New methods for quantitative climate reconstructions applied to the Levant

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Steps for local climate reconstructions

1) Formulate a mathematical model (Bayesian hierarchical model)

1) Pollen counts in lake sediments (drilled cores) and assign these pollen (and macro fossils) to plants

1) Assign modern plant distributions to modern climate (machine learning)

1) Assign the depth of the core to ages (e.g. Bacon model)

1) Overview of variable names

- $\mathbb{P}$: Probability distribution
- $\boldsymbol{C}$: Climate, contains modern $\boldsymbol{C_m}$ and past $\boldsymbol{C_p}$ climate information
- $\boldsymbol{P}$: Proxy, contains modern $\boldsymbol{P_m}$ and past $\boldsymbol{P_p}$ proxy information
- $\boldsymbol{P_s}$: Proxy selected
- $\boldsymbol{A}$: Age
- $\boldsymbol{D}$: Depth (lake sediment) or distance (speleothems)
- $\boldsymbol{Y}$: Variables like $\boldsymbol{C}$, $\boldsymbol{P_s}$ etc.
- $\boldsymbol{\Theta}$: Parameter of selected proxy
- $\boldsymbol{\Theta_1}$: Parameter of selected proxy: link between modern climate $\boldsymbol{C_m}$ and modern taxa distributions $\boldsymbol{P_m}$ (Set of transfer function parameters)
- $\boldsymbol{\Theta_2}$: Parameter of selected proxy: taxa combinations and their occurrence in relation to depth
- $\boldsymbol{E_p}$: Explained variance of proxy, contains $\boldsymbol{E_I}$ (Isotopes), and $\boldsymbol{E_T}$ (Taxa)

1) Reconstruction model

$$
\begin{aligned}
\mathbb{P}(\boldsymbol{C}, \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta}) &= \int_{\mathcal{P}_s} \mathbb{P}(\boldsymbol{C}, \boldsymbol{P}, \boldsymbol{P_s}, \boldsymbol{D}, \boldsymbol{\Theta}) \, d\boldsymbol{P_s} \\
&= \int_{\mathcal{P}_s} \mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{P_s}, \boldsymbol{D}, \boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta}) \, d\boldsymbol{P_s} \\
\Leftrightarrow \mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta}) &= \int_{\mathcal{P}_s} \mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{P_s}, \boldsymbol{D}, \boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta}) \, d\boldsymbol{P_s}
\end{aligned}
$$

1) Reconstruction model

Consider $\mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{P_s}, \boldsymbol{D}, \boldsymbol{\Theta})$ in more detail:

$$\begin{aligned}\mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{P_s}, \boldsymbol{D}, \boldsymbol{\Theta}) &\overset{1.}{=} \mathbb{P}(\boldsymbol{C} \mid, \boldsymbol{P_s}, \boldsymbol{D}, \boldsymbol{\Theta}) \overset{2.}{=} \mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P_s}, \boldsymbol{\Theta}) \overset{3.}{=} \mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P_s}, \boldsymbol{\Theta_1}) \\ &\overset{4.}{=} \frac{\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{C}, \boldsymbol{\Theta_1}) \cdot \mathbb{P}(\boldsymbol{\Theta_1} \mid \boldsymbol{C}) \cdot \mathbb{P}(\boldsymbol{C})}{\mathbb{P}(\boldsymbol{P_s}, \boldsymbol{\Theta_1})} \\ &\overset{5.}{=} \frac{\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{C}, \boldsymbol{\Theta_1}) \cdot \mathbb{P}(\boldsymbol{\Theta_1})}{\mathbb{P}(\boldsymbol{P_s}, \boldsymbol{\Theta_1})}\end{aligned}$$

With the following assumptions and applications:

1. $\boldsymbol{C}$ is conditionally independent of $\boldsymbol{P}$ if $\boldsymbol{P_s}$ is given. This means that $\boldsymbol{P_s}$ explains enough variability of the core.
2. The link between $\boldsymbol{C}$ and $\boldsymbol{P_s}$ is conditionally independent of depth. This means that no evolution of plants has taken place over time.
3. The relation between $\boldsymbol{C}$ and $\boldsymbol{P_s}$ is described only by the parameter $\boldsymbol{\Theta_1}$. Furthermore, $\boldsymbol{\Theta_1}$ and $\boldsymbol{\Theta_2}$ are a priori independent: $\mathbb{P}(\boldsymbol{\Theta}) = \mathbb{P}(\boldsymbol{\Theta_1}) \cdot \mathbb{P}(\boldsymbol{\Theta_2})$.
4. Application of Bayes'theorem.
5. $\boldsymbol{\Theta_1}$ is conditionally independent $\boldsymbol{C}$ and $\boldsymbol{C}$ is uniformly distributed over the entire climate space.

1) Reconstruction model

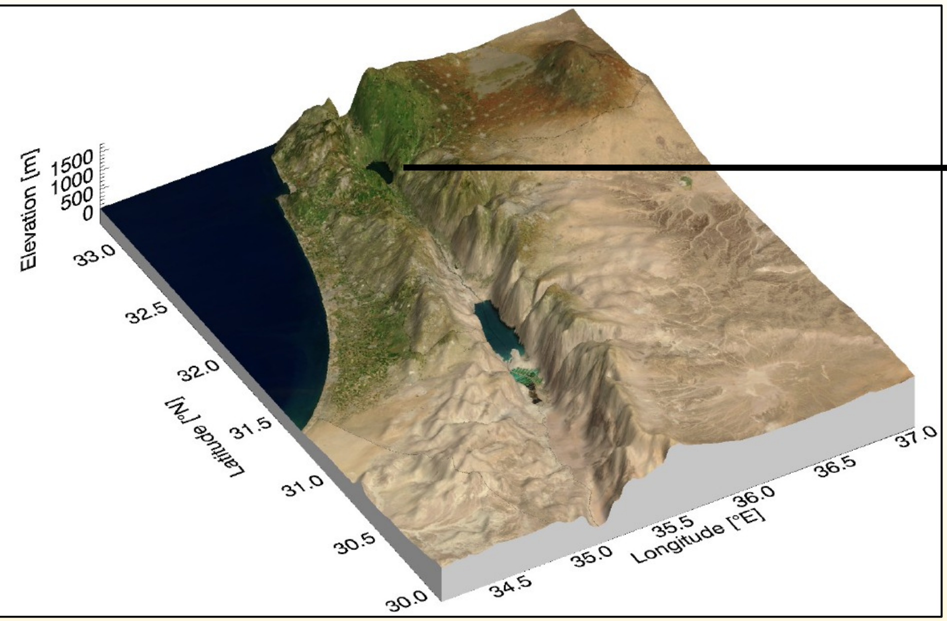
Ultimately, these assumptions lead to the following model:

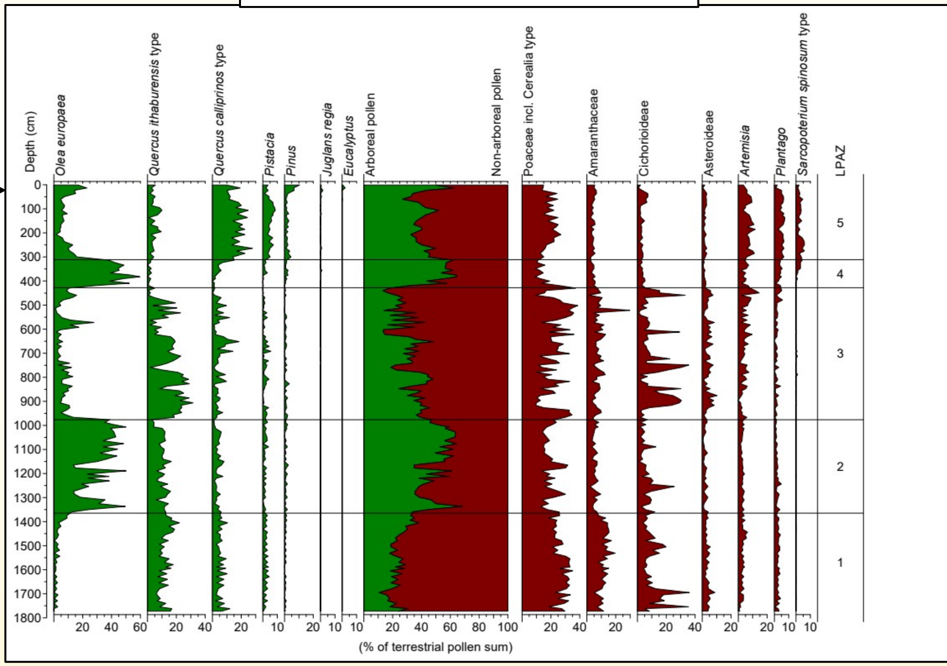
$$\mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta}) = \int_{\mathcal{P}_s} \frac{\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{C}, \boldsymbol{\Theta_1}) \cdot \mathbb{P}(\boldsymbol{\Theta_1})}{\mathbb{P}(\boldsymbol{P_s}, \boldsymbol{\Theta_1})} \cdot \mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta_2}) \, d\boldsymbol{P_s}.$$

2) Plant information from Sea of Galilee

Overall question: Which of the proxy information found in the core provides a desired climate reconstruction?

$$\mathbb{P}(P_s \mid P, D, \Theta_2)$$





3) Assign modern plant distributions to modern climate

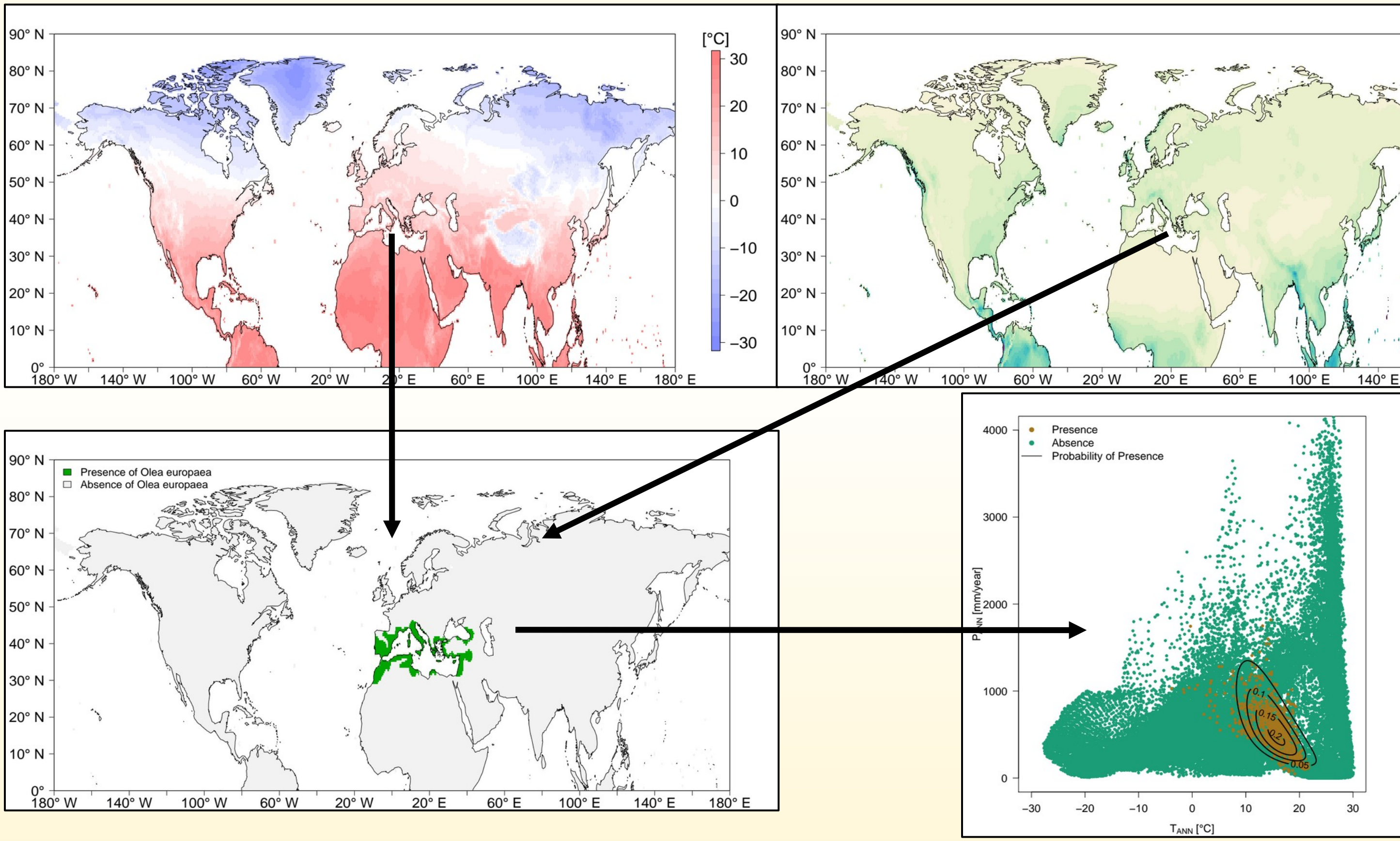
- Assign recent climate (CRU Data) to the plant distributions:
  classification problem (presence and absence of taxa)

- Unbalanced Dataset:
  SMOTE (Synthetic Minority Oversampling Technique)

- Find a ML-algorithm that best fits the SMOTEd data:
  Machine Learning Competition

3.1) Assign modern plant distributions to modern climate

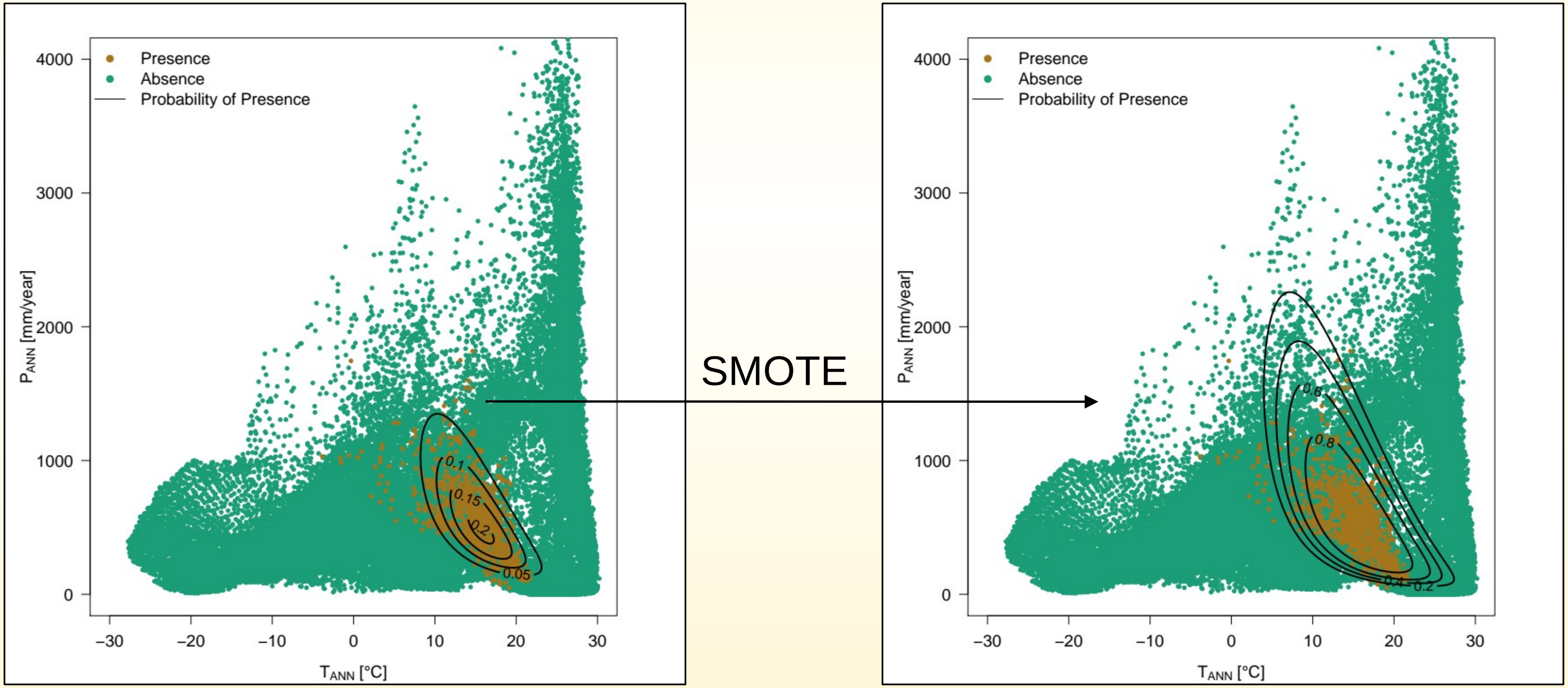
- Assign the recent climate (CRU Data) to the plant distribution: classification problem (presence and absence of taxa)



3.2) Assign modern plant distributions to modern climate

- Unbalanced Dataset:
  SMOTE (Synthetic Minority Oversampling Technique)

$$\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{C}, \boldsymbol{\Theta_1})$$



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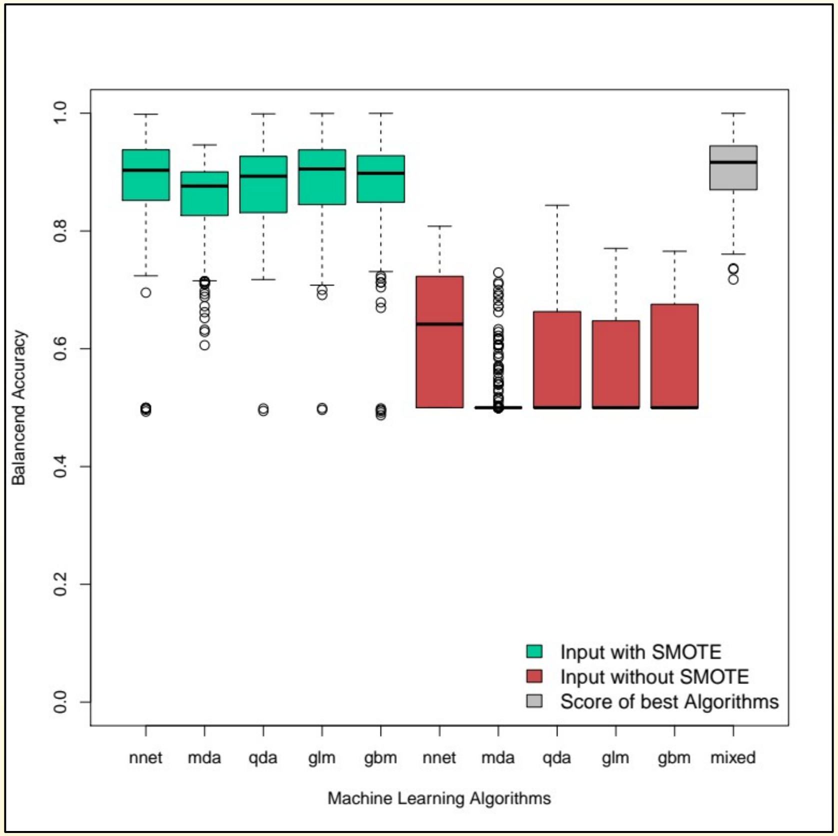
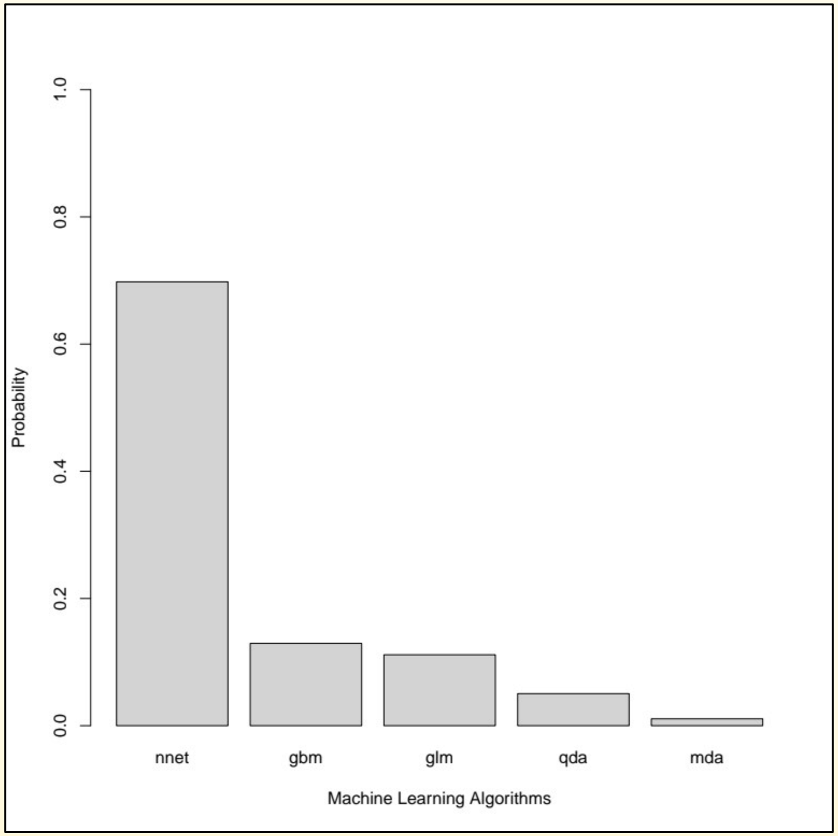
3.3) Assign modern plant distributions to modern climate

- Find a ML-algorithm that best fits the SMOTED data:
  Machine Learning Competition





3.3) Assign modern plant distributions to modern climate

Information about the machine learning algorithms used:

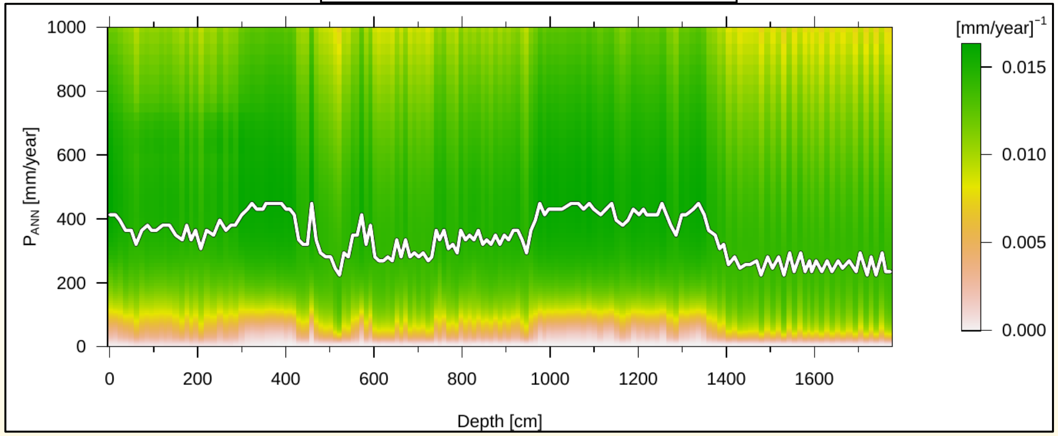
Algorithm:	Shortcut:
Generalized Linear Model	glm
Artificial Neural Networks	nnet
Quadratic Discriminant Analysis	qda
Mixture and Flexible Discriminant Analysis	mda
Stochastic Gradient Boosting	gbm

1) – 3) Climate reconstruction in terms of depth

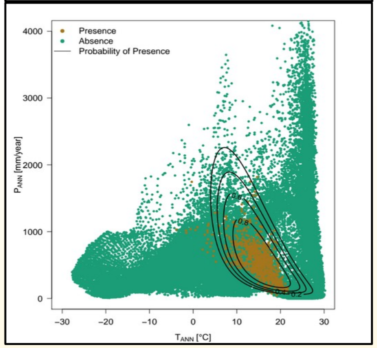
$$\mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta}) = \int_{\mathcal{P}_s} \frac{\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{C}, \boldsymbol{\Theta_1}) \cdot \mathbb{P}(\boldsymbol{\Theta_1})}{\mathbb{P}(\boldsymbol{P_s}, \boldsymbol{\Theta_1})} \cdot \mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta_2}) \, d\boldsymbol{P_s}.$$

- A possible climate reconstruction as a function of a given set of selected proxy information
- A variety of different climate reconstructions are possible -> MCMC simulation

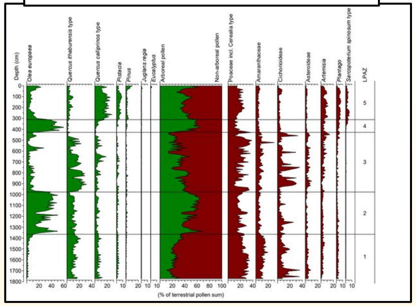
$$\mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta})$$



$$\frac{\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{C}, \boldsymbol{\Theta_1}) \cdot \mathbb{P}(\boldsymbol{\Theta_1})}{\mathbb{P}(\boldsymbol{P_s}, \boldsymbol{\Theta_1})}$$



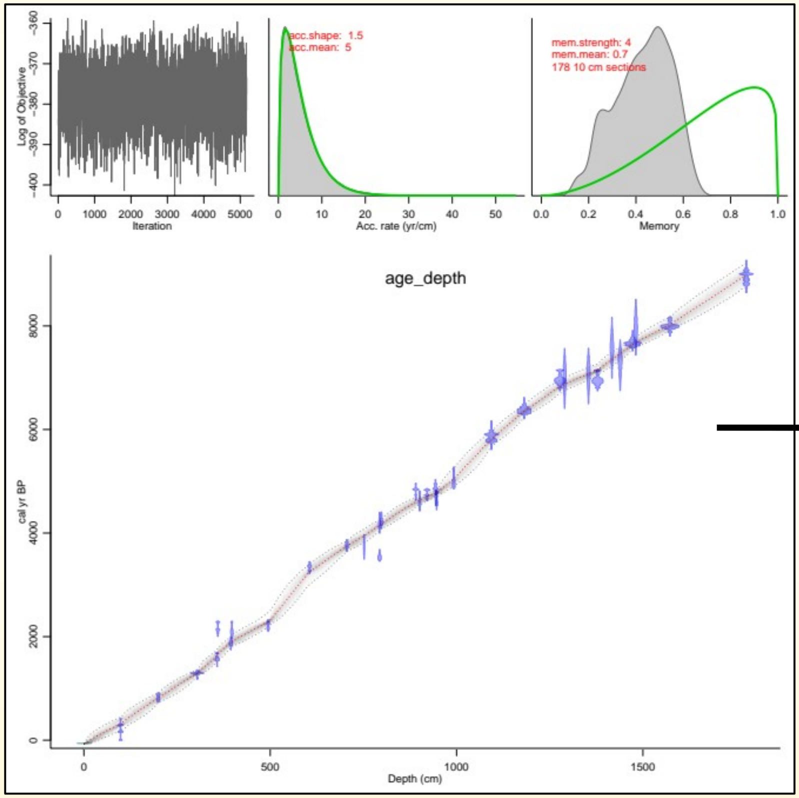
$$\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta_2})$$

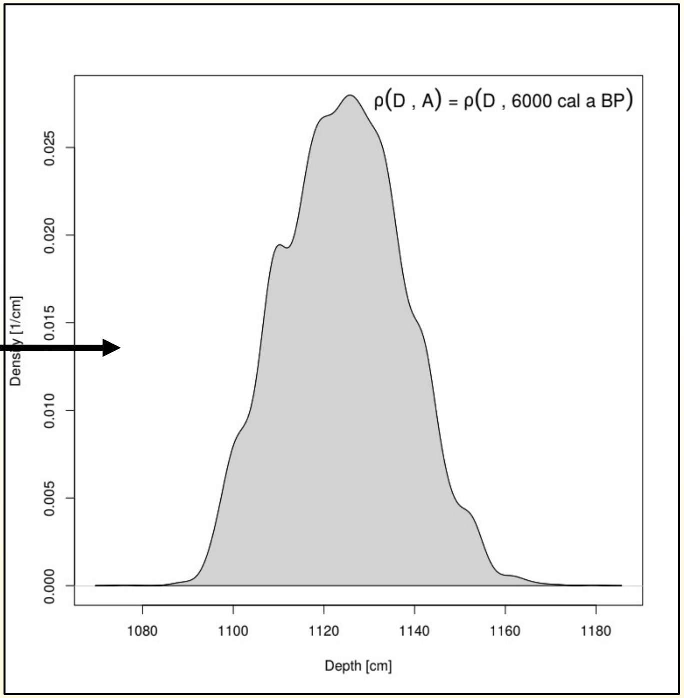


4) Assign the cores depth to age (Bacon model)

How can we continue to account for age uncertainty?

Result of the new function *Bacon.d.Age* in the *rbacon* package in R





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4) Climate reconstruction in terms of age

Age-Depth Transformation:

$$
\begin{aligned}
\mathbb{P}(\boldsymbol{Y}, \boldsymbol{P}, \boldsymbol{A}, \Theta) &= \int_{\mathcal{D}} \mathbb{P}(\boldsymbol{Y}, \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{D}, \Theta)\, d\boldsymbol{D} \\
&= \int_{\mathcal{D}} \mathbb{P}(\boldsymbol{Y} \mid \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{D}, \Theta) \cdot \mathbb{P}(\boldsymbol{D} \mid \boldsymbol{A}, \boldsymbol{P}, \Theta) \cdot \mathbb{P}(\boldsymbol{P}, \boldsymbol{A}, \Theta)\, d\boldsymbol{D} \\
\Leftrightarrow \mathbb{P}(\boldsymbol{Y} \mid \boldsymbol{P}, \boldsymbol{A}, \Theta) &= \int_{\mathcal{D}} \mathbb{P}(\boldsymbol{Y} \mid \boldsymbol{P}, \boldsymbol{D}, \Theta) \cdot \mathbb{P}(\boldsymbol{D} \mid \boldsymbol{A})\, d\boldsymbol{D}
\end{aligned}
$$

Assumptions:

- $\boldsymbol{Y}$ is conditionally independent from $\boldsymbol{A}$ if $\boldsymbol{D}$ is given.

4) Climate reconstruction in terms of age

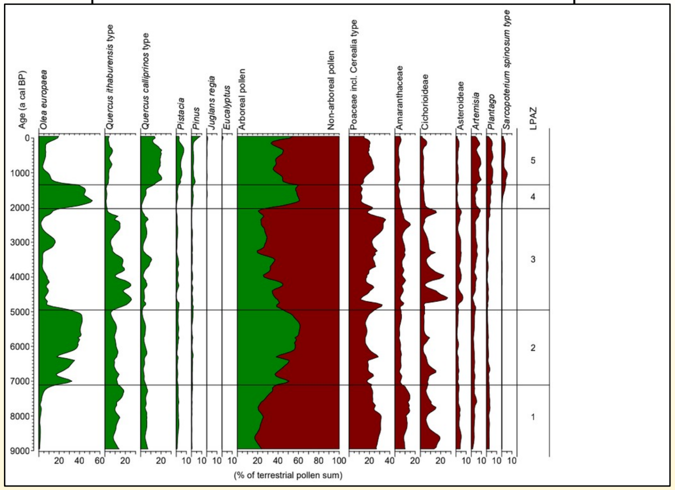
$$
\begin{aligned}
\mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{\Theta}) &= \int_{\mathcal{D}} \mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{D} \mid \boldsymbol{A}) \, d\boldsymbol{D} \\
&= \int_{\mathcal{D}} \int_{\mathcal{P}_s} \frac{\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{C}, \boldsymbol{\Theta_1}) \cdot \mathbb{P}(\boldsymbol{\Theta_1})}{\mathbb{P}(\boldsymbol{P_s}, \boldsymbol{\Theta_1})} \cdot \mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta_2}) \, d\boldsymbol{P_s} \cdot \mathbb{P}(\boldsymbol{D} \mid \boldsymbol{A}) \, d\boldsymbol{D} \\
&= \int_{\mathcal{P}_s} \frac{\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{C}, \boldsymbol{\Theta_1}) \cdot \mathbb{P}(\boldsymbol{\Theta_1})}{\mathbb{P}(\boldsymbol{P_s}, \boldsymbol{\Theta_1})} \cdot \int_{\mathcal{D}} \mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta_2}) \cdot \mathbb{P}(\boldsymbol{D} \mid \boldsymbol{A}) \, d\boldsymbol{D} \, d\boldsymbol{P_s} \\
&= \int_{\mathcal{P}_s} \frac{\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{C}, \boldsymbol{\Theta_1}) \cdot \mathbb{P}(\boldsymbol{\Theta_1})}{\mathbb{P}(\boldsymbol{P_s}, \boldsymbol{\Theta_1})} \cdot \mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{\Theta_2}) \, d\boldsymbol{P_s}
\end{aligned}
$$

4) Climate reconstruction in terms of age

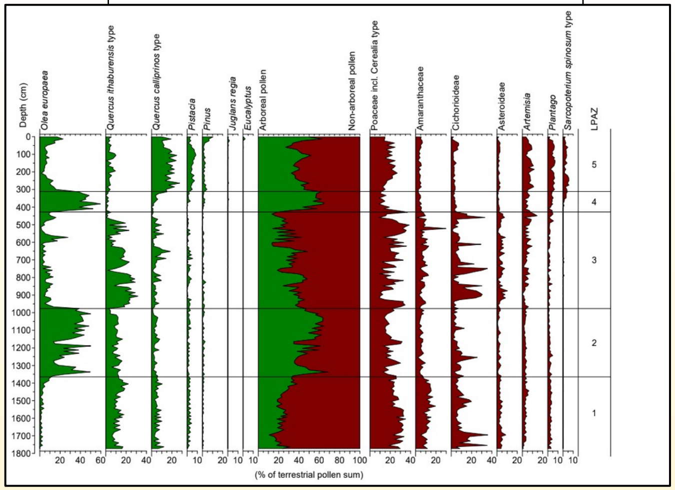
$$\mathbb{P}(\boldsymbol{Y} \mid \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{\Theta}) = \int_{\mathcal{D}} \mathbb{P}(\boldsymbol{Y} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{D} \mid \boldsymbol{A}) \, d\boldsymbol{D}$$

- Transformation from depth to age: behaves like a convolution with changing kernel smoothers
- The result is a data-driven smoothing of the reconstruction in terms of depth
- Easy to implement and computationally fast: matrix multiplication

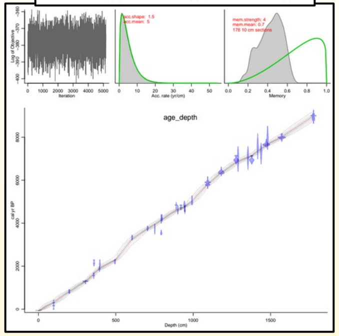
$$\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{\Theta_2})$$



$$\mathbb{P}(\boldsymbol{P_s} \mid \boldsymbol{P}, \boldsymbol{D}, \boldsymbol{\Theta_2})$$



$$\mathbb{P}(\boldsymbol{D} \mid \boldsymbol{A})$$

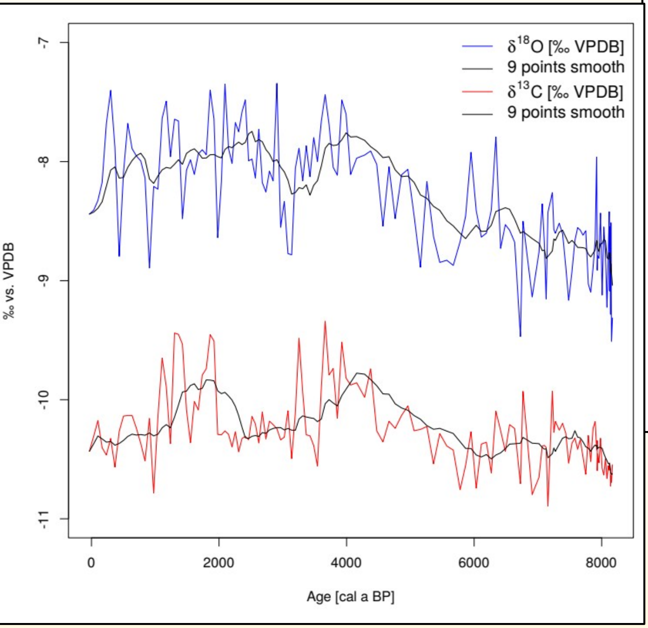


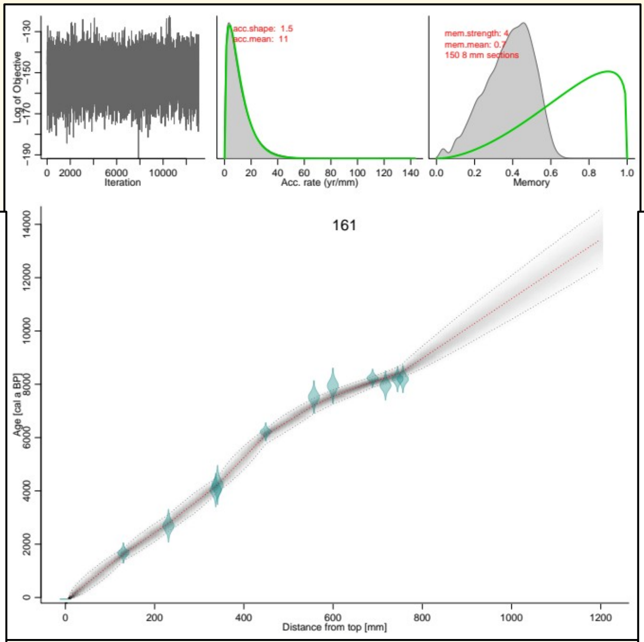
4) Interlude: Age uncertainties regarding speleothems

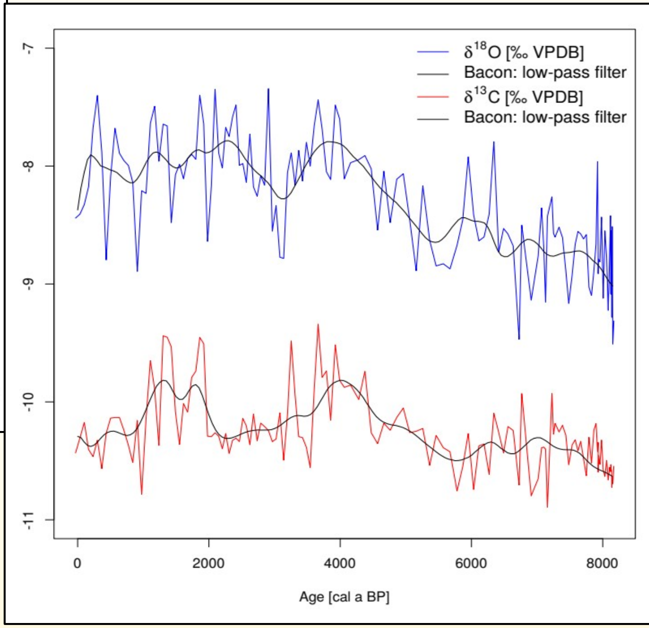
Age-distance model:

Now:

Common way for smoothing:







1) Climate reconstruction (MCMC)

- Overall question: Which of the proxy information found in the core provides a desired climate reconstruction?

- To find desired taxa combination from the core, an MCMC simulation (with Metropolis-Hastings algorithm) is performed.

- What is a desired climate reconstruction?

- For this purpose, the following Bayesian Hierarchical Model is solved:

$$\mathbb{P}(\boldsymbol{C}, \Theta \mid \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{E_p}) \propto \mathbb{P}(\boldsymbol{E_I} \mid \boldsymbol{C}, \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\boldsymbol{E_T} \mid \boldsymbol{C}, \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\boldsymbol{C_m} \mid \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\Theta \mid \boldsymbol{P})$$

1) Reconstruction model (extended)

$$\begin{aligned}\mathbb{P}(\boldsymbol{C},\boldsymbol{\Theta} \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{E_p}) &\propto \mathbb{P}(\boldsymbol{E_I} \mid \boldsymbol{E_T},\boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{E_T} \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \\ &\quad \mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{\Theta} \mid \boldsymbol{P},\boldsymbol{A}) \cdot \mathbb{P}(\boldsymbol{P},\boldsymbol{A}) \\ &\propto \mathbb{P}(\boldsymbol{E_I} \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{E_T} \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \\ &\quad \mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{\Theta} \mid \boldsymbol{P})\end{aligned}$$

With the following assumptions and applications:

- $\mathbb{P}(\boldsymbol{E_p}) = \mathbb{P}(\boldsymbol{E_I}) \cdot \mathbb{P}(\boldsymbol{E_T})$; $\boldsymbol{E_I}$ and $\boldsymbol{E_T}$ are a priori independent
- $\mathbb{P}(\boldsymbol{E_I} \mid \cdot) = \mathbb{P}(\boldsymbol{E_T} \mid \cdot) = \mathrm{Beta}(5{,}2)$
- $\mathbb{P}(\boldsymbol{C} \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) = \mathbb{P}(\boldsymbol{C_p} \mid \boldsymbol{C_m},\boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{C_m} \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) = \mathbb{P}(\boldsymbol{C_m} \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta})$
- $\mathbb{P}(\boldsymbol{C_m} \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) = \mathcal{N}(\boldsymbol{C_m} \mid \mu(\boldsymbol{C_{m,KG}}), \sigma(\boldsymbol{C_{m,KG}}))$
- $\mathbb{P}(\boldsymbol{P},\boldsymbol{A}) = \mathcal{U}$
- $\mathbb{P}(\boldsymbol{\Theta} \mid \boldsymbol{P},\cdot) = \mathbb{P}(\boldsymbol{\Theta} \mid \boldsymbol{P})$

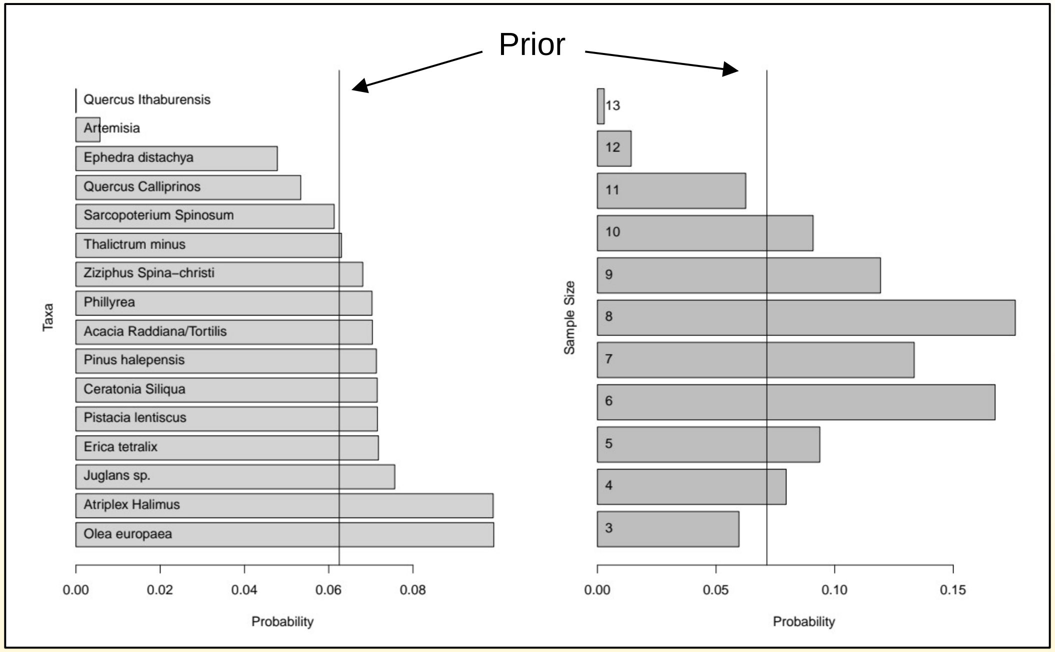
$$\begin{aligned}\mathbb{P}(\boldsymbol{C},\boldsymbol{\Theta} \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{E_p}) &\propto \mathbb{P}(\boldsymbol{E_I} \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{E_T} \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \\ &\quad \mathbb{P}(\boldsymbol{C_m} \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{\Theta}) \cdot \mathbb{P}(\boldsymbol{\Theta} \mid \boldsymbol{P})\end{aligned}$$

1) – 4) Climate reconstruction (MCMC)

$$\mathbb{P}(\boldsymbol{C},\Theta \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{E}_p) \propto \mathbb{P}(\boldsymbol{E}_I \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\Theta)\cdot\mathbb{P}(\boldsymbol{E}_T \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\Theta)\cdot \mathbb{P}(\boldsymbol{C}_m \mid \boldsymbol{P},\boldsymbol{A},\Theta)\cdot\mathbb{P}(\Theta \mid \boldsymbol{P})$$

$$\mathbb{P}(\Theta \mid \boldsymbol{P})$$

- Sample parameter given the number of proxies
- This can be splitted in the sample size and the corresponding taxa of each MCMC-Iteration



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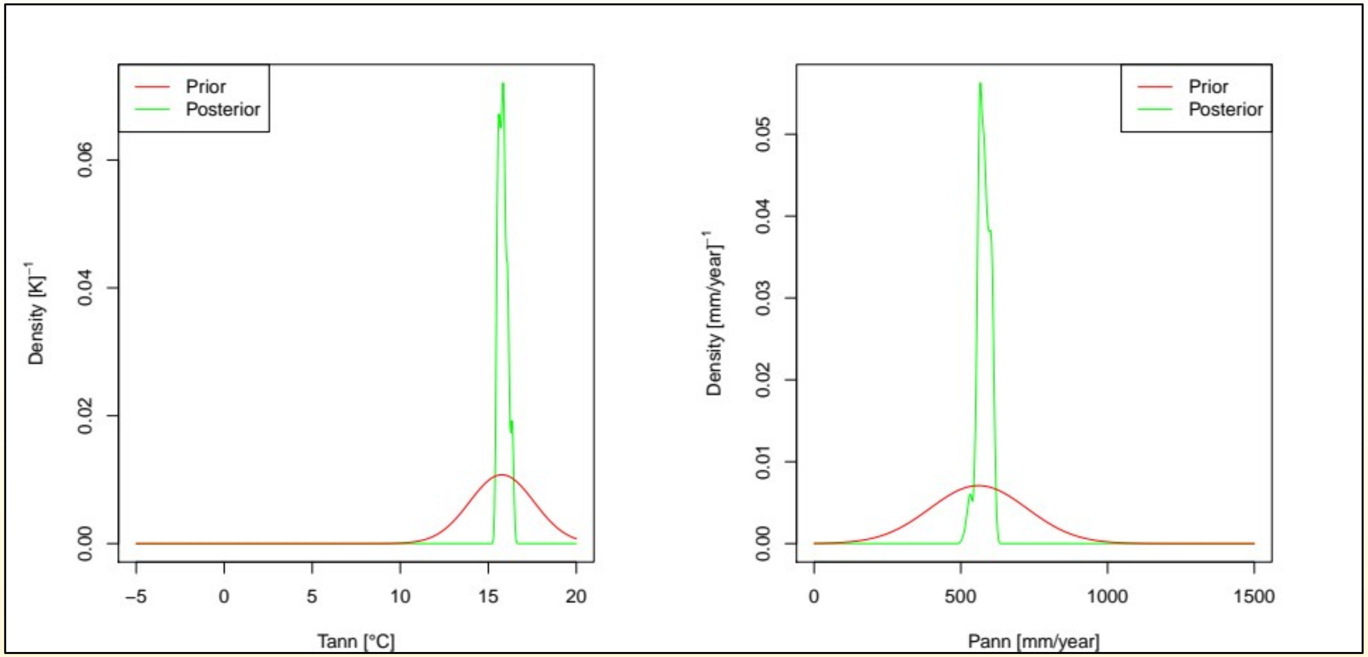
$$\mathbb{P}(\boldsymbol{C}, \Theta \mid \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{E}_p) \propto \mathbb{P}(\boldsymbol{E_I} \mid \boldsymbol{C}, \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\boldsymbol{E_T} \mid \boldsymbol{C}, \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\boldsymbol{C_m} \mid \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\Theta \mid \boldsymbol{P})$$

$$\mathbb{P}(\boldsymbol{C_m} \mid \boldsymbol{P}, \boldsymbol{A}, \Theta)$$

- Modern Koeppen-Geiger climate of the site as a reference for the modern median of the climate reconstructions
- During the MCMC-Simulation, the reconstructions follow this prior distribution

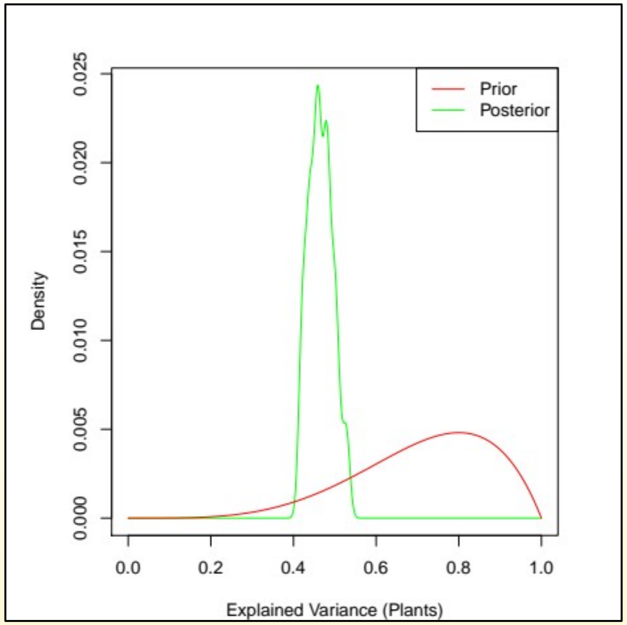


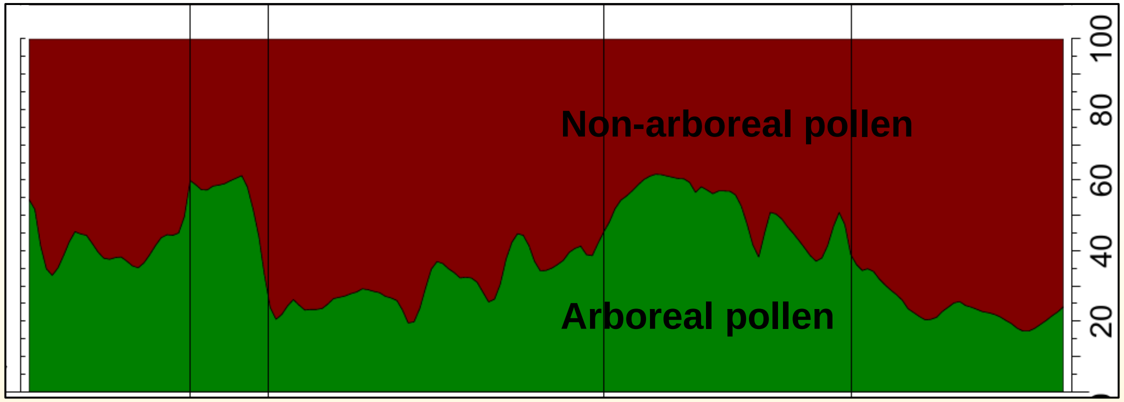
1) – 4) Climate reconstruction (MCMC)

$$\mathbb{P}(\boldsymbol{C}, \Theta \mid \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{E}_p) \propto \mathbb{P}(\boldsymbol{E}_I \mid \boldsymbol{C}, \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\boldsymbol{E}_T \mid \boldsymbol{C}, \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\boldsymbol{C}_m \mid \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\Theta \mid \boldsymbol{P})$$

$$\mathbb{P}(\boldsymbol{E}_T \mid \boldsymbol{C}, \boldsymbol{P}, \boldsymbol{A}, \Theta)$$

- Probability distribution for the explained variance between:
  - Arboreal taxa curve and
  - Median from reconstructed annual precipitation



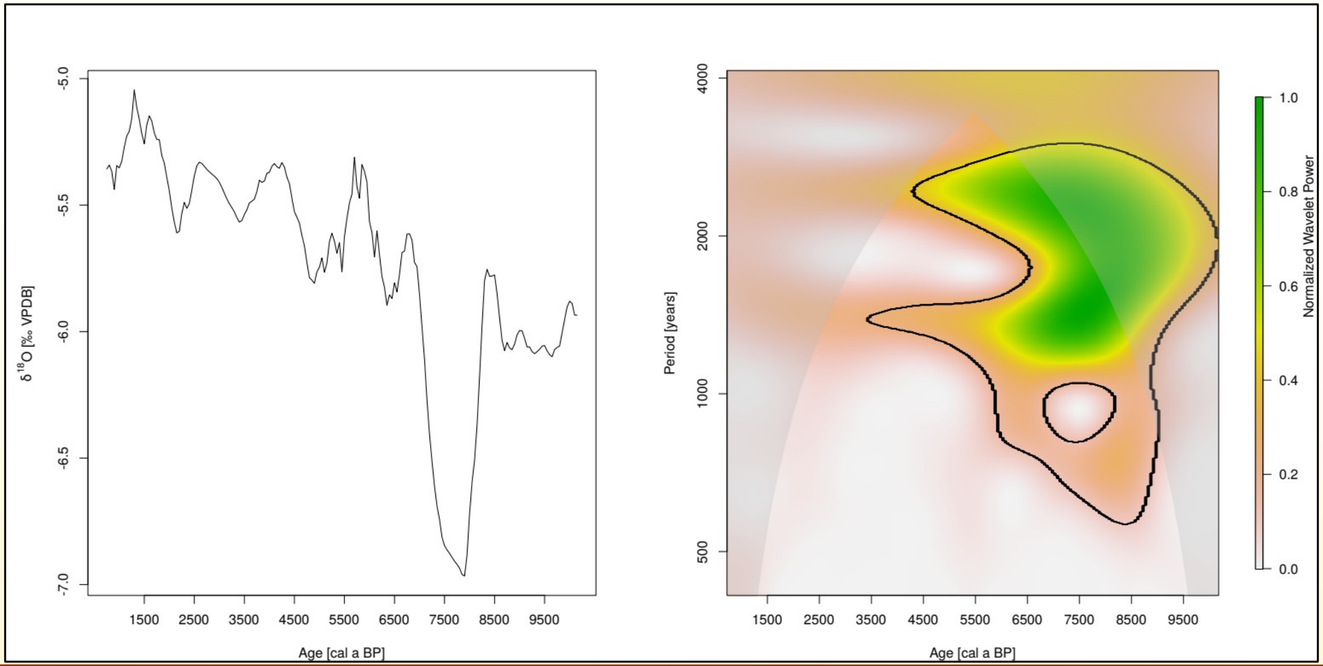


1) – 4) Climate reconstruction (MCMC)

$$\mathbb{P}(\boldsymbol{C},\Theta \mid \boldsymbol{P},\boldsymbol{A},\boldsymbol{E}_p) \propto \mathbb{P}(\boldsymbol{E}_I \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\Theta)\cdot\mathbb{P}(\boldsymbol{E}_T \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\Theta)\cdot \mathbb{P}(\boldsymbol{C}_m \mid \boldsymbol{P},\boldsymbol{A},\Theta)\cdot\mathbb{P}(\Theta \mid \boldsymbol{P})$$

$$\mathbb{P}(\boldsymbol{E}_I \mid \boldsymbol{C},\boldsymbol{P},\boldsymbol{A},\Theta)$$

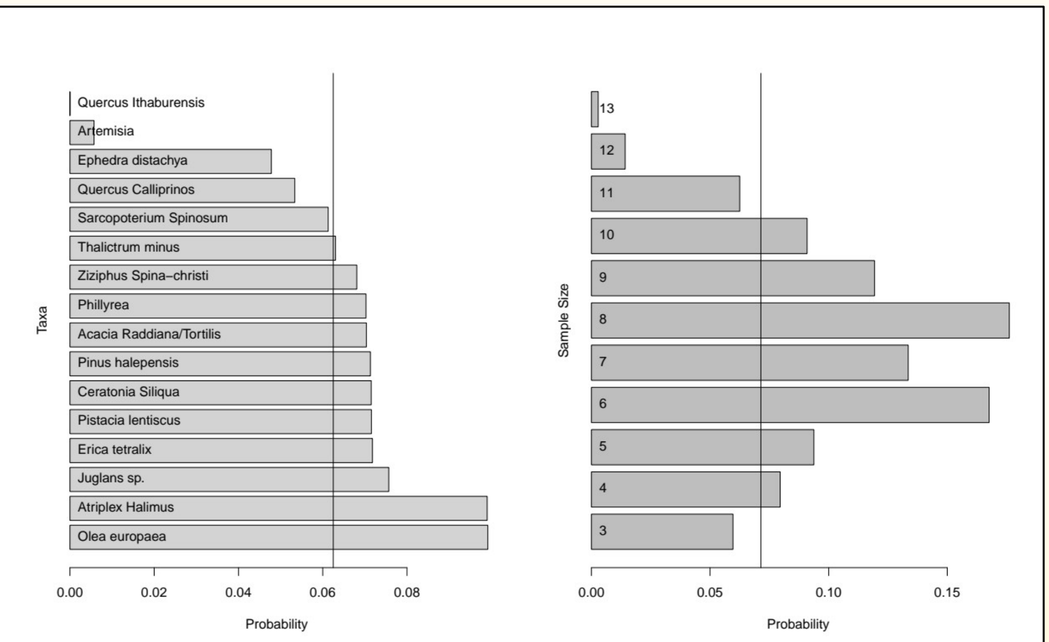
- Probability distribution for the explained variance between:
  - Wavelet pattern (right plot) of isotopic information from Soreq Cave and
  - Wavelet pattern of median from reconstructed annual precipitation

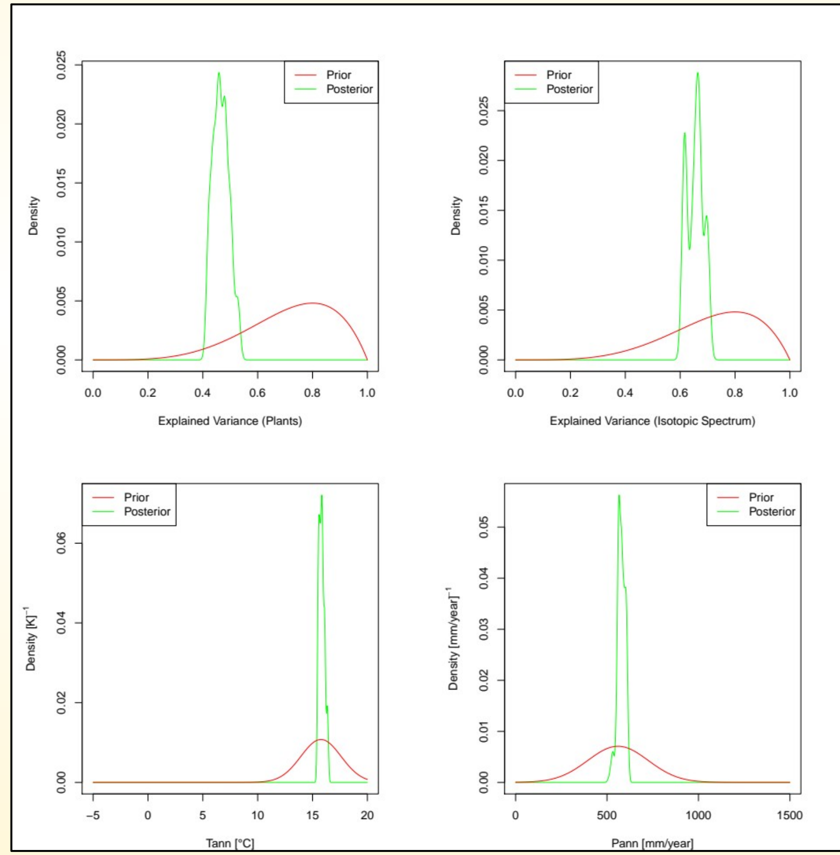


1) – 4) Climate reconstruction (MCMC)

$$\mathbb{P}(\boldsymbol{C}, \Theta \mid \boldsymbol{P}, \boldsymbol{A}, \boldsymbol{E}_p) \propto \mathbb{P}(\boldsymbol{E}_I \mid \boldsymbol{C}, \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\boldsymbol{E}_T \mid \boldsymbol{C}, \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\boldsymbol{C}_m \mid \boldsymbol{P}, \boldsymbol{A}, \Theta) \cdot \mathbb{P}(\Theta \mid \boldsymbol{P})$$

Prior and posterior distributions of the sample parameter:

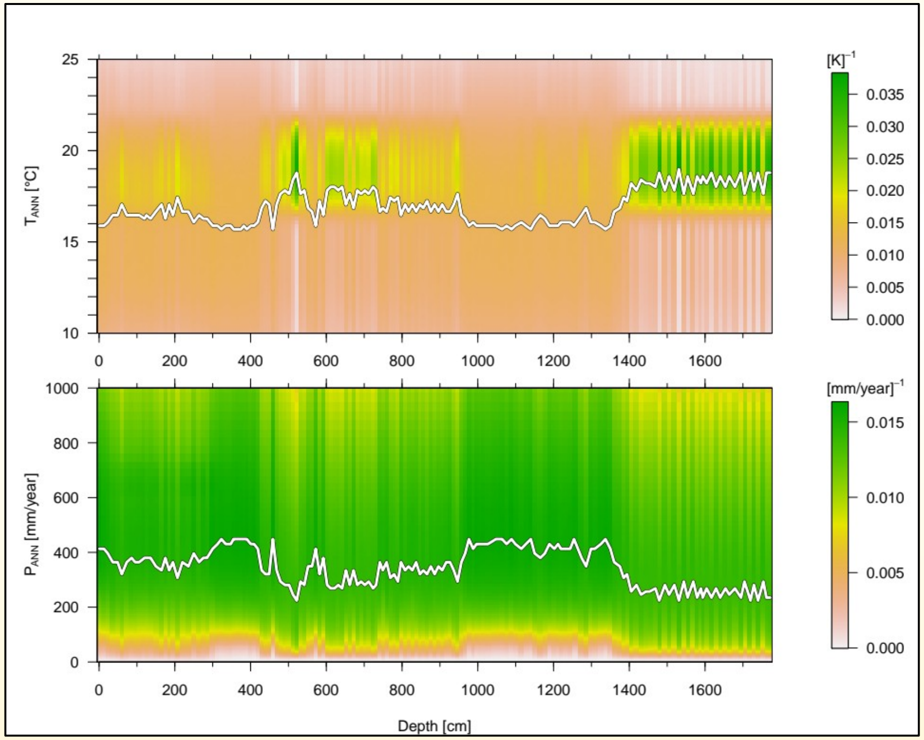


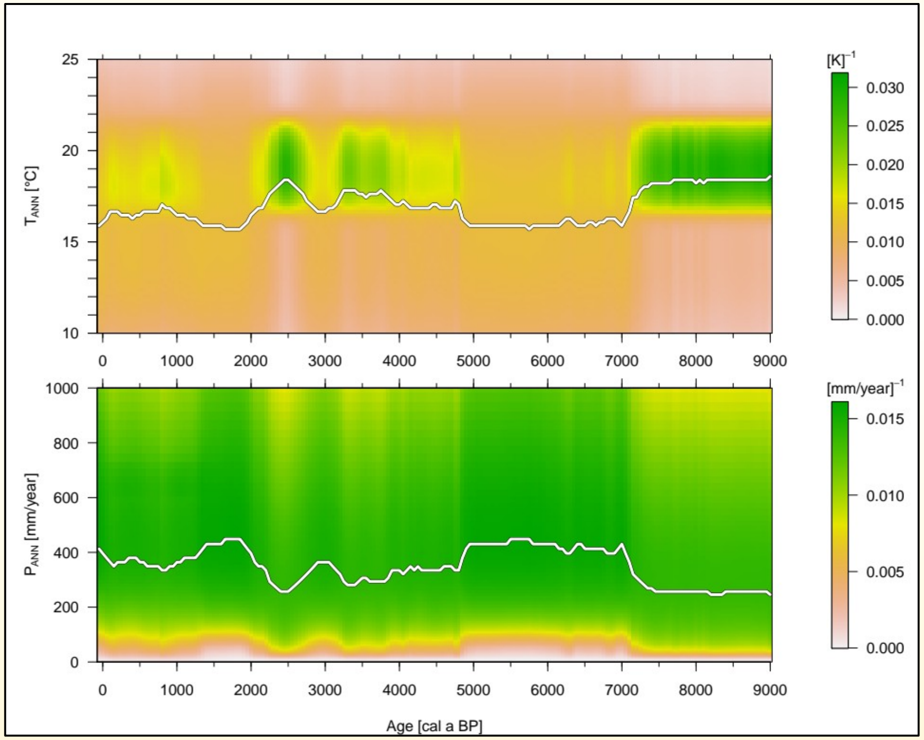


1) – 4) Climate reconstruction (MCMC)

$$\mathbb{P}(C, \Theta \mid P, A, E_p) \propto \mathbb{P}(E_I \mid C, P, A, \Theta) \cdot \mathbb{P}(E_T \mid C, P, A, \Theta) \cdot \mathbb{P}(C_m \mid P, A, \Theta) \cdot \mathbb{P}(\Theta \mid P)$$

Final climate reconstruction of See of Galilee based on multiple proxy information





Summary

- New model for quantitative paleo climate reconstructions: Bayesian hierarchical modelling
- Obtain proper transfer functions using machine learning competition
- Account for age uncertainties once an age-depth model is available
- Age-depth transformation can be used for any kind of proxy (next slide)

New methods for quantitative climate reconstructions applied to the Levant

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