Metamodeling for Bias Estimation of Biological Reference Points.

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Introduction

- Hello. My name is Nick Grunloh.
- Talking about: A Metamodeling approach for assessing RP bias in two parameter models of productivity.
- Collaboration with UC Santa Cruz, SWFSC, and funded by NOAA Sea Grant.

Basic Modeling Structure

- Context: Single Species Surplus-Production Models.
- Production models are an admittadly simple setting, but…
  - have plenty of dark secrets that we dont tend to talk about.
- Even being simple:
  - they capture many relevant dynamics for management sake
  - and are plenty instructive.
- General Structure:
  - Observe an index of abundance
  - Assume the index is proportional to biomass with proportionality constant q.
  - I_t forms a response variable with lognormal residuals.
- Most of the action here comes from the biomass process model.
  - Biomass is modeled as a (typically) nonlinear ODE.
  - Growth via a nonlinear production function, $P(B)$
  - Removals via natural mortality and catch.
    - Instantaneous removal rates lumped here under $Z(t)$.
- For management mostly interested in Biological RP Inference.
  - I should say: RP are functions of productivity parameters.
- Commonly RPs are ways of noticing MSY.
  - Here I focus on two:
    - Fmsy: fishing rate to result in MSY (Relative. Fmsy/M)
    - Bmsy: population biomass at MSY (Relative. Bmsy/B0)

RP Constraints

- Conceptually $\frac{F^*}{M}$ and $\frac{B^*}{B_0}$ coexist in an entire 2D space.
- (Mangel et.al., 2013) Canadian Journal of Fisheries
  - Two parameter BH model: RP space is limited to a 1D curve
  - **Right:** Plot Relative Bmsy against Relative Fmsy
    - black: posterior samples of the RPs for a 3 parameter Shepherd-like model. (cowcod)
    - red: posterior samples of the RPs for a 2 param BH model.
    - the red posterior is squashed into the curve $\frac{1}{x+2}$
    - Refer to this subspace of RP's as the BH line.
  - **Next:** Mangel et. al. suggests looking into 3-parameter curves

Schnute (1985)

- I'm working with a 3 parameter production function as developed in Schnute (1985)
  - A number of important 2 parameter special cases (Logistic, Ricker)
    - Most importantly here the Beverton-Holt when $\gamma = -1$.
- Generate a species off of the BH line, with the 3 parameter Schnute model.
- Simulate Schnute data and fit those data under the BH Model. * Observe how RPs under BH model are biased relative to true Schnute RPs.

- **Right Panel:** On the right you can see the Schnute production function and how it uses its third γ parameter to get dramatically different productivity behavior.
- In terms of RPs these different behaviours move us off the BH line.

Breadcrumb Slide

- Understanding the mapping of broad RP space onto these constrained 2 parameter spaces is complicated even in simple cases.
  - Chaos in the Dynamical System -Time Integrator Inaccuracy
  - Model Identifiability -Global Optimization
- Production models are simplified places which are easier to hunt down the many computational issues, and are simple enough to make it possible to understand the mechanisms
- At the link provided here you can see our anlysis of the mechanisms of Bias for the Schaefer Model.

Simulation Design

- Again, we use Schnute to generate data broadly in RP-space.
- In order to do this, one would need to invert the relationship between RPs and productivity parameters.
- Schnute and Richards (1998) show that it's not analytically possible to invert this relationship and numerically inverting is unstable.
- However Schnute and Richards (1998) do provide some results which we have used to generate approximate LHS designs in RP space.
- **Next:** With a design in place Schnute data can be generated for example in the upper right.
- Fitting the BH model against those data will neccessarily land somewhere on the $1/(x+2)$ BH line. (Say the red dot)
- The aim is then to understand the behaviour of these bias arrows broadly in RP space.
  - Will One reference point be prioritized over the other?
  - Is there a compromise between RPs?
  - Is the mapping a shortest distance onto the BH line?
- **Next:** Design locations used to train a GP metamodel of $\hat{RP}$.
- Particular BH fits are as helpful as their standard errors, but in repeated sampling metamodeling can discern global RP bias trends.

Catch

- Assume synthetic catch series, To complete the model specification.
- I show Catch in red and the population in black.
- Two cases: Low and High contrast
- In all cases, the intitial biomass is fixed to K.
- Low Contrast:
  - Catch held at to come to equilibrium at MSY
  - low contrast, relatively low information setting
  - Exponential decay from K to Bmsy
- High Contrast:
  - fishing increases accelerates as technology and fishing techniques improve rapidly until management practices are applied to bring the stock into equilibrium at MSY.
  - high contrast, relatively high information setting
  - wiggles about until coming to equilibrium

High Contrast

- Here we Visualize RP Biases as a bias field.
- Color indicates the MLE estimate percent error from the Truth
- Arrows indicate the Direction of Bias (from Truth to BH MLE)
- **Next:** For example data is generated off of the line (say here)
- **Next:** and then fit w/ BH. (maps to the red dot)
- We can observe a few things:
  - Overall As Model misspecification increase (far from the line), estimation bias increases.
  - In high contrast example we can see a fairly reasonable mapping.
    - Resembles a shortest distance mapping onto the BH line.
    - Neither RP dominates bias; both RPs fail togehter

Low Contrast

- In the low constrast evironment:
  - lower information content in the data
  - we see a higher bias pattern overall
- **Next:** When Model Misspecification is large (in the upper part) we see an interesting limiting behaviour of BH
  - **Next:** the arrows in the upper part of this picture shoot off to the less.
  - Looking at the yeild fit BH yeild curve we can see that we are drastically underestimating steepness.
  - this pushes the BH yeild curve toward the limiting flat symmetric case as relative Fmsy goes to 0.
  - at this level of model misspecification this pattern prioritzes relative Bmsy over relative Fmsy.
- **Next:** For better specified Models: **Next**
  - bias pattern returns to something like shortest distance mapping
  - in this shortest distance mapping neither RP dominates bias;
  - both RPs compromise to fail togehter
- **Next:** It is interesting to note that for the lower information setting we are only allowed to misspecify model so much before we observe this “Catstrophic’ ’ inferential failure.

Conclusion

- We have a rich simulation environment for describing global RP bias.
- It's a robust and easily extensible simulator that is hardened against a lot of numerical failings of ODE models.
- We will use this framework to further extend this analysis to study how patterns my be affected by dynamics of individaul growth and maturity.
- This study reminds us that RP are not observable quantities, but rather modeled quantites that are subject to Model misspecification, uncertainty, and bias.
- In particular the severly constrained setting of using a two parameter production function we are going to pay for our modeling mistakes primarily via estimation bias.
- The role of contrast in our data series serves to distribute information amoung our RP estimates, but
- The information content in our data also interacts with how poorly we are misspecifying our models of management RPs and so we should be very thoughtful about choosing models of population productivity as misspecified models my produce horribly biased estimate of RPs.