

Climate outweighs human effects on vegetation properties during the early-to-mid Holocene

Vivian A. Felde

vivian.felde@uib.no

Department of Biological Sciences, University of Bergen, PO Box 7803, NO-5020 Bergen, Norway
<https://orcid.org/0000-0002-2855-0894>

Ondřej Mottl

ondrej.mottl@gmail.com

Department of Biological Sciences, University of Bergen, PO Box 7803, NO-5020 Bergen, Norway
<https://orcid.org/0000-0002-9796-5081>

Suzette G. A. Flantua

s.g.a.flantua@gmail.com

Department of Biological Sciences, University of Bergen, PO Box 7803, NO-5020 Bergen, Norway
<https://orcid.org/0000-0001-6526-3037>

Kuber P. Bhatta

Department of Biological Sciences, University of Bergen, PO Box 7803, NO-5020 Bergen, Norway
<https://orcid.org/0000-0001-7837-1395>

Hilary H. Birks

Department of Biological Sciences, University of Bergen, PO Box 7803, NO-5020 Bergen, Norway
<https://orcid.org/0000-0001-6881-9133>

John-Arvid Grytnes

Department of Biological Sciences, University of Bergen, PO Box 7803, NO-5020 Bergen, Norway
<https://orcid.org/0000-0002-6365-9676>

Henry Hooghiemstra

Institute for Biodiversity and Ecosystem Dynamics, University of Amsterdam, Amsterdam, 1090 GE, The Netherlands <https://orcid.org/0000-0003-2502-1644>

Sandra Nogu  

Department of Animal Biology, Plant Biology and Ecology, Universitat Aut  noma de Barcelona, Bellaterra (Cerdanyola del Vall  s), Catalonia, Spain <https://orcid.org/0000-0003-0093-4252>

Triin Reitalu

Institute of Ecology and Earth Sciences, University of Tartu, 51014 Tartu, Estonia
<https://orcid.org/0000-0002-6555-3066>

Alistair W. R. Seddon

Department of Biological Sciences, University of Bergen, PO Box 7803, NO-5020 Bergen, Norway
<https://orcid.org/0000-0002-8266-0947>

Manuel J. Steinbauer

Bayreuth Center of Ecology and Environmental Research (BayCEER) & Bayreuth Center of Sport Science (BaySpo), University of Bayreuth, 95447 Bayreuth, Germany <https://orcid.org/0000-0002-7142-9272>

Cajo J. F. ter Braak

Biometris, Wageningen University & Research, 6708 PB, Wageningen, The Netherlands
<https://orcid.org/0000-0002-0414-8745>

Thomas Giesecke

Department of Physical Geography, Utrecht University, Princetonlaan 4, Utrecht, 3584 CB, The Netherlands <https://orcid.org/0000-0002-5132-1061>

Simon J. Goring

Department of Geography, University of Wisconsin-Madison, 550 N Park St, Madison WI 53706, USA
<https://orcid.org/0000-0002-2700-4605>

Simon G. Haberle

ARC Centre of Excellence for Australian Biodiversity and Heritage/School of Culture, History and Language, ANU College of Asia and the Pacific, The Australian National University, Canberra, ACT 2600, Australia <https://orcid.org/0000-0001-5802-6535>

Annika V. Herbert

ARC Centre of Excellence for Australian Biodiversity and Heritage/School of Culture, History and Language, ANU College of Asia and the Pacific, The Australian National University, Canberra, ACT 2600, Australia <https://orcid.org/0000-0001-9322-043X>

Petr Šmilauer

Department of Ecosystem Biology, University of South Bohemia, CZ-37001 České Budějovice, Czech Republic <https://orcid.org/0000-0003-3065-5721>

Willy Tinner

Institute of Plant Sciences and Oeschger Centre for Climate Change Research, University of Bern, CH-3013 Bern, Switzerland <https://orcid.org/0000-0001-7352-0144>

John W. Williams

Department of Geography, University of Wisconsin-Madison, 550 N Park St, Madison WI 53706, USA
<https://orcid.org/0000-0001-6046-9634>

Darcy Bird

Department of Anthropology, Washington State University, College Hall 150, Pullman WA 99164, USA
<https://orcid.org/0000-0003-3466-6284>

Jacob Freeman

Anthropology Program, Utah State University, 0730 Old Main Hill, Logan, UT 84321, USA

<https://orcid.org/0000-0001-7402-8450>

Eugenio Gayo

Departamento de Geografía & Center for Climate and Resilience Research (CR)2, Universidad de Chile, Chile <https://orcid.org/0000-0003-0746-0512>

Julie A. Hoggarth

Department of Anthropology, Baylor University, One Bear Place #97173 Waco, TX 76798, USA
<https://orcid.org/0000-0001-8612-8846>

Claudio Latorre

Departamento de Ecología, Pontificia Universidad Católica de Chile, Chile <https://orcid.org/0000-0003-4708-7599>

Lux Miranda

Department of Information Technology, Uppsala University, SE 75105 Uppsala, Sweden
<https://orcid.org/0000-0002-3753-7405>

Erick Robinson

Native Environment Solutions LLC, 3858 N Garden Center Way Suite 300, Boise, ID 83703, USA
<https://orcid.org/0000-0002-0789-3724>

Xianyong Cao

Group of Alpine Paleoenvironment and Human Adaptation (ALPHA), State Key Laboratory of Tibetan Plateau Earth System, Environment and Resources (TPESER), Institute of Tibetan Plateau Research, Chinese Academy of Sciences, Beijing, China <https://orcid.org/0000-0001-5633-2256>

Fahu Chen

Group of Alpine Paleoenvironment and Human Adaptation (ALPHA), State Key Laboratory of Tibetan Plateau Earth System, Environment and Resources (TPESER), Institute of Tibetan Plateau Research, Chinese Academy of Sciences, Beijing, China <https://orcid.org/0000-0002-8874-1035>

H. John B. Birks

Department of Biological Sciences, University of Bergen, PO Box 7803, NO-5020 Bergen, Norway
<https://orcid.org/0000-0002-5891-9859>

Research Article

Keywords:

Posted Date: July 10th, 2024

DOI: <https://doi.org/10.21203/rs.3.rs-4692574/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

Abstract

Controversies exist regarding the extent of past human influence on terrestrial ecosystems and the relative importance of human versus climatic factors in shaping Holocene vegetation. However, there has been no systematic examination of these issues at a global scale.

Here we integrate palaeoecological, archaeological, and palaeoclimate data to assess the influence of humans and climate in driving patterns of past vegetation during the early and middle Holocene (8500 - 2000 years before present) as recorded by pollen-assemblage properties. We quantify and summarise the patterns of change in different properties from individual records to a global scale and assess the relative importance of humans and/or climate in influencing them. Additionally, we assess whether the internal relationships among these properties changed through time.

While we find evidence that humans have high localized impact on vegetation dynamics in various regions and times periods, when considered globally, humans appear to be a secondary factor, during the early-to-mid Holocene. Our results underscore the value of merging multidisciplinary palaeodata to provide a holistic understanding of millennia-spanning relationships between humans, climate, and vegetation across different spatial scales.

MAIN TEXT

Human activity has transformed and is continuing to transform the Earth's terrestrial ecosystems^{1,2,3}. Over recent centuries, both land-use intensity and the human population have undergone exponential growth, resulting in profound impacts on ecosystems in ways that fundamentally differ from those experienced previously in geological history^{4,5,6,7}. Archaeological and palaeoecological evidence show that much of Earth's land has been inhabited by humans for millennia, transforming natural landscapes into "anthromes" (i.e. anthropogenic biomes) through activities such as hunting, fire use, deforestation, and cultivation⁸. Human impact likely varied with human migrations, societal development, technological advancements, and population densities, altering natural systems in different regions at varying rates¹. Although some have argued that humans have shaped most of nature over the last 12,000 years⁸, so far there has been no quantitative analysis of palaeoecological records to assess the magnitude of human influence on properties of past vegetation globally.

Properties of past vegetation can be derived from fossil pollen-assemblage properties with examples including indices of richness, diversity, and temporal and spatial compositional turnover⁹. Several prior studies have documented regional to continental changes patterns in various aspects of plant diversity during the Holocene^{e.g. 10,11,12,13,14}. However, the underlying causes remain poorly understood, and a major challenge is understanding the influence of past human activity in relation to climate, a well-documented driver of vegetation dynamics throughout the Pleistocene and Holocene^{e.g. 15,16}.

Various hypotheses have emerged regarding when the extent of human impact on past vegetation increased at global- to continental-scales. Ruddiman¹⁷ proposes an anthropogenic era that started during the early Holocene with widespread human impact on terrestrial ecosystems inducing changes in the global carbon cycle, as determined from anomalies in CO₂ (~ 8 thousand years before present (ka BP) where present = 1950 CE) and CH₄ (~ 5 ka BP) concentrations detected in ice cores. Lyons et al.¹⁸ suggest that significant human activity altered taxon co-occurrence patterns from the middle Holocene (~ 6 ka BP), although challenged by Bertelsmeier & Ollier¹⁹ and Telford et al.²⁰. Several continental-scale studies using fossil pollen data link a change in vegetation to an increase in human activity during the middle to late Holocene^{e.g. 21,12,11}. A global analysis found an accelerated rate-of-change in pollen composition from ~ 4.6 ka BP, but with substantial regional differences¹³ although no attempt was made to discern the causes of this acceleration. These findings underscore that the relationship between humans and vegetation during the Holocene was complex, with periods of increased human influence at different spatial scales. No consensus thus yet exists regarding whether early-to-mid Holocene humans had a substantial impact on macroecological patterns.

Palaeoecological studies have also documented how climate shapes vegetation dynamics at regional to continental scales. These range from individual taxa that track suitable climate conditions within areas limited by their ability to disperse and establish²², to the formation of vegetation types are governed by Holocene climate variations^{e.g. 23,24,25,15}. This variation includes different temporal variability on decadal to centennial scales, such as changes in warming-cooling events and wet-dry phases during the Holocene²⁶, complicating the inference of regional patterns in vegetation dynamics and their relation to human impact.

Several region-specific syntheses using fossil pollen aimed to quantify the long-term effects of human activity and climate, and demonstrated that human impact exceeded climate and significantly changed vegetation patterns at different times during the Holocene^{e.g. 27,28,29,30}. However, these studies use a single extrinsic driver at a time, mainly focus on one vegetation property, and are not directly comparable across regions due to their use of different proxies and methodologies. The recent surge in open-access repositories housing extensive palaeoecological and archaeological records^{31,32,33}, alongside palaeoclimate databases³⁴, creates new opportunities to combine different sources of information from independent proxies to quantify the still-unknown relative effects of human influence and climate on comparable regional to global scales.

To address the question of how widespread and profound was the early human influence on terrestrial ecosystems, we seek to quantify and formally attribute the relative influence of early-to-mid Holocene (8.5–2 ka BP) human and climate impact on past pollen-assemblage properties (hereafter properties) at a global scale, encompassing climate zones and continents. These properties are Hill's diversity numbers of palynological richness (N₀), diversity (N₁, N₂), and evenness (N₂/N₁, N₁/N₀), turnover (detrended canonical correspondence analysis axis 1; DCCA 1), rate-of-change (RoC), density of diversity changes (DDC), and density of compositional change (DCC) (see **Methods**). We analyse temporal and

spatial patterns of these properties and the internal relationships between properties collectively to evaluate the overall importance of humans in relation to climate as a reference. We explore two hypotheses. Our first hypothesis (H1) proposes that human impact was the primary driver of temporal changes in properties at the climate-zone and continental scales during the early-to-mid Holocene (8.5–2 ka BP). We compare the importance of human impact relative to climate in two ways, spatially and temporally; 1) between records summarised within different climate zones and continents (spatial), and 2) the spatial extent of properties across continents between time slices (temporal). Our second hypothesis (H2) proposes that human impact significantly altered the internal relationships between the properties of vegetation within climate zones and continents during the early-to-mid Holocene. If the amount and extent of past human impact are an important driver of change in past pollen assemblages, then we expect human impact to be as high or even exceed the influence of climate.

We harmonised 1262 fossil pollen records from North America, Central and South America, Europe, Asia, and Oceania (Fig. 1; **Methods**; **Extended Data** Fig. 1). Rather than adhering to geopolitical borders, the continental regions are pragmatically divided according to physical geography and dominant vegetation types. After filtering datasets by our selected criteria, Africa was excluded as the pollen data were too sparse (< 11 in total, see **Methods**). The response data are matrices of properties represented by N0, N1, N2, N2/N1, N1/N0, DCCA1, RoC, DCD, and DCC. The predictor variables of past human activity are the summed probability density (SPD) of archaeological radiocarbon dates³³ and an expert-based detection of ‘human-impact events’, which are identified based on anthropogenic indicator taxa in individual pollen diagrams (**Methods**; **Extended Data** Fig. 2). Palaeoclimate is represented by summer and winter precipitation, mean annual temperature, and minimum temperature of the coldest month extracted from the CHELSA-TraCE21k Paleoclimate database version 1³⁴.

To quantify the amount and extent to which past human activity and palaeoclimate are important predictors of changes in the properties (H1), we employed hierarchical variation partitioning (HVARPART), using redundancy analysis (RDA) with standardisation of properties as responses, and past human presence and activity and palaeoclimate as predictors (**Methods**; **Extended Data** Fig. 3). This method is a robust approach for evaluating the importance of predictors³⁵. The importance (adjusted R^2) of each predictor is the sum of the averaged unique and average shared partitions accounting for different orders of predictors in the model³⁵. The ratio of predictor importance of human activity and palaeoclimate relative to each other are calculated within and between individual records for each 500-year time slice (Fig. 1; **Methods**). To summarise the predictor importance for the continental regions and subdivisions of the Köppen-Geiger climate zones³⁶, we calculated the mean ratios of the individual predictor importance weighted by the sum of the predictor’s importance. Our analyses focus on the early-to-mid Holocene (8.5–2 ka BP) because we only assessed time slices for which sufficient SPD could be built (Table 1), which are limited by a lack of compiled datasets of radiocarbon dates for past humans during the last 2 millennia in Europe and Asia³³. However, to support our past human-presence reconstructions, we complement the temporal analysis by using human-impact events as a human-activity predictor (**Methods**).

Table 1

Data summary for each continental region. Number of pollen records included in the analyses for the assessed period of 8.5–2.0 calibrated thousand years before present (cal ka BP), the number of records with summed probability densities (SPD) within a 250 km or 500 km radius of the site, and the number of records with human-impact events.

Continents	Number of fossil pollen records	Number of records with SPD 250 km	Number of records with SPD 500 km	Number of records with human-impact events detected
North America	554	512	43	217
Central & South America	87	65	15	87
Europe	396	383	14	143
Asia	177	47	64	95
Oceania	48	37	1	28

To quantify changes in the internal relationships between properties in response to humans and palaeoclimate (H2), we interpolated estimated properties at 500-year time slices within climate zones across continents. We used a principal component analysis (PCA) with standardisation of all properties to quantify the correlation and covariance for each time slice and employed symmetrical Procrustes sum-of squares (m^2) to estimate the total change in configurations between the properties in pairwise time slices within climate zones³⁷ (see **Methods**). This provided pairwise m^2 distance matrices that are used as response variables in HVARPART to quantify the importance of past human activity and climate on changes in relationships between all the properties within regional climate zones for the period 8.5–2 ka BP (Fig. 1). To determine the general patterns of past humans (SPD) and palaeoclimate for the different climate zones, we used a hierarchical generalised additive model (HGAM³⁸), in a Bayesian modelling framework (Extended Data Figs. 4–8). Subsequently, the predicted mean trend from the model is integrated as a predictor in the HVARPART analyses.

Palaeoclimate has a substantially greater importance than past human presence for changes in the past properties, a trend consistent globally (Fig. 2). Our spatial analysis shows high variation in the ratios of predictor importance of past human presence and palaeoclimate in driving changes in past properties during the early and middle Holocene (Fig. 2). Both have been important in shaping patterns of properties at individual sites with the ratio of importance of past humans ranging between 0 and 0.57, and palaeoclimate from 0–0.90. As spatial scale increases, so does the relative importance of climate. At the climate zone level, weighted mean ratios range from 0–0.71 for humans to 0.29–1 for palaeoclimate. On continental scales, these ratios are 0.16–0.32 for humans to 0.68–0.85 for palaeoclimate. Despite being less important than palaeoclimate, the importance of human presence is higher in certain climate zones (except Polar and Cold climate zones) than its weighted mean across continents. Outliers in Oceania are based on too few sites to be considered robust (< 5 records).

Palaeoclimate is also the dominant driver accounting for temporal variation in spatial patterns of past properties across continents (Fig. 3). Our temporal analysis with SPD or human-impact events as predictors, reveals the varying importance of human presence, human-impact events, and palaeoclimate over time (Fig. 3). The trends between the analyses run with SPD as the predictor or with human-impact events are relatively consistent among the different regions, except in Asia where human importance by SPD is likely underestimated due to limited radiocarbon dates, and human-impact events indicate an increasing extent of human impact across the continent after 3.5 ka BP. In Europe, SPD are likely underestimated after 3 ka BP, though the extent of human impact is relatively stable after this period as assessed by human-impact events (Fig. 3). The weighted mean ratios for human presence (SPD) in relation to palaeoclimate, and human-impact events in relation to palaeoclimate are presented in **Extended Data Tables 3 and 4**.

Palaeoclimate rather than past human presence is also the primary predictor for internal changes in relationships between properties within climate zones between 8.5 and 2 ka BP globally (Fig. 4). The spread and distance in the time trajectories indicate the amount of change in correlations between the properties in different time slices, and whether changes in these internal relationships are temporarily or continually changing in different directions (Fig. 4). The coldest regions, in particularly Europe and North America's Polar, Cold, and Temperate without dry season zones, show, overall, considerably less change in internal relationships between properties compared to other climate zones. This may suggest climatic filtering on past assemblages and underlying ecological processes remaining unchanged or changing synchronously during the investigated period. In contrast, other regions with higher environmental variation in Cold, Temperate, Tropical, and Arid zones globally are more dynamic and show that internal relationships between properties evolve in different directions, mainly caused by climatic variability, but also influenced in some regions by a varying degree of past human presence.

Our findings thus refute hypotheses that early-to-mid Holocene human activities were a primary driver for changes in assemblage properties of vegetation (H1) or in the internal relationships between the properties (H2) at continental to global scales. While past humans have acted as strong disturbance factors at specific sites, their importance is considerably lower than that of palaeoclimate during the early and middle Holocene, and the human signal decreases with increasing spatial scales. Even though humans were most likely present in all studied locations, population densities and land use type and intensity varied spatially. An increasing impact on macroecological scales does not emerge before population sizes increase across continents during the middle Holocene (> 5 ka BP) and is not spatially coherent. Consistent increasing human importance is mainly revealed in Asia (human-impact events) and Oceania (human-impact events and SPD) that surpasses palaeoclimate at 2.5 or 2.0 ka respectively. In North America, Central and South America, and Europe, palaeoclimate remains the dominant driver of vegetation dynamics throughout the early-to-mid Holocene, albeit with increasing human importance after 2.0, 1.0, or 3.5 ka BP, respectively. A higher weighted mean of human importance in some climate zones compared to the weighted continental means (Fig. 2), may indicate that the extent of human influence was greater at some sites in these regions. Early Holocene peaks in human importance correspond with initial cultivation events, despite their limited extent or small populations (Fig. 3).

Humans have affected ecosystems throughout the Holocene, but the impact was localised and secondary to climate for most of the early-to-mid Holocene. These results align with research showing climate can have a strong and consistent filtering on pollen assemblages as assessed by comparing local and regional assembly pools³⁹. The observed increase of RoC in vegetation starting from 4.6 ka BP to the present detected in different regions by Mottl et al.¹³ can now be more closely linked to the increasing extent of human presence and impact globally. A weak trend of climate mismatch throughout the middle and late Holocene might be the result of constraints on species dispersal caused by human-induced habitat fragmentation³⁹. Although the degree of human importance increased during this period, it did not exceed climate impact for most regions, except in Asia. This finding supports the likely human-induced changes in the vegetation property patterns detected by Cao et al.⁴⁰ in eastern Asia. Rapid rate-of-compositional changes during the late Holocene suggest interactions between changes in regional climate and human activity shaping novel vegetation patterns^{e.g.41} during the late Holocene to the present. This aligns with the ongoing challenge of defining global tipping points⁴² for terrestrial ecosystems. Therefore, attempts to define a global *Anthropocene* ≠ era in ecological datasets is challenging or even impossible due to the high heterogeneity between regions and factors affecting assemblages of taxa in varying degrees both temporally and spatially.

Considering uncertainties in proxies due to missing data or data gaps, especially in relation to past human proxies younger than 3 ka BP, future studies using more data and improved proxies may provide further insights into the importance of human activities on the property patterns of past vegetation. By comparing similarities and differences between regional and site-based property patterns and their relationships to environment and human activity, important drivers particularly during the late Holocene (younger than 4 ka BP), may be uncovered.

Through numerical analyses of fossil pollen, archaeological, and palaeoclimate data, we explored the complex historical legacies of humans and past climate on early-to-mid Holocene vegetation via pollen-assemblage properties. This study uniquely quantifies diverse properties patterns of past vegetation, offering a holistic view of their dynamics across temporal and spatial scales. Our results challenge the hypothesis of extensive global human impact in the early and middle Holocene. Our findings show it was consistently low compared to climate, supporting the view that climate is the primary driver for shaping terrestrial vegetation globally, and signals of localised high effects of past humans are not transferrable to broader spatial scales. Therefore, evidence for strong site-based human impacts should not be generalised to a continental or global scale.

Declarations

DATA AVAILABILITY

The source data are deposited and available for download via Zenodo (DOI: 10.5281/zenodo.11369243; <https://doi.org/10.5281/zenodo.11369243>).

CODE AVAILABILITY

All R code and workflows to reproduce the data processing, filtering, data analyses, and figures are available at: <https://github.com/HOPE-UIB-BIO/PastHumanImpact>

ACKNOWLEDGEMENTS

HJBB, VAF, OM, SGAF, KPB, MJS, TR, AWRS, SN, HHB, and JAG were fully or partly funded by the European Research Council Advanced Grant Humans on Planet Earth – Long-term impacts on biosphere dynamics (HOPE) awarded to HJBB (grant no. 741413). SGAF was funded by the Trond Mohn Research Foundation (TMF) and University of Bergen for the Startup Grant on “Past, Present, and Future of Alpine Biomes worldwide” awarded to SGAF (grant no. TMS2022STG03). XC and FC were financed by the National Natural Science Foundation of China (grant no. 41988101). AVH and SGH were funded by the Australian Research Council’s Centre of Excellence for Australian Biodiversity and Heritage (CABAH). OM was funded by the Czech Science Foundation PIF grant (23-063861), by Charles University Research Centre program (UNCE/24/SCI/006), and by Institutional Support for Science and Research of the Ministry of Education, Youth and Sports of the Czech Republic. TR was supported by Estonian Research Council (PRG874, PRG1993). Thanks to Cathy Jenks for editorial help, and Beate Helle for help with figure design. We thank and acknowledge all data contributors and data curators of the open accessible databases we have used. We dedicate this manuscript to Eric C. Grimm (1951–2020), who was initially involved in the HOPE project. We express our deep gratitude for his long dedication and groundbreaking work in palaeoecological research, and his initiatives in developing the Neotoma Palaeoecology Database and community, and the Canadian Archaeological Radiocarbon Database.

AUTHOR CONTRIBUTIONS

HJBB developed the concept and idea, obtained the ERC grant, provided human-impact event detection for the Northern Hemisphere, and pollen harmonisation for the Northern Hemisphere; VAF, OM, SGAF, & KPB assembled and processed data, developed R code and workflows; OM & SGAF developed an automated process for human detection in fossil pollen records in Central and South America; OM & VAF performed data analyses and visualisations; VAF, OM, & SGAF planned, structured, and wrote initial manuscript drafts; MJS, TR, AWRS, SN, HHB, & JAG contributed to initial discussions and methodological developments; HHB provided human-impact events for the Northern Hemisphere; HH & SGAF provided human-impact/presence indicators and pollen harmonisation for Central & South America; SGH & AVH provided data, pollen taxa harmonisation, and human-impact events for Oceania; CJFB & PŠ provided code for implementing DCCA in R, and gave advice on data analyses and summaries; TG, JWW, SJG, & WT provided regional knowledge and feedback for interpretations of the results and development of the manuscript; DB, JF, ER, JAH, EG, CL & LM provided code, advice, and feedback on the use of the p3k¹⁴C radiocarbon database and the methodology to create summed

probability densities of past humans; XC & FC contributed fossil pollen data from Asia. VAF, OM, & SGAF are joint first authors. All authors contributed with comments and edits in preparing this manuscript.

COMPETING INTEREST DECLARATION

The authors declare no competing interests.

ADDITIONAL INFORMATION

Supplementary Information is available for this paper.

Correspondence and requests for materials should be addressed to Vivian A. Felde (vivian.felde@uib.no) and/or Ondřej Mottl (ondrej.mottl@gmail.com) and/or Suzette G.A. Flantua (s.g.a.flantua@gmail.com).

References

1. Ellis, E. C., et al. Used planet: A global history. *Natl. Acad. Sci. U.S.A.* **110**, 7978-7985 (2013).
<https://doi.org/10.1073/pnas.1217241110>
2. Díaz, S., et al. Pervasive human-driven decline of life on Earth points to the need for transformative change. *Science* **6471**, 366 (2019) <https://doi.org/10.1126/science.aax3100>
3. Rockström, J., et al. Safe and just Earth system boundaries. *Nature* **619**, 7968, 102-111 (2023).
<https://doi.org/10.1038/s41586-023-06083-8>
4. Rockström, J., et al. A safe operating space for humanity. *Nature* **7263**, 461, 472-475 (2009).
<https://doi.org/10.1038/461472a>
5. Barnosky, A. D. Palaeontological evidence for defining the Anthropocene. Geological Society, London, Special Publications 395, 149-165 (2013). <https://doi.org/10.1144/sp395.6>
6. Steffen, W., et al. Trajectories of the Earth system in the Anthropocene. *Natl. Acad. Sci. U.S.A.* **33**, 115, 8252-8259 (2018). <https://doi.org/10.1073/pnas.1810141115>
7. Albert, J. S., et al. Human impacts outpace natural processes in the Amazon. *Science* **379**, 6630, eab05003 (2023). <https://doi.org/10.1126/science.abo5003>
8. Ellis, E. C., et al. People have shaped most of terrestrial nature for at least 12,000 years. *Natl. Acad. Sci. U.S.A.* **17**, 118 (2021). <https://doi.org/10.1073/pnas.2023483118>.
9. Birks, H. J. B., Felde, V. A., Bjune, A. E., Grytnes, J-A., Seppä, H., Giesecke, T. Does pollen-assemblage richness reflect floristic richness? *Palaeobot. Palynol.* **228**, 1-25 (2016).
<https://doi.org/10.1016/j.revpalbo.2015.12.011>
10. Blarquez, O., Carcaillet, C., Frejaville, T., Bergeron, Y. Disentangling the trajectories of alpha, beta and gamma plant diversity of North American boreal ecoregion since 15,500 years. *Ecol. Evol.* **2** (2014).

<https://doi.org/10.3389/fevo.2014.00006>

11. Giesecke, T., et al. Postglacial change of the floristic diversity gradient in Europe. *Nature Commun.* **10**, 1 (2019). <https://doi.org/10.1038/s41467-019-13233-y>
12. Roberts, N., et al. Europe's lost forests: a pollen-based synthesis for the last 11,000 years. *Rep.* **8**, 716 (2018). <https://doi.org/10.1038/s41598-017-18646-7>
13. Mottl, O., et al. Global acceleration in rates of vegetation change over the past 18,000 years. *Science* **372**, 6544, 860-864 (2021). <https://doi.org/10.1126/science.abg1685>
14. Bhatta, K. P., et al. Exploring spatio-temporal patterns of palynological changes in Asia during the Holocene. *Ecol. Evol.* **11** (2023). <https://doi.org/10.3389/fevo.2023.1115784>
15. Williams, J. W. Quaternary vegetation distributions. In: Gornitz, V. (eds) *Encyclopaedia of Palaeoclimatology and Ancient Environments*. Encyclopedia of Earth Sciences Series. Springer, Dordrecht (2009). https://doi.org/10.1007/978-1-4020-4411-3_199
16. Lang, G., Ammann, B., Behre, K-E., Tinner, W. *Quaternary vegetation dynamics of Europe*. Verlag Paul Haupt, 1-688 (2023).
17. Ruddiman, W. F. The Anthropogenic greenhouse era began thousands of years ago. *Climate Change* **61**, 261-293 (2003). <https://doi.org/10.1023/B:CLIM.0000004577.17928.fa>
18. Lyons, S. K., et al. Holocene shifts in the assembly of plant and animal communities implicate human impacts. *Nature* **529**, 80-83 (2016). <https://doi.org/10.1038/nature16447>
19. Bertelsmeier, C. & Ollier, S. 2016. Questioning Holocene community shifts. *Nature* **537**, 7618, E4-E5 (2016). <https://doi.org/10.1038/nature1911>
20. Telford, R. J., Chipperfield, J. D., Birks, H. H. & Birks H. J. B. How foreign is the past? *Nature* **538**, 7626, E1-E2 (2016). <https://doi.org/10.1038/nature20096>
21. Flantua, S. G. A., et al. Climate variability and human impact in South America during the last 2000 years: synthesis and perspectives from pollen records. *Past* **12**, 483-523 (2016). <https://doi.org/10.5194/cp-12-483-2016>
22. Williams, J., Shuman, B. N., Thompson, W. III, Bartlein, P. J., Leduc, P.L. Late-Quaternary vegetation dynamics in North America: Scaling from taxa to biomes. *Ecol. Monogr.* **74**, 309-334 (2004). <https://doi.org/10.1890/02-4045>
23. Overpeck, J. T., Webb, R. S., Webb III, T. Mapping eastern North American vegetation change of the past 18 ka: No-analogs and the future. *Geology* **20**, 1071-1074 (1992).
24. Huntley, B. European vegetation history: Palaeovegetation maps from pollen data - 13 000 yr BP to present. *Quat. Sci.* **5**, 103-122 (1990). <https://doi.org/10.1002/jqs.3390050203>
25. Petit, J-R., et al. Climate and atmospheric history of the past 420,000 years from the Vostok ice core, Antarctica. *Nature* **399**, 429-436 (1999). <https://doi.org/10.1038/20859>
26. Wanner, H., Mercalli, L., Grosjean, M., Ritz, S. P. Holocene climate variability and change; a data-based review. *Geol. Soc.* **172**, 254-263 (2014). <https://doi.org/10.1144/gjs2013-101>

27. Reitalu, T., et al. (2013). Long-term drivers of forest composition in a boreonemoral region: the relative importance of climate and human impact. *Biogeogr.* **40**, 8, 1524-1534 (2013). <https://doi.org/10.1111/jbi.12092>
28. Kuosmanen, N., et al. The role of climate, forest fires and human population size in Holocene vegetation dynamics in Fennoscandia. *Veget. Sci.* **29**, 3, 382-392 (2018). <https://doi.org/10.1111/jvs.12601>
29. Marquer, L., et al. Quantifying the effects of land use and climate on Holocene vegetation in Europe. *Sci. Rev.* **171**, 20-37 (2017). <https://doi.org/10.1016/j.quascirev.2017.07.001>
30. Nogué S., et al. The human dimension of biodiversity changes on islands. *Science* **372**, 488-491 (2021). <https://doi.org/10.1126/science.abd6706>
31. Williams, J. W., et al. The Neotoma paleoecology database, a multiproxy, international, community-curated data resource. *Res.* **89**, 1, 156-177 (2018). <https://doi.org/10.1017/qua.2017.105>
32. Uhen, M. D., et al. Paleobiology Database user guide version 1.0. *PaleoBios* **40**, 11, 1-56 (2023). <https://doi.org/10.5070/P9401160531>.
33. Bird, D., et al. p3k14c, a synthetic global database of archaeological radiocarbon dates. *Data* **9**, 1-27 (2022). <https://doi.org/10.1038/s41597-022-01118-7>
34. Karger, D. N., Nobis, M., Normand, S., Graham, C. H., & Zimmermann, N. E. CHELSA-TraCE21k – high-resolution (1 km) downscaled transient temperature and precipitation data since the Last Glacial Maximum. *Past* **19**, 2, 439-456 (2023). <https://doi.org/10.5194/cp-19-439-2023>
35. Lai, J., Zou, Y., Jinlong, Z., & Peres-Neto, P. R. Generalizing hierarchical and variation partitioning in multiple regression and canonical analyses using the rdacca.hp R Package. *Ecol. Evol.* **13**, 4, 782-788 (2022). <https://doi.org/10.1111/2041-210X.13800>
36. Beck, H. E., et al. Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Data* **5**, 1, 180214 (2018). <https://doi.org/10.1038/sdata.2018.214>
37. Peres-Neto, P. R. & Jackson, D. A. How well do multivariate data sets match? The advantages of a Procrustean superimposition approach over the mantel test. *Oecologia* **129**, 2, 169-178 (2001). <https://doi.org/10.1007/s004420100720>
38. Pedersen, E. J., Miller, D. L., Simpson, G. L., & Ross, N. Hierarchical generalized additive models in ecology: an introduction with mgcv. *7*, e6876 (2019). <https://doi.org/10.7717/peerj.6876>
39. Knight, C. A., et al. Community assembly and climate mismatch in Late Quaternary Eastern North American pollen assemblages. *Nat.* **195**, 166-180 (2020). <https://doi.org/10.1086/706340>
40. Cao, X., et al. Human activities have reduced plant diversity in eastern China over the last two millennia. *Change Biol.* **28**, 4962-4976 (2022). <https://doi.org/10.1111/gcb.16274>
41. Finsinger, W., Brewer, S., Giesecke, T., Leydet, M. Emergence patterns of novel vegetation assemblages over the past 15,000 years in Europe. *Letters* **20**, 336-346 (2017). <https://doi.org/10.1111/ele.12731>

42. Brook, B., Ellis, E. C., Perring, M. P., Mackay, A. W., Linus, B. Does the terrestrial biosphere have planetary tipping points? *Trends Ecol. Evol.* **28**, 396–401 (2013). <https://doi.org/10.1016/j.tree.2013.01.016>

METHODS

FOSSILPOL Workflow

Raw pollen datasets were curated using the R-Fossilpol package, adhering to the guidelines in Flantua et al.⁴³ and our Fossilpol project website^{44,45}. Most data records were sourced from the Neotoma Paleoecology Database³¹. For regions with data gaps (i.e. Asia), we accessed additional data from private sources, albeit under CC BY-NC-ND 4.0 licence¹⁴. **Extended Data** Table 1 provides an overview of the parameters employed in our FOSSILPOL workflow to initiate and process the compilation of pollen records. This compilation underwent further refinement during subsequent data-processing stages to yield a final, high-quality compilation of pollen records suitable for numerical analyses.

Harmonisation tables

A pivotal procedure in the FOSSILPOL workflow, aimed at achieving dataset consistency both within and across regions, is the taxonomic and nomenclatural standardisation of pollen types. Analysts from diverse backgrounds and schools may employ varying identification criteria and nomenclature, resulting in a wide spectrum of pollen taxonomic levels and names. To facilitate meaningful numerical comparisons across different pollen records, it is imperative to ensure a consistent level of pollen taxonomy. To address this challenge, we developed harmonisation tables for various regions, thereby mitigating potential biases associated with taxonomic variations. The regional harmonisation tables encompass Europe, Levant, Siberia, Southern Asia, Northern America, Central and South America, and the Indo-Pacific region, and are available in Birks et al.^{14,46}. These tables served as inputs to the FOSSILPOL workflow described above.

Workflow for data processing and analyses

We created a Github repository which contains all R scripts and custom-made functions required to run the workflow of this project from data input to outputs. Additionally, all data that are open access have been uploaded to ZENODO. This provides full transparency of our data processing and analyses. Specific links are provided under **Data availability** and **Code availability**.

Data filtering

The primary dataset is categorised into two main files: "data_assembly," which houses all pollen records and chronological tables, and a separate script "data_meta," containing general site information. To ensure the highest possible data quality and facilitate numerical comparisons across multiple pollen records, several filtering criteria were carefully chosen and applied. These criteria encompass the removal of potentially duplicated pollen records, sorting assemblages (samples) by age, elimination of

assemblages (samples) with a total pollen count below a specified threshold (referred to as pollen sum), exclusion of pollen records falling outside defined age ranges, removal of assemblages (samples) based on the age of the last control point, and the exclusion of assemblages (samples) beyond the specified age ranges of interest. Additionally, pollen records were eliminated if the total number of samples (N) fell below a certain threshold. All criteria used in the FOSSILPOL workflow are detailed in **Extended Data Table 1**.

These filtering procedures were systematically applied to the chronologies, raw pollen counts, harmonised pollen counts, and age uncertainties derived from the age-depth models (Bchron)^{47,48}. While the preferred minimum number of pollen grains was initially set at 150, this threshold resulted in a significant loss of pollen records, particularly in regions with limited data coverage. Consequently, this threshold was adjusted to 25, with the condition that less than 50% of the samples have a low pollen sum. This adjustment allows for the retention of more pollen records; however, it should be noted that in such cases, the estimates of pollen-assemblage properties (below) may exhibit reduced robustness. Furthermore, to enhance data reliability, pollen records with less than 5 samples were removed from subsequent analyses. See data summaries in **Extended Data Fig. 1**.

Detection of past human activities

To assess the historical influence of past human activities on past vegetation (= pollen-assemblage properties), we created two proxies of past human presence for each record. First, we detected human events from pollen records based on expert knowledge and second, we quantified human presence, relying on radiocarbon dates from archaeological sites and summed probability densities (SPD)³³. As a result, we can use both proxies to assess the importance of past human presence and activity across regions and continents (**Extended Data Fig. 2**). This also helps to mitigate the potential issue of circularity wherein human events are detected from the same pollen records used to estimate pollen-assemblage properties.

Human events derived from fossil pollen records

Human-event detection methods were employed to identify periods of human activity in each pollen record, with a binary expert-based approach employed for most continents and an automated process based on a literature review developed for Central and South America.

These methods are:

Detection of human events in pollen diagrams:

1. Examination of each pollen record by one or more regional specialists, resulting in the recording of the age of selected events. Event types are continent-specific and may have different interpretations even if the taxon involved is distributed across continents (see **Extended Data Table 2**).
2. Development of an algorithm to derive binary variables (0/1) associated with each event type detected in each pollen record. A new vector was constructed using average ages between levels

(samples) of identified event types, considering that human impact may have occurred in the intervals between samples in the fossil pollen record.

3. Creation of a matrix using the new age vector in conjunction with the event types. Binary values (0/1) were assigned to different event types based on their presence (i.e., detection of the event's age). This assignment adhered to logical principles, and binary values were adjusted to compile event data for each pollen record. This resulted in a binary matrix of ages and event types for each record.
4. Note that the absence of human events in a record does not necessarily imply the absence of humans; rather, it suggests that there is insufficient evidence to confirm human activity as detectable in the pollen record.

Detection using human-indicator taxa:

An automated process was employed to identify past human impact in Central and South America through a literature review targeting pollen types associated with human presence and/or activity⁴⁹.

1. Anthropogenic pollen indicators were identified from the literature as single human indicators or combined variations in a group of indicators (i.e. "human indices").
2. A computer algorithm was developed to assess each pollen record, systematically considering the combinations of taxa recorded alongside specific indicator groups. The algorithm evaluated whether the signal of a pollen indicator for human presence was weak or strong, applying a defined threshold.
3. Two categories were established: "human-event indicators", representing a single taxon associated with human activity categorised as having "weak" or "strong" impact; and "human-event indices", comprising combinations of taxa classified similarly.
4. For each pollen record, the human-event indicators and human-event indices were assessed for their presence at each level, with classification as "no impact," "weak impact," or "strong impact". Specifically, the presence of a single pollen grain of a human indicator signified "weak" impact, while the presence of more than one pollen grain of a strong impact indicator denoted "strong" impact. Additionally, the pollen type *Pinus* was considered a human indicator outside its native distribution, and for human-event indices (step c), any quantity of pollen grains had to be present for the specific combination of taxa to be classified.

Past human presence from archaeological radiocarbon dates

We used a global dataset of archaeological radiocarbon (¹⁴C) dates sourced from Bird et al.³³. The quantification of summed probability densities (SPD) required us to select a specific distance around each pollen record, enabling the collection of archaeological ¹⁴C dates within that proximity.

We carefully filtered ^{14}C dates for validity, considering geographical location (longitude and latitude), and '*LocAccuracy*' > 0. These refined ^{14}C dates were categorised based on their geographical distance from the respective pollen records, employing a radius of 250 km. The radius was selected to have a reasonable coverage of ^{14}C dates around each site. However, some sites lacked ^{14}C dates, and in these cases, we increased the radius to 500 km. The main assumption is that humans were everywhere present within this distance.

For each pollen record, we computed a time-based SPD variable with radiocarbon dates subjected to calibration using the "*calibrate()*" function from the *rcarbon* package⁵⁰. Appropriate calibration curves ("IntCal20", "ShCal20", "mixed"^{51,52}) were applied, with the mixed curve generated using the "*rcarbon::mixCurves()*" function, setting $p = 0.5$. Calibration curve assignment was based on geographical location, following Hua et al.⁵³.

The estimation of SPD involved using the "*spd()*" function from the *rcarbon* package ranging from present to 12 ka BP. Records with fewer than 50 radiocarbon dates were excluded to maintain robust SPD estimates. We used a moving window of 100 years to smooth the non-normal peaks. Typically, the number of ^{14}C dates decreases strongly toward younger material, particularly over the last 2000 years in Eurasia³³. To maintain consistency and allow comparison across continents, we focus on the time range of 8.5–2 ka across all records, and interpolated values from the curves at every 500 years. Regrettably, we excluded Africa as a region from our analysis because at the start of our project (2018) the coverage of pollen records available was too sparse.

Palaeoclimate

Palaeoclimate from the CHELSA-TraCE21k downscaling algorithm was downloaded from the CHELSA database³⁴. The selected bioclimatic variables are *bio1*: annual mean temperature ($^{\circ}\text{C}$), *bio6*: minimum temperature of the coldest month ($^{\circ}\text{C}$), *bio18*: precipitation of warmest quarter ($\text{kg m}^{-2} \text{quarter}^{-1}$, = mm), and *bio19*: precipitation of coldest quarter ($\text{kg m}^{-2} \text{quarter}^{-1}$, = mm). The climate values were extracted for the co-ordinates for each *dataset_id* (pollen record) to retrieve the full time series for every 100 years for each climate variable. The variables were selected to represent major differences in climatic conditions in all the regions with respect to differences in temperature, moisture, or seasonality.

Pollen biodiversity indices

We calculated pollen-assemblage properties^{e.g.¹⁴ as proxy indices for past vegetation properties for each pollen record in our dataset compilation. The estimates reflect different aspects of pollen assemblages and include palynological richness, diversity, evenness, compositional change and turnover, and rate-of-change (RoC).}

All variables were calculated using the newly developed *R-Ecopol* package⁵⁴. The base functions used in this package are derived from other packages. Examples are *mvpard*⁵⁵ to derive pollen zonations with multivariate regression trees, *vegan*⁵⁶ for other multivariate techniques and dissimilarity indices, and *R-*

Ratepol^{57,58} to estimate RoC. Functions from *iNex7*^{59,60} were modified to extract interpolated Hill numbers based on a minimum sample size. We also developed R functions to run detrended canonical correspondence analysis (DCCA) using *Canoco 4.5*⁶¹.

Pollen richness, diversity, and evenness

Palynological richness, diversity, and evenness were estimated using Hill's effective species numbers N0, N1, and N2, and the associated evenness ratios of N2/N1 and N1/N0⁶². The effective species numbers mainly differ in how rare taxa are weighted in comparison to abundant taxa depending on the parameter q in the formula⁶²:

$$D^q = \left(\sum_{i=1}^T p_i^q \right)^{1/(1-q)}$$

where D is the diversity estimate, and p is the proportion of taxon T_i . When q is 0, rare and abundant taxa have equal weight, and the number is simply the number of taxa in the sample. The equation is not defined for q = 1, but when it approaches 1, it equals the exponential of the well-known Shannon index and provides the number of equally common taxa. When q = 2, it is the same as the inverse Simpson diversity index and is the number of abundant taxa. Rare taxa receive a low weight. The advantage of using effective species numbers is that they provide easily interpretable units and contain the doubling effect⁵⁹. To standardise pollen sample sizes, we used the rarefaction approach developed by Chao et al.⁵⁹. These estimates were rarefied to the number of n = 150 grains, or in a few cases to a lower sum (minimum n = 25). Some pollen records from Asia were only available as pollen percentages; these are rarefied to the minimum sum of the percentages. The ratios (e.g. N2/N1) between any diversity numbers will be 1 if all taxa in a sample are equally abundant, hence these ratios reflect changes in evenness between rare, equally common, and abundant taxa.

Despite our efforts to standardise richness and diversity estimates based on a standard sample size, there remain unaccountable biases, which include variations in total pollen production and pollen representation^{63,64}.

Compositional turnover

We estimated the compositional turnover using detrended canonical correspondence analysis (DCCA) with age as the explanatory variable⁶¹. Changes in weighted average (WA) scores (*CaseR* scores²³) are measures of compositional turnover in standard deviation (SD) units⁶⁵. The WA scores were regressed with time using a second-order polynomial (age + age²) to allow more flexibility in the turnover pattern within a pollen record. The total range of *CaseR* scores along DCCA axis 1 is a measure of total compositional change for a sequence, whereas the pattern of individual *CaseR* scores along DCCA axis 1 is a measure of turnover between individual samples within the sequence. The response data are pollen percentages without any transformation to maintain the chi-square distances between samples that is

implicit in DCCA, whereas the ages are the median ages derived from the age-depth model for each sequence.

Rate-of-change

To quantify the rate-of-change (RoC) of composition, we used the *R-Ratepol* package^{57,58}. RoC was calculated using moving windows of 500-year time bins, with five shifts for each bin where samples were randomly selected. This approach, as demonstrated by Mottl et al.^{57,58}, enhances the accurate identification of RoC peak points compared to more traditional methods. The RoC values are reported as dissimilarity per 500 years, employing the chord dissimilarity coefficient⁶⁷. Standardisation of sample size was performed within each working unit, ensuring consistency at 150 grains or the lowest number detected in each dataset.

Change-point detection and density estimations

For the calculation of change points in all the estimates of pollen-assemblage properties, we used conventional regression trees (RT) for single variables with Euclidean distances. An algorithm was developed to identify transitions between resulting groups or zones per variable by coding these transitions as binary variables (0/1). A change point was designated as 1, with the mean ages between two consecutive samples representing the timing of this significant change, determined individually for each pollen-assemblage property.

Compositional change was calculated using multivariate regression trees (MRT) with age as the sole constraining variable. MRT is, in general, a robust tool to explore and predict changes in multivariate datasets using external predictor variables^{66,67}. This technique has been adopted in palaeoecology to detect zones in pollen diagrams or shifts between periods of homogeneous assemblages in time⁶⁷. We used the pollen taxa in percentages without any data transformations as the response variable and the median ages derived from the age-depth model as the constraining variable. The recursive partitioning is based on chi-square distances⁶⁸ between pollen samples constrained by time. The number of cross-validations was set to 1000, and the optimal sized tree was chosen based on the 1SD rule⁶⁷.

Significant change points for richness, diversity, and evenness variables were integrated into one variable (DDC), while significant change points for compositional turnover, compositional change, and rate-of-change were combined into a second variable (DCC). The density of these two variables was computed using a Gaussian kernel and rescaled to specific age ranges for each individual pollen record, including minimum and maximum ages. To address boundary concerns in density estimation, the data were reflected to 0, and interpolated values were extracted at every 500-year time step.

Equal temporal spacing of samples

We ensured equal temporal spacing of samples across all response variables, as this is crucial for temporal analyses in hypothesis 1 and hypothesis 2. This entailed analysing samples distributed across time and space in intervals of 500 years. To achieve equal spacing, we compared three methods of

interpolation: generalised additive model (GAM), hierarchical generalised additive model (HGAM), and simple linear interpolation. After repeated testing, we decided to use linear interpolation as the preferred method, as it maintained the correlation structure between multivariate response variables closest to the original estimates, compared to GAM or HGAM. The latter models occasionally exhibited unexpected patterns in single pollen diversity estimates, which affected these correlations. Given the impracticality of individually assessing each model for every variable across all records (numbering over 1000), we opted for linear interpolation as the simplest approach.

After all data-processing steps, a total of 1262 records were available for analyses. For an overview of data coverage, see [Extended Data Fig. 1](#).

Spatial units for analysis

The analyses focus on three levels of spatial units: 1) individual records, 2) sub-regions within continents using the divisions of the Köppen-Geiger climate zones³⁴, and 3) continental regions.

We used five major climate zones, namely Polar, Cold, Temperate, Arid, and Tropical for visualisation, but since the Cold and Temperate zones are so widespread across the Northern Hemisphere, we sub-divided these into Cold without Dry Season & Very Cold Summer, Cold without Dry Season & Cold Summer, Cold Dry Winter, Cold Dry Summer, Cold without Dry Season & Warm Summer, Cold without Dry Season & Hot Summer, Temperate without Dry Season, Temperate Dry Winter, and Temperate Dry Summer. This resulted in 12 climate zones that we used in the analyses.

Numerical analysis of hypothesis 1

To calculate the importance of human events and climate for changes in past properties, we used hierarchical variation partitioning (HVARPART) developed by Lai et al.³⁵. This approach calculates the importance of each predictor by partitioning the unique and shared variation for all possible combinations of predictor orders in a full model. The predictor importance is then the sum of the average unique and shared variation³⁵. To obtain an estimate of predictor importance, we used redundancy analysis (RDA) with standardised response variables as the pollen-assemblage properties are of mixed units. Past humans represent one predictor, whereas climate is represented as a group of predictors by the selected variables of summer precipitation, winter precipitation, annual temperature, and winter temperature. We used the adjusted r^2 total predictor importance and the average unique partitions as they correct for the number of samples and predictors in the model. To compare the predictor importance of humans and climate, we estimated the individual importance ratios for each record as follows:

Predictor importance ratio = predictor importance / (predictor importance human + predictor importance climate)

The analysis was run in two ways:

1. to analyse the *spatial changes*, HVARPART was run within a single sequence. To summarise the results on broader scales within the continents, we used the Köppen-Geiger climate zones to categorise subregions and calculated the weighted mean ratios of the total predictor importance from each record using the sum of the predictor importance of humans and palaeoclimate as weights.
2. to analyse the *temporal patterns* for each continent, HVARPART was run for samples within each 500-year time slice.

We restructured the data in the temporal analysis so that each analysis was conducted for samples across each continent at individual time slices. The predictor groups in each time slice consist of the SPD or group of human-detection events (**Extended Data Table 2**) together with the matrix of palaeoclimatic variables. It was necessary to filter out time slices with fewer than 5 samples. Additionally, for some slices, the analysis failed when the SPD indicated zero presence. In these instances, there were an insufficient number of predictors, leading to missing results for those specific time slices. HVARPART analyses were run using the *rdacca.hp* R package³⁵. Two site-based examples to analyse spatial changes are provided in **Extended Data Fig. 3**.

Numerical analysis of hypothesis 2

To test if the interrelationships between the pollen-assemblage properties have changed over time (H2), we performed a principal component analysis (PCA) with standardisation of the properties within each 500-year time slice where samples are grouped at the subregional levels of climate zones within each continent. We performed a Procrustes sum-of-squares analysis to compare the changes in the properties between time slices³⁷. We used symmetric scaling (m^2) creating distance matrices representing changes in the interrelationship between properties, where 0 indicates the relationship remained constant, and 1 indicates the relationship between one or several properties has changed considerably. Each climate zone is represented by the m^2 -distances between time slices for the period 8.5–2 ka BP. This was used as a response matrix in the HVARPART analysis.

Bayesian modelling was employed to establish overarching trends in past human presence (SPD) and palaeoclimate³⁸. It is important to note that the predictions generated by these models encapsulate the prevailing trends in past human presence and palaeoclimate as relevant to the distribution of our compiled records and these patterns may not directly represent the broader historical human presence and palaeoclimate conditions in various climate zones; see **Extended Data Figs. 4–8**. Subsequently, these variables were employed as predictors in the second HVARPART analysis, aimed at quantifying the importance of past human or palaeoclimate to the variability in the interrelationships between properties within climate zones. The general trends were also modelled for the human-impact events in different climate zones across the continental regions (**Extended Data Fig. 9**).

METHOD REFERENCES

1. Flantua, S. G. A., et al. A guide to the processing and standardisation of global palaeoecological data for large-scale syntheses using fossil pollen. *Global Ecol. Biogeogr.* **32**, 1377–1394 (2023). <https://doi.org/10.1111/geb.13693>
2. Flantua, S. G. A., et al. *FOSSILPOL project* web page (2023): <https://hope-uib-bio.github.io/FOSSILPOL-website/index.html>
3. Flantua, S. G. A., et al. *R-package to provide tools for FOSSILPOL workflow*. RFossilpol package version 0.0.3 (2023): <https://github.com/HOPE-UIB-BIO/R-Fossilpol-package>
4. Birks, H.J.B., et al. Approaches to pollen taxonomic harmonisation in Quaternary palynology. *Rev. Palaeobot. Palynol.* **319**, 104989 (2023). <https://doi.org/10.1016/j.revpalbo.2023.104989>
5. Haslett, J., & Parnell, A. C. A simple monotone process with application to radiocarbon-dated depth chronologies. *J. Royal Stat. Soc.: Series C* **57**, 4, 399–418 (2008). <https://doi.org/10.1111/j.1467-9876.2008.00623.x>
6. Parnell, A. C., Haslett, J., Buck, C. E., Allen, J. R. M., Buck, C. E., et al. A flexible approach to assessing synchronicity of past events using Bayesian reconstructions of sedimentation history. *Quat. Sci. Rev.* **27**, 1872–1885 (2008). <https://doi.org/10.1016/j.quascirev.2008.07.009>
7. Flantua, S. G. A., & Hooghiemstra, H. Anthropogenic pollen indicators: Global food plants and Latin American human indicators in the pollen record. *Nature Sci Data* **10**, 721 (2023). <https://doi.org/10.1038/s41597-023-02613-1>
8. Crema, E. R., & Bevan, A. Inference from large sets of radiocarbon dates: software and methods. *Radiocarbon* **63**, 1, 23–39 (2021). <https://dx.doi.org/10.1017/RDC.2020.95>
9. Reimer, P. J., Williams, A. E. N., Bard, E., Bayliss, A., Blackwell, P.G., et al. The IntCal20 Northern Hemisphere Radiocarbon Age Calibration Curve (0–55 cal kBP). *Radiocarbon* **62**, 725–757 (2020). <https://doi.org/10.1017/RDC.2020.41>
10. Hogg, A. G., Heaton, T. J., Hua, Q., Palmer, J. G., Turney, C. S., et al. SHCal20 Southern Hemisphere Calibration, 0–55,000 Years cal BP. *Radiocarbon* **62**, 759–778 (2020). <https://doi.org/10.1017/RDC.2020.59>
11. Hua, Q., Barbetti, M., & Rakowski, A. Atmospheric radiocarbon for the period 1950–2010. *Radiocarbon* **55**, 4, 2059–2072 (2013). https://doi.org/10.2458/azu_js_rc.v55i2.16177
12. Mottl, O. *REcopol: Analyse fossil pollen records*. R package version 0.0.3 (2024). <https://hope-uib-bio.github.io/R-Ecopol-package/>
13. Therneau T. M., Atkinson, B., Ripley, B., De'ath G. mpart: Multivariate partitioning_. R package version 1.6-2 (2014). <https://CRAN.R-project.org/package=mpart>.
14. Oksanen J, Simpson G, Blanchet F, Kindt R, Legendre P, et al. vegan: Community Ecology Package. R package version 2.6-4 (2022). <https://CRAN.R-project.org/package=vegan>.
15. Mottl, O., et al. Rate-of-change analysis in palaeoecology revisited: a new approach. *Rev. Palaeobot. Palynol.* **293**, 104483 (2021). <https://doi.org/10.1016/j.revpalbo.2021.104483>
16. Mottl, O., et al. R-Ratepol package: R-package for estimating rate of change (2021). <https://github.com/HOPE-UIB-BIO/R-Ratepol-package>
17. Chao, A., et al. Rarefaction and extrapolation with Hill numbers: a framework for sampling and estimation in species diversity studies. *Ecol. Monogr.* **84**, 1, 45–67 (2014).

<https://doi.org/10.1890/13-0133.1>

18. Hsieh, T. C., Ma, K. H., & Chao, A. Inext: an r package for rarefaction and extrapolation of species diversity (Hill numbers). *Meth. Ecol. Evol.* **7**, 12, 1451–1456 (2016). <https://doi.org/10.1111/2041-210x.12613>
19. ter Braak, C. J. F., & Šmilauer, P. *CANOCO Reference manual and CanoDraw for Windows User's Guide: Software for Canonical Community Ordination (version 4.5)*. Microcomputer Power. www.canoco.com. <https://edepot.wur.nl/405659>
20. Hill, M. O. Diversity and evenness: a unifying notation and its consequences. *Ecology* **54**, 427–432 (1973). <https://doi.org/10.2307/1934352>
21. Odgaard, B. V. Palaeoecological perspectives on pattern and process in plant diversity and distribution adjustments: a comment on recent developments. *Divers. Distrib.* **7**, 4, 197–201 (2001). <https://doi.org/10.1111/j.1472-4642.2001.00110.x>
22. Odgaard, B. V. Fossil pollen as a record of past biodiversity. *J. Biogeogr.* **26**, 7–17 (1999). <https://doi.org/10.1046/j.1365-2699.1999.00280.x>
23. Birks, H. J. B. Estimating the amount of compositional change in late-Quaternary pollen-stratigraphical data. *Veget. Hist. Archaeobot.* **16**, 197–202 (2007). <https://doi.org/10.1007/s00334-006-0079-1>
24. De'ath, G. Multivariate regression trees: A new technique for modelling species-environment relationships. *Ecology* **83**, 1105–1117 (2002).
25. Simpson, G. L., & Birks, H. J. B. Statistical learning in palaeolimnology. In Birks H. J. B. et al. (eds.). *Tracking Environmental Change Using Lake Sediments, vol. 5: Data Handling and Numerical Techniques (Developments in Paleoenvironmental Research)*. Springer (2012). https://doi.org/10.1007/978-94-007-2745-8_9
26. Prentice, I. C. Multidimensional scaling as a research tool in Quaternary palynology - a review of theory and methods. *Rev. Palaeobot. Palynol.* **31**, 71–104 (1980).

Figures

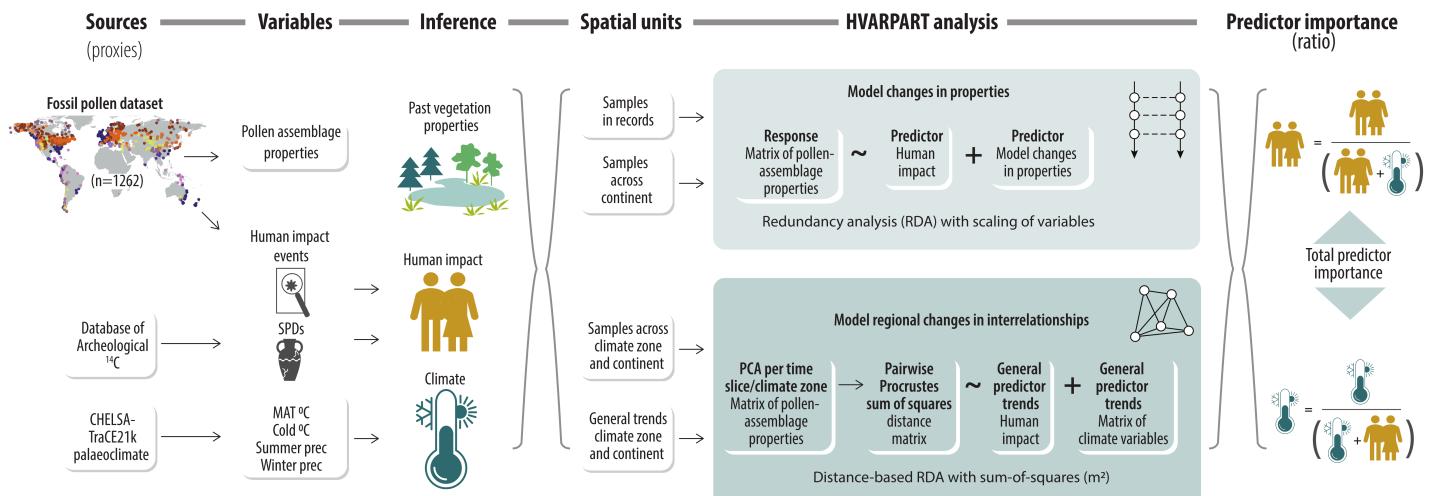


Figure 1

Conceptual workflow figure for data preparation and quantification of the importance of past humans and climate on past vegetation properties at different spatial and temporal scales. From left to right are shown the main sources of proxy data (Sources (proxies)), what variables are derived from the data (Variables), what they can infer (Inference), data aggregation (Spatial units), the models of the hierarchical variation partitioning analyses and attribution (HVARPART analysis), and the quantification of the ratios of predictor importance between past humans and climate (Predictor importance (ratios)). See **Methods** for more detailed explanations. Data summaries of fossil pollen records, radiocarbon dates, and human-impact events are shown in **Extended Data Figures 1-2**. Two site-based examples of quantification of predictor importance between past human presence and climate combined are shown in **Extended Data Figure 3**. The general predictor trends of past human presence in different climate zones for each continental region are shown in **Extended Data Figure 4**, and the palaeoclimate represented by mean annual temperature (MAT°C), minimum temperature of the coldest month (Cold °C), precipitation of warmest quarter (summer prec), and precipitation of coldest quarter (winter prec) for different climate zones are shown in **Extended Data Figures 5-8**. The general trends for human-impact events in different climate zones are shown in **Extended Data Figure 9**.

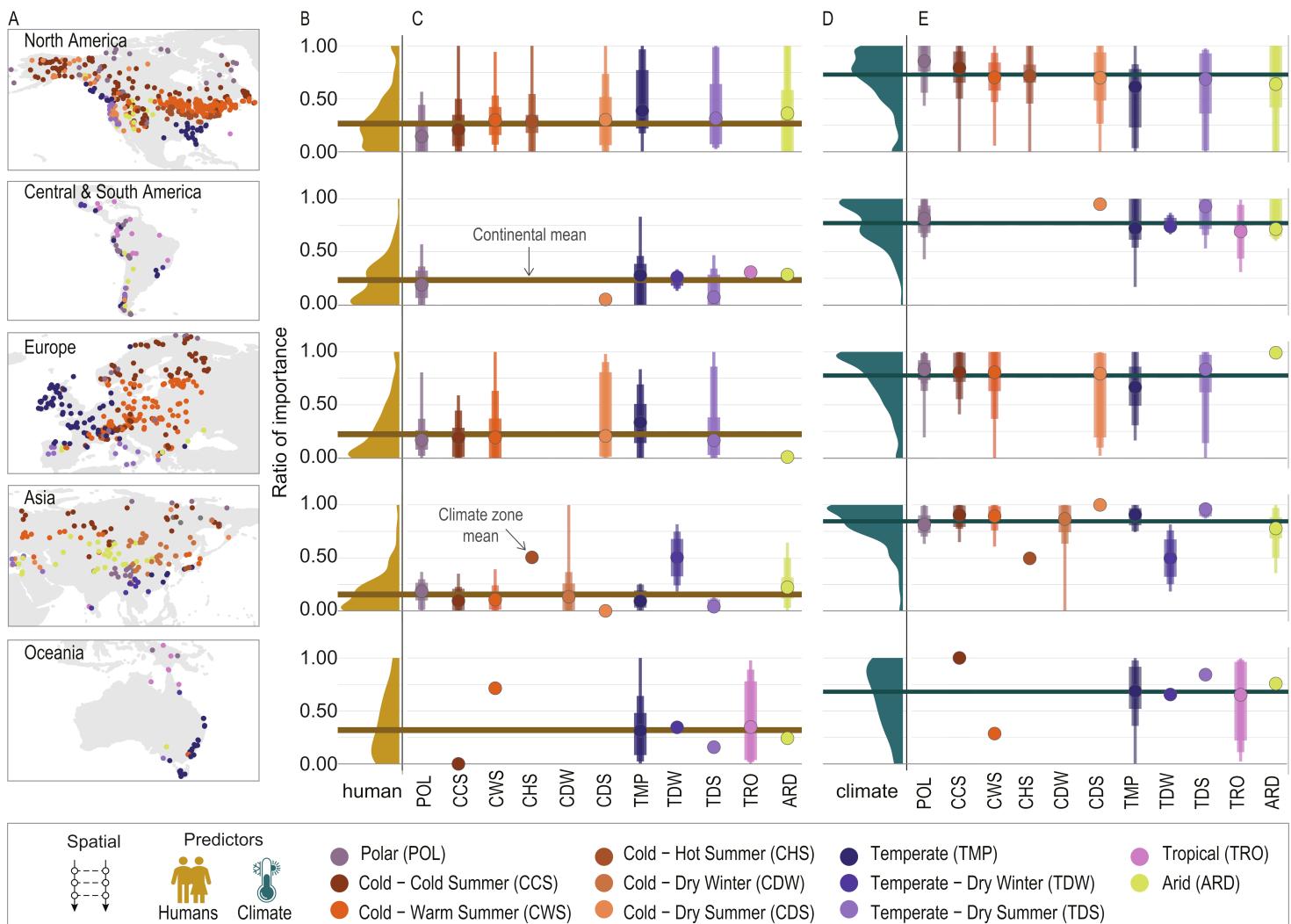


Figure 2

Ratios of predictor importance of past human presence and palaeoclimate on variability in pollen-assemblage properties (as a proxy of past vegetation) across climate zones and continents. Each row represents a continent: North America, Central and South America, Europe, Asia, and Oceania. The colours represent Köppen-Geiger climate zones³⁶. Panel A) shows the spatial distribution of individual records represented by coloured dots on the regional maps (Number of records listed in **Table 1**; **Extended Data Figure 1**). Note that we are only showing the parts of the map with records. Panel B) shows the regional density curves of the distribution of human importance ratios within a continent (colour gold). Panel C) shows the weighted mean ratios of importance (y-axis) of past humans summarised at the level of continents (horizontal gold line) and climate zones (circles). Panel D) shows the regional density curves of the distribution of palaeoclimatic importance ratios within a continent (colour teal). Panel E) shows the weighted mean ratios of importance (y-axis) of palaeoclimate (colour teal) at the level of continents (horizontal teal line) and climate zones (circles). For each climate zone, the different shading and width of the lines are the percentile ranges (50th, 75th, and 95th) of individual ratios per records. Only climate zones with > 2 records are used in this visualisation.

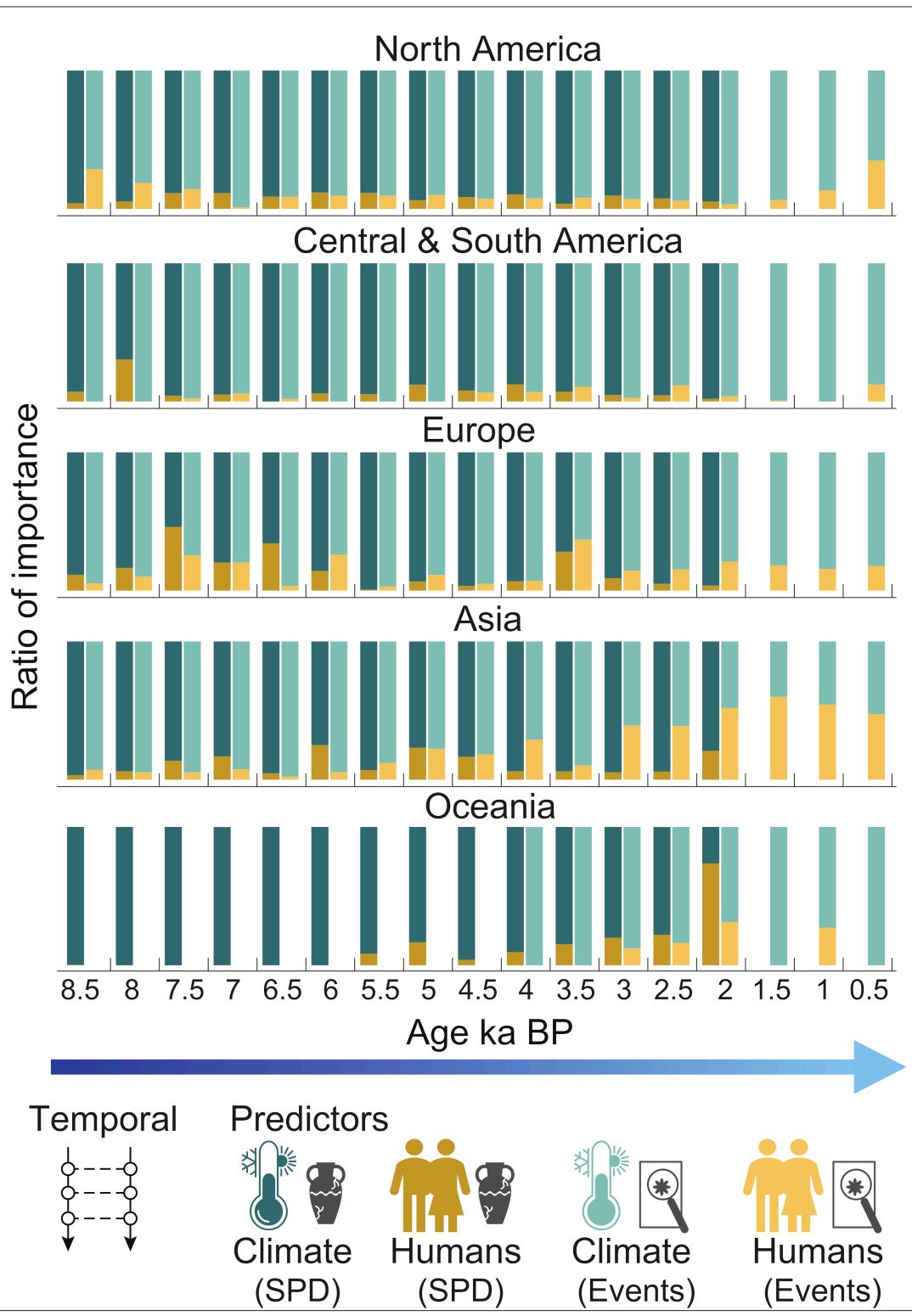


Figure 3

Ratios of predictor importance of past human presence (SPD and Events) to palaeoclimate within time slices for each continent. The bar charts show the ratios of importance of past human presence (Humans (SPD)) as a predictor to palaeoclimate (dark-shaded bars), and human-impact events (Humans (Events)) as a predictor to palaeoclimate (light-shaded bars) for the hierarchical variation partitioning

(HVARPART). The human-impact events cover additional time slices from 2.0–0.5 ka where SPD are lacking. The ratio of importance (y-axis) varies from 0 to 1.

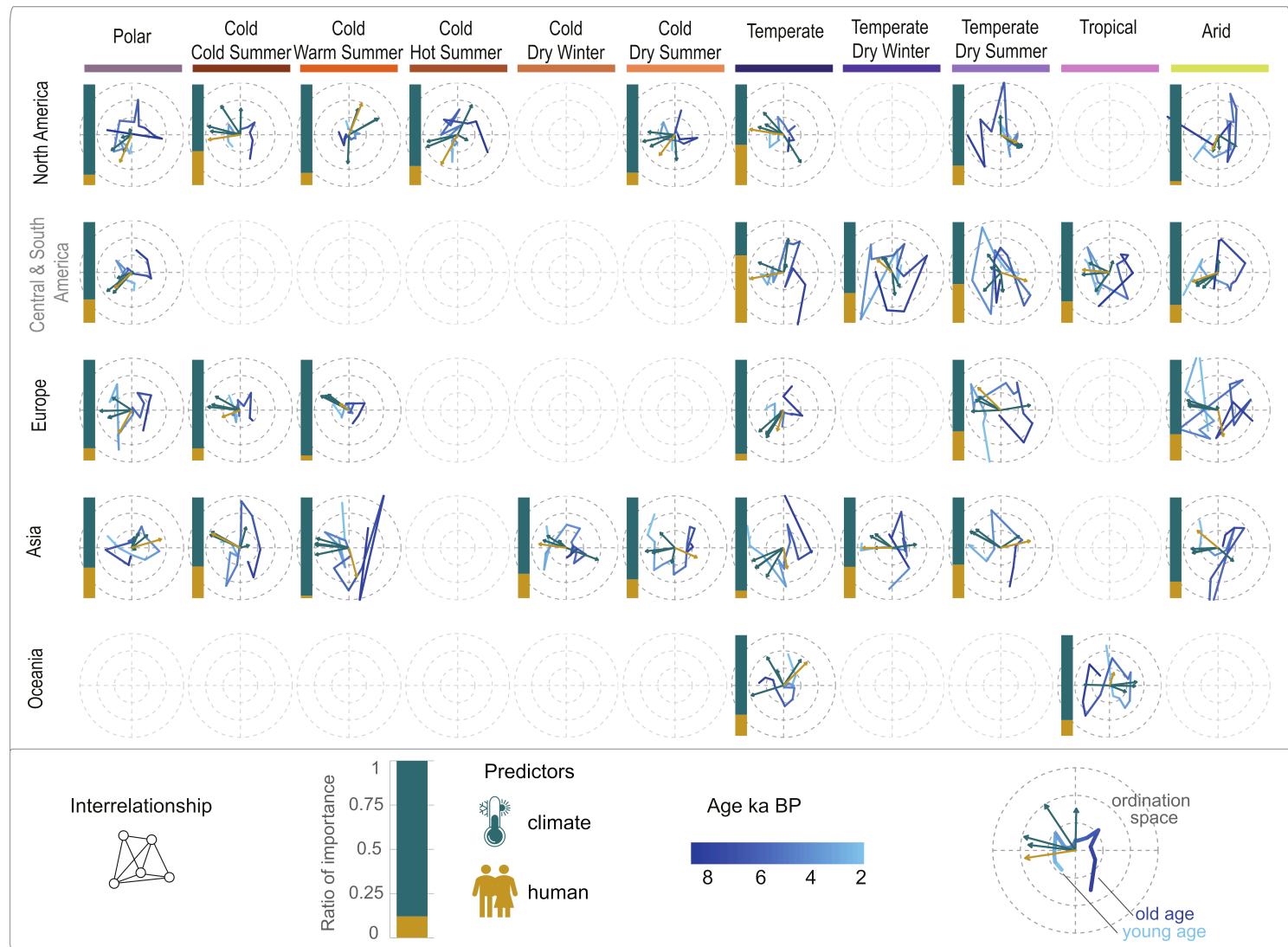


Figure 4

Ratios of importance of past human presence in relation to palaeoclimate on the variability in internal relationships between the pollen-assemblage properties (as a proxy of past vegetation). Each row represents a continental region as follows: North America, Central and South America, Europe, Asia, and Oceania. All panels left: Bar charts with the ratios of predictor importance of past human presence (gold) in relation to climate (teal) for changes in internal relationships for the period 8.5–2 ka BP (y-axis on a scale 0–1). All panels right: The sample scores of the dbRDA are plotted as time trajectories, ordination space (grey circles) scaled to similar units to allow overall comparison in variability between climate zones and continental regions. The time trajectories (blue lines) show the direction of changes, where it starts at time slice 8.5 ka (dark blue) and progresses towards 2 ka (light blue). The arrows show the predictors: past human presence (gold), and palaeoclimatic variables (teal).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [PastHumanImpactsubmissionSM.pdf](#)