Geophysical Research Letters

RESEARCH LETTER
10.1029/2020GL089044

Key Points:
- Proxy-derived estimates of past sea surface temperatures are biased toward epeiric seas in the Paleozoic and coasts in the Cenozoic
- In the modern ocean, sea surface temperatures from these environments systematically deviate from open ocean values at the same latitude
- These deviations, related to ocean dynamics, must be considered when reconstructing latitudinal gradients and assessing model fidelity

Supporting Information:
- Supporting Information S1

Citation:
Judd, E. J., Bhattacharya, T., & Ivany, L. C. (2020). A dynamical framework for interpreting ancient sea surface temperatures. Geophysical Research Letters, 47, e2020GL089044. https://doi.org/10.1029/2020GL089044

Received 27 MAY 2020
Accepted 8 JUL 2020
Accepted article online 17 JUL 2020

Abstract Efforts to estimate past global mean temperature and latitudinal gradients must contend with spatial heterogeneity in sea surface temperatures (SSTs). Here, we use modern SSTs to show that the environments from which most paleoclimatic data are drawn, shallow epeiric seas and continental margins, are systematically offset from zonal mean temperatures. Epeiric seas are warmer and more seasonal than open-ocean values from the same latitudes, while continental margins exhibit consistent and predictable deviations related to gyre circulation. Warm temperatures inferred from Paleozone proxy data may largely reflect that these data derive almost entirely from epeiric seas. Moreover, pseudoproxy analysis using Paleogene sampling localities demonstrates how undersampling of the full range of dynamical environments associated with gyre circulation can generate spurious estimates of latitudinal temperature gradients. Recognition of these global patterns permits a predictive framework within which to more robustly interpret proxy data, improve Earth system models, and reconstruct ancient dynamic regimes.

Plain Language Summary Geochemical analyses provide estimates of past sea surface temperature. These data are integral to calculating global climate metrics, such as the latitudinal temperature gradient. For myriad reasons, the sites of these data are not evenly distributed across the global oceans but, instead, are biased toward two environments—continental margins and shallow continental seas. It is therefore important to determine the extent to which these environments reflect broader climatic conditions. We use global ocean data to demonstrate that modern shallow, restricted seas are consistently warmer and more seasonal than anticipated for their given latitude. Because all sea surface temperature data older than ~200 Ma come from these environments, this observation could help explain why many Paleozoic temperatures appear unrealistically hot. Similarly, nearshore environments exhibit consistent offsets from the open ocean, both in terms of annual temperature and seasonal range, depending on their position within a gyre. This observation helps explain some of the longitudinal heterogeneity in paleoclimate data and should be used to inform locations to target for future data collection. Ignoring environment-specific patterns can lead to spurious estimates of global climate metrics. However, cognizance of and correction for sampling location biases can improve interpretations of ancient climates.

1. Introduction

Substantial attention within the paleoclimate community focuses on quantifying key climate metrics, such as average global temperature, climate sensitivity, and the latitudinal temperature gradient (Caballero & Huber, 2013; Cramwinckel et al., 2018; Evans et al., 2018; Hollis et al., 2019; Zhu et al., 2019). These parameters are relatively easy to calculate in today’s well-instrumented world, but efforts to characterize them in deep time present the unique challenge of inferring broad, zonal averages from a sparsely sampled world. The majority of sea surface temperature (SST) data, even for well-studied time intervals, come primarily from continental margins (Dowsett et al., 2013; Hollis et al., 2019). Undersampling of the open ocean further intensifies prior to 200 Ma, as nearly all paleo-SST data are restricted to epeiric seas due to recycling of the ocean floor and alteration during orogenesis along continental margins (Holmden et al., 1998). The specialized environments from which proxy data derive calls into question whether they can be used to estimate global mean climate parameters, or whether they reflect primarily local dynamical processes. In many cases, local-scale dynamics are invoked post hoc to explain proxy data disagreement (e.g., Hollis et al., 2012), but to date no study has presented a systematic global analysis of the dynamical processes that influence offsets between proxy locations and global mean climate parameters.
Here, through analysis of modern globally gridded SSTs, we show that zonal heterogeneity of modern SSTs is significant, but first-order patterns are systematic and therefore predictable in deep time based on paleogeography and its impacts on ocean dynamics. We explore how undersampling or oversampling of these regions can lead to underestimations or overestimations of the latitudinal temperature gradient, consider the extent to which Earth system models (ESMs) capture these patterns, and present a framework with which these data can be used to reconstruct past ocean dynamics.

2. Data and Methods

2.1. SST Data

SST data come from the Japan Meteorological Agency Centennial in situ Observation Based Estimates of SST, Version 2 (COBE-SST2) (Hirahara et al., 2014). This globally gridded reanalysis data set is averaged between 1981 and 2010, providing a climatological mean and eliminating secular trends related to ongoing anthropogenic warming and quasi-decadal scale climate oscillations. The data have a mean monthly temporal resolution and a 1° × 1° spatial resolution (N = 43,723 ocean grid cells). These data were used to calculate a suite of climate parameters, including the mean annual temperature (MAT), mean annual range of temperatures (MART), and their respective zonal anomalies ([MAT]*, [MART]*).

2.1.1. Calculation of MAT and MART

MAT was calculated by taking the arithmetic mean of the mean monthly temperatures for each ocean grid cell and MART was calculated by taking the difference in temperature between the warmest and coldest month for each ocean grid cell. This accounts for the fact that the timing of the warmest and coldest month might differ in different oceanographic settings. Overall, individual profiles of mean monthly temperatures exhibit sinusoidal oscillations, consistent with the theoretical prediction based on intra-annual variability in solar insolation at a given latitude (Haney & Davies, 1976). This pattern breaks down slightly in the high latitude (70°–90°N/S), where winter SSTs are constrained by the freezing point of salt water, and in equatorial regions of deep convection (Figure S1 in the supporting information).

2.1.2. Calculation of [MAT]* and [MART]*

To investigate spatial patterns in the direction and magnitude of deviations from zonal means, we introduce two new parameters: the zonal MAT anomaly ([MAT]*), or deviation from the zonal mean of a given site's mean annual temperature, and the zonal MART anomaly ([MART]*), or deviation from the zonal mean of a site's seasonal range of temperature. These parameters were calculated by averaging all ocean grid cells within a latitudinal band and subtracting the zonal mean from each individual value within that band. The units of both of these parameters are °C, indicating the absolute magnitude of the deviation.

2.1.3. Environment-Specific Data Subdivisions

We investigate spatial patterns within epeiric seas, by identifying 10 semi-enclosed or marginal seas to use as modern analogs and extracting SSTs from all grid cells within these basins. To avoid conflating coastal processes with epeiric sea patterns, we intentionally avoided selecting marginal seas with strong connections to powerful boundary currents, such as the Sea of Japan. Additionally, we subdivided the data into eight separate data sets representing the eastern and western boundaries of the northern and southern Atlantic and Pacific Oceans. These data sets consist of all ocean grid cells that fall within 500 km of coastline, are between ±15°N/S and ±55°N/S, and are not already previously categorized as belonging to an epeiric sea modern analog (Figure S2).

2.2. IODP Locations and Eocene and Pliocene SST Sites

To constrain spatial patterns in the geographic distribution of proxy-derived SST data, we use the latitude and longitude of IODP sites. Coordinates for all IODP drill holes were extracted from the Drill Hole File from the IODP website (http://www.iodp.org/resources/maps-and-kml-tools; N = 3,886). Because this data set includes all drill hole, rather than individual legs or expeditions, latitudes and longitudes of the sites were rounded to one decimal and duplicate coordinates were removed (N = 1,356). The distance between each location and the nearest coastline was calculated using the dist_from_coast function found on the MATLAB file exchange.

Additional coordinates of Pliocene SST sites dominantly come from the PRISM4 compilation (Dowsett et al., 2013). Sites of Eocene SST data dominantly come from the DeepMIP PMIP4 (Hollis et al., 2012) and
similar compilations (Evans et al., 2018). Locations with multiproxy records were only counted once and distance to the nearest coastline was calculated as with the IODP data set.

2.3. Surface Ocean Circulation Data

Surface current vector data come from the nonlinear inverse model ECCO V4r3, which estimates the time-mean ocean circulation using available ocean data and the MITgcm (Forget et al., 2015; Fukumori et al., 2017). Mean monthly data were averaged between 1992 and 2015, to minimize variability from quasi-decadal scale climate oscillations, and were regridded from a 0.5° × 0.5° resolution to a 1° × 1° spatial resolution to match the SST data. Mean annual flow direction and 1σ standard deviations were calculated using the CircStat MATLAB Toolbox (Berens, 2009).

2.4. Pseudoproxy Approach

The modern coordinates for Paleogene proxy-derived SST data come from the DeepMIP compilation (Hollis et al., 2019). Sites from high latitudes (>55°N/S), the Indian Ocean, and those with no obvious modern analog were removed from the compilation, resulting in 15 Late Paleocene, 18 Paleocene-Eocene Thermal Maximum, and 14 Early Eocene Climatic Optimum pseudoproxy sampling locations. Each site was assigned a representative basin and environment (Table S1) and a sampling swath was established by extracting all grid cells from that environment within ±5° of the modern latitude. For example, Lodo Gulch, located in California, USA (36.59°N, 120.64°W) was assigned to the Pacific Ocean eastern boundary; its sampling swath, therefore, includes all Pacific Ocean eastern boundary grid cells between 31.59°N and 41.59°N.

For each time interval, a latitudinal SST gradient was estimated by extracting one modern SST from each of the sampling swaths and fitting the data with a second-order polynomial. The exercise was repeated 1,000 times, allowing for determination of the mean and standard deviation of the pseudoproxy-inferred latitudinal temperature gradient. Note that the exercise was repeated using the same latitudinal bands but extending the sampling swaths across all longitudes. Using this approach, we found no statistically significant reduction to the modern gradient, confirming that any inflation or reduction to the latitudinal temperature gradient direct reflections environment-specific sampling biases, rather than over or under sampling of specific latitudes irrespective of environment.

2.5. ESM Simulations

We compare observed spatial patterns in SST with historical ESM simulations from CCSM4 (Danabasoglu et al., 2012), CESM (Kay et al., 2015), and HadCM3 (Johns et al., 2003). For consistency with the COBE-SST2 data, modeled mean monthly SSTs were regridded to a 1° × 1° spatial resolution and averaged over 1976 to 2005 (i.e., the last 30 years of the model simulation). Using climatological averages and similar time intervals for observed and modeled data avoids any offsets that could be related to anthropogenic forcing (e.g., compared preindustrial model SST to a late twentieth century climatology, which could have a strong fingerprint of warming).

3. Zonal Heterogeneity and Tectonic Configurations

Global maps of [MAT]° and [MART]° reveal large-scale systematic heterogeneity along latitudinal bands, qualitatively reflecting processes associated with the wind-driven ocean circulation (Figures 1a and 1b). Though the modern zonally averaged pole-to-equator temperature gradient is ~30°C, 70% of discrete latitudinal bands exhibit more than 5°C variability in MAT, and 14% of latitudes exhibit more than 10°C variability (Figure 1c). Similar variability is also observed in the paleo record, where, for example, during greenhouse intervals with suppressed latitudinal gradients, longitudinal variability in proxy temperature estimates within narrow latitudinal bins can even exceed the inferred latitudinal temperature gradient (Evans et al., 2018; Hollis et al., 2019). While some of the variance of paleo-SST estimates may be due to uncertainty in proxy calibration, time averaging, or analytical error, much of the longitudinal variation could alternatively reflect true spatial heterogeneity arising from ocean dynamics.

The majority of latitudes exhibit a broad range of MAT and MART values, but the magnitude and trend of the variability is hemispherically asymmetric (Figures 1c and 1d). The variance of both MAT and MART across latitudes exhibits a statistically significant positive relationship with the amount of land cover (Figure S3), suggesting this pattern is largely driven by tectonic configuration and can thus be predicted
even in the past. This is best exemplified in the high latitudes where the range of both MAT and MART in the Southern Hemisphere begins rapidly decreasing at ~55°S, yet boreal ranges remains high up to ~70°N. With no landmasses to divert zonal flow, the modern Antarctic Circumpolar Current homogenizes high-austral SSTs, while meridional flow within subpolar gyres in the noncontiguous high-boreal ocean basins amplifies the zonal heterogeneity of SSTs (Judd et al., 2019). This observation implies that the presence or absence and latitudinal position of circum-global currents should be considered when evaluating paleo-SSTs to determine meridional temperature gradients. It also suggests that large landmasses inflate zonal variability and highlights that past changes in tectonic configuration and ocean gateways exert an important influence on regional SST patterns.

4. Environment-Specific Variability in SSTs

Two types of geologic settings produce the vast majority of marine paleotemperature proxy data: epeiric seas and continental margins. To visualize the offsets related to these environments, we cross plot of [MART]* and [MAT]*. Locations emblematic of zonal mean climate will plot near the origin; indeed, over 40% of modern SST data fall within ±1°C of the zonal mean for both variables (Figure S4). However, a disproportionate number of data from epeiric seas and continental margins exhibit greater than 1°C deviation from the zonal mean. These deviations are nonrandom and driven by the particular dynamics in each of these environments.

4.1. Epeiric Seas and Semi-enclosed Basins

Subduction has recycled nearly all oceanic crust and accompanying sediment older than about 180 Ma (Müller et al., 1997), and many materials used to reconstruct SST (e.g., organic biomarkers and most microplankton) are unavailable until the late Mesozoic or early Cenozoic (Brassell, 2014; Schouten et al., 2004; Tappan & Loeblich, 1973). By necessity therefore, nearly all Paleozoic and many Mesozoic SST reconstructions rely instead on the geochemistry of skeletal macrofossils preserved within marine successions.
deposited on the continents. Given the prevalence of and reliance on these pre-Cenozoic epeiric SST records, our ability to reconstruct ancient climate systems hinges on how representative these environments are of global climate conditions at any given time.

Today, there are few true epeiric seas. However, we identify 10 semi-enclosed and marginal seas from across a range of latitudes to use as modern analogs (Figure 2a). On a cross plot of [MART]$^*$ and [MAT]$^*$, 75% of the data from epeiric sea analog locations plot in the upper right-hand quadrant, indicating warmer and more seasonal conditions than the zonal mean (Figure 2b and Table S2). In total, 81% of epeiric sea analog data are warmer (i.e., +[MAT]$^*$) and 92% more seasonal (i.e., +[MART]$^*$) than zonally anticipated. Across the entire global data set ($N = 43,723$), only 141 cells have [MART]$^*$ and [MAT]$^*$ values both exceeding +2.5°C, and remarkably, 114 (~80%) of these come from epeiric seas.

This analysis demonstrates that semi-enclosed basins are unusually warm and seasonal compared to the majority of open ocean locations situated at the same latitudes. These bodies of water are smaller and shallower, and often seasonally stratified, allowing surface waters to change temperature more rapidly than larger, deeper ocean basins. The surface of ice-free epeiric seas may heat up more strongly with the development of a summer thermocline. Seasonal runoff with strong temperature variability may also contribute to an amplified seasonal cycle in many semi-enclosed basins. This result has important, broad-reaching implications for paleoclimate studies: SST records older than the Cretaceous very likely overestimate zonal, and therefore global, temperatures.

The oxygen isotope record of skeletal carbonate and apatite over the Phanerozoic exhibits a secular depletion trend with increasing age, interpreted to reflect (1) the oxygen isotopic evolution of seawater ($\delta^{18}O_{sw}$) through geologic time, (2) a true temperature signal from a much warmer Paleozoic world, or (3) the increased influence of diageneric alteration with age (Jaffrés et al., 2007; Veizer & Prokoph, 2015). While thorough screening for altered materials has removed some of the most suspect values (Grossman, 2012), broadly, the trend holds true. However, mounting evidence suggests that epeiric seas are chemically and dynamically decoupled from the open ocean. Several authors have demonstrated geochemical differences between coeval open ocean and epeiric sea water masses (Brand et al., 2009; Holmden et al., 1998) and intrabasinal trends in isotope values that suggest epeiric seas have nonmarine seawater compositions (Brand et al., 2009; Jimenez et al., 2019; Montañez et al., 2018; Roark et al., 2017) ($\delta^{18}O_{sw}$). This hypothesized epeiric sea-open ocean $\delta^{18}O_{sw}$ offset, corroborated by observations of $\delta^{18}O_{sw}$ from modern epeiric sea analogs (LeGrande & Schmidt, 2006), is likely driven by many of the same factors generating warmer and more seasonal epeiric SSTs. Given the finding here, we propose that low skeletal $\delta^{18}O$ values in the Paleozoic can, in part, be explained by distinctive nonmarine $\delta^{18}O_{sw}$ values combined with the fact that these environments were likely warmer and more seasonal than their open ocean counterparts. A secular trend in $\delta^{18}O$-inferred temperature may therefore instead reflect changes in the proportional representation of environments from which samples are drawn over time.

### 4.2. Gyre Circulation

While most geochemically derived paleotemperature data from the Paleozoic are relegated to epeiric seas, many later Mesozoic and Cenozoic SST data come from settings in proximity to a continental margin, where both sedimentation rate and preservation potential are higher than in the deep sea (Gregor, 1985). For example, in both the Eocene and Pliocene, epochs of particular interest for studies attempting to constrain future climate sensitivity and latitudinal temperature gradients using analogs from the past (Burke et al., 2018),
more than half of all sampling localities are found within 500 km of a coastline (Figure 3a). SSTs in these environments are significantly offset from the zonal mean, resulting from first-order features of gyre circulation.

Eastern and western ocean margins each feature deviations in both [MART]* and [MAT]* related to patterns of wind-driven surface ocean circulation (Forget et al., 2015; Fukumori et al., 2017). Along western margins, 88% of data with poleward flow are warmer than the zonal mean (Figures 3b and S5 and Table S2), reflecting advection of warm water by the fast-moving western boundary currents of subtropical gyres. Seventy-nine percent of data from the western margins are also more seasonal than the zonal mean, reflecting the strong seasonality in meridional advection of warm water. This pattern reverses in the higher latitudes of the noncontiguous Northern Hemisphere ocean basins (>40°N), where equatorward flow from the subpolar gyres generates anomalously cold [MAT]* values (Figures 3c and S5 and Table S2). On eastern ocean margins, 90% of lower-latitude westward flowing locations have negative [MAT]* values, highlighting the role of upwelling and radiative cooling in generating cold temperatures in subtropical eastern margins (Seager et al., 2003). The majority of data from eastern margins are much less seasonal than western margins, and poleward of 40°N/S, eastward advection of warm waters from western ocean margins generates anomalously warm [MAT]* values (Figure 3c).

The paleoclimatic implications of these systematic patterns of [MART]* and [MAT]* are broad and often overlooked. For time intervals where paleoclimatic data preferentially come from eastern or western ocean boundaries, estimates of latitudinal temperature gradients may be significantly steepened or attenuated simply as a result of sampling bias. We explore this further by using a pseudoproxy approach to test the extent to which the known latitudinal temperature gradient can be approximated from modern SSTs derived only from locations for which there are paleo-SST data. Coordinates were drawn from the sampling localities included in the DeepMIP compilation for three time intervals within the Paleogene: the late Paleocene, the Paleocene-Eocene Thermal Maximum, and the Early Eocene Climactic Optimum (Hollis et al., 2019) (Table S1). A second-order polynomial fit through all zonal mean values produces a gradient of 26.2°C between 55°N/S; however, by including fewer modern SSTs, drawn only from regions for which there are paleodata, this gradient is reduced to 19.8°C, 19.5°C, and 21.7°C, respectively (Figure 3d). This measurable attenuation reflects a strong Paleogene sampling bias toward North Atlantic western boundary sites within the subtropical gyre, and eastern boundary sites from higher latitudes and epeiric seas (Figure S6), all of which culminates in compounding warmer-than-anticipated SSTs and a flattening of the inferred gradient. The steeper (albeit still reduced) gradient of the Early Eocene Climatic Optimum is due to the addition of several higher-latitude South Pacific western boundary locations. In the modern ocean, these sites help anchor the high latitudes; however given the noncontiguous nature of the Eocene Southern Ocean, it is unlikely to have had the same effect in deep time. Incidentally, shallower gradients are inferred throughout much of the Paleogene (Cramwinckel et al., 2018; Evans...
et al., 2018). While it is expected that greenhouse climates exhibit reduced pole-to-equator temperature gradients and it logically follows that shallower latitudinal gradients may decrease zonal variability, the magnitude of these reductions remain unclear. Nonetheless, this example demonstrates the ease with which the modern gradient can be artificially suppressed or inflated when using sparse and unevenly distributed data.

5. Comparison With Historical Simulations From ESMs

Many efforts to assess climate sensitivity and latitudinal temperature gradients in deep time focus on inter-comparisons of ESM simulations and proxy data (Caballero & Huber, 2013; Haywood et al., 2016; Hollis et al., 2019). In many cases, model simulations require unrealistic boundary conditions (e.g., extremely high pCO₂) to capture patterns present in proxy data (Huber & Caballero, 2011; Lunt et al., 2012) and many ESMs diverge dramatically in their predictions of the seasonal temperature cycle (Gasson et al., 2014). Recently, paleoclimatic data assimilation efforts have shown promise for characterizing past latitudinal temperature gradients (e.g., Tierney et al., 2019). To what extent can models successfully capture observed offsets in [MAT]* and [MART]* in coastal and epeiric sea environments?

Comparisons among three ESMs commonly applied in paleoclimate studies—CCSM4, CESM, and HadCM3—suggest that models reasonably simulate zonally heterogeneous SST patterns, with some key exceptions (Figure 4). Within western boundaries, the models, particularly CESM and CCSM4, show regions that are much warmer than observations, especially at confluence regions with strong eddy heat transport (e.g., where the Gulf Stream diverges from the North American coastline; the Brazil–Malvinas Confluence) (Figures 4 and S7). Coarse resolution ocean models, which do not resolve mesoscale processes, are unlikely to capture the correct magnitude of temperature in these regions (Kwon et al., 2010; Ma et al., 2016). For similar reasons, all three models substantially underestimate seasonality along the frontal regions of the North Atlantic and Pacific western boundaries, although this pattern is not consistently manifest across all western boundaries. Furthermore, the models differ in their performance along eastern margins. Model MAT and [MAT]* tend to exceed observed values, with the most dramatic offsets at locations of upwelling. CESM, which features an atmospheric model with updates to the cloud parameterization scheme resulting in a less negative short-wave cloud feedback (Gettelman et al., 2012), is more consistent with observed values.

The ESMs also show substantial spread in their estimates of temperature seasonality. Interestingly, while HadCM3 routinely overestimates the seasonality of temperature over land (Gasson et al., 2014), in the ocean MART and [MART]* are more consistently underestimated, particularly in highly seasonal (e.g.,

![Figure 4. Comparison of modeled and observed temperature parameters for three climatologically averaged historical ESM simulations. Positive (red) and negative (blue) indicate regions where ESMs overestimate or underestimate the temperature parameters, respectively.](image-url)
MART > 10°C) Northern Hemisphere locations (Figures 4 and S7). Conversely, CCSM4 and CESM preferentially overestimate seasonality in the Southern Hemisphere. However, these two models do not exhibit substantial biases in simulated mean annual temperature or seasonality in modern semi-enclosed basins (e.g., the Mediterranean). This suggests that these models may more successfully capture offsets between ancient epeiric seas and zonal mean temperatures.

Overall, models generally perform well but struggle to capture patterns of mean and seasonal temperature variability in specific dynamical environments. In particular, the deviation from observed values of model nearshore MAT and MART outputs, especially in confluence regions, suggests that unresolved coastal dynamical processes in ESMs could be partially responsible for many proxy-model mismatches in paleoclimatic modeling studies.

6. Lessons for Interpreting Paleo-SST Data

The analyses presented here demonstrate that proxy-based SST records are unevenly distributed across global paleo-oceans and that comparable settings in the modern ocean exhibit consistent, geographically systematic offsets from zonal mean values that are not always captured in coarse resolution ESMs. These observations are robust in the modern world and consistent with our current understanding of ocean dynamics. However, the precise manifestation of these patterns likely varies with changing boundary conditions. For example, the relationship between zonal variability and percent land cover may also be dependent on the zonal lacunarity of landmasses (e.g., Pangea). Similarly, the magnitude of SST amplification and direction of δ¹⁸Osw offset between epeiric seas and open ocean values is likely dependent upon water volume, latitudinal position, and other orographic and tectonic constraints. These nonanalogous considerations warrant further investigation through targeted studies. However, incorporating these insights from the modern ocean can result in more dynamically rigorous interpretations of ancient ocean temperature data and help resolve proxy-model mismatches. We outline three specific lessons below.

First, researchers must use caution when evaluating data drawn from epeiric seas, as these values are nearly always warmer and more seasonal than the zonal means. Isotope-enabled ESM simulations from models known to effectively capture the seasonality and temperature of modern semi-enclosed basins, as well as paired conventional oxygen and clumped isotope analyses, will be especially useful in deconvolving the concomitant influence of nonmarine δ¹⁸Osw and zonally inflated SSTs and, ultimately, backing out mean global climate conditions.

Second, time intervals where proxy data are only available for certain sides of ocean basins will preferentially reflect certain dynamical regimes that are systematically offset from the zonal mean. Extreme caution should be used when attempting to infer latitudinal temperature gradients from these data sets. Data assimilation methods may be helpful, provided that the models used in these efforts capture zonal heterogeneity in temperature. In addition, data from certain environments, especially regions of intense eddy heat transport, are unlikely to represent zonal mean conditions nor are they likely to be captured by models. A corollary of this lesson is that future sampling efforts for Cenozoic paleoclimate should focus on capturing signals from undersampled dynamical regimes (e.g., undersampled ocean margins).

Finally, our work highlights the importance of constraining the dynamical regimes from which proxy data are drawn in order to contextualize MAT data. Western and eastern boundary current environments are most reliably differentiated based on their [MART]* values (Figure 3). These seasonal deviations also have implications for interpreting proxy-derived MAT, as many proxies are postulated to have seasonal biases in certain environments (Fraile et al., 2009; Hollis et al., 2009; Malevich et al., 2019; Sluijs et al., 2009). Our results suggest that these seasonal biases may play a larger role along western ocean boundaries and epeiric seas, where MART is inflated. The addition of seasonal data may therefore help constrain the dynamical regimes and identify region-specific seasonal biases in MAT estimates.

Targeted generation of proxy data from undersampled dynamical regimes and paired measurements of mean temperature and seasonality will allow for better resolution of patterns in, and reasons for, zonal heterogeneity in observed paleotemperatures. A dynamical perspective of this heterogeneity based on the modern ocean allows for improved estimates of global MAT, latitudinal temperature gradients, and climate sensitivity and could even provide insights relative to shifts in the strength and position of gyre
circulation. Ultimately, capitalizing on the framework laid out above provides a way forward, where disagreements among proxy data are no longer impediments to an understanding of ancient temperatures but rather offer greater clarity about past thermal gradients and ocean dynamics.

Data Availability Statement

No new data are presented in this work. The COBE-SST2 data product is available through Hirahara et al. (2014) (https://psl.noaa.gov/data/gridded/data.cobe2.html), the ECCO V4r3 through Fukumori et al. (2017) (https://www.ecco-group.org/products.htm), the PRISM Pliocene compilation through the supporting information of Dowsett et al. (2013), and the DeepMIP Eocene compilation through the supporting information of Hollis et al. (2019).

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