Estimating abundance and demography of black bear populations using multiple, disparate data sources

Paul B. Conn

Research Statistician

Anonymous Natural Resource Agency

Seattle, WA

paulconnvict@gmail.com

Goals of workshop

In the next 1.5 hours, I hope to (in no particular order):

1. Increase your awareness of the advantages AND limitations of integrated population models
2. Convey to you what the heck an “integrated population model” is
3. Guide you through different types of procedures for fitting integrated population models to available sources of bear data (Bayesian and otherwise)

Goals of workshop

In the next 1.5 hours, I hope to (in no particular order):

4. Guide you through different types of procedures for fitting integrated population models to available sources of bear data
5. Introduce you to available software options
6. Give you some intuition as to whether your results are going to be worth a damn
7. Provide a few examples of integrated population models in use

Goals of workshop

In the next 1.5 hours, I hope to (in no particular order):

8. Describe how power analysis can (and should!) be used to help evaluate how much extra data you're going to have to collect
9. Take a few questions

What this workshop is not

This isn't a self-affirmation workshop. Most of you probably don't have sufficient data to reliably apply these approaches (at least right now).

What the heck is an integrated population model?

It’s a term that my coauthors and I (Fieberg et al. 2010, PLoS ONE) invented to get more literature citations.

- A different name for a fisheries stock assessment model fitted to wildlife data
- If using a Bayesian /hierarchical modeling framework, other names could be used (state space model, hidden process model)
- Use available data to estimate parameters of a very simple population model

Data requirements for some common fisheries stock assessment models

Model type	Age structure	Removals	Indices	Natural Mortality	Biology
Statistical catch-age	x	x	x	x	x
Catch free	x		x	x	x
Stock reduction		x	x	x	x
Tuned VPA	x	x	x	x	
VPA/Cohort analysis	x	x		x	
Surplus production		x	x		

- Haddon, 2001. Modelling and Quantitative Methods in Fisheries
- Quinn and Deriso, 1999. Quantitative Fish Dynamics

Outputs for some common fisheries stock assessment models

Model type	Abundance at age	Biomass	Fishing* mortality	Recruitment*	Mgmt. reference points
Statistical catch-age	x	x	x	x	x
Catch free			x		x
Stock reduction	x	x	x	x	x
Tuned VPA	x	x	x	x	x
VPA/Cohort analysis	x	x	x	x	
Surplus production		x	x		x

- Haddon, 2001. Modelling and Quantitative Methods in Fisheries
- Quinn and Deriso, 1999. Quantitative Fish Dynamics

Possible data sources: Bear populations

- Age-at-harvest
- Reporting surveys
- Indices of abundance
- Mark-recapture-recovery data
- Telemetry data
- Reproductive ecology studies
- Meta-analysis
- Covariates thought to influence survival/harvest (hunter effort, forage index)

Age-at-harvest Data

Data commonly obtained for fish and wildlife populations

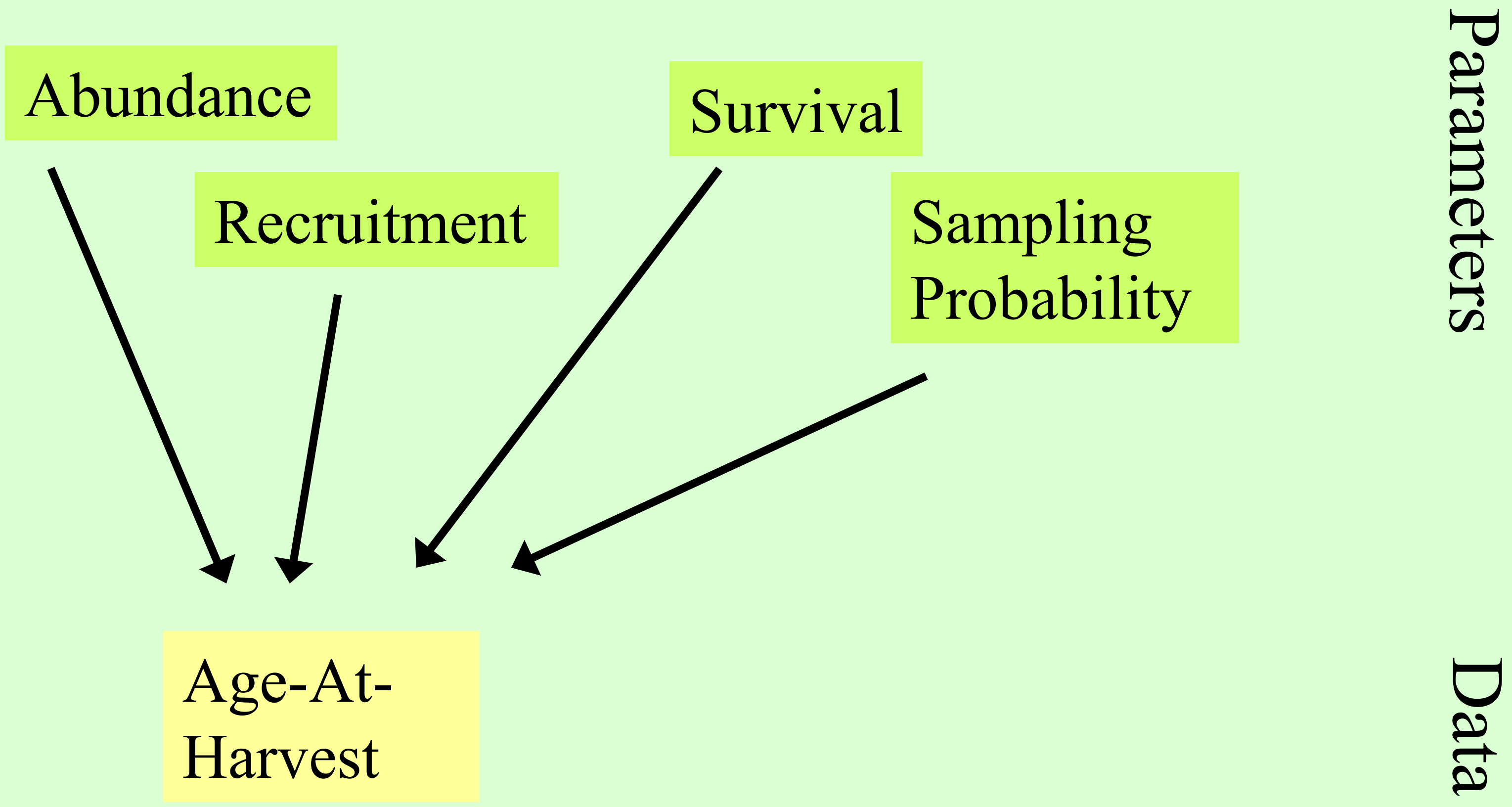
- Hunter check stations
- Parts collection surveys
- Fishing boat surveys

Observed age-at-harvest matrix

$$
\begin{array}{ccccc|c}
C_{11} & C_{12} & C_{13} & C_{14} & C_{1A+} & \text{Year} \\
C_{21} & C_{22} & C_{23} & C_{24} & C_{2A+} & \downarrow \\
C_{31} & C_{32} & C_{33} & C_{34} & C_{3A+} & \\
C_{41} & C_{42} & C_{43} & C_{44} & C_{4A+} & \\
\end{array}
$$

Age $\longrightarrow$

Age-at-harvest Data



Age-at-harvest Data – how to interpret ?

Age

Year

160	240
144	216
128	192
112	168

Age-at-harvest Data – how to interpret ?

H1: The population is decreasing and harvest rates are staying the same

Age →

Year ↓

160	240
144	216
128	192
112	168

Age-at-harvest Data – how to interpret ?

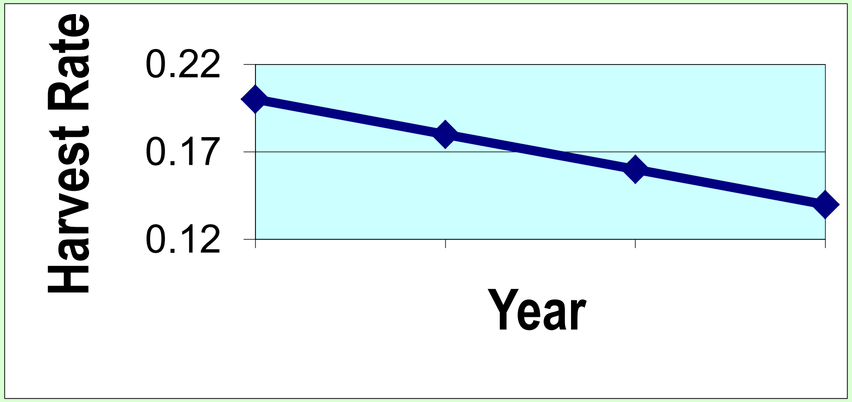
H1: The population is decreasing and harvest rates are staying the same

Age →

Year ↓

160	240
144	216
128	192
112	168

H2: Abundance is constant and harvest rates are decreasing



Age-at-harvest data

Abundance

Recruitment

Survival

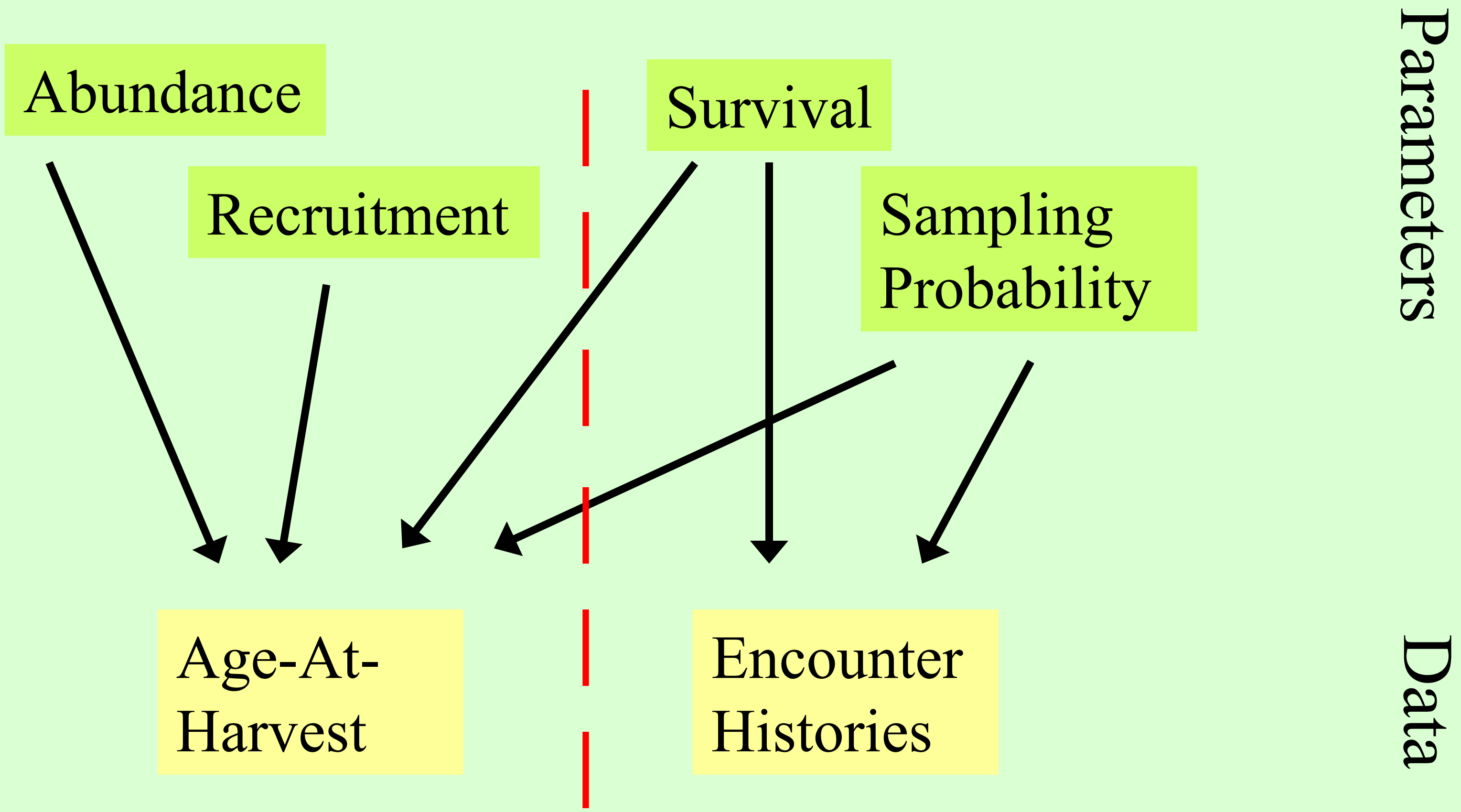
Sampling Probability

Parameters

Age-At-Harvest

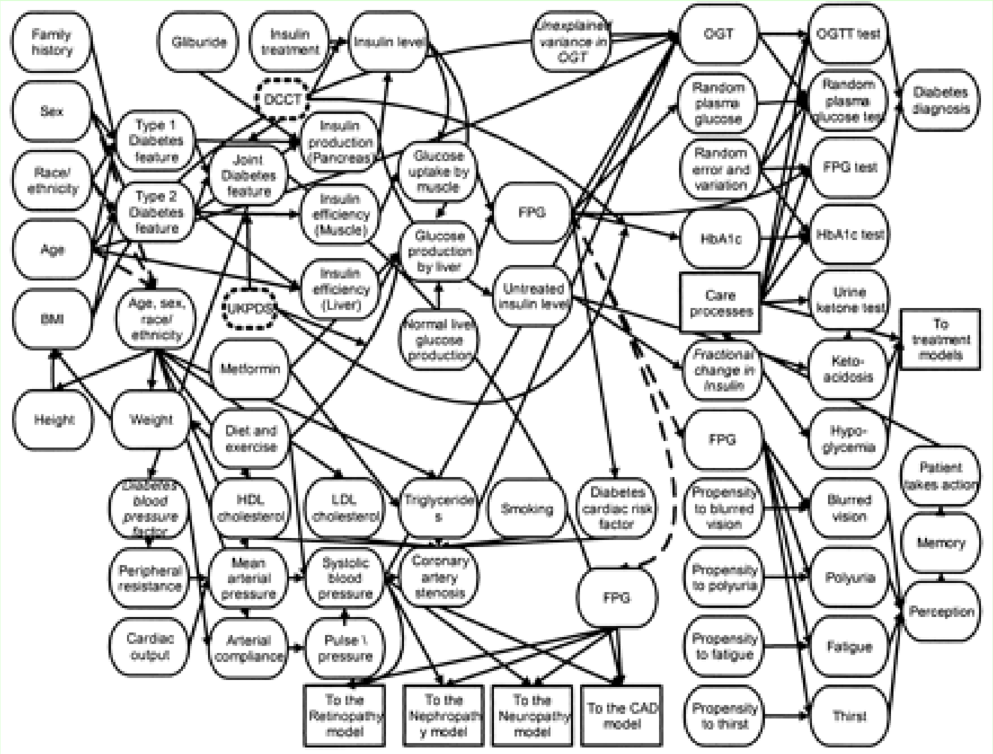
Data

Age-at-harvest data supplemented with data from marked animals



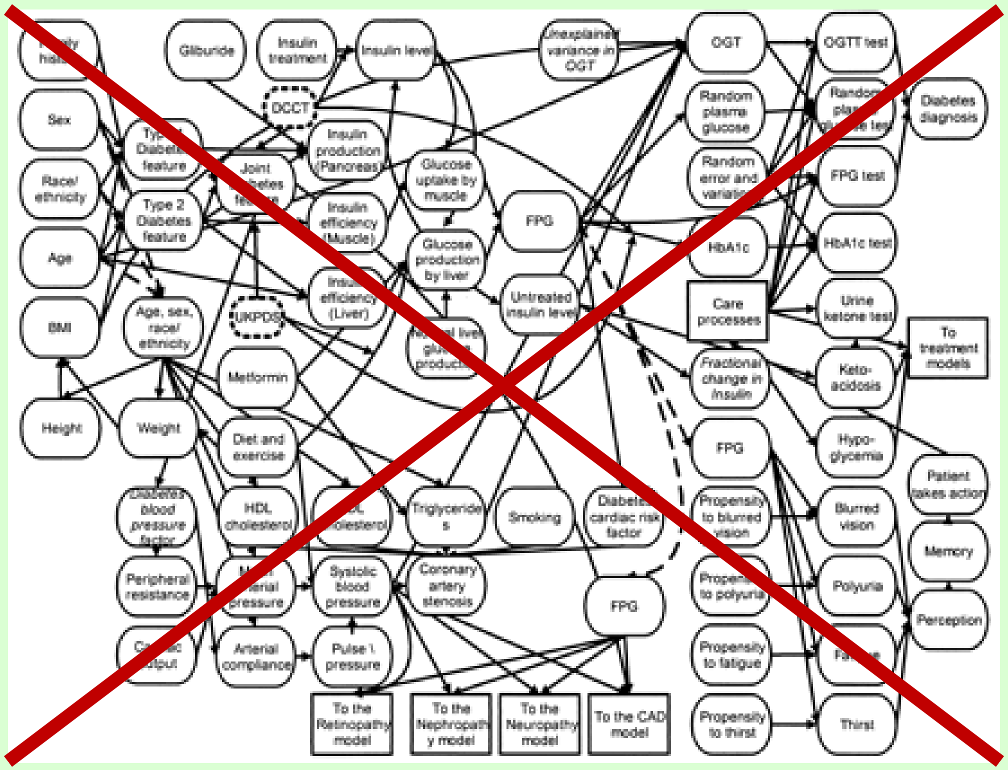
Step 1 of Integrated Population Modeling:

Construct a population model that best matches your available data sources



Step 1 of Integrated Population Modeling:

Construct a population model that best matches your available data sources



Step 1 of Integrated Population Modeling:

Construct a population model that best matches your available data sources

Realism

Too Complex – Not enough data to reliably estimate parameters

Just right…

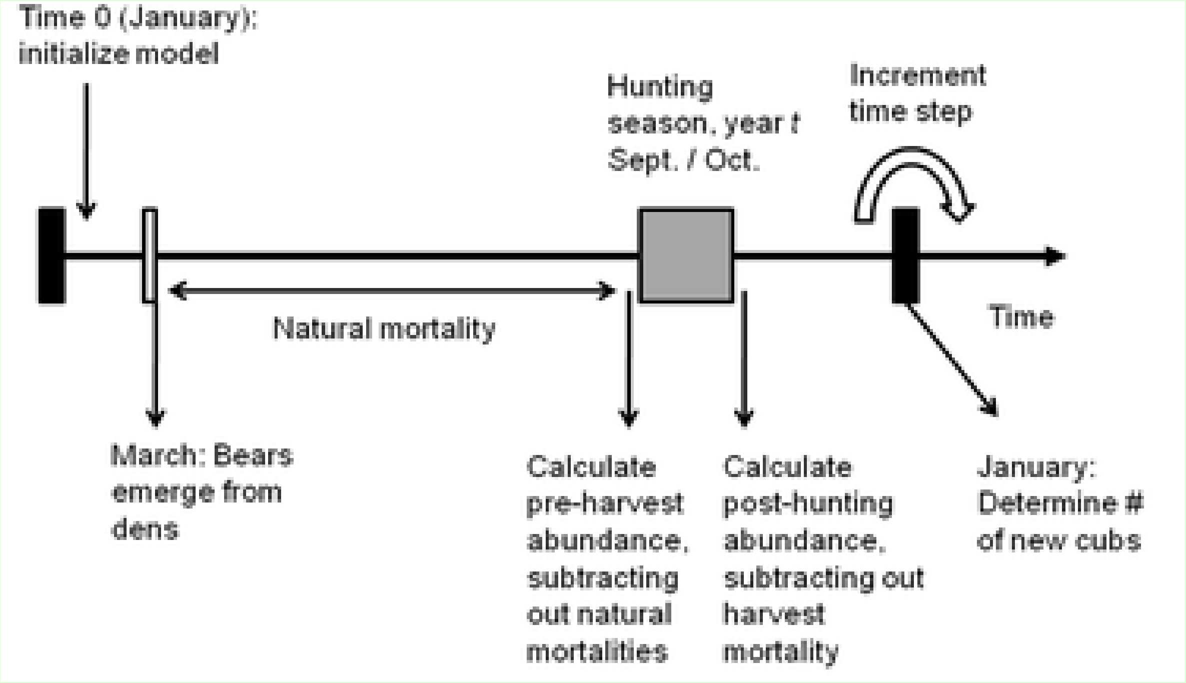
Too Simple – Can't "adequately" capture dynamics; e.g. decreasing survival because survival assumed constant

Precision

Step 1 of Integrated Population Modeling:

Construct a population model that best matches available data sources

Example 1: Minnesota black bears

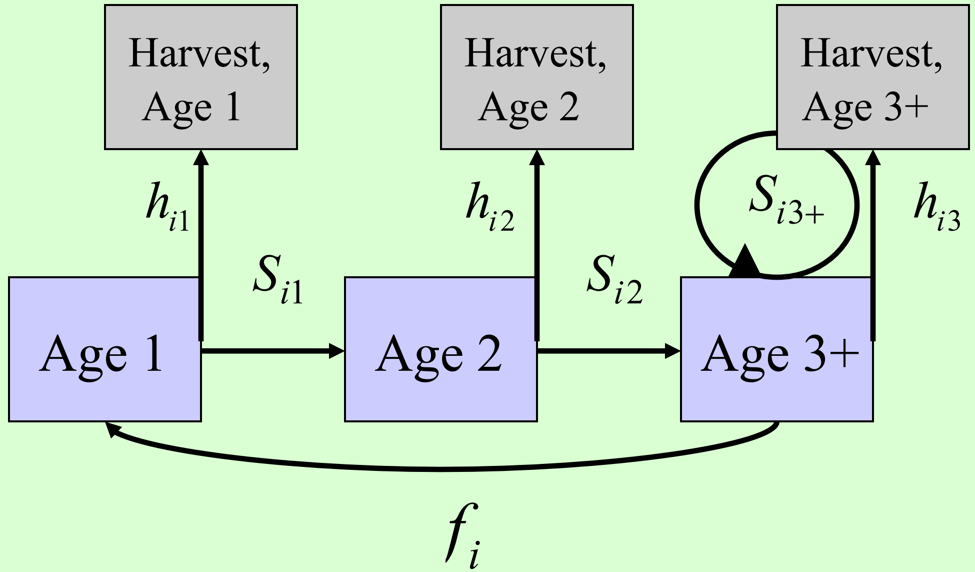


Step 1 of Integrated Population Modeling:

Construct a population model that best matches available data sources

Different types of auxiliary data often result in different model parameterizations

Example: Mark-recapture-recovery data

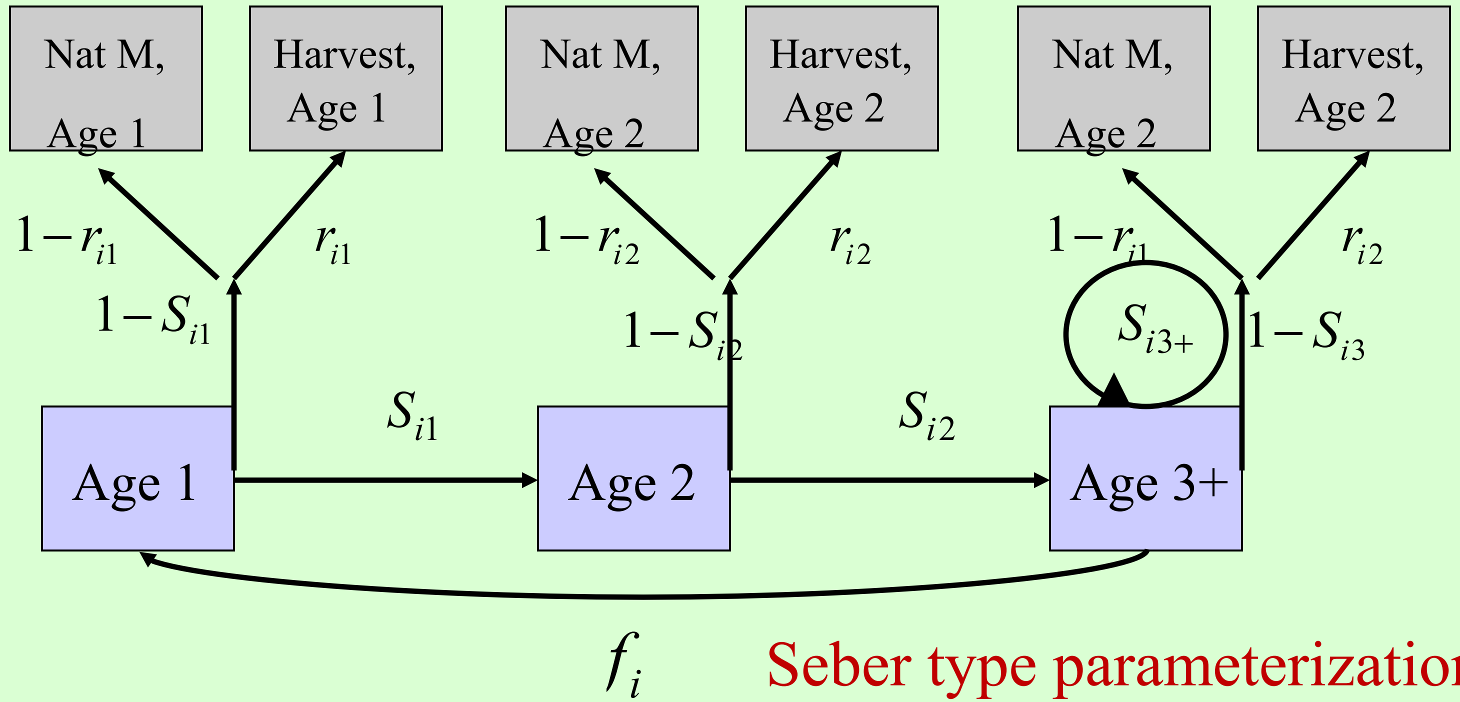


Brownie type parameterization

Step 1 of Integrated Population Modeling:
Construct a population model that best matches available data sources

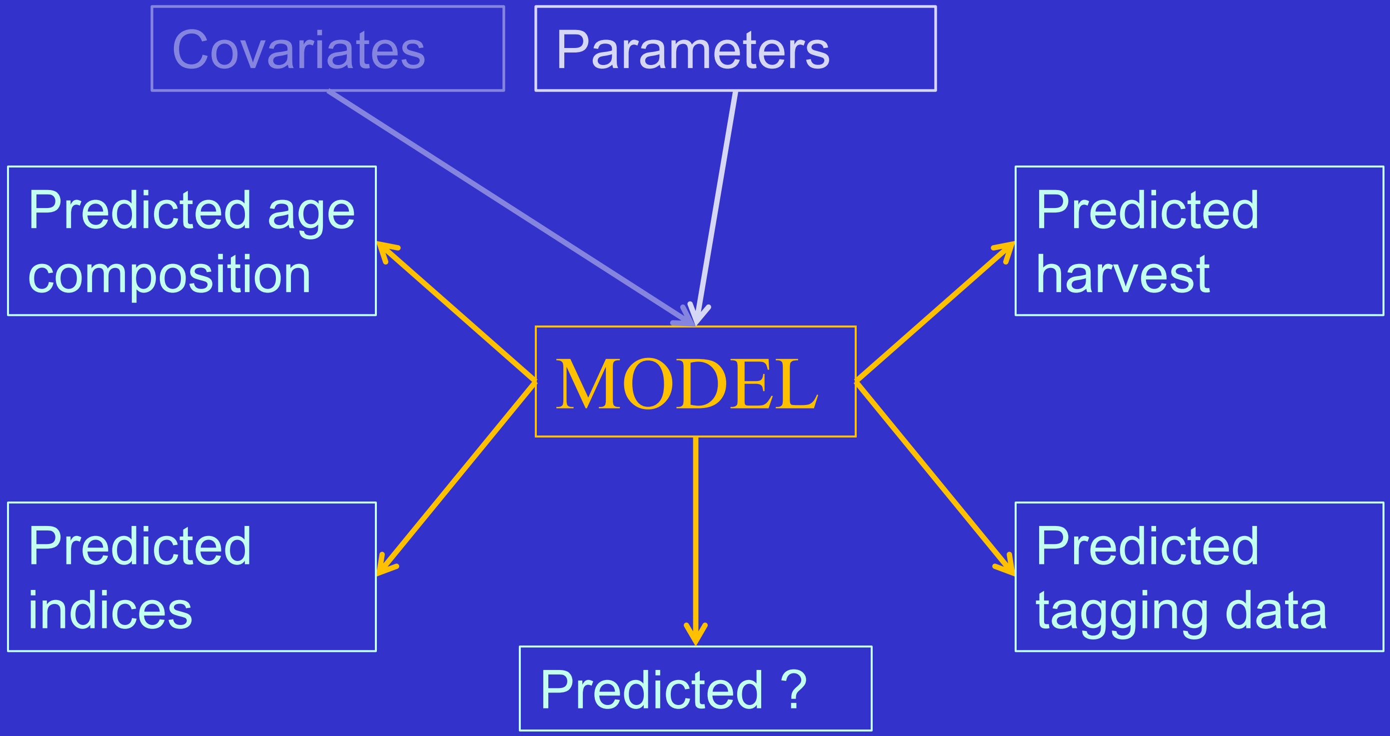
Different types of auxiliary data often result in different model parameterizations

Example: Radio telemetry

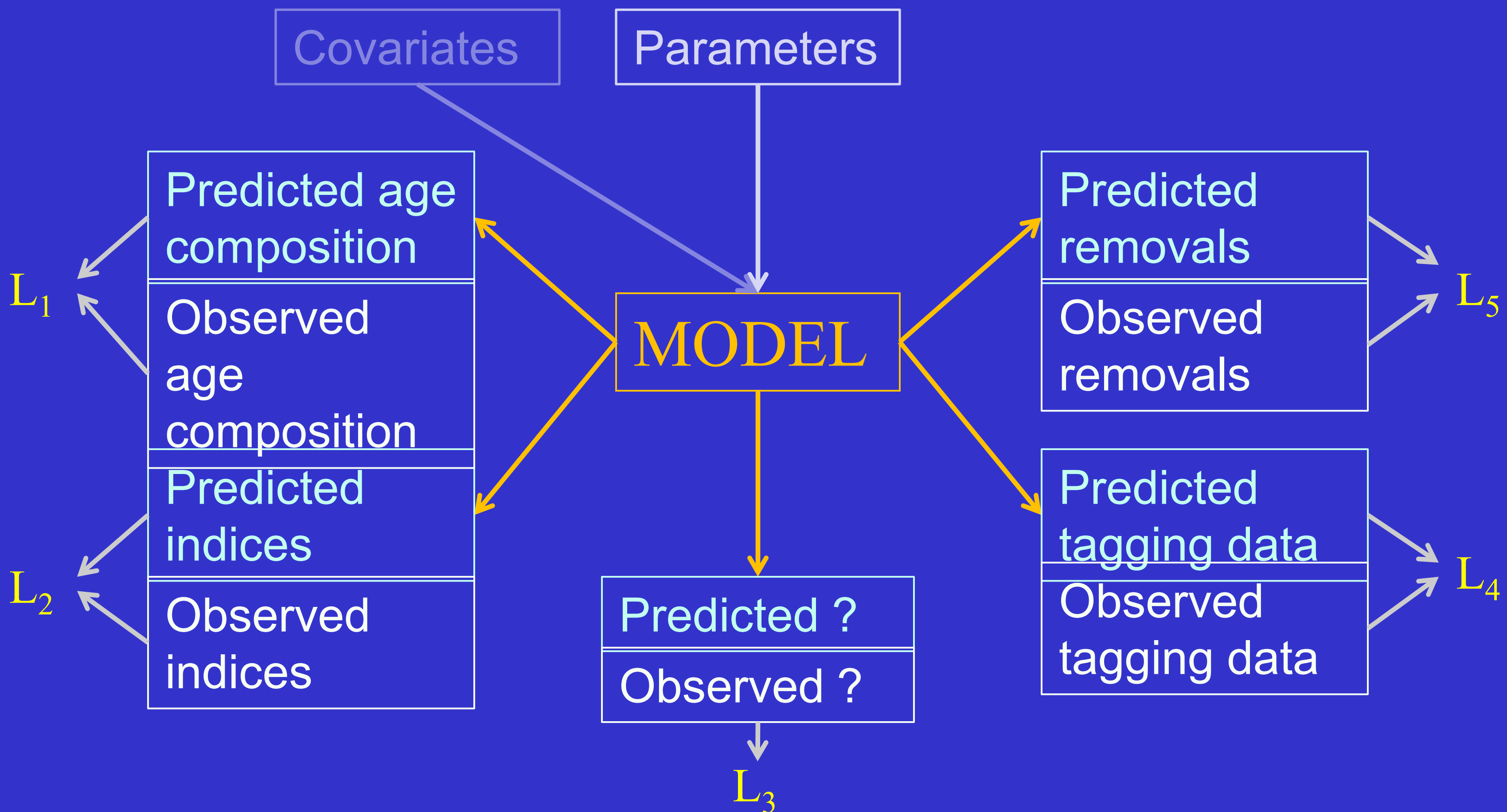


Seber type parameterization

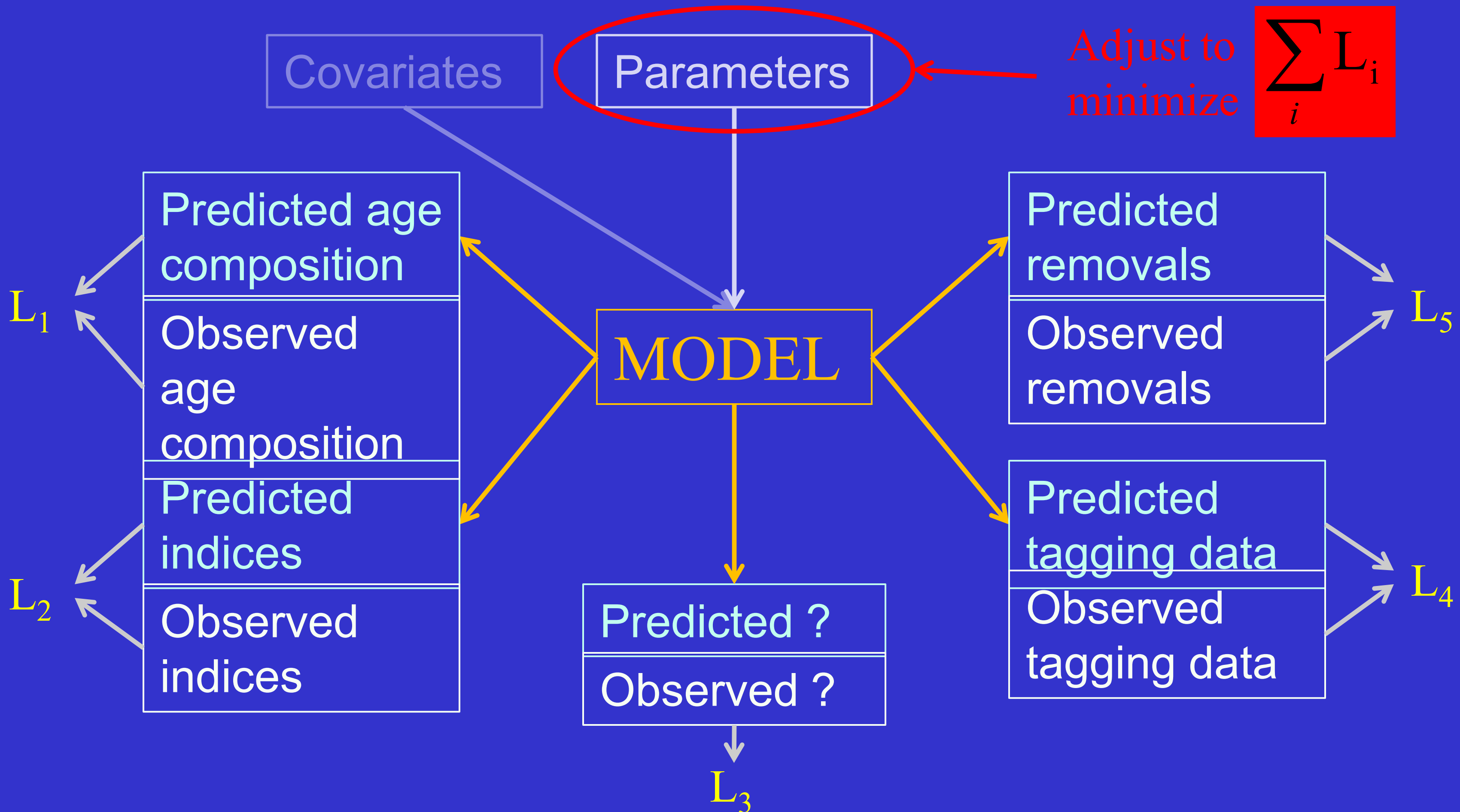
Step 2: Fit the model



Step 2: Fit the model



Step 2: Fit the model



Estimation approaches

1) Minimize an objective function (as with previous slide)

- Sum of squares
- χ^2 = [Observed-Expected]/Expected
- -Log likelihood (*maximum likelihood*)
- -(Log likelihood + Log priors)

  (*MAP – maximum a posteriori*)

Estimation approaches

2) Bayesian inference

- Markov chain Monte Carlo (simulating from joint posterior)
- Incorporates prior beliefs about likely ranges of a parameter (though these can be "vague")
- Allows hierarchical modeling (models within models)

Estimation: Plusses and minuses

Direct optimization

- Typically much simpler to code
- Limitations on how the types of stochasticity considered

Bayesian

- Harder to debug
- Easy to incorporate multiple layers of modeling (e.g. random effects). Random effects really help when >8-10 years of data.

Estimation: Other issues

- Different data sources are typically on different scales – how to weight different components so that there on roughly the right scale? Can we downweight data sources that we don't believe in?

Largely an unresolved problem that may require some subjective reasoning. Iterative reweighting (in the context of MLE or MAP estimation) is one approach that tries to get around this issue.

Software

(1) Excel – "solver" may be able to handle minimization for simple problems

Pros:

- Most accessible
- Interactive

Cons:

- Some data difficult to model (mark-recapture)
- Poor numerical performance
- Programming difficult to replicate

Software

(2) ADMB – AD Model Builder; de facto tool in fisheries assessments, freeware

Pros:

- Fast stable optimization for MLE, MAP, etc.
- Variance/conf intervals are standard output
- Has switches to turn on Bayesian inference/random effects

Cons:

- Pseudo-C++ coding needed, a little bit of a learning curve

Software

(3) R Programming environment; freeware

Pros:

- Lots of people are using it!
- Transparent

Cons:

- Optimization slower, arguably less reliable than ADMB
- Variance estimates usually take more work
- Custom MCMC samplers often needed

Software

(4) WinBUGS, JAGS; freeware

Pros:

- Lots of people are using it!
- Nice tools for Bayesian inference (pseudo-code)

Cons:

- Quirky
- Bit of a learning curve
- Can be slow to fit

A word on model testing

Model testing is important for

- Eliminating programming errors (bugs)
- Ensuring that you're actually able to estimate all the parameters in your model

•Expected value data (analytic-numeric) you should be able to get back the same parameter values you used to generate data

•Simulated data – get at estimator properties (bias, confidence interval coverage, MSE, etc.)

A word on model testing

Signs that you’re not able to estimate all parameters with the data you have:

- Variance estimates that are off the wall (Survival estimated at 1.00 with an SE of 100)
- Warnings that Hessian is ‘singular’ or ‘not positive-definite’
- Bayesian posteriors similar to prior distributions
- Multiple modes in Bayesian posteriors

Questions before I go into a few examples?

Example 1: Model developed for Pennsylvania black bear

- Data available: Age-at-harvest
- Mark-recovery data
- Some reproductive biology, but not used during modeling

Conn, P. B., D. R. Diefenbach, J. L. Laake, M. A. Ternent, and G. C. White. 2008. Bayesian analysis of wildlife age-at-harvest data. Biometrics 64:1170-1177.

Conn, P.B., G.C. White, and J.L. Laake. 2009. Simulation performance of Bayesian Estimators of Abundance Employing Age-at-harvest and mark-recovery data. In Thomson, DL and Cooch, EG, editors. Modeling Demographic Processes in Marked Populations. Springer, New York.

Model for age-at-harvest data

Notation

C_{ij}	Harvest by time and age
N_{ij}	Abundance immediately prior to harvest
S_{ij}	Survival
h_{ij}	Probability of recovery
f_{ij}	Recruitment process intensity
[X|Y]	The conditional distribution of X given Y
BOLD	Vector (collection) of parameters

Model for age-at-harvest data

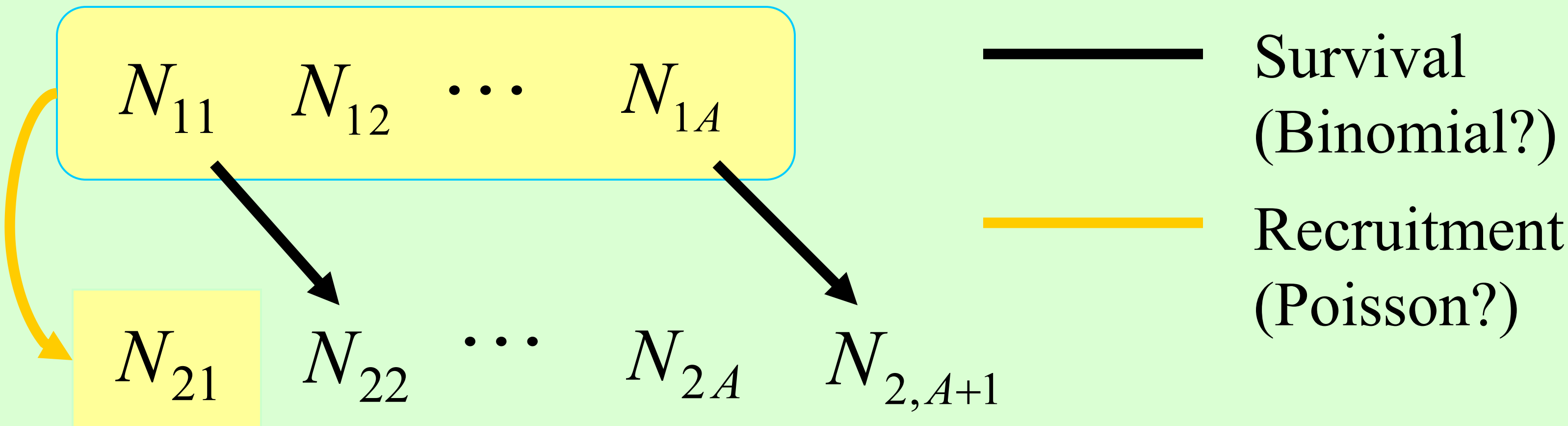
Population Dynamics Submodel

$$N_{11} \quad N_{12} \quad \cdots \quad N_{1A}$$

Condition on initial abundance vector, survival and recruitment rates

Model for age-at-harvest data

Population Dynamics Submodel – 2nd Year



$$
\begin{aligned}
[\mathbf{N_{2\cdot}}|\mathbf{N_{1\cdot}}, \mathbf{f_{1\cdot}}, \mathbf{S_{1\cdot}}] = \; & [N_{22}|N_{11}, S_{11}] \times \cdots \times \\
& [N_{2,A+1}|N_{1A}, S_{1A}] \times \\
& [N_{21}|\mathbf{N_{1\cdot}}, \mathbf{f_{1\cdot}}].
\end{aligned}
$$

Model for age-at-harvest data

Population Dynamics Submodel – All Years

$$
\begin{tikzcd}
N_{11} \arrow[dr] & N_{12} & \cdots & N_{1A} \arrow[dr] & \\
N_{21} \arrow[dr] & N_{22} & \cdots & N_{2A} \arrow[dr] & N_{2,A+1} \arrow[d] \\
N_{31} & N_{32} & \cdots & N_{3A} & N_{3,A+1} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
N_{Y-1,1} \arrow[dr] & N_{Y-1,2} & \cdots & N_{Y-1,A} \arrow[dr] & N_{Y-1,A+1} \arrow[d] \\
N_{Y1} & N_{Y2} & \cdots & N_{YA} & N_{Y,A+1}
\end{tikzcd}
$$

$$
[\mathbf{N} | \mathbf{N_1}_{\cdot}, \mathbf{S}, \mathbf{f}] = \prod_{i=1}^{Y-1} [\mathbf{N_{i+1,\cdot}} | \mathbf{N_{i\cdot}}, \mathbf{f_{i\cdot}}, \mathbf{S_{i\cdot}}]
$$

Model for age-at-harvest data

Observation Process Submodel

$$
\begin{tikzcd}[column sep=small]
N_{11} \arrow[dr] & & N_{12} \arrow[dr] & & \cdots & N_{1,A-1} \arrow[dr] & & N_{1A} \arrow[dr] & \\
& C_{11} & & C_{11} & & & C_{1,A-1} & & C_{1A} \\
N_{21} \arrow[dr] & & N_{22} \arrow[dr] & & \cdots & N_{2,A-1} \arrow[dr] & & N_{2A}+N_{2,A+1} \arrow[dr] & \\
& C_{21} & & C_{22} & & & C_{2,A-1} & & C_{2A} \\
\vdots & & \vdots & & \ddots & \vdots & & \vdots & \\
N_{Y-1,1} \arrow[dr] & & N_{Y-1,2} \arrow[dr] & & \cdots & N_{Y-1,A-1} \arrow[dr] & & N_{Y-1,A}+N_{Y-1,A+1} \arrow[dr] & \\
& C_{Y-1,1} & & C_{Y-1,2} & & & C_{Y-1,A-1} & & C_{Y-1,A} \\
N_{Y1} \arrow[dr] & & N_{Y2} \arrow[dr] & & \cdots & N_{Y,A-1} \arrow[dr] & & N_{YA}+N_{Y,A+1} \arrow[dr] & \\
& C_{Y1} & & C_{Y2} & & & C_{Y,A-1} & & C_{YA}
\end{tikzcd}
$$

Typical choice for $[C_{ij} \mid N_{i-1,j-1}]$: Binomial

Model for age-at-harvest data

The joint likelihood for age-at-harvest data *and* abundance after the first year can thus be given by

$$
\begin{aligned}
L_{age-at-harvest} &= [\mathbf{C}, \mathbf{N} | \mathbf{N_{1\cdot}}, \mathbf{S}, \mathbf{h}, \mathbf{f}] \\
&= [\mathbf{C} | \mathbf{N}, \mathbf{h}][\mathbf{N} | \mathbf{N_{1\cdot}}, \mathbf{S}, \mathbf{f}]
\end{aligned}
$$

where

$$
\begin{aligned}
[\mathbf{C} | \mathbf{N}, \mathbf{h}] &= [C_{1A} | N_{1A}, h_{1A}] \prod_{i=2}^{Y} [C_{iA} | N_{iA} + N_{i,A+1}, h_{iA}] \times \\
&\quad \prod_{i=1}^{Y} \prod_{j=1}^{A-1} [C_{ij} | N_{ij}, h_{ij}].
\end{aligned}
$$

Model for age-at-harvest data

ISSUE 1: Parameters NOT IDENTIFIABLE without extra information!!!!

SOLUTION: Following Gove et al. (2002), I suggest basic inference on the joint likelihood

$$L = L_{age-at-harvest} \times L_{auxiliary}$$

Model for age-at-harvest data

ISSUE 2: Maximum likelihood estimation prohibitively difficult

SOLUTION: Specify prior distributions (possibly noninformative) and conduct a Bayesian analysis.

Model for age-at-harvest data

Model Assumptions

- No aging error
- Animals behave independently
- Demographic parameters are the same for all individuals in a given age- and sex-class for a given time interval
- No Immigration/Emigration
- Auxiliary data not included in age-at-harvest matrix

Simulation Testing

3 Simulation modules - All assumed mark-recovery data were available to help model harvest process

A) Response surface design to quantify estimator performance under a number of biological scenarios when all model assumptions are met.

B) Estimator performance when aging errors occur

C) Estimator performance when data from marked animals included in both portions of likelihood

Simulation Testing

Bayesian Implementation Notes

- MCMC via the Metropolis-Hastings within Gibbs hybrid update in C++
- Noninformative priors used in all cases
- Markov chains mixed poorly; if Gelman-Rubin statistics indicated convergence, last half of 2 chains of length 1 million combined to generate a sample from the posterior
- Posterior mode used as point estimator

Simulation Testing

Module 1: Large scale performance

Simulations varied by

- *Estimation model complexity*
- *Number of marked releases*
- *Study duration*
- *Age classes*
- *Initial abundance*
- *Survival*
- *Reporting rate*
- *Population trend*

Simulation Testing

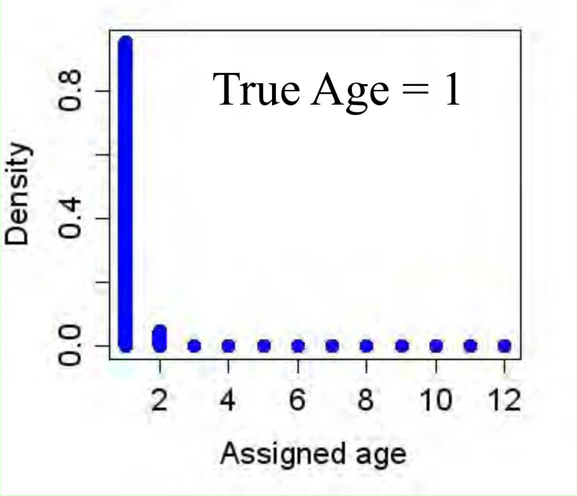
Module 1: Large scale performance

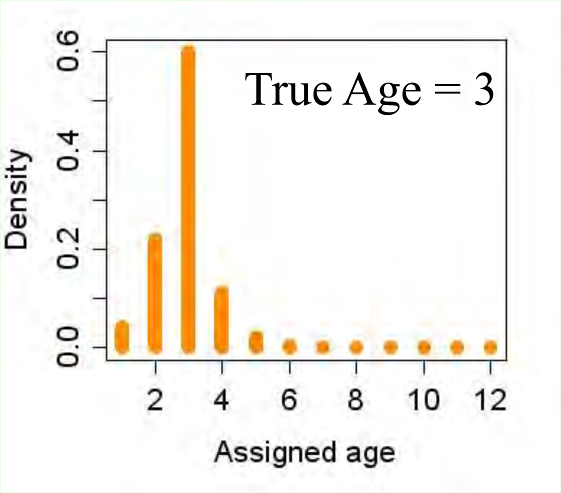
- Percent relative bias on abundance = 1.8 (SE 0.4)
- Absolute bias decreased with sample size
- Credible interval coverage close to “nominal”
- CV on abundance predicted to range from 0.016 to 0.24

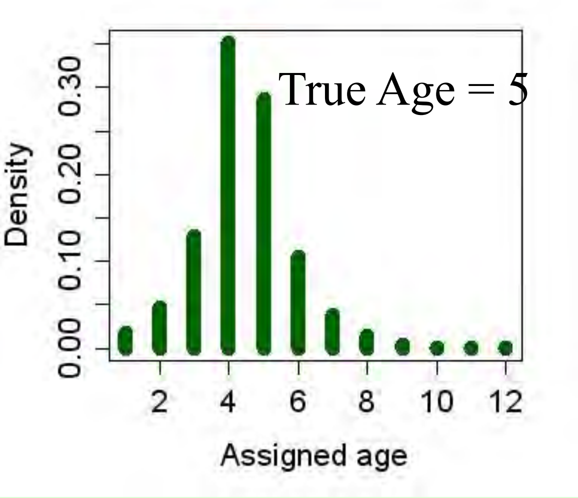
Simulation Testing

Module 2: Performance under aging error

No systematic differences between model performance measure when aging errors were permitted.

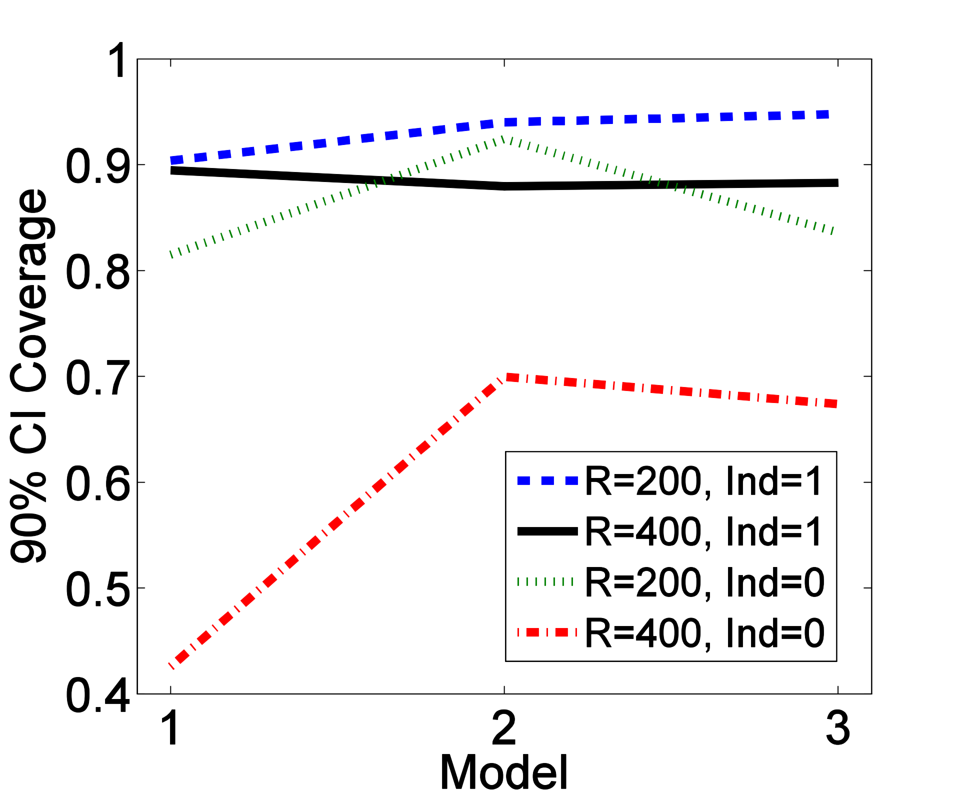






Simulation Testing

Module 3: Performance when likelihoods not independent



Simulation Testing

Summary

• Minimal (positive) bias, good coverage, high precision when all assumptions are met

• Robust to errors in age determination, at least with aging error models considered here

• Caution: measures of precision may be overly optimistic when data from marked animals included in both portions of the likelihood, especially when model complexity is low or when the number of marked individuals make up a substantial portion of the population

Pennsylvania Black Bear Example

Biologists enter dens to manage bears

By MICHAEL RUBINKAM, Associated Press Writer Thu Mar 15, 5:58 PM ET

MILFORD, Pa. - Mark Ternent squeezes his bulky frame into the narrow opening of a bear den and shines a flashlight into the eyes of a 200-pound female..

Photo: Duane Diefenbach

Pennsylvania Black Bear Example

- Obtained age-specific marking and harvest records for females for 1986-1999 (40-220 marked/year, 600-1500 harvested/year)
- Compiled mark-recovery encounter histories for females initially captured March-November
- Diffuse Priors
- Goal: Estimate abundance, survival, recruitment, recovery rate for female portion of population (November to November)

Photo: Duane Diefenbach

Photo: Duane Diefenbach

Pennsylvania Black Bear Example

Photo: Duane Diefenbach

Compared DIC of 4 a priori models for population dynamics

- Recruitment rate (log link):

  f(•) or f(year)

- Survival, recovery probability (logit link):

  S(age)h(age) or S(age+year)h(age+year)

All models included overdispersion random effects on the logit of recovery probability (Barry et al. 2003):

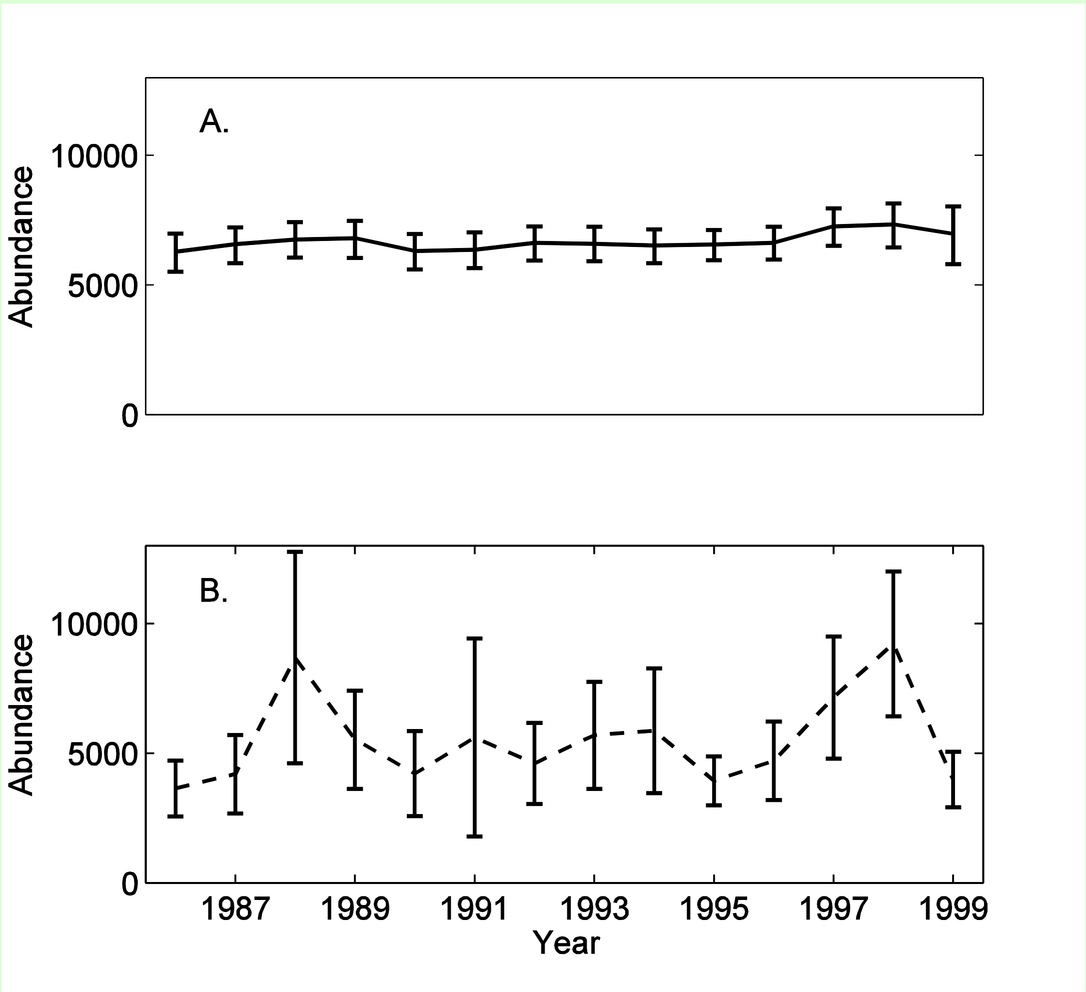
$$\epsilon_{ij} \sim \mathrm{Normal}(0, 1/\tau^2)$$

Pennsylvania Black Bear Example

Model Selection Results

Model	ΔDIC	p_B
S(a+t)h(a+t)f(t)	0.0	0.67
S(a+t)h(a+t)f(dot)	6.0	0.58
S(a)h(a)f(t)	28.9	0.50
S(a)h(a)f(dot)	34.1	0.49

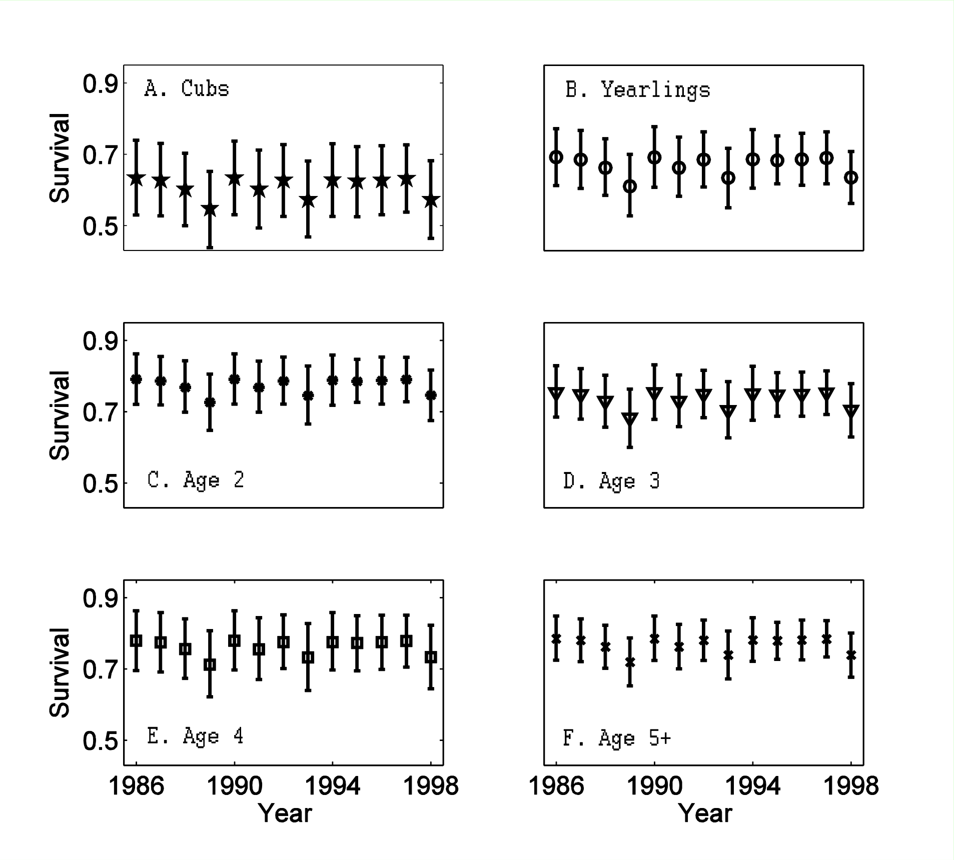
Pennsylvania Black Bear Example

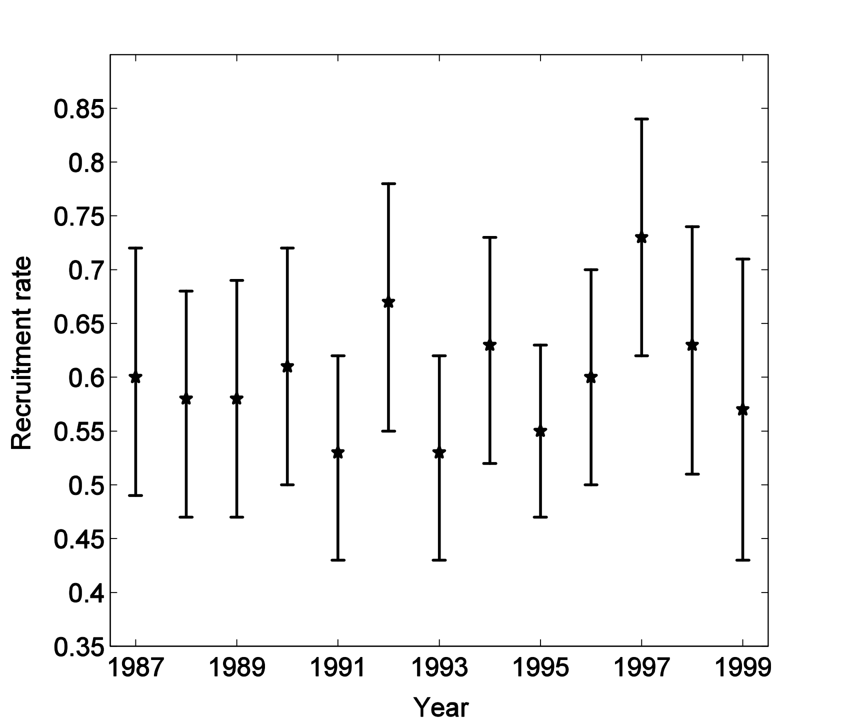


A. Bayesian Model

B. Lincoln-Petersen

Pennsylvania Black Bear Example





Pennsylvania Black Bear Example

Summary

1. Joint age-at-harvest model produces estimates which are much more precise than single season approaches (e.g. L-P). Thus, less sampling effort needed. Also, greater biological realism because they are required to be internally consistent.

2. Caution needed when interpreting final estimates when temporary emigration a possibility

3. Further evaluation of model assumptions needed (e.g. tag loss, pre-harvest mortality following marking)

Example II: Integrated Population Modeling of Black Bears in Minnesota: Implications for Monitoring and Management

Joint work with John Fieberg, Dave Garshelis, Karen Noyce – MN Dept. of Natural Resources

Kyle Shertzer, Paul Conn – National Marine Fisheries Service

May 2011

These slides pilfered from J. Fieberg

Outline

- Data sources in MN
- Integrated population modeling approach
- Simulation results
- MN black bears

Fieberg JR, Shertzer KW, Conn PB, Noyce KV, Garshelis DL, 2010 Integrated Population Modeling of Black Bears in Minnesota: Implications for Monitoring and Management. PLoS ONE 5(8): e12114. doi:10.1371/journal.pone.0012114

Importance of Harvest Data

- Relatively inexpensive to collect
- Can be obtained over large geographical areas

Question: are "large harvests" due to:

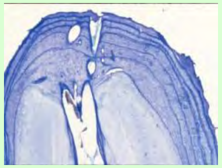
- High population size (N), average harvest rates
- Average N, with above average harvest rates

Key: age data and temporal covariates

Example Harvest Matrix

Year/Age	0.5	1.5	2.5	3.5	4.5	5.5	6.5
1989	7	478	535	143	221	103	84
1990	6	607	545	369	132	175	106
1991	10	432	649	275	249	64	78
1992	28	649	609	598	288	268	84
1993	17	1001	580	318	286	175	152
1994	7	569	642	297	157	171	94
1995	**29**	**1233**	**800**	**703**	**390**	**231**	**296**
1996	5	502	524	228	200	83	55
1997	17	721	849	563	193	176	112
1998	35	1394	722	594	435	174	179
1999	48	903	1054	365	312	284	100
2000	44	1216	682	666	244	215	197
2001	61	1274	1446	468	505	186	172
2002	20	603	404	301	90	149	46
2003	76	811	1156	432	351	114	168

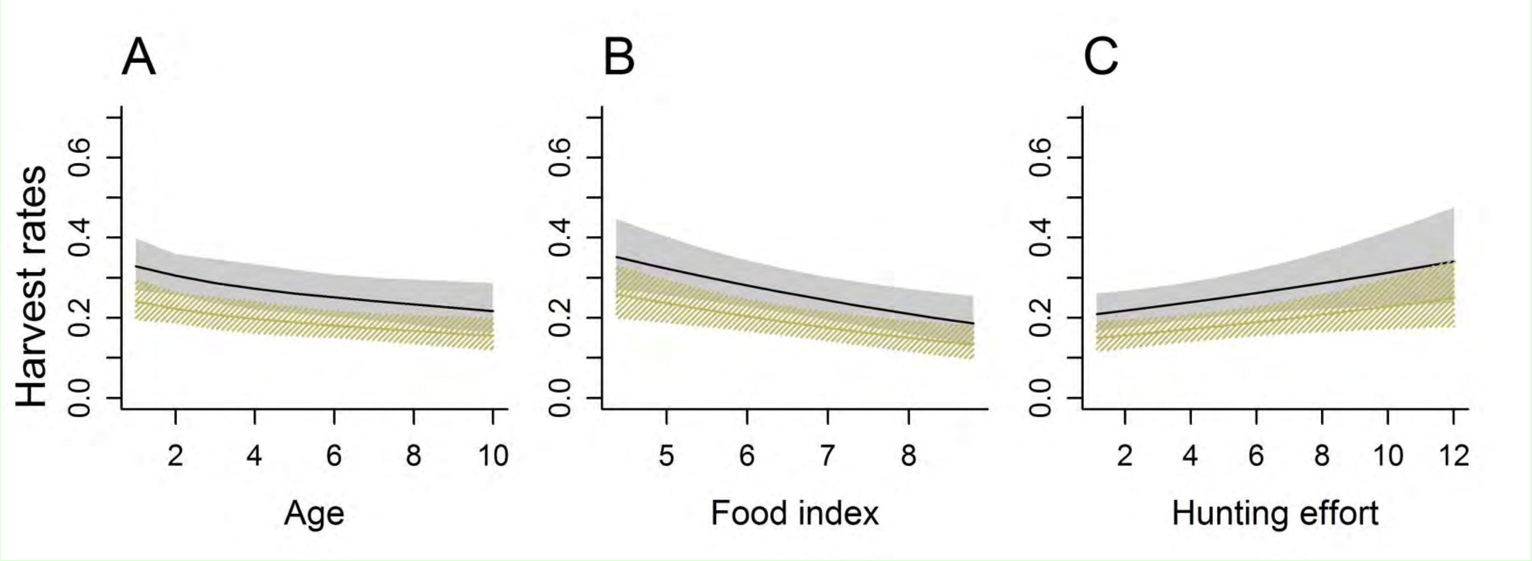
Data Sources for Model



- Harvest records since 1980
  - Total harvest from check stations
  - Teeth for aging (~70% compliance)
- Temporal covariates
  - Natural food availability index
  - Measures of hunter effort
- Population estimates from statewide mark-recapture studies (1991, 1997, 2002, 2008)

Additional information

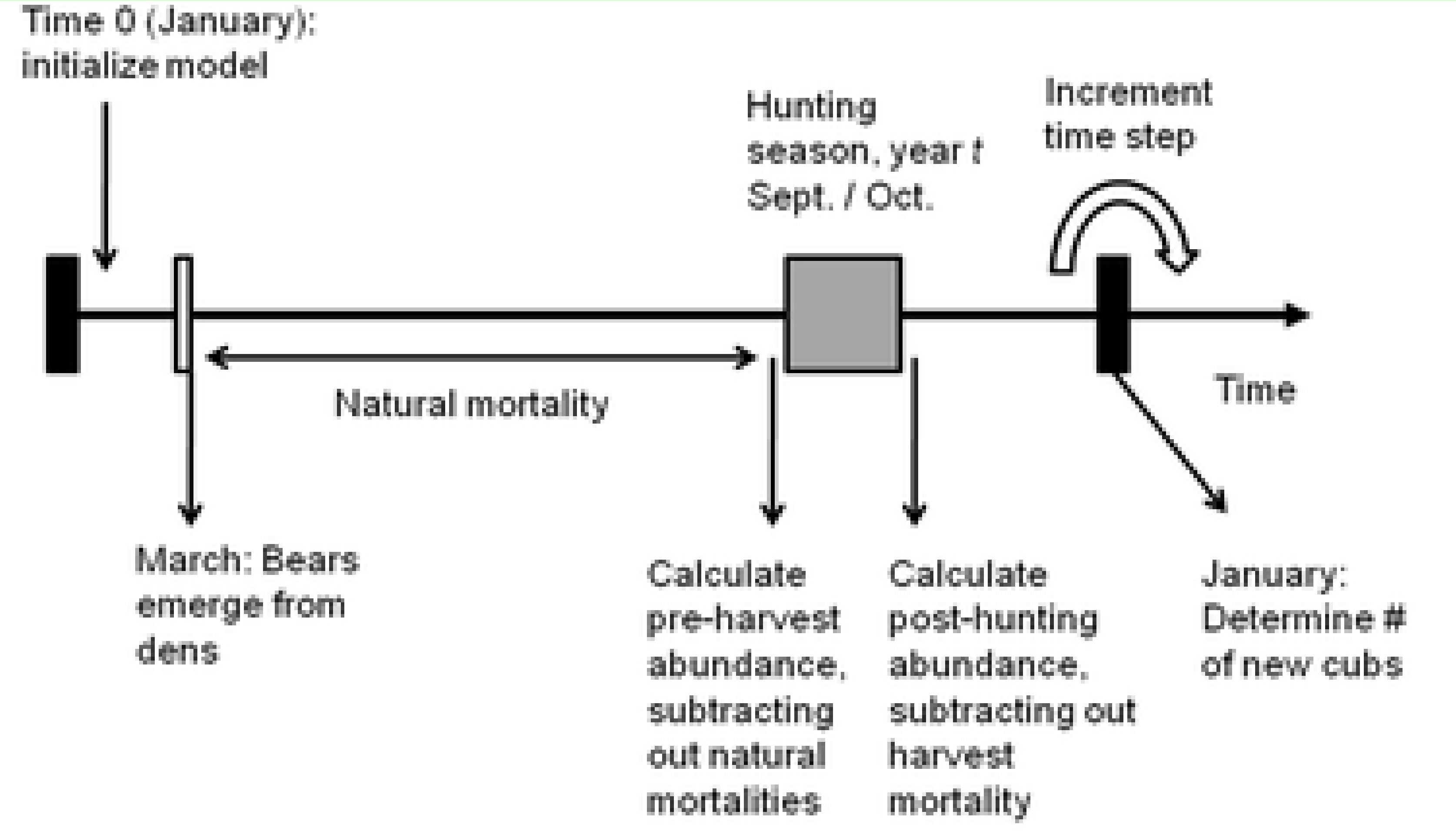
- Telemetry data (3 study sites)
  - Mortality rates (hunting, non-hunting)
- Estimates of cub survival, litter size from den checks



Basic approach

- Specify deterministic population model
  - Natural mortality rates
  - Harvest rates
- Estimate age distribution in 1980, cubs in years 1981-2008.
- Minimizing a χ^2 objective function:

$$\Lambda_0 = \sum_{\text{sex}} \sum_{\text{years}} \sum_{\text{ages}} \left(\text{Harvest}_{\text{obs}} - \text{Harvest}_{\text{expected}}\right)^2 \Big/ \text{Harvest}_{\text{expected}}$$


Time 0 (January):
initialize model
Hunting
season, year t
Sept. / Oct.
Increment
time step
Natural mortality
Time
March: Bears
emerge from
dens
Calculate
pre-harvest
abundance,
subtracting
out natural
mortalities
Calculate
post-hunting
abundance,
subtracting out
harvest
mortality
January:
Determine #
of new cubs

Population Dynamics Submodel

Ages (cub to 10+)

Years 1980-2008

$$\begin{array}{ccccc}
N_{11} & N_{12} & \cdots & N_{1A} & \\
N_{21} & N_{22} & \cdots & N_{2A} & N_{2,A+1} \\
N_{31} & N_{32} & \cdots & N_{3A} & N_{3,A+1} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
N_{Y-1,1} & N_{Y-1,2} & \cdots & N_{Y-1,A} & N_{Y-1,A+1} \\
N_{Y1} & N_{Y2} & \cdots & N_{YA} & N_{Y,A+1}
\end{array}$$

No. of cubs (1981-2007)

Initial Abundances (1980)

Fixed: cub survival, female yearling survival

Estimated parameters:
- Male yearling survival
- Adult (age 2+) survival by sex

Harvest rate model:
N(yr,sex,age)-> H(age,sex,yr)

Two Harvest models

- H(a,s,f,e) : age, sex, food availability, hunting effort = “Food-Effort model”
  - Recover relationships observed in telemetry data?
- H(a,s,yr): age, sex, year effects = “Year model”
  - 29 yr parameters…
    push limits of the data…

Mark-Recapture Estimates

- Add a penalty term to χ^2 objective function :

$$\Lambda_o + w^*[(N_{model} - N_{tet})/SE(N_{tet})]^2$$

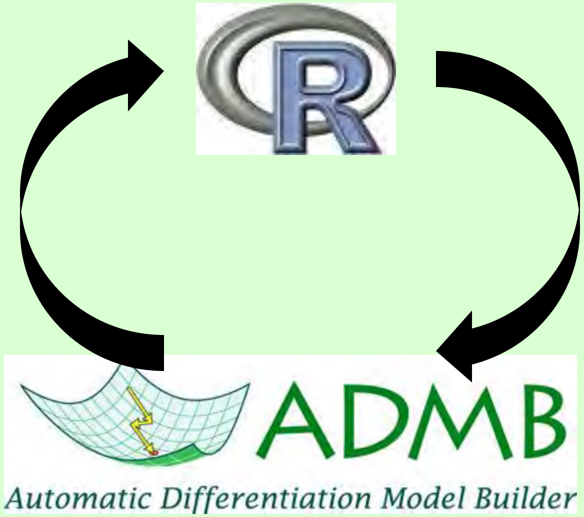
- Tried weights, w, of 0, 1, and 200

- Strike a balance (fit age-at-harvest, M-R)

Questions

- How robust is the modeling approach?
  - Food-Effort model versus Year model?
- How useful are the M-R data?
- Effect of weighting?

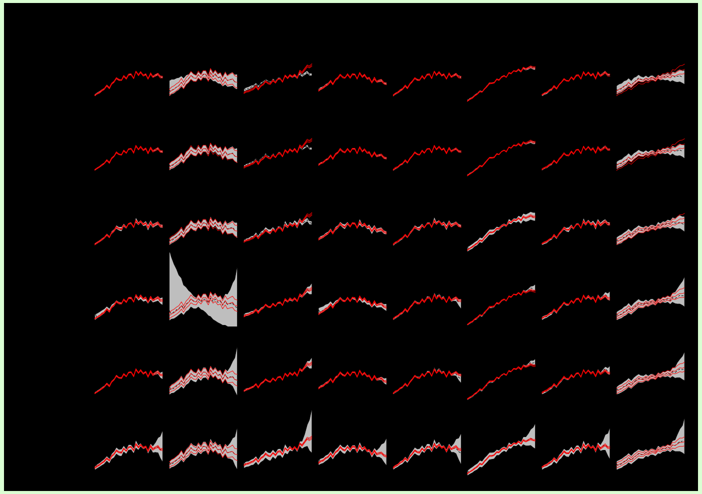
…simulations

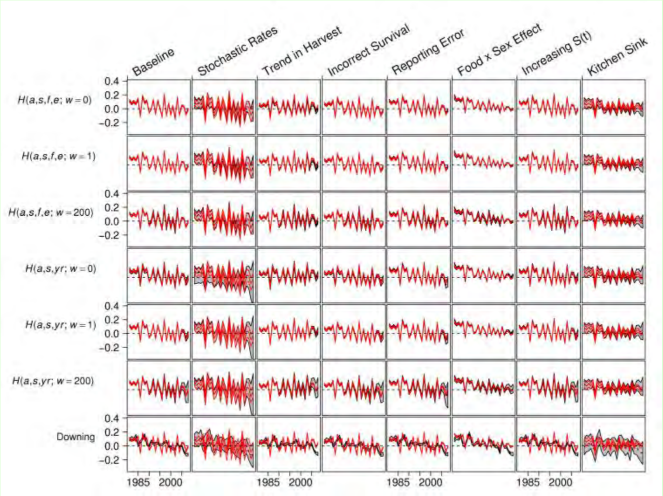


Simulation Scenarios

Looked at several forms of model mis-specification

- Stochastic survival/harvest
- Trends in harvest/survival rates
- Reporting errors (yearlings under-reported)
- Food by sex interaction
- "Kitchen sink" (all of the above)





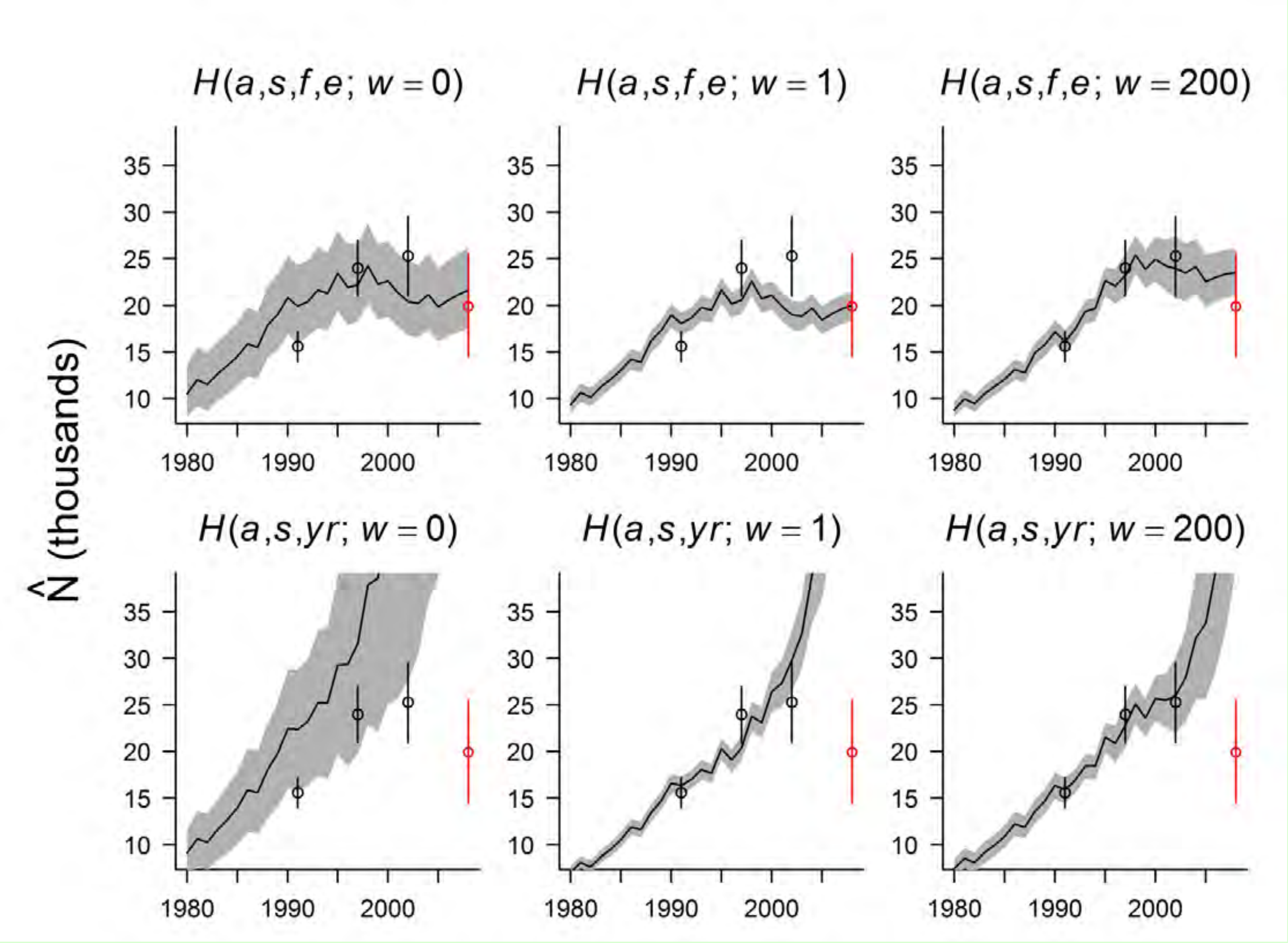
Some conclusions

- Estimates of abundance often biased
- Trends robust to model mis-specification
- Year model sometimes unstable, imprecise at end of time series
- M-R data
  - Helped to get scale right
  - Weighting influenced MSE for trends

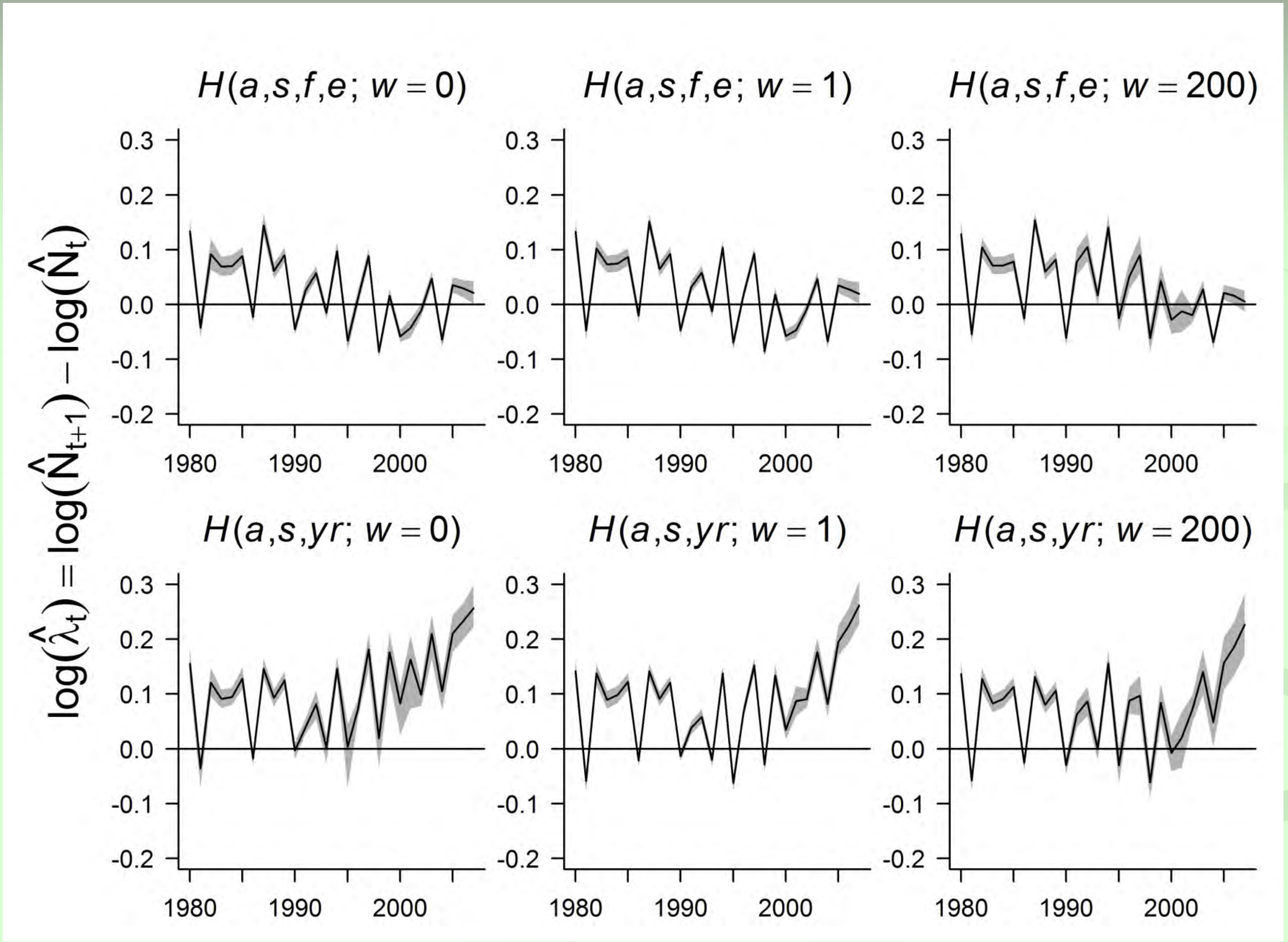
…MN black bear data (1980-2008)

- Fit both harvest models
- With and without mark-recapture data.

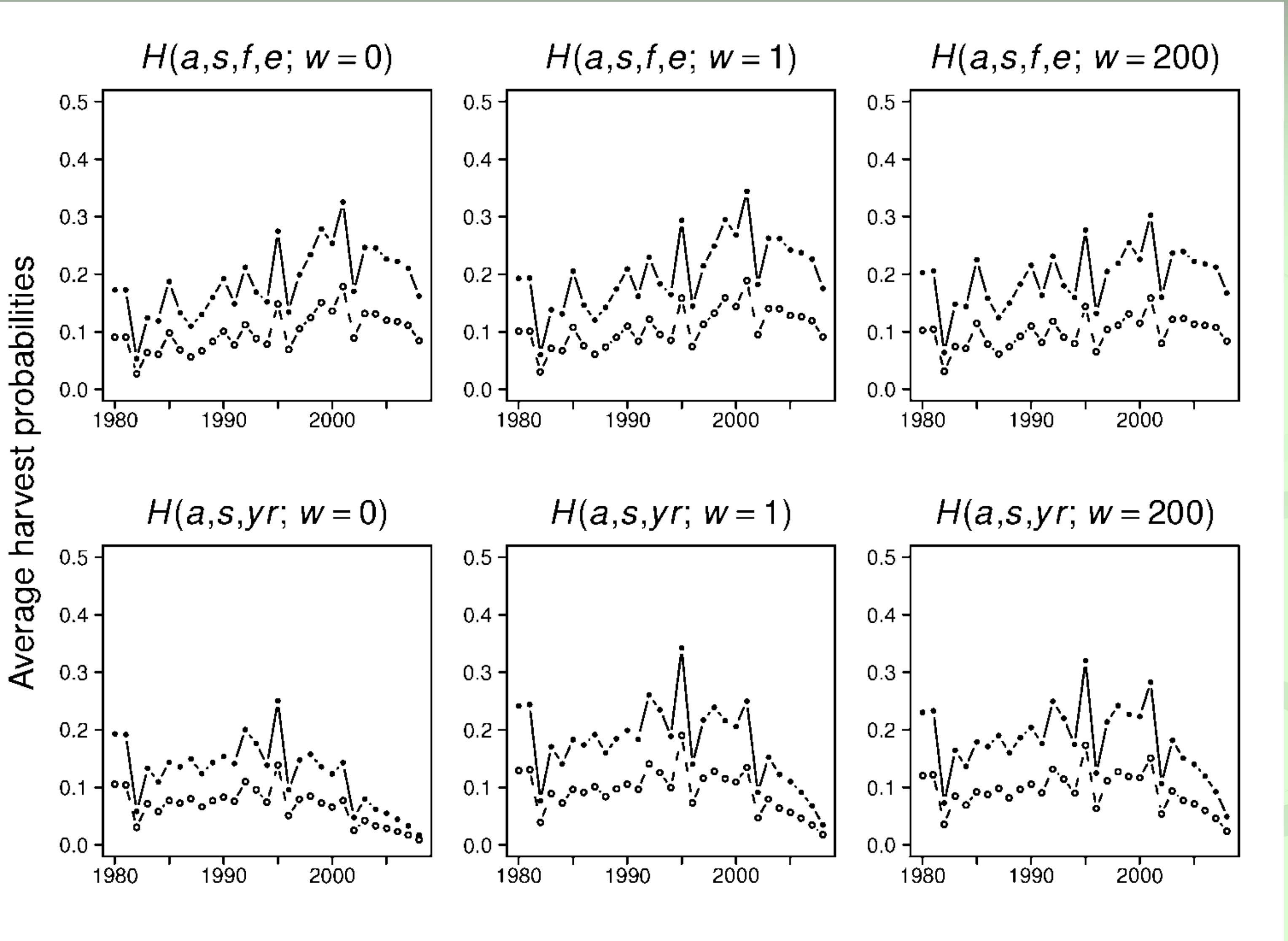
Application to MN black bears



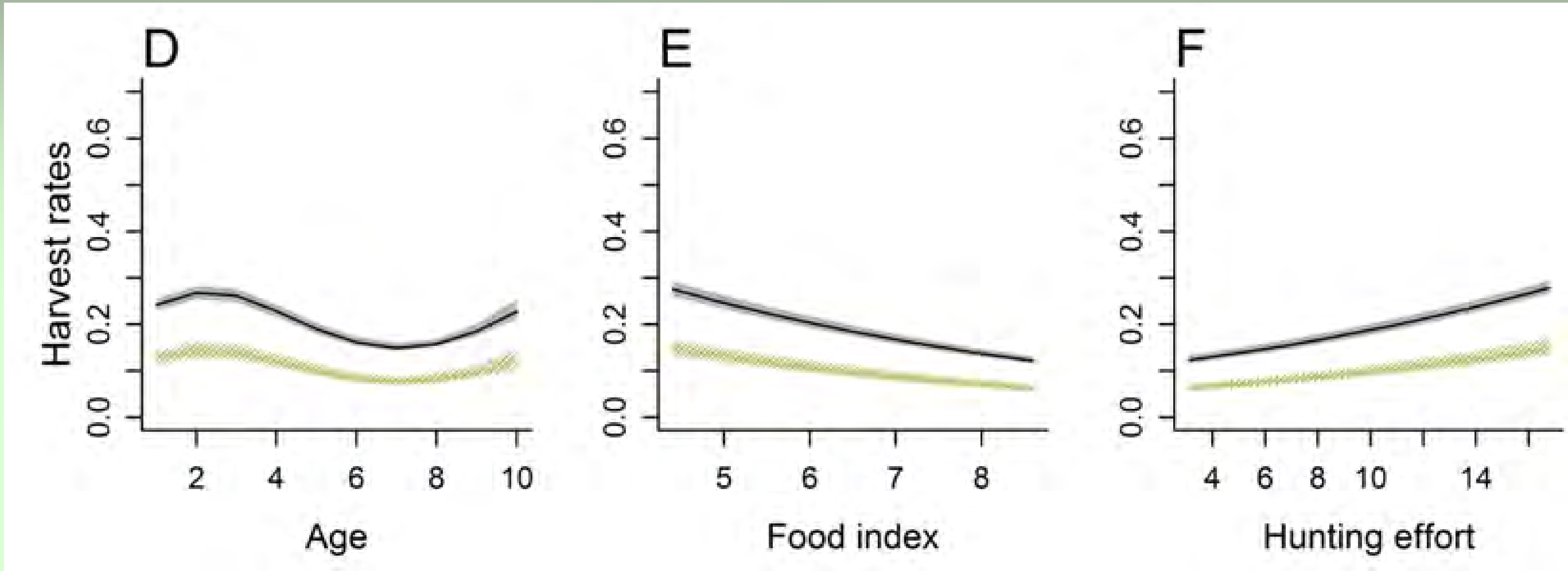
Yearly transitions



Harvest rates

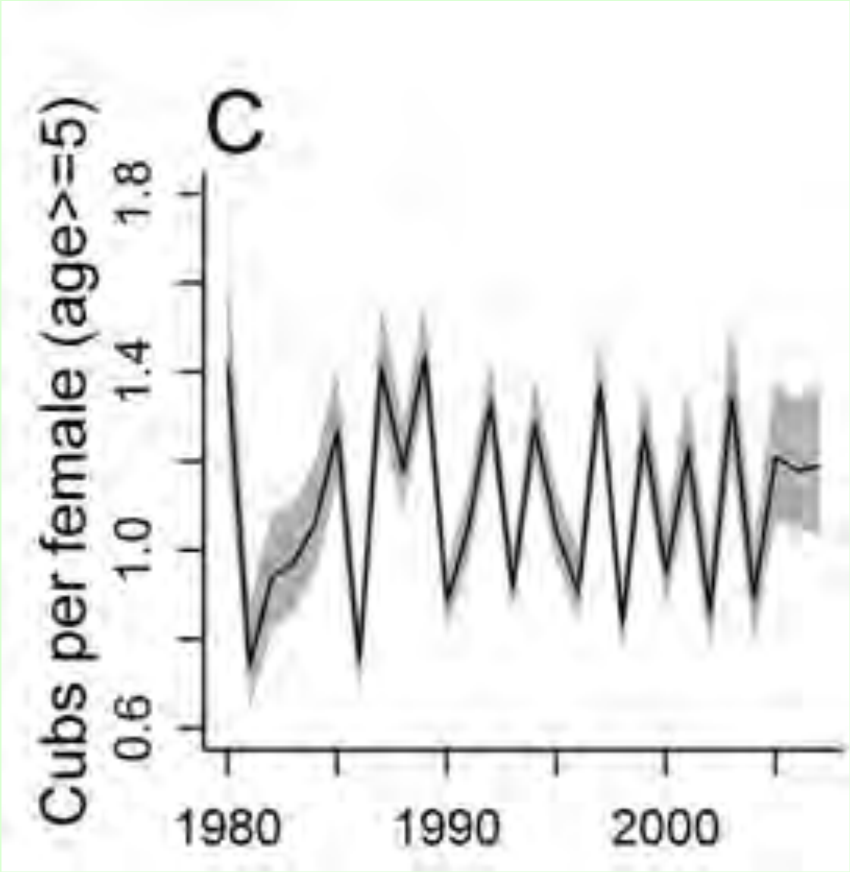


Harvest Rates



- Effects of food and hunting effort agree with telemetry data
- Non-linear age trend
  - May reflect model mis-specificaiton

Recruitment dynamics



Harvest Model Conclusions

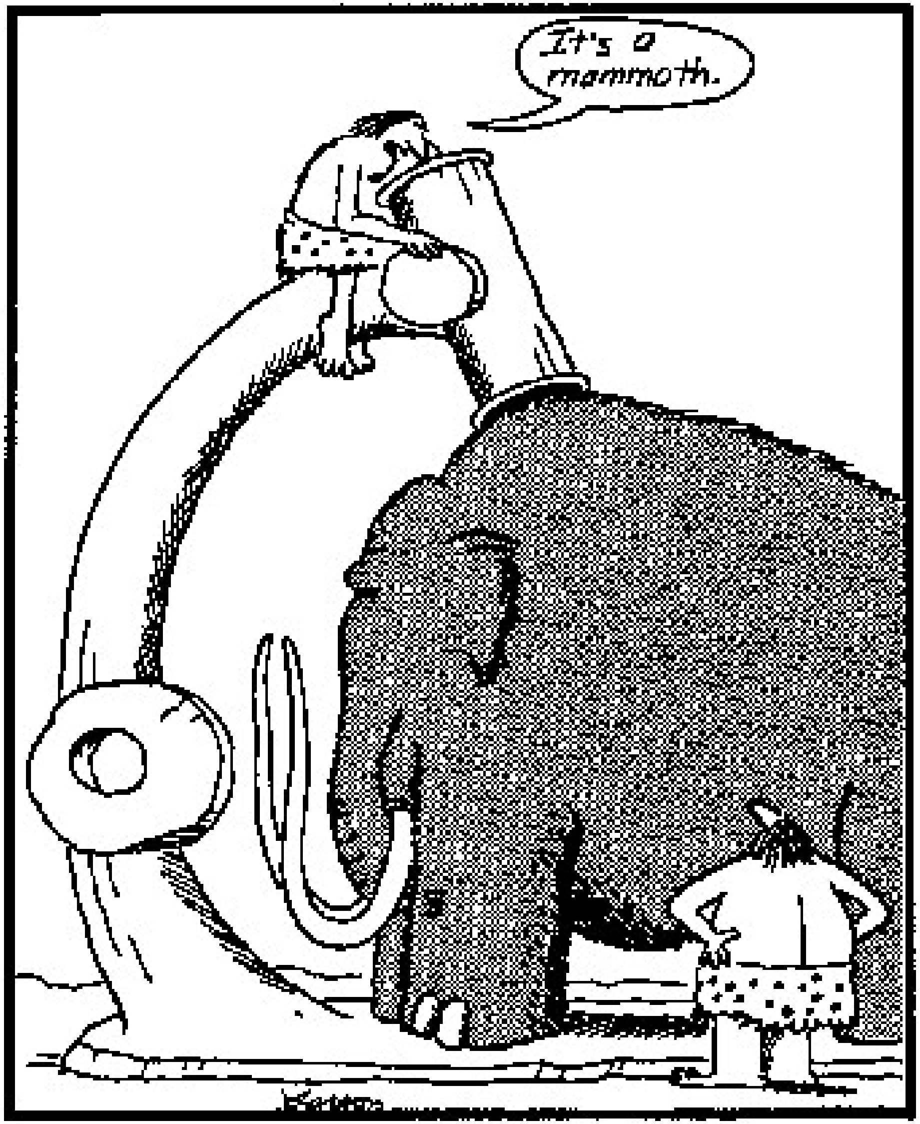
- Absolute abundance estimates may be biased due to model mis-specification
- Robust trend estimates
  - But may require data explaining year-to-year variability in harvest
- With M-R data…robust and viable population monitoring program

Future directions

- Model recruitment dynamics
- Incorporate random effects
  - Allow more flexibility in Food-Effort model
  - Borrow strength in latter years with less information (Year model)
- Explore methods for estimating uncertainty
  - bootstrap, cross-validation, large sample asymptotics

Complex….

Is all this necessary?

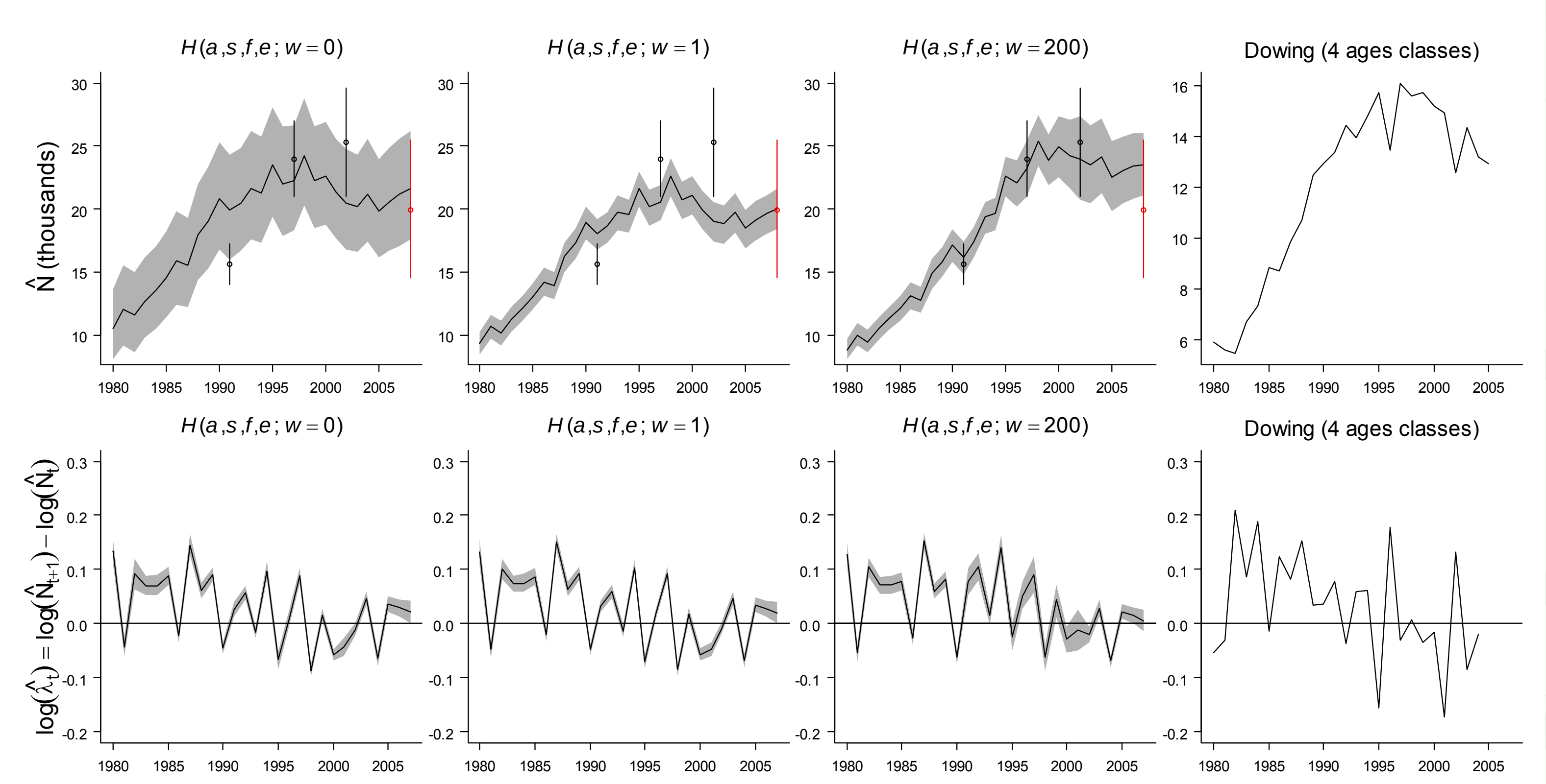


Early microscope

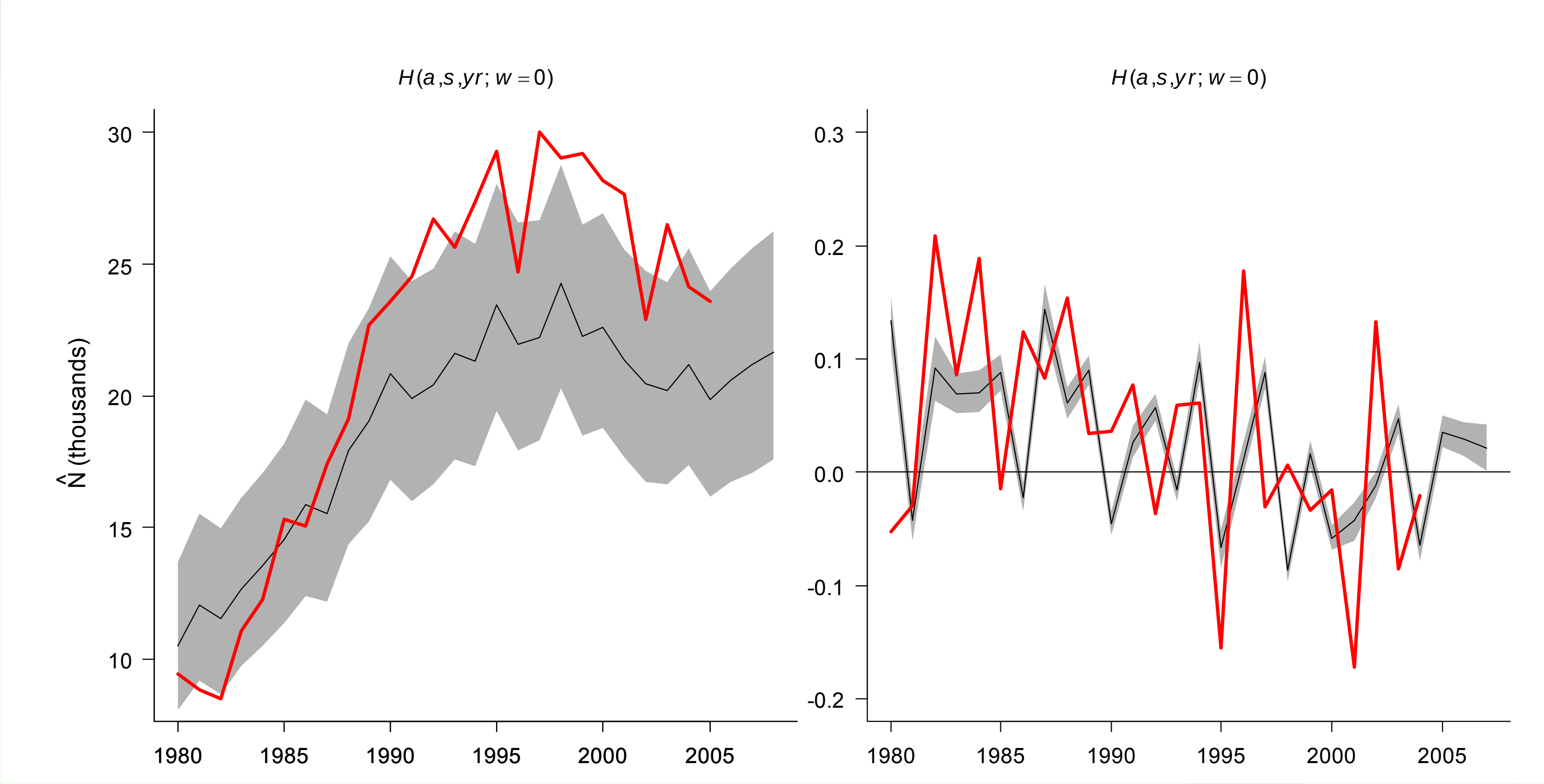
Alternatives?

- Downning reconstruction
  - Assumes constant ratio of hunting to non-hunting mortality
  - Constant harvest rates for last 2 age classes
  - Collapsed to yearlings, age 2, age 3, age 4+
- Other reconstruction approaches

Models Estimates and Downing Reconstruction



Models versus Downing Reconstruction



- Large scale trends similar
- Different assumptions and methods (so, slightly different trends).

Tradeoffs

- Simplicity (Downing +++)
- Flexibility, ability to incorporate additional data (Model +++)
- Estimates for recent years (Model +)
- Test hypotheses (Model +++)

Summary: MN black bears

- Integrated population modeling likely will be a useful tool for monitoring black bears in MN
- Simulation exercises were critical for developing intuition on what model structures provided useful inferences (models with freely time-varying parameter stank)

The importance of power analysis

- I hope you don’t come away from this workshop thinking that all you need to do is collect a little bit of extra data to use these methods
- A better question is “how MUCH more data do I need to collect?” (i.e. how many animals to I need to put radio-collars on, etc.)

The importance of power analysis

- Power analysis: a simulation or expected value data exercise that relates necessary sample sizes to a desired outcome (e.g. a coefficient of variation on estimated abundance = 0.2)

Example: Colorado Power Analysis

Questions

1. Would joint modeling with age-at-harvest data and data from marked individuals be a viable means of monitoring black bear populations in CO??
2. If so, how long would studies need to be and how many individuals would need to be marked per year?

Colorado Power Analysis

- Focused on radio telemetry studies as these give the most information per animal marked
- Focused on females (again)
- Focused on estimation of population trend rather than absolute abundance

$$N_{i0} = N_{i\cdot} - \sum_{j=2}^{A+1} N_{ij}$$

$$N_{i\cdot} = \beta_0^N + \beta_1^N i$$

Colorado Power Analysis

Simulating Data

Individual based model adapted from White, Gill, and Beck (unpublished manuscript) allowing for individual heterogeneity and a Markov model for cub status.

- Adult females (age 5+) breed every other year
- # female cubs per adult female = 0-3, with probabilities determined by Beck (1991)
- Heterogeneity, covariance between initial marking probability and recovery rate

$$\begin{bmatrix} \epsilon_i^p \\ \epsilon_i^h \end{bmatrix} \sim f\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0.10 & \sigma_{ph} \\ \sigma_{ph} & 0.10 \end{bmatrix} \right)$$

Colorado Power Analysis

Simulating Data

Three possible population models:

Model A_1:

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0.37 \\ 0.6 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.85 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.85 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.88 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.88 & 0.88 \end{bmatrix}$$

$E(h) = 0.06, 0.05$

$\lambda = 0.998$

Model A_2:

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0.37 \\ 0.6 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.83 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.83 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.86 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.86 & 0.86 \end{bmatrix}$$

$E(h) = 0.08, 0.06$

$\lambda = 0.981$

Model A_3:

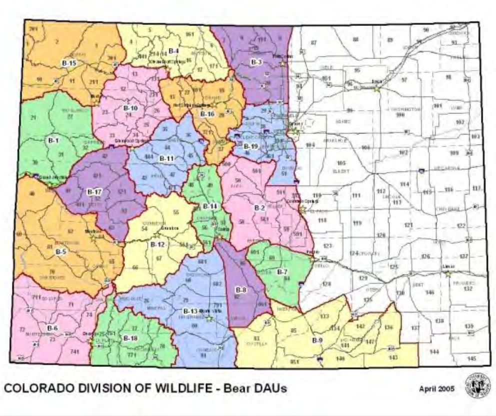
$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0.37 \\ 0.6 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.805 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.805 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.825 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.825 & 0.825 \end{bmatrix}$$

$E(h) = 0.104, 0.085$

$\lambda = 0.958$

Colorado Power Analysis

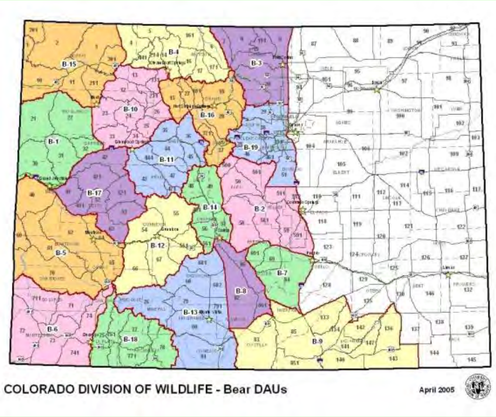
Simulation Inputs:



RSD_1: No Censoring

- Number of years = 5 or 10
- Population size (250 or 500)
- Number of animals marked per year (10, 20, or 30)
- Correlation between recovery and initial marking probability = 0.0 or 0.5
- λ = 0.998, 0.981, 0.958

Colorado Power Analysis



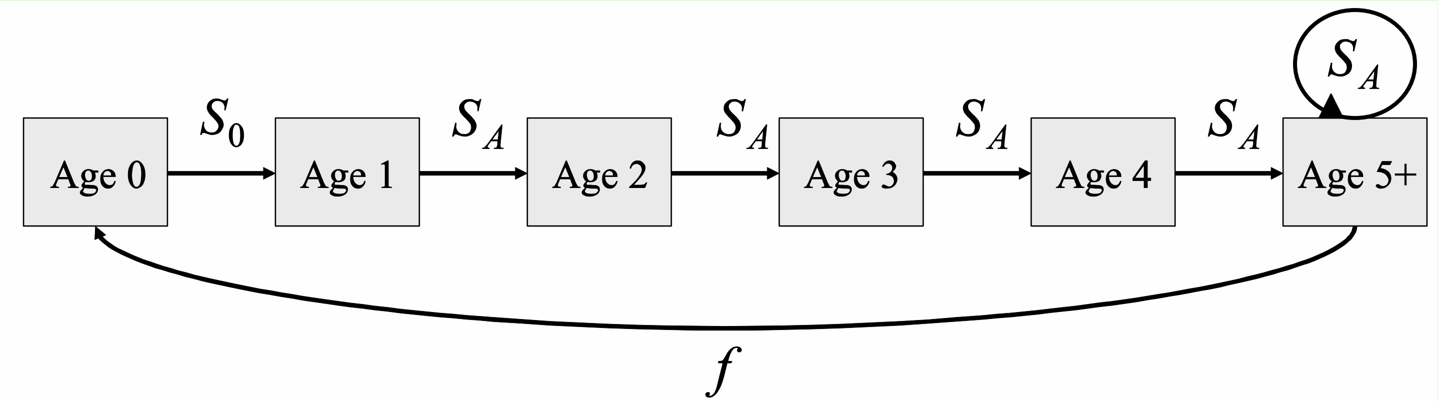
Simulation Inputs:

RSD_2: Censoring

- Number of years = 10
- Population size (250 or 500)
- Number of animals marked per year (10, 20, or 30)
- Correlation between recovery and initial marking probability = 0.0
- λ = 0.998, 0.981, 0.958

Colorado Power Analysis

Estimation Model



h fixed to zero for cubs and constant over remaining age classes

Colorado Power Analysis

Response Variables

For each simulation input combination, I performed 5 simulations. Conditional on convergence, I recorded the following with respect to β_1^N:

- Percent relative bias (% Bias)
- 90% Bayesian HPD interval coverage
- Coefficient of variation (CV)
- Whether or not 0 was within 90% HPD interval

Colorado Power Analysis

Results: Convergence rates

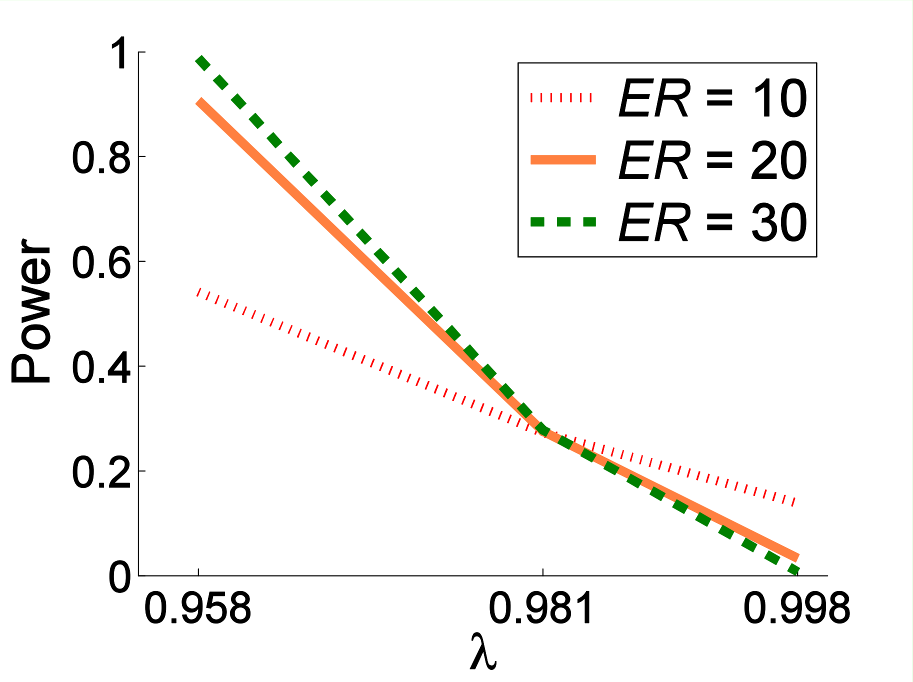
Years	Design	Expected Releases		
		10	20	30
5	RSD_1	0.55	0.87	0.97
10	RSD_1	1.00	0.98	1.00
10	RSD_2	0.90	1.00	1.00

Colorado Power Analysis

Results: Power to detect population declines

5 year studies: Little to no power to “detect” population declines (10-35% for λ=0.958).

10 year studies: Power depends on λ and the number of expected releases per year



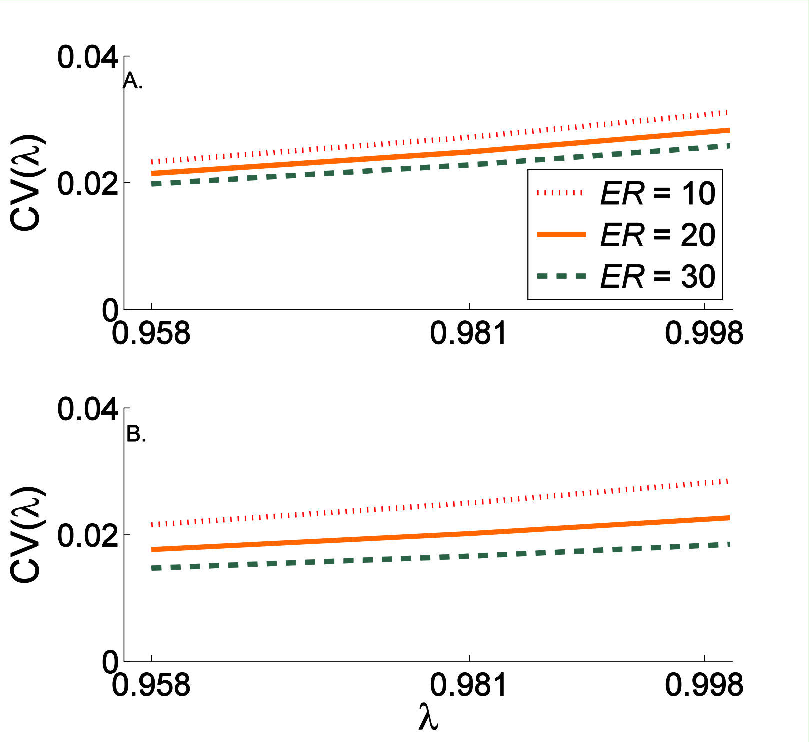
Colorado Power Analysis

Results: Coverage, %Bias, CV

- Coverage close to "nominal" over all simulation inputs

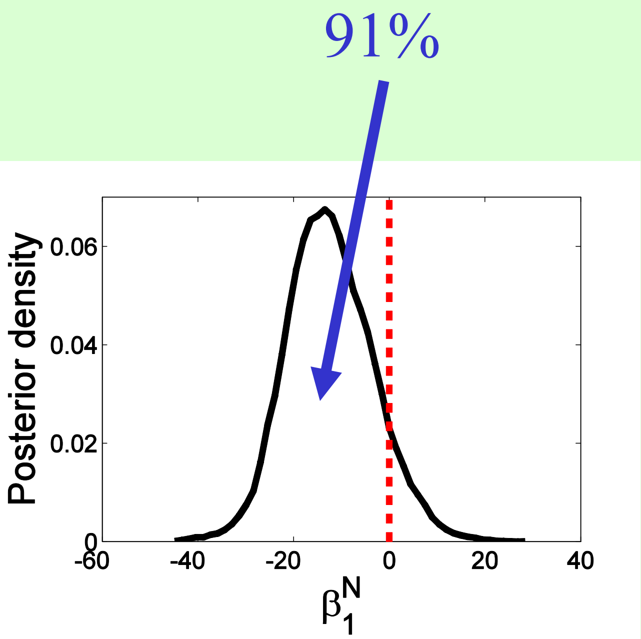
- %Bias of β_1^N / N_1. = -1.6 (SE 0.2).

- CV on λ was predicted to be 2% to 3% for 10 year studies (results of RSD_2)



Colorado Power Analysis

Summary



• "Power" to detect population trends reasonable for 10 year studies; however "power" not the whole story.

• Apparent negative bias in trend estimator would favor conservative management if not taken into account.

• Abundance, correlation in marking and recovery probabilities not important factors for trend estimation.

Final Thoughts

- Hidden process/state space/integrated population modeling attempts to simultaneously make use of ALL available data
- Potential for permitting relationships among parameters and even incorporating individual level random effects (fitness?, tradeoffs?, density dependence?)

Final Thoughts

If you're serious about implementing such a sampling program/modeling approach the biggest bang for your buck is probably

(1) Visiting your agency biometrician

(2) Consult/contract out to a recently graduated quantitative fisheries or wildlife masters/PhD student that will still work for Top Ramen

(3) Consult/contract out with a higher paid consultant

Questions?