Automated retrieval of sea surface salinity from satellite data and investigation of the spatiotemporal variation of ocean salinity across the West and Central African coasts

Authors

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Abstract

Sea Surface Salinity (SSS) is an important variable that affects the physical properties of the oceanic environment. Satellite sensors have been developed to routinely acquire SSS concentrations. However, many in the broader scientific community do not engage with this data, because it requires relevant remote sensing skills and tools to extract and process into formats that can be readily utilized by non-remote sensing experts. To address this issue, we used Python, PostgreSQL database, and Power BI visualization tool, to develop an automated tool, that facilitates the retrieval, processing, analysis, and visualisation of data from the Optimally Interpolated Sea Surface Salinity (OISSS) dataset, comprising data from the Aquarius/SAC-D, Soil Moisture Active Passive (SMAP), and Soil Moisture and Ocean Salinity (SMOS) satellite missions. Using this tool, we extracted long term series of SSS from 2011 to March 2022. In addition, an interactive reporting dashboard was developed in this research to enable users to visualize and interrogate the underlying dataset. Analysis of this data revealed detailed spatiotemporal patterns of SSS variations in the study area across varying spatial and temporal scales. We were able to identify the cold and hot spots of SSS, as well as longitudinal (inter- and intra-annual) variations in SSS concentrations. We anticipate that the outcome of this research will boost further research in this area, contribute to future climatic change studies and stimulate the democratization of remote sensing data. Climatic changes have been found to have profound effects on ocean salinity. The data obtained in this research could also feed into machine learning models for predicting future impacts of climate change on salinity concentrations across the ocean. In addition, the ability to monitor the salinity on a regular basis can be deployed alongside other relevant variables to forecast future climatic changes. Due to the fact that salinity is an excellent indicator for water cycle changes, the ability to routinely monitor salinity at relatively higher spatial and temporal resolutions is of great significance to the local community, as it could be used to understand current and future water cycle regimes in the area. The water cycle has profound effect on various socio-economic activities including agriculture and food security, ecology, hydrology (water quality), and drought.

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Resumé

La salinité de surface de la mer (SSS) est une variable importante qui affecte les propriétés physiques de l'environnement océanique. Des capteurs satellitaires ont été mis au point pour mesurer régulièrement les concentrations de SSS. Cependant, de nombreux membres de la communauté scientifique au sens large ne s'intéressent pas à ces données, car elles requièrent des compétences et des outils de télédétection adaptés afin de les extraire et de les convertir dans des formats facilement utilisables par des profanes en télédétection. Pour résoudre ce problème, nous avons utilisé Python, la base de données PostgreSQL et l'outil de visualisation Power BI pour développer un outil automatisé qui facilite l'extraction, le traitement, l'analyse et la visualisation de données du jeu de données OISSS (Salinité de la surface de la mer avec interpolation optimale), qui comprend des données provenant des missions satellitaires Aquarius/SAC-D, SMAP (Passif actif de l'humidité du sol) et SMOS (humidité du sol et salinité de l'eau). Grâce à cet outil, nous avons extrait des séries à long terme de SSS de 2011 à mars 2022. En outre, un tableau de bord interactif a été développé dans le cadre de cette recherche pour permettre aux utilisateurs de visualiser et d'interroger le jeu de données sous-jacent. L'analyse de ces données a révélé des schémas spatio-temporels détaillés des variations de la SSS dans la zone d'étude à différentes échelles spatiales et temporelles. Nous avons pu identifier les points froids et chauds de la SSS, ainsi que les variations longitudinales (inter- et intra-annuelles) des concentrations de SSS. Nous pensons que les résultats de cette recherche encourageront des recherches supplémentaires dans ce domaine, contribueront aux futures études sur le changement climatique et stimuleront la démocratisation des données de télédétection. Les changements climatiques ont des effets profonds sur la salinité des océans. Les données obtenues dans le cadre de cette recherche pourraient également alimenter des modèles d'apprentissage automatique pour prédire les impacts futurs du changement climatique sur les concentrations de salinité dans les océans. En outre, la capacité de surveiller régulièrement la salinité peut être utilisée avec d'autres variables pertinentes pour prévoir les changements climatiques à venir. La salinité étant un excellent indicateur des modifications du cycle de l'eau, la capacité de surveiller régulièrement la salinité à des résolutions spatiales et temporelles relativement plus élevées revêt une grande importance pour les communautés locales, car elle pourrait être utilisée pour comprendre les régimes actuels et futurs du cycle de l'eau dans une région. Le cycle de l'eau a un effet profond sur diverses activités socio-économiques, notamment l'agriculture et la sécurité alimentaire, l'écologie, l'hydrologie (qualité de l'eau) et la sécheresse.

Resumen

La Salinidad de la Superficie del Mar (SSS) es una variable importante que afecta a las propiedades físicas del entorno oceánico. Se han desarrollado sensores satélites para detectar concentraciones de SSS con normalidad. Sin embargo, gran parte de la comunidad científica en general no trabajan con estos datos, porque hacen falta capacidades y herramientas apropiadas de detección remota para extraerlos y procesarlos en formatos que quienes no sean expertos en detección remota puedan utilizar con facilidad. Para resolver este problema usamos Python, la base de datos PostgreSQL, y la herramienta de visualización Power BI, para desarrollar una herramienta automatizada que facilite la recogida, procesado, análisis y visualización de datos del conjunto de datos de Salinidad de la Superficie del Mar de Interpolación Óptima (OISSS), que incluye datos de las misiones satélite de Aquarius/SAC-D, Pasivo Activo de Humedad del Terreno (SMAP), y Humedad del Terreno y Salinidad del Océano (SMOS). Usando esta herramienta extrajimos series de SSS a largo plazo desde el 2011 a marzo del 2022. Además se desarrolló un tablero interactivo de información durante la investigación para permitir a los usuarios visualizar y consultar el conjunto de datos subyacente. El análisis de estos datos reveló patrones espaciotemporales detallados de variaciones de la SSS en el área de estudio a lo largo de escalas espaciales y temporales. Pudimos identificar los puntos calientes y fríos de SSS, así como las variaciones longitudinales (inter- e intra-anuales) en las concentraciones de SSS. Anticipamos que el resultado de esta investigación fomentará más investigaciones en esta área, contribuirán a estudios futuros sobre el cambio climático, y estimularán la democratización de los datos de detección remota. Se ha determinado que los cambios climáticos tienen profundos efectos en la salinidad oceánica. Los datos obtenidos en esta investigación también se podrían introducir en modelos de aprendizaje automático para predecir futuros impactos del cambio climático en las concentraciones de salinidad en todos los océanos. Además, la capacidad de hacer el seguimiento regular de la salinidad se puede emplear junto con otras variables relevantes para predecir futuros cambios climáticos. Debido al hecho de que la salinidad es un indicador excelente de los cambios en el ciclo del agua, la capacidad de hacer el seguimiento de la salinidad con normalidad a resoluciones espaciales y temporales relativamente más altas tendrá gran trascendencia para la comunidad local, ya que se puede usar para entender los regímenes actuales y futuros del ciclo del agua en el área. El ciclo del agua tiene profundos efectos en diversas actividades socioeconómicas como la agricultura y seguridad alimentaria, ecología, hidrología (calidad del agua), y sequía.

1 Introduction

Sea Surface Salinity (SSS) provides information on the concentration of dissolved salts in the upper centimeter of the ocean surface. It is a key parameter that contributes to global ocean circulation and the earth's climate, as well as providing fundamental information for ocean biogeochemistry (Fine et al., 2017; Land et al., 2015, 2019; Siedler et al., 2001; Wang et al., 2022). Hence, it can affect marine ecosystems (organisms and plant community), the physical properties of the oceans (temperature, density, pressure, waves, and currents), as well as the water cycle and ocean circulation (Jang et al., 2022; Pradesh, 2019). Importantly, salinity in conjunction with temperature determines seawater density, which in turn drives many ocean processes such as vertical mixing, double diffusion, horizontal circulation, and near-surface stability. Salinity also plays a crucial role in modulating the air-sea interaction (surface fluxes of heat and CO_2) due to its impact on boundary layer processes. Hence, even small variations in SSS can have dramatic effects on the ocean system. Furthermore, the ocean water freezing point also depends on salinity (it takes longer for more saline water to freeze than less saline water). Thus, making the investigation of salinity variation imperative.

There is a wide range of spatiotemporal variations in the distribution of salinity within the oceans, seas, and lakes, even though the relative abundance of the major salts in seawater is largely constant. This variation is both horizontal and vertical. Sea surface salinity is mainly controlled by the balance between evaporation and precipitation. Hence, high salinity concentrations are recorded in the regions around 20° to 40° North and South (sub-tropical central gyre regions), where evaporation is extensive, but rainfall is minimal. Globally, the average salinity in the oceans and the seas is 35‰ (Droppleman et al., 1970; NASA, 2022).

Due to the importance of sea salinity in global water balance estimation, evaporation rates, and ocean currents, it is crucial that salinity is continuously monitored to have a good understanding of its variability and potential impacts on ocean process and water balance. While some parts of the world are currently experiencing increasing salinity levels, others are experiencing decreasing salinity. For instance, the Arctic is experiencing an increase in temperature (IPCC, 2018), which is modifying the freshwater cycle in the region and leading to decreasing salinity (Carmack et al., 2016). However, in the Barents Sea, which is also within the same Artic region, both temperature and salinity are increasing due to the increase of salty water supply from the North Atlantic waters, that is the so-called 'Atlantification' (Lind et al., 2018). Such changing dynamics in salinity variation demonstrate the need for continuous monitoring of SSS variation, to facilitate understanding of the underlying factors triggering this and their potential impact. This is especially important with increasing climatic changes that may further alter salinity concentrations across the oceans (Bindoff et al., 2019). Changes in ocean salinity concentrations could significantly alter local salinity regimes, which in turn could affect ecosystem composition in nearby communities, as well as altering interactions between organisms. This would have profound effects on communities in developing countries, especially those in West and Central Africa with much reliance on ecosystem services from the marine environment (ocean, estuaries, and fresh waters). This could have significant effects on the local economy by affecting fishing industry, reducing freshwater availability (water quality), as well as soil salinity imbalances that could affect food security. In addition, varying salinity concentrations could alter species distribution marine, estuarine, and freshwater species, although the magnitude of the impacts depends on the underlying physiology and tolerances of organisms and their ability to cope with salinity fluctuations on both long- and short-time scales (Smyth and Elliott, 2016).

Hence, within the past two decades, salinity variations across the global seas and oceans have regularly been observed by satellites (Boutin et al., 2021; D'Addezio et al., 2019; Fournier et al., 2015; Gierach et al., 2013; Grodsky et al., 2012; Jang et al., 2022; Korosov et al., 2015b; Lagerloef, 2012; Lee et al., 2012; Melzer & Subrahmanyam, 2015; Rani et al., 2021; Reul et al., 2020; Reul et al., 2014; Supply et al., 2020). Deployment of satellite methods enabled consistent measurement of weekly, monthly, interannual, and decadal variations in salinity. Currently, sea surface salinity values derived from various satellite sensor data are enabling widescale routine monitoring of salinity variability, seawater plumes, and climate change on global, and regional scales.

Despite having been collected by various satellite sensors for over a decade, sea surface salinity measurement is not regularly available to many users, especially researchers in developing countries, or to non-remote sensing specialists who lack the necessary skills and tools to extract these data from satellite data. This limits the extensive study and wider understanding of the spatiotemporal variations of ocean salinity in many areas and their attendant impact on the marine environment and climate change. Due to the importance of the oceanic environment, some projects have been dedicated to alleviating access to key oceanic variables to interested parties. The Copernicus Marine Service is a key program of the European Union, is one of such projects that is used to provide free, regular and systematic information on the state of the ocean (including salinity), on a global and regional scale. However, users are constrained to only data available on the visualization platform, some of which are presented at a relatively coarse spatial resolution (e.g. Global Ocean- Real time in-situ observations objective analysis product presented at a 0.5 degree spatial resolution) (Szekely, 2022). Hence, in this study, we aimed to develop an automated approach (End-to-End Extract,

Transform, Load, and Report (ETLAR) data pipeline) to extract sea surface salinity from satellite data. Using the developed method, we investigated the spatio-temporal variation of ocean salinity across the western coast of Africa. We set out to achieve the following key objectives: develop an automated technique for easy and quick retrieval of salinity data from satellite data into commonly used data format, investigate and map spatiotemporal variations of sea surface salinity across the western coast of Africa, identify spatial and longitudinal trends and pattern in SSS in the region, and create sea surface salinity data store and visualization service to facilitate easier access to data, interrogation of SSS data, and routine reporting of salinity variations in the study area.

2 Variation of sea surface salinity

The horizontal distribution of ocean salinity is conventionally studied in relation to latitudes. Generally, salinity decreases from the equator towards the poles. However, the highest salinity concentration is hardly recorded near the equator despite the fact that this zone records high temperature and evaporation. This is due to high rainfall activity in this zone that reduces the relative proportion of salt in the waters. Thus, salinity around the equator is roughly around 35 ‰. The highest salinity concentrations are generally observed between latitudes 20°–40° N (36 ‰) because this zone is characterized by high temperature and evaporation rates, with relatively low rainfall. The average salinity of 35 ‰ is recorded between latitudes 10°–30° S in the southern hemisphere. The zone between 40°–60° latitudes in both hemispheres records low salinity (31 ‰ in the northern hemisphere) and (33 ‰) in the southern hemispheres. Salinity further decreases in the polar zones because of the influx of meltwater (Antonov & Levitus, 2006).

2.1 Key factors controlling SSS

The key factors controlling sea surface salinity include evaporation, precipitation, the influx of freshwater (from rivers), ice melts, atmospheric pressure, wind direction, and circulation of oceanic water (Durack et al., 2012; Qu et al., 2014; Skliris et al., 2014). Salinity positively correlates with the rate of evaporation (the greater the evaporation, the higher the salinity concentration and vice versa). Evaporation due to high temperature with low humidity (dry condition) causes higher salinity levels. Hence, salinity is higher near the tropics than at the equator because although both the areas record a high rate of evaporation it is less humid (dry air) over the tropics of Cancer and Capricorn.

Precipitation is inversely related to salinity (higher volumes of precipitation result in lower salinity and vice versa). High-frequency rainfall events can substantially affect salinity concentration on varying spatial scales (Akhil et al., 2016; Boutin et al., 2016). Therefore, the regions of high rainfall (equatorial zone) generally, record comparatively lower salinity than the regions of low rainfall (sub-tropical high-pressure belts).

It may be simply stated that the volume of water in the oceans is increased due to heavy rainfall and thus the ratio of salt to the total volume of water is reduced.

Furthermore, meltwater from the polar areas supplies extra water in the temperate regions that increase the volume of water and therefore reduce salinity. Hence, the impact of ice melt on salinity is noticeable in polar regions, where such processes produce substantial sea surface salinity gradients (Brucker et al., 2014). In addition, the influx of water from rivers also affects the salinity of oceans. Strong river outflow normally causes strong gradients in sea surface salinity (Fournier et al., 2015; Gierach et al., 2013; Grodsky et al., 2012; Korosov et al., 2015a; Reul et al., 2014). Thus, low-salinity concentration usually indicates sources of fresh water, such as rivers and streams that are feeding the ocean (Burrage et al., 2008; Schroeder et al., 2012). Even though such rivers often carry natural and anthropogenic contamination from the land to the sea and can directly impact marine ecosystems with a higher level of salinity, the quantity of water in the inflow normally neutralizes the concentration of salt, thus, leading to an overall reduction of salinity concentration. This is especially noticeable around the mouths of major rivers. For instance, comparatively low salinity is found near the mouths of the River Niger, River Congo, the Amazon River, etc. The effect of the influx of river water is more pronounced in enclosed seas (e.g. the Dniester, the Dneiper, the Danube). This also accounts for the relatively low salinity (17 ‰) in the Black Sea, as it receives an influx from many rivers in Europe. However, in places where evaporation exceeds the influx of fresh river waters, salinity concentration increases (e.g. the Mediterranean Sea records salinity levels of about 40 ‰).

Atmospheric pressure and wind direction are other factors that affect salinity. Anticyclonic conditions with stable air and high-temperature increase the salinity of the surface water of the oceans. Sub-tropical high-pressure belts represent such conditions to cause high salinity. Winds also help in the redistribution of salt in the oceans and the seas as winds drive away saline water to fewer saline areas resulting in a decrease of salinity in the former and an increase in the latter. Ocean currents affect the spatial distribution of salinity by mixing seawaters. Equatorial warm currents drive away salts from the western coastal areas of the continents and accumulate them along the eastern coastal areas. The high salinity of the Mexican Gulf is partly due to this factor. The North Atlantic Drift, the extension of the Gulf Stream increases salinity along the north-western coasts of Europe. Similarly, salinity is reduced along the northeastern coasts of North America due to the cool Labrador Current.

2.2 Historic development in ocean salinity measurement/monitoring

Despite its long-recognized importance, salinity was historically under-sampled across the globe, due to

the challenges posed by using traditional methods to measure salinity. Before the deployment of electronic instruments in salinity measurements, accurate salinity measurements relied on complex chemical analysis to precisely determine the salinity content of water samples in laboratories or on research vessels. Hence, salinity observations were very sparse. This was improved through the development of conductivity-temperature-depth (CDT) technology that allowed salinity to be inferred through conductivity measurements. This led to the routine observation of salinity profiles, although observations were still limited in space and time, because of the sparseness of hydrographic sections performed by research vessels. However, the deployment of autonomous Argo profiling float array (Roemmich et al., 1999) improved this situation by enabling routine sampling of high-quality salinity profiles down to 2000m depth on a global scale (Stammer et al., 2021; Stammer et al., 2019; Weller et al., 2019).

Subsequently, various gridded salinity products of the historical data sets (climatologies) such as the World Ocean *Atlas* (WOA; Antonov & Levitus, 2006; Boyer and Levitus, 2002; Zweng et al., 2018) and EN4 data set (Good et al., 2013) were developed based on historical salinity observations. These are used for salinity and freshwater change studies (Curry et al., 2003; Palmer et al., 2019). Furthermore, numerical ocean models were developed and used in simulating salinity variations and their impacts on ocean processes (e.g., geostrophic flow fields or sea level), using atmospheric forcing fields.

Recent development in satellite remote sensing resulted in the measurement of sea surface salinity from space. This technology is based on inferring surface salinity from satellite sensor measurements of microwave radiance emitted from the top mm of the sea. Detailed technical information on the basic physics of salinity measurement from space, various salinity missions as well as satellite SSS products quality assessment is provided by (Reul et al., 2020). This has led to regular global measurement of sea surface salinity roughly every three days with a relatively high spatial resolution (Vinogradova et al., 2019).

2.3 Satellite monitoring of sea surface salinity

Before the deployment of satellite remote sensing in ocean salinity measurement, SSS was poorly sampled globally. Estimation of sea surface salinity from space began in 2009, following the launch of the Soil Moisture and Ocean Salinity (SMOS) mission. SMOS is one of the European Space Agency's Earth Explorer missions and provided global observations of variability in two important climate variables: SSS and soil moisture, due to continuous exchange in the earth's water cycle between the oceans, the atmosphere, and the land. The sensor can detect salinity at 50 km, which is a relatively high spatial resolution (Bell et al., 2004; Glenn et al., 2004; Rani et al., 2021).

Following the success of this mission, NASA, in collaboration with Argentina's space agency, Comisión Nacional de Actividades Espaciales (CONAE) launched Aquarius in 2011, to study the links between ocean circulation, the global water cycle, and climate. The Aquarius mapped global changes in ocean surface salinity with a resolution of 150 km and 7 days repeat cycle. Hence, provided information on how salinity changes week on week, month on month, season to season, and year to year, until June 2015 when some of the components malfunctioned. The salinity measurement from space was continued with NASA's Soil Moisture Active Passive (SMAP) satellite. Although SMAP's mission is primarily focused on the water content of the soil, its highly sensitive radiometer operates on a similar wavelength as Aquarius, and thus, has been used as a replacement for Aquarius, while providing a continuous record of essential information on the ocean, water cycle, and climate. SMAP has a repeat cycle of 8 days with a spatial resolution of 40 km (better than
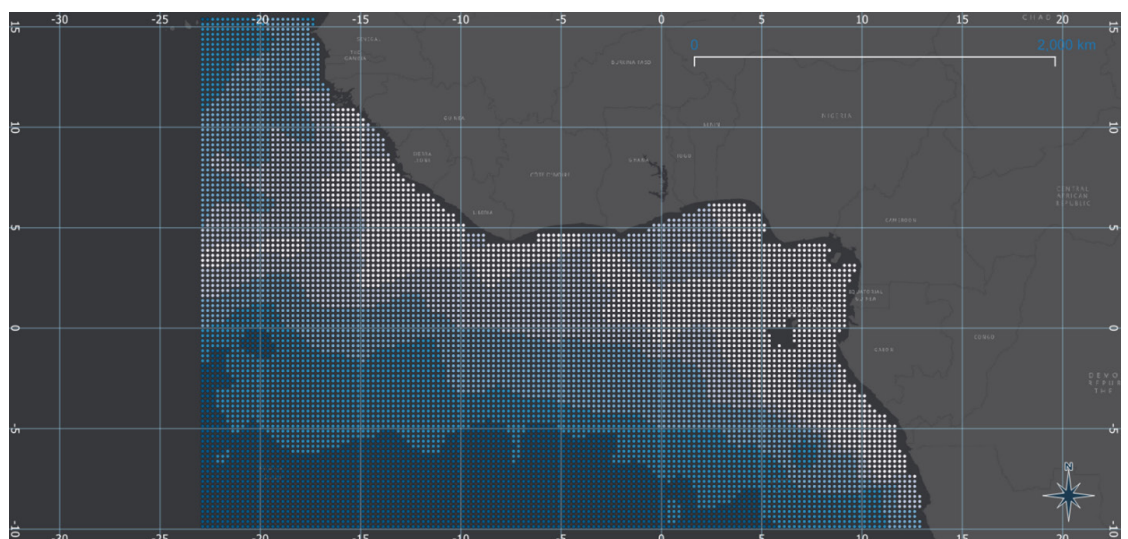

Fig. 1 Map of the study area based on OISSS_L4_multimission_global_7d_v1_0_2012-01-07_nc (01/07/2012).

Aquarius). However, SMAP's 40-km data are noisier than Aquarius data. Thus, some SMAP data products are spatially averaged to larger footprints (60–70 km) to reduce the noise. Due to the success of the missions, various satellite products such as the Optimally Interpolated Sea Surface Salinity (OISSS) products have been developed to combine data from the various missions and process them into a continuous and consistent SSS record.

3 Study area

The study area spans the coastal areas of West Africa, between latitudes (15.5° N and 10.0° S) and longitudes (13° E and 23.0° W) as shown in Fig. 1. It cuts across the coast of the following West African countries: Nigeria, Benin Republic, Togo, Ghana, Ivory Coast, Liberia, Sierra Leone, Guinea, Guinea-Bissau, The Gambia, Senegal, and those in Central Africa: Cameroun, Gabon, Equatorial Guinea, Republic of Congo, Democratic Republic of Congo, and Angola. The Equator and Central Meridian pass through the study area, which extended towards the middle of the South Atlantic Ocean. Due to its proximity to the Equator, the bulk of the study area experiences high rainfall and temperature events. However, there are also many rivers such as the Niger, Congo, Sanaga, Rey, Campo, Muni, Volta, Cavalla, Casamance, Gambie, and Geba, flowing into the ocean from most of the countries, which modulate the salinity concentrations in the ocean waters around this area.

4 Methodology

4.1 Data

Data used in this research were sourced from the Multi-Mission Optimally Interpolated Sea Surface Salinity (OISSS) Level 4 dataset, a new global multi-satellite sea surface salinity (SSS) product, made available through the Physical Oceanography Distributed Active Archive Center (PO.DAAC) tool. The product is a combination of data from a suite of satellites (Aquarius/SAC-D, Soil Moisture Active Passive (SMAP) satellite missions, and Soil Moisture and Ocean Salinity (SMOS)), processed into a continuous and consistent 4-day or monthly SSS record. The OISSS product covers the global ocean, including the Arctic and Antarctic areas free of sea ice. However, it does not cover internal seas, such as the Mediterranean and the Baltic Sea.

The dataset used in this research covers SSS acquired from August 2011 to the present. Data from August 2011 to June 2015, were derived from the Aquarius satellite, while the rest are from SMAP satellite-based SSS. The data were processed with Optimum Interpolation analysis on a 0.25-degree grid at a 4-day interval (Melnichenko et al., 2016). A bias correction was applied to the data product to correct the satellite retrievals for large-scale biases concerning in-situ data. Where there is any gap in SMAP data (June–July 2019, when the SMAP satellite was in a safe mode and did not deliver scientific data) SSS

data from the ESA's Soil Moisture and Ocean Salinity (SMOS) satellite were used to fill the gap in SMAP observations. The consistency and accuracy of the new SSS dataset were validated against in situ salinity from Argo floats and moored buoys. The mean root-mean-square difference (RMSD) between the Aquarius/SMAP OISSS dataset and concurrent in-situ data globally is around 0.19 psu and product bias is about zero (Melnichenko et al., 2016). The SSS data in the PO.DAAC tools are provided in network Common Data Form (netCDF-4 format). This is a hierarchical data format, with the metadata included in the data file, thus making it amenable to programming codes.

4.2 Methods

A key aspect of this research is the development of an End-to-End Extract-Load-Transform-and-Report (ETLAR) data pipeline capable of extracting SSS information from the OISSS presented in netCDF-4 data format. To build the ETLAR data pipeline, several automated tools were developed with Python codes for extracting the raw datasets from the PO.DAAC tool, transformation and processing of the extracted data, and analysis, visualizations. Python was chosen because of its simplicity and flexibility in handling different programming tasks. It is a high-level, general-purpose programming language, with dynamic semantics and many built-in libraries, which has made it very attractive for Rapid Application Development (RAD). The interactive reporting dashboard for the presentation of the processed data was built with Power BI. PowerBI is a leading interactive data visualization software product that is freely available. It is a unified and scalable platform for self-service and enterprise business intelligence (BI), its power lies on its ability to integrate and process data from disparate sources and present these with interactives visuals that could draw out underlying trends in the data. It was chosen for this project because it is free, powerful visualization capabilities and ease of deployment of dashboard on the web. The data extraction tool developed with Python was built with the capability to extract the entire global data. However, there was also a provision for it to accept the bounding box coordinates as parameters used in clipping the global data to a specific area. In this research we used the following boundary coordinates to clip the extracted data to the study area (max_lat = 15.5, min_lat = -10.0, max_lon = 13.0, min_lon = -23.0), before further processing was conducted. For each data point in the data, the SSS value, the longitude, and latitude were extracted. Overall, 959 OISSS data files were processed over 9361 data points that were found within the study area.

The extracted SSS values were reprocessed (integrated and grouped) based on their coordinates (longitude and latitude), such that for every data point, the coordinate and associated SSS values across the various years for every 4 or 7 days (depending on availability) were grouped as a record. This yield-
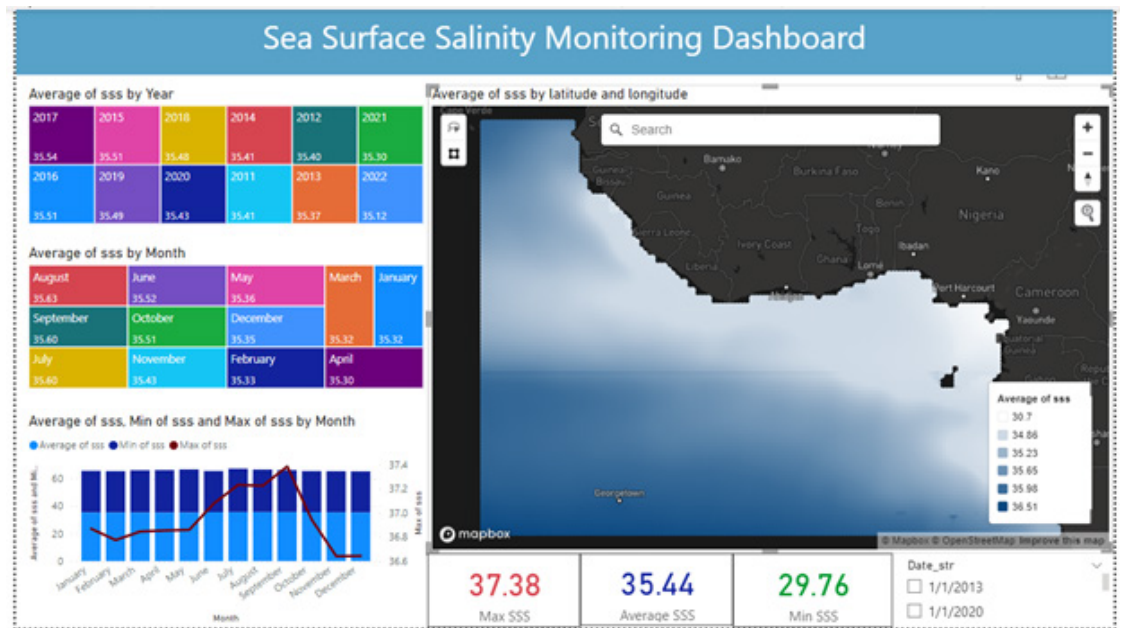
Fig. 2 A page in the interactive dashboard developed in this research.

ed geospatial time series of the salinity value covering the entire period of study (August 2011 – March 2022). The transformed data provided the basis for longitudinal analyses of the extracted SSS values and the identification of spatiotemporal variations of salinity values at each location and across the entire study area.

Subsequently, the data were further analyzed, and relevant statistics were computed from them, to better understand the data. Annual and monthly maximum, minimum, and mean salinity values recorded across the study area were identified. These were used to plot longitudinal trajectories of salinity variations across years and months.

Furthermore, an automated visualization process to support the regular production of time series maps of the spatial distribution of SSS concentrations on a weekly, monthly, or annual basis was developed, and relevant maps were generated. Subsequently, the various automated processes developed were integrated into a fully functional End-to-End Extract Transform Load (ETL) data pipeline for the seamless processing of satellite-derived sea surface salinity data into meaningful information presented in conventional data formats (CSV, shapefile) loaded into any data warehouse, data visualization or business intelligence tools, that can be utilized by non-remote sensing experts.

4.2.1 Computation of Sea Surface Salinity statistics
Concerning statistics of the SSS values across the study area, the maximum, average (mean and median), and minimum values of SSS recorded against each data point in the study area for each month and year were extracted. The monthly and annual statistics were computed from the data to summarize the key patterns and trends in the data. In addition, the maximum, minimum, and mean salinity recorded

across the entire study area and period were identified for each of these epochs.

Concerning annual statistics of SSS values across the study area, the maximum, mean, and minimum values of SSS recorded against each data point for each year were extracted. These were further aggregated at annual levels and the annual maximum, mean, median, and minimum of the maximum and minimum values across the study area for each year in the study period were plotted to investigate any trend in the degree of variation across the years.

4.2.2 Development of interactive reporting dashboard
PowerBI tool was used to develop an interactive reporting dashboard to enable users to interact with the generated datasets (Fig. 2). Relevant visual widgets and charts were used to develop the various interfaces. This will enable the public, especially non-remote sensing experts to visualize and interact with the results generated in this research. The dashboard shows the key statistics of the SSS values in the study area, in addition to maps and graphs showing the annual, monthly, and weekly variations in the SSS values. In addition, users can drill down to individual data points and investigate the values across various timescales.

The combination of the End-to-End Extract ETL tool (developed with Python) with the Power BI-based reporting dashboard yielded the ETLAR tool.

5 Results
In this research we found that generally, SSS values varied spatially and temporally across the study area and period. Lower salinity values are recorded closer to the coasts. This is especially noticeable around the eastern flanks of the study area around the coasts of Nigeria (River Niger estuary), Came-
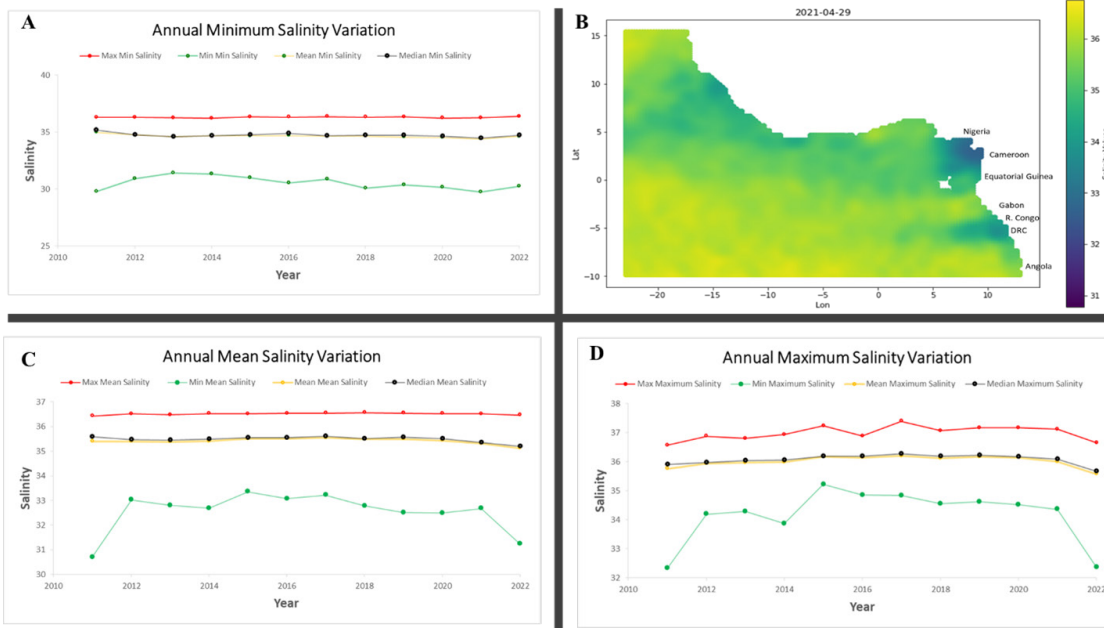
Fig. 3 Summary results from the research: (a) shows variations in minimum SSS values recorded across the study area over the years. (b) shows the spatial variation of aggregated sea surface salinity across the study area within a 4-day period centered around the 29th of April 2021. (c) shows variations in average salinity values recorded across the study area over the years. (d) shows variations in maximum SSS values recorded across the study area over the years.

roon (Rey Estuary), Equatorial Guinea (mouth of Rio Muni), Gabon (Gabon Estuary), and Angola (mouth of River Congo), which contain the mouth of major rivers in the respective countries (Fig. 3b). Higher SSS values were recorded farther into the Southern Atlantic Ocean.

Results obtained from this study shows that Sea surface salinity (SSS) within the study area were slightly less than 38 psu. Overall, average SSS of 35.41 psu was observed for the study area, with maximum value of 37.38 psu recorded in September 2017 at a location (longitude: 10.125, latitude: -8.625) off the coast of Luanda, Angola, and minimum value of 29.75 psu recorded in December 2021 at location (longitude: 5.625, latitude: 3.875) off the coast of Brass in the Bight of Biafra, Nigeria.

Fig. 3a shows the statistical trend of the annual minimum values. Maximum minimum value of 36.378 was recorded in 2018 at location (longitude: -22.375, latitude: -9.875) deep inside the South Atlantic Ocean between continental Africa and South America. Minimum minimum value of 29.749 was recorded in 2020 at a location (longitude: 6.375, latitude: 3.875) off the Bight of Biafra, off the coast of Nigeria.

The statistical trends obtained from the annual mean values are shown in Fig. 3c. Mean average annual value of 35.43 psu was observed. Maximum average annual value of 36.562 was recorded in 2018 at a location (longitude: -21.875, latitude: -9.875) deep inside the South Atlantic Ocean between continental Africa and South America. Minimum average value of 30.698 was recorded in 2011 at location (longitude: 9.625, latitude: 2.875) off the coast of Cameroon.

Fig. 3d shows the statistical trend observed for the maximum annual values. The year 2011 appeared to have lower SSS values compared to other years. However, this may be due to the fact that only partial data was collected for that year from August. Maximum maximum value of 37.384 was recorded in 2017 at location (longitude: 10.125, latitude: -8.625) off the coast of Luanda, Angola. Minimum maximum value of 32.327 was recorded in 2011 at location (longitude: 9.625, latitude: 3.125) off the coast of Cameroon.

With respect to monthly aggregates of SSS, we observed that mean SSS across the study area tend to be highest between June and September with a peak in August, while lowest values are recorded in November/December (Fig. 4a).
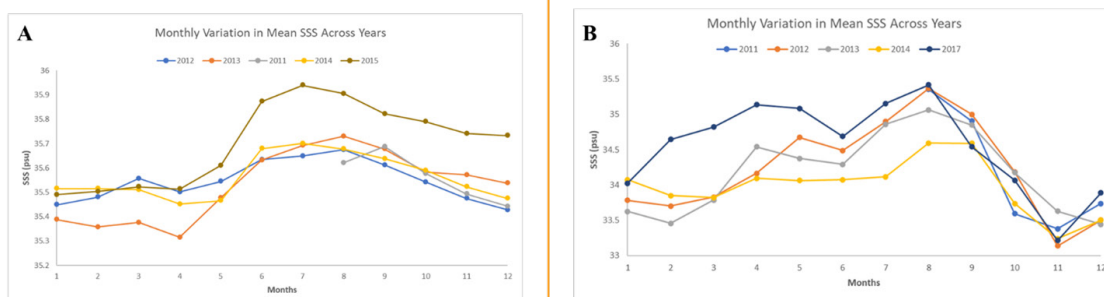
Fig. 4 Monthly variation of mean SSS across the study area for selected years. (a) shows variation for the entire study area. (b) shows variation for Nigeria.
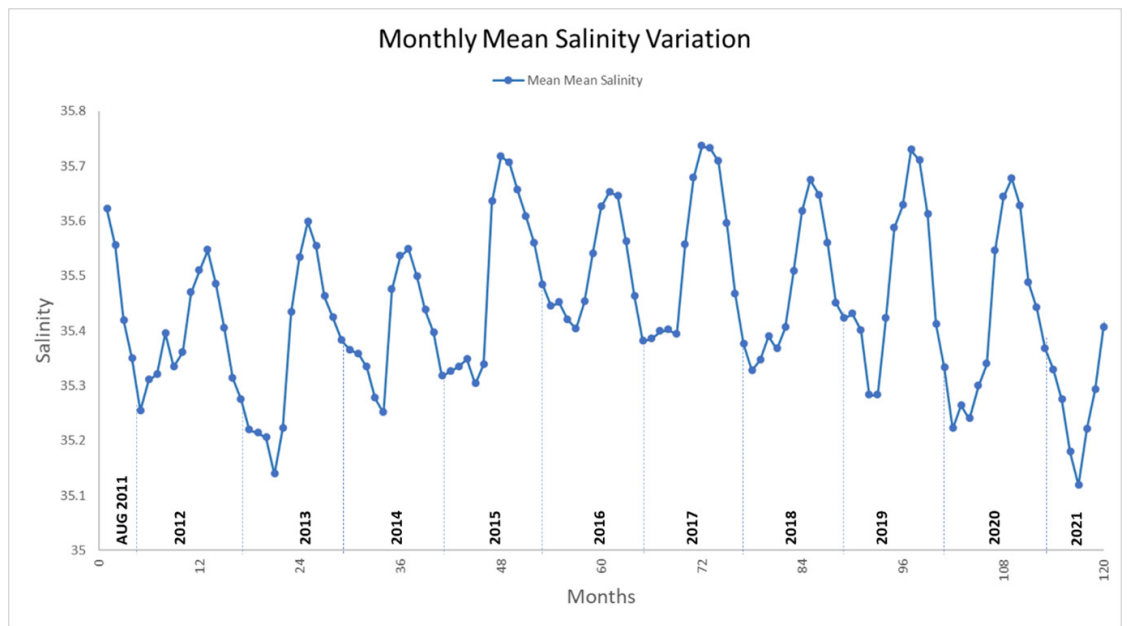
Fig. 5 Variations in average monthly salinity values recorded across the study area over the years.

This pattern was not only observed at the regional level (entire study area), locally, this pattern was also observed within the coast of Nigeria (Fig. 4b). Hence, suggesting that this pattern is consistent across the study area.

The longitudinal variation of the mean monthly salinity across the study period is shown in Fig. 5. This shows the sinusoidal variation of the SSS values across the months, year on year.

With respect to mapping of the SSS variations of individual data points, we developed the capability to map the variations in SSS at different aggregation levels (4-day), monthly, and annual. An illustration of the mapping of the sub-weekly (4 days) spatiotemporal variation in the salinity values of all data points in the study area is shown in Fig. 6.

Time series maps of average monthly sea surface salinity of individual data points is shown in Fig. 7. Expectedly, inter monthly SSS variations observed here are noticeable compared to the intra monthly variations (Fig. 6). Lower SSS values were observed from May for September compared to the rest of the months. This contradicts the trend observed for the entire study area where the months of June to August were observed to have higher SSS values (Fig. 4).

Spatiotemporal variation in annual mean salinity is shown in Fig. 8. The Fig. shows that the annual means recorded at each data point are fairly stable, without massive variation observed. The observation for 2011 and 2022 were observed to be slightly different and may have been skewed due to incomplete data.

Fig. 9 shows some pages from the interactive dashboard developed as part of this project. Key indicators shown are the maximum, average, and minimum SSS values. As an interactive dashboard, the values of these indicators can change depending on what options are selected by the dashboard user. By default, the values of the indicators are based on overall values for the entire study period. But users can drill down to a specific, year, month or weekly, for the entire study area or individual data point. For example, Fig. 9D shows the values derived for 2021 as against that of the entire study area shown in Fig. 9a. In the same vein, Fig. 9b shows averages from one data point, which can be selected by clicking on the map.

6 Discussion

In this research, we developed an automated method that can extract, process, and analyze sea surface salinity (SSS) data from the Optimally Interpolated Sea Surface Salinity (OISSS) dataset, a satellite product derived from the Aquarius and SMAP satellite missions. The technique developed has capability to process SSS values obtained from satellite data at various spatial scales (global, regional, national or for any specific location in the world) and temporal scale (sub-weekly, monthly, and annual).

Analysis of the SSS values extracted in this research revealed key trends in the variation of sea surface salinity in the study area across varying timescales. Key summaries of the trends were generated to enable quick understanding of the variations. A wide variance in salinity was observed for the study area with values ranging from a minimum of 29.749 psu to a maximum of 37.384 psu. This is due to the fact that the study area spanned through 5 latitudes and 8 latitudes, with varying influence of river inflow, evaporation rates and rainfall. The cold spots of salinity concentration were closer to the coasts especially those in the eastern flank of the study whereas the hot spots of SSS where towards the western flank of the study area towards the South Atlantic Ocean. The

waters off the coast of Nigeria and Cameroon were found to be less saline than those of other countries within the study area, with an observed minimum SSS value of 29.749 psu, average salinity of 34.1 psu and maximum salinity of 35.8 psu. This reduced salinity is directly linked to the large river discharges (inflow) from the mouths of the major rivers in the area (River Niger and Rey River). Lower salinity values were also recorded closer to the coasts of other countries where major rivers flow into the ocean such as Equatorial Guinea (mouth of Rio Muni), Gabon (Gabon Estuary), Angola (mouth of River Congo), Senegal (River Casamance), The Gambia (River Gambie), and Guinea-Bissau (Rio Geba; Fig. 3).

Noticeable variations in the annual maximum and minimum values were observed, however, it was found that in general, annual mean salinity variation in the study area is fairly stable, with not much noticeable variation year-on-year. Although, a slightly higher annual mean value was observed in 2017. This relatively stable annual means observed at each data point indicate that the dynamic forces acting within the study are stable (in equilibrium; Fig. 8). Despite the stability observed in the annual means, intra-annual (monthly) variations were observed, with certain months of the year having higher salinity than others, due to interplay between the various key drivers of salinity (e.g. rainfall, inflow from rivers, and evaporation). However, this intra-annual variation were also found to be stable year on year, suggesting a stable pattern of variation.

The relatively high spatial resolution of the data used in this research, provides the capability for research to have detailed understanding of variations in sea surface salinity. The data points used in generating the SSS values are spread over a 0.25-degree grid. Hence, providing the capability to map the spatio-temporal variations of individual datapoints at approximately 28 km interval. The 28 km spatial resolution of data is quite useful as it enabled the understanding of variations SSS for a specific point or across a wider area of interest. This is very relevant considering that it would have been practically impossible to achieve this level of precision on a continuous basis, using traditional methods such as those used in deriving the underlying data used in the Copernicus Marine Service. Furthermore, continuous coverage of SSS can be derived from the discrete values recorded at the data points, by deploying spatial interpolation methods. In addition, further aggregations can be made from these individual values to regional or global summaries, which can provide useful insights to the patterns of variation and associated impacts on regional climatic conditions. This enhanced flexibility in data analysis and visualization incorporated in this research gives this an edge over existing marine visualization services such as the Copernicus Marine currently in existence, which somewhat have some rigidity in the user interactivity with the interface. In addition, this work also differs
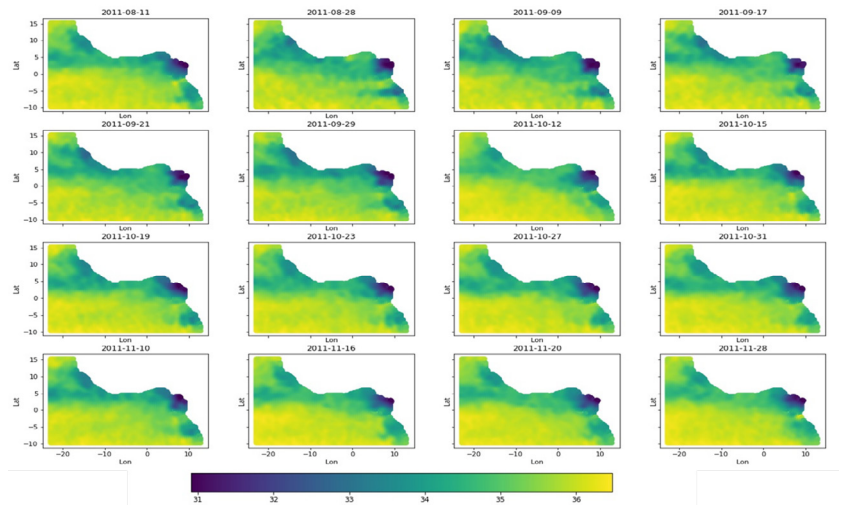

Fig. 6 Sub-weekly (4-day) spatiotemporal variation of sea surface salinity between August and November 2011.
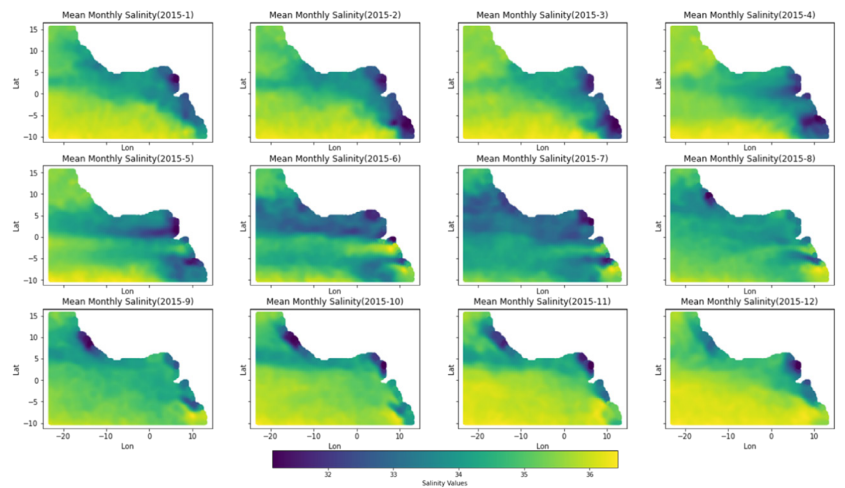

Fig. 7 Spatiotemporal variation in average monthly salinity at each data point in the study area in 2015.
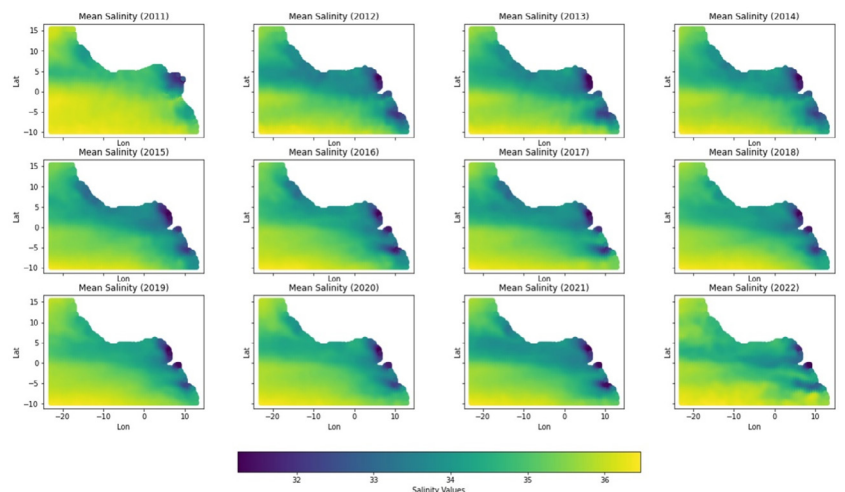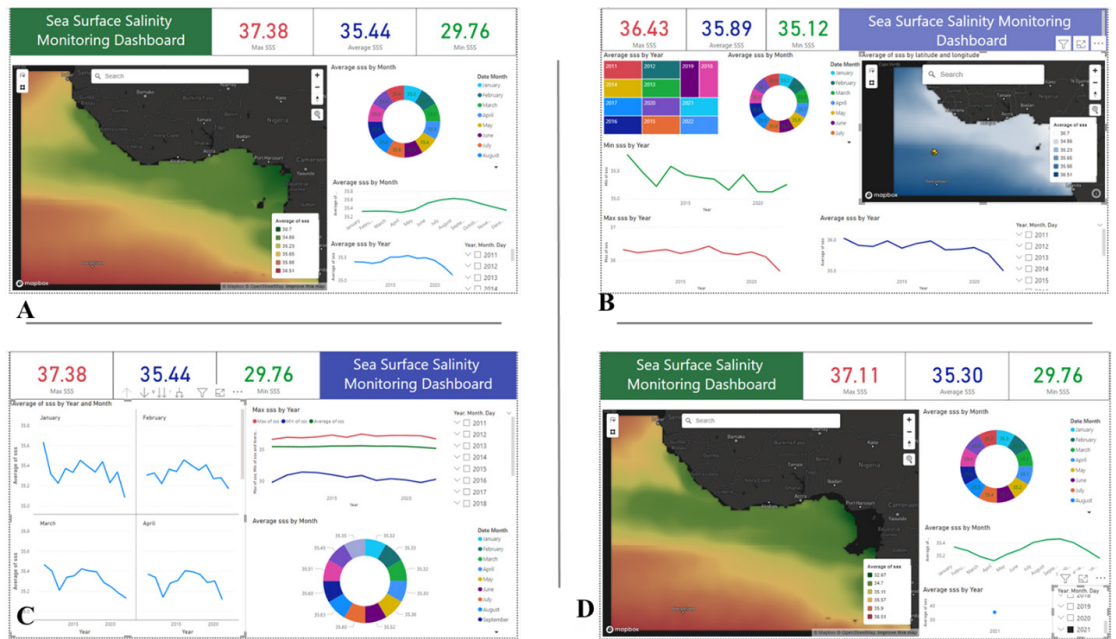

Fig. 8 Spatiotemporal variation in annual mean salinity.

Fig. 9 A snippet of the interactive dashboard developed in this project showing summary statistics.

from the products of the Copernicus Marine due to the fact that the data used in the Copernicus Marine are produced from statistical models based on data obtained from global networks of different types of instruments: Argo floats (Argo[1], OceanSites[2], GOSUD[3], EGO[4], ITP), Meteorological data exchange network (Global Telecommunication System, GTS), conductivity-temperature-depth profiler (CTD), expendable bathythermograph (XBT) and expendable conductivity-temperature-depth profiler (XCTD), moorings, drifting buoys and sea mammals (Szekely, 2022; Copernicus Marine Service, 2023).

The monthly SSS variation observed across individual data points with decreased SSS around the months May, June, July, August, and September (Fig. 7) is particularly interesting as those months coincides with the peak of the rainy season in most of parts of the study area. This suggests that the inflow of runoff water into the sea from various estuaries dotting the study area, exerts some level of impact on the salinity levels in the ocean. However, whereas the monthly variations at individual data points showed decreased SSS values from May to September (Fig. 7), mean monthly values computed with all data points across the study area, showed that the months of June to August generally, had higher SSS values (Fig. 4). These apparent contradictory trends stem from the fact that the study area spanned through a diverse range of latitude (-10° to

15°) and longitude (-23° to 13°) as shown in Fig. 1. Both trends are useful in understanding the influence of SSS on climate. Whereas the observations from the data points can be used to understand localized impacts, the trend obtained from the aggregated values might have more influence on regional and global climatic conditions, as it shows the trend pulled from all data points in the study area.

Significantly, the automated Extract Load Transform and Report (ETLAR) developed in this research will contribute in the democratization of remote sensing data (Lefebvre et al., 2021; Mariam, 2021). Hence, making it available for the wider research community and the public to access and use, without having to deploy complex remote sensing data processing. Sea Surface Salinity is an important ocean variable for understanding key ocean and climate processes (Jang et al., 2022). The Global Climate Observing System (GCOS) program has designated it as an Essential Climate Variable. Key components of water cycle evaporation (E) and precipitation (P) have been found to correlate with SSS (Durack, 2015; Lindstrom et al., 2015; Wüst, 1936). Hence, sea surface salinity patterns provide a reflection of the overlying patterns of evaporation and precipitation. This makes it possible to use SSS to infer atmospheric freshwater fluxes (E–P) at any given point in time. For instance, SSS could be deployed as an efficient global rain gauge (Schmitt, 2008). Furthermore. the interplay between sea surface

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[1] International profiling float network (www.argo.net, accessed 12 Sep. 2023) and its European component (https://www.euro-argo.eu, accessed 12 Sep. 2023).

[2] OceanSITES is a worldwide system of long-term, open-ocean reference stations (OceanSITES is a worldwide system of long-term, open-ocean reference stations) and its European component (https://www.emso.eu, accessed 12 Sep. 2023).

[3] International Global Ocean Surface Underway Data (https://www.gosud.org, accessed 12 Sep. 2023).

[4] International Glider network (https://www.ego-network.org, accessed 12 Sep. 2023).

salinity and temperature also contributes to the vertical flow through the thermohaline circulation that constitutes part of the large-scale ocean circulation (Dinnat et al., 2019) as well as acoustic velocities observed in estuaries (Anejionu & Ojinnaka, 2011). Therefore, the democratization of sea surface salinity data will stimulate wider interest in this area of study, as well as enabling the wider public to appreciate the importance of remote sensing in solving societal issues.

Furthermore, results obtained from this research make it possible for future trends of the SSS values to be predicted. Indeed, with the amount of data collected from the satellite data, machine learning techniques could be deployed to predict future SSS values and trends. Such predictions could play a vital role in modelling future climatic conditions in the region. With adequate computing resources, the automated scripts developed in this research can be deployed for global studies to present SSS data on a near-realtime basis (subject to data availability), as well as support global predictive analytics of future SSS values. The sea surface salinity data generated in this study can also be used alongside other relevant ocean dynamics data to investigate oceanic impacts on global climate change under varying conditions. Conversely, the ability to regularly monitor salinity in a consistent manner can lead to a better understanding of the effects of changing climate on salinity concentrations across the globe. It has been found that climatic changes have substantially amplified ocean salinity in the past 50 years (Chinese Academy of Sciences, 2023). According to the report, as the Earth is warming, the global water cycle amplifies, which subsequently affects the salinity concentrations.

This research has further highlighted the benefits of satellite-derived ocean salinity values. The traditional methods of measuring sea surface salinity observations (buoy networks, ships) which offer reliable datasets is costly and relatively slowly. Hence, making it impractical for covering large geographic areas on a regular basis. By using data derived from satellite data detailed analysis of the spatiotemporal variation in sea surface temperature has been determined. This is expected to play critical role in subsequent research that would be conducted in the study of the dynamics at play in the regional (across the coasts of Africa) and global waters. The processing of the extracted data and presentation in an interactive dashboard will enable active engagement of the scientific community and the general public with the data, thus aiding the maximization of the impact of the research. An ongoing work is developing a web interface that would enable the research community and the general public to easily access this data from the internet. The PowerBI used in developing the dashboard has inbuilt tools that facilitate web publishing of dashboards. We expect that the web interface will host information on other relevant ocean variables currently being derived from remote sensing satellites.

We encountered certain limitations in the course of this work. The first limitation was orchestrated by computing resources. Satellite data processing is a resource-intensive tasks and we have processed data from multiple years. To process global salinity data in a timely manner distributed computing resources, which could leverage on cloud computing technologies would be required. Due to this limitation, we were only able to process data from West and Central Africa.

Another limitation was the use of satellites in this project. Despite its numerous advantages, the accuracy of satellite-derived salinity cannot match those obtained from in-situ instruments (Bao et al., 2019). Hence, it has to be pointed out that, that the results obtained in this research may not be absolute. However, satellite data provides the capability for consistent, rapid, and general monitoring of salinity variations across the globe.

7 Conclusion

Sea surface salinity is an important ocean dynamic that contributes to oceanic and climatic condition. Due to its crucial role in ocean dynamic process, it can also be used to infer changes in the global climate. As with other ocean phenomenon, remote sensing systems have been developed to regularly obverse global sea surface salinity from space. Satellite remote sensing offers realistic solutions to such challenges encountered in acquiring and monitoring sea surface salinity on a regular basis. Salinity monitoring is necessitated by constant variability in salinity across the globe and its impact on local and global climatic regimes.

This research developed automated techniques for extracting and processing sea surface salinity data from relevant satellite data. The technique was used to extract available SSS data off the coast of West Africa, over an extended period (2011–2022). The data extracted from a satellite product provided useful insights into the SSS variations across various data points in the study area across weeks, months, and years. This is a key advantage of deployment of satellite sensors in monitoring sea surface conditions.

Sea surface salinity values in the study area were found to be less that 38 psu within the period of study. The waters off the coast of Nigeria and Cameroon (River Niger estuary and Rey Estuary) appear to be less saline than those of other countries within the study area, with an observed minimum SSS value of 29.749 psu, average salinity of 34.1 psu and maximum salinity of 35.8 psu.

Significantly, the techniques developed in this research can be deployed/adapted to extract from other satellite data such as sea surface temperature, sea surface topography, sea winds, ocean waves and sea surface topography. This will lead to the democratization of satellite-derived data to non-remote sensing experts. Thus, the wider research community and the general publish could actively engage with the data, originally obtained from a satellite sensor.

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