## Improving Age Composition Estimates:

 Evaluating a Bayesian-like Method for Estimating Ages from Spines withVascularized Cores
Lynn Waterhouse, Guelson da Silva, Lisa Ailloud, and John Hoenig


## Methods for Aging Fish

- Tagging
-Otoliths
-Jaw, other bones
-Opercular series
-Scales
-Fin spines



## Methods for Aging Fish

-Tagging
-Otoliths
-Jaw, other bones
-Opercular series
-Scales
-Fin spines

Non-lethal, quick sample, doesn't affect market value

## Problem with Using Fin Spines/Rays:

Many fish have vascularization in the core

Marlin Skipjack<br>Yellowfin Catfish<br>Brown trout White suckers

Zone of vascularization expands with growth, obliterating earliest growth rings


Guelson da Silva


$\sqrt{\prime \prime}$

## Dealing with Spines Featuring Central Vascularization

1. Naïve model (assume observed rings = true age)
2. Impute with representative samples from each size (Holden and Meadows 1962 \& Seed 1968)
3. Simple ratio method (Andrade et al. 2004)
4. Multiple regression (Andrade et al. 2004)
5. K-means cluster analysis (Die and Drew 2008)

# Dealing with Spines Featuring Central Vascularization 

## 1. Naïve model (assume observed rings = true age)

2. Impute with representative samples from each size (Holden and Meadows 1962 \& Seed 1968)
3. Simple ratio method (Andrade et al. 2004)
4. Multiple regression (Andrade et al. 2004)
5. K-means cluster analysis (Die and Drew 2008)
6. Bayesian-like imputation

Methods we compare today

## Bayesian-like Ring Imputation for Age Numbers (BRIAN)

Goal: estimate number missing rings to get total age

$$
\text { age }=\text { rings }_{\text {inner }}+\text { rings }_{\text {outer }}
$$

rings $_{\text {inner }}=\left\{\begin{array}{l}0 \text { no obliteration in young fish } \\ \text { Not Available in old fish }\end{array}\right.$

# Bayesian-like Ring Imputation for Age Numbers (BRIAN) 

Assume spine width follows von Bertalanffy* curve
rings $_{\text {inner }} \sim$ Poisson $\left(\mu_{v}\right)$
$\mu_{v}=$ mean number of rings in vascularized region for fish of spine width v

Calculate $\mu_{\mathrm{v}}$ by solving von Bertalanffy eqn for age given vascularized width v

Data required for Bayesian method (BRIAN Model)
1.Count of observed rings $\left(C_{i}\right)$
2.NA when some rings may be missing $\left(X_{i}\right)$ 0 if no missing rings
3. Spine width $\left(D_{i}\right)$
4. Vascularized region width $\left(D_{1 i}\right)$

## BRIAN Model

## Vascularized Width



Missing

## Age from vascularized region

rings
$t_{0}, \mathrm{~K}, D_{\infty}$ von Bertalanffy
parameters for spine growth

# Bayesian-like Ring Imputation for Age Numbers (BRIAN) 

## Why Bayesian-like instead of Bayesian?

-Priors not purely hierarchical
-Methods used in data science where interest is in prediction

## Model Evaluation \& Comparison

1. Naïve model
2. Bayesian Ring Imputation for Age Numbers (BRIAN)

Using:

- Simulated datasets
- Yellowfin tuna data


## Simulated Data - 1000 fish

- Ages 1 to 10
- Uniform age distribution
- Spine width based on age (von Bertalanffy model)
- Add random error (sd=0.1)
- Vascularized region proportional to spine radius
- Random error added in logit space on proportion of spine vascularized (sd=sqrt(0.003))
-Calculate location of each ring
- Scale by ratio spine width to expected width
- Notion small fish are always small, big fish are always big


## Simulated Data - part 2

-Calculate \# of missing rings

- Determine if rings are missing
- If you believe you have 1 year olds in data, use smallest $1^{\text {st }}$ ring diameter
- Otherwise assume all fish are censored (have missing rings)
rings $_{\text {inner }}=\left\{\begin{array}{l}0 \text { no obliteration in young fish } \\ \text { Not Available in old fish }\end{array}\right.$


## Preliminary Results Naïve method

## Naïve Model Results

| True Age | Naïve Age (Observed Rings) |  |  |  |  |  |  |  |  |  |  | No. <br> Fish <br> True <br> Age |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |  |
|  | 1 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 93 |
|  | 2 | 0 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 91 |
|  | 3 | 0 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 86 |
|  | 4 | 0 | 0 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 111 |
|  | 5 | 0 | 0 | 0 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 | 88 |
|  | 6 | 0 | 0 | 0 | 0.08 | 0.92 | 0 | 0 | 0 | 0 | 0 | 98 |
|  | 7 | 0 | 0 | 0 | 0 | 0.43 | 0.58 | 0 | 0 | 0 | 0 | 120 |
|  | 8 | 0 | 0 | 0 | 0 | 0 | 0.75 | 0.25 | 0 | 0 | 0 | 114 |
|  | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0.92 | 0.08 | 0 | 0 | 100 |
|  | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.93 | 0.07 | 0 | 99 |

## Preliminary Results BRIAN method

## BRIAN Model Results

Mode of Posterior Estimated Age

|  |  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | Fish <br> True <br> Age |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 93 |
|  | 2 | 0 | 0.82 | 0.18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 91 |
|  | 3 | 0 | 0 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 86 |
| True | 4 | 0 | 0 | 0 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 111 |
| Age | 5 | 0 | 0 | 0 | 0 | 1.00 | 0 | 0 | 0 | 0 | 0 | 0 | 88 |
|  | 6 | 0 | 0 | 0 | 0 | 0.01 | 0.89 | 0.10 | 0 | 0 | 0 | 0 | 98 |
|  | 7 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.68 | 0.20 | 0 | 0 | 0 | 120 |
|  | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0.11 | 0.79 | 0.10 | 0 | 0 | 114 |
|  | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.10 | 0.87 | 0.03 | 0.00 | 100 |
|  | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.09 | 0.88 | 0.03 | 99 |

## Preliminary Results comparison

Naïve model max age 9 BRIAN model max age 11

Naïve model $\rightarrow$ greater bias older fish, only does well young fish

BRIAN model is unbiased, gets it right >74\%

## Parameter Estimates from von Bertalanffy Naive vs. BRIAN method

| Parameter | True Value | BRIAN Model |  | Naïve Model |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Median | 95\% CI | Median | 95\% CI |
| $\boldsymbol{t}_{0}$ | -0.1 | -0.12 | -0.17, -0.08 | 0.29 | 0.22, 0.30 |
| K | 0.4 | 0.39 | 0.38, 0.40 | 0.60 | 0.58, 0.62 |
| $\boldsymbol{D}_{\infty}$ | 4 | 4.0 | 4.0, 4.1 | 3.9 | 3.9, 4.0 |

Naïve estimate of K is 50\% higher
$\rightarrow$ Total mortality estimate will be 50\% higher using Beverton-Holt mean length estimator

$$
\hat{Z}=\frac{K\left(L_{\infty}-\bar{L}\right)}{\left(\bar{L}-L_{c}\right)}
$$

## Parameter Estimates from von Bertalanffy Naive vs. BRIAN method



## Yellowfin Tuna Example

Thunnus albacares
Atlantic ocean


Dataset from AOTTP and Universidade Federal Rural do Semi-Árido - UFERSA (Brazil)

## Yellowfin Tuna Data: Is there evidence vascularization affects apparent growth?

7

6 Observed Ring Count

2

- $N=1$

$\mathrm{N}=100$
$\mathrm{N}=43$


## Yellowfin Tuna Example: von Bertalanffy Estimates

|  | BRIAN Model |  | Naïve Model |  |
| :---: | ---: | ---: | ---: | ---: |
| Parameter | Median | $95 \%$ CI | Median | $95 \%$ Cl |
| $\boldsymbol{t}_{\mathbf{0}}$ | -0.65 | $-0.76,-0.57$ | -0.09 | $-0.33,0.14$ |
| $\boldsymbol{K}$ | 0.09 | $0.06,0.12$ | 0.09 | $0.06,0.15$ |
| $\boldsymbol{D}_{\infty}$ | 13.3 | $10.5,18.4$ | 23.4 | $16.0,29.6$ |

## Yellowfin Tuna Data:

 von Bertalanffy growth curve - Naïve model

## Yellowfin Tuna Data: von Bertalanffy growth curves



Estimated Age (BRIAN)

## BRIAN Model Flexibility

Other growth models can be used instead of von Bertalanffy

With simulated data, model still runs if $100 \%$ of your data has missing rings from vascularization

## Broader Application

Utilize data in more efficient manner
$\rightarrow$ Increase sample size by collecting from catch \& release anglers and commercial fishermen
$\rightarrow$ Avoid naïve mistake of underestimating age, overestimating K and Z


## Atlantic Tropical Tuna Age \& Growth Study

ICCAT Atlantic Ocean Tropical Tuna Tagging Programme


Grace Chiu
\& ESTDatS
@ VIMS


## Thank You



