DATA REPOSITORY ITEM 2002115

METHODS

Site Chronologies

Sample ages were determined by linearly interpolating from established age-control points. Age controls included stratigraphic correlations between the lacustrine $\delta^{18}O$ record and the GISP (Greenland Ice Sheet Project) and GRIP ice core records, radiocarbon dates calibrated to calendar years (Stuiver and Reimer, 1993), pollen stratigraphic dates (Yu and Eicher, 1998), and modern ages assigned to core tops (Table 1). Neither the stratigraphic correlation between the local $\delta^{18}O$ record and ice-core $\delta^{18}O$ nor the required assumption of synchronicity affects lead-lag relationships between the $\delta^{18}O$ and pollen records within each core, although these factors could affect the estimated sample resolution and uncertainty of the temporal lags. For this paper, relative differences among sample ages are more important than absolute ages, reducing the impact of errors in age assignment.

Principal Component Analysis

The pollen data were converted to percentages by using a pollen sum comprising all terrestrial pollen types. Pollen types with average abundances of $<$0.1% were discarded prior to PCA analysis. Principal components analysis was performed upon the correlation matrix, and each site was analyzed separately. We retained the factor scores for the first three principal components for cross-correlation with the climate-proxy time series, except for Splan Pond, where only the first two principal components explained a significant proportion of the variance. The first three principal components explained 48%–67% of the variance in each pollen record.

Cross-Correlation Analysis

To prewhiten the pollen principal component and climate-proxy time series, we performed first-order differencing and fitted autoregressive moving average (ARMA) models to each time series that was not already white noise after differencing (Wei, 1990), by using the ETS procedure in the SAS statistical package to identify and confirm all ARMA models. We identified the preliminary ARMA model order from autocorrelation and partial autocorrelation plots, estimated the ARMA model, and checked the residuals to assure that no significant auto-correlations remained after filtering the data with the identified ARMA model (Wei, 1990). All time series were either white noise after differencing or required only a first-order autoregressive model [AR(1)] for prewhitening.

We calculated a geostatistical approximation of the cross-correlation function by calculating the temporal distance between samples in years, rather than sample number, and calculating the correlation for all pairs of points separated by a time interval $t_i \pm w$, where $w$ is defined to be twice the minimum time step in the climate time series (Kirchner and Weil, 2000). This approach groups together unevenly spaced samples into
temporal bins of constant width and produces results similar to those generated by Fourier transform approaches (Kirchner and Weil, 2000).

We estimated the significance level ($\alpha = 0.05$) for each cross-correlation from the percentile intervals drawn from the distribution of 5000 bootstrap iterations (Efron and Tibshirani, 1993). For each bootstrap iteration, we (1) simulated a new random time series by using the same ARMA model and variance structure as the original differenced climate or principal component time series, (2) fitted a new ARMA model of the same order as the original ARMA model [e.g., AR(1)] to the simulated time series (although the order was the same, the ARMA parameters differed), (3) prewhitened the simulated data by using the new ARMA model, and (4) calculated cross-correlations for the prewhitened simulated time series. We ignored significant cross-correlations that indicated either large negative lags (i.e., the situation in which vegetation change led climate change by >100 yr) or large positive lags where the sample size was small relative to the time lag. Cross-correlations with very short negative time lags (<100 yr) may occur when the climatic and pollen records are nearly synchronous (owing to different sampling intervals in the climatic proxy and pollen records or blurring in the sedimentary record). Very short negative time lags thus may constitute evidence for a close coupling between climatic change and vegetational response within the resolution of the sedimentary record and were retained for this analysis. By applying cross-correlation analysis, we assume that the vegetational signature captured in the pollen records responds linearly to the climate signature captured in the $\delta^{18}$O and chironomid records. This assumption is unlikely to be true in detail, but may serve as a rough approximation for the aggregate vegetational response to climate.

REFERENCES CITED


