The catchability in a spatial context: a simulation exercise

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The catchability (q) links the catch per unit effort and the biomass of a given stock. Assuming spatial distributions of fish and fishing effort are uniform in space, fishing mortality is also proportional to the fishing effort. Departure from these underlying assumptions reduces the use of this latter relationship. One solution often used in practice is to consider small regions where the spatial distributions can be considered uniforms. The objective of this study is to analyse the impact of different spatial distributions of fishermen on the catchability.

Fish density is modelled by a georeferenced variable. This continuous model suits well demersal species which are distributed everywhere. For pelagic species a point process would be prefered but the catchability gets then a more complex expression. Fishing effort is randomly allocated in space according to a probability map (the map of the fishing intensity). Fishing efficency is assumed to be 1, i.e. all fish in the filtered surface are caught.

In a spatial context, analytical solutions for the catchability are not available when fishing intensity is not uniform. So the mean of a large number of simulations is used to estimate it. Several types of probability distributions are considered from spatially homogeneous to spatially heterogeneous. Catchability increases with the heterogeneity of the fishing effort distribution, being maximum when both the fish and the fishermen are highly heterogeneous in space. In practice, when distributions are highly heterogeneous, the catchability might be significantly under-estimated if the distributions are assumed uniformed.

Key words: spatial structure, catchability, simulations.

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Introduction

Catchability, usually denoted q, is defined as the proportionality that exists between Catch Per Unit of Effort (*CPUE*) and fish abundance A: $CPUE = q \cdot A$. From this definition, catchability appears to be a quantity whose units are inverse of those of the fishing effort. Catchability and fishing effort are then linked by the definition of a unit of fishing effort. One can notice that this is not in complete accordance with other interpretations where the catchability is rather considered as the probability for a random fish to be caught by a unit of fishing effort (Gascuel, 1995). Mathematically, a probability is a number without unit.

The usefulness of catchability in fisheries management comes from the fact that under some assumptions on the spatial distributions of fish and/or fishing effort, the fishing mortality rate F is equal to the catchability times the fishing effort E: $F=q\cdot E$. Knowing the link between fishing effort and fishing mortality makes it possible to act on fishing mortality through fishing effort management.

Early in the mathematical developments (Beverton and Holt, 1957), the requirement of uniform distributions was considered as a serious restriction for the use of the proportionality between fishing effort and fishing mortality. One alternative often used consists in dividing the studied area in several sub-areas where one can consider that fish and/or fishermen are uniformly distributed. Several papers discuss the impact of non uniform spatial distribution of fishing effort in qualitative terms (e.g., Fréon and Misund, 1999). Hancok et al. (1995) studied the level of cooperation between vessels in a horse mackerel fishery but did not quantify the effect on catchability. Gauthiez (1997) based on a model where fish and fishing effort are known spatial distributions defined the catchability as their product. However, stochastic characteristics of effort allocation are not taken into account in his work. In the present paper, I intend to illustrate the potential of using stochastic point processes to quantify impact of fishing effort allocation on catchability. In these models, functions that drive the spatial distribution of fishing effort are interpreted as probability field i.e. numerical models giving the probability for a fisherman to be at a given location at a given time. Strong simplifications (fishing efficiency equal to 1; full gear efficiency) are made in this study and no real data are considered. Possible improvements and data conditioning are discussed.

When no density dependency is included in the model, the question raised becomes rather that of the sampling techniques: what is the information provided by preferential fishing?

Expression of the catchability in a spatial context

Fish density is represented by a georeferenced **deterministic** variable denoted z(x). The point x gets 1, 2 or 3 dimensions depending on the situation. For simplicity reasons, a 1D notation is used without lose of generality. Fish abundance over a given area S, is the space integral of the fish density over S:

$$A(S) = \int_{S} z(x) dx$$

This kind of model suites particularly demersal species whose distribution can be considered continuous in space. For pelagic species, this no longer holds but, one can adopt a point process type of model where z(x)/A represents the density of probability to get a school at point x. This kind of model would end up with a similar but more complicated expressions for the catchability. It is not considered here.

The fishing process is represented by the geographical set of the prospected zones. This set is denoted E. Its surface area, denoted |E|, corresponds to the overall fishing effort in terms of filtered surface (nominal fishing effort; no standardization is considered here). The fishing process gets two basic ingredients: a set of germs representing the vessel locations and a population of objects representing the surfaces filtered by the vessel gears (trawl, long-line, seine, etc) centered on these germs. Various situations can be considered depending on the random or deterministic characteristics of each component of the model. I have considered that:

germs are points of a **non homogeneous Poisson point process** X with intensity f(x) (Lantuéjoul, 2002). That means that both the number of vessels and their locations are modeled by random processes, and that the spatial distribution of the different fishing vessels is **not** uniform. This is consistent with a situation where the number of vessels present in the study area S during one unit of time is varying due to vessels movements and where fishermen are not homogeneously distributed in space due to some prior knowledge of fish distribution. In a non homogeneous Poisson point process, the number of vessels present in an area S follows a Poisson distribution with parameter $f(S) = \int_S f(x) dx$. The average number of vessels

present is then f(S). The probability field f(x) drives the location of germs in space (i.e. the spatial allocation of fishing effort). It is nothing but the fishing intensity field.

• The population of objects implemented on the set of germs is a family of **random** rectangles W(x).

The fishing process, modelled by a random set, might then be formulated as follow:

$$E = \bigcup_{x \in X} W(x)$$
$$|E| = \sum_{x \in X} |W(x)|$$

Catches are function of the fishing process E and are further denoted C(E). They correspond, in the ideal and virtual case where fishing efficiency is equal to 1, to the sum of the fish densities over the filtered surfaces:

$$C(E) = \sum_{x \in X} \int_{W(x)} z(x) dx$$

This makes C(E) a random quantity. Catchability is then the expected value of the CPUE divided by the abundance :

$$q = E\left\{\frac{CPUE}{A}\right\} = \frac{1}{A}E\left\{\frac{C(E)}{|E|}\right\} = \frac{1}{A}E\left\{\frac{\sum_{x \in X} \int_{W(x)} z(x)dx}{\sum_{x \in X} |W(x)|}\right\}$$

Analytical solutions being only available for cases where distributions are uniform, a Monte Carlo approach based on simulations are used to compute the expected value.

Simulation algorithm

In the present paper, the study area S corresponds roughly to the North Sea (Fig. 1). Fish distribution z(x) is simulated on a very fine grid by the Turning Bands method with a spherical variogram model (Chilès and Delfiner, 1999). The grid is 0.0125° by 0.0125° (approximately 0.42 n.mi. by 0.75 n.mi.). Data simulated by a Turning Bands algorithm are Gaussian. They have then been transformed as follow: $z_{new} = \exp(0.85 \cdot z_{old})$. The abundance is A = 1.04 e + 12 individuals.

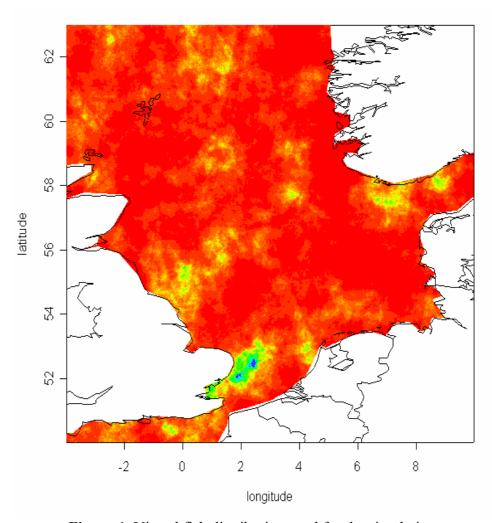


Figure 1. Virtual fish distribution used for the simulations.

In order to study the effect of fishing effort allocation on catchability, five fishing intensity fields f(x) have been used. The first situation assumes that fishermen have a perfect knowledge of fish distribution and that their spatial distribution is driven by a probability field equal to the fish distribution. In other words, the probability to fish is directly proportional to fish abundance : $f_0(x) = z(x)$. The four other situations mimic cases where the knowledge of the fish distribution is less and less accurate. This is generated by moving averages of the fish distribution z(x) with larger and larger neighborhoods. Neighborhoods are squares of +/- of 10, 25 and 100 grid cells. The corresponding fishing intensity fields are denoted respectively $f_{10}(x)$, $f_{25}(x)$ and $f_{100}(x)$ (Fig. 2). At the extreme, the last case corresponds to a uniform distribution of fishing effort over the fishing ground which could be the case when absolutely nothing is know about the fish distribution. This is the case when the fishing mortality coefficient is proportional to the fishing effort ($F=q \cdot E$).

For a given fishing intensity field, the simulation of points honoring this spatial distribution is done by an acceptation-rejection technique (Lantuéjoul, 2002). The number of vessels generated in each simulation follows a Poisson distribution with parameter equal to 500. That is to say that the mean number of vessels present in the North Sea is 500. A visual check of the result can be found Figure 2 where one can see that the distribution of fishing operations becomes more and more uniform as we use a more and more uniform fishing intensity field.

Considering a trawl fisheries, objects implemented on the Poisson point process are random rectangles with fixed width (10 m) and random length uniform between 1 km and 5 km. No density dependency is taken into account in order, for instance, to link the duration of a tow to the local fish density, the previous or neighboring catches, etc. As fish density is only known at discrete points (i.e. the grid nodes) it is difficult to integrate the fish density under the filtered surfaces. I rather multiplied the fish density at points location by the filtered surfaces:

$$C(E)^* = \sum_{x \in X} W(x)z(x)$$

For each of the 5 situations considered in this analysis, 400 simulations have been made. For each simulation a mean CPUE is computed. These are denoted CPUE.0, CPUE.10, CPUE.25, CPUE.100 and CPUE.unif respectively. The catchability coefficients (q_0 , q_{10} , q_{25} , q_{100} , q_{unif}) are then estimated by the average of the 400 mean CPUEs divided by the total abundance. As A is the same for all simulations, catchability coefficients are directly given by the mean CPUEs.

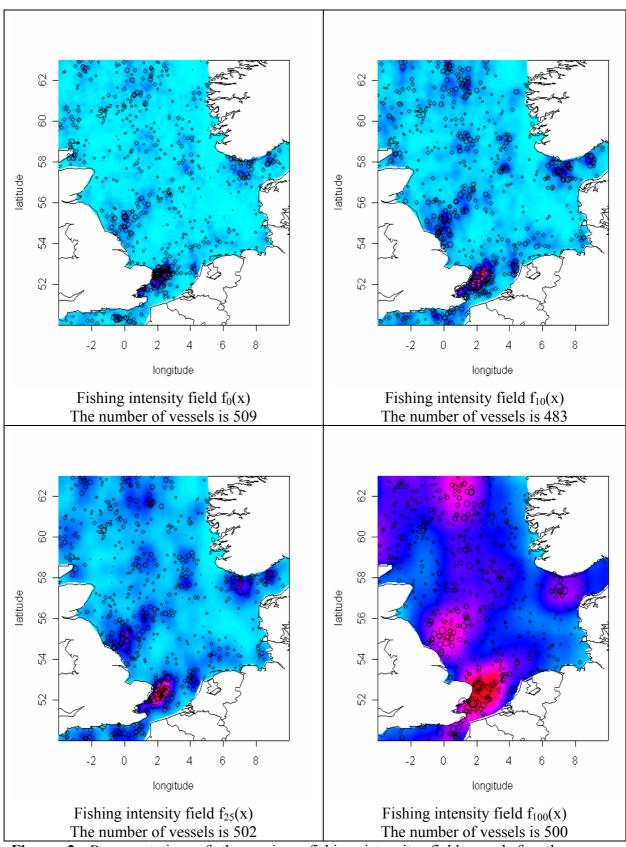


Figure 2. Representation of the various fishing intensity fields used for the simulations $(f_0(x), f_{10}(x), f_{25}(x), f_{100}(x))$. The uniform case is not represented. Superimposed to each map are examples of fishing effort distributions with a symbol proportional to the catch.

Results & discussions

Histograms of the 400 mean CPUE obtained for each of the 400 simulations generated for each of the 5 fishing intensity fields ($f_0(x)$, $f_{10}(x)$, $f_{25}(x)$, $f_{100}(x)$, $f_{unif}(x)$) are given Figure 3. Catchability coefficients correspond to the mean value of each histogram up to a division by the total abundance. It happens that when fishermen have a perfect knowledge of the fish distribution and that they distribute themselves according to this distribution (first case; $f_0(x)$ and CPUE.0), catchability is nearly twice the value it has when fishermen are distributed homogeneously. In between, catchability decreases regularly.

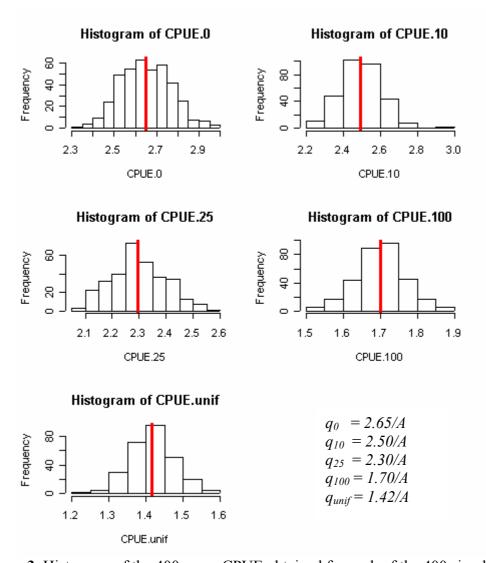


Figure 3. Histogram of the 400 mean CPUE obtained for each of the 400 simulations generated for each of the 5 fishing intensity fields $(f_0(x), f_{10}(x), f_{25}(x), f_{100}(x), f_{unif}(x))$. The mean values are represented by a vertical red lines.

In fisheries practice, catchability is often estimated through the well known equation q = F/E (Hilborn and Walters, 1992) where F, the mortality coefficient is estimated by Virtual Population Analysis and E is computed from effort data. This key equation based on the assumption that fish and/or fishermen are homogeneously distributed in space allows a control of fish mortality by a management of fishing effort (F = qE).

Hence, any under-estimation of the catchability coefficient induces an equivalent under-estimation of the fishing mortality rate. In the virtual and very simplistic example simulated in this paper, assuming that fishing effort is uniformly distributed in the North Sea while it is rather distributed according to probability field $f_{25}(x)$ would end up to an 37% under-estimation of the fishing mortality rate. That is to say that when the fishing mortality F is said to be 1, it should have been 1.6.

In highly harvested areas, one can consider that fishermen have an advanced even not precise knowledge of fish distribution: local rich spots are probably not known but rich areas are mapped. Such a situation could correspond to a probability field given by $f_{100}(x)$, or $f_{50}(x)$ (not considered explicitly here) or even $f_{25}(x)$. The increase of catchability when a better fit between fish and fishermen distributions is observed, is real. The risk to significantly under-estimate fishing mortality is then real.

Limits of this analysis are obvious. One of the major ones is the lack of data in the definition of the parameters of the model. Simulating a fish distribution conditionally to real fish densities does not represent a strong methodological difficulty. Conditional geostatistical simulation algorithms exist. Setting, estimating or choosing the parameters of the non homogeneous point process is much more challenging. Information like VMS records (when available) could provide a very useful material with regard to the parameterization of such point processes.

Fishing efficiency has been assumed equal to 1. It is obviously wrong. However the results obtained would not have changed if it was random and independent of fish distribution. The variability of the mean CPUEs would have changed but not their expected value. Still, it would be more sensible to consider density dependency processes.

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