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Spatial indicators of fishing pressure: Preliminary analyses and possible developments

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ABSTRACT

Ecological indicators of fishing pressure in space are an important part of the Data Collection Framework (DCF) established by the European Commission in its attempt to apply an ecosystem approach to fisheries. These indicators are devised to use the information provided by the Vessel Monitoring System, a mandatory tool for EU fishing vessels which allows to record fishing activity in space and time. This study reports and analyzes trends of DCF fishing pressure indicators in the years 2007–2010 for the Italian trawlers in seven Mediterranean geographic sub-areas and the related trends of landing per unit effort. In addition, new versions of these indicators are developed and their performances compared to the DCF ones by a simulation approach. The rationale for these new version of indicators is based on: (i) the development of a formal definition of "fishing ground", allowing for innovative statistical analyses of fishing patterns in space and time; (ii) the revision of issues affecting DCF indicators. Results provide: (i) the first extensive documentation of space use by fisheries through time; (ii) evidences of subtle yet significant changes in fishing pattern which, in agreement to other studies, indirectly support a decline of fisheries resources in the Mediterranean; (iii) improved versions of DCF fishing pressure indicators, obtained via the identification and analysis of fishing grounds and the assessment of aggregation by Gini's G index. The latter point could mark an important progress in order to overcome some critical weakness evidenced by DCF indicators. Moreover, the statistical identification and analysis of fishing grounds could represent a valuable insight in quantitative investigations of fisheries impacts and effects, even beyond indicators computation.

1. Introduction

At the end of a progressive scientific, social, and institutional awareness rising from: (1) the sub-optimal or critical status of many aquatic living resources; (2) the complex dynamics of stocks exploitation given by interactions among species and among fleets; and (3) the different environmental effects of the various fishing gears (ICES, 2009), European fisheries research and management bodies revised fundamental aspects of fisheries management. European Union formally started to move toward an ecosystem approach to fisheries (EAF – FAO, 2008) in 2008, when the European Commission established the Data Collection Framework (DCF) of the common fishery policy (EC, 2008a,b). The DCF describe a panel for long-term surveying and use of data required to support provision of scientific advices for the implementation of an EAF into the EU Common Fisheries Policy. Ecological indicators are, among others, integral part of this approach.

As one of the main objectives of EAF is to mitigate effects of fisheries on stock and ecosystems, it demands (via DCF) increasingly spatially resolved fisheries data. The importance of resolve fishing effort at a fine spatial scale is justified by the observation that they allow to effectively assess both levels of fishing pressure acting on different subunits of the environment (de Juan et al., 2009) and status of exploitation of living resources (Rose and Kulka, 1999; Walters, 2003). Thus, the analysis of these indicators as well as the searching for better version of them is a key topic in this framework. This work attempts to address both these aspects.

1.1. The Vessel Monitoring by satellite System for fisheries vessels

The quantification of the spatial extent of fishing activities has been made possible by the fact that, since 2002, the Vessel Monitoring by satellite System (VMS) has been introduced by the European Union (EC, 2002) for remote control of fishing vessels purposes. Today, VMS is a powerful tool in fishery management since it allows for high resolution analyses of fishing activity and quantitative evaluations of fishing effort at both spatial and temporal scales (Bastardie et al., 2010; Lee et al., 2010). VMS technology is based

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on the presence on board of each fishing vessel of an automatic transmitting station (the so-called *blue box*), which periodically sends information about vessel position, speed, and prow heading. When initially introduced, the VMS was mandatory for vessels with length over all (LOA) ≥ 24 m, but this threshold has been progressively lowered in 2004 (LOA ≥ 18 m), 2005 (LOA ≥ 15 m), and 2012 (LOA ≥ 12 m). At present, it could be affirmed that all the commercial fishing fleets operating in European waters are almost completely (≥90% of fishing vessels) represented by VMS-equipped vessels.

1.2. Ecological indicators of fishing effort within the DCF

Indicators are generally defined as variables, pointers or indexes of a phenomenon (Garcia et al., 2000) that are helpful to support management decision-making, to track progress toward meeting management objectives, and to aid communication with non-specialist audiences (Garcia et al., 2000; Rice, 2000; Rochet and Trenkel, 2003). In fisheries sciences, the general framework for managing environment by ecological indicators is the pressure-state-response (PSR) system (Garcia et al., 2000), which uses pressure indicators (P) to measure the pressure impacting an ecosystem component, state indicators (S) to measure the state of the ecosystem component, and response indicators (R) to measure the response of managers to the change in state (see Jennings, 2005 for details). Consistently, all these categories are represented in the DCF list of nine indicators for monitoring the impact of fisheries on the ecosystem (EC, 2003). Three of these nine indicators are aimed to evaluate different aspects of fishing pressure as depicted by localization of fishing events (i.e. coordinates of points in which fishing vessels deployed gears) in space and time. These are: Indicator 5 (*extension of fishing activities*), Indicator 6 (*aggregation of fishing activities*), and Indicator 7 (*areas not impacted by mobile bottom gears*). These indicators are computed using a grid with square cells (3 km × 3 km), and require high temporal frequency (native or interpolated) of spatial surveys on vessels activity. The first indicator (5) simply represents the total sea area, computed as sum of cells, interested by the fishing activity for each métier, each month. It is aimed to provide a global spatial quantification of the fishing effort, without further information about the pattern. The second indicator (6) represents the minimal area, computed as a sum of cells, within which 90% of VMS records were obtained, each month. It is aimed to assess the area accounting for the major part of fishing effort, while the cells with low values of effort (i.e. number of fishing points) are not considered. This indicator is generally inspected together indicator 5, as these two combined measurements would give an assessment of spatial magnitude of fishing effort. The last indicator (7) is computed annually and states the total proportion of the area by depth strata (0–20 m, 20–50 m, 50–80 m, 80–130 m, 130–200 m, >200 m) in each marine region that has not been fished with bottom gear in the preceding 1 year period.

These three indicators are collected within the DCF in order to construct time series to be directly analyzed or compared with other data (e.g. landings data or revenues). In fact the use of spatial information about fishing effort can be crucial in order to produce better assessment of fish stock status (Walters, 2003; Ralston and O'Farrell, 2007). Despite the number of fisheries publications on other ecological indicators have flourished over the last years (Smith et al., 2000; Fulton et al., 2005; Rice and Rochet, 2005; Rijnsdorp et al., 2006; Piet et al., 2007; Woillez et al., 2007; Blanchard et al., 2010), no published studies exist which report temporal analysis for the DCF pressure indicators.

However, DCF establishes that fishing activities and related indicators have to be disaggregated, following the métiers classification (http://datacollection.jrc.ec.europa.eu/dcf-fish/bio-metier/sampling), in order to efficiently assess fishing impacts on communities. Among the different métiers usually practiced in EU waters, the Bottom Otter Trawl (OTB) represents the main class of activities in terms of fishing effort, catches and impacts on the environment (Smith et al., 2000; Gascoigne and Willsteed, 2009). This is also true for the Mediterranean sea, where among 4500 trawlers operate, the majority of which are bottom trawlers involved in demersal multi-species fisheries (Browman and Stergiou, 2004; de Juan et al., 2009; EC, 2002).

The first aim of this study is to explore variation over time for the DCF pressure indicators 5 and 6 for OTB and the analysis of the relationships between the indicators and another crucial data series represented by OTB landing.

1.3. Identification of fishing grounds by spatio-temporal analysis of fishing effort

Together and beyond computation of pressure indicators, information provided by VMS data can be used to identify, monitoring and eventually modeling evolution trough time of fishing grounds, which are critical areas for both fishing activity and species. Interestingly, a new question rises from this challenge: while the term "fishing ground" is largely present in literature and several recent studies invoked the analysis of fishing ground (Hutton et al., 2004; de Juan et al., 2009 among others), it seems that no explicit definition exists to clearly identify these entities. The only available reference can be found inside that of fishing effort: "The amount of fishing gear of a specific type used on the fishing grounds over a given unit of time" (FAO, 1997). In this way, fishing grounds should be defined as the areas in which fishing effort is deployed, but this definition is intuitively vague about what they are and does not capture the aspects inherent the dynamics by which fishermen operate. It could be possible to argue that a better definition of fishing ground should explicitly refer to the spatial and temporal dimensions of exploitation. In fact, when looking at fishing activity on a temporal and/or spatial scale (and this is exactly the case when working with VMS), a definition which takes into account for the obvious fact that fishing grounds are entities with their own dynamics in space and time is needed. To clarify this argumentation, let us consider a fishing activity focused on demersal fish species (i.e. trawl). Each haul of a vessel, at a given time, can be assimilated to a bet: each fisherman spends time and fuel (and risks his net) to catch fish. The area in which the haul is done is chosen on the basis of previous experiences (historical evaluation) as well as considerations about environmental characteristics. The bet will be done to maximize expectation about catches and to minimize risks and costs, and areas yet known by each fisherman for their productivity would be generally preferred. However, several factors and events (e.g. productivity decline, competition, and market prices) could force fishermen to play their bets in other, lesser known areas. That is, fishers adopt a complex behavior in exploiting the environment: they routinely concentrate their effort in already known areas, but also periodically (or sporadically) explore new ones (Seijo et al., 1998; Salas et al., 2004). In addition, fishermen could behave strategically, and their fishing location could also be determined by their interaction with other participants in the fishery (Hicks et al., 2012).

Here fishing grounds are theoretically defined as "areas in which fishing activity is routinary carried out as a result of a strategy aimed to maximize economic gains". In this way, fishing grounds are entities emerging from the pattern depicted by fishermen behavior at a given spatial and temporal reference scale. It accounts for both individual strategies and interactions among fishermen. Using this definition, the identification of fishing grounds can be performed using the concept of spatio-temporal autocorrelation of the fishing pressure: looking at a temporal scale that encloses cyclical patterns linked to seasonality (generally the year-scale for temperate zones, such as the Mediterranean sea) fishing effort in fishing grounds should be characterized by a significant and positive degree of spatio-temporal autocorrelation. In contrast, fishing effort over "accessory" fishing areas would exhibit not significant values of spatio-temporal autocorrelation. This issue is addressed in the present study, in which a method is developed and proposed to identify fishing grounds.

1.4. Toward a new version of ecological indicators of fishing pressure

The argumentation exposed above could be used to detect some limits, and then to suggest possible improvements for the DCF pressure indicators. A major drawback of the DCF indicators 5 and 6 could be identified in the fact that both of them consider, as input for computation, the count grid directly obtained by plotting the fishing positions. This leads to the fact that a number of cells containing just one or few fishing points are retained throughout the analysis. As a consequence, DCF indicator 5 could intuitively produce an overestimation of exploited areas. An immediate solution could be represented by the computation of the indicator 5 just on cells belonging to fishing grounds. In the meantime, it seems that the present formulation of DCF indicator 6 is affected by a level of arbitrariness, since the threshold of 90% in grouping of fishing points is not justified by evidences (Fock, 2008; ICES, 2009). Other largely known indexes exist which could be applied to assess the spatial aggregation of fishing effort. One of these is the Gini's *G* coefficient (Gini, 1936), which is a measure of statistical dispersion quantified as the inequality of a distribution of a variable among statistical units (cells) could be profitably used to compute an improved version of indicator 6.

As for the DCF version, also the trends obtained for these new version of indicators 5 and 6 are analyzed. The last aim of this paper is to evaluate and compare the performance of the two set of indicators, following the rationale described in Jennings (2005).

2. Materials and methods

2.1. Mediterranean sea, Italian Geographic Sub Areas and Data Collection Framework

For scientific and managerial purposes (even within the DCF), the Mediterranean sea has been partitioned in 28 Geographic Sub Areas (GSA – GFCM, 2007). Trawling activity is managed at a local scale and regulation is based on effort limits (the fishing activity is forced to stop for about one month in the summer, during the reproduction phase of many fish species – Caddy, 1993) instead of total allowable catch (TACs) as in European countries bordering the North Sea (Papaconstantinou and Farrugio, 2000; Smith et al., 2000; Alemany and Alvarez, 2003). Italy is in charge of collection and management of data for seven GSAs, namely GSAs 9, 10, 11, 16, 17, 18 and 19 (see Fig. 1). VMS signals sent by Blue-Box of equipped vessels are directly collected from the "Comando Generale delle Capitanerie di Porto", while data about landings is collected at an harbor scale through a sample survey conducted by the Institute for Economic Research in Fishery and Aquaculture (IREPA – www.irepa.org). This survey is stratified in order to obtain an understanding of the quantity and average price of fish products landed in Italy from EU fishing vessels, during each month of the year. Detailed information about statistical procedures are available online (http://www.irepa.org/images/stories/irepa/sistan/samplingmethodology.pdf).

In this study the monthly landings, in tons, for the Italian professional trawlers were used. These data are available online on the SISTAN (Italian National Statistic System, http://www.irepa.org/index.php?option=com_content&view=article&id=17&Itemid=29&lang=en).

The VMS dataset used in this study comprises all the signals generated, from January 2007 to December 2010, by the trawls belonging to Italian professional fishing fleet and equipped by a *blue box*. These data were filtered in order to standardize the number of fishing vessels represented throughout the final dataset, so that signals related to vessels not equipped by VMS at the begin of 2007 were excluded. The final dataset accounts for the activity of 1646 vessels (Fig. 1), that is above 60% of the whole Italian commercial trawl fleet with LOA larger than 12 m. Fig. 1 also shows the proportion of vessels represented for each GSA.

2.2. Pre-processing of VMS data

VMS signals were processed following the rationale proposed by Bastardie et al. (2010) and the methodological procedures set up by Russo et al. (2011a,b). Fishing tracks were interpolated at a standard frequency of 30 min between successive pings, as indicated within the DCF, using the approach described in Russo et al. (2011a). The high frequency tracks so obtained were inspected in order to identify and separate fishing from steaming points. This has been done using a simple speed filter (fishing points were associated to a speed range of 0–4 knots), following a largely used approach which has been validated for towed gear such as trawl (Piet et al., 2007; Lambert et al., 2012). Finally, the fishing points identified this way were grouped per month and plotted over a 3 km × 3 km square grid (Fig. 2a). The output of this procedure was represented by 48 count grids in which a value (number of fishing points) was associated to each cell (Fig. 2b). These grids were used as inputs for the following analyses.

2.3. Computation of and trend analysis for DCF pressure indicators

The DCF version of ecological indicators of fishing pressure 5 and 6 were computed as reported in ICES (2009). The indicator 5 represents, for each GSA, the total area of the cells in which at least one fishing point is recorded for the reference month. The indicator 6 represents the minimal area, for each GSA, in which falls the 90% of the total number of fishing points recorded in that month. This can be computed by sorting, in a decreasing order, cells by fishing points and then cutting the series when the cumulated number of fishing points reaches the 90% of the total value. The monthly values of both these indicators were standardized by dividing for the area of each GSA in which the depth is between 0 and −800 m (the extremes of continental shelf), that is the portion interested by trawl effort. This allowed to obtain comparable values between different GSAs.

2.4. Identification of fishing grounds

The monthly counts for each cell were used as input data for the analysis of the spatio-temporal autocorrelation pattern. A significant autocorrelation pattern implies the lack of independence for the variable of interest between units (grid cells in this case) due to their positions in space and time (Fortin and Dale, 2005). Thus, cells in which effort (number of fishing points) is stable trough time and similar to the neighboring cells will exhibit high value of autocorrelation, whereas cells sporadically visited or largely different by the neighbors will exhibit low values. The Griffith's spatio-temporal index (STI) of autocorrelation (Griffith, 1981; Henebry, 1995; Fortin and Dale, 2005) was computed. The Griffith's STI generalizes the well known Moran's index of spatial autocorrelation by taking into

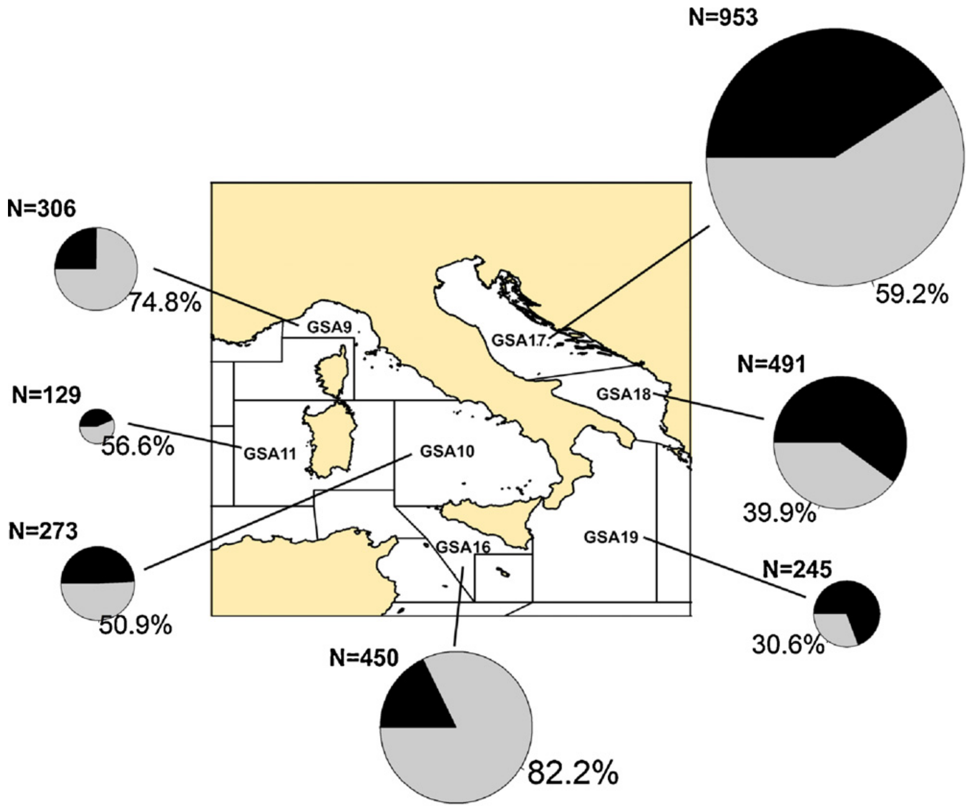

Fig. 1. The seven Italian GSAs with pies representing the size of the fleet and the relative proportion of vessels equipped by VMS.

account for time as an additional dimension. The general expression of the Griffith's STI is:

$$STI(D_{s'}T) = (nT - n)\frac{\sum_{t=2}^{T}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ijt-1}(D_s)z_{it}z_{jt-1}}{\sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ijt-1}(D_s)\sum_{t=1}^{T}\sum_{i=1}^{n} z_{it}^{2}} \quad (1)$$

where T is the temporal depth, n is the number of spatial units (the total number of grid cells), z is the deviation of the observed data (the number of fishing points) from the overall mean of the observations, i and j are indexes for two generic cells of the map, and D_s is the spatial distance (or class of spatial distance, as in this case) among cells, w_{ijt} is the weight obtained as a function of distance between two cells, at a given temporal distance. The expected value of Griffith's STI for a random pattern (no correlation) is given by:

$$E(STI) = \frac{-(T-1)}{T(nT-1)} \quad (2)$$

which is approximately zero for large values of T or n, as in this case. In summary, cells characterized by significant autocorrelation in space and time will exhibit STI values larger than zero. It should

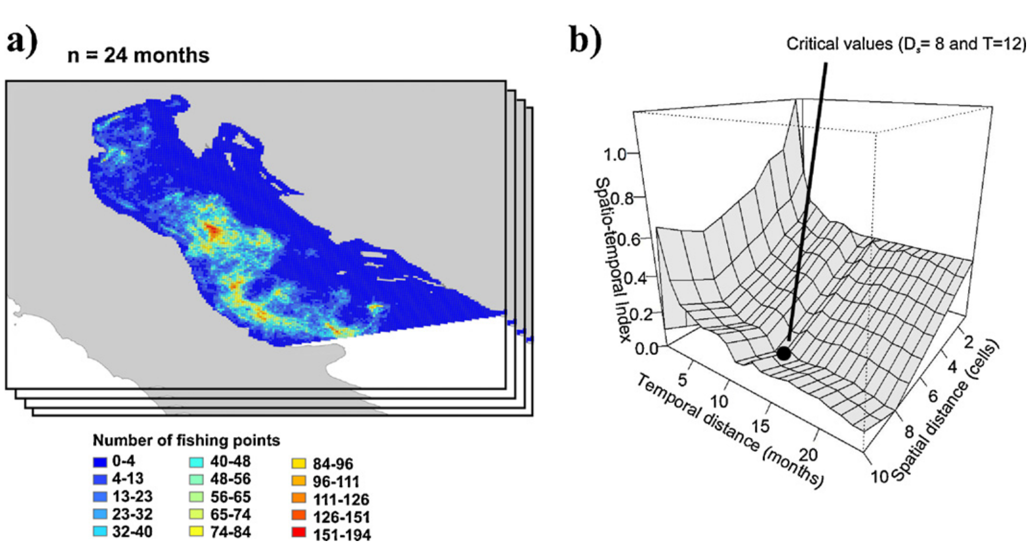

Fig. 2. Sample series of 3 km × 3 km square cells grids representing the pattern of fishing effort in the GSA17 (North Adriatic Sea). The amount of effort for each cell is represented by a color scale; these grids were used to compute the Griffith's STI against different values of spatial and temporal distances, producing the variogram in (b). The critical values at which independence is realized (spatial and temporal domain of the pattern, as detailed in Fortin and Dale, 2005) are indicated. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

be stressed that this index assumes complete isotropy, that is independence of variation in all directions. Theoretically, this could not be the case for fishing grounds located close to a slope or bordering distinct habitat types, so that additional covariates should be added to model in order to take into account for the anisotropic component. However, in the case of bottom trawls which operate in a large range of depth/habitat types, this effect may be minor and negligible.

The measure of this degree of spatio-temporal dependence is a function of the spatial class and temporal depth at which the index is computed. In this study, the variation of the Griffith's index on the whole grid (merging all the seven Italian GSA) was investigated by varying the spatial distance (D_s) from 1 to 30 cell neighbors and the temporal depth (T) from 1 to 48 months, respectively, to identify its critical spatial and temporal scales. The statistical significance of each value was computed by performing 100 random permutations of the grid and recomputing the index value. The spatio-temporal pattern obtained was characterized by larger values at short temporal and spatial distances and fluctuations around the expected value at large distances. As this closely corresponds to the theoretical expectation when patchiness occurs, the critical values ($D_s = 8$ and $T = 12$, respectively) were identified as the values at which independence is realized (Fortin and Dale, 2005). These values were used to compute the Griffith's STI at local scale in order to evaluate the degree of spatial autocorrelation of each cell. This approach is exemplified in Fig. 2, in which the fishing pattern for GSA17 is represented together with the variogram of the STI index against spatial and temporal distances.

The local expression of the Griffith's STI, for a given cell, is:

$$STI_i(D_s, T) = (nT - n)\frac{\sum_{t=2}^{T}\sum_{j=1}^{n} w_{ijt-1}(D_s) z_{it} z_{jt-1}}{\sum_{t=2}^{T}\sum_{j=1}^{n} w_{ijt-1}(D_s) z_{it} z_{jt-1} \sum_{t=1}^{T} z_{it}^2} \quad (3)$$

In this way, the pattern of spatio-temporal autocorrelation was analyzed for each cell, for each year. The yearly distributions are showed in Fig. 3. In all the four cases the distribution seems to be composed by two parts, the rightmost one corresponding to cells with an high value of the Griffith's STI. The homogeneity of these four distributions was tested using the Kolmogorov–Smirnoff test (R Development Core Team, 2008), which reports the expected result that they can consider the data as a whole. This suggested the existence of a conservative phenomenon underpinning the data pattern. It was assumed that each of these distributions is a mixture with two components, in which the rightmost component corresponds to fishing grounds. The other component, values <0, can be explained as the result of exploration activity (i.e. searching for new fishing grounds) or noise. In this way, the identification of fishing grounds can be reduced to the decomposition of this mixture and the assignment of each cell to one of the two components. Considering Eq. (2), a cell was simply defined as belonging to a fishing ground if the observed value of its local Griffith's STI is higher than 0. This allocation procedure was repeated for each year, and the output was represented a binary vector for each year which identify cells belonging to fishing ground.

As exploratory measure, the mean and the variance in the number of fishing points was computed for cells assigned/non-assigned to FG, for each year.

2.5. New version of indicators 5 and 6: fishing ground extension and Gini's index

A new version of ecological indicators of fishing pressure 5 was computed using the output of the procedure presented in Section 2.2: this new indicator, called fishing grounds extension (FGE) represents the total area of the fishing grounds exploited, for each GSA, for each month. The basic difference with the DCF version of this indicator is that, in this case, only cells belonging to fishing grounds were considered. Thus, cells with a low Griffith's STI (sporadically visited or isolated from other exploited cells) were not considered. As for the DCF version, the value of this indicator was divided by the total areas of continental shelf in the GSA to standardize and compare it between GSAs.

A new version of indicator 6 (aggregation of fishing effort) was instead computed by the Gini's index (Gini, 1936) applied to the vector scoring the number of fishing points for each cell of each grid. The Gini's index ranges from 0, when all units score equally, to a theoretical maximum of 1 in an infinite population in which all units but one score 0 (Weiner and Solbrig, 1984). Sorting the observations x_i, a vector $x_{(i)}$ of non-decreasing number of fishing points was obtained. Denoting with A_i the cumulative sums of $x_{(i)}$, the Gini's G can be computed as follows:

$$G = 1 - \frac{2}{n-1}\sum_{i=1}^{n-1} Q_i \quad (4)$$

where n is the number of cells and $Q_i = A_i/A_n$.

2.6. Computation of LPUE

Two series of landings per unit effort (LPUE) were computed by dividing monthly landings by: (1) non standardized values of DCF indicator 5; and (2) non standardized values of FGE indicator. This gave a measure (in terms of tons/km^2) of the mean yield associated to unit surface.

2.7. Trend analysis

Both a linear and a quadratic-trend models were fitted to each of the indicator time-series using a least-squares regression framework. It was conjectured that the periodic pattern hides a time trend. Hence, a model was built up and, using a model selection technique, the empirical support in favor of this hypothesis was verified. A simple, yet reasonable, model can assume that the behavior of the different series is built up additively of four components:

$$y_t = c + T_t + S_t + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma^2) \quad (5)$$

where c is a constant (the intercept), T_t is a temporal trend, S_t is a seasonal pattern and ε_t is an error term. The seasonal pattern can be captured using a set of dummy variables. Two alternative sets of dummy variables were used: the first one accounting for monthly and the second one accounting for seasonal variation, respectively. In both cases, the reference month is the one in which the temporal stop of the fishing activity is applied (September), so that the expected value for that month is captured by the constant term (c).

The choice to associate the constant term to the temporal stop is coherent with the consideration that the level of fishing effort observed during the temporal stop intuitively represent a baseline of the model. Given that D_m equals one if t denotes an observation coming from the mth month, it is possible to obtain:

$$S_t = \sum_{m=1}^{11} \delta_m D_m \quad (6)$$

for the monthly model while, given that D_s equals one if t denotes an observation coming from the sth season, it follows that:

$$S_t = \sum_{s=1}^{4} \delta_s D_s \quad (7)$$

for the seasonal model. Notice that in this case the temporal stop represents a fifth "season".

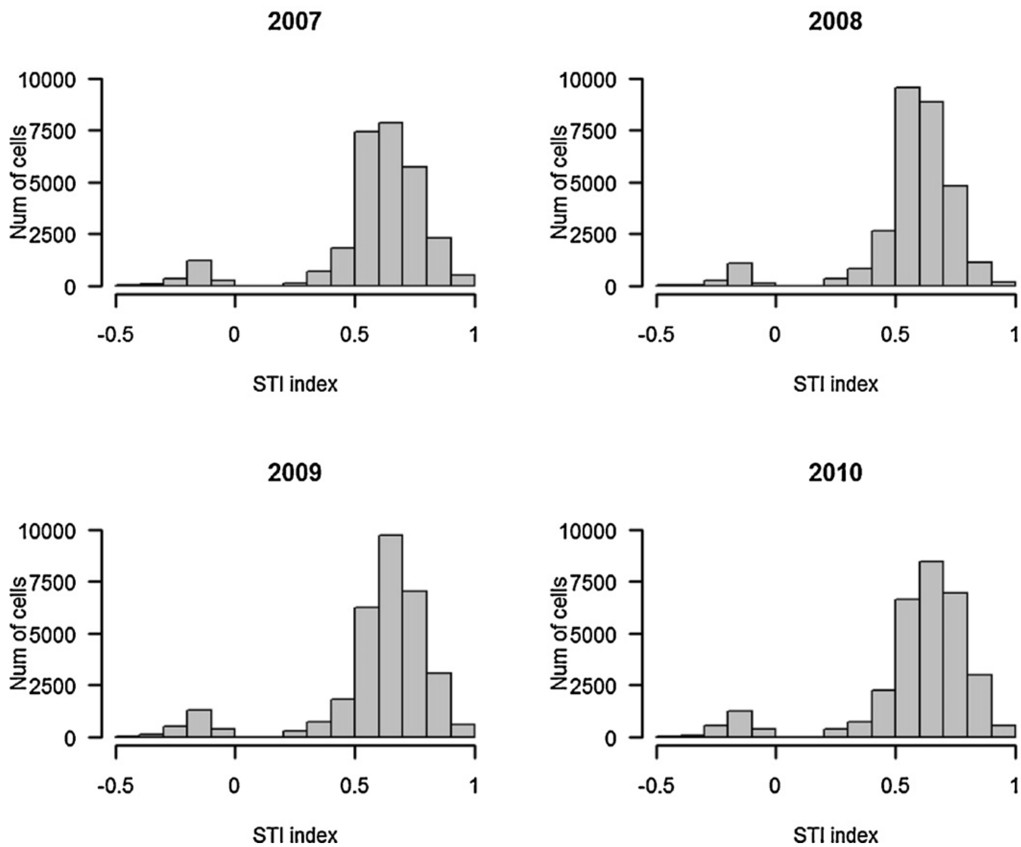

Fig. 3. Distribution of the local Griffith's STI index obtained for each year. The right component has been assumed identify cells belonging to fishing grounds and it was used to compute the monthly values of the FGE.

The parameters δ_m and δ_s can be interpreted as the expected level of fishing pressure in month m or season s if c and T_t were equal to zero. The trend will assume a simple form, linear or quadratic, besides the possibility of having no time trend. Hence, the most general model, which nests all the others, for the monthly model, is:

$$y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \sum_{m=1}^{11} \delta_m D_m + \varepsilon_t \tag{8}$$

Estimation is very straightforward: any inferential method can be used, as the resulting model remains in the standard multiple regression class.

2.8. Comparison between DCF and new version of indicators

Indicators' trends reflect noise and signal, where signal refers to a change of the measured phenomenon (e.g. LPUE), and noise is a random variation associated to stochastic fluctuations of the phenomenon itself (Jennings, 2005). In the statistical analysis of indicators' trends, a type 1 error occurs when it is possible to conclude that a true trend exists, when it does not, that is noise is erroneously confused to signal. In the same way, a type 2 error occurs when it is concluded that a trend is not occurring, when it actually is, that is signal is erroneously confused to noise. When the signal detection theory is applied to indicators (Rice, 2003), it is possible to compare the performance of different indicators that have been developed to assess the same phenomenon using a simple matrix scoring the relationship between real events and events recorded by indicators. Fulton et al. (2005) described a method to assess the influence of noise and the relative responsiveness of indicators to true changes generated by an operating model. A simplified version of this approach was used to compare the performance of the DCF indicators 5 and 6 against the two new indicators proposed in this paper.

Three different scenarios, each composed by 100 series of monthly data (48 observations), were simulated. Each series started from the observed spatial effort (fishing points on the grid) of a randomly selected GSA in a randomly selected month, and was then generated by the addition of a temporal dependent trend (refers to Eq. (8)) in which the expected value of the dispersion of fishing points was changed. The series belonging to the three scenarios were then characterized by an expected value of the aggregation respectively equal, greater than and lesser than the observed one. Conversely, the extension of the exploited area will behave inversely with respect to the aggregation.

We attempted to obtain realistic scenarios, in the sense that they differ from the observed one, still remaining similar to it. The location of each single fishing point was then modeled as a multinomial distribution with support given by the grid of cells, each having a probability p_i. The (estimated) probabilities p_i of this distribution were obtained by the observed frequencies. The different scenarios were obtained operating a transformation of these probabilities. Our transformation depends on two tuning parameters, λ and γ:

$$\widetilde{p_{l,t}}\sim = \lambda + p_i + \gamma p_i^2 \tag{9}$$

$$p'_{i,t} = \frac{\widetilde{p_{l,t}}}{\sum \widetilde{p_{l,t}}} \tag{10}$$

In this specification, Eq. (9) modifies the observed frequencies in the desired direction, while Eq. (10) is just a normalization step, which allow the probabilities to sum up to unity. If λ and γ are set to zero, a constant trend is obtained, while changing γ it is possible to obtain the different scenarios. The parameter λ allows to maintain the positivity of the probabilities. Besides, notice that the probabilities $p'_{i,t}$ change month by month, so that the dispersion varies following a temporal trend. The simulation of a synthetic dataset using the new values $p'_{i,t}$ is straightforward: the location of each fishing point was sampled using a multinomial distribution with probabilities given by $p'_{i,t}$. The respective time series of both DCF indicators, as well as FGE and Gini's G, was computed for each series. These indicators were then analyzed as described in Section 2.6, and the agreement of the inferences was compared to the characteristics of the used scenario. The results were summarized in a matrix and used to assess the different performances of the indicators.

3. Results

3.1. Analysis of trends for pressure indicators and related LPUE

Figs. 4a and 5a show the values of the DCF indicators for the seven GSAs. A first impressive result is that, in all cases, the behavior of indicator 6 closely follows that of indicator 5, up to an additive constant. Indicator 5 ranged between values close to zero, corresponding to the temporal stop of fishing activity, and values larger than 1. However, the mean value throughout the GSAs is around 0.5, reporting that the half of the total available area is exploited on average. The values also show important fluctuations, which seem to be seasonal with an yearly frequency. Within each year, the maximum effort in terms of exploited area is deployed between March and August, while temporal stop in September is followed by a slow reprise of the activity. In general, both indicators seem to be stationary during the inspected period 2007–2010. Application of model selection returned coherent results (Table 1). The Akaike (1974) criterion allowed to determine that both indicators 5 and 6 were better fitted by a model based on monthly dummies. The fitted values for these monthly dummies resulted always significant for all months and for both indicators, and were not reported for the sake of conciseness. Notice that, apart from dummies, optimizing the Akaike's criterion leads to coefficients which are not always significant. It is important to stress that, although the Akaike's criterion is a widely accepted approach in model selection, additional checks should be performed in order to judge the fit of the selected models to the data. The absence of outliers and the lack of residual autocorrelation structures in the selected models gave support to the employed class of models and seemed to guarantee the adequacy of the approach.

The trends of extension of fished areas, that is DCF indicator 5, evidenced a linear dependence from time, with the exception of GSA19 (quadratic dependence from time) and GSA9 (no dependence from time). However, only in one case (GSA11) a significant increase through time was detected. The situation was different for indicator 6: GSA9 showed a significantly decreasing trend through time, while GSA16 was characterized by an increasing trend.

Patterns obtained for the new versions of indicators are showed in Figs. 4b and 5b. Also in this case, the indicator of spatial extension of fishing effort, quantified as areas of fishing grounds, evidenced seasonality. The mean values of this indicator ranged from 0.2 (GSA19) to 0.6 (GSA9 and GSA10). The patterns for extension of fishing grounds seemed also to be quite stable and less variable than those described for DCF indicator 5. The Akaike's criterion allowed to determine that the indicator trends were better fitted by a model based on monthly dummies (Table 1), and these monthly dummies resulted always significant for all months. Two GSAs (GSA9 and GSA16) were characterized by a quadratic dependence from time, the other five by a linear one. Statistically significant trends were detected for GSA9, GSA17, GSA18, GSA19 (decreasing) and for GSA16 (increasing). The absolute values of the estimated linear coefficients were very similar.

The new version of indicator 6, defined by Gini's index, evidenced increasing patterns for all the GSAs (Fig. 5), the average values changing from 0.5 (in 2007) to 0.7 (2010), but particularly apparent for the trends of GSA9 and GSA17. The variability around these trends were remarkably smaller than that obtained for the other indicators. Model selection via Akaike's criterion allowed to establish that, in this case, the indicator trends were better fitted using seasonal dummies (Table 1). While all the dummies resulted statistically significant, the dependence from time was defined as quadratic in all cases. Moreover, all the trends showed an increasing pattern in the last part.

Fig. 6 shows the LPUE patterns obtained, for the seven GSAs, using the fished areas (DCF indicator 5) and the areas occupied by fishing grounds, respectively. The behaviors evidenced, in both cases, large fluctuations, with the maximum values occurring just after the temporal stop of the activity. The mean productivities for the different GSAs ranged from 10^2 tons/km^2 per month (GSA9, GSA10, GSA11 and GSA19) to 10^3 tons/km^2 per month (GSA17). The patterns seemed also to be coherent between the two versions, with the one computed on fishing grounds showing higher values. This is reasonable considering that DCF indicator 5, computed on the overall exploited areas, systematically returned values larger than those of extension of fishing grounds. The Akaike's criterion selected the seasonal models. Two of the trends related to DCF indicator 5 evidenced a linear and significant dependence from time (GSA10 and GSA11), with a decreasing trend. The LPUE based on fishing grounds areas also evidenced a linear significant decreasing trend for GSA10 and GSA16, while a linear increasing trend was detected for GSA19.

3.2. Comparison between DCF and new version of indicators

Results of the comparison between the performance of the DCF indicators 5 an 6 against the two new indicators proposed in this paper are summarized in Table 2. The matrices of confusion were simplified and only the diagonal elements were showed, since: (1) no type 2 error occurred, that is no trend was identified where there was not (scenario 1); (2) there was no mismatch between scenarios 2 and 3, that is when model selection failed, it always selected scenarios 1.

While it is possible to observe that both groups of indicators correctly classified all the 100 simulated time series belonging to scenario 1, their performances were different for the other two scenarios: the DCF version of indicators reported percentages of correct classification around 60%, whereas the new version of indicators showed markedly higher values (around 85%).

4. Discussion

Moving toward an ecosystem approach to fisheries requires, among others, indicators which can efficiently describe the pressures affecting the ecosystem (Garcia et al., 2000; Rice, 2000, 2003; Rochet and Trenkel, 2003; Jennings, 2005; FAO, 2008). The new generation of indicators established within the Data Collection Framework comprises three indicators aimed to capture, via the technological facility provided by VMS, some key aspects of the spatial pressure exercised by fisheries. While Lambert et al. (2012) recently addressed some methodological issues of indicators' computation, this paper represents the first attempt to extensively analyze the signals of these indicators, as well as to take a further step in the development of better versions of the same indicators. In addition, the relationship between spatial effort and landings was inspected by the analysis of the LPUE, that is a

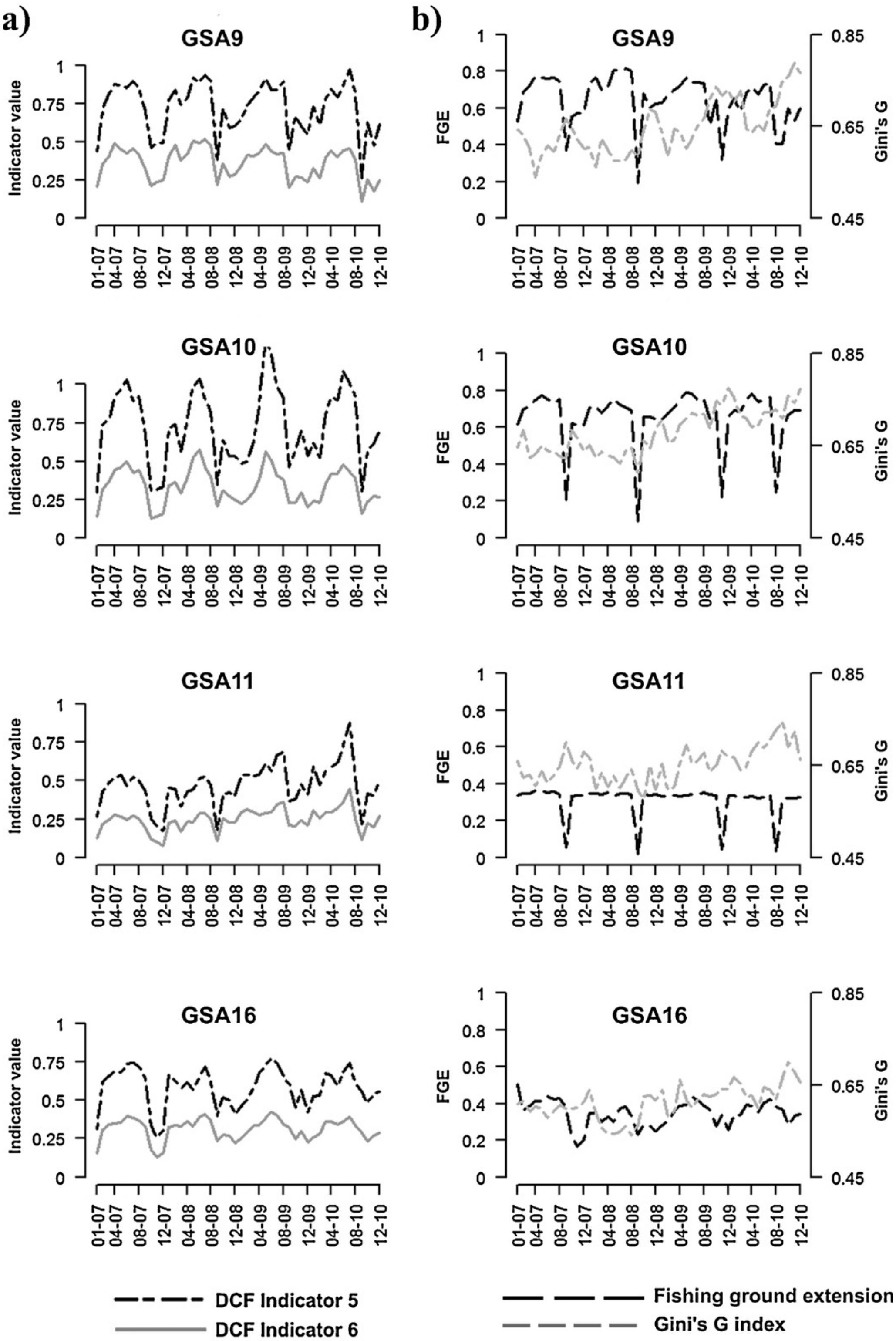

Fig. 4. (a) Monthly series for the DCF indicator 5 (extension of fishing activity) and 6 (aggregation of fishing activity) in the inspected period, for GSAs 9–16; (b) monthly series for the FGE indicators 5 (fishing ground extension) and 6 (Gini's *G* index of aggregation) in the inspected period, for GSAs 9–16. Two different scales were used to represent both indicators in the same plot.

crucial issue in assessing exploitation status of resources (Walters, 2003). The case of study, represented by the fishing effort deployed for bottom otter trawl in the Italian seas, seems to be a good subject since it corresponds to the main fisheries activity in the Mediterranean, and it is also characterized by the fact that a complex set of resources is exploited in a variety of habitats on the continental shelf (Smith et al., 2000). The data used to compute all the indicators were obtained by interpolating VMS fishing tracks

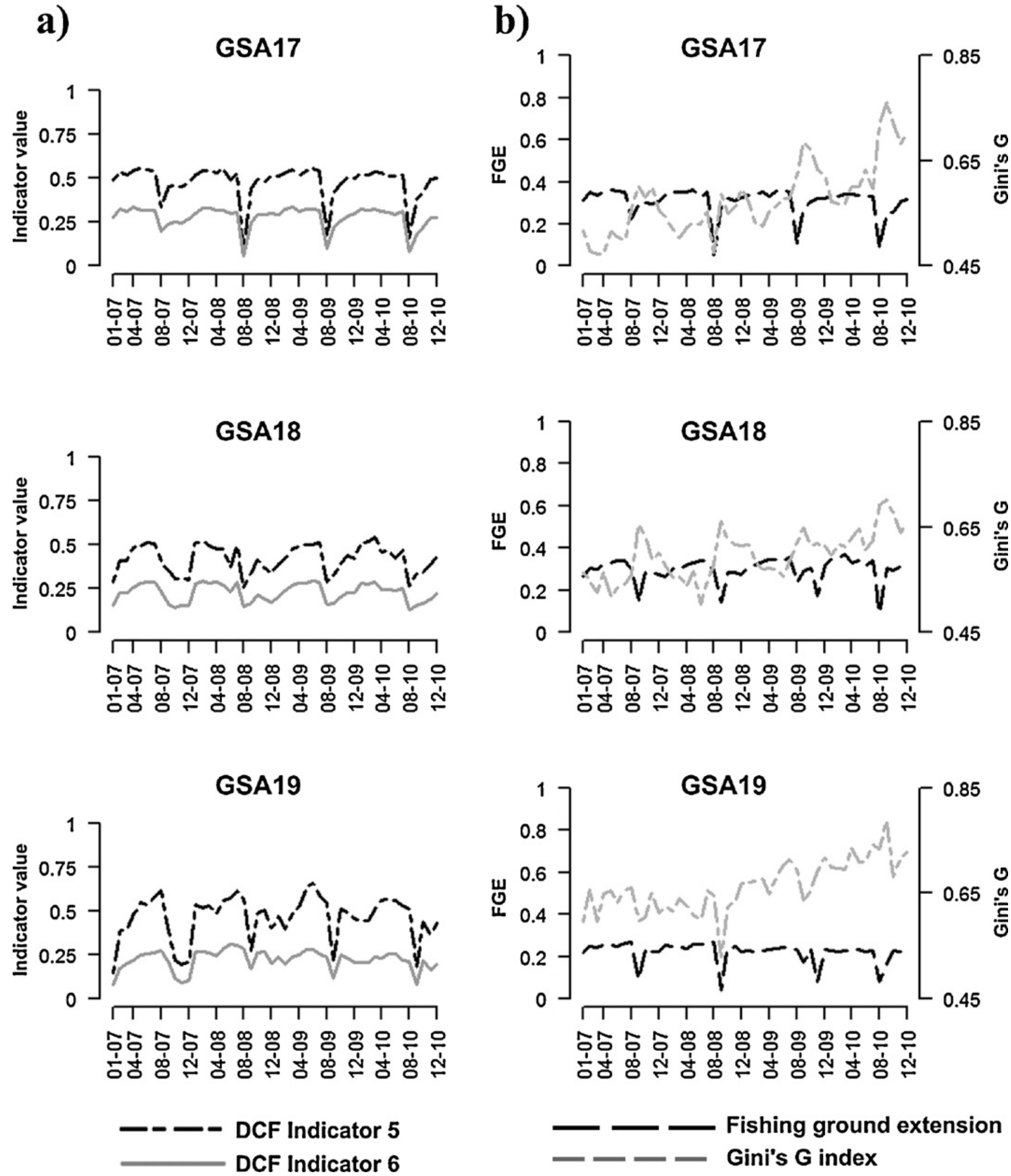

Fig. 5. (a) Monthly series for the DCF indicator 5 (extension of fishing activity) and 6 (aggregation of fishing activity) in the inspected period, for GSAs 17–19; (b) monthly series for the FGE indicators 5 (fishing ground extension) and 6 (Gini's *G* index of aggregation) in the inspected period, for GSAs 17–19. Two different scales were used to represent both indicators in the same plot.

in order to obtain high frequency distribution of fishing activity (Russo et al., 2011a), as recommended within the DCF (EC, 2008a,b). This is an important issue in assessing fished areas for towed gears (Lambert et al., 2012).

Pressure indicators are essential for management since they have the desirable properties of ease of measurement and rapid response times. The use of indicators generally involves definition of reference points, directions or trajectories as management objectives to be reached. However, while the use of reference points is common for status indicator, required trajectories or directions are generally used for pressure and response indicators (Jennings, 2005). In this way, analysis of the trends is the correct approach for this type of indicators.

Concerning the trends for DCF indicators 5 and 6, results evidenced that: (i) there is a strong seasonality in the data. Even if different approaches exist and could be preferred if appropriate data are not available, the chosen approach to the analysis of trends (a time dependent relation with monthly or seasonal dummies to capture the seasonal part of signal) seems to be appropriate and sound; (ii) the actual formulation of indicators 5 and 6 determines a redundancy, as the second one is similar to the first one up to an additive constant (Figs. 4a and 5a). Thus, scant information is provided by indicator 6 if the indicator 5 is available, that is exactly the case since DCF requests that the patterns of these two indicators were reported and analyzed together; (iii) the general pattern of exploitation did not vary through the inspected period (years 2007–2010), with the only exception of GSA11, in which a significant increase of the exploited areas was detected (Table 1).

In contrast, the new version of indicator 5, that is FGE, allowed to detect statistically significant trends for GSA9, GSA17, GSA18, GSA19 (decreasing) and for GSA16 (increasing). This means that the proportion of space systematically exploited is varying trough above all GSAs, but in different ways. It is possible to notice that in all cases, with the exception of GSA19, the patterns of the two

Table 1
Results of the model selection and coefficient estimation for the indicators and related LPUE series. Arrows used for summarize each trends are referred to the last phase when the identified model contains a significant β_2 term and can be interpreted as stable (→), increasing (↑), and decreasing (↓).

	GSA9	GSA10	GSA11	GSA16	GSA17	GSA18	GSA19
DCF indicator 5 – extension of fished areas							
Model	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
β_0	0.441^{***}	0.390^{***}	0.178^{***}	0.522^{***}	0.434^{***}	0.316^{***}	0.138^{*}
β_1		2×10^{-3}	$4 \times 10^{-3***}$	1×10^{-3}	-1×10^{-3}	1×10^{-3}	0.010^{**}
β_2							$-1 \times 10^{-4*}$
Trend	→	→	↑	→	→	→	↑
New indicator 5 – fishing grounds extension (FGE)							
Model	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
β_0	0.366^{***}	0.383^{***}	0.182^{***}	0.391^{***}	0.289^{***}	0.202^{***}	0.137^{***}
β_1	0.003			$-7 \times 10^{-***}$	$-6 \times 10^{-4***}$	$-6 \times 10^{-4***}$	$-6 \times 10^{-4***}$
β_2	$-9 \times 10^{-5*}$			$1.5 \times 10^{-4***}$			
Trend	↓	→	→	↑	↓	↓	↓
DCF indicator 6 – aggregation of fishing effort							
Model	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
β_0	0.187^{***}	0.235^{***}	0.092^{***}	0.278^{***}	0.218^{***}	0.134^{***}	0.084^{***}
β_1	0.005^{*}		0.002	$6 \times 10^{-4***}$	9×10^{-4}	0.002	0.006
β_2	$-1 \times 10^{-4**}$				-3×10^{-5}	-5×10^{-5}	-1×10^{-4}
Trend	↓	→	→	↑	→	→	→
New indicator 6 – Gini's index							
Model	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
β_0	0.645^{***}	0.601^{***}	0.667^{***}	0.599^{***}	0.601^{***}	0.629^{***}	0.593^{***}
β_1	-0.002	3×10^{-4}	-0.003^{*}	-0.002	-5×10^{-4}	2×10^{-4}	-7×10^{-4}
β_2	$9 \times 10^{-5***}$	$5 \times 10^{-5*}$	$9 \times 10^{-5***}$	$7 \times 10^{-5***}$	$8 \times 10^{-5***}$	$4 \times 10^{-5*}$	$7 \times 10^{-5**}$
Trend	↑	↑	↑	↑	↑	↑	↑
DCF Ind 5 based LPUE							
Model	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
β_0	1.407^{***}	1.474^{***}	2.016^{***}	2.459^{***}	2.940^{***}	2.551^{***}	1.353^{***}
β_1		-0.00388^{**}	-0.01011^{*}	-0.00218			
	→	↓	↓	→	→	→	→
NEW Ind 5 based LPUE							
Model	Seasonal	Seasonal	Seasonal	Seasonal	Seasonal	Seasonal	Seasonal
β_0	1.485^{***}	1.837^{***}	2.270^{***}	2.604^{***}	3.130^{***}	2.661^{***}	2.236^{***}
β_1		$-7 \times 10^{-3*}$	$-5 \times 10^{-3*}$				$5 \times 10^{-3*}$
β_2							
Trend	→	↓	↓	→	→	→	↑

Asterisks (*) mark the different levels of statistical significance:
* p-Values less than 0.05.
** $p < 0.005$.
*** $p < 0.0005$.

indicators (DCF 5 and FGE) are coherent, with the FGE being much less variable. This naturally drives us to conjecture that FGE is a more sensitive measure of the real phenomenon whereas the large fluctuations of DCF 5 mask the trend that remains hidden. This conjecture is strongly supported by the results of the comparison between DCF and new version of indicators (Section 3.2): while none of the indicators gave wrong results in terms of false positives, DCF indicators were characterized by a stronger tendency to do not detect trend when it is present than the new proposed indicators. Although the procedure applied to assess the performance of the two classes of indicators (DCF against FGE/Gini's G) is just a simplified version of the method reported in Jennings (2005) and of the model described in Fulton et al. (2005), it allowed to establish that the high level of fluctuation (noise) of the DCF indicators probably precludes an effective response of these indicators to changes in the real pattern of fishing effort.

The same rationale could be applied to comparative analysis of DCF 6 and Gini's G. While in the first case just two non-constant trends were detected, Gini's G recognized a significant increase in fishing effort aggregation throughout Italian seas. The patterns for this index are also very similar and coherent each other, suggesting that the existence of a common phenomenon. Moreover, Gini's G was characterized by a seasonal scale of replication. This fact could be related to the observation that it is the least variable between the computed indexes. Thus, by following the argumentation exposed above, it is able to capture the trend underpinning the short scale

Table 2
Results of the comparison between DCF and new version of indicators by trend detection on 100 simulated time series for three different scenarios. The table reports the percentages of correct classification, for each indicator, on the 100 simulations belonging to each scenario. Values smaller than 100 (occurring for scenarios 2 and 3) imply that missing series were classified as belonging to scenarios 1 (no trend).

	Scenarios		
	1: Extension and aggregation equal	2: Decreasing extension, increasing aggregation	3: Increasing extension, decreasing aggregation
DCF 5	100	62	53
FGE	100	81	78
DCF 6	100	59	63
Gini's G	100	93	87

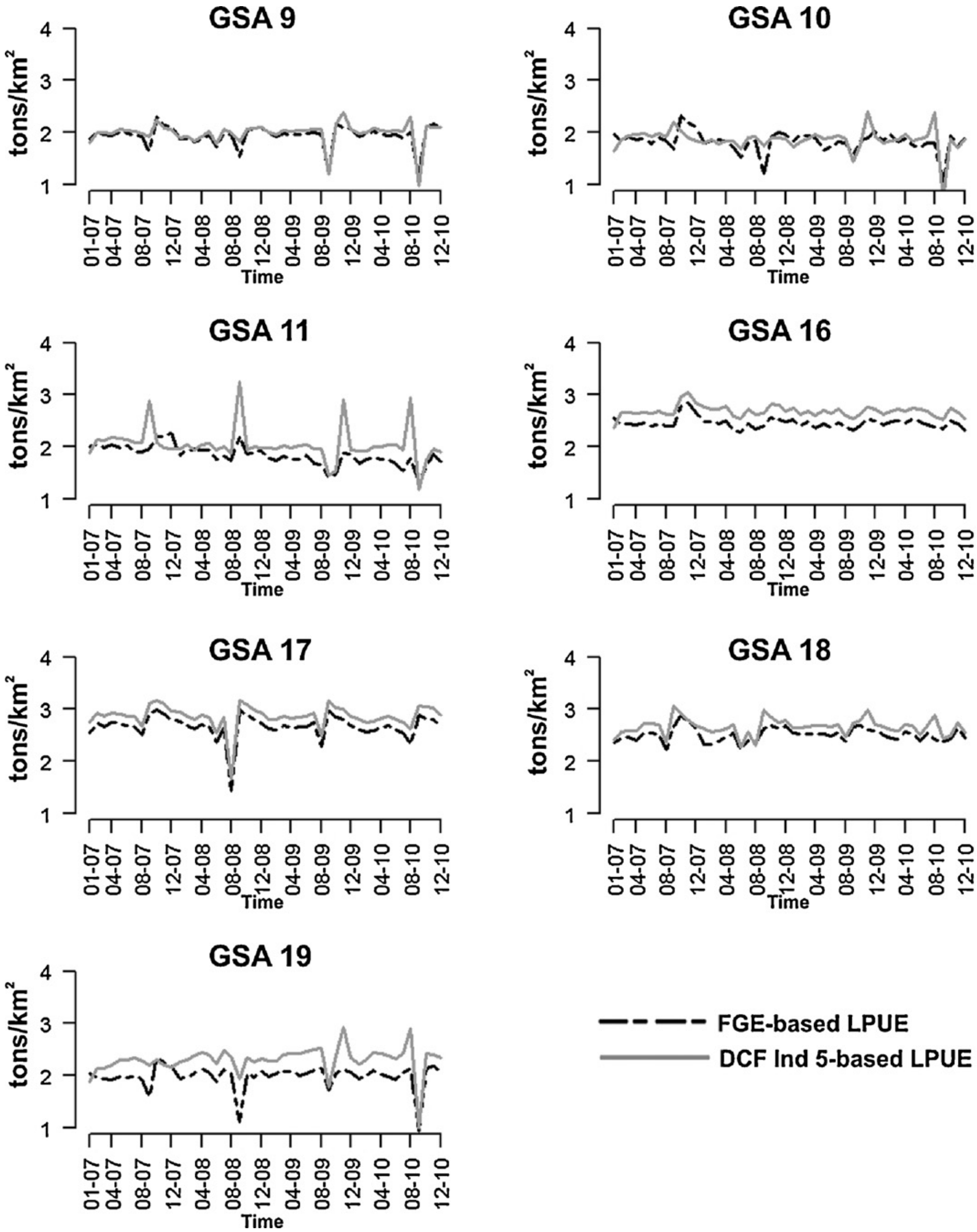

Fig. 6. Monthly series for the LPUE computed on DCF indicator 5 (extension of fished areas) and on FGE indicator (fishing ground extension), respectively.

(monthly) variability. Even in this case, this new version of DCF 6 scored better than the original one (Table 2).

Globally, these findings seem to confirm the initial criticism to DCF indicators 5 and 6. As they are computed on the whole grid which contains cells with few fishing points, they are largely influenced by variation of size and/or composition of this group of cells. In this way it is intuitive that DCF indicator 5, giving the same weight to cells characterized by very different values of fishing effort, probably leads to a less sensitive measurement of the really use of space by fisheries. Similarly, the use of Gini's *G* as index of fisheries aggregation is a robust way to assess dispersion, since it is not affected by the presence of null values (Woillez et al., 2007).

Generally, it is possible to compare two or more indicators on the basis of an independent source of data (e.g. comparing different estimates of fishing pressure to the ecological status of the benthic community – Lambert et al., 2012). Here, it is important to stress that the aim of pressure indicators is to quantify the spatial extension and aggregation of fishing effort, and not its effects on habitats. The simulation approach used in this study to assess the differential performance of DCF indicators against new ones was selected because it is considered as the most robust and suitable in this framework (Jennings, 2005) since it effectively evaluates indicators power in terms of their ability to capture and return the information provided by data.

While the values of productivity reported by landing data are coherent with the literature and the relative production between different GSAs also agreed existing data (Caddy et al., 1995), the values of LPUE obtained as ratio of landings and DCF 5 or FGE were remarkably higher that those previously published. This is due to the fact that, in this study not all the shelf areas was used as reference for the demersal landings, but just the proportion occupied by FG. However, the analysis of LPUE trends obtained by DCF 5 and FGE reported very similar results, since a significant decreasing trend was detected for two GSAs located in the Tyrrhenian Sea. The meaning of this kind of signal has been extensively discussed in some milestone studies (Rose and Kulka, 1999; Walters, 2003). In brief, a lowering of LPUE values indicates a substantial decline of resources, especially if an increase of the exploited area is observed. In this way, the decreasing LPUE trends and the general increasing aggregation evidenced by the Gini's *G* should be considered as a warning, in which they support the current evaluation about the critical status of demersal resources of the Mediterranean sea (FAO, 2005). Similarly, the situation could be critical also for other GSAs (namely GSA9, GSA17, GSA18 and GSA19) in which the LPUE did not show significant trends but FGE is lowering while aggregation (Gini's *G*) is increasing. In fact, these last two phenomena could determine an "hyperstability" effect: shoaling behavior and range contraction during stock declines leads to an apparent stability of catches and landings (Hilborn and Walters, 1992). In effect, Ceriola et al. (2008) documented a decline of fisheries resources for GSA18.

It should also be noticed that the results reported in this study can be considered as a sound measure of spatial use and resource trend, since they are neither affected by possible hidden assumptions about abundance trends in spatial cells that were not fished nor biased by incorrect use of ratio estimators (see Walters, 2003).

Another finding for both types of LPUE trends was the presence of large fluctuations, with maximum observed values of 10^3 tons/km^2 per month in some GSAs. These values can be explained by looking at the position of these "spike". In effect, they closely follow the temporal stop that yearly characterizes fishing activity. A similar phenomenon has been documented by different authors (Relini et al., 1996; Pipitone et al., 2000; Machias et al., 2001; Sánchez et al., 2007) for the LPUE computed on temporal fishing effort, and it has been related to the cumulative effect of two factors: the augmented availability of resources, determined by the temporal stop of the activity, and the ability of fishers to concentrate their spatial effort, just after the end of the stop, in areas characterized by high density of fish. Hence, these spikes are not artifacts but evidences of a well defined phenomenon.

The methods presented in this study conceptually follow the first pioneer study of Witt and Godley (2007), which firstly faced off the question about the variability trough space and time of fishing effort, in view of the use of this information for spatially explicit management purposes. Moreover, the definition of fishing ground proposed in this study attempts to fill a conceptual and methodological vacuum in fisheries science. The explicit reference to the economic aspects could provide the rationale to interpret the dynamic aspects of fishing ground existence and evolution: their genesis (from areas never visited to occasionally exploited, and then to routinary exploited) and their movement through space (difference in position of fishing ground among years) could be understood when economic variables (such as market price or fuel cost) are considered. Although this is not the object of the present study, it is a promising challenge for future researches. The existence of fishing grounds dynamics is directly suggested by the fact that the Griffith's STI reported a critical value of time (that is the temporal distance at which independence is realized, see Fig. 2) of 12 months. In this way, it follows that fishing grounds have a yearly life time. Ultimately, we attempted to provide a general definition of fishing ground, which could be useful in the analysis of different fisheries obeying to different rules and dynamics. Far from being just a theoretic issue, a spatio-temporally explicit definition of fishing grounds could be very helpful for both scientific and management purposes. An example of the utility of this definition is that, although the negative impact of trawl activity has been largely documented in literature (Smith et al., 2000; Hiddink et al., 2006), there is no general consensus about the quantitative relationship between trawling disturbance and ecosystem alteration. This reasonably due to the fact that existing knowledge of the direct effects of trawling is limited to site-specific and/or small scale experimental studies (Hiddink et al., 2006), and that level of fishing effort among different sites were defined in a qualitative or semi-quantitative way (de Juan et al., 2009). In addition, few studies exist reporting fishery-scale distribution of the fishing activity (e.g. Witt and Godley, 2007), and still fewer methods exists to analyze the pattern of fishing activity in its spatial and temporal dimensions. All these combined issues could be effectively addressed using an approach such as the one presented in this study, marking a new step in this framework of investigation. Looking beyond, the set up of methods to track the real dynamic underpinning the use of environment by fisheries could allow to better explore the temporal pattern of fishing effort and thus to develop spatially explicit models and adequate management strategies (FAO, 1998).

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