Analysis of CPUE for the 2025 IOTC Blue Shark Stock Assessment

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Abstract

This document presents a comparison of the six catch per unit of effort (CPUE) series submitted for consideration in the 2025 IOTC blue shark assessment in the Indian Ocean. The goal of this analysis is to investigate any relative differences between model inputs so that data conflict is not introduced into the model via indices of abundance (CPUE series) that imply different, conflicting states of nature (i.e. do alternative indices of abundance indicate that the stock is increasing or the stock is decreasing). Results show potential groupings of the CPUE series which may indicate similar spatiotemporal dynamics or operational practices. Several pairings show low or near-zero correlations, suggesting these indices may be relatively independent or reflect uncorrelated processes. This could be due to differences in gear type, target species, region, or aggregation scale. The reader is cautioned that a single influential point may cause a strong spurious correlation, and care in interpreting the results is recommended.

Introduction

This document presents a comparison of the six catch per unit of effort (CPUE) series submitted for consideration in the 2025 IOTC blue shark (*Prionace glauca*) assessment in the Indian Ocean. The goal of this analysis is to investigate any relative differences between model inputs so that data conflict is not introduced into the model via indices of abundance (CPUE series) that imply different, conflicting states of nature (i.e. do alternative indices of abundance indicate that the stock is increasing or decreasing?).

Data and methods

Catch and Effort Data

Six CPUE series were accepted for the 2025 assessment. The fleets cover different time periods and areas of the Indian Ocean. All six CPUE series are based on catch and effort from surface longline fisheries although the definition of catch (numbers or biomass) and effort (i.e. sets, days or trips) differs among them. The CPUE series considered have been submitted by Spain, South Africa, Japan, Chinese Taipei, Portugal and Reunion. For the most part the indices cover similar time frames over the recent decades, though the starting and ending years differ slightly. For this analysis as in the assessment, data after 2023 were not used.

The Spanish series covers the period from 2001 to 2023 and is based on a combination of trip level logbook data as well as trip records voluntarily reported by observers from the Spanish surface longline fleet targeting swordfish and in the Indian Ocean. The Spanish data used consisted of trip records of the Spanish longline fleet targeting swordfish covering the 2001-2023 period. Nominal effort per trip was defined as thousands of hooks. The nominal catch per unit of effort was initially obtained as number of fish per thousand hooks. A proxy indicator of skipper targeting criteria was used to classify trips as either “swordfish only” or “swordfish and/or blue shark”.

The Japanese CPUE indices of blue shark abundance are based on records of blue shark caught by the Japanese tuna-longline fishery in the Indian Ocean from 1994 to 2023 and are based on logbook data, which were filtered to include those vessels which had blue shark report ing rates similar to that in theobserver data. The predicted annual CPUEs revealed a gradual increase in CPUE overall. However, the recent decrease in fishing effort and reduced area and data coverage have widened the confidence intervals significantly since 2019. In 2023, the CPUE values were very high, with a notably wide confidence interval.

The Chinese Taipei blue shark catch and effort data originated from the logbook records of the Chinese Taipei longline fishing vessels operating in Indian Ocean from 2005-2024. The Chinese Taipei longline fishery in the Indian Ocean targets different tuna species depending on the area; vessels targetalbacore tuna in the mid-high latitudes, and target bigeye tuna in the low latitudes. Blue shark caught by Chinese Taipei longliners in the Indian Ocean were mainly observed in the temperate waters between 30 and 40 degrees south, with similarly high catch rates in lower latitudes. (Huy Huynh and Tsai, 2025).

The Réunion data covers the time period from 2007 to 2024, and is based on the French swordfish-targeting longline fishery operating in the south-west Indian Ocean. Observer and self-reported data collected aboard commercial longliners, the standardized CPUE series shows a slight decreasing trend, more precisely a substantial decrease between 2011 and 2019 followed by a stabilisation since 2019 (Sabarros et al 2025).

The South African data are based on blue shark caught by the South African pelagic longline fishery operating in the South Atlantic- and Indian ocean, across the boundary of IOTC and IATTC. Given the spatio-temporal nature of the data, the standardised index of abundance was generated based on a model that takes advantage of this information to learn about the long-term trend in the abundance of modelled stock, accounting both for catchability and abundance covariates. Data from both indicator vessels (former shark longline vessels that continue to catch a significant proportion of sharks) and from the entire large pelagic longline fleet were considered. This fleet targets multiple tuna species, thus, to account for changes in targeting, a multivariate index of species composition of the catch was included in the model.

Methods

The CPUE time series for blue shark in the Indian Ocean are plotted in along with a *lowess* smoother fitted to CPUE each year using a general additive model (GAM) to compare trends for the submitted CPUEs [using the FLR package in R R]. Residuals from the smoother fits to CPUE are compared to identify deviations from the overall trends. This allows conflicts between indices (e.g. highlighted by patterns in the residuals) to be identified.

Correlations between indices are evaluated in via pairwise scatter plots for CPUE indices where they overlap. The lower triangle shows the pairwise scatter plots between indices with a regression line, the upper triangle provides the correlation coefficients, and the diagonal provides the range of observations. along with a linear model fit between them.

A hierarchical cluster analysis evaluated for the indices using a set of dissimilarities. This analysis can identify similar and diss-similar trends. If indices represent the same stock components, then it is reasonable to expect them to be correlated. If indices are not correlated or are negatively correlated, i.e. they show conflicting trends, then this may result in poor fits to the data and bias in the parameter estimates obtained within a stock assessment model. Therefore, correlations can be used to select groups of indices that represent a common hypothesis about the abundance of the stock over time (Rice 2022, IOTC 2017).

Cross-correlations for the region are plotted with a lag from -10 to 10, (i.e., the correlations between series when they are lagged by -10 to 10 years) which can help determine whether there is a relationship between two time series. This approach can be particularly useful when comparing indices of abundance for bycatch species derived from fleets targeting different species (i.e. tropical vs temperate tunas) or aggregated at different levels (trips vs sets). If all CPUE series are thought to represent the overall dynamics of the stock, careful examination of how one index may lead or lag another, temporal shifts or delays in population dynamics may become apparent. For example, a strong correlation at a positive lag might indicate that changes in one index precedes changes in another, possibly suggesting sampling of separate parts of the stock (e.g. juvenile vs adult).

Conversely, correlations at negative lags may reflect delayed responses in one component of the population to changes in another. Overall, lagged cross-correlation helps clarify potential lead-lag relationships between datasets, offering insights into the relative similarity of the CPUE series. A careful interpretation of the results is suggested given the bycatch nature of this species and the changes in target species, reporting and fleet dynamics over time. The diagonals show the autocorrelations of an index lagged against itself. This can help identify whether a relationship exists between the CPUE series and earlier years, which would be identified by a large correlation, with the correlations on both sides that quickly become small.

All analyses were conducted using R and FLR, including the *diags* package which provides a set of common methods for reading these data into R, plotting and summarizing them (e.g., see: http://www.flr-project.org/).

Results and conclusions

The overall trend for the indices is stable trend, slightly increasing throughout the 2000s to the early 2000s. Prior to 2000 only data from Japan exist for this assessment and show a slightly increasing trend. The South African CPUE is generally increasing from 2000 to 2018, with some fluctuation after which it is decreasing. This is the only trend that has been decreasing over the last 6 years, though the Reunion (EU_REU) shows a decreasing trend from 2012, which stabilized around 2018. Similarly, the Portuguese series shows a decline between 2008 and 2009, indicating a possible change in the fishery or data collection.

Overall Figures 1 and 2 indicate that these series also follow the overall trend, and may provide evidence of a stable or gradually increasing trend in the stock trajectory. Fluctuations around the mean trend by a slight decrease in recent years. In the South African (ZAF) time-series, the residuals indicate that only the last three years are below the mean (since 2010). Differences in the size, sign and trend in the residuals may be evidence of a more rapidly decreasing trend in the stock trajectory in recent years than the overall trend. However, in the cases of blue shark– which could be considered a bycatch species in the tuna and swordfish fisheries, this may also indicate a shift in targeting preferences for the main target species.

Correlations between indices are evaluated in Figure 3. The lower triangle shows the pairwise scatter plots between indices with a regression line, the upper triangle provides the correlation coefficients, and the diagonal provides the range of observations. The strongest correlation is between Spain and Japan (0.412), though this may be influenced by the last, very larger value in the Japanese series. The 2023 point in the Japanese series influences the relationship between and Reunion (EU_REU) (Corr: -0.316), suggesting a somewhat strong inverse relationship. This might indicate that these two fleets are sampling different components of the stock, possibly due to targeting different tuna species, or that they are influenced by contrasting environmental or operational factors. A positive correlation is also evident between Spain and Portugal as well as Japan and Spain, which may imply similar spatiotemporal dynamics or operational practices, possibly sampling overlapping subpopulations. Several pairings show low correlations, suggesting these indices may be relatively independent or reflect uncorrelated processes. This could be due to differences in gear type, target species, region, or aggregation scale.

The hierarchical cluster analysis (Figure 4) identified two groupings of time-series. The first group includes Portugal and Reunion (EU PRT and EU REU). This group is characterized by time-series which are lightly correlated with each other, and represent a lower-than-average trend in recent years. . The second group includes South Africa, Chinese Taipei, Spain and Japan. This group CPUE is characterized by a positive correlation between Chinese Taipe, Japan and Spain, while South Africa has a weak positive correlation with Chinese Taipei, and a small negative correlation with Spain and Japan. A single influential point may cause a strong spurious correlation, so it is important to look at the plots as well as the correlation coefficients. Also, a strong correlation could be found by chance if two series only overlap for a few years.

Lagged cross-correlations are plotted in Figure 5 reveals several notable patterns among the CPUE indices, suggesting differing degrees of temporal alignment and operational linkages. The Portuguese fleet showed strong internal cross correlations and also exhibited well-defined negative correlations with the South African fleet at plus and minus 4 years. Most notably, it showed a strong negative correlation at lag 0, reinforcing the inverse relationship previously seen in the pairwise correlation matrix. This result may indicate that these two fleets are sampling distinct components of the population or operating in regions with asynchronous abundance signals. Additionally, the South African series exhibited positive correlations with Japan positive lags (approximately +2 to +10 years), suggesting that changes in one index may precede increases in the other, potentially reflecting migratory movement or ontogenetic progression.

Taken as a whole the analysis here shows a potential grouping of CPUE Series

- Portugal and Reunion (possibly including South Africa), and
- Chinese Taipei, Spain and Japan, again with the possible inclusion of South Africa, and
- All CPUE series.

Noting that the inclusion of CPUE series should reflect the assumptions about the stock, and species biology, even with highly correlated CPUE series, introducing series of relative abundance that outside the range of biologically possible growth will introduce misfit in a stock assessment model.

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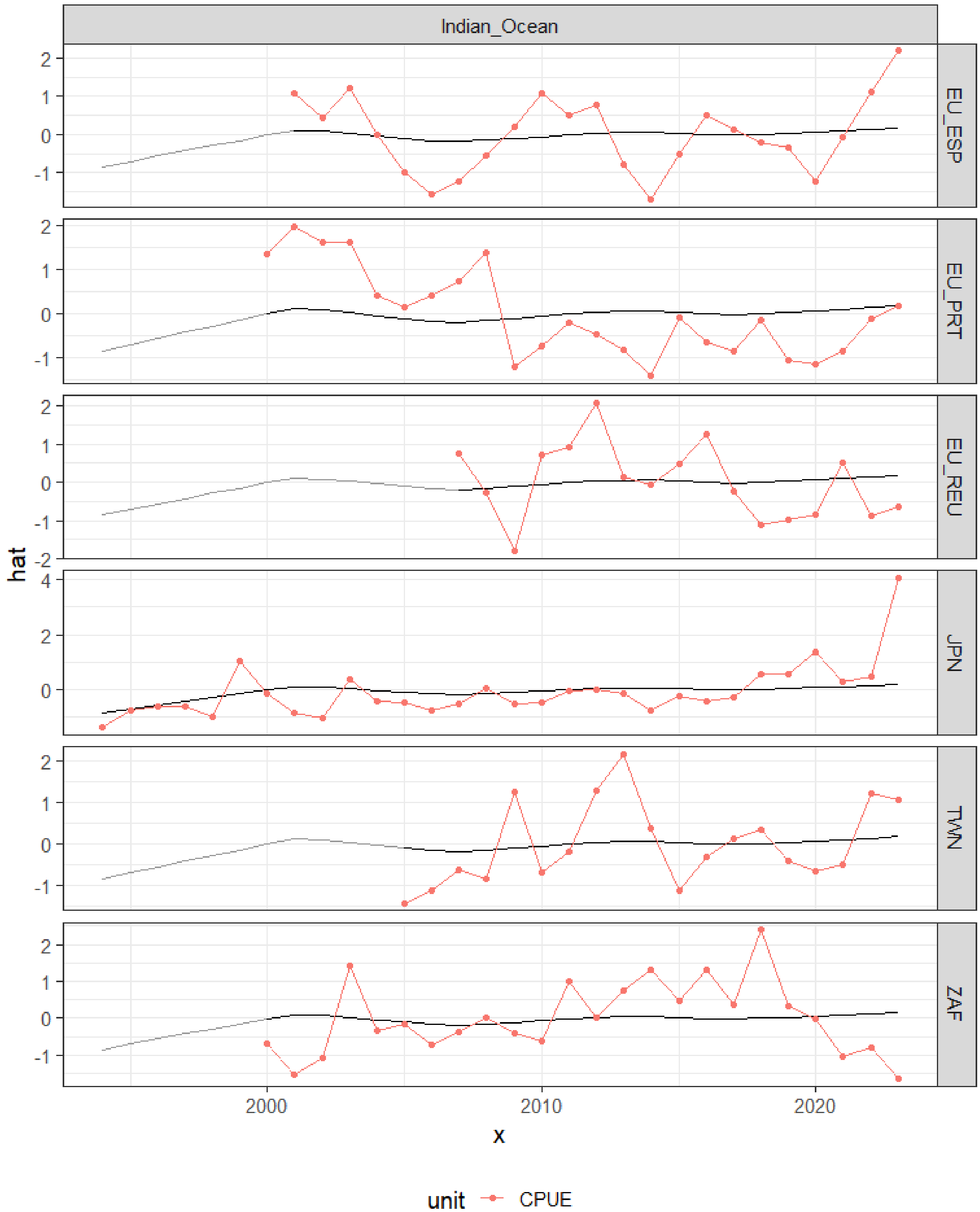

Figure 1. Indian Ocean time series of CPUE indices; Points are the standardized values, continuous black lines are a lowess smoother showing the average trend by area (i.e. fitted to year for each area with series as a factor). X-axis is time, Y-axis are the scaled indices.

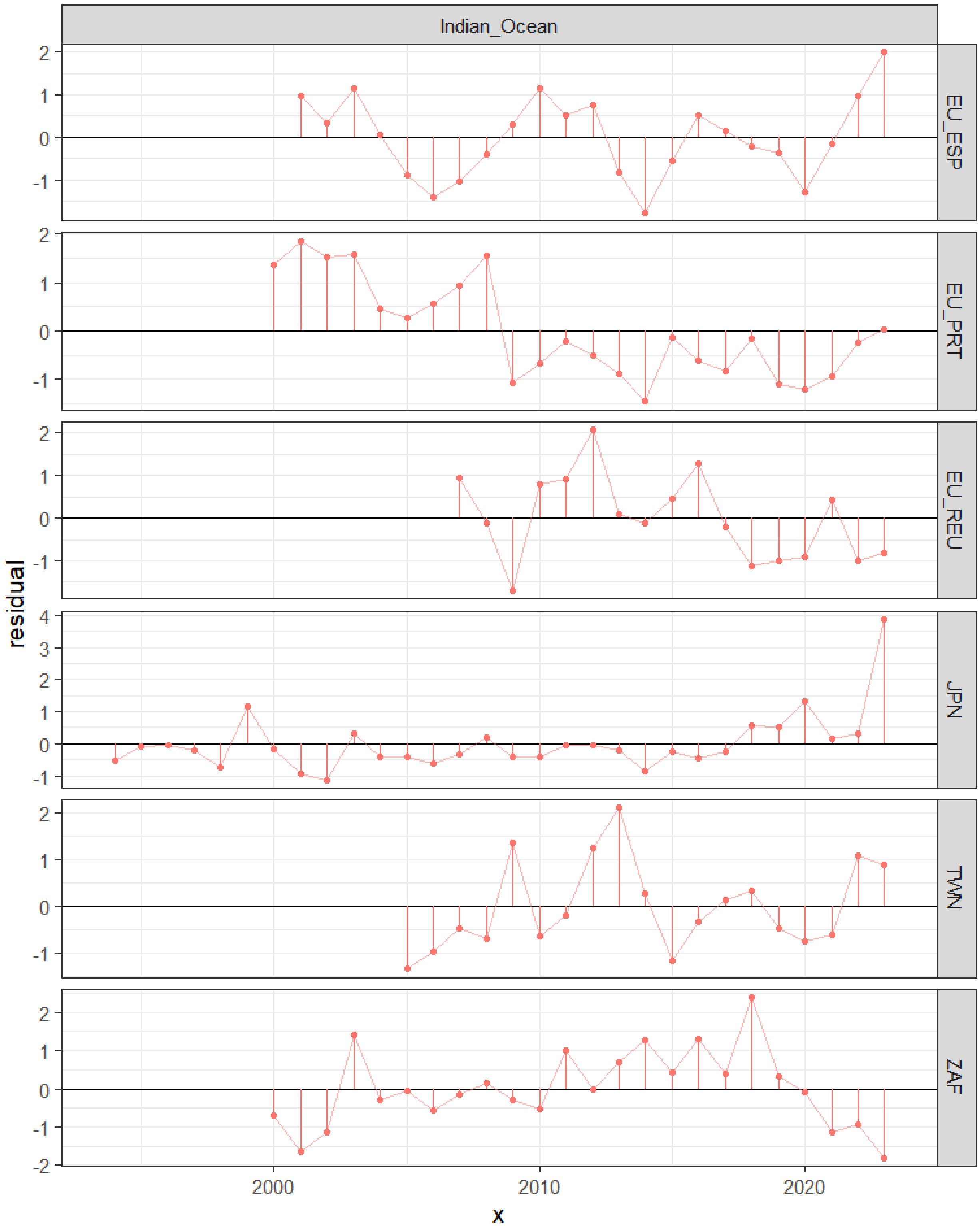

Figure 2. Time series of residuals from the smooth fit to CPUE indices. X-axis is time, Y-axis are the scaled indices.

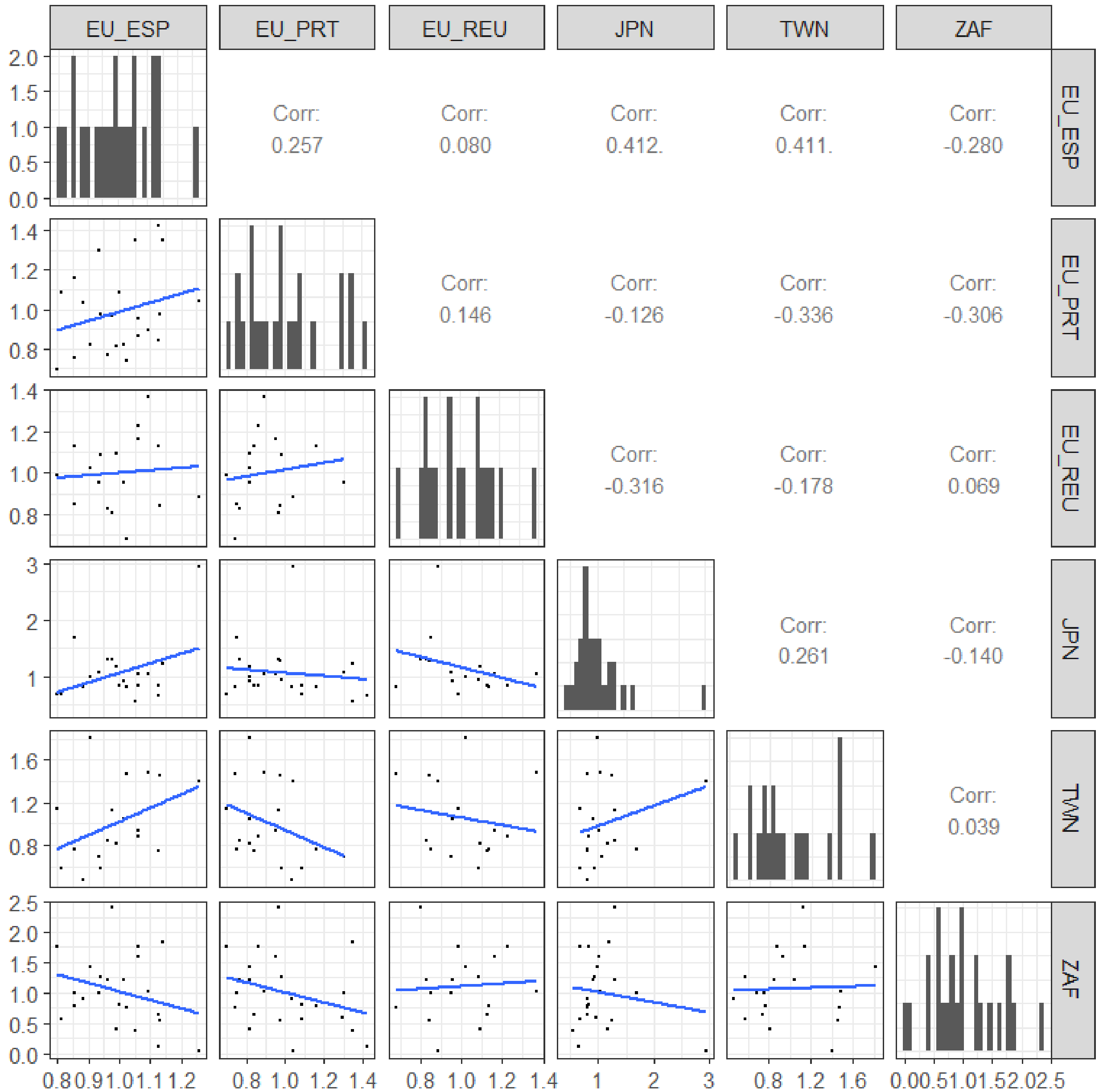

Figure 3. Pairwise scatter plots for CPUE indices. X- and Y-axis are scaled indices.

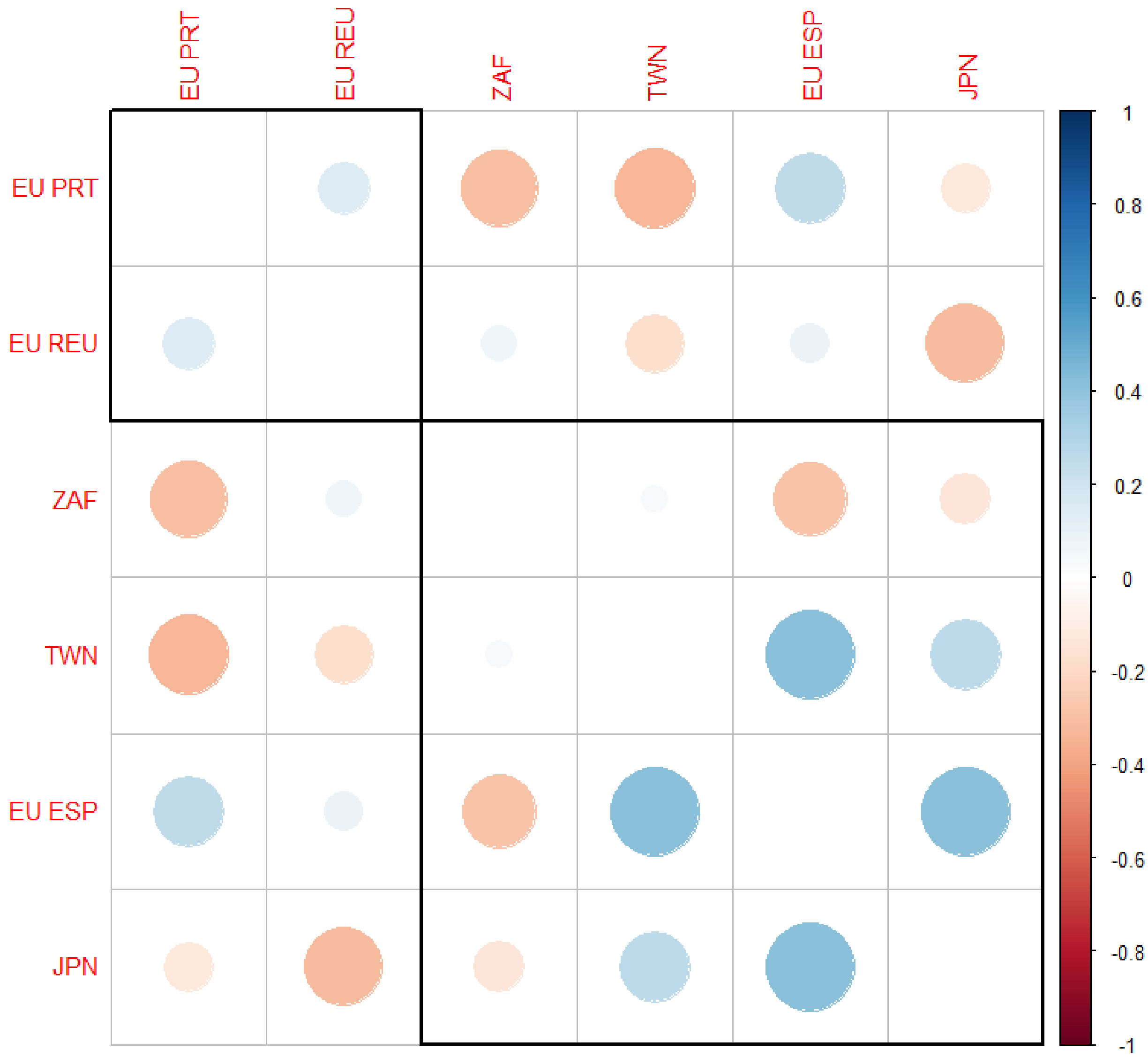

Figure 4. Correlation matrix for CPUE indices; blue indicates positive and red negative correlations, the order of the indices and the rectangular boxes are chosen based on a hierarchical cluster analysis using a set of dissimilarities.

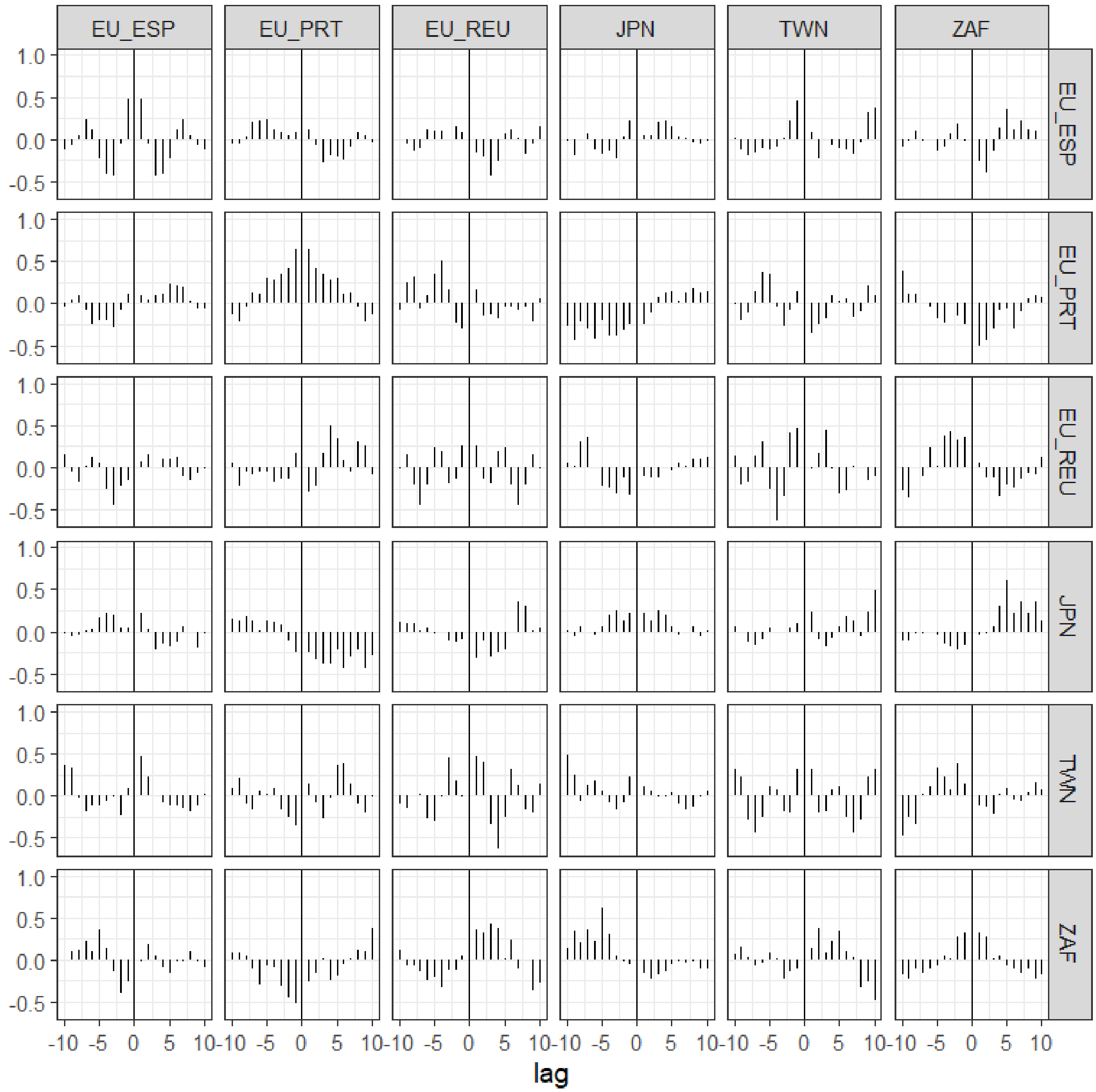

Figure 5 Cross-correlations between CPUE indices to identify lagged correlations (e.g., due to year-class effects). X-axis is lag number, and y-axis is cross-correlation.