Spatio-temporal distribution of swordfish (*Xiphias gladius*) catches and catch rates from the Kenyan industrial longline fishery

ABSTRACT

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This study aimed to assess their catches in a spatio-temporal distribution perspective by employing combined approach for longline industrial fishing catch logbooks, fishery-independent data from the national observer scheme between 2022 and December 2024. The annual swordfish landed by Kenyan industrial longliners were 16MT, 261MT, 217MT and 131.5 MT in 2021, 2022, 2023 and 2024 respectively. There was a typical annual cycle in the catch quantities landed, with high values from May to December, and displacement of the fishing operation Southward 39° E to 45° E and 2° S to 5°S. The pattern of the spatial-temporal distribution of fishing and catch rates of swordfish (*Xiphias gladius*) from the Kenyan industrial longline fleet to be assessed using comparative analysis. The generalized analysis to include variables such as latitude, longitude, date, depth, number of hooks and catches to depict spatial and temporal distribution of catches and catch rates of swordfish.

Key Words: Kenya, Coastal waters, Swordfish (Xiphias gladius), spatial, temporal, distribution, management

Introduction

The Kenya marine waters extend from the Somalia border (1°30 S) to Tanzania (5°25 S) (Fig. 1) and the exclusive economic zone (EEZ) covers 200 nautical miles with an area of 230,000 km2 (Fulanda et al., 2011, Munga et al., 2013). The marine environment is characterized by warm tropical conditions, with temperatures ranging between 25 °C and 31 °C (Obura, 2001). The marine environmental conditions are influenced by the Inter-Tropical Convergence Zone (ITCZ) movement that drives ocean currents. The swordfish is a migratory species found in marine waters across temperate, tropical, and subtropical seas, including the Indian Ocean. It is an important catch for both artisanal and commercial fishing in the region.

Identifying significant associations between catches of pelagic species and environmental conditions is essential to interpret the CPUE of highly migratory species (Schick et al., 1994), as the fishing strategies and performance of longline fleets are influenced by the availability and gear vulnerability of fishing resources, which are related to the environment where the target species occur (Ricker, 1975).

There was a typical annual cycle in the catch quantities landed, with high values from May to December, and displacement of the fishing operation Southward 39° E to 45° E and 2° S to 5°S. The pattern of the spatial-temporal distribution of fishing and catch rates of swordfish (*Xiphias gladius*) from the Kenyan industrial longline fleet to be assessed using comparative analysis.

Materials and Methods

The study was undertaken using industrial longline catch data (2022-2024) from the Kenyan EEZ.

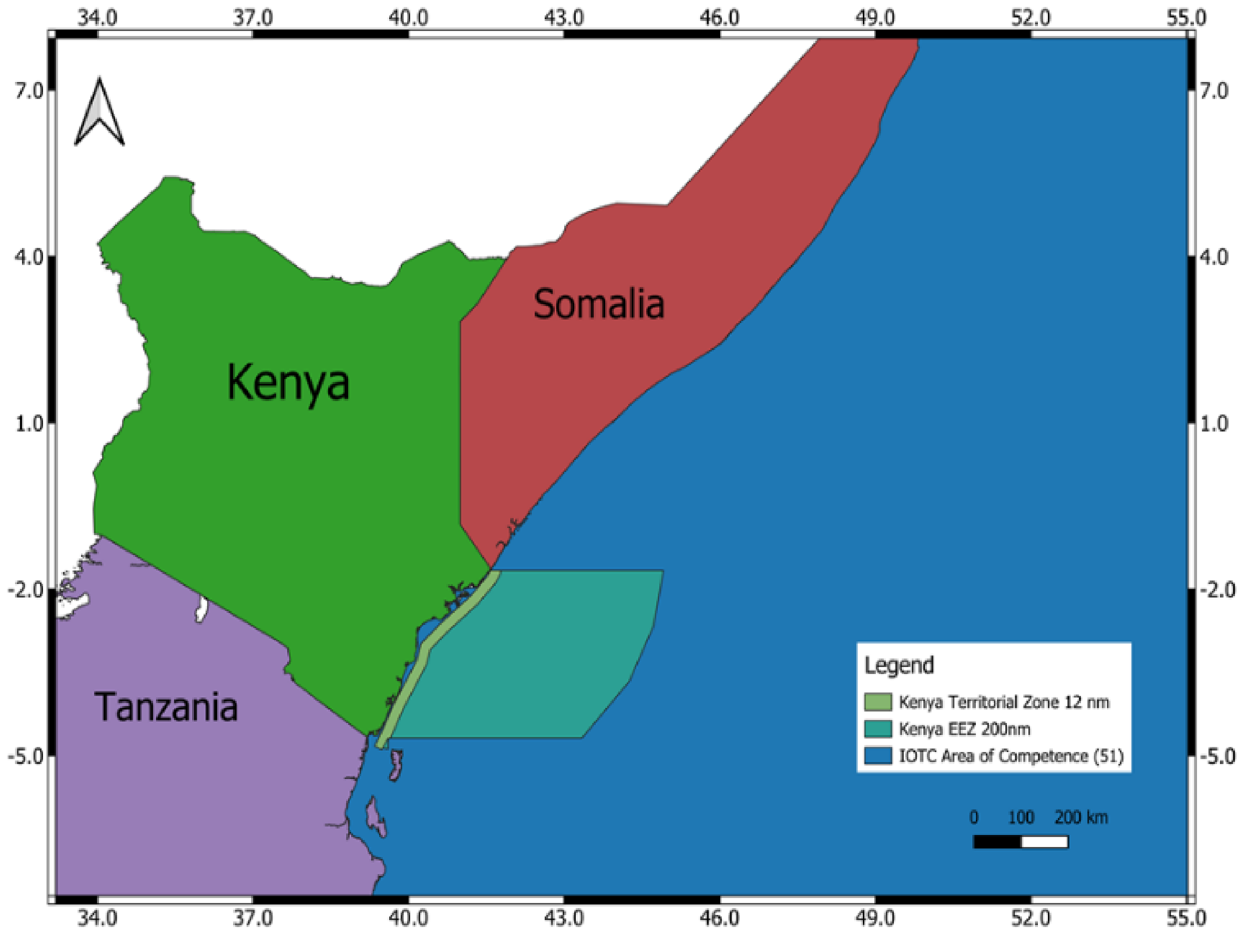

Figure 1 Study area, Kenyan Marine waters

Data Preparation

The dataset comprised of individual records of (n = 1088) that were collected annually and were subsets to the following variables: date, latitude and longitude (decimal degrees), number of hooks deployed, depth of shallowest and deepest hook (m), number of pieces caught and total weight (kg). However, longline sets that lacked positional or effort data were removed (< 0.1% of records).

Description of CPUE

The conventional application for CPUE data obtained from fishery-dependent data has been the primary source of relative index of abundance employed in fish stock assessment (Ramos-Cartelle et al., 2025). Furthermore, research has shown that this index could be examined as an indicator of change in abundance over time (Punt et al., 2013). In this study, CPUE is defined as the total catch (kg) per 1000 hooks deployed:

CPUE_nominal = C / E x 1000

Whereby, C is the catch (kg) and E is the number of hooks within individual sets. Thus, all CPUE values are expressed in catch (kg) per 1000 hooks.

Temporal Parameters

The study considered two temporal scales: annual (2022, 2023 and 2024) and seasonal (NEM (October to March) and SEM (April to September).

Spatial Stratification

The coordinate positions were rounded to a 5° x 5° (lat-lon) global grid and a Kenya's map and coastline was overlayed to provide a bounding box latitude (-5,-1) and longitude (39, 52). Thereby, the grids within the Kenyan EEZ were used to visualize the summed effort (total hooks) and mean CPUE within each cell. The grid cells with records for both catch and effort data will be presented in graduating colours or heatmaps while grid cell that did not have records will be presented in white colour.

Key Assumptions

- Hooks within a longline set are partially homogenous (typical within 5km) (cite).

Software and Reproducibility

The computations in this study have been performed in Rstudio version 2024.12.1 and key packages comprised of data.table, sf, rnaturalearth and rnaturalearthdata

RESULTS

Annual Catches 2022-2024

The annual swordfish landed by Kenyan industrial longliners were 261MT, 217MT and 131.5 MT in 2022, 2023 and 2024 respectively. The landings are proportionate with the efforts (number of hooks and fishing days) applied during the years

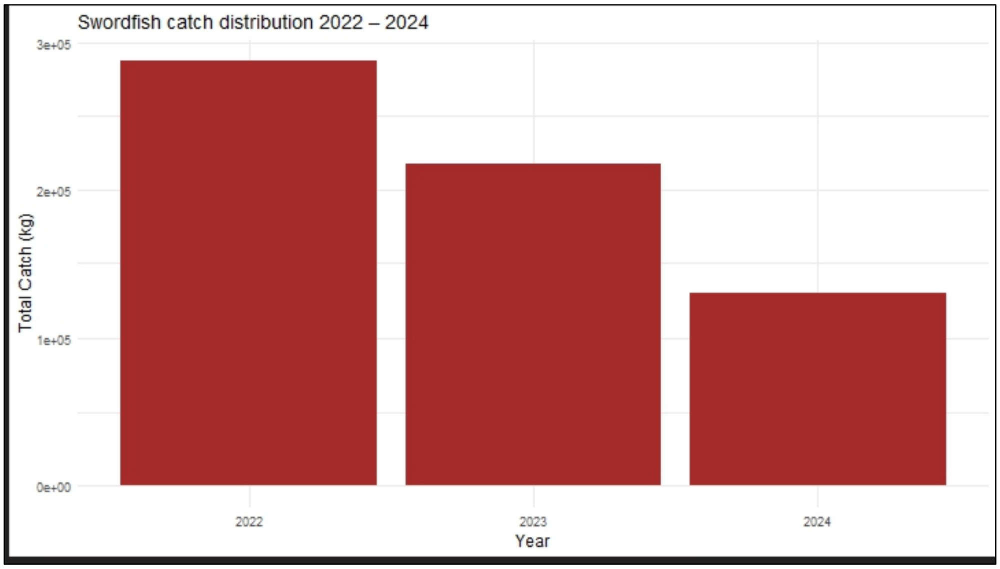

Figure 2; Annual Swordfish catch landings 2022-2024

Distribution of Nominal CPUE at the 5° Grid Cell

High CPUE appears to co-locate with high effort spatially across the 5° grids. The dataset was complete thus, no zero catches per unit of effort was recorded between 2022 and 2024.

Figure 2; Spatial distribution of Swordfish catch rates 2022-2024

In figures 2 above illuminates a clear spatial heterogeneity in swordfish nominal CPUE across Kenya's coastal waters. Some 5° grid cells consistently show higher CPUE, suggesting hotspots of swordfish presence or fishing success.

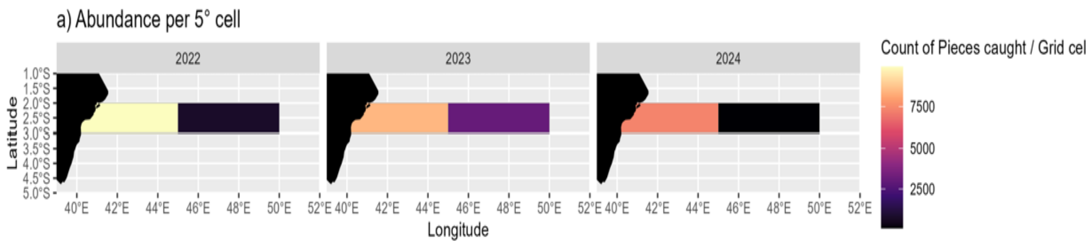

Figure 3; Spatial distribution of Swordfish abundance 2022-2024

Similarly, the figure above reveal pronounced spatial heterogeneity in abundance across Kenya's coastal grid, some cells consistently yield higher CPUE, pointing to potential swordfish hotspots or effort concentration areas. the

Temporal Distribution of catch and CPUE

In figure 3 above temporal trends and variability as shown by mean nominal CPUE over 2022–2024, with error bars showing variability across grid cells—tells a complementary story as in abundance. Trend shows a slight increase in nominal CPUE over between 2023 and 2024, it suggests that swordfish catch rates per unit effort are rebounding. Conversely, a decline between 2022 and 2023 may be an indication of a potential localized depletion or changing environmental conditions.

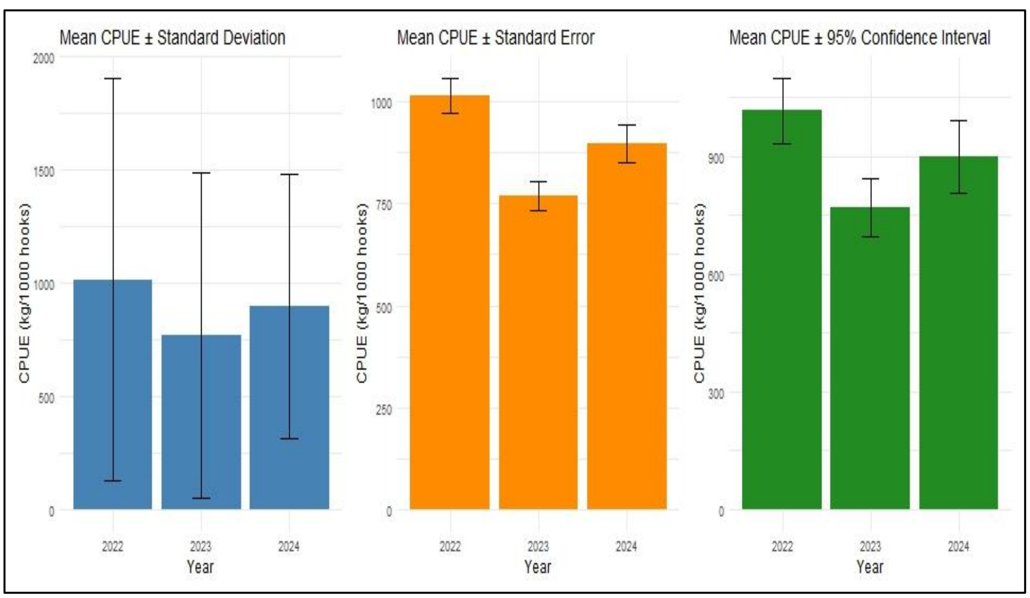

Figure 3; Temporal distribution of Swordfish CPUE 2022-2024

Seasonal Distribution of Catch Abundance and Nominal CPUE Per 5° Grid Across 2022-2024

This temporal distribution of the swordfish catches and abundance could be partly attributed to the seasonal changes in the temperature of the sea water, sex and size of the individual fish, and availability of food in the environment (Mueni et al., 2019; Lan et al., 2014; and Ward and Elscot, 2000) and the type of fishing gears (Herrmann et al., 2018; and Tuda et al., 2016). The high catch rates seem to coincide with the spawning season (October through to April) for swordfish in the Indian Ocean (Lan et al., 2014; and IOTC, 2017).

Analysis indicates a pattern of improved average catch rates in second and third quarters of each year highest corroborating a typical annual cycle in the catch quantities landed, with high values from May to December, and displacement of the fishing operation Southward 39° E to 45° E and 2° S to 5°S.

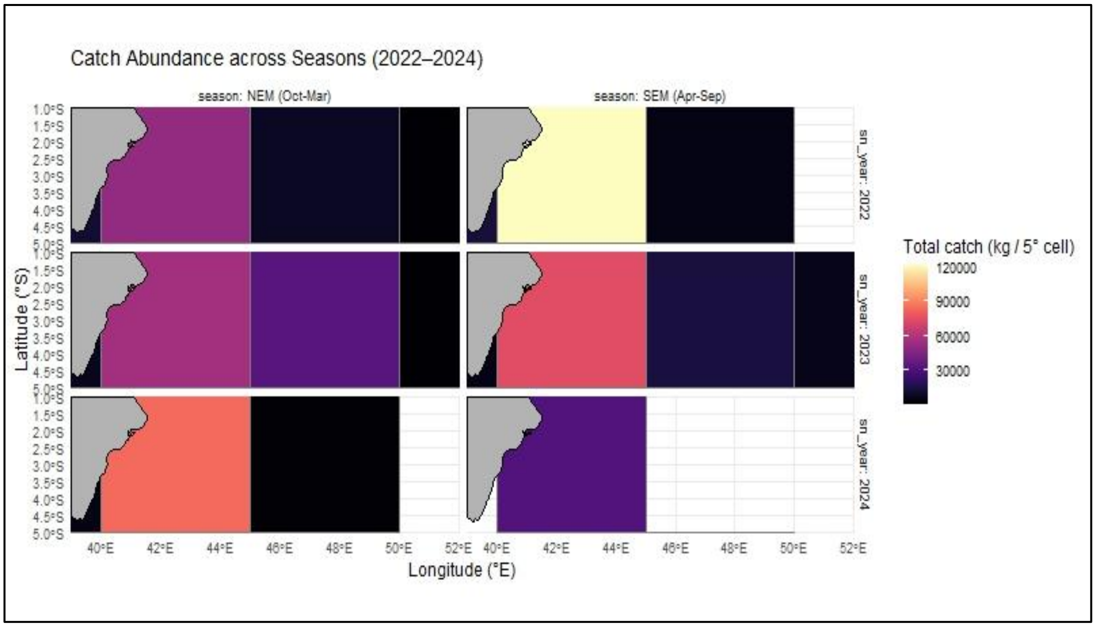

Figure 4a; Seasonal distribution of Swordfish Abundance 2022-2024

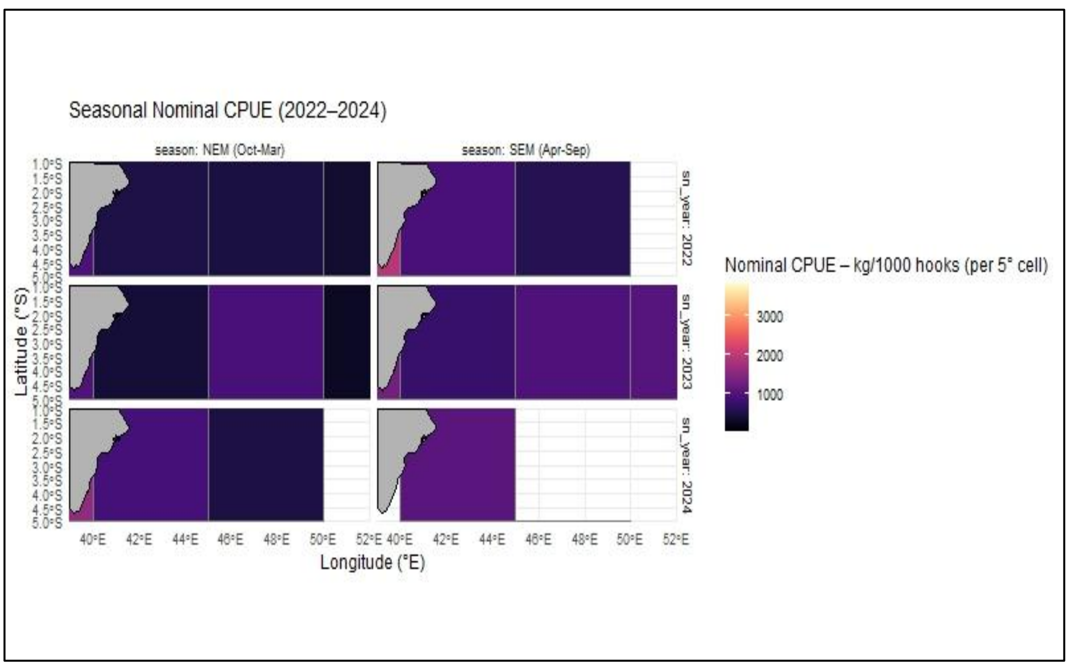

Figure 4b; Seasonal distribution of Swordfish CPUE 2022-2024

Conclusion

This study provides insight into tempo-spatial distribution swordfish catch rates and abundance in Kenya marine waters associated with variables: date, latitude and longitude, number of hooks deployed, depth of shallowest and deepest hook (m).

Swordfish fishery presents a well-defined spatial-seasonal pattern depending on North east and south eastern monsoon. high catches recorded during NEM between August and October.

Furthermore, the results showed hotspots, which enables to minimize the costs of fishing operations and increase the catches of target species, redirecting the fleet to these areas while reducing the accidental capture of other species, avoiding an ecological impact of fishing.

Regarding habitat, swordfish prefer deeper colder waters with a low concentration of chlorophyll. Knowledge about the distribution of this species reduces uncertainties, which can facilitate the assessment, management, and monitoring strategies of stocks aimed at swordfish fisheries in the Indian ocean.

Sound knowledge and good understanding of the distribution and seasonal abundance of the swordfish fishery is important for sustainable conservation and management of the fishery

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