SCRS/2015/146 Collect. Vol. Sci. Pap. ICCAT, 72(6): 1544-1552 (2016)

A CONSIDERATION OF ADDITIONAL VARIANCE IN THE MEDITERRANEAN AERIAL SURVEY BASED ON ELECTRONIC SATELLITE TAGS

G. Quílez Badía[1], S. Tensek[2], A. Di Natale[2], A. Pagá García[2], A. Cañadas[3], T. Kitakado[4], L.T. Kell[2]

SUMMARY

The GBYP aerial survey is intended to provide a fisheries independent index of abundance. Abundance estimates from successive years, however, may vary more than would be expected on the basis of survey observation error alone, due to inter-annual variations in the numbers of fish moving into or out of the survey areas or changes in vertical migration related to oceanographic conditions. The objective of this paper is to propose a methodology that could be used to estimate additional variance and be used to possibly design an integrated tagging and aerial survey.

RÉSUMÉ

Les prospections aériennes du GBYP visent à fournir un indice d'abondance indépendant des pêcheries. Les estimations de l'abondance d'années successives peuvent toutefois varier davantage que prévu en fonction des erreurs d'observation des prospections, en raison des variations interannuelles dans le nombre de poissons se déplaçant à l'intérieur ou à l'extérieur des zones de prospection ou des changements dans les migrations verticales liées aux conditions océanographiques. L'objectif de ce document est de proposer une méthodologie qui pourrait servir à estimer la variance supplémentaire et à concevoir une prospection aérienne et une autre prospection de marquage intégrées.

RESUMEN

La prospección aérea del GBYP tiene como objetivo proporcionar un índice de abundancia independiente de la pesquería. Sin embargo, las estimaciones de abundancia de años sucesivos pueden variar más de lo esperado en base solo al error de observación de la prospección, debido a las variaciones interanuales en los números de peces que entran o salen de las zonas de prospección o a los cambios en la migración vertical relacionados con las condiciones oceanográficas. El objetivo de este documento es proponer una metodología que podría utilizarse para estimar la varianza adicional y ser utilizada para diseñar una prospección aérea y otra de marcado integradas.

KEYWORDS

Additional Variance, Aerial Survey, Cost benefit, Power Analysis, Tagging

1. Introduction

The over-riding objectives of fisheries management are the long-term sustainable use of fishery resources and the development of ways to optimise the benefit derived from them (Cochrane and Garcia, 2009). While the aim of a robust management framework is to ensure that objectives are met with high probability despite the presence of uncertainty or stressful environmental conditions (Radatz *et al.*, 1990). To provide robust scientific management advice requires that our understanding of biological and ecological processes and data collection schemes are sufficient (Kell *et al.*, 2015).

[1] WWF Mediterranean Programme Office, Carrer Canuda, 37, 3er, 08002 Barcelona, Spain
[2] ICCAT Secretariat, C/Corazón de María, 8, 28002 Madrid, Spain
[3] Pradillos 29, 28491 Navacerrada. Spain
[4] Faculty of Marine Science, Tokyo University of Marine Science and Technology

One of the main inputs in tuna stock assessments is commercial catch per unit effort (CPUE), used as a proxy for relative abundance. It has long been recognised, however, that CPUE does not accurately reflect trends in population abundance (e.g. Beverton and Holt, 1993; Harley *et al.*, 2001; Maunder *et al.*, 2006; McKechnie *et al.*, 2013; Polacheck, 2006). It has also been stated many times by the SCRS, that the fisheries data available to the SRCS for the bluefin assessment are unreliable. It is also known that oceanographic factors that affect the spatial distribution of populations vary (Fromentin *et al.*, 2013; Bonhommeau *et al.*, 2013; Di Natale and Tensek S., 2015) and the allocation of effort in response to management and economic drivers affects catch and effort independently of stock abundance (e.g. Paloheimo and Dickie).

Aerial surveys are commonly used to provide fisheries independent indices for cetaceans (Hammond *et al.*, 2002) and have recently been used to develop indices of abundance for large pelagics (Basson and Farley, 2014; Fromentin *et al.*, 2003). When designing any monitoring programme it is essential to determine the magnitude of population change that can be detected within management time scales (Nicholson and Jennings, 2004). This can be done by conducting a power analyses (see Gerrodette, 1987; Fortuna *et al.*, 2014) if the variance of the index is known. See http://www.iccat.es/GBYP/Documents/ASURVEY/PHASE%203/Aerial_Survey_Feasibility_Study_Phase3.pdf for a power analysis conducted for the GBYP aerial survey.

Abundance estimates from successive years, however, vary more than would be expected on the basis of survey observation error alone; due to inter-annual variations in the numbers of fish moving into or out of the survey areas or changes in vertical migration related to oceanographic conditions. This additional variance, due to process error, reflects the extent to which abundance estimates from repeat surveys of the same area in successive years will vary more than would be expected due to observation error alone.

The objective of this paper is to propose a methodology that could be used to estimate the magnitude of additional variance. We first evaluate the power of an aerial survey to detect changes in population abundance for surveys with different assumed levels of precision and potential population growth rates. We then show how additional variance could be estimated and discuss how electronic tags could be used to help design an integrated tagging and aerial survey for use as an empirical management procedure (Hillary *et al.*, 2013).

2. Material and Methods

An aerial survey of bluefin tuna has taken place since 2010 during the spawning season in the Mediterranean in areas where schools can be sighted close to the surface (Di Natale, 2011). If the vertical distribution of individuals in the spawning season varies by year, this may lead to inter-annual variability over and above that due to sampling alone. Therefore, integrating the variance of the abundance estimates over survey areas will only account for sampling variance. The missing variance component, additional variance, is due to the behaviour of individuals which may vary between years.

As part of the GBYP, there is also an electronic tagging programme, with electronic satellite tags, designed to monitor the migration behaviour of fish over a maximum of twelve months; these tags report average time spent within a depth band. It may be possible to evaluate the impact of changes in the probability of detecting individuals due to vertical migration. It is more difficult to evaluate the impact of inter-annual difference in the use of survey (i.e. spawning) areas since the life of tags is only a maximum of twelve months. The time series of data is usually less, due to premature releases or fishing events. Other internal archival electronic tags, that have a recording life of up to nine years have been deployed under the GBYP, but none of these tags has been recovered so far. The approach discussed, however, could evaluate additional variance due to inter-annual variation in spatial distribution given a suitable tagging programme.

2.1 Material

The aerial survey conducted by the GBYP is based on a line transect sampling survey (Cañadas *et al.*, 2010; Cañadas and Vazquez, 2010). The areas surveyed in 2014 are shown in **Figure 1**. Timing of the aerial surveys coincides with the peak of the spawning season, usually for about five weeks, varying from year to year depending on operational constraints. In 2015 the survey was conducted between June 1st and July 5th. The electronic tagging programme was designed to monitor the migration of fish over a twelve month period, these tags also reported average time spent within a depth band (in metres), i.e. at surface, between 0 and 2m, 2 and 10m and below 10m. Data related to bluefin tunas in the Mediterranean Sea during the spawning season are available from 41 electronic satellite tags from 2011 through 2015.

Usually, the GBYP aerial survey is able to detect tunas from the surface to up to a depth of 10m (for sightings just below or very close to the aircraft if tunas are not at the surface). Therefore, the percentage of time spent in the first 10m has an impact on the sighting probabilities of the survey.

2.2 Methods

2.2.1 Power Analysis

A power analysis was conducted to evaluate the ability of the survey to detect trends for different population growth rates. The conditional population growth rates (*r*) at F_{MSY} and five times F_{MSY} were estimated using the Leslie Matrix (Caswell, 1989), as 0.08 and 0.22 respectively. A significance level of 5% and a detection power of 60% were used, based on conventional practice. Survey CVs considered were 20%, 30% and 40%.

2.2.2 Additional Variance

All equations are given in **Table 1**.

If an area of A blocks is covered at least once during two survey periods and $\tilde{N}_{ay}$ is the actual abundance in the a^{th} block in year y, $\hat{I}_{ay}$ the relative abundance estimate and q the constant of proportionality, then assuming that the abundance estimates are multivariate log-normally distributed then they are given by equation (1), where $\tilde{\varepsilon}_{ay}$ is a random error. The corresponding variance is given by equation (2) where n is the sampled numbers, $\hat{w}$ the effective sample width (ESW) and $\hat{E}[s_i]$ mean school size (MSS).

If the estimates share common parameters such as ESW and MSS across years and blocks then the error terms are correlated and the covariance between the two abundance estimates is given by equation (3), (Buckland *et al*., 2001).

To make the errors, $\varepsilon=(\varepsilon_1,\ldots,\varepsilon_d)'$, satisfy the unbiasedness of abundance estimates and the variance-covariance formula (equation (3)), the mean, variance, and covariance of the errors in log space are given by equation (4), while if abundance varies randomly over year by equation (5), where N_{ay} is the expected abundance in the a^{th} block in year y, and ρ_{ay} is a random effect accounting for inter-annual changes in the distribution of the fish population in the surveyed area.

The random effects are assumed to be independent and identically distributed (IID) with a normal distribution, equation (6), where σ is the additional coefficient of variation since $Var[\tilde{N}_{ay}]=\sigma^2 N_{ay}^2$.

The parameter of interest in this study is the additional variance σ^2, equation (7). Where $Y=log\hat{}N$ is the vector of log-abundance estimates, X is the design matrix for the fixed-effects in the linear predictor for $logN_{ay}$, D and $\tilde{Z}$ and are the variance-covariance matrix for $\rho=(\ldots,\rho_{ay},\ldots)$ and ε.

The best unbiased estimator of β is given by equation (8), where $Y^*=Y+½Zdiag(D)+½diag(\hat{}\sigma)$ and $V(\sigma^2)=\hat{}\sigma$, and equation (9). Uncertainty is assessed by the inverse of the second derivative with respect to σ^2.

3. Results

The aerial survey gave biomass estimates of 15,553t (-), 46,234t (40%) and 9,100t (45%) in 2010, 2011 and 2013 respectively, equivalent estimates in numbers were 561,369 (41%) and 138,650 (35%) in 2011 and 2013 respectively. Numbers in brackets give the survey CV.

A power analysis was conducted for three levels of survey CV (20%, 30% and 40%) and annual and biennial survey frequencies (**Figure 2**). This shows, for example, that for a survey CV of 40% it would take 12 years before a population increase due to a 0.1 population growth rate could be detected.

The variations in depth of individuals are shown by month and year in **Figure 3**, while **Figures 4** and **Figure 5** show the change in oceanographic conditions in July between 2013 and 2014. Areas in black show zones where the oceanography is potentially not suitable for bluefin tuna spawning, having temperatures out of the best suitable range of 20.5 to 26 degree C. These plots show that there are environmental factors that may affect the distribution of bluefin and hence the probability of detection, i.e. q the relationship between population abundance ($\tilde{N}$) and the index (I).

4. Conclusions

- An aerial survey index with a CV of 40% means that a population growth rate of +/-0.25 will take about 6 years to detect. The estimate of a 40% CV is solely based on the survey (i.e. measurement) error, additional variance due to factors such as changes in vertical migration and spatial distribution will mean the true CV in the aerial survey index will be greater.

- Tagging data could be used to estimate changes in the distribution of spawning adults between years. This may allow *q* to be estimated by year and hence the survey indices to be adjusted. Before this can be done, however, it is important to estimate the magnitude of additional variance in the survey. Then to conduct a cost benefit analysis where different survey designs and their costs are compared to the survey CV.

- Then tagging data should be analysed independently to provide estimates of process error, and compared to those from the aerial survey. This will help to specify a simulation study that could be used as an observation error model (OEM) as part of a management strategy evaluation (MSE). Either to evaluate whether the aerial survey could be used as an empirical harvest control rule (HCR), or a tagging aerial survey be developed using adaptive management.

- The objective was to discuss the potential impact of variations in temporal and spatial distribution and to propose a methodology that could be used to design an integrated tagging study and aerial survey. Process error or additional variance results from the fact that the estimated sampling variances for the abundance estimates do not account for variability of abundance level, especially due to inter-annual changes in distribution of the population in the surveyed areas. If the additional variance is ignored, uncertainty on abundance estimates tends to be underestimated (Kitakado *et al*., 2008). Process error can be estimated if replicates of the surveys in each block are conducted in different years (Kitakado *et al*., 2005).

References

Basson, M. and Farley, J. H. (2014). A standardised abundance index from commercial spotting data of southern bluen tuna (*Thunnus maccoyii*): Random effects to the rescue. PLoS one, 9(12):e116245.

Beverton, R. and Holt, S. (1993). On the dynamics of exploited fish populations, volume 11. Springer.

Bonhommeau, S., Etienne, M.-P., Fromentin, J.-M., R., H., and Kell, L. (2013). Eastern bluefin tuna (*Thunnus thynnus, L.*) reproduction and reproductive areas and season. ICCAT Collect. Vol. Sci. Pap., 69(2):891-912.

Buckland, S. T., Anderson, D. R., Burnham, K. P., Laake, J. L., Borchers, D., and Thomas, L. (2001). Introduction to distance sampling estimating abundance of biological populations.

Cañadas, A., Hammond, P., and Vazquez, J. (2010). Elaboration of 2011 data from sst and the aerial survey on spawning aggregations. ICCAT GBYP 2010, Phase 1.

Cañadas, A. and Vazquez, J. (2010). Short-term contract for assessing the feasibility of a large-scale aerial survey on bluefin tuna spawning aggregations in all the Mediterranean Sea for obtaining useful data for modelling purposes. ICCAT GBYP Phase 3, Final report.

Caswell, H. (1989). Matrix population models. Wiley Online Library.

Cochrane, K. L. and Garcia, S. M. (2009). A fishery manager's guidebook. John Wiley & Sons.

Di Natale, A. (2011). ICCAT GBYP Atlantic-Wide Bluefin Tuna Research Programme 2010 GBYP coordinator detailed activity report for 2009-2010. Collect. Vol. Sci. Pap. ICCAT, 66(2):995-1009.

Di Natale, A. and Tensek S., P. G. A. (2016). *In press.* SCRS/2015/154. Is the bluefin tuna facing another 2013? 17 p.

Fortuna, C. M., Kell, L., Holcer, D., Canese, S., Filidei Jr, E., Mackelworth, P., and Donovan, G. (2014). Summer distribution and abundance of the giant devil ray (*Mobula mobular*) in the Adriatic Sea: Baseline data for an iterative management framework. Scientia Marina, 78(2):227-237.

Fromentin, J.-M., Farrugio, H., Deflorio, M., and De Metrio, G. (2003). Preliminary results of aerial surveys of bluefin tuna in the western Mediterranean Sea. Collective Volume of Scientific Papers, 55(3):1019-1027.

Fromentin, J.-M., Reygondeau, G., Bonhommeau, S., and Beaugrand, G. (2013). Oceanographic changes and exploitation drive the spatio-temporal dynamics of Atlantic bluefin tuna (*Thunnus thynnus*). Fisheries Oceanography.

Gerrodette, T. (1987). A power analysis for detecting trends. Ecology, pages 1364-1372.

Hammond, P., Berggren, P., Benke, H., Borchers, D., Collet, A., Heide-Jorgensen, M., Heimlich, S., Hiby, A., Leopold, M. F., and Oien, N. (2002). Abundance of harbour porpoise and other cetaceans in the North Sea and adjacent waters. Journal of Applied Ecology, 39(2):361-376.

Harley, S. J., Myers, R. A., and Dunn, A. (2001). Is catch-per-unit-effort proportional to abundance? Canadian Journal of Fisheries and Aquatic Sciences, 58(9):1760-1772.

Hillary, R., Ann Preece, A., and Davies, C. (2013). MP estimation performance relative to current input CPUE and aerial survey data. CCSBT Extended Scientific Committee held in Canberra, 1309(19).

Kell, L., Levontin, P., D. C., Harley, S., D., K., Maunder, M., I., M., G., P., and Sharma, R. (2015). Fisheries management science: an introduction to simulation based methods. In Edwards, C. and Dankel, D., editors, Fisheries management science: an introduction to simulation based methods.

Kitakado, T., Shimada, H., Okamura, H., and Miyashita, T. (2005). Review of abundance estimate and additional variance for the western North Pacific stock of Bryde's whales. Technical report, Paper SC/57/PFI1. 20pp.

Kitakado, T., Shimada, H., Okamura, H., and Miyashita, T. (2008). Cla abundance estimates for western North Pacific Bryde’s whales and their associated CVs with taking the additional variance into account. Technical report, Paper SC/60/PFI13 submitted to the IWC Scientific Committee, 2008 (unpublished). 25pp.

Maunder, M. N., Sibert, J. R., Fonteneau, A., Hampton, J., Kleiber, P., and Harley, S. J. (2006). Interpreting catch per unit effort data to assess the status of individual stocks and communities. ICES Journal of Marine Science: Journal du Conseil, 63(8):1373-1385.

McKechnie, S., Hoyle, S., and Harley, S. (2013). Longline CPUE series that account for changes in the spatial extent of fisheries. Technical report, WCPFC-SC9-2013/SA-IP-05.

Nicholson, M. D. and Jennings, S. (2004). Testing candidate indicators to support ecosystem-based management: the power of monitoring surveys to detect temporal trends in fish community metrics. ICES Journal of Marine Science: Journal du Conseil, 61(1):35-42.

Paloheimo, J. and Dickie, L. (1964). Abundance and fishing success. Rapports et Proces-Verbaux des Réunions du Conseil International pour l’Exploration de la Mer, 155.

Polacheck, T. (2006). Tuna longline catch rates in the Indian Ocean: Did industrial fishing result in a 90% rapid decline in the abundance of large predatory species? Marine Policy, 30(5):470-482.

Radatz, J., Geraci, A., and Katki, F. (1990). IEEE standard glossary of software engineering terminology. IEEE Std, 610121990:121990.

Tidd, A. N., Hutton, T., Kell, L., and Padda, G. (2011). Exit and entry of fishing vessels: an evaluation of factors affecting investment decisions in the North Sea English beam trawl fleet. ICES Journal of Marine Science: Journal du Conseil, 68(5):961-971.

Table 1. (Equations)

$$log\hat{I}_{ay} = log(q) + log(\tilde{N}_{ay}) + \tilde{\varepsilon}_{ay} \tag{1}$$

$$v\hat{a}r(\hat{I}) = \hat{I}_i^2 \left\{ \frac{var(n_i)}{n_i^2} + \frac{var(\hat{w})}{\hat{w}^2} + \frac{var(\hat{E}[s_i])}{\hat{E}[s_i]^2} \right\} \tag{2}$$

$$c\hat{o}v(\hat{I}_i, \hat{I}_j) = \hat{I}_i \hat{I}_j \left\{ \frac{var(\hat{w})}{w^2} + \frac{var(\hat{E}[s])}{\hat{E}[s]^2} \right\} = \hat{I}_i \hat{I}_j CV_{ij}^2 \tag{3}$$

$$\begin{aligned} E[\varepsilon] &= -\tfrac{1}{2}log(1 + CV_i^2) \\ Var[\varepsilon_1] &= -\tfrac{1}{2}log(1 + CV_i^2) \\ Cov[\varepsilon_i, \varepsilon_j] &= log(1 + CV_{ij}^2)(i \neq j) \end{aligned} \tag{4}$$

$$log(\widetilde{N}_{ay}) = logN_{ay} + \rho_{ay} \tag{5}$$

$$\tilde{N}(-\frac{1}{2}log(1 + \sigma^2), log(1 + \sigma^2)) \tag{6}$$

$$\begin{aligned} &Y = X\beta + Z\rho + \varepsilon \\ &\rho \sim N(-\tfrac{1}{2}diag(D), D), D = log(1 + \sigma^2)I \\ &\varepsilon \sim N(-\tfrac{1}{2}diag(\hat{\sigma}), \hat{\sigma}), \hat{\sigma} = (log(1 + CV_i^2 j))_{ij} \end{aligned} \tag{7}$$

$$\beta(\sigma^2) = (X'V(\sigma^2)^{-1})^{-1}X'V(\sigma^2)^{-1}Y^* \tag{8}$$

$$l_{REML}(\sigma^2) = -\frac{1}{2}|V(\sigma^2)| - \frac{1}{2}log|X`V(\sigma^2)^{-1}X| - \frac{1}{2}(Y^* - X\beta V(\sigma^2))'V(\sigma^2)^{-1}(Y^* - X\beta(\sigma^2)) \tag{9}$$

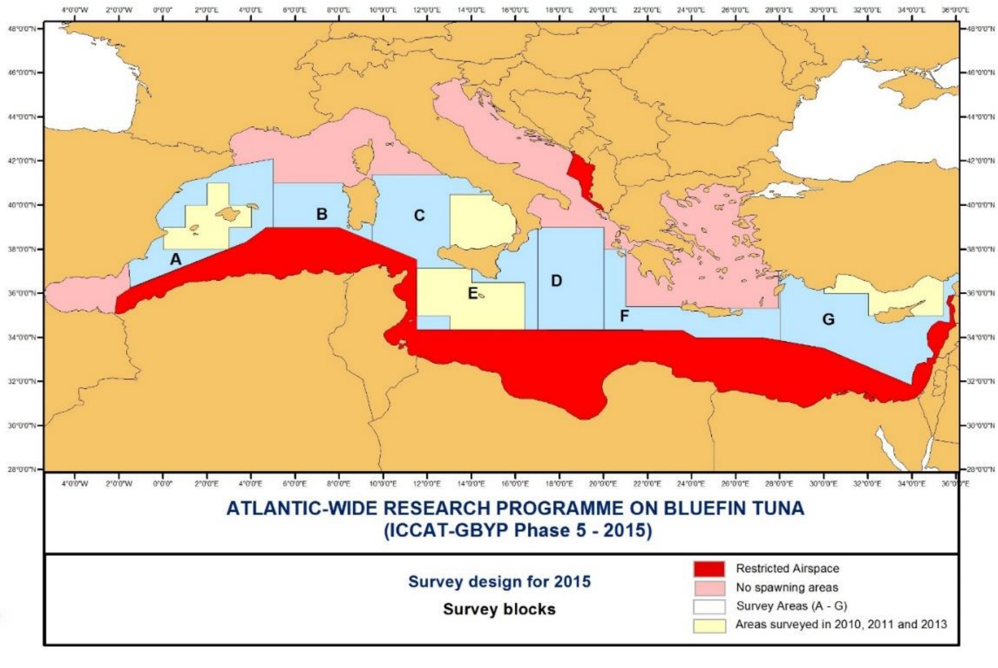

Figure 1. ICCAT GBYP aerial survey on spawning aggregations, areas surveyed in 2015.

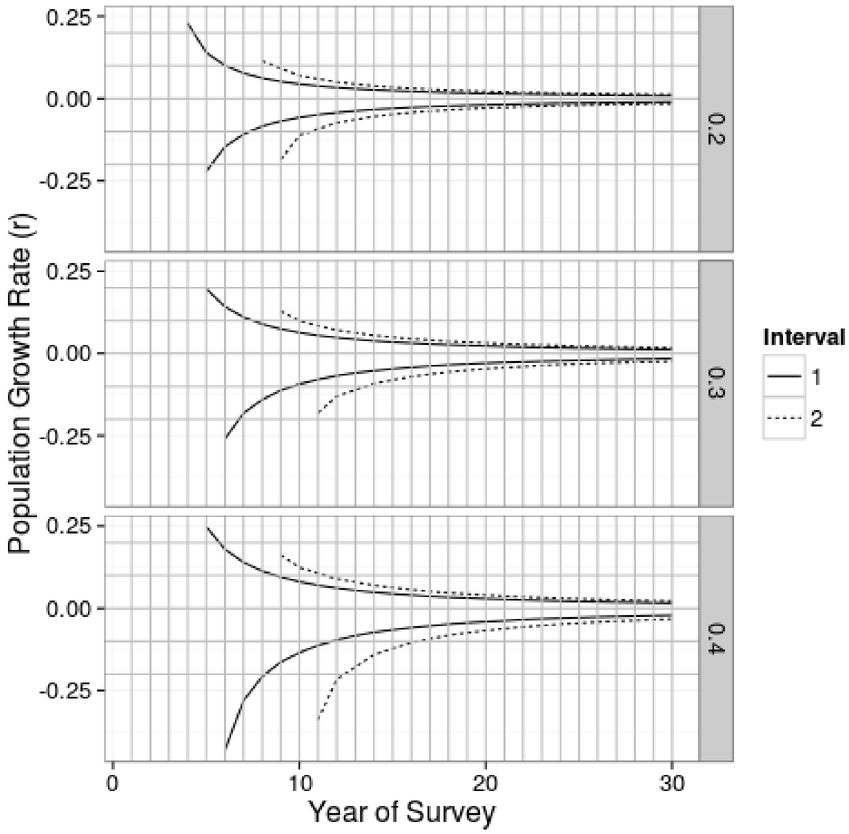

Figure 2. Power Analysis: Power analysis; contours correspond to a probability of 0.6 that a change in the population size will be detected. i.e. the time (x-axis) taken to detect a change is given by the intercept between a curve and horizontal line corresponding to a given population growth rate (y-axis); panels correspond to survey CVs of 20,30 and 40%.

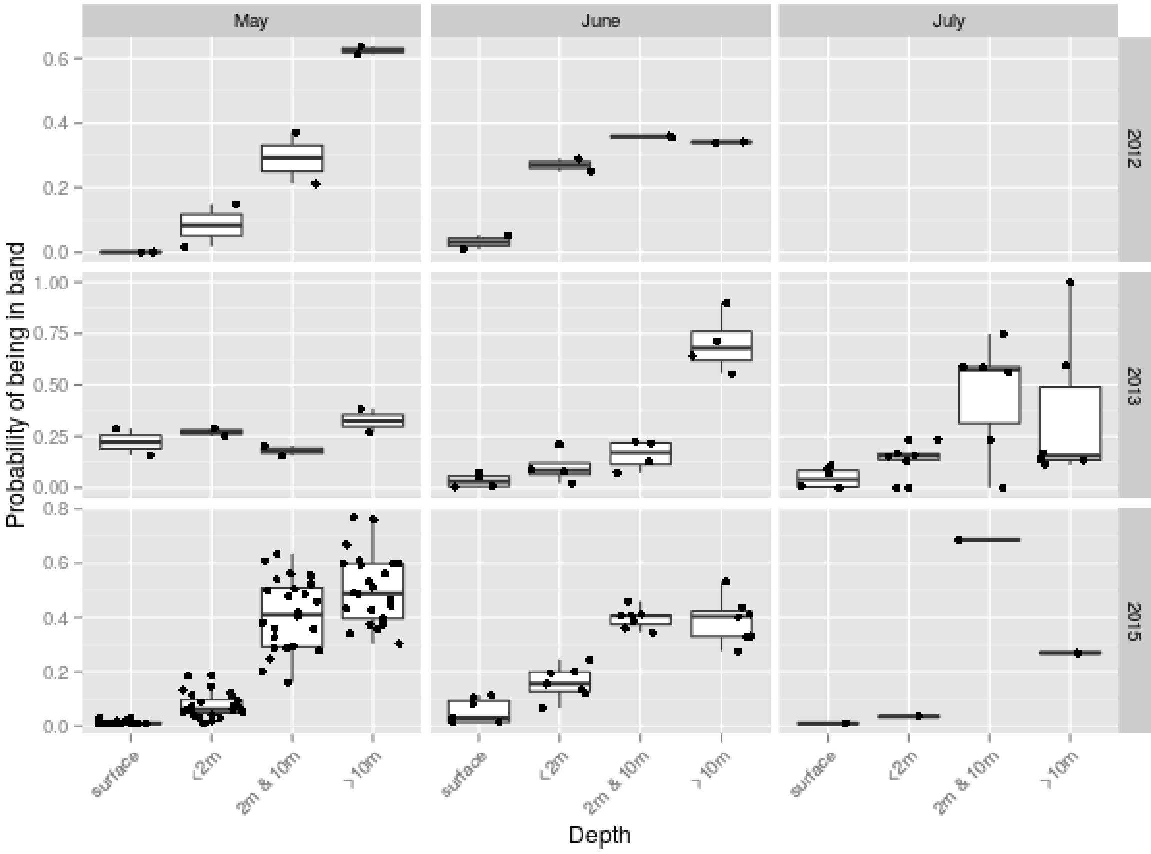

Figure 3. Depth Distribution of electronic tags; implanted under ICCAT GBYP 2012-2015.

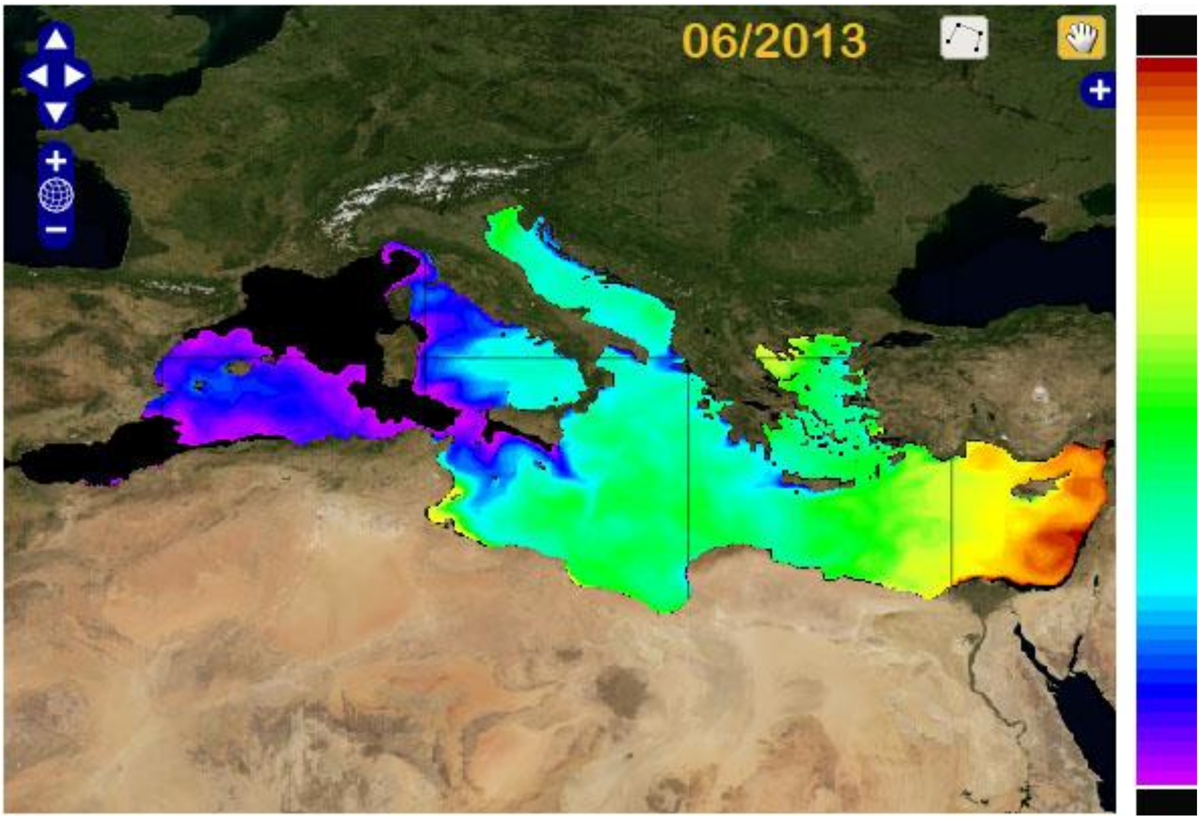

Figure 4. Sea surface temperature in July 2013, scale goes from 26 (red) to 20.5 (blue) degrees Celsius.

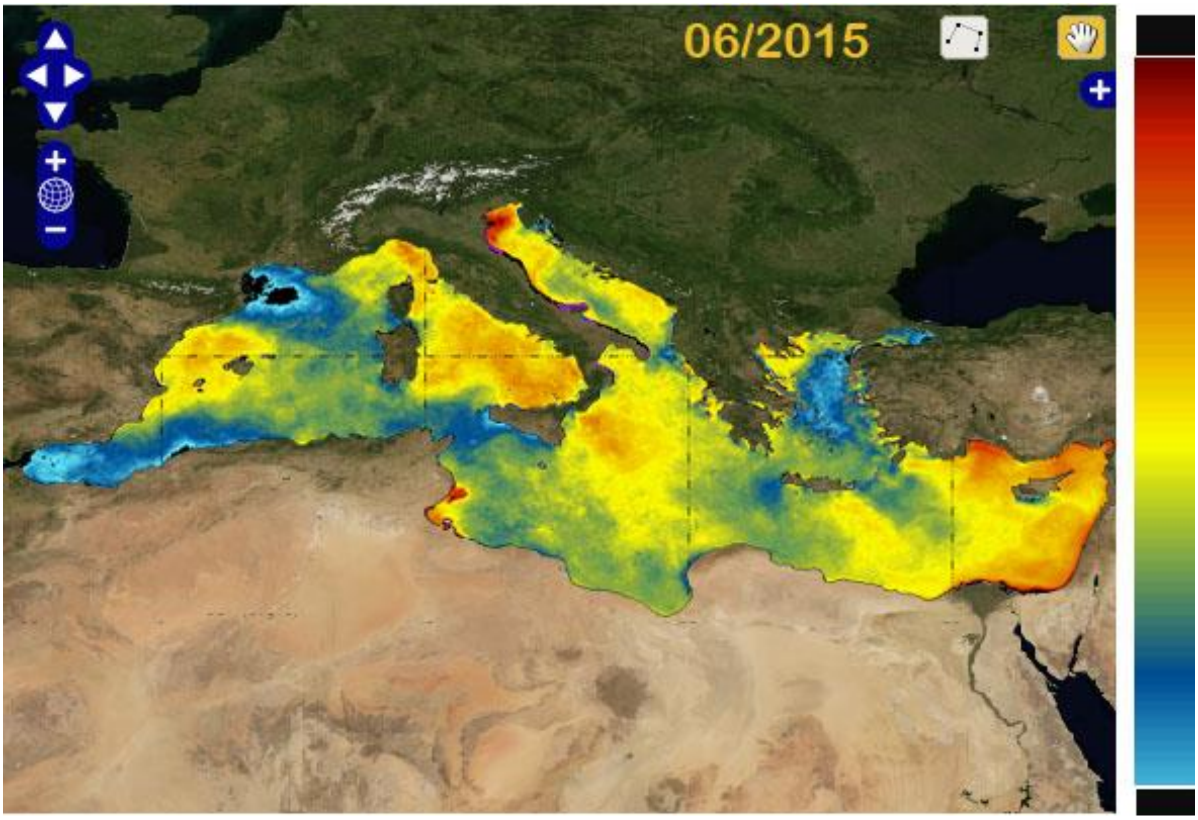

Figure 5. Sea surface temperature in July 2015, scale goes from 26 (red) to 20.5 (blue) degrees Celsius.