Estimation of Age Composition using Maximum Likelihood from Length Frequency Distribution of Nile Tilapia (Oreochromis niloticus) in Lake Tana, Ethiopia

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Abstract

Estimation of age composition of fish using Length frequency distribution is common if there is no aging of individual fish using otoliths or tag and recapture methods. It can be done by using maximum likelihood. The objectives of this study, therefore, to estimate age compositions; and the Von Bertalanffy growth coefficient and asymptotic length of the Nile tilapia stock. Available length-frequency data from Bahirdar Fisheries and Other Aquatic Life Research Center's annual progressive reports for Nile tilapia fishery was compiled into 63 groups with 0.5-cm size classes (11-11.5 cm to 41.5-42cm). Length-frequency observations consisted of the actual number of catch at length measured of the specious by year was used for this study. Estimation of age composition in to age cohorts and estimation of the proportions each age cohort was done using maximum likelihood. The number of age classes of the stock was selected using an index of AIC. According the result of minimum AIC, a stock having three cohorts was selected with the proportion in the population of 0.14, 0.285, and 0.875 for the 1st, 2nd and 3rd cohorts, respectively. It was found also that this estimation is statistically significant at a significant level of less than 1%. The Von Bertalanffy growth coefficient and asymptotic length were also estimated. The growth parameter measured in the change in average length per cohort was 0.435cm and highly significant; and the asymptotic fish length was 44.11 cm.

Keywords: length frequency distribution, Maximum Likelihood, , age composition, Nile tilapia, asymptotic length, growth parameter.

Introduction

Nile Tilapia (*Oreochromis niloticus*) is a deep-bodied fish with cycloid scales. It is one of the the three main tropical fish species groups targeted by fishermen in Lke Tana in the first place and the second by volume/or number next to large Labeobarbus specious.

A number of different methods are commonly used to obtain age of fish. The three majour methods are analysis of tag and recapture data; analysis of the hard parts of the fish like otoliths; and analysis of cohort progressions in length frequency distributions (Hallier and Gaertner, 2006; Sparre and Venema,1998).

Aging of individual fish in temperate zones based predominantly on annuly of scales, otolises and other bony structures of fish, which is difficutl to apply in tropics (Pauly and Morgan, 1987; Sparre and Venema, 1998). Temperate zone fish, subject to yearly seasonality water temperature and thus growth, can often by aged this way. Most fishery models these days in this zone are age based, meaning that the model fish population is broken down by the numbers of fish in each age group.

Temperate zone stock assessment is, therefore, done by ageing them directly. Ageing is most often done by counting rings in hard parts of the fish body, such as otoliths or scales. The so-called year-rings are formed through a daily addition (daily ring) to the size of the scale or otolith. The difference in deposits made in the winter and in the summer can be detected and one year ring, composed of a summer and a winter part, can be distinguished from the next. Moreover, temperate fish species usually spawn once per year in a relatively short time span, which makes it easy to distinguish year classes or cohorts (Sparre and Venema, 1998).

As far as tropical fish is concerned, fish material is added daily to hard parts, which can be distinguished as daily growth rings. However, the lack of a strong seasonality makes the distinction of seasonal rings and therefore also of year rings problematic for many tropical species. Aging of fish using tag and recapture data methods are rarely used in fishery research.

Catch -at -length-based models are primarily used for invertebrates, where no otolith or other hard body parts are available to age individual animals. Sometimes, the quality of fishery model estimates, even where age samples are available, can be improved by incorporating length as an additional independent variable (Sparre and Venema, 1998). In tropical fisheries, there is often a heavy reliance on size frequency data only, which will incur a significant penalty in accuracy (Quin II and Deriso, 1999)

Recently there is shift towards using catch-at-length-based models in stock assessment methods, much of modern stock assessment remains based on catch-at-age models, which estimate population sizes and derive exploitation history by summing catches over time on a cohort-by-cohort basis (Ailloud *et al*, 2014). Therfore, there has been a great uprising in interest in catch-at-length-based methods of assessing fish populations. This is due to an increasing problems of applying the better known age based methods, this is especially true in tropical areas where aging of fish is less precise on their scales or otoliths; the development of improved methods of analysing length data; and the increased availability of computers that put within the reach of all the computational power needed to take advantage of some of the new methods (Gulland and Rosenberg, 1992)

In many application of fish stock assessment, it is necessary to find a substitute for age dependent data. Collecting age specific data can a problem because of the inherent technical difficulty in determining the age of tropical fish and because, even when possible, it is expensive. Thus, the proxy measurement of length or size has become popular (Gallucci, 1996).

Population size may be analyzed for indicators of age grouping if individuals of fish cannot be aged totally or reliably. This age determination initiated with the anticipation that peak size frequency represent the mode of year classes or cohort. Fish hatched in the same year tend to be in the same size range, with most fish being close to an average size. Therefore, there trends to be a statistically normal distribution of size around a normal (most frequent distribution).

In addition, length is the most common information collected in fisheries research, perhaps due to its ease of collection. A histogram of frequencies of length often shows distinct modes that hypothetically represent distinct age classes. Length frequency distribution (LFD) has been used since 1892 to decompose a length frequency histogram into component age classes (Ricker 1975). The oldest method, simple inspection of the histogram, is the least reliable. Other graphical methods and curve fitting techniques are also subjective (Quin II and Deriso, 1999)

In recent years, there are techniques that have been developed to read daily rings in the otoliths of many fish species. This has enabled the development of age reading on tropical species, in particular of fish with short life spans, or young fish. These techniques are still very time consuming and will be difficult to apply on a routine basis. They may however, serve to validate the results obtained from the analyses of length-frequencies.

A further complication of tropical fish stock assessment as compared to temperate waters is that the number of species caught is very high. This does not only affect sampling and data collection procedures, it also makes it more difficult to apply the models (Quin II and Deriso, 1999).

The above mentioned differences can easily explain the slow rate of development of fish stock assessment in the tropics compared to that in temperate areas. However, it is important for the construction of assessment models and for fishery management decisions. In order to address this question, the ideal source of information would be reliable, high precision catch atage data, such as those provided in some cases by daily ring studies of otoliths which allow assessing the stock precisely. However, such precise catch at age data are not available for Nile Tilapia in Lake Tana. So, we investigate the issue by applying a LFD to length frequency distributions of research survey data.

Besides, LFD has been useful tool in stock assessment with the help of software packages developed primarily to estimate growth parameters and age composition from length frequency data using ELEFAN (Pauly and David, 1981) and MULTIFAN-CL (Fournier et al., 1998). In most of these procedures, LFD is used to estimate growth parameters to support the stock assessment without any test of statistical robustness. However, in this paper we extended LFD to back to rough estimate the average age of distinct age classes and to test the robustness of the estimated parameters.

Therefore, the objectives of this study are:

- To estimate age compositions of Nile tilapia stock from length frequency distribution using likelihood estimator;
- To estimate the Von Bertalanffy growth coefficient and asymptotic length of the Nile tilapia stock

Data and Method of Ananlysis

Data on the African cat fish are available from a historic data that was collected from Bahirdar Fisheries and Other Aquatic Life Research Center's annual progressive report. The center has collected a research survey data for more than more than 13 years. It has a total of six sampling sites both from the southern and northern part of Lake Tana. Data were sampled starting from year 2000 only from three sampling sites every month. Then the program has been expand it sampling to six and collect every other month from November 2009 till now. The gillnets used had mesh sizes of 60, 80, 100, 120 and 140 mm stretched mesh. The size of a single mesh panel was 3 m by 50 m. The nets were set at 6:00 p.m. and collected at 6:00 a.m. Representative sampling sites/habitats were selected. They are Abbay, Zegie, and Gerima in the southern part, and Dirma, Sekela, and Gedamat in the northern part of the Lake. The sites selected reflect the different habitat types present in the lake such as river mouths, deep water, muddy or rocky bottoms, and dense stands of aquatic macrophytes (Dereje, 2014).

Therefore, a total of 2432 fish length frequency data were collected from January 2000 to September

2012. We assume them to be representative of all Nile tilapia caught in the lake. We established a length frequency of 0.5cm (5mm) interval with a total of 63 classes.

To derive the maximum likelihood function of LFD, following the approaches of Andrade and Kinas, (2004); and Quin II and Deriso, (1999), we assume that the probability density function of length l for a given age class i to be normal:

$$f_i(l)=\frac{1}{\sqrt{2\pi\sigma_i^2}}\exp\left[-\frac{(l-\mu_i)^2}{2\sigma_i^2}\right] \quad (1)$$

The derivation of the maximum likelihood method assumes that the length frequency distribution is multinomial; the probability density function (PDF) of length $f_a(l)$ for each age group *a* is described by unknown parameter vector; the number of age groups *A* is known, and each length measurement falls into one and only one interval. (Quin II and Deriso, 1999).

where i = 1, . . . , A refers to the index for the age class with mean age a_i, μ_i the mean length predicted for age class i, and σ_i the corresponding standard deviation (s.d.). We assume that μ_i is related to a_i by a von Bertalanffy growth equation and that σ_i is proportional to the square root of a_i:

$$\sigma_i=\sigma\sqrt{a_i} \quad (2)$$

where a_i we use the more general mean age a_i,

In all, k length intervals $((l^{j-1}, l^j)$, indexed by j (j=1, . . . , k), are defined. The probability that a length measurement for a fish in age class i is in length interval j is

$$F_{ji}=\int_{l^{j-1}}^{j} f_i(l)dl \quad (3)$$

If N is the number of fish measured and g_i the true proportion of fish in age class i, then the expected number of fish of size class j is

$$L_j=N\sum_{j=1}^{A} F_{ji}g_i \quad (4)$$

The proportion of fish in size class j is then

$$P_j=\frac{L_j}{N}=\sum_{j=1}^{A} F_{ji}g_i \quad (5)$$

Finally, if the k-dimensional vector of observed length frequency $L^{Obs}=\{L_j^{Obs}\}$ is assumed to follow the multinomial distribution

$$f(L^{Obs})=\binom{N}{L_1^{Obs},\ldots L_k^{Obs}}\prod_{j=1}^{k} P_j^{L_j^{Obs}} \quad (6)$$

then the negative log-likelihood function to be minimized is

$$\ell(L^{Obs}|\{\mu_i\},\{g_i\},\sigma)=-\sum L_j^{Obs}\log\left(\sum_{j=1}^{A} F_{ji}g_i\right) \quad (7)$$

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We used the von Bertalanffy parameters to describe the growth process.

$$l_t = l_\infty \left[1 - \exp^{-k(t-t_0}\right]$$

Where t_0 - theoretical age at which the length of the fish (L_0) is zero,

l_∞ - Assymptotic length or length where age is infinity or the age at which growth of length becomes zero

k -growth parameter

l_t - length at age t

Following Kolding and Giordano, (2002) and Sparreand Venema S.C ,(1998), l_∞, t_0 , and k was computed as follows: since l_∞ is interpreted as the average length of very old fish, we can estimate it as a starting value using either the length of the largest fish for small sample size or the average of the last 10 fishes for the large sample size, . Since our sample is large we used the later approach, the length of the largest fish.
So, l_∞ = 39.14 cm

$$k = \frac{1}{t_2 - t_1} \times \ln\left(\frac{l_\infty - l(t_1)}{l_\infty - l(t_2)}\right) \qquad (8a)$$

For the number of age class equals to 1, we can apply the growth parameter k as follows

$$k = \frac{\ln(l_{\max}) - \ln(l_{\min})}{t_2 - t_1} = \frac{\ln(42) - \ln(11)}{1-0} = 1.34$$

Where $l_{\max} = 42\,cm$, the largest length in our data set and

$l_{\min} = 11\,cm$, the smallest length in our data.

Then, the computed k = 1.34 is applied to equation number (8b), we can find $l(t_1)$ = 28.823

$$k = \frac{1}{t_1 - t_0} \times \ln\left(\frac{l_\infty - l(t_0)}{l_\infty - l(t_1)}\right) \qquad (8b)$$

k = 1.34 is applied only if the stock has only one cohort. k= 1.34/2, 1.34/3, 1.34/4, . . .1.34/j for a stock having 2, 3, 4, . . . , j cohorts, respectively. So, will have different k values for different model. Here, the model is the number of age classes. The computed values of k were taken as initial values for model specification in Newton methods of algorithm

Applying k = 1.34 and $l(t_1)$ = 28.823 to equation (8b), results t t_0 = -0.34

$$t_0 = t_1 + \frac{1}{k} \times \ln\left(1 - \frac{l(t_1)}{l_\infty}\right) \qquad (9)$$

t_0 gives us the start of the curve, i.e. where the theoretical length is zero. It is calculated by inserting l_∞ and K in the equation for a known length at age *t (equation 9)*

Hence, the model used to predict mean length μ_a for a given mean age a was

$\mu_a = 39.14\left[1 - \exp^{-1.34(a-0.16)}\right]$ for a model having one age group

$\mu_a = 39.14\left[1 - \exp^{-0.67(a-0.16)}\right]$ for a model having two age groups

$\mu_a = 39.14\left[1 - \exp^{-0.447(a-16)}\right]$ for a model having three age groups

$\mu_a = 39.14\left[1 - \exp^{-0.335(a-0.16)}\right]$ for a model having four age groups
$\mu_a = 81.5\left[1 - \exp^{-0.268(a-0.16)}\right]$ for a model having five age groups

Note that the term age group connotes that more than one age class may be represented in an age group. .Following equation (2), standard deviation of for the different age/cohort groups are calculated using the following functions

$\sigma_i = 5.67\sqrt{a_i}$ where a_i is the mean age group

At first the number of age classes, needs to be specified in advance to fit a LFD to data, A,. In order to deal with this unknown number, we fitted a set of models from A = 1 to a maximum as large as necessary to represent all discernible age classes, and used an index Akaike Information Criterion, AIC to choose the best fit (Michael and Taylor, 2014). For this purpose Newton methods of algorithm was used to estimate the population parameters. It was modeled using Von Bertalanffy growth function with the default starting values of the parameters to be estimated. These are the proportion of age class/ or cohort, mean length of each cohort and their standard deviation.

For A age classes, there are 2×A parameters to be estimated. Andrade and Kinas, (2004) state that in the applications of the LFD, the solutions appeared to be highly dependent upon the starting values of the parameters, because the shape of the negative log likelihood function is not informative or has several local minima. Therefore, they suggest that each optimization procedure would be tried with 10×A random starting parameter sets. But for our purpose, 5×A random starting parameter sets, were used systematicaaly. Therefore, each optimization procedure was tried with 5×A random starting parameter sets. For instance, for A = 3, 15 random starting parameter sets were simulated and the optimization was applied 15 times. Then minimum negative log-likelihood for each set of starting parameters were selected as the final model. Besides, the selected model was run based on the estimated proportion of the algorithm's output and the observed frequencies using statistical/Econometrics software. The statistical/Econometrics output was used to remodel the algorithm. The results of statistical/Econometrics output is also used to test the robustness of the model and can generate data for simulation purpose. The growth parameter and asymptotic length were also estimated from linear regression models of Gulland and Holt Plot.

Result and Discussion

The estimation of catch age composition from length composition assumes, among other things that age class/cohort exhibits Von Bertalanffy growth. We use parameterization such that growth is specified by three parameters, k -the growth coefficient, t_0 - theoretical age at which the length of the fish (L_0) is zero, and l_∞ asymptotic length or the age at which growth of length becomes zero. These parameters can be transformed to provide the usual Von Bertalanffy growth parameter $l(t)$.

There is a good correspondence between estimated mean length at age and noticeable model in the length frequency samples for Nile tilapia. We tested by comparing the indexed of Akaike Information Criteria (AIC). As it is depicted in the annex (Figure 1), slicing of age composition also support the theoretical basis of age composition using LFD.

$$\text{AIC} = -2 \log \text{L}(\hat{\theta}|\text{y}) + 2\text{K} \quad (10)$$

where K is the number of estimable parameters and $-2 \log \text{L}(\hat{\theta}|\text{y}) = \ell(L^{Obs}|\{\mu_i\},\{g_i\},\sigma)$, in our case is the log-likelihood at its maximum point of the model estimated. This can be further refined this estimate to correct for small data samples: $\text{AICc} = \text{AIC} + \frac{2\text{k}(\text{k}+1)}{\text{n - k - 1}}$; where n is the sample size and K and AIC are defined above. If n is large with respect to K, this correction is negligible and AIC is sufficient. AICc is more general, however, and is generally used in place of AIC.

The best model is then the model with the lowest AICc (or AIC) score. It is important to note that the AIC and AICc scores are ordinal and mean nothing on their own. They are simply away of ranking the models. So it can be used for comparison for a given data set. That is calculating AIC or AICc value for each model with the same data set, and the best model is the one with minimum AIC value.

Table 1: Summary of AIC and AICc result for models relating the Number of Age classes for age composition.

Model	log likelihood	K	AIC	AICc	Rank
1	-7,935.51	2	15,875.02	15,875.22	5th
2	-7695.24	4	15,398.48	15,399.17	4th
3	-7,668.71	6	15,349.42	15,350.92	1st
4	-7,668.71	8	15,353.42	15,356.09	2nd
5	-7668.71	10	15,357.42	15,361.65	3rd

Number of age class equals to 3 (model 3) received the lowest AIC as well as AICc score (AIC =15,349.42 and AICc = 15,350.92), indicating that this model is the most fit model for the given length frequency data. There is decisive evidence in favor of model 3 relative to the other models (Number of age class equals to 1, 2, 4 and 5). So the number of age class /or cohort in of Nile Tilapia in Lake Tana equals to 3

Table 2: Summary of proportion, Mean Length and standard deviation of the selected model,

Cohort /Age Class	proportion	Mean length (cm)	Standard error
One	0.14	16.891	1.045
Two	0.285	22.116	1.080
three	0.575	32.360	3.495

Table 2 provides the algorithm results of model 3, after optimization using 15.combinations of random starting values. The proportion of age is distributed to 0.14, 0.285, and 0.575 for 1st , 2nd , and 3rd cohorts, respectively. As far as the mean length of the cohorts is concerned, it equals to 16.891 with a standard deviation of 1.045, 22.116 with a standard deviation of 1.080, and 32.36 with a standard deviation of 3.495 for 1st , 2nd, and 3rd cohort, respectively.

Once the best model is established, one can use the traditional null-hypothesis testing for the given best model in order to establish the scale of the relationship between the variables. This is the same as what is normally presented in regression analysis. Table 3 provides the regression results for model 3. The statistically highly significant chi Squared value (χ^2) is the test for the overall goodness of fit of the model. .

Table 3: Results of the Multinomial Logit Model

Dependent variable	log likelihood
Log likelihood function	-198.855
Restricted log likelihood	-207.638
Chi squared [3 d.f.]	17.565***
Estimation based on N = 189, K = 4	
Inf.Cr.AIC = 405.7 AIC/N = 2.147	

	1st Cohort	2nd Cohort	3rd Cohort
Proportion	-88.64*** (25.83)	-42.14** (18.17)	0
Frequency	0.0084** (0.0043)	0.0055NS (.0043)	0

*Note: The parentheses are the standard error of the estimate and ***Significant at 1percent level, **significant at 5 % level, *significant at 10 % level and NS-Non-Significant*

As depicted in Table 3, there is a significant positive and negative relationship among the two cohorts and the reference group on the two variables. In comparison to 3rd cohort, which is normalized to zero, the true probability is associated with lower likelihood to both 1st and 2nd cohorts. As far as the observed frequency is concerned in comparison to 3rd cohort, observed frequency is associated with higher likelihood to 1st cohort.

Table 4: Estimation of growth parameter and asymptotic length from linear regression

	coefficients
(Constant)	19.188*** (0.000)
Mean length	-0.435*** (0.000)

*Note: The parentheses are the standard error of the estimate and ***Significant at 1percent level, **significant at 5 % level*

So from the Table 4, we can directly estimate the growth parameter and asymptotic length. The growth parameter from linear regression analysis is simply the negative of coefficient of mean length which equals to 0.435 cm per cohort. As far as the asymptotic fish length is concerned, it is the negative of ratio of constant coefficient to mean length coefficient, which equals to 44.110 cm.

Summary, Conclusion and Recommendation

Length-based models are primarily used when no otolith is available to age individual animals. Sometimes, the quality of fishery model estimates, even where age samples are available, can be improved by incorporating length as an additional independent variable. Through the advancement of computer, slicing of age composition using length frequency distribution can be done using ELFAN, MULTIFAN and others software. So the objective of this study is to slice of age composition in to cohorts using maximum likelihood and to test statistical robustness of slicing and to estimate growth parameter and asymptotic length of Nile tilapia stock. A research survey data of Nile tilapia of Lake Tana was used for this purpose.

Using maximum likelihood a possible number of age groups were tested and using AIC, the fish stock in the lake is represented by 3 age cohorts. The proportions of the cohorts are 0.14, 0.285 and 0.575, respectively. AIC was used to select the best model based on this criterion it is found that model 3 (three age cohorts) is the true number of age cohort of the stock. A Highly statistical significant of χ^2 is an indication of the best fit of the model. Each of the independent variables are also statistically and independently significant in the specification of the model, 3rd cohort is normalized zero.

Estimating of age composition was also used to estimate the growth parameter of the stock and asymptotic fish length. The growth parameter measured in the change in average length per cohort was 0.435cm and highly significant; and the asymptotic fish length was 44.11 cm.

Estimating age composition and parameter estimation require robustness statistical test. Estimating of age composition in to cohorts using FLD of maximum likelihood can be used to test statistical robustness of the estimation of parameters. So estimating age composition in addition to aging, it can be used to test statistical robustness of the estimation of parameters.

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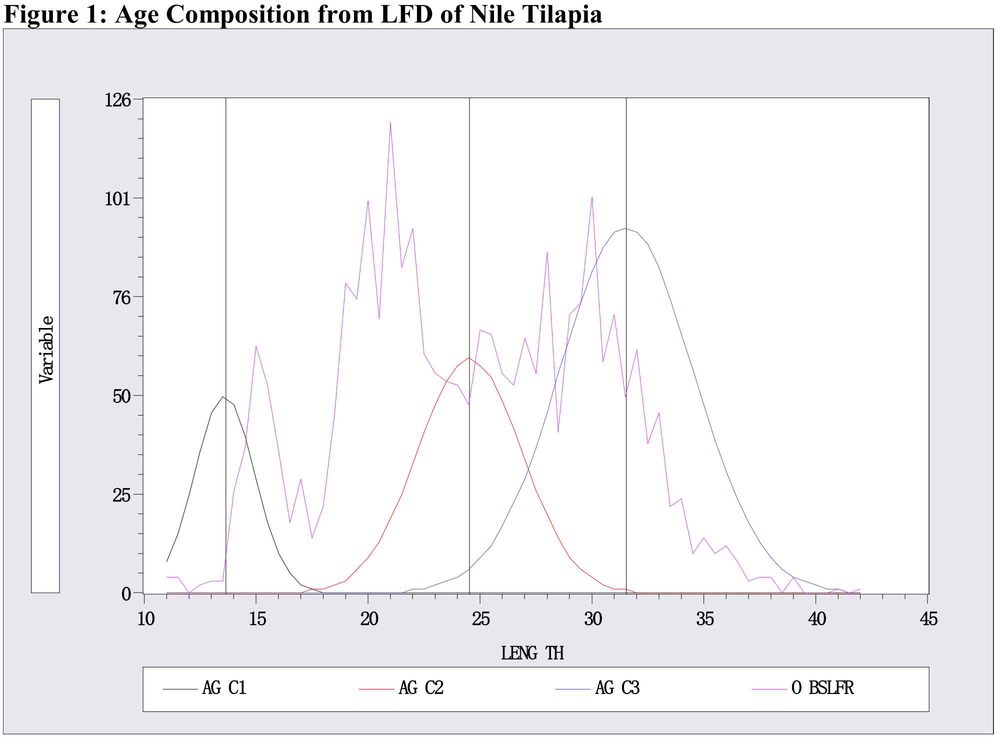
ANNEXES

Figure 1: Age Composition from LFD of Nile Tilapia



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