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The analysis of convergence in ecological indicators: An application to the Mediterranean fisheries

M. Grazia Pennino[a,*], Jose Maria Bellido[a], David Conesa[b], Marta Coll[c,d], Emili Tortosa-Ausina[e]

[a] Instituto Español de Oceanografía, Centro Oceanográfico de Murcia, Murcia, C/Varadero 1, San Pedro del Pinatar, 30740, Murcia, Spain
[b] Departament d'Estadística i Investigació Operativa, Universitat de València, C/Dr. Moliner 50, Burjassot, 46100, Valencia, Spain
[c] Institut de Recherche pour le Développement, UMR MARBEC & LMI ICEMASA, University of Cape Town, Private Bag X3, Rondebosch, Cape Town 7701, South Africa
[d] Institut de Ciències del Mar (ICM-CSIC), Barcelona, Spain
[e] Department d'Economia, Universitat Jaume I, Campus del Riu Sec., 12080, Castelló de la Plana, Spain

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ABSTRACT

Ecological indicators are increasingly used to examine the evolution of natural ecosystems and the impacts of human activities. Assessing their trends to develop comparative analyses is essential. We introduce the analysis of convergence, a novel approach to evaluate the dynamic and trends of ecological indicators and predict their behavior in the long-term. Specifically, we use a non-parametric estimation of Gaussian kernel density functions and transition probability matrix integrated in the R software. We validate the performance of our methodology through a practical application to three different ecological indicators to study whether Mediterranean countries converge towards similar fisheries practices. We focus on how distributions evolve over time for the Marine Trophic Index, the Fishing in Balance Index and the Expansion Factor during 1950–2010. Results show that Mediterranean countries persist in their fishery behaviors throughout the time series, although a tendency towards similar negative effects on the ecosystem is apparent in the long-term. This methodology can be easily reproduced with different indicators and/or ecosystems in order to analyze ecosystem dynamics.

1. Introduction

Ecological indicators are used in many ecological studies to examine the evolution of natural ecosystems and impacts of human activities. Comparing their trajectories and their behavior to develop comparative analyses is fundamental (Dale and Beyeler, 2001; Shin and Shannon, 2010).

An important topic is whether indicators are converging to the same behavior, thus highlighting that an ecosystem is moving towards a similar environmental status, for which we need to compare the indicators trends over time and predict the tendencies of the indicators in the long-term. Here, we present a novel methodology adapted from previously contributions in the field of Economics (Barro and Sala-i-Martin, 1992; Quah, 1993a; Quah, 1993b) and its first application to Ecology research. Opposite to the previous contributions (Barro and Sala-i-Martin, 1992) that based the analysis only in the mean and standard deviation of the indicators, our approach deals with the entire distribution, allowing us to give a more detailed vision of their behavior. Specifically, the analytical strategy we adopt involves three steps: (1) the evaluation of the external shape of the distribution of the indicators of interest; (2) the assessment of convergence or/and divergence of indicator patterns; and (3) the prediction in the long-term of the indicators' trends.

Ecological indicators are used to estimate the condition of the marine ecosystems to provide an early warning signal of changes in the exploitation of fishing resources, or to diagnose the cause of an environmental problem (Dale and Beyeler, 2001; Niemi and McDonald, 2004; Mitsch et al., 2005; Turnhout et al., 2007). They are able to quantify the magnitude of an ecological response to such an exposure and, they additionally provide a simple and efficient method for examining the ecosystem structure and function (Dale and Beyeler, 2001; Fulton et al., 2005; Cury et al., 2005). In this

* Corresponding author at: Instituto Español de Oceanografía, Centro Oceanográfico de Murcia, Murcia, Spain.
E-mail address: graziapennino@yahoo.it (M.G. Pennino).

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study, we use the analysis of convergence to investigate whether Mediterranean countries tend to converge in three ecological indicators calculated to characterize the impact of fishing in this basin: the Marine Trophic Index (Pauly and Watson, 2005), the Fishing in Balance index (Pauly et al., 2000; Christensen, 2000) and the Expansion factor (Kleisner et al., 2014). We calculate these three indicators per country and analyze, using the proposed distribution dynamics model, whether Mediterranean countries evolve to better or worse fishing practices and, consequently, we can forecast their impact based on those long-term tendencies.

This example takes into account the dynamic nature of ecosystems, especially when subjected to an industry, such as fishing, which is continuously undergoing rapid changes. Countries can differ on how they adjust to shifts in the fishery industry (new technologies, market prices and national laws), either in their speed of adaptation or in their degree of preparation for such shifts.

Nowadays it is widely accepted that a continuous failure (or lack) of fishing management is one of the most important factors both of the decreasing trend in world catches (Pauly and Zeller, 2016) and the higher impact of fisheries on the marine ecosystems (Hollingworth et al., 2000; Worm et al., 2006; Akpalu, 2009; Doyen et al., 2012 Worm and Branch, 2012). Therefore, the United Nations Food and Agriculture Organization (FAO) has called for the application of an Ecosystem Approach to Fisheries Management (EAFM), which aims to a sustainable exploitation of commercial fisheries (Pikitch et al., 2004; Cotter et al., 2009). A number of different methods and indicators for evaluating fisheries interactions in the ecosystem are now available (*e.g.* http://www.ebmtools.org). However, many of these methods are unsuitable for data-poor situations because they require detailed information that is generally difficult to achieve (Rosenberg et al., 2014).

The Mediterranean basin is a complex region that includes many different ecosystems characterized by a high level of marine biodiversity (Coll et al., 2010). The Mediterranean is at the crossroads between three continents, Asia, Africa and Europe, with very different cultural backgrounds, forms of governments and levels of development (Gonzalez-Riancho et al., 2009). Mediterranean fisheries are highly diverse and geographically varied, not only because of the existence of different marine environments, but also because of different socio-economic situations, and fisheries status (Colloca et al., 2013). The heterogeneity between countries can be investigated by the study of the behavior of the fishery exploitation in the different Mediterranean countries. Our hypothesis is that overfishing in developed countries could have generated negative effects/symptoms in the ecosystem that could be identified, prevented and cushioned in developing countries before they appear or are very high, thus preventing overexploitation of marine resources.

2. The analysis of convergence

2.1. Nonparametric estimation of the univariate density functions

The first step to evaluate how the entire distribution of a particular indicator evolves over time is to estimate non-parametrically their corresponding density functions for each sample year, or groups of years. The implications of this method for the analysis of dynamics are as follows: if the probability mass of a given indicator tends to be more markedly concentrated around a certain value, convergence for such an indicator is achieved. This outcome would imply that the behavior of the different countries tends to become gradually more similar in terms of the indicators being used. On the contrary, the opposite outcome (divergence) would be achieved if the probability mass was increasingly spread across a wider range, implying greater heterogeneity in the behavior of countries.

Different methods are available to estimate the density function of an indicator (Tortosa-Ausina, 2002). Here we propose the use of kernel smoothing. This technique is one of the most widely used in many situations, its properties are easily understood, and its discussion make it easier to deal with other methods (such as the naive estimator, the orthogonal series estimator, or the penalized maximum likelihood estimator) (Silverman, 1986; Scott, 1992).

This type of visual analysis (since we focus on how the shape of the distributions evolves) provides a flexible way to identify the real structure of the data without imposing any parametric model. Consequently, the use of these techniques makes it possible to reveal certain data structures such as, for example, a bimodal structure (which is impossible to uncover through a parametric unimodal model).

The kernel smoothing consists primarily of estimating the following density function for any indicator of interest:

$$\hat{f}(x) = \frac{1}{Sh}\sum_{s=1}^{S} K\left(\frac{x - Ei_s}{h}\right), \quad (1)$$

where S is the number of countries being analyzed, Ei_s is the specific indicator, K is a kernel function and h is the bandwidth, window width or smoothing parameter.

There are multiple options for the kernel selection, including, among others, the Epanechnikov, triangular, Gaussian or rectangular methods. In our case, and based on the easiness of computation, we use the Gaussian kernel, which univariate expression is:

$$K(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}t^2}. \quad (2)$$

After incorporating this kernel, Eq. (1) becomes:

$$\hat{f}(x) = \frac{1}{Sh}\sum_{s=1}^{S} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\frac{(x - Ei_s)}{h}}. \quad (3)$$

Whereas kernel selection determines the form of the bumps when the smoothing parameter h influences it differently, by determining the width of such bumps. However, bandwidth selection is far more important than kernel selection.

In this regard, the performance of the plug-in bandwidth proposed by Sheather and Jones (1991), based on the second generation method solve-the-equation plug-in-approach, is superior, in terms of a better balance between bias and variance, to the first generation methods (as shown by Jones et al., 1996). It is available through several statistical software packages such as R (R Development Core Team, 2016). In the particular case of R, it is included in the "*KernSmooth*" package, by Matt Wand (Wand, 2015), via the "*dpik*" (direct plug-in) function.

2.2. Intra-distribution mobility

Nonparametric estimation of the univariate density functions provides information on the *shape* of the densities but conceals some dynamic patterns. In particular, it can be argued that the evolution of the densities might not offer a clear pattern either towards convergence or divergence while significant intra-distribution movements were taking place simultaneously. In other words, although the external shape of the density function might remain unaffected over time, changes in countries' relative positions, intra-distribution mobility or *churning* could be taking place.

In order to overcome such shortcomings, a law of motion of the cross-section distribution is required; *i.e.* dynamics can be modeled with more precision. Finding out such a law and, therefore, drawing conclusions on the dynamics of the cross-section distribution of a given indicator, requires modeling the stochastic process that takes