Supplement of Geochronology, 6, 503–519, 2024
https://doi.org/10.5194/gchron-6-503-2024-supplement

Supplement of

Towards the construction of regional marine radiocarbon calibration curves: an unsupervised machine learning approach

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SUPPLEMENTARY MATERIAL

Table S1 summarises the most important software packages used in our analysis. The scripts and complete python environment specifications are hosted at: https://gitlab.com/earth15/ocean_data_clusters.

Table S1: Principal python packages used.

Package name	**Version**	**Usage**	**Reference**
python	3.9.14	Main scripting language	("The Python Language Reference — Python 3.9.14 Documentation")
numpy	1.22.4	Data manipulation	Harris et al. (2020)
matplotlib	3.5.3	Data visualisation	Hunter (2007)
nctoolkit	0.8.4	NetCDF file manipulation, spatiotemporal statistics	https://nctoolkit.readthedocs.io/en/latest/info.html
sktime	0.14.0	Time series K-Medoids	Löning et al. (2019)
tslearn	0.5.2	Time series K-Means, time series normalisation	Tavenard et al. (2020)
kneed	0.8.2	Locating the elbow point in a plot	https://kneed.readthedocs.io/en/stable/index.html
scipy	1.9.3	Hierarchical clustering	Virtanen et al. (2020)
xesmf	0.6.3	Regridding (nearest_s2d algorithm)	Zhuang et al. (2022)

Figure S1. *Clustering results using K-medoids on un-normalised data from the CM2Mc interglacial run. As for Figure 4 of the main text, but for K increased to K=9.*

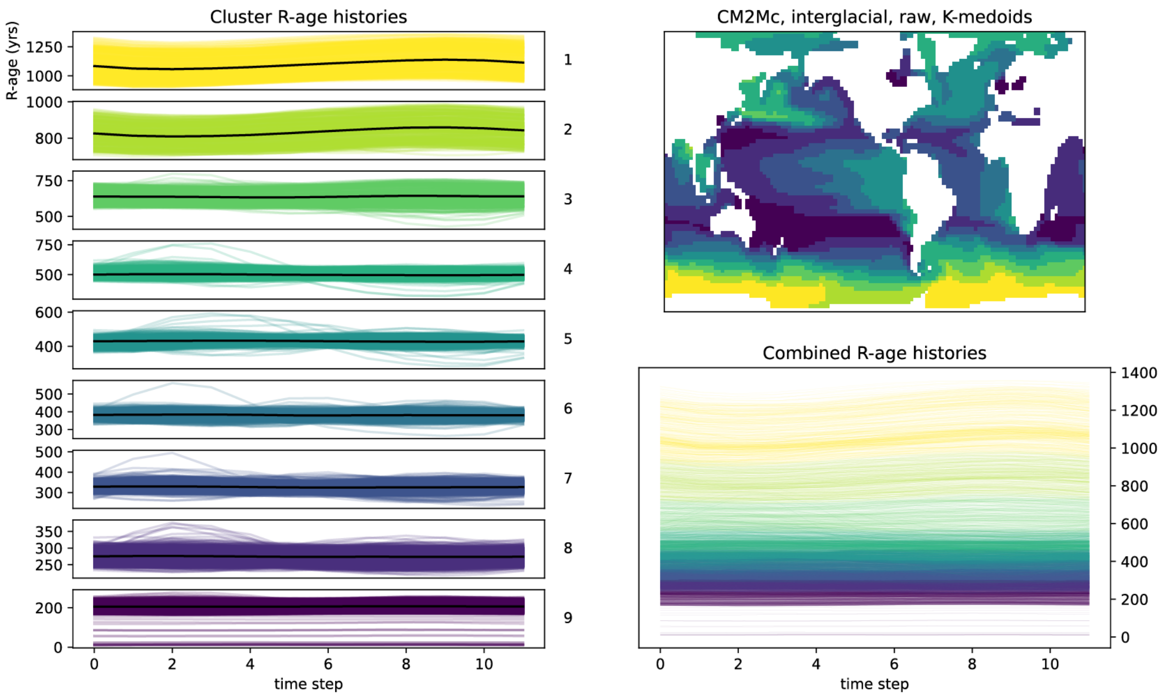


Figure S2. *Clustering results using K-Medoids on UVic (U-Tr run) normalised data. As for Figure 8 of the main text, but for K increased to K=8.*

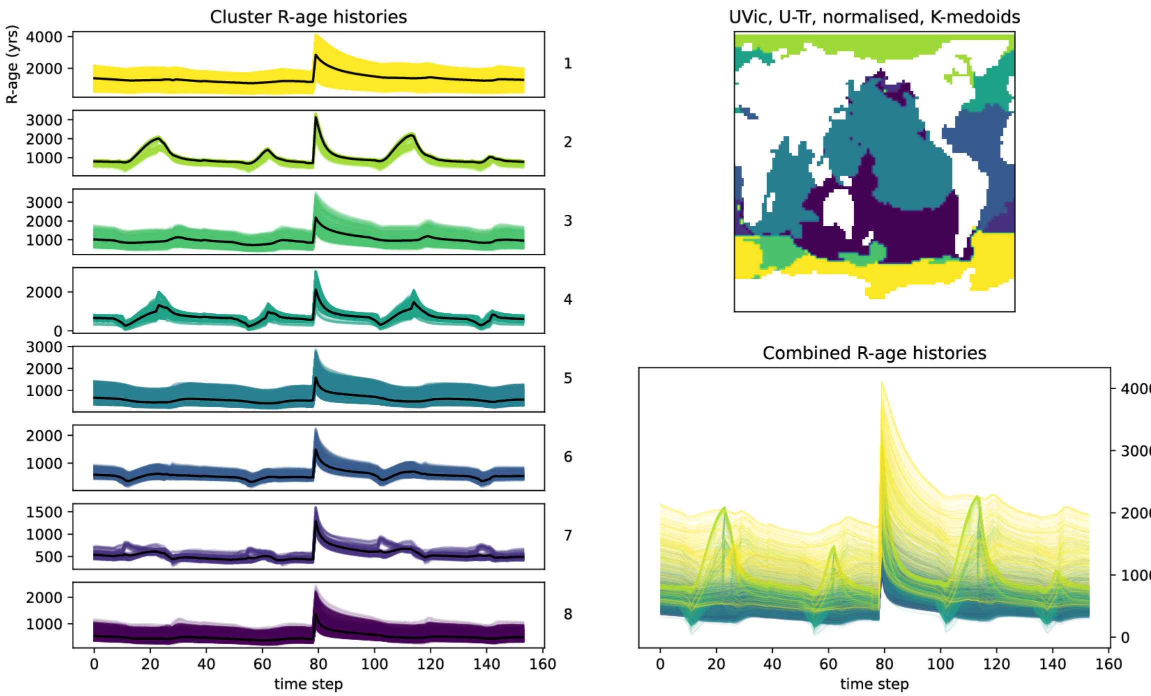


Figure S3. *Comparison of clustering results between the two UVic runs (left: U-Tr; right: U-TrS), using K-medoids on normalised data. The colour-coded Venn diagrams quantify overlap between the two maps. Note the strong agreement between the two resulting cluster geographies*

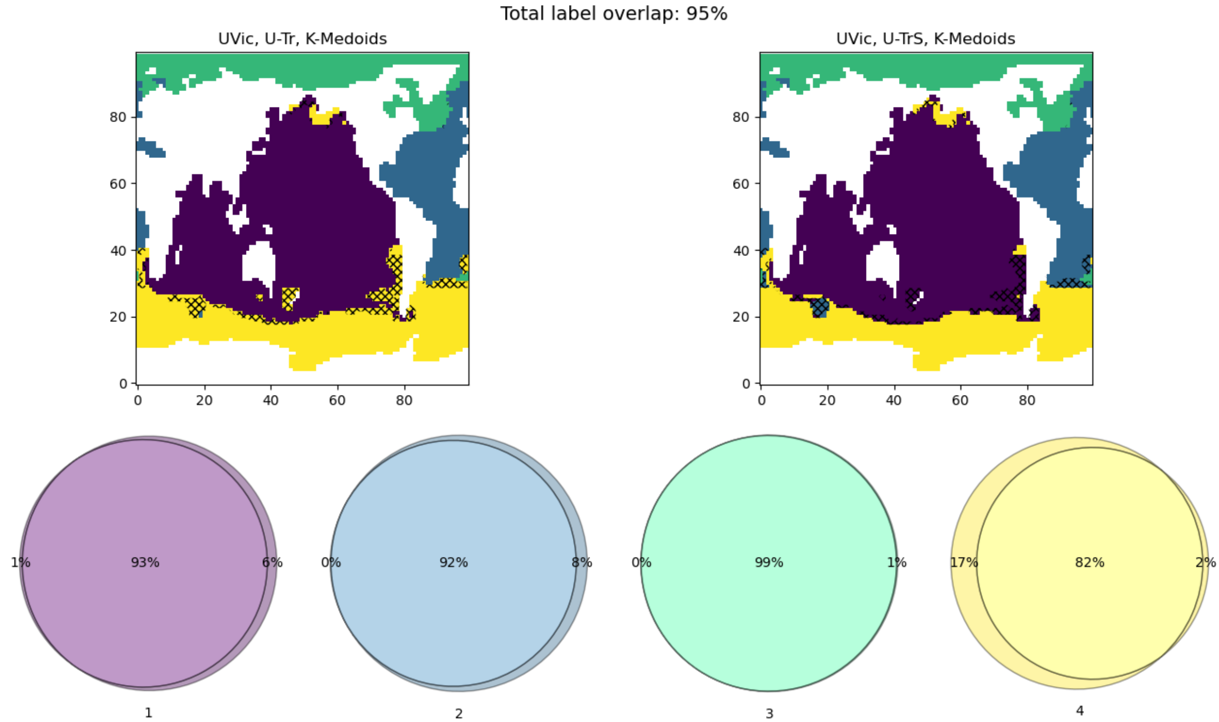


Figure S4. *The variance (a.) and mean (b.) of the distribution of R-age offsets in CM2Mc glacial data, when computed relative to three different references: the running mean of the global surface ocean, analogous to e.g. Marine20 (column 1); the medoid of the shape-based cluster to which the subcluster belongs (column 2); and the subcluster's own medoid (column 3). Crucially, and in contrast to Figure 13 of the main text, the geographic definitions of the clusters and their medoids are derived from a different model run (UVic U-Tr). UVic cluster labels were re-gridded to match the resolution of the CM2Mc data.*

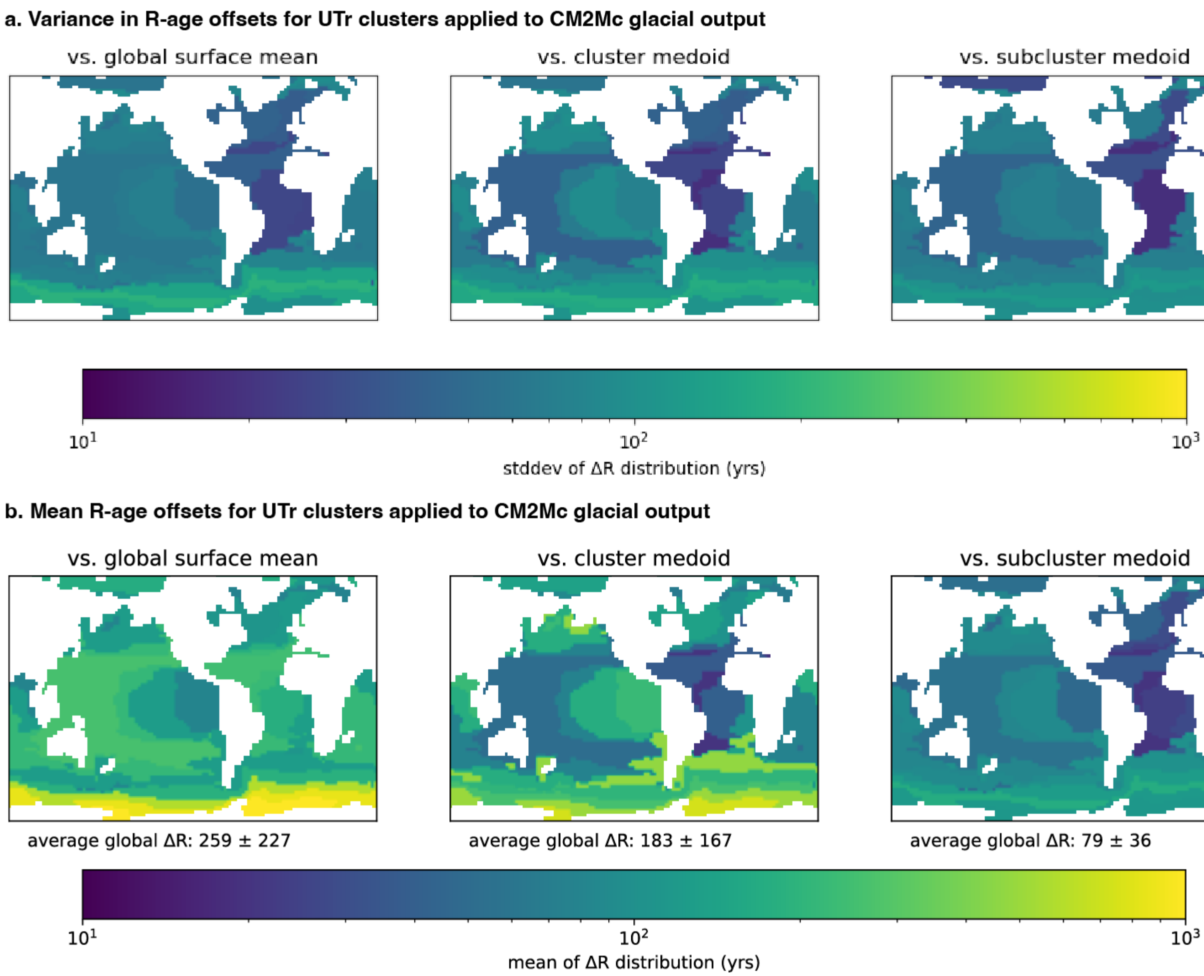
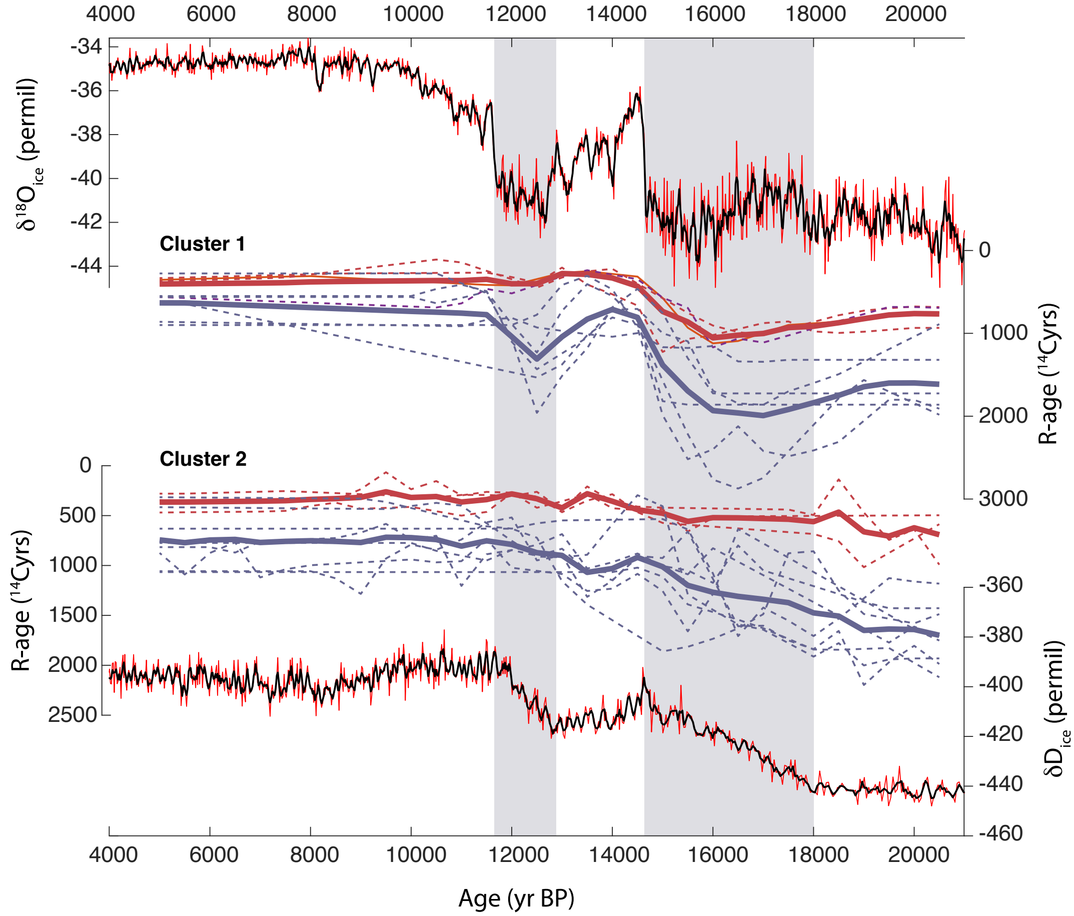


Figure S5. *Tentative hierarchical clustering of R-age reconstructions spanning the last deglaciation (Skinner et al., 2023). Plot a: Greenland ice-core temperature proxy, NGRIP $\delta^{18}O_{ice}$ (heavy black line is 3-point running mean). Plot b: amplitude-based sub-clusters (K = 2, red and blue lines) belonging to shape-based Cluster 1; heavy lines indicate the sub-cluster averages and dashed lines indicate the clustered time-series data. Plot c, as for plot b, but for sub-clusters within the shape-based Cluster 2. Plot d: Antarctic ice-core temperature proxy, EDC δD_{ice} (heavy black line is 3-point running mean). Vertical bars indicate approximate timing of North Atlantic stadials corresponding to the Younger Dryas and Heinrich Stadial 1.*



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