Statistical Inference in Paleoecology, with a Focus on Bayesian Hierarchical Modeling

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(Some) Paleoecological Data Sources

- Counts of pollen grains from sediment cores in lakes and other depositional environments
 - Inference: vegetation composition, vegetation types, ecosystem boundaries
- Counts of charcoal particles from sediment cores
 - Inference: fire frequency and severity
- Ring widths from tree cores
 - Inference: growth, biomass and carbon balance
- Fire scar data from tree cores
 - Inference: fire frequency and severity

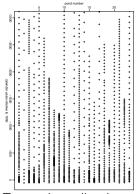


(Some) Goals of Paleoecology

- Understand past distributions of vegetation and changes in those distributions
- Use long-term data to understand the nature of vegetation dynamics:
 - competition
 - species dispersal/spread
 - species declines and causes of those declines impacts of disturbance, disease, herbivory, climate
 - stability of species assemblages
- Understand patterns and rates of large-scale disturbance

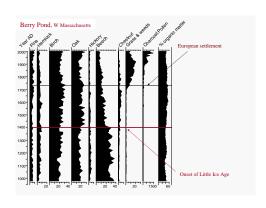
Challenges of Paleoecological Data Sources

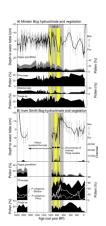
- Sparsity and irregularity in space and time
 - Certain proxies are only available in certain regions
 - Many records of limited duration
- Lack of replication
- Proxies are not direct measurements of the quantities we care about
- Calibration data are scarce
- Calibration against modern data may be less relevant for periods in the past (the no analog problem)
- Many of the quantities of interest do not have paleodata proxies
- Dating is uncertain and dating methods are expensive



Temporal sampling density for 23 ponds in central New England

Analysis of Pollen Diagrams





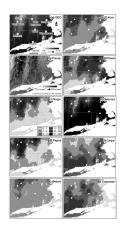
Booth et al. (2012) Ecology 93:219

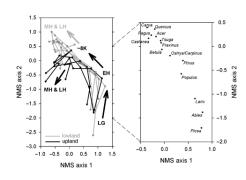
Pollen in a Spatial Context



Fig. 5. Curves showing beech public percentages planted against age in thousands of radiocarbon years for school disc. Beech mage limiting permitted to be constally in showing by the distribution. It is that the thereties, Curves are shown for all supplished store (49) used. Six mambers are given at the bestion of each curve. Vertical scales are in thousands of years before treneur. Distributed curve in the standard claim scaled in accordance multiplication by 10.

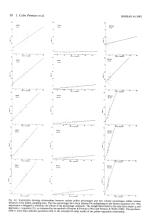
Dimension Reduction

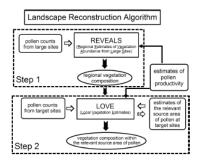




Oswald et al. (2007); J of Biogeography 34:900

Calibrating Pollen to Vegetation

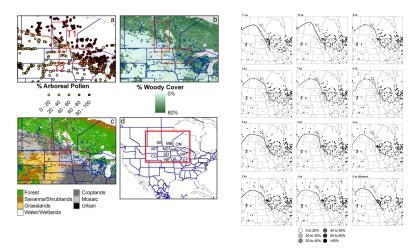




Sugita (2007); The Holocene 17:243

Prentice (1987); Boreas 16:43

Ecosystem Boundary Reconstruction



Williams et al. (2009); Global and Planetary Change 66:195

Fire History Reconstruction

Fire return intervals from peak detection

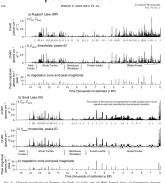


Fig. 4. Charcoal records for (a) Ruppert, (b) Xindi, (c) Code, and (d) Wild Tussock lakes. (i) Interpolated charcoal Year, "C malestal feedbast care (pi) stoughelt, (pi) watch, (p) watch, (p) with a finite factor (pi) stoughelt, (pi) watch, (p) watch, (p) with a finite factor (pi) stoughelt (pi) watch (count screening (see Methods for details), and + combols in musch ii with no arearest teak magnitude value correspond

Interpreting sediment charcoal records and detecting changes in fire regimes We introduce three general tools that facilitate the interpretation of fire history from sediment-charcoal

analysis. For example, while >0.8 in most records, SNI values were consistently < 0.5 for the 8000-0 yr BP in the section was not suitable for peak identification. Second, our use of a Gaussian mixture model to determine threshold values for neak identification allowed us to records. First, the signal-to-noise index provides a semi-treat all charcoal records with one set of semi-objective

Local area burned from background charcoal

Table 3. Alternative regression models relating charcoal accumulation in a composite record to area burned from AD 1675 to 1960 (n = 19). Positive reduction of error (RE) values indicate that the model is a better predictor of area burned than the mean of the series alone (i.e. the model has skill). Cross-validation involved constructing 5000 models based on a random subset of data points (53%) and then calculating the

Sites contributing	Model: y = ax ^b	F-stat	P	r²	r ² aq	RE	Cross-validation RE _{made}
DU, DR, MA, WT	a = 60202; b = 2.250	93.31	0.0000	0.80	0.79	0.78	0.67
MA.WT	a = 25950; b = 1.711	40.55	0.0000	0.61	0.59	0.46	0.52
WT	a = 70780; b = 4.936	36.50	0.0000	0.66	0.64	0.53	0.65

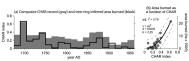


Figure 4. Comparison between the four-site composite charcoal record and area burned within the entire study. (a) Composite charcoal record, expressed as a charcoal accumulation rate (CHAR) index (gray bars, left y-axis), and area burned (thick line, far right y-axis) for the Ac 1675-1960 calibration period. (b) Scatter plot of area burned as a function of CHAR from the two series in (a) with the best-fit power model and adjusted r2 statistic. Dashed lines represent 90% confidence intervals for new predictions

Higuera et al. (2011) Ecological Applications 21:3211



Overview

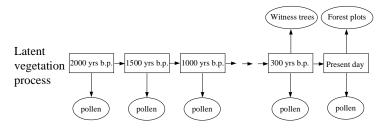
- Hierarchical statistical models build a (possibly complicated) statistical model that relates data to unknown quantities of interest in (relatively simple) stages.
 - Measurement model: Data are related to a latent process (often a space-time process representing a relevant field)
 - Process model: Latent process is modeled stochastically (potentially with deterministic components) that build in appropriate dependencies
 - Parameter model: Additional 'tuning' parameters govern the behavior of the latent process.
- The goal is to make inference (including uncertainty assessment) about the key quantities of interest, which may be the latent process or parameters or functionals of those.
- Given a model, there are standard (but sometimes inadequate) computational approaches to computing the inferences



Example: STEPPS Model for Vegetation Reconstruction

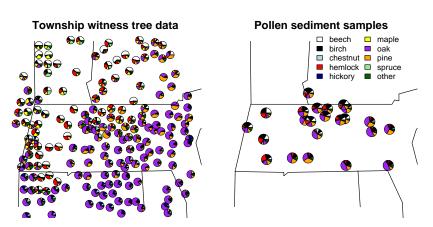


Vegetation data



Pollen data

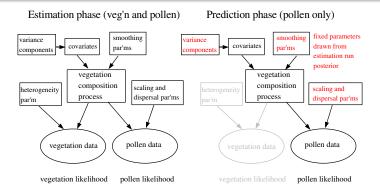
Calibration Data



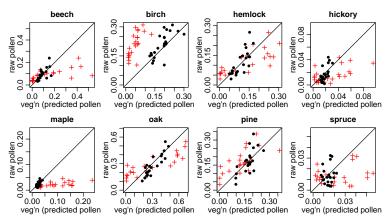
183 towns, 26-3149 trees per town

23 ponds, 500 grains per pond

A Cartoon of the Model



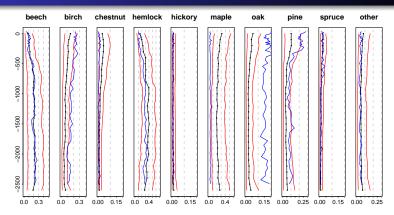
Calibration of Pollen to Vegetation



+ = raw pollen vs. spatially-smoothed vegetation

ullet = raw pollen vs. model-predicted pollen based on vegetation, accounting for species-specific pollen production and for long-distance pollen dispersal

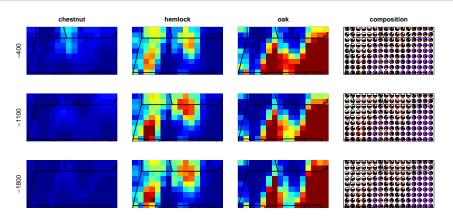
Inference: Time



- --- raw pollen proportions
- $\bullet -=$ model-estimated vegetation proportions
- ---= uncertainty estimates



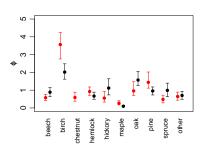
Inference: Space



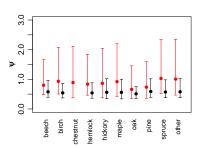
We can also present spatial predictions in the context of uncertainty, in particular assessing our confidence in changes over time and differences across space.

Inference: model parameters

Pollen scaling



Long-distance dispersal range



red = colonial estimates
black = modern estimates

Key Aspects of Hierarchical Approach

- Sparsity and irregularity in space and time: Borrow strength and smooth in space & time
- Certain proxies are only available in certain regions
 - Many records of limited duration
- Lack of replication: Smoothing in space accounts for a form of replication
- Proxies are not direct measurements of the quantities we care about:
 Calibrate to direct measurements
- Calibration data are scarce
- Calibration against modern data may be less relevant for periods in the past (the no analog problem)
- Many of the quantities of interest do not have paleodata proxies
- Dating is uncertain and dating methods are expensive: Include dating uncertainty in statistical model, e.g., the BACON model (Blaauw & Christen 2011)

Open Issues

- Data sparsity
- Data dropout tends to have large effects e.g., losing an observation far from other observations can cause large changes in predictions
- To what extent can we interpret parameter estimates as physically meaningful?
- Computation can be difficult

PalEON: A PaleoEcological Observatory Network

 Multi-institution collaboration of paleoecologists, statisticians, and ecosystem modelers



- Overarching goal: Use paleodata to help understand global change
- Current focus on northeastern/midwestern US over the past 3000 years

Motivation for PalEON

- Paleoecological data have not been used extensively in considering global change, even though they are the only data on long-term changes
- Proxies are often not directly related to quantities of interest for global change and are not in a form directly useful for quantitative analysis
- Terrestrial ecosystem models and paleodata are at different spatial and temporal scales

PalEON Goals

Develop networks of paleodata, synthesized statistically, to inform ecosystem models:

- Assess models against paleodata
- Initialize models based on paleodata
- Assimilate paleodata into models
- Improve model formulations
- Prioritize new data collection