Land temperature variability driven by oceans at millennial timescales

Raphaël Hébert (✉ raphael.hebert@awi.de)

Alfred Wegener Institut Helmholtz Centre for Polar and Marine Research <https://orcid.org/0000-0002-9869-4658>

Ulrike Herzschuh

Alfred Wegener Institute for Polar and Marine Research <https://orcid.org/0000-0003-0999-1261>

Thomas Laepple

Alfred-Wegener-Institut Helmholtz-Zentrum für Polar- und Meeresforschung

Article

Keywords: land temperature variability, timescales

Posted Date: March 8th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-147890/v1>

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Version of Record: A version of this preprint was published at Nature Geoscience on October 31st, 2022.
See the published version at <https://doi.org/10.1038/s41561-022-01056-4>.

1 Land temperature variability driven by oceans at millennial 2 timescales

3 *R. Hébert^{1,2}, U. Herzschuh^{1,2,3} & T. Laepple^{1,4}

4 Affiliations:

5 ¹Alfred Wegener Institute, Helmholtz Centre for Polar and Marine Research, Potsdam, Germany.

6 ²Institute of Environmental Sciences and Geography, University of Potsdam, Germany

7 ³Institute of Biochemistry and Biology, University of Potsdam, Germany

8 ⁴University of Bremen, MARUM – Center for Marine Environmental Sciences and Faculty of Geosciences, 28334
9 Bremen, Germany

10 *Correspondence: raphael.hebert@awi.de

11 **Variations in regional temperature have widespread implications for society, but our**
12 **understanding of the amplitude and origin of long-term natural variability is insufficient. This**
13 **is especially the case for terrestrial temperature variability which is currently thought to be**
14 **weak over long timescales. Here, we provide the first comprehensive estimate of regional**
15 **temperature variability from annual to millennial timescales based on sedimentary pollen**
16 **records and instrumental data from the Northern Hemisphere. We show that the short-term**
17 **random variations are overprinted by strong ocean-driven climate variability on multi-**
18 **decadal and longer timescales. This may cause substantial climate change at the regional scale**
19 **in the coming century, contrasting the rather monotonous warming projected by climate**
20 **models. Due to the marine influence, regions characterized by stable oceanic climate at sub-**
21 **decadal timescales experience stronger long-term variability while continental regions with**
22 **higher sub-decadal variability show weaker long-term variability. This fundamental**
23 **relationship between the timescales provides unique insight into the mechanisms governing**
24 **slow terrestrial climate variability and sets the basis to project its amplitude.**

25 Improving our ability to characterize internal and natural climate variability is pivotal to improve
26 our long-term climate projections¹, particularly at the regional scale². The statistics of the natural
27 variability can be quantified up to decadal timescales using instrumental observations, but indirect
28 climate proxies are needed for the longer timescales.

29 Proxy-model comparisons aiming to validate climate models generally focus on whether long term
30 (forced) trends found in proxies can be reproduced by Global Climate Models (GCMs)^{3,4}. In this
31 regard, land pollen-based climate reconstructions in northern mid-latitudes were shown to be
32 consistent with the forcing and simulated warming⁵. However, the long-term multi-millennial trend
33 is a rather limited measure which does not evaluate the ability of climate models to simulate
34 realistic climate variability, both forced and internal, at all timescales. To evaluate climate
35 variability across timescales, we consider the power spectral density (PSD, or simply spectrum)
36 $S(\Delta t)$, which provides an estimate of how variance is distributed with frequency, or equivalently
37 with timescale Δt . Mitchell (1976)⁶ provided the classical view of climate variability being
38 dominated by specific quasi-periodic processes such as solar variations linked to orbital cycles over
39 a mostly random and uncorrelated (i.e. white) noise background. Since then, an increasing number
40 of climate proxies have shown a contrasting view of a variance that continuously increases with
41 increasing timescale. Such a behaviour is often well approximated by a power-law scaling
42 relationship^{7,8} and can be summarized by the scaling exponent β such that $S(\Delta t) \sim \Delta t^\beta$.

43 Several studies have suggested that GCMs can simulate realistic climate variability for global mean
44 temperature across timescales^{9,10} which is dominated by the response to external forcing. However,
45 at the regional scale, where only a small fraction of the variability is forced¹¹, the skill of GCMs has
46 been called into question for slow timescales^{12,13}. Marine proxies suggest a strong scaling of
47 regional sea-surface temperature (SST) variance from annual to millennial timescales ($\beta \approx 1$)⁷ which
48 contrasts with the weak scaling found in GCMs ($\beta \approx 0.1$)^{14,15}. This leads to an increasing discrepancy
49 between reconstructed SST and model simulations at longer timescales, reaching two orders of
50 magnitude in variance at the millennial timescale⁷.

51 On land, instrumental temperatures show a fundamentally different behaviour compared to the
52 oceans, with only a weak timescale dependency up to multi-decadal scales ($\beta \approx 0.1$)^{14–16}; this low-
53 frequency weather has been termed “macroweather regime” and starts at sub-monthly timescales¹⁷.
54 This difference can be explained by the much smaller heat capacity of land surfaces compared to
55 the oceanic mixed layer¹⁸. If the macroweather-type behaviour over land would hold on to longer
56 timescales, internal variability would only play a minor role on the uncertainty of regional climate
57 projections¹⁹. However, a different scaling behaviour of ocean and land at longer timescales would
58 imply an increasingly large variability discrepancy between terrestrial and marine regions which
59 seems physically implausible and in contradiction with both diffusive energy balance models²⁰ and
60 GCMs¹⁵. This leaves us with the conundrum that we must either reject altogether the marine proxies
61 or see a fundamental change of variability in the terrestrial domain on longer timescales.

62 Given the limited instrumental record, this fundamental question on the scaling of variability
63 between land and ocean cannot be answered from observations without terrestrial proxy data.
64 Holocene Greenland ice-core δ^{18O} timeseries suggest that the weak scaling behaviour found in the
65 instrumental data extends to millennial timescales (akin to white noise with $\beta \approx 0$)²¹. However, it is
66 unclear whether the climate variability derived from the Greenland ice-cores is representative for
67 other terrestrial regions²² and to what extent the proxy variability reflects temperature variability²³.
68 In order to elucidate the behaviour of climate variability over land at timescales longer than
69 centennial, we compiled and analysed an extensive collection of recent Holocene Northern
70 Hemisphere pollen data covering the past 8000 years, providing the largest spatial coverage of any
71 land-based proxy at millennial timescales. This compilation of pollen data comprises 985 unique
72 records from the northern hemisphere, 363 of which from North America, 487 from Europe, and
73 135 from Asia including the most complete dataset for China²⁴ and Siberia²⁵. We produced summer
74 (June–July–August) temperature reconstructions (hereafter simply termed temperature) as summer
75 temperatures are usually well correlated with other variables driving vegetation growth²⁶. Our
76 results are not sensitive on the choice of summer temperature (Extended Data Fig. 1) or a potential
77 influence of precipitation (Extended Data Fig. 2). Pollen-based reconstructions rely on the
78 assumption of dynamical equilibrium between climate and vegetation. This assumption is timescale
79 dependent and is generally more valid at longer timescales²⁶. In this respect, millennial scale
80 estimates of temperature variability should thus be particularly robust. In addition, the comparison
81 with instrumental and tree-ring data (Extended Data Figure 3) suggests that temperature variability
82 derived from pollen assemblages also reliably captures faster timescales. Finally, we verified that
83 the estimates of millennial variability were not systematically biased by human influences (see
84 Extended Data Fig. 4).

85 Pollen-based reconstructions, once coupled with instrumental data²⁷, enable us to establish for the
86 first time a comprehensive picture of regional land temperature variability from inter-annual to
87 millennial timescales (Fig. 1). The spectrum of instrumental air temperature shows a rather flat
88 scaling behaviour that is characteristic of the macroweather regime. At longer timescales, however,
89 the pollen-based reconstructions show a strong increase in variability with increasing timescale
90 (Fig. 1a). This suggests that even in the relatively stable recent Holocene, there exists significant
91 centennial to millennial scale temperature variability. This behaviour clearly differs from the rather
92 flat macroweather regime and resembles power-law scaling with an exponent β near unity for
93 timescales longer than centennial. Traces of this increased scaling behaviour at multi-decadal
94 timescales already appear in the instrumental record and is corroborated by dendrochronological
95 timeseries (Extended Data Fig. 3).

96 We benchmark our result against three transient climate models simulations of the recent Holocene:
97 IPSL²⁸, ECHAM5²⁹ and the last 8000 years of the TraCE-21ka deglaciation experiment³⁰ (i.e. after
98 the last freshwater forcing events). The transient simulations of these GCMs show the weak scaling
99 behaviour characteristic of the macroweather regime, although with higher annual to decadal
100 variability relative to the instrumental data as previously recognized¹⁵. However, they fail to capture
101 the increase in variability observed in the reconstructions at multi-decadal timescales. Instead, they
102 show a relatively weak increase at multi-centennial timescales and a sharp increase at millennial
103 timescales due to spectral leaking from the orbital 23-ka precession cycle (Fig. 1a, Extended Data
104 Fig. 5). As a result of this divergence in variability scaling there is an increasing deficit in
105 temperature variability observed in the simulations compared to the reconstructions. The range of
106 variance ratios between the reconstructions and the different model simulations increases from 7-10
107 over 100-300 years to 17-56 (19-102 with orbital detrending) over 1000-3000 years, resembling the
108 discrepancy between models and proxy data for regional SST variability⁷.

109 Comparing the reconstructions over land with estimates of marine variability⁷ shows they have a
110 very similar low-frequency behaviour (Fig. 1b). This supports the view that both components will
111 vary more coherently as climatic variability becomes a global phenomenon over longer timescales²⁰
112 also indicated by coherent land and ocean average temperatures⁵. Energy-balance models suggest
113 that this parallel behaviour of land and oceans on long timescales is due to heat exchange between
114 the land and ocean compartments. In such models, land air temperature can be described as a linear
115 combination of the SST and a time-dependent forcing over land³¹; the resulting variability spectrum
116 over land is then a linear combination of the spectra of each term (Fig. 1b) when the two are
117 uncorrelated (see Supplementary Information). In this framework, the change in scaling behaviour
118 can be regarded as a transition from the macroweather regime at shorter timescales, dominated by a
119 weakly scaling forcing component akin to white noise over land¹⁸, to an oceanic regime dominated
120 by the SST component at timescales longer than decadal. Interestingly, the parallel behaviour
121 between land and ocean temperature spectra on multi-decadal to millennial timescales provides no
122 evidence for additional terrestrial slow climate feedbacks. The oceanic component present in land
123 temperature variability appears amplified by a factor of ~ 4 in PSD or ~ 2 in amplitude. This factor is
124 similar to the land-sea warming contrast³² observed during the last century³³ and within the range of
125 land-sea warming ratios measured in GCMs³⁴. This is thought to be the result of local feedbacks, for
126 example the evaporation feedback, when moisture availability over land limits evaporative cooling
127 in comparison with marine regions³⁵, and also because of the asymmetry in the land-ocean heat
128 exchange which favours land due to its lower specific humidity³⁴.

129 The extensive spatial coverage of the pollen-based reconstructions allows us to perform a spatial
130 analysis of the millennial scale temperature variability $PSD_{1000-3000 \text{ years}}$ (the mean PSD over 1000-
131 3000 year) (Fig. 2a) and investigate the potential link to oceanic influence. The spatial coherency
132 (Moran's $I=0.19$, $p<0.001$, see Methods) demonstrates that the variability estimates are not drowned
133 out by local noise. Over Europe, with its large number of records, millennial scale variability
134 decreases inland along the path of prevailing winds blowing from the Atlantic Ocean, and is lowest
135 over Fennoscandia where blocking events are most frequent³⁶. Similarly, China's high millennial
136 variability would be linked to the persistent oceanic influence carried by the dominant easterlies at
137 that latitude, while further north in eastern Siberia the dominant westerlies bring little oceanic
138 influence. This further suggests that higher millennial variability relies on higher connectivity to
139 oceans, as implied by energy-balance models, although compounded with local sensitivity. The high
140 variability in central Asia remains an outlier given the strong continentality there, but the
141 significance is lower because of the sparseness of records. It is also possible that the lower
142 connectivity to oceans is compensated by the stronger local climate sensitivity³³ which may be
143 linked to hydrological feedback due to the arid conditions³⁵. Meanwhile, in North America the
144 lowest millennial variability is found in the prairies, near the centre of the continent, where the
145 westerlies predominantly blow from the north-west and the oceanic influence is lowest.

146 We use the instrumental data to study the mechanisms governing the spatial distribution of the
147 millennial variability and the continuum of variability. The scaling of variability in instrumental
148 data has already been shown to be related to the strength of the annual cycle and of the sub-decadal
149 variability⁸. If we aggregate the instrumental data and reconstructions based on the sub-decadal
150 variability $PSD_{2-10 \text{ years}}$ (the mean PSD over 2-10 years; Fig. 3, Extended Data Fig. 6, Extended Data
151 Fig. 7), a clear relationship appears with the emergence of the low-frequency regime, quantified by
152 the multi-decadal scaling exponent $\beta_{10-60 \text{ years}}$ (β regressed over 10-60 years): locations with lower
153 sub-decadal variability thus show a stronger increase of variability towards longer timescales, as
154 indicated by higher multi-decadal scaling (Fig. 2b,c, Fig. 3, Extended Data Fig. 7). We should thus
155 expect an inversion where regions of low (high) sub-decadal variability, typically characterized by
156 more maritime (continental) influences, would become regions of high (low) variability at long
157 timescales.

158 Indeed, this hypothesized relationship is confirmed by the pollen-based reconstructions. Their
159 estimates of millennial temperature variability $PSD_{1000-3000 \text{ years}}$ show a strong anti-correlation with
160 the sub-decadal variability $PSD_{2-10 \text{ years}}$ ($r=-0.95$, $p<0.01$) and a strong correlation with the multi-
161 decadal scaling $\beta_{10-60 \text{ years}}$ ($r=0.91$, $p<0.01$). These significant strong relationships between the pollen-
162 based reconstructions and independent instrumental temperature data demonstrate a fundamental
163 link of temperature variability from sub-decadal to millennial timescales. The spatial pattern of the
164 variability (Fig. 2 and Extended Data Fig. 5) further suggests that this relationship is caused by
165 varying marine influence. In addition, this can explain the relation of the amplitude of the annual
166 cycle (an indicator for continentality) with the inter-annual variability scaling in the instrumental
167 relationship proposed by Huybers and Curry (2006)⁸. Therefore, our findings complete the linkage
168 between seasonal and millennial land temperature variability.

Our results indicate that current GCMs underestimate regional temperature variability over land at timescales longer than multi-decadal (Fig. 1a, Extended Data Fig. 5). In combination with the spatial pattern of variability (Fig. 2), this suggests that the deficit in low-frequency variability is related to an underestimation of marine variability⁷. The interpretation of climate sensitive proxies remains an area of active research, and in principle, it remains possible that the observed model-data mismatches stem from non-climatic variability. However, several lines of evidence argue against this interpretation. Firstly, there are no known archival processes yet which could artificially create such power-law scaling in sedimentary archives³⁷. Specifically, the known processes such as counting errors, spatial or temporal aliasing, and bioturbation in the sediment cannot explain the power spectra of variability found here. Secondly, the consistency between independent marine and terrestrial archives (Fig. 1b) provides further support for the temperature variability reconstruction. Finally, the spatial relationship with the independent instrumental temperature data (Fig. 3) also indicates that this is no artefact from the proxy data.

Thus, pollen-based reconstructions support the paradigm of an increasing continuum of climate variability with increasing timescales⁸, in contradiction with the local temperature variability in current GCM simulations and the classical picture of Mitchell⁶. More importantly, our results extend previous findings from instrumental data⁸ and demonstrate a fundamental link between inter-annual, multi-decadal and millennial timescales driven by the interaction of marine and terrestrial temperature variability modulated by continentality.

This fundamental behaviour of temperature variability has implications for the relative impact of natural and anthropogenically forced variability. High latitude regions characterised by high inter-annual variability show a weaker oceanic regime and, ultimately, less natural variability on long timescales. As these regions are also highly sensitive to anthropogenic forcing, the impact of anthropogenic warming, relative to natural variability, will be greater. However, regions of strong maritime influence, where most of the world's population is located, could see large natural variability, that is not covered by current GCM projections which tend to display monotonous warming³³. It is thus possible that until now, the stronger natural variability at multi-decadal timescales in maritime regions has partly overshadowed the anthropogenic warming in those regions which could explain their lower observational transient climate sensitivity³³. Integrative archives such as glaciers should be particularly sensitive to this increased memory¹⁶ and could be used to verify our findings. Large compilations of climate archives have the potential to inform us on the spatial patterns of slow variability and their underlying causes, and further studies combining multiple proxies over land and ocean show great promise to improve our understanding of the spatio-temporal correlation structure of climate variability.

Author Contributions

R.H., T.L. and U.H. designed the research. U.H. performed the pollen-based reconstruction. T.L. contributed the interpretation of the marine archives. R.H. and T.L. developed the methodology. R.H. performed the data analysis and wrote the first draft of the manuscript. R.H., T.L., and U.H. contributed to the interpretation and to the preparation of the final manuscript.

208 **Acknowledgements**

209 This is a contribution to the SPACE ERC and GLACIAL LEGACY ERC projects; these projects
210 have received funding from the European Research Council (ERC) under the European Union's
211 Horizon 2020 research and innovation programme (grant agreement no. 716092 and no. 772852).
212 This work is further a contribution to the PALMOD project. The work profited from discussions at
213 the CVAS working group of the Past Global Changes (PAGES) programme. We thank A.
214 Dallmeyer, A. Dolman, I. Kröner, T. Kunz, S. Lovejoy and K. Rehfeld for useful discussion. We
215 acknowledge P. Huybers for comments on the manuscript. We thank P. Braconnot and J. Cretat, and
216 J. Jungclaus for, respectively, providing the IPSL and ECHAM5 simulations, and T. Böhmer and X.
217 Cao for their support compiling the database. We thank all original data contributors who made
218 their proxy data available and acknowledge the Neotoma Palaeoecology Database.

219 **Competing interests**

220 The authors R.H., U.H. and T.L. declare no competing interests.

221 **Materials & Correspondence**

222 Correspondence and materials request should be addressed to R.H.

Figure 1| Average spectral estimates of local land temperature over the Northern Hemisphere. **a**, Average spectral estimates of land air temperature from pollen-based reconstructions, instrumental data and model simulations extracted at the pollen record locations. Also shown are the spectra estimated after applying a 23-ka sinusoidal detrending (dashed, see Methods). 90% confidence intervals are given (shaded). The number of pollen records contributing to each timescale is indicated below (brown axis). **b**, Average spectral estimates from reconstructed annual sea-surface temperature derived from marine archives⁵, and from instrumental data at the corresponding locations. The pollen-based and instrumental average spectra from **a** are reproduced. Also shown are linear combinations of power-laws with slope $\beta=1.2$ and white noise series (dashed green for land, dashed blue for sea and dashed grey for the white noise levels) corresponding to the energy-balance model approximation.

Figure 2| Spatial patterns of temperature variability in instrumental data and pollen-based reconstructions. **a**, Map of millennial variability estimated from the temperature spectra of pollen-based reconstructions as the mean PSD over the 1000-3000 year timescale band. The PSD shown in the background are smoothed using Gaussian weights with a 300 km scale. Overlaid circles are the average of all pollen records closest to the corresponding instrumental grid point. **b**, Map of the multi-decadal scaling exponent β from the spectra of instrumental temperature records fitted over the 10-60 year timescale band. **c**, Map of sub-decadal variability, mean PSD over the 2-10 year timescale band, estimated from the spectra of instrumental temperature records. In a-c, the circles indicate the instrumental grid points which were the closest to pollen records.

Figure 3 | Spectral estimates of land temperature as a function of sub-decadal variability. a, Spectral estimates of the instrumental temperature ($\Delta t < 60$ years) and of the pollen-based reconstructions ($\Delta t > 100$ years) binned according to sub-decadal instrumental variability (See Methods and Extended Data Fig.7). Dashed lines indicate estimated instrumental multi-decadal scaling exponents $\beta_{10-60 \text{ years}}$. 90% confidence intervals are given (shaded). **b,** Relation of the instrumental sub-decadal temperature variability $\text{PSD}_{2-10 \text{ years}}$ and the pollen-based millennial temperature variability $\text{PSD}_{1000-3000 \text{ years}}$. The size of the points is proportional to the errors on the millennial variability estimates. **c,** As in **b**, but between $\beta_{10-60 \text{ years}}$ and $\text{PSD}_{1000-3000 \text{ years}}$.

224 **Methods**

225 **Reconstructions**

226 The modern pollen dataset used for calibration consists of 15,532 sampling sites. For each fossil
227 record location, we selected a unique subset of modern sites within a 2000 km radius in order to
228 increase the reliability of the reconstructions and avoid a bi-modal climate optimum³⁸. The fossil
229 dataset includes taxonomically harmonized fossil pollen data from North America and Europe
230 obtained via the Neotoma Palaeoecological Database³⁹, and from Asia combining Cao et al. (2020)²⁵
231 and Cao et al. (2014)²⁴. A fossil database comprising 985 records was compiled based on the
232 requirement that the resulting spectral estimates covered timescales at least one fifth of an order of
233 magnitude, i.e. 0.2 in a base 10 logarithm, below one third the length (to avoid the well-known
234 multitaper low-bias at long timescales)⁴⁰. The European and Asian datasets were combined keeping
235 the 70 most common taxa according to Hill's second number.

236 The modern climate data used for calibration was the average of the June, July and August
237 climatologies, i.e. the summer temperature, for the years from 1970-2000 as obtained from
238 WorldClim 2.1⁴¹. The Weighted Averaging Partial Least Square (WAPLS)⁴² method was used to
239 calibrate transfer functions relating the pollen-assemblages to the summer temperature, with leave-
240 one-out cross validation. The pollen percentages were square-root transformed to decrease the
241 dominance of abundant taxa with high productivity. The number of retained WAPLS components
242 was selected using a randomization t-test. The same method was also applied to reconstruct annual
243 mean temperature (Extended Data Fig. 1) and annual precipitation (Extended Data Fig. 2), also
244 using the climatologies from WorldClim 2.1⁴¹ for the calibration of each variable.

245 **Significance Testing**

246 Following Telford and Birks (2011)⁴³, we tested the summer temperature reconstructions for
247 significance using the R package “palaeoSigs” and found that 228 out of 985 reconstructions were
248 significant ($p < 0.1$). However, this significance test is rather conservative and several reasons can
249 create type II errors (false negatives), including for example a low diversity of taxa, a small number
250 of sub-fossil observations, an input climate signal that is less variable, or an inadequate training
251 set⁴³. A higher p-values therefore does not necessarily mean that the summer temperature has not
252 been recorded, but rather that the information is insufficient to confirm it. Thus, instead of unduly
253 discarding most records, we decided to include all records in the main analysis. We show that our
254 conclusions are robust and continue to hold even if we restrict our analysis to the ‘significant
255 locations’ only ($p < 0.1$) which yielded similar results to the ‘not significant locations’ ($p > 0.1$)
256 (Extended Data Fig. 8).

257 **Testing for Anthropogenic Impacts**

258 We considered all series covering entirely the last 8-ka showed and defined two temporal windows:
259 the more recent (0-4ka) and the more distant (4ka-8ka) past. The 1000-2000 year timescale band
260 was taken to calculate the variance ratio between the two 4ka windows. We only included those
261 series in our analyses whose spectral estimates covered at least one tenth of an order of magnitude
262 (on a base 10 logarithmic scale) for both time periods; a criterion that was met by 344 records. We

found no systematic variance increase in the more recent half of the series as the mean of the distribution of the logarithm of the variance ratios did not significantly differ from zero ($p>0.1$). In fact, the more recent period, where human impacts may have contributed to an increased variability, is about 6 % less variable than the earlier one. Likewise, the spatial distribution (Extended Data Fig. 4) did not show any obvious spatial patterns that could be related to human occupation, displaying a non-significant Moran's I of 0.014 ($p>0.1$; see Methods). If human occupation was the dominant driver of millennial scale variability, we would have expected to observe an increase in variability over both Europe and China, where human occupation has been increasing the most over the last 4000 years compared to the preceding 4000 years. We thus conclude that human impacts on vegetation did not have a significant enough impact on the slow variability to systematically bias millennial scale variability estimates.

Instrumental Data

For the instrumental dataset we used the Berkeley Earth Surface Temperature (BEST) land and ocean product covering the period from 1850-2020. The equal area product is used for calculations, while the regular $1^\circ \times 1^\circ$ product was used for visual display. The instrumental data was detrended from anthropogenic influences to a first-order component⁴⁴ proportional to historical timeseries of doublings in atmospheric carbon dioxide concentration⁴⁵. There are 403 grid points which comprise pollen records (circles on Fig. 2). Using alternative instrumental datasets⁴⁶ leads to similar conclusions.

Model Data

Three model simulations of the recent Holocene were considered, namely the IPSL²⁸, the ECHAM5²⁹ and the CCSM3⁴⁷. The first two are recent Holocene transient simulations of the past 6,000 years, and the latter is the TraCE-21ka deglaciation experiment³⁰. We only retained the last 8,000 years of TraCE-21ka since it is comparable to the recent Holocene transient simulations as they contain no more freshwater forcing events which were the main drivers of the deglaciation. We selected the average 2-meter summer air temperature (June-July-August) and averaged it annually.

Since the long-term trends in summer temperature are linked to the precession in the Earth's orbit, we also analysed the timeseries after detrending for a 23-ka sinusoid rather than use the standard linear detrending performed before computing spectral estimates. This approach attempts to minimize power leakage from the orbital forcing frequencies onto the observed frequencies (Fig. 1a, dashed lines). The reduction in leaked power was not nearly as important in the case of the pollen-based reconstructions (Fig. 1a, Extended Data Fig. 5).

Spectral Estimates

The power spectral density estimates were calculated using the multitaper method⁴⁸, adapted for irregular sampling through linear interpolation⁴⁹, with the number of tapers $n_{\text{tapers}}=3$ and the time-bandwidth parameter $\omega=2$, which yield up to $n_{\text{tapers}}*\omega=6$ degrees of freedom for the individual spectral estimates. Only timescales greater than twice the maximal resolution were kept to minimize power loss due to the interpolation³⁷.

The confidence intervals were derived from the chi-squared distribution (χ^2) of the multitaper estimates. The degrees of freedom of the χ^2 were limited to a maximum based on the expected

effective spatial degrees of freedom at a given timescale in order to avoid obtaining over-confident estimates. The approximate relationship assumed for the maximum degrees of freedom $v_{\max}$ as a function of timescale is: $v_{\max}=40 \Delta t^{-0.3}$. This corresponds to about 20, 10, and 5 degrees of freedom at the decadal, centennial and millennial timescales respectively³⁷. They were multiplied by six, the number of degrees of freedom for the multitaper estimates with three independent tapers, and further modulated by a factor of spatial representativity $f_{\Delta t}$ calculated as the fraction of the land area represented by the spatial distribution of the data.

For each point over land we calculated the effective number of records N_{Eff} on a regular 1° by 1° degree grid using a Gaussian kernel:

$$N_{\text{Eff}} = \sum_{i=1}^n e^{\frac{-d_{i,j}}{2\sigma^2}}$$

where $d_{i,j}$ is the geographical distance between the i^{th} data record (out of n records with a PSD estimate at the given timescale Δt) and the j^{th} grid point where N_{Eff} is calculated, and σ is a characteristic decorrelation scale which we took as $\sigma=300$ km. N_{Eff} was also used for Fig. 2a in order to modulate the opacity of the background as a function of nearby records. The factor of spatial representativity for a given timescale was then calculated as:

$$f_{\Delta t} = \frac{\sum_{j=1}^m \min(N_{\text{Eff},j}, 1) \cos(\theta_j)}{\sum_{j=1}^m \cos(\theta_j)}$$

where m is the number of grid points covering the land area north of the southernmost pollen record.

Variance Ratios

Variance ratios were computed by taking the ratio between the mean PSD over the same timescale band between different series after interpolating in the spectral domain. Since the ratio of two χ^2 distributed variables follows an F-distribution, the ratios were multiplied by $(d-2) d^{-1}$ where d is the number of degrees of freedom of the denominator²².

Sub-Decadal Variability Binning

The data was aggregated based on the mean sub-decadal variability $\text{PSD}_{2-10 \text{ years}}$, defined as the mean PSD over the 2-10 year timescale band. We calculated $\text{PSD}_{2-10 \text{ years}}$ for each of the 403 instrumental grid point for which pollen records were present nearby, ordered the results, and split them into eight non-overlapping bins (Extended Data Fig. 7). Each pollen record was assigned to the nearest instrumental grid point and averaged in the spectral domain. Varying the number of bins, for example using twenty bins instead of eight, leads to similar correlations (Extended Data Fig. 7).

Correlation

The Pearson's correlation was calculated between the instrumental sub-decadal variability $\text{PSD}_{2-10 \text{ years}}$, the instrumental multi-decadal scaling exponent $\beta_{10-60 \text{ years}}$, and the pollen-based millennial variability $\text{PSD}_{1,000-3,000 \text{ years}}$ after binning the instrumental grid points near pollen records into 8

subsets according to the $\text{PSD}_{2-10 \text{ years}}$ amplitudes (see previous section). The standard errors on the millennial variability estimates, i.e. $\sqrt{2 \text{DoF}}$, where DoF is the total degrees of freedom for the PSD estimate, were used as weights for the correlation calculation and for visual representation in Fig. 3b,c.

Moran's I

Moran's I spatial autocorrelation index was calculated using the method from Gittleman and Kot (1990)⁵⁰ as implemented in the R-package "ape"⁵¹. The weight matrix used corresponds to the inverse of the distance between sites.

Code and Data Availability

All relevant code and data is available to the editor and the reviewers of this article upon request, and will be made publicly available in a GitHub repository upon publication.

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Extended Data Figure 1 | Summer and Annual Temperatures Spectra - Comparing the average spectra at the location of pollen records for the mean summer temperature (dashed) and the mean annual temperatures (solid). 90% confidence intervals are given (shaded). The IPSL and ECHAM5 model results exhibit a slightly lower variability in their annual temperature than in their summer temperature over all timescales, except for the longest timescale since it is dominated by leaked power from the Earth's orbital precession which mainly affects summer temperature in the Northern Hemisphere during the Holocene. On the other hand, TraCE-21ka generally shows a slightly higher variability in its annual compared to its summer temperature. Although the pollen-based reconstructions calibrated for annual temperature are thought to be less reliable than the summer temperature reconstructions, they give a very similar result. This shows that our conclusions are robust against uncertainties in the seasonal attribution of pollen variability.

Extended Data Figure 2 | Comparison of pollen-based precipitation reconstructions and climate models. Same as Extended Data Fig. 1, but for precipitation instead of summer temperature. While most locations should reflect temperature, here we also tested the boundary case of assuming that all sites reflect precipitation. Even in this extreme case, the main results hold, namely increasing climate variability over land as a function of timescale and a corresponding deficit of variability in the climate models. In all cases, there was little difference between the estimates with (dashed) and without (solid) sinusoidal detrending. The three climate models vastly disagree in terms of the amplitude of precipitation variability, but they all show a large deficit of variability at long timescales compared to the pollen-based reconstructions. Thus, even if precipitation would affect parts of our records, this cannot reconcile the model-proxy discrepancy.

Extended Data Figure 3 |Spectral estimates from tree ring series. Spectral estimates of land temperature variability obtained from the pollen-based reconstructions and dendrochronological results from tree ring width (TRW) and maximum latewood density (MXD) measurements are shown (solid). The average instrumental spectral estimates at the corresponding locations for each dataset are shown alongside for reference (dashed). See Supplementary Information for details about the data, TRW and MXD differences, and interpretation. 90% confidence intervals are given (shaded)

Extended Data Figure 4 | Variance ratio between late and mid-Holocene temperature variability. Shown are the $\log_2$ of the variance ratios α (i.e. the number of doublings) for the 1000-2000 years timescale band of the late Holocene (4ka-0ka BP) and for the mid-Holocene (8ka-4ka). A positive $\log_2 \alpha$ implies that the later period, where human impacts should be more important, was more variable.

Extended Data Figure 5| Comparison of millennial scale variability in the reconstructions and models. **a-c** Millennial temperature variability $\text{PSD}_{1000-3000 \text{ years}}$ (mean PSD for the timescale band 1000-3000 years) for the pollen-based reconstructions after smoothing with a Gaussian kernel with a characteristic scale of 300 km (see Methods). **d-l** Millennial temperature variability $\text{PSD}_{1000-3000 \text{ years}}$ for the three climate models (without smoothing). The results with different detrending methods before computing the power spectra are compared: **d,g,j** without detrending, **e,h,k** with linear detrending and **f,i,l** with a 23-ka sinusoidal detrending. The same colour scale is used for all maps. While the typical pollen-based variability would be generally between 10 and 1000 $K^2 \text{ year}^{-1}$, the models yields a variability 1-2 orders of magnitude smaller, between 0.1 and 10 $K^2 \text{ years}^{-1}$, with some regions reaching up to 100 $K^2 \text{ year}^{-1}$.

Extended Data Figure 6 | Location of the records contributing to each spectral bin. a. Shown are the location of individual pollen records which were considered in the analysis. The colours correspond to those in Fig. 3, indicating which records are included in the binning of each spectrum. **b.** Shown are the grid points of the instrumental dataset which are near pollen records. The colours also indicate the corresponding bins as in **a** and Fig. 3. Each of the 8 non-overlapping bins contain 50 grid points based on the sub-decadal variability (see Methods).

Extended Data Figure 7 | Spectral estimates of land temperature as a function of sub-decadal variability using twenty bins. As in Fig.3, but using twenty bins instead of eight. While the result is noisier than in Fig. 3, the correlation is still highly significant, which shows that our result is not sensitive to the number of bins.

Extended Data Figure 8 | Comparison of pollen-based reconstructions based on their statistical significance. A total of 985 pollen records which provided spectral estimates were tested for statistical significance and separated into ‘significant locations’ ($p < 0.1$) and ‘not significant locations’ ($p > 0.1$). The resulting average spectra overlap and are fairly similar over a wide range of timescales. The average spectra of the instrumental data at the corresponding locations are shown alongside for reference (dashed). 90% confidence intervals are given (shaded).

Figures

Figure 1

Average spectral estimates of local land temperature over the Northern Hemisphere. a, Average spectral estimates of land air temperature from pollen-based reconstructions, instrumental data and model simulations extracted at the pollen record locations. Also shown are the spectra estimated after applying a 23-ka sinusoidal detrending (dashed, see Methods). 90% confidence intervals are given (shaded). The number of pollen records contributing to each timescale is indicated below (brown axis). b, Average spectral estimates from reconstructed annual sea-surface temperature derived from marine archives5, and from instrumental data at the corresponding locations. The pollen-based and instrumental average spectra from a are reproduced. Also shown are linear combinations of power-laws with slope $\beta=1.2$ and white noise series (dashed green for land, dashed blue for sea and dashed grey for the white noise levels) corresponding to the energy-balance model approximation.

Figure 2

Spatial patterns of temperature variability in instrumental data and pollen-based reconstructions. a, Map of millennial variability estimated from the temperature spectra of pollenbased reconstructions as the mean PSD over the 1000-3000 year timescale band. The PSD shown in the background are smoothed using Gaussian weights with a 300 km scale. Overlaid circles are the average of all pollen records closest to the corresponding instrumental grid point. b, Map of the multi-decadal scaling exponent β from the spectra of instrumental temperature records fitted over the 10-60 year timescale band. c, Map of sub-decadal variability, mean PSD over the 2-10 year timescale band, estimated from the spectra of instrumental temperature records. In a-c, the circles indicate the instrumental grid points which were the closest to pollen records. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning

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Figure 3

Spectral estimates of land temperature as a function of sub-decadal variability. a, Spectral estimates of the instrumental temperature ($\Delta t < 60$ years) and of the pollen-based reconstructions ($\Delta t > 100$ years) binned according to sub-decadal instrumental variability (See Methods and Extended Data Fig.7). Dashed lines indicate estimated instrumental multi-decadal scaling exponents $\beta_{10-60 \text{ years}}$. 90% confidence intervals are given (shaded). b, Relation of the instrumental sub-decadal temperature variability $\text{PSD}_{2-10 \text{ years}}$ and the pollen-based millennial temperature variability $\text{PSD}_{1000-3000 \text{ years}}$. The size of the points is proportional to the errors on the millennial variability estimates. c, As in b, but between $\beta_{10-60 \text{ years}}$ and $\text{PSD}_{1000-3000 \text{ years}}$.

Supplementary Files

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