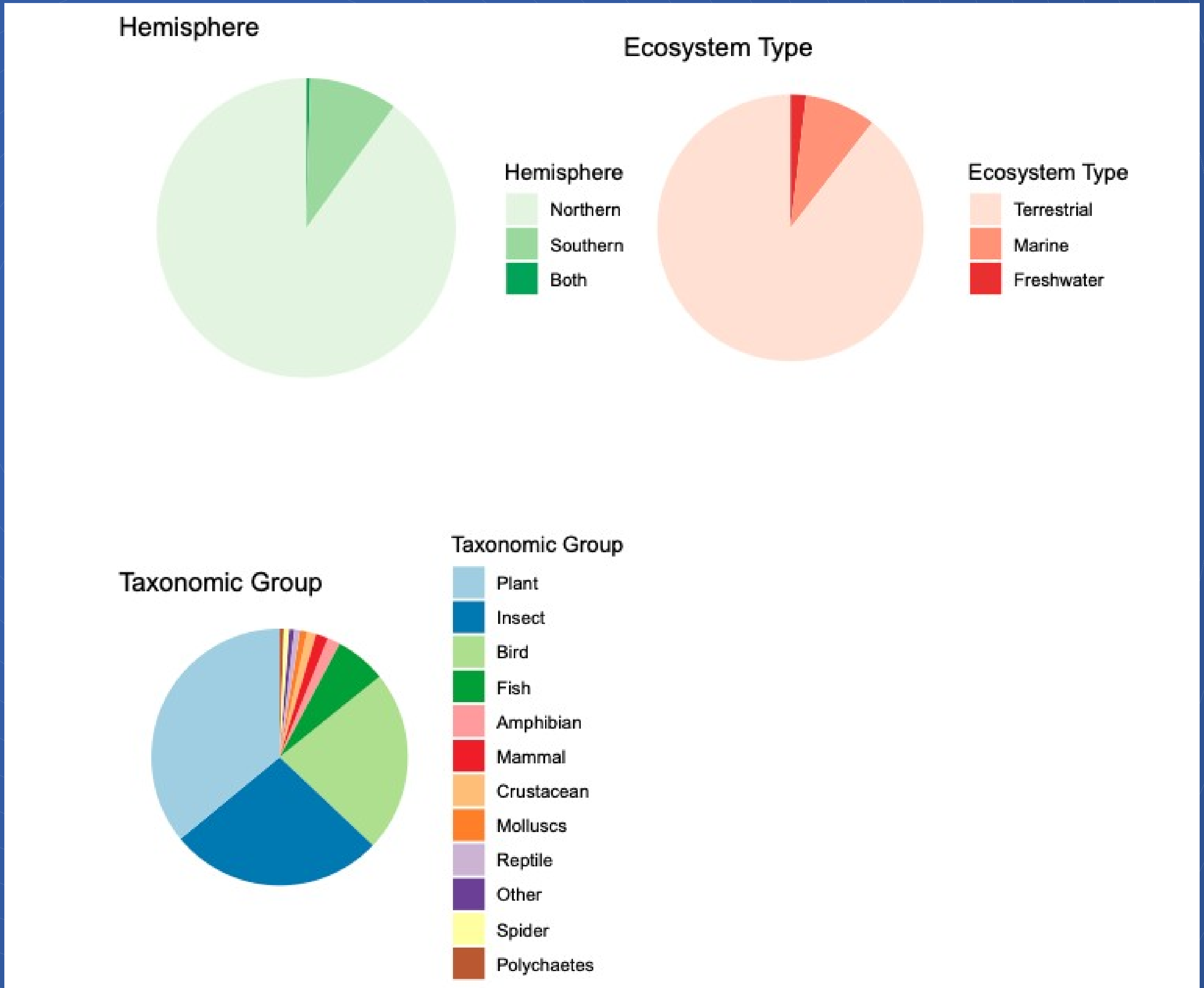


Synthesis: What's going on overall?

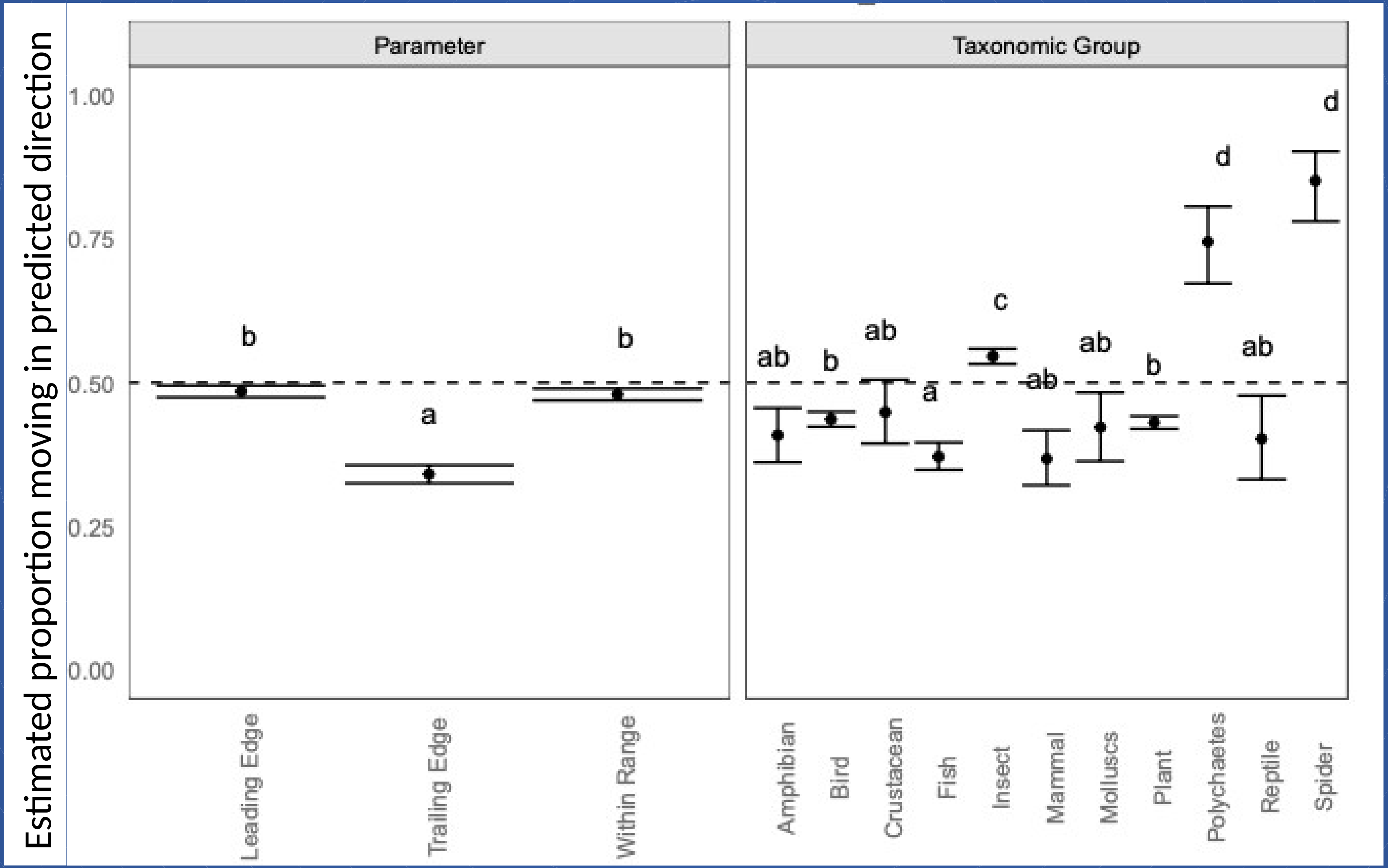
Assessed direction of range change

- Significant poleward, up elevation, greater depth = support
- No significant change or other direction = no support

Total of 29,881 range shift observations



Synthesis: What's going on overall?



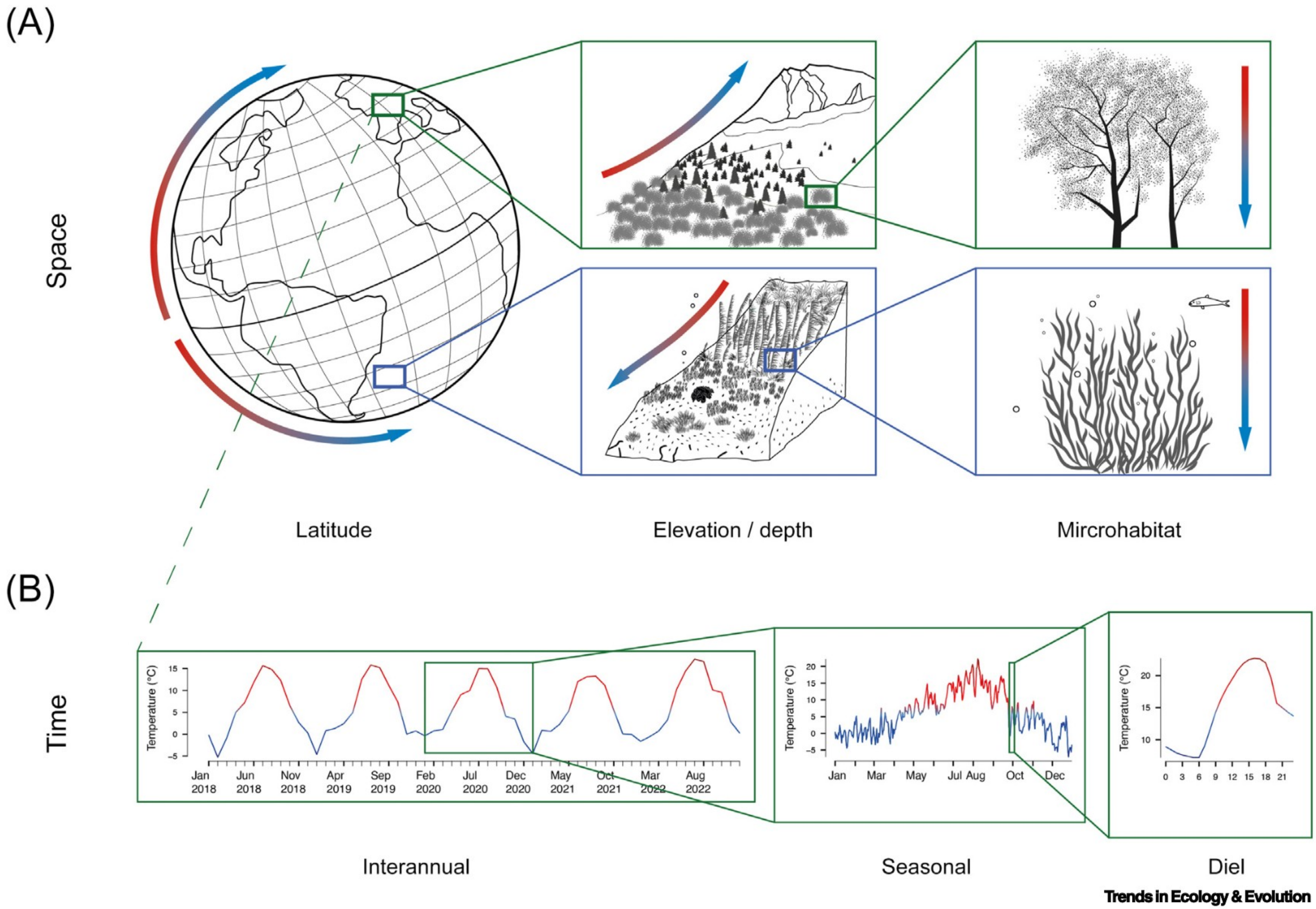
Synthesis: What's going on overall?

47% shifted significantly in the direction expected

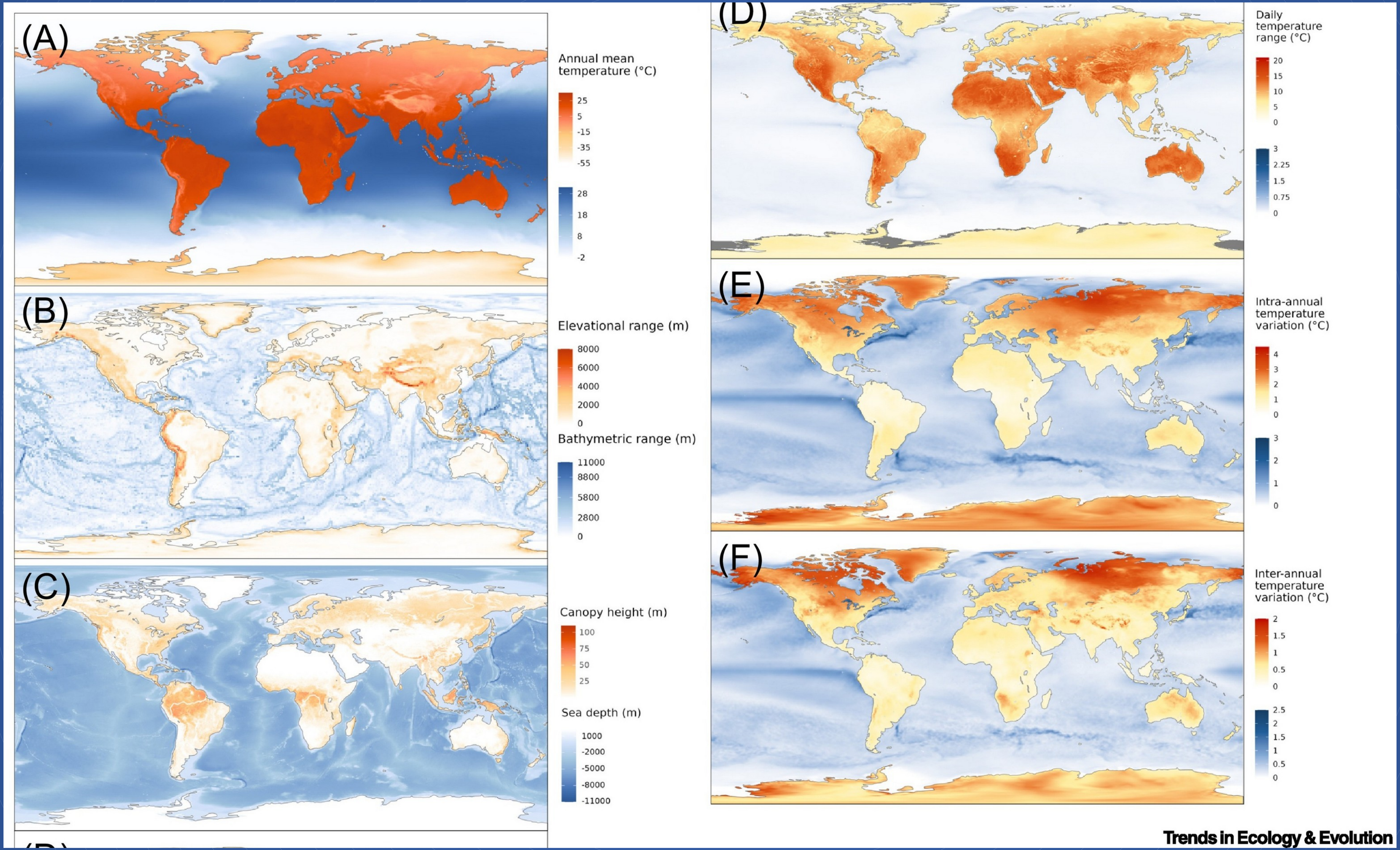
50% shifted significantly polewards

43% shifted significantly upwards

36% shifted significantly deeper



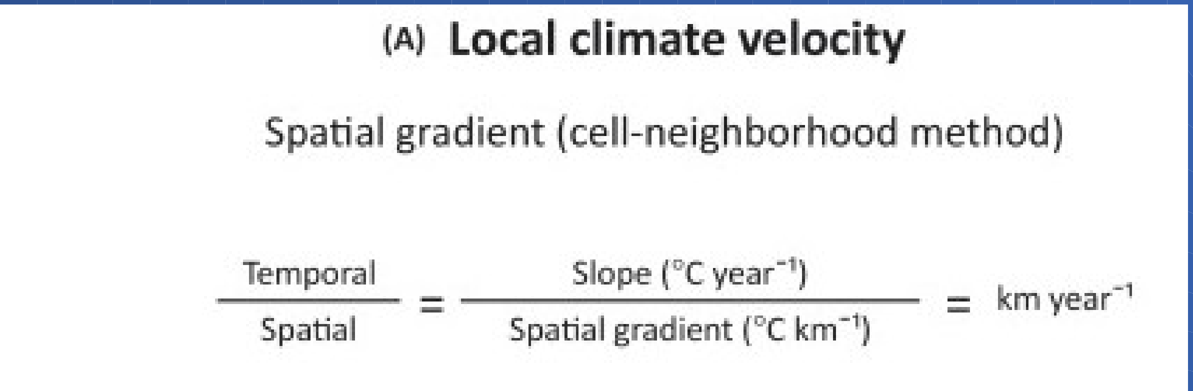
(A)
Space
Latitude
Elevation / depth
Mircrohabitat
(B)
Time
Temperature (°C)
Jan 2018
Jun 2018
Nov 2018
Apr 2019
Sep 2019
Feb 2020
Jul 2020
Dec 2020
May 2021
Oct 2021
Mar 2022
Aug 2022
Jan
Mar
May
Jul
Aug
Oct
Dec
Interannual
Seasonal
Diel
Trends in Ecology & Evolution

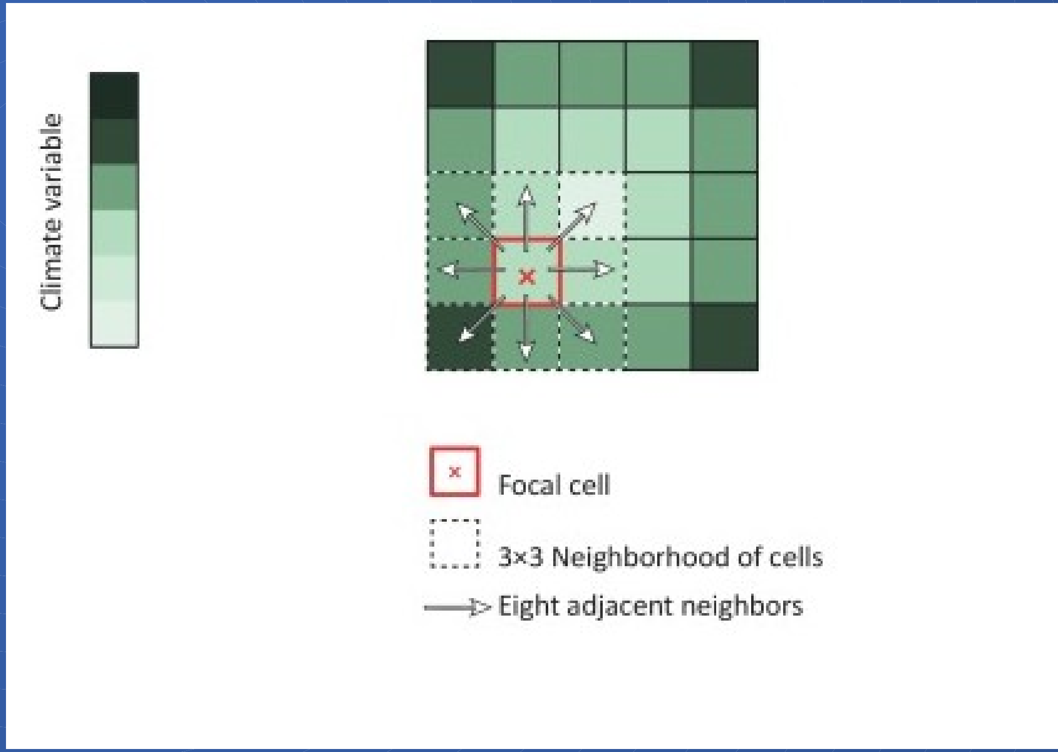


Fredston et al. (2025) TREE: https://www.cell.com/trends/ecology-evolution/fulltext/S0169-5347(25)00087-4

Climate velocity

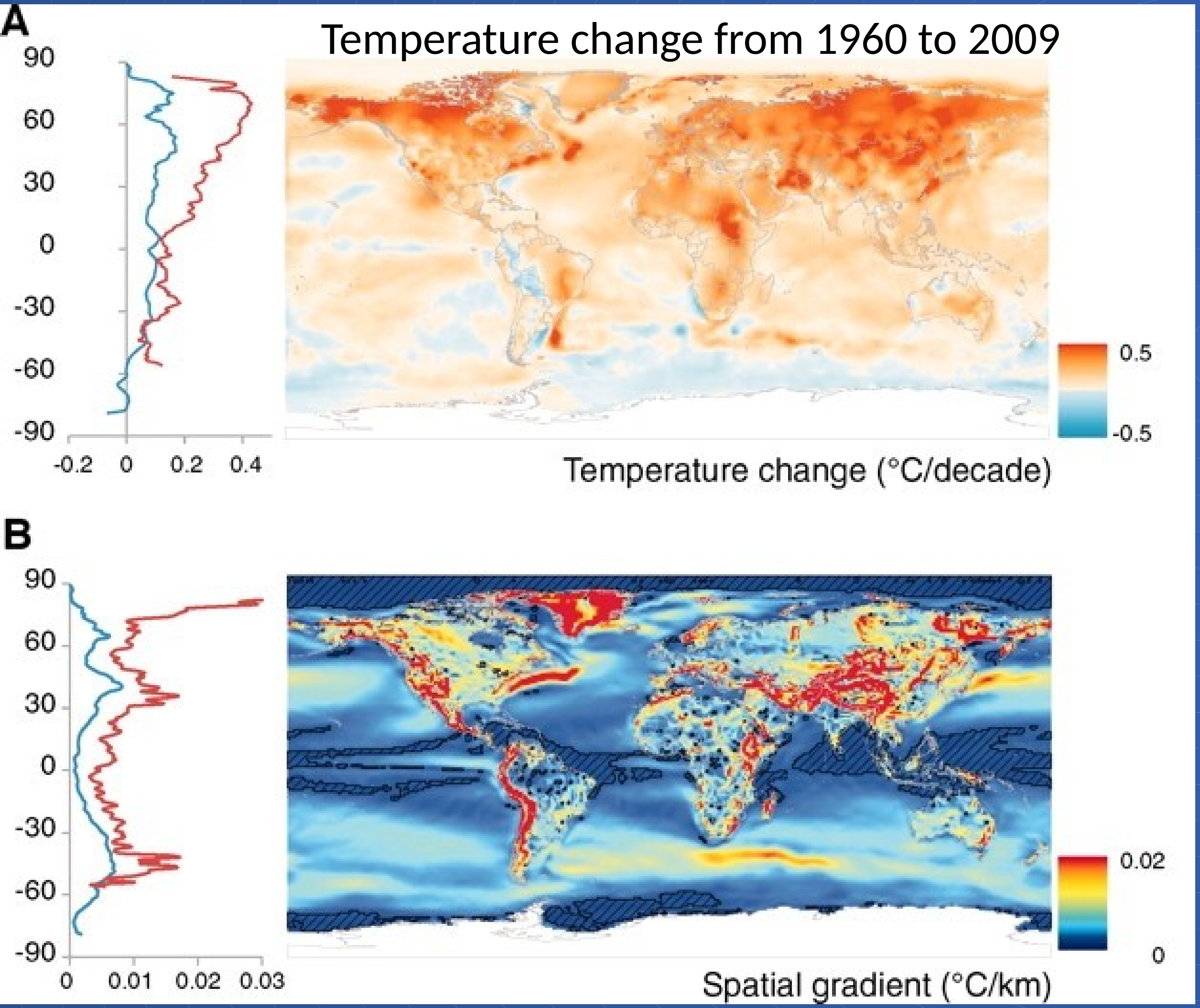
"Climate velocity is a vector that describes the speed and direction that a point on a gridded map would need to remain static in climate space"

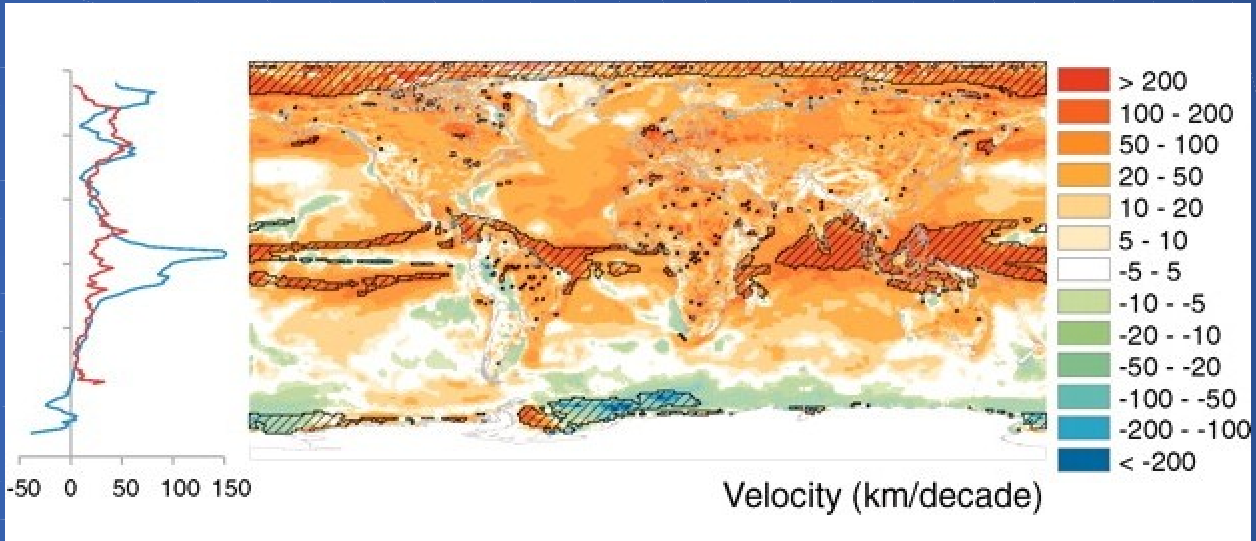




Loarie et al. 2009 Nature 462: 1052
Brito-Morales et al. 2018 Trends Ecology Evolution 6: 441

Evidence for range shifts:
Climate velocity on land and oceans





(A) Local climate velocity

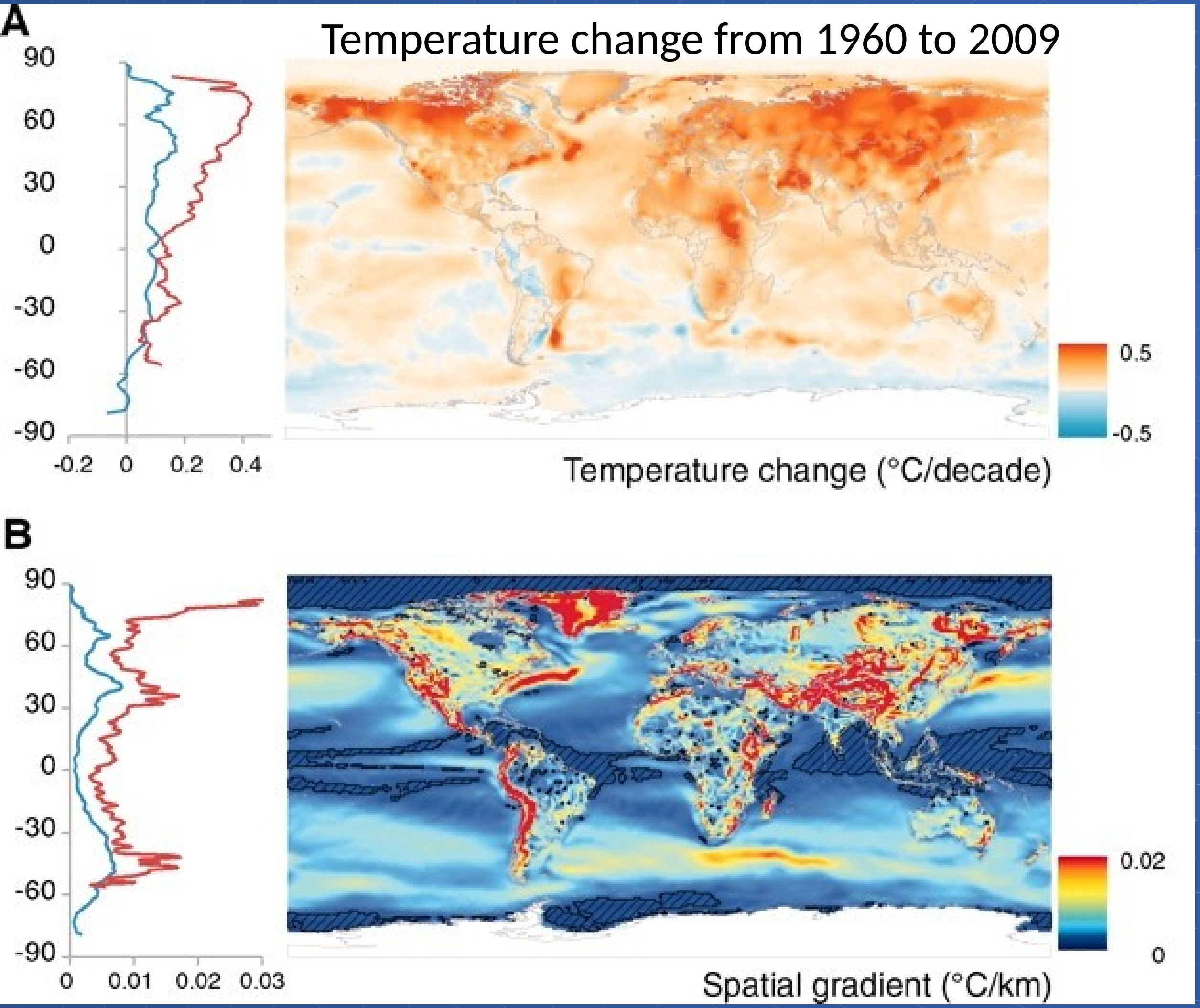
Spatial gradient (cell-neighborhood method)

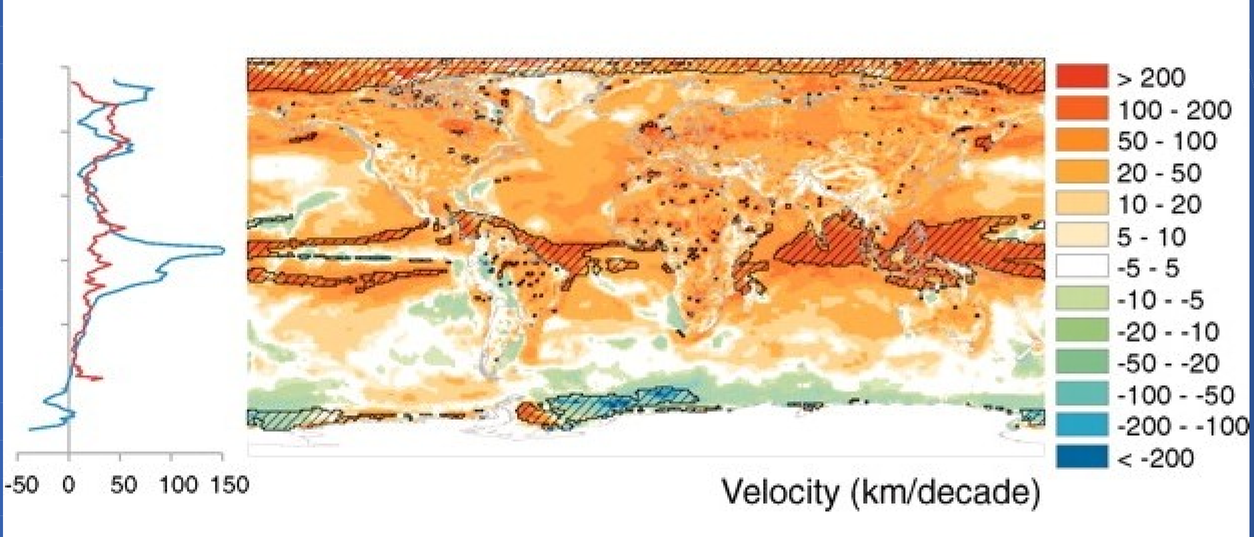
$$\frac{\text{Temporal}}{\text{Spatial}} = \frac{\text{Slope } (^{\circ}\text{C year}^{-1})}{\text{Spatial gradient } (^{\circ}\text{C km}^{-1})} = \text{km year}^{-1}$$

Burrows et al. 2011 Science 334:652

Evidence for range shifts:

Climate velocity on land and oceans





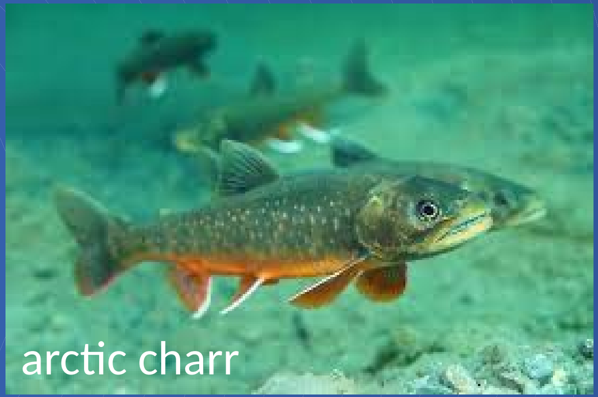
To track a consistent climate need to
- Travel a long way in marine systems (especially tropics) = HIGH VELOCITY
- Travel very short distances on mountains = LOW VELOCITY

Burrows et al. 2011 Science 334:652

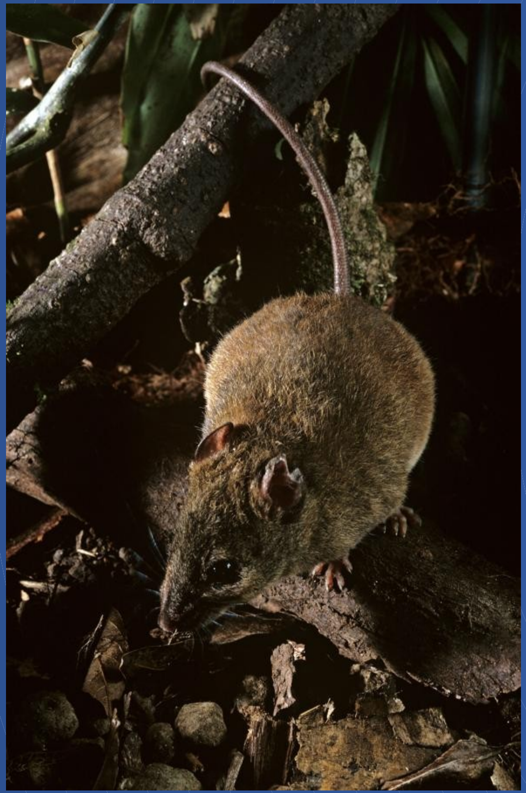
Climate range shifts in a Scottish context

Winners: warm adapted species spreading northwards

Losers: cold-adapted species that have nowhere colder to go (within the UK)



Evidence for range shifts:
climate change and extinction



Bramble cay melomys
(*Melomys rubicola*)

Found on Bramble Cay (10ft above sea level) adjacent to great Barrier Reef. 3m above sea level

Last seen by fishermen in 2009

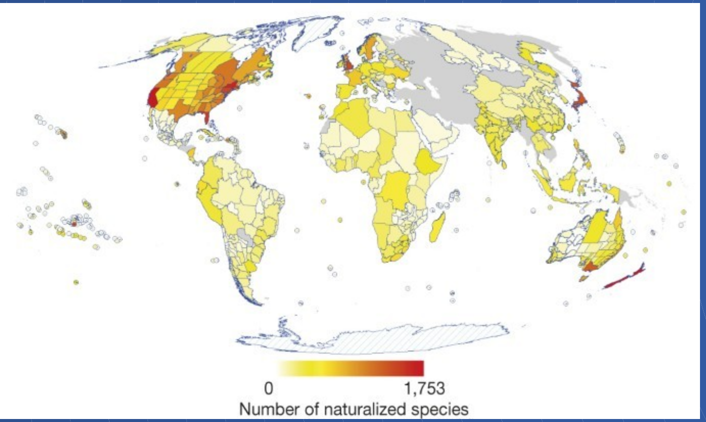
Declared extinct by Australian government in 2019

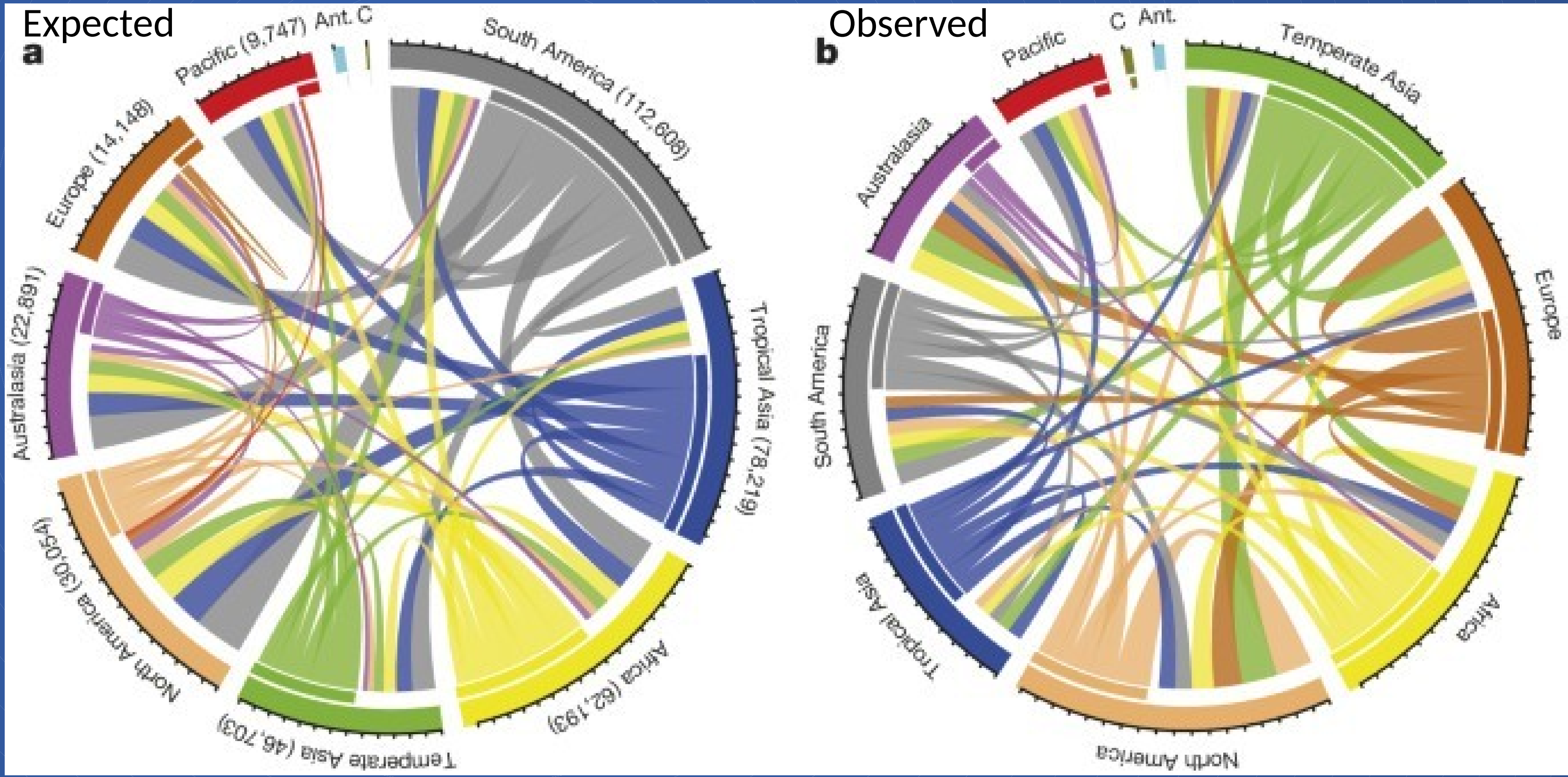
Cause of extinction: repeat inundations of v. small island driven exacerbated by sea level rise.

2014

Other anthropogenic influences on species distributions: land-use change

Other anthropogenic influences on species distributions: introduced/alien species





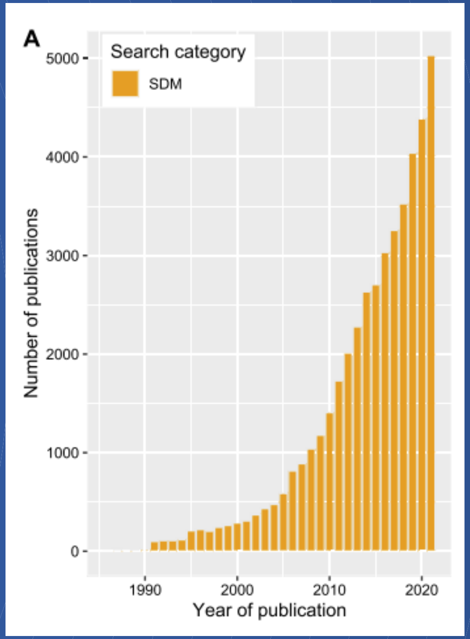
Van Kleunen et al. (2015) *Nature* 525: 100

How have species distributions changed? summary

- Terrestrial: Poleward and elevation shifts
- Marine: Poleward and depth shifts
- Leading edge tends to be extending faster than trailing edge contraction
  - Could be due to slower time for extinction (last individual) versus faster time colonization (first individual)
  - Could also arise if temperature is more of a constraint on species distributions at the cold edge
- In many cases the rate and direction of change is consistent with hypothesis that many range shifts are due to climate change

2. Predicting the future: How will species distributions change?

- Why predict?
- How to do it
- Applications of SDMs
- Critiquing correlative SDMs
- A more positive note: The next generation of SDMs



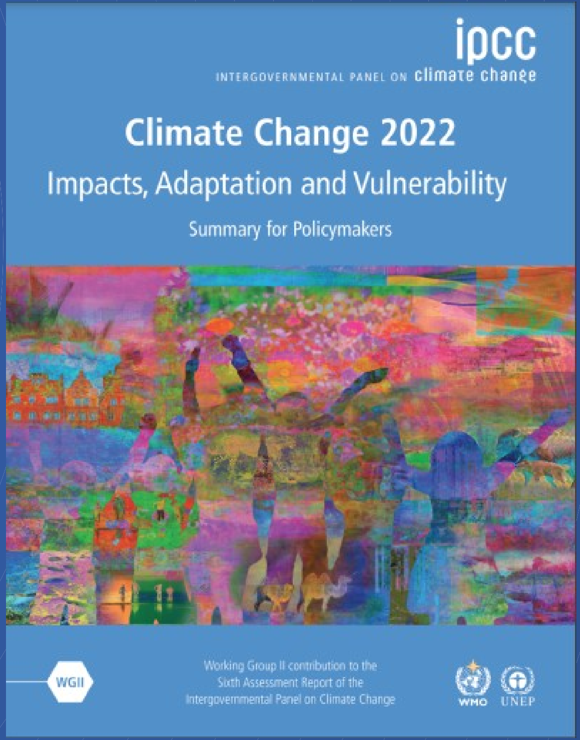
From Zurrel et al. 2023 Cambridge Prisms: Extinction

For a general introduction to SDMs see Elith, J. and Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. *Annual review of ecology, evolution, and systematics*, *40*, pp.677-697.

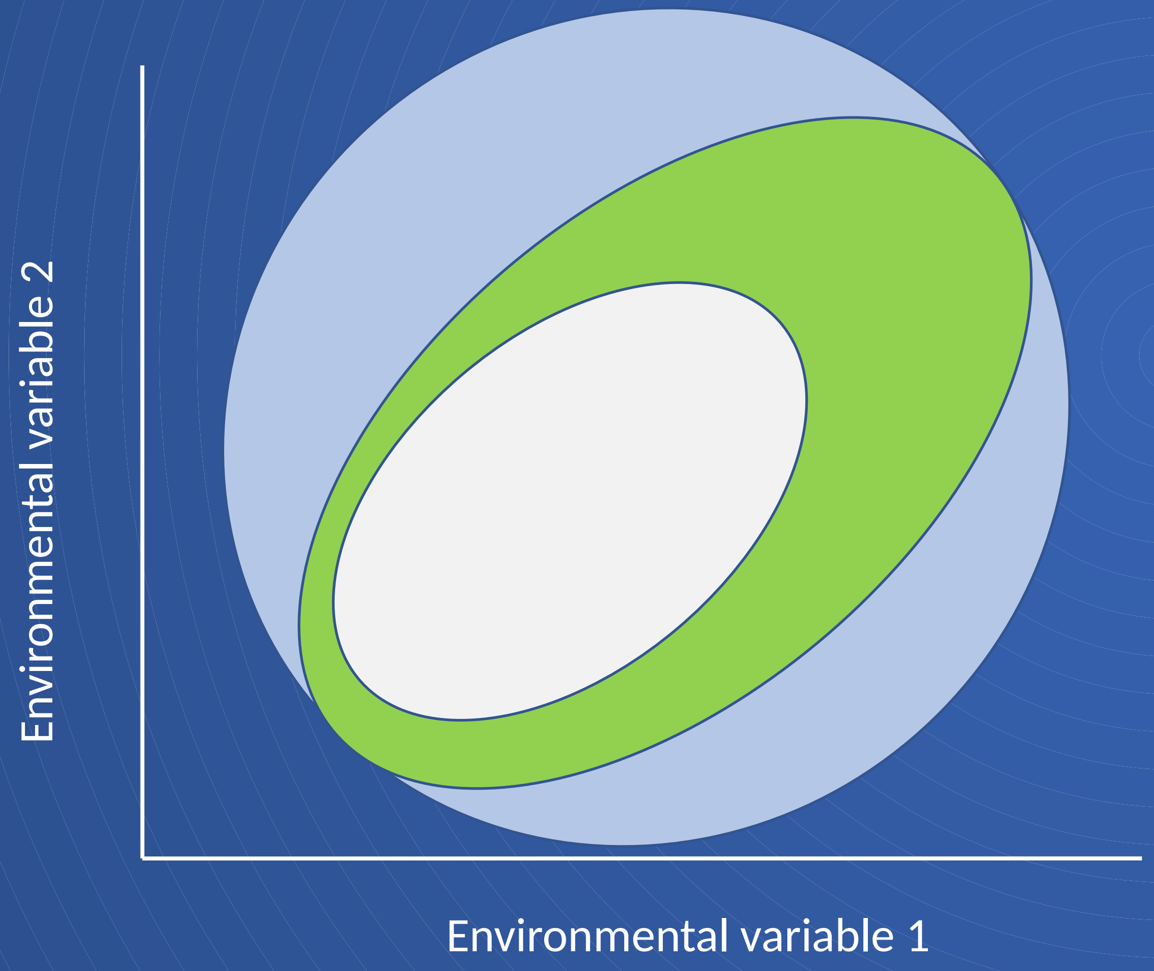
Spoiler. Predicting the future is hard. …So why should we even try?

- Policymakers want predictions to understand the risk/opportunity that climate change poses to
  - biodiversity
  - crop yields
  - pests, vectors and disease

- Conservation wants this to Identify species that are most at risk and may benefit from interventions, e.g., assisted migration



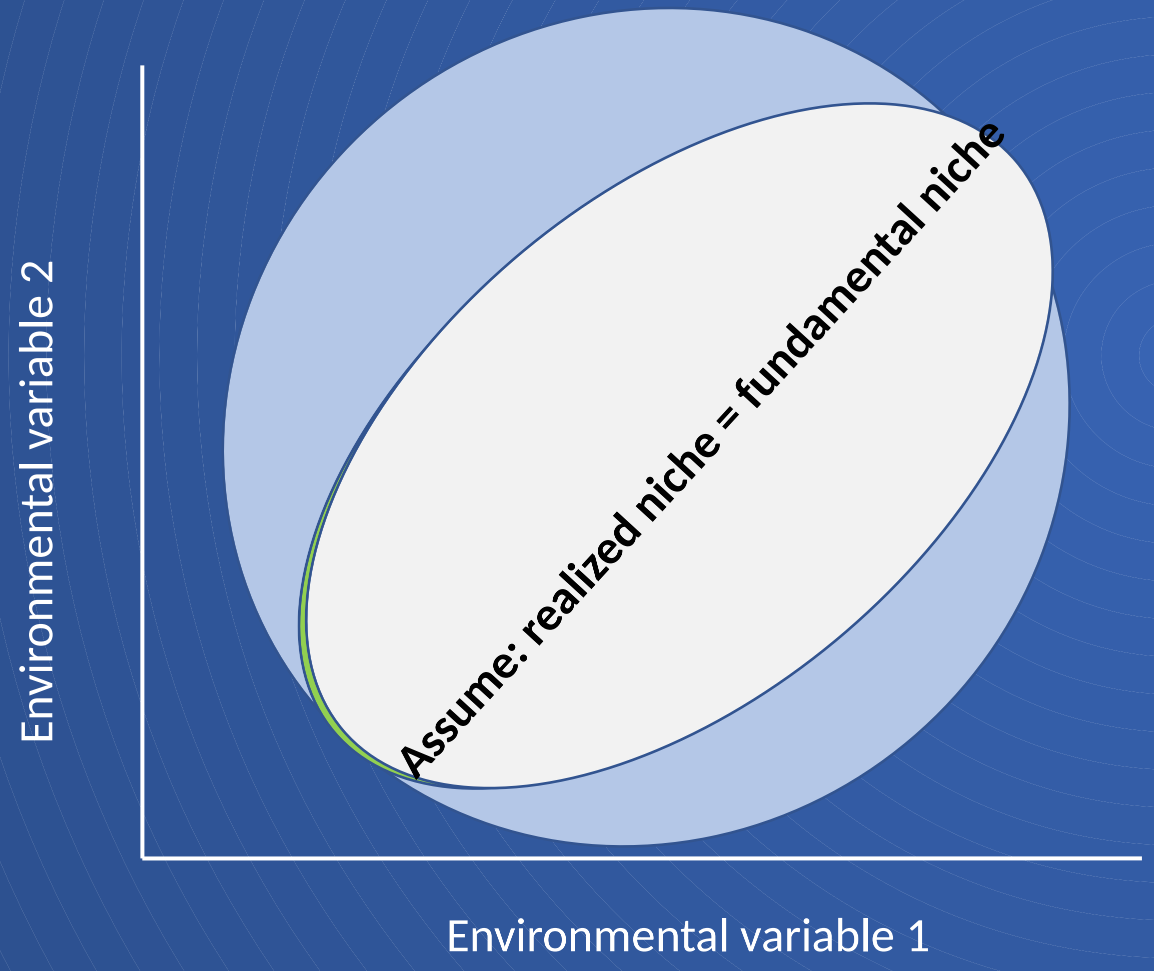
The niche: Hutchinsonian niche hypervolume



- Environmental variation – how the environments (co)vary in time and space
- **Fundamental niche** – the environments a species or population could persist in without competition etc.
- **Realised niche** – the environments that a species or population are found in.

- There are likely to be many more than two axes -> hence why we talk about a niche **hypervolume**
- Climate variables are often thought to represent important niche axes.

The niche: Hutchinsonian niche hypervolume



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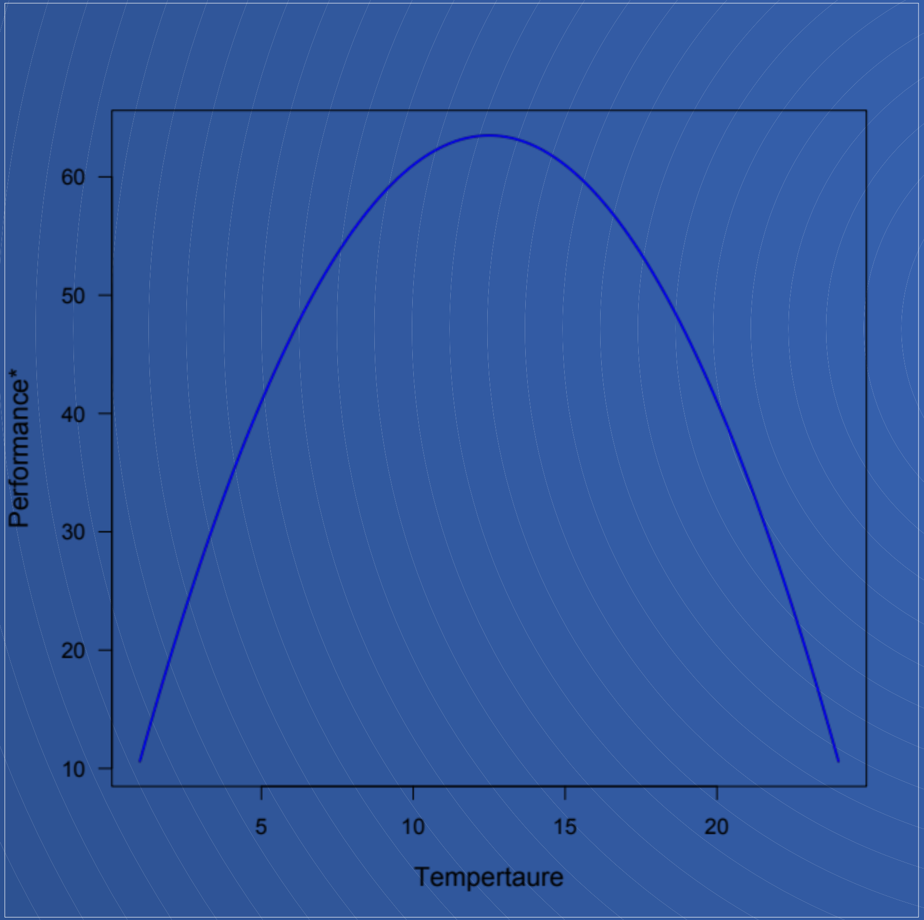
Modeling a climate niche



*Performance could be measured as:

- Population growth rate
- Productivity
- Fitness
- Abundance
- Occurrence

So all we need to do is to model performance as a function of climate.
-> what would the R code look like to model the relationship on the left?

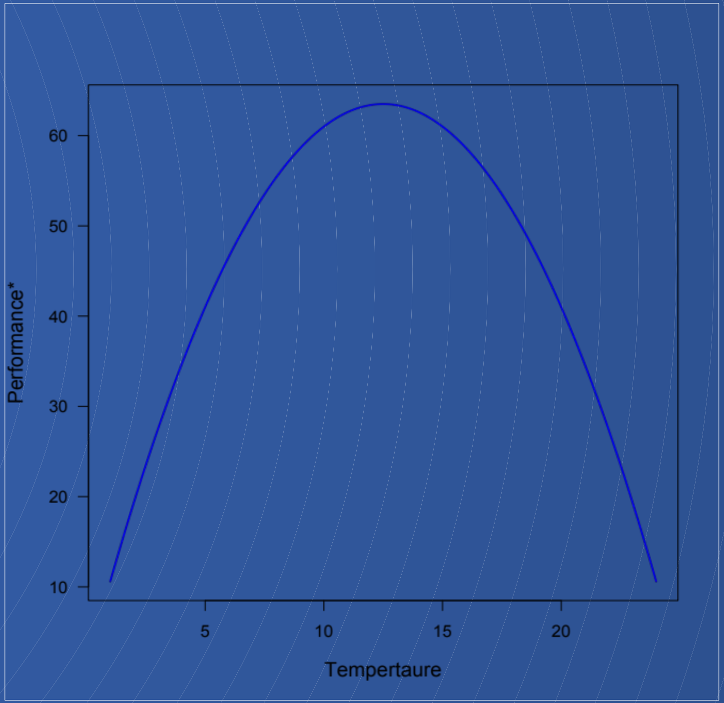
```
model<-lm(performance~temperature+I(temperature^2))
```

The basic premise of forecasting using a correlative species distribution model
(aka: environmental niche model, habitat modeling etc.)

1. **Spatial model**: Construct a model of how spatial (i.e. across grid cells) variation in multiple climate variables predict spatial variation in species performance (usually occurrence, can be abundance).

2. **Climate projection:** Obtain projections of how the climate variables change under a future scenario.

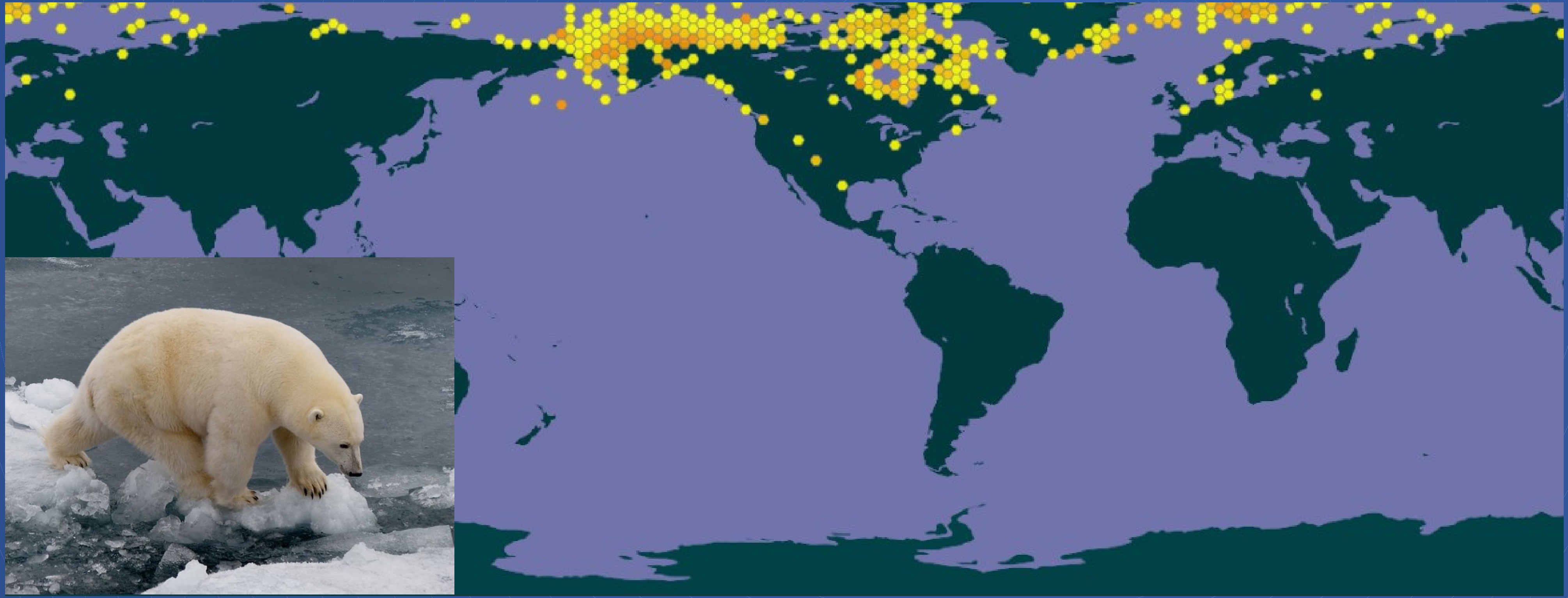
3. **Temporal Prediction** of the future climate suitability (performance) of each grid cell under future conditions (& consider the ability of the species to reach that location).

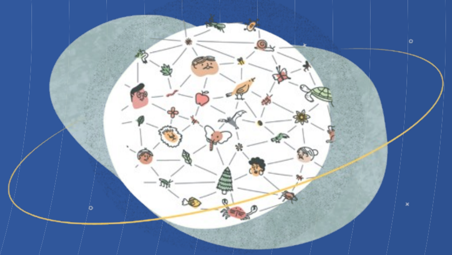


For an excellent introduction see:
Elith and Leathwick (2009) Annual Reviews Ecol. Evol. Syst. 40:677

Species distribution modeling step-by-step

1. Gridded data on species (or population) occurrence





https://www.gbif.org/

Considerations?

-> Decide on a grid cell size

-> Does the dataset include absences or just presences?

Species distribution modeling step-by-step

2. Gridded data on climate variables

- WORLDCLIM: https://www.worldclim.org/data/bioclim.html

Historical climate data

This is WorldClim version 2.1 climate data for 1970-2000. This version was released in January 2020.

There are monthly climate data for minimum, mean, and maximum temperature, precipitation, solar radiation, wind speed, water vapor pressure, and for total precipitation. There are also 19 “bioclimatic” variables.

The data is available at the four spatial resolutions, between 30 seconds (~1 km2) to 10 minutes (~340 km2). Each download is a “zip” file containing 12 GeoTiff (.tif) files, one for each month of the year (January is 1; December is 12).

variable	10 minutes	5 minutes	2.5 minutes	30 seconds
minimum temperature (°C)	tmin 10m	tmin 5m	tmin 2.5m	tmin 30s
maximum temperature (°C)	tmax 10m	tmax 5m	tmax 2.5m	tmax 30s

Fick, S.E. and R.J. Hijmans, 2017. WorldClim 2: new 1km spatial resolution climate surfaces for global land areas.
International Journal of Climatology 37 (12): 4302-4315
.

-> Interpolated from data collected by climate stations (plus some satellite data where weather stations are few)

- https://crudata.uea.ac.uk/cru/data/hrg/

label	variable	units
cld	cloud cover	percentage (%)
dtr	diurnal temperature range	degrees Celsius
frs	frost day frequency	days
pet	potential evapotranspiration	millimetres per day
pre	precipitation	millimetres per month
rhm	relative humidity	percentage (%)
ssh	sunshine duration	hours
tmp	monthly average daily mean temperature	degrees Celsius
tmn	monthly average daily minimum temperature	degrees Celsius
tmx	monthly average daily maximum temperature	degrees Celsius
vap	vapour pressure	hectopascals (hPa)
wet	wet day frequency	days
wnd	wind speed	metres per second (m/s)

-> Interpolated from data collected by climate stations
-> Monthly means at a 0.5 degree scale.

Considerations? -> Which types of variables to include in the model?
-> Which seasons or times of year?

Species distribution modeling step-by-step

3a. Build a model of climate as a predictor of species presence and **absence**

- A straightforward approach is to use a GLM with binomial family errors.
- Climate variables included as linear or quadratic (or cubic) terms. Potential to include interactions between terms.

```
model<-glm(presabs~clim1+I(clim1^2)+clim2+I(clim2^2),family="binomial")
```

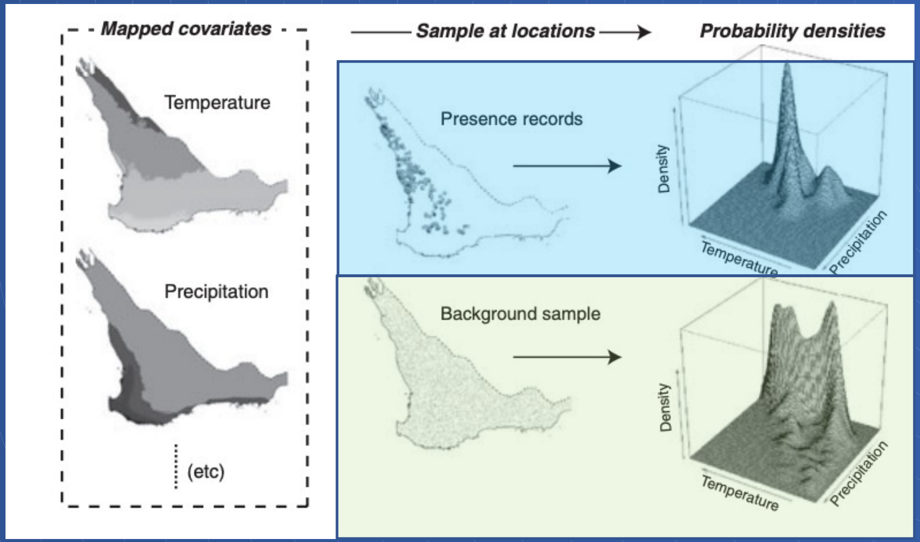
- Other popular methods include general additive models (GAMS) and machine learning

Considerations? -> Do we include statistical interactions?
-> What shape of relationship between climate variable and abundance to model?
-> What modeling approach to take?

Species distribution modeling step-by-step

3b. Build a model of climate as a predictor of species presence

MaxEnt: A very popular method that uses machine learning



Probability of species presence conditioned on environment (z)

Probability density of covariates where species is present

Probability density of covariates in background data

$$\Pr(y = 1 \mid \mathbf{z}) = f_1(\mathbf{z}) \Pr(y = 1) / f(\mathbf{z})$$

Prevalence = proportion of occupied sites in the landscape

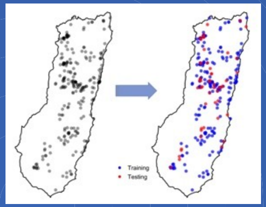
Considerations: Application of this method requires the ecologist to carefully define the landscape of interest across which the background sample is generated.

This paper gives an excellent explanation of how Maxent works: Elith, J., Phillips, S.J., Hastie, T., Dudík, M., Chee, Y.E. and Yates, C.J., 2011. A statistical explanation of MaxEnt for ecologists. *Diversity and distributions*, *17*(1), pp.43-57.

Species distribution modeling step-by-step

4. Model evaluation: Spatial cross-validation (using AUC)

i. Divide a region up into a training and testing samples

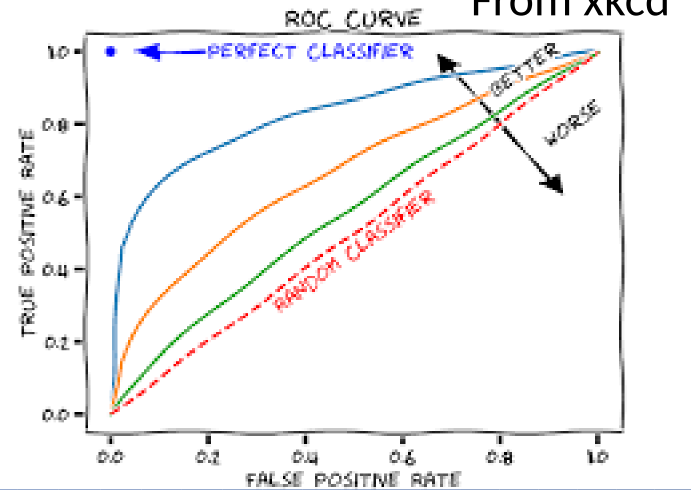


ii. Generate the receiver operator characteristic (ROC) by considering different probability thresholds and calculating sensitivity and 1-specificity.

iii. A larger area under curve (AUC) corresponds to more accurate prediction

iv. Often repeat this process many times with random subdivisions of data into training and testing

Sensitivity: where the species is found and is correctly predicted to be



From xkcd

1- specificity = where the species isn’t found, but is incorrectly predicted to be

Considerations?

-> How to divide data into training and testing datasets?
-> What metric to use to evaluate performance? (AUC is just one option)
-> What counts as good performance?

ROC walk through

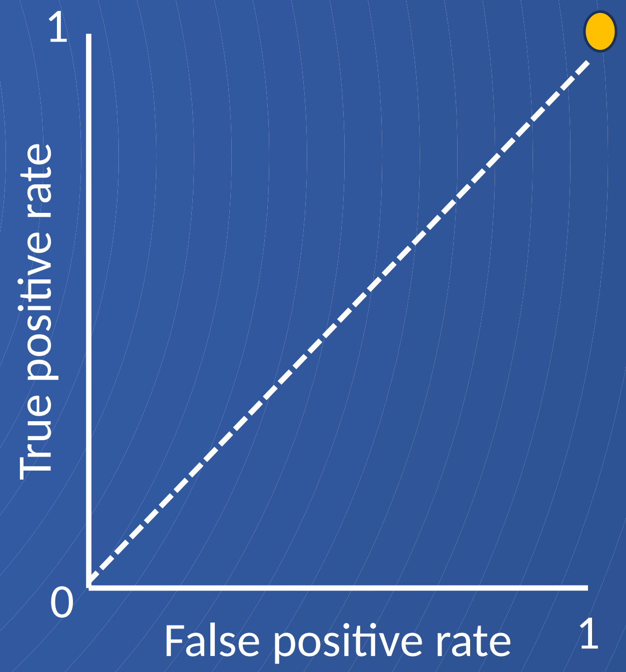
1. Threshold = 0
- False positive = 9/9 = 1
- True positive rate = 7/7 = 1

Presence/absence data

1	0	1	1
1	1	1	0
0	0	0	0
1	0	0	0

Predicted probability

0.4	0.4	0.3	0.9
0.6	0.5	0.4	0.4
0.2	0.1	0.1	0.2
0.2	0.1	0.1	0.2



ROC walk through

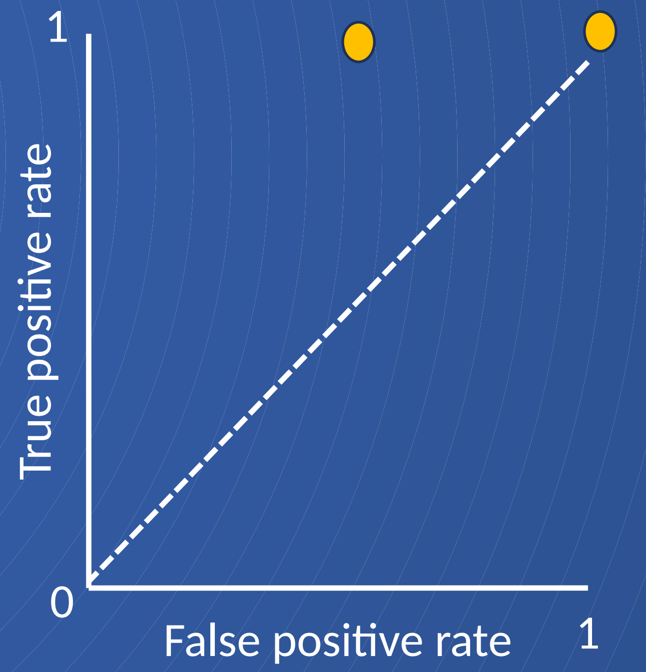
2. Threshold = 0.2
- False positive = 5/9 = 0.56
- True positive rate = 7/7 = 1

Presence/absence data

1	0	1	1
1	1	1	0
0	0	0	0
1	0	0	0

Predicted probability

0.4	0.4	0.3	0.9
0.6	0.5	0.4	0.4
0.2	0.1	0.1	0.2
0.2	0.1	0.1	0.2



ROC walk through

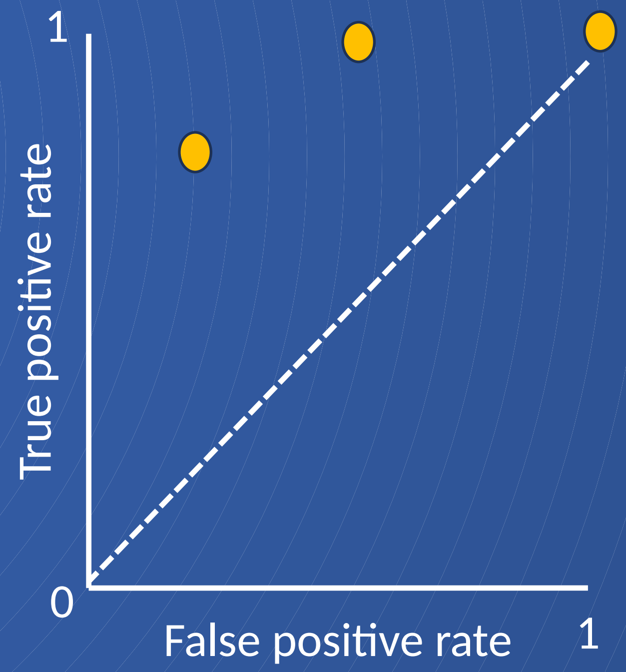
3. Threshold = 0.3
- False positive = 2/9 = 0.22
- True positive rate = 6/7 = 0.85

Presence/absence data

1	0	1	1
1	1	1	0
0	0	0	0
1	0	0	0

Predicted probability

0.4	0.4	0.3	0.9
0.6	0.5	0.4	0.4
0.2	0.1	0.1	0.2
0.2	0.1	0.1	0.2



ROC walk through

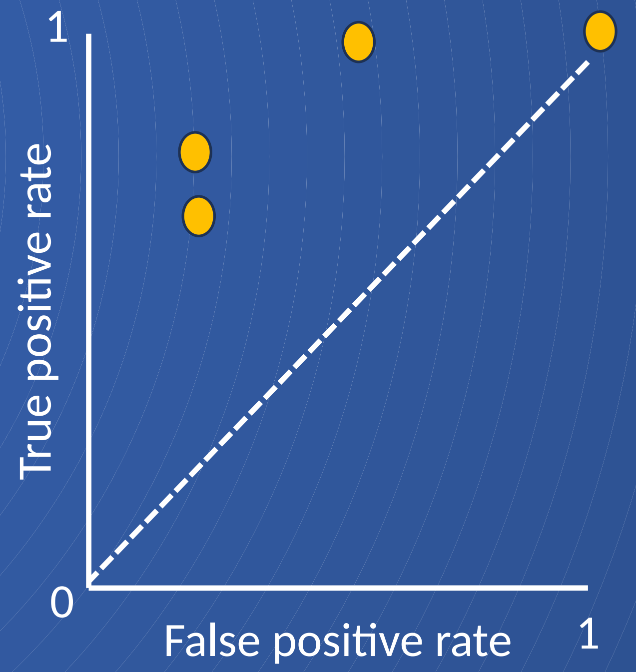
4. Threshold = 0.4
- False positive = 2/9 = 0.22
- True positive rate = 5/7 = 0.71

Presence/absence data

1	0	1	1
1	1	1	0
0	0	0	0
1	0	0	0

Predicted probability

0.4	0.4	0.3	0.9
0.6	0.5	0.4	0.4
0.2	0.1	0.1	0.2
0.2	0.1	0.1	0.2



ROC walk through

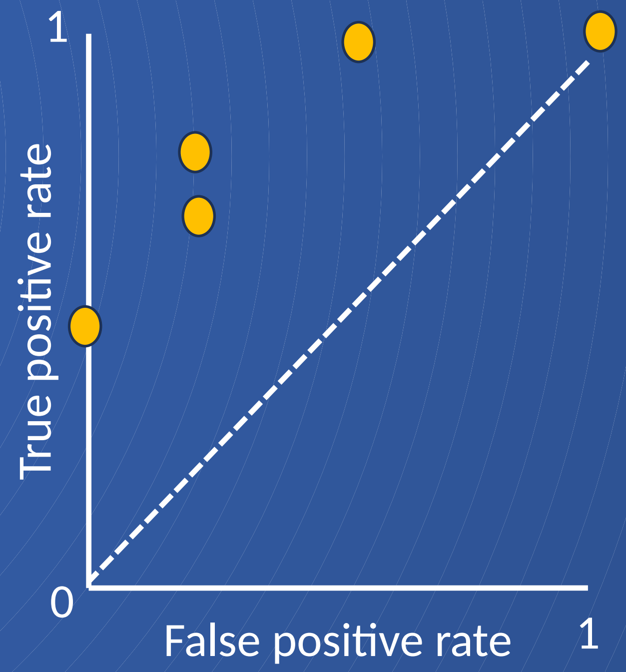
5. Threshold = 0.5
- False positive = 0/9 = 0
- True positive rate = 3/7 = 0.42

Presence/absence data

1	0	1	1
1	1	1	0
0	0	0	0
1	0	0	0

Predicted probability

0.4	0.4	0.3	0.9
0.6	0.5	0.4	0.4
0.2	0.1	0.1	0.2
0.2	0.1	0.1	0.2

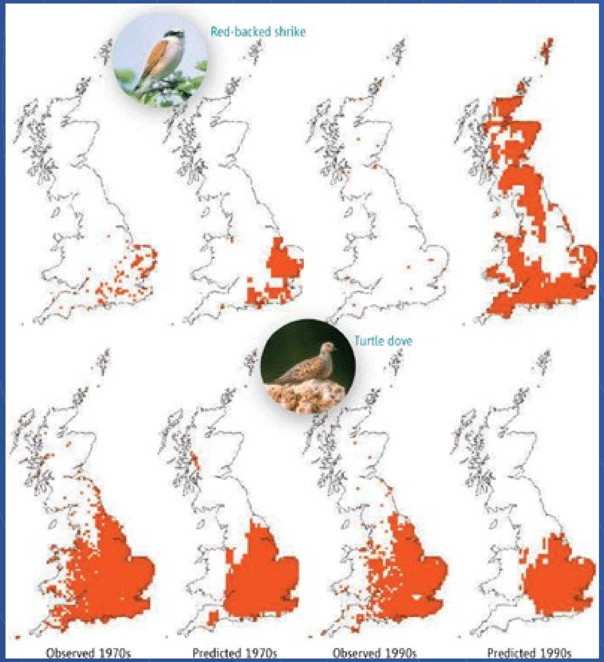


Species distribution modeling step-by-step

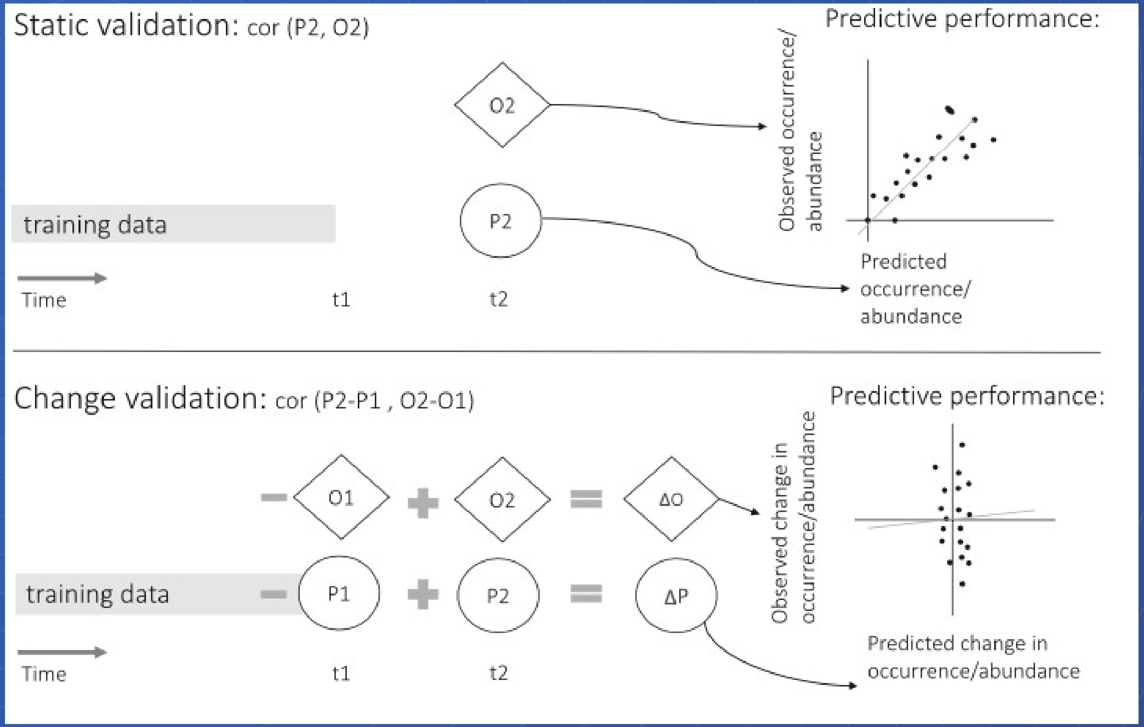
4. Model evaluation: Temporal validation

Requires spatial data on presence/absence for at least two time points

O = occurrence
P = Prediction



Araujo & Rahbek 2006 Science 313: 5972

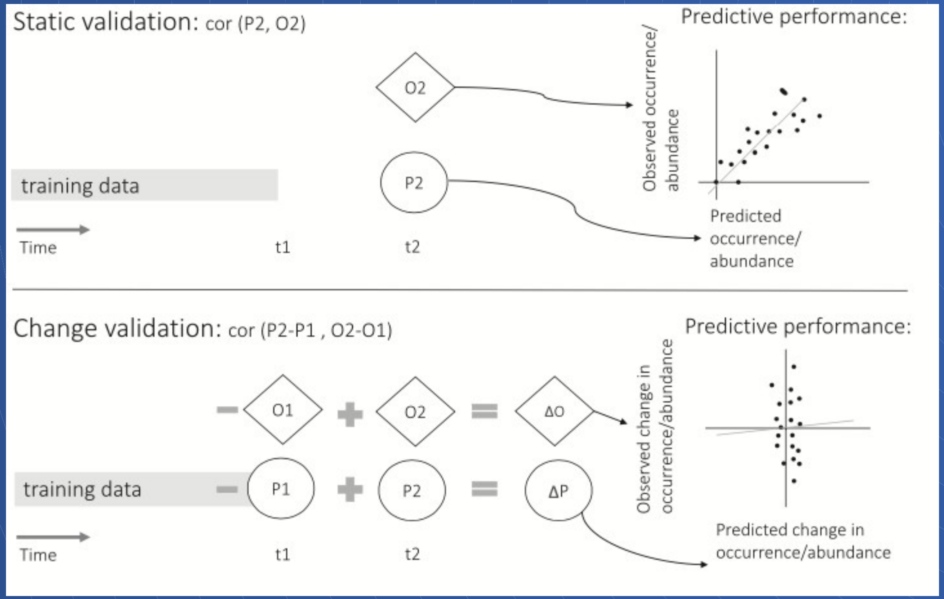


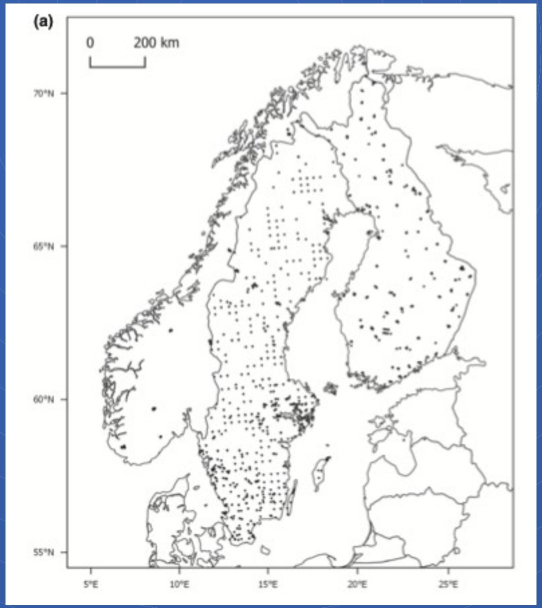
Piirainen et al. 2023 Diversity and Distribution 29: 654

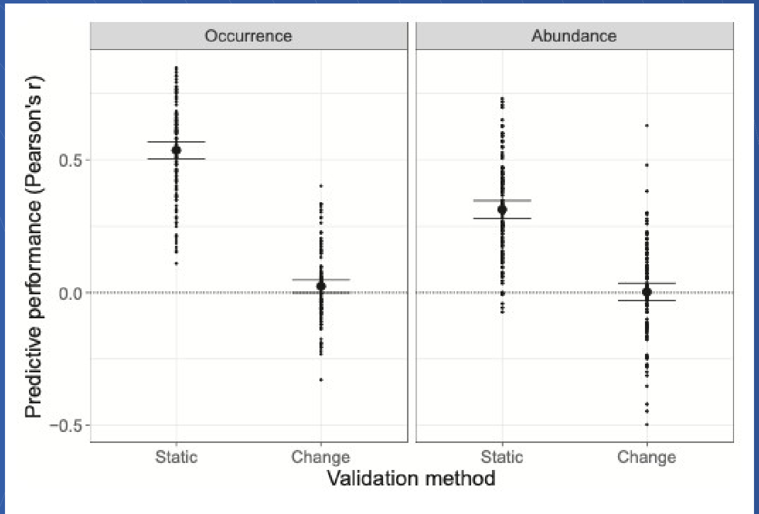
Species distribution modeling step-by-step

4. Model evaluation: Temporal validation

Requires spatial data on presence/absence for at least two time points







Take home:
Across > 100 species the models did a good job of predicting where a species would be.
But a very poor job of predicting the bits of a range that would change

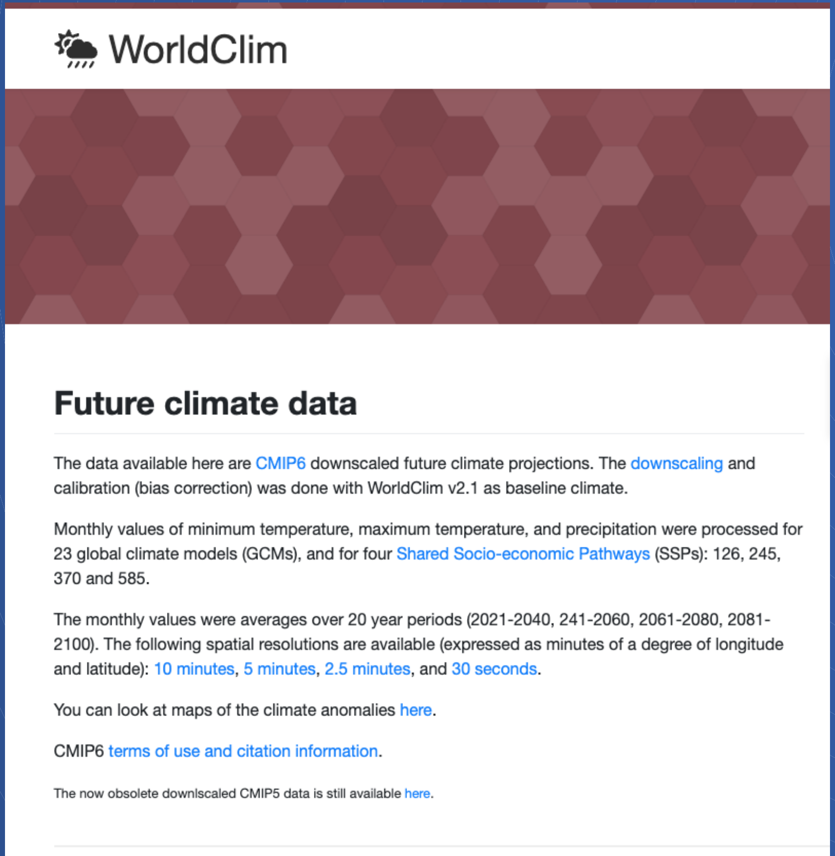
Bird survey data from 1975-1999 = training, 2013-2016 = testing

Piirainen et al. 2023 Diversity and Distribution 29: 654

Species distribution modeling step-by-step

5. Project future distribution

Require projections of future spatial variation in climate for all predictor variables


WorldClim

Future climate data

The data available here are CMIP6 downscaled future climate projections. The downscaling and calibration (bias correction) was done with WorldClim v2.1 as baseline climate.

Monthly values of minimum temperature, maximum temperature, and precipitation were processed for 23 global climate models (GCMs), and for four Shared Socio-economic Pathways (SSPs): 126, 245, 370 and 585.

The monthly values were averages over 20 year periods (2021-2040, 241-2060, 2061-2080, 2081-2100). The following spatial resolutions are available (expressed as minutes of a degree of longitude and latitude): 10 minutes, 5 minutes, 2.5 minutes, and 30 seconds.

You can look at maps of the climate anomalies here.

CMIP6 terms of use and citation information.

The now obsolete downlscaled CMIP5 data is still available here.

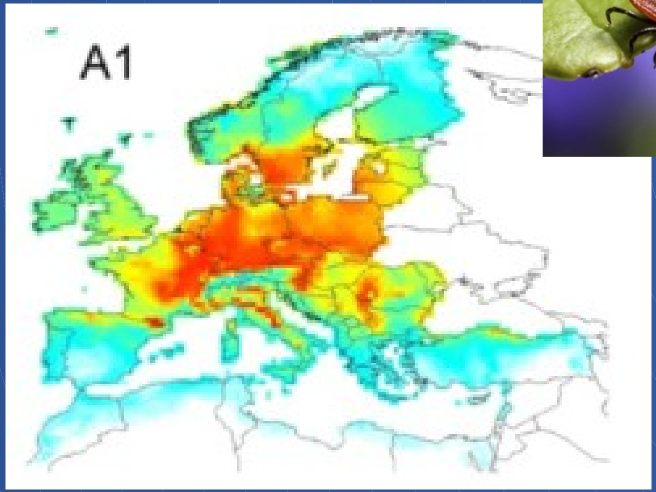
Considerations?

-> How far in the future?
-> Which SSP (shared socioeconomic pathway)?
-> Which model?

Species distribution modeling step-by-step

5. Project future distribution

Project future climate suitability



Ixodes ricnus

Considerations?

-> Can the species reach the suitable climate?
-> How does the modelled probability of occurrence translate into actual occurrences?

Williams, et al. 2015. *Parasites & vectors*, *8*(1) 1.

Applications: Future extinction

- Analysis across 5527 amphibian species.
- Compares baseline period (1980) to future (2080)
- Considers 3 major threats:
  (1) Loss of range by climate change
  (2) Overlap of range with *Batrachochytrium dendrobatidis* (also modelled with SDM)
  (3) Land-use change

SDM details

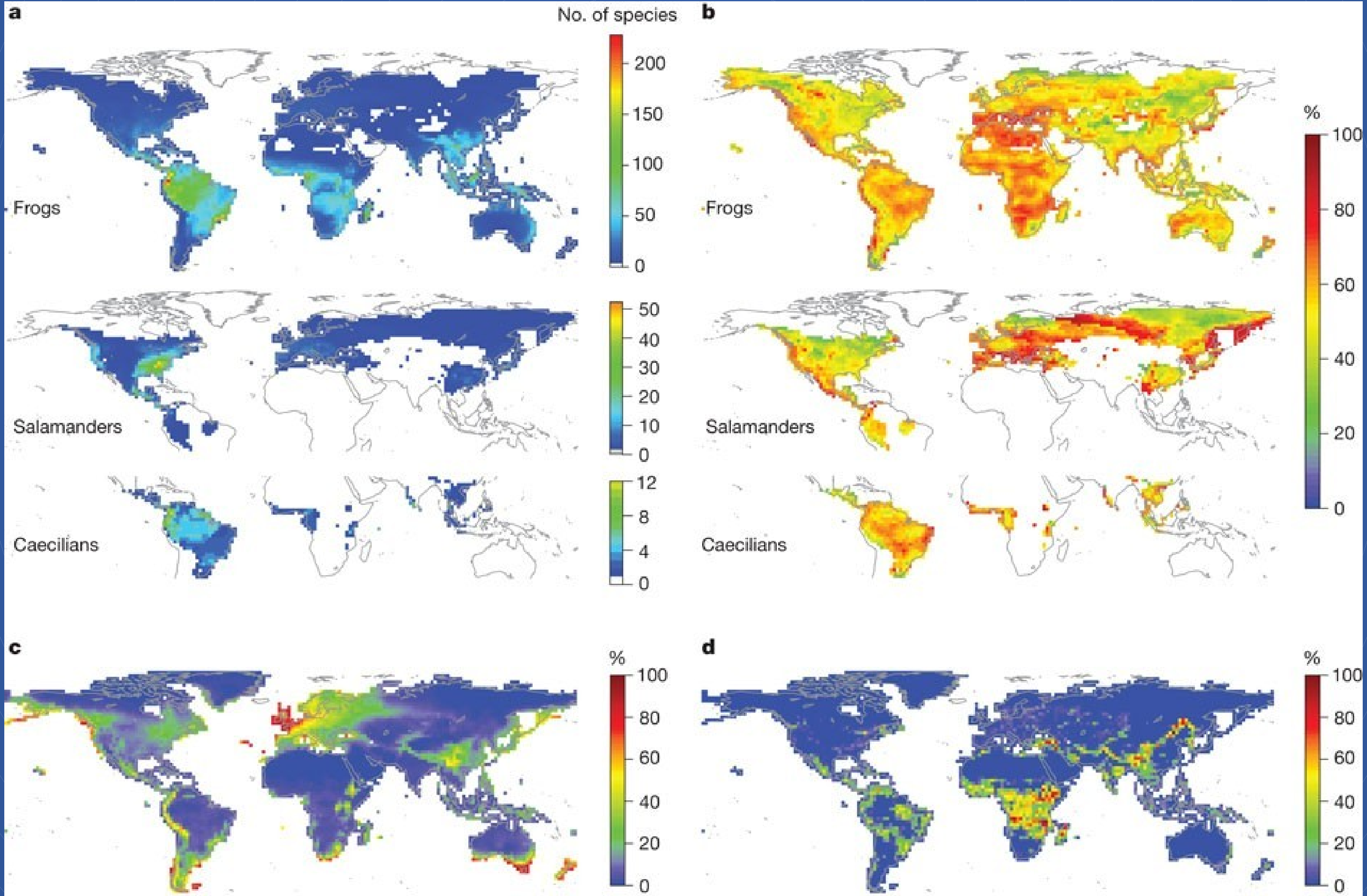
- For each species they ran 3 modelling algorithms x 14 climate models x 3 emissions scenarios x 2 time periods ("Ensemble forecasting")

- Calculated the change in future suitability of locations within the current range of each species (i.e did not allow dispersal beyond range)

Hof, et al. 2011. *Nature 480: 516*

Applications: Future extinction

A = species richness



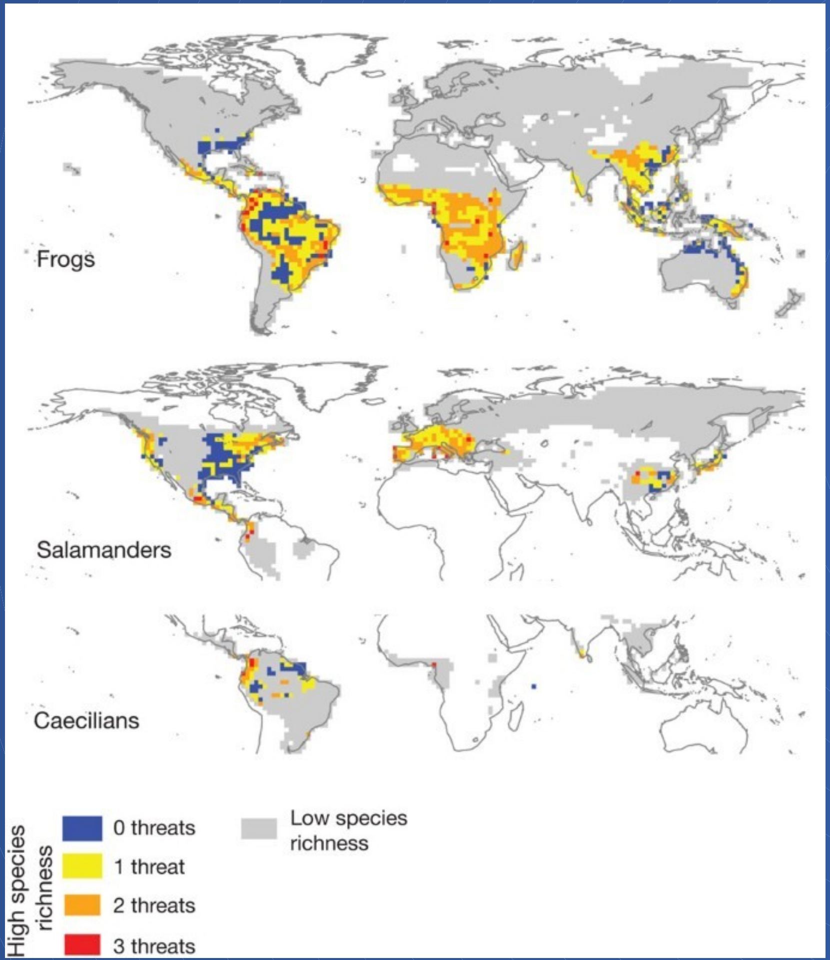
B = Proportion of species predicted to lose climate suitability in 2080

C = Probability of chytrid fungus in 2080

D = % of land that will change from natural to anthropogenic use

Hof, et al. 2011. *Nature 480: 516*

Applications: Future extinction



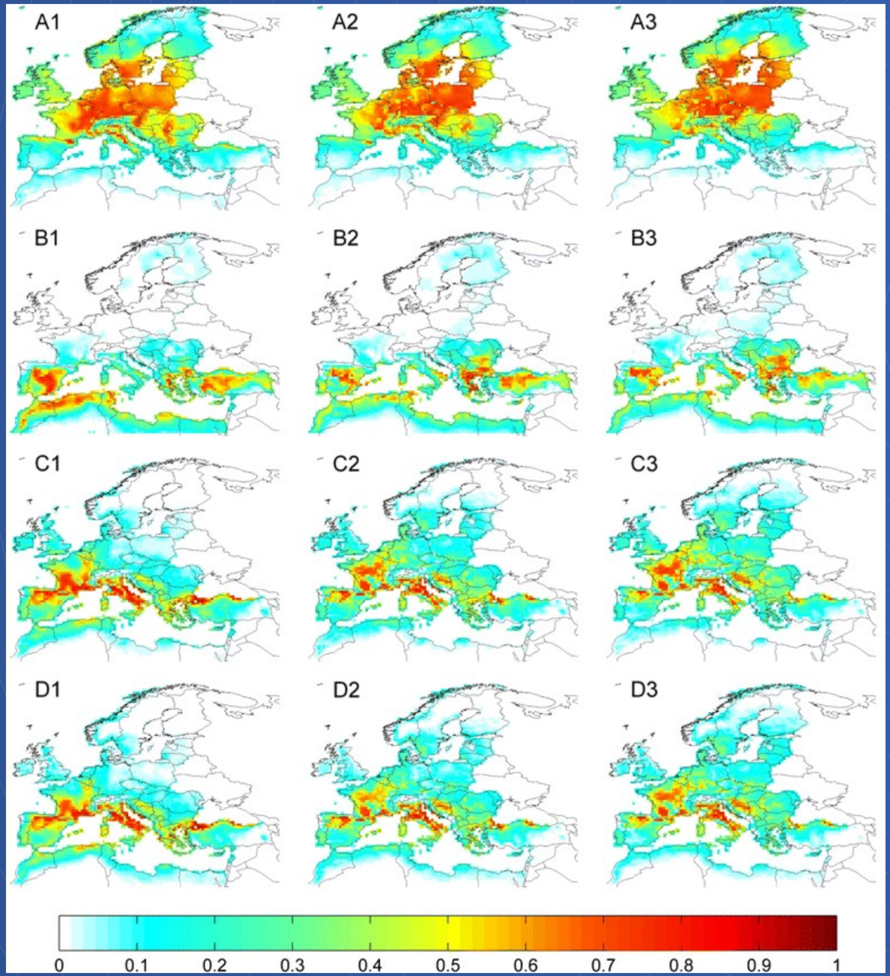
Take home message:
Some regions and some species are especially exposed to multiple threats

Hof, et al. 2011. *Nature 480: 516*

Applications: Parasites and vectors

2010 2050 2098

4 tick species (A –D)



Climate suitability

Context

Tick borne diseases a serious problem for animal and human health (e.g., lyme disease, encephalitis)

Methods

- MaxEnt for modeling
- Future projections based on RCP 4.5 (40 year averages centred on 3 different periods)

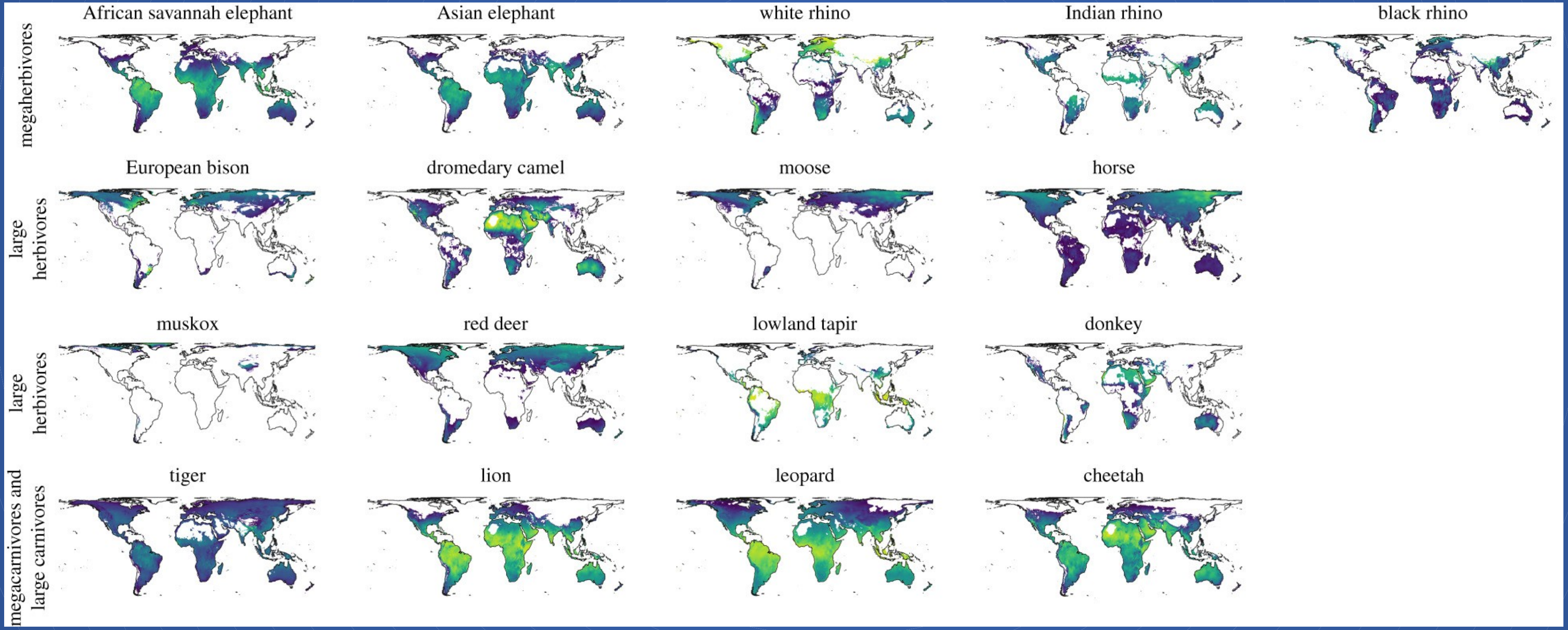
Conclusions

- Climate predicts distributions and on the basis of changing climate they project a northward shift

Williams, et al. 2015. *Parasites & vectors*, *8*(1) 1.

Applications: Trophic rewilding candidates

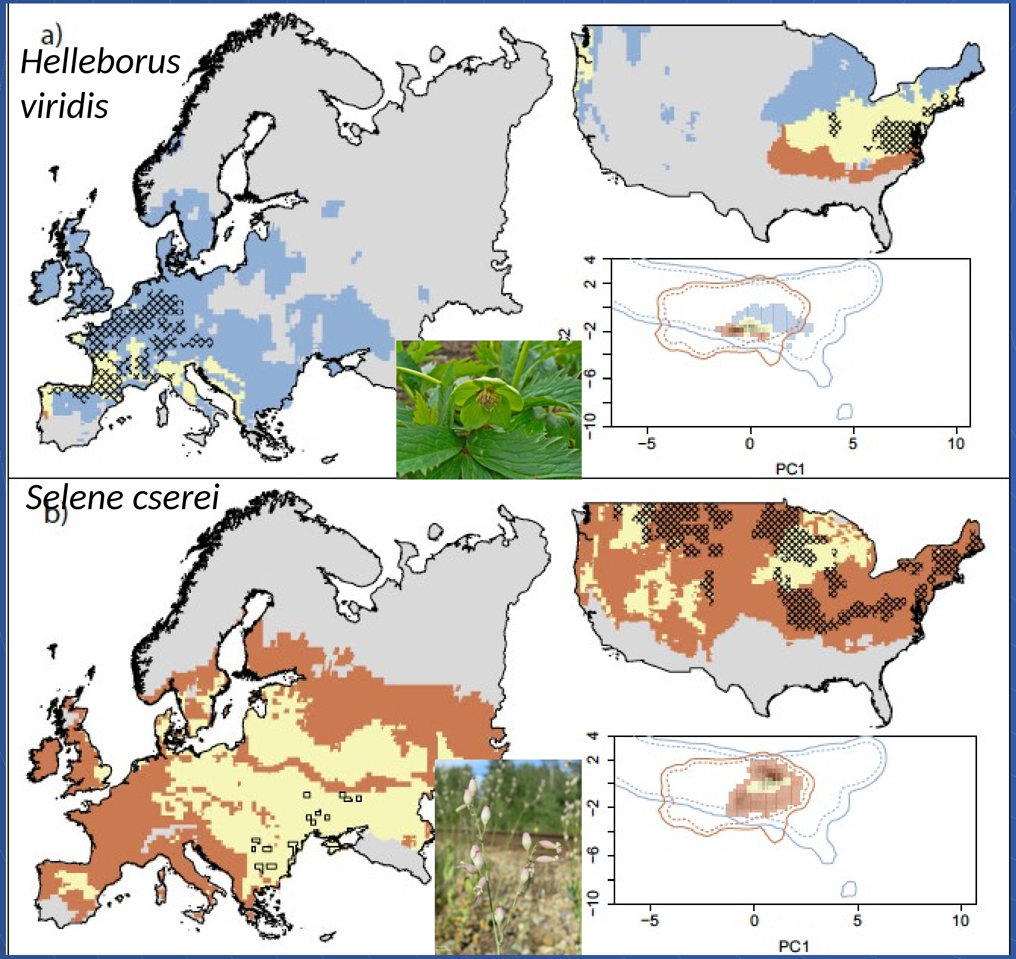
Predicted climate suitability for 2070 under RCP 8.5



Concludes that climate change will not impact negatively on the potential of these species to be used for trophic rewilding

Jarvie & Svenning (2018) Proc R Soc 373

Applications: predicting invasion success?



Key

Hatched shading: where species is found

Blue: climate suitability based on native range

Orange: climate suitability based on US range

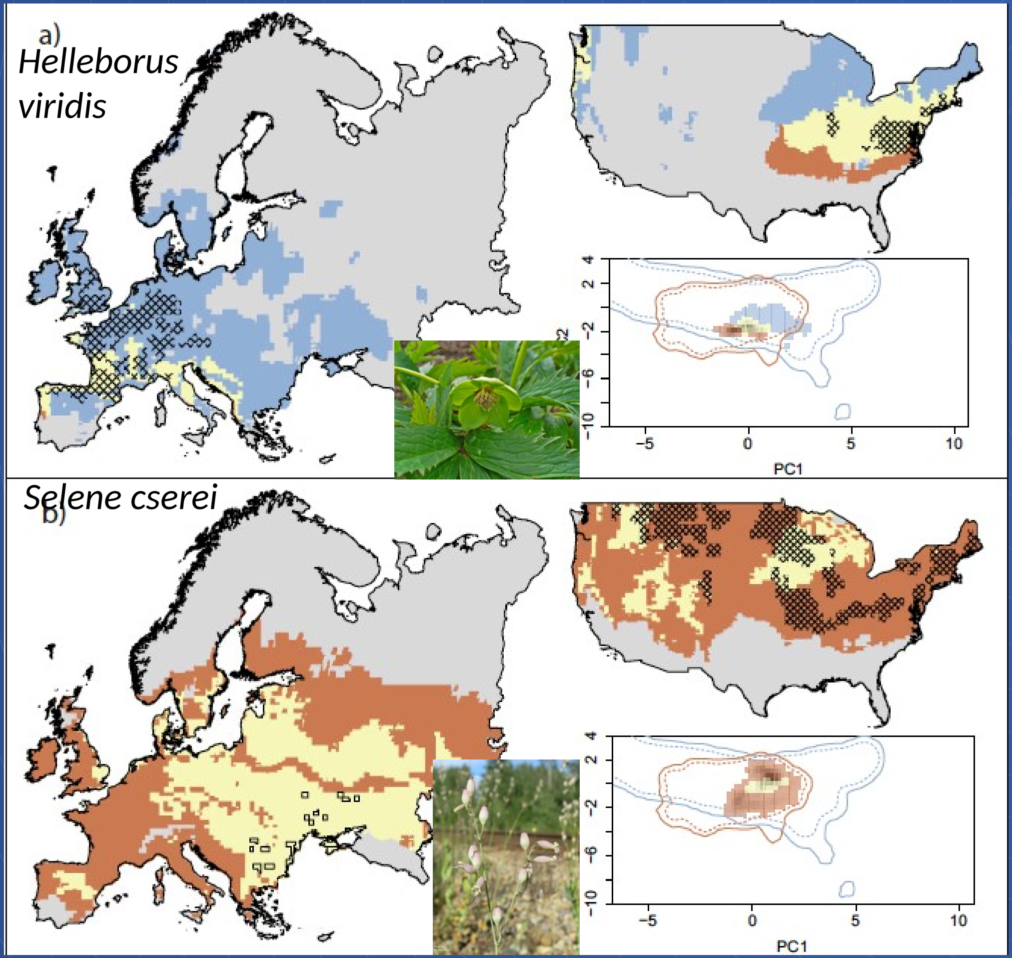
Yellow: based on both

Native range disequilibrium?

Range expansion during invasion?

Early and Sax (2014) *Global Ecology Biogeography*

Applications: predicting invasion success?



Key

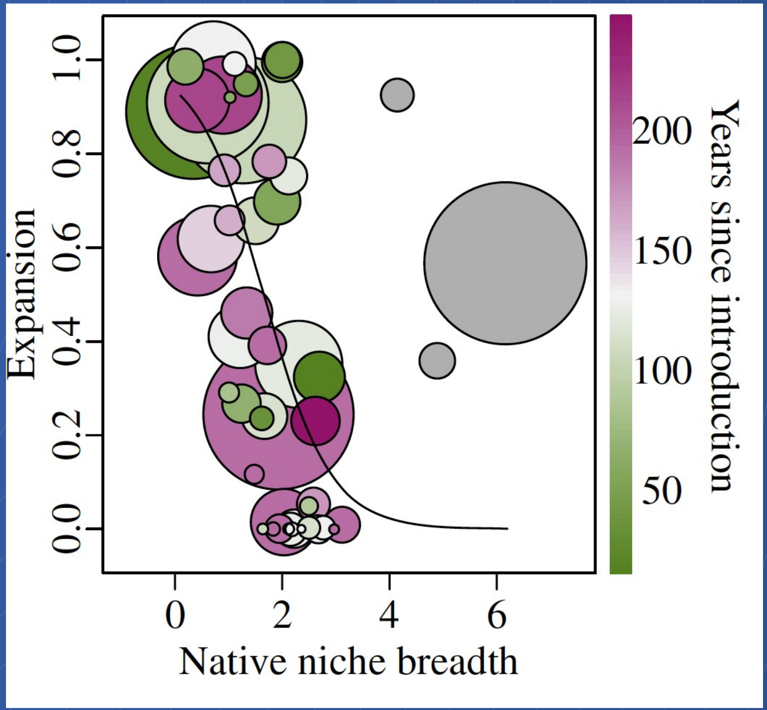
Hatched shading: where species is found

Blue: climate suitability based on native range

Orange: climate suitability based on US range

Yellow: based on both

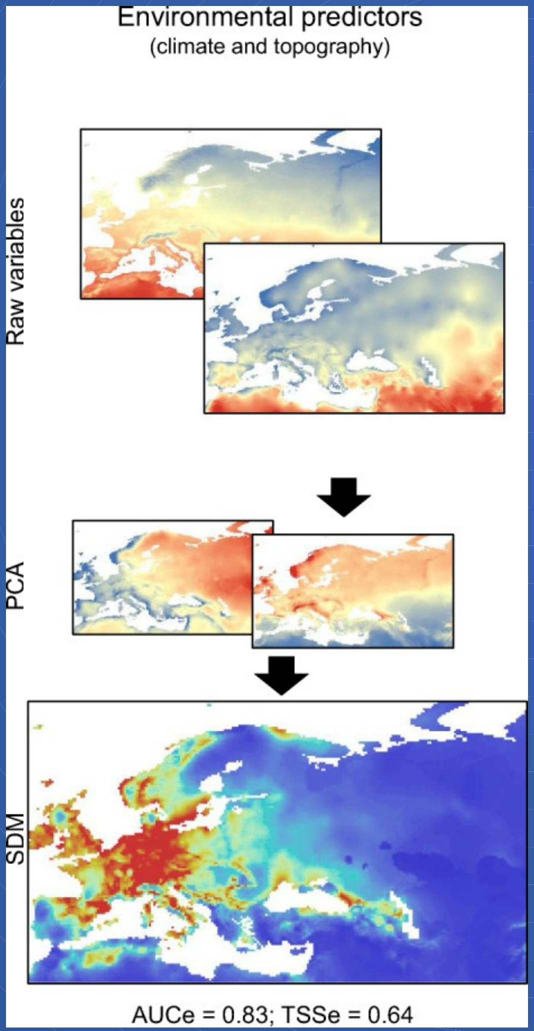
Analysis across 51 species



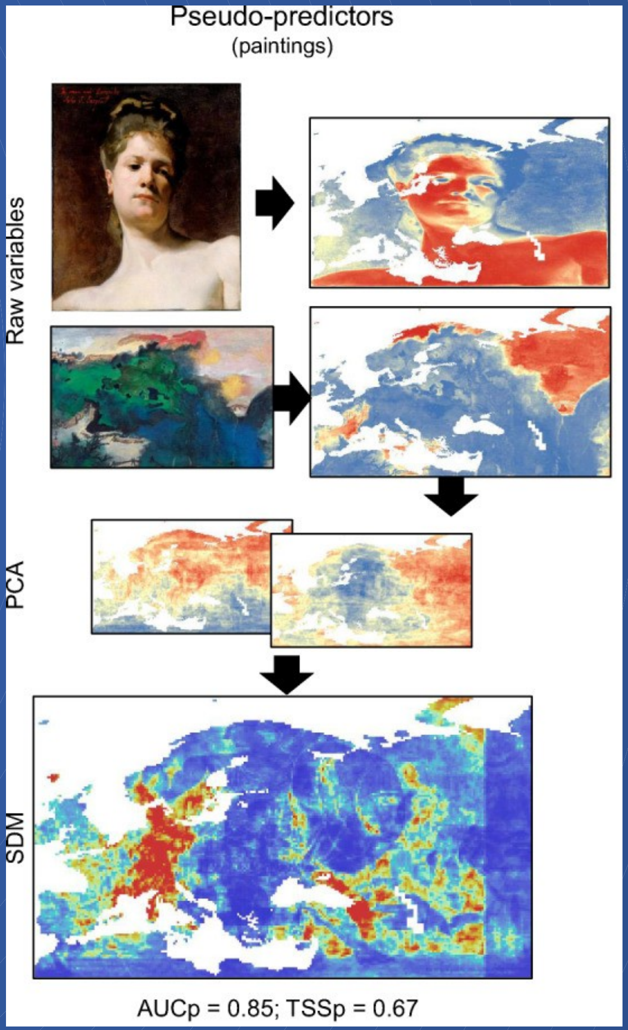
Early and Sax (2014) *Global Ecology Biogeography*

Criticisms of SDMs: Can a painting predict a species distribution?

- 497 red listed species in Europe from GBIF
- Worlclim full set of 19 predictors
- Used principal component analysis of predictors to avoid colinear predictors
- Method = MAXENT (allowing for interactions and hinge and quadratic effects of variables)
- Used cross validation to test predictive performance

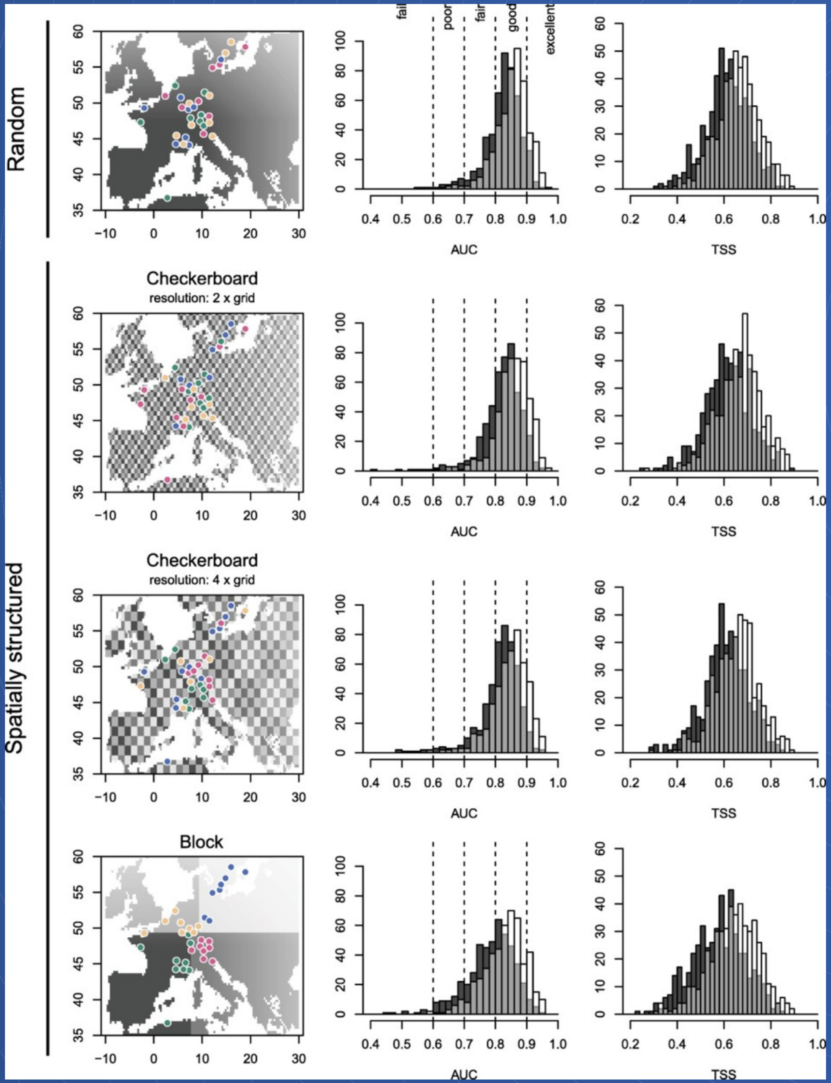


- Same species
- 20 pseudo-predictors generated from paintings
- Cropped paintings to Europe coastline
- Method = as before

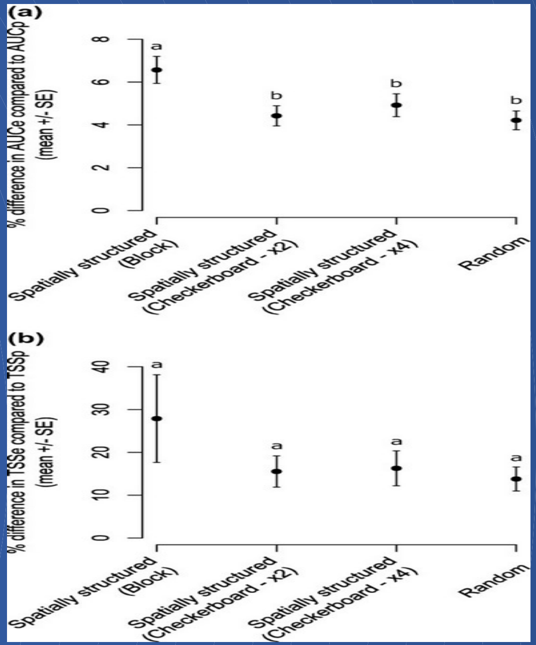


Forcade et al. 2017 GEB 27: 245

Criticisms of SDMs: Can a painting predict a species distribution?



Dark grey = paintings
Light gray = overlap
White = environmental variables



Take homes
-> Often pseudo-predictors from a painting led to predictions that would be classified as good or excellent.
-> Sometimes painting outperformed real climate data
-> The courser the resolution of the cross validation the bigger the difference between the two predictor types

Forcade et al. 2017 GEB 27: 245

Criticisms of correlative SDMs

- Biology

  Decisions we make in modeling that fail to capture important aspects of species biology

- Statistics

  Statistical assumptions we violate

- Projection

  Issues that arise when we forecast future distributions.

Criticisms of SDMs: Biology

- Realised climate niche may be much smaller than the fundamental climate niche
    - Species interactions may be important limiting factors
    - Barriers to dispersal

- True causal drivers may not be included - often just crude climate data (e.g., minimum winter temperature).

- The grain size used for analyses may be inappropriate, e.g., populations may use microclimate - this may allow populations to “hang-on” locally.

- Different populations of a single species may be **locally adapted** and respond to different drivers.

Dormann (2007) *Basic & Applied Ecology,* 387

Criticisms of SDMs: Statistics

- There is little information in presence/absence data (1/0). Data on abundance is less often used, but much more informative.

- Spatial autocorrelation (non-independence) is usually ignored. This tricks us into thinking correlations are more statstically significant than they really are, and we are more confident than we should be.

- For species with small ranges we have little data. As a result, models may be too simple and fail to capture their climatic niche (e.g., as we saw with Early and Sax)

- Environmental variables are often highly correlated in space, which makes it tricky to identify and estimate the effect that the true driver has on species presence/absence.

- Model validation often uses spatial data that are not independent. Very rarely are predictions validated over time (i.e. most validation is in space)

Dormann (2007) *Basic & Applied Ecology,* 387

Criticisms of SDMs: Projection

- Assumes space can substitute for time, which may not be true at least in the short term, e.g., populations may take a long time to adapt or migrate.

- Projection may involve no-analogue climates – extrapolations are less reliable than interpolations.

- Projections of change are themselves highly uncertain – especially in terms of future spatial variation.

- Projections often made for the distant future and not on a short-term horizon that would allow for more validation.

Dormann (2007) *Basic & Applied Ecology*, 387

“Projections of species distributions are not merely generating hypotheses to be tested by later data. They are presented as predictions of tomorrow’s diversity and policy makers and the public will interpret them as forecasts, similar to forecasts of tomorrow’s weather.”

Dormann (2007)

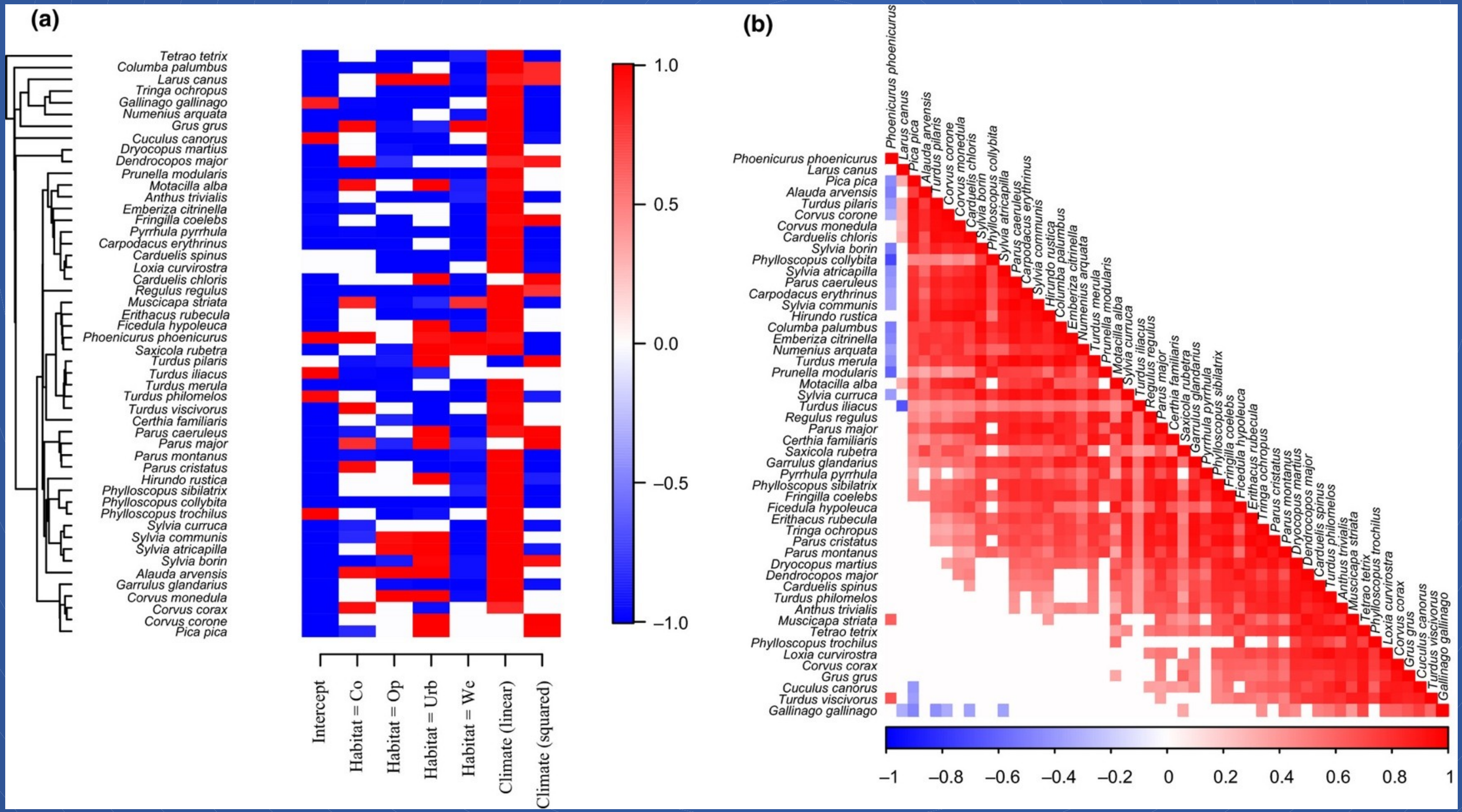
Ending on a more optimistic note

….the next chapter for species distribution modeling

The next generation of SDMs: Joint species distribution models

- Models the covariation in occurrence probabilities between species
- So brings species interactions into the model process but in a statistical way

Analysis of Finnish birds

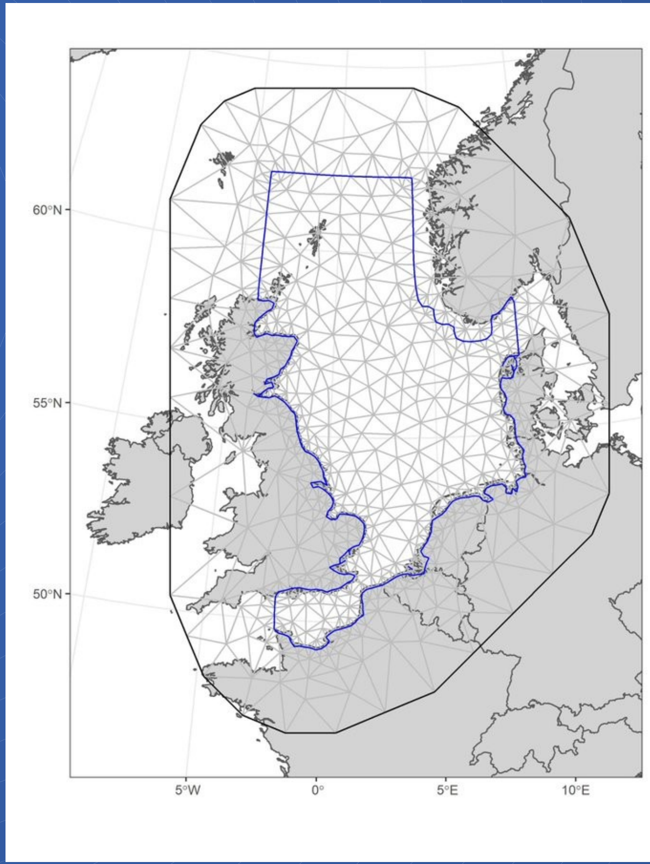


Methods for fitting such models include HMSC

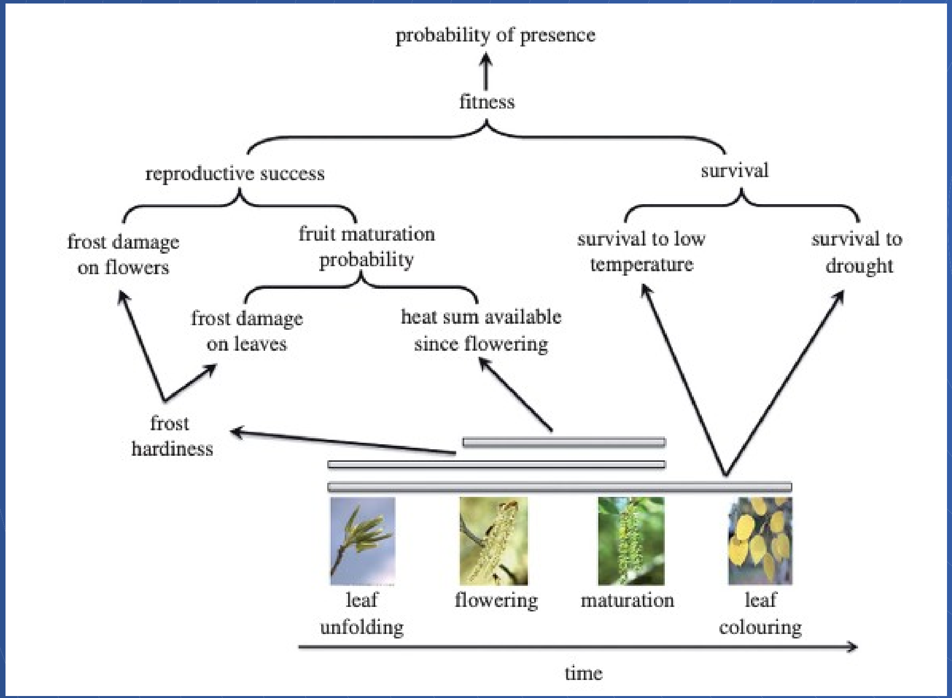
Tikhonov et al.. *MEE*, *11*(3), 442

The next generation of SDMs: Models that allow for spatial autocorrelation

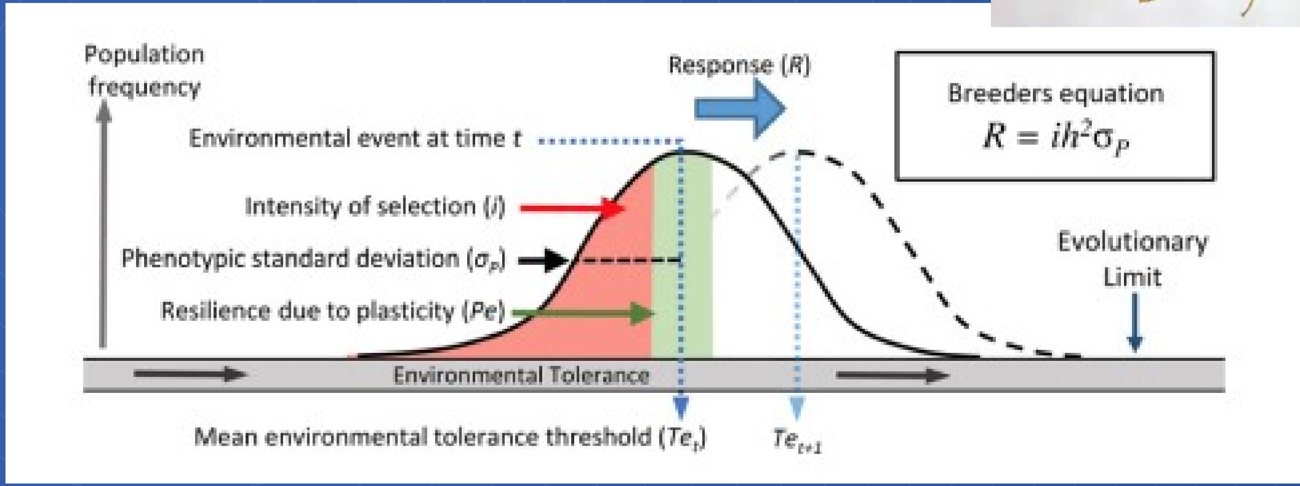
And R-INLA



The next generation of SDMs: Mechanistic (or process-based) SDMs



PHENOFIT
Chuine & Beaubien (2001) Ecology Letters



AdaptR
Bush et al. (2016) Ecology Letters

Other uses for SDMs