INTRODUCTION

The sea surface temperature (SST) is a key essential climate variable (ECV, e.g. Bojinski et al., 2014) and a key essential ocean variables (EOV, e.g. Lindstrom et al., 2012), with observations and datasets of the SST used in many studies. These include, inter alia: climate monitoring reports (e.g. IPCC, 2014; Blunden et al., 2019); boundary layer for atmospheric/oceanographic model forcing (e.g. Dee et al., 2011); validation and assessment of coupled models (e.g. Flato et al., 2013); air–sea interaction studies; and ecosystem studies (Villegas-Hernández et al., 2015).

Due to its widespread use and importance, simple gridded and statistically reconstructed/infilled datasets of the sea surface temperature have been created. These include datasets spanning the period ~1,850—present on a relatively coarse resolution and covers the Atlantic Ocean. The dataset is based on in situ sea surface temperature observations from the International Comprehensive Ocean-Atmosphere Data Set interpolated using Kriging to infill gaps and is available from the Centre for Environmental Data Analysis (CEDA) archive. Compared to existing datasets, the resolution is increased by a factor of 4 spatially and 6 temporally.

KEYWORDS

Atlantic Ocean, ICOADS, reconstruction, Sea Surface Temperature, SST, VOS

1 | INTRODUCTION

The sea surface temperature (SST) is a key essential climate variable (ECV, e.g. Bojinski et al., 2014) and a key essential ocean variables (EOV, e.g. Lindstrom et al., 2012), with observations and datasets of the SST used in many studies. These include, inter alia: climate monitoring reports (e.g. IPCC, 2014; Blunden et al., 2019); boundary layer for atmospheric/oceanographic model forcing (e.g. Dee et al., 2011); validation and assessment of coupled models (e.g. Flato et al., 2013); air–sea interaction studies; and ecosystem studies (Villegas-Hernández et al., 2015).

Due to its widespread use and importance, simple gridded and statistically reconstructed/infilled datasets of the sea surface temperature have been created. These include datasets spanning the period ~1,850—present on a relatively coarse resolution (e.g. Rayner et al., 2003; Hirahara et al., 2014; Huang et al., 2017; Kennedy et al., 2019) and datasets spanning the satellite era (~1980 – present) at higher resolutions (e.g. Merchant et al., 2014, 2019). The longer datasets...
typically have a monthly resolution and a spatial resolution of either 1° or 5°, with all the datasets based on the observations available within the International Comprehensive Ocean-Atmosphere Data Set (ICOADS, Freeman et al., 2017). The primary differences between datasets are the treatment of biases in the observations and the infilling/gridding methods used. This dataset (ICOADS) is discussed further in Section 2, including known problems with the data. The datasets spanning the recent past typically have much higher resolution; for example, the recent European Space Agency (ESA) Climate Change Initiative (CCI) SST dataset (Merchant et al., 2014, 2019) has a daily temporal resolution and 1/20° spatial resolution. These datasets are typically based on satellite data.

While the resolution of models (oceanographic, atmospheric, coupled) has increased with computing power, the resolution of gridded SST products, particularly those that extend before 1980, has largely remained static. This is due to inadequate sampling over large regions of the global oceans prior to the satellite era. While the sampling does not justify higher resolution products over much of the global oceans, the North Atlantic is an exception. In this region, the sampling density is much higher due to the density of shipping lanes and trade between Europe and the rest of the world (e.g. see Figure 1). In this paper, we describe a new SST dataset, making use of the increased sampling to produce an intermediate resolution dataset for the Atlantic. The new dataset, ‘ACSIS Atlantic Ocean

FIGURE 1 Map of the Atlantic Ocean showing the number of pentads with a measurement for each grid cell. Maximum number of pentads is 4,748
medium resolution SST dataset', contains spatially interpolated estimates of the sea surface temperature on a 0.5° spatial grid, 5-day temporal resolution and spans the period 1950 – 2014. Section 2 describes the source observations and interpolation methods. Section 3 provides information on the new dataset, its location and format. Section 4 describes uses of the dataset and its limitations.

2 | DATA PRODUCTION METHODS

2.1 | Input data, spatial domain and data selection

2.1.1 | Input data

The new dataset described in this paper is based on the SST observations available from the ICOADS Release 3 (ICOADS R3.0 hereafter; Freeman et al., 2017). The ICOADS R3.0 contains weather reports made on board ships, including the upper ocean, spanning the period ~1650–2014. Data from other platforms, for example drifting buoys, are also included. A near real-time (NRT) update to ICOADS, ICOADS R3.0.1, is available but there have been issues with the data included in this update (Freeman et al., 2019). Consequently, only R3.0 has been used. Once the issues with the NRT update have been resolved, an updated version of the new dataset described in this paper will be produced.

The early weather reports in ICOADS are typically based on visual observations of the weather (present weather, wind force, sea state, ice), with instrumental observations (air temperature, sea temperature, pressure) beginning in the mid-19th century. More recently, the observations have included instrumental observations of wind speed and humidity. Beginning in the late 1980s and early 1990s, there are an increasing number of drifting buoy observations, with the drifting buoys dominating the in situ SST record from the mid-2000s onwards (e.g. Huang et al., 2017).

The SST observations were made using a variety of methods, ranging from measuring the temperature of a sample of water collected in a canvas bucket, through engine intake measurements to infrared radiometric observations (Kent et al., 2007), with the bucket and engine intake measurements the most common. Each method of observation has suffered from distinct biases and, as the methods used have changed over time, time varying biases exist in the raw data. For example, the measurements based on samples collected in buckets are biased cold due to cooling of the water sample in the buckets prior to measurement. Similarly, the temperature measurements of water sampled from the engine cooling intake tend to be biased high due to heat from the engine room. Prior authors and dataset developers (e.g. Kennedy et al., 2011a; Kennedy et al., 2011b; Hirahara et al., 2014; Huang et al., 2017; Kennedy et al., 2019) have applied bias corrections to reduce the impact of the biases on the climate record. A summary of the prior work on understanding and reducing the impact of these biases and the impact on the uncertainty in the SST climate record can be found in Kennedy (2014) and Kent et al. (2017). Recent work by others has included the examination of biases in different types of buckets (e.g. Carella et al., 2017; Chan and Huybers, 2019).

Within the new dataset, nearly all observations for the period 1950 – 2014 and within the selected spatial domain (section 2.1.1) from ICOADS R3.0 have been used. This includes all ship based and drifting buoy observations. Those from moored buoys and other platforms have been excluded due to either a short period of record (e.g. Argo) or sparse point locations (e.g. moored buoys). In addition to ICOADS R3.0, global daily-mean sea surface temperatures, presented on a 0.05° latitude–longitude grid, with gaps between available daily observations filled by statistical means, spanning 1981 to 2016 from the ESA SST CCI SST version 2.0 product (SST CCI analysis, Good et al., 2019; Merchant et al., 2019) have been used to define covariances between grid cells (Section 2.3), estimate the sampling uncertainty (Section 2.2) and define the climatology.

2.1.2 | Spatial Domain and Selection of Data

The Atlantic Ocean in this dataset is as defined in the International Hydrographic Organization (IHO) publication S23, ‘Limits of oceans and Seas’ 3rd edition. Individual grid points are masked by this region and by the presence of data in the CCI SST gridded dataset. The extent of the grid covering the entire Atlantic Ocean is from 60°S to 68°N and 98°W to 20°E and the temporal coverage is from 1 January 1950 to 31 December 2014 with the first five-day period centred around mid-day GMT 3 January 1950. This produces a full grid of 256 x 236 points spatially, and 4,748 time steps. There are, in total, 33,080 grid cells per time step to interpolate and a total of 157,063,840 grid boxes. There are 83,536,825 observations from ships and drifting buoys in the region during the period occupying 22,790,841 grid boxes (14.5% of the total number of grid boxes) of which 14,291,205 have one single observation (63%) and 3,904,988 have two observations (17%). The maximum number of observations in a single grid cell is 1,121 from 10 individual buoys from a point in the middle of the North Atlantic (25.25°N, 37.75°W). We only used data from the ICOADS dataset if the trimming flag was less than or equal to 5.
2.2 | Initial Gridding

2.2.1 | Calculation of Super-observations

For each grid box where there are data, we calculated the mean, median, trimmed mean (5th percentile at each end), sample standard deviation, sample trimmed standard deviation and interquartile range. The trimmed mean and sample standard deviations only differ from the mean and sample standard deviation if there are more than 10 observations in the grid box. Also recorded in the gridded ICOADS data file are the number of buoys and ships per grid box and the number of unique ships and buoys. These are useful if attempting to calculate the input data uncertainties.

The super-observations are then expressed as residuals from the 1981–2014 Climatology derived from the CCI SST analysis. The climatology consists of a mean together with annual, semi-annual and tri-annual terms fitted using least squares. We chose to use the CCI SST analysis rather than from the ICOADS dataset itself because there are regions, especially the Southern Atlantic Ocean (Figure 1) where the data are too sparse to derive a good climatology. The climatology does not include the trend since it may not reflect that over the whole 1950–2014 period.

FIGURE 2 | Regional Variability of SST for the Atlantic Region in terms of the standard deviation derived from the CCI SST analysis dataset
Kennedy et al. (2011a, 2014), the observational uncertainties are a product of three main errors: random measurement, bias and sampling errors. They estimated the measurement error to be 0.74°C and 0.26°C for ships and drifting buoys, respectively, and the bias error to be 0.71°C and 0.29°C for those platforms. We also performed several tests on the ICOADS data to derive estimates of the measurement and bias error. These included fits to the sample standard deviations as a function of the number of ships and buoys and unique ships and buoys per grid box, direct comparison with the CCI SST analysis for a small sample of grids with abundant data and examining the distribution of sample standard deviations from grid cells with there was either only one vessel or all the vessels were different. We estimate the uncertainties to be 1.47°C and 0.38°C for the ship and buoy bias error and 0.73°C and 0.24°C for the measurement errors, respectively. Our bias errors are larger than Kennedy et al. (2011a) because individual measurement biases had not been removed from the ICOADS data prior to this (see Bias Reduction section below). This will imply that we are slightly cautious with our bias error when propagating to our observational uncertainties for the interpolation.

The sampling error is the error that arises when a finite number of observations are used to estimate a grid box average from a field that is spatially varying in that area. The sampling uncertainty term was given by Kennedy et al. (2011a) by the following equation.

\[ \sigma^2_{se} = \frac{\sigma^2_s}{n} \left(1 - r^2\right) \]

where \(n\) is the number of observations in a grid box; \(\sigma^2_s\) is the variance of the SST anomalies at a point and assumed to be constant within a given grid box. \(r\) is the average correlation between any two points within the grid box. Kennedy et al. (2011a) calculated \(\sigma^2_s\) from grid boxes with very large \(n\) and estimated \(r\) by calculating inter-grid box correlations and taking averages in space and combining these with their equivalent time correlations. Here, we use the CCI SST analysis to derive \(\sigma^2_s \left(1 - r^2\right)\) by simply estimating the variance from the intra-grid values. Since the CCI SST analysis is daily with a resolution of 1/20th degree that gives 10x10x5 values with which to calculate the variance in each grid box Figure 2. We note that estimating sampling uncertainty from the SST CCI analysis assumes that spatial variability at very small scales is correct. However, the SST CCI analysis already encodes assumptions about the small-scale spatial structure and its relationship to observational error in the satellite retrievals and therefore may bias the sample uncertainty estimates but we feel this is still a sensible approach to assigning sampling uncertainties for each grid box.

The sampling uncertainty from a single observation, \(\sqrt{\sigma^2_s \left(1 - r^2\right)}\), has a seasonal cycle, particularly in coastal zones, upwelling regions, fronts and narrow currents. We also see this in the ICOADS grids where we have a plenitude of data for example, Figure 3. To take this into account and extend the sampling uncertainty over the whole time frame of the dataset, we fit a climatology (mean, annual, semi-annual, tri-annual) to the CCI grid box variability and use this to derive our sampling uncertainty for the interpolation. Since the standard deviations are not normally distributed and to avoid producing anything negative, we fit the climatology in least squares assuming a log-normal distribution.

### 2.3 | Interpolation

Many methods have been used previously for reconstructing historical sea surface temperature records, including optimal interpolation (Lorenc, 1981; Reynolds and Smith, 1994) or Simple Kriging (Krige, 1951; Cressie, 1990); optimal smoothing,
Kalman Filter and reduced space optimal interpolation (Kaplan et al., 1998); variational Bayesian principal component analysis (VBPCA; Ilin and Kaplan, 2009); and reduced space Kalman smoother (Karspeck et al., 2012). Here, we use Simple Kriging, interpolating the super-observations calculated in 2.2.1. to estimate spatially complete fields of the SST. As part of the Kriging process, the mean field is subtracted from the super-observations by subtracting the climatological mean to give anomalies. These are then interpolated by using Equations 2 and 3:

\[ z_k = CH^T (HCH^T + HRH^T)^{-1} Hd \]  
(2)

and

\[ C_{zk} = C - CH^T (HCH^T + HRH^T)^{-1} HC \]  
(3)

Where \( z_k \) are the interpolated values, and their covariance (\( C_{zk} \)), over the whole grid, \( C \) is the spatial covariance of the signal, \( R \) is a diagonal matrix (nominally, if disregarding observational correlations,) of the estimated variances of the errors in the observations, \( H \) is a matrix that maps the data for a given epoch to the full set of grid points, and \( d \) is the full vector of climatology-removed observations (0 for missing observations). The spatial covariance terms \( C \) have been estimated using the ESA CCI SST analysis data. Rather than estimating the spatial covariances using a parametric approach, for example using variograms, we have estimated the covariance between grid boxes directly from the ESA CCI SST analysis data. Figure 4 illustrates the range in variation in the cross-correlation for three points in the Atlantic Ocean derived from the ESA CI SST derived covariance. A point in the vicinity of the Gulf Stream (Figure 4, middle) has a smaller correlation distance than the other two points. This is similar to the approach taken by Church et al. (2004) when reconstructing global sea level using tide gauges and a satellite altimetry field. In this dataset, we have ignored inter-grid observational correlations in \( R \) simply because we assert that given the temporal scale used and that we are interpolating spatially, the correlations would have a negligible effect in the interpolation. However, note that intra-grid correlations are accounted for via the methodology described below. We can take two approaches here to estimate the variance of the super-observations calculated in 2.2.1. First, we can calculate a theoretical uncertainty based on the values derived in 2.2.2 and using the equation (adapted from Kennedy et al., 2011a equation 8).

\[ \sigma_{err}^2 = \frac{1}{n} \left( \frac{n_s \sigma_{m_{\text{ship}}}^2 + n_b \sigma_{m_{\text{buoy}}}^2}{n_s + n_b} \right) + \frac{1}{n^2} \left( \frac{n_s^2}{m_s} \sigma_{b_{\text{ship}}}^2 + \frac{n_b^2}{m_b} \sigma_{b_{\text{buoy}}}^2 \right) + \frac{1}{n} \sigma_s^2 \left( 1 - r \right) \]  
(4)

where \( n_s \) and \( n_b \) (\( n_s + n_b = n \)) are the number of ship and buoy measurements in a grid box and \( m_s \) and \( m_b \) are the number of ships and buoys in a grid box. Also \( \sigma_{m_{\text{ship}}} \) and \( \sigma_{m_{\text{buoy}}} \) are the ship and buoy measurement uncertainties and \( \sigma_{b_{\text{ship}}} \) and \( \sigma_{b_{\text{buoy}}} \) are the bias uncertainties. For simplicity, this assumes that each of the \( m \) ships and buoys makes the same number of observations in the grid box and the measurement and bias uncertainties are the same for all ships and buoys.

A second approach is to use the sample standard deviations (or the trimmed sample standard deviations) as these reflect the true variations in the observations. If the error came from just one source, then we would calculate the uncertainty of the observation as

\[ \sigma_{err}^2 = \frac{1}{n} \sigma_{\text{sample}}^2 \]  
(5)

where \( \sigma_{\text{sample}}^2 \) is the sample standard deviation. However, where there are more than one source of noise, and these depend on the number of ships, buoys and the number of measurements; this is too simplistic. In addition, where the sample sizes are small, the sample standard deviations are likely to be biased (Cochran, 1934) or not quantifiable if there is only one observation in the grid cell. Therefore, we take a hybrid approach to estimating the measurement uncertainties. For grid cells with only one or two observations, we use the estimates from Equation 4. For all other grid cells, we calculate a predicted sample standard deviation using the measurement, bias and sample uncertainties and taking care of biases due to small sample sizes. If a grid cell sample standard deviation is less than the predicted value, we use the estimates from Equation 4. If it is larger, then we take the ratio of the predicted sample standard deviation and Equation 4 and scale the sample standard deviation by this ratio.

2.4 Bias reduction

As noted in section 2.1.1, the SST observations contain biases and prior authors have developed bias corrections to reduce the impacts of these biases. Rather than developing a new bias correction, we have interpolated the bias correction from the HadSST.0.0.0 dataset (Kennedy et al., 2019) to our analysis grid. The bias correction was derived by taking the difference between the median and the unadjusted SST anomalies grids (HadSST.4.0.0.0_median.nc and HadSST.4.0.0.0_unadjusted.nc). This interpolated bias adjustment has then been subtracted from the super-observations to give a bias-adjusted dataset.
2.5 Verification

To validate the data, we again use the SST CCI analysis dataset. Figure 5 shows a map of mean absolute error (MAE) for the differences between our interpolated results and the CCI SST analysis residuals (CCI SST analysis minus the climatology). We calculate an overall mean absolute error of 0.39°C. We also calculate the MAE for the whole region as a function of time step (Figure 6). The MAE has gradually reduced from around 0.45°C in the early 1980s to about 0.35°C now. We also examined the correlation and coherence between the two datasets both spatially and temporally (Figure 7). The magnitude squared coherence (Stoica and Moses, 2005) acts as a form of correlation in the frequency domain. We see that the spatially averaged coherence between the two datasets increases at longer periods (Figure 7). The obvious drops in coherence are at the annual and its harmonics which are expected because the climatology has been removed from both sets. The increasing correlation at longer periods can also be seen in the middle panels of Figure 7 which show averaged coherence at low, median and high frequencies. Lower coherence between the two datasets at shorter periods is to be expected for several reasons. First, the power-law nature of many geophysical series (Agnew, 1992) including SST (e.g. Bürgert and Hsieh, 1989) means that the largest signals are at the longest periods and are likely to have the highest correlation. Secondly, random measurement noise will manifest itself more at higher frequencies for the same reason as above, reducing the correlations at short periods. Finally, the CCI SST analysis is subject to some degree of smoothing when infilling gaps in observations (Merchant et al., 2019). This again will be at short periods and wavelengths, reducing the correlation there. Overall the correlation (Figure 7, top right) is greatest in the Northern Atlantic Ocean except in the region of the gulf stream. It is not necessarily where the data is the densest (Figure 1) but tracks more where the SST variation is lowest (Figure 2). However, in the Southern Atlantic Ocean, the lower correlation outside of the regions of high variability is probably due to data density. Overall the correlation has increased over time from the start of the CCI dataset to the present (Figure 7, bottom). Finally, note that Figure 7 top right and middle left are similar since they both reflect the low-frequency correlation. However, Figure 7 top left is the Pearson correlation coefficient calculated in the time domain and the coherence in Figure 7 middle left is calculated in the spectral domain.

Figure 8(top) shows a map of the uncertainty averaged over 1950 – 2014. Over the majority of the ocean, the uncertainty is in the range 0.2–0.4°C, increasing to over 1°C in the high variability regions. Figure 8(bottom) shows the time series of the spatially averaged uncertainty over the same period. The uncertainty decreases from ~0.45°C during the 1950s to just over 0.3°C by 2014. The impact of the drifting buoy network can be seen in the mid-2000s, with a sharp decrease in the uncertainty.

Figure 9 shows the mean anomaly (w.r.t. 1981–2014) for a sample month (January 1963) from HadSST4.0.0.0, ERSST5 (Huang et al., 2017) and the new dataset at their native spatial resolutions, 5°, 2° and 0.5°, respectively. Also shown are the products averaged or interpolated to
the other resolutions. In general, good agreement is seen between the different products but with some differences. These are expected due to different gridding methods and/or bias adjustments. The increased spatial variability and finer structures are clearly visible in the new product. Figure 10 shows a time series of the spatially averaged anomaly (w.r.t 1981–2014) for the three datasets. Again, there is generally good agreement overall but with differences between individual time periods.

To validate the estimated (formal) uncertainties derived from Equation 4, we split the grids into groups depending on the formal uncertainty size in steps of 0.2°C and then

**Figure 5** Map of mean absolute error between the ICOADS interpolated and the CCI SST analysis residuals

**Figure 6** Mean absolute error between the ICOADS interpolated residuals and the CCI SST analysis residuals as a function of time
produced boxplots for the differences between this dataset and the CCI SST analysis (Figure 11). We use Tukey style whiskers (1.5 × interquartile range, IQR) past the 25th to 75th percentile boxes. The increasing spread with increasing formal uncertainty validates those uncertainties. Overall, if we take the differences and divide by the formal uncertainties, we find that the uncertainties slightly conservative with a median value of 1.4. The formal uncertainties should therefore be scaled by 1.4 to be more realistic.

As a final test to validate the performance of the interpolation where grid cells had no super-observations, we performed an internal test with the CCI SST analysis only. Here,
we sampled the CCI SST data at the times and positions of the ICOADS measurements and then interpolated these in the same way as before. We then took all the grid cells that had no super-observations and compared the interpolated with the actual CCI SST values (Figure 12). Similar to Figure 11, we split the comparison as a function of the formal uncertainties. The scatter plots are colour-coded based on the density of the points in the region. Points with a density of less than 1,000 per °C are removed for clarity. We find good correlation (0.95) between the interpolated values and the CCI data for unsampled regions for the formal uncertainties of between 0 and 0.2°C. As the formal uncertainties increase, the correlation decreases and is indicative of a slight reduction in the magnitude of the anomalies. We acknowledge that we are pushing the boundaries with these resolutions especially in data sparse regions such as the Southern Hemisphere. However, we are still confident that the results are useful. Figure 13 is an example of a point in the Southern Atlantic Ocean with low correlation (0.56) and a small number (26) of observations. The fit is still good, particularly at long wavelengths.

FIGURE 8 Mean uncertainty in ICOADS interpolated SST (top) over 1950–2014 and (bottom) spatially averaged over the Atlantic Ocean
**Figure 9** Monthly mean SST anomaly for January 1963 (w.r.t 1981–2014) for HadSST4 (left column), ERSST5 (middle column) and this dataset (right column) at native resolution and averaged to the resolution of the other datasets.

**Figure 10** Spatially averaged SST anomalies over Atlantic Ocean for HadSST4 (solid black), ERSST5 (dotted black) and this dataset (red dashed). HadSST4 and ERSST5 have been interpolated to the same grid as the new estimates (0.5°, 5 day) prior to averaging and only grid cells with estimates in all 3 datasets used. For comparison, the spatially complete values for the new dataset are also shown in blue. A 6-point running mean filter has been applied to all time series for clarity.
**FIGURE 11**  Box plot of the ICOADS interpolated SST minus CCI SST analysis as a function of the derived formal uncertainty. Red lines indicate the median, box indicates the 25th to 75th percentile, and the whiskers are Tukey style ($1.5 \times$ IQR) beyond the percentiles. Dotted lines indicate the expected 25th and 75th percentile based on the formal uncertainty. Dashed lines indicate the predicted $1.5 \times$ IQR.

**FIGURE 12**  Scatter plots of CCI SST analysis estimates mapped to ICOADS measurement times and positions and then interpolated as for the dataset versus the CCI SST analysis. Only grid cells that do not include ‘observations’ are included. Colours represent the density of points in the region. Points where the density is less than 1,000 points per °C are removed for clarity. The white ellipses are the 50th, 95th and 99th percentiles derived from the estimated covariance between the two datasets. The results have been partitioned as a function of the formal uncertainties (range given in the top left of each plot).
The dataset is available from the Centre for Environmental Data Analysis (CEDA) archive in annual CF complaint NetCDF files, with a total of 65 annual files are available. Each file contains: the 5-day mean sea surface temperature; the corresponding climatological value, the sea surface temperature anomaly and the uncertainty in the sea surface temperature. The data are freely open and available with no restrictions on use but prior registration is required to download the data. More information on the CEDA archive and access to the data can be found at http://archive.ceda.ac.uk/.

The new dataset presented in this paper has been developed as part of the UK North Atlantic Climate System Integrated Study (ACSIS) for use in validating and comparing with regional climate models. Other potential uses include boundary forcing for regional re-analyses, monitoring and assessment of regional climate change and other studies requiring SST at a resolution higher than typical for the in situ products (i.e. <1 month, <1°) and spanning the satellite and presatellite era. Future plans for the dataset include updating to use the ICOADS NRT updates once the known issues have been resolved and investigation of whether a resolution of 0.25° daily is feasible with the in situ data.

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This article has earned an Open Data badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. The data is available at http://dx.doi.org/10.5285/83b0cd7e7cc6495a90b4cb967ead3577 Learn more about the Open Practices badges from the Center for OpenScience: https://osf.io/tvyxz/wiki

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