



# New insights in interpolating fishing tracks from VMS data for different métiers

Tommaso Russo<sup>a,\*</sup>, Antonio Parisi<sup>b</sup>, Stefano Cataudella<sup>a</sup>

<sup>a</sup> Laboratory of Experimental Ecology and Aquaculture – Department of Biology – “Tor Vergata” University of Rome, via della Ricerca Scientifica s.n.c., Rome 00133, Italy

<sup>b</sup> SEFeMEQ – Department of Financial Economics and Quantitative Methods – Faculty of Economics – “Tor Vergata” University of Rome, via Columbia 2, Rome 00133, Italy

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## ABSTRACT

The Vessel Monitoring by satellite System (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 scale. Given that the main VMS limit is represented by the temporal resolution (generally 2 h) of signals, a series of approach has been developed to interpolate vessels positions. The newest and most powerful method in this framework is based on cubic Hermite splines (cHs), which have been efficiently tested against the conventional straight line interpolation over a dataset representing fishing activity by beam trawl. However, this method has never been applied on other different gears and/or métiers. Here we propose a new approach (CRm), which is a modification of the Catmull–Rom algorithm (CR). This new method takes into account for the different aspects involved in vessel navigation, such as the combined actions of human control and drift by sea current and wind (if present). The drift component is not observed, but is estimated within the method, using the VMS data. This method has been developed in order to model the behaviour of vessels that operate using different gear types. The CRm method was compared to the cHs method, using three reference datasets (each containing VMS signals at intervals of 20 min) corresponding to three different métiers largely used in Mediterranean fisheries: *bottom otter trawl for demersal species* (OTB), *trammel nets for demersal species* (GTR), and *purse seine for small pelagic fish* (PS), which differ each other for the dynamic aspects connected to the use of fishing gears, and represent an archetype of the three groups actually used to classify fishing gears (namely towed, active and passive). The comparison was carried out both analyzing the error affecting interpolation of single tracks and converting the interpolated tracks into gridded data to be used for computation of ecological indicators of fishing pressure. All the results coherently evidences that the CRm algorithm performs better in interpolating trawl tracks (OTB) and that, moreover, it is able to capture the complex behaviour characterizing the trajectories of vessels performing the other two inspected métiers (GTR and PS). Finally, CRm allows a better estimation of fishing effort, as measured by ecological indicators. These findings support the idea that the conceptual formulation of CRm method is appropriate to model whatever fishing tracks presently generated by fishery vessels and could be efficiently applied in order to obtain better estimation of fishing pressure and, if sensitivity data are available, of fishing impacts.

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## 1. Introduction

The Vessel Monitoring by satellite System (VMS), which has been introduced in 2002 by the European Union (EC, 2002) for remote control purposes of fishing vessel with length over all (LOA) higher than 15 m, is now 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). Today, VMS technology is based on the presence of 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. However, the main problem of using VMS data for scientific and managing purposes is the low frequency at which *blue boxes* send the signal, that is not sufficient to satisfactorily reconstruct the fishing tracks (Hintzen et al., 2010). This problem limits the application of VMS data in different crucial tasks, such as the study of the effects of fishing gears on more sedentary ecosystem components (Piet and Quirijns, 2009) and the assessment and forecasting of fleet responses to management actions (Mills et al., 2007; Vermard et al., 2010). Thus, most of the potential use of VMS data is linked to the development of suitable method to analyze trajectories from discrete recorded positions. The possibility to reconstruct the complete spatio/temporal path of each vessel via some sound interpolating algorithm is a key step, and

\* Corresponding author. Tel.: +39 06 72595974; fax: +39 06 72595965.

E-mail addresses: [Tommaso.Russo@uniroma2.it](mailto:Tommaso.Russo@uniroma2.it) (T. Russo),

[Antonio.Parisi@uniroma2.it](mailto:Antonio.Parisi@uniroma2.it) (A. Parisi), [cataudel@uniroma2.it](mailto:cataudel@uniroma2.it) (S. Cataudella).

the list of studies facing off this problem is rapidly growing up (Piet et al., 2000; Deng et al., 2005; Bertrand et al., 2005; Kourti et al., 2005; Hiddink et al., 2006; Mills et al., 2007; Hintzen et al., 2010; Lee et al., 2010; Vermard et al., 2010; Walker and Bez, 2010). These studies applied different approaches, that can be summarized in three groups: (1) state-space modelling (Lee et al., 2010; Vermard et al., 2010; Walker and Bez, 2010); (2) random walks (Bertrand et al., 2005, 2007); (3) spline interpolation (Hintzen et al., 2010). State-space models have been invoked mainly to take into account for the discrete, error-prone and incomplete nature of recorded VMS positions (Vermard et al., 2010). However, the error associated to registration of VMS position had rapidly decreased during last years, according to the evolution of *blue box* technology, then it is actually small enough to be ignored (Walker and Bez, 2010). Random walks have been applied to characterize and quantify the entire movement of foragers, but they retain a limit: they are designed neither to interpolate VMS signals nor to separate out fishing and travelling time (Vermard et al., 2010). In contrast, spline interpolation methods seem to be characterized by important advantages: they are easy and fast to compute and lead to appreciable results in terms of distance from the real path of vessels (Hintzen et al., 2010).

Spline interpolation was originally proposed by Tremblay et al. (2006) to reconstruct animal tracks, and recently applied by Hintzen et al. (2010) in the fishery context to interpolate the trajectories of fishing vessels. These authors demonstrated that Hermite splines can estimate the fishing track between VMS position registrations better than the commonly used linear interpolation, which underestimates the length of fishing tracks and produces unrealistic representations of vessels behaviour.

The application developed by Hintzen et al. (2010) is limited to a type of towed gears (i.e. trawls). Although trawls surely represent one of the most important gear type, a large list of gears and related métiers (that are homogeneous subdivisions, either of a fishery by vessel type, or of a fleet by voyage type, reflecting the fishing intention, e.g. the species targeted, the area visited, and the gear used, at the start of a fishing trip – Marchal, 2008) still remains unaccounted. This seems to be a major drawback because the European Commission, in the attempt to implement an ecosystem approach to marine management (COM, 2008) via the Data Collection Regulations and the Data Collection Framework for the Common Fishery Policy (EC, 2008a,b), identifies, for the fishing activity in the Mediterranean and Black Seas, a list of 28 métiers (see Table 1 of ICES, 2009b) of level 5 (a level is a scale in the progressive description of fishing activity), comprising towed, active and passive ones. In this way, a more general approach is needed, which will be able to take into account that each gear type, and therefore each métier, is characterized by a different activity of vessel in terms of course and operative speed during fisheries operations (Flewwelling et al., 2002). This implies that fishing tracks can largely differ among different métiers, passing from simpler situations, as those of towed gears, which generally proceed straight when fishing, to more complex situations, as those of passive gears, which can be dragged by current and/or wind along nonlinear trajectories. Thus, a validated general method to interpolate VMS signals of vessels belonging to the different métiers still lacks.

This paper faces this problem by introducing a general approach based on the decomposition of vessels movement in the different components represented by engine action and drift generated by sea current and wind. This basic idea is used to analyze and interpolate the VMS signals of three different métiers played by the Italian fleet in spring and summer 2009. After decomposition of the movement in its different components, the method interpolates the trajectories of fishing vessels between successive VMS data points using a modified version of the Catmull–Rom (CR) interpolation method, which is a kind of cubic Hermite spline (Catmull and

Rom, 1974). The performance of our method, named “Catmull–Rom modified” (CRm), in interpolating VMS data was tested using as a reference the algorithm proposed by Hintzen et al. (2010) (H in the following sections).

## 2. Materials and methods

### 2.1. Data description

Two datasets were used in the present work. The first dataset, called high frequency (HF), contained VMS positions at intervals of 20 min. These data, provided by the Italian “Ministry of the Agricultural, Alimentary and Forestry Politics”, originated by a random subsample of the Italian fishery fleet for which the *blue boxes* were set to send signals at a higher frequency than the one used by the rest of the fleet (2 h). The second dataset, called low frequency (LF), was obtained by the HF one by sampling points at frequency of 2 h, the common frequency used for the Italian fleet. Each point of the two datasets contained information about position (latitude and longitude in the World Geodetic System, 1984), vessel speed ( $\text{km h}^{-1}$ ), and prow heading (radian). In order to compute Euclidean distances, the coordinates were converted in Universal Transverse Mercator (UTM) coordinate system. Notice that, in VMS, the speed is not the ratio between distance covered between two points in the LF dataset and time elapsed (2 h), but just an instantaneous evaluation of vessel speed at given time and position (FAO, 1998). The same holds also for the prow heading. The vessel, however, follows a path which is determined, on longer time intervals (until 2 h), by different factors (engine, wind, drift).

Considering that the position information was recorded with an accuracy of 0.1 s ( $\pm 15$  m), the error associated to VMS position was considered as negligible (EC, 1993), and was ignored.

The European Commission published a list of fishing métiers and gear types (Gascoigne and Willstead, 2009) classified in three categories: (1) *towed gears*: gears that are towed across the seabed (trawls and dredges); (2) *passive gears*: gears that are placed on the seabed and does not move until lifted by the fishing vessel (e.g. anchored nets and lines, pots); (3) *active gears*: gears that involve movement of the fishing vessel to deploy but is not actively towed (seine nets and trolling lines). In this study, three series of fishing tracks were used, one for each of these different categories. The three series of tracks belong to three different métiers following the current EU classification at level 5 (ICES, 2009b): (1) *bottom otter trawl for demersal species* (OTB), that is a net with the mouth kept open by doors or otter boards and may have tickler chain or (more often) rockhopper discs in contact with bottom; (2) *trammel nets for demersal species* (GTR), that are nets that hang vertically in the water, with one edge weighted and anchored to remain in contact with the bottom; (3) *purse seine for small pelagic fish* (PS), that are small-mesh nets deployed in a circle round the school of fish and then cinched in by drawstrings at the bottom.

Each series contained a number of 25 fishing courses randomly selected from a larger dataset corresponding to the fishing activity carried out by Italian fleet in spring and summer 2009. Each track belonging to the LF dataset contains 4–15 observations, so that the corresponding track in the HF dataset contains 24–90 points. These tracks were selected to contain at least, the 20% of points corresponding to fishing activity. The mean total length (in terms of time) of each track was 32 h. In this study, the overall fishing tracks, even comprising navigation, fishing, steaming and floating phases, were interpolated. Then, each series of points obtained was subdivided in its components using the logbook information appositely collected on board for this purpose by scientific personnel. The precise times of start and end of operations were collected in these logbooks, ensuring the possibility of precisely reconstruct the sequence of

phases. The annotation of start/end of fishing phases was collected taking into account the existing operational differences among the different gears: for each gear, the temporal extremes of fishing activity coincided to the real moment of put in action of gear (e.g. times of starting and end of net deployment were annotated, whereas, for purse seine, activity related to uses of FAD was not classified as fishing). The series of tracks belonging to the three métiers were used to compare the interpolation methods described below, both in terms of possibility of reconstruct the entire tracks and to identify the fishing areas swept by different gears.

## 2.2. Interpolation methods

Following the argumentation presented by Hintzen et al. (2010), several interpolation techniques could potentially be used to interpolate fishing trajectories from VMS data points. Among these, cubic Hermite spline could be considered as an optimal compromise between computability (in terms of difficulty and computational time needed) and reliability (in terms of goodness of results). Cubic Hermite splines are characterized by some advantages: they pass through all registration points available (in contrast with other approach, such as Beziér's curves) and can be parameterized in order to take into account for the available data about heading and speed at registration points. However, cubic Hermite splines comprise a large amount of techniques differing, among other aspects, in the number of points needed to interpolate the trajectory between two points. These differences cannot be simply considered as mathematical details, since they are connected to practical aspects of the series that we would like to interpolate. In this way, the analysis of the phenomenon under study can help in finding the best interpolation method. Here, three methods were applied to the points contained into the LF dataset to interpolate the real tracks, while points of the HF dataset were used to compare the accuracy of the three methods as described in the following sections. Starting from the approach proposed by Hintzen et al. (2010), we elaborate a new one, which is aimed at realistically interpolate fishing tracks of vessels using whatever gear type.

### 2.2.1. Cubic Hermite splines

All the methods explored in the present work are members of the large family of cubic Hermite splines. A cubic Hermite spline is a third-degree spline with each polynomial of the spline in the Hermite form. Using the data about times ( $t_i$ ), positions ( $X_i$ ) and tangent vectors ( $T_i$ ), is possible to use cubic Hermite splines to obtain an interpolation  $S(t)$  of the points. Splines satisfy the requirements:

$$S_i(t_i) = X_i, \quad S_i(t_i + 1) = X_{i+1}, \quad S'_i(t_i) = T_i \quad (1)$$

Hence, the spline will pass exactly on the control points  $X$  (that are the points into the LF dataset) and the spline derivatives in those points will match the vectors  $T$ . The splines are generally expressed in Hermite form (see, for example, Abramowitz and Stegun, 1964) as:

$$S_i(t) = H_0\left(\frac{t-t_i}{\Delta t_i}\right) X_i + H_1\left(\frac{t-t_i}{\Delta t_i}\right) X_{i+1} + H_2\left(\frac{t-t_i}{\Delta t_i}\right) \Delta t_i T_i + H_3\left(\frac{t-t_i}{\Delta t_i}\right) \Delta t_i T_{i+1} \quad (2)$$

where  $\Delta t_i = t_{i+1} - t_i$ ,  $H_0(x) = 2x^3 - 3x^2 + 1$ ,  $H_1(x) = -2x^3 + 3x^2$ ,  $H_2(x) = x^3 - 2x^2 + x$  and  $H_3(x) = x^3 - x^2$ , but we can express them as:

$$S_i(t) = A_i + \left(\frac{t-t_i}{\Delta t_i}\right) B_i + \left(\frac{t-t_i}{\Delta t_i}\right)^2 C_i + \left(\frac{t-t_i}{\Delta t_i}\right)^3 D_i \quad (3)$$

where  $A_i = X_i$ ,  $B_i = \Delta t_i T_i$ ,  $C_i = 3(X_{i+1} - X_i) - \Delta t_i(2T_i + T_{i+1})$  and  $D_i = -2(X_{i+1} - X_i) + \Delta t_i(T_i + T_{i+1})$ .

Independent of the chosen approach, an interpolation procedure is composed by two steps: (1) computing tangents at control

points and (2) computing interpolated positions. The key aspect that distinguishes between different methods of the cubic Hermite splines family is the way of computing tangent vectors. The different definitions used by the Hintzen et al. (2010) algorithm, the Catmull and Rom (1974) algorithm, and the one we developed, are described in the following subsections.

### 2.2.2. H method (Hintzen et al., 2010)

We prefer the code H to identify the method of Hintzen et al. (2010), instead of the code cHs (stands for cubic Hermite splines) used by the authors, since the denomination cubic Hermite splines is too general and comprises the other two approaches used in the present work. In the H method (Fig. 1a), two polynomials are used to separately describe the interpolation in the longitudinal and latitudinal directions in relation to time. The tangents of these two polynomials are directly calculated using heading and speed data provided by blue box, instead of inferring them by the data positions. Notice that, for active and passive gears, it is often the case in which the real track and the prow follow different directions; this is consistent with the behaviour connected to different métiers (as showed in the following sections).

### 2.2.3. CR method (Catmull and Rom, 1974)

The Catmull–Rom (Catmull and Rom, 1974) tangent vectors, in their simplest specification, can be expressed as:

$$H_i^{CR} = \frac{X_{i+1} - X_{i-1}}{2} \quad (4)$$

In this approach, the tangent is viewed as the average change in position between the sample position and its neighbouring sample positions. Thus, the Catmull–Rom method uses three control points to compute each tangent vector (Fig. 1b), while it needs four control points to interpolate the trajectory between two points.

### 2.2.4. CRm method (CR modified method)

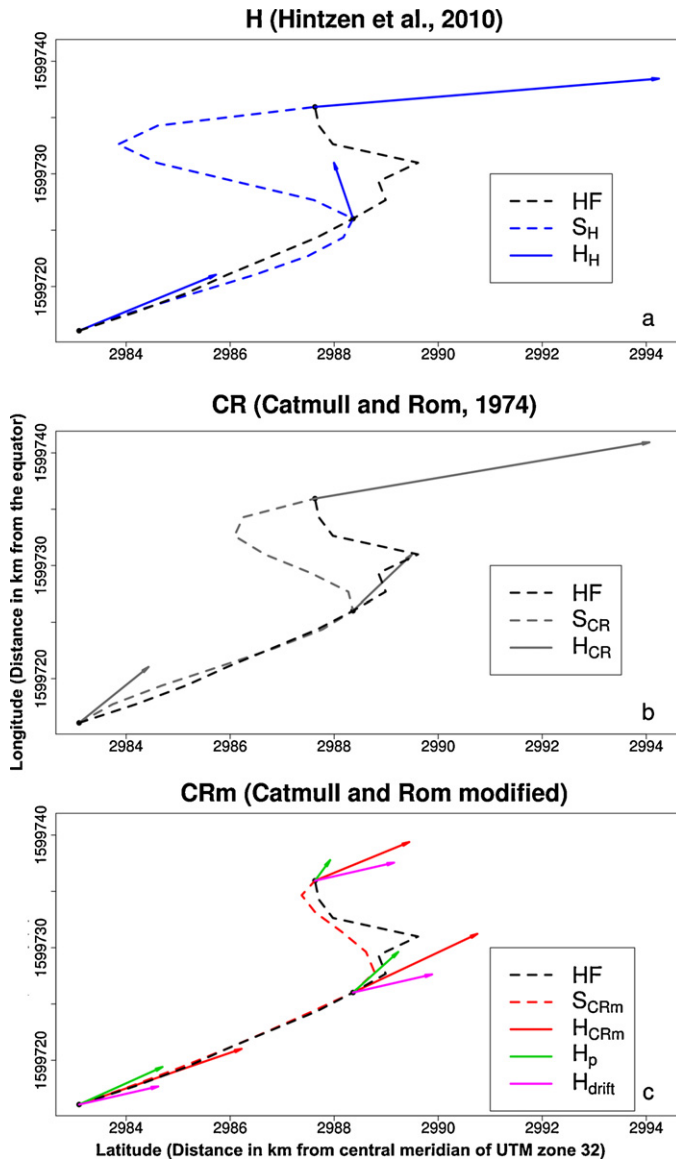
When interpolating tracks of the vessels using CR tangent vectors, it is possible to notice that this specification is not the best choice for the problem at hand. In particular, winding tracks are not accurately interpolated and the systematic effect of the drift on the trajectory is ignored, even if this effect is generally not negligible. We related the first problem to the norm (that is the length) of the tangent vectors and the second one to the direction of those vectors.

We corrected the norm of the tangent vectors in order to approximately adjust for  $L_{i-1}^{i+1}$ , the length of the real track between  $X_{i-1}$  and  $X_{i+1}$ . A downward biased approximation  $\hat{L}_{i-1}^{i+1}$  of this length will be given by the sum of the (euclidean) distances  $\|X_{i-1} - X_i\|$  and  $\|X_i - X_{i+1}\|$ :

$$H_i^{Est} = \frac{\hat{L}_{i-1}^{i+1}}{\|H_i^{CR}\|} H_i^{CR} \quad (5)$$

To correct the direction, we will assume that the real heading of a vessel between two recorded positions is the vectorial sum of two components: the one actively determined by boat rudder and engine ( $H^P$ ) and the one represented by the combined actions of sea current and of wind eventually present ( $H^{drift}$ ). While  $H^P$  is under the human control,  $H^{drift}$  is an environmental factor that could be indirectly evaluated via the VMS data. In fact, VMS data do not contain any measurement about the drift, but they provide the data about  $H^P$ . If we assume that  $H^{Est}$  is a good estimate of the real direction, for each control point, we can decompose  $H^{Est}$  in its two components  $H^P$  and  $H^{drift}$  (Fig. 1c):

$$H^{Est} = H^P + H^{drift} \quad (6)$$

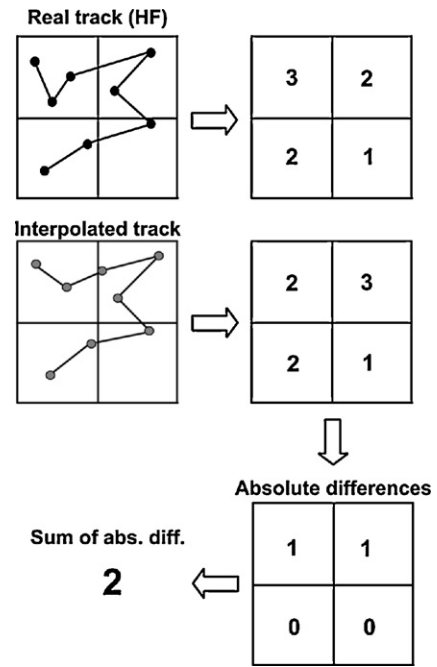


**Fig. 1.** Schematic representation of the three interpolation algorithms starting with two succeeding VMS records ( $P_1$  and  $P_2$ ) towards an estimated one. (a) The real trajectory, as described by HF dataset, is represented by a black dashed line. The heading of the vessel at  $P_1$  and  $P_2$ , used to interpolate the path ( $S_H$  – blue dashed line), is computed following Hintzen et al. (2010), and represented by the small arrows in blue ( $H_H$ ). (b) Here the tangents expressing the direction of vessel at  $P_1$  and  $P_2$ , computed by the CR method, are represented by grey arrows ( $H_{CR}$ ), while the interpolated trajectory is represented ( $S_{CR}$ ) by the grey dashed line. (c) Here the tangents expressing the heading of the vessel at  $P_1$  and  $P_2$ , computed by the CRm method, are represented by red arrows ( $H_{CRM}$ ), while the green ones ( $H_p$ ) represent the heading provided by Blue Box and the violet ( $H_{drift}$ ) ones the heading of drift. The interpolated trajectory ( $S_{CRM}$ ) is represented by the red dashed line (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

An estimate of the drift effect will be given by the median  $\hat{H}^{drift}$  computed on the values of  $H^{drift}$ .

In this way, our method is devised to obtain an estimate of the drift without using external (oceanographic) data. This estimate will be used to correct the direction of tangent vectors.

Taking the median  $\hat{H}^{drift}$  as an estimate of the drift step implies that the behaviour of the current at the microscale (that is a squared area of 10 km side) containing the fishing track is considered stable. This assumption is coherent with the results of recent studies, in which it has been showed that the Mediterranean circulation is substantially homogeneous at the mesoscale (circular surface area



**Fig. 2.** Exemplification of the procedure applied to compute, starting from track data, the spatial grid of values at the basis of ecological indicators of pressure 5–7: both real and interpolated sequences of VMS positions are plotted on a common grid, and the number of signals is computed for each cell of the grid. Then, the absolute difference between each pair of corresponding cells is computed. Finally the sum of absolute differences will be a measure of the divergence between the real and the interpolated track.

with radius between 10 and 14 km) level (Robinson et al., 2001; Pujol and Larnicol, 2005; Rinaldi et al., 2010). The real heading  $H^{CRM}$  of the vessel at each point is finally estimated as the vectorial sum of prow heading and median sea current heading.

$$H^{CRM} = \hat{H}^{drift} + H^p \quad (7)$$

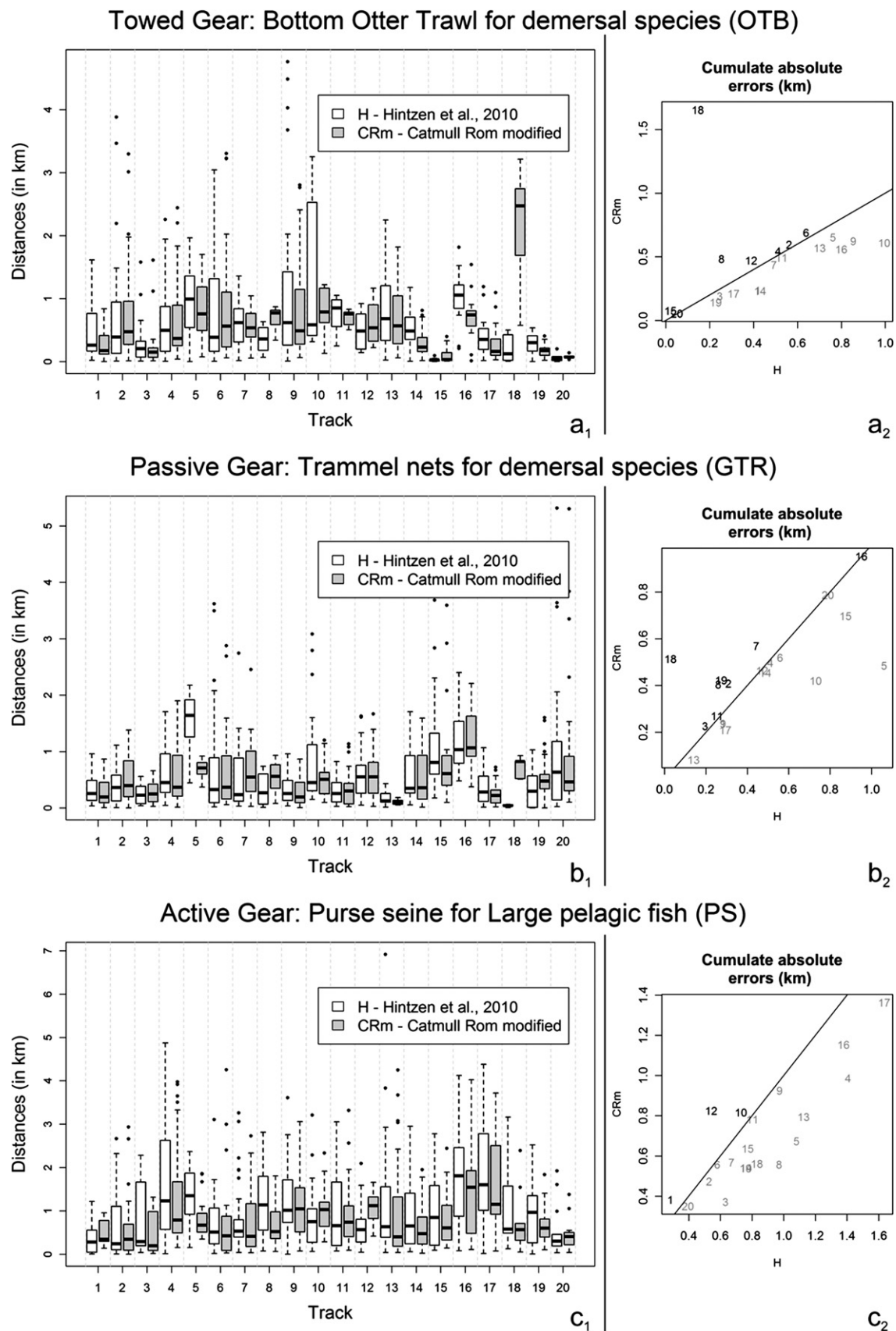
The pattern of values obtained for  $\hat{H}^{drift}$  were graphically inspected to evaluate the quantitative importance of this component for the different métiers. Further, the distributions of  $\hat{H}^{drift}$  for the three métiers were statistically tested for homogeneity in order to assess if the estimations of drift obtained by CRm method were independent from the métiers analysed. The three series of values for the estimated drift were compared by means of a paired two-sample Wilcoxon rank sum and signed rank test (Hollander and Wolfe, 1973) provided in the R environment (R Development Core Team, 2009), package ExactRankTests (Hothorn and Hornik, 2010). The null hypothesis was that the three series of drift estimations belong to the same distribution.

### 2.3. Comparison

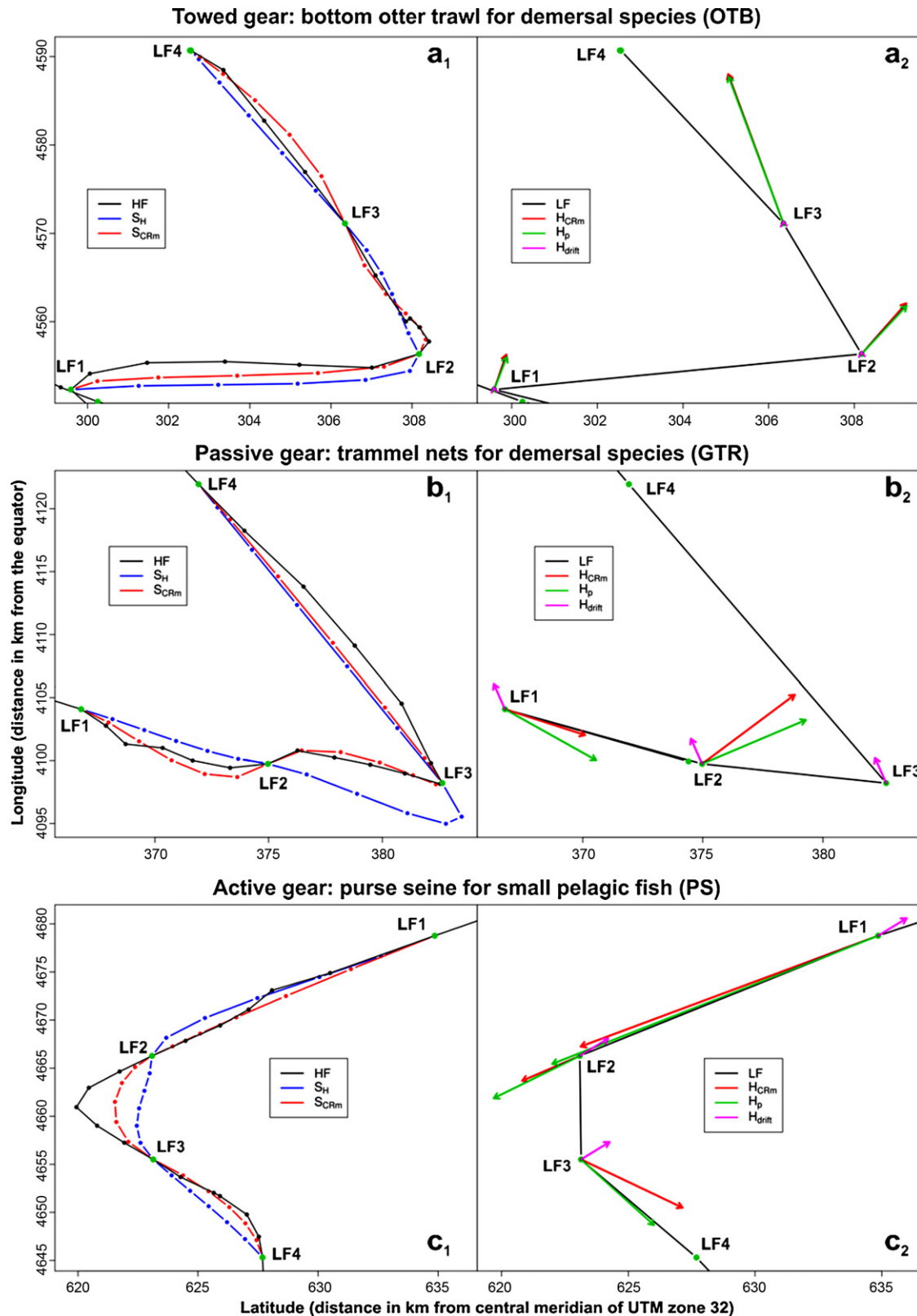
The fit of H, CR and CRm interpolation methods was compared by computing, for each track of each métiers, two indexes: the average and the sum (as reported in Hintzen et al., 2010) of the linear distances among interpolated points and real coordinates (those of the HF dataset). The average distance represents a measure of the mean error affecting each interpolation approach, while the sum was used to obtain an overall measure of discrepancy between interpolated and real tracks. Higher values indicated a poorer fit for both indexes.

Interpolated tracks can be used in order to compute both spatial extent and aggregation of fishing activity following the ecological indicators adopted by the European Commission in implementing an ecosystem approach to marine management (COM, 2008). The

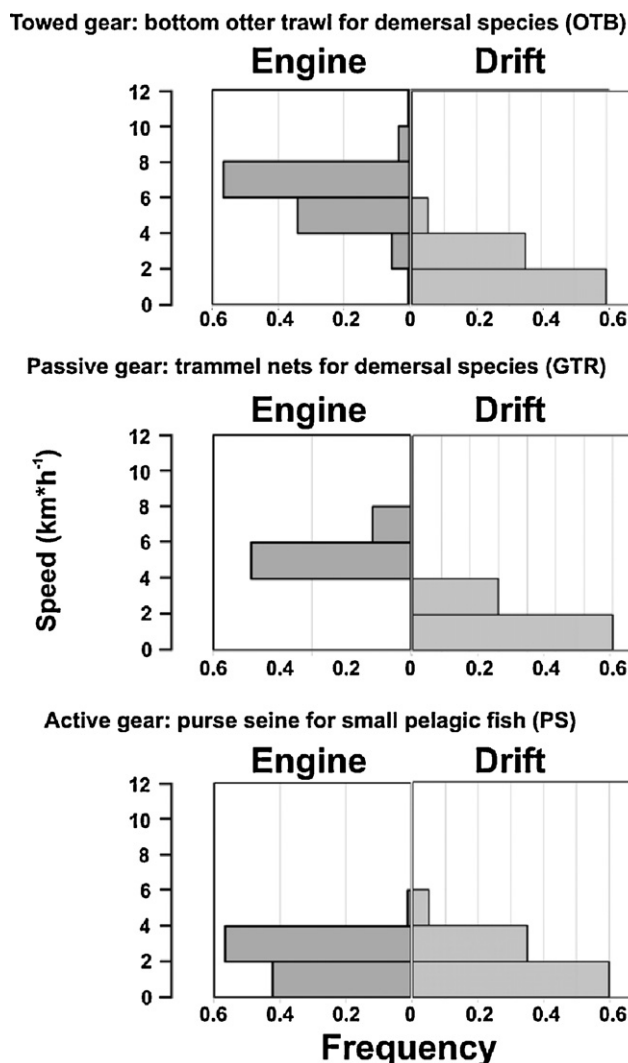




**Fig. 3.** Comparisons of the distances between the real tracks and the estimated ones based on the H method (from Hintzen et al., 2010 – in white) and on the CRm method (light grey) presented in different boxplots for each gear type: (a<sub>1</sub>) OTB, (b<sub>1</sub>) GTR and (c<sub>1</sub>) PS. The first and third quantile of each dataset are represented by the boxes, while minimum and maximum observations, not being outliers, are represented by the dotted vertical lines. Outlying results (more than 1.5 times the interquartile distance away from the 1st or 3rd quantile) are represented by black points. Scatterplots of the Cumulate absolute errors computed using H and CRm methods, respectively, for: (a<sub>2</sub>) OTB, (b<sub>2</sub>) GTR and (c<sub>2</sub>) PS. The value obtained for each track is represented by number. The solid line represents correspondence between the two methods, while black numbers identify tracks for which H method performs better and grey numbers identify tracks for which CRm method performs better.



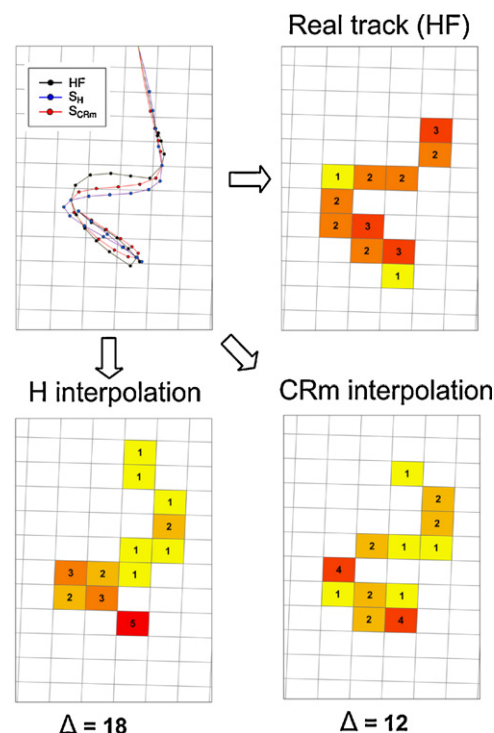
**Fig. 4.** Comparisons between the real high frequency track (black points and black solid line HF) and those estimated by means of the H method (blue points and blue solid line  $S_H$ ), and the CRm method (red points and line  $S_{CRm}$ ) for each gear type: (a<sub>1</sub>) OTB, (b<sub>1</sub>) GTR and (c<sub>1</sub>) PS. Green points represent VMS signals at low frequency (LF) (control points). Representations of the vectors used to compute the interpolation following the CRm method, for each gear type: (a<sub>2</sub>) OTB, (b<sub>2</sub>) GTR and (c<sub>2</sub>) PS.  $H_p$  (in green) is the prow heading as provided in the original VMS dataset,  $H_{CRm}$  (in red) is the tangent vector computed by CR modified method, and  $H_{drift}$  (in purple) is the drift vector. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)



**Fig. 5.** Comparisons between the distributions of the norms of the engine propulsion vectors  $H_p$  and the estimated drift vectors  $H^{drift}$ , for the three different inspected métiers.

basic step is the computation of the number of fishing points (that are VMS signals) on a grid with square cells of size equals to 3 km, for each métiers. This “activated” grid (that is a grid where, at least, one signal is assigned to each cell) is then used to compute the ecological indicator of pressure 5 (indicator of the spatial extent of fishing activity, that is the total number of cell of the activated grid), 6 (indicator of the extent to which fishing activity is aggregated, that is the number of cells containing the 90% of VMS records), whereas the “inactivated” one is used to compute the indicator 7 (indicator of the area of seabed that has not been impacted by mobile bottom fishing gears). The purpose of indicator 5 is to assess the overall extension of areas interested by fishing activity, while the indicator 6 is aimed to assess the areas in which the fishing effort is mainly concentrated (it is computed by selection of cells with the highest number of fishing points, until the 90% of total is reached), and the indicator 7 (which is computed annually, instead of the other two indicators computed monthly) is aimed to assess the extension of undisturbed areas.

Following this approach, each HF track and its three interpolations (H, CR and CRm) were plotted on a given grid, and the number of fishing points occurring in each cell of the grid were counted (Fig. 2). Then, the sum of absolute differences ( $\Delta$ ) was computed between the grid obtained for each interpolation method and the



**Fig. 6.** Sample of track for purse seine (PS) used to compute the grid at the basis of both spatial extent (Indicator 5, that is the number of cell occupied by a given track), and aggregation of fishing activity (Indicator 6, that is the number of cells within which 90% of VMS records were obtained). The number of VMS signals assigned to each cell is visualized by number and a corresponding color scale (red color for high values, yellow for low values, respectively), while the sum of absolute differences ( $\Delta$ ) is reported for the grid obtained from H and CRm interpolations, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

one obtained from the real track. This  $\Delta$  was used as a common measure of distance for all the three indicators 5–7: higher values indicate a higher error, since a disagreement between real and interpolated grids has an effect both on the estimation of the number of cells occupied by fishing signals (Indicators 5 and 7) and on the aggregation of fishing activity (Indicator 6).

Finally, the tracks belonging to each métiers were used to evaluate the estimation of the total fishing impact obtained from interpolated data. A subseries of at least 10 tracks located in the same fishing area was identified for each métier, and these tracks were interpolated and plotted on the grid. Then, a quantitative comparison was carried out between the grids obtained for HF and the three interpolation approaches. The final maps were: (a) visualized (with the same 3 km  $\times$  3 km resolution of grid) using a color scale to map the amount of points assigned to each cell, and (b) compared by computing the value of  $\Delta$ , that is the cumulate difference of assigned points between corresponding cells of HF (used as reference) and interpolated datasets.

In the next sections, together with the results of the H and CRm methods, we also report the results of the CR method, in order to highlight the improvements obtained by the modified version of CR on the plain version. For the sake of conciseness and clarity, however, we decided not to show graphical results for CR.

### 3. Results

The comparison of the averages and of the sums of the linear distances among interpolated points and real coordinates (Table 1 and Fig. 3a<sub>1</sub>, b<sub>1</sub> and c<sub>1</sub>) highlights that, in the major part of tracks belonging to the three métiers, the CRm obtains the best perfor-

**Table 1**

Results of error computation for the three different interpolation algorithms applied on the dataset corresponding to the three different métiers. This analysis was carried out by computing and comparing the linear distances among coordinates of interpolated and real (HF) points. The second column of the table reports, for each métier, the number of cases (and the relative percentage) in which one of the algorithm results to be the characterized by the smallest value of  $\Delta$ , while the third column reports the range of  $\Delta$ , as described by the mean and standard deviation.

Method	N of cases in which the mean error is the smallest	Mean $\pm$ standard deviation (km)
Bottom otter trawl for demersal species (OTB)		
H	2/25 (8%)	1.18 $\pm$ 0.53
CR	0	1.06 $\pm$ 0.44
CRm	23/25 (92%)	0.65 $\pm$ 0.22
Trammel nets for demersal species (GTR)		
H	0	1.45 $\pm$ 0.72
CR	4/25 (16%)	1.27 $\pm$ 0.64
CRm	21/25 (84%)	0.98 $\pm$ 0.35
Purse seine for large pelagic fish (PS)		
H	0	1.27 $\pm$ 0.35
CR	1/25 (4%)	1.18 $\pm$ 0.43
CRm	24/25 (96%)	0.81 $\pm$ 0.28

manes. In fact, CRm interpolation resulted to be the best approach in 92% (for OTB), 84% (for GTR) and 96% (for PS) of tracks, respectively. In contrast, the H interpolation performed better in just two OTB tracks. The original CR method resulted the best approach for some tracks (four belonging to GTR and one belonging to PS) and, in general, it leads to intermediate results between H and CRm. This is evident by looking at the values of mean error affecting each interpolation method (Table 1): H method is characterized by the largest values (always larger than 1 km for all métiers) whereas CRm method is characterized by the smallest ones (always smaller than 1 km for all métiers), and CR ranged in an intermediate position between these two extremes. The scatterplots contrasting the cumulate absolute errors (Fig. 3a<sub>2</sub>, b<sub>2</sub> and c<sub>2</sub>) computed using H and CRm methods show that, with some exceptions (e.g. track 18 in OTB), when H method performs better, it gives results very similar to CRm.

Fig. 4 shows a track for each métier, consisting of 3 succeeding interpolations between 4 VMS positions at low frequency (2 h interval). These tracks have been chosen because they offer a visual explanation of the different features commonly found applying the different interpolation algorithm. It is clear that the different components related to engine and drift have different weights in the situations corresponding to the three métiers analyzed: the effect of drift is very small (almost negligible) for OTB, whereas it is not unimportant for the other two gears. Moreover, it is evident that the differences between H and CRm interpolations can be explained in terms of the ability of each interpolation method to accommodate winding portions of trajectories: CRm interpolations seems to be better than H interpolation in capturing large deviation from a linear path, while the two methods give very similar results for the linear portions of trajectories. This is particularly true for PS (looking at interpolation between LF2, LF3 and LF4 in Fig. 4c), where larger is the deviation from a linear path, larger are the errors affecting both interpolation methods, with the CRm even more powerful in approximating the curve described by the vessel trajectory. In contrast, H interpolation seems to be occasionally characterized by large deviation from the real track (e.g. interpolation between LF2 and LF3 in Fig. 4b). This is not the case of CRm, that seems to be more stable. Fig. 5 shows the distributions of the vessel speed values, as reported by *blue blox* data, and the estimated values for the drift. It seems that, while OTB and GTR works at speed values larger than those of drift, in PS fishing the role of engine and of drift are comparable. Moreover, the Wilcoxon rank sum and signed rank test did not reject the null hypothesis of homogeneity of the three series (OTB versus GTR:  $p$ -value = 0.4354; GTR versus PS:  $p$ -value = 0.08688; OTB versus PS:  $p$ -value = 0.4533). Two critical points are evident: (1) the estimated distribution of the drift is very similar in the three situations, and (2) the relative contribution of

the two components (engine and drift, respectively) progressively changes passing from OTB to GTR and then to PS.

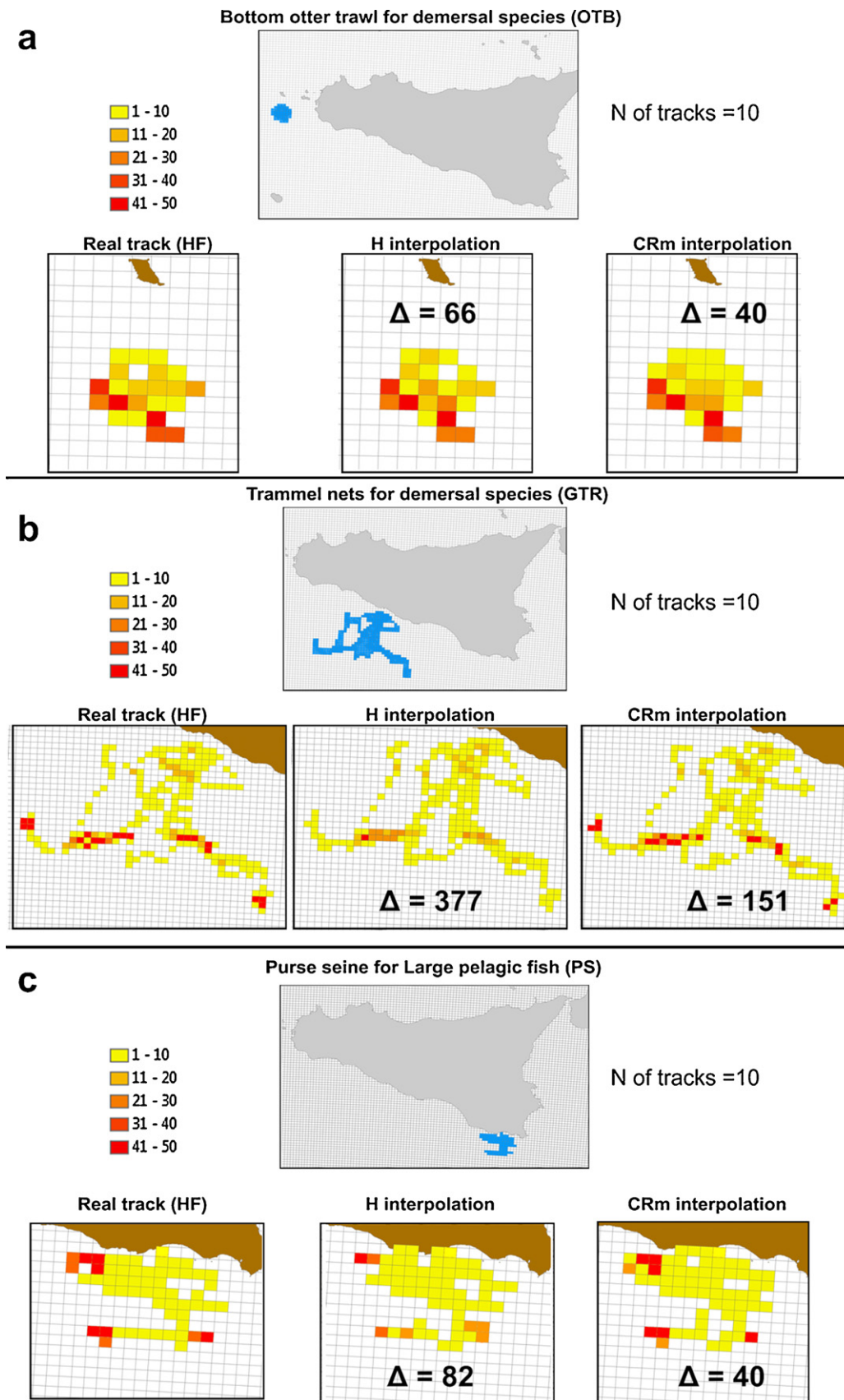
The comparison of the different activated grids, generated by using the original HF data and the H, CR and CRm interpolated ones, evidences that the range of error characterizing the CRm method is remarkably smaller than those of H method, with the original CR scoring in the intermediate position. Fig. 6 illustrates the output of this procedure for a single exemplificative track belonging to PS. These differences concern both the list of cells “activated” and the number of VMS signals assigned to these cells.

Finally, Fig. 7 shows the output of the analysis aimed to evaluate the additive effect of error characterizing each interpolation method. Each map, independently from the interpolation algorithm used, contains cells with a low and cells with an high number of assigned points. The discrepancies between the reference map, obtained using HF data, and the maps obtained using the H and CRm interpolated data, are computed as a  $\Delta$  value, that is the cumulate difference among the number of points for the cells of HF map and that of the H and CRm maps, respectively. The results suggested that the error affecting the different methods determines a cumulative effect when multiple tracks are interpolated and used to analyze the fishing effort within a given area. This can be only indirectly inferred, by looking at the value of  $\Delta$ , for OTB (Fig. 7a), since in this case the maps obtained from high frequency and interpolated data are very similar and the identified areas with high number of assigned points can be largely overlapped. In contrast, both graphical and numerical results for GTR (Fig. 7b) and PS (Fig. 7c) evidence a progressive decoupling of the patterns: while the values of  $\Delta$  remain stable for CRm, they increase for H, and the differences between the 2 maps from interpolated data are evident. In fact, the areas with high number of assigned points are not efficiently identified by the analysis of data interpolated by the H method, whereas those identified by the map of CRm data are remarkably well defined and coherent with those of the map of HF data.

#### 4. Discussion

The present work reports a further step in the development of an appropriate and efficient approach to the interpolation of fishing tracks between VMS registrations. Although a powerful method based on cubic Hermite splines has been recently proposed (Hintzen et al., 2010), the method introduced in this study remarkably enhances the ability to reconstruct the trajectories of trawl fishing vessels and extends this possibility to virtually whatever gears and/or métiers. That is, CRm method is useful in identifying fishing position for towed gears but also in improving the probability map of the different locations where passive and active gears were released. The CRm method explicitly introduces a new fac-





**Fig. 7.** Output of the comparative analysis of activated grids obtained from 10 tracks for each of the three métiers, located in the same fishing area. The figure on the top of each box visualized (in blue) the area in which each series of tracks is located (always near the Sicily region). The three map on the bottom of each box shows the distribution of fishing effort, represented by a color scale (red color for high values, yellow for low values). The sum of absolute differences ( $\Delta$ ) is reported for the grid obtained from H and CRm interpolations, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

tor, exploiting an important piece of information (already available in the VMS records), about the dynamic underpinning the spatial behaviour of vessels. Actually, it is devised to model the dynamics behind the spatial behaviour of vessels performing very different types of fishing activity. This is due to the decomposition of the vessel movement into two different components: the first related to boat rudder and engine (under the human control) and the second represented by the combined actions of sea current and wind, if eventually present. To the best of our knowledge, all the other existing methods are developed to model trajectories of trawls, that is a kind of towed gear always operating with the vessel in active movement at almost constant speed and direction: obviously, this happens when the effects of sea current and wind are negligible. In contrast, when the vessel is operating at very low speed and/or the human control is mainly devoted to regulating boat orientation in space (as in the case of GTR, when the vessel is shouting or hauling the nets), the effect of drifting could be not negligible, and it could be the main force in determining not linear (winding) trajectory of vessel through space. Mathematically speaking, the different ability to accommodate winding trajectories is explained by the construction of tangent vectors in the different methods. The simple specification of the tangent in H method reflects in a poorer interpolating accuracy when the path is too sinuous. The CR method, instead, behaves more satisfactorily. The contribution given by the CRm method is evident in all the cases, thanks to the modification of the norm of the CR tangents, and becomes even more important when the drifting action is not negligible. The fact that, in the CRm formulation, the tangent are computed using three control points is reasonably linked to the ability of this approach to accommodate complex trajectories: the more are the number of points used, the more is the power of the algorithm in capturing the “planned” trajectory of the vessel in space. This is evident, at a glance, by looking at the discrepancies among coordinates of interpolated and real points for a single track (Figs. 3 and 4).

As mentioned, CRm method needs four control points to interpolate tracks (instead of the H needing just two), so it could be argued that very short fishing tracks (three points or less) cannot be interpolated. However, fishing tracks reported in VMS are always preceded and followed by navigation tracks (since legislation imposes a minimum distance from the coast in the operative range of vessel) so that there is practically no loss in using the proposed method.

Although the H interpolation is able to identify deviation from a straight heading, so that it obviously performs markedly better than the commonly used straight line methods developed and applied by Eastwood (2007) and Stelzenmuller et al. (2008), it seems to systematically underestimate the curves described by vessel trajectory and is unable to reproduce the erratic behaviour of fishing vessels, such as sudden changes in direction, as stressed by Hintzen et al. (2010). This problem is remarkably reduced when using CRm algorithm. Secondly, the differences between differently interpolated trajectories result in statistically different evaluation of fishing effort in the space, as described by the  $3\text{ km} \times 3\text{ km}$  grid imposed by European Commission (COM, 2008). This is clear in both looking at single tracks and at the complex patterns obtained for series of tracks, and can be explained as the cumulated effect of error in single points. Hence, the CRm method has the ability to supply more accurate information at higher spatial resolution and could represent a better approach in interpolating fishing tracks that will be used for the assessment of the ecological indicators 5–7 (Bastardie et al., 2010; COM, 2008). Although we did not compute the final values of the ecological indicators 5–7 for the overall Italian fleet, the results of comparison between grids filled with fishing points (Fig. 7) clearly suggest that the chosen interpolation method can have an important effect on the error affecting the values of the indicators. Thus, the CRm method is a natural candidate to enhance

the computational ability of assessing the impact of fishing via the ecological indicators 5–7 of spatial extent of fishing.

The values obtained for the estimated drift (graphically summarized in Fig. 5) are in agreement with the values reported for the Mediterranean (Pujol and Larnicol, 2005), ranging between 0 and 4 km/h. Moreover, these distributions agree among the different métiers, which therefore differ for the relative importance of this component, as evidenced above. As the Wilcoxon test indicates that drift estimates are not métier-specific, our analysis of drift component is, at least preliminary, correct and sound. However, it is important to stress that here the CRm method was not applied for oceanographic purposes. Thus, the values obtained for the drift cannot be closely considered as indirect measures of sea current and wind, whereas they simply accommodate for the discrepancy between the engine push and the real trajectories described by fishing vessels.

Another important point is that, while the H approach needs an optimization step (which we do not perform here because we do not have a ‘training set’ of tracks) to tune some parameters in order to account for different behaviours of vessels, CRm method is totally automatic and free from any arbitrary constant. It automatically adapts to different métiers (and vessel behaviours), detecting the drifting action on the track. The apparent flexibility of CRm method is of great importance, since the accuracy of interpolation is critical in studies aiming at determining the impact of fishing on a specific ecosystem component for different métiers commonly used in the Mediterranean as well as in all the marine ecosystem of Europe (Frid et al., 1999; Blyth et al., 2004; Tillin et al., 2006; Craeymeersch et al., 2000). In conclusion, the will of thoroughly monitoring and analyzing the effect of fishing activity cannot abstract from the availability of an interpolation method that is able to soundly perform on all the métiers, even comprising towed, active, and passive gears, since all these types are recognized to have significant adverse impacts on marine ecosystem (ICES, 2009a).

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