Deriving Statistically Reliable Abundance Index from Landing Data: An Application to Taiwanese Coastal Dolphinfish Fishery with Multi-Species Feature

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Abstract

Data from coastal fisheries are often incomplete as these fisheries are usually small-scale, rendering them exempt from logbook submission requirements. Catch of dolphinfish (*Coryphaena hippurus*) by Taiwanese fisheries ranked second in the world but has dramatically declined to very low levels in recent years. In order to address this decline, an abundance index needed to be assessed. However, due to the small-scale of the fisheries, logbook data was not available to calculate catch per unit of effort (CPUE). This study aimed to estimate a statistically reliable index by: (1) assigning effort matrices to landing data using coastal surveillance radar data; (2) standardizing the 2001–2015 CPUE while using four approaches (classifying fishing tactics by multivariate techniques and principal component analysis) to differentiate the fisheries' effort towards catching dolphinfish from that of other target species; and (3) evaluating performances of the standardization models using a coefficient of determination estimated by cross-validation and bootstrap procedures. The approach that used a delta-generalized additive model with direct principal component procedure demonstrated the best fit. This study presented an example of deriving a statistically reliable abundance index from data-incomplete situations common for coastal fisheries, which allows follow-up population dynamics studies possible. The resulted index for dolphinfish in the Taiwanese region showed two seven-year cycles with a prominent decline in 2015. Reasons for the fluctuation are unknown but may be due to environmental factors, the fast-growing nature of the fish, and heavy exploitation of the stock by Taiwanese fisheries.

<A> Introduction

Over-capacity and overfishing have caused anthropogenic threats to coastal ecosystems, which are among some of the most productive marine ecosystems (Jackson et al. 2001; Halpern et al. 2008). Data from fisheries in coastal regions are frequently incomplete as they are often exempt from logbook submission requirements or have a complicated multi-species or multi-gear nature which causes regulation difficulties in traditional management systems.

Logbooks provide essential catch and effort data for calculating catch per unit effort (CPUE) to index stock abundance. When logbooks are not available or incomplete, commercial landing data can be utilized to represent catch if there is no discarding due to size-specific high-grading, at-sea dumping resulting from catches in excess of the quota, black market landings, or losses due to fish handling or processing (FAO 1990-2017). Meanwhile, fishing effort can be estimated either through appropriate assumptions, such as taking each fish landing event (assumed as a trip) as a multiplier of fishing day (e.g., Sonderblohm et al. 2014), or by applying fishery-specific algorithms to fishery-independent information such as vessel monitoring system (VMS), coastal surveillance radar system (CSRS), or voyage data recorders (VDR) (e.g., Lee et al. 2010; Chang 2014; 2016). The CPUE can then be calculated. However, this raw CPUE is seldom proportional to abundance over the whole exploitation history because many factors can affect CPUE. One of the most commonly applied fisheries analyses is standardization of CPUE data to remove the effect of those confounded factors in an attempt to make CPUE proportional to abundance (Maunder and Punt 2004; Maunder et al. 2006). Target effect (the effect of changing target species, Maunder et al. 2006) is one of the most significant confounding factors for multi-species coastal fisheries.

Dolphinfish (Coryphaena hippurus) is a highly migratory species widely distributed throughout tropical and subtropical waters of the three Oceans (Palko et al. 1982), and is utilized by many coastal countries, including Taiwan (Sakamoto and Kojima 1999; Rivera and Appeldoorn 2000). The total catch of dolphinfish by Taiwanese fisheries has been second only to Japan in the world (http://www.fao.org/fishery/species/3130/en). The catch has shown three distinct stages historically (Figure 1): a low population period from 1953 through 1973; a period of steadily increasing catch between 1973 and 1991; and a third period of high catches commencing in 1992 due to an increase of fishing vessels (Chang et al. 2013b). An unknown proportion of distant-water catches were included in the third period; the catch was highly variable and has since declined from a peak of 15,800 mt in 1998 to around 10,000 mt in mid-2000s, and further to 4000 mt in 2015. The decline was observed in domestic fishing ports (Figure 2) and reported by coastal fishers, where concerns regarding the status of the stock and an urgent need to estimate an abundance index emerged. However, coastal dolphinfish fisheries are considered small-scaled in terms of vessel size and exempt from logbook submission in Taiwan. Thus, no catch and effort data are available from the logbook system and the traditional approach to estimate abundance index is not feasible at this time.

This study completed three tasks to obtain a statistically reliable abundance index for dolphinfish under the data incomplete situation. Dolphinfish are seldom discarded because of their high commercial value and thus the recorded landings of dolphinfish by this fishing sector approximately equals total catches. Thus, the first task was to obtain appropriate effort data. It can be simply assumed that each fishing landing event (each trip) at the fishing auction represents a fishing day (Sonderblohm et al. 2014). The actual fishing days per trip (FDPT), however, may vary from one to three days depending on vessel size (tuna fishing vessel FDPT may be longer than that for traditional dolphinfish vessels, Chang et al. 2017). The assumption of a single fishing day per trip thus may underestimate the fishing effort by larger sized vessels. Therefore, this study estimates the FDPT by vessel size based on available data from CSRS which were originally installed for security and enforcement purposes (Chang 2014).

The second task was to standardize the CPUE calculated from landing data and FDPT estimates with consideration of target effect (the effect of different fishing tactics). There are approximately 15 different fishing gears harvesting more than 200 fish species that inhabit the highly diverse coastal ecosystems off Taiwan (Chang 2016). Except for some key fisheries, such as the precious coral fishery or bluefin tuna fisheries that have specific license regulations, fishing vessels can legally change their targets or even fishing methods for the seasonal abundant species without reporting to the fishery authorities. Thus, several target species (fishing strategies or tactics, He et al. 1997; Pelletier and Ferraris 2000) may be involved in the data of a fishing gear, and target effect becomes an important confounding factor that needs to be considered when estimating the abundance index (Maunder and Punt 2004; Chang et al. 2011).

Four approaches were designed to address the second issue. The first two pre-classified professional vessels from the data using two clustering approaches, k-means and hierarchical clustering analysis (HCA) (Silva et al. 2002), and standardized the CPUE by using the common one-stage generalized linear model (GLM). The other two approaches directly standardized the CPUE without separation of professional vessels, using a two-stage GLM (delta-GLM, Lo et al. 1992) with HCA clustered target factor and a two-stage generalized additive model (delta-GAM) with direct principal component (DPC) procedure (Winker et al. 2014).

The third task was to select the final model with best statistical performance of the four standardization models. This study considered two categories of methods introduced by Hinton and Maunder (2004) for CPUE models evaluation: the Akaike information criterion (AIC) and pseudo-coefficient of determination (R^2) (Faraway 2016), and the cross-validation and bootstrap (Zhang and Yang 2015) for estimating the ‘bootstrap-R^2’ (was referred as ‘overall-R^2’ in Chang et al. 2017).

This study presents the first credible CPUE index for the Taiwanese dolphinfish fishery from the final model. The approaches used in this study could be used by other fisheries to derive an abundance index with a similar data-incomplete situation.

<A>Methods

<C>The data.—Dolphinfish catch in the Kuroshio Current off eastern Taiwan is generally landed in the three major fishing ports, Suao, Singang, and Tungkang (from north to south of Taiwan); catches from the three ports composes over 80% of the annual total catches in Taiwan. Commercial landing data from the three ports from 2001–2015 was available for this study and contains daily landing information (vessel identification, unloading date, fishing port, and weight by species) by vessel; however, no information of FDPT was available. Suao had comparatively the highest catch in the early 2000s but declined substantially after 2007 (Figure 2). Singang is currently the major dolphinfish landing port. Dolphinfish catch was also high in Tungkang (Figure 2), however, the historical catch included an unknown but high proportion of frozen fish likely caught from different stocks in the Pacific Ocean or Indian Ocean.

Dolphinfish catch in the three fishing ports show strong seasonality (Figure 2). Two fishing seasons occur in both Suao and Singang: from April to June (with comparatively higher catches) and from September to November (Chang et al. 2013a). Growth performance and mitochondrial DNA analysis determined the fish from the two seasons are from the same stock (Chang et al. 2013a), like the fish in Mexico (Alejo-Plata et al. 2011). In contrast, Tungkang has only one fishing season mainly due to the cost of fishing during the second small season. Considering the different nature of the fishing season, and more importantly the difficulty in separating the catches from distant waters as indicated above, Tungkang data was excluded from this study.

Dolphinfish was caught by many fisheries in Taiwan including miscellaneous fish longline (MLL), tuna longline, gillnet, and many other gears. MLL that fished mainly in coastal area accounted for 84% of the coastal catch during 2011–2015 and was considered the major gear for dolphinfish. The size of the fishing vessels, by Taiwanese vessel size definition, mainly ranged from powered rafts[1] <5 gross registered tonnage (GRT) (termed as CTR vessel category) and powered vessels of <5, 5–10, 10–20, 20–50, and 50–100 GRT (CT0–CT4 categories, respectively).

This study used 2001–2015 landing data of the MLL fishery. A review on the data suggested a general bimonth cycle of landing amount by species, thus a bimonthly period was used as a variable representing the periodical variations. Vessels with less than five landing trips in a bimonth period were excluded from the study to avoid data noise, and the rest of the data was referred to as Data_0 (199,605 trips). The data set contained more than 20 species which were grouped into dolphinfish (DOL), tunas (TUNA), billfishes (BIL), sharks (SHK), and other fishes (‘others’). The most

[1] Raft is a powered, usually plastic tubes made, small boat.

important species in the group of ‘others’ was sea breams which was also a major target species of MLL fishery.

<C>Estimation of fishing effort. —The commercial landing data provided no information on fishing effort. We assumed that Taiwanese small vessels that lack freezing facilities and fish in nearshore coastal waters typically unload their catch daily to keep the catch fresh. Therefore a trip can be generally considered as representing one fishing day (Sonderblohm et al. 2014). However, larger vessels may operate more days at sea before returning to ports for landing, so the relationship between FDPT and vessel size needs to be defined.

To estimate the FDPT by vessel size, this study used data from the land-based CSRS that are operated by the Coast Guard Administration (CGA) in Taiwan for security purposes. The data included information on time (in minutes), position (in geographic seconds), and speed (to the nearest 0.1 knot). Presumably the speed of any fishing vessel will be zero when in port, high when heading for or returning from the fishing ground and navigating between fishing grounds, and low when fishing. Therefore, fishing activities can be identified based on vessel speed information in the radar data (Lee et al. 2010; Chang and Yuan 2014). A simplified description of the criteria used to derive fishing days from the radar data (see details in Chang 2014) included: (1) records for which speed was zero within 0.01 nm of the coastline were assumed to derive from vessels remaining in port; (2) records for which speed >5 knots were assumed to be navigating (e.g., transiting to or between fishing grounds); and (3) the rest data with speed <5 knots were considered as fishing. A vessel-day with incomplete records (an ad hoc criterion: <120 records, i.e., less than two hours, in a day; about 20% of total days), was considered non-informative and was excluded. An incomplete trip without clear identification of both leaving and returning to port or without a corresponding dolphinfish landing record after return to port was also excluded.

The current CSRS design was not created with the convenience of data retrieval for research purposes in mind. Additionally, there are also security considerations in retrieving the data; the retrieval of one year’s worth of daily radar data took several months from ten CGA stations (Figure 2). Therefore, it is infeasible to obtain a series of data from the current systems. This study used 2010 data from the eastern coastline CGA stations that contained about 10 million records, and a subset of 2015 data compiled from 15 randomly selected vessels of all sizes for reviewing the consistency of FDPT-vessel size relationships between these two periods.

The FDPT-vessel size relationship was analyzed using data from vessels of CT0–CT4. FDPT was assumed to be one for rafts (CTR), which have a very limited capacity for staying over one day at sea and was generally poorly identified in the CSRS. A general linear model (GLM) was performed to test the significance of the relationship for 2010 data, considering FDPT as a model response and both the vessel size and 3-month calendar season as factors. Heterogeneity of FDPT by vessel size from both the complete 2010 data and subset 2015 data was tested using the information of mean and standard deviation (SD) of FDPT by a simple meta-analysis. Mean differences were calculated and tested using the function “metacont” of R package (Chen and Peace 2013). If the FDPT were significantly different among vessel sizes, then the mean FDPT by vessel size category were applied to the whole series of landing data for estimating fishing effort assuming no significant annual variation. There was no substantial change observed in the structure of MLL vessels in terms of navigating power and storage facilities, therefore, the assumption was considered reasonable.

<C>CPUE standardizations with considerations of target effect.—Except for some specifically regulated species, fishing vessels can legally undertake multiple fishing methods for target species other than they are licensed for without reporting to the authorities. For example, the MLL fishery can freely shift their target species to sea breams, dolphinfish, tunas and other fishes. Therefore, target issue is the most confounding factor to be addressed in the standardization process.

Four approaches were designed to standardize the CPUE, dolphinfish catch in weight (kg) per trip divided by FDPT, with considerations of the target effect. The first and second approaches classified professional vessels in advance and applied a commonly used GLM procedure with lognormal error assumption to the professional data. The third and fourth approaches directly standardized the CPUE of Data_0 without separation of professional vessels but used a delta-GLM with HCA clusters and a delta-GAM with principle component (PC) scores that derived from a principle component analysis (PCA) to present target factor in the model.

The vessels primarily fishing for dolphinfish were referred as professional vessels, instead of targeting vessels, to avoid confusion with the ‘target factor’ in the standardization models. This study used two methods to classify professional vessels either in the first half year (January to June) or in the second half year (July to December). Some vessels may be professional vessels in one half-year but not the other, so the classification was performed for every half-year and results were combined afterwards by year. The first method used the k-means clustering, a prototype-based partitional clustering technique that attempts to find a specific number of clusters (k) which are represented by their centroids (Tan et al. 2006). The intention of this application was to develop a general rule to classify the professional vessels using catch composition for the management agencies. Since k-means starts with a random choice of cluster centers, it may yield different clustering results on different runs of the algorithm. In addition, k-means clustering assumes the joint distribution of features within each cluster is spherical which is hard to be satisfied. Therefore, this study applied the second method using HCA, which produces a hierarchical clustering by starting with each point as a singleton cluster and then repeatedly merges the two closest clusters until a single, all-encompassing cluster remains (Tan et al. 2006). The number of clusters (k) for the two approaches was decided by the ‘elbow method’ (Kassambara 2017). Data from the professional dolphinfish vessels defined by k-means clustering were referred to as Data_1, and those defined by HCA was referred to as Data_2.

For the first and second approaches, the covariates considered in the GLM included: year (2001–2015), bi-monthly period (1–6), target factor, fishing port (Suao and Singang), and vessel size category (CTR, CT0–CT4). Ln(CPUE+0.1) are modelled assuming a lognormal distribution. A simple forward method was used to determine the variables to be included in the model. Standardized residuals and quantile-quantile plots were used to examine the violation of lognormal assumption. Although the models were applied to professional vessels’ data, the landing data also suggested that those vessels shifted their target species from dolphinfish to other abundant species within the half-year period. Therefore, the HCA was applied again to each dataset and the computed cluster code was assigned as an assumed target factor. The first two approaches were referred to as 'Data1_kmeans+GLM_HCA' and 'Data2_HCA+GLM_HCA', respectively.

Data_0 contained many zero-dolphinfish landing records resulting from dolphinfish abundance seasonality and target effects. To address the effect of high zero records, the third approach used a two-stage delta-GLM which consists of a positive-catch model (PCM) and a zero-proportion model (ZPM) (Lo et al. 1992). For the positive catch model, Ln(CPUE) are modelled assuming a lognormal distribution; while the zero-proportion model predicts the presence or absence of dolphinfish using logistic regression. The standardized index was the product of these model-estimated components. Further model descriptions can be found in Maunder and Punt (2004). The same covariates as designed for the GLM of the previous two approaches were included in the delta-GLM (i.e., year, bi-monthly period, target effect, fishing port and vessel size category). The target effect was simply addressed by the HCA on catch composition data, and the approach was referred to as 'Data0+dGLM_HCA'. Without classification of professional vessels, the number of data records for this approach was substantially higher than the previous two approaches.

The fourth approach applied the DPC procedure (Winker et al. 2013): The procedure uses continuous PC scores derived from a PCA of the catch composition data, as nonlinear predictor variables in a GAM to adjust for the effect of temporal variations in fishing tactics (Winker et al. 2014). Each CPUE record was assigned PC scores which were used as continuous, rather than categorical, variables in the model. GAM was a semi-parametric extension of GLM with the underlying assumption that the functions are additive and that the components are smooth (Guisan et al. 2002). GAM was used, instead of GLM (MacNeil et al. 2009), because of the concern whether GLM is suitable to handle potentially nonlinear relationships between CPUE and PC covariates (Winker et al. 2013). The optimal number of PCs were decided based on Cattel's scree-test in combination with the Kaiser-Guttman rule (Guttman 1954; Cattell 1966).

To address the issue of high fractions of zero catches, the fourth approach adopted a similar procedure as the third approach, using a two-stage delta-GAM that composed of a PCM and a ZPM. The same covariates as previous approaches were used in the model. This approach is termed as ‘Data0+dGAM_DPC’.

<C>Selection of final standardization model.—Hinton and Maunder (2004) introduced three categories of methods to evaluate the performance of the standardization models: The first two (likelihood ratio/AIC/Bayes factors, and cross validation) are based on the ability to predict the catch or CPUE by assuming that the models most accurately predicting the mentioned factors are the most efficient predictors of relative abundance. The third category (system-based testing) is based on the consistency of the estimates, with auxiliary information on the year effect that represents the annual relative levels of abundance (see Chang et al. 2017 for a demonstration). Currently there is no integrated stock assessment model developed for the dolphinfish stock in the Kuroshio Current and not many data on the stock are available, hence the third method is not feasible in this case. Therefore, this study applied the first two methods to evaluate model performances.

The AIC can avoid the overfitting issue due to adding parameters to the model by introducing a penalty term for the number of parameters (Yu et al. 2014) and was used to decide the final variable combination of each model run (with smallest values). AIC can also be used to compare performances of different model; however, the AIC are based on likelihood function, which in its turn depends on sample size. As such, caution is required when comparing one-stage GLMs and two-stage delta-GLMs using AIC with different sample sizes (Hoffmann 2016). In addition, it is complicated for the cases using two-stage delta-GLM or delta-GAM because of the difficulties in defining the variance parameters of the likelihood function.

Therefore, this study used AIC to decide the final variable combination of each model but used ‘bootstrap-R^2’, which determines the overall correlation between the actual and predicted values while avoiding overfitting issues (Chang et al. 2017), to compare model performance. Pseudo-R^2 (Faraway 2016) was used only for single model discussion. The bootstrap-R^2 was calculated through cross validation and bootstrap procedure (Efron 2004; Zhang and Yang 2015). The data were firstly split randomly into two subsets: a model-building set and a validation set. The validation set provided the observed CPUE and the predicted (theoretical) CPUE that calculated from the model built from model-building set, and the R^2 value was then calculated from these pairs of data. The final mean and standard deviation of R^2 was obtained from 200 replications of the above procedures and was then termed as bootstrap-R^2 (see details in Chang et al. 2017). Iterating 200 times was sufficient as a larger number of iterations did not produce substantially different estimates.

<A>Results

<B>Estimation of Fishing Effort

This study identified 2,497 trips from 59 vessels (CT0–CT4) in 2010 for studying the relationship between FDPT estimated from radar data and vessel size categories. The remaining trips could not be used due to a lack of corresponding radar records. This lack of radar records was due to a variety of reasons, including environmental factors (see Chang 2014) or landing vessels associated with ports not covered by the radar data.

The GLM on the relationship of FDPT to vessel size and season on 2010 data suggested that the FDPT are significantly different among vessel size categories ($F_{4,1852}$ = 13.403, $P < 0.001$) but not significantly different among seasons ($F_{3,1852}$ = 0.293, $P = 0.830$). The box-plot distribution of FDPT by vessel size is shown in Figure 3; and the mean ± SD, calculated from the GLM with only vessel size as factor, are 1.143 ± 0.378, 1.222 ± 0.328, 1.386 ± 0.521, 1.799 ± 0.698, and 2.375 ± 0.744, for CT0–CT4, respectively. The meta-analysis on the mean and SD by vessel sizes of 2010 complete data and 2015 subset data suggested no significant heterogeneity was observed (Cochran Q = 2.97, $P = 0.563$). There was no observation of substantial changes in equipment for the vessels to fish longer at sea during the studying period, therefore, the means were used as multipliers and applied to the whole study period to estimate the fishing days. The fishing day per trip for CTR were all assumed as one day.

<B>Classification of Professional Vessels

The scree plot from the elbow method (Figure 4A) suggests five clusters as the optimal cluster number for the k-means clustering method. Each cluster has different dominant species compositions (Figure 5A) indicating five different types of target vessels: dolphinfish, billfishes, tunas, ‘others’, and sharks. The catch composition of a dolphinfish cluster against the clusters of the other four fish groups (Figure 6) suggests 40% as the rule-of-thumb dolphinfish composition threshold for classifying professional vessels: a vessel could be classified as a dolphinfish professional vessel when its dolphinfish catch ratio is higher than 40% in a half-year period. By this rule, 3,856 (in 2012) to 6,415 trips (in 2007) from 64 (2012) to 133 (2007) vessels were classified as professional trips during the study period. Total professional trips were 73,883 (Data_1).

The HCA method also suggests five optimal number of clusters (Figure 4B) and the same five types of target vessels (Figure 5B). Cluster 1 was defined as the professional trips which comprises 3,584 (2012) to 6,099 (2007) trips from 57 (2012) to 128 (2007) vessels. Total professional trips were 71,490 (Data_2).

<B>Targeting Factors for CPUE Standardizations

Scree plots for selecting the number of clusters for the HCA as target factors in the GLMs in the first two approaches (Data1_kmeans+GLM_HCA and Data2_HCA+GLM_HCA), did not show clear ‘elbows’ (Figures. 4C and 4D), i.e., the elbows cannot be unambiguously identified as those in Figures. 4A and 4B. This might be because the major target effect has already been accounted for by the classification of professional vessels in the two approaches. Three clusters for the GLM on Data_1 and four clusters for the GLM on Data_2 were decided through arbitrary tests (Figures. 4C and 4D).

Different from the first two approaches, the scree plot for the third approach (Data0+dGLM_HCA) applied to original Data_0 has shown a clear ‘elbow’ (Figure 4E). Five clusters were defined as mainly targeting tunas with bycatch of dolphinfish and ‘others’, solely on dolphinfish, on billfishes, on sharks, and on ‘others’, respectively (Figure 5E), and had almost the same as the results from the professional vessels classification. This clustering result represented the different targeting clusters in the MLL landing data. The catch compositions of each cluster were consistent over time (Figure 7A). Dolphinfish (Cluster 2) was caught mainly in the second-third and fifth-sixth bimonthly periods (Cluster 2 in Figure 7B), however, the proportion varied by year. Dolphinfish was mainly fished by small vessels of CTR and CT1–2 (>75%)

(Figure 7C), and the Cluster 2 fishing effort peaked in 2007 and declined thereafter (Figure 7D).

For the fourth approach (Data0+dGAM_DPC), the Cattel's scree-test in combination with the Kaiser-Guttman rule suggested optimal three PC axes (eigenvalue greater than one). Dolphinfish targeting effect was mainly associated with PC1: lower scores representing stronger targeting on dolphinfish and, vice versa, higher scores representing stronger targeting on other fishes (Figures 8 and 9). PC2 and PC3 were mainly associating with targeting effect of the rest fish groups.

<B>CPUE Standardizations and Final Model Selection

Statistics of the final standardization model runs of the four approaches with smallest AIC of each model run were shown in Table 1. The diagnostic residual plots and quantile-quantile plots suggested normality in the distribution of the residuals and no patterns within covariates for the GLMs and the PCMs of the delta-GLM and delta-GAM. The Kolmogorov–Smirnov tests indicate that the residual distributions do not significantly differ from the normal distribution assumption ($p > 0.100$). The analyses of deviance suggested that all the main effects, including target effects, were significantly different from zero ($p < 0.001$).

Since the two classified professional datasets are different with different sample sizes, the AIC cannot be used to compare the performance of the approaches. The bootstrap-R^2 of the first two approaches were 0.268 ± 0.002 (mean ± SD) and 0.297 ± 0.003 (Table 1), respectively, indicating that the second approach using HCA to define professional data has a slightly better fit. The bootstrap-R^2 of the last two approaches were 0.387 ± 0.003 and 0.873 ± 0.001, respectively. Obviously, the fourth approach that used delta-GAM with DPC procedure has a higher model fitting performance and was considered as the 'optimal' standardization model.

Though there were differences in model fitting results, generally the four standardized CPUE time series had similar trends (Figure 10A). According to the optimal model result, the standardized CPUEs showed an increasing trend beginning in 2001, peaking in 2007, and followed by a drastic drop in 2008 with a continuous decline to its lowest level in 2012. Afterward the CPUE increased to its second peak in 2014 but with a second decline in 2015. The decline in 2015 was more substantial in this approach than in the first two approaches. The standardized CPUE trends obviously differed from the nominal CPUEs which almost showed no trend (Figure 10B).

<A>Discussion

<B>Estimation of Fishing Effort

Accurate fishing effort data is crucial to understanding stock dynamics through calculation of CPUE as a proxy of abundance. Fishing effort information is commonly sourced from logbooks submitted by fishers, although many studies have discussed concerns on the accuracy and sufficiency of the information from this source (Bordalo-Machado 2006; Chang and Yuan 2014; Walter et al. 2014). High-resolution measurement of fishing effort can be derived from fishery-independent high-tech data, such as VMS or VDR data (Gerritsen and Lordan 2011; Chang and Yuan 2014; Chang 2016) in the absence of reported fishing effort. However, many fisheries are unable to afford the installation of these systems. As a result, many studies rely on landing records to estimate effort by assuming that each landing event represents a fishing day (one FDPT) (e.g., Leitão et al. 2014; Sonderblohm et al. 2014).

Logbook data was not available for the small-scale coastal dolphinfish fishery in Taiwan. This study derived effort from landing data on trip basis but adjusted the FDPT by vessel size according to inferences from radar data. Radar data suggested the FDPT for the MLL fishery has a significantly positive relationship with vessel size but has no statistical relationship with season. Generally, vessels smaller than 20 GRT (CT0–CT2) landed catches daily (FDPT = 1); and vessels larger than 20 GRT (CT3–CT4) fish for about two days on average before landing (Figure 3). Radar data showed that the dolphinfish fishing ground is not far from the coastline (Chang 2014), and the fish were mainly caught by small MLL (< 20 GRT, estimated mean FDPT < 1.5) (Figure 7) who have limited navigation power and storage capacity. Most were aged vessels and operated within the nearshore coastal waters of Taiwan; more newly built vessels generally shifted to be tuna longliners fishing for higher valued tunas and marlins in farther areas or in the high seas. Hence, if there was no geo-referenced data such as radar data or VMS/VDR data to estimate the relationship, it might be plausible to assume that most fishers unload their catch every fishing day to supply the fresh product preferable to Taiwanese markets.

The 2010 radar data that was used to adjust the FDPT by vessel size covered over 85% of the professional vessels and was considered representative. However, the CSRS has a limitation in scanning range (normally 12 nm of the coastline but can be farther in fine weather). Larger vessels may fish beyond the limit, in which case the trip will be excluded if the records within the limit are less than two hours in a day before the vessel returns to port (may be different from its leaving port). This situation may diminish the effect to adjust the underestimation of effort for large vessels. However, the composition of vessel size was rather stable for dolphinfish-targeting clusters across the years (except for 2005 and 2006; Figure 7C), i.e., the proportion of bias might be generally consistent through time. In addition, the majority of vessels were small MLL vessels (even for 2005 and 2006) that normally fished for dolphinfish in nearshore coastal waters, which means the magnitude of underestimation might not be large. Hence, we assumed the estimated mean FDPT were applicable, and the uncounted efforts might have limited impact on the relative CPUE series.

<B>Classification of Fishing Tactics within the MLL Fishery

Total landing records from the MLL fishery (Data_0) was almost double that of the professional datasets Data_1 and Data_2 (Table 1), suggesting that the original data contained a high proportion of vessels that had not fished for dolphinfish or only occasionally caught dolphinfish as bycatch. Catch compositions of the clusters in Figure 5 indicated that the fishery has several target species and therefore is a multi-species multi-fleet fishery, or a mixed fishery with different target species. Heterogeneity of targeting tactics in the fishery will degrade the accuracy when assessing the relationship between the total fishing effort and the resulting fishing mortality on the exploited stock; hence the targeting tactics of the fishery need to be classified in advance (He et al. 1997; Pelletier and Ferraris 2000).

Species composition of the catch was commonly used to classify the targeting tactics through simple multivariate techniques by considering the similarities between the species assemblages (He et al. 1997; Silva et al. 2002). Target species may not be accurately reflected by the species composition itself, however, in many cases, this can be mitigated by associating the clusters with additional information such as vessel characteristics (He et al. 1997; Pelletier and Ferraris 2000).

In this study, the first three approaches using species composition multivariate techniques obtained similar results of five clusters with different targeting tactics (Figures 5A, 5B and 5E). Clusters from Figure 5E were supplemented with additional information and demonstrated that the MLL fishery actually contained five métiers with specific target species (Figure 7) rather than simply 'miscellaneous fishes'. Métier-1 was mainly vessels <50 GRT targeting tunas with bycatch of dolphinfish and sharks in Suao where the three fish groups were abundant in the coastal waters. Métier-2 consisted of vessels < 20 GRT targeting dolphinfish during the main fishing seasons of March–June and September–December (bi-month basis). This fleet contributed the highest fishing effort in the fishery. Métier-3 consisted largely of vessels of 10–50 GRT from Singang targeting billfish in autumn and winter when the Northeast monsoon was strong. Métier-4 was mainly by 5–20 GRT vessels targeting sharks in Suao from November through February. Métier-5 was mostly vessels <5 GRT targeting 'other' species.

Classification of vessels with the same targeting tactics is an important topic of fisheries management (Russo et al. 2011). Dolphinfish is an important target species to Taiwanese fisheries, and managers with no computation capacity requested a simple rule to identify professional vessels to facilitate management purposes. The k-means clustering results (Figure 6) in this study suggested a simple 40% rule, dolphinfish catch composition during a half-year period, which is easily understandable and acceptable to fishers. Although the selection of a fixed value could be arguable because the catch ratio would vary by year and region, empirically, however, the professional vessels classified using this 40% rule have similar performances as those using HCA, which requires intensive computation, in the CPUE standardization (Data2_HCA+GLM_HCA, Table 1) and the resulted relative CPUE trends of both approaches were almost identical (Figure 10A). Nevertheless, the fixed criterion may need to be reviewed periodically.

<B>CPUE Standardizations and Model Performances

The AIC were only used to define the final parameter combinations and were not used to compare model performances because the datasets contained different sample sizes (Hoffmann 2016). The larger a sample size, the larger the calculated likelihood, and therefore AIC becomes smaller. AICs could not be combined for the delta models (delta-GLM and delta-GAM) either, which was concerning since model runs of each step implies a different variance parameter and it is not clear if the variance parameter should be counted in the AICs.

Alternatively, R^2 determines the correlation between the actual and predicted values and can be a straightforward statistic for model selection in linear models when the number of parameters is fixed (Kutner et al. 2005). There are more parameters in two-stage delta models than in a one-stage model, which may increase the likelihood of overfitting and produce misleadingly high R^2. Estimating the bootstrap-R^2 value through cross-validation and bootstrap procedures (Efron 2004; Zhang and Yang 2015) could avoid the illusion of increased R^2.

The bootstrap-R^2 of the first two approaches applying GLM to professional data (Table 1) suggested the second approach has slightly better fitting performance than the first one. Meanwhile, the bootstrap-R^2 of the two delta methods showed higher values than the first two approaches, especially when applying the DPC procedure developed by Winker et al. (2013): 0.873 for the fourth approach (Data0+dGAM_DPC) compared to 0.387 for the third approach (Data0+dGLM_HCA) and 0.268–0.297 for the first two approaches with classification of professional vessels. This suggested that it is unnecessary to classify professional vessels for CPUE standardization in this context. Mechanisms for the significant difference between the fourth approach and the other three approaches were not examined. The difference likely resulted from the advantages introduced in Winker et al. (2013), where the DPC approach can avoid determining the optimum number of clusters with rather artificial boundaries and the combinations of different proportions of targeting tactics are modelled as a continuum of all possible combinations.

Another possibility of the high bootstrap-R^2 in the fourth approach was the overfitting of a large of amount of zero-catch in the Data_0. The pseudo-R^2 of PCM component of the delta-GAM with positive dolphinfish catch was 0.530, while that of ZPM was

0.954, implying that zero-catch records might have substantial effect on the estimation of bootstrap-R^2. Winker et al. (2013) directly removed the zero-catch records, assuming that only a minor fraction of observed zeros would result from failed targeting effort (‘true zero’) in abundant target species. However, this study assumed that the decline of dolphinfish catches would result in an increasing proportion of zeros, and thus why the delta-method was applied. This could increase the estimation of bootstrap-R^2 in delta-GAM. However, this was not observed in the delta-GLM case (the third approach), perhaps because the zero-catch records had been assigned to the bycatch clusters from the HCA method. Even so, the pseudo-R^2 of 0.530 for PCM is still much higher than the other approaches, suggesting the fourth approach had a better fitting performance than the other approaches. An additional test using one-stage GAM on positive catch records (removed all zero-catch records) resulted in almost identical CPUE series with that of delta-GAM, except for a slightly lower CPUE level in 2007.

The first two approaches used data from pre-defined professional vessels. It may be arguable that professional vessels may make every effort to increase their fishing efficiency when dolphinfish abundance becomes lower, and consequently may result in a rather stable CPUEs over time. This concern was considered insignificant for this study because dolphinfish is not a high-ranked profitable species such as tunas and billfishes, and the major targeting vessels are relatively small and traditional. In addition, dolphinfish is just one of the targets of the multi-species mixed fishery and there is no restriction for the fishery to shift target species. When the catch rate of dolphinfish is low and unprofitable, the small-scale vessels may have neither strong incentive nor capability to improve their fishing efficiency for dolphinfish and may simply switch to target other fish groups.

Hyperstability may occur when a fishery targets fish spawning aggregation in which the CPUE remains elevated as stock abundance declines (Ellis and Wang 2007; Erisman et al. 2011). On the other hand, hyperdepletion may occur when ignoring the effect of an unfished area to the overall stock trend index, especially for fisheries that move progressively across large region (Walters 2003). Inclusion of spatial effect in the standardization model may help avoid these situations (Walters 2003). The geo-location information should be available from radar data, however, as previously explained, there are limitations in obtaining the data. MLL vessels usually fish in adjacent waters close to home ports where they land the catch. Interviews with industry leaders confirmed the assumption that the fishing areas were consistent throughout the studied period. In addition, including fishing ports as a covariate, as in the study of Pacific bluefin tuna CPUE standardization with similarly incomplete data (Chang et al. 2017), could mitigate the deficiency in the lack of spatial data.

Distribution of dolphinfish is correlated with environmental variables such as sea surface temperature and ocean current (Martínez-Ortiz et al. 2015). Lack of geo-location data of the operations has also limited the use of environmental information as covariates in the models in this study. However, environmental variables are often highly correlated to each other and may also correlate with other spatial and temporal factors. Therefore, the effects of many environmental factors may not be significant in the standardization models even if the factors were included (e.g., Su et al. 2008). The dolphinfish fishing ground was relatively small and in the warm Kuroshio Current (Figure 7 of Chang 2014), which means environmental changes in the region may not have been large enough to be influential and were rather implied in the bi-month factor.

<B>Summary and Management Implications

Dolphinfish catch has substantially declined during recent decades, driving the need to develop credible CPUE indices. However, due to the small-scale coastal fisheries catching dolphinfish, logbooks were unavailable to provide information for the calculation of CPUE. This study, for the first time, examined Taiwanese coastal fisheries that are complicated with multi-gear and multi-tactics features and selected MLL for developing the indices. The study assumed landing weight was equivalent to catch, since generally no market discarding occurred on this species, and then assigned a reliable effort matrix (in number of fishing days) as well as targeting information to the landing data. The effort was estimated based on the common practice of assuming one fishing day for one landing event but was adjusted by vessel size using radar data from CSRS.

Four approaches were designed to standardize the CPUE, taking into account the target effect for this multi-species fishery. The first two pre-classified professional vessels through two multivariate statistical methods before performing the standardization with one-stage GLM. A simple rule for identifying the professional vessels was determined for managers to serve management purposes. The other two directly standardized the CPUE using dedicated two-stage GLM or GAM to address the abundant zero-catch data and using an HCA clustering technique or DPC procedure to address the target issue. Based on bootstrap-R^2, this study suggested the fourth approach, i.e., the use of the DPC procedure to address the target effect in the delta-GAM, as the optimal model, and that pre-classification of professional vessels might not be necessary in the standardization.

The index from the optimal model showed two seven-year cycles with peaks in 2007 and 2014 (Figure 10), and the last year (2015) showed a concerning decline. While there is no information to explain the causes of these fluctuations, they may be associated in part with environmental factors on the recruitment (as in the Gulf of Mexico, Kitchens and Rooker 2014) and the exceptionally fast growth rates and early maturation nature of the fish (Oxenford 1999; Schwenke and Buckel 2008; Chang et al. 2013a). It may also be related to the heavy exploitation from 2004–2007 and low fishing pressure after 2007 (Figure 7D, Figure 1), as well as the fishing pressures of Japan, the largest dolphinfish harvester, exploiting the same stock as Taiwan (Chang et al. 2013a), and thus cooperation in analyzing the indices and further designing management regulations should be encouraged.

In 2015, a basic Fisheries Improvement Project (FIP) for the dolphinfish fishery in eastern wasters off Taiwan (Hsin-Kang Mahi Mahi FIP[2]) was established with the participation of representatives from stakeholders[3], research institutions and governments. The FIPs are for fisheries that are willing to mitigate fisheries impacts on marine resources by encouraging the sharing of responsibility by the private sectors and not subject to a high standard ecolabeling approach. Although there is no management measure stipulated for dolphinfish fisheries, the implementation of the FIP should have positive impacts on the stocks while at the same time facilitating the collection of better data from the fisheries. Before higher quality data can be

[2] http://www.taiwanfip.tw/fip_introduction_en.html

[3] Including service wholesaler, processing plant, trade agents and local fishermen.

sufficiently collected for scientific analyses, this study provides an alternative and statistically reliable abundance index from an incomplete data situation to understand the regional stock status and for precautionary fishery-impact mitigation planning, which is the goal of the FIP.

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FIGURE CAPTIONS

FIGURE 1. Historical catches of dolphinfish in Taiwan during 1953–2015 (including coastal and distant-water catches). Catches over 1953–1992 were estimated from Chen et al. (1999), and those over 1993–2015 were adopted from the Fisheries Agency (2008-2017).

FIGURE 2. Catch trends of dolphinfish and other major species groups during 2001–2015 (DOL, TUNA, BIL, SHK for dolphinfish, tunas, billfishes and sharks, respectively) from the three major fishing ports of Taiwan (red solid stars: Suao, Singang and Tungkang). Catches of Tungkang contained an unknown proportion of frozen products that were considered caught in distant waters. Circles along the coast are locations of the coastal surveillance radar stations in the eastern Taiwan.

FIGURE 3. Fishing days per trip (FDPT) against vessel sizes.

FIGURE 4. Scree plots of different clustering methods. Left panels are for classifying professional vessels using (A) k-means clustering on Data_1 and (B) HCA clustering on Data_2. Right panels are for defining target factors in the standardization models using HCA clustering on (C) Data_1, (D) Data_2 and (E) Data_0.

FIGURE 5. Catch composition by cluster of different clustering methods. Left panels are for classifying professional vessels using (A) k-means clustering on Data_1 and (B) HCA clustering on Data_2. Right panels are for defining target factors in the standardization models using HCA clustering on (C) Data_1, (D) Data_2 and (E) Data_0. DOL, TUNA, BIL, SHK, and 'others' represent dolphinfish, tunas, billfishes, sharks, and other fishes, respectively.

FIGURE 6. Catch composition of various clusters defined from k-means clustering method, by major fish groups. DOL, TUNA, BIL, SHK, and 'others' represent dolphinfish, tunas, billfishes, sharks, and other fishes, respectively. Each circle point is one-trip data belonging to one of the clusters defined by the k-means clustering method: black for dolphinfish clusters, green for tunas clusters, cyan for sharks clusters, red for billfishes clusters, and blue for other-fishes clusters. Generally, a dolphinfish cluster has catch composition approximately over 40%.

FIGURE 7. Annual catch composition (A) by species, (B) by bi-month, and (C) by vessel size category, and (D) annual fishing days, of the five clusters obtained from HCA clustering method on Data_0. DOL, TUNA, BIL, SHK, and ‘others’ represent dolphinfish, tunas, billfishes, sharks, and other fishes, respectively.

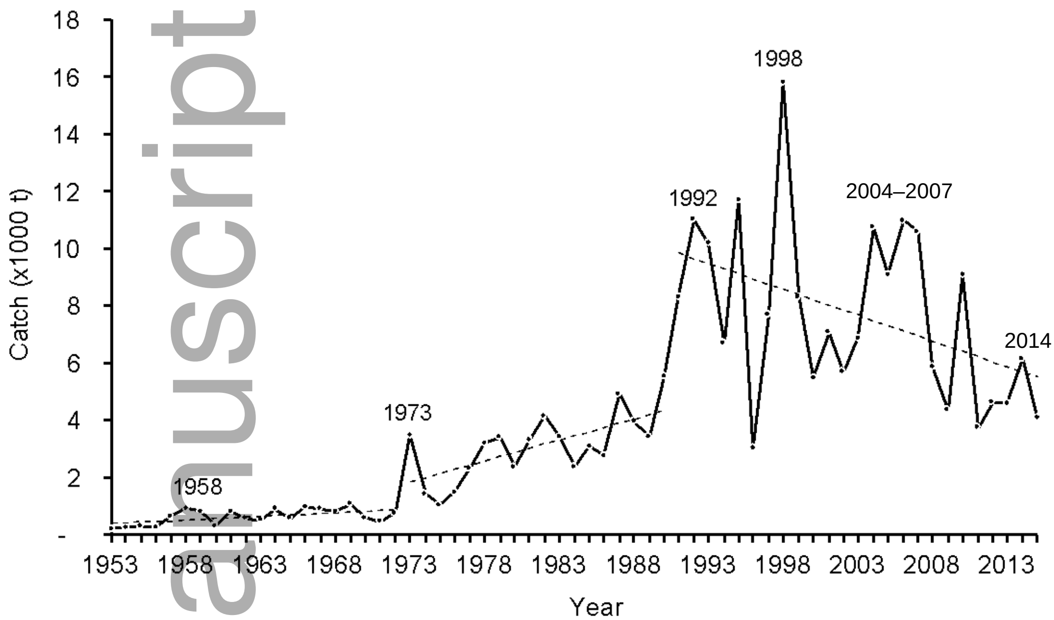
FIGURE 8. Correlations biplots showing the loadings of the fish groups plotted on principle components (A) PC1 and PC2, (B) PC1 and PC3, and (C) PC2 and PC3.

FIGURE 9. Scatter plots between dolphinfish CPUE and the principle components (PC1–PC3).

FIGURE 10. Comparisons of dolphinfish relative CPUE standardized by the four approaches (A): GLM with HCA clustered target factor on professional vessel data that classified using k-means method (Data_1) and HCA method (Data_2); delta-GLM with HCA clustered target factor on original data (Data_0); and, delta-GAM with DPC procedure on original data (Data_0). Panel (B) shows the nominal CPUE of different datasets.

TABLE 1. Statistics and bootstrap-R^2 of the four standardization approaches. ZPM stands for zero-proportion model and PCM for positive-catch model. The bold values are bootstrap-R^2 for comparison of model performance.

	Null deviance	**Null d.f.**	**Residule deviance**	**Residule d.f.**	**Pseudo-R^2**	**Bootstrap-R^2**
1st approach: GLM with HCA targeting factor on professional Data_1 from k-means method (Data1_kmeans+GLM_HCA)						
	362979	73882	264507	73853	0.271	**0.268 ± 0.002**
2nd approach: GLM with HCA targeting factor on professional Data_2 from HCA method (Data2_HCA+GLM_HCA)						
	351744	71489	247649	71460	0.296	**0.297 ± 0.003**
3rd approach: delta-GLM with HCA targeting factor on original Data_0 (Data0+dGLM_HCA)						
ZPM	274722	199604	165622	199570	0.397	
PCM	257093	109755	173649	109722	0.325	
						0.387 ± 0.003
4th approach: delta-GAM with DPC targeting factor on original Data_0 (Data0+dGAM_DPC)						
ZPM	274722	199604	12774	199557	0.954	
PCM	257093	109755	120831	109699	0.530	


18
16
14
12
10
8
6
4
2
-
Catch (x1000 t)
1958
1973
1992
1998
2004–2007
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1953
1958
1963
1968
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1978
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Year

Fig. 1

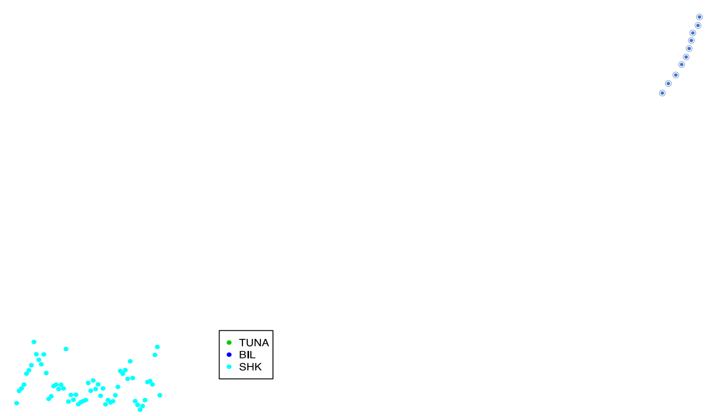


Fig. 2

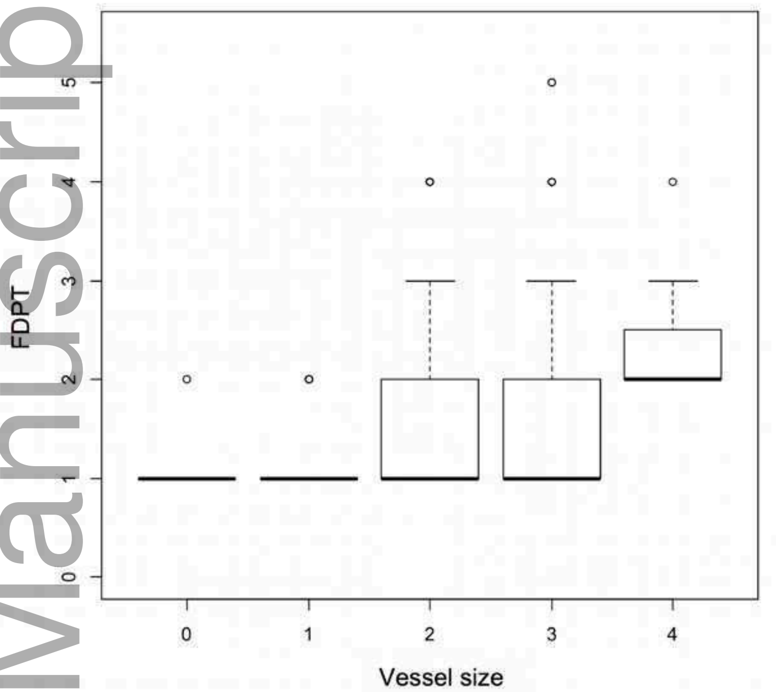
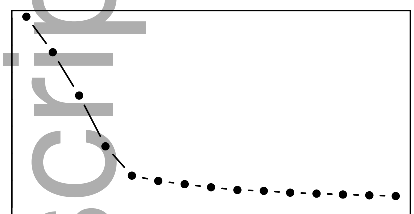


Fig. 3



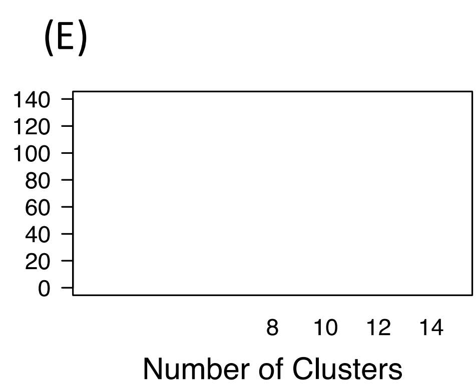


Fig. 4

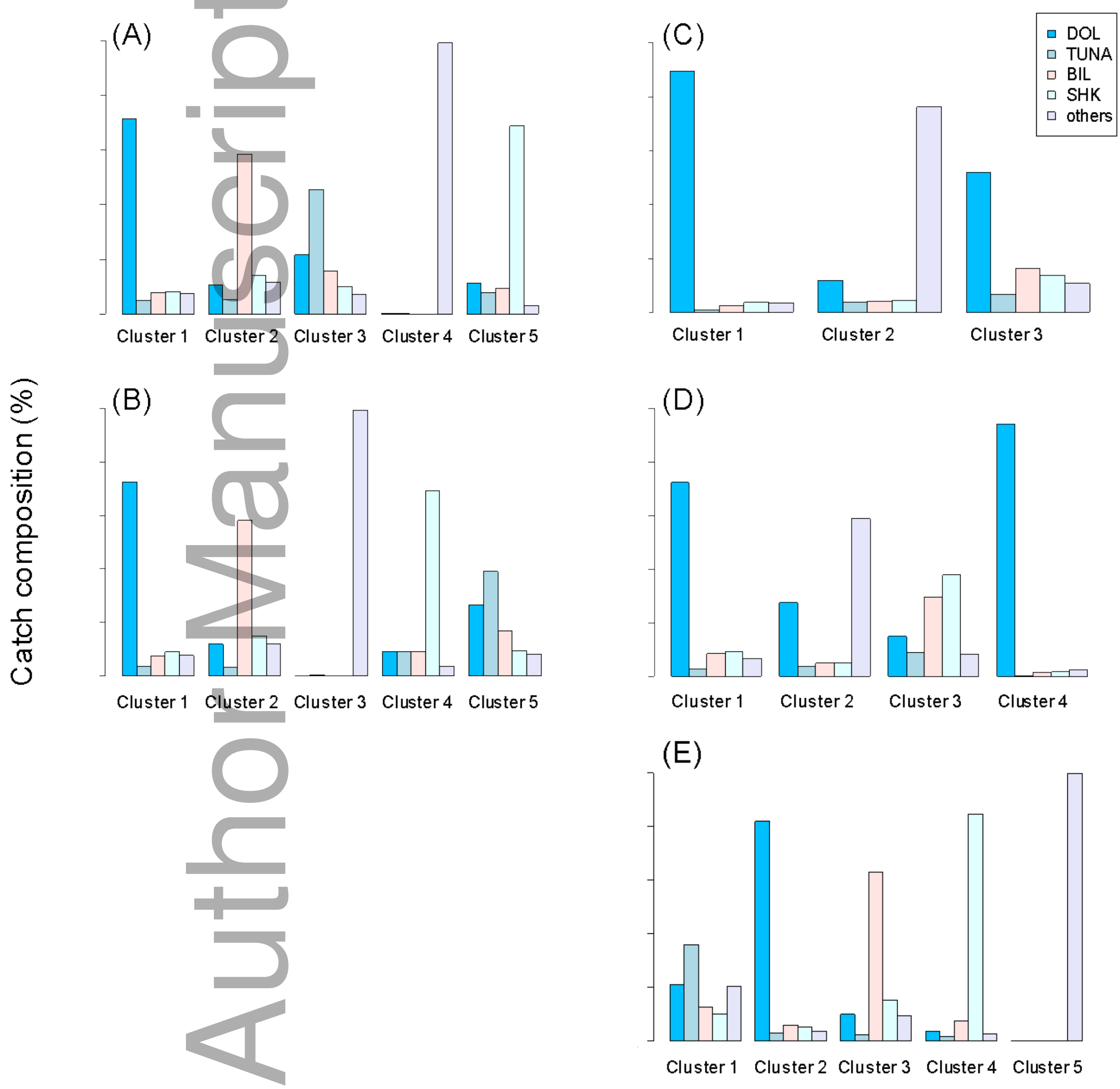

(A)
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
(B)
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
(C)
DOL
TUNA
BIL
SHK
others
Cluster 1
Cluster 2
Cluster 3
(D)
Cluster 1
Cluster 2
Cluster 3
Cluster 4
(E)
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Catch composition (%)

Fig. 5

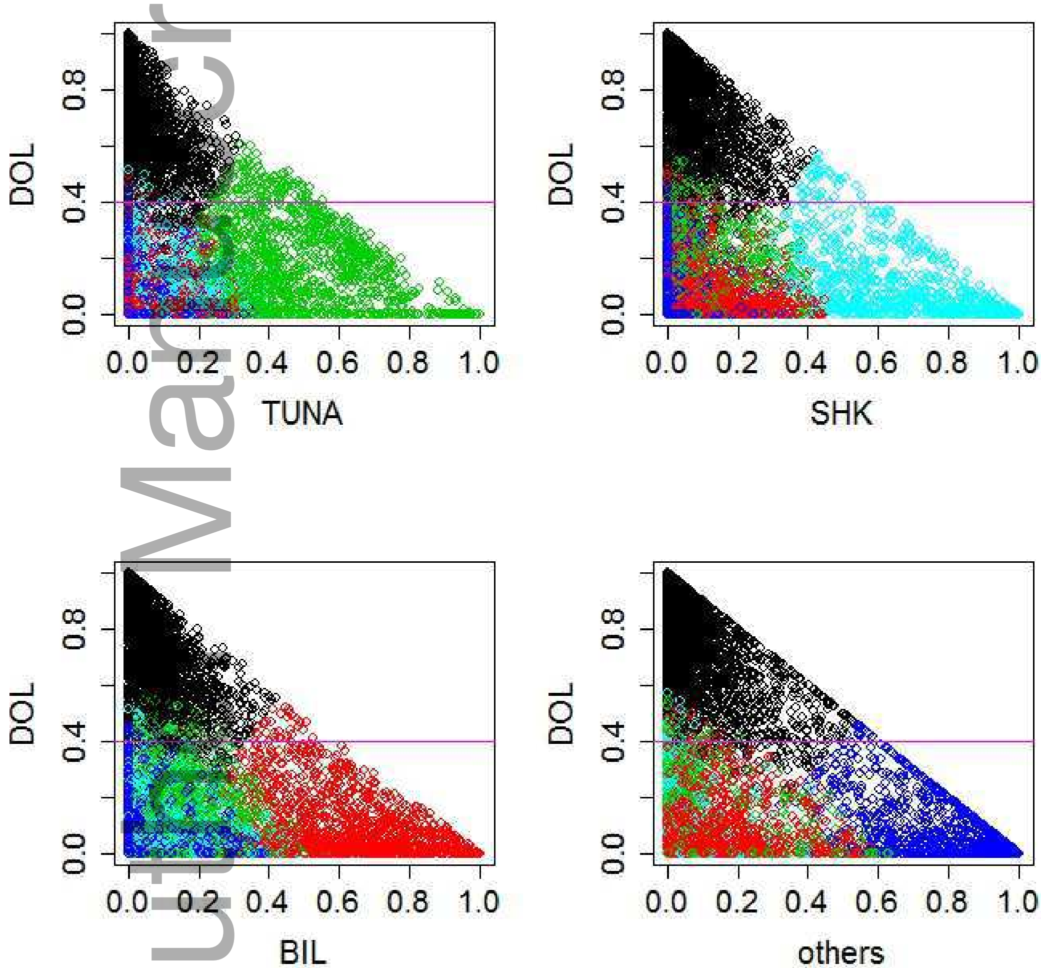


Fig. 6

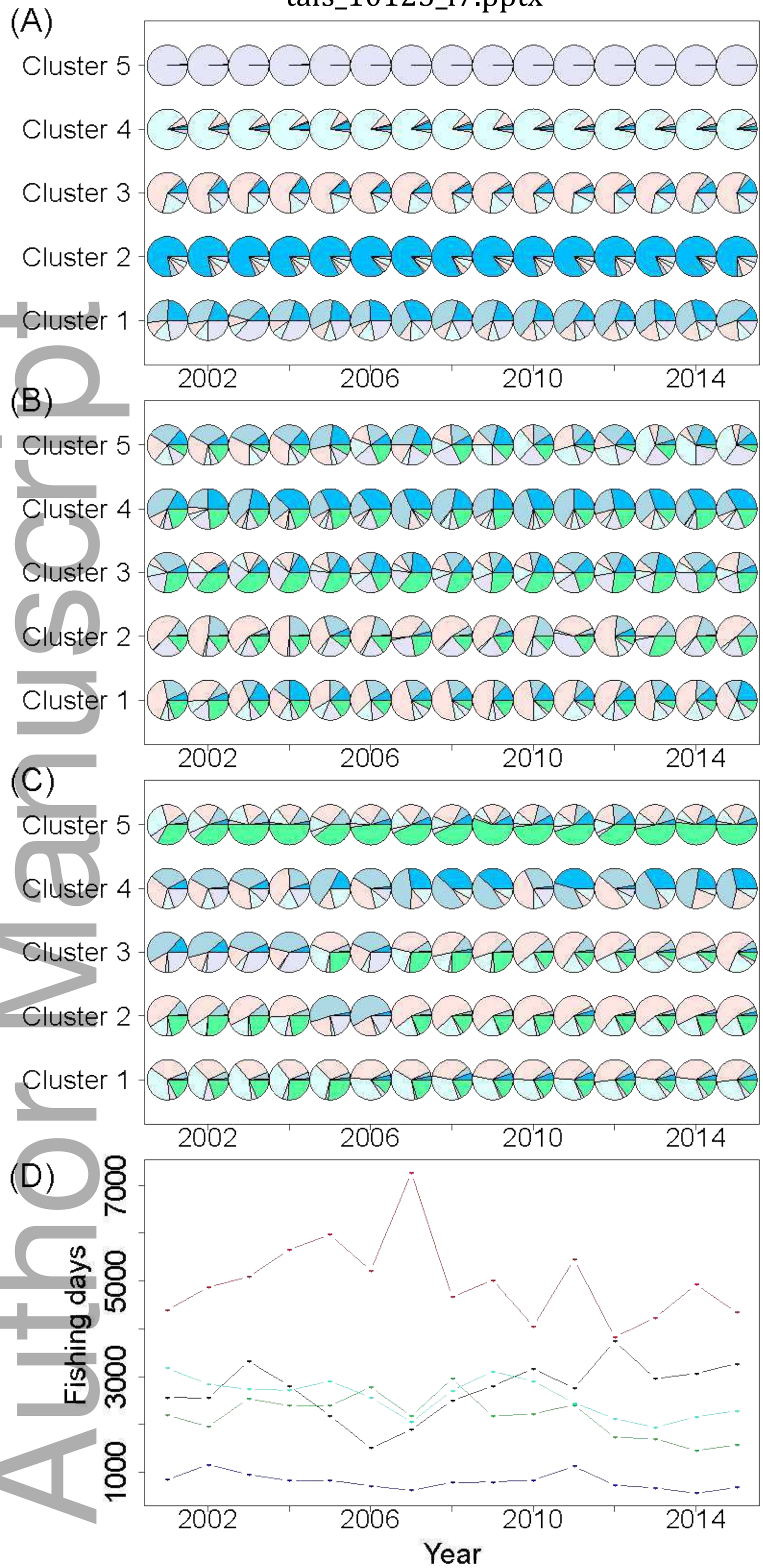

(A)
Cluster 5
Cluster 4
Cluster 3
Cluster 2
Cluster 1
2002
2006
2010
2014
(B)
Cluster 5
Cluster 4
Cluster 3
Cluster 2
Cluster 1
2002
2006
2010
2014
(C)
Cluster 5
Cluster 4
Cluster 3
Cluster 2
Cluster 1
2002
2006
2010
2014
(D)
Fishing days
1000
3000
5000
7000
2002
2006
2010
2014
Year

Fig. 7

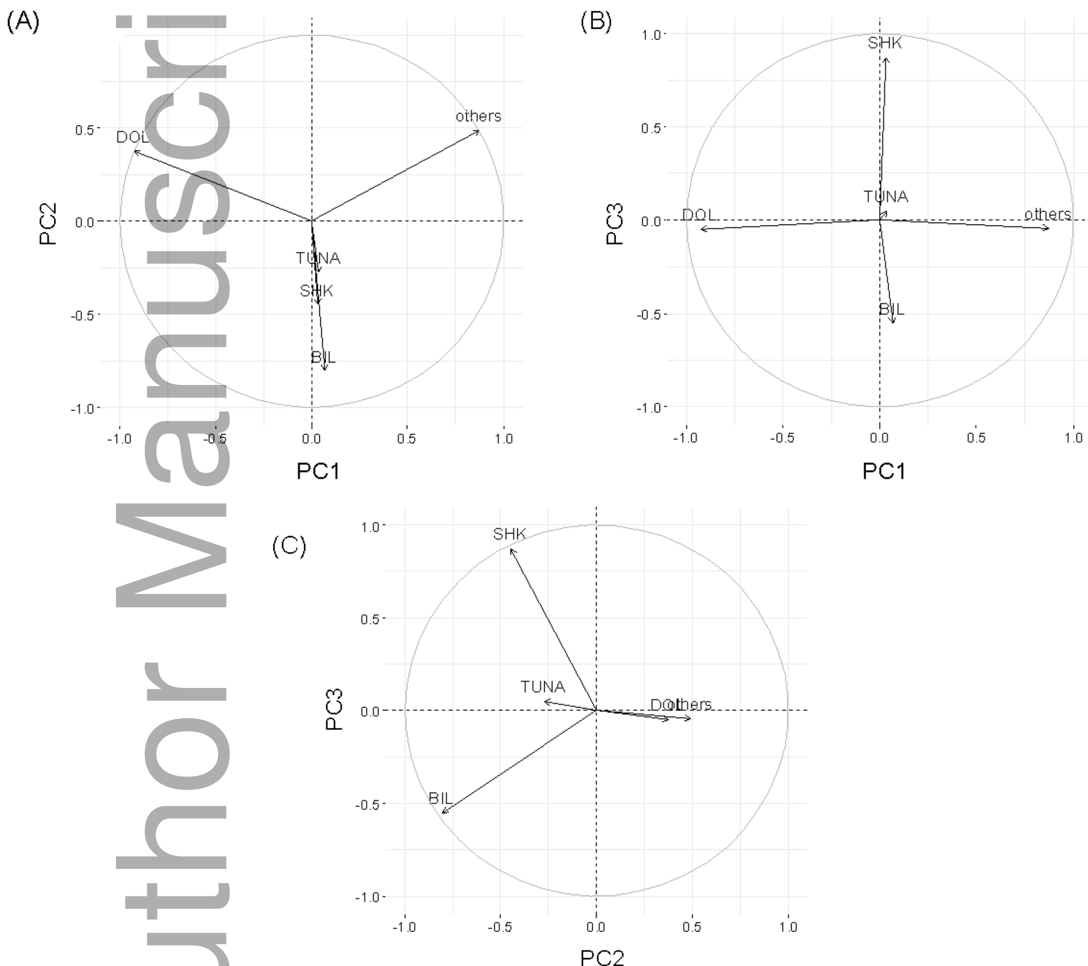

(A)
PC2
PC1
others
DOL
TUNA
SHK
BIL
0.5
0.0
-0.5
-1.0
-1.0
-0.5
0.0
0.5
1.0
(B)
PC3
PC1
SHK
TUNA
DOL
others
BIL
1.0
0.5
0.0
-0.5
-1.0
-1.0
-0.5
0.0
0.5
1.0
(C)
PC3
PC2
SHK
TUNA
DOL
others
BIL
1.0
0.5
0.0
-0.5
-1.0
-1.0
-0.5
0.0
0.5
1.0

Fig. 8

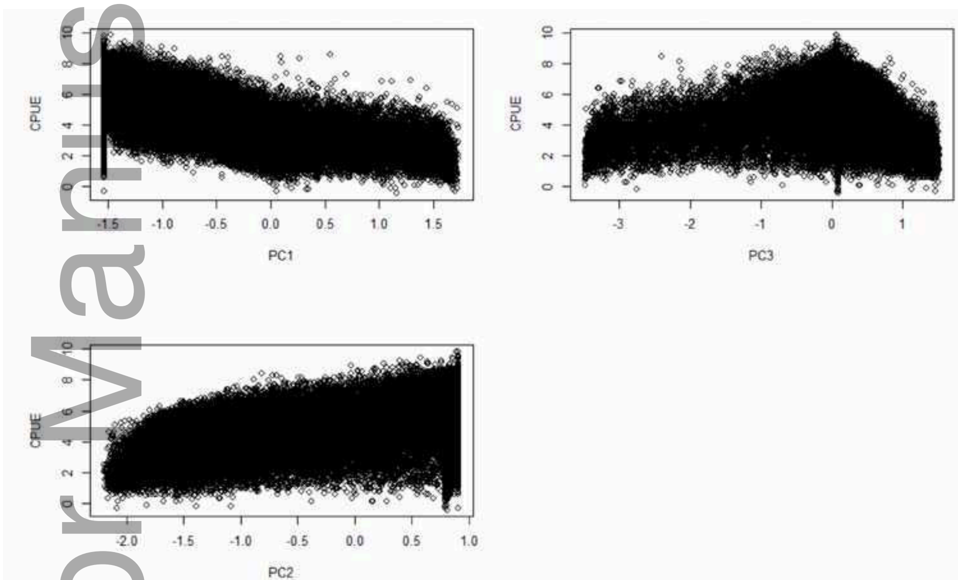


Fig. 9

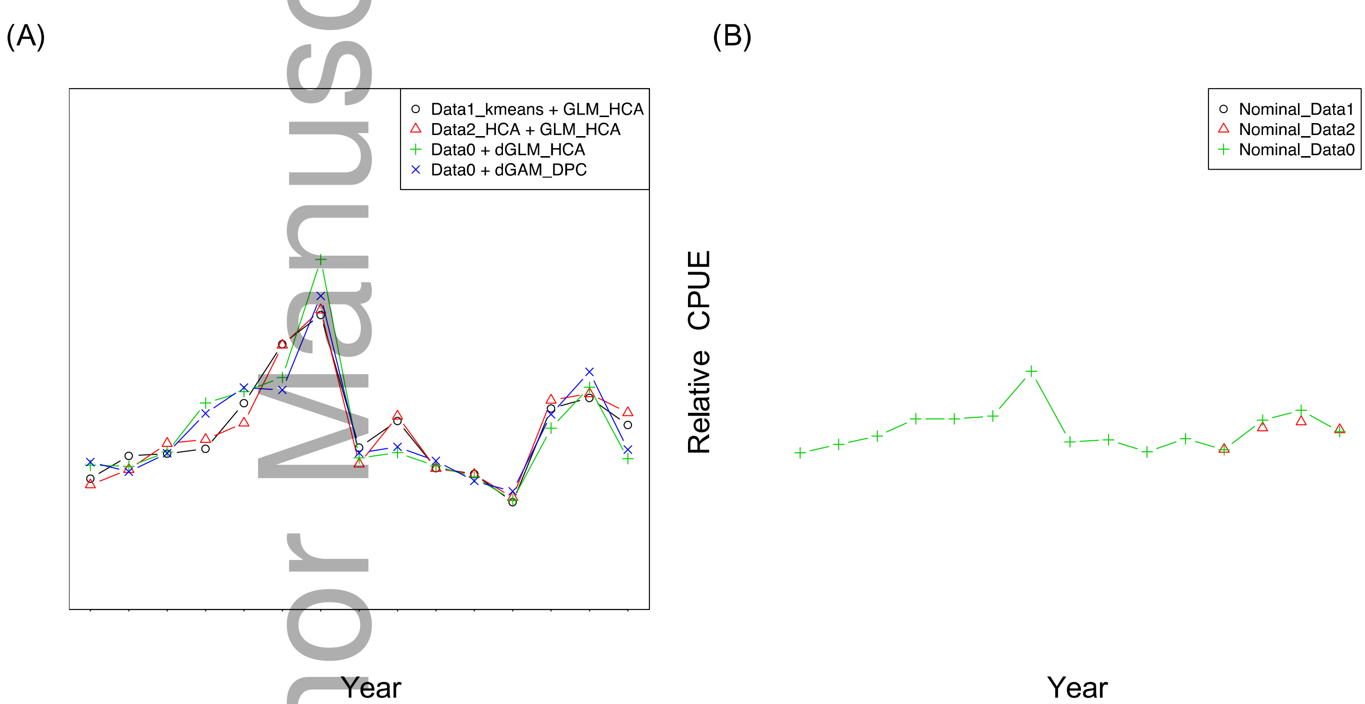

(A)
Data1_kmeans + GLM_HCA
Data2_HCA + GLM_HCA
Data0 + dGLM_HCA
Data0 + dGAM_DPC
Year
(B)
Nominal_Data1
Nominal_Data2
Nominal_Data0
Relative CPUE
Year

Fig. 10