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Causal feedbacks in climate change

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The statistical association between temperature and greenhouse gases over glacial cycles is well documented[1], but causality behind this correlation remains difficult to extract directly from the data. A time lag of CO_2 behind Antarctic temperature—originally thought to hint at a driving role for temperature[2,3]—is absent[4,5] at the last deglaciation, but recently confirmed at the last ice age inception[6] and the end of the earlier termination II (ref. 7). We show that such variable time lags are typical for complex nonlinear systems such as the climate, prohibiting straightforward use of correlation lags to infer causation. However, an insight from dynamical systems theory[8] now allows us to circumvent the classical challenges of unravelling causation from multivariate time series. We build on this insight to demonstrate directly from ice-core data that, over glacial–interglacial timescales, climate dynamics are largely driven by internal Earth system mechanisms, including a marked positive feedback effect from temperature variability on greenhouse-gas concentrations.

Earth system models[9] have been an effective, albeit indirect, way to quantify causality in the climate system. The effects of CO_2 and other greenhouse gases (GHGs) on Earth's temperature are relatively well understood, but estimates of the effect of temperature variability on GHG dynamics remain uncertain[10–12]. Quantifying the actual strength of this effect is challenging, because it involves a plethora of mechanisms that are difficult to measure and sometimes oppose each other. For instance, increased photosynthesis at higher CO_2 levels implies a negative feedback, whereas enhanced plant and soil respiration at higher temperatures leads to carbon release and a positive feedback[13]. A warmer climate may induce the release of CO_2, CH_4 and N_2O from terrestrial ecosystems, especially in polar regions[14]. Furthermore, at higher temperatures, marine $CaCO_3$ neutralization of anthropogenic CO_2 decreases[15], and methane is released from hydrate storages below the sea floor, which may amplify global warming[16]. Overall, higher global temperatures are believed to cause a net increase in atmospheric concentrations of GHGs, implying a positive feedback in warming[10,11,17–19]. However, given the complexity of the mechanisms and models, uncertainty over the feedback effect remains large.

This issue raises the question if there are more direct, model-independent estimates of the feedback effect based on the strikingly parallel dynamics of temperature and GHGs over the Pleistocene ice ages (Fig. 1a). Data-based approaches for unravelling the causation operating behind this correlation have hitherto largely focused on phase lags between past climate data sets[3], but these lags vary over time. A slight lead of Antarctic temperature over CO_2 variations has been argued to point to temperature as a driver of CO_2 changes[2]. However, more recent studies cast doubt on the existence of a significant time lag of CO_2 behind either Antarctic[4] or global[5] temperature at the last glacial termination, with variations in methane and temperature seeming nearly synchronous at the Bølling transition[20]. Meanwhile, the latest data on an earlier termination[7] and inception[6] show periods of significant time lags between CO_2 and Antarctic temperature. A simple moving-window scan of optimal time displacement for correlation (Supplementary Fig. 1c) supports the emerging view that the time lag of CO_2 behind temperature as recorded in the Vostok ice core[1] has varied widely over the past 400 kyr. Although errors in dating may contribute to such variation, detailed recent studies[6,7,21] confirm that these lags do vary substantially over time.

What is not common knowledge, however, is that variable time displacements are in fact expected of nonlinear dynamical systems, following from so-called mirage correlations—correlations between variables that come and go or even change sign[8]. Correlation is indeed a poor tool for analysing nonlinear dynamical systems. This issue can be illustrated by an analysis of some well-known models (Supplementary Fig. 1a,b). Similar to the Vostok data, in these models one variable lags behind the other during some periods but this lag can disappear or even lead during other episodes. This raises the possibility that the lingering controversy over variable lags may be partly a product of using an inappropriate lens (simple cross-correlation) to infer causation.

There is a powerful new methodological approach, however, that can help distinguish causality from spurious correlation in multivariate time series from deterministic dynamical systems[8]. The technique—convergent cross-mapping (CCM)—is based on a theorem proved by Takens[22,23], stating that the essential information of a multidimensional dynamical system is retained in the times series of any single variable of that system. CCM is based on the idea that Takens' theorem can be used to detect if two time-series variables belong to the same dynamical system. Effectively, if variable X is influencing a paired observed variable Y, then based on the generalized Takens' theorem[23], we can expect that variable X can be reliably predicted from the time-series history of variable Y. Thus CCM measures the extent to which the recent historical record of the affected variable Y (or its proxies) reliably estimates states of a causal variable X (or its proxies). This estimation skill is quantified by calculating the correlation coefficient ρ between predicted and observed values of X. A key property that distinguishes direct or indirect causation from simple correlation is convergence. This means that cross-mapped estimates improve in estimation skill with the length L of the time series that is used to predict X from Y. The level to which predictive power converges ('CCM skill'[8] hereafter) can be viewed as an estimator of the strength of the causal link. The essential mechanics of CCM are detailed in ref. 8 and summarized in three one-minute animations (Supplementary Appendix of ref. 8 or http://simplex.ucsd.edu/Movie_Sall.mov).

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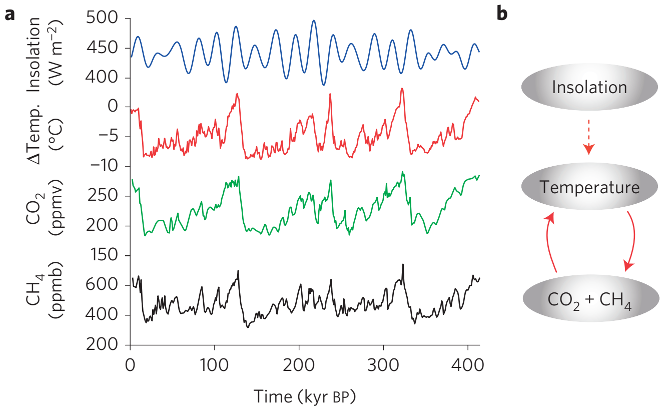

Figure 1 | Causation inferred from time series of insolation, temperature and GHGs. a, Fluctuations in orbitally driven insolation (65° N) and in temperature and GHGs inferred from the Vostok ice core[1]. **b**, Schematic of causality inferred from the patterns in this study. Temperature and GHGs exhibit strong feedbacks, whereas orbital forcing has a relatively small role in influencing temperature.

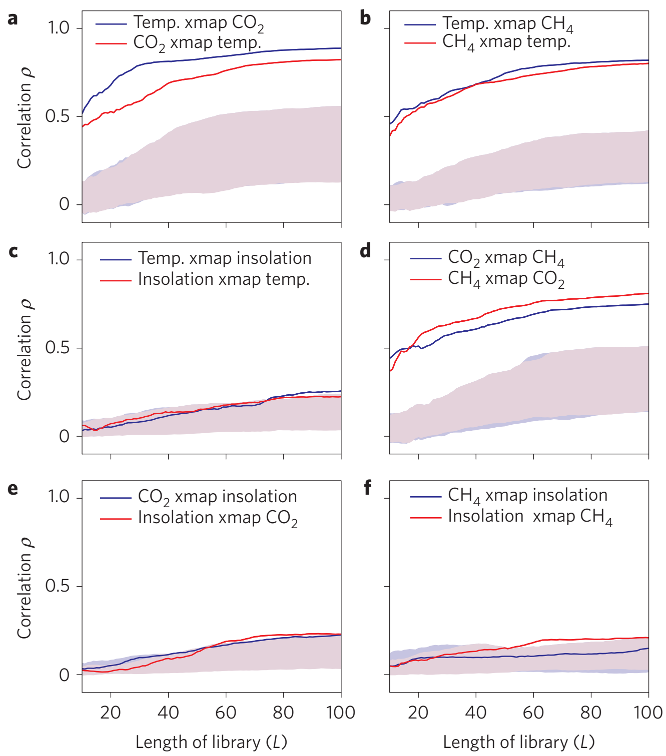

Figure 2 | Correlation of cross-mapped versus observed values as a function of the length of the time series. Shaded areas are the 5th to 95th percentiles of CCM skill for 100 surrogate time series[30] from the null model (swap model; the shaded areas are the 5th to 95th percentiles of CCM skill for 100 generated time series[30] from a null model see Methods) (red area = null model for the red line; blue area = null model for the blue line; overlap = purple). Convergence is significant for all pairs of variables except the ones involving insolation.

Here we use CCM to analyse time series of atmospheric temperature and CO_2 and CH_4 concentrations reconstructed from the Vostok ice core[1], covering about 400 kyr (Figs 1a and 2), and the EPICA ice core[24,25], which together with Vostok spans about 800 kyr (Supplementary Fig. 2). Our results show that there is no significant causal association between orbital variables (for example, insolation) and either temperature or GHGs (Fig. 2c,e,f and Supplementary Fig. 7). By contrast, the significant CCM signature apparent between the two GHGs and temperature (Fig. 2a,b,d) confirms that these are in fact interacting parts of the climate system. These results represent direct empirical evidence (from data rather than models) that internal Earth system mechanisms governed much of the dynamics of the climate system during the Pleistocene and lend credence to the view that pacemaker effects from orbital variations are relatively small (10% for high frequencies and up to 50% for low frequencies) compared with the stronger intrinsic mechanism of the climate system[3,26].

Because the CCM analysis shows strong coupling within the Earth climate system (correlation coefficients of 0.75–0.87) the possibility of dynamic synchrony must be addressed to infer the direction of causation[8]. Synchrony implies that CCM will converge in both directions even though causation is unidirectional. This occurs when one variable Y is a 'slave' of the other, (that is, Y responds closely to the forcing of X, but Y has no effect on X (see Supplementary Methods)). However this potential difficulty can be addressed when system response times are slow enough such that causes can be clearly seen to precede effects. Simply put, causation with synchrony can be established when dynamic causes are shown to unambiguously precede dynamic effects. This occurs when optimal CCM skill occurs with a time lag that reflects the timescale (delay) of system response (illustrated in a simple model in Supplementary Methods), and is especially apparent when the response times in either causal direction are asymmetrical (X to Y, or Y to X). Note that identifying the lags for optimal CCM skill, especially those that are not symmetric, is entirely different in theory and approach from identifying the lag for optimum cross correlation between time series (which is necessarily symmetric).

For each pair of variables, we determined the time displacement that results in the highest CCM skill (Supplementary Fig. 9). In a bi-directionally coupled system with instantaneous response there should be no significant differences in the optimal displacements in either direction. For instance, with simple red noise, the optimum lag for CCM corresponds to half the length of the vectors used for prediction both ways (Supplementary Fig. 12). By contrast, the climate system variables all show clear asymmetries in lags for maximum CCM skill.

The peak for CCM estimates of temperature based on the GHG time series (that is, the effect of temperature on GHGs) has an optimal lag that is 2–6 kyr behind that for estimates of GHGs based on temperature time series (Fig. 3 and Supplementary Fig. 9 and Supplementary Table 3). CCM consistently indicates a negative optimal lag for all of the 100-point samples (the level at which CCM converged). Resampling the data using bootstraps (see Supplementary Information) reveals that this difference is highly significant ($p < 0.002$, the smallest p-value obtainable in the bootstrap samples) and that a systematic misalignment error of gas-age up to ~1,500 yr can be tolerated without changing the significance ($p < 0.05$) (Supplementary Fig. 13). Additional analysis of a null model with only a unidirectional effect of GHGs on temperature (synchronous forcing, see Supplementary Methods), reveals that the observed asymmetry in lags for optimal CCM in the Vostok data is unlikely under this scenario (for CO_2 $p < 0.002$ and for CH_4 $p < 0.03$), and confirms that we can rule out unidirectional forcing by GHGs on temperature (a greenhouse effect without feedback of temperature on GHG levels). Thus, the response of GHGs to temperature change seems to be significantly slower than the rapid (essentially instantaneous) response of temperature to changes in GHGs. This analysis is sufficient to demonstrate that temperature influences GHGs, and is consistent with the idea that GHGs drive temperature on a faster timescale.

Less surprising is our finding of CCM convergence when estimating GHGs from the temperature time series (that is, the

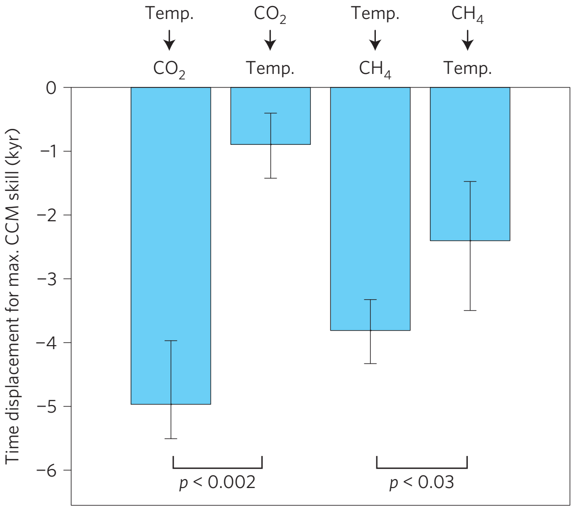

Figure 3 | Time displacements maximizing CCM skill corresponding to causal relationships indicated above the bars. The responses of CO_2 and CH_4 to temperature have significantly larger lags (the indicated p-values are from a bootstrapped paired-samples test) than the corresponding greenhouse effects of gases on temperature. The error bars show the 5th and 95th percentiles of 500 bootstrapped library sets. The lags together with the convergence of CCM (Fig. 2) imply that a marked positive feedback effect of temperature on GHGs has operated over the glacial cycles.

effect of GHGs on temperature; Supplementary Figs 10 and 11). This result corroborates (albeit directly) the already well-established greenhouse effect itself (GHG->temperature) (although we note that the lag CCM result is not by itself sufficient to show this (Supplementary Information)).

More interestingly, we also find negative displacements for CCM associated with a 'proxy' link from the salt (Na) content of the ice record to GHGs (Supplementary Fig. 9). Sea salt in the ice cores is probably a proxy for sea-ice extent, as the salt mainly originates from wind erosion of the sea-ice surface[27]. Thus CCM results for Na are consistent with the view that the Pleistocene climate fluctuations were driven largely by the effects of expanding and shrinking ice caps, both on land and sea, modulating the accumulation and release of a large store of carbon in the deep ocean.

In conclusion, our analysis provides direct confirmation that internal Earth system mechanisms rather than orbital forcing have controlled climate dynamics over the Pleistocene cycles. Moreover, they demonstrate the existence and importance of a feedback effect of temperature variability on GHGs in driving the dynamics (Fig. 1b). This confirms the existence of a positive feedback operating in climate change whereby warming itself may amplify a rise in GHG concentrations. As CCM infers causality directly from the time series, the consistency of our results with elaborate mechanistic analysis represents remarkable empirical confirmation and, moreover, provides a clock for the response times involved. We suggest that this new and powerful approach may also help to assess causality behind the numerous other time series we have for the Earth system.

Methods

We used the Vostok ice core[1] on local temperature, CO_2, CH_4, sodium, dust (http://www.ncdc.noaa.gov/paleo/icecore/antarctica/vostok/vostok_data.html) and July insolation[28] at 65° N (http://www1.ncdc.noaa.gov/pub/data/paleo/climate_forcing/orbital_variations/berger_insolation). All time series were linearly interpolated to produce equidistant estimates spaced by 1 kyr. The CCM algorithm follows ref. 8, which is based on nonlinear state space reconstruction. This method reconstructs the manifold of the dynamical system based on one variable X only. E time-lagged values of X (time lags $0, \tau, 2\tau, \ldots (E-1)\tau$) are used as coordinate axes to reconstruct this 'shadow attractor manifold'. The algorithm then finds points on this shadow manifold that are close together and tests whether paired observations of another variable Y are also close together. This is done by predicting each value of Y on the basis of the closest points in X using simplex projection (see details in ref. 8). After this each predicted value of Y is compared with the observed Y (using Pearson's correlation ρ). This procedure is repeated using a subset of the time series of X with different lengths L. It is expected that the prediction improves with the length of the time series L until it converges to a maximum level. To measure the convergence we fitted an exponential function ($\rho = \rho_{max} - \rho_0 e^{-c(L-L_0)}$) to the relationship between predicted and observed values based on the different subsets of X. L = length of the used subset, L_0 = first length used = 10, ρ_{max} the maximum correlation coefficient, ρ_0 the correlation at $L = 10$ and c a convergence speed. The cross-mapping variables are labelled following the convention of ref. 8, where 'Y xmap X' quantifies the causal effect of X on Y by predicting X_t from E lagged time-series fragments of Y_t. We used $E = 4$, $\tau = 2$ kyr by default as this combination gave a good unfolding of the attractor (visual inspection of Supplementary Fig. 14) and above $E = 4$ there was no clear improvement of the predictability of temperature and the GHGs (Supplementary Fig. 15) using simplex projection[29]. We also tested other values of embedding dimension E and embedding lag τ, which gave very similar results (Supplementary Fig. 3).

Robustness was tested by varying CCM parameters (Supplementary Fig. 3), exploring other ways of interpolation (Supplementary Fig. 4 and Supplementary Tables 1 and 2), and repeating the analysis on the oldest part of the EPICA ice-core data[24,25] and a high-resolution part of the ice cores of the past 22 kyr (ref. 21; Supplementary Fig. 2). In addition we examined the significance of the results using two conservative null models. For the default null model we generated 100 surrogate data sets which were randomly shifted in phase by choosing a random break point and swapping the order of both segments. This procedure destroys the dynamic interdependency between time series, but preserves nearly all short-term behaviour. We also used a second null model, generating 100 time series for each variable having the same frequency spectrum as observed, but with the frequencies randomly shifted in phase[30] (see Supplementary Fig. 5). With each of these 4×100 time series all original variables were predicted using cross-mapping. An interaction is considered to be significant only if the CCM skill of the real time series is outside the range of the 5th and 95th percentiles computed from the randomly generated time series (that is, in Fig. 2 lines above the shaded areas indicate significant CCM).

For synchronous (that is, strongly correlated) variables, one-way causation is hard to distinguish from bi-directional causation. Therefore we also analysed the effect of time displacements on CCM skill. This was done by displacing the time series up to 10 kyr backwards and forwards before measuring the CCM skill using 500 bootstrapped library sets of length 100. The optimum CCM time lag was determined by finding the optimum in a Gaussian filtered relation (bandwidth = 5) of the CCM skill as function of the time lag. We did the same in a null model (see Supplementary Information).

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References

1. 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).
2. Fischer, H., Wahlen, M., Smith, J., Mastroianni, D. & Deck, B. Ice core records of atmospheric CO_2 around the last three glacial terminations. *Science* **283,** 1712–1714 (1999).
3. Shackleton, N. J. The 100,000-year ice-age cycle identified and found to lag temperature, carbon dioxide, and orbital eccentricity. *Science* **289,** 1897–1902 (2000).
4. Pedro, J. B., Rasmussen, S. O. & Van Ommen, T. D. Tightened constraints on the time-lag between Antarctic temperature and CO_2 during the last deglaciation. *Clim. Past* **8,** 1213–1221 (2012).
5. Shakun, J. D. *et al.* Global warming preceded by increasing carbon dioxide concentrations during the last deglaciation. *Nature* **484,** 49–54 (2012).
6. Landais, A. *et al.* Two-phase change in CO_2, Antarctic temperature and global climate during Termination II. *Nature Geosci.* **6,** 1062–1065 (2013).
7. Schneider, R., Schmitt, J., Köhler, P., Joos, F. & Fischer, H. A reconstruction of atmospheric carbon dioxide and its stable carbon isotopic composition from the penultimate glacial maximum to the last glacial inception. *Clim. Past* **9,** 2507–2523 (2013).
8. Sugihara, G. *et al.* Detecting causality in complex ecosystems. *Science* **338,** 496–500 (2012).
9. Le Treut, H. *et al.* in *Climate Change 2007: The Physical Science Basis* (eds Solomon, S. *et al.*) 93–127 (IPCC, Cambridge Univ. Press, 2007).
10. Friedlingstein, P. *et al.* Climate–carbon cycle feedback analysis, results from the C4MIP model intercomparison. *J. Clim.* **19,** 3337–3353 (2006).

11. Cox, P. M., Betts, R. A., Jones, C. D., Spall, S. A. & Totterdell, I. J. Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model. *Nature* **408,** 184–187 (2000).
12. Friedlingstein, P., Dufresne, J. L., Cox, P. M. & Rayner, P. How positive is the feedback between climate change and the carbon cycle? *Tellus B* **55,** 692–700 (2003).
13. Cramer, W. *et al.* Global response of terrestrial ecosystem structure and function to CO_2 and climate change: Results from six dynamic global vegetation models. *Glob. Change Biol.* **7,** 357–373 (2001).
14. Schuur, E. A. G. *et al.* The effect of permafrost thaw on old carbon release and net carbon exchange from tundra. *Nature* **459,** 556–559 (2009).
15. Archer, D. *et al.* The importance of ocean temperature to global biogeochemistry. *Earth Planet. Sci. Lett.* **222,** 333–348 (2004).
16. Archer, D., Buffett, B. & Brovkin, V. Ocean methane hydrates as a slow tipping point in the global carbon cycle. *Proc. Natl Acad. Sci. USA* **106,** 20596–20601 (2009).
17. Friedlingstein, P. *et al.* Positive feedback between future climate change and the carbon cycle. *Geophys. Res. Lett.* **28,** 1543–1546 (2001).
18. Prentice, I. C. *et al.* in *Climate Change 2001: The Scientific Basis* (eds Houghton, J. T. *et al.*) 183–238 (IPCC, Cambridge Univ. Press, 2001).
19. Hansen, J. *et al.* Climate change and trace gases. *Phil. Trans. R. Soc. A* **365,** 1925–1954 (2007).
20. Rosen, J. L. *et al.* An ice core record of near-synchronous global climate changes at the Bølling transition. *Nature Geosci.* **7,** 459–463 (2014).
21. Parrenin, F. *et al.* Synchronous change of atmospheric CO_2 and Antarctic temperature during the last deglacial warming. *Science* **339,** 1060–1063 (2013).
22. Takens, F. in *Symposium on Dynamical Systems and Turbulence* (eds Young, L. S. & Rand, D. A.) 366–381 (Lecture Notes in Mathematics, Springer, 1981).
23. Deyle, E. R. & Sugihara, G. Generalized theorems for nonlinear state space reconstruction. *PLoS ONE* **6,** e18295 (2011).
24. Loulergue, L. *et al.* Orbital and millennial-scale features of atmospheric CH_4 over the past 800,000 years. *Nature* **453,** 383–386 (2008).
25. Lüthi, D. *et al.* High-resolution carbon dioxide concentration record 650,000–800,000 years before present. *Nature* **453,** 379–382 (2008).
26. Hays, J. D., Imbrie, J. & Shackleton, N. J. Variations in the earth's orbit: Pacemaker of the ice ages. *Science* **194,** 1121–1132 (1976).
27. Wolff, E. W. *et al.* Changes in environment over the last 800,000 years from chemical analysis of the EPICA Dome C ice core. *Quat. Sci. Rev.* **29,** 285–295 (2010).
28. Berger, A. & Loutre, M. F. Insolation values for the climate of the last 10 million years. *Quat. Sci. Rev.* **10,** 297–317 (1991).
29. Sugihara, G. & May, R. M. Nonlinear forecasting as a way of distinguishing chaos from measurement error in time series. *Nature* **344,** 734–741 (1990).
30. Ebisuzaki, W. A method to estimate the statistical significance of a correlation when the data are serially correlated. *J. Clim.* **10,** 2147–2153 (1997).

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Author contributions

M.S. and E.H.v.N. conceived the research. All authors contributed to the design of the research. E.H.v.N. and H.Y. analysed the data. All authors contributed to writing the manuscript.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to E.H.v.N. or G.S.

Competing financial interests

The authors declare no competing financial interests.