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Research Paper

Natural and fishing mortalities affecting eastern sea garfish, *Hyporhamphus australis* inferred from age-frequency data using hazard functions

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ABSTRACT

Estimates of age-specific natural (*M*) and fishing (*F*) mortalities among economically important stocks are required in age-structured models to determine sustainable yields and, ultimately, facilitate effective resource management. Here we used hazard functions to estimate mortality rates for eastern sea garfish, *Hyporhamphus australis*—a pelagic species that forms the basis of an Australian commercial lampara-net fishery. Data describing annual (2004–2015) age frequencies (0–1 to 5–6 years), yield, effort (boat-days), and average weights at age were used to fit various stochastic models to estimate mortality rates by maximum likelihood. The model best supported by the data was characterised by: (i) the escape of fish aged 0–1 years increasing from approximately 90 to 97% (assumed to be a result of a mandated increase in stretched mesh opening from 25 to 28 mm); (ii) full selectivity among older age groups; (iii) a constant *M* of 0.52 ± 0.06 year^{-1}; and (iv) a decline in *F* between 2004 and 2015. Recruitment and biomass were estimated to vary, but increased during the sampled period. The results reiterate the utility of hazard functions to estimate and partition mortality rates, and support traditional input controls designed to reduce both accounted and unaccounted *F*.

1. Introduction

Hemiramphidae is a cosmopolitan teleost family comprising > 60 species; most of which are targeted throughout their tropical and temperate distributions by various active and passive fishing gears (Berkeley and Houde, 1978; Sokolovsky and Sokolovskaya, 1999; Jones, 1990; Jones et al., 2002; McBride and Styer, 2002; McBride and Thurman, 2003; Stewart and Hughes, 2007). In Australia, > 15 species are sought, with the endemic eastern sea garfish, *Hyporhamphus australis* among the most economically important (Stewart and Hughes, 2007; Stewart et al., 2015).

Considered a unit stock, almost the entire catch of *H. australis* is landed by up to 50 beach- and boat-based commercial fishers using lampara nets off central and southern New South Wales (NSW) (Stewart et al., 2004). Traditionally, *H. australis* fishers used a minimum mesh size of 25 mm (stretched mesh opening; SMO) which along with excessive effort led to declines in annual catches from peaks of ∼200 t in the early 1990s to ∼35 t after 2007 (present study and Stewart et al., 2004). In response to concerns over stock status and in the absence of detailed population assessments, the minimum SMO in lampara nets was increased to 28 mm (initiated in 2006 but not fully adopted until 2009–10 as fishers replaced their existing nets) and effort was reduced. These input controls resulted in the fishery constantly landing ∼45–50 t per annum (Stewart et al., 2015). Ancillary recreational (mostly hook-and-line) catches of *H. australis* are minor (< 5 t per annum; Henry and Lyle, 2003); only ∼15% of which are discarded, and with variable associated mortality, depending on their handling (Butcher et al., 2010).

Notwithstanding a stabilized harvest of *H. australis*, very few data are published describing their population dynamics (but see Stewart and Hughes, 2007) and despite such information considered an essential prerequisite for effectively managing exploitation (King, 2007). Pivotal among population-dynamic parameters to assess fish stocks with age-structured models (and ultimately harvestable yields) are estimates of natural (*M*) and accounted fishing (*F*) mortalities which, along with unaccounted fishing mortality, are summed to provide total mortality (*Z*). Estimating mortality rates and the factors affecting the survival of individuals in a population has been the preoccupation of

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scientists for at least three centuries (Chiang, 1968).

For many fisheries, mortalities are estimated using stock-assessment models. Natural mortality is one of the most important stock-assessment parameters for fishery management, but is notoriously difficult to estimate (Lee et al., 2011). Consequently, many researchers have used empirical relationships between life-history traits and environmental factors to estimate *M* (Pauly, 1980; Hoenig, 1983; Jensen, 1996; Then et al., 2015). Similarly, when the data required for sophisticated stock assessment models are unavailable, *F* often is derived simply by subtracting *M* from *Z*, with the latter estimated using catch curves (King, 2007). Other methods for estimating *Z* have included standard linear regression on log-transformed age-frequency data, but recent studies imply these should be avoided (e.g. Millar, 2015).

There exist long-term (from 2004) age-frequency data (from otolith readings; Stewart and Hughes, 2007) for *H. australis* which have been used within the above types of empirical relationships by Stewart et al. (2005) to provide preliminary estimates of *Z* and *M* at 3.0–3.4 and 0.8, respectively. However, in the absence of robust hypothesis testing, such values are subjected to numerous assumptions and lack the necessary rigor to derive other important population parameters.

As an alternative approach to concurrently estimate the *M* and *F* of *H. australis* using age-frequency data, here we applied survival analysis; a statistical method developed outside the field of fisheries research. Specifically, in the middle of last century, demographers, epidemiologists, insurers and zoologists developed methods to analyse age data for a cohort (or a group of cohorts) and presented the results in the form of life tables. Many researchers showed that even when multiple causes of mortality exist and individuals dying of a particular cause are not available for observation, the age distributions of dead individuals can be used to infer mortality rates (e.g. Caughley, 1966; Spinage, 1972). This approach subsequently received formal mathematical treatment from the point of view of the theory of stochastic processes by Chiang (1968), who formulated the joint probability distribution of the number of deaths, which ultimately provided the statistical foundation to estimate mortality parameters by maximum likelihood. More recently, Cox and Oakes (1984) introduced key concepts and definitions under the banner of 'survival analysis', presenting statistical methods to estimate mortalities for practitioners in areas as diverse as medical research, actuarial sciences, engineering and econometrics.

There are few examples where survival analysis methods have been applied in fisheries (Dupont, 1983; Neilson et al., 1989; Ferrandis, 2007; Kienzle, 2016) or marine science more broadly (Stolen and Barlow, 2003; Manocci et al., 2012). Despite limited application, survival analysis applies readily to cases where age data are measured from a sample of catch. The traditional approach of partitioning mortality as *M* and *F* falls naturally into the competing-risk framework, which is a statistical method to construct life tables accounting for multiple sources of mortality (Chiang, 1968; Cox and Oakes, 1983; Dupont, 1983). Further, unlike some other stock assessment methods, survival analysis can be applied when only data describing ages, weights, catches and effort are available (Kienzle, 2016).

Considering the above, our aims here were to quantify the mortality of *H. australis* using hazard functions following the approach described in Kienzle (2016). Further, we sought to use the subsequent model outputs along with the original data to estimate various aspects of population dynamics, including recruitment and biomass.

2. Material and methods

2.1. Data

Four data groups were obtained from various sources to estimate the required parameters and quantities describing the entire stock of *H. australis* between 2004 and 2015. The first data group comprised the total number of fish aged in each year (all assessed for accuracy and precision via age-bias plots and coefficient of variation estimates) which varied between 216 and 462 otolith measurements collected from commercial catches at several landing sites in NSW (see Stewart and Hughes, 2007 for methodology). In the model (section 2.2), these data are denoted as a matrix $S = [s_{i,j}]$, $i = 0, 1, \ldots, 10$ and $j = 0, 1, \ldots, 5$. Index i represents (fishing) year intervals from 2004–5 to 2014–15. Index j represents age-groups from 0 to 1 to 5–6 (Supplementary material, Tables 1 and 2). The data contain 16 cohorts, numbered by convention from the top right-hand side to the bottom left-hand side of the age sample matrix (S) using k varying from 0 to 15. The number of age groups (r_k) belonging to each cohort varies between 1 and 6, and is given by:

$$r_k = \begin{cases} k+1 & \text{if } k < 5, \\ 6 & \text{if } 5 \le k < 11, \\ 16-k & \text{if } 11 \le k \end{cases}$$

The second data group was annual yields derived from landed catch records from year intervals 2004–5 to 2014–15 (Supplementary material, Table 3). The annual yields are defined as $Y = [y_i]$, where index i represents the year interval to be the same as index i of S_{ij}.

The third data group was annual fishing effort obtained from mandatory logbooks from year intervals 2004–5 to 2014–15 (Supplementary material, Table 3). The annual effort is defined as $E = [e_i]$, where index i represents year interval to be the same as index i of y_i (Supplementary material, Table 3). The last data group was average weight for each age group caught each year estimated using weights collected during surveys of commercial landings. The data are denoted as a matrix $W = [w_{i,j}]$, where indices i and j are the same as $s_{i,j}$ of S (Supplementary material, Table 4).

Several quantities were derived from these data to perform subsequent calculations. First, the proportion $p_{i,j}$ of fish in age group j observed in year i was calculated using $s_{i,j}$:

$$p_{i,j} = s_{i,j} / \sum_{x=0}^{5} s_{i,x} \tag{1}$$

Second, the estimated annual number of fish c_i caught in year i was calculated using y_i, $p_{i,j}$ and $w_{i,j}$:

$$c_i = \frac{y_i}{\sum_{x=0}^{5} p_{i,x} w_{i,x}} \tag{2}$$

Finally, the estimated number of fish $\tilde{c}_{i,j}$ of age-group j caught in year i:

$$\tilde{c}_{i,j} = c_i p_{i,j} \tag{3}$$

2.2. Stochastic models and mortality estimation

A stochastic population model was used to estimate mortality rates by maximum likelihood using the matrix of age sample (S) based on a competing-risk model (Chiang, 1968; Dupont, 1983; Ferrrandis, 2007) assuming two sources of mortality (M and F) affected *H. australis*. Natural mortality was represented by an 11-row × six-column matrix (M), the elements ($m_{i,j}$) of which give the magnitude of hazard due to natural causes that fish are exposed to in each year interval.[1] Similarly, F was represented by an 11-row × six-column matrix (F) with elements ($f_{i,j}$) quantifying the magnitude of F fishes are exposed to during each year interval. In order to build a life table for each cohort k, we calculated the probability of members of each cohort dying from fishing in an interval j given they were alive at the beginning of this interval (Chiang, 1968):

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[1] All models for *Hyporhamphus australis* described later in this section assumed $m_{i,j}$ are constant across ages and years. However, this assumption can be relaxed and more complex patterns of M could be fitted to the data.