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Key Points:

- Gridded sea-surface-temperature (gSST) and in situ loggers record similar temperature variations on decadal to monthly timescales
- Excess variability in coral-based temperature reconstructions relative to gSST is not due to differences in spatial scale

Supporting Information:

Supporting Information may be found in the online version of this article.

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Temperature Variability on Coral Reefs Versus Gridded SST – The Long and the Short of It

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Abstract Coral-based temperature reconstructions and gridded sea-surface-temperature (gSST) data sets both provide valuable insights into tropical climate variability. However, coral records often exhibit greater interannual to decadal variability than is observed in gSST products or Earth System Models (ESMs). This discrepancy is often attributed to large differences in spatial scale: coral records reflect conditions over areas of only a few square centimeters, while gSST and ESM grid cells span 1 to 10,000 km². In situ temperature loggers on coral reefs allow us to isolate the effects of spatial scale from other non-climatic influences on coral temperature records. Many logger studies focus on hourly to monthly timescales, temperature biases, and whether gSST can capture temperature extremes associated with coral bleaching and mortality; however, paleoclimate reconstructions provide an understanding of variability on longer timescales. Here, we compare the power spectral density and coherence of logger temperature and gSST on daily to decadal timescales using logger data from 42 sites on the Great Barrier Reef. We find that temperature variations recorded by loggers on reefs are well correlated with and have the same amplitude as gSST variations at decadal to annual timescales. Therefore, the excess decadal variability commonly seen in coral-based temperature reconstructions cannot be attributed to a general effect of spatial scale.

Plain Language Summary Coral-based temperature records are used to study past ocean temperatures. However, these records sometimes show more year-to-year and decade-to-decade variation than gridded temperature data sets from satellite- and ship-based measurements. One possible explanation is that corals measure temperature at a very small local scale, while global data sets average conditions over large areas. To test this idea, we analyzed data from temperature loggers placed at 42 sites across the Great Barrier Reef and compared them to gridded sea-surface temperature (gSST) data sets. We looked at how well the two matched at timescales from days to decades. Our results show that the variability of reef logger temperatures and gSST is very similar at annual to decadal timescales. This means that the extra variability often seen in coral-based temperature reconstructions is unlikely to be caused by differences in spatial scale alone.

1. Introduction

Tropical climate variability is a key driver of global climate variability with important modes on inter-annual (Indian Ocean Dipole, Saji et al., 1999, and El Niño-Southern Oscillation, Timmermann et al., 2018), interdecadal (Pacific Decadal Oscillation, Mantua et al., 1997; Power et al., 1999) and multidecadal timescales (Atlantic Multidecadal Oscillation, Schlesinger & Ramankutty, 1994). We rely on reconstructions from temperature-sensitive proxies to quantify past climate variability over timescales longer than, and in periods prior to, the instrumental record. Much of our knowledge of past variation in tropical sea-surface-temperature (SST) comes from Sr/Ca and δ^{18} O isotopes archived in coral skeletons (Correge, 2006; Felis, 2020). The temperature signals they contain can be reconstructed at monthly resolution, making it possible to count annual temperature cycles and have highly accurate chronologies. As such, corals provide a valuable information source against which to compare the tropical sea-surface-temperature variability simulated by earth system models (ESMs) (Dee et al., 2017; Laepple & Huybers, 2014; Parsons et al., 2017).

However, the temperature signal experienced by individual coral colonies, which record the temperature signal at a spatial scale from a few mm of a single polyp to several meters over a large Porites colony, may differ significantly from the gridded temperatures from satellites or simulated by ESMs, which represent means over many square kilometres (e.g., MPIOM high resolution version: $0.4 \times 0.4^{\circ}$, approximately 44×44 km or

DOLMAN AND LAEPPLE 1 of 10

2000 km², (Jungclaus et al., 2013)). Indeed, calibrated coral records frequently suggest more inter-annual and inter-decadal temperature variability than is seen in either instrumental or gridded gSST (hereafter gSST) (Dee et al., 2017; Dolman et al., 2025; Laepple & Huybers, 2014; Parsons et al., 2017; Scott et al., 2010 and references therein). This excess variability is often attributed to the large difference in spatial scales represented by coral-based reconstructions and gSST. It is argued that corals record temperature fluctuations on much smaller spatial scales that are not captured by the larger boxes of gridded temperature products, and that temperature variations are much larger at these reef-scale resolutions (DeLong et al., 2007; von Reumont et al., 2016). Similarly, when records from closely located colonies do not correlate well with each other, or the correlation with gSST is poor, it can be unclear whether these differences are due to very local temperature anomalies or metabolic effects from the coral (e.g., Evans et al., 2000; Pfeiffer et al., 2009).

While there are undoubtedly real differences in temperature variations over small spatial distances in complex 3D reef environments (Cyronak et al., 2020; Lee et al., 2020; Safaie et al., 2018), the importance of these spatial differences likely depends on timescale, as temperature anomalies will spread out over time due to mixing and diffusion in the ocean and atmosphere; thus, local processes which decorrelate colony-scale and gSST fluctuations on day-to-day or shorter timescales may diminish in importance at inter-annual and longer timescales (Jones et al., 1997; Kunz & Laepple, 2024). Contrary to the diffusivity argument, the physical structure of reefs and coastal environments influences ocean currents and is persistent over geological timescales. Coral colonies live at different depths in on-shore versus off-shore environments, and are frequently located near coasts where currents bringing cooler/warmer water can shift on inter-annual to decadal timescales. Therefore, persistent spatial differences cannot be discounted out of hand. Furthermore, even given a link between spatial and temporal scales, the actual timescale at which a given pair of spatial scales becomes linked still needs to be determined.

Addressing these questions by comparing gSST with temperature reconstructions from the corals themselves is challenging because corals are complex biological organisms, it would be difficult to separate spatial and spatial-scale effects from other sources of uncertainty such as inter-colony differences in the calibration with temperature (Correge, 2006), the potentially timescale dependent effect of overgrowth of the skeleton ("biosmoothing" Gagan et al., 2012), varying growth rate effects (Barnes et al., 1995), or other biological changes effecting the "vital effects" of the organism over time (Cohen, 2002; Meibom et al., 2003). To sidestep these issues, we take advantage of in situ temperature loggers located in typical coral reef environments. Temperature loggers record the local temperature signal at approximately the same spatial scale as individual coral colonies; therefore, if logger temperatures and gSST agree with each other, then this removes the spatial scale as an explanation for the average discrepancy between gSST and temperature reconstructions from corals.

Existing studies comparing reef-located logger temperatures with gSST have focussed on daily or shorter timescales, often concerned with how well satellite-based SST products can predict or represent the conditions experienced by corals (Bos & Pinsky, 2025); in particular biases in temperature (Castillo & Lima, 2010; Gomez et al., 2020; Margaritis et al., 2025) and whether they miss temperature extremes that can trigger bleaching and coral mortality (Bos & Pinsky, 2025; Lachs et al., 2025; Margaritis et al., 2025; Safaie et al., 2018). However, in the context of past climate reconstruction, we are typically concerned with variation on longer timescales and at larger spatial scales. Examining monthly resolution logger and satellite SST data from Jarvis Island, Alpert et al. (2016) found no statistical difference in their mean and variance over an approximately 10-year period; however, this and other time-domain analysis mixes the variation across monthly to decadal timescales. The total variance of a monthly resolution SST timeseries will be dominated in most cases by the variance of the annual cycle. Any differences at other timescales might be obscured by either agreement or disagreement in the annual cycle amplitude. Here we use frequency based analyses (power spectra) to isolate variance at different timescales. Additionally, we analyze daily anomalies, removing the influence of the annual cycle on other frequencies. We compare logger and gSST variations at shorter (daily) and longer inter-annual to decadal timescales, and consider on what timescales temperature records from individual coral colonies should be representative of larger spatial scale gSST from models and instruments, as well as the timescales at which gSST can inform us about conditions experienced by coral colonies. We use composite logger deployments of at least 10 years to (a) compare the power spectral density (PSD) of in situ versus satellite gSST at daily to decadal temporal scales, and (b) measure the coherence of logger and gSST temperatures to examine correlation across daily to decadal timescales.

DOLMAN AND LAEPPLE 2 of 10

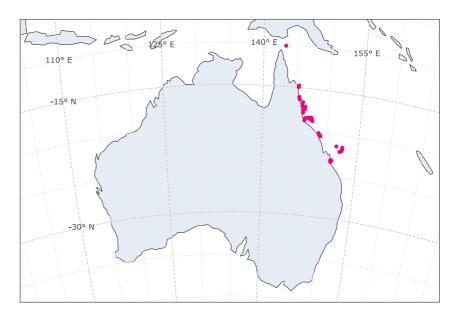


Figure 1. Locations of the 42 coral reef sites with 10 or more years of unbroken in situ temperature logger measurements.

2. Materials and Methods

2.1. AIMS In Situ Logger Data

In situ temperature logger data were downloaded as daily mean values from the AIMS Sea Water Temperature Observing System (AIMS Temperature Logger Program) (Australian Institute of Marine Science (AIMS), 2017) using the AIMS Data Platform API and the R package "dataaimsr."

Sites were initially identified for which data spanned at least a 10-year period. These data consisted of multiple sequential, 1–3 years duration logger deployments at each site, potentially across several subsites, and included large gaps. Where there were logger deployments at multiple subsites at the same site and time, two approaches were used to obtain a single timeseries per site: (a) taking means across subsites, and (b) joining timeseries together from single subsites at a given time.

- (a) Daily mean recorded temperature was calculated for each site by averaging across subsites. The geographical distance between subsites was calculated to later screen for very distant subsites. The maximum distance between subsites in the final data set was 5.85 km. The difference in depth between subsites was also calculated to check for the effects of changing logger deployment depth over time. Gaps of up-to 7 days in these site-composite temperature series were filled by linear interpolation, and those with gaps longer than 7 days were treated as separate time series (site-runs). These gap-filled site-runs were then screened for continuous runs of at least 10 years.
- (b) For site-runs identified in (a) with multiple subsites, the median longitude, latitude and logger depth were calculated across all observations. For each timepoint (day), the values from the logger closest to the median location for that site-run were retained, and any others were discarded. Given a tie in distance to the median location, the logger nearest to the median depth was used. If there were still multiple deployments (there were occasionally replicated deployments at exactly the same location), the mean of their values was used. In this way, at a given time, values at a site always consisted of observations from a single point in space. Gaps of up-to 7 days were then filled as for method (a). This resulted in 45 10+ year time series at 42 sites (Figures 1, S1 and Table S1 in Supporting Information S1) in which there were 523 interpolated values out of a total of 220547 data points (0.24%).

Method (a) has the potential to reduce the variability of logger timeseries by averaging across spatial variability of up to 5.85 km between subsites at a site. Method (b) in contrast might exaggerate logger variability by misattributing spatial variability to temporal variability at the timescale in which loggers were swapped out (1–3 years). Analyses were run on both data sets with only very tiny quantitative differences in the results. Here

DOLMAN AND LAEPPLE 3 of 10

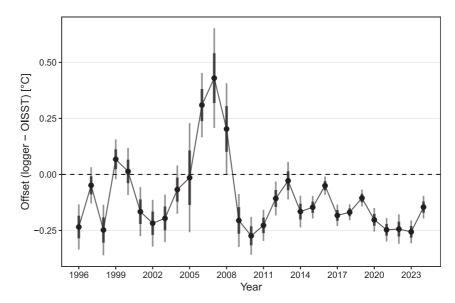


Figure 2. Mean annual offset between logger temperature and OISST (logger - OISST) averaged across all sites (± 1 and 2 SE). In situ reef loggers typically record temperatures approximately 0.2°C cooler than OISSTv2.1. However, there was a strong anomaly in the years 2006–2008 in which in situ temperatures were on average warmer than OISST.

we present only results from method (b), which more closely approximates the situation where one logger record presents one hypothetical record from a single coral colony.

2.2. Gridded SST Data

Optimum Interpolation Sea Surface Temperature (OISST) Version 2.1 data (Huang et al., 2021) were downloaded at daily resolution on a $0.25 \times 0.25^{\circ}$ grid from NOAA PSL at https://www.psl.noaa.gov/data/gridded/data.noaa.oisst.v2.highres.html Accessed 2025.01.23. OISST data were extracted for each of the 42 logger sites using distance weighted remapping (CDO command "remapdis") and matched by year and day to the daily resolution logger temperatures.

2.3. Logger Data Issues

While processing and examining the logger and OISST data, it became apparent that there were issues with some logger data in the period of 2006–2009. The in situ reef loggers typically recorded temperatures approximately 0.2°C cooler than OISST. This is consistent with the warm bias found in OISSTV2.1 for the GBR region (Huang et al., 2021). However, there was a strong anomaly in the years 2006–2008 in which in situ temperatures were on average warmer than OISST (Figure 2).

Large offsets between logger temperatures and OISST frequently started and ended with changes in logger deployment (loggers being replaced with new/reconditioned ones). The same new offset could sometimes be seen in separate loggers deployed at the same time at different subsites and depths at the same reef site. This occurs for example, at Kelso Reef in 2005–2006 (Figure S2 in Supporting Information S1) and Dip Reef in 2007–2008 (Figure S3 in Supporting Information S1). The effect is most clear in the difference between the logger temperature and OISST but can also be seen in the logger data. Therefore, there is good reason to be suspicious of some of the logger data in the 2006–2008 period.

The suggested logger data anomalies have little effect on the power spectrum analysis but destroy the coherence between logger temperatures and OISST on longer timescales. Therefore, in coherence plots, we indicate whether timeseries included the years 2006–2008.

2.4. Power Spectral Analysis

To compare the variability of logger temperature and OISST at different timescales, we estimate their power spectral density (PSD), which expresses the variability in a timeseries as a function of frequency (or equivalently

DOLMAN AND LAEPPLE 4 of 10

periodicity, 1/frequency). To reduce the influence of the annual cycle, which will otherwise dominate estimates of PSD and variance, we first calculate daily temperature anomalies by subtracting from each value the mean temperature for the corresponding day of the year calculated for that logger or OISST record. The power spectra of logger temperature and OISST were then estimated separately for each unbroken timeseries of daily anomalies (45 site-runs at 42 sites) using the adaptive multitaper method. This method reduces estimation uncertainty and leakage in the spectral estimates (Springford et al., 2020; Thomson, 1982). We used only three tapers to limit the loss of frequency resolution and downward bias in power estimates for the lowest frequencies that come from tapering.

For each site-run, the logger to OISST PSD ratio was calculated by dividing the respective spectra at each resolved frequency. As these spectra were estimated from time series of the same length, their ratio was unaffected by tapering biases. Mean logger and OISST spectra, and mean PSD ratios were calculated by averaging spectra and their ratios across site-runs, after interpolating onto a common frequency axis.

2.5. Coherence

As we expected the correlation between logger temperature and gSST to be dependent on timescale, to assess correlation, we estimated the squared coherency spectrum between pairs of timeseries. The squared coherency is similar to a conventional squared correlation coefficient but depends on frequency (Storch & Zwiers, 1999). Coherency was calculated separately for each site-run. As there was good reason to be suspicious of records covering the period 2006–2008, in coherence plots we indicate whether a timeseries included the years 2006–2008.

3. Results

We first compare the mean power spectrum (averaged across sites) of the in situ logger and OISST daily temperature anomalies (Figure 3a). Both show a general increase in power spectral density (PSD) with timescale. The downward spikes at the frequency of the annual cycle ($f = 1 \text{ yr}^{-1}$) and its harmonics are an artifact of removing the annual cycle. Across timescales from decadal ($f = 1/10 \text{ yr}^{-1}$) down to monthly ($f = 12 \text{ yr}^{-1}$), mean PSD was nearly identical for in situ logger temperatures and OISST (Figure 3a). At shorter than monthly timescales, the PSD of the logger and OISST temperatures start to diverge, with the logger PSD falling below that of the OISST.

To examine this more closely, we calculated the logger and OISST PSD ratio for each site-run (continuous logger timeseries at a site), and the mean across site-runs (Figure 3b). Average logger PSD was only slightly higher than OISST PSD across a broad frequency range, from decadal to monthly. Over the longer decadal to inter-annual timescales, the logger to OISST ratio varied from 0.44 to 1.98 between site-runs, with a mean ratio of 1.16 (Table 1), indicating only 16% higher average PSD for logger data than for OISST (Figure 3b). However, at monthly to inter-daily timescales, the logger to OISST ratio declined below one so that by timescales of 3–4 days (approx. $f = 100 \text{ yr}^{-1}$) average logger variability was less than half that of OISST (Fig 2b and Table 1). As the same PSD does not necessarily imply that the logger and the OISST data are correlated, we also examine the squared coherency as a function of timescale (Figure 3c). Again, at longer timescales, the coherence between the logger temperature and OISST was high. Between decadal and inter-annual timescales, squared coherence averaged 0.90 for site-runs that did not include the problematic 2006–2008 period. Site-runs which included logger deployments in 2006–2008 were particularly affected by what seems to be a calibration issue which biases coherence down on longer timescales (see Section 2 and Supporting Information S1). In contrast to the PSD ratio (Figure 3b), coherence begins to decline at timescales between annual and monthly, so that squared coherence is only 0.5 at monthly timescales (Figure 3c).

To study the influence of logger depth, we examined the PSD ratio and coherence of logger temperatures and OISST as a function of logger deployment depth for different timescales (Figure 4). At sub-monthly timescales, the logger-OISST variance ratio was strongly related to differences in logger depth across site-runs, but this effect became weaker with increasing timescale. At decadal to annual timescales, there is no relationship between logger depth and the PSD ratio (Figure 4a). In contrast, while squared coherency declines at faster timescales (Figure 3c), there is no relationship between coherency and logger depth (Figure 4b).

DOLMAN AND LAEPPLE 5 of 10

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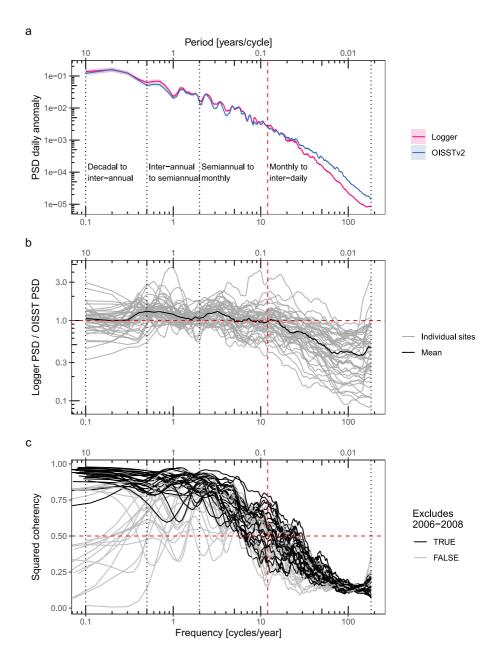


Figure 3. A comparison of power spectral density (PSD) and coherence across decadal to inter-daily timescales for in situ logger and OISST daily temperature anomalies. (a) PSD of in situ logger and OISST daily temperature anomalies averaged across 45 timeseries (site-runs) at 42 coral reef sites. (b) The ratio of logger to OISST PSD for individual site-runs (gray lines) and the mean ratio across all site-runs (black line). (c) Coherency between logger and OISST daily temperature anomalies for each site-run. Lines in gray indicate timeseries that included the years 2006–2008 for which we observed issues with some of the logger data.

4. Discussion

This direct comparison of gridded satellite SST with reef-located in situ temperature loggers demonstrates that, despite the very large difference in spatial resolution, there is little difference in variability, and high coherence between logger and gSST temperatures from decadal down to inter-annual timescales. This means that the large differences in inter-annual to decadal variability seen between gridded instrumental SST and temperature reconstructed from corals are unlikely to be due to the difference in spatial scale.

DOLMAN AND LAEPPLE 6 of 10

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Table 1
The Ratio of In Situ Logger to OISST PSD at Decadal to Inter-Daily Timescales

Freq. band	Freq. band name	Mean	Standard deviation	Min	Median	Max
(0.09,0.5]	Decadal to inter-annual	1.16	0.31	0.44	1.13	1.98
(0.5,2]	Inter-annual to semiannual	1.20	0.23	0.96	1.17	2.23
(2,12]	Semiannual to monthly	1.09	0.39	0.61	1.03	2.90
(12,182]	Monthly to inter-daily	0.53	0.25	0.18	0.50	1.21

Note. Logger to OISST PSD ratio is calculated for daily anomalies over decadal to inter-annual, inter-annual to semi-annual (2 cycles per year), semi-annual to monthly, and monthly to inter-daily timescales. Shown are summary statistics across 45 site-runs at 42 reef sites.

In contrast, at inter-daily timescales, the coral-scale and gridded temperature fluctuations are essentially uncorrelated, indicating that OISST contains no information about the daily fluctuations in temperature experienced by corals. Part of the decorrelation at this temporal scale could be due to the limitations of the gSST product. In particular, statistical infilling of missing observations from surrounding clear-sky data and model priors may preserve the correct variability in the OISSTv2.1 product, but not capture the correct phase of variations, and thus reduce coherency on monthly to daily timescales. These monthly to daily timescale results are consistent with previous studies that have found that even much higher resolution satellite based SST fails to capture the

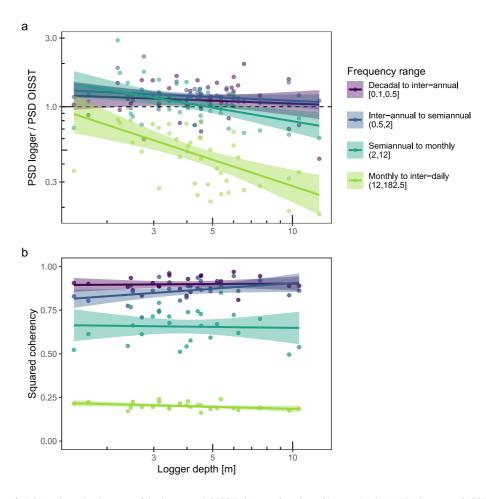


Figure 4. PSD ratio and coherence of the logger and OISSTv2.1 as a function of logger depth. (a) The logger to OISST PSD ratio against depth at four different timescales. Frequency bands are given in units of cycles per year. The horizontal dashed line shows a ratio of 1, indicating logger temperature PSD equal to OISST PSD. (b) Squared coherency between logger temperatures and OISST as a function of depth and timescale.

DOLMAN AND LAEPPLE 7 of 10

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temperature conditions experienced by corals at daily timescales, for example, Bos and Pinsky (2025) who compared AIMS logger data with the 0.01° resolution NASA Multi-scale Ultra-high Resolution Sea Surface Temperature product, Margaritis et al. (2025), who compared the European Space Agency's Climate Change Initiative for SST product to loggers at six sites in the Caribbean, or Lachs et al. (2025) who compared CoralTemp v3.1 ($0.05^{\circ} \sim 5$ km grid) and the Multiscale Ultra-high Resolution MUR v4.1 ($0.01^{\circ} \sim 1$ km grid) to logger temperatures in Palau.

In addition to becoming decorrelated, at timescales shorter than monthly, logger PSD declined relative to OISST and this difference is strongly related to the depth at which the logger was deployed (Figure 4a). The lower PSD in logger records at inter-daily timescales is likely because fluctuations in temperature at the ocean skin surface on these timescales are driven by interactions with atmospheric weather patterns, but these are buffered at depths greater than 1 m due to the thermal inertia of the water buffering the downward propagation of the surface signal.

Importantly, the discrepancies between loggers and gSST at monthly to daily timescales are less relevant to questions about model-proxy and instrumental-proxy comparisons, as temperature reconstructions from corals are not typically resolved at higher than monthly resolutions. At inter-annual to decadal timescales, logger and OISST PSD were approximately equal, and coherency was high, even for loggers deployed at depths of 10 m. Loggers (and corals) located at depths of 1–10 m should therefore consistently capture decadal temperature signals.

The increasing similarity between point and grid scale temperature fluctuations as timescale increases is likely a general consequence of ocean circulation and diffusive processes, as the phenomenon is also seen in stochastically forced climate and energy balance models (Kim & North, 1991; North et al., 2011; Rypdal et al., 2015) and has been confirmed in global observations of temperature variability on decadal and shorter time scales (Jones et al., 1997; Kim & North, 1991). Therefore, although this analysis was geographically restricted to the Australian Great Barrier Reef, we would expect these results to generalize to other reef building regions. Hence, in principle, temperature reconstructions from point-scale proxies such as coral skeletons should be suitable for comparison with gridded ESM model output. Likewise, gridded SST products can be used to validate the variation of temperature-sensitive point proxies on these timescales. Where there are large average differences in variance on monthly to decadal timescales between proxies and gridded SST, these must be a feature of the proxy that is unrelated to spatial scale.

5. Conclusions

Whether the temperature variability experienced by coral colonies on reefs is representative of SST variability at the scale of SST product and ESM model grids will, in general, depend on the temporal scale of interest, and in specific cases, on the physical characteristics of the local site in relation to the wider ocean. In general, as the timescale increases, SST variations become more similar in amplitude and more coherent between spatial scales. This was confirmed by examining temperatures recorded by loggers at 42 reef sites on the Australian Great Barrier Reef, which had the same average variability and were coherent with gridded SST from annual up-to decadal timescales. Therefore, discrepancies in variance between coral based temperature reconstructions and gridded SST cannot in general be explained by the different spatial scales they represent.

Data Availability Statement

Code to download and process the AIMs logger data, and to reproduce the analyses presented in this manuscript, is publicly available in a Github repository and archived at Zenodo (Dolman, 2025). NOAA OI SST V2 High Resolution Data set data were provided by the NOAA PSL, Boulder, Colorado, USA, from their website (NOAA, 2025). In situ temperature logger data were provided by the AIMS Sea Water Temperature Observing System (Australian Institute of Marine Science (AIMS), 2017). Spectral analysis was performed in R (R Core Team. (2024).

References

Alpert, A. E., Cohen, A. L., Oppo, D. W., DeCarlo, T. M., Gove, J. M., & Young, C. W. (2016). Comparison of equatorial Pacific sea surface temperature variability and trends with Sr/Ca records from multiple corals. *Paleoceanography*, 31(2), 252–265. https://doi.org/10.1002/ 2015PA002897

Australian Institute of Marine Science (AIMS). (2017). AIMS sea water temperature observing system [Dataset]. AIMS Temperature Logger Program. https://doi.org/10.25845/5b4eb0f9bb848

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DOLMAN AND LAEPPLE 8 of 10

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- Barnes, D. J., Taylor, R. B., & Lough, J. M. (1995). On the inclusion of trace materials into massive coral skeletons. Part II: Distortions in skeletal records of annual climate cycles due to growth processes. *Journal of Experimental Marine Biology and Ecology*, 194(2), 251–275. https://doi.org/10.1016/0022-0981(95)00091-7
- Bos, J. T., & Pinsky, M. L. (2025). Fine resolution satellite sea surface temperatures capture the conditions experienced by corals at monthly but not daily timescales. *Coral Reefs*. 44(2), 423–434. https://doi.org/10.1007/s00338-024-02611-8
- Castillo, K. D., & Lima, F. P. (2010). Comparison of in situ and satellite-derived (MODIS-Aqua/Terra) methods for assessing temperatures on coral reefs. *Limnology and Oceanography: Methods*, 8(3), 107–117. https://doi.org/10.4319/lom.2010.8.0107
- Cohen, A. L., Owens, K. E., Layne, G. D., & Shimizu, N. (2002). The effect of algal symbionts on the accuracy of Sr/Ca paleotemperatures from coral. Science, 296(5566), 331–333. https://doi.org/10.1126/science.1069330
- Correge, T. (2006). Sea surface temperature and salinity reconstruction from coral geochemical tracers. *Palaeogeography, Palaeoclimatology*, *Palaeoecology*, 232(2–4), 408–428. https://doi.org/10.1016/j.palaeo.2005.10.014
- Cyronak, T., Takeshita, Y., Courtney, T. A., DeCarlo, E. H., Eyre, B. D., Kline, D. I., et al. (2020). Diel temperature and pH variability scale with depth across diverse coral reef habitats. *Limnology and Oceanography Letters*, 5(2), 193–203. https://doi.org/10.1002/lol2.10129
- Dee, S. G., Parsons, L. A., Loope, G. R., Overpeck, J. T., Ault, T. R., & Emile-Geay, J. (2017). Improved spectral comparisons of paleoclimate models and observations via proxy system modeling: Implications for multi-decadal variability. *Earth and Planetary Science Letters*, 476, 34–46. https://doi.org/10.1016/j.epsl.2017.07.036
- DeLong, K. L., Quinn, T. M., & Taylor, F. W. (2007). Reconstructing twentieth-century sea surface temperature variability in the southwest Pacific: A replication study using multiple coral Sr/Ca records from New Caledonia. *Paleoceanography*, 22(4), 1–18. https://doi.org/10.1029/2007pa001444
- Dolman, A. (2025). EarthSystemDiagnostics/DolmanLaeppleLoggerGSST2025: v0.1 (Version v0.1). Zenodo. https://doi.org/10.5281/zenodo. 15096109
- Dolman, A., McPartland, M., Felis, T., & Laepple, T. (2025). Coral records exaggerate past decadal tropical climate variability. *Research Square*. https://doi.org/10.21203/rs.3.rs-3924954/v1
- Evans, M. N., Kaplan, A., & Cane, M. A. (2000). Intercomparison of coral oxygen isotope data and historical sea surface temperature (SST): Potential for coral-based SST field reconstructions. *Paleoceanography*, 15(5), 551–563. https://doi.org/10.1029/2000PA000498
- Felis, T. (2020). Extending the instrumental record of ocean-atmosphere variability into the last interglacial using tropical corals. *Oceanography*, 33(2), 68–79. https://doi.org/10.5670/oceanog.2020.209
- Gagan, M. K., Dunbar, G. B., & Suzuki, A. (2012). The effect of skeletal mass accumulation in *Porites* on coral Sr/Ca and δ^{18} O paleothermometry: Skeletogenesis and coral thermometry. *Paleoceanography*, 27(1), 1–16. https://doi.org/10.1029/2011PA002215
- Gomez, A. M., McDonald, K. C., Shein, K., DeVries, S., Armstrong, R. A., Hernandez, W. J., & Carlo, M. (2020). Comparison of Satellite-Based Sea Surface Temperature to In Situ Observations Surrounding Coral Reefs in La Parguera, Puerto Rico. *Journal of Marine Science and Engineering*, 8(6), 453. https://doi.org/10.3390/jmse8060453
- Huang, B., Liu, C., Banzon, V., Freeman, E., Graham, G., Hankins, B., et al. (2021). Improvements of the Daily Optimum Interpolation Sea Surface Temperature (DOISST) Version 2.1. *Journal of Climate*, 34(8), 2923–2939. https://doi.org/10.1175/JCLI-D-20-0166.1
- Jones, P. D., Osborn, T. J., & Briffa, K. R. (1997). Estimating sampling errors in large-scale temperature averages. *Journal of Climate*, 10(10), 2548–2568. https://doi.org/10.1175/1520-0442(1997)010<2548:ESEILS>2.0.CO:2
- Jungclaus, J. H., Fischer, N., Haak, H., Lohmann, K., Marotzke, J., Matei, D., et al. (2013). Characteristics of the ocean simulations in the Max Planck Institute Ocean Model (MPIOM) the ocean component of the MPI-Earth system model. *Journal of Advances in Modeling Earth Systems*, 5(2), 422–446. https://doi.org/10.1002/jame.20023
- Kim, K.-Y., & North, G. R. (1991). Surface temperature fluctuations in a stochastic climate model. *Journal of Geophysical Research*, 96(D10), 18573–18580. https://doi.org/10.1029/91JD01959
- Kunz, T., & Laepple, T. (2024). Effective spatial degrees of freedom of natural temperature variability as a function of frequency. *Journal of Climate*, 37(8), 2505–2518. https://doi.org/10.1175/JCLI-D-23-0040.1
- Lachs, L., Donner, S., Edwards, A. J., Golbuu, Y., & Guest, J. (2025). Higher spatial resolution is not always better: Evaluating satellite-sensed sea surface temperature products for a west Pacific coral reef system. Scientific Reports, 15(1), 1321. https://doi.org/10.1038/s41598-024-84289-0
- Laepple, T., & Huybers, P. (2014). Ocean surface temperature variability: Large model-data differences at decadal and longer periods. Proceedings of the National Academy of Sciences, 111(47), 16682–16687. https://doi.org/10.1073/pnas.1412077111
- Lee, I.-H., Fan, T.-Y., Fu, K.-H., & Ko, D. S. (2020). Temporal variation in daily temperature minima in coral reefs of Nanwan Bay, Southern Taiwan. Scientific Reports, 10(1), 8656. https://doi.org/10.1038/s41598-020-65194-8
- Mantua, N. J., Hare, S. R., Zhang, Y., Wallace, J. M., & Francis, R. C. (1997). A Pacific interdecadal climate oscillation with impacts on salmon production. Bulletin of the American Meteorological Society, 78(6), 1069–1080. https://doi.org/10.1175/1520-0477(1997)078<1069: APICOW>2.0.CO:2
- Margaritis, G., Kent, E. C., & Foster, G. L. (2025). Intercomparison of satellite-derived SST with logger data in the Caribbean—Implications for coral reef monitoring. PLOS Climate, 4(1), e0000480. https://doi.org/10.1371/journal.pclm.0000480
- Meibom, A., Stage, M., Wooden, J., Constantz, B. R., Dunbar, R. B., Owen, A., et al. (2003). Monthly Strontium/Calcium oscillations in symbiotic coral aragonite: Biological effects limiting the precision of the paleotemperature proxy. Geophysical Research Letters, 30(7). https://doi.org/10.1029/2002GL016864
- NOAA. (2025). NOAA OI SST V2 high resolution dataset [Dataset]. https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.highres.html
- North, G. R., Wang, J., & Genton, M. G. (2011). Correlation models for temperature fields. *Journal of Climate*, 24(22), 5850–5862. https://doi.org/10.1175/2011JCLI4199.1
- Parsons, L. A., Loope, G. R., Overpeck, J. T., Ault, T. R., Stouffer, R., & Cole, J. E. (2017). Temperature and precipitation variance in CMIP5 simulations and paleoclimate records of the last millennium. *Journal of Climate*, 30(22), 8885–8912. https://doi.org/10.1175/JCLI-D-16-0863.1
- Pfeiffer, M., Dullo, W.-C., Zinke, J., & Garbe-Schönberg, D. (2009). Three monthly coral Sr/Ca records from the Chagos Archipelago covering the period of 1950–1995 A.D.: Reproducibility and implications for quantitative reconstructions of sea surface temperature variations. *International Journal of Earth Sciences*, 98(1), 53–66. https://doi.org/10.1007/s00531-008-0326-z
- Power, S., Casey, T., Folland, C., Colman, A., & Mehta, V. (1999). Inter-decadal modulation of the impact of ENSO on Australia. *Climate Dynamics*, 15(5), 319–324. https://doi.org/10.1007/s003820050284
- R Core Team. (2024). R: A language and environment for statistical computing. R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/
- Rypdal, K., Rypdal, M., & Fredriksen, H.-B. (2015). Spatiotemporal long-range persistence in Earth's temperature field: Analysis of stochastic-diffusive energy balance models. *Journal of Climate*, 28(21), 8379–8395. https://doi.org/10.1175/JCLI-D-15-0183.1

DOLMAN AND LAEPPLE 9 of 10

- Saji, N. H., Goswami, B. N., Vinayachandran, P. N., & Yamagata, T. (1999). A dipole mode in the tropical Indian Ocean. *Nature*, 401(6751), 360–363. https://doi.org/10.1038/43854
- Schlesinger, M. E., & Ramankutty, N. (1994). An oscillation in the global climate system of period 65–70 years. *Nature*, 367(6465), 723–726. https://doi.org/10.1038/367723a0
- Scott, R. B., Holland, C. L., & Quinn, T. M. (2010). Multidecadal trends in instrumental SST and coral proxy Sr/Ca records. *Journal of Climate*, 23(5), 1017–1033. https://doi.org/10.1175/2009JCL12386.1
- Springford, A., Eadie, G. M., & Thomson, D. J. (2020). Improving the lomb–scargle periodogram with the Thomson Multitaper. *The Astronomical Journal*, 159(5), 205. https://doi.org/10.3847/1538-3881/ab7fa1
- von Reumont, J., Hetzinger, S., Garbe-Schönberg, D., Manfrino, C., & Dullo, W. -Chr. (2016). Impact of warming events on reef-scale temperature variability as captured in two Little Cayman coral Sr/Ca records. *Geochemistry, Geophysics, Geosystems*, 17(3), 846–857. https://doi.org/10.1002/2015gc006194
- von Storch, H., & Zwiers, F. W. (1999). Statistical analysis in climate research. Cambridge University Press. https://doi.org/10.1017/CBO9780511612336
- Thomson, D. J. (1982). Spectrum estimation and harmonic analysis. *Proceedings of the IEEE*, 70(9), 1055–1096. https://doi.org/10.1109/proc. 1982.12433
- Timmermann, A., An, S.-I., Kug, J.-S., Jin, F.-F., Cai, W., Capotondi, A., et al. (2018). El Niño-Southern Oscillation complexity. *Nature*, 559(7715), 535-545. https://doi.org/10.1038/s41586-018-0252-6

DOLMAN AND LAEPPLE 10 of 10