The environmental factors drive the productivity of marine fish stocks and the recent studies have shown that in the coming years many stocks will be increasingly affected by climate change including global ocean warming, ocean acidification, oxygen loss and other long-term and more regional environmental changes such as salinity, nutrient redistribution or eutrophication and pollution (Roessig et al. 2005; Cochrane et al. 2009; Hollowed et al. 2013; Portner et al. 2014). These factors influence marine ecosystems, marine organisms and fish stocks not only through direct impacts on individual physiology and life history but also indirectly via changes in primary productivity or ecological interactions, spatial configuration of habitats or planktonic larval transport (Doney et al. 2012).

One of the main ways that the environment influences fish population dynamics is by modulating recruitment, usually in the form of young of the year survival. Explicitly including environmental variables underlying this modulation into stock assessments can help determine whether changes in recruitment are a result of changes in spawning–stock biomass or changes in recruit survivorship to the population structure (Schirripa et al. 2009). Numerous studies reported in the fisheries literature attempt to explain the effects of various environmental factors on recruitment (Sutcliffe, 1973; Drinkwater, 1987; Leggett et al., 1984, Carscadden et al. 2000, Chen & Ware 1999, Chen 2001, Chen and Irvine 2001, Levi et al. 2003, Mikkelsen and Pedersen 2004, Sinclair & Crawford 2005, Megrey et al. 2005).

This lecture note aims at giving an overview on a semiparametric model developed by Chen and Irvine (2001), which incorporates environmental and fishery data to analyse stock-recruitment relationships. Unlike traditional stock-recruitment models that assume a log-linear relationship between recruitment
and environmental and fishery variables, this model uses a nonparametric smoothing algorithm, which helps to quantify the underlying empirical relationships and enables more accurate parameter estimates.

Ricker in 1975 proposed an exponential functional relationship to relate the spawning stock with recruits and it is represented as

\[ R_t = S_t e^{(a-bS_t)} \]  

(1)

where \( R_t, S_t, a, b \) describe recruits and spawning stock at time, \( a \) and \( b \) are the population productivity at low density and capacity limited by density-dependence, respectively. These parameters can be estimated using standard linear regression analysis. It is assumed that recruitment is log-linearly distributed, then the revised form is

\[ \log \frac{R_t}{S_t} = a - b S_t + \varepsilon_t \]  

(2)

Where \( \log \frac{R_t}{S_t} \) is the response \( y_t \) of the linear model that represents the recruitment rate per unit of spawning biomass, and \( \varepsilon_t \) is the Gaussian error, such that \( \varepsilon_t \sim N(0, \sigma^2) \). The main biological assumption of the Ricker model is that high values of \( b \) cause an over compensation, reducing survival of pre-recruits at higher spawning stock size. This does not occur with other stock recruitments models. Chen & Irvine (2001) extended the Ricker model to include environmental variables as follows:

\[ y_t = a - b S_t + \sum_{i} c_i Z_{ij} + \varepsilon_t \]  

(3)

where \( Z_{ij} \) with \( i \in \{1, \ldots, k\} \) represents the environmental variables measured at time \( t \).

Equation (3) can be expressed in terms of linear regression as follows:

\[ y_t = x_t^T \beta + Z_t^T \gamma + \varepsilon_t \]  

(4)
where \( y_t \) corresponds to the response vector, which in population theory represents an approximation to the population productivity, \( \hat{\beta} = (a, -b)^T \), and \( x_t = (1, S_i^*) \) represents the vectors for biological and spawning biomass parameters while \( \gamma = (c_1, \ldots, c_k)^T \) and \( z_t = (Z_{1,t}, \ldots, Z_{k,t}) \) are the values for a group of \( k \) parameters and predictors associated with environmental effects. It is assumed that predictions spread around an additive error of the form \( \varepsilon_t \sim N(0, \sigma^2 I) \), where \( I \) is the identity matrix for the group of parameters (Espindola \textit{et al} 2016).

Although the Extended Ricker Model parameter (equation 4) can be estimated using multiple linear regression, a number of relevant works (Hilborn 1985, 1992; Jacobson and MacCall 1995, Stocker \textit{et al} 1985, Fargo and McKinnell 1989, Chen and Irvine 2001) have shown that relation between \( y_t \) and \( z_t \) may take different functional forms that clearly fail the assumption of log-linearity.

Chen \& Irvine (2001) proposed another form for relaxing the log-linearity assumption between \( y_t \) and \( z_t \) by implementing a non-parametric function, \( g(.) \) for the co-variables \( z_t \) to include in the Extended Ricker Model such that \( z_t \rightarrow g(z_t) \). Thus, the vector \( z_t = (Z_{i,t}, \ldots, Z_{k,t}) \) can be represented in an additive form through \( (z_t) = \sum_{i=1}^{k} g_i(Z_{i,t}) \) which defines a group of functions \( g(.) \) that can be solved non-parametrically, thus avoiding the use of parameter vectors such as \( \gamma = (c_1, \ldots, c_k) \). Then the model can be rewritten as:

\[
y_t = x_t^T \beta + g(z_t) + \varepsilon_t
\]  

(5)

where \( g(z_t) \) is the non-parametric term, for which in the theoretical approach of Generalized Additive Models (GAM) is commonly used as smoothing technique. The equation 5 includes two components, where the first involves a parametric term \( x_t^T \beta \) equivalent to the right side of the Ricker Model, while the
second corresponds to a non-parametric term \( g(\cdot) \) that represents the environmental variables. Thus,

\[
y_t = f(x_t) + g(z_t) + \varepsilon_t
\]

represents a semi-parametric version of the Ricker model. This approach was applied by Chen and Irvine (2001) to southeast Alaska pink salmon \( (Oncorhynchus gorbuscha) \) with sea surface temperature as the environmental variable and West Coast Vancouver Island herring \( (Clupea harengus) \) with sea surface temperature and hake biomass as two environmental variables. Results from diagnostic tests indicated that semi-parametric version of the Ricker model performed better than the traditional Ricker model and Extended Ricker model. The recruitment rate was modelled in relation to spawning biomass and to sea surface temperature (SST) for the jackmackerel \( (Trachurus murphyi) \) population off the Chilean coast using the Ricker model by Espindola et al (2016). The results showed that inclusion of SST improved the fit of the recruitment model. They have concluded that incorporating an environmental variable into stock-recruitment relationships may be a promising method for simultaneously considering effects from fishing and the environment, and is particularly relevant for managing fisheries in light of climate change.

In an ecosystem or fisheries management context, however, what often matters most is not necessarily how the climate or ocean abiotic conditions will change, but how the biological components of an ecosystem might respond to environmental change (Payne et al. 2016). To answer these types of questions, it is necessary to combine or integrate the environmental factors with models of population dynamics and fish stock assessment.

References


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