



Variable causality in Cenozoic climate-carbon cycle interactions

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Abstract (162 words)

Numerous reconstructions of global climate and the carbon cycle have underpinned conceptual models of the governing feedbacks driving their interaction. However, causal relationships between such reconstructions and their quantification are required to understand the driving mechanisms of past global climate change. Here, utilizing continuous high-resolution deep ocean foraminifer stable carbon and oxygen isotope ratios for the past 66 million years, we inspect the causal relations in the climate-carbon cycle system using machine learning approaches. We find that these records are strongly causally related in some periods, particularly during warm climate states, but causation is insignificant in other periods. Intriguingly, the causal dynamics appear to be influenced by long-term modulation cycles of eccentricity and obliquity, suggesting an orbital influence on the mechanistic coupling between climate and carbon cycling. Moreover, our results are consistent with strengthening positive feedbacks between the global carbon cycle and the climate leading towards both abrupt warming and cooling events hypothesized to be due to the passing of tipping points.

1. Introduction

Sedimentary proxy data of the Earth's climate-carbon cycle system unveil that during the Cenozoic era (past 66 million years), the Earth's system went through a long-term drop in temperature and atmospheric $p\text{CO}_2$ interspersed with a plethora of trends, rhythms, and aberrations (Hönisch et al., 2023a; Zachos et al., 2001). Cenozoic climate and carbon cycling trends are well-known, partly owing to the high-resolution reconstructions based on, respectively, the oxygen and stable carbon isotope ratios of deep ocean benthic foraminifer carbonate shells. These reconstructions suggest that on geological timescales, climate, and carbon cycle processes were intertwined, and their interaction was governed by (quasi) periodic solar insolation changes, greenhouse gas levels, and ice volume (Westerhold et al., 2020). The synergy between climate and carbon cycle processes on long timescales has been often established by estimating the mutual correlation of these two, or



similar time series (Franke and Donner, 2019; Hu et al., 2017). Typically, the inherent aim when applying such techniques to paleo-proxy records is temporal and/or spatial calibration or correlation between multiple proxies and locations. However, the causal interaction amidst the systems represented by the proxies stems from conceptual earth system models.

Recent advances in data-driven modeling, machine learning, and nonlinear time series analyses have facilitated the analysis of real-world observational time series, which complement mathematical modeling and experimental studies. Methods such as transfer entropy (Paluš et al., 2018; Schreiber, 2000), Granger causality (Granger, 1969), convergent cross mapping (Van Nes et al., 2015; Sugihara et al., 2012; Ye et al., 2015), and reservoir computing causality (Huang et al., 2020a) have been developed to discern the causal relationship among various components of complex systems. One major advantage of such methods, along with calculating the mutual correlation between two variables, is that they are directional, which enables identification of the leading variable. These methods therefore grant the opportunity to assess causation between climate variability and the carbon cycle as reflected in proxy records to underpin the processes governing and modulating variability in earth system models.

The variability in stable carbon isotope ratios ($\delta^{13}\text{C}$) of deep ocean benthic foraminifera ($\delta^{13}\text{C}_{\text{BF}}$) reflects that of the $\delta^{13}\text{C}$ of deep ocean dissolved inorganic carbon ($\delta^{13}\text{C}_{\text{DIC}}$), the dominant reservoir of the global exogenic carbon pool. The exchange of carbon with distinct $\delta^{13}\text{C}$ between different carbon reservoirs and the deep ocean occurs at different timescales. On timescales of up to 10^4 years, the $\delta^{13}\text{C}_{\text{BF}}$ signal reflects the partitioning of carbon between the atmosphere, biosphere, and the ocean (Sarmiento, 2013). For example, a decrease in (terrestrial) biomass during glacial periods causes $\delta^{13}\text{C}_{\text{DIC}}$ to drop, since the strongly ^{13}C -depleted carbon from this biomass is mixed with the ocean-atmosphere system. On longer timescales ($> 10^5$ years), global exogenic $\delta^{13}\text{C}$ is impacted by interaction with the rock reservoir, notably the ratio of ^{13}C -depleted organic carbon versus inorganic carbon burial. Variability in the oxygen isotope ratio $\delta^{18}\text{O}$ of deep ocean benthic foraminifera ($\delta^{18}\text{O}_{\text{BF}}$) reflects variations in deep-sea temperatures, which determines fractionation during calcification, and the mass of the ^{18}O -depleted cryosphere, which determines the $\delta^{18}\text{O}$ of the residual seawater. Under ice-free conditions, $\delta^{18}\text{O}_{\text{BF}}$ is a direct indicator of deep ocean temperature, in turn, often considered a proxy for global average surface temperature (Goudsmit-Harzevoort et al., 2023). The temperature (in)directly affects a myriad of carbon cycle processes such as CO_2 solubility, primary productivity, chemical weathering, and marine organic matter preservation, while the carbon cycle determines the effective quantity of greenhouse gases (carbon dioxide and methane) in the atmosphere that impacts global temperature. Therefore, strong causality is expected between $\delta^{13}\text{C}$ and $\delta^{18}\text{O}$ throughout the Cenozoic, as described in conceptual mechanistic models (Berner, 1991; Walker et al., 1981). However, proof of causality is typically lacking.

Here, we explore the intricate causal interplay of climate-carbon cycle dynamics using the CENOGRID, which is the highest-resolution and most complete record of Cenozoic global temperature/ice volume, and the global carbon cycle, based on $\delta^{18}\text{O}_{\text{BF}}$ and $\delta^{13}\text{C}_{\text{BF}}$, respectively



(Westerhold et al., 2020). The resolution of the records is 1- 4 kyr depending on the time interval, which makes it ideal to apply causality analyses to probe bidirectional causal interactions between climate-carbon cycle dynamics on time scales of 10^5 years and longer. We focus on two techniques involving attractor reconstruction with the assumption that the climate-carbon cycle is a coupled dynamical system. Reservoir Computing Causality (RCC) is a type of Echo State Network (ESN) framework that is particularly suitable for data-driven modeling as the reservoir can exhibit temporal behavior and mimic the dynamics (Jaeger, 2003; Lukoševičius and Jaeger, 2009; Yildiz et al., 2012). Convergent Cross Mapping (CCM) (Sugihara et al., 2012) is a state-space reconstruction-based technique that has been applied successfully to discern Eocene transient global warming events (hyperthermals) (Setty et al., 2023) and Pleistocene glacial-interglacial cycles (Van Nes et al., 2015; Weinans et al., 2021). We applied both techniques in a moving window, namely, Dynamic Reservoir Computing Causality (DRCC) and Dynamic Convergent Cross Mapping (DCCM) (Setty et al., 2023) to the CENOGRID dataset, to assess the dynamics of causal association amidst the global carbon cycle and the climate through time. Additionally, we apply a moving window convergence test and study the effect of time displacement, namely, Extended-RCC analysis (ERCC), to lend additional confidence to the causal association derived with both methods. Finally, we used spectral and wavelet analysis to investigate any cyclic patterns in causality in climate-carbon cycle dynamics.

2. Material and Methods

2.1 High-resolution benthic foraminifer stable isotope record

CENOGRID is a composite record using sediment archives from 14 ocean drilling records preferentially including the genera *Cibicidoides* and *Nuttallides* to minimize systematic interspecies isotopic offsets (Westerhold et al., 2020). The records were calibrated to La2010b orbital solution (Laskar et al., 2011). The chronology has an accuracy of ± 100 thousand years (kyr) in the Palaeocene and Eocene, ± 50 thousand years (kyr) between the Oligocene to middle Miocene, and ± 10 thousand years (kyr) from late Miocene to Pleistocene. Furthermore, the temporal resolution for the reconstructed time series in the Palaeocene and Eocene was 5 kyr, and Oligocene to Pleistocene was 2 kyr. This high-resolution reconstruction of the global climate and carbon cycle makes the record ideal to investigate the climate-carbon cycle dynamics. The original dataset was used to generate a resampled dataset with the resolution fixed at 2.5 kyr for the whole Cenozoic, from 67 Ma ago till present. This resampled dataset is the dataset used for analysis in the main paper.

2.2 Causality Analysis

Causality analyses based on attractor/state space reconstruction are powerful methods to study the association and feedback mechanisms amongst systems, such as climate-carbon cycle systems that are dynamically related. Although there are numerous techniques to quantify association, two



techniques based on attractor reconstruction, namely, RCC and convergent cross mapping (CCM) were chosen for this study as we assume that the climate and carbon cycle are part of the dynamical Earth system impacted by the latitudinal and intra-annual distribution of solar radiation at the Earth's surface. This assumption was made based on numerous paleoclimatology studies indicating the imprint of insolation on both climate and the carbon cycle in the geological timescales (Lourens, 2021; Lourens et al., 2005; Mudelsee et al., 2014; Westerhold et al., 2020; Zachos et al., 2001).

2.3 Reservoir Computing Causality (RCC) framework

Reservoir computing causality (RCC) is a recently developed data-driven causality technique which uses an echo state recurrent neural network to reconstruct the state space (Huang et al., 2020b, a). This method enables us to quantify the causal association between two variables. Suppose we have two variables C and O from an arbitrary system, with $C(t)$ and $O(t)$ as the observed time series, respectively. The time series $C(t)$ and $O(t)$ were first divided into a training set (70%) and a testing set (30%). Using the training set from $C(t)$, the corresponding training set of $O(t)$ was reconstructed using the RC prediction model. The Reservoir computing (RC) prediction model has 3 layers – the input to-reservoir layer, the dynamic reservoir neuron layer, and the reservoir-to-output layer (Figure S1). To estimate the reconstructed time series $\hat{O}(t)$ from $C(t)$, the input-to-reservoir layer in RC prediction model nonlinearly transforms the input training set of $C(t)$ into a reservoir state $r(t)$ using a dynamic reservoir of N neurons. The second layer consists of a matrix M of $N \times N$ sparsely connected neurons that is constant throughout the procedure. Importantly, the dynamic reservoir displays Echo State Property (Cucchi et al., 2022; Lukoševičius and Jaeger, 2009) and this property is crucial for the reservoir to simulate the temporal dynamics of nonlinear systems and reconstruct the attractor or state space. The reservoir state $r(t)$ is transformed to estimate $\hat{O}(t)$ in the third reservoir-to-output layer using linear regression. Tikhonov regularization is used in the third layer to reduce over-fitting.

After the dynamic neural network is trained on the training set to predict the corresponding training set of $\hat{O}(t)$, the learned temporal dynamics is applied on the test set of $C(t)$ to estimate the remaining $\hat{O}(t)$. Finally, the estimated training and test set are concatenated to create a reconstructed. After the dynamic neural network is trained on the training set to predict the corresponding training set of $\hat{O}(t)$ time series. The RCC skill is the Pearson's correlation between the original $O(t)$ and reconstructed $\hat{O}(t)$, and it is referred to as $\delta^{13}C \rightarrow \delta^{18}O$, and vice-versa ($\delta^{18}O \rightarrow \delta^{13}C$) in the study.

2.4 Convergent cross mapping (CCM)

Taking the same two variables C and O from an arbitrary system, CCM estimates one variable from another using state-space reconstruction (SSR) and simplex projection (Sugihara et al., 2012). As CCM has no training phase, the time series are not divided into training and test set. For SSR, time lag- τ and embedding dimension are chosen to be 1 and 6, respectively (Figure S2). To estimate



$\hat{O}(t)$ from $C(t)$, the attractor MC was first reconstructed using $C(t)$ and the reconstructed $\hat{O}(t)$ was generated through nearest neighbors of each time point of the time series (simplex projection; leave-one-out cross validation). The CCM skill is the linear correlation (Pearson) between the original $O(t)$ and reconstructed $\hat{O}(t)$. Here, the brief description of the method is provided and we refer the reader to (Casdagli et al., 1991; Gibson et al., 1992; Kantz and Schreiber, 1997; Van Nes et al., 2015; Setty et al., 2023; Sugihara et al., 2012; Weinans et al., 2021; Ye et al., 2015) for more detailed descriptions of CCM, SSR and the application of the method on paleoclimate records.

2.5 Significance calculation of the causal skill

The statistical significance of the RCC skill and CCM skills were calculated by generating 100 null models having the same power spectrums the original dataset (Ebisuzaki, 1997) which keeps the autocorrelation structure of the dataset intact. This ensures that the causal association between the climate and carbon cycle was not calculated due to a common external forcing, such as insolation, affecting both the systems.

2.6 Dynamical causality analysis

We applied both RCC and CCM in a moving window approach to study the long-term dynamics of climate-carbon cycle interactions during the Cenozoic, and the moving window versions are referred to as DRCC and DCCM, respectively (Setty et al., 2023). The methods were applied on paired $\delta^{13}C$ and $\delta^{18}O$ record of the Cenozoic era with a resolution of 2.5 kyr and they include the abrupt and extreme events of the era. The RCC and CCM skill of $\delta^{13}C \rightarrow \delta^{18}O$ could be employed as an extent of causal effect of carbon cycle on the climate, and likewise for $\delta^{18}O \rightarrow \delta^{13}C$. The window size for both DRCC and DCCM was 400 data points (1 Ma) and the window was made to move by 1 data point, from older to younger age. For DRCC, the reservoir size N was 5% of the window and the training and test set ratio was 70:30. While for DCCM, the library size was 399 (maximum possible library size), time lag- τ was 1 and embedding dimension was 6. These parameters were the same for both $\delta^{13}C \rightarrow \delta^{18}O$ and $\delta^{18}O \rightarrow \delta^{13}C$. We used MATLAB ccm toolbox to perform the DCCM analysis (Van Nes et al., 2015; Setty et al., 2023), and RCC toolbox to perform DRCC, moving window convergence test and ERCC. The detailed sensitivity of DRCC analysis to data noise reduction (Figure S3), detrending (Figure S4 and S5), and different window size (Figure S6) are given in the Supplementary Information. For similar sensitivity analysis of DCCM, we refer to (Setty et al., 2023).

2.7 Moving window convergence test and ERCC analysis

We performed two additional tests, convergence testing and time-displacement analysis using RCC framework to differentiate inaccurate correlation from causation on the paired benthic $\delta^{13}C$ and $\delta^{18}O$ record of the Cenozoic era (Cobey and Baskerville, 2016). We apply a novel technique to



perform the convergence test using RCC framework taking inspiration from the convergence testing of CCM analysis (Sugihara et al., 2012). Furthermore, as shown in Figure 2, we apply this test in a moving window (400 data points; 1 Ma) throughout the $\delta^{13}C$ and $\delta^{18}O$ record of the Cenozoic era. For a training and test set ratio varying from 5:95 till 95:5 with increments of 5%, we test whether the RCC skill increases and converges to a stable skill with increasing training set percentage. As depicted by examples Figure S7A, in case of causation, the RCC skill improves and eventually settles to a certain skill, while in Figure S7B, in case of no causation, the RCC skill does not improve and there is no observed convergence with rising training set percentage.

The extended RCC (ERCC) analysis was conducted to probe high bidirectional causality stems from an external factor ('confounder') influencing the two systems under study and whether the "effect" precedes the "cause". The analysis was also employed in a moving window (400 data points; 1 Ma) for the entire $\delta^{13}C$ and $\delta^{18}O$ record. As depicted in Figure 3, the RCC skills were calculated between $C(t)$ and $\hat{O}(t + d)$, and $O(t)$ and $\hat{C}(t + d)$ for time displacement (d) ranging from -20 (past) to 20 (future). As illustrated by examples in Figure S7C, if the maximum RCC skill occurs for d less than 0, then we assume causal association, and as in Figure S7D, if the maximum RCC skill occurs for d greater than 0, then we assume there was so causal association between climate and the carbon cycle.

2.8 Spectral analysis

The results of the dynamic causality analyses (RCC and CCM skills) were further investigated using wavelet analysis to inspect the frequencies or cycles affecting the causal relationship of the climate-carbon cycle dynamics (Cazelles et al., 2008; Grinsted et al., 2004; Torrence and Compo, 1998). We focus on long-term modulations of Earth's orbit and tilt given by eccentricity and obliquity changes in the past 66 million years. We further applied Multi-Taper and Blackman-Tukey method on the detrended RCC and CCM skills to investigate long-term cycles potentially affecting the climate-carbon cycle system (Li et al., 2019; Paillard et al., 1996). For the wavelet analysis, we applied the MATLAB routine of (Torrence and Compo, 1998), including the determination of the 95% confidence level. The Gaussian filters are calculated in AnalySeries 1.1 (Paillard et al., 1996) using a central frequency of 0.000424 (#/kyr) and a band width of ± 0.000100 to extract the ≈ 2.360 Myr periodicity of the long-term eccentricity modulation, and a central frequency of 0.000844 (#/kyr) and a band width of ± 0.000100 to extract the ≈ 1.190 Myr periodicity of the long-term obliquity modulation, respectively. Although spectral and wavelet analysis of the CENOGRID and other records have revealed the influence of long-term modulation of eccentricity and obliquity on different epochs (Liebrand et al., 2017; Mudelsee et al., 2014; Turner, 2014; Westerhold et al., 2020), we still do not expect these cycles to show up in the causal skills, especially after removing the long-term cyclic trends.



3. Results

3.1 Quality and confidence

We depict the causal effect of climate ($\delta^{18}O$) on the carbon cycle ($\delta^{13}C$) as ' $\delta^{18}O \rightarrow \delta^{13}C$ ' and the carbon cycle on climate as ' $\delta^{13}C \rightarrow \delta^{18}O$ ', respectively (Figure 1). The strength of the causal association is quantified by the RCC and CCM skills, which range between -1 and 1. While negative values are mathematically possible, causal skills below 0 are not plausible in the Earth System and therefore should be interpreted as no causality. Causal skill values that overlap with the range found within the null model (horizontal shaded regions in Figure 1), are also interpreted as implying no causality. We interpret skills to reflect low, moderate, and high causality if they are significant and below 0.45, 0.45-0.7, and 0.7-1, respectively. Along with Figure 1, Figures 2, and 3, depict the moving window convergence test and moving window ERCC analysis using the RCC framework. Figure S7 includes examples illustrating when the two tests are considered as a pass or a fail. Throughout this study, we conclude that the climate 'causally' affected the carbon cycle at a particular moment and *vice-versa*, only if both the RCC and CCM skills are within the 95% confidence level, and both moving window convergence test and ERCC analysis suggest causal association (Table 1 and Figure 1, 2 and 3). Furthermore, the results are robust for detrending bandwidths (Figure S4 and S5) and different window sizes (Figure S6).

Although dynamic causality analysis and wavelet and spectral analysis enabled us to study climate-carbon cycle dynamics throughout the Cenozoic era, there were time intervals where the methods applied were inconclusive. In these time intervals, we surmise influence of low signal-to-noise ratio, strong unidirectional effect, and stronger effect of periodicity/autocorrelation in the proxy records. Our sensitivity analyses on varying window sizes and detrending bandwidths on the original dataset indicate that major observations in the causal skills are robust (Figures S4 and S6). Furthermore, the 95% confidence levels and the causal skills after detrending and reducing variability of the original dataset (Figures S5) display that the general causal dynamics were unaffected between 40 to 34 Ma. Here the skills were significant in the detrended records (Figure S5), while they were all insignificant in the records after smoothing (Figure S3). This possibly entails the choice of the null model generation technique, which could make it unsuitable under the presence of strong imprint of the slow Milankovitch cycles between 40 to 34 Ma (Ebisuzaki, 1997). Our causal analysis studying the effect of coupling strength and additive noise on a stochastic climate-carbon cycle model demonstrates that with increasing coupling, the RCC skills can differentiate the main driver. However, when the signal-to-noise ratio decreases, the causality analysis struggles to separate the signal from a strong noise and this reduces the causal skill (See Supplementary Text S1, Figures S8 and S9).



Figure 1: Dynamic Causality Analysis using a 1 Ma moving window A) Carbon cycle and climate proxies $\delta^{13}\text{C}$ (‰) (blue line) and $\delta^{18}\text{O}$ (‰) (purple line), respectively B) RCC Skills of $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ (blue line) and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ (purple line) with their respective 95% confidence level (shaded region); C) CCM Skills of $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ (blue line) and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ (purple line) with their respective 95% confidence level (shaded region); The blue, red, and light blue vertical bars represent carbon cycle disruption, climate warming, and ice sheet growth, respectively, while the horizontal shaded regions in B and C represent 95% confidence level generated from 100 surrogate null models with the same power spectra. Reading the dynamic causality analyses figures from left to right (older age to younger age), the vertical bars starting from left indicate Paleocene Carbon Isotope Maximum (PCIM), Paleocene Eocene Thermal Maximum (PETM), Early Eocene Climatic Optimum (EECO), Eocene Oligocene transition (EOT), Oligocene/Miocene transition (OMT), Miocene Climatic Optimum (MCO), and Mid-Pleistocene transition (MPT).

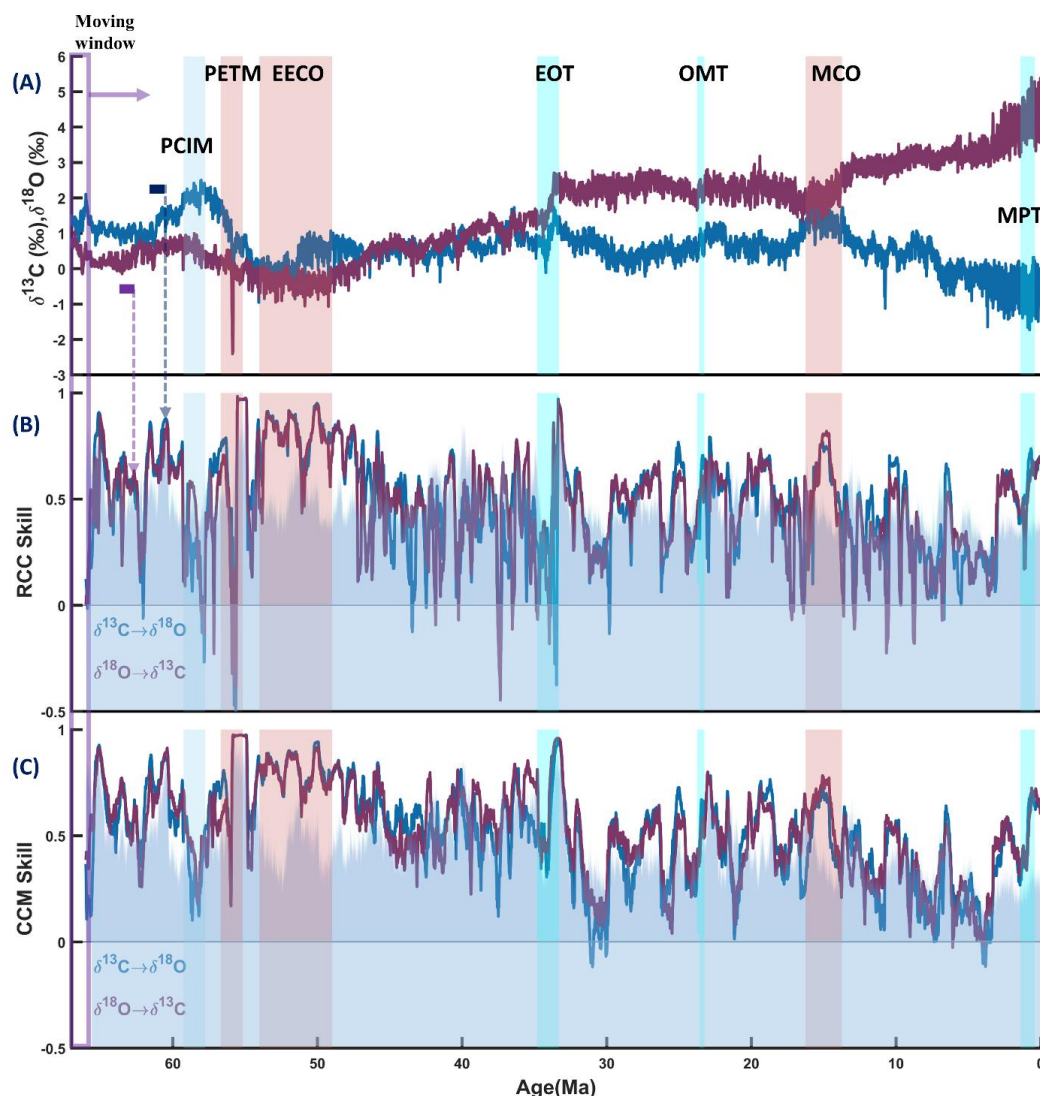




Figure 2: Moving window Convergence test (RCC) using a 1 Ma moving window (bottom to top)
A) Carbon cycle proxy $\delta^{13}\text{C}(\text{‰})$ (blue line); B) Moving window convergence test of $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$
with each point in the shaded region representing RCC Skill for training fraction increasing from
0.05 to 0.95; C) Climate proxy $\delta^{18}\text{O}(\text{‰})$ (purple line); D) Moving window convergence test of
 $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ with each point in the shaded region representing RCC Skill for train fraction
increasing from 0.05 to 0.95. In case of convergence, the color shifts from blue/green to dark red
for train fraction changing from 0.05 to 0.95.

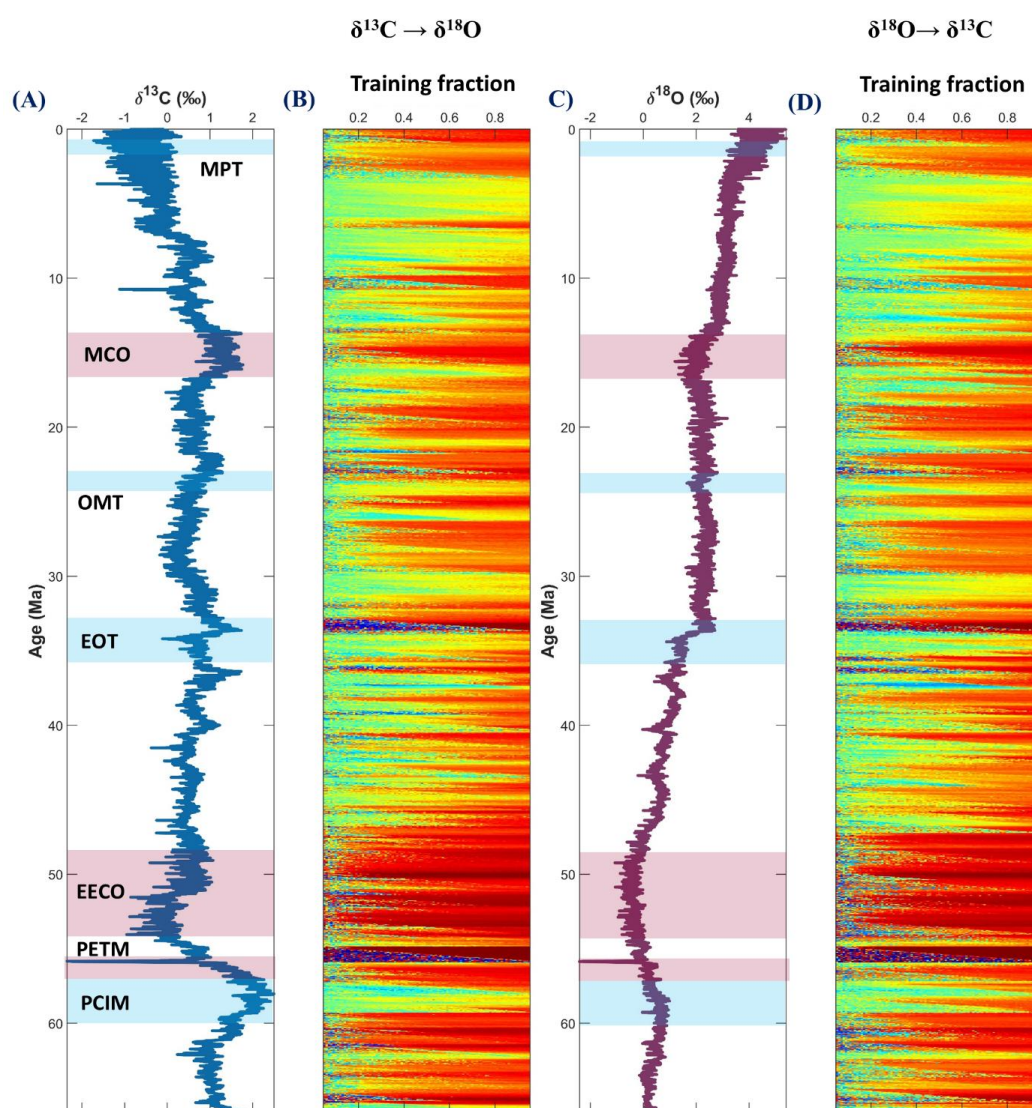
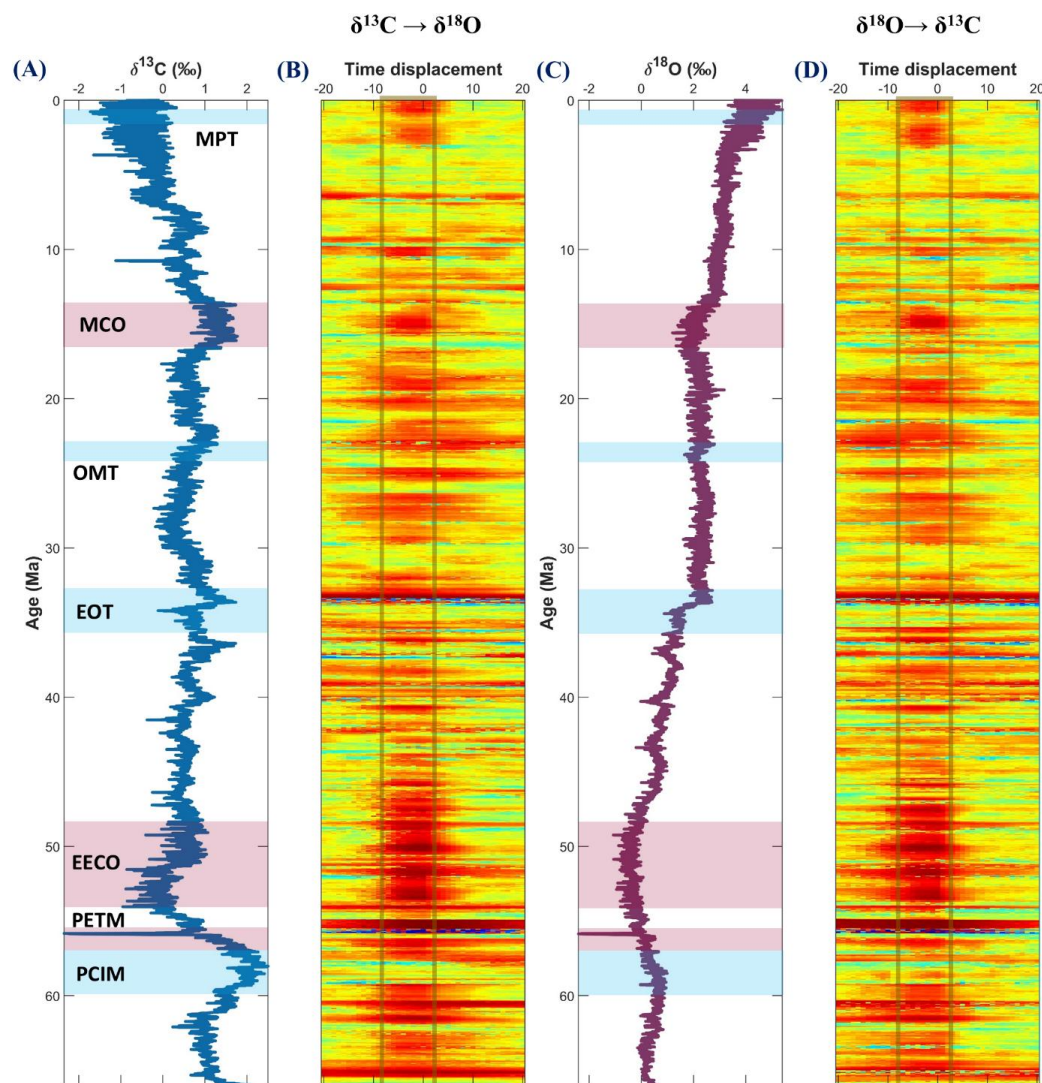




Figure 3: Moving window Extended RCC (ERCC) analysis using a 1 Ma moving window (bottom to top) A) Carbon cycle proxy $\delta^{13}\text{C}$ (‰) (blue line); B) Moving window ERCC of $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ with each point in the shaded region representing RCC Skill for time displacement increasing from -20 to 20; C) Climate proxy $\delta^{18}\text{O}$ (‰) (purple line); D) Moving window ERCC of $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ with each point in the shaded region representing RCC Skill for time displacement increasing from -20 to 20. In case of ‘real causality’, the red color maximum (darkest red) should be for time displacement of 0 or below.





3.2 Causality in Cenozoic climate and carbon cycle

Very high bidirectional causal association between climate and the carbon cycle for an extended period occurred during two time intervals, namely the globally warm phases of the Early Eocene Climatic Optimum (EECO) (Lauretano et al., 2018; Westerhold et al., 2018) and Miocene Climatic Optimum (MCO) (Fokkema et al., 2024; Kochhann et al., 2017; Steinhorsdottir et al., 2021; Tian et al., 2013). The EECO, spanning ~5 Ma, has the highest bidirectional causal association (≈ 0.9) between climate and carbon cycle in the Cenozoic. During the MCO, spanning ~3 Ma, bidirectional causal skills are also very high (≈ 0.8). Throughout the EECO, the difference between $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ is almost zero (Figure 10), suggesting very strong interaction in both directions. During the MCO, $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ is slightly greater than $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ for both RCC and CCM skills, suggesting climate was a more important driver of the carbon cycle than *vice versa* (Figure S10). Causal skills are also high during the relatively warm Pliocene phase (~3 Ma) and the strong glacial-interglacial cycles of the last million year of the Pleistocene. For the EECO, MCO, mid-Pliocene, and Pleistocene, the moving window convergence test and ERCC analysis are consistent with causal association.

Causal relations become insignificant in both directions around the relatively cool Paleocene Carbon Isotope Maximum (PCIM; ~58 Ma), the late Miocene (including the Late Miocene Carbon Isotope Shift; LMCIS), and parts of the Pliocene. The moving window convergence and ERCC analyses also do not support causal relations during these periods. The causal association of the climate-carbon cycle system decreases towards the middle Eocene and late Miocene, which coincide with cooling trends. This epoch also includes the warming phase termed Middle Eocene Climatic Optimum (MECO, ~40 Ma), however, the causal association between climate-carbon cycle dynamics is inconclusive here (Table 1).

Table 1: Column 1 includes the important events and periods, and their corresponding ages is given Column 2. For the events, the age at which they occur is given while for the periods, the Age region during which they occur given. For periods, the average skills, and their significance over the time region is given. The DCCM and DRCC causal skills in both directions, that is, $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ in Figure 1 are given in Column 3-6 and in case the skills are not significant, then that is mentioned as NS. If NS is not mentioned, then the causal skills are within 95% confidence. If there are causality trends observed before events, then they are mentioned as increasing ($\uparrow$) & decreasing ($\downarrow$). Column 7-10 are the moving window (1 Ma) convergence RCC test and ERCC analysis. Columns 7 and 8 are whether the $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ converge in the 1 million window prior to the events, and the general convergence during the Age region of the important period in Figure 2. Columns 9 and 10 are whether the $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ show maximum RCC causal skills for $d = 0$ or lower in the 1 million window prior to the events, and during the Age region of the important period in Figure 3. If the convergence and ERCC tests are passed or failed, then it is mentioned as 'Yes' and 'Fails', respectively. If the two analyses are not clear before the event or during the period, then it is mentioned as 'Unsure'.



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Events and Period	Age (Ma)	$\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ (Causal skills)		$\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ (Causal skills)		Convergence RCC (moving window)		ERCC (moving window)	
		DCCM	DRCC	DCCM	DRCC	$\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$	$\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$	$\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$	$\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$
LDE	62.2	0.5, ↓	0.5	0.5, ↓	0.5	Unsure	Yes	Unsure	Unsure
PCIM	58.5-57.5	0.1, NS	0.1, NS	0.1, NS	0.4, NS	Fails	Yes	Fails	Yes
PETM	55.952	↑, 0.7	↑, 0.7	↑, 0.6	↑, 0.6	Yes	Yes	Yes	Yes
EECO	54-49	0.8-0.9	0.8-0.9	0.8-0.9	0.8-0.9	Yes	Yes	Yes	Yes
MECO	40.05	0.6	0.1 NS	0.5	0.1 NS	Yes	Yes	Unsure	Unsure
EOT	34.2	0.4, NS	0.4, NS	0.5, ↑	0.3, NS	Unsure	Yes	Fails	Unsure
OMT	23.172	↑, 0.6	↑, 0.6	↑, 0.55	↑, 0.55	Yes	Yes	Yes	Yes
MCO	17-14	0.75-0.8	0.75-0.8	0.75-0.8	0.75-0.8,	Yes	Yes	Yes	Yes
MMCT	13.8	0.34	0.5	0.44	0.27, NS	Yes	Yes	Yes	Yes
LMCIS	8.3-6	0.3, NS	0.3, NS	0.3, NS	0.3, NS	Unsure	Yes	Fails	Fails
Mid-Pliocene Warm Climates	3.3-3	0.57	0.63	0.6	0.68	Yes	Yes	Yes	Yes
Pleistocene ice ages	1.27-0.7	0.6-0.7	0.6-0.7	0.6-0.7	0.6-0.7	Yes	Yes	Yes	Yes

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376 Numerous abrupt and extreme global warming and cooling events occurred during the Cenozoic
377 that are hypothesized to be due to the passing of a tipping point (Boettner et al., 2021; Setty et al.,
378 2023; Westerhold et al., 2020). Interestingly, before several of these events, the RCC and CCM
379 skills increased (Table 1 and Figure 1). Before the transient global warming phase Paleocene
380 Eocene Thermal Maximum (PETM), and glacial expansion of the Oligocene Miocene Transition
381 (OMT), the causal skills were significant but moderate (≈ 0.5 - 0.6), with greater $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ than
382 $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ suggesting stronger effect of carbon cycle on climate than *vice versa* (Figure S10).
383 However, not all abrupt transitions in the Cenozoic era are preceded by significant causal
384 associations between the climate-carbon cycle systems and consistent results amongst RCC and
385 CCM skills. For the late Danian warming event (LDE), and strong ice sheet expansion during the

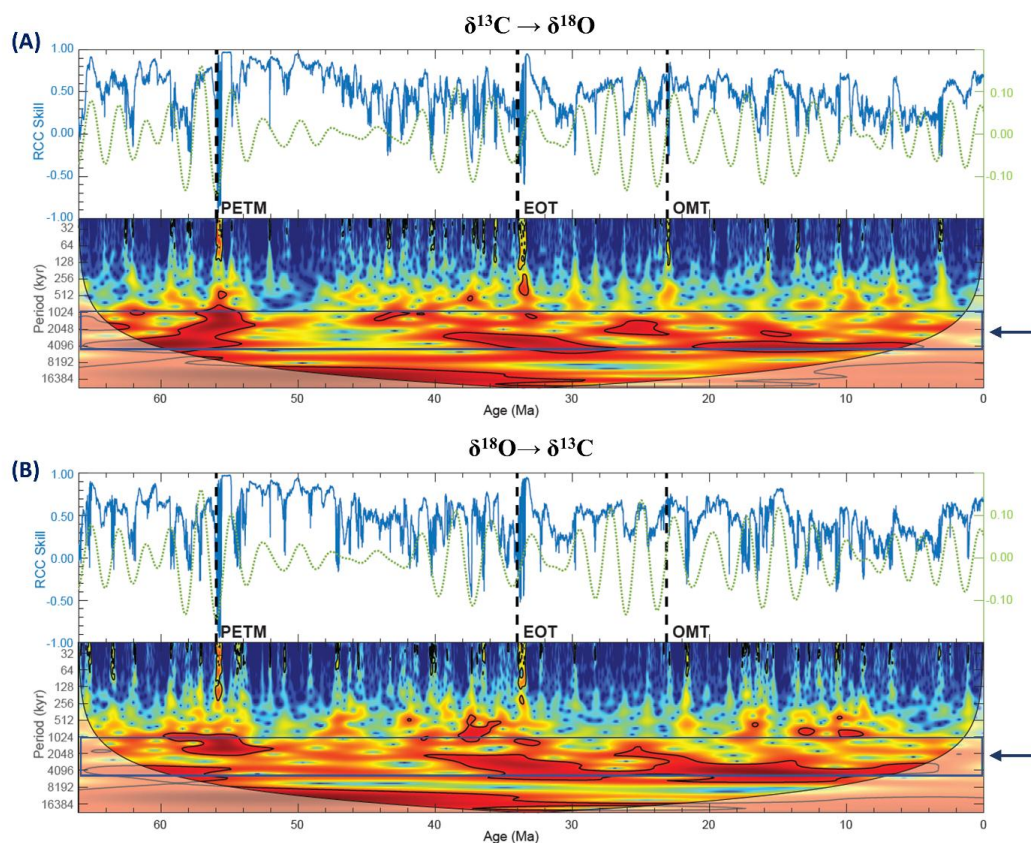


Eocene Oligocene Transition (EOT), there are discrepancies with either insignificant RCC or CCM skills, hampering the final determination of the causal association of climate-carbon cycle dynamics in the run-up towards these events. Also, the moving window convergence test and ERCC analysis imply that the causal association between climate-carbon cycle dynamics before LDE and EOT is inconclusive. Interestingly however, RCC and CCM dynamic causal analysis on the detrended dataset resulted in significant causal skills before LDE, MECO, and EOT (Figure S5). Likewise, analysis on the dataset after noise reduction, led to insignificant causal skills from 40 Ma up to the EOT transition (Figure S3). This indicates that both $\delta^{13}\text{C}$ and $\delta^{18}\text{O}$ here have strong periodicity, which makes the method used for null model generation improper for this time interval (Ebisuzaki, 1997).

Significant power of a 2.36 Ma and 1.2 Ma cycle is recorded in the wavelet analysis of both the $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ RCC skills (Figure 4) and CCM Skills (Figure S11). Because the isotope records are orbitally tuned, we can attribute this to the long-term modulation of eccentricity and obliquity, respectively (Figures S12, S13; S14, and S15). Other significant peaks might also relate to long-term modulations of obliquity and eccentricity, but we did not analyze these in detail since they are rarely described in the literature ('Lourens and 'Hilgen, 1997). The imprint of eccentricity modulation increases from PCIM up to 54 Ma ago for $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ and up to the PETM for $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and they are within the 95% confidence level. Interestingly, throughout the EECO, which has strong bidirectional causality, no strong cyclicity is recorded for both $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ (Figure 4 and S11). From ~40 Ma to 2 Ma, the ~2.4 Ma eccentricity and a longer ~4.5 Ma cycle have a strong influence on $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$. The longer ~4.5 Ma cycle is dominant for $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$. This is also recorded in the spectral analysis on the detrended RCC and CCM skills (Figure S13) further revealing a very strong signal of ~4.5 Ma. Additionally, various other frequencies between 1.6 and 3 Ma throughout the Cenozoic are within and beyond the 90% confidence level. Towards the expansion of the East Antarctic Ice Sheet (EAIS) during the EOT, and the OMT, the influence of 1.2Ma obliquity cycles increases for both $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ causal skills.



Figure 4: Wavelet analysis and Gaussian filters of the RCC skills. A) Wavelet analysis of RCC Skills of $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ (blue line) and Gaussian filters (green line) B) Wavelet analysis of RCC Skills of $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ (blue line) and Gaussian filters (green line). The regions within the box include 1.2 and 2.36 Ma cycle corresponding to the long-term modulation of obliquity and eccentricity.





4. Discussion

4.1 Trends in causality

Various long-term $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ trends stand out against the backdrop of varying causal associations of climate-carbon cycle dynamics (Figure 1). The high bidirectional causal association during EECO and MCO are preceded by almost insignificant skills both ways during PCIM (~58 Ma ago) and early Miocene, respectively. The high causal association during EECO could reflect a strong coupling of climate-carbon cycle dynamics through an organic carbon capacitor (Dickens, 2003; Setty et al., 2023) which stores ^{13}C -depleted carbon over long timescales, perhaps during the PCIM, and the stored carbon gets rapidly released over a short time when triggered (e.g., by an increase in temperature) (Dickens et al., 1995). This rapid release of carbon forms a positive feedback loop where the newly released carbon amplifies the ongoing warming resulting in a concurrent decrease in both $\delta^{13}\text{C}$ and $\delta^{18}\text{O}$ values (Setty et al., 2023). Both atmospheric $p\text{CO}_2$ and global temperature were very high and variable during EECO and our results support the notion that this resulted from very high mutual causality between climate and carbon cycle through the greenhouse effect (Cramwinckel et al., 2018; Hönlisch et al., 2023; Westerhold et al., 2020). Moreover, we speculate that the initiation of a similar organic capacitor coupling could explain the transition from negligible to high causal association between the early Miocene and the MCO, for which a role for organic carbon burial dynamics has long been proposed (Sosdian et al., 2020; Vincent and Berger, 1985). Such capacitors may have become larger and more stable during cold climates, while warmer climates could make the capacitor less resilient (Dickens et al., 1995; Komar et al., 2013). Finally, causal skills decrease during the middle and late Eocene and late Miocene (Figure 1). Potentially, long-term cooling led to increased resilience of such dynamic organic carbon reservoirs, resulting in more stable, colder climate states with less dominant climate-carbon cycle dynamics. Such long-term trends, typically determined by the long carbon cycle, which is driven by the balance between volcanic carbon input and weathering fluxes might not be picked up by our analysis because changes therein might result in $\delta^{18}\text{O}$ variability but without changes in $\delta^{13}\text{C}$ (Kump and Arthur, 1999).

The short-term rises in causal interaction before various warming and cooling events, such as the PETM and OMT suggest cascading amplification of the warming or cooling, destabilizing the Earth system. Preceding the warming events, the amplifying interactions of climate-carbon cycle dynamics could develop through water-vapor feedbacks that can be further magnified by precipitation and cloud feedbacks (Zhu et al., 2019). Before the cooling events, albedo and vegetation feedbacks could have been propelled and this is pointed out by the dynamic causality analysis. The events have been further hypothesized to be due to tipping points with the PETM being preceded by early warning signals in climate, while the OMT is preceded by a loss of resilience in both climate and the carbon cycle (Armstrong McKay and Lenton, 2018; Boettner et al., 2021; Setty et al., 2023). The causality analysis sheds light on the synchronous system instability pertaining to strong causal coupling amongst climate-carbon cycle dynamics even if only one of the systems is preceded by loss of resilience.



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483 Even though the LMCIS was preceded by early warning signals in the carbon cycle (Boettner et
484 al., 2021) our results do not point to a strong causal association between climate-carbon cycle
485 dynamics. Also, most of the late Miocene and Pliocene lacks causality between $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and
486 $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$. Previous studies have pointed towards an anti-phase $\delta^{13}\text{C} - \delta^{18}\text{O}$ relationship (Turner,
487 2014), the dominance of stochastic processes (Meyers and Hinnov, 2010) and the absence of
488 multiplicative noise (Arnscheidt and Rothman, 2021) during the Pliocene to explain the climate-
489 carbon cycle dynamics. Our study suggests there might have been less intense interaction between
490 the two systems. Furthermore, these studies indicate that the weak interactions continue towards
491 the Pleistocene. However, our analyses suggest that the climate-carbon cycle dynamics get
492 entangled again resulting in an increasing causal relationship between $\delta^{13}\text{C} - \delta^{18}\text{O}$ throughout the
493 Pleistocene, with the appearance of strong amplitude glacial-interglacial cycles. This supports that
494 carbon cycling and climate across these cycles, i.e., redistributions of carbon between the
495 atmosphere, biosphere and deep ocean reflected in $\delta^{13}\text{C}_{\text{BF}}$, and ice volume and temperature
496 variability reflected in $\delta^{18}\text{O}_{\text{BF}}$, were causally related.

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498 4.2 Orbital cycles in causality

499 The wavelet and spectral analyses on $\delta^{13}\text{C} \rightarrow \delta^{18}\text{O}$ and $\delta^{18}\text{O} \rightarrow \delta^{13}\text{C}$ causal skills demonstrate a
500 pronounced “heartbeat” consisting of long-term modulations of eccentricity (~ 2.36 Myr) and
501 obliquity cycles (~ 1.2 Myr) present especially from 45 Ma. This points to an (indirect) effect of
502 orbital forcing on the mechanism of the causality between climate and the carbon cycle. Moreover,
503 the relative dominance of eccentricity and obliquity cycles provide indications of whether low-
504 latitude processes such as precipitation, or high latitude processes such as ice-sheet dynamics play
505 a key role in the nonlinear interaction between climate-carbon cycle dynamics (Cramwinckel et al.,
506 2018; Hönisch et al., 2023). The intensity of the insolation cycles increases before several abrupt
507 events (PETM, OMT, and perhaps EOT) along with coinciding extremes of the cycles consistent
508 with an orbital trigger for these events (DeConto and Pollard, 2003; Lourens et al., 2005; Zachos et
509 al., 2001). The impact of these long-term modulations of eccentricity and obliquity is intriguing
510 because their forcing is relatively small relative to the primary cycles. However, they may have
511 played a role in the timing of early Eocene transient global warming events (Korassidis et al., 2022;
512 Lourens et al., 2005; Prothero and Heaton, 1996), and forced pulses of rodent lineage turnover
513 throughout the Oligocene and Neogene (Van Dam et al., 2006). Our records suggest that these
514 modulations impact the causal interaction between long term climate and the carbon cycle as well
515 (Prothero and Heaton, 1996).

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5. Conclusion

The study illuminates the dynamic interaction between climate and the carbon cycle over the past 66 million years as the Earth system changed from greenhouse to icehouse climate states. Our causality analysis suggests that the climate and the carbon cycle were most tightly coupled when the background temperature and atmospheric $p\text{CO}_2$ were highest, under (almost) ice-free conditions. This suggests that abrupt global warming events driven by feedbacks between climate and atmospheric carbon could rather be a characteristic of the greenhouse world. The strong causality during the EECO and to a slightly lesser extent MCO, stand out in the entire Cenozoic era indicating the heightened positive feedbacks/interactions between temperature and greenhouse gases (Cramwinckel et al., 2018; Hönlisch et al., 2023). Somewhat reduced causal interaction occurred during somewhat cooler climate states, but stronger causality is recorded with the intensification of northern hemisphere glaciation during the late Pleistocene. Our analyses suggest an orbital control on climate-carbon cycle causality, with a notable role for long-term modulations of eccentricity and obliquity. Additionally, as many of the abrupt and extreme events focused on in this study are hypothesized to be useful as analogues of future Earth systems, the analyses may help to understand and constrain the implications of the ongoing Anthropogenic climate change and triggering large-scale Earth system tipping phenomena.

Supplement

Supplementary Material includes Supplementary Text S1, and Figures S1 to S15.

Code and Data availability

All the data needed to evaluate conclusions in the paper are present in the paper and/or the Supplementary Materials. The codes and toolboxes used for the analysis and creating figures in the paper will be freely available on Zenodo (Currently available with restricted access here : <https://zenodo.org/records/22646443>).

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Author contributions



All authors designed the study. SS performed the mathematical analyses, except spectral and wavelet analysis, with the help of HD, EvN, and IvdL. LL performed the spectral and wavelet analysis. All authors contributed to the interpretation of the results. SS designed all the figures, with input from other co-authors for the main figures in the manuscript. SS and AS drafted the paper with input from all authors.

Competing interests: Authors declare that they have no competing interests.

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