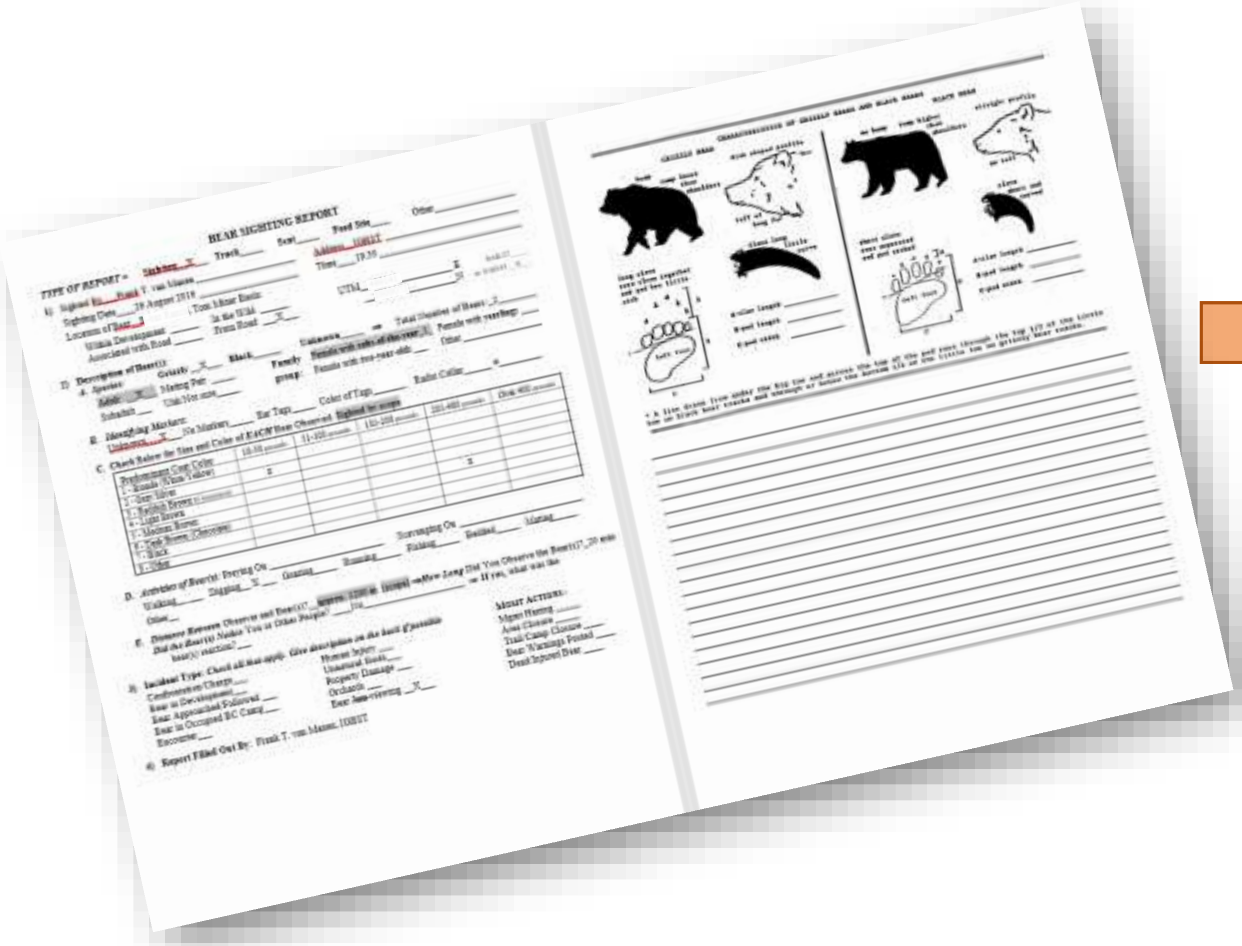
Advancing Demographic Monitoring of Grizzly Bears

INTERAGENCY GRIZZLY BEAR STUDY TEAM

Overview

- Need for re-assessment of Chao2 estimation
- Address underestimation bias
- Smoothing annual variation and detecting change

Overview of current monitoring approach

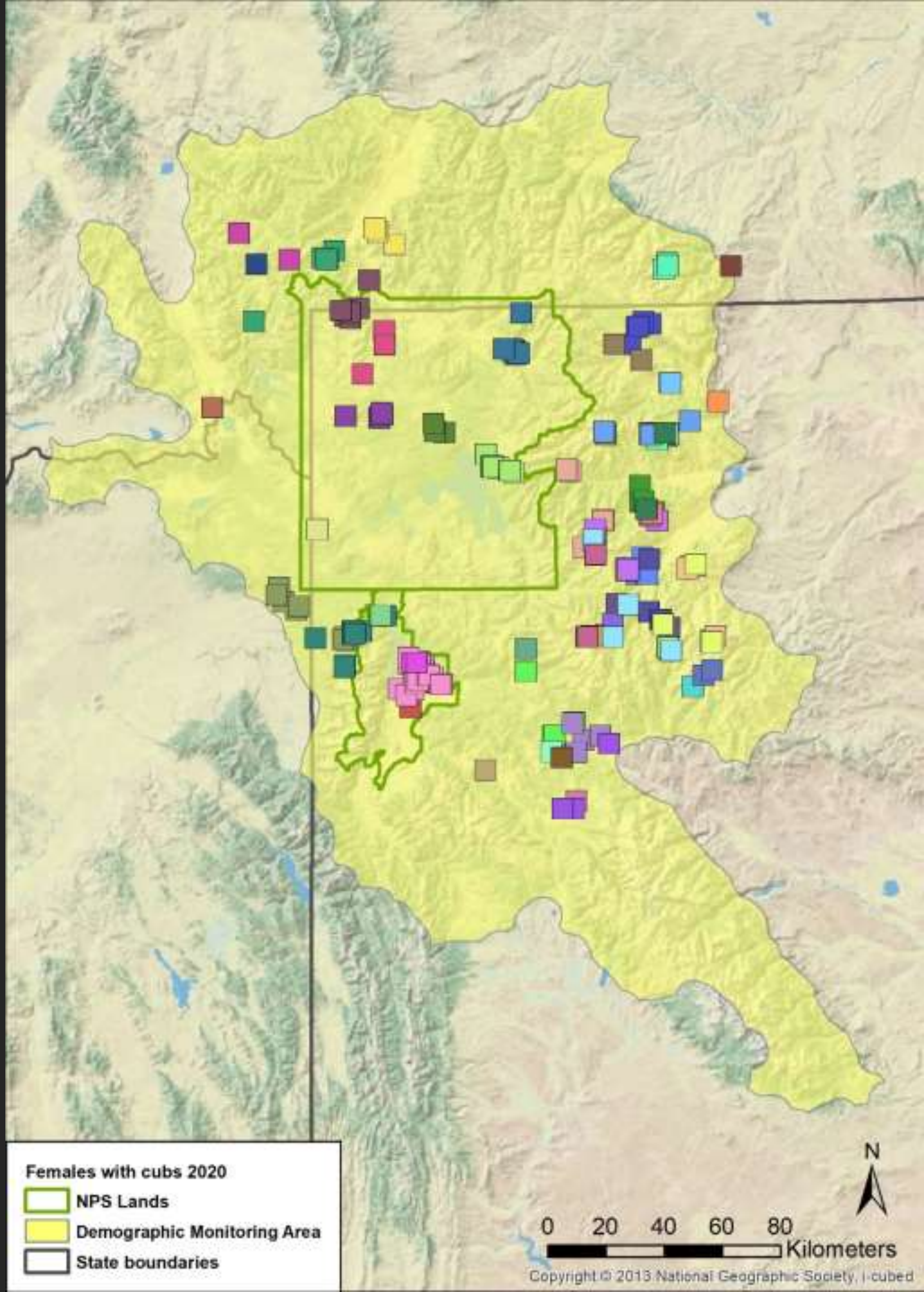


Focus on females with cubs

- Recognizable and important segment of population
- Assumed to be adequate measure of trend in overall population

Knight et al. (1995)
“rule set”

- Identify unique females with cubs
- Litter size, distance, timing of sightings
- Based on biological criteria but conservative by design



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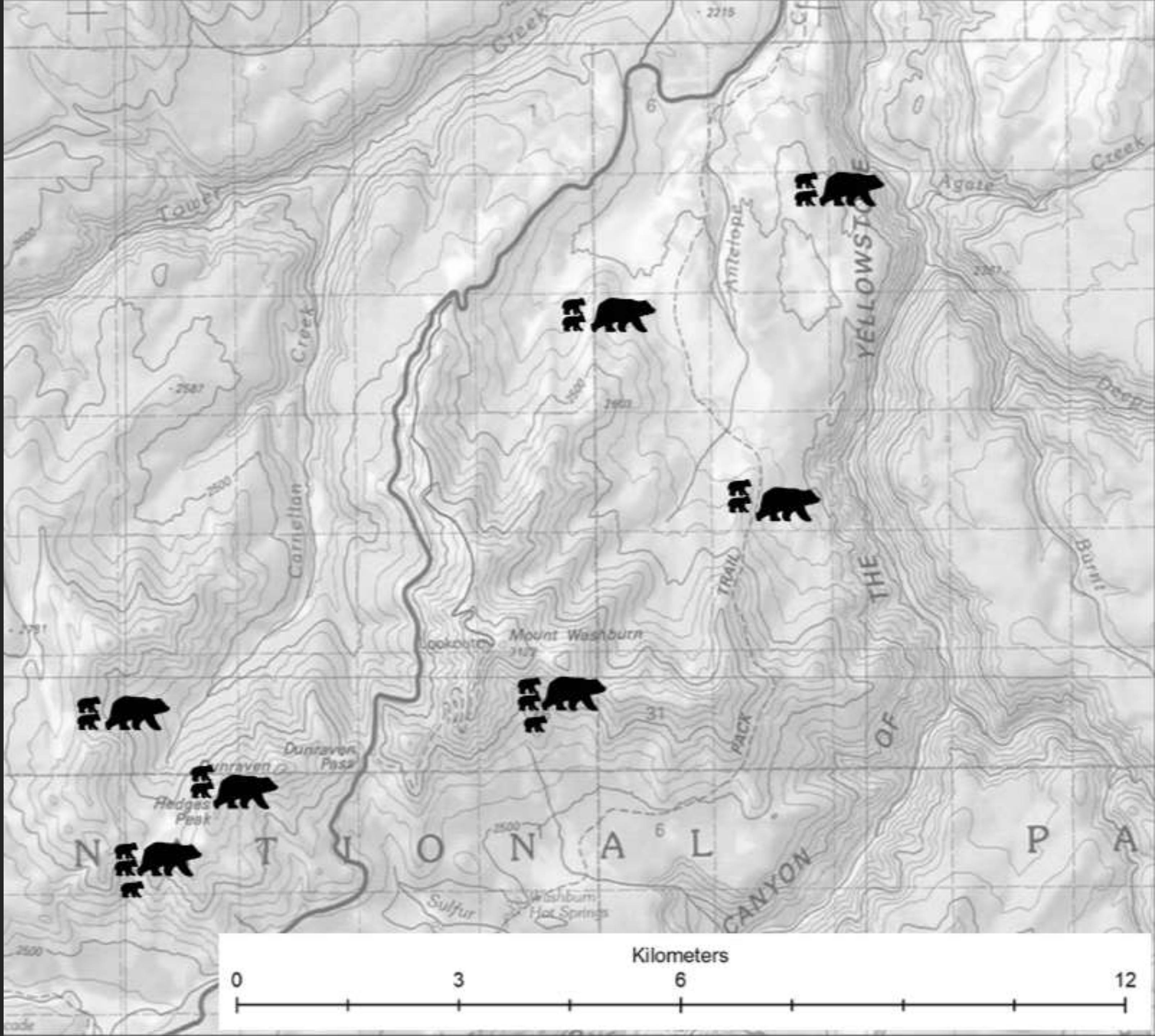
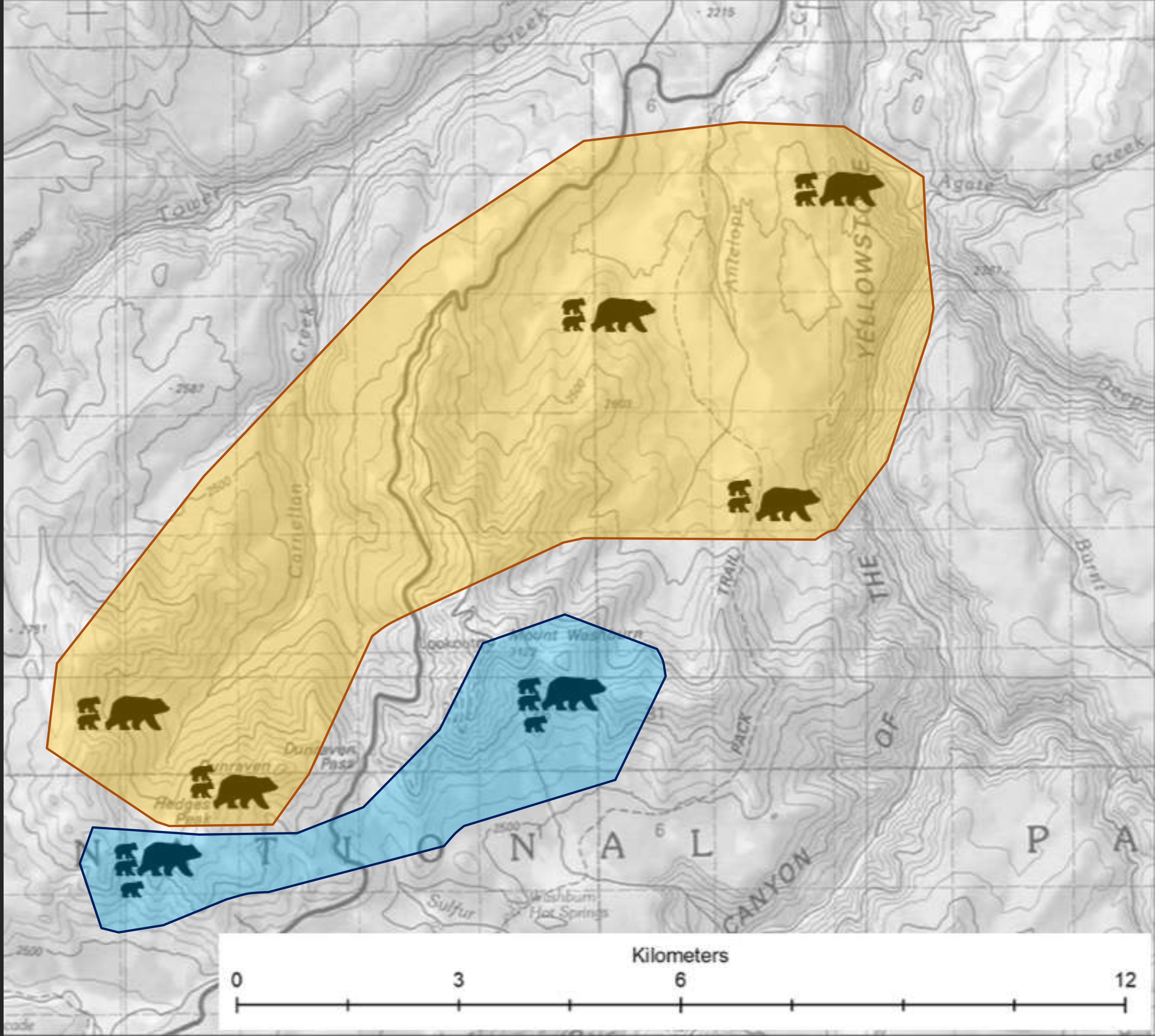
Identifying unique females with cubs

- Contributing factors
  - Date and time of location
  - Number of cubs
  - Collared/not collared
  - Observer/pilot
  - Distance criterion



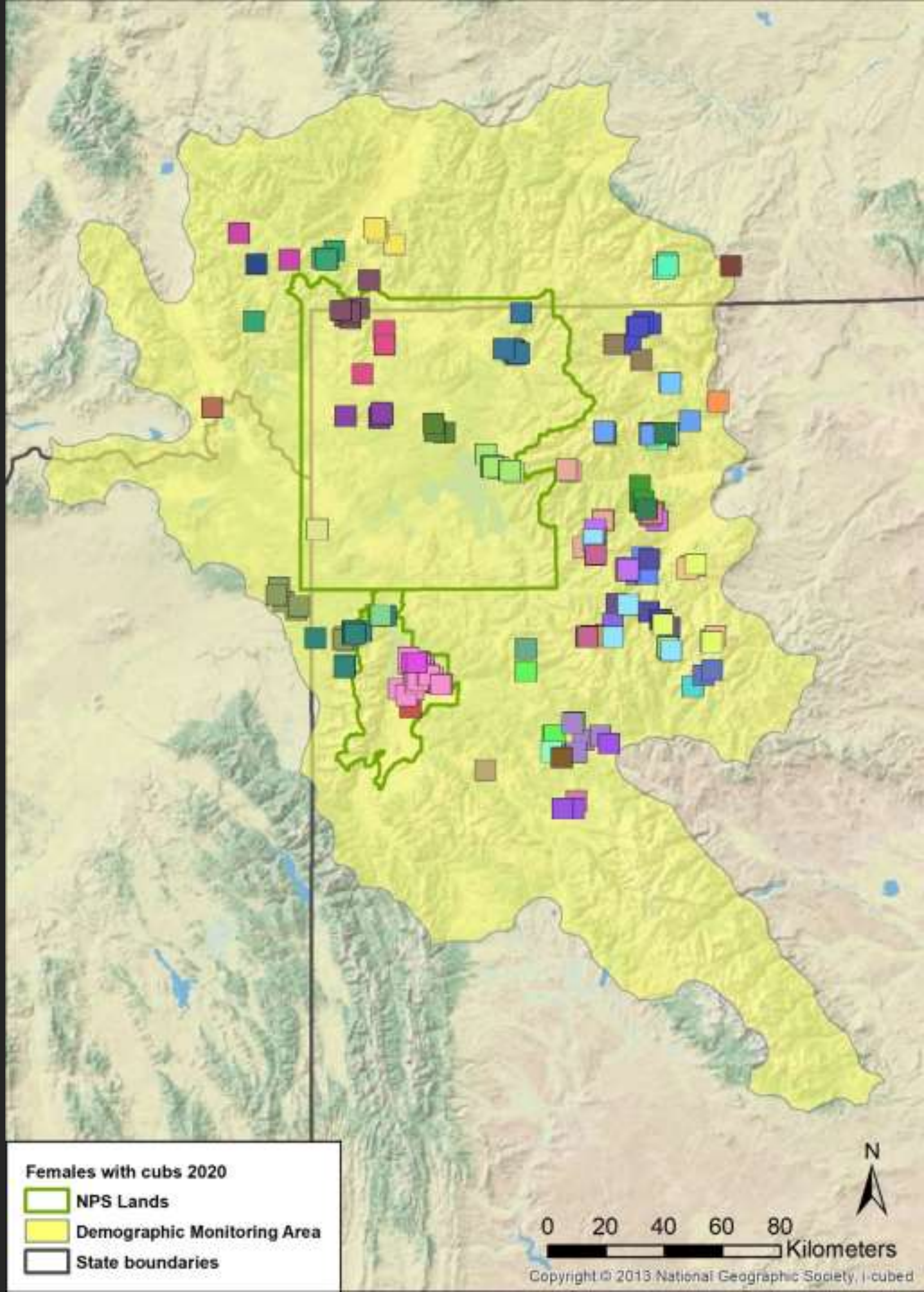
Identifying unique females with cubs

- Example
  - Number of cubs
  - Distance criterion = 30 km



What is “Chao2”?

- *m* = unique females with cubs sighted
- Chao2 = *m* + adjustment
- Adjustment accounts for unobserved females with cubs



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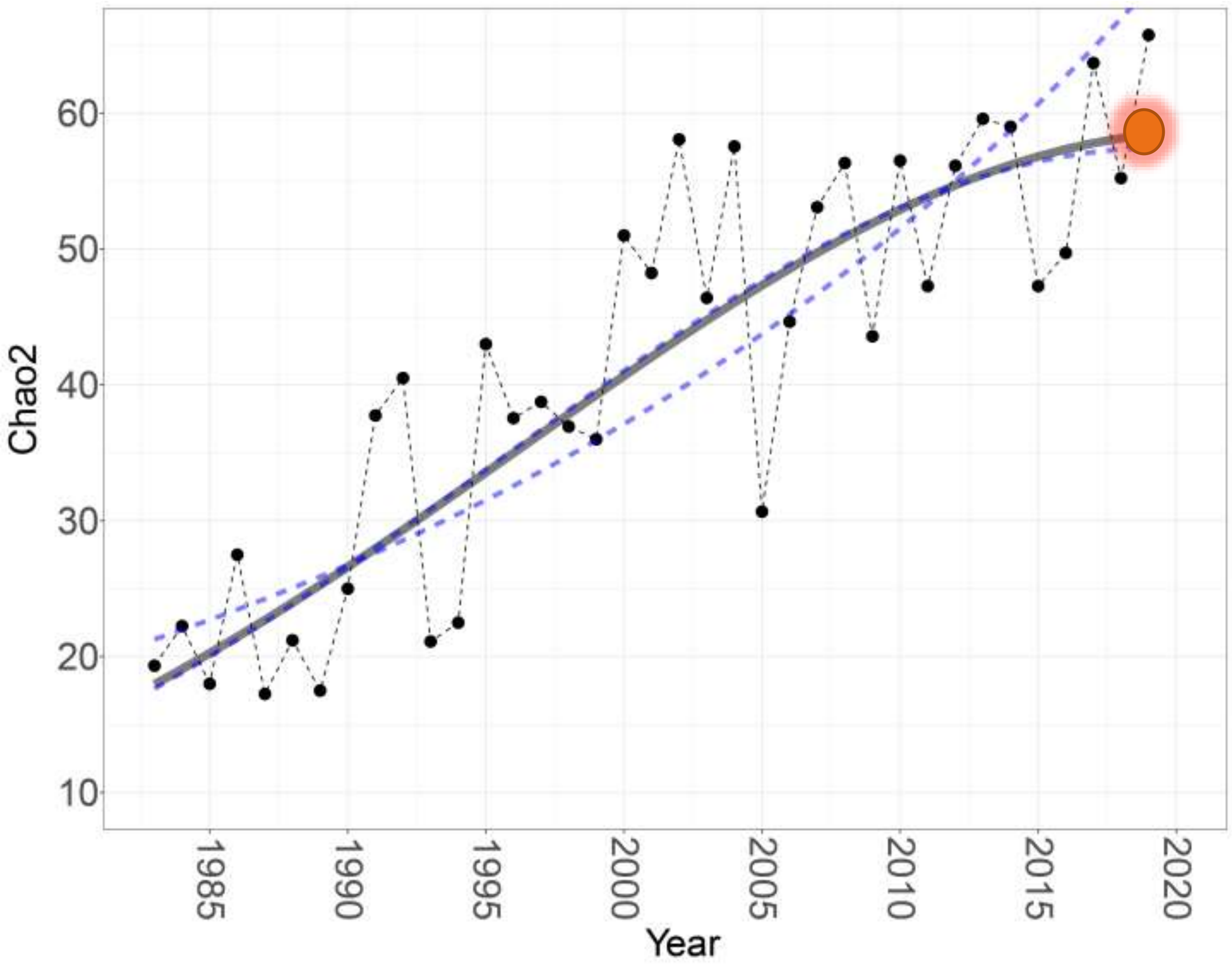
IGBST annual reports

Table 6. Annual Chao2 estimates for the numbers of female grizzly bears with cubs in the Greater Yellowstone Ecosystem, 1983–2019. Estimates in parenthesis for 2012–2019 are specific to the Demographic Monitoring Area (DMA). The number of unique females observed ($\hat{N}_{Obs}$) includes those located using radio telemetry; m is the number of unique females observed using random sightings only; and $\hat{N}_{Chao2}$ gives the nonparametric bias-corrected estimate, per Chao (1989). Also included are the number of females with cubs sighted once (f_1) or twice (f_2), and the annual estimate of relative sample size ($n/\hat{N}_{Chao2}$), where n is the total number of observations obtained without the aid of telemetry. Females with cubs sighted ≥3 times can be derived ($f_{3+} = m - (f_1 + f_2)$).

Year	$\hat{N}_{Obs}$	m	f_1	f_2	$\hat{N}_{Chao2}$	n	$n/\hat{N}_{Chao2}$
1983	13	10	8	2	19	12	0.6
1984	17	17	7	3	22	40	1.8
1985	9	8	5	0	18	17	0.9
1986	25	24	7	5	28	82	3
1987	13	12	7	3	17	20	1.2
1988	19	17	7	4	21	36	1.7
1989	16	14	7	5	18	28	1.6
1990	25	22	7	6	25	49	2
1991	24	24	11	3	38	62	1.6
1992	25	23	15	5	41	37	0.9
1993	20	18	8	8	21	30	1.4
1994	20	18	[illegible]	7	23	29	[illegible]

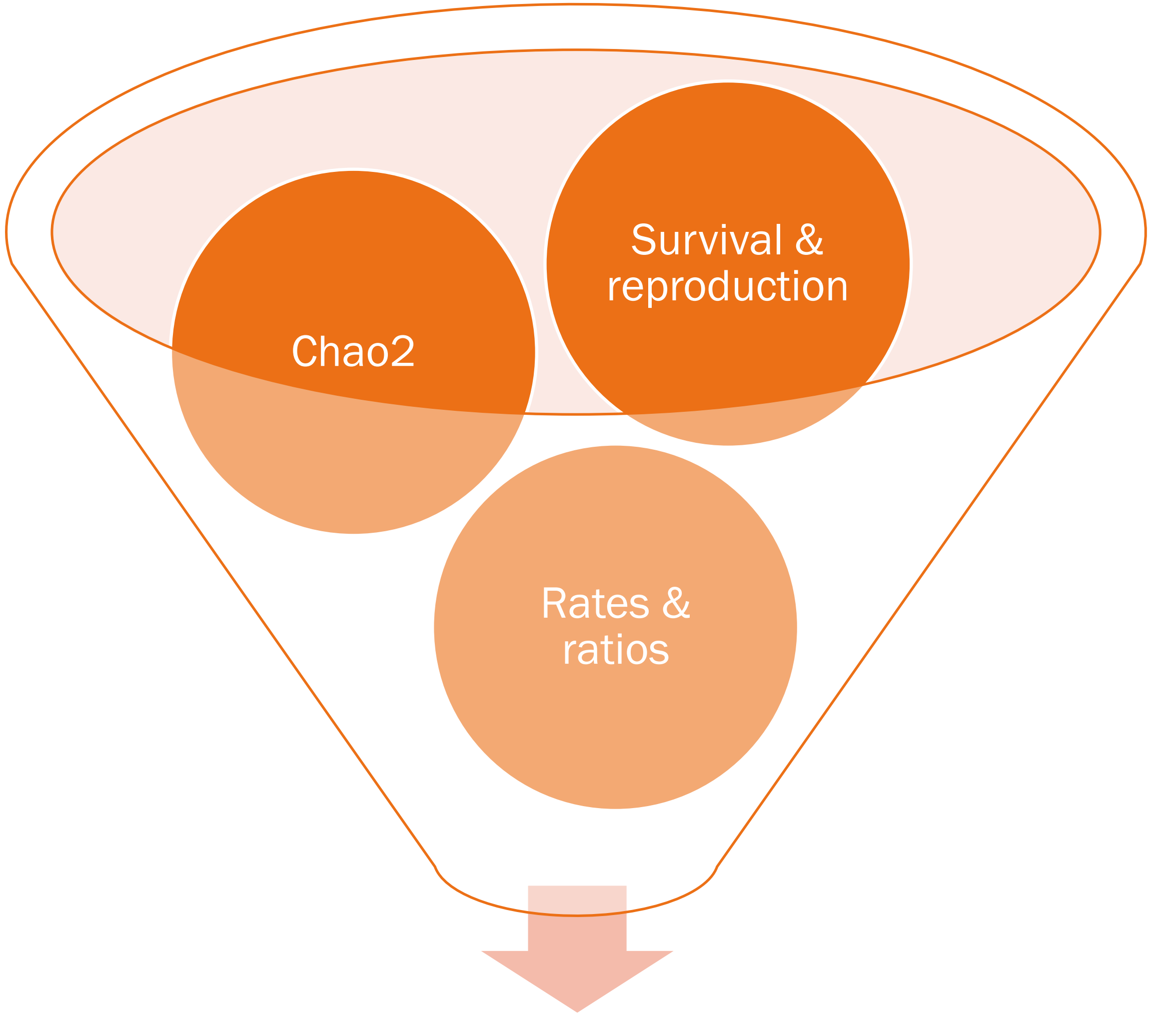
IGBST annual reports



From Chao2 to total population

- Protocol in place since 2007
- Updated vital rates since 2012

IGBST (2012)



Total size by population segment

Independent age females

Independent age males

Dependent young

Need for re-assessment: main issues

1. Underestimation bias

2. Model averaging

Part I

Correcting underestimation bias

The issue

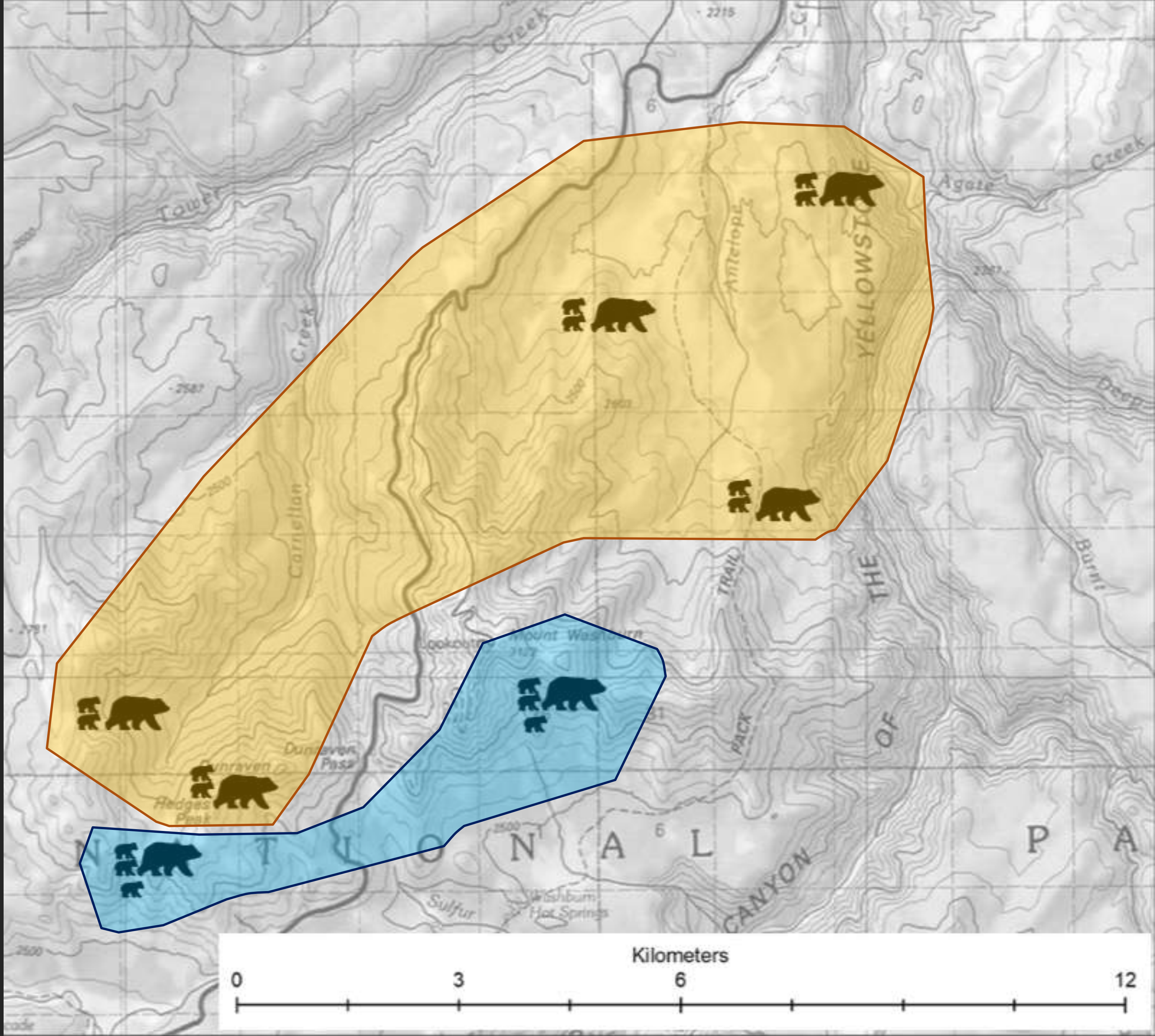
- Underestimation of unique females with cubs (*m*)
- Conservative distance criterion
- Bias increases with more females with cubs in population (Schwartz et al. 2008)

Searching for an alternative

- Focus on distance criterion
- Retrospectively applicable
- We do not know truth: need simulations
- We can simulate sighted bears (*m*) and sighting frequencies

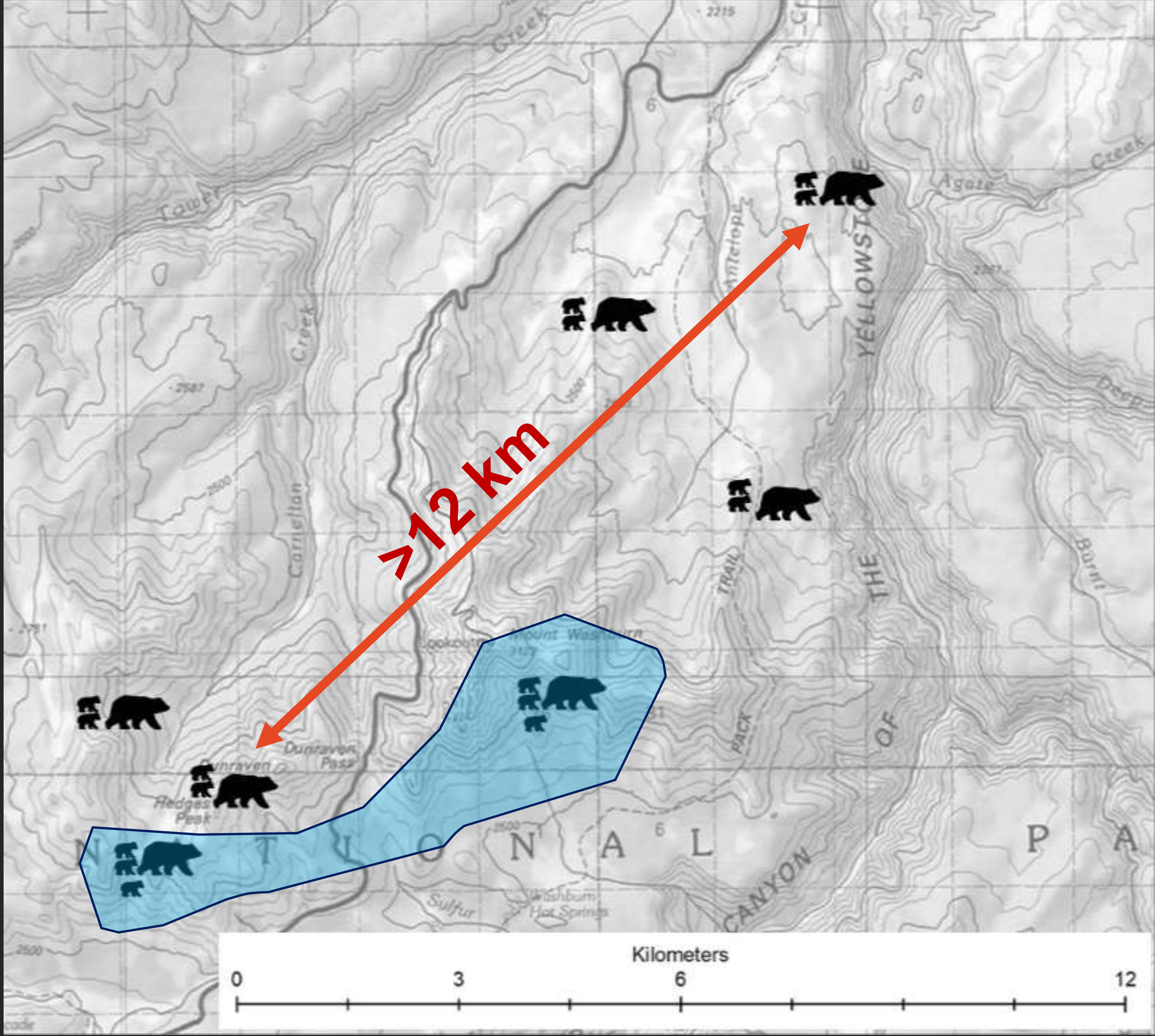
Identifying unique females with cubs

- Contributing factors
  - Litter size
  - Distance
- Improve accuracy
  - Alternate distance criterion



Identifying unique females with cubs

- Alternate criterion
  - Example: 12 km



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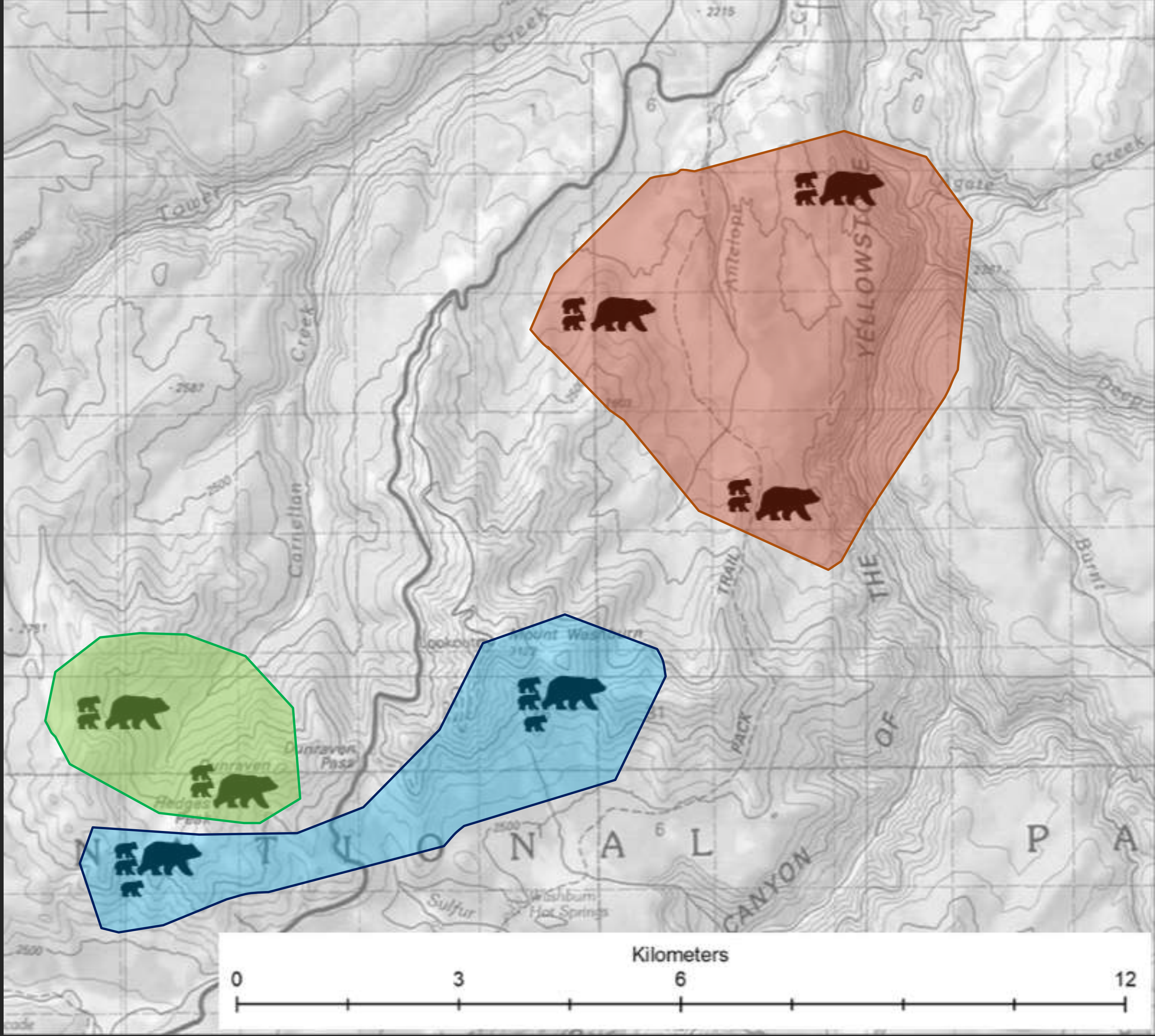
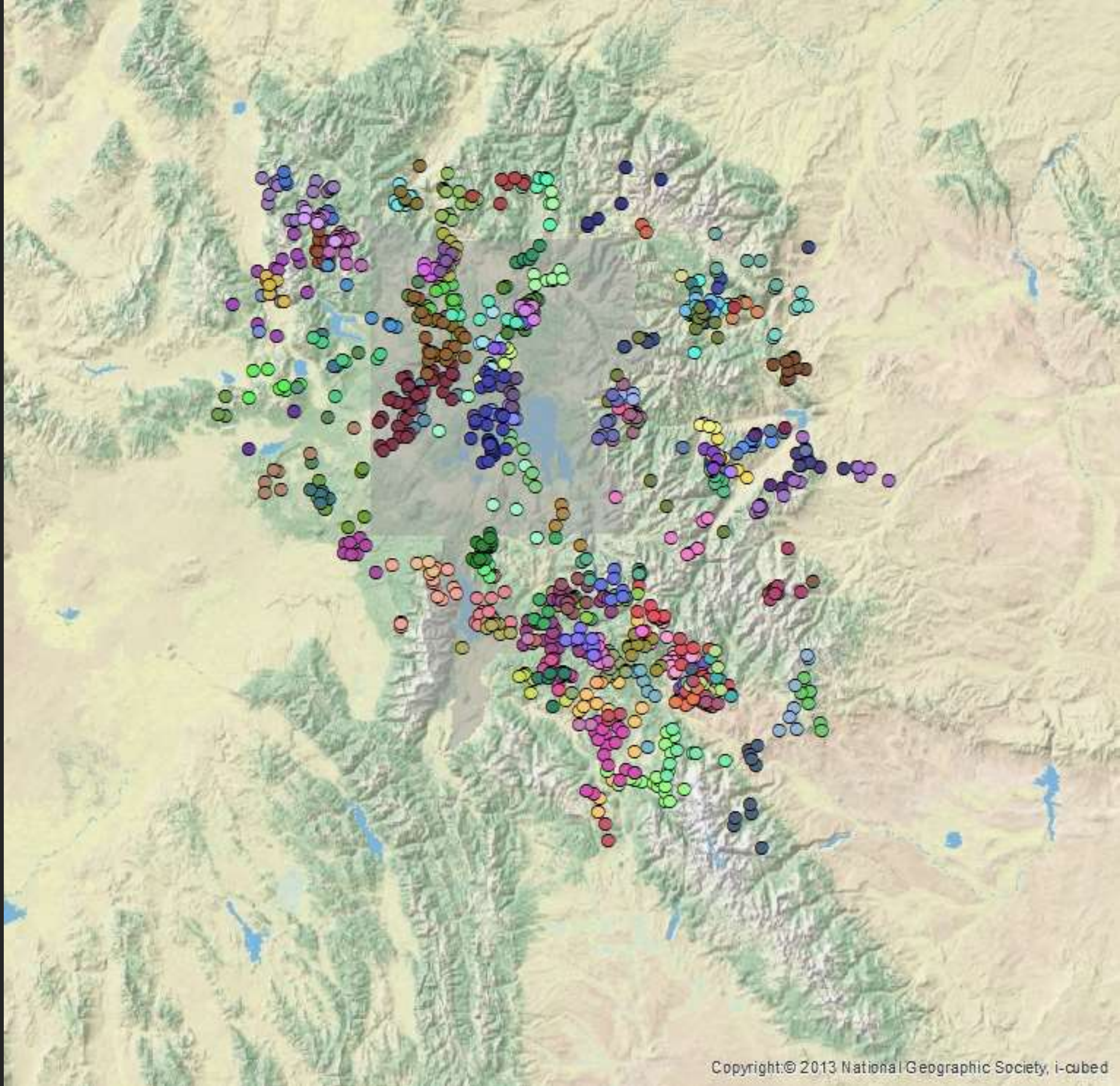
Identifying unique females with cubs

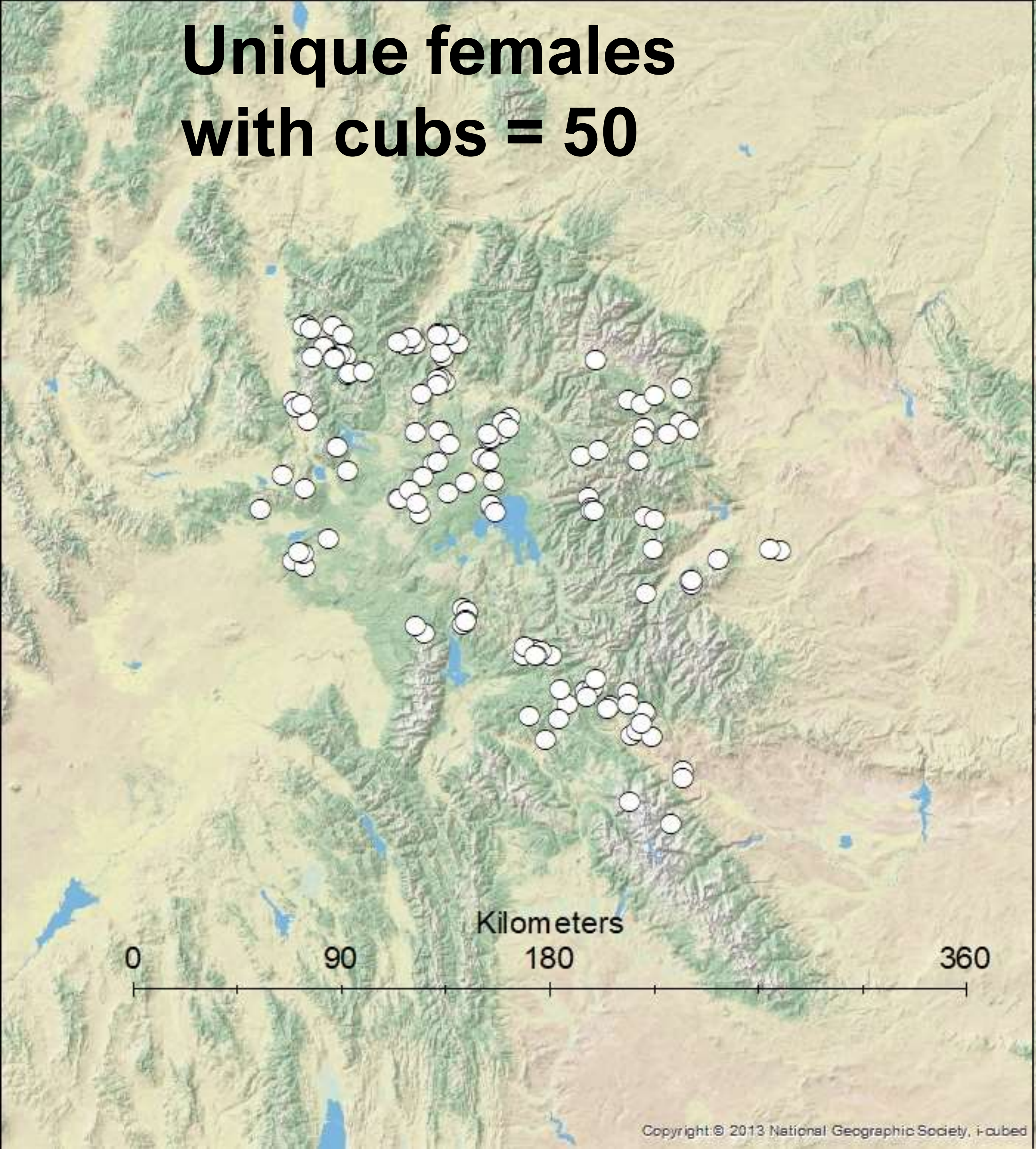
- Alternate criterion
  - Example: 12 km

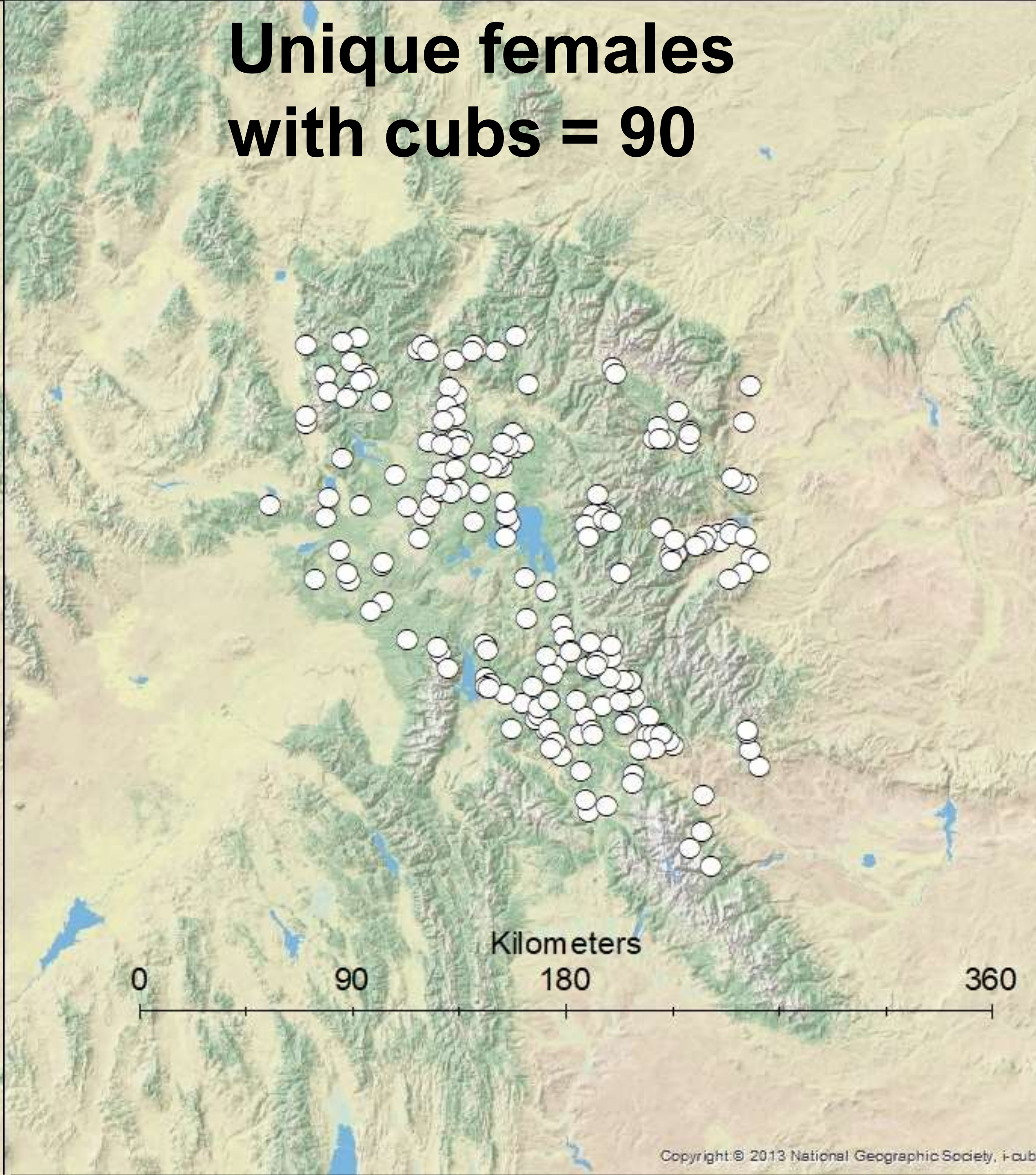


Simulation approach

- Telemetry data as “pool”
  - 1997 – 2019
  - 1139 female with cub locations (117 bears)
- Keep “bear ID” hidden from rule set, but use it to assess accuracy
- Test distance criteria from 12 to 30 km in 2-km steps




Unique females
with cubs = 50
Kilometers
0
90
180
360
Copyright © 2013 National Geographic Society, i-cubed


Unique females
with cubs = 90
Kilometers
0
90
180
360
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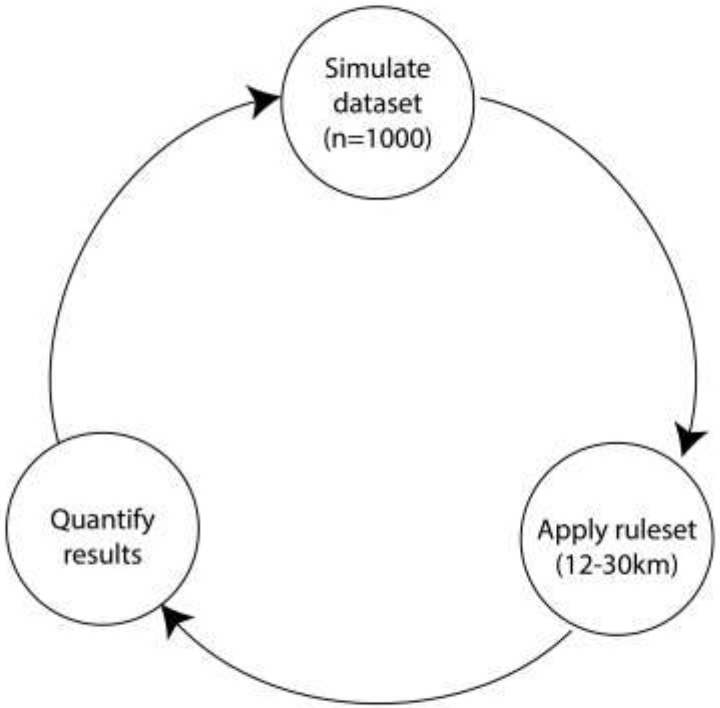
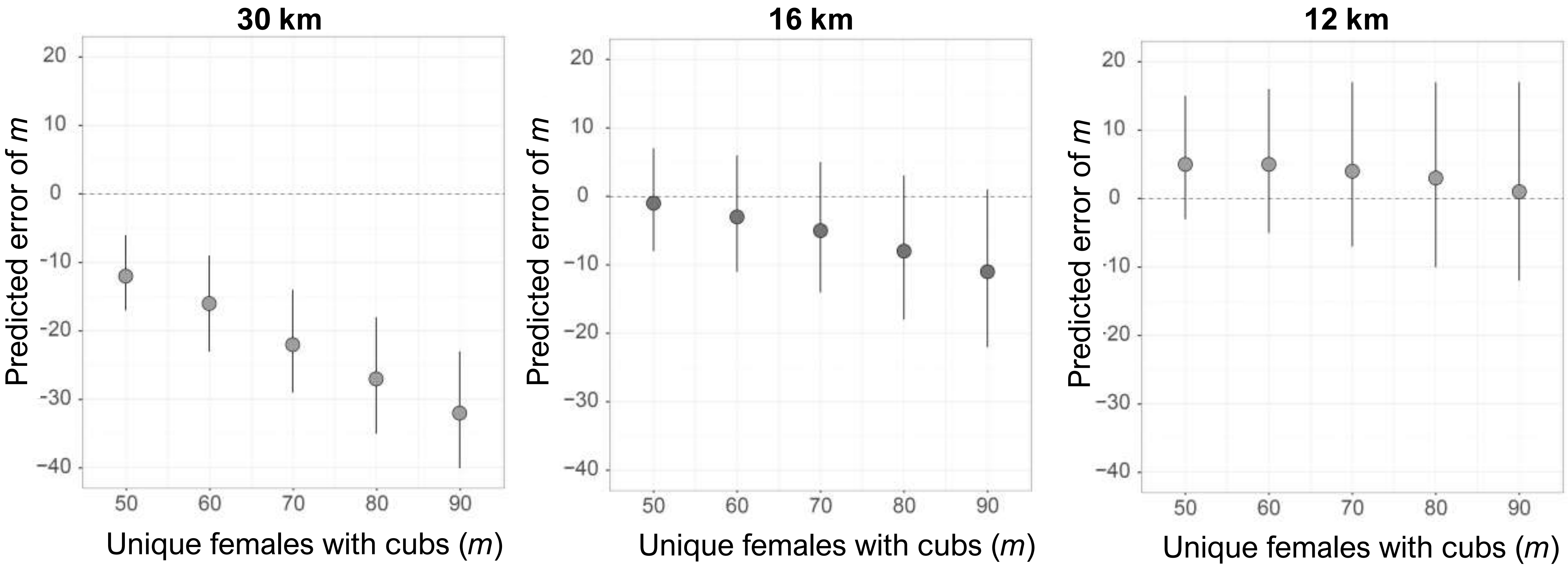
Approach

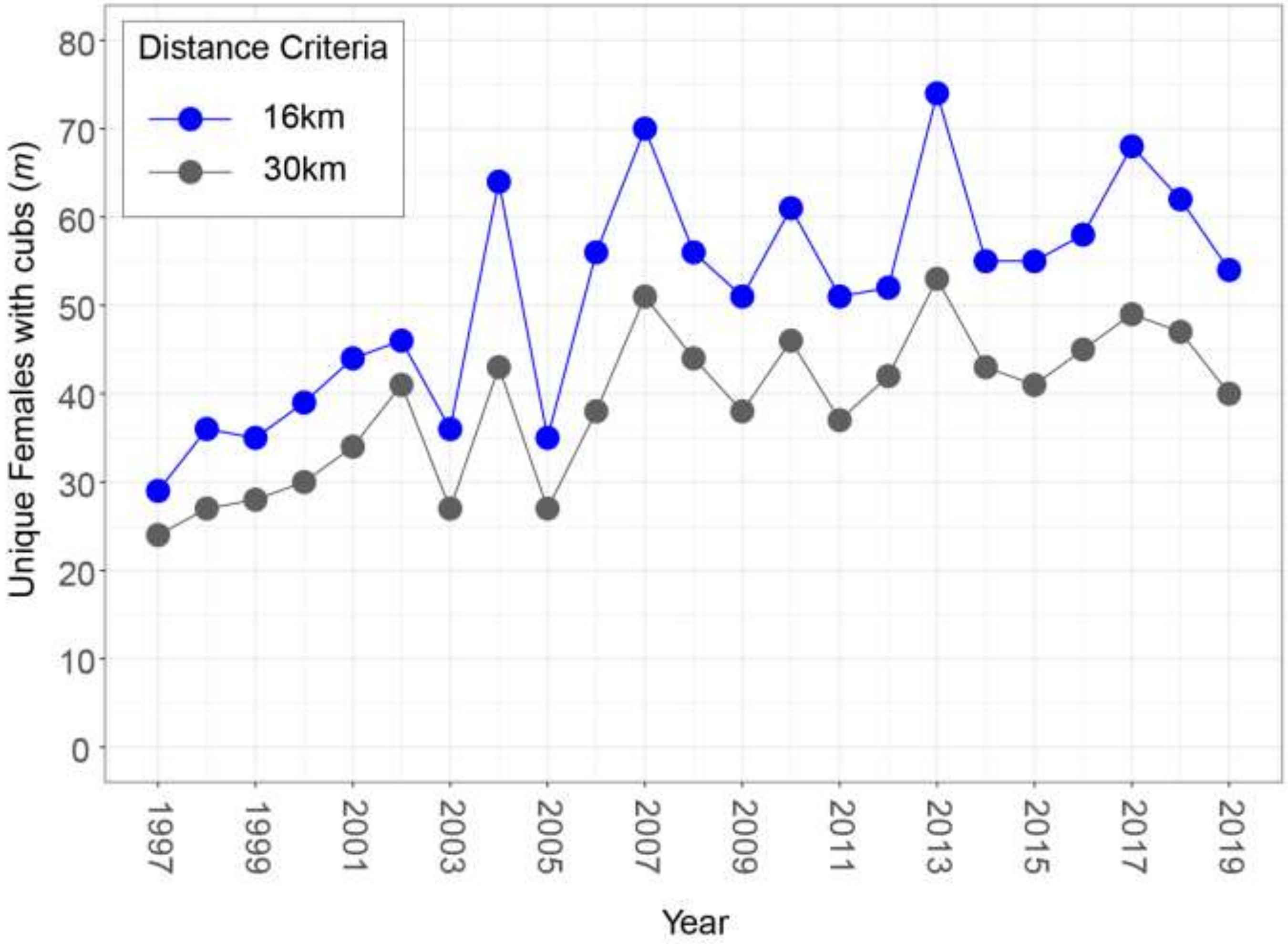
- Simulated levels = 50, 60, 70, 80, 90 females with cubs
- For each *level* performed sequence in diagram
- 50,000 total replicates



Results: bias of *m* under distance criteria



Comparison: *m* for 30 km vs. 16 km



Part I: Summary

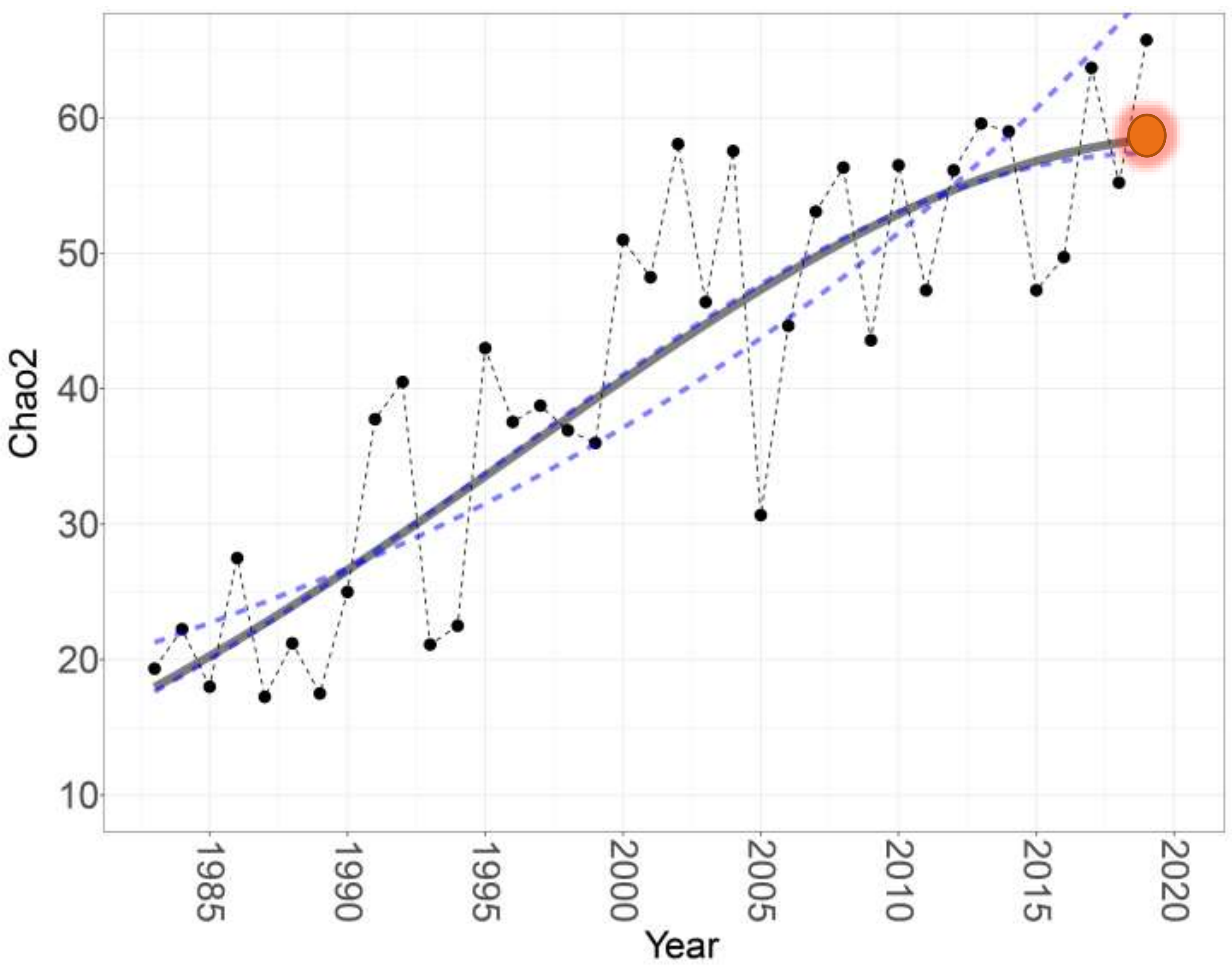
- Alternate distance criterion improves accuracy
- Additional implications for sighting frequencies and Chao2

Part II

An alternative to model averaging

Purpose of model averaging

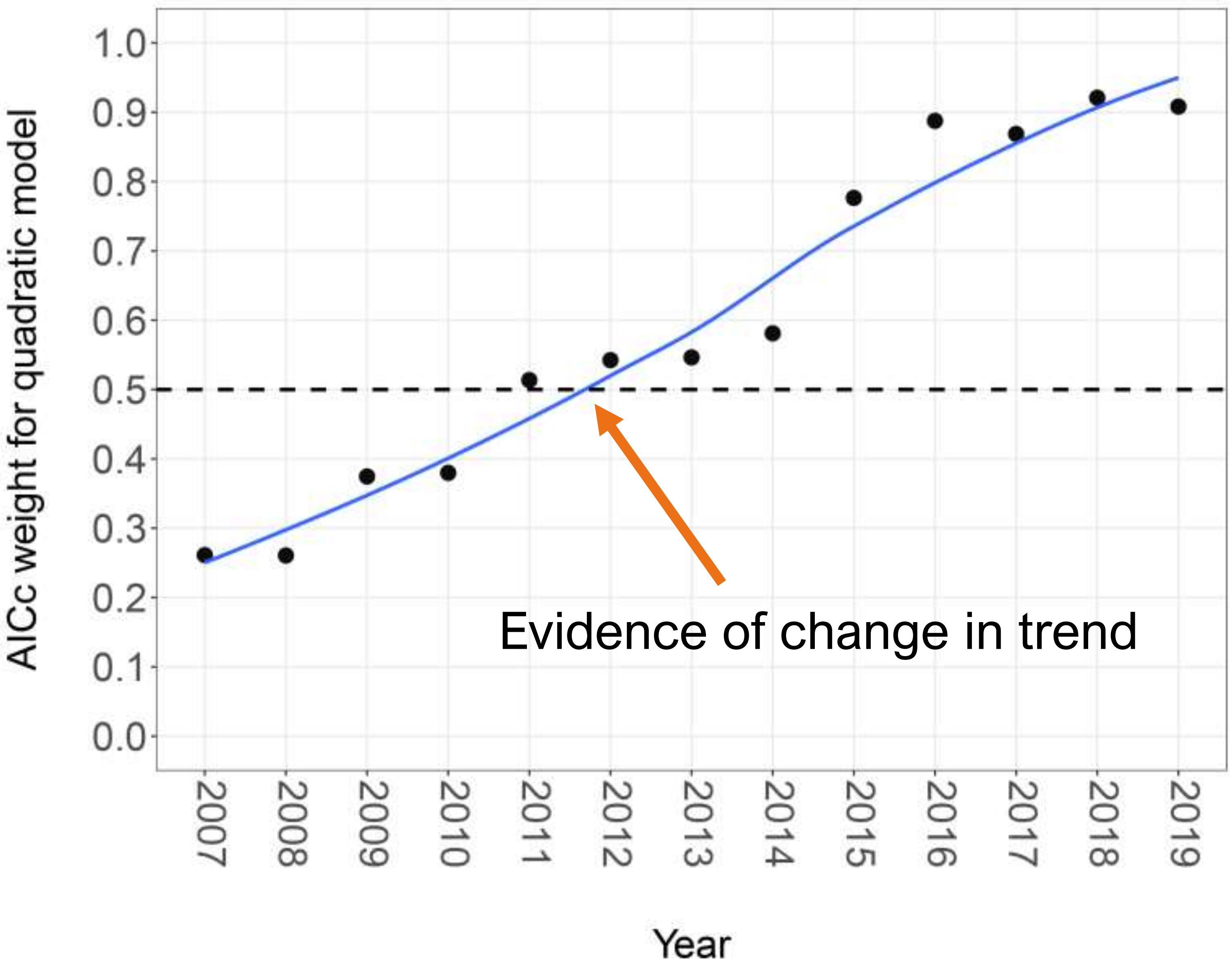
- Smoothing
- Detect change in trend



Preliminary Information-Subject to Revision. Not for Citation or Distribution

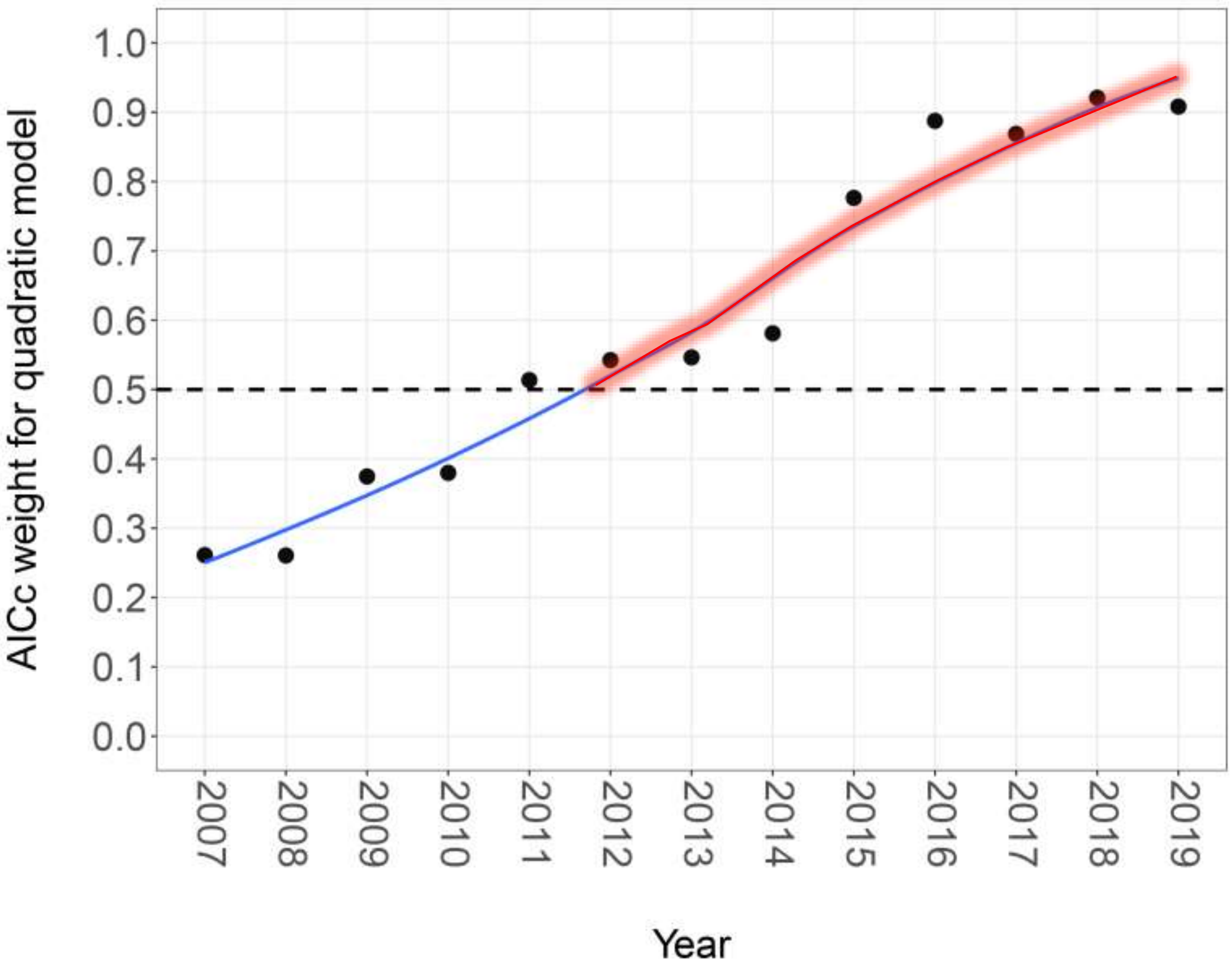
Purpose of model averaging

- Smoothing
- Detect change in trend



The issue

- Weight will continue to be on quadratic model
- Limits ability to detect trend changes in future
- Will eventually fit a decline (biasing estimates low)



Searching for an alternative

“Science works through replication, rectification and modification.”

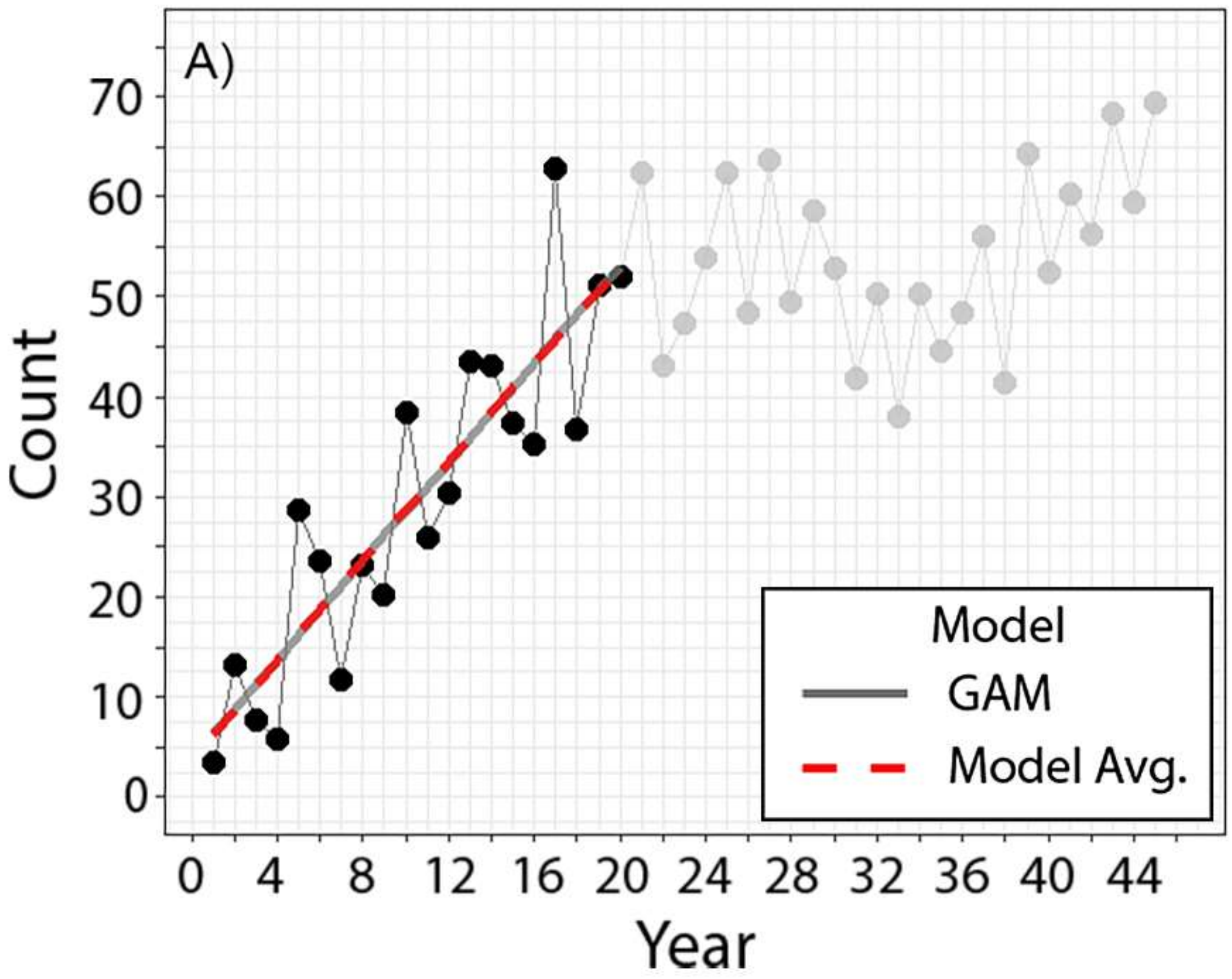
— Abhijit Naskar

- Build off previous work
- Retrospectively applicable
- Increase usefulness for management
- Improve inference on changes in trend

Alternative approach

- Generalized Additive Models (GAMs)
  - Similar to model averaging, but not limited to linear and quadratic models
  - More flexible in terms of shapes of trends
  - Enhances interpretation

GAMs
vs.
Model Averaging



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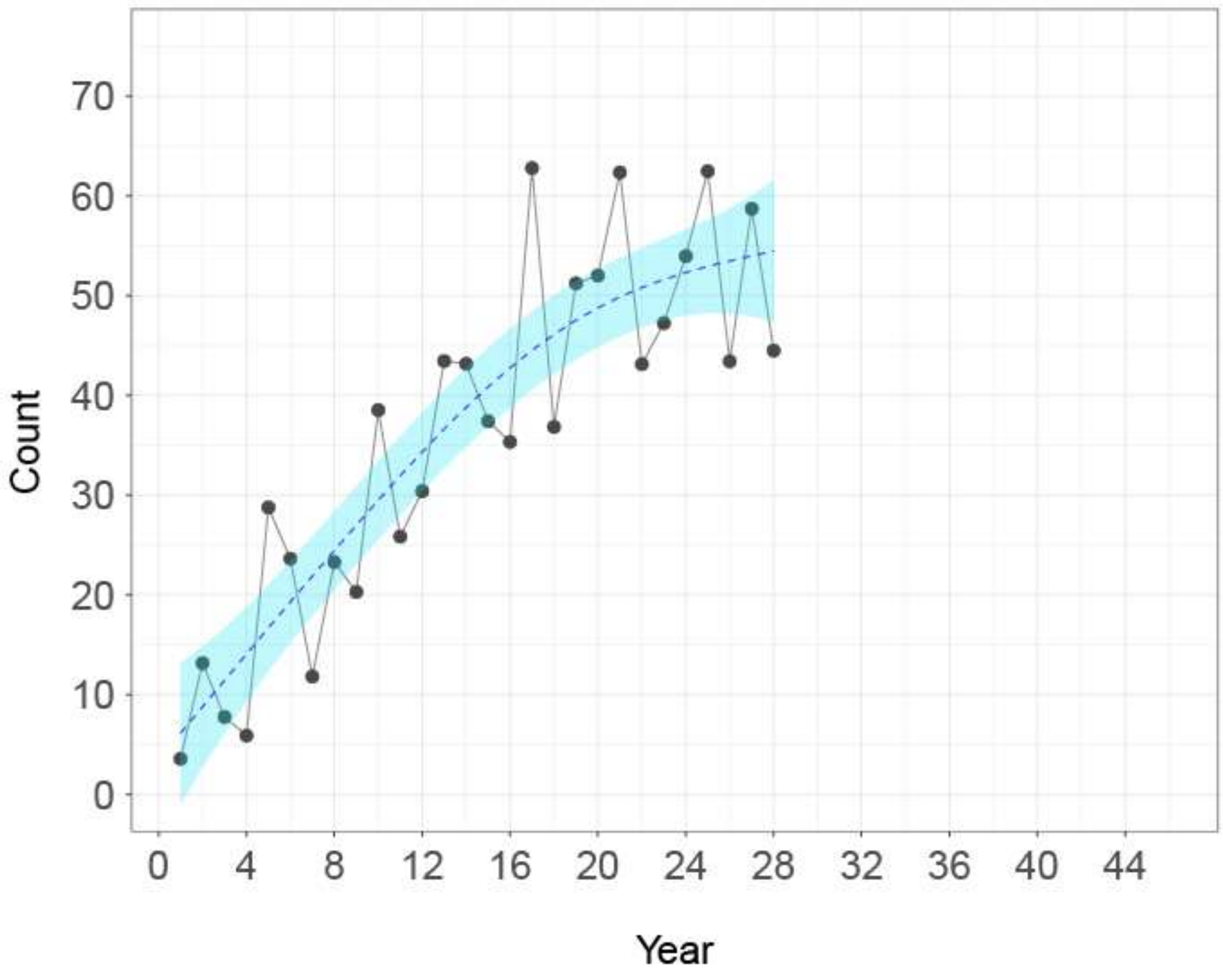
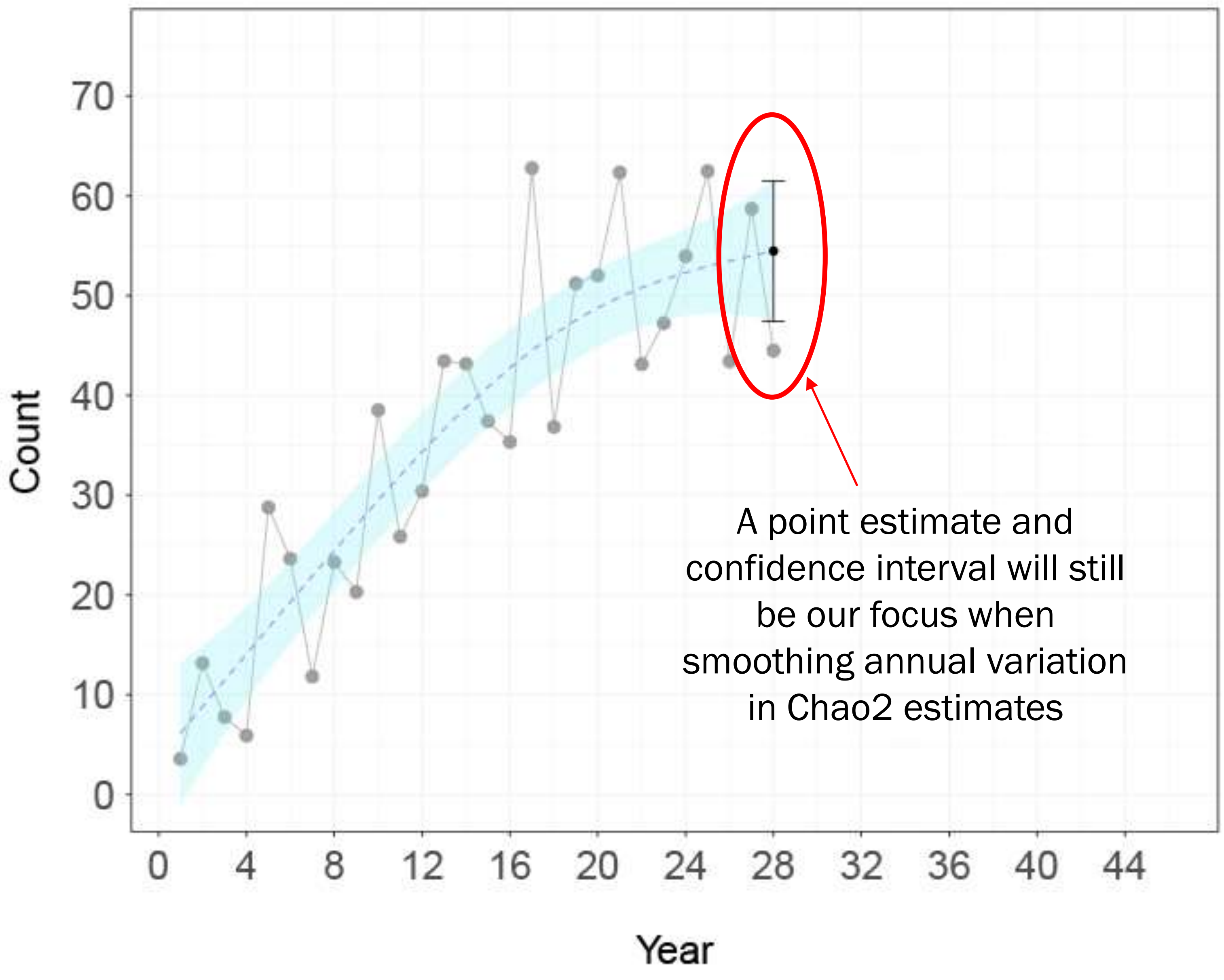
Similarity to model averaging

- Models fit each year to updated time series



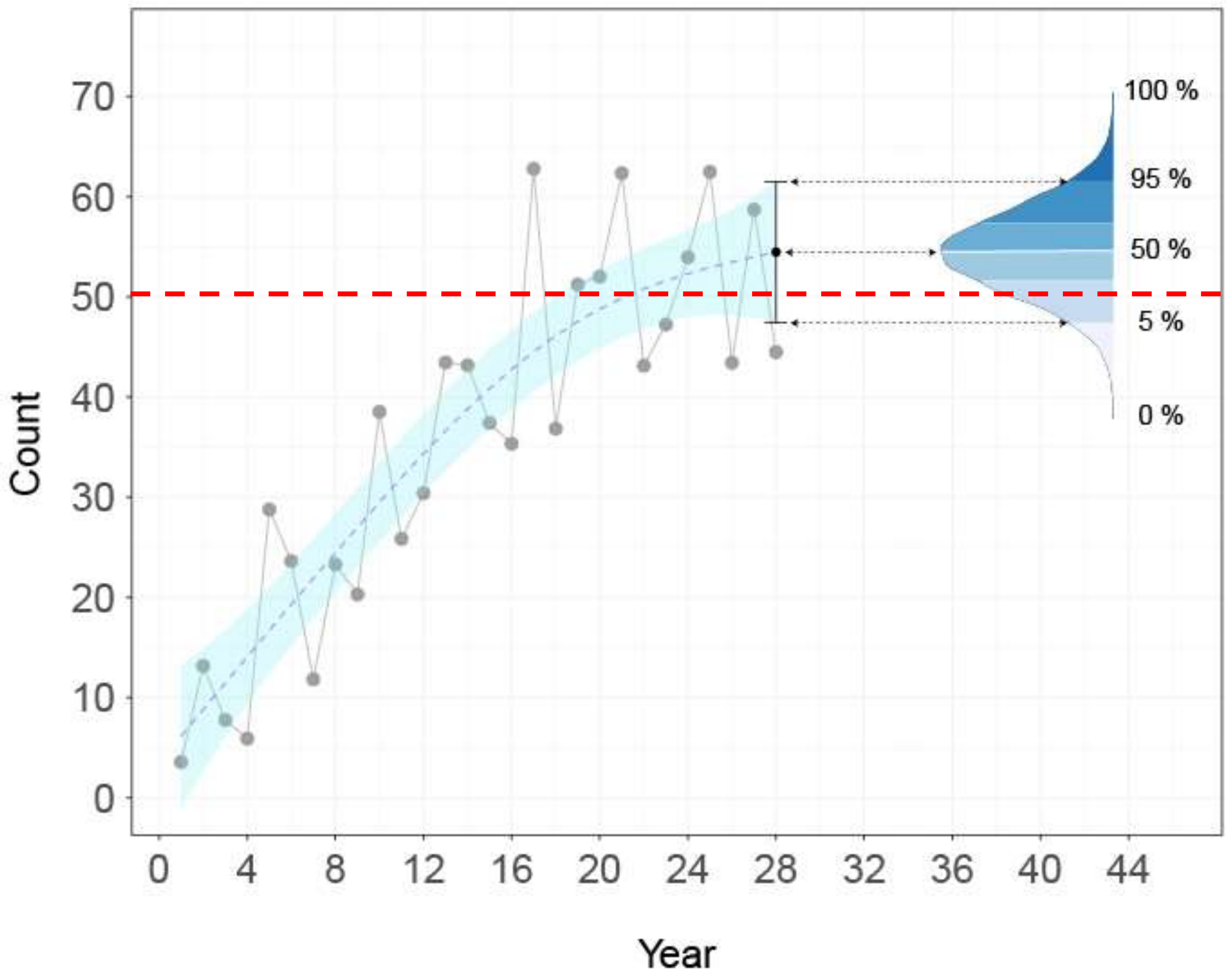
Similarity to model averaging

- Models fit each year to updated time series
- Last year of the fitted model is the annual smoothed Chao2 estimate

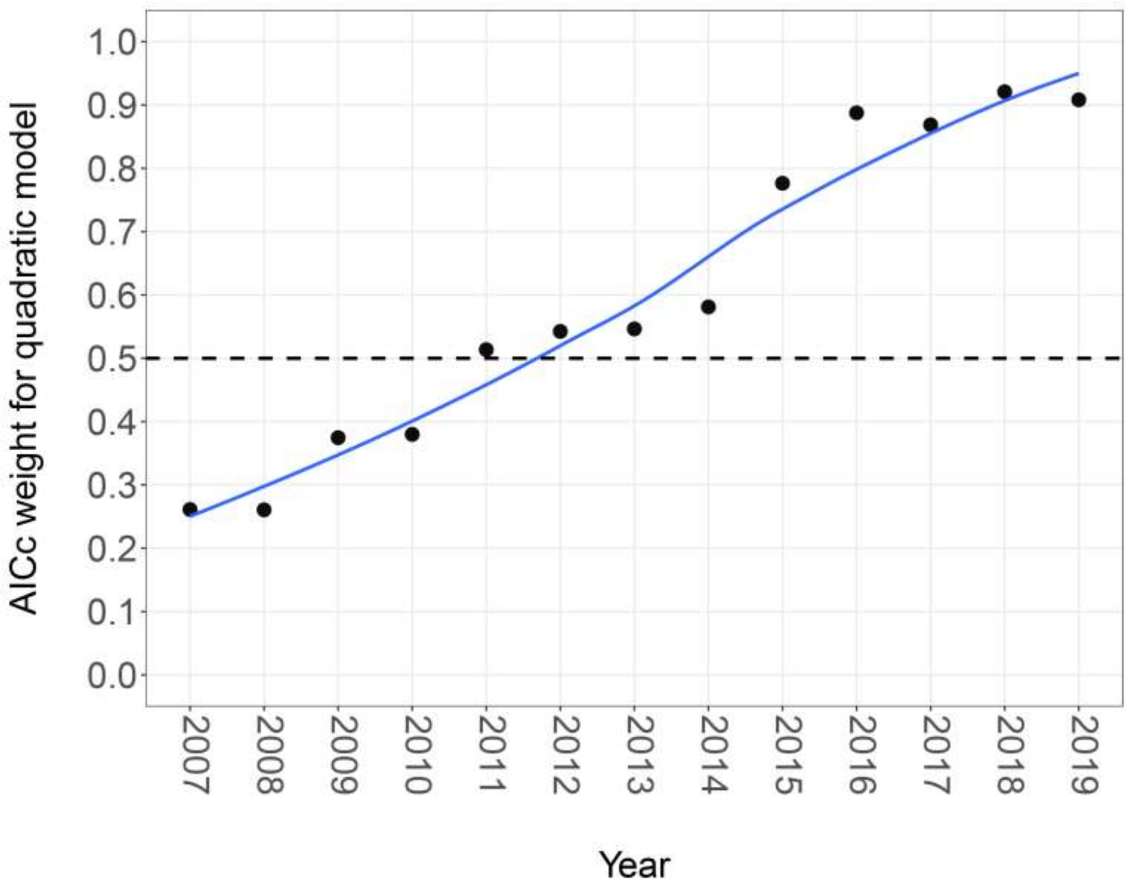


Additional insights for management

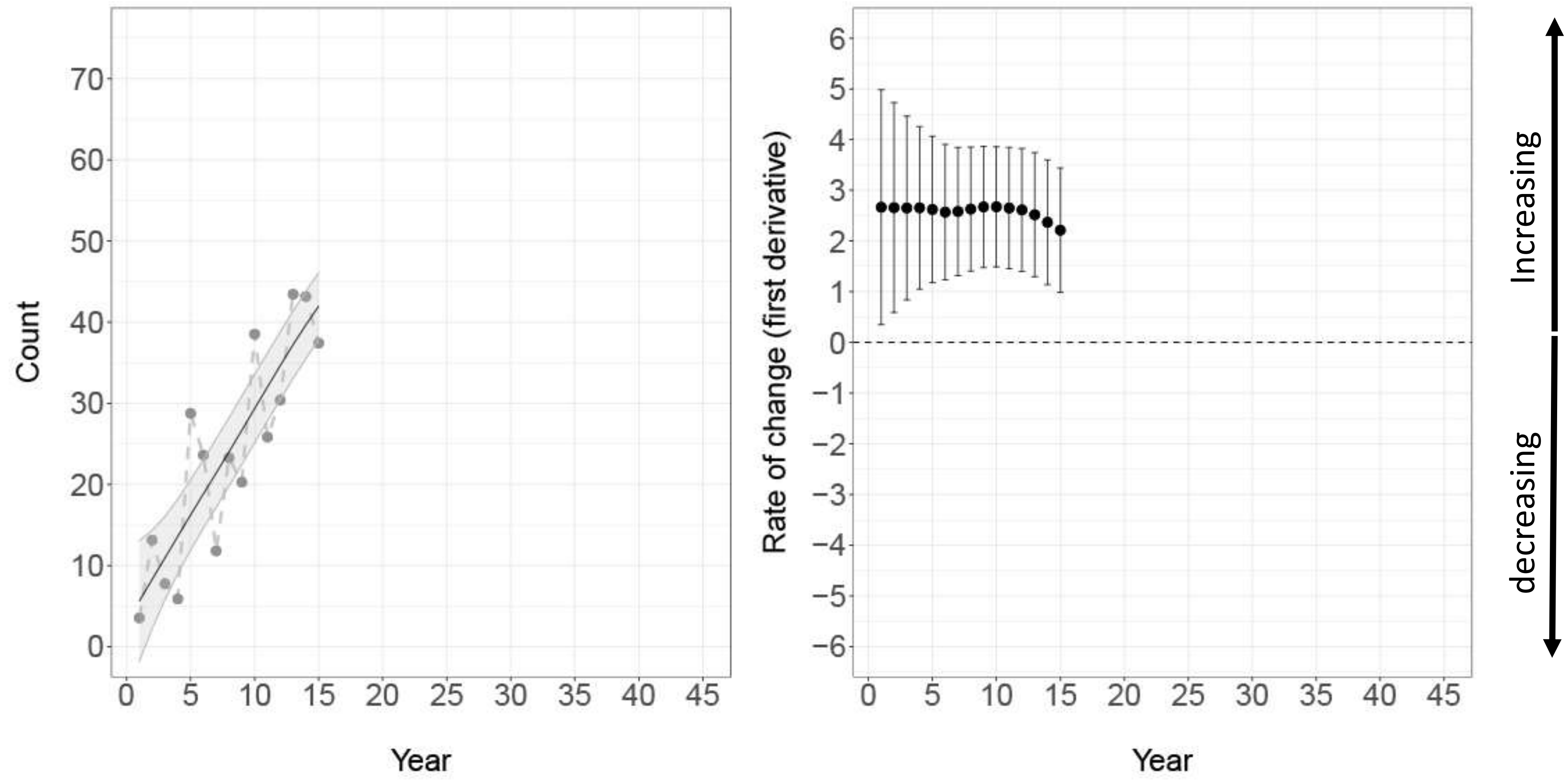
- Distribution better reflects uncertainty
- Allows probability statements regarding population monitoring metrics
  - E.g., what is probability estimate is greater than 50?



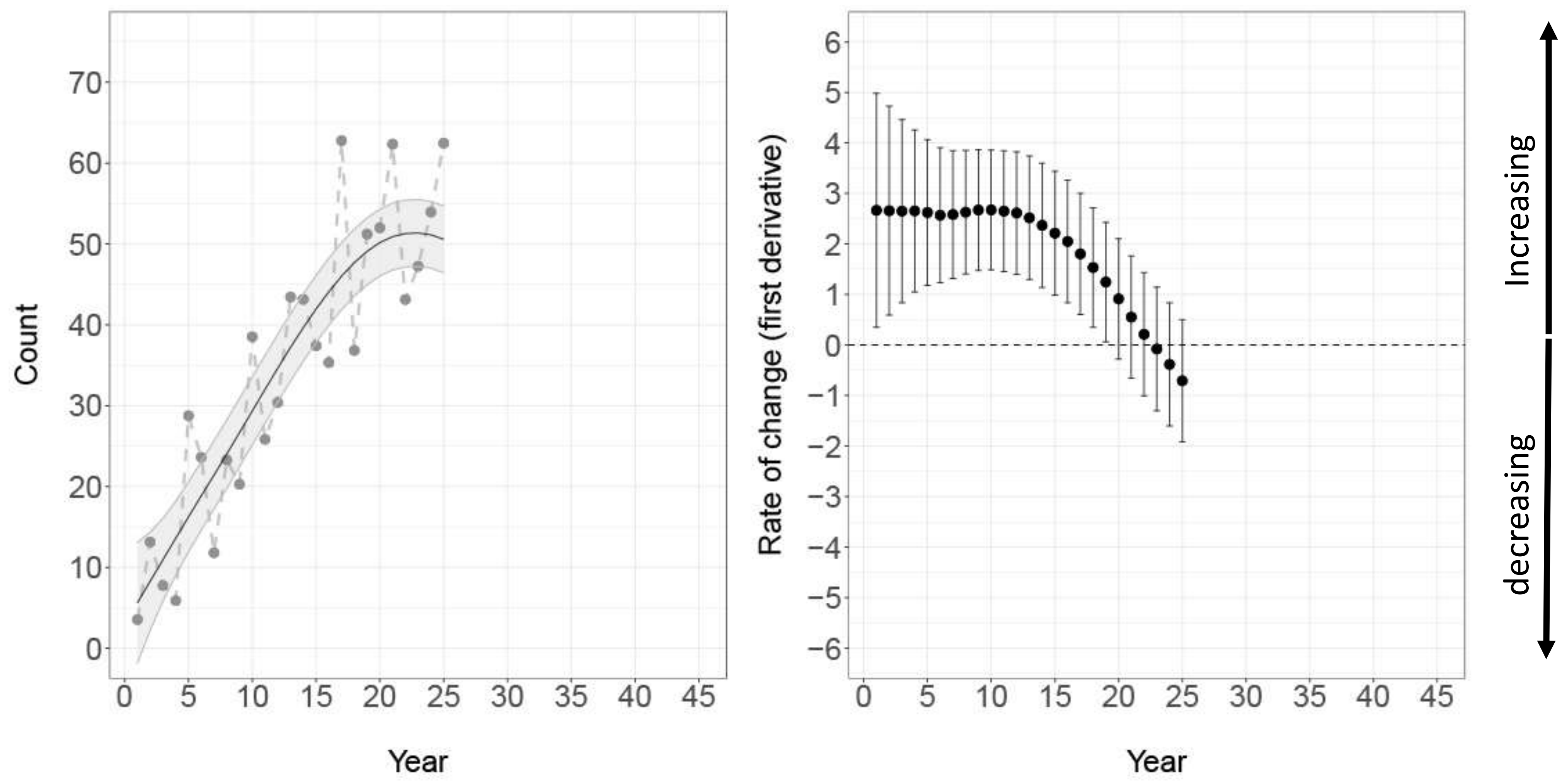
Changes in trend



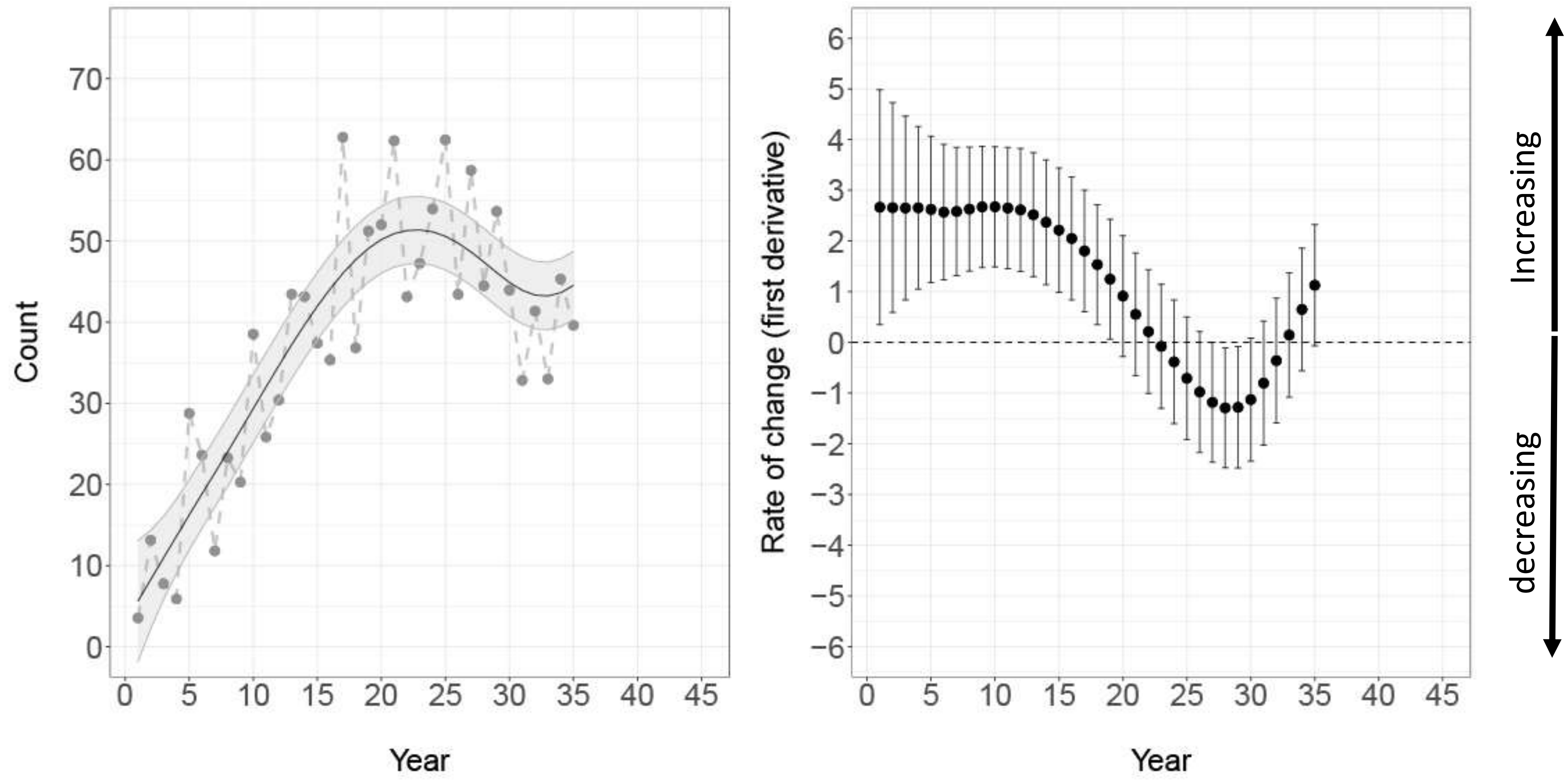
Changes in trend



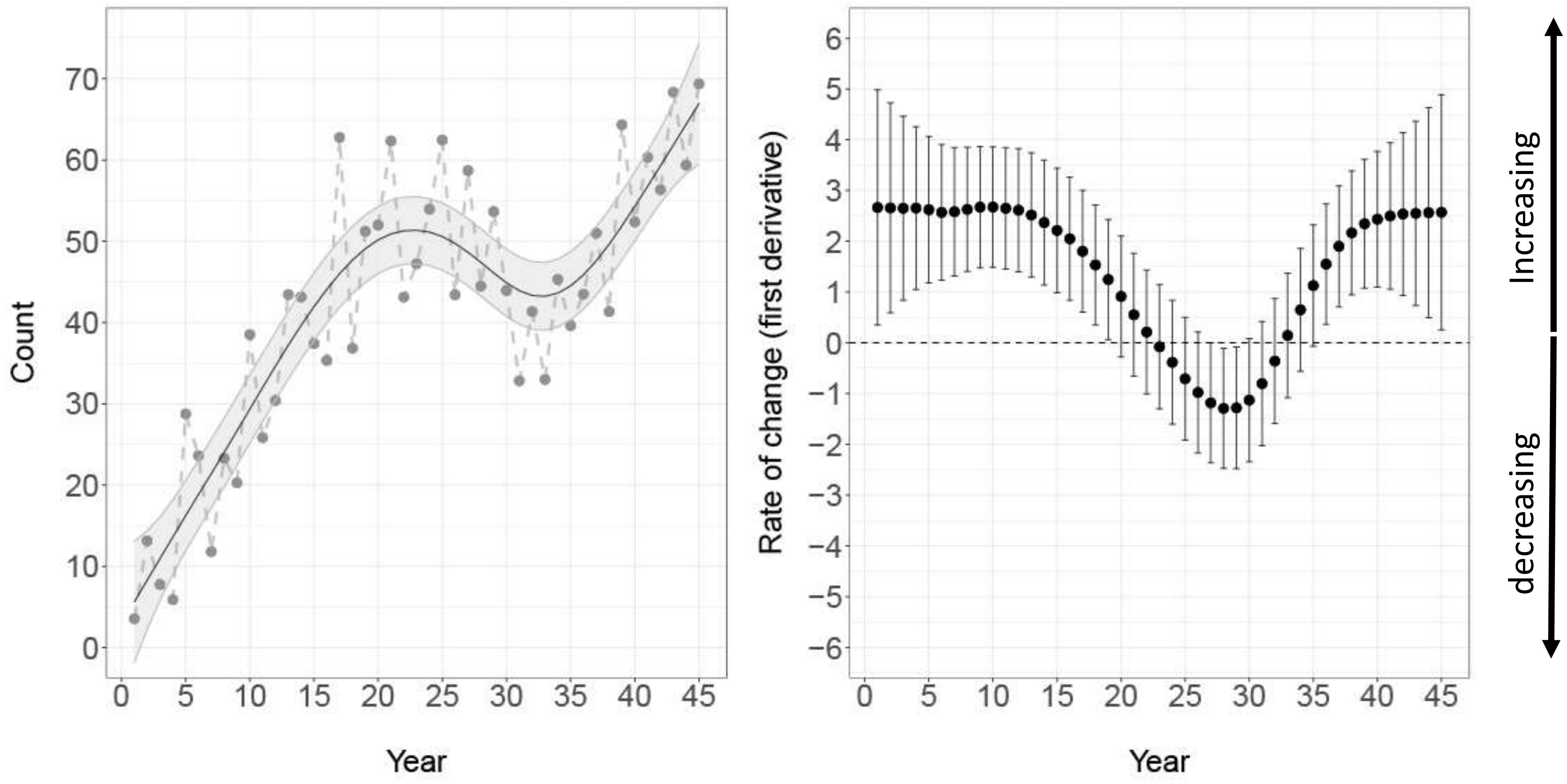
Changes in trend



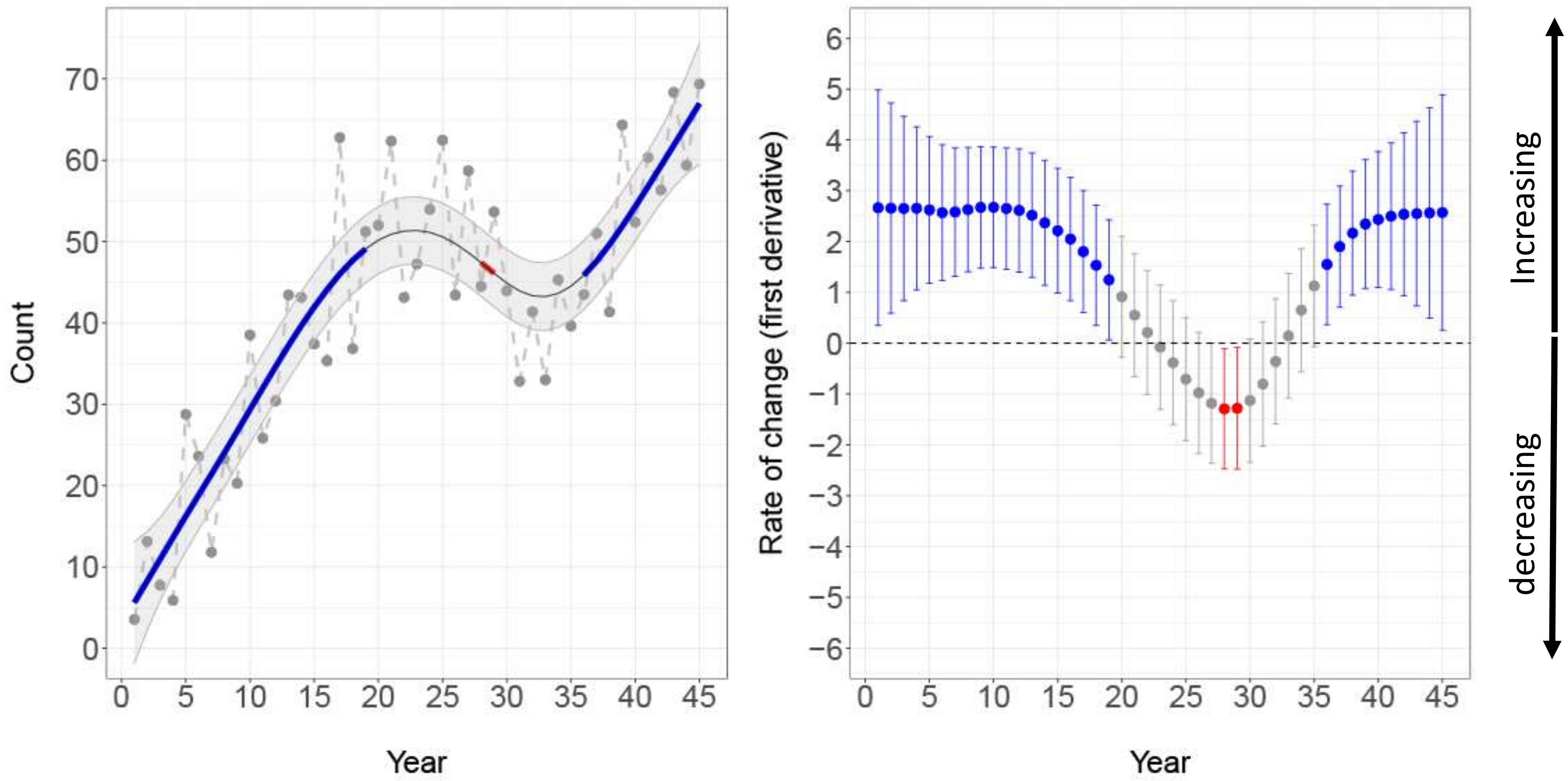
Changes in trend



Changes in trend

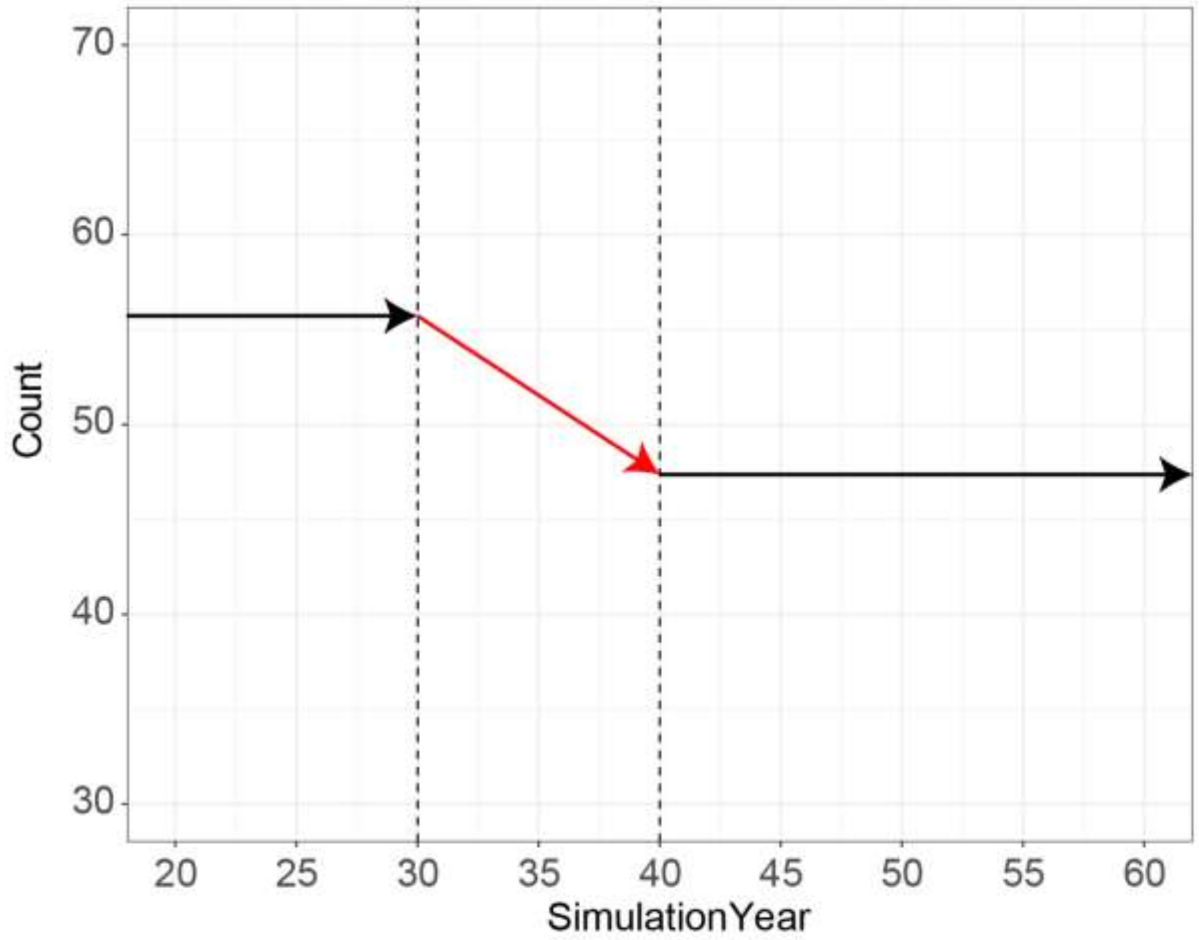


Changes in trend



What can the rate of change approach do for us?

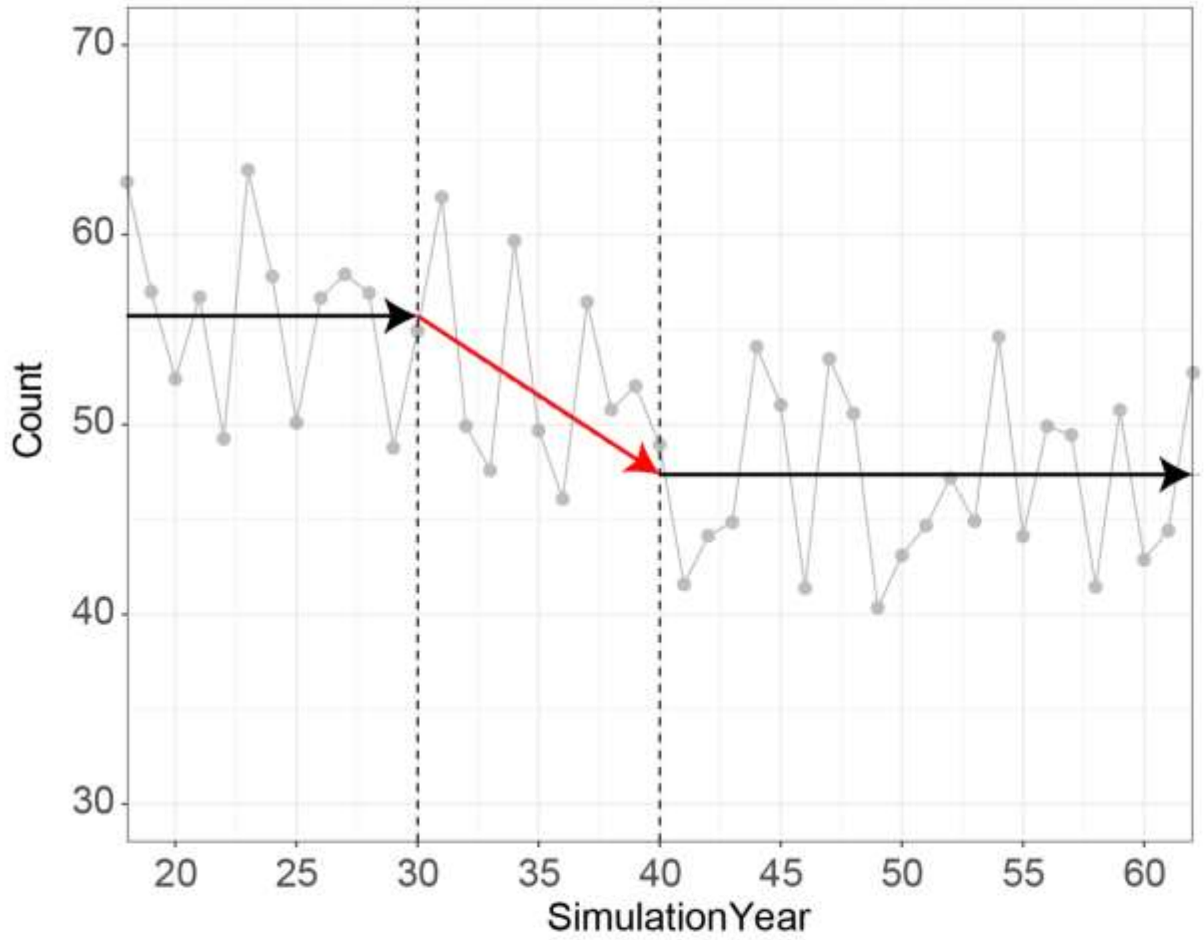
Detecting change: simulation framework



Simple structure:

- stable – decline – stable

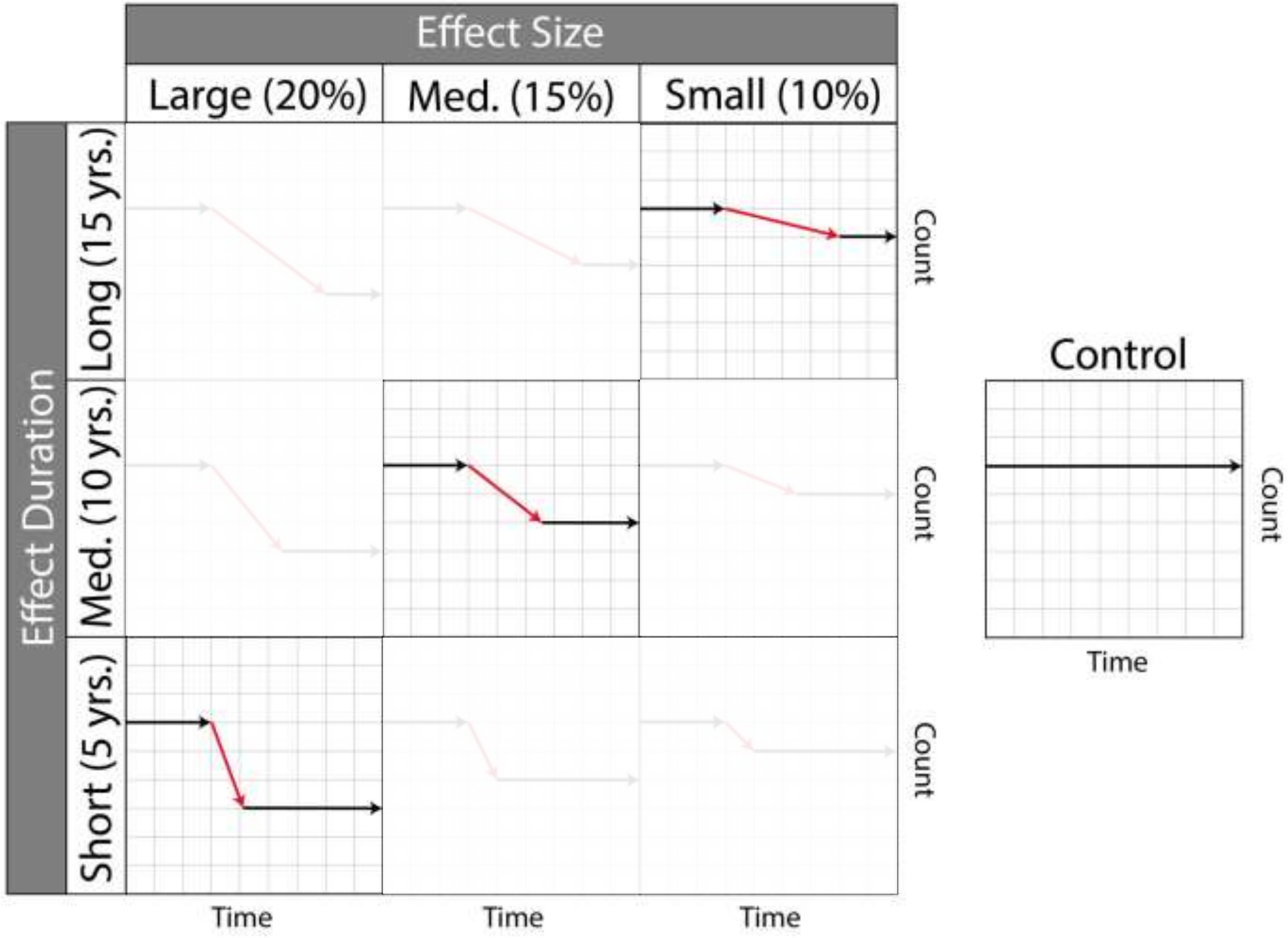
Detecting change: simulation framework



Simple structure:

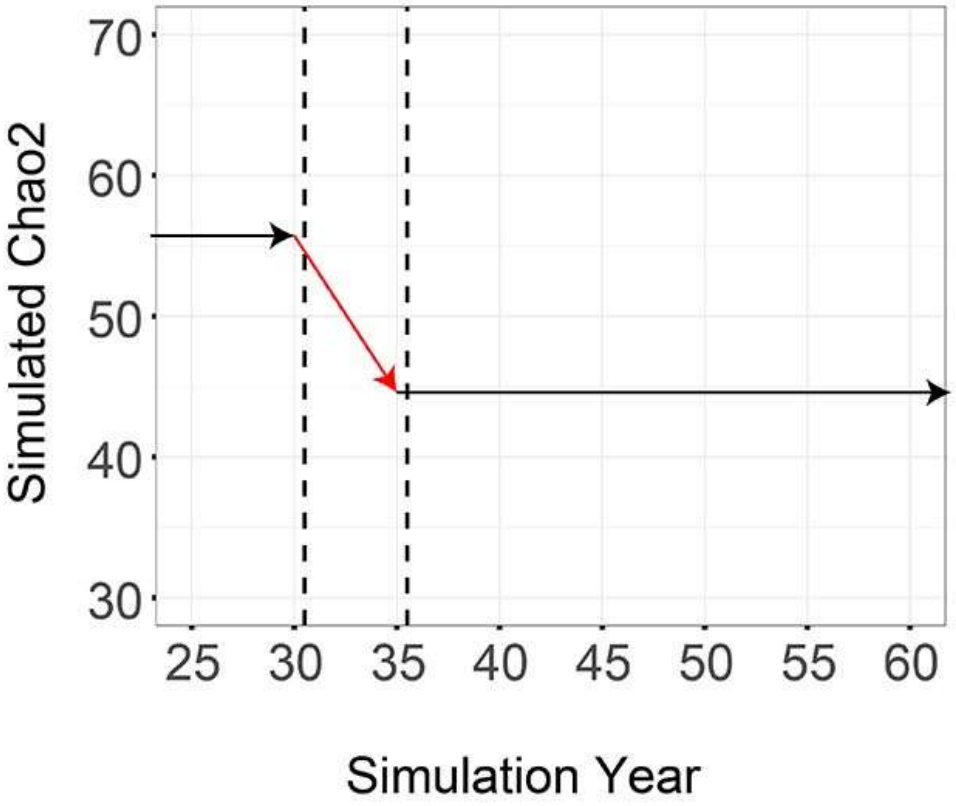
- stable – decline – stable
- Added a time series of “noise” to create different realizations of Chao2 trends

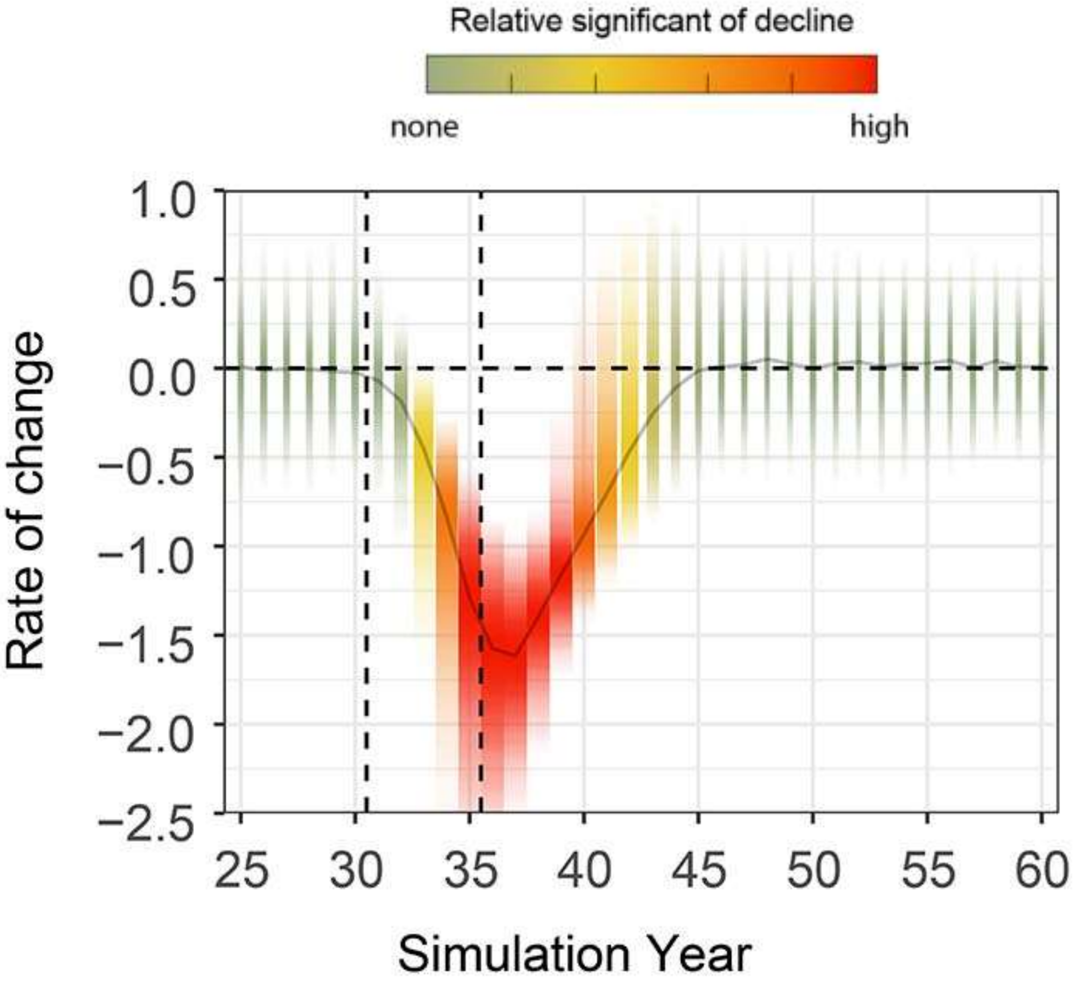
Power to detect change



Detecting change

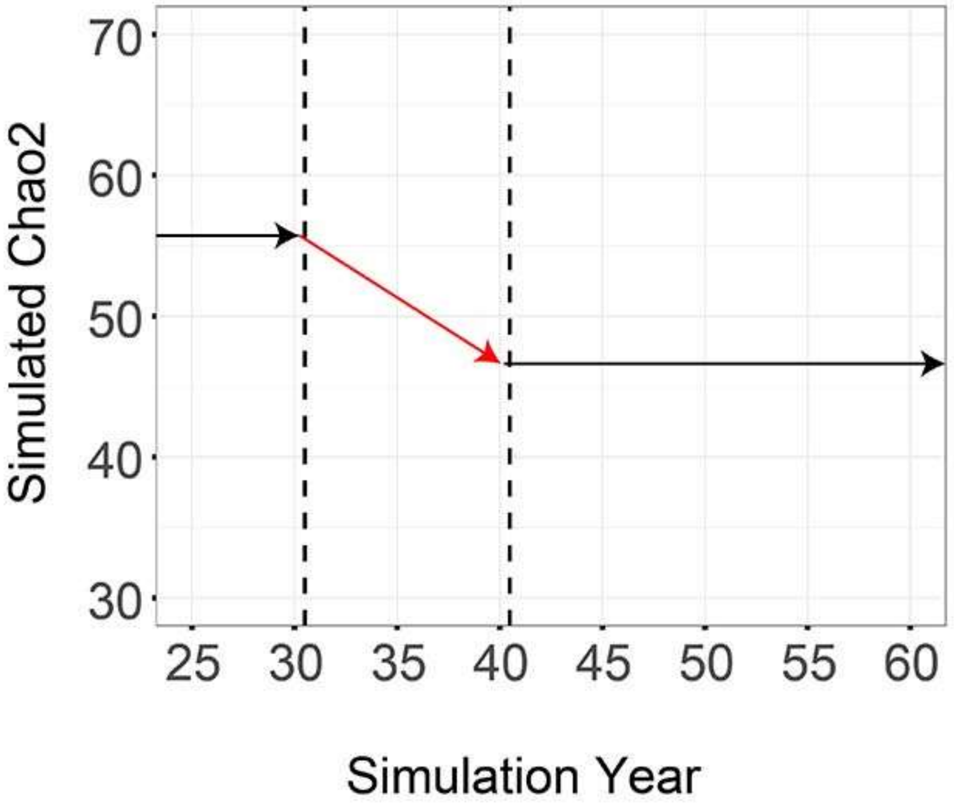
<u>Simulation Parameters:</u>
Decline duration = 5 years
Decline magnitude = 20% (~10 Chao2 units)

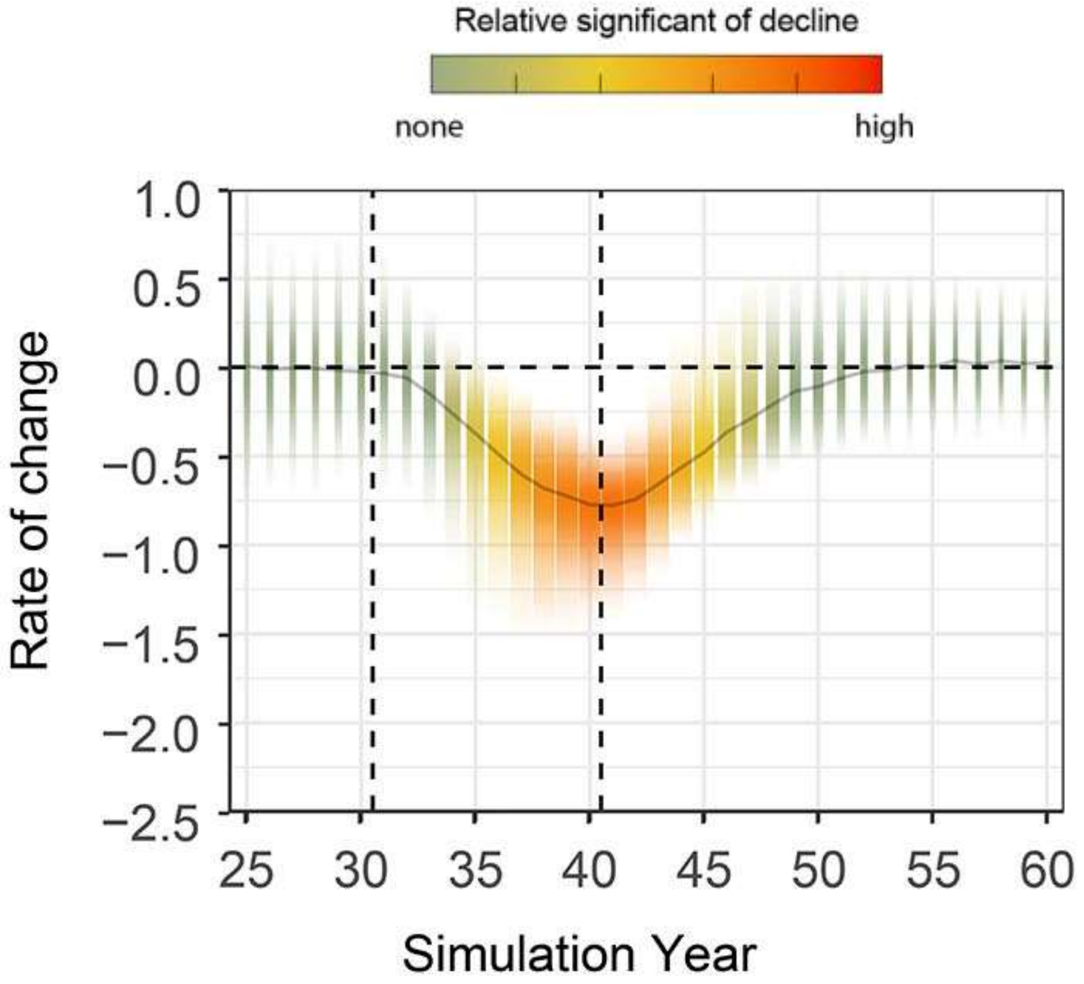




Detecting change

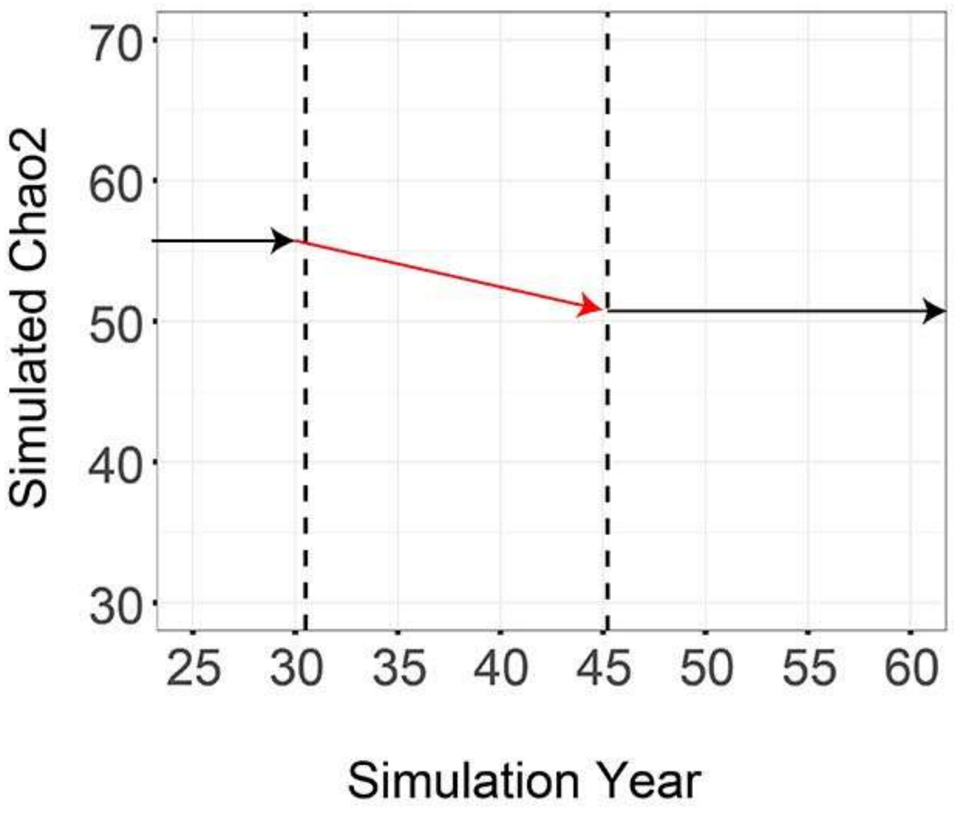
<u>Simulation Parameters:</u>
Decline duration = 10 years
Decline magnitude = 15% (~8 Chao2 units)

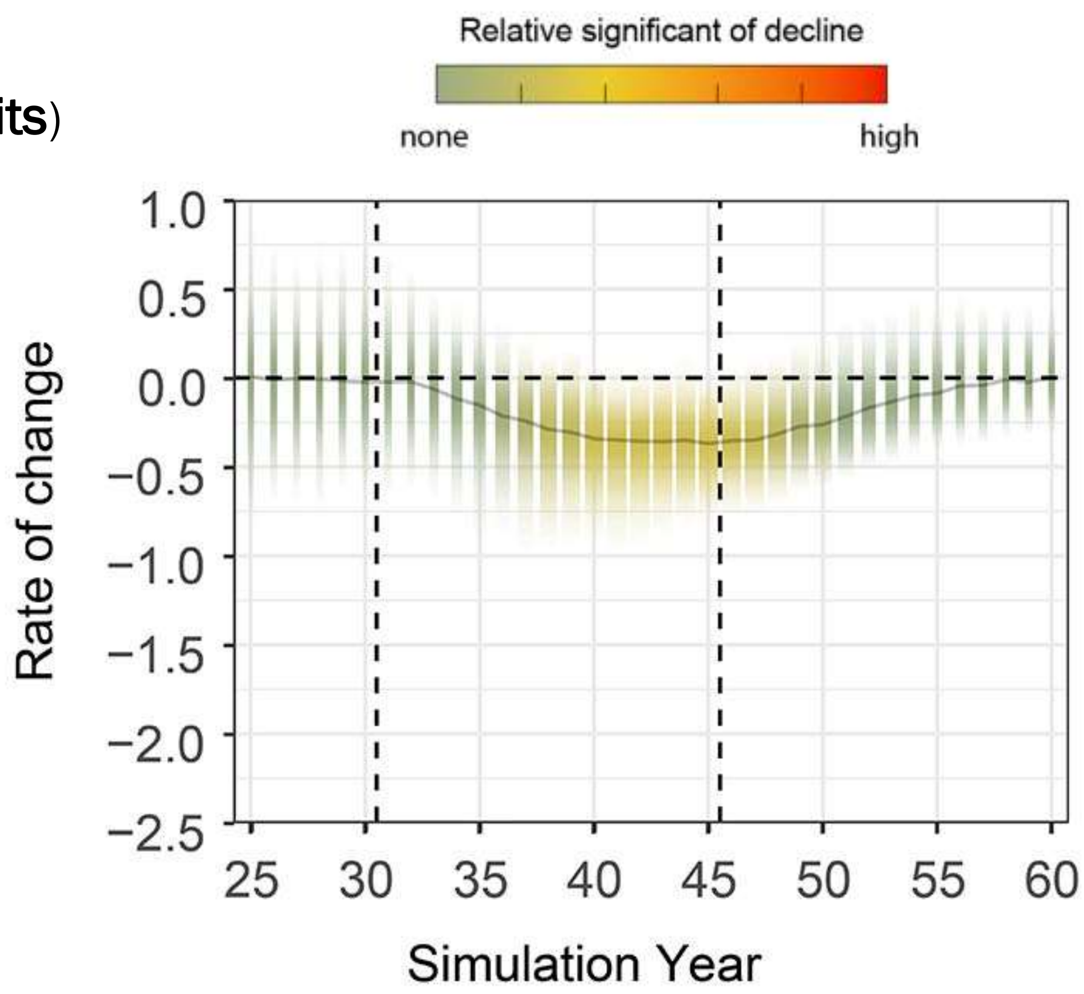




Detecting change

<u>Simulation Parameters:</u>
Decline duration = 15 years
Decline magnitude = 10% (~5 Chao2 units)



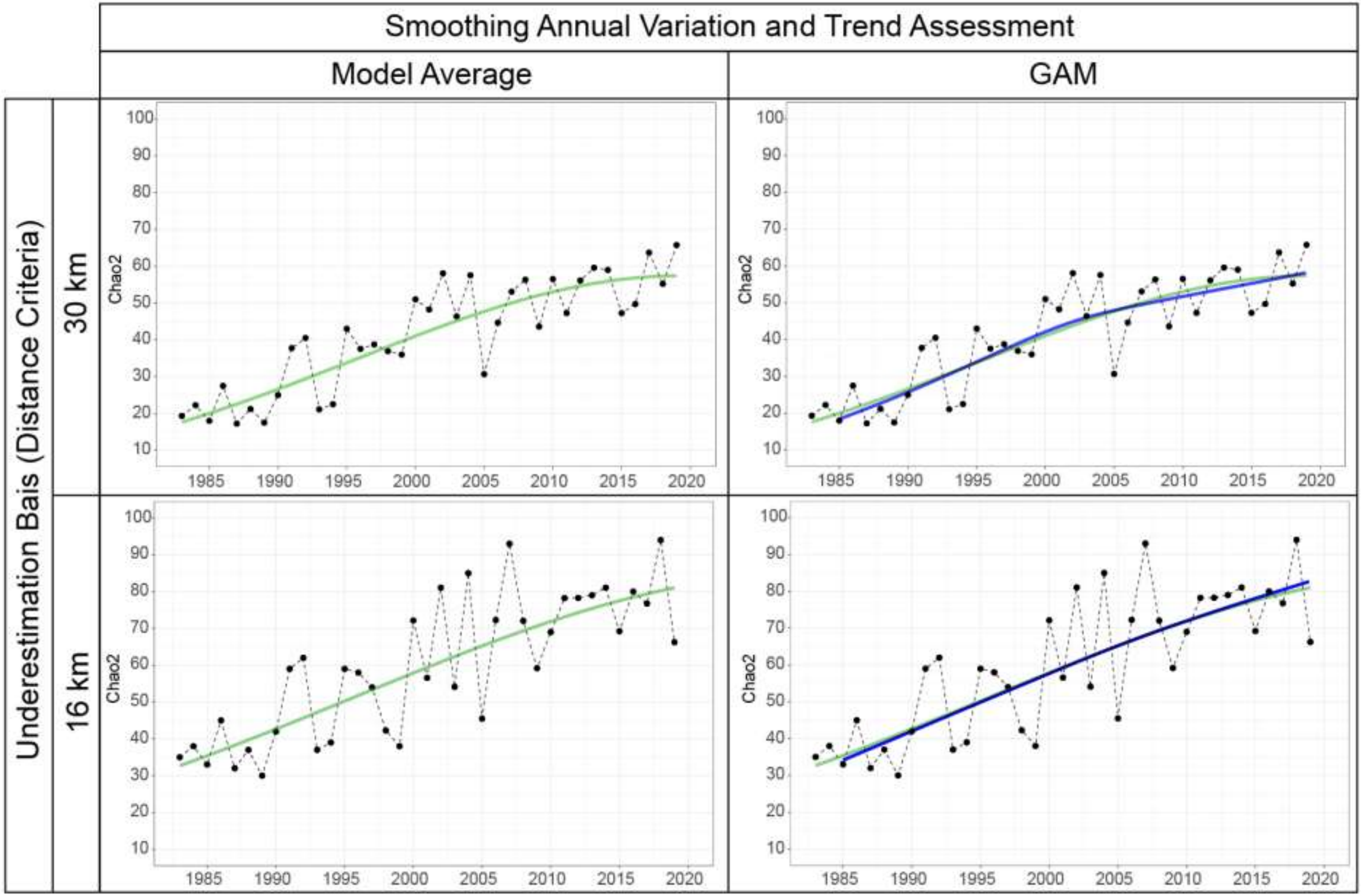


Part II: Summary

- GAMs suitable alternative
- Enhance inference regarding trend
- Applicable to any time series

Putting it all together….

Jake Davis


Smoothing Annual Variation and Trend Assessment
Model Average
GAM
Underestimation Bais (Distance Criteria)
30 km
16 km
Chao2
100
90
80
70
60
50
40
30
20
10
1985
1990
1995
2000
2005
2010
2015
2020

Next steps

- Finalize report
- Integrate findings into ongoing investigations (Integrated Population Models, vital rate analyses)
- Develop comprehensive recommendations to update IGBST monitoring protocol

Acknowledgments

- Mike Ebinger, USGS
- IGBST members and agencies