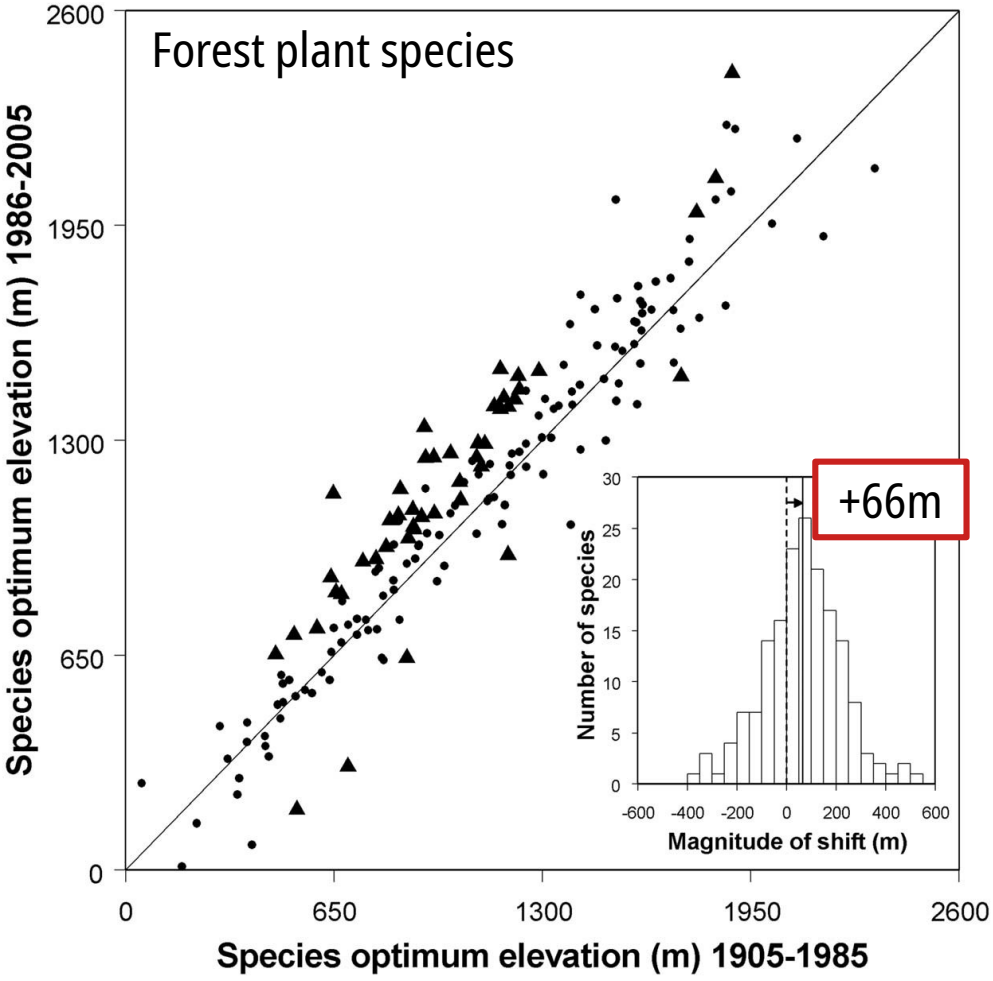
Comité de suivi individuel – 2ème année

Reliability of species distribution model projections

V. Van der Meersch, sous la direction de I. Chuine

Linogravures par C. Rescan

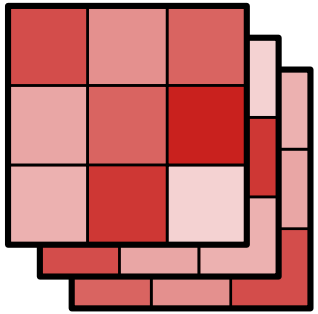
WHAT WE OBSERVE: SPECIES RANGE SHIFTS



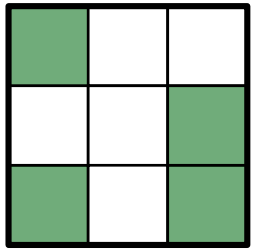
Lenoir et al. (2008)

HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Correlative niche models



Bioclimatic predictors



Current distribution

HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Correlative niche models

HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Correlative niche models

FIND PATTERNS

HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Correlative niche models

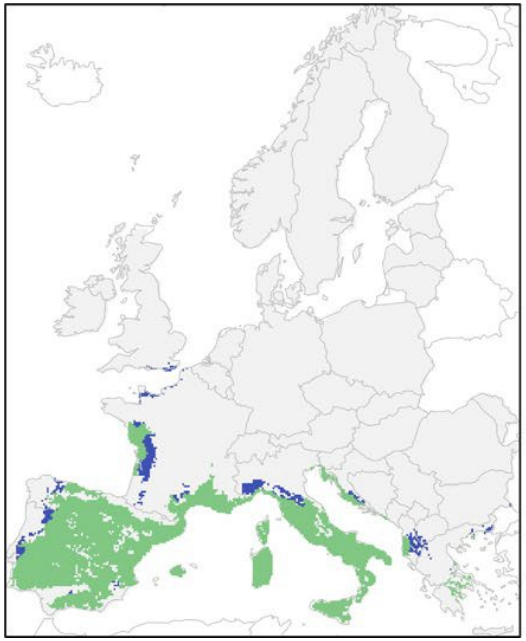
HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Correlative niche models

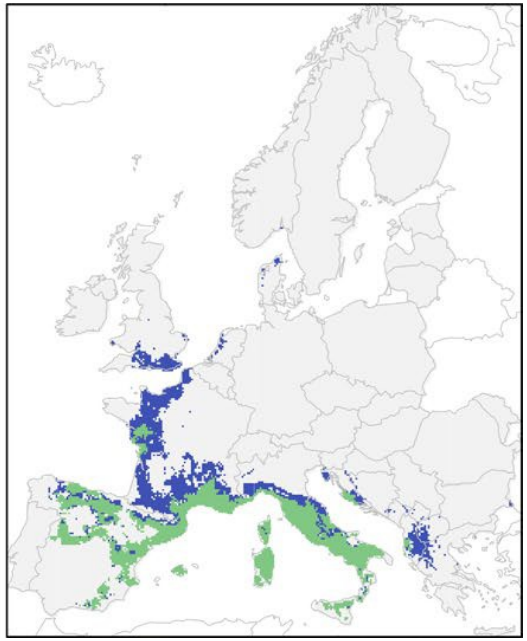
? MAIN HYPOTHESIS: CORRELATIONS HOLD TRUE

HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Example: *Quercus ilex* projected range shift



CURRENT



2095

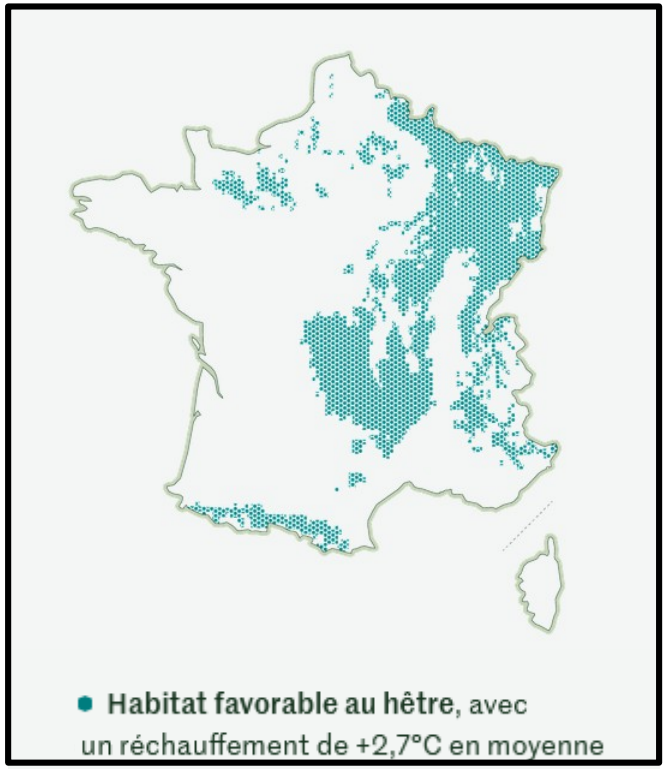
Present

Suitable

Mauri et al. (2022)

HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Example: *F. sylvatica* future distribution and mainstream media



Le Monde

"Le hêtre, victime parfaite du réchauffement climatique"

Sources: Mauri et al. (2022)

HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Key advantages

- easy handling of the models
- calibration can be envisaged for many species
- standard methods, reproducibility

HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Approach criticized: lack of biological realism?

Ecology, 101(1), 2020, e02912
© 2019 by the Ecological Society of America

Correlative climatic niche models predict real and virtual species distributions equally well

VALENTIN JOURNÉ,[1,2,4] JEAN-YVES BARNAGAUD,[3] CYRIL BERNARD,[1] PIERRE-ANDRÉ CROCHET,[1] AND XAVIER MORIN[1]

"high predictive power [...] not necessarily reflect causal relationships between climate and species distributions"

HOW WE COULD PREDICT THE FUTURE: POPULAR STATISTICAL APPROACHES

Approach criticized: lack of biological realism?

RESEARCH ARTICLE

Methods in Ecology and Evolution BRITISH ECOLOGICAL SOCIETY

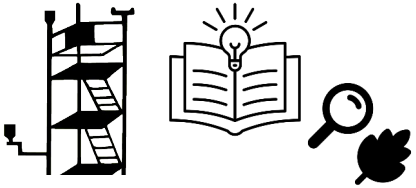
The effects of climate change on Australia's only endemic Pokémon: Measuring bias in species distribution models

Dan L. Warren[1,2] | Alex Dornburg[3] | Katerina Zapfe[3,4] | Teresa L. Iglesias[5,6]

Consistent predictions from meaningless data

HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

Process-based models, in a nutshell



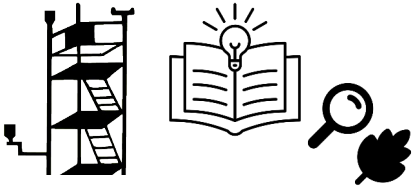
Experimentations

A priori knowledge

Observations

HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

Process-based models, in a nutshell



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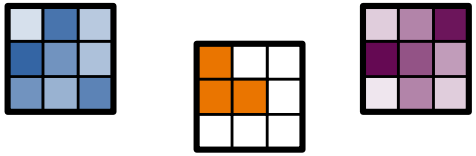

Processes

HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

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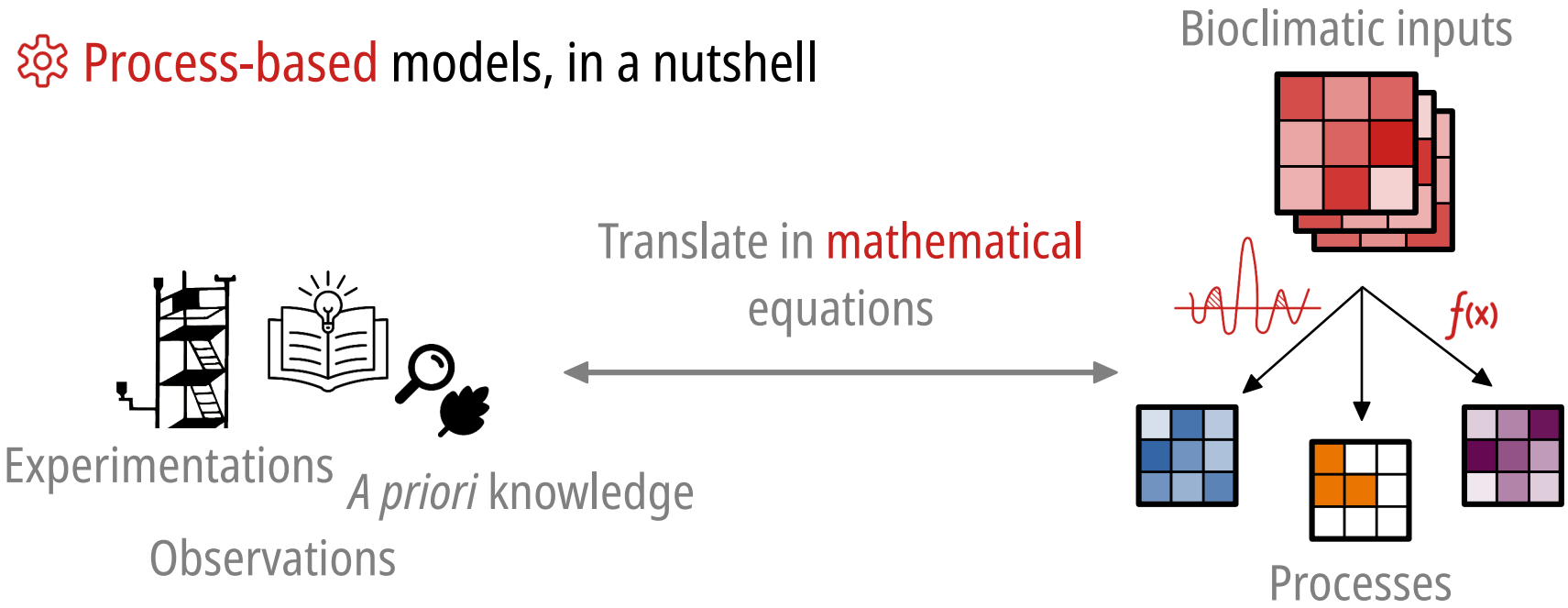

HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

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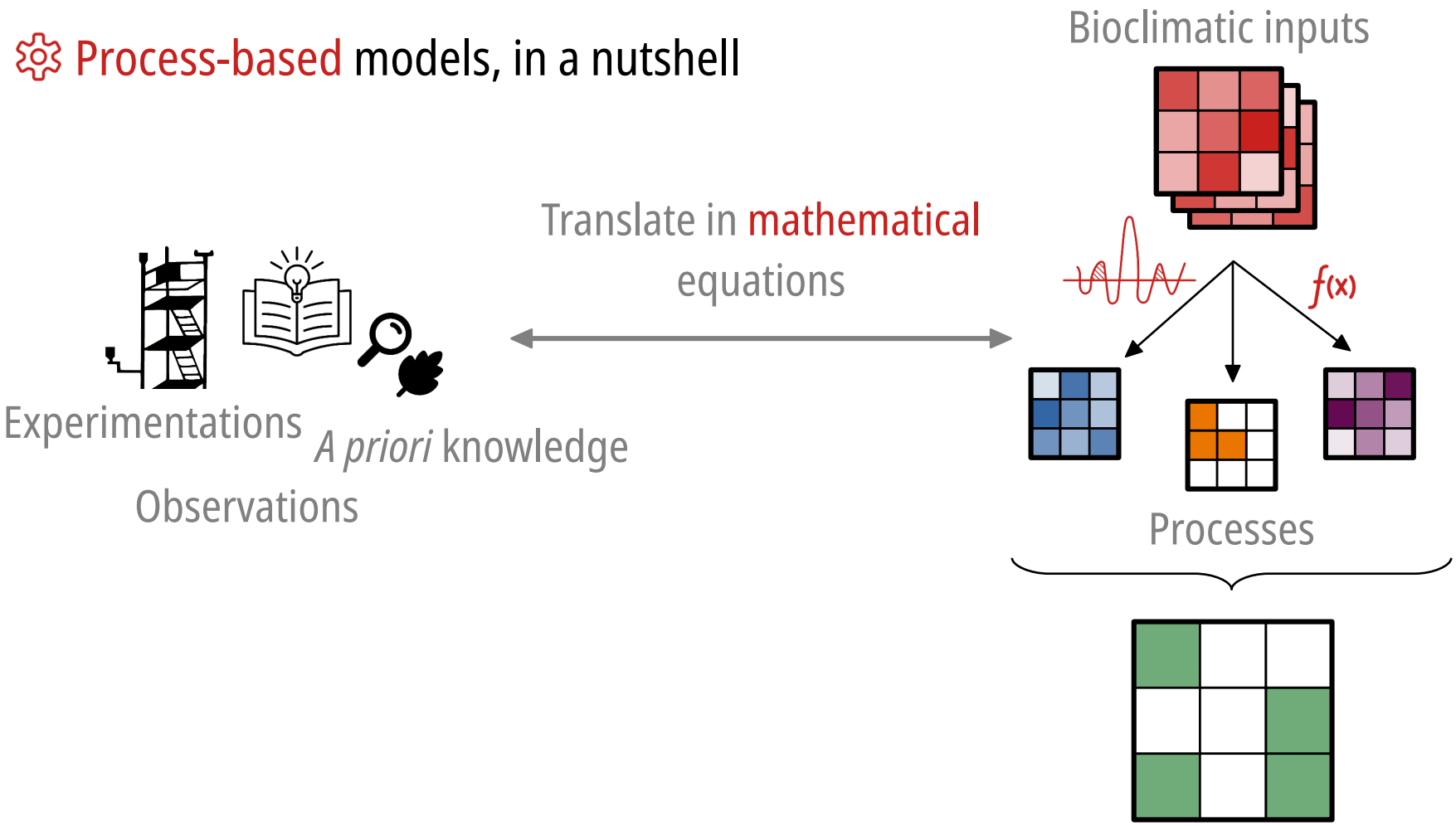
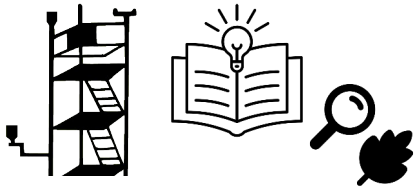


HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

Process-based models, in a nutshell

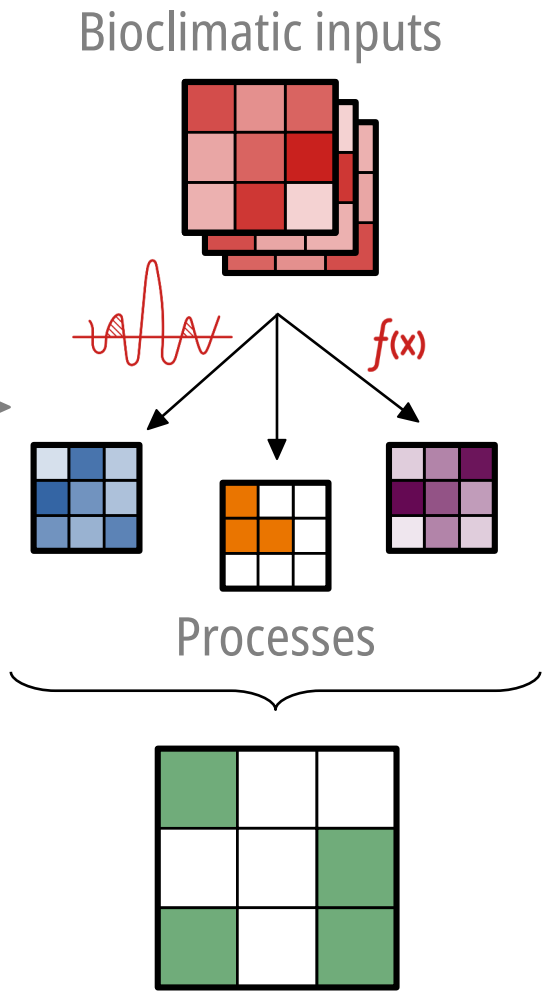


Experimentations

A priori knowledge

Observations

Translate in mathematical equations

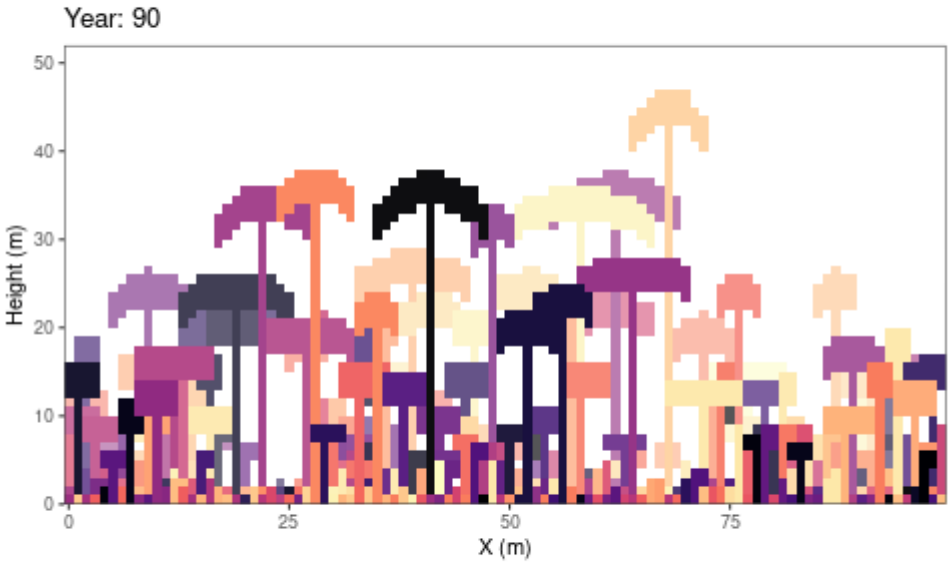


DESCRIBE PROCESSES

HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

e.g. individual-based models

TROLL model (Maréchaux & Chave, 2017),
ForCEEPS model (Morin et al., 2021)...

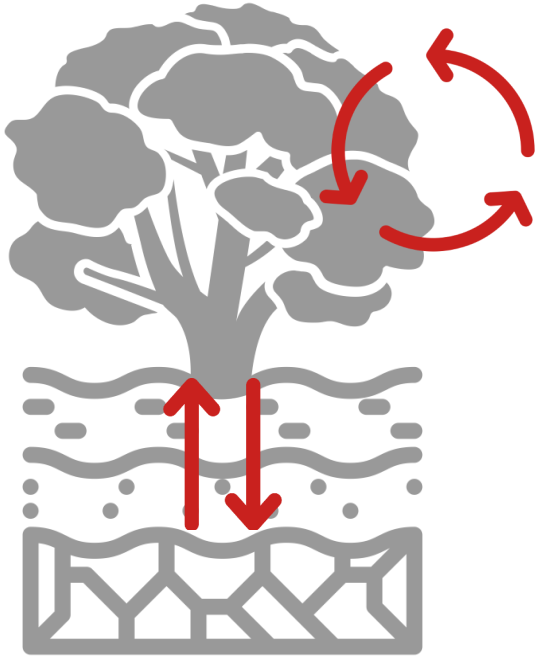


Schmitt et al. (2023)

HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

- e.g. “average tree” models

CASTANEA model (Dufrêne et al., 2005),
PHENOFIT model (Chuine & Beaubien, 2001)...



HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

PHENOFIT: focus on phenology

FITNESS = Reproductive success × Survival

Frost resistance

Thermal energy

Frost and drought

Leaf unfolding

Flowering

Fruit maturation

Leaf senescence

HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

Key advantages: greater comprehension of the complexity of ecosystems?

- mathematical formalisation of current knowledge, with a direct biological interpretation
- further validation of our understanding of processes against observations
- testing new hypotheses

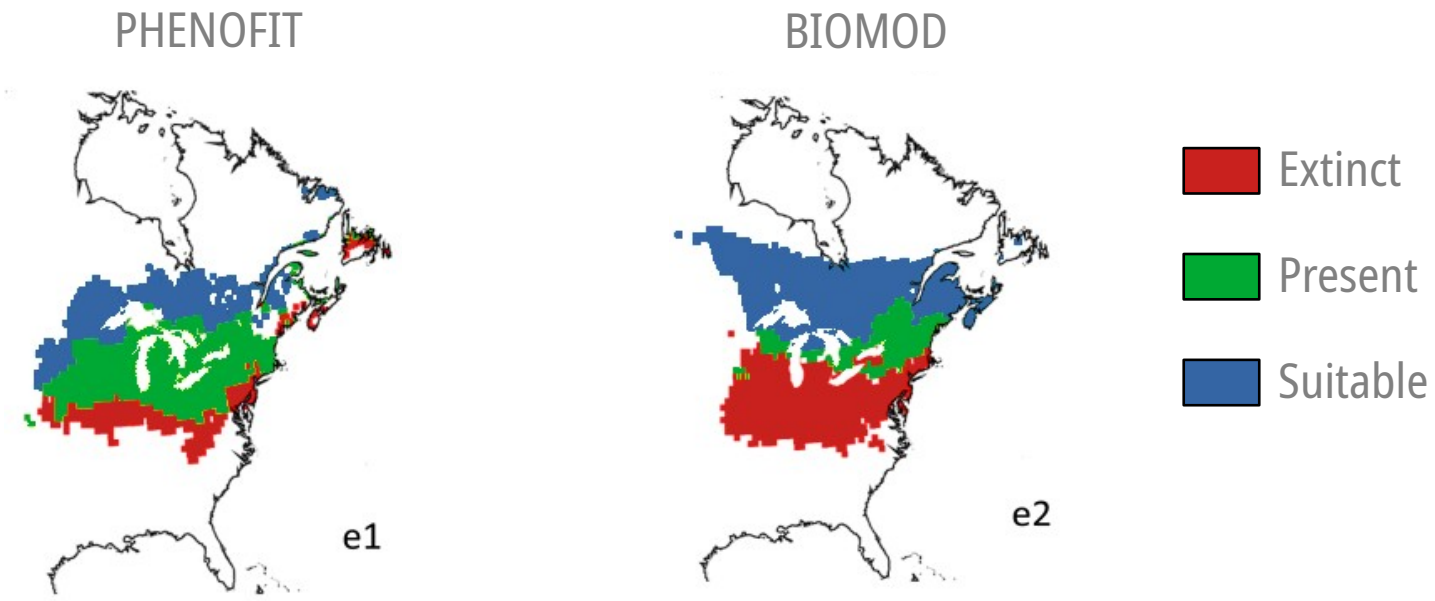
HOW WE COULD PREDICT THE FUTURE: PROCESS-BASED APPROACHES

Main drawbacks: finding the appropriate amount of complexity?

- take more time to develop, more challenging to use
- data available to calibrate them only for a few species
- important role of modeller subjectivity
- lack of transparency

HOW WE COULD PREDICT THE FUTURE: DIVERGENCE BETWEEN APPROACHES

Different predictions, e.g. *Quercus bicolor* in 2100



Correlative models more pessimistic?

Adapted from Morrin & Thuiller (2009)

HOW WE COULD PREDICT THE FUTURE: CONTINUITY AMONG MODELS

Correlative models

Process-based models

Adapted from Dormann et al. (2012)

HOW WE COULD PREDICT THE FUTURE: CONTINUITY AMONG MODELS

Correlative models

Process-based models

- implicit representation of processes

- explicit representation of processes

Adapted from Dormann et al. (2012)

HOW WE COULD PREDICT THE FUTURE: CONTINUITY AMONG MODELS

Correlative models

Process-based models

- implicit representation of processes
- calibrated with current distribution data

- explicit representation of processes
- calibrated with process-related data

Adapted from Dormann et al. (2012)

HOW WE COULD PREDICT THE FUTURE: CONTINUITY AMONG MODELS

COMMON ASSUMPTION: PROCESS-BASED MODELS MIGHT PROVIDE **MORE ROBUST PROJECTIONS** IN NOVEL CONDITIONS

e.g. Evans (2012), Singer et al. (2016), Urban et al. (2016), Zurell et al. (2016)

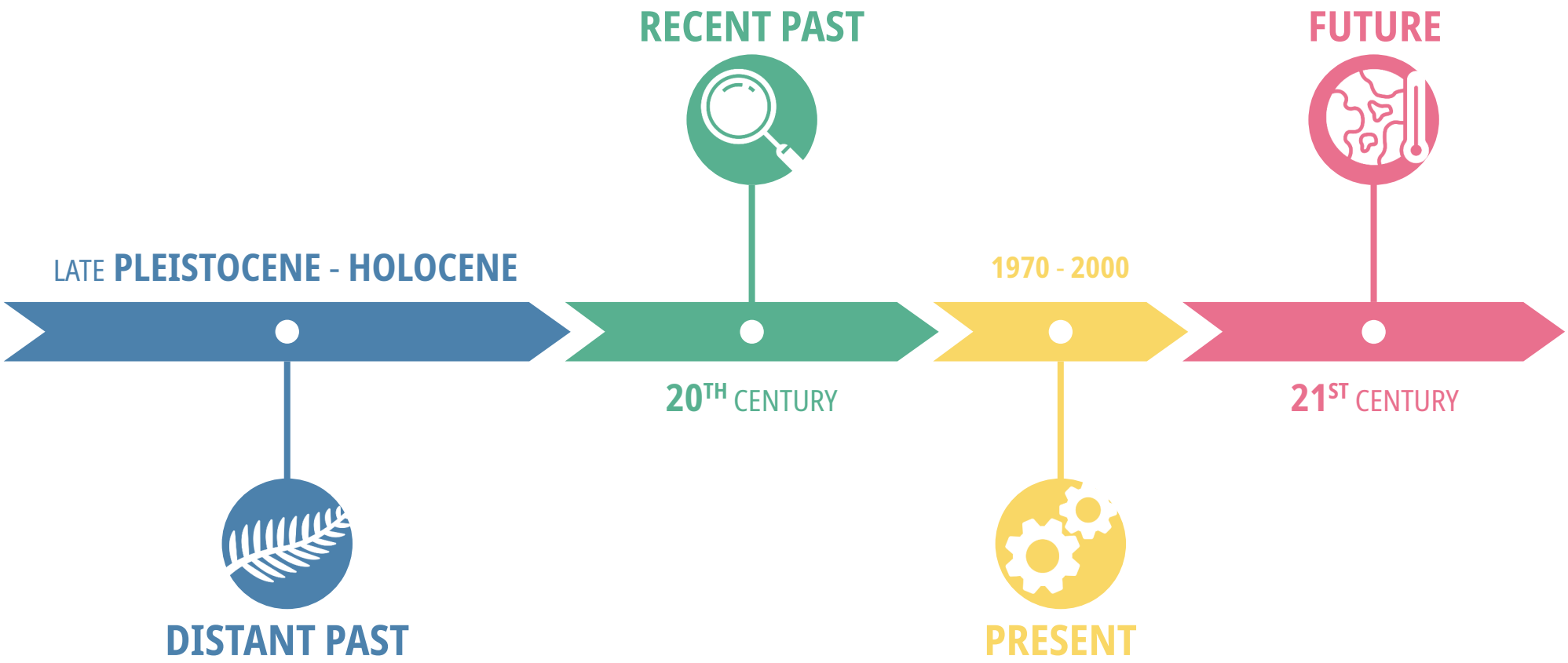
HOW WE COULD PREDICT THE FUTURE: CONTINUITY AMONG MODELS

COMMON ASSUMPTION: PROCESS-BASED MODELS MIGHT PROVIDE MORE ROBUST PROJECTIONS IN NOVEL CONDITIONS

YET TO BE VERIFIED

e.g. Evans (2012), Singer et al. (2016), Urban et al. (2016), Zurell et al. (2016)

THESIS FRAMEWORK



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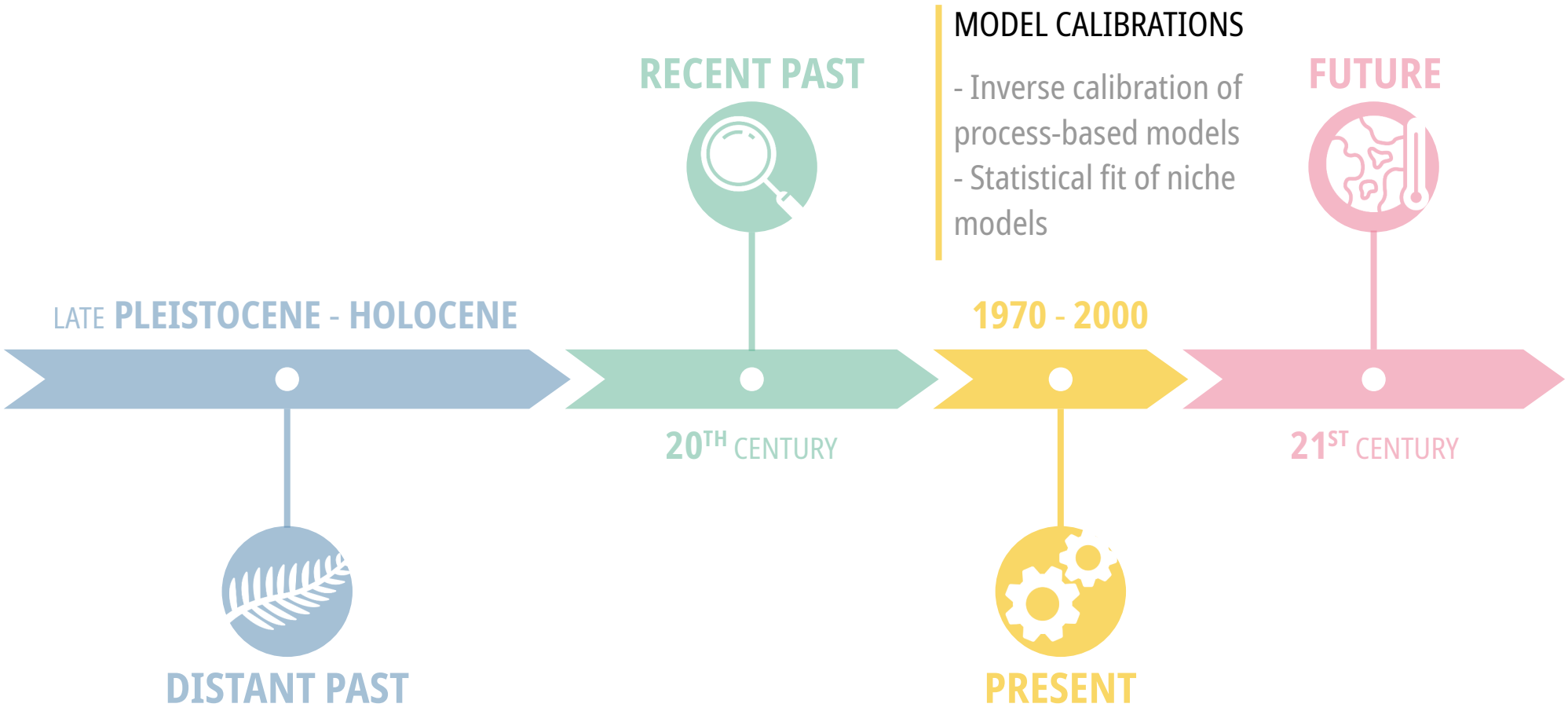

INVERSE CALIBRATION OF PROCESS-BASED MODELS

Correlative models

Process-based models

Adapted from Dormann et al. (2012)

INVERSE CALIBRATION OF PROCESS-BASED MODELS

Correlative models

Process-based models

Fitted process-based models

Adapted from Dormann et al. (2012)

INVERSE CALIBRATION OF PROCESS-BASED MODELS

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Process-based models

Fitted process-based models

- calibrated with current distribution data
- explicit representation of processes

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INVERSE CALIBRATION OF PROCESS-BASED MODELS

Correlative models

Process-based models

Fitted process-based models

- calibrated with current distribution data
- explicit representation of processes

Combine both approaches

Adapted from Dormann et al. (2012)

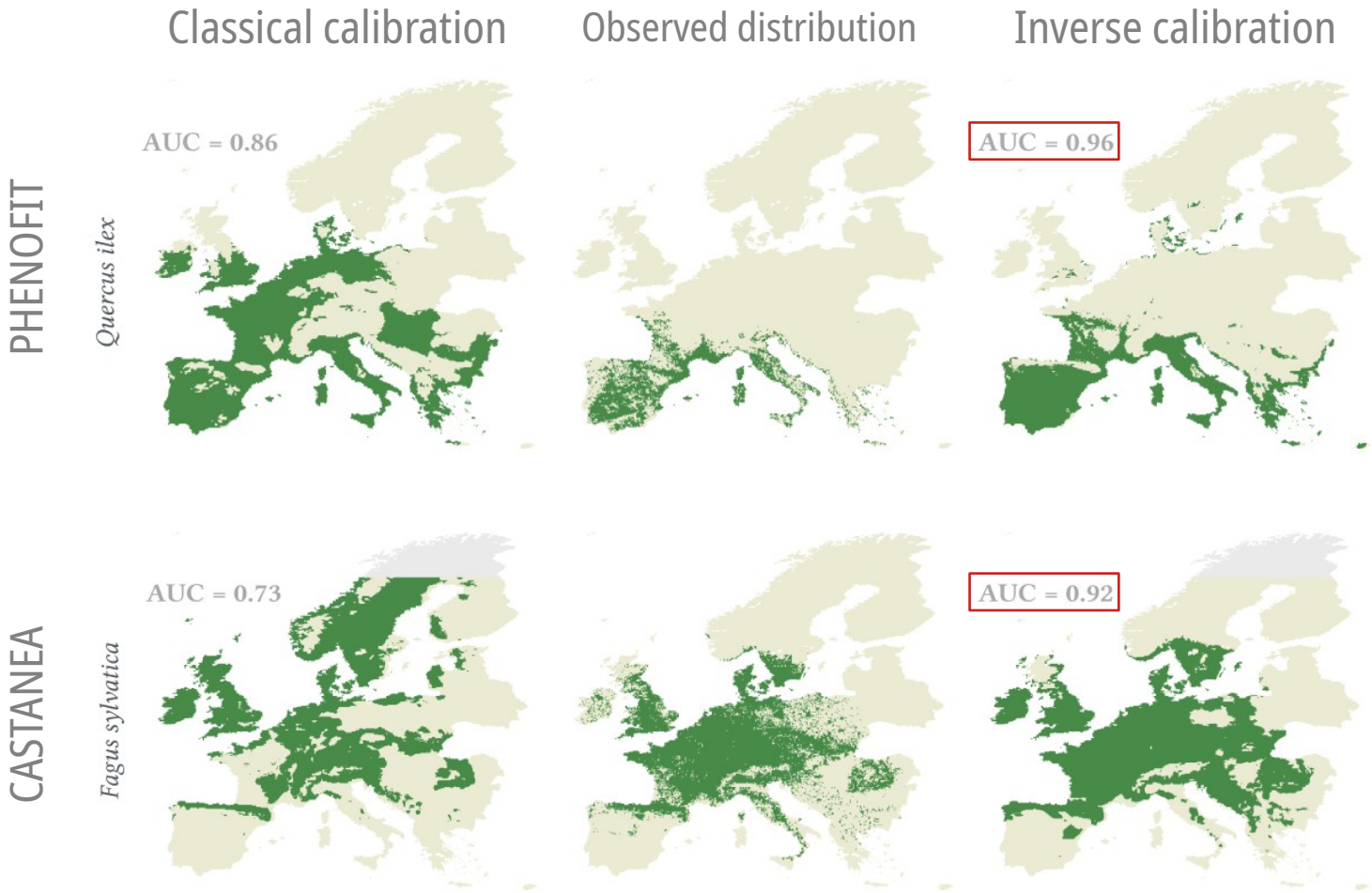
REMINDER : OPTIMISATION ALGORITHM

CMA-ES: covariance matrix adaptation – evolution strategy

- based on the principle of evolutionary biology, via recombination, mutation and selection of the most fit candidate solutions

- widely accepted as a robust optimization algorithm for nonlinear and nonseparated optimization problems in continuous domain

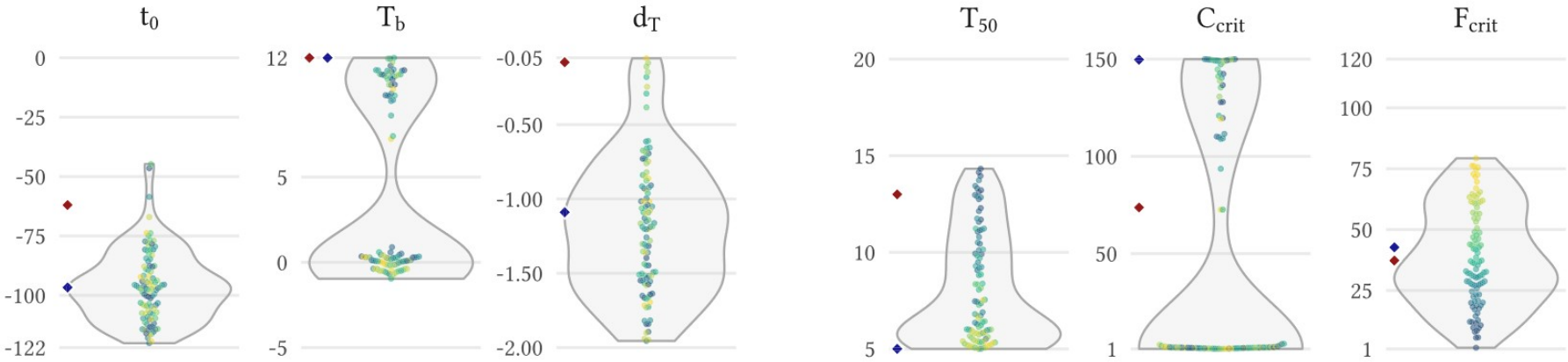
RESULTS OF CALIBRATION



Van der Meersch & Chuine (2023)

RESULTS OF CALIBRATION

Expected issue: non-identifiability of parameter values



Effects of stochasticity of CMA-ES calibration on PHENOFIT leaf unfolding model parameters

Van der Meersch & Chuine (2023)

RESULTS OF CALIBRATION

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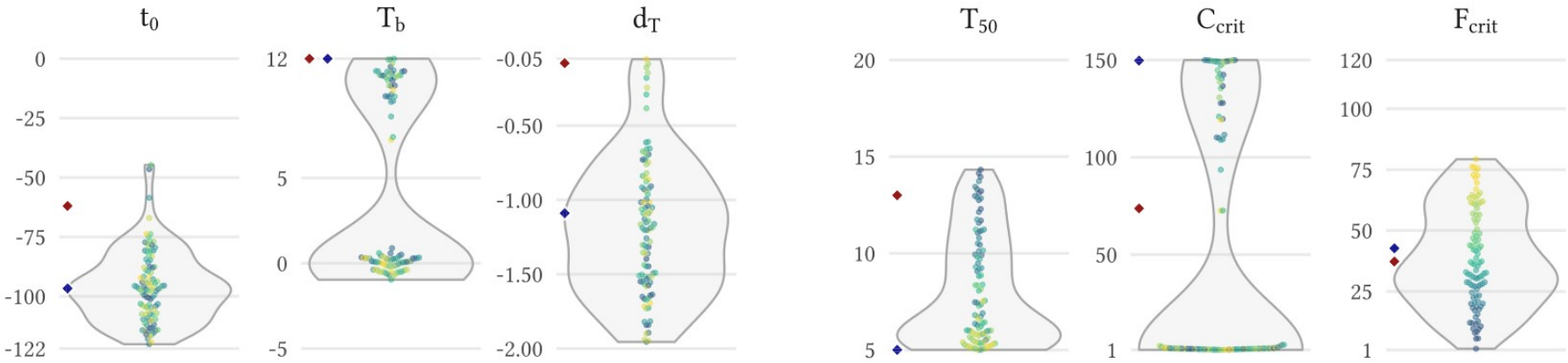


Effects of stochasticity of CMA-ES calibration on PHENOFIT leaf unfolding model parameters

multiple parameter sets produce equally good fits to the observed data

Van der Meersch & Chuine (2023)

FIRST PUBLICATION

Received: 30 November 2022 | Accepted: 20 April 2023

DOI: 10.1111/2041-210X.14119

Methods in Ecology and Evolution

RESEARCH ARTICLE

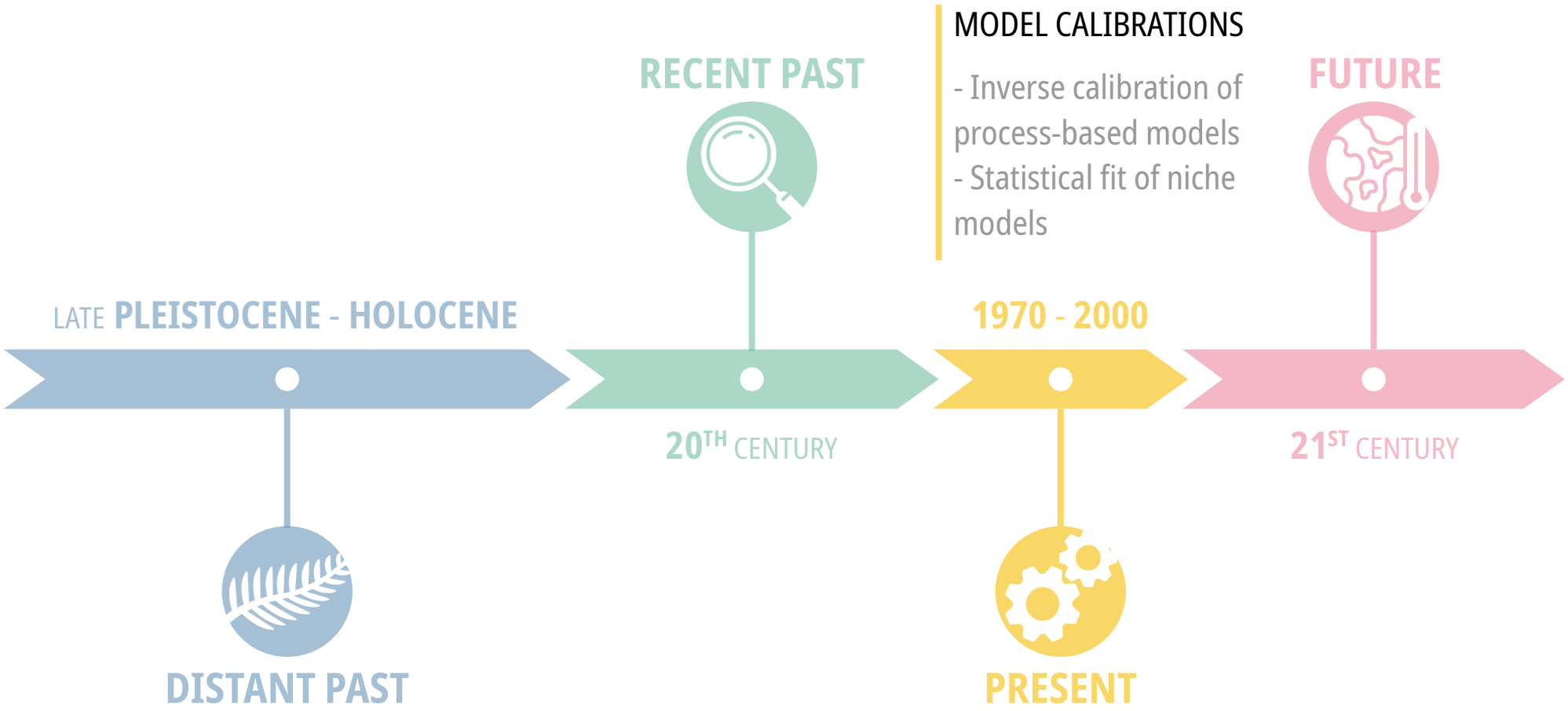
Estimating process-based model parameters from species distribution data using the evolutionary algorithm CMA-ES

Victor Van der Meersch | Isabelle Chuine

poster presentation during the SFE2/GFO conference in Metz (Nov. 2022)

Van der Meersch & Chuine (2023)

THESIS FRAMEWORK



CALIBRATION OF CORRELATIVE MODELS

- presence-only approach, with these models (Valavi et al. 2022):

  GLM with lasso regularization

  GAM

  BRT

  Random Forest down-sampled

  (background points sampled irrespective of the location of species records)

CALIBRATION OF CORRELATIVE MODELS

- presence-only approach, with these models (Valavi et al. 2022):

  GLM with lasso regularization
  GAM
  BRT
  Random Forest down-sampled

  (background points sampled irrespective of the location of species records)

- predictors:

  minimum temperature of the coldest month (frost tolerance)
  GDD >5°C April-September (growth)
  total precipitation (accumulated water)
  water balance June-July (summer drought)

  + pH, water holding capacity

CALIBRATION OF CORRELATIVE MODELS

- 5-fold environmental block cross-validation to estimate errors

CALIBRATION OF CORRELATIVE MODELS

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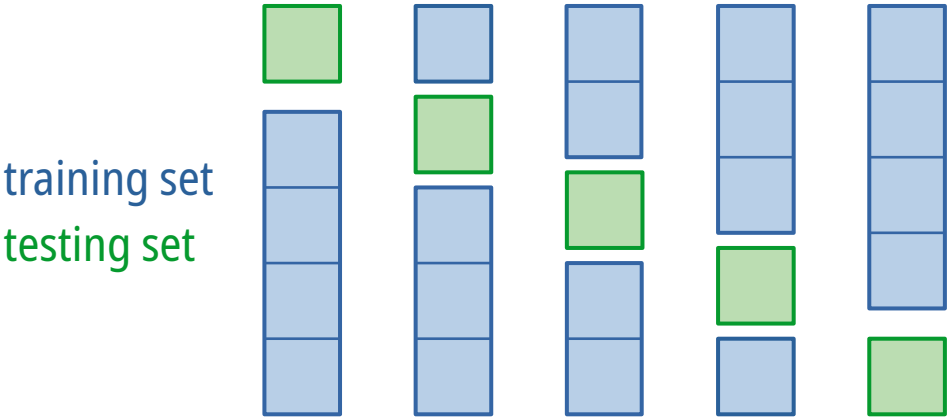

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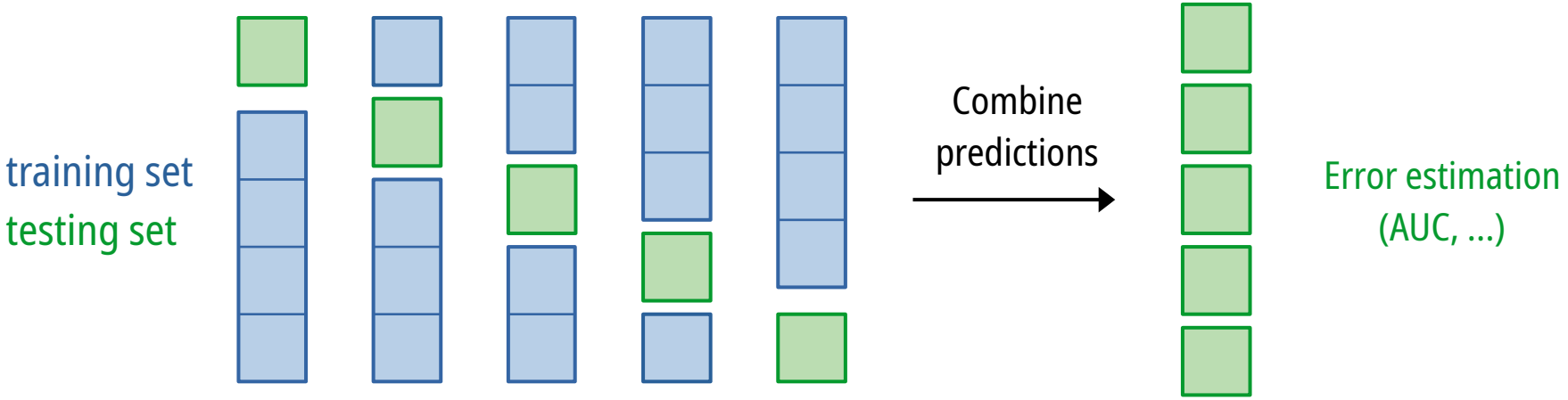

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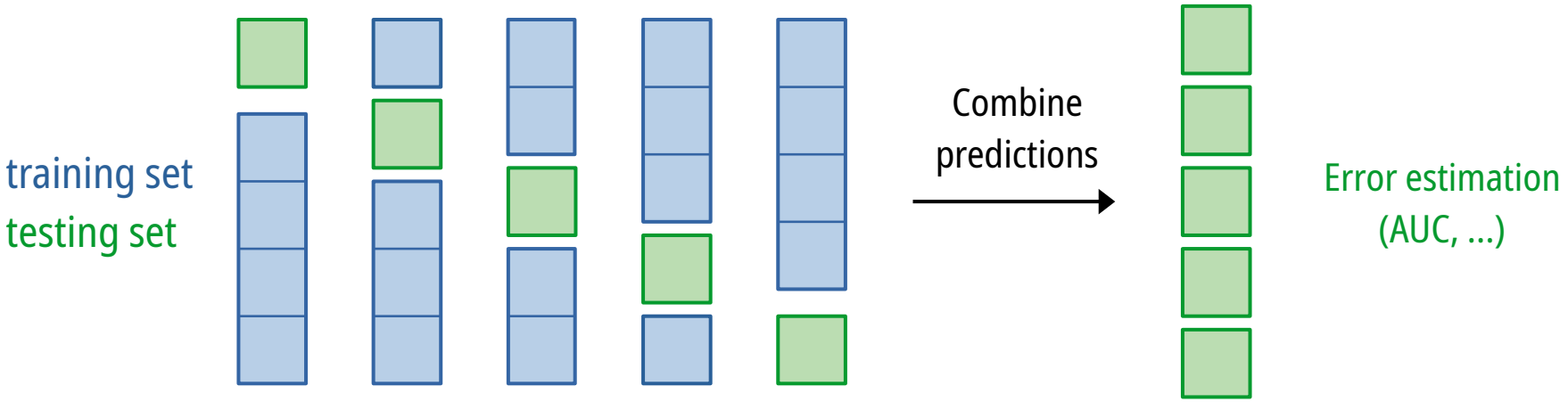
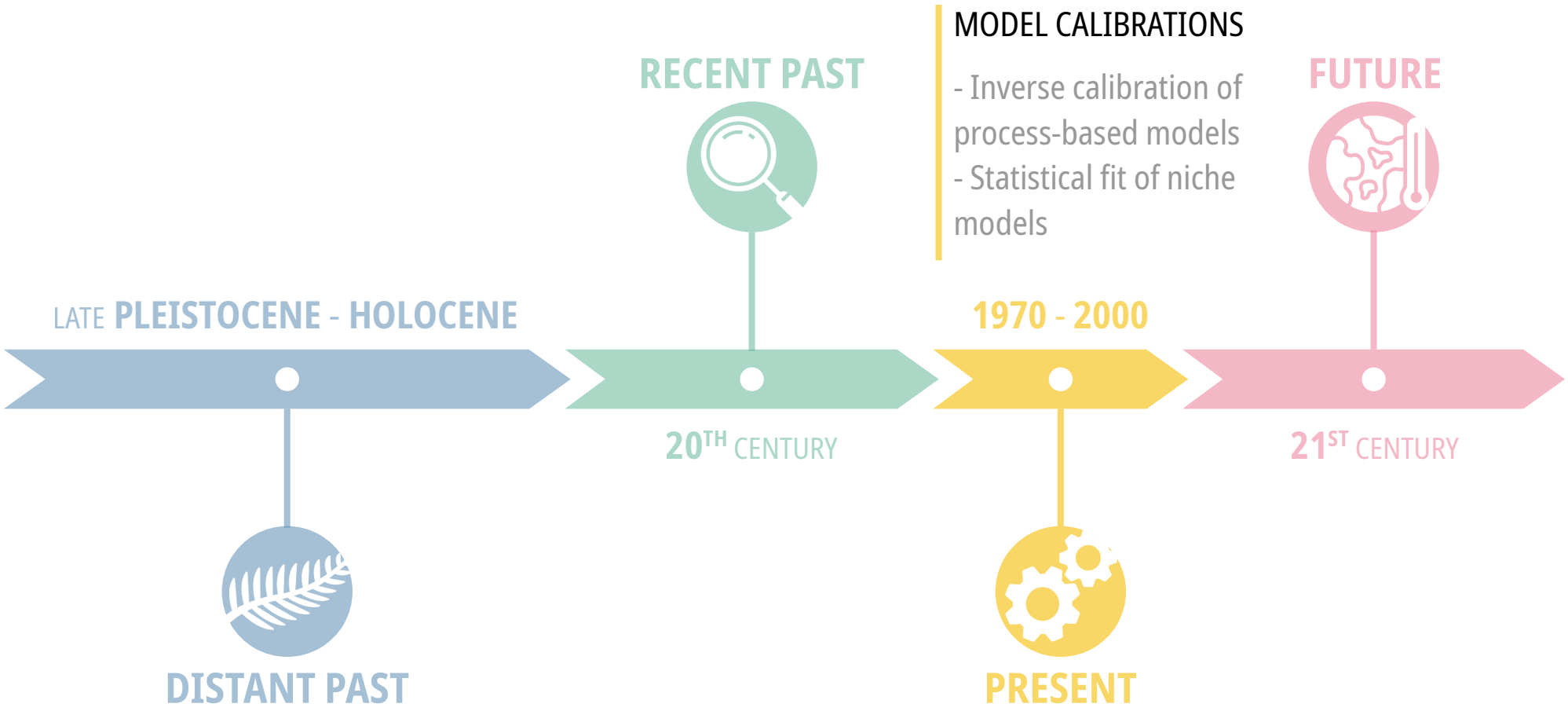


- final model: all the available data used to fit the model

"favours final prediction quality over perfect accuracy of error estimates"

THESIS FRAMEWORK



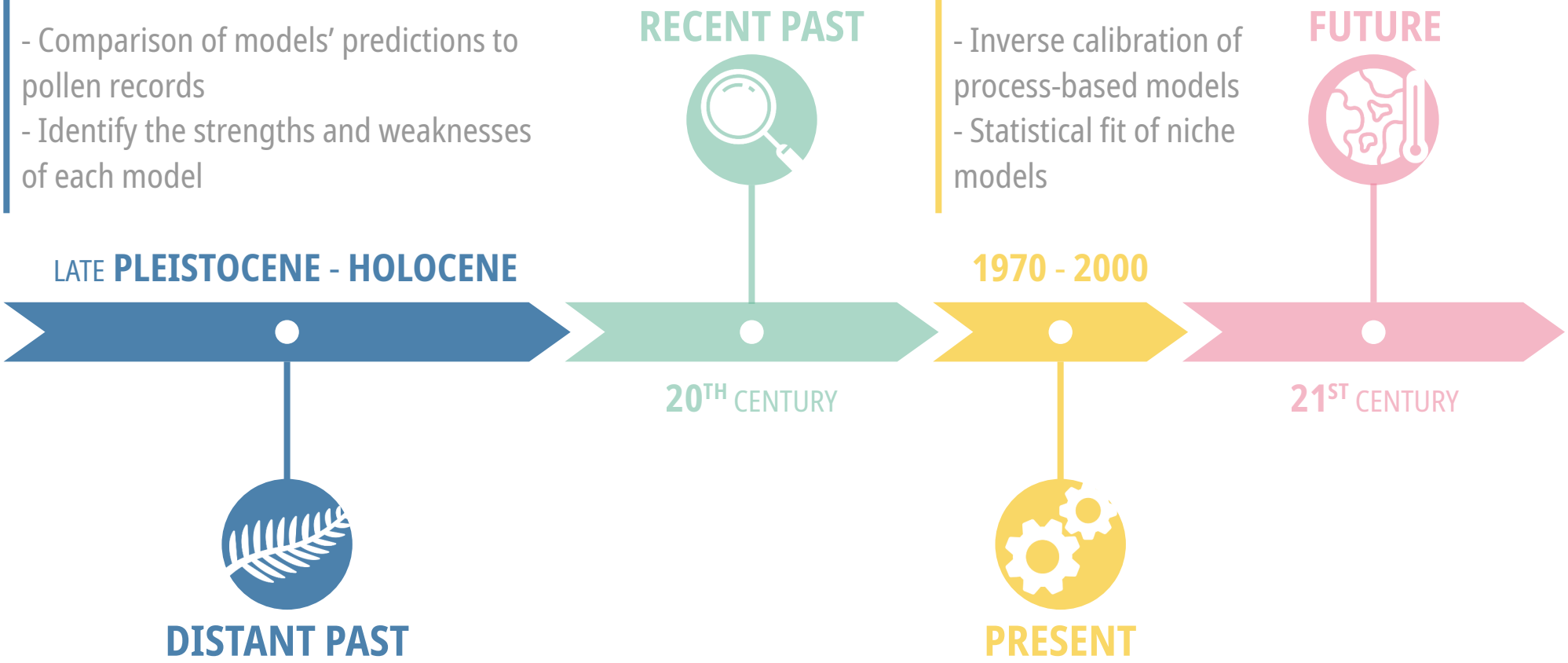
THESIS FRAMEWORK

LESSONS FROM THE PAST

- Comparison of models' predictions to pollen records
- Identify the strengths and weaknesses of each model

MODEL CALIBRATIONS

- Inverse calibration of process-based models
- Statistical fit of niche models



INSIGHTS FROM THE PAST: PROCESSING PALEOCLIMATE SIMULATION

- monthly data from HadCM3B general circulation model simulations
- 0.5° spatial resolution, bias corrected

nature > scientific data > data descriptors > article

Data Descriptor | Open Access | Published: 07 November 2019

A simulated Northern Hemisphere terrestrial climate dataset for the past 60,000 years

Edward Armstrong, Peter O. Hopcroft & Paul J. Valdes

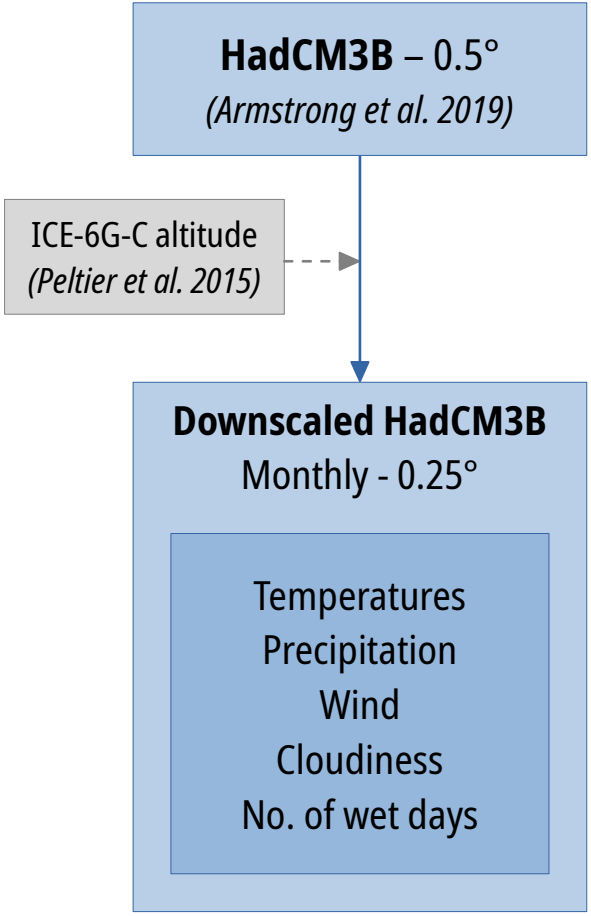
- collaboration with E. Armstrong, who generated specific variables for this project

INSIGHTS FROM THE PAST: PROCESSING PALEOCLIMATE SIMULATION

HadCM3B – 0.5°

(Armstrong et al. 2019)

INSIGHTS FROM THE PAST: PROCESSING PALEOCLIMATE SIMULATION



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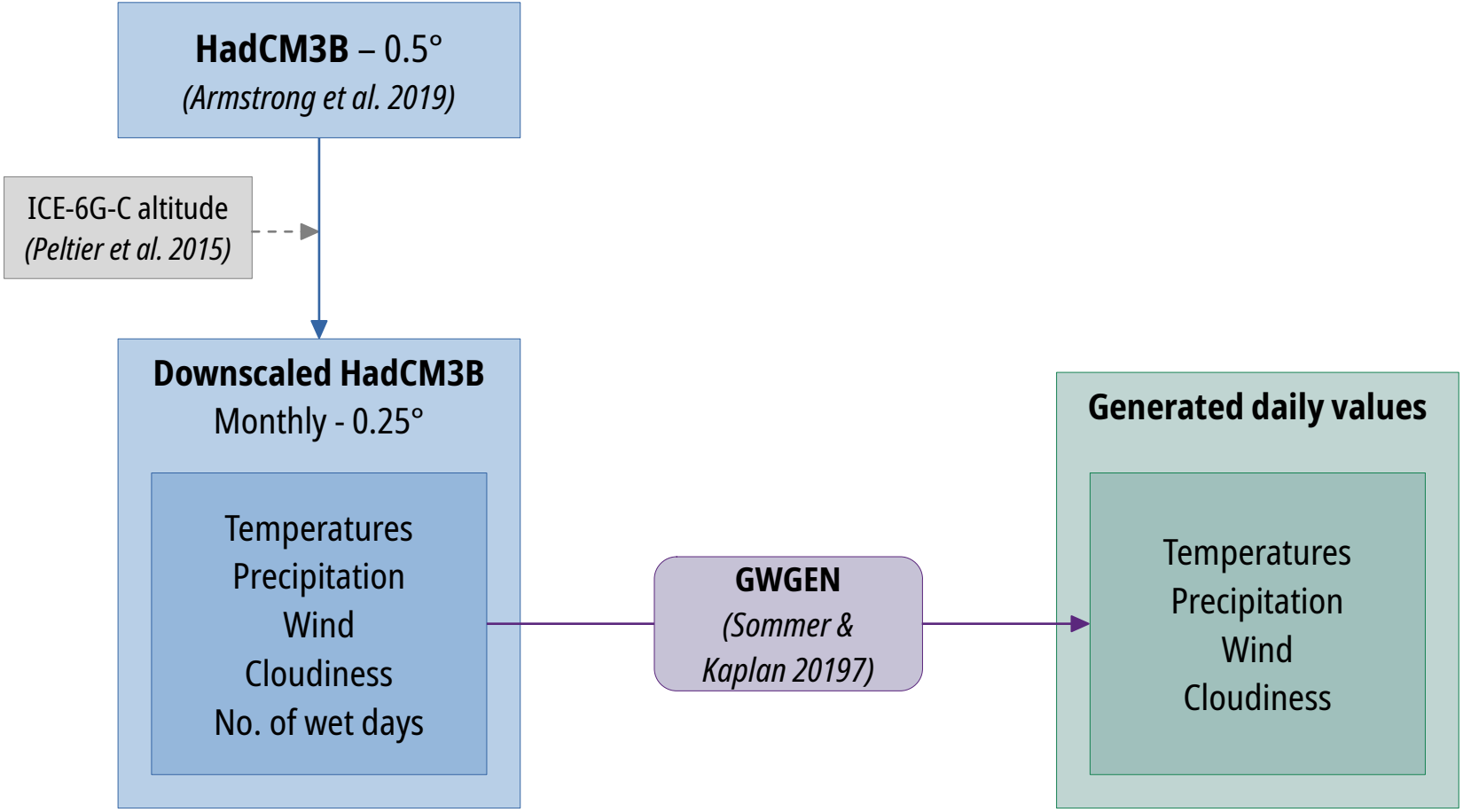

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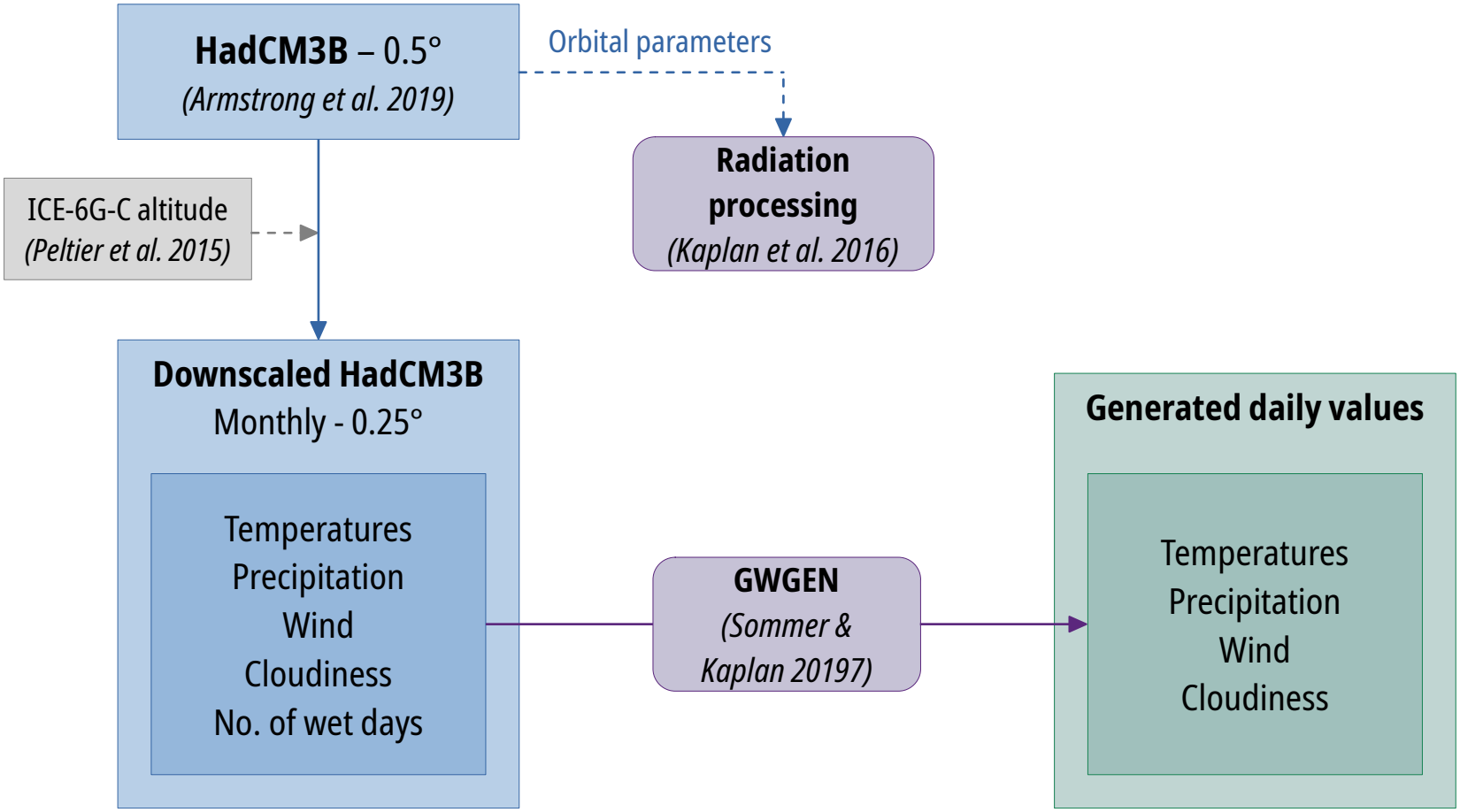

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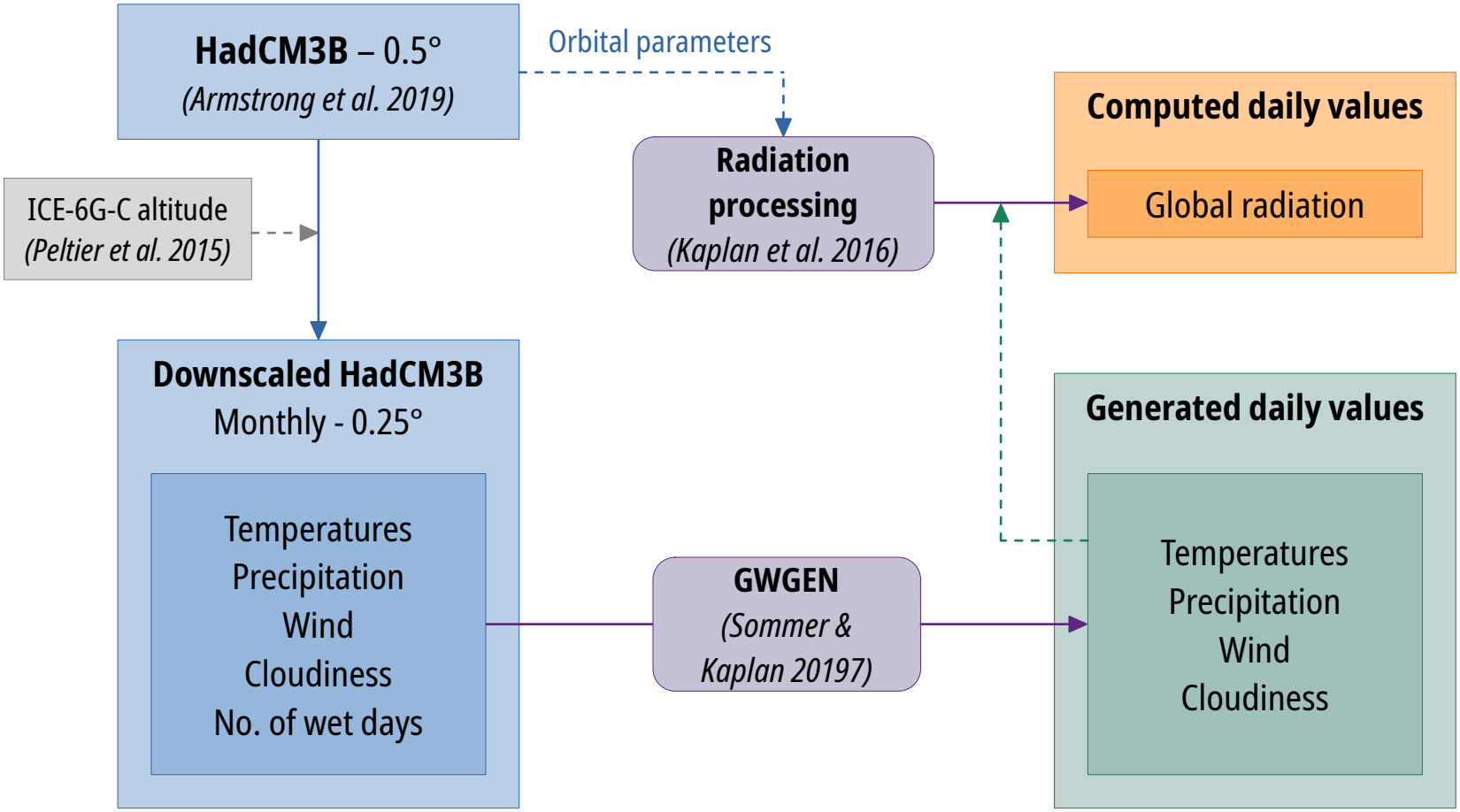

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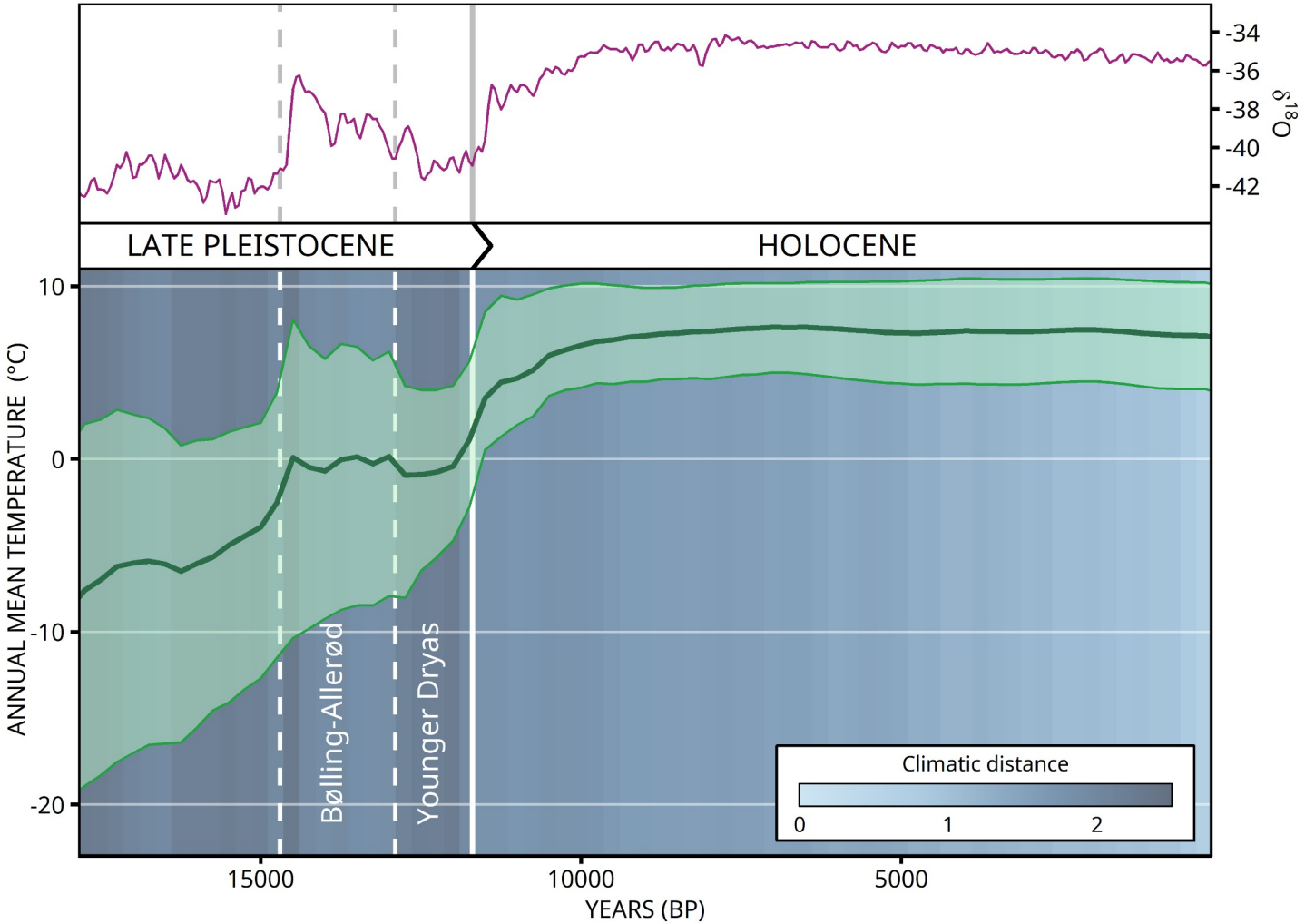
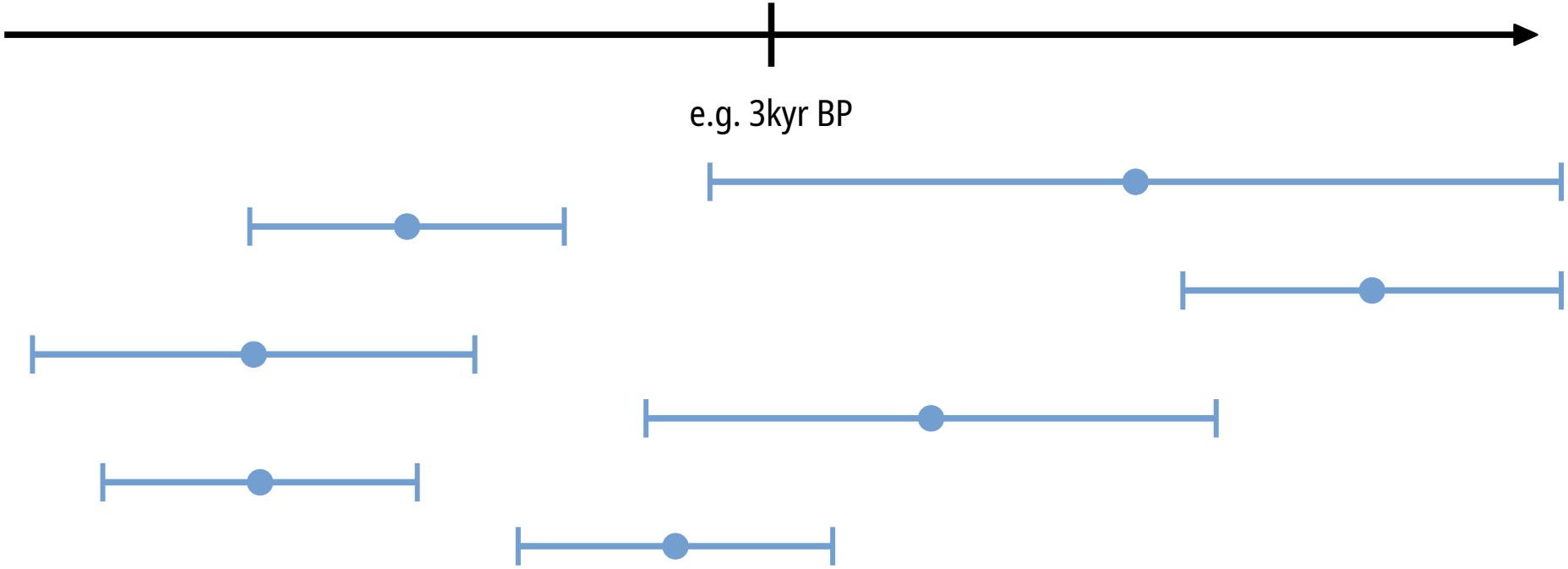


INSIGHTS FROM THE PAST: PROCESSING POLLEN FOSSIL RECORDS

- global databases: EPD, Neotoma
- LegacyPollen: records from Neotoma, standardized chronologies with age uncertainties (and taxonomically harmonized)
- three genera: *Fagus*, *Abies*, *Quercus*

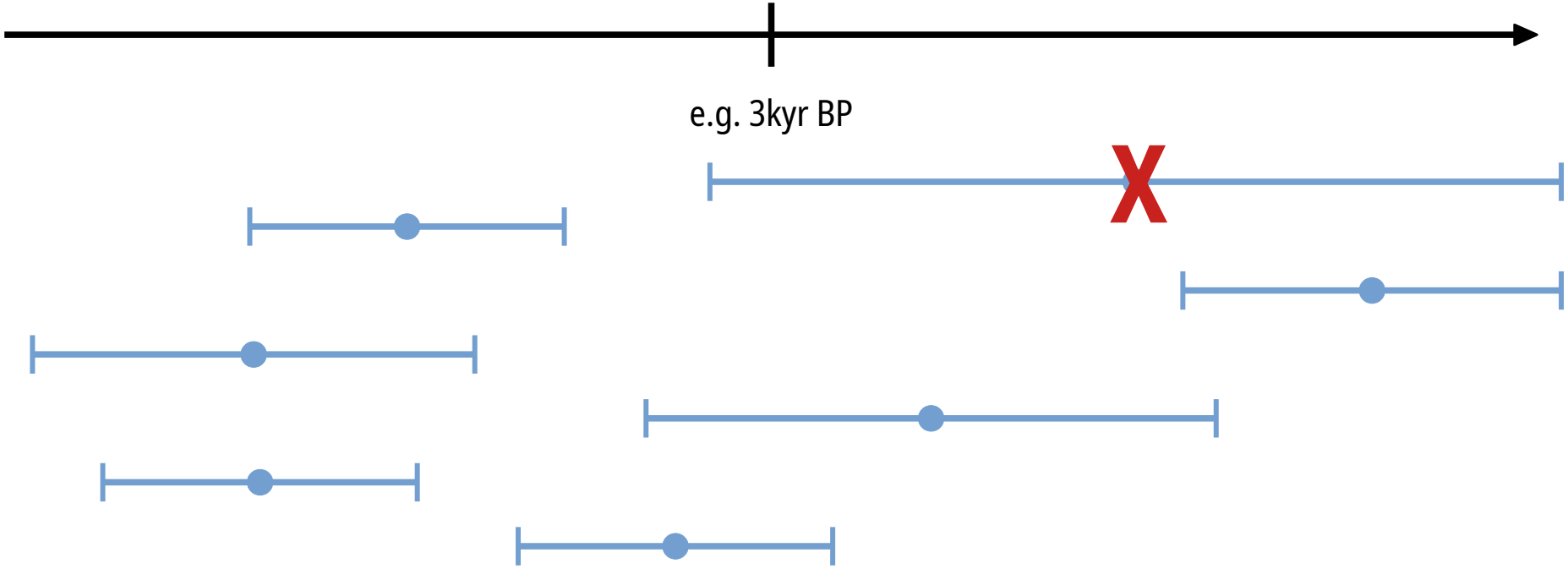
  → *Q. robur, Q. petraea, Q. ilex*
- 500-year windows

INSIGHTS FROM THE PAST: PROCESSING POLLEN FOSSIL RECORDS



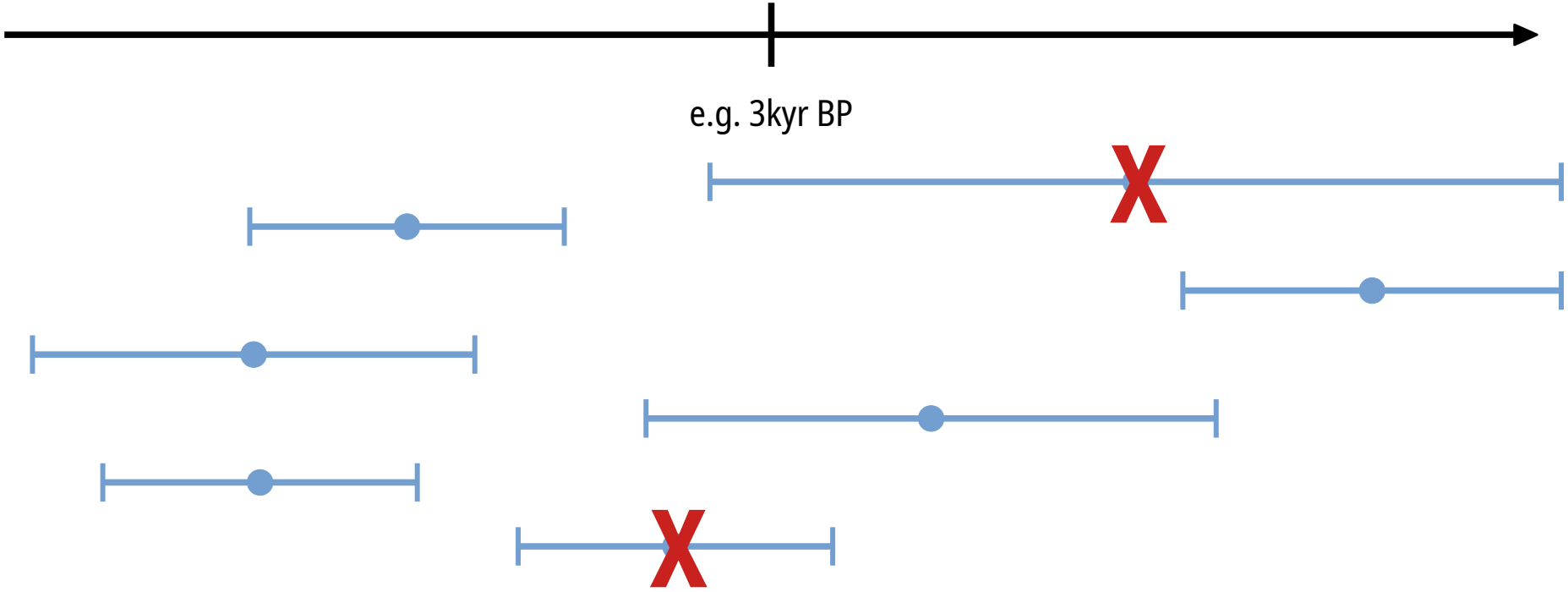
Multiple samples within the same site

INSIGHTS FROM THE PAST: PROCESSING POLLEN FOSSIL RECORDS



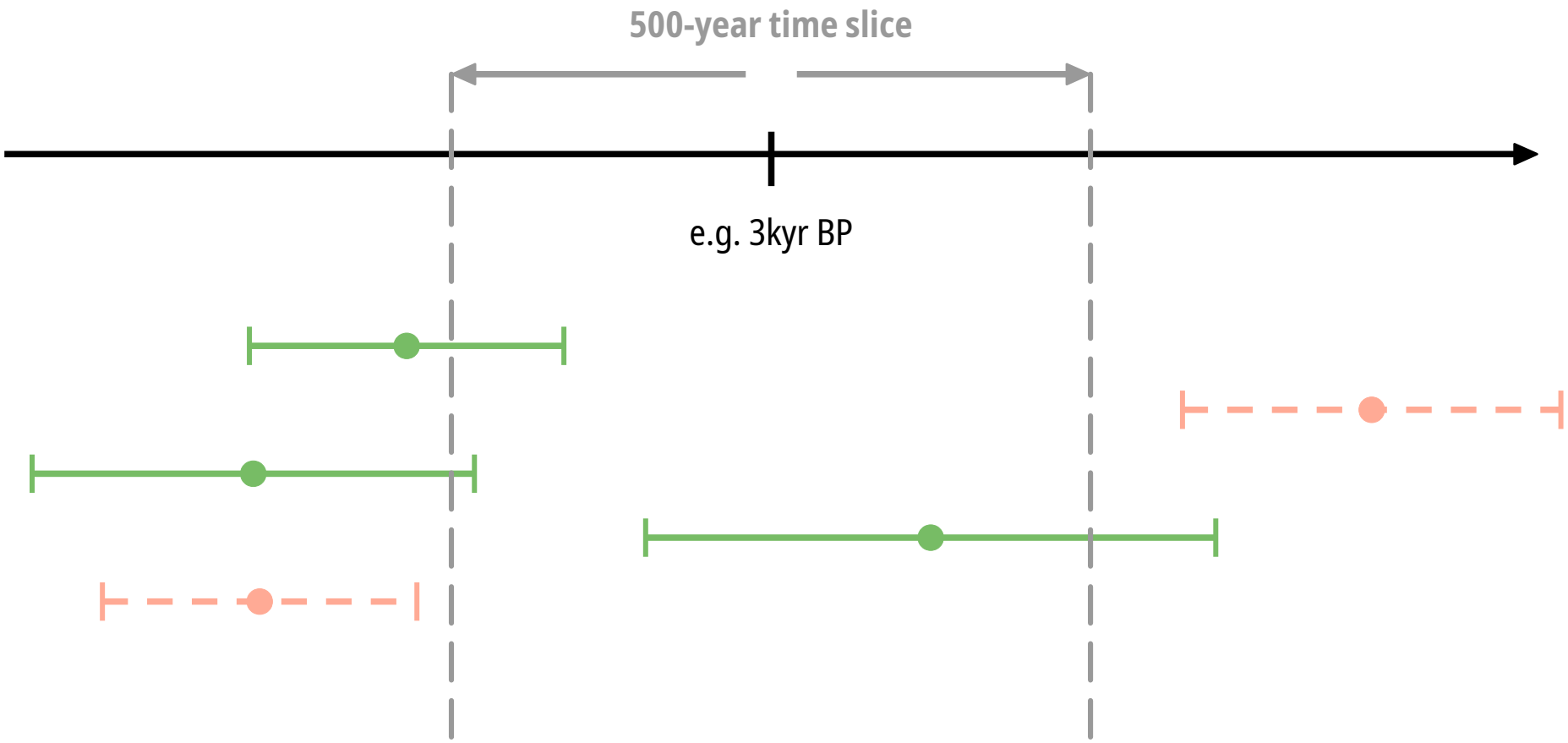
Keep only samples with uncertainty <= 500 years

INSIGHTS FROM THE PAST: PROCESSING POLLEN FOSSIL RECORDS



Keep only samples with at least 200 pollen grains

INSIGHTS FROM THE PAST: PROCESSING POLLEN FOSSIL RECORDS



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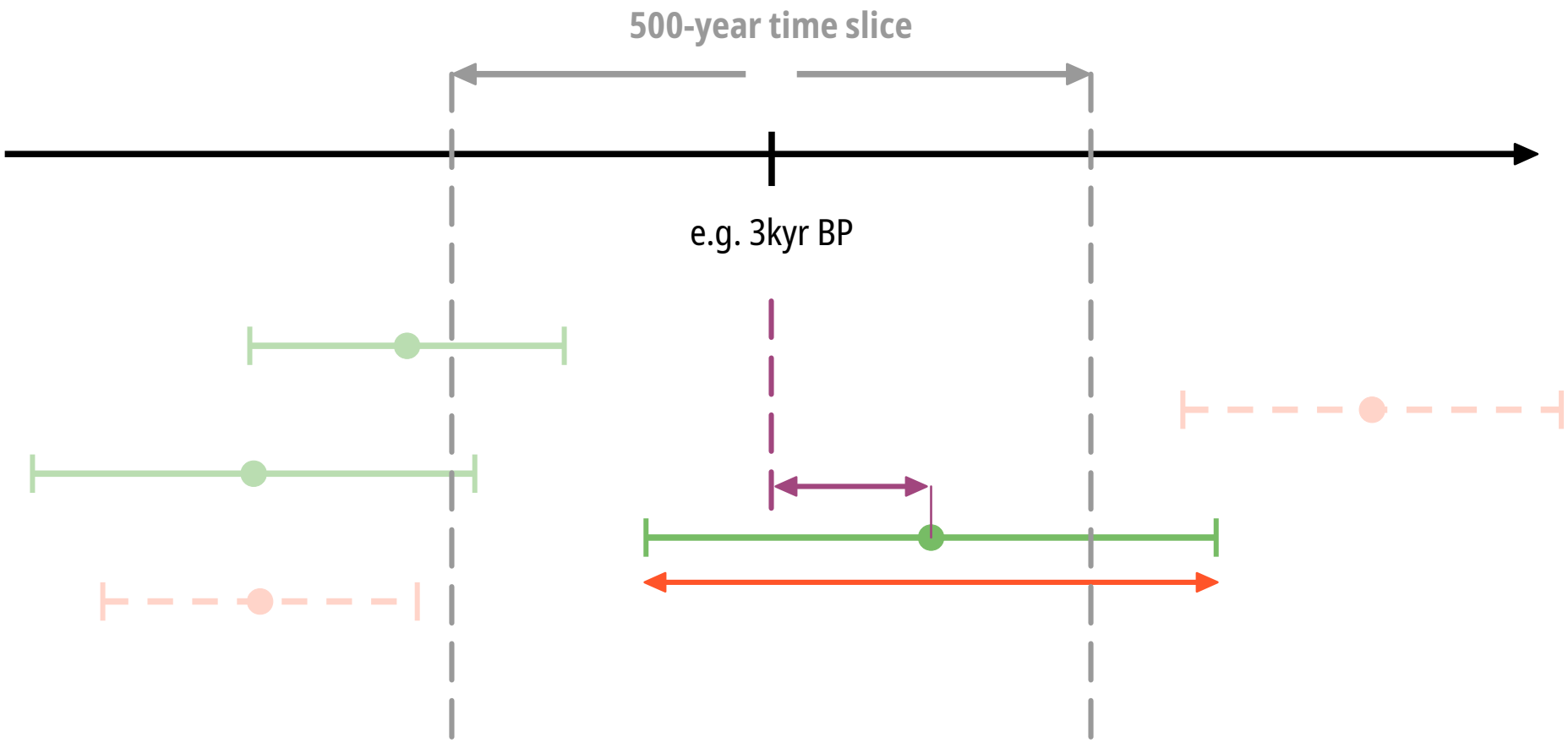
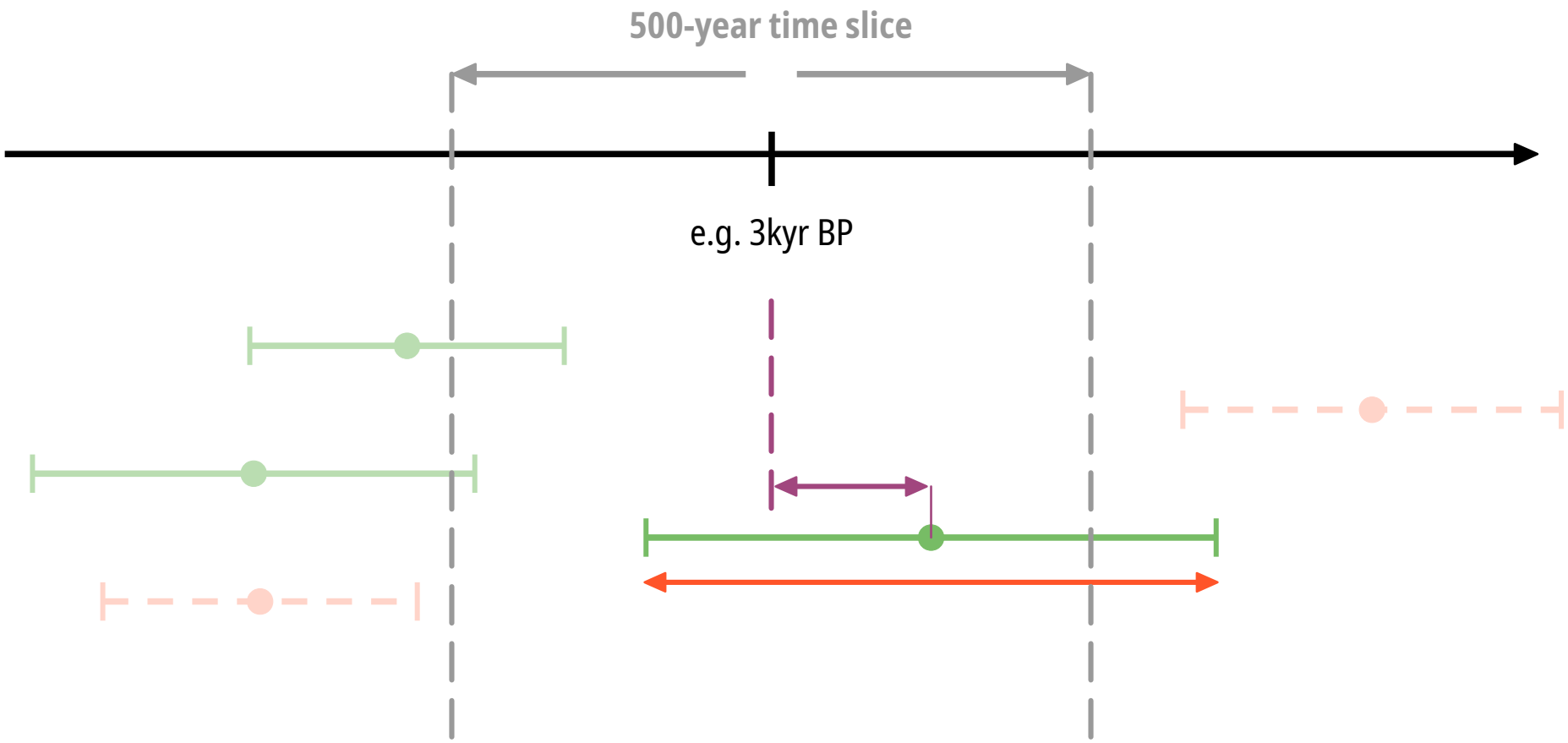


Weighted mean of pollen counts, taking into account both **uncertainty** and **time distance**

INSIGHTS FROM THE PAST: PROCESSING POLLEN FOSSIL RECORDS



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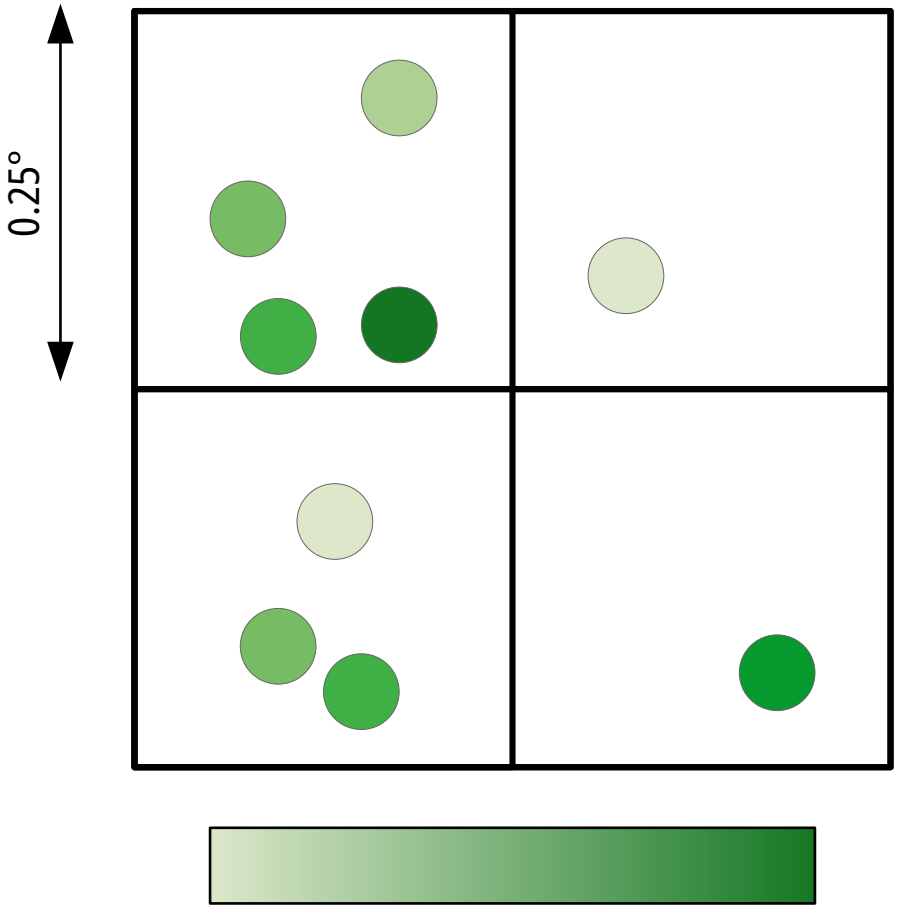

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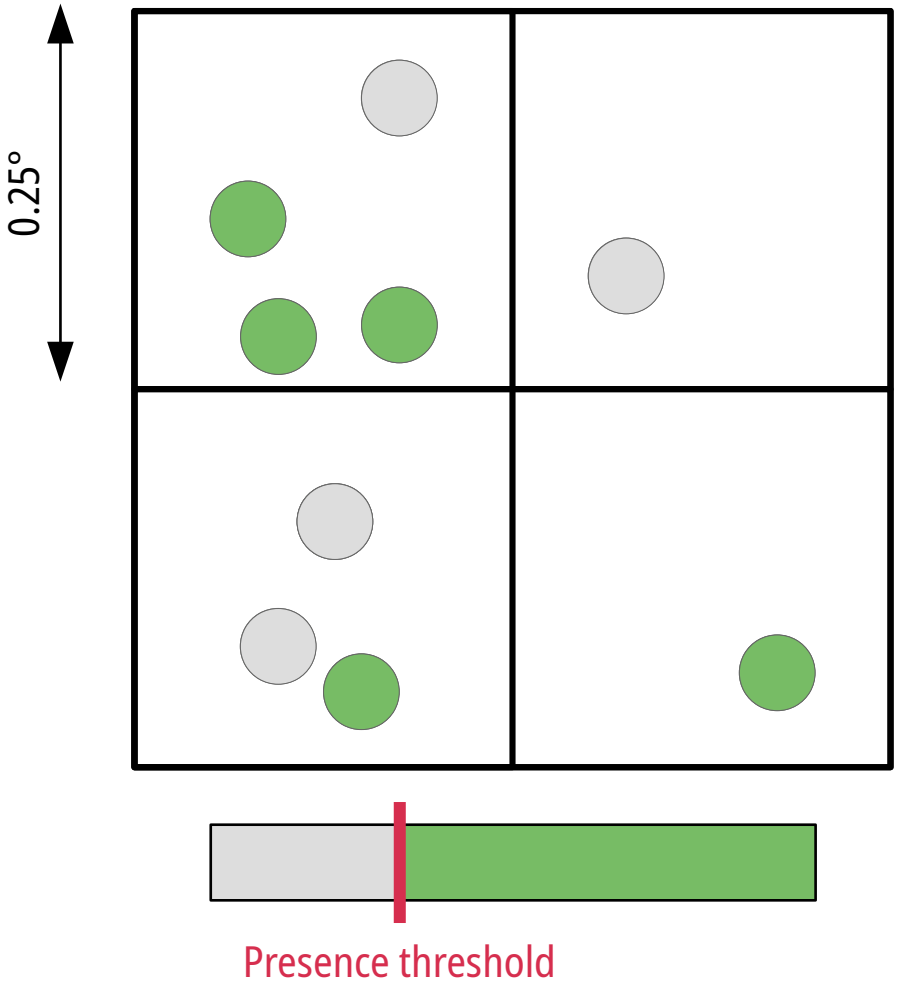
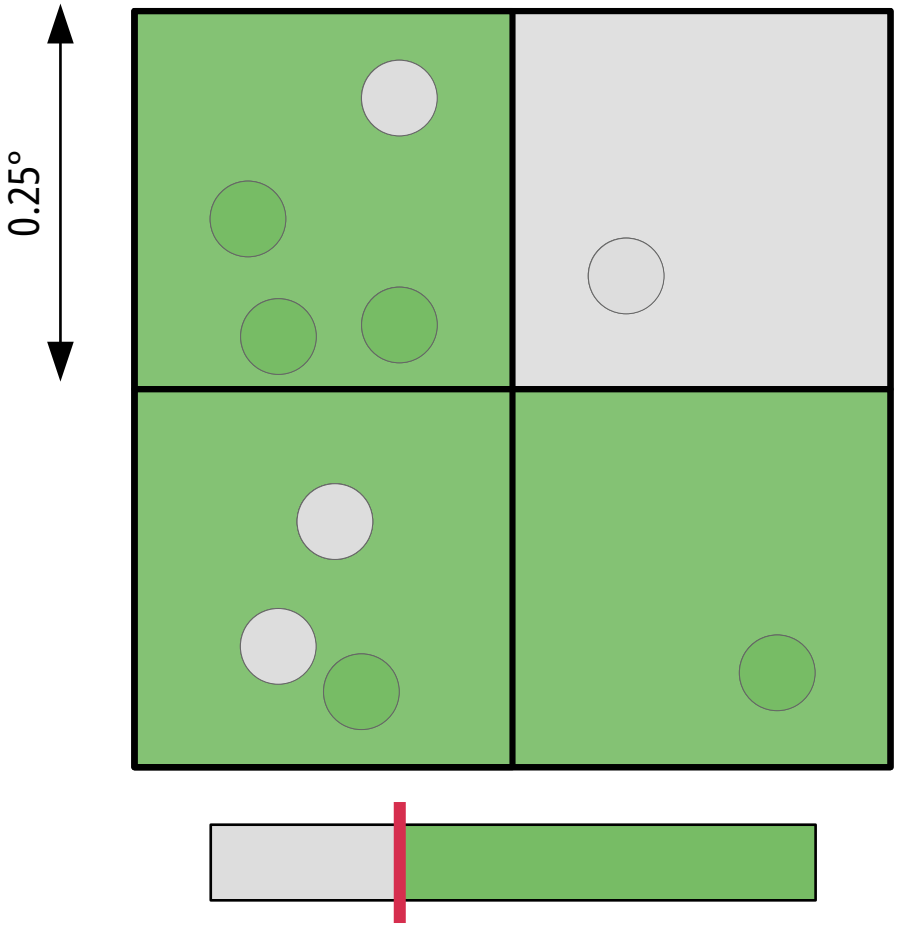


- specific threshold:
  1% for *Fagus*, *Abies*
  2.5% for *Quercus*

INSIGHTS FROM THE PAST: PROCESSING POLLEN FOSSIL RECORDS



"One is enough"

INSIGHTS FROM THE PAST: MIGRATION SIMULATIONS

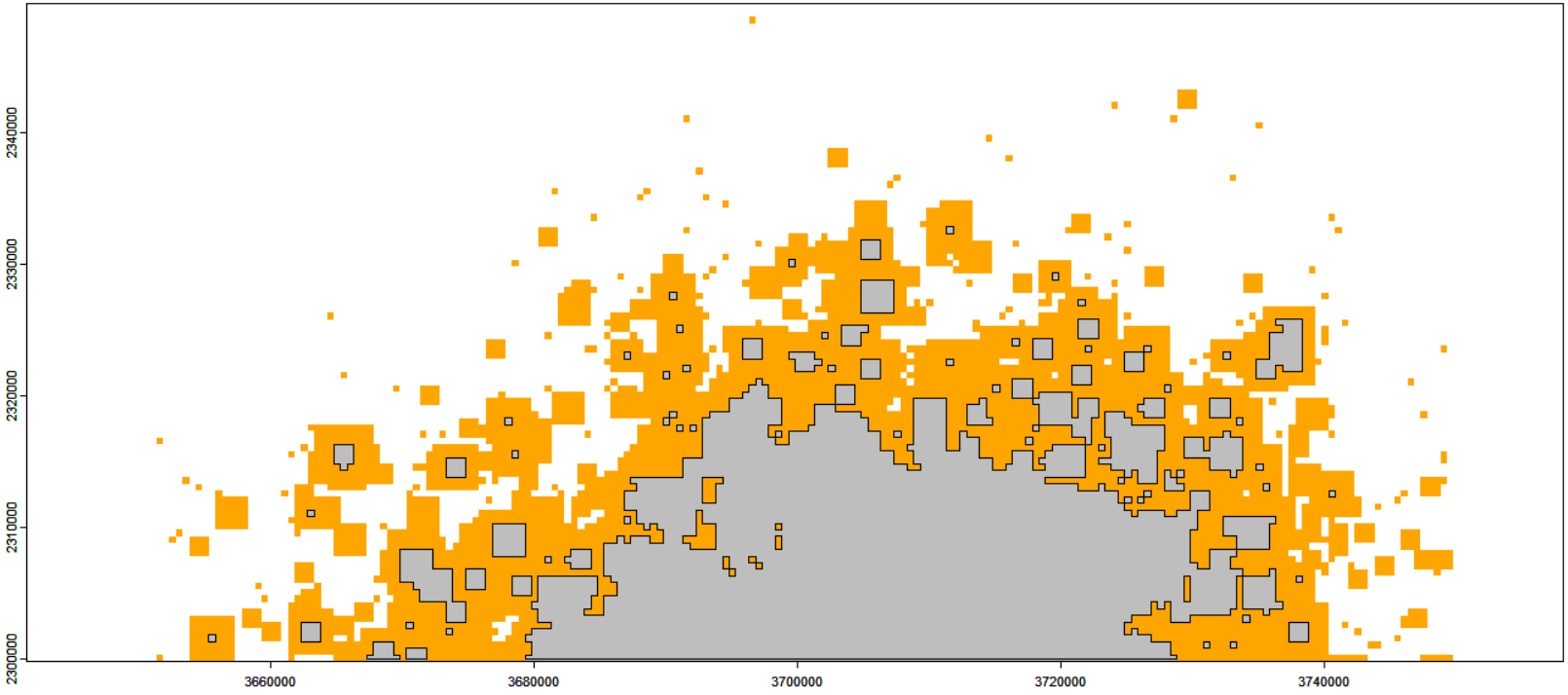
- simple cellular automaton (MigClim – modified to incorporate both short-distance and long-distance dispersal kernels)

- dispersal kernels from Zani et al. (2022), for each species

- 500m resolution, yearly step (habitat suitability updated each 250 years)

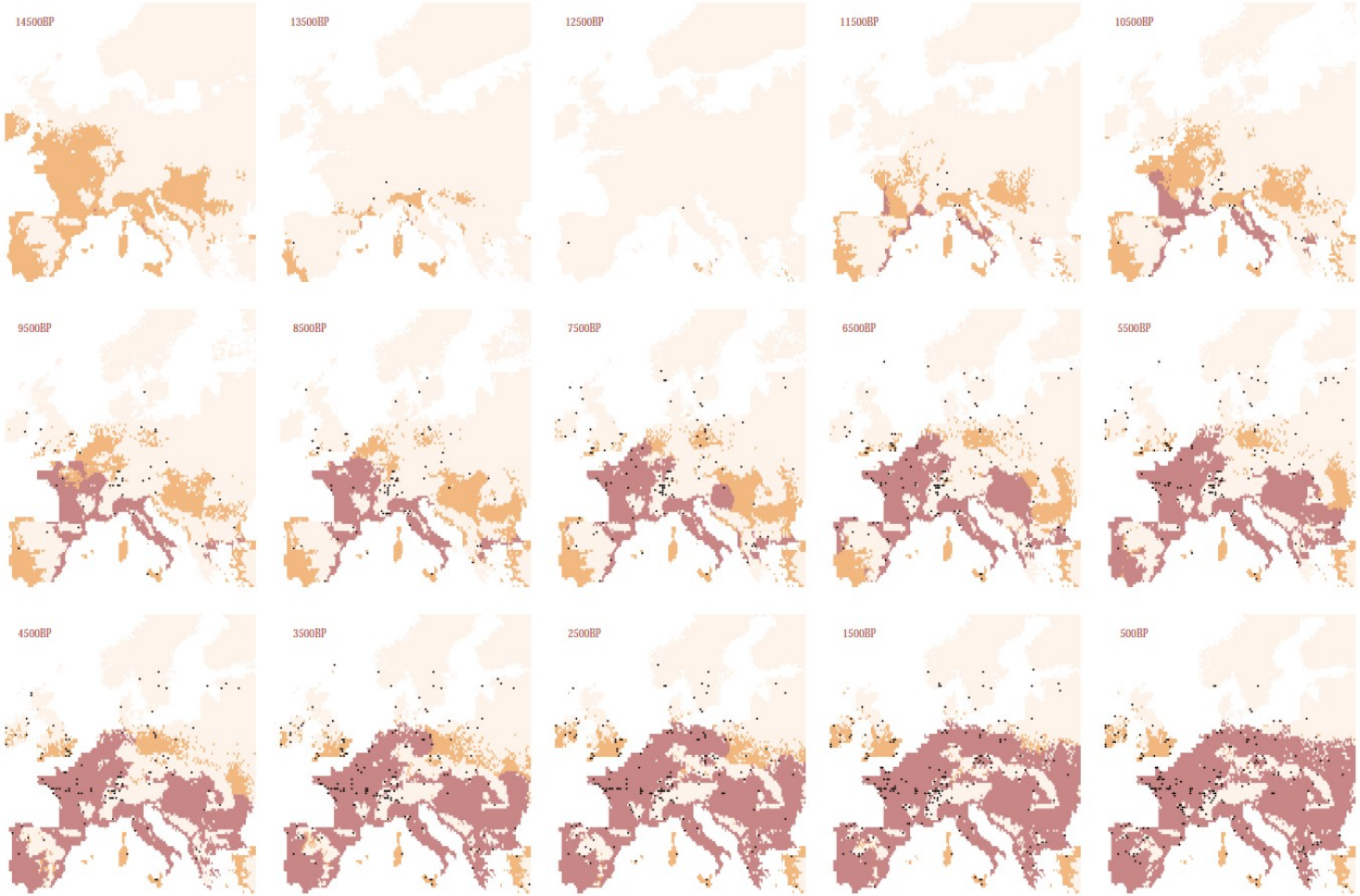
INSIGHTS FROM THE PAST: MIGRATION SIMULATIONS

“Fine scale” migration



e.g. zoom on *Fagus* migration during one century

INSIGHTS FROM THE PAST: MIGRATION SIMULATIONS



e.g. *Quercus* simulations with PHENOFIT

INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY

? HOW TO ASSESS THE TRANSFERABILITY OF OUR MODELS IN (PAST) NOVEL CONDITIONS

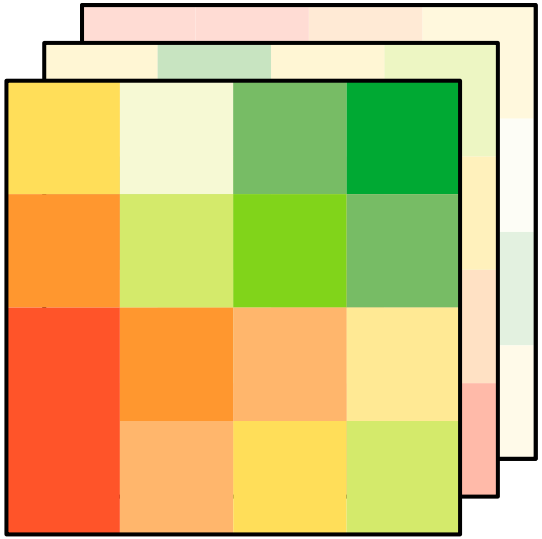
→ WE NEED BOTH:

- a novelty metric
- a measure of model performance

INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY

PAST CLIMATE

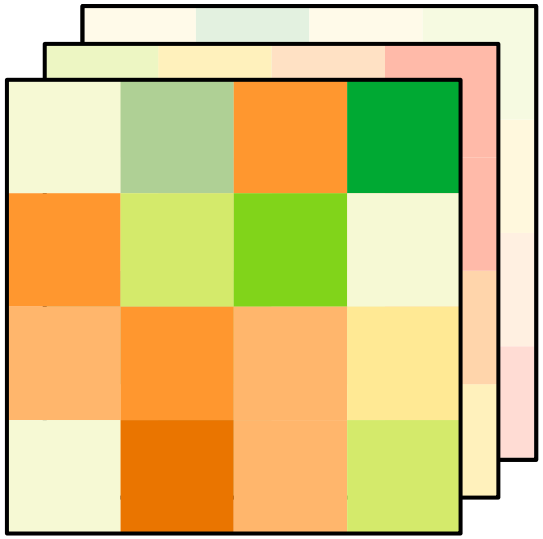
e.g. 9000 years BP



N predictors

BASELINE CLIMATE

Calibration conditions



N predictors

INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY

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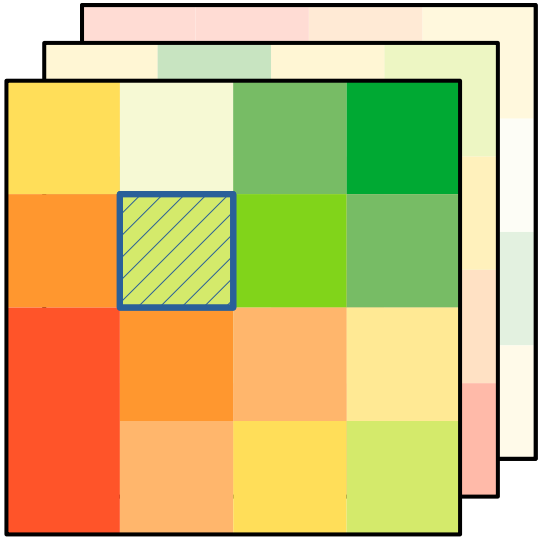
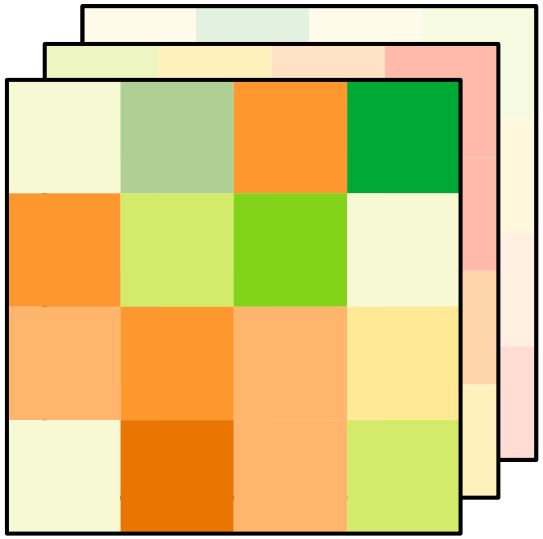


BASELINE CLIMATE

Calibration conditions

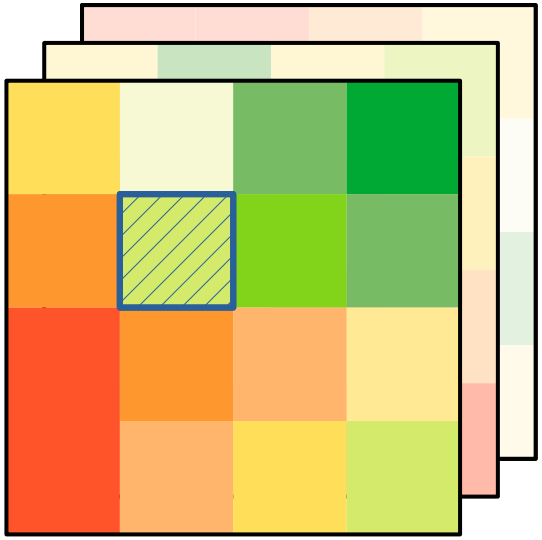


From each cell:

INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY

PAST CLIMATE

e.g. 9000 years BP



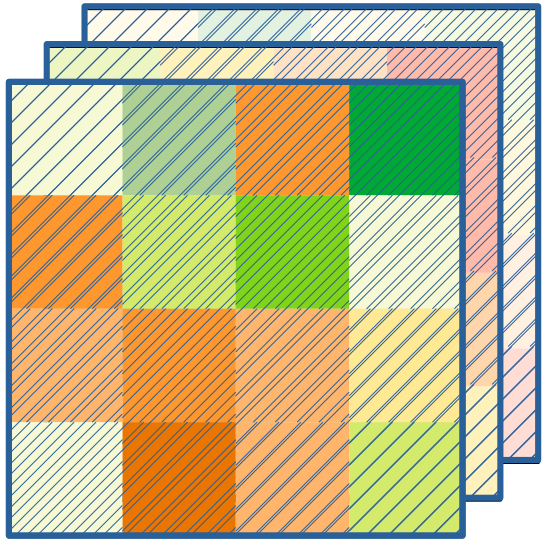
Minimum

distance

(N-dimensional)

BASELINE CLIMATE

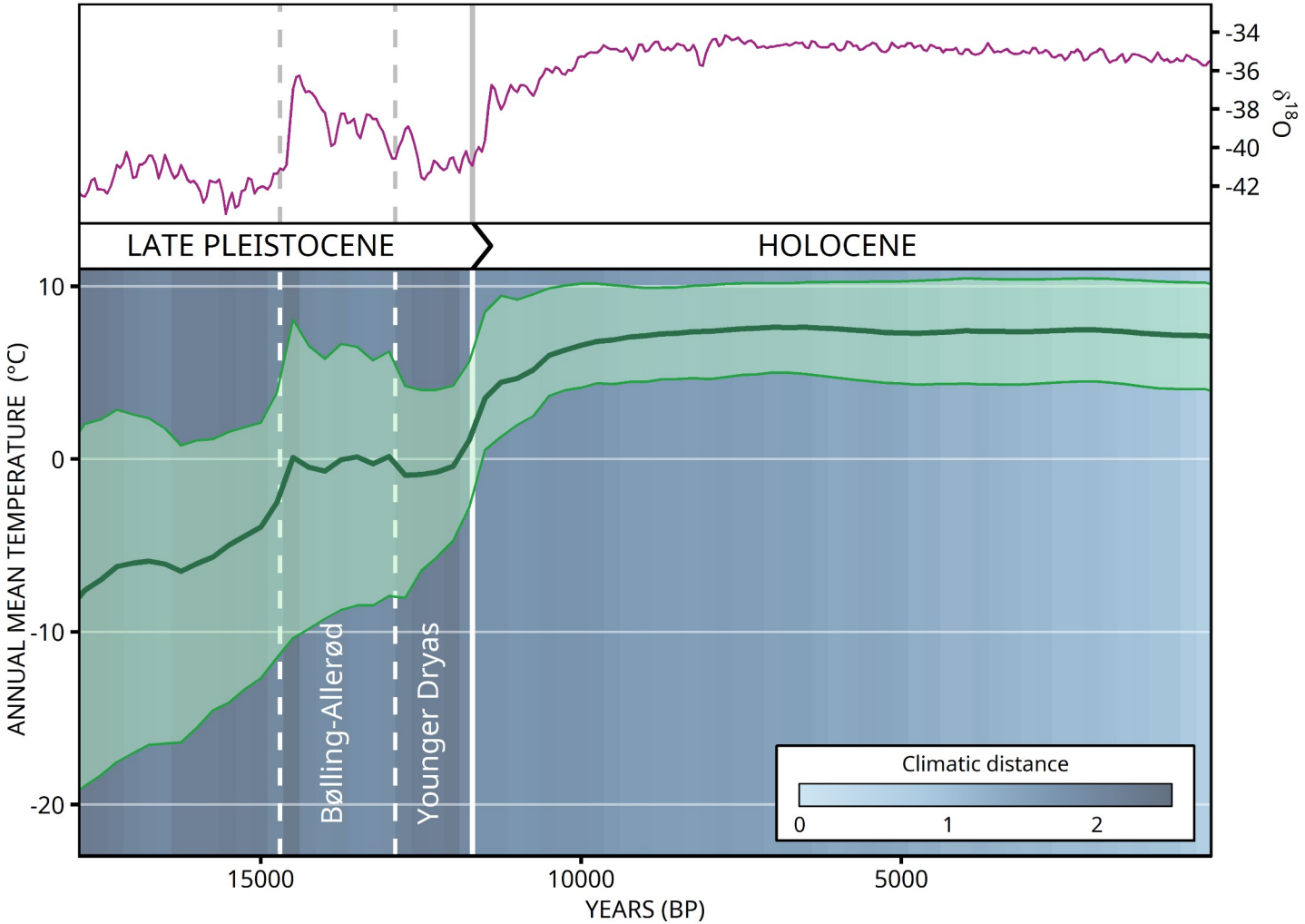
Calibration conditions



From each cell:

To the set of all cells
in the calibration period

INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY



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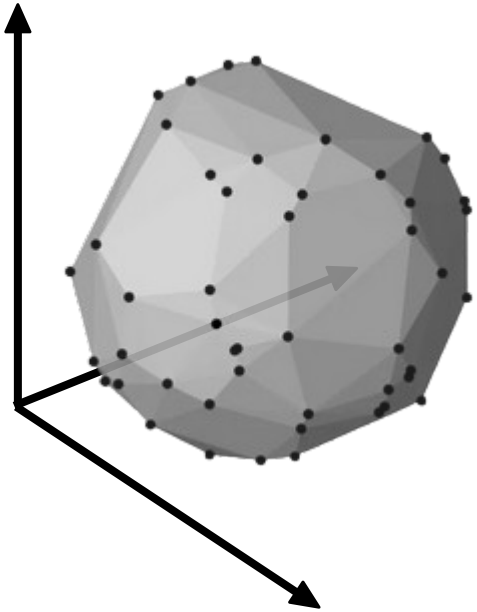

N-dimensional hypervolume

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PAST CLIMATE
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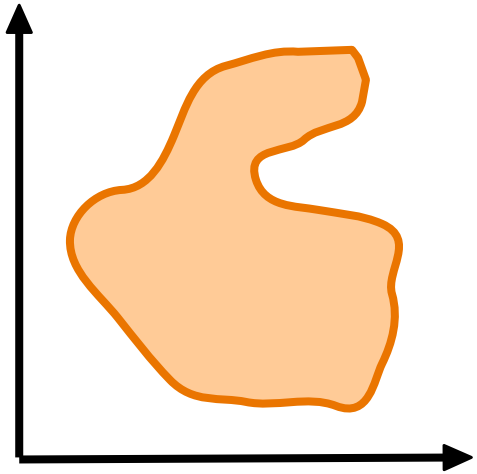

N-dimensional hypervolume

BASELINE CLIMATE
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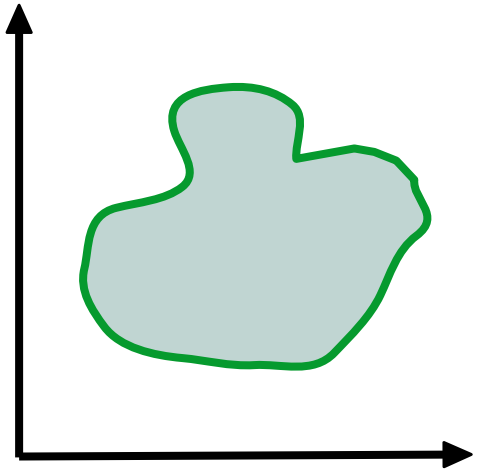

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e.g. 9000 years BP

BASELINE CLIMATE
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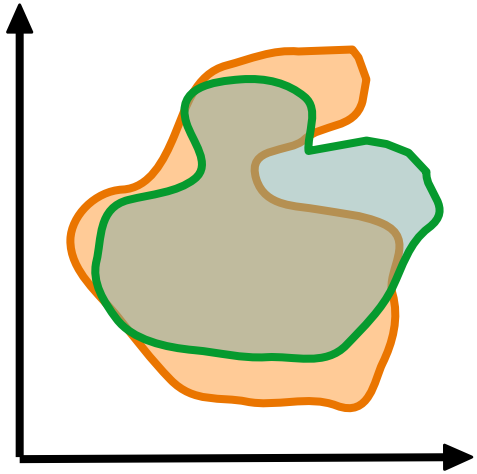
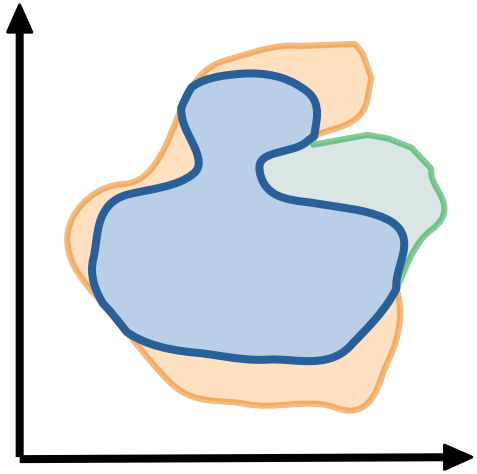


INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY

PAST CLIMATE
e.g. 9000 years BP

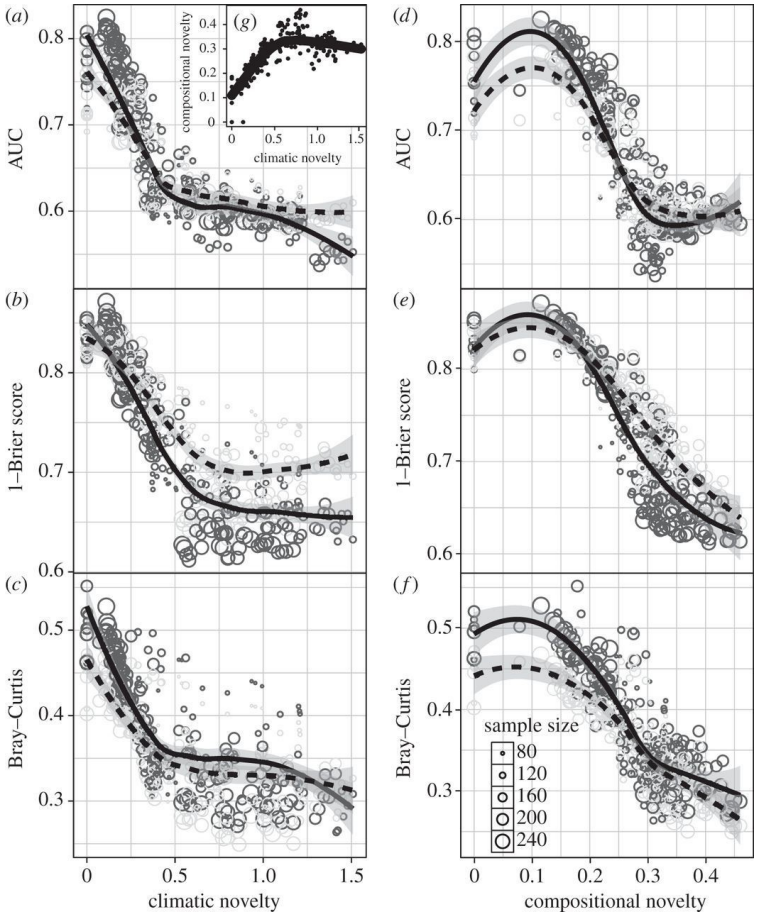
BASELINE CLIMATE
Calibration conditions

Hypervolume overlap

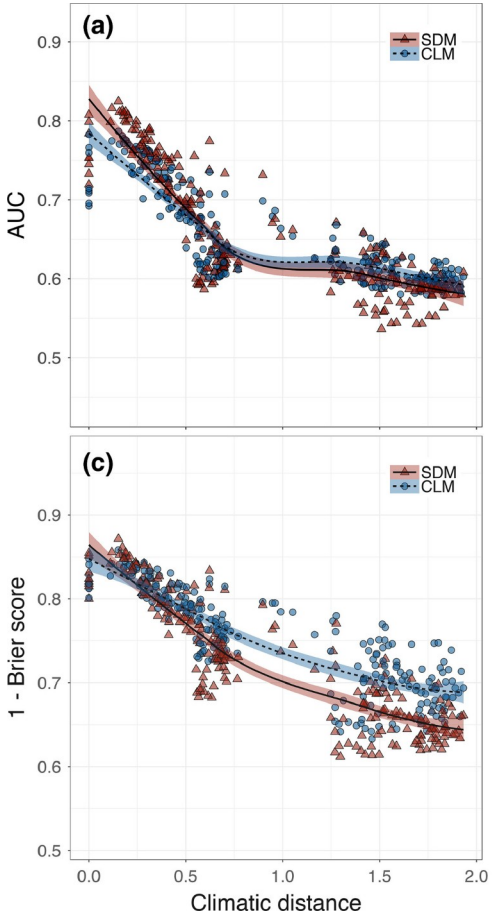


(Sørensen similarity)

INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY

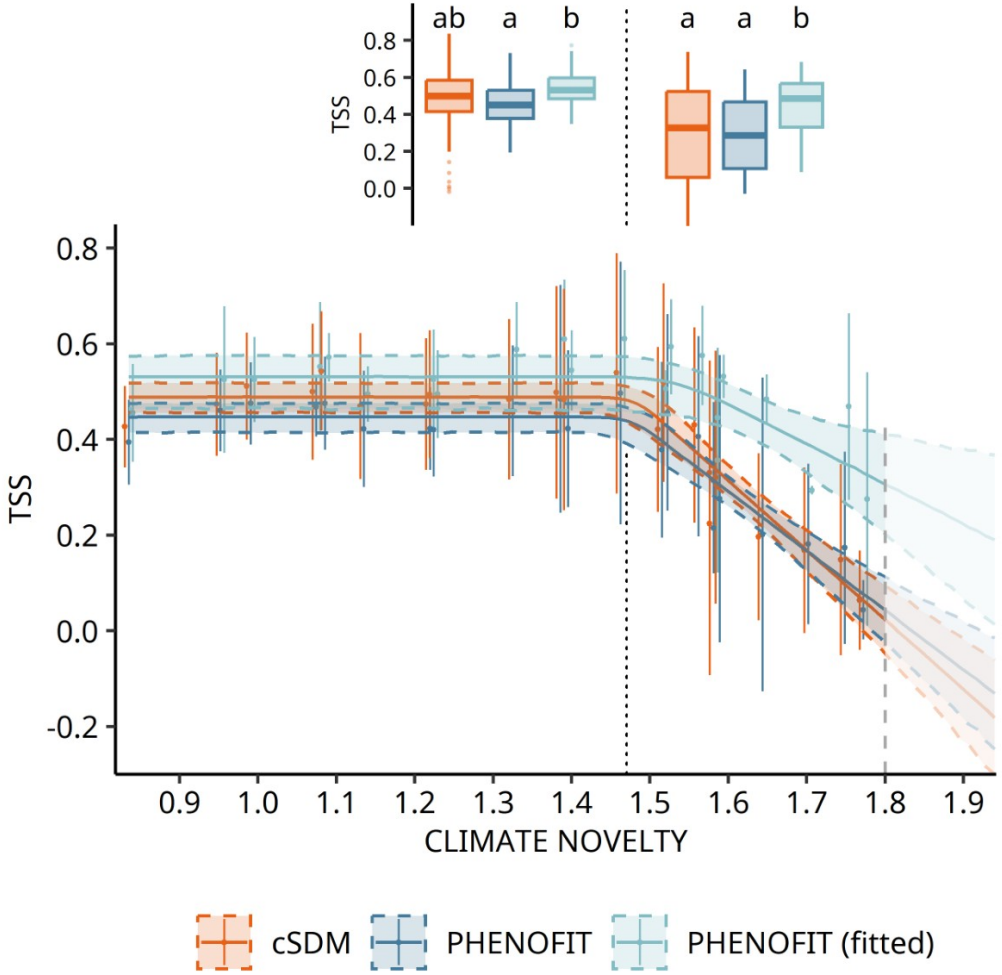


Maguire et al. (2016)



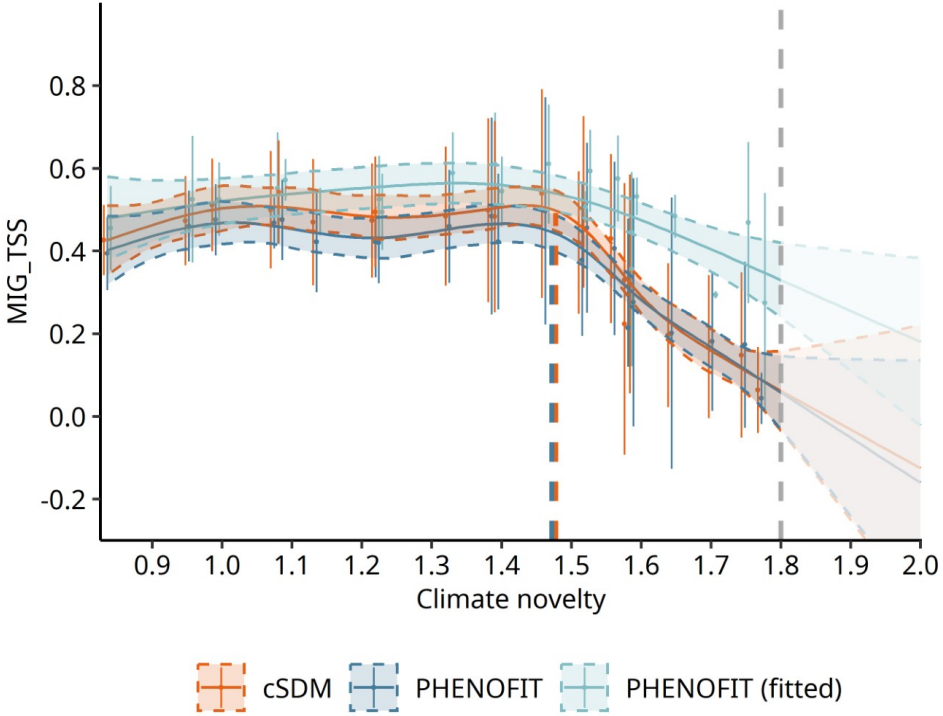
Fitzpatrick et al. (2018)

INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY



INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY

- same patterns with a GAM



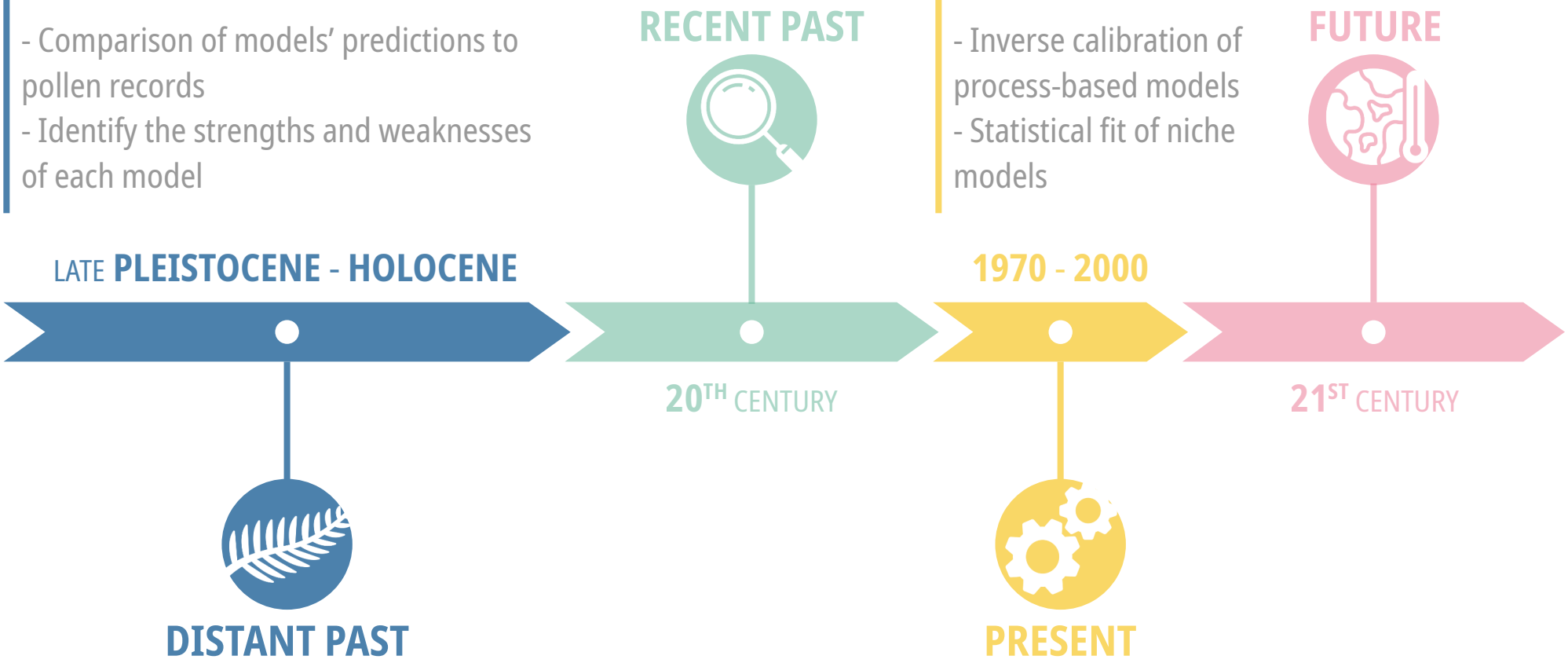
THESIS FRAMEWORK

LESSONS FROM THE PAST

- Comparison of models' predictions to pollen records
- Identify the strengths and weaknesses of each model

MODEL CALIBRATIONS

- Inverse calibration of process-based models
- Statistical fit of niche models



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LATE **PLEISTOCENE - HOLOCENE**

DISTANT PAST

RECENT PAST

20TH CENTURY

FINE-SCALE COMPARISONS

Assessing the importance of climate variability at the leading and trailing edge of tree species ranges

1970 - 2000

PRESENT

FUTURE

21ST CENTURY

RECENT PAST: FINE-SCALE COMPARISON IN SWITZERLAND

- take advantage of the richness and precision of Swizz NFI data
- compare the models in the recent past (1980-2020) at a high spatiotemporal resolution
- identify regions of greatest discrepancy and the causes of these discrepancies

→ Collaboration with D. Scherrer and G. Stadelmann (WSL, Suisse)

(+ provide process-based future projections of Swiss forest species distribution)

THESIS FRAMEWORK

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21ST CENTURY

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Assessing the importance of climate variability at the leading and trailing edge of tree species ranges

FUTURE PROJECTIONS

Elaboration of consensual maps of species projected occurrences and associated uncertainty

FUTURE PREDICTIONS AND UNCERTAINTIES

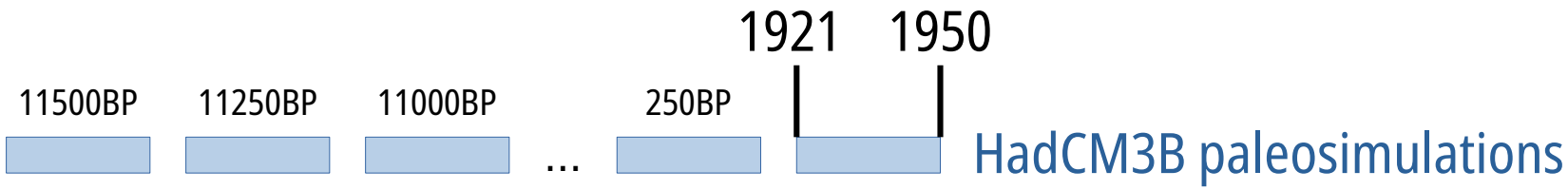
? How to quantify model uncertainties under future climate scenarios ?

→ compute the same climatic distance

- CMIP6 future simulations downscaled on Europe (IPSL, Noel et al. 2022)

FUTURE PREDICTIONS AND UNCERTAINTIES

? How to quantify model uncertainties under future climate scenarios ?



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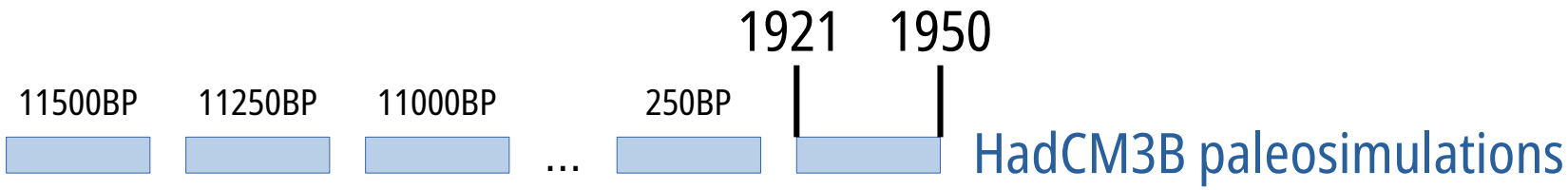

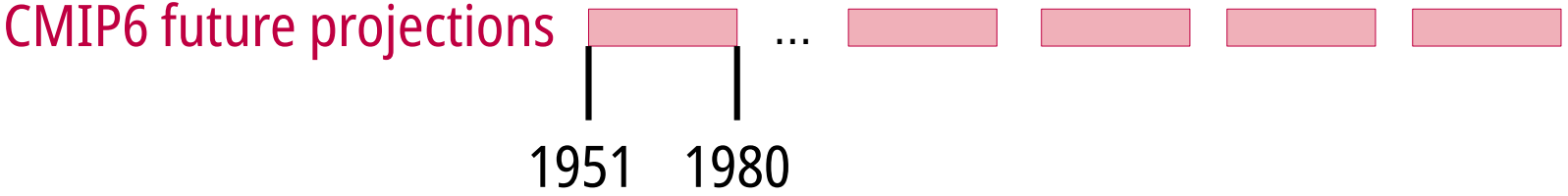

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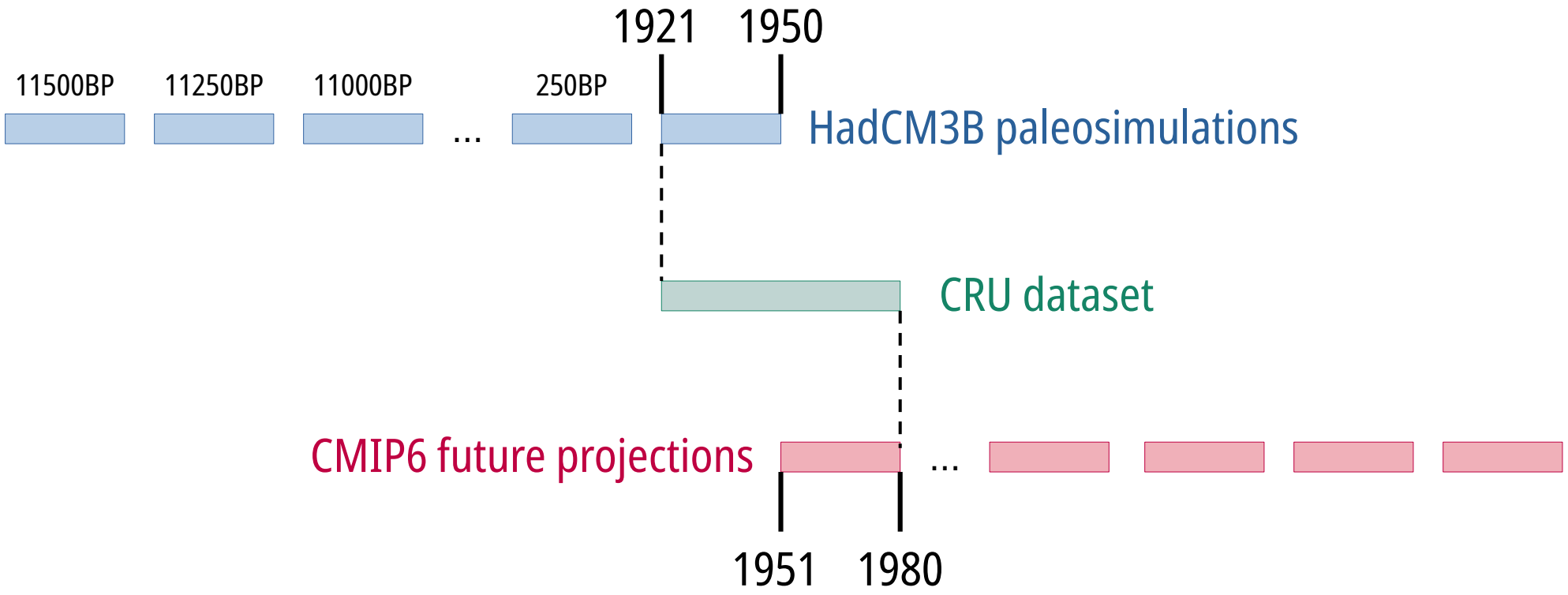

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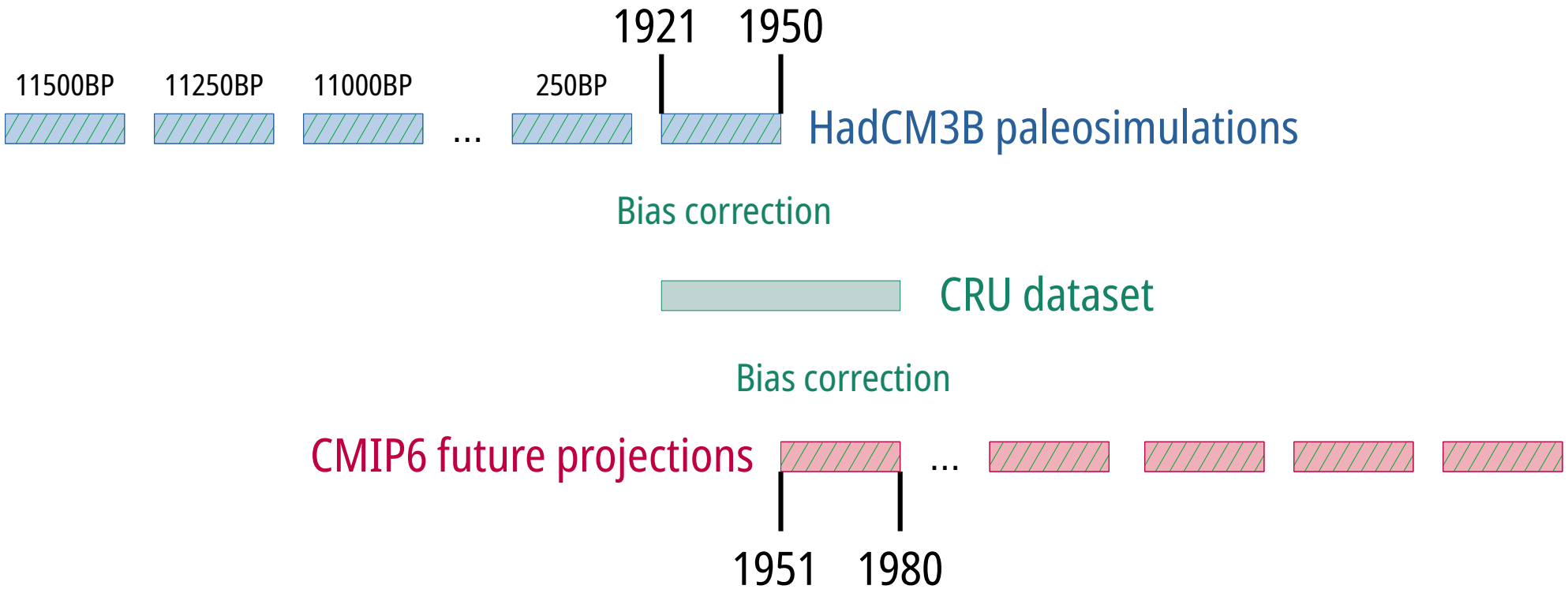


FUTURE PREDICTIONS AND UNCERTAINTIES

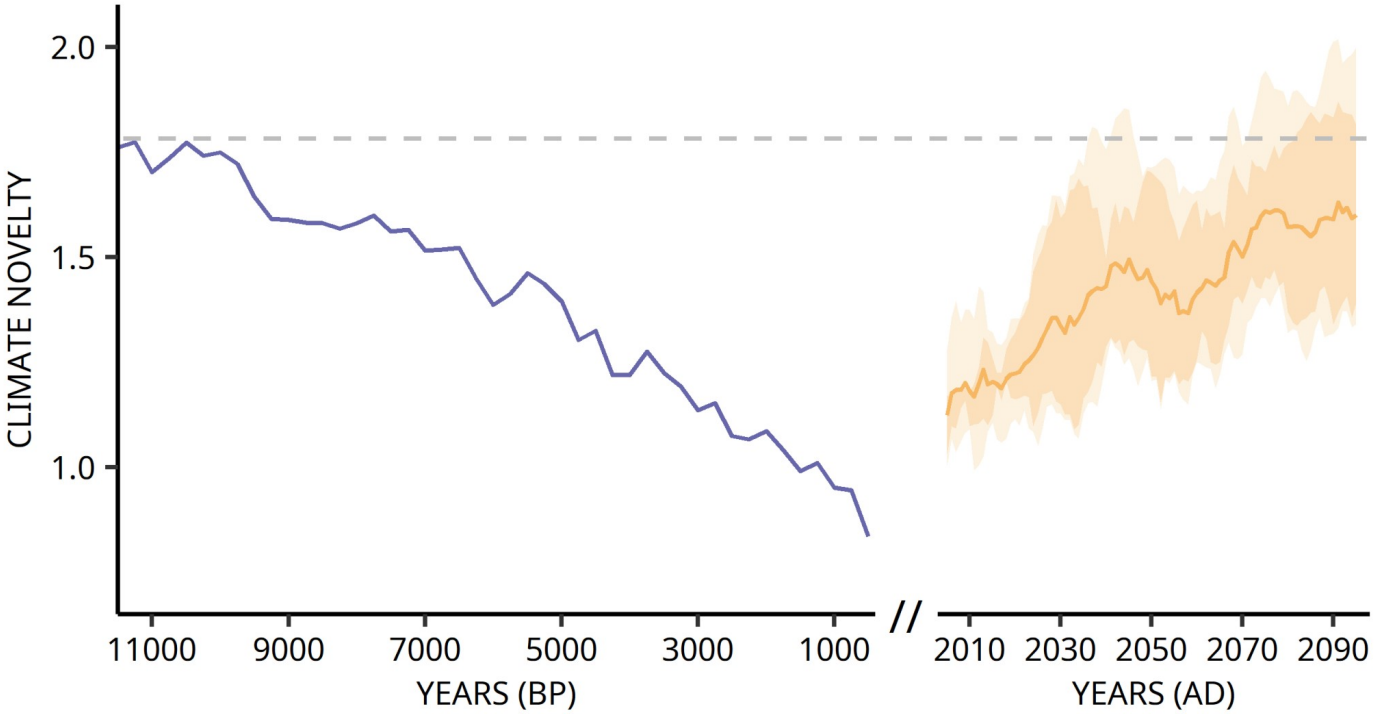
? How to quantify model uncertainties under future climate scenarios ?

After bias correction:

climate_novelty(HadCM3B 1920-1951) = climate_novelty(CMIP6 1951-1980) = 0

FUTURE PREDICTIONS AND UNCERTAINTIES

Strong uncertainties by the end of the 21th century



FUTURE PREDICTIONS AND UNCERTAINTIES

- distant past simulations allow models to be evaluated in conditions that are significantly different from present

- but past conditions are not analogous to these expect over the 21st century

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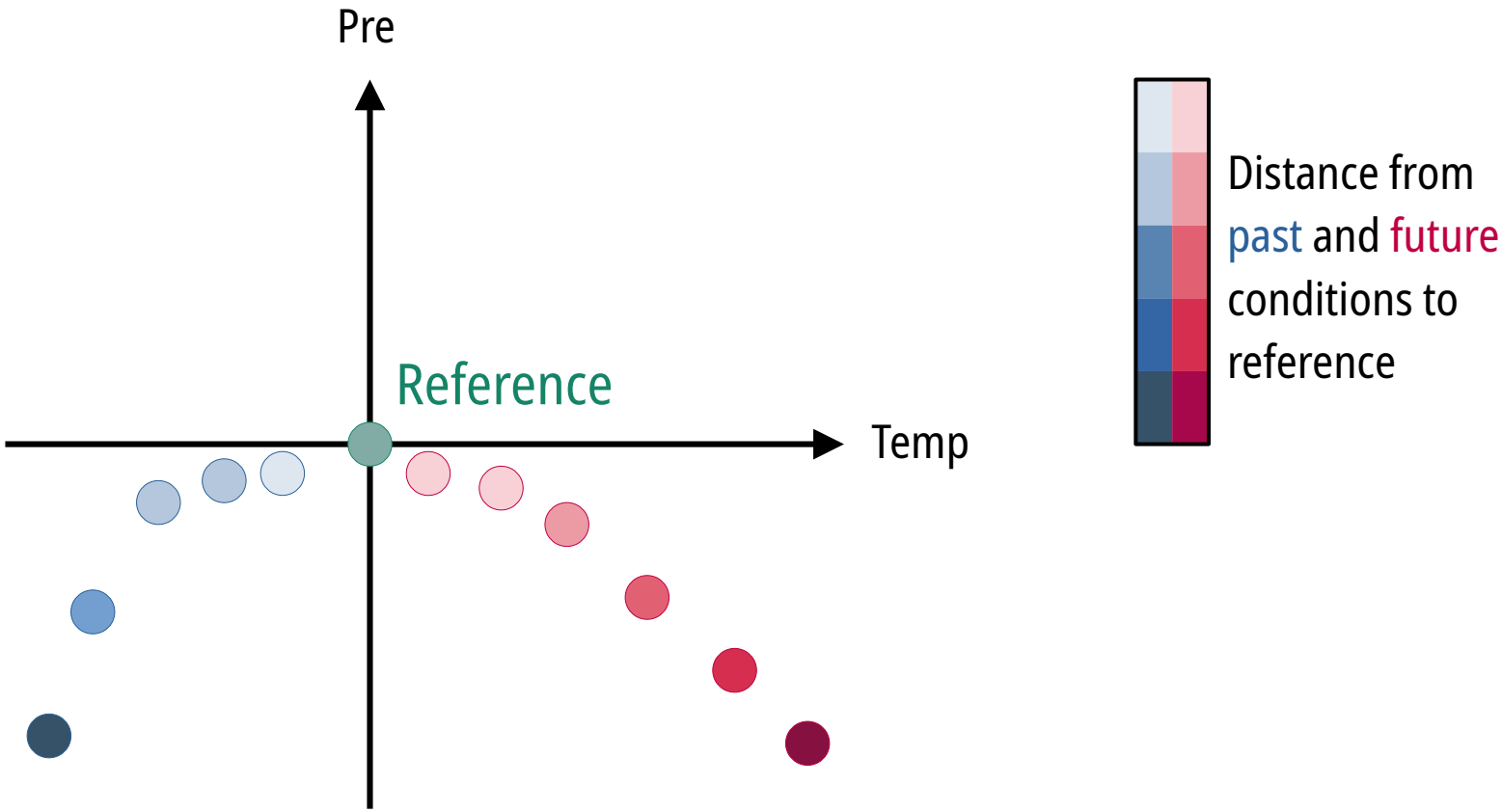
- distant past simulations allow models to be evaluated in conditions that are significantly different from present

- but past conditions are not analogous to these expect over the 21st century

  → but still increase our confidence that models represent the essential processes, implicitly or explicitly

  (same problem with GCMs ?)

INSIGHTS FROM THE PAST: MODEL ROBUSTNESS AGAINST CLIMATE NOVELTY



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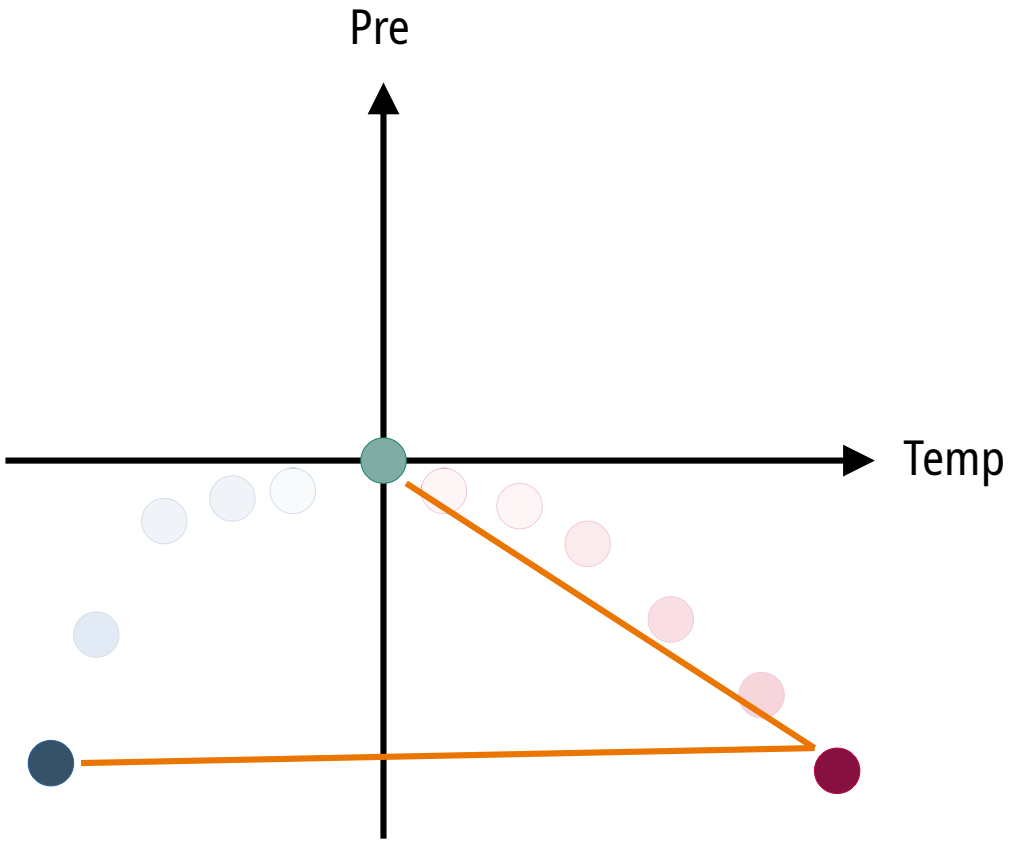

Distance from past and future conditions to reference

Which “analogue” point is the closest ?

FUTURE PREDICTIONS AND UNCERTAINTIES

? What does the accuracy of a model simulation of past distribution really say about the accuracy of its projections in future climate ?

FUTURE PREDICTIONS AND UNCERTAINTIES

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→ forecast proficiency

FUTURE PREDICTIONS AND UNCERTAINTIES

? Better communication on model uncertainties is crucial

- a more comprehensive understanding of the potential errors by decision-makers
- prevents the misinterpretation of model outputs as deterministic representations of the reality
- directly linked to risk assessment

NEXT POINTS

- last paleosimulations (CASTANEA),
  analysis and redaction

- fine-scale simulations in Switzerland (recent past)

- future simulations
  how to link the likelihood of projections to the past transferability?

- further analyse the inverse calibration outcomes
  what can we learn ? deficiencies in model parametrization/structure?

ADDITIONAL POINTS

- collaboration with Elizabeth Wolkovich (UBC, Canada)
  (visiting period at CEFE in 2023)

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- collaboration with Elizabeth Wolkovich (UBC, Canada)
  (visiting period at CEFE in 2023)

  → conceptual paper: trade-off between growing season length (future warming) versus risk (climate variability)

  Case study with PHENOFIT: does means vs variability shifts lead to increases of decreases in fitness?

Additional points

- internship project (if corresponding funding is obtained) as part of the CEMEB "*Equipe de recherche junior*": analyse discrepancies between different modelling approaches (hybrid statistical model, PHENOFIT fitted and PHENOFIT), focus on frost vulnerability (present and future conditions)

Integrative Models for Forests: Understand and Simulate the Impacts Of Novel climates (IMFUSION)

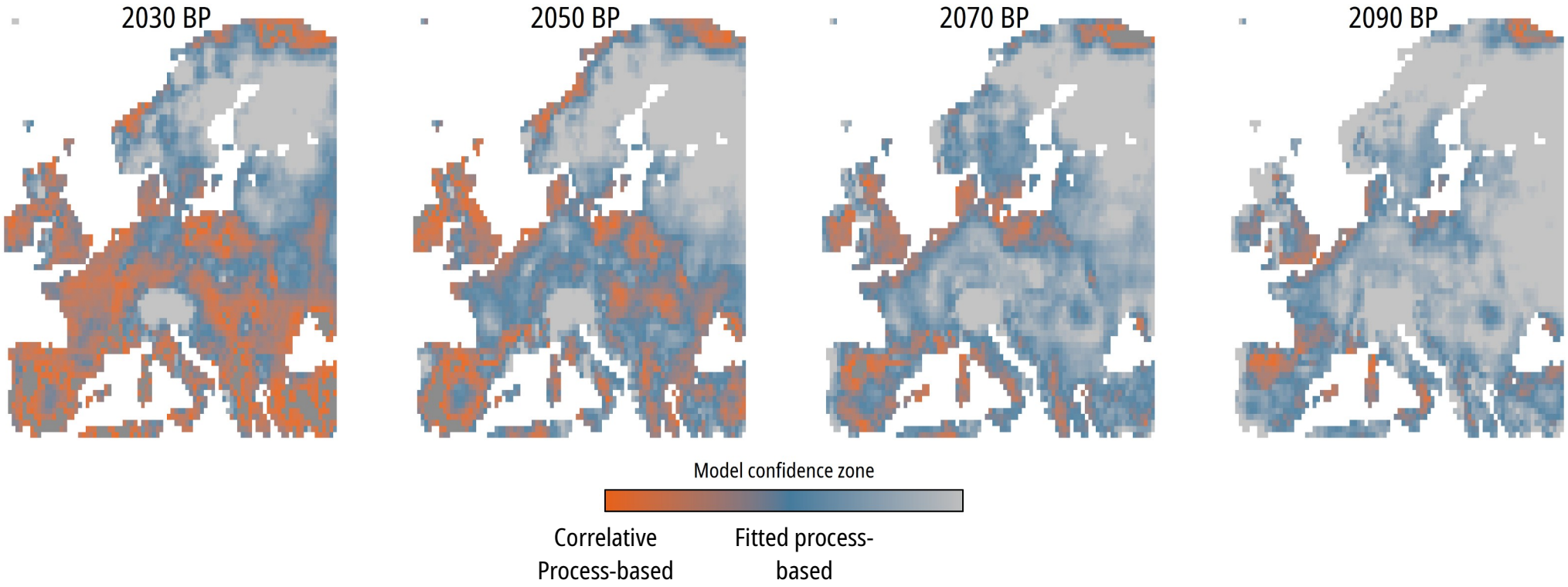
Collaboration with Anne Baranger (PhD student at LESSEM, Grenoble)

THANK YOU !

Linocut print by C. Rescan

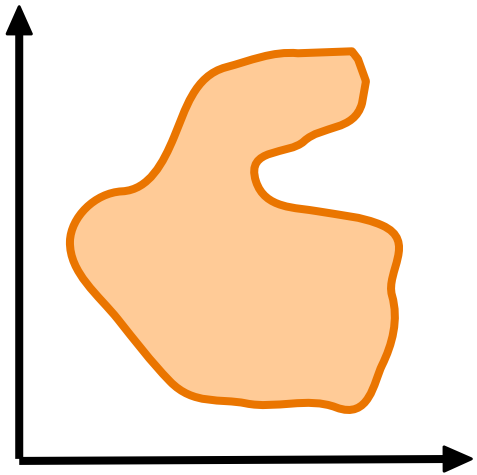
IMPLICATIONS FOR FUTURE CONFIDENCE IN MODEL PROJECTIONS

Strong uncertainties by the end of the 21th century



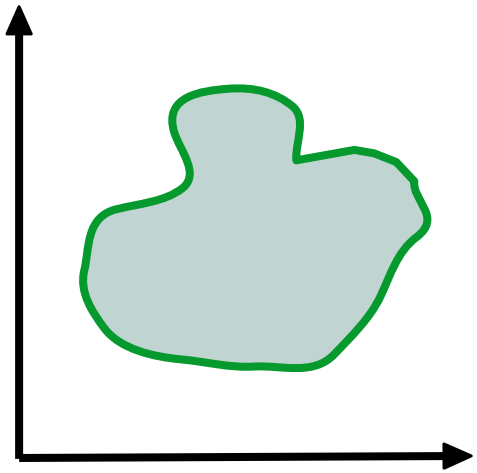
INSIGHTS FROM THE PAST: COMPARE MODEL PROJECTIONS

Predicted niche model A



N-dimensional hypervolume

Predicted niche model B



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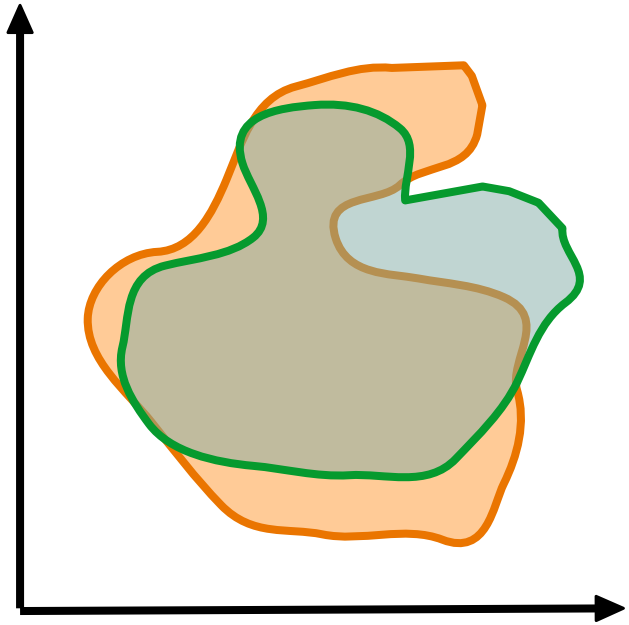
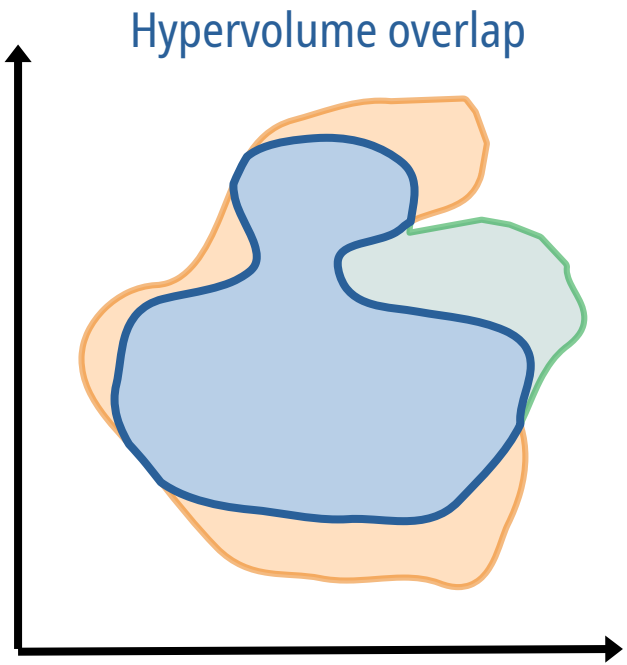
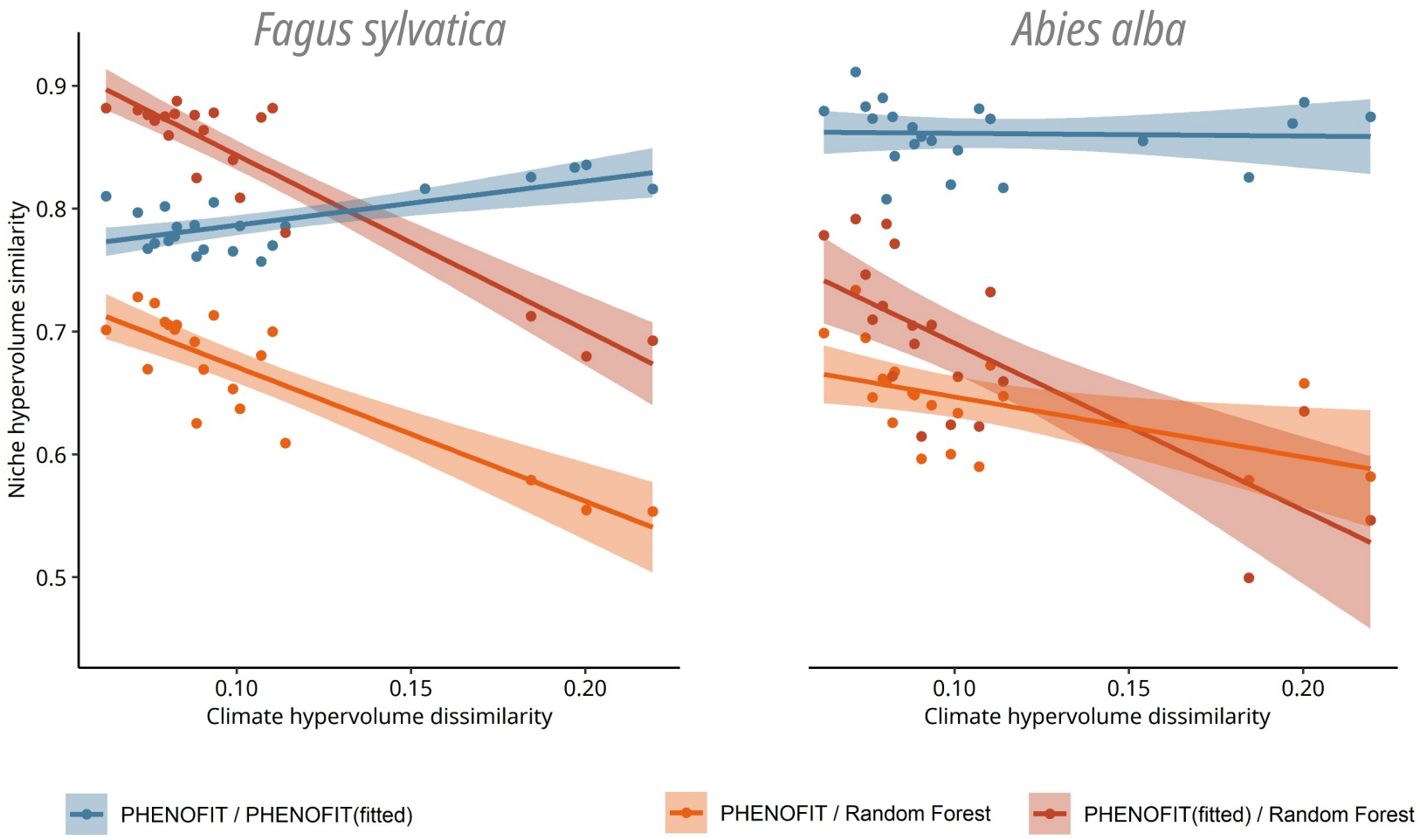


INSIGHTS FROM THE PAST: COMPARE MODEL PROJECTIONS



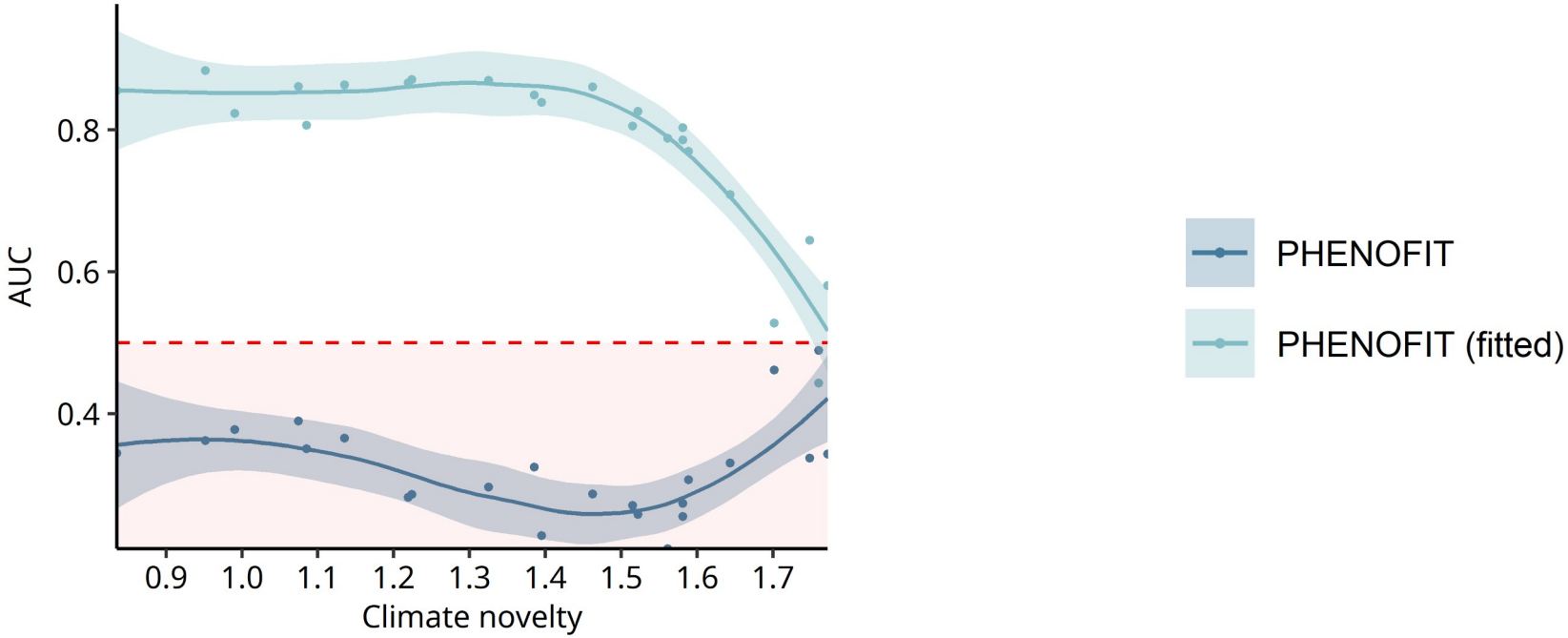
$$\text{Sørensen similarity} = \frac{2\,|A \cap B|}{|A| + |B|}$$

INSIGHTS FROM THE PAST: COMPARE MODEL PROJECTIONS



CHALLENGES TO PROCESS-BASED APPROACHES

Palaeoecology: a tool for model diagnostics?



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CHALLENGES TO PROCESS-BASED APPROACHES

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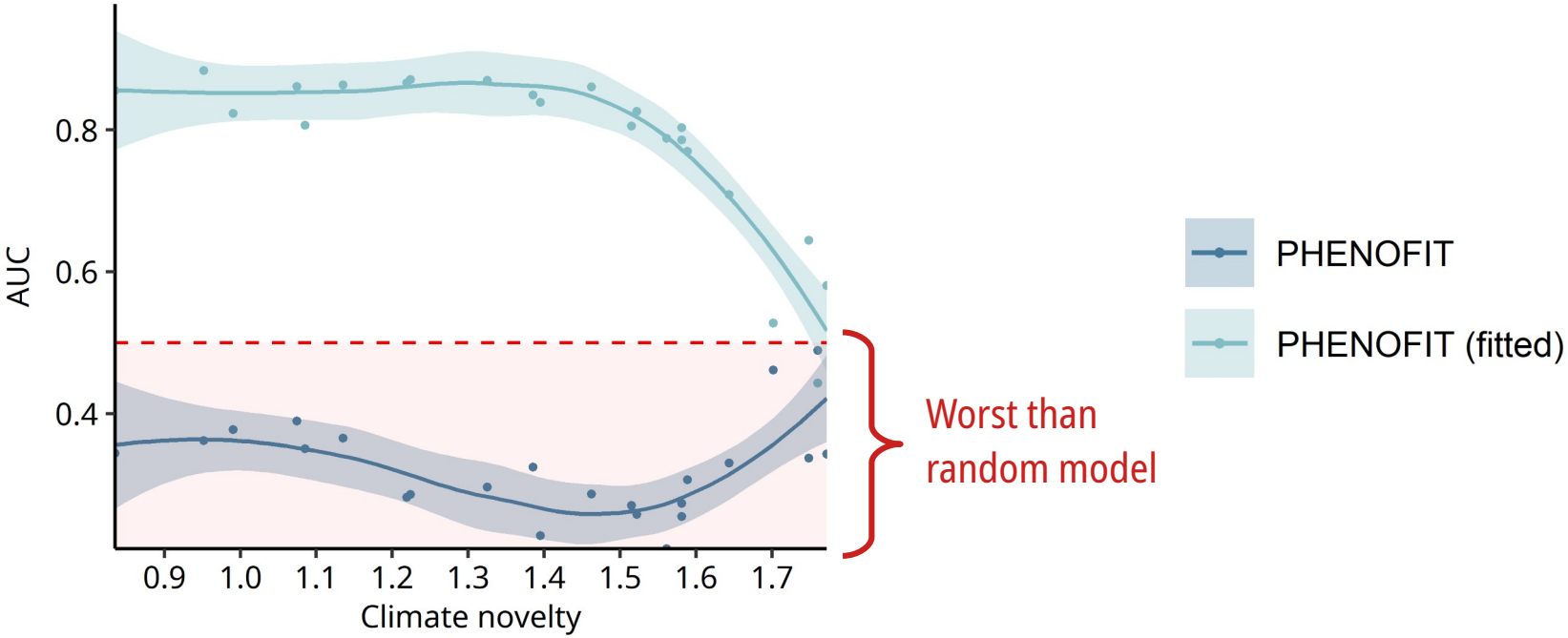

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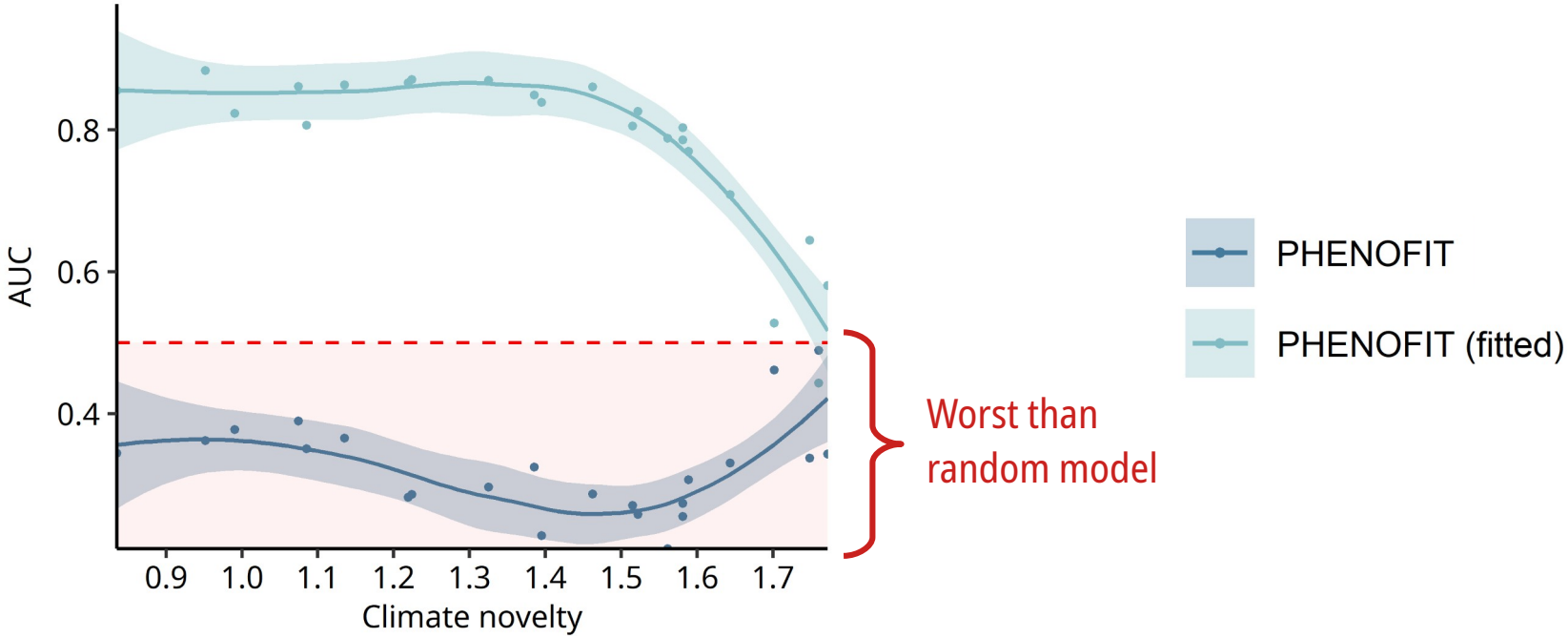
CHALLENGES TO PROCESS-BASED APPROACHES

Palaeoecology: a tool for model diagnostics?



Bad calibration due to scarce data rather than a model misspecification?

Larix