Forecasting tropical ENSO-induced drought conditions using sea surface height in the Western Pacific

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ABSTRACT

The interannual variability of rainfall caused by the El Niño-Southern Oscillation (ENSO) results in significant deviations in hydrologic conditions. Forecasting ENSO and its impacts are mainly based on Central Pacific Sea surface temperature (SST) anomalies which satisfactorily correlate with timing and, to a lesser extent, the intensity of drought conditions in the Philippines and the Western Pacific during the El Niño phase. Changes in sea surface height (SSH) are also brought about upon ENSO through seawater density changes with temperature and oceanographic processes. Here, we report that the associative nature of SSH and drought, as measured by surface runoff, has a better correlation ($r > 0.693$, $p < 0.05$) in terms of the expected timing (1 to 3 month lag) and intensity compared to using SST indices. Furthermore, since SSH is co-located with its corresponding forecasted decrease in runoff, a localised prediction can be made which further increases the accuracy of this predictive tool and can be used in tandem with SST-based ENSO indices. In the wake of a changing climate, the ability to forecast the timing and volume of rainfall and surface water availability is of utmost importance, especially within the context of food and water security.

1. Introduction

The El Niño-Southern Oscillation (ENSO) results in significant deviations in continental rainfall primarily in the Eastern Pacific, but its effects on the water cycle are felt via atmosphere-ocean teleconnections across the globe (Alexander et al., 2002; Behera et al., 2021; Diaz et al., 2001; Kousky et al., 1984; Zhang et al., 2022). ENSO is triggered by sea surface temperature (SST) anomalies emanating from the Central and Eastern Pacific and is primarily used to predict the ensuing ENSO impacts. Significant work has been done in fine-tuning SST-based indicators such as constraining the region of warming, resulting in the identification of the Niño Index Regions and the development of the ENSO indices (Rasmusson & Carpenter, 1982; Ren & Jin, 2011; Santosó et al., 2017; Trenberth, 1997). Further, the recognition of different ENSO ‘flavors’ has led to the development of other indices (Trenberth & Stepania, 2001), the use of dynamic ocean–atmosphere coupled models (Tozuka & Yamagata, 2003; Wengel et al., 2021), and improved data assimilation and interpolation techniques (Kirtman, 2003; Zambrano Mera et al., 2018) in order to extend and potentially improve the accuracy of predictions for impacts associated with ENSO teleconnections. A majority of these improvements are geared towards predicting impacts in the Eastern Pacific (e.g. Echevin et al., 2018; Jaranilla-Sanchez et al., 2011; Ludescher et al., 2013; M. Q. Villafuerte & Matsumoto, 2015); however, research is increasingly focusing on forecasting ENSO impacts in other regions owing to this phenomenon’s far-reaching effects on global climate variability on interannual timescales, occurring every two to seven years (Ham et al., 2019; Sarachik & Cane, 2010; Thirumalai et al., 2017).

Many counter-intervening processes are in operation in the Central and Eastern Pacific, including the timing of the annual cycles of outgoing longwave radiation which affects atmospheric convection and in turn controls the location and intensity of warming in the tropical Pacific (Liu et al., 2011; Trenberth, 1997; W. Zhou & Chan, 2007). Further, ocean–atmosphere coupled models have also been found to be less accurate in predicting the global SST pattern during weak ENSO events (Sohn et al., 2016). Similar ocean–atmosphere interactions in the Western Pacific and other parts of the globe may likewise complicate the ensuing ENSO impact in the countries bordering the Western Pacific. Zhao et al. (2021) recognise the variability of the atmospheric characteristics in the western Pacific that in turn affects the translation of SST anomalies to precipitation changes in the region. Thus, a more localised indicator of interannual variability is required to provide better predictive capabilities for these countries beyond the indices based solely on the Central...
and Eastern Pacific SST anomalies. In this work, we explore such an indicator using sea surface height (SSH) as a predictive tool for tropical drought as measured by the ensuing decrease in river runoff.

SSH is directly tied to SST as water expands with higher temperatures thus warmer waters result in higher SSH areas (Casey & Adamec, 2002; Jones et al., 1998). On a larger scale, SSH changes in the Pacific Ocean are also brought upon by strong eastward Kelvin waves during ENSO events (Nezlin & McWilliams, 2003). The relationship of SSH with temperature led Shi et al. (2020) to develop an SSH-based index that approximates the available potential energy (APE) variations in the ocean. This index was demonstrated to differentiate the Central Pacific from Eastern Pacific El Niño types rather than the more traditionally used SST-based indices. Additionally, researchers have previously recognised the strong association \( r = 0.7 \) between low rainfall conditions and low sea level measurements in Panjung, Indonesia during ENSO events (Harger, 1995). Harger attributed this observation to the surging of the waters to the east of the Pacific, leaving a ‘thinned-out’ western region.

Situated in the equatorial Western Pacific, the Philippine Archipelago is ten thousand kilometres away from the Central Pacific yet extremely affected by ENSO variability, albeit with the reverse sign of what is experienced in the Eastern Pacific. During the El Niño phase, drought conditions are felt across the different islands of the country (Harger, 1995; Lyon & Camargo, 2009). SST anomalies generally correlate with drought conditions in the Western Pacific but become less accurate with regard to the onset and expected intensity of drought vis a vis the intensity of ENSO conditions. In fact, the onset of the 2009–2010 moderate intensity El Niño years resulted in extensive rainfall in the Philippines (Yumul et al., 2010), the opposite of the canonically expected sign. Meteorological records show that each ENSO event is unique due to other compounding factors, such as the variation of rainfall and temperature in the years preceding the event and the presence of large-scale monsoon systems. The former appears to modulate the intensity of the succeeding ENSO event, as seen from data in east Indonesia where upward-moving temperature records during non-ENSO periods delivered a hotter dry season (Harger, 1995). Meanwhile, the regional monsoon-related processes have been associated with a seasonal reversal of rainfall signatures between boreal summers in the Philippines and boreal falls (October to December; Harger, 1995; Lyon et al., 2006). Spatial variations related to the magnitude of decrease in rainfall due to El Niño conditions were also observed across the country. Drought indices, such as the Standard Precipitation Index (SPI) and Standardised Precipitation Evapotranspiration Index (SPEI), have revealed the western and southeastern seaboard experience relatively higher drought magnitudes and intensities, with the latter having a longer duration of droughts (Salvacion, 2021).

The latest Intergovernmental Panel on Climate Change (IPCC) report concluded that it will be virtually certain that the ENSO will remain the dominant mode of interannual variability for rainfall in a warmer world. Moreover, it is very likely that rainfall variability related to changes in the strength and spatial extent of ENSO teleconnections will lead to significant changes at regional scale (IPCC, 2021). As such, this is a compelling reason why our predictive capabilities of droughts, particularly those induced by El Niño (Benitez, 2021; Izumi et al., 2014; Perez et al., 2016; Yumul et al., 2010) should be further enhanced.

Given the motivating need for a more localised indicator of drought (Dariagan et al., 2021; Dawe et al., 2009; Porio et al., 2019), this paper presents the use of local SSH measurements as a high-resolution indicator of drought conditions across the Philippine Archipelago in an analogous sense to using ENSO indices for such forecasting. Even with only several months in advance, the accurate prediction of local hydrologic conditions coupled with an effective water management programme will allow for climate change adaptation measures to be implemented. To the best of our knowledge, while SST and SST-based ENSO indices have been previously used to look at drought and extreme rainfall (Hilario et al., 2009; Jose et al., 1996; Lyon & Camargo, 2009; Lyon et al., 2006; M. Villafuerte & Matsumoto, 2014; Villafuerte et al., 2014, 2015, 2015), this is the first time that it is being reported that SSH data is used for localised ENSO-related drought prediction for the Philippines.

2. Methods

2.1. Data

The primary data used for this study were monthly composites of SSH and runoff from satellite altimetry records and the Global Runoff Reconstruction (GRUN) Ensemble dataset, respectively. Drought is herein quantified based on stream discharge, in particular the amount of decrease in the minimum observed flow in rivers. In the following sections, we introduce the origin and data handling of these datasets.

2.1.1. Satellite altimetry data

Daily level-4 SSH products with a spatial resolution of 0.25° (~27 km) were retrieved from the Copernicus Marine Environmental Monitoring Service (CMEMS) database. These datasets are the products of the most recent version of the Data Unification and Altimeter Combination System – delayed time (DUACS DT2018), implemented since April 2018 to produce merged datasets of all available satellite
2.1.2. GRUN Ensemble

The GRUN Ensemble dataset is a global runoff product derived from a machine learning algorithm trained using streamflow observations from the Global Streamflow Indices and Metadata Archive (GSIM). It has a spatial resolution of 0.5° (~55 km) spanning from 1901 to 2019. Only discharge data from catchment basins with areas between 10 and 2,500 km² were used as training input to the algorithm (Ghiggi et al., 2021, 2019). This version of the GRUN dataset (Ghiggi et al., 2021) improves upon the first iteration (Ghiggi et al., 2019) by using temperature and rainfall data from an ensemble of 21 global datasets as input to the developed algorithm. Validation of the runoff product utilised discharge data from basins with more than 10,000 km² of area and its accuracy was assessed against nine other global hydrological models (Ghiggi et al., 2021).

One of the earliest local-scale validations of the GRUN algorithm was conducted by Ibarra et al. (2021) by comparing the original version of the runoff product against discharge gauges across the Philippines. They found reasonable utility in the log₁₀-transformed data at the country scale, which further improves when a nationwide bias correction derived from the river gauge comparison is applied. Further, recent work on coastal runoff correlation in the Philippines to chlorophyll-a concentrations has successfully used the GRUN gridded datasets to assess the relationship between the two parameters across the country. Custado and David demonstrated the direct impact of runoff on the productivity of several open coasts and embayments across the country; meanwhile, variable influence was inferred for upwelling areas (Custado & David, 2021a, 2021b).

2.1.3. River gauge data

The Philippines has daily stream gauge data for more than 100 rivers with gauging programmes starting as early as the turn of the twentieth century (Toletino et al., 2016). Unfortunately, like in many other countries, most gauging data are not continuous and thus we use the global GRUN dataset as a proxy for stream flow in parts where data are sparse. For this study, stream gauging data of seven of the 18 major river basins of the country were selected on the basis of location, period of the gauging data available and the size of the drainage basin area (Figure 1). These were directly compared to SSH values of the grid overlapping with each of the rivers’ outlet to the ocean as a verification of our methods.

2.2. Data pre-processing

The GRUN data files were transformed to 0.25° × 0.25° spatial resolution using the conservative nearest-neighbour interpolation method to match with the retrieved SSH data. Daily SSH data were averaged to obtain monthly composites. All the data were spliced to an area bounded by 3.125 to 22.125°N and 114.125 to 131.875°E. River gauge data were converted from litres/second to mm/day to match with the GRUN dataset using the basin areas reported in Ibarra et al. (2021).

2.3. Data analysis

The runoff dataset was log₁₀-transformed following Ibarra et al. (2021) based on their comparison to the original version of GRUN, while the SSH dataset was not normalised or log₁₀-transformed. We do this because runoff values vary by several orders of magnitude.
magnitude and represent heavy-tailed distributions, while SSH values only vary by a small amount (~37%).

In order to minimise the influence of seasonal cycles and long-term linear trends, all datasets were deseasonalised and detrended prior to correlation analysis. The seasonality was removed by taking the 12-month centred moving average of each time series. Afterwards, linear regression was applied to each time series to obtain the corresponding linear trend, represented by the resulting equation of the line. The linear trends were then subtracted from the deseasonalised data to obtain the detrended time-series datasets.

Linear correlation analysis was implemented on all the grids within the spatial and temporal overlaps of the data (1993 to 2019, n = 312) at −12 to 12-month time lag/time ahead relative to SSH. Streamflow values were log$_{10}$-transformed and correlated with the SSH grid at the discharge site of the drainage basins where the gauges are located. Figure 1 shows the location of the river gauge and corresponding gauges in seven of the major river basins of the country. It also shows the actual coverage of the SSH and GRUN grid used in this study.

3. Results and discussion

3.1. River gauge, GRUN and SSH data

A comparison between actual stream gauge data of major rivers in the Philippines with at least ten years of data is provided in Table 1. As reported more extensively by Ibarra et al. (2021), actual stream gauge and the global gridded runoff dataset generally show a fair correlation between them which can further be
Table 1. Correlation coefficients (r-value) of log_{10}-transformed river gauge data with the corresponding log_{10}-transformed GRUN and raw SSH data. The GRUN data analysed are within the grids where the river gauges are located. The time lag indicated in the correlation with SSH refers to the time lag in months of SSH with the highest r-value. A positive time lag means SSH precedes runoff; a negative time lag means the opposite.

| River          | Period covered of analysis (mm/ yyyy) | Correlation with GRUN (r-value, p < 0.05) | Correlation with SSH (r-value, p < 0.05) | Time lag (months, with respect to runoff) |
|----------------|--------------------------------------|------------------------------------------|----------------------------------------|------------------------------------------|
| Agusan River   | 01/1993 – 12/ 2009                    | 0.603                                    | 0.711                                  | -2                                      |
| Cagayan River  | 01/1993 – 12/ 2012                    | 0.859                                    | 0.747                                  | 0                                       |
| Jalaur River   | 01/1993 – 12/ 2010                    | 0.858                                    | 0.844                                  | -1                                      |
| Libuganon River| 10/2000 – 12/ 2009                    | 0.627                                    | 0.389                                  | 0                                       |
| Cagayan de Oro River | 01/1993 – 12/ 2004 | 0.719                                    | 0.536                                  | 0                                       |
| Sibuguey River | 01/1993 – 12/ 2010                    | 0.827                                    | 0.738                                  | 0                                       |
| Sindangan River| 01/1993 – 12/ 2010                    | 0.785                                    | 0.831                                  | -1                                      |

improved upon correction of systematic biases. The same table directly correlates stream gauge data with SSH where the r-value is given for the lag time that showed the highest correlation. Data for SSH also show high correlation with actual stream gauge data for almost all of the large basins considered. This points to the validity of the two parameters’ strong association, and which we then carry over to investigating GRUN-SSH correlations in the analyses detailed below.

3.2. Nationwide analysis between GRUN and SSH time series

Using the GRUN dataset, we now correlate river runoff and sea surface height as a national aggregate, regionally and at the basin level. The national annual averages of GRUN and SSH are plotted in Figure 2 where it clearly shows the seasonal cycle of stream runoff including a short dry spell that is usually centred around August every year. A similar but more erratic seasonal cycle is also observed in SSH. Deseasonalizing and detrending

![Figure 2](image-url)

**Figure 2.** Monthly time series of GRUN and SSH, national means during periods of overlap (1993–2019) and the Multivariate ENSO Index (MEI; 1993–2018). Top: monthly time series of GRUN and SSH; middle: deseasonalized and detrended time series of GRUN and SSH; bottom: the MEI. Horizontal lines in the first two panels correspond to the overall raw (top panel) and detrended (middle panel) mean values of GRUN and SSH. Highlighted time periods (in grey) correspond to the nine relatively strong El Niño events (peak MEI > 1) used in the regression analysis. From left to right, these time periods are: (1) 12/1989 to 07/1995, (2) 04/1997 to 07/1998, (3) 04/2002 to 02/2004, (4) 04/2004 to 09/2005, (5) 05/2006 to 05/2007, (6) 05/2009 to 05/2010, (7) 04/2012 to 01/2013, (8) 03/2014 to 08/2016 and (9) 04/2017 to 08/2017.
the data as shown in the lower figure removes quarterly and month-to-month variability to clearly show the years with the lowest runoff values corresponding well to El Niño years including the two most recent strong El Niño years of 1997–1998 and 2015–2016. The same figure presents the strong association of runoff and SSH with a noticeable time lag during some years. The detrended plot not only shows the similar pattern between the two datasets but also the high association of detrended SSH and runoff values. Again, also evident in Figure 2 are the lowest SSH and runoff values centred on the two strong El Niño events of 1997–98 and 2015–2016. These two events are more than 1.5 mm/day lower than mean runoff and about 0.1 m lower than mean SSH.

Table 2. Correlation coefficient values of national means, log GRUN vs. SSH and SST, SST vs. SSH, and MEI vs. SSH at each time lag relative to SSH/SST/MEI. A positive time lag means the SSH/SST/MEI precedes runoff; a negative time lag means the opposite.

| Time lag (months, SSH/SST with respect to runoff) | log GRUN vs SSH (1993–2019) | log GRUN vs SST (2002–2019) | SSH vs SST (2002–2019) | r-value, p < 0.05 | GRUN vs MEI (1950–2018) | r-value, p < 0.05 |
|------------------------------------------------|----------------------------|----------------------------|------------------------|-------------------|------------------------|-------------------|
| −8                                              | 0.570                      | 0.689                      | 0.576                  | −0.505            | 0.683                   | −0.835            |
| −7                                              | 0.638                      | 0.721                      | 0.620                  | −0.569            | 0.692                   | −0.835            |
| −6                                              | 0.699                      | 0.734                      | 0.657                  | −0.623            | 0.752                   | −0.835            |
| −5                                              | 0.752                      | 0.729                      | 0.685                  | −0.667            | 0.793                   | −0.835            |
| −4                                              | 0.793                      | 0.707                      | 0.700                  | −0.698            | 0.821                   | −0.835            |
| −3                                              | 0.821                      | 0.667                      | 0.699                  | −0.715            | 0.835                   | −0.835            |
| −2                                              | 0.835                      | 0.612                      | 0.682                  | −0.714            | 0.833                   | −0.835            |
| −1                                              | 0.833                      | 0.543                      | 0.649                  | −0.696            | 0.817                   | −0.835            |
| 0                                               | 0.817                      | 0.463                      | 0.601                  | −0.663            | 0.787                   | −0.835            |
| 1                                               | 0.787                      | 0.375                      | 0.541                  | −0.614            | 0.745                   | −0.835            |
| 2                                               | 0.745                      | 0.287                      | 0.473                  | −0.554            | 0.693                   | −0.835            |
| 3                                               | 0.693                      | 0.203                      | 0.399                  | −0.489            | 0.612                   | −0.835            |

Wavelet analyses (cf. Zeri et al., 2019) of the national averages with and without removing the seasonal cycle and detrending shows a one-year periodicity between SSH and runoff (Figure 3). Further, as shown by the arrows in the wavelet analyses, across the time-series SSH consistently leads or shows no lag with runoff nationally. This is supported by the correlation coefficients derived from the two datasets (Table 2), as r-values are highest when SSH leads runoff by 1 to 2 months (r = 0.833–0.835, p < 0.05). However, significant correlation between the two parameters still exists even at an SSH lag of 3 months (r = 0.693, p < 0.05). Table 2 also shows that SSH generally correlates with runoff better than the Multivariate ENSO Index (MEI) and the 4-km Level 3 SST data product processed by the National Aeronautics and Space Administration (NASA), particularly during positive time lags. The SST dataset is derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) – Aqua sensor. Map-view representations of the correlations at several time lags of SSH relative to runoff generally show relatively high r-values across the country (Figure 4). This further suggests the utility of SSH data as a predictor for average runoff levels at the national scale.

3.3. Region-based analysis of SSH and GRUN

To expand the associative nature of SSH and runoff, we further our analysis by grouping coastal areas around the Philippines that show similar SSH versus runoff trends. Nine geographic regions are identified in Figure 5 to have coherent characteristics. An illustration of the calculated correlation coefficients for each region is presented in Figure 6. Interestingly, higher
Figure 4. Map of correlation coefficients (1993–2019). Left to right: (a) at 6 months that SSH precedes runoff, (b) at 2 months that SSH precedes runoff, (c) at no time lag. Time lag in months.

Figure 5. Study area divided per region according to the magnitude of correlation coefficients at −1 month time lag. Left: identified regions; right: reference correlation map at 1 month time lag of SSH.

Figure 6. Correlation coefficients between log_{10}(runoff) and SSH at each region from −12 to 12 months of time lag of SSH. The regions are listed in the plot legend according to the magnitude of correlation coefficients calculated; Palawan and Batanes have the highest and lowest peak r-values, respectively. A positive time lag means SSH precedes runoff; a negative time lag means SSH leads runoff. See Supplementary Table 1 for the matrix of values plotted here.
SSH and runoff correlations are found on the western side of the country, particularly in Palawan, and the Zamboanga and Sulu region. The lowest SSH versus runoff correlations are observed in areas directly in contact with the Western Pacific such as northern Luzon (Batanes and Cagayan) and the eastern coast of the country (Eastern Luzon and Eastern Mindanao and Samar).

Other than the different correlation values between SSH and runoff, the time lag with the maximum r-value at each identified region also differs from one another (Figure 6). The regions of Palawan, Zamboanga and Sulu, and Southern Mindanao achieve the highest correlation with r-values of 0.914, 0.900 and 0.813, respectively, at time lags from −1 to −3 months. For Southern Mindanao, the highest correlation is achieved at time lag = −3, whereas for the two other regions the time lag with the highest correlation is at t = −1. Significant correlations (r = 0.734 to 0.775) are also observed for the rest of the regions at time lags of either t = −1 or −2, except for the northernmost islands of the Batanes region, which attains its highest correlation with no time lag. Presumably, the Batanes region is the least affected by SSH variations as it is already 20 degrees north of the equator. Runoff estimates may likewise be off due to the small catchment size of the small, individual islands of the region (Ibarra et al., 2021).

### 3.4. Drought prediction using SSH during positive phase ENSO events

In this section, we discuss ENSO-induced drought and its prediction using SSH. For this, we select significant El Niño events (n = 9) based on the MEI within the period of overlap between the GRUN and SSH datasets (1993 to 2018) and isolate the minimum runoff and SSH values that correspond to such events. These El Niño events are identified by the time periods with consistent positive MEI and with a maximum value of MEI > 1: (1) 12/1993 to 07/1995, (2) 04/1997 to 07/1998, (3) 04/2002 to 02/2004, (4) 04/2004 to 09/2005, (5) 05/2006 to 05/2007, (6) 05/2009 to 05/2010, (7) 04/2012 to 01/2013, (8) 03/2014 to 08/2016 and (9) 04/2017 to 08/2017. Table 3 provides the correlation coefficients, which again shows the high association between minimum SSH and minimum runoff during drought conditions for most regions. This is especially true for the western side of Luzon (r = 0.937) and Southern Mindanao (r = 0.901) which are the country’s largest agricultural lands and regions that are highly susceptible to drought conditions (Roberts et al., 2009; Sutton et al., 2019; Tongson, 2019; Rojas, 2020). Table 3 shows the time lag wherein SSH can be used as a predictor for minimum runoff during strong El Niño events. Peak correlations range from a 4 month time lag to no lag at all depending on the region.

Given the results from the preceding sections, we propose the future development of an SSH-based drought forecasting tool for water management purposes, especially when an El Niño event is forecasted (e.g. Dawe et al., 2009; Yumul et al., 2010; Wang et al., 2013; Y. Zhou & Wu, 2016; Zeri et al., 2019; Porio et al., 2019; Manalo et al., 2020; Costa et al., 2020). First, the MEI or similar ENSO indices are used to determine the background state of the climate system in the Pacific Ocean with a predictive horizon of 6 to 12 months. If the MEI is greater than 0, drought conditions regionally can be forecasted using the prevailing SSH and the SSH vs. runoff regressions presented above within a 2- to 4-month window of the dry season. A nationwide network of SSH gauging stations must therefore be established for real-time analysis to be possible. Based on the historical correlation of SSH and runoff per region, an appropriate range of probable drought levels based on historical and projected runoff data (calculated as a decrease in rainfall for non-irrigated areas) could then be provided per basin in each and every region.

### 4. Conclusions

This study highlights the importance of similar predictive tools that are associative in nature and not necessarily causative. The high correlation of SSH and runoff detailed in this study provides an additional tool for ENSO-induced drought prediction with a shorter predictive horizon (2–4 months lead time).
but of higher accuracy compared to using the standard central Pacific SST-based tools used to characterise ENSO for global teleconnections. SST anomalies are translated into changes in local SSH values which presumably are affected by other oceanographic factors beyond just SST and subsequently drive local-scale rainfall and drought conditions. These compounding factors are beyond the scope of this research but may include the seasonal timing of such anomalies, ocean–atmosphere interactions and ocean circulation dynamics. We presume that the same factors are also imposed on factors influencing rainfall amount and resulting stream runoff thus leads to the higher correlation between SSH and runoff instead of the causative SST information from the Pacific Ocean basin. This inference is useful for the development of a drought forecasting tool associated with El Niño events with greater accuracy and skill.

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Data availability

The datasets used in this paper are available through the following: GRUN (Gighi et al., 2021), the river discharge datasets (Ibarra et al., 2021; Tolentino et al., 2016) and SSH from the Copernicus Marine Environmental Monitoring Service (CMEMS) database (https://marine.copernicus.eu/). The R and Python code needed to reproduce the analyses presented is available as a supplemental zip file.

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