Alkenone isotopes show evidence of active carbon concentrating mechanisms in coccolithophores as aqueous carbon dioxide concentrations fall below 7 mol L$^{-1}$
Alkenone isotopes show evidence of active carbon concentrating mechanisms in coccolithophores as aqueous carbon dioxide concentrations fall below 7 µmol L\(^{-1}\)

Marcus P. S. Badger
School of Environment, Earth & Ecosystem Sciences, The Open University, Milton Keynes, MK7 6AA, UK

Correspondence: Marcus P. S. Badger (marcus.badger@open.ac.uk)

Received: 25 September 2020 – Discussion started: 2 October 2020
Revised: 6 January 2021 – Accepted: 8 January 2021 – Published: 15 February 2021

Abstract. Coccolithophores and other haptophyte algae acquire the carbon required for metabolic processes from the water in which they live. Whether carbon is actively moved across the cell membrane via a carbon concentrating mechanism, or passively through diffusion, is important for haptophyte biochemistry. The possible utilization of carbon concentrating mechanisms also has the potential to over-print one proxy method by which ancient atmospheric CO\(_2\) concentration is reconstructed using alkenone isotopes. Here I show that carbon concentrating mechanisms are likely used when aqueous carbon dioxide concentrations are below 7 µmol L\(^{-1}\). I compile published alkenone-based CO\(_2\) reconstructions from multiple sites over the Pleistocene and recalculate them using a common methodology, which allows comparison to be made with ice core CO\(_2\) records. Interrogating these records reveals that the relationship between proxy CO\(_2\) and ice core CO\(_2\) breaks down when local aqueous CO\(_2\) concentration falls below 7 µmol L\(^{-1}\). The recognition of this threshold explains why many alkenone-based CO\(_2\) records fail to accurately replicate ice core CO\(_2\) records, and it suggests the alkenone proxy is likely robust for much of the Cenozoic when this threshold was unlikely to be reached in much of the global ocean.

1 Introduction

Alkenones are long-chain (C\(_{37}–39\)) ethyl and methyl ketones (Fig. 1; Brassell et al., 1986; Rechka and Maxwell, 1987) produced by a restricted group of photosynthetic haptophyte algae (Conte et al., 1994). Produced by a narrow group of organisms which live exclusively in the photic zone, alkenones allow probing of algal biogeochemistry, and as alkenones are often preserved in the sedimentary record, alkenones can also provide information about past environmental conditions.

Two main proxy systems based on alkenone geochemistry exist: one allows reconstruction of sea surface temperature (SST) and relies on the changing degree of unsaturation of the C\(_{37}\) alkenone (U\(_K^37\)) (Brassell et al., 1986), whilst a second for atmospheric CO\(_2\) concentration is based on reconstructing the isotopic fractionation which takes place during photosynthesis (\(\varepsilon_p\)) (Laws et al., 1995; Bidigare et al., 1997). It is the second system using the stable carbon isotopic composition of the preserved alkenones for reconstructing atmospheric CO\(_2\) concentration (referred to throughout as CO\(_2(\varepsilon_p-alk)\)) which is the focus of this study.

In the modern ocean, alkenones are produced primarily by two dominant coccolithophore species: *Emiliania huxleyi* and *Gephyrocapsa oceanica*. *E. huxleyi* first appeared 290 kyr ago and began to dominate over *G. oceanica* around 82 kyr ago (Gradstein et al., 2012; Raffi et al., 2006). However alkenones are commonly found in sediments throughout the Cenozoic, with the oldest reported detections from mid-Albian-aged black shales (Farrimond et al., 1986). Prior to the evolution of *G. oceanica*, alkenones were most likely produced by other closely related species from the Noelaerhabdaceae family (Marlowe et al., 1990; Volkman, 2000). Micropalaeontological and molecular data split the coccolith-bearing haptophytes into two distinct phylogenetic clades: the Isochrysidales and Coccolithales. The Isochrysidales contain the modern alkenone-producing taxa, including *E. huxleyi* and *G. oceanica*, and fossil reticulofenestrids. Meanwhile the non-alkenone-producers are separated into...
recently discrepancies have emerged between CO$_2$ values (around 400 µatm) in the Pliocene (Pagani et al., 2009) and worlds of the Palaeocene and Eocene to close to modern-day values (around 400 µatm) in the Pliocene (Pagani et al., 2005, 2011; Pearson et al., 2009; Anagnostou et al., 2016; Foster et al., 2017; Sosdian et al., 2018; Super et al., 2018; Zhang et al., 2013; Beerling and Royer, 2011). However, recently discrepancies have emerged between CO$_2$(p$_{\text{alk}}$) and other CO$_2$ proxies at the < 400 µatm atmospheric CO$_2$ concentrations of the Pleistocene (i.e. Badger et al., 2019, 2013a, and compare Badger et al., 2013b, and Pagani et al., 2009, with Martínez-Botí et al., 2015). Whilst the long-standing differences between alkene (Pagani et al., 1999), δ$^{13}$B (Foster et al., 2012), and stomatal proxies (Kürschner et al., 2008) in the Miocene CO$_2$ reconstructions have been partially resolved with new SST records (Super et al., 2018), differences remain in the Pliocene (Pagani et al., 2009; Badger et al., 2013b; Martínez-Botí et al., 2015) and Pleistocene (Badger et al., 2019).

Carbon concentrating mechanisms

One plausible reason for the discrepancies between CO$_2$(p$_{\text{alk}}$) and other proxies for atmospheric CO$_2$ is the operation of active carbon concentrating mechanisms (CCMs) in haptophytes. These are potentially important as CO$_2$(p$_{\text{alk}}$) assumes purely passive uptake of carbon into the haptophyte cell purely via diffusion (Laws et al., 1995; Bidigare et al., 1997). The potential for CCMs to affect CO$_2$(p$_{\text{alk}}$) has long been known (Laws et al., 1997, 2002; Cassar et al., 2006), and recent work has refocussed efforts on understanding CCMs in CO$_2$(p$_{\text{alk}}$) (Bolton et al., 2012; Bolton and Stoll, 2013; Stoll et al., 2019; Zhang et al., 2019, 2020). Cocolithophores are thought to have low-efficiency CCMs – especially compared to diatoms, dinoflagellates, and Phaeocystis – with evidence that CCMs play a minor role in cocolithophore biochemistry in the CO$_2$-replete worlds of the early Cenozoic (Bolton et al., 2012; Reinfelder, 2011). Direct evidence from experimentation with the marine diatom Phaeodactylum tricornutum suggests that both passive diffusive uptake and active CCMs operate at the same time, with active uptake used to moderate internal cell CO$_2$ concentrations to minimize energy use during transport to carboxylation sites (Laws et al., 1997). CO$_2$, unlike some other nutrients, is abundant within the water column, especially when considering the dissolved inorganic carbon (DIC) reservoir which includes bicarbonate (HCO$_3^-$), carbonate (CO$_3^{2-}$), and dissolved CO$_2$(HCO$_3^-$). However, due to the relatively slow diffusion of dissolved [CO$_2$]$_{\text{aq}}$ through water and the slow kinetics of the bicarbonate-to-[CO$_2$]$_{\text{aq}}$ transformation, surface water [CO$_2$]$_{\text{aq}}$ can still be depleted by photosynthetic activity. This can become particularly problematic in species which form blooms and at the cell boundary of species with limited motility. It should be no surprise therefore that many marine photosynthetic organisms have evolved with mechanisms to concentrate carbon within the cell.

The enzyme carbonic anhydrase (CA) can catalyse the dehydration of HCO$_3^-$ to [CO$_2$]$_{\text{aq}}$ to speed up availability of carbon if the [CO$_2$]$_{\text{aq}}$ reservoir is depleted and has been observed in several haptophytes, including cocolithophores (Rost et al., 2003; Riebesell et al., 2007). The exact contribution of CA remains unclear, but two possible mechanisms for CCMs have been postulated (Reinfelder, 2011): (1) CA catalyses dehydration of HCO$_3^-$ at the cell surface, which then allows increased CO$_2$ to diffuse into the cell passively, and (2) HCO$_3^-$ is transported into the cell and then converted by CA. Both of these options will likely impact the CO$_2$(p$_{\text{alk}}$) proxy, firstly by changing the effective [CO$_2$]$_{\text{aq}}$ within the cell (and so impacting ε$_{\text{p}}$) and secondly by imparting another carbon isotopic fractionation during CA catalysis which is not considered by the CO$_2$(p$_{\text{alk}}$) proxy system. However CA activity in cocolithophores does not appear to be regulated by CO$_2$ as it is in diatoms and Phaeocystis (Rost et al., 2003), which may indicate a less-well-developed CCM in cocolithophores.

Calcifying cocolithophores (which include alkenone producers E. huxleyi and G. oceanica) may be able to utilize HCO$_3^-$ directly as a carbon source (Trimborn et al., 2007), with precipitation of CaCO$_3$ providing an acid for the dehydration of HCO$_3^-$, but this still requires sufficient HCO$_3^-$ entering the cell, and it is unclear whether calcification aids DIC acquisition (Riebesell et al., 2000; Zondervan et al., 2002). The light-dependent leak of carbon (as CO$_2$ and DIC) back from haptophyte cells (including the cocolithophore E. huxleyi) to seawater (Tchernov et al., 2003) suggests that CCMs are energy intensive and can concentrate DIC within the cell. Even with active CCMs, it appears that in the ocean
cocolithophores are CO₂ limited under some circumstances (Riebesell et al., 2007).

2 Materials and methods

Calculating CO₂ from alkenone δ¹³C values: the CO₂(ε₀−alk) proxy

In this study I use the now large number of published CO₂(ε₀−alk) records which overlap with ice core records of atmospheric CO₂ concentration (Tables 1 and 2) to explore the relationship between CO₂(ε₀−alk) and CCMs in the Pleistocene, where our understanding of atmospheric CO₂ concentration is best.

Multiple records of CO₂(ε₀−alk) have been published for the Pleistocene (Fig. 2, Table 1), allowing direct comparison with ice-core-based CO₂ records (Table 2). These records are globally distributed in longitude but are concentrated at low-latitude sites, largely as there is a general preference for sites which have (in the modern ocean) surface waters close to equilibrium with the atmosphere (Fig. 2, Table 1). In longer-term palaeoclimate studies there has also been a preference for low-latitude gyre sites in the belief that these sites are more likely to be oceanographically stable over long time intervals (Pagani et al., 1999). Most of the records included here (Table 1, Fig. 2) were generated with the aim to reconstruct atmospheric CO₂ concentration; however one, the MANOP Site C of Jasper et al. (1994), was used to explicitly reconstruct changing disequilibrium due to oceanographic frontal changes over time and is excluded from the following analysis.

Whilst these sites do only span a relatively small latitudinal extent, the diversity of settings does allow for investigation of any secondary controls on alkenone δ¹³C values (δ¹³Calkenone) – in particular, differences in oceanographic setting and SST to test the hypothesis that low [CO₂]a (Table 2) breaks the relationship between δ¹³Calkenone and atmospheric CO₂ concentration, as might be expected if haptophytes are able to actively take up carbon from seawater to meet metabolic demand (i.e. activate CCMs).

To facilitate fair comparison between sites and consistent comparison with the ice core records, all CO₂(ε₀−alk) records were recalculated using a consistent approach. The approach is based on Bidigare et al. (1997), which updated the initial approach of Jasper and Hayes (1990) to CO₂(ε₀−alk). This approach removes some additional corrections used in the original publication of the records (such as growth rate adjustment for NIOP 464; Palmer et al., 2010) but does allow for direct comparison to be made. For all sites the “b” term was estimated using modern-day surface [PO₄³⁻] (Bidigare et al., 1997; Pagani et al., 2009).

An overview of how CO₂(ε₀−alk) data are typically generated is given in Badger et al. (2013b). Briefly, to calculate ε₀ requires the stable carbon isotopic composition of the dissolved CO₂ (δ¹³CCO₂aq) and haptophyte biomass (δ¹³Corg).

The isotopic fractionation between δ¹³Calkenone and δ¹³Corg is first corrected assuming a constant fractionation (εalkenone) of 4.2‰ (Garcia et al., 2013; Popp et al., 1998; Bidigare et al., 1997):
and

\[
\delta^{13}C_{CO_2(aq)} = \left( \frac{\delta^{13}C_{CO_2(g)} - \delta^{13}C_{alkenone}}{1000} + 1 \right) \times \left( \frac{\delta^{13}C_{CO_2(g)} + 1000}{\delta^{13}C_{CO_2(g)} + 1000} - 1 \right) \times 1000, \tag{5}
\]

Finally \( \varepsilon_p \) can be calculated:

\[
\varepsilon_p = \left( \frac{\delta^{13}C_{CO_2(aq)} + 1000}{\delta^{13}C_{CO_2(g)} + 1000} - 1 \right) \times 1000, \tag{6}
\]

and from that \([CO_2]_{aq}\) is calculated using the isotopic fractionation during carbon fixation \((\varepsilon_f)\) and \(b\), which represents the summation of physiological factors:

\[
[CO_2]_{aq} = \frac{b}{\varepsilon_f - \varepsilon_p}. \tag{7}
\]

Here \( \varepsilon_f \) is assumed to be a constant 25 % (Bidigare et al., 1997). In the modern ocean the \( b \) term, which accounts for physiological factors such as cell size and growth rate, shows a close correlation with \([PO_4]^-\) (Bidigare et al., 1997; Pagani et al., 2009). However, the relationship between \( b \), growth rate, and \([PO_4]^-\) has recently been questioned (Zhang et al., 2019, 2020) but for the purposes of this analysis is assumed to hold. This is discussed further below. Values for SST, \( \delta^{13}C_{alkenone}, \delta^{13}C_{carbonate}, \) salinity, and \([PO_4]^-\) are either taken from the original publications or estimated from modern ocean estimates (Takahashi et al., 2009; Antonov et al., 2010; Garcia et al., 2013). Providing that the atmosphere is in equilibrium with surface water, the concentration of atmospheric CO\(_2\) can be calculated from \([CO_2]_{aq}\) (and vice versa if atmospheric CO\(_2\) concentration is known) using Henry’s law:

\[
pCO_2 = \frac{[CO_2]_{aq}}{K_H}. \tag{8}
\]

The solubility coefficient \((K_H)\) is dependent on salinity and SST, and here it is calculated following the parameterization of Weiss (1970, 1974).

Table 1. Sites with Pleistocene CO\(_2\)(\(\varepsilon_p-\text{alk}\)) records. Note that the MANOP Site C record was generated to track changes in surface water-atmosphere equilibrium, not atmospheric \(pCO_2\), so, although it is included here for completeness, it is not included in the analysis. Distance from the coast is calculated from the intermediate-resolution version of GSHHG and computed using Generic Mapping Tools (Wessel and Smith, 1996; Wessel et al., 2019).

<table>
<thead>
<tr>
<th>Site</th>
<th>Age interval (kyr)</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Water depth (m)</th>
<th>Distance from coast (km)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>05PC-21</td>
<td>0.5–188</td>
<td>38°24’N</td>
<td>131°33’E</td>
<td>1721</td>
<td>108</td>
<td>Bae et al. (2015)</td>
</tr>
<tr>
<td>DSDP 619</td>
<td>3–92</td>
<td>27°11.61’N</td>
<td>91°24.54’W</td>
<td>2259</td>
<td>489</td>
<td>Jasper and Hayes (1990)</td>
</tr>
<tr>
<td>NIOP 464</td>
<td>7.8–29</td>
<td>22°9’N</td>
<td>63°21’E</td>
<td>1470</td>
<td>333</td>
<td>Palmer et al. (2010)</td>
</tr>
<tr>
<td>ODP 999</td>
<td>11.1–258</td>
<td>12°44.639’N</td>
<td>78°44.360’W</td>
<td>2839</td>
<td>249</td>
<td>Badger et al. (2019)</td>
</tr>
<tr>
<td>ODP 925</td>
<td>20–580</td>
<td>4°12.249’N</td>
<td>43°29.334’W</td>
<td>3042</td>
<td>626</td>
<td>Zhang et al. (2013)</td>
</tr>
<tr>
<td>MANOP Site C</td>
<td>0.8–253</td>
<td>0°57.2’N</td>
<td>138°57.3’W</td>
<td>4287</td>
<td>998</td>
<td>Jasper et al. (1994)</td>
</tr>
<tr>
<td>GeoB 1016-3</td>
<td>1.3–196</td>
<td>11°46.2’S</td>
<td>11°40.9’E</td>
<td>3410</td>
<td>185</td>
<td>Andersen et al. (1999)</td>
</tr>
</tbody>
</table>

The full record for ODP Site 925 extends to 38.62 Ma.

Table 2. Sources of ice core data, as compiled by Bereiter et al. (2015). WAIS – West Antarctic Ice Sheet; TALDICE – TALos Dome Ice CorE; and EDML – EPICA Dronning Maud Land. Age given as gas age relative to 1950.

<table>
<thead>
<tr>
<th>Age interval (kyr)</th>
<th>Ice core location</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>–0.051 to 1.8</td>
<td>Law Dome</td>
<td>Rubino et al. (2013)</td>
</tr>
<tr>
<td>1.8–2</td>
<td>Law Dome</td>
<td>MacFarling Meure et al. (2006)</td>
</tr>
<tr>
<td>11–22</td>
<td>WAIS</td>
<td>Marcott et al. (2014)</td>
</tr>
<tr>
<td>22–40</td>
<td>Siple Dome</td>
<td>Ahn and Brook (2014)</td>
</tr>
<tr>
<td>40–60</td>
<td>TALDICE</td>
<td>Bereiter et al. (2012)</td>
</tr>
<tr>
<td>60–115</td>
<td>EDML</td>
<td>Bereiter et al. (2012)</td>
</tr>
<tr>
<td>105–155</td>
<td>Dome C</td>
<td>Schneider et al. (2013)</td>
</tr>
<tr>
<td>155–393</td>
<td>Vostok</td>
<td>Petit et al. (1999)</td>
</tr>
</tbody>
</table>
concentration of dissolved carbon (\[\text{CO}_2\text{(aq)}\]) not only atmospheric \(\text{CO}_2\) but also temperature, alkalinity, and other oceanographic factors which control the equilibrium state between surface waters at the atmosphere (Fig. 2), the multiple sites in different settings now give the opportunity to test whether other factors are important in controlling the accuracy of \(\text{CO}_2\text{(ep-alk)}\).

To produce time-equivalent estimates of atmospheric \(\text{CO}_2\) concentration for comparison with the ice core records, a simple linear interpolation of the Bereiter et al. (2015) compilation was initially used (Fig. 4). This assumes that both the age model of the ice core and the published age models of the sites are correct and equivalent. This is almost certainly not the case, and so for the calculations below, a ±3000 year uncertainty is included for ages of both the ice core and \(\text{CO}_2\text{(ep-alk)}\) values. Figure 4 shows that \(\text{CO}_2\text{(ep-alk)}\)-based atmospheric \(\text{CO}_2\) concentration agree with ice core \(\text{CO}_2\) at some sites and at some times, but not throughout. Sites 05-PC21 (Baee et al., 2015) and DSDP Site 619 (Jasper and Hayes, 1990) perform quite well throughout, whilst ODP Site 999 (Badger et al., 2019) and NIOP 464 (Palmer et al., 2010) only appear to agree at higher values of \(\text{CO}_2\), and at ODP Site 925 (Zhang et al., 2013) and GeoB 1016-3 (Andersen et al., 1999) there is very little overlap between the two methods of reconstructing atmospheric \(\text{CO}_2\) concentration.

To explore whether \([\text{CO}_2\text{(aq)}]\) is an important influence on \(\text{CO}_2\text{(ep-alk)}\), I calculate predicted \([\text{CO}_2\text{(aq)}]\) \((\text{ICO}_2\text{(aq)}\text{(predicted)})\) for each of the samples. To calculate \([\text{CO}_2\text{(aq)}]\text{(predicted)}\), the time-equivalent value of atmospheric \(\text{CO}_2\) concentration from the ice core record is used in combination with Eq. (8) to calculate \([\text{CO}_2\text{(aq)}]\) at the time of alkenone production for each sample. Reconstructed estimates of SST and salinity are used as for \(\text{CO}_2\text{(ep-alk)}\) above, along with any estimated surface water–atmosphere disequilibrium. Points in Fig. 4 are then coloured by \([\text{CO}_2\text{(aq)}]\text{(predicted)}\).

Inspection of Fig. 4 suggests a connection between \([\text{CO}_2\text{(aq)}]\text{(predicted)}\) and the skill of \(\text{CO}_2\text{(ep-alk)}\) to reconstruct atmospheric \(\text{CO}_2\) concentration. The points clustering around the 1 : 1 line are lighter in colour (so with higher \([\text{CO}_2\text{(aq)}]\text{(predicted)}\)) whilst points falling away from the 1 : 1 line have lower \([\text{CO}_2\text{(aq)}]\text{(predicted)}\). To explore this relationship, I progressively restricted the included samples on the basis of \([\text{CO}_2\text{(aq)}]\text{(predicted)}\) and at each stage calculated a Pearson correlation coefficient \((r)\) and coefficient of determination \((r^2)\) for each subset. Under this analysis the correlation progressively increased as more of the low \([\text{CO}_2\text{(aq)}]\text{(predicted)}\) samples were excluded (Fig. 5). All analyses were performed in R (R Core Team, 2020) using RStudio (RStudio Team, 2020). This suggests that the fidelity of the \(\text{CO}_2\text{(ep-alk)}\) depends on the concentration of \([\text{CO}_2\text{(aq)}]\), improving at higher levels of \([\text{CO}_2\text{(aq)}]\).

To further investigate this potential relationship, I progressively exclude samples based on \([\text{CO}_2\text{(aq)}]\text{(predicted)}\) with a step size of 0.05 \(\mu\text{mol L}^{-1}\), again calculating Pearson correlation coefficients and coefficients of determination between ice core and \(\text{CO}_2\text{(ep-alk)}\) for each subsample of the population. The result is shown in Fig. 6. Here the analysis shows, similar to Fig. 5, that, as the samples with lowest \([\text{CO}_2\text{(aq)}]\text{(predicted)}\) are progressively removed, the correlation between ice core and \(\text{CO}_2\text{(ep-alk)}\) increases. Furthermore, this continues only up until \([\text{CO}_2\text{(aq)}]\text{(predicted)}\) reaches
7 µmol L$^{-1}$. Above this, the coefficient of determination plateaus, until the subsample reaches such a small size that spurious correlations become important (Fig. 6b).

3.2 Sensitivity and uncertainty tests

It is possible that the pattern seen in Fig. 6b could emerge from a dataset shaped with increasing density surrounding the 1 : 1 correlation line without being driven by changes in [CO$_2$]$_{aq}$--predicted. To explore this possibility, I ran a series of sensitivity experiments. In these, rather than reducing the sample by filtering by [CO$_2$]$_{aq}$--predicted, the whole dataset (Table 1) was randomly ordered and then stepwise subsampled. To make this equivalent to the [CO$_2$]$_{aq}$--predicted analysis above, I set the size of each subsample to be equal to each step in the original analysis. This produces a randomly selected but same-sized subsample such that the size of the subsample reduces in the same way as shown in Fig. 6b. Pearson correlation coefficients and coefficients of determination were calculated for each subsample as above, and I repeated this 1000 times, with the order of each sample randomized each time.

To allow for possible age model uncertainties, a 3000-year (1σ) uncertainty was also applied to each sample. This uncertainty was applied to the age of each sample prior to sampling of the ice core record, and it is applied as a normally distributed uncertainty. Uncertainty in CO$_2$($\varepsilon_p$--alk) measurements is typically calculated using Monte Carlo modelling of all the parameters (i.e. Pagani et al., 1999; Badger et al., 2013a, b); however this was not done in all the published work (Table 1), and some differences in approach were found across the published work. Therefore to create CO$_2$($\varepsilon_p$--alk) uncertainty estimates for each value in this study, I emulate the uncertainties based on the CO$_2$($\varepsilon_p$--alk) value. I built a simple emulator (Fig. 7) by running Monte Carlo uncertainty estimates for all of the included datasets (Table 1) using the same estimates of uncertainty for each variable in the CO$_2$($\varepsilon_p$--alk) calculation as applied in Badger et al. (2013a, b). This then allows the uncertainty to be included in the [CO$_2$]$_{aq}$--predicted calculation as well as CO$_2$($\varepsilon_p$--alk), and it allowed for uncertainty estimates to be site-ambivalent.

The result is shown in Fig. 6c and d, and it suggests that the 7 µmol L$^{-1}$ break point remains valid. The absolute value of $r^2$ is reduced, even at higher [CO$_2$]$_{aq}$--predicted, but this would be expected given the addition of uncertainty in the age model, as the published age is most likely to align with the ice core. Given the rapid rate of change at deglaciations, this effect is likely to be particularly pronounced in this dataset as many records have high temporal resolution around deglaciations in order to attempt to resolve them.
Any small age model offset introduced by the error modelling in these intervals also clearly has the potential to induce large differences between the CO$_2$(\text{p$_\text{alk}$}) and ice core values. Figure 6c and d clearly demonstrate that it is the filtering by [CO$_2$]$_{\text{aq}}$-predicted rather than any spurious correlations which determines the shape of the data in Fig. 6a.

4 Discussion

The plateau in $r^2$ in Fig. 6a and c suggests that below a [CO$_2$]$_{\text{aq}}$-predicted of $\sim$7 µmol L$^{-1}$ CO$_2$(\text{p$_\text{alk}$}) is no longer as good a predictor of ice core CO$_2$ as when [CO$_2$]$_{\text{aq}}$-predicted $>$ 7 µmol L$^{-1}$. This is clear from comparing the relationship between samples where [CO$_2$]$_{\text{aq}}$-predicted $<$ 7 µmol L$^{-1}$ with those where [CO$_2$]$_{\text{aq}}$-predicted $>$ 7 µmol L$^{-1}$ in Fig. 8. Here the $r^2$ for the former of 0.15 is substantially less than the latter of 0.55. I suggest that this is because below this threshold the fundamental assumption of CO$_2$(\text{p$_\text{alk}$}), that carbon is passively taken up by haptophytes, no longer holds true. One obvious explanation for why this would be the case is that at low levels of [CO$_2$]$_{\text{aq}}$ haptophytes have to rely more on active uptake of carbon via CCMs in order to satisfy metabolic demand. Similar behaviour has been recognized in some culture studies (Laws et al., 1997, 2002; Cassar et al., 2006), with some evidence that the diatom Phaeodactylum tricornutum has a similar CCM threshold of 7 µmol L$^{-1}$ (Laws et al., 1997). Whilst the evidence for the mechanism of CCM is poorer for coccolithophores than it is for diatoms, any CCM would be expected to compromise the CO$_2$(\text{p$_\text{alk}$}) proxy, either by increased supply of [CO$_2$]$_{\text{aq}}$ or by further carbon isotopic fractionation effects during carbon transport, or both (Stoll et al., 2019).

By applying a threshold value for [CO$_2$]$_{\text{aq}}$-predicted of 7 µmol L$^{-1}$ to the published records (Table 1), values of CO$_2$(\text{p$_\text{alk}$}) which are influenced by active CCMs can be eliminated. Recognition of this new threshold value of [CO$_2$]$_{\text{aq}}$-predicted allows for a new record of Pleistocene CO$_2$(\text{p$_\text{alk}$}) to be compiled. This compilation then much better replicates the glacial–interglacial pattern of CO$_2$ change over the last 260 kyr (Fig. 9). Whilst this present compilation does rely on ice core CO$_2$ records to estimate [CO$_2$]$_{\text{aq}}$-predicted, and therefore has little direct utility as a CO$_2$ record, it does demonstrate that recognition of a threshold response allows accurate CO$_2$ reconstruction using CO$_2$(\text{p$_\text{alk}$}). This may represent the point at which isotopic effects of CCMs (plausibly through increased CA activity or HCO$_3^-$ dehydration to meet C demand) overwhelm the assumptions of the CO$_2$(\text{p$_\text{alk}$}) proxy. This, as well as

https://doi.org/10.5194/bg-18-1149-2021

Biogeosciences, 18, 1149–1160, 2021
the behaviour shown in Fig. 6a and c, suggests that from the standpoint of the CO$_2$(ε$_p$−alk) proxy CCMs may effectively be considered either active or not, and that when [CO$_2$]$_{aq}$ is plentiful passive uptake dominates, at least sufficiently in most oceanographic settings that CO$_2$(ε$_p$−alk) can accurately record atmospheric CO$_2$ concentration. This implies that, if areas of the ocean (or intervals of time) with low [CO$_2$]$_{aq}$ can be avoided, accurate reconstructions of atmospheric CO$_2$ concentration can be acquired using CO$_2$(ε$_p$−alk).

As [CO$_2$]$_{aq}$ is affected by both SST via the temperature dependance of the Henry’s law constant and atmospheric CO$_2$ concentration, for CO$_2$(ε$_p$−alk) to be effective in reconstructing atmospheric CO$_2$ concentration, areas of warm wa-
Figure 9. Revised compilation of Pleistocene CO$_2$(ε$_p$–alk) vs. ice core records. The compiled published records (Table 1) are shown as circles, coloured red where [CO$_2$]$_{aq}$–predicted is below a threshold of 7 µmol$^{-1}$ and blue where [CO$_2$]$_{aq}$–predicted > 7 µmol$^{-1}$. The solid blue line is a loess filter (span 0.1) through the [CO$_2$]$_{aq}$–predicted > 7 µmol$^{-1}$ values, with 95 % confidence intervals (dashed blue line). The black line is the ice core compilation of Bereiter et al. (2015) (Table 2).

There have been recent attempts to correct for CCMs in CO$_2$(ε$_p$–alk)-based reconstructions of atmospheric CO$_2$ concentrations (Zhang et al., 2019; Stoll et al., 2019; Zhang et al., 2020). However, these assume that CCMs are always active and crucially do not fundamentally break the relationship between ε$_p$ values and atmospheric CO$_2$ concentration. However if this is not the case, and the relationship between ε$_p$ values and atmospheric CO$_2$ concentration fails at Pleistocene levels of atmospheric CO$_2$, then Pleistocene records cannot be used to develop corrections of CO$_2$(ε$_p$–alk) to be applied throughout the Cenozoic. If, as suggested by the analyses presented here, CCMs only act at lower [CO$_2$]$_{aq}$, and largely only in conditions prevalent throughout the late Pliocene and Pleistocene, it is plausible that corrections based on Pleistocene records could overcompensate for CCMs in the rest of the Cenozoic, when the assumption of passive carbon uptake inherent in CO$_2$(ε$_p$–alk) as traditionally applied may still be valid.

5 Conclusions

Reconstructions of past atmospheric CO$_2$ concentration with proxy tools like CO$_2$(ε$_p$–alk) are critical for understanding how the Earth’s climate system operates, as long as the tools used can be relied upon to be accurate and precise. This re-analysis of existing Pleistocene CO$_2$(ε$_p$–alk) records reveals that below a critical threshold of [CO$_2$]$_{aq}$ of 7 µmol$^{-1}$ the relationship between δ$^{13}$C$_{alkenone}$ and atmospheric CO$_2$ concentration breaks down, plausibly because below this threshold haptophytes are able to actively take up carbon using CCMs in order to satisfy metabolic demand.

Although reconstructing the low levels of atmospheric CO$_2$ concentration in the Pleistocene glacials and areas of the global ocean where [CO$_2$]$_{aq}$ is less than 7 µmol$^{-1}$ will be impossible, for much of the Cenozoic the CO$_2$(ε$_p$–alk) proxy retains utility. If care is taken to avoid regions and oceanographic settings where [CO$_2$]$_{aq}$ is expected to be abnormally low, CO$_2$(ε$_p$–alk) remains an important and useful proxy to understand the Earth system.

Code and data availability. This paper relies exclusively on previously published data, available with the original papers and in publicly available repositories. An R notebook supplement is available alongside this paper, along with data files, which allow full replication of all analyses performed.

Supplement. The supplement related to this article is available online at: https://doi.org/10.5194/bg-18-1149-2021-supplement.

Competing interests. The author declares that there is no conflict of interest.

Acknowledgements. I am grateful to Gavin Foster and Tom Chalk for frequent and stimulating discussions on alkenone paleobarometry. I thank all authors who made full datasets available online. I thank Kirsty Edgar for comments on various drafts and the two anonymous reviewers, whose comments greatly improved this paper.

Financial support. Financial support for this work was provided by the School of Environment, Earth and Ecosystem Sciences, The Open University.

Review statement. This paper was edited by Jack Middelburg and reviewed by two anonymous referees.

https://doi.org/10.5194/bg-18-1149-2021
Ahn, J. and Brook, E. J.: Siple Dome ice reveals two modes of millennial CO$_2$ change during the last ice age, Nat. Commun., 5, 11273, https://doi.org/10.1038/ncomms11273, 2014.


R Core Team: A language and environment for statistical computing, available at: https://www.r-project.org/ (last access: 9 October 2020), 2020.


M. P. S. Badger: CCMs in coccolithophores at low CO$_2$


