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On the non-parametric changepoint detection of flow regimes in cyclone Amphan

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Abstract The Bay of Bengal was witness to a severe cyclone named *Amphan* during the summer of the year 2020. The National Institute of Ocean Technology (NIOT), INDIA moorings BD08 and BD09 happened to be in the vicinity of the cyclone. The highly instrumented mooring recorded near-surface meteorological parameters like wind speed, sea surface temperature, and near-surface pressure. This article explores the possibility of using a non-parametric algorithm to identify different flow regimes using a one-month long time-series data of the near-surface parameters. The changes in the structure of the time series signal were statistically segmented using an unconstrained non-parametric algorithm. The non-parametric changepoint method was applied to time series of near-surface winds, sea surface temperature, sea level pressure, air temperature and salinity and the segmentations are consistent with visual observations. Identifying different data segments and their simple parameterization is a crucial component and relating them to different flow regimes is useful for the development of parametrization schemes in weather and climate models. The segmentations can considerably simplify the parametrization schemes when expressed as linear functions. Moreover, the usefulness of non-parametric automatic detection of data segments of similar statistical properties shall be more apparent when dealing with relatively long time series data.

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1. Introduction

In recent years, a series of moorings have been deployed to obtain valuable time series data related to basic climate variables like wind speed, air temperature, air pressure, sea surface temperature, salinity, and ocean currents. Data from these moorings are useful to carry out process-based weather and climate studies. Further the time series data especially the winds are used for reliable design and computations of structural loads on marine structures and moorings. The variability in the time series is seldom stationary over time and, for instance during cyclonic events the variability change is quite dramatic and significant.

Over the Indian subcontinent, the months of March, April, and May are considered the spring inter-monsoon period. In general, during the spring inter-monsoon time, the skies are relatively cloud-free with light winds and intense ocean heating. However, in the year 2020, the environmental conditions during the month of May were unusual in some aspects. A significant synoptic-scale disturbance developed, which progressed into a super cyclone named *Amphan* during May of 2020 over the Bay of Bengal. *Amphan* subsequently made landfall over West Bengal, India, on May 21, 2020.

An automated changepoint analysis is helpful for the fast detection of significant changes or breaks in the changing structure of a time-series signal. This article explores the usefulness of a non-parametric change point detection approach (Killick and Eckley, 2014) to isolate various data segments (regimes) which relate to the air-sea interaction regimes during a fast-moving cyclone. This approach relies on meteorological variables recorded by the NIOT buoys BD08 and BD09. These buoys are located near 18°N and 89°E, which happened to be in the vicinity of cyclone *Amphan*. Cyclone Amphan initially started as a depression on 16th May 2020 with winds of 25 knots (KT), and by midnight of 17th May, it developed into a cyclonic storm (CS), achieving winds exceeding 45 KT. During this period, the depression veered towards the head of the Bay of Bengal. The cyclonic storm further intensified into an extremely severe cyclonic storm (ESCS) by midnight of 18th May, achieving winds of the order 100 KT. The ESCS further intensified into a super cyclonic storm (SuCS) during the early hours of the day. The storm stayed on the course moving in the northerly direction, maintaining wind speeds in the range 95—120 KT's during the 18—20th of May. It moved further North, maintaining wind speed in the range of 95—80 KT, and finally made landfall on 20th May with winds decreasing to 50—20 KT. A steady drop in sea level pressure from pre-cyclone values of about 1010 mb to the lowest value of 970 mb during the 19—20th of May is observed. Pressure dips are associated with the passage of frontal structures. During the passage of the frontal systems, we observe significant veering in the direction of the wind. These are essentially non-stationary conditions. One of the usefulness of changepoint algorithms is to detect statistically similar data segments in the time series. Figure 1 shows the trajectory followed by the cyclonic storm Amphan, based on the report released by Indian Meteorological Department (IMD, 2020). The color bar on the left shows the bathymetry in meters, and the color bar on the right shows the wind speed in knots.

The atmosphere and the oceans exchange mass, momentum, and energy through the marine surface boundary layer. In most situations, the bulk of the transfer processes occurs over the top 10 percent of the atmospheric/oceanic boundary layer. However, in extreme weather conditions, in cyclones, depressions, the depth of the marine boundary layer can show considerable variations. Ocean and atmospheric boundary layers interact across a wide span of temporal and spatial scales (Fedorov and Ginzburg, 1992).

High near-surface winds lead to substantial mixing in the upper surface layers of the ocean and give rise to deep mixed layers. Observations, laboratory experiments, and numerical simulations show that the exchange of momentum and energy across the air-sea interface and various scaling laws are different for low winds, moderate winds, and high wind regimes (Zweers et al., 2010). According to Fedorov and Ginzburg (1992), the air-sea interaction processes can be broadly classified into five different regimes (time series segments with varying mean and variance) based on forcing factors like wind speed, roughness length etc.

In numerical weather models, the exchange of momentum (C_d), sensible heat (C_e) and latent heat (C_h) across the air-sea interface is expressed in terms of the exchange coefficients. All the relevant detailed equations are fully elaborated in Edson et al. (2013). The exchange coefficients of momentum (drag coefficients) over the years have been parameterized in terms of the winds at 10 m from the mean sea level. However, a lot of scattering and outliers have been observed in the fitted curves. The scatter is mainly attributed to the dependence of the exchange coefficients on variables like wind speed and waveage. It is difficult to parameterize these exchange coefficients in terms of the abovementioned variables. Intensive field experiments and observations have given insights into other processes that are in play, particularly the dependence of sea state and the influence of sea spray during high wind conditions. Similarly, at very low wind conditions, the drag coefficients show a significant amount of scatter. These are again attributed to mechanisms that need further study. However, in conditions where the surface winds are less than 30 m s^{-1}, to first-order, the drag coefficient increases with an increase in moderate wind speed (about 5—6 m s^{-1}) and decreases for wind speeds beyond 30 m s^{-1} (Zweers et al., 2010). The above observations are equally valid for the exchange coefficients of sensible and latent heat.

In the atmospheric/oceanographic community, the COARE bulk algorithm happens to be a widely used algorithm which estimates the fluxes of momentum (τ), sensible (shf) and latent heat (lhf) at the air-sea interface using more easily measurable averaged quantities of wind speed, air temperature, sea surface temperature, relative humidity, solar insolation, longwave radiation, rain, wave speed and wave heights (Edson et al., 2013).

Figure 2 shows the time series of friction velocity (u_*), the momentum flux (τ), the sensible heat flux (shf) and the latent heat flux (lhf) during the month of May 2020 at 18°N, 89°E computed using the COARE bulk algorithm (Fairall et al., 2003; Edson et al., 2013; Yu, 2019). The friction velocity (top panel) was less than 0.2 m s^{-1} till 16th May and the influence of increasing winds can be seen reflected in high values of u_* on 17—21 days of the month. The friction

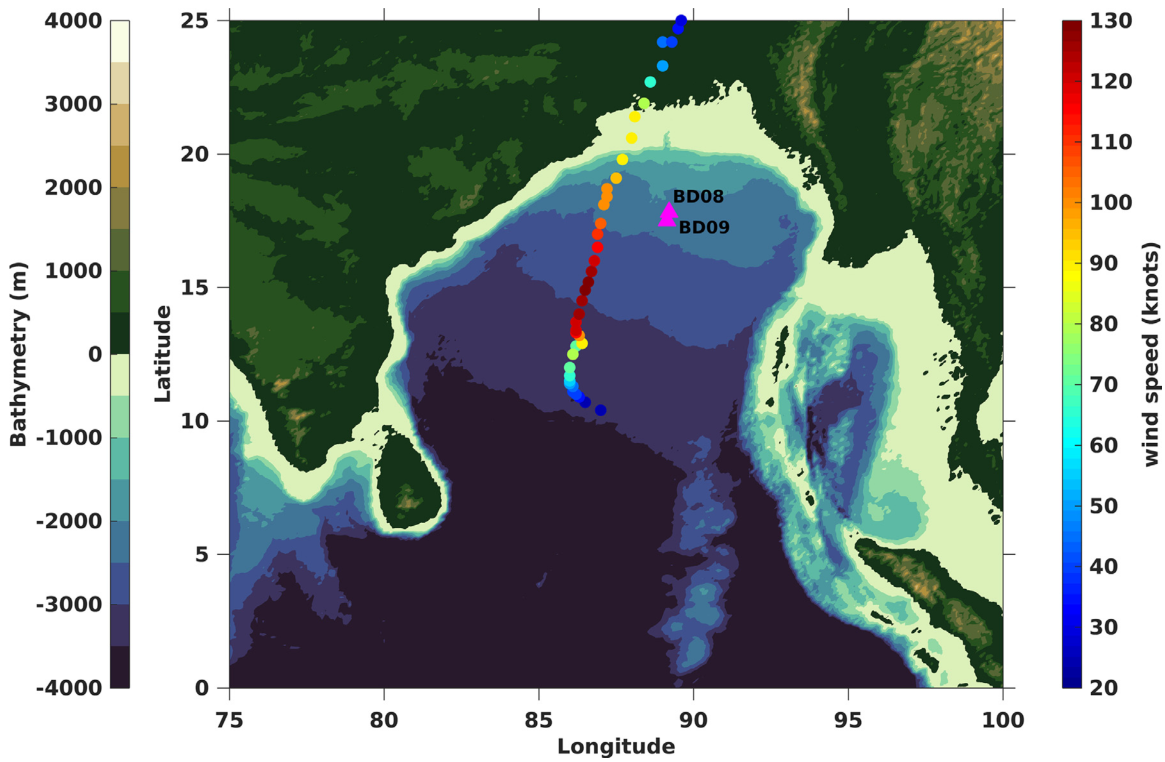

Figure 1 Track followed by the cyclone *Amphan* over the Bay of Bengal.

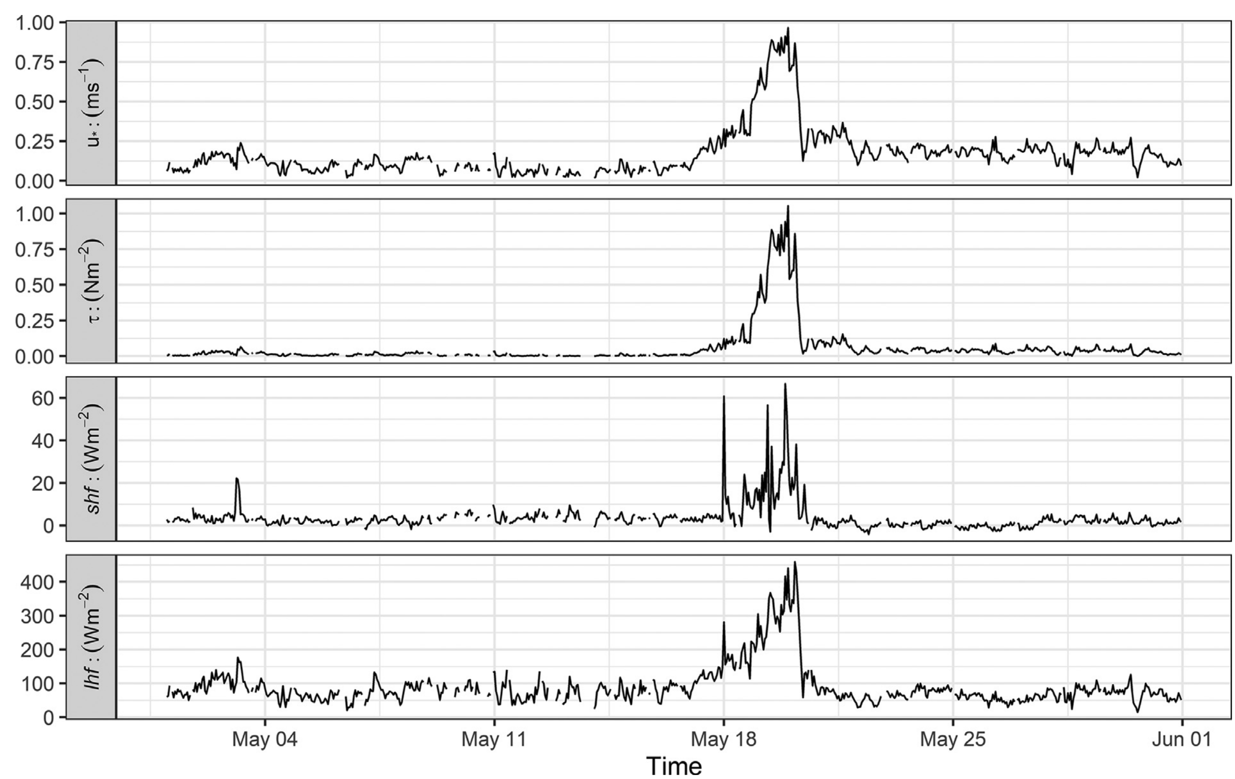

Figure 2 Significant changes in the structure of the signal (friction velocity, wind stress, sensible heat flux and latent heat flux) are observed during 17—31 May 2020.

velocity is a crucial parameter in all the exchange processes related to air-sea interaction. The lower panel (b) shows the time series of momentum flux computed by the COARE algorithm. Panel (c) and (d) show the time series of sensible and latent heat fluxes, respectively.

The motivating factor to show the time series of these variables which are non-stationary over time, is that these variables computed from bulk algorithms are in turn, parameterized using fast sampled direct eddy covariance measurements (Edson et al., 2013). Eddy covariance measurements strictly assume that the second moments (covariances) of these variables are assumed to be at least wide sense stationary (Bendat and Piersol, 2011). This is where the need and importance of changepoint analysis become more apparent. Changepoint algorithms can be effectively used to extract data segments that are stationary over time and useful when the data is voluminous in size.

This article focuses on the changing structure of near-surface meteorological and ocean variables like air temperature and sea surface temperature (SST) cyclonic conditions. The time series data are objectively segmented using a robust changepoint algorithm using an unconstrained optimization technique. Here we objectively extract the changes in the time series mean and variance. The changes in the mean and variance of each variable across different segmentations, for example, the wind, are compared and correlated with other variables like sea surface temperature and salinity and air temperature.

This article uses a robust parametric approach to detect changes in mean and variance in the near-surface wind field during cyclone *Amphan*. Automatic detection of changes in the flow structure is a relatively new application in oceanographic studies. Some of the first studies on changepoint analysis related to oceanographic data have been carried out by Killick and Eckley (2014) to analyze wave height classification over the open oceans. This article identifies the changing wind regimes using the PELT changepoint algorithm proposed by Killick and Eckley (2014). The algorithm also detects changes in mean and variance in air temperature, sea surface temperature, and sea surface salinity. Often there is some degree of correlation in all these variables. An important result from this study is that the change in mean and variance in the wind speed data relates well to similar changes in other variables. Truong, et al. (2020) succinctly reviews the background literature related to changepoint analysis and the relative advantages and limitations.

The PELT method developed by Killick and Eckley (2014) uses a number of objective criteria like the Bayesian information criteria (BIC) to fit the time series with the appropriate model with a minimum error (cost) function. The article is organized as follows. In Section 2, the data and methods are briefly described. Section 3 gives an overview of the changepoint methodology and results with reference to the buoy data described in Section 4. The summary and related discussion on the limitations of this study is given in Section 5.

2. Data and methods

A subset of the data for the month May of 2020 is extracted which showed the significant changes because of the passage of cyclone *Amphan* over a short period of time. The NIOT buoys are instrumented with near-surface and sub-surface sensors for acquiring meteorological and oceanographic data over extended periods of time. The sensors comply with the specifications as recommended by the IMET group in terms of accuracy and reliability. The data are acquired at hourly intervals. For every hour interval, the last ten minutes interval is taken as the data acquisition window. The raw data is sampled at the rate of 1Hz for most of the meteorological sensors. These meteorological parameters are sampled over the last 10 minutes of every hour. These hourly samples are used for analysis. Similar averaging is done for all the other variables. Detailed information on the sensors, their make, accuracy and precision are provided in Venkatesan et al. (2013).

Near Surface winds at 3 m from the mean sea level are measured by a Lambrecht 1453 S2 F1000 anemometer. It provides the wind speed and direction, wind speed in the range 0—60 m s^{-1}. Other variables that are measured along with the winds are the air temperature and relative humidity (Rotronic MP-101A), sea level pressure (Vaisala PTB330), shortwave and longwave radiations (Kipp and Zonen Pyranometer), and the sea surface temperature (SBE 37-SMP). A common data logging interface samples the data at the same time and provides a time stamp, and the change points identified in the wind speed time series are later mapped to other variables. It is encouraging to note that the changes in the wind speed regimes correlate well with the changing structure of the other near-surface variables.

3. Changepoint algorithm

Changepoints are broadly defined as instances in time, such that the statistical properties of the time series show significant differences before and after a given instance. Changepoint analyses are often referred to as segmentations, structural breakpoints (Truong et al., 2020). The changepoint algorithm is briefly described as follows. Let the time series be represented as $\{x_1, x_2 \ldots\ldots x_n\}$. The data are assumed to be an instance of distribution with parameter vector θ. It is assumed that there occurs a significant change in properties of the time series at some time τ. A change is defined in terms of the difference in properties between these two segments. A change in the structure of the time series can arise from a change in the mean, or a change in variance or some other parameter change in the distribution of the underlying data (Chen and Gupta, 2012). The general structure of any changepoint algorithm is as follows (Killick and Eckley, 2014).

3.1. The Changepoint algorithm

Input:

A time series of n data points; $x_1, x_2, .., x_n$.
A test statistic $\lambda(.)$ which depends on the data.
A changepoint position estimator $\hat{k}(.)$.
A threshold rejection value c_α.

- Initialize the sets $C = []$ and $S = \{[1, n]\}$
- DO WHILE: $S \neq 0$

- Choose an element of $\{S\}$; denote this element as $[s, t]$.
- If $\lambda(y_{s:t}) < c_\alpha$ delete $[s, t]$ from S
- If $\lambda(y_{s:t}) > c_\alpha$ then:
    - DELETE $[s, t]$ from S
    - Calculate $r = \hat{k}(y_{s:t}) + s - 1$ and add r to C
    - if $r \neq s$ add $[s, r]$ to S
    - if $r \neq t - 1$ add $[r + 1, t]$ to S

- END DO

Output:

- The set of changepoints C

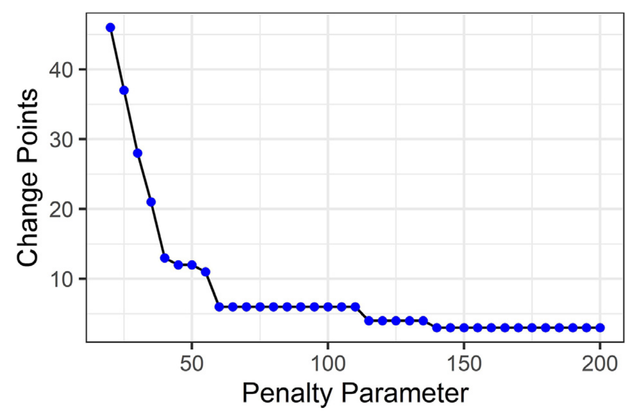

Figure 3 Estimation of a number of changepoints.

3.2. Multiple change points

The changepoint algorithm for a single change can be extended for multiple changepoints in the time series. Assuming an ordered sequence of data, $x_{1:n} = \{x_1, x_2, ...x_n\}$ and let $p_{1:m} = \{p_1, p_2, ...p_m\}$ be the m number of changepoints in the time series x with a position in between 1 and $M - 1$ inclusive, which splits the data into $m + 1$ segments. Further, assuming that $p_1 = 0$, $p_{m+1} = n$ and the points are ordered such that $p_i < p_j$, if and only if $i < j$. Then the i^{th} segment contains values $x_{p_{i-1}+1:p_i}$ (Haynes et al., 2017; James and Matteson, 2015; Ross, 2015).

The time series is modeled as $x_j = f(t_j) + e_j; 1 \leq j \leq n$ such that $f(t)$ is a function which is representative of the distribution from which x_j is derived and e_j is the sequence of errors in the data segment. Assuming that the function f is piecewise constant, there exist changepoints such that $f(t) = \mu_k \; \forall \; p_{k-1} < t < p_k$. Taking the error terms as a sequence of independent and identically distributed Gaussian variables, x_j is then a sequence of independent Gaussian variables. The time series is therefore modeled as $x_j \sim N(\mu_k, \sigma^2)$ for $p_{k-1} < j < p_k$. The model depends on the parameters $(\theta = \mu_1, \mu_2, ...\mu_m; \sigma^2, p_1, p_2, ...p_m)$. A likelihood function is constructed as $L(\theta; x_1, x_2, ...x_n) = P(x_1, x_2, ...x_n, \theta)$, where P is the probability density function.

The likelihood ratio L_k/L_{k-1} of successive time series segments across $k - 1$; k checks the goodness of fit based on the rates of their likelihood. The goodness of fit is taken as the test statistic, which is computed by maximizing across the entire parameter space and the next fit is found by imposing a constraint. The constraint is the null hypothesis. If the null hypothesis is supported by the observed data, the two likelihoods would not differ by more than the sampling error. A loss (cost) function is computed across each segment of the data. The number of segments is inferred through the minimization of the segmentation cost. Multiple changepoints in the time series are identified by minimizing the loss (cost) function C, which is the negative of the log of the likelihood ratio. Across multiple segments of data, the cost function is simply the sum of the individual segments.

$$\sum_{n=1}^{m+1} [Cx_{p_{i-1}+1:p_i})] + \beta f(m) \tag{1}$$

where C is a cost function for any segment of the time series and $\beta f(m)$ is a penalty to guard against over fitting. Different cost functions are used in changepoint detection such as negative log-likelihood (Horváth, 1993), quadratic loss and cumulative sums or those based on both log-likelihood and length of the segment (Chen and Gupta, 2012; Hopkins et al., 2010; Jackson et al., 2005).

In many applications, the number of change points k is either assumed to be known apriori. When k is known apriori, the changepoint problems are solved as a constrained minimization problem. When k is not known, then the approach is to compute $C_{k,n}$ and the corresponding time series segments for a range of $k = \{0, 1, \ldots, K\}$ where K is some chosen maximum number of change points. The number of changepoints are subsequently estimated by minimizing $C_{k,n} + f(k, n)$ over k for a suitable penalty function $f(k, n)$. These class of problems are the unconstrained minimization problems. It is difficult to estimate an optimal penalty function $f(k, n)$ for unconstrained optimization Killick and Eckley (2014).

If the penalty function is linear in k, with $f(k, n) = \beta k$ for some $\beta > 0$ (which may depend on n), then the number of changepoints and corresponding segmentations are

$$\min_{k,\tau} \left[\sum_{j=0}^{k} C\left(y_{\tau_j+1:\tau_{j+1}}\right) \right] + \beta k \tag{2}$$

The minimization in the above equation is efficiently implemented by a dynamic programming algorithm (Killick and Eckley, 2014).

An efficient implementation of the optimal partition algorithm by Jackson et al. (2005) is provided by Killick and Eckley (2014) where the solution space of the changepoints are made optimal in their changepoint package (Killick and Eckley, 2014). It is implemented by pruning the solution space of the changepoint search space, making the algorithm computationally efficient. The changepoint package implements the minimization of the negative log-likelihood cost function with options for using binary segmentation, segment neighborhoods, and pruned exact linear time (PELT) to search the changepoints. To avoid overfitting, the penalty functions provided in the package include the Akaike's Information Criterion (AIC), Schwarz Information Criterion (SIC), Bayesian Information Criterion (BIC), and the Modified Bayesian Information Criterion (MBIC) (Maidstone et al., 2017).

When the number of changepoints is not known a priori, we compute the cost and minimize the cost for different penalties. Figure 3 shows the number of change points and the associated penalty in computing the cost function. The

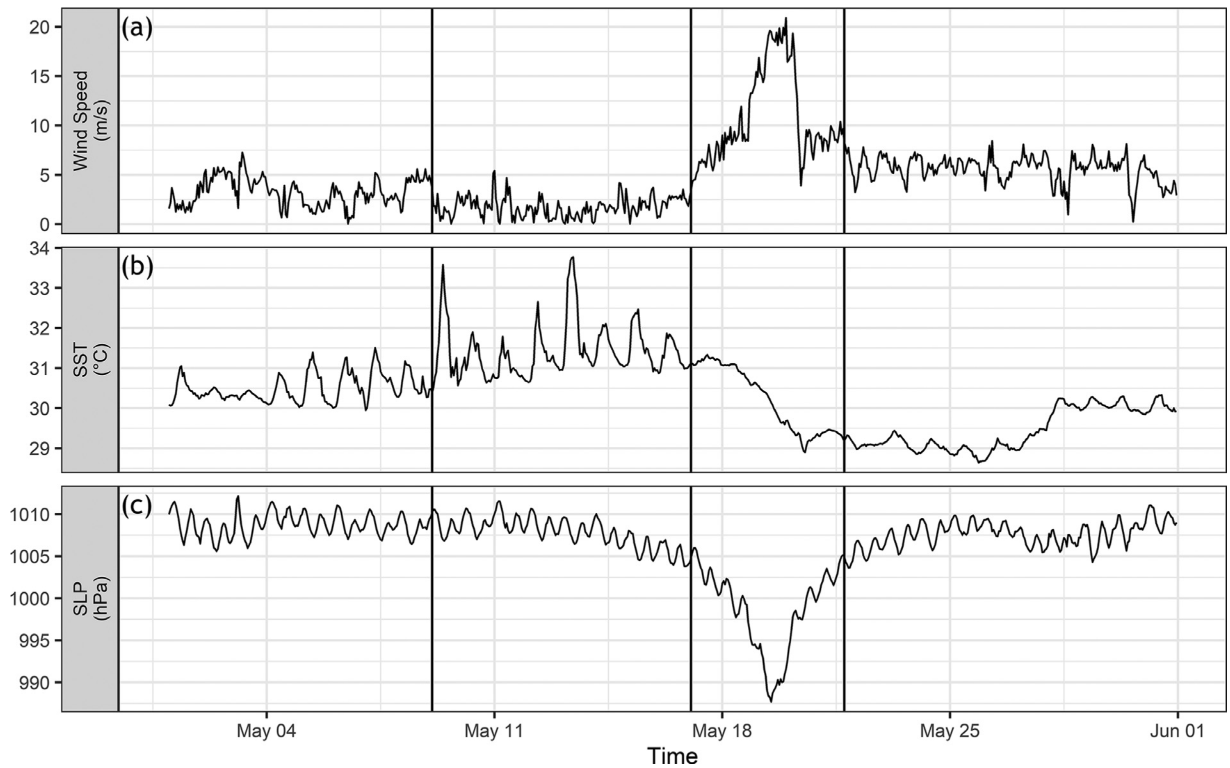

Figure 4 Time series of wind speed, sea surface temperature, sea level pressure, and location where there is a significant change in the signal.

number of change points that can be inferred is two to three for this one-month time series wind speed data. It is shown in later paragraphs that the partitioning of the time series data into two to three regimes is consistent with observational studies, which show distinct flow regimes at different wind speeds. Note that because this is a purely statistical procedure, some background knowledge on air-sea interaction processes helps correctly estimate the different number of regimes in the flow.

4. Results and discussions

Figure 4 shows the time series of wind speed, sea surface temperature (SST), and mean sea level pressure (SLP) in the three panels for the month of May 2020. Three distinct wind speed time epochs in panel (a) can be visually seen, as predicted by the change point algorithm detailed in the preceding paragraphs.

The first epoch from the change point algorithm, which is the first week, shows moderate windy conditions, while the next week, which is segment number two, according to the changepoint algorithm, shows somewhat weak winds with much less variation at the small time scales. The time epoch from May 16 to the end of the time series record corresponds to the third regime of the changepoint algorithm. In the third regime, the winds start picking up strength during May 16—17, and there is a steady rise in the wind speed. This is the epoch where there is the most significant change in wind speed. It is encouraging to see that these three epochs or flow regimes can be mapped to other variables like sea surface temperature (SST) and sea level pressure (SLP) data. The different flow regimes are shown in panels (b) and (c) of Figure 4. There is a steady rise in SST in the first epoch, which corresponds to a particular type of flow regime, with somewhat moderate diurnal(daily) variability in the temperature. The second epoch is the flow regime during May 9—17, during which there is enhanced diurnal variability in SST. However, the increasing trend in the mean temperature is somewhat diminished in the second regime. The third epoch shows the cyclone-induced cooling regime after May 17. In general, in most observations cyclone induced cooling in SST is expected. Similarly, panel (c) shows that the SLP is steady till May 09 and shows the tendency to reach lower levels during the latter half of the second epoch, which corresponds to the second regime. Epoch three corresponds to the third flow regime, which shows a drastic fall in the SLP. The distinct regimes can also be observed in the air temperature and salinity data in Figure 5. The air temperature data and SST data have a similar trend with much more small-scale air temperature variability. Note the drastic fall in the third regime. The response of air temperature is much faster compared to SST. The ocean responds much more slowly compared to the atmosphere. Panel (b) of Figure 5 shows the salinity time series. Notwithstanding the variability at the time scales smaller than one day, the salinity increases till the end of May 08. After that, it is more or less steady. Later during the third epoch, the salinity shows a steady rise peaking to values near 33 psu. A significant drop is also seen in the third epoch of salinity, which is perhaps associated with heavy precipitation during the cyclone.

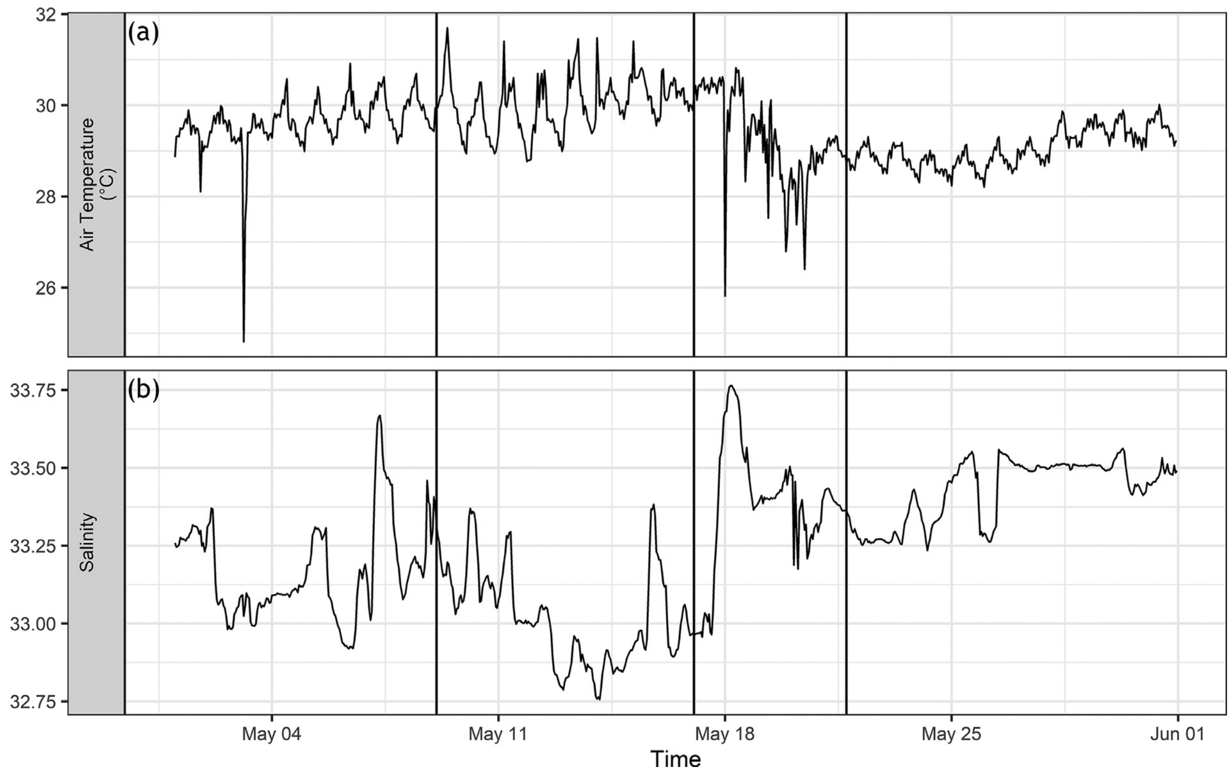

Figure 5 Significant changes in the air temperature and salinity from the changepoint algorithm.

5. Summary and conclusions

In this article, a non-parametric changepoint algorithm is validated over time-series of key environmental variables like wind speed, air temperature, sea surface temperature, sea level pressure, sea surface salinity during the passage of cyclone *Amphan* over the Bay of Bengal. The time-series data for this study is obtained from the NIOT moorings BD08 and BD09 located at 18°N, 89°E in the head of the Bay of Bengal. Cyclones are associated with fast-changing flow regimes. Algorithms to detect changes in time-series data fall in two broad categories, wherein in the first instance, the number of changes is known. These algorithms model and detect changes by minimizing the loss function by constrained optimization. However, when the number of changes in the time series structure is not known a priori, it is difficult to model and detect changes in the structure of the time-series signal. This class of problems falls under unconstrained optimization. One such changepoint algorithm proposed by Jackson et al. (2005) and efficiently implemented by Killick and Eckley (2014) is tested for oceanographic time-series data during cyclone conditions.

It is shown that the PELT algorithm gives the expected time series segments highlighting the various flow regimes in fast-evolving cyclonic conditions. The segmentation into different regimes and time epochs is clearly seen in SST, SLP, AT and SSS. This ability to carry out segmentation of the time series data into different regimes or segments is useful and has a number of applications. Apart from its usefulness to detect outliers, the segmented time series can be analyzed as standalone processes in an objective manner, thereby separating out many of the mechanisms that drive the processes. Here we have only looked at a month of time series data. This does not really show the advantage of an objective changepoint algorithm to detect changes in flow fields and structure. Changepoint detection algorithms' real usefulness becomes more apparent while analyzing extremely long data records, wherein it is nearly impossible to visually/manually look for changes in mean and variance. This work is in that direction. In the future, the algorithm would be tested for longer time series data looking for significant features and also would be extended to satellite imagery.

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References

Chen, J., Gupta, A.K., 2012. Univariate Normal Model. In: Parametric statistical change point analysis: with applications to genetics, medicine, and finance. Springer Science & Business Media, 7—88.

Bendat, J.S., Piersol, A.G., 2011. Random data: analysis and measurement procedures. John Wiley & Sons, 640 pp.

Edson, J.B., Jampana, V., Weller, R.A., Bigorre, S.P., Plueddemann, A.J., Fairall, C.W., Miller, S.D., Mahrt, L., Vickers, D., Hersbach, H., 2013. On the exchange of momentum over the open ocean. J. Phys. Oceanogr. 43 (8), 1589—1610. https://doi.org/10.1175/JPO-D-12-0173.1

Fairall, C.W., Bradley, E.F., Hare, J.E., Grachev, A.A., Edson, J.B., 2003. Bulk parameterization of air—sea fluxes: Updates and verification for the COARE algorithm. J. Climate 16 (4), 571—591. https://doi.org/10.1175/1520-0442(2003)016⟨0571:BPOASF⟩2.0.CO;2

Fedorov, K.N., Ginzburg, A.I., 1992. The near-surface layer of the ocean. VSP, Utrecht, The Netherlands, 256 pp.

Haynes, K., Eckley, I.A., Fearnhead, P., 2017. Computationally efficient changepoint detection for a range of penalties. J. Comput. Graph. Stat. 26 (1), 134—143. https://doi.org/10.1080/10618600.2015.1116445

Hopkins, J., Challenor, P., Shaw, A.G.P., 2010. A new Statistical Modeling approach to ocean front detection from SST satellite images. J. Atmos. Ocean Tech. 27 (1), 173—191. https://doi.org/10.1175/2009JTECHO684.1

Horváth, L., 1993. The maximum likelihood method for testing changes in the parameters of normal observations. Ann. Stat. 21 (2), 671—680.

IMD, 2020. Super Cyclonic Strom "AMPHAN" ove the sourtheaast Bay of Bengal (16th—21st May 2020): Summary. [Online] Available at: https://internal.imd.gov.in/press_release/20200614_pr_840.pdf

Jackson, B., Scargle, J.D., Barnes, D., Arabhi, S., Alt, A., Gioumousis, P., Gwin, E., Sangtrakulcharoen, P., Tan, L., Tsai, T.T., 2005. An algorithm for optimal partitioning of data on an interval. IEEE Signal Proc. Let. 12 (2), 105—108. https://doi.org/10.1109/LSP.2001.838216

James, N.A., Matteson, D.S., 2015. ecp: An R Package for Nonparametric Multiple Change Point Analysis of Multivariate Data. J. Stat. Softw. 62 (7), 1—25. https://doi.org/10.18637/jss.v062.i07

Killick, R., Eckley, I., 2014. changepoint: An R package for changepoint analysis. J. Stat. Softw. 58 (3), 1—19. https://doi.org/10.18637/jss.v058.i03

Maidstone, R., Hocking, T., Rigaill, G., Fearnhead, P., 2017. On optimal multiple changepoint algorithms for large data. Stat. Comput. 27, 519—533. https://doi.org/10.1007/s11222-016-9636-3

Ross, G.J., 2015. Parametric and nonparametric sequential change detection in R: The cpm package. J. Stat. Softw. 66 (3), 1—20. https://doi.org/10.18637/jss.v066.i03

Truong, C., Oudre, L., Vayatis, N., 2020. Selective review of offline change point detection methods. Signal Process. 167, 107299. https://doi.org/10.1016/j.sigpro.2019.107299

Venkatesan, R., Shamji, V., Latha, G., Mathew, S., Rao, R., Muthiah, A., Atmanand, M., 2013. In situ ocean subsurface time-series measurements from OMNI buoy network in the Bay of Bengal. Curr. Sci. 104 (9), 1166—1177.

Yu, L., 2019. Global air—sea fluxes of heat, fresh water, and momentum: energy budget closure and unanswered questions. Annu. Rev. Mar. Sci. 11 (1), 227—248. https://doi.org/10.1146/annurev-marine-010816-060704

Zweers, N., Makin, V., De Vries, J., Burgers, G., 2010. A sea drag relation for hurricane wind speeds. Geophys. Res. Lett. (21) 37. https://doi.org/10.1029/2010GL045002