Inter Annual and Seasonal Cycle of Satellite Derived Sea Surface Salinity in the Bay of Bengal

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Abstract

A spatial and temporal variation of sea surface salinity (SSS) is vital to understand the dynamics of the seasonal and inter-annual changes in the marine environment. In the present study, Soil Moisture Active-Passive (SMAP) derived daily SSS product and Moderate Resolution Imaging Spectroradiometer (MODIS-Aqua) remote sensing reflectance (Rrs) based SSS images (Algorithm by Qing et al, 2013), applied in the coastal and offshore region of the Bay of Bengal (BoB). SMAP data validation with in situ data (offshore and coastal water, 10 and 15 points) showed good correlation at offshore water and less correlation at coastal water ($R^2 = 0.707/0.499$, $SEE = \pm 0.291/\pm 0.546$, $MNB = -0.0029/-0.0089$ and $RMSE = \pm 0.092/\pm 0.139$) respectively. Similarly, MODIS-Aqua Rrs derived salinity data validated with *in-situ* SSS and observed the correlation as follows with $R^2 = 0.908/0.891$, $SEE = \pm 2.395/\pm 1.512$, $MNB = 0.0718/0.0361$, $RMSE = \pm 0.760/\pm 0.316$ in offshore and coastal water respectively during April and August 2019. The salinity data observed in the range of 32 to 34.5psu. High SSS mean (35.6-35.8psu) observed during the spring inter-monsoon and low salinity (34.6-34.9psu) observed during winter monsoon phase as depicted from decadal scale interpretation. The present study inferred that MODIS aqua derived SSS is better than SMAP based SSS at coastal and offshore region of the western BoB, irrespective of their resolution and spectral differences. More data points based validation would provide the scope for further improvements and seasonal studies on salinity variability using ocean color sensors reflectance based datasets.

1. Introduction

Salinity is a fundamental parameter of the ocean which influences the hydrological cycle, ocean circulation and climate changes (Bao et al. 2019). Bay of Bengal (BoB) occupies the tropical zone as a source of low saline waters on the surface because of the large amount of freshwater drained from the rivers in east coast of India (Sasamal, 1990). Salinity variations of major effect on physical and biochemical processes affect in the marine environment (Feng et al. 2009). Traditional methods of *in situ* measurements of Sea Surface Salinity (SSS) such as those from vessels and buoys are expensive and time-consuming which lead to large limitations in spatiotemporal coverage (Qing et al. 2013 and Sun et al. 2019). However remote sensing has paid a great attention to utilize the satellite data for SSS retrieval. Consequently SSS from satellite measurements would be very supportive to climatologists and Oceanographers (Marghany and Hashim 2011).

A number of SSS estimation approaches have been developed in recent years using remote sensing technology with optical and microwave remote sensing methods (Font, et al. 2008; Talone et al. 2010; Banks et al. 2012). For example, the microwave remote sensing data (Aquarius, Soil Moisture Active Passive (SMAP) and Soil Moisture and Ocean Salinity (SMOS)) it can provide global ocean SSS data for researchers to record further SSS differences. However, spatial and temporal resolution are too coarse, Aquarius had a spatial resolution of 100–150 km and an exact repeat of 7 days, SMOS has an average 43 km spatial resolution with 18 days repeat cycle and a 3–5 days visit period, SMAP has a 40 km spatial resolution and an 8 days repeat time of 2–3 days (Vinogradova, et al. 2019). Satellite derived salinity

data products are show some limitation in the estimation of SSS in the estuarine and coastal zones (Sun et al. 2019).

In previous research, several algorithms have been developed to estimate SSS using MODIS aqua derived remote sensing reflectance data in the marine environment. Few researchers for estimating SSS concentration (Qing et al. 2013, Yu et al. 2017, Sun et al. 2017 and Wang and Deng 2018) from these selected of varied approaches that are prevalent for SSS retrieval from ocean colour data. Each algorithm is applied to different channels reflectances derived from satellite ocean colour data and each uses different aspects are used to retrieve SSS concentrations. Marghany and Hashim 2011 developed the Box-Jenkins algorithm and similarly multi-linear regression model established for SSS retrieving of MODIS reflectance data (Qing et al. 2013, Yu et al. 2017 and Sun et al. 2017) artificial neural network model by Bao, (2019); Wang and Deng (2018); Chen et al. (2017) and model improved SSS algorithm by Zhou et al. (2012). Due to the high temporal frequency and better retrieval of MODIS Aqua data have been widely utilized in the marine environments (Wang and Deng 2017).

Salinity plays a vital role together with temperature, it help to determine water density and thus is intimately linked to the horizontal and vertical movement and furthermore has the potential to impact the amplitude of intra-seasonal variability of the SST in the BoB (Vinayachandran et al. 2012). Changes in SSS and SST have a strong impact on the development of marine organisms (swaitek 2019), Furthermore, SSS and SST play an exceptionally significant role in the marine ecosystem, uncertainty of temperature rise is unfavourable to the marine environment such as phytoplankton growth causing excessive eutrophication of marine reservoirs (Siegel et al. 2008) as well as the multiplication of toxic blue-green algae (Stromer 2011).

The goal of this paper involved to examining the long term variability of SSS in the BoB at seasonal and inter-annual time scale from the 2003 to 2019. Over the last decades, SSS observing system of the BoB has been improving reliably by remote sensing techniques and it has now become possible to monitor from season to season and year-to-year basin-scale variations. The SSS model developed using the *in-situ* observations was compared with SMAP direct product of SSS and MODIS water reflectance derived SSS algorithm established by Qing et al. 2013. Matchups between in situ measurements of SSS and satellite ocean color allows for the validation, comparisons of the BoB performances and estimation on the spatial and temporal patterns at seasonal and inter-annual changes and forecasting of SSS in the BoB were also analysed in this study.

2. Materials And Methodology

2. 1. In-situ

The datasets used in this study were collected from two cruises of Sindhu Sankalp (SSK-127) and CRV Sagar Purvi (CRVSP-03/2019) that carried out during April 5th to 14th and August 15th to 19th in the year of 2019 respectively. At each hydrographic station (Fig. 1), CTD data were obtained through a Seabird 911 plus V 5.2 multi-parametric probe with redundant by salinity sensor. At each sampling station the

CTD were three times casting from the vessel's underway system approximately up to 20m depth through differential global positioning systems. Before and after the field casting, the CTD was calibrated with Milli-Q water to confirm that its performance was within factory specifications.

2. 2. Remote Sensing Observations

The performance of refined SSS algorithm developed by Qing et al. 2013, these model was calibrated with *in-situ* datasets based on the better assess the algorithm used in this study was expressed as follow.

$$SSS = e^{10(7.8*Rrs(488)-11.325*Rrs(555)+2.183*Rrs(667)+1.530)}$$

The satellite remotely sensed data used in this study were subsequently water leaving reflectances of (Rrs) (488, 555 and 667 nm) data extracted from the MODIS Aqua level 2 and 3 products with a resolution of 1km and 4km were downloaded from the ocean colour website (<https://oceancolor.gsfc.nasa.gov>) and then processed using the SeaDAS software version 7.3. Level 3 products are utilized for analysis of seasonal and inter-annual variation of SSS in the entire BoB due to their finer spatial resolution. In the interim there are inherent differences in SSS in the SMAP satellite and other reflectance satellite data while the comparison of MODIS Level 2 data with SMAP for validation with *in-situ* measurements.

2. 3. Statistical Analysis

The evaluation process was made by comparing satellite derived values with the *in-situ* measurements. Statistical fitting was applied to these data using Sigma Plot (Ver.12.0) statistical software. Mean normalized bias (MNB), root mean square error (RMSE) and Standard error of the estimate (SEE) were analyzed to examine the performance between *in-situ* and satellite data followed by Poornima et al. 2018. The forecasting of SSS method was followed by Ray (1993) by using IBM Statistics version 24.

3.0. Results And Discussion

The spatial SMAP SSS were quantitatively compared with *in-situ* measurements at offshore and coastal leads to difficulties in validating SMAP data. The SMAP satellite Level-2 data is sampled along swath with a resolution of approximately 40km and further MODIS retrieved SSS data is 4km. Through the *in-situ* CTD data measure salinity coordinates utilize temporal averaging collocated in SeaDAS version 7.5.1. Hence, validating SMAP satellite and MODIS retrieved SSS with *in-situ* measurements on the same spatial and temporal scales is an important for ensuring the reliability of the corroboration.

3.0.1. Validation of SMAP with In-situ SSS of offshore and coastal waters of BoB

To perform validation between satellite SMAP and *in-situ* SSS at offshore and coastal stations, covering a large span of the BoB. The good correlation coefficient of $R^2 = 0.707$ and $SEE = \pm 0.291$ at offshore

(Fig. 2.C), but the deprived correlation coefficient of $R^2 = 0.499$ and $SEE = \pm 0.546$ at coastal region (Fig. 3.C). These coastal features have major impacts on the accuracy of SMAP in the BoB. Recently, Grodsky et al. (2018) used SMAP derived SSS retrieval with *in-situ* SSS for open ocean conditions that is almost away from coastal impacts due to the discharge of the freshwater. Subrahmanyam et al. (2018) SMAP largely SSS variation is associated with the variations in the magnitude of riverine flux in coastal system (Papa et al. 2012) with the variations in freshwater flux also. Similarly Cuervo et al. 2019 also reported Saildrone *in-situ* values correlations with SMAP were lower of 0.39 and root mean square difference of 0.37 and biases of 0.46 PSU at California Baja coast. Furthermore, Grodsky et al. 2018 monitoring strong sampling variability of SMAP data resulted in the deprived correlation of SMAP and buoy salinity anomaly data correlations of 0.25 in the Gulf of Maine at coastal region.

The performance of SMAP with *in-situ* SSS (Fig. 4.a) showed the 70% underestimation and 30% overestimation in offshore as well as (Fig. 4.b) showed the 95% underestimation and 5% overestimation in coastal region of *in-situ* SSS spread above the 1:1 line mean Normalized Bias (MNB) = -0.0029/-0.0089 and RMSE = $\pm 0.092/0.139$ in offshore and coastal respectively. In the present study, SMAP shows an underestimation and negative bias, this can be examined SMAP with *in-situ* SSS anomalies is not clear resolution in the BoB. In this case, posit that this is probably due to SMAP negative bias issues. While Sun et al. 2019 also indicated SMAP products show coarse spatial distribution, probably with a certain limitation in the detection of fine characteristics. Moreover, ubiquitous is scarce spatial coverage in the coastal regions and SMAP derived SSS, show that a pragmatic remedy to Fig. 2a and 3a around these SSS bias issues is the computation and utilize of SMAP derived SSS anomalies; anomalies are created that make the difference relative to a satellite SSS climatology in the offshore region. Therefore, in this study ultra-investigated higher resolution of spatial-temporal variability of the SSS based on satellite-derived products in the coastal and offshore is necessary.

3.0.2. Validation of MODIS retrieved SSS with In-situ SSS of offshore and coastal waters of BoB

The MODIS (Qing et al. 2013) derived SSS and validated with *in-situ* SSS obtained the good correlation coefficient (Fig. 2.c) of $R^2 = 0.908$ and $SEE = \pm 2.395$ and the significant correlation (Fig. 3.c) of $R^2 = 0.891$ and $SEE = \pm 1.512$ in offshore and coastal region respectively. Margany et al. (2011) validated MODIS Aqua derived SSS by using linear regression model with *in-situ* measurements at Kula Terengganu and Phany coastal water with positive correlation of $R^2 = 0.96$. Wang and Deng (2018) developed ANN algorithm for the retrieval of SSS in coastal waters at Gulf of Mexico with correlation of $R^2 = 0.89$. In the BoB, satellite derived SSS studies are scarce; therefore, the spatiotemporal variability of the SSS was very much essential to study coastal and offshore region.

The performance of MODIS retrieved SSS and *in-situ* SSS (Fig. 4.c and 4.d) showed the 100% overestimation in coastal and offshore regions from the 1:1 line mean Normalized Bias (MNB) = 0.0718/0.0361 and RMSE = $\pm 0.760/0.316$ in offshore and coastal respectively. Similarly, Yu et al. 2017 obtained, the $R^2 = 0.76$, with RMSE = ± 3.02 in coastal region of Bohai Sea. These results determine that

the MODIS derived SSS estimating models have a great potential than SMAP based in the BoB at coastal region.

3.0.3. Seasonal variability of SSS with SST

To examine the penetrative behavior of seasonal salinity in the surface of the BoB. In this present study stated that the seasons are categorized as spring inter-monsoon (March to May), summer monsoon (June to August), fall inter-monsoon (September to October) and winter monsoon (November to February) (Prasannakumar et al. 2010).

The long term variability of SSS and SST were spatially and temporally varied, with highest variability of SSS and SST occurs in spring inter-monsoon season and lowest variability of SST was occur in winter monsoon, lowest value of SSS fluctuate in fall and winter monsoon, Fig. 5 shows the variation of seasonal salinity from 2003 to 2019 while the high salinity recorded (35.949 PSU) in the spring inter-monsoon 2016 and the low salinity value (34.929 PSU) in the fall inter-monsoon 2016. The minimum SST was registered in winter monsoon 2007 (27.554°C) and the maximum temperature was observed in spring inter-monsoon 2016 (30.325°C). The difference of salinity may relate to the seasonal variation of river discharge (Chamarthi et al. 2009). The figure.5 clearly shows SSS and SST trend were shows its peak in spring inter-monsoon followed by summer monsoon with comparatively lower range and when compared with summer monsoon, fall inter-monsoon remains slightly higher and abrupt low during winter monsoon from 2003 to 2019.

3.0.3.1. Spring inter-monsoon (SIM)

During SIM, SST varies from 29.2 to 30.3°C and SSS range from 35.6 to 35.9 PSU respectively. Large variations of SSS and SST observed during the SIM in the present study and might be due to intense solar radiation, strong stratification because of high heat absorption and less wind force (Prasanakumar et al. 2002). Similarly, net heat flux observed the highest level during SIM season which continued the warmest SST (Narvekar and kumar., 2006) even though excess evaporation over precipitation and the least amount of freshwater run off from rivers adjoin the BoB during SIM led to the highest SSS (Prasannakumar et al. 2010). Rao & Sivakumar, 2003 also conversed low-salinity waters flow from the BoB, where precipitation and river runoff exceeds evaporation into the BoB, characterized by high salinity due to enhanced evaporation.

3.0.3.2. Summer monsoon (SM)

During SM, SST and SSS were not as much of SIM (28.6 to 29.3°C and 34.9 to 35.3 PSU) respectively. The Fig. 5. visibly reduce SSS and SST, amplitudes season to the start of the southwest monsoon, nearly half of the BoB becomes upwelling zone. The occurrence of upwelling is the significant characteristic during SM (Sarma 2003) it responds very rare case in the BoB. Prasannakumar et al. (2002) examined of the basin-wide wind revealed that in the Arabian Sea wind is about 3–4 m/s stronger than that in the BoB and is also consistent with Comprehensive Ocean Atmosphere Data Set (COADS) climatology (Woodruff

et al. 1987). These winds continue to weaken through September, making geostrophic, Ekman drift, eddy and shallow deepen more relevant to the surface flow field (Li et al. 2017) and SM cycle is also concomitant with Rossby-wave radiation in the offshore (McCreary et al. 1993), but nonlinear interactions (Vinayachandran and Yamagata, 1998) and eddies are likely to be important at the shorter scales associated with the meanders. Eddy-driven vertical mixing due to horizontal or vertical current shear might play a role in these meanders (Klein and Lapeyre, 2009) that react not drastic variation in the SSS and SST.

3.0.3.3. Fall inter-monsoon (FIM)

During FIM, SST was slightly higher than SM (28.9 to 29.6°C) whereas SSS values not shown that much variations (34.8 to 35.4 PSU). In the present study, SST increases by 0.3°–1.2°C compared to SM because of increased solar radiation. The increased SST due to large surface heating and weak sea surface wind enhances the development of stratification (Akhil et al. 2014). But lowest SSS observed in this season when the southwest monsoon wind weakens during September month, the East India Coastal Current (EICC) reverses, flowing southward along the entire coast, an area of low salinity water moves north to south along the Indian coast (Akhil et al. 2014). The EICC is also influenced by wider circulation in the Indian Ocean (Schott et al. 2009) and positive (Indian Ocean Dipole) IOD is concomitant with a weaker southward EICC show the lower salinity in the northern Bay (Pant et al. 2015).

3.0.3.4. Winter monsoon (WM)

During WM season very lowest SST was recorded in 2007 (27.5°C); SST range varies from 27.5 to 28.2°C. There is no drastic variation in SSS found 35.1 and 35.3 PSU in this season whereas interestingly the highest value of 35.3 PSU is less range when compared to other seasons. When the southwesterly wind weakens and the flow starts changing its direction from northeast. The low salinity area increases during the month of November when the northeasterly wind is strong. This may be due to the discharge of fresh river water and winter precipitation carried by ocean currents. Although the ocean receives more heat with riverine input, slightly cooler SST results because entrainment cooling is more effective, latent heat loss cooling is more effective (despite less latent heat loss), and penetrative radiation is greater, but overall, the SST differences are small (Howden and Murtugudde 2001). SSS in the BoB during this period is about 3 PSU fresher than the average Arabian Sea value of 36.2 PSU (Prasannakumar et al. 2002). The freshwater influx induces the near surface stratification in BoB and it forms the low salinity layer at the sea surface during WM when compared to the other seasons. Sarangi, (2011); Akhil et al. (2014) also discussed SST was decreased because there has been cooling of water in the Indian coast, ~ 4°C deviation from the coastal BoB due to cyclonic wind stress, the churning and vertical stratification of water. In the way, the salinity is very prominent during the peak of WM (Paul et al. 2008).

3.0.4. Inter-annual variation of SSS with SST

A detailed analysis of the inter-annual variability of salinity in the BoB and the role of various mechanisms such as horizontal advection, river runoff, local freshwater flux in terms of evaporation and

precipitation and the impact of remote sensing has not yet been noted in the BoB. In this study, a detailed analysis is done to examine the inter-annual variability and different factors responsible for the anomalous variations by using remote sensing. In particular, the anomalous low salinity waters observed during the year of 2016 in fall inter-monsoon and 2018 in summer monsoon.

In the year of 2016, observed highest salinity and temperature in the spring inter-monsoon (35.959 PSU) and the lowest salinity recorded in fall inter-monsoon (34.867 PSU) and the sudden rises of salinity in winter monsoon (35.236 PSU). During the late FIM Kyant cyclone (25–26 October) and winter monsoon occurred dual cyclones were affected during the BoB such as Nada (26 November to 1 December) and Vardah (7–11 December). The small salinity fluctuation on October was associated mainly with heavy precipitations (~ 143 mm) and slightly low wind speeds (Ye et al. 2019). Abrupt rise of SST and SSS in winter monsoon is the irrefutable evidence that the salinity from the surface region up to 50 m depth increases (1–1.5 PSU) due to cyclone prompted vertical mixing (Chacko 2018). The amplitude of SSS change evident in the MODIS observations map agrees. The precipitation accompanied by a tropical cyclone can dilute the SSS in the surface, which can decrease the $p\text{CO}_2\text{sea}$ (Sun et al. 2014) due to the storm-induced strong vertical mixing uplifted subsurface waters (up to depths of 60 m) to the surface layer at the BOB (Chacko, 2017). The significant of certain FIM currents also perceptible (Fig. 5.) show possible contributing mechanisms on the relations between the observed seasonality and dynamical variability might include changes in the velocity of the currents which directly reduce salt transport by the jets and variability of the salinity in the source regions which transmit downstream seasonally (Hormann et al. 2019).

In 2018, highest salinity and temperature in the spring inter-monsoon (35.921 PSU and 29.713°C) and the lowest salinity recorded in summer monsoon (34.929 PSU and 28.675°C) due to the depression formed over northwest BoB during the summer monsoon month of August. It lay as a well-marked low pressure area over northwest BoB and adjoining West Bengal, Andhra Pradesh and Odisha coasts extremely heavy rainfall 204.5mm reported by Indian Meteorological Department in August 2018. In this case, Fig. 5 represents large runoff during the summer monsoon and low freshwater supply during winter. Year-to-year precipitation and runoff anomalies sometimes vary in phase. The IOD and El-Nino-Southern Oscillation (ENSO) are additional, but weaker sources of influence on the BoB circulation patterns, associated with changes in wind patterns in addition to rainfall at the surface and unusual circulation patterns within the marine (Currie et al. 2013).

In the year, 2012, 2016, 2017 and 2018 high salinity present in spring inter-monsoon more than 35.9 ppt. Contradictory, low saline and SST were present during summer monsoon in the year of 2012 (35.0 PSU), 2017 (35.0 PSU), 2018 (34.9 PSU) and 2016 in fall inter-monsoon (34.8 PSU). Durand et al. (2009) suggested that intra-seasonal fluctuations are driven by remote forcing of the equatorial Madden Julian Oscillation. Obviously, the seasonal variability of salinity is dominated by the annual component. Rao and Sivakumar [2003] studied the inter-annual variability of SSS and its relation to El-Nino in the tropical Indian Ocean and their study revealed that the BoB has significant variability in SSS associated with low saline waters during El-Nino years. In this study understood that the El-Nino observed in the years 2004,

2006, 2009, 2014, 2015 and 2017 and La-Nina years 2007, 2008, 2010, 2011 and 2016, neutral years are 2003, 2005, 2012, 2018 and 2019. However, few studies investigated (Girishkumar et al. 2015) that although El-Nino leads to positive SST anomaly in the BoB, the number of tropical cyclones reduces due to changes in less favorable environment conditions. Earlier studies have revealed that salinity variability and its related freshwater flux anomaly play a main role in ENSO evolution through their influence on horizontal pressure gradients, surface stratification and thermocline of the ocean (Zhu et al. 2014). The changes in SSS are to a huge extent forced by surface freshwater fluxes (evaporation minus precipitation), with further contribution from marine processes such as advection, entrainment and diffusion (Ren et al. 2011).

4.0. Conclusion

Finally, the *in-situ* results indicate that MODIS Aqua water reflectance data is more accurate for SSS obtained by using Qing et al. (2013) retrieval algorithm and is well suitable for BoB. Hence, the seasonal variability of salinity in BoB is temporal by the variability in river discharges and intense solar radiation and the seasonal pattern of surface circulation, there can be anomalous distribution of low salinity waters forced by IOD is associated with EICC influence by water circulation in BoB. In this study, the evaporation-precipitation flux, river discharge, IOD, El-Nino, ENSO and cyclone were important factors influencing the seasonal and inter-annual SSS and SST variability in the BoB. The forecasting indicated decadal for SSS depict the seasonal and inter-annual variation due to El-Nino and La-Nina years and forecasting of salinity not much vary. However, present study understanding on SSS variability would considerably improve with adequate high quality forthcoming measurements of salinity, evaporation, precipitation, river runoff parameters by using remote sensing and forecasting SSS diffusive processes might balance by the surface fresh water forcing and substantially modulated by the SST and wind-driven processes in the BoB.

Declarations

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Authors' contributions

Kandasamy Priyanka: Overall preparation, cruise participated, Data analysis, Manuscript writing. Ranjit Kumar Sarangi: review & editing. Ramalingam Shanthi and Durairaj Poornima: review and software helping. Ayyappan Saravanakumar: Resources, Supervision, Project administration, Visualization.

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Availability of data and materials

Data that supports the findings of this study are not publicly available and can only be provided upon reasonable request through proper channel from corresponded author (asarvaan@gmail.com).

competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Conflicts of Interest:

The authors declare no conflict of interest.

Ethics approval and consent to participate:

Not applicable.

Consent for publication:

Not applicable

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Figures

Figure 1

Maps showing the study area along the BoB

Figure 2

The sea surface salinity maps a) Soil Moisture Active Passive (SMAP) and b) retrieved of sea surface salinity by using MODIS data in the BoB c) Regression plot of in-situ CTD with SMAP and MODIS Retrieved SSS in off shore region

Figure 3

a) The sea surface salinity maps a) Soil Moisture Active Passive (SMAP) and b) retrieved of sea surface salinity by using MODIS data in the BoB at coastal region c) Regression plot of in-situ CTD with SMAP and MODIS Retrieved SSS in coastal region

Figure 4

Comparison plots of a) SMAP SSS with in-situ SSS along offshore b) SMAP SSS with in-situ SSS along coastal c) MODIS derived SSS with in-situ along offshore SSS d) MODIS coastal derived SSS with in-situ along coastal

Figure 5

Inter-annual and seasonal variations of sea surface salinity variables registered during 2003-2019