Spatiotemporal forecasting of plant populations and the need to partition forecast uncertainty

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COLLABORATORS

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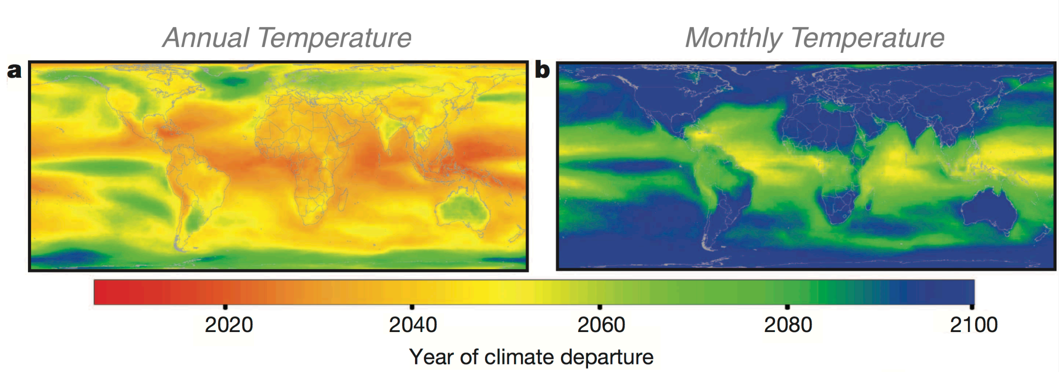
Mevin Hooten (CSU)

RAPID ENVIRONMENTAL CHANGE



Mora et al., 2013, *Nature*

IT'S BEEN A LONG TIME COMING

VIEWPOINT

Ecological Forecasts: An Emerging Imperative

James S. Clark,[1*] Steven R. Carpenter,[2] Mary Barber,[3] Scott Collins,[4] Andy Dobson,[5] Jonathan A. Foley,[6] David M. Lodge,[7] Mercedes Pascual,[8] Roger Pielke Jr.,[9] William Pizer,[10] Cathy Pringle,[11] Walter V. Reid,[12] Kenneth A. Rose,[13] Osvaldo Sala,[14] William H. Schlesinger,[15] Diana H. Wall,[16] David Wear[17]

Clark et al., 2001, *Science*

THE TIME IS NOW

PERSPECTIVE

Iterative near-term ecological forecasting: Needs, opportunities, and challenges

Michael C. Dietze[a,1], Andrew Fox[b], Lindsay M. Beck-Johnson[c], Julio L. Betancourt[d], Mevin B. Hooten[e,f,g], Catherine S. Jarnevich[h], Timothy H. Keitt[i], Melissa A. Kenney[j], Christine M. Laney[k], Laurel G. Larsen[l], Henry W. Loescher[k,m], Claire K. Lunch[k], Bryan C. Pijanowski[n], James T. Randerson[o], Emily K. Read[p], Andrew T. Tredennick[q,r], Rodrigo Vargas[s], Kathleen C. Weathers[t], and Ethan P. White[u,v,w]

Edited by Monica G. Turner, University of Wisconsin–Madison, Madison, WI, and approved December 29, 2017 (received for review June 7, 2017)

Dietze et al., 2018, *PNAS*

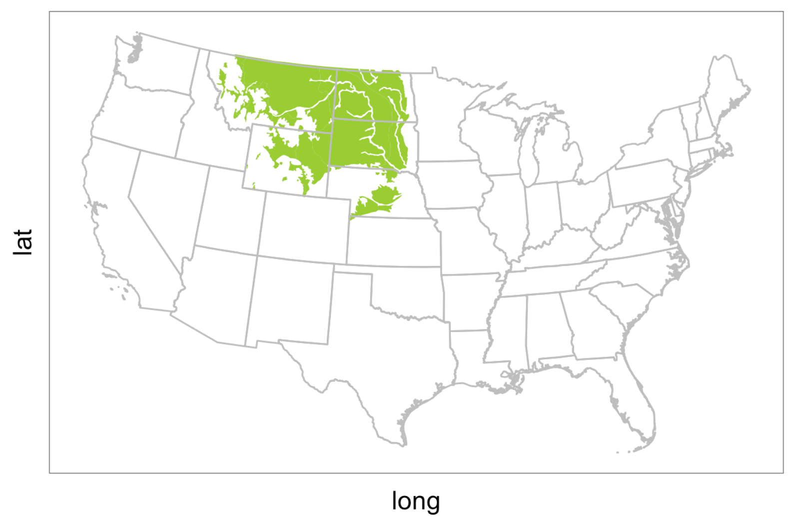
ROAD MAP

1. Do we need demographic data?
2. Scaling up plant population forecasts
3. Partitioning forecast uncertainty – a new agenda for ecology

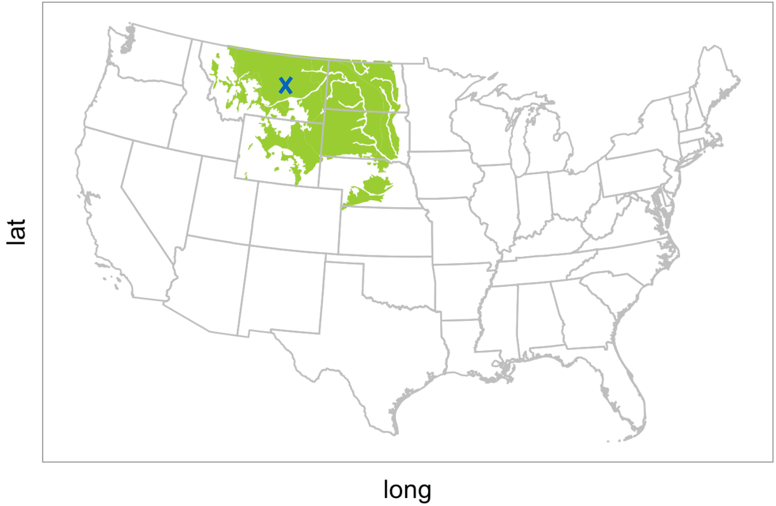
§ 1

Do we need demographic data?

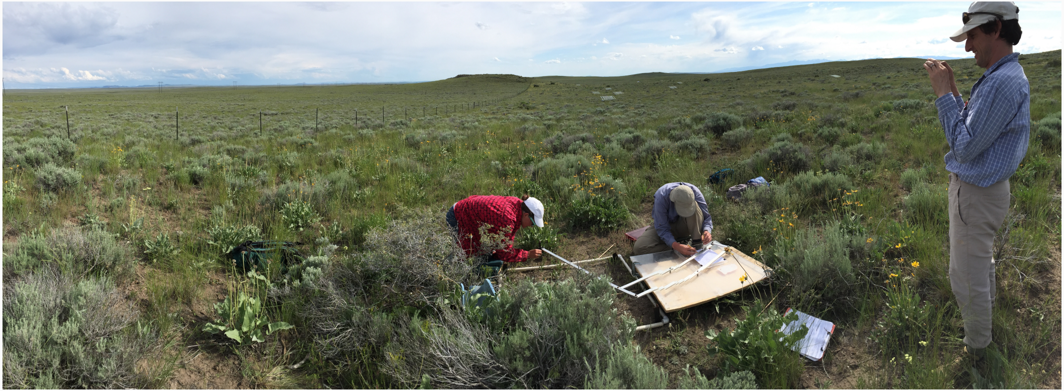
WHAT LAND MANAGERS WANT



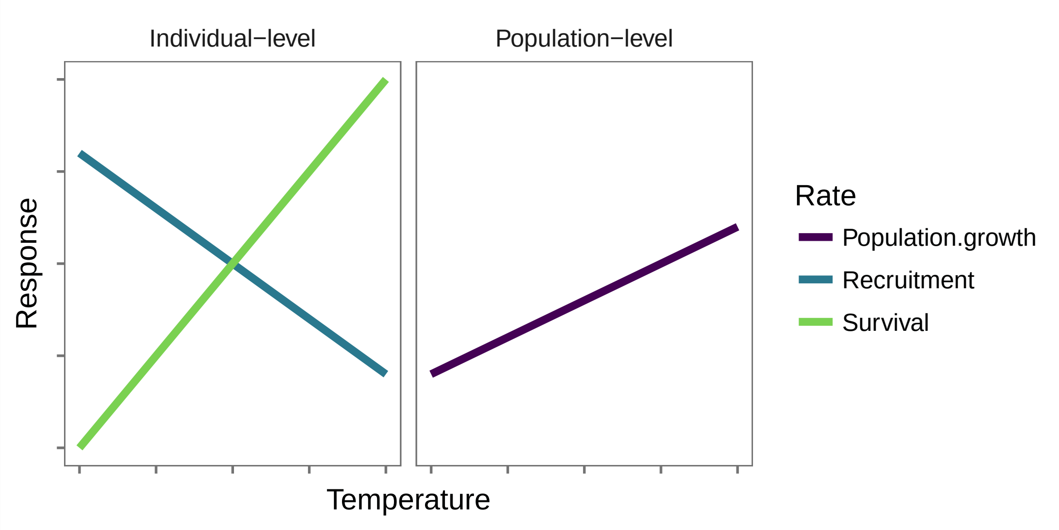
WHAT LAND MANAGERS GET



REALLY HARD WORK



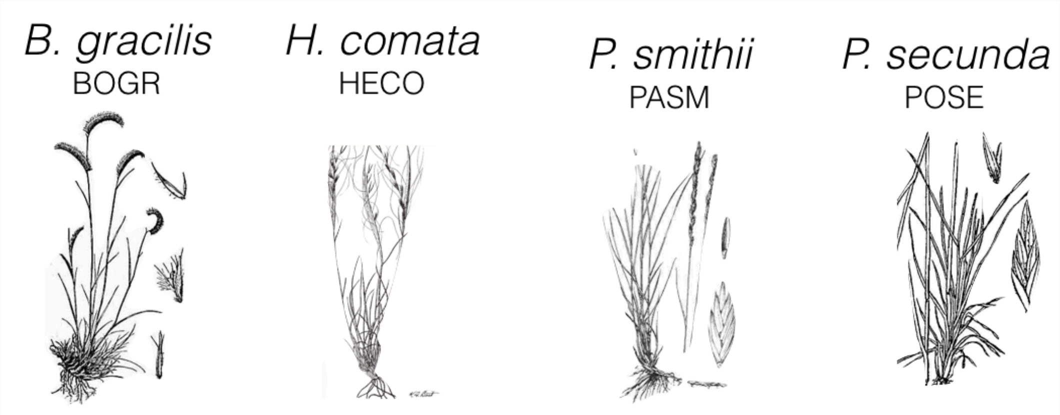
AGGREGATE POPULATION-LEVEL DATA



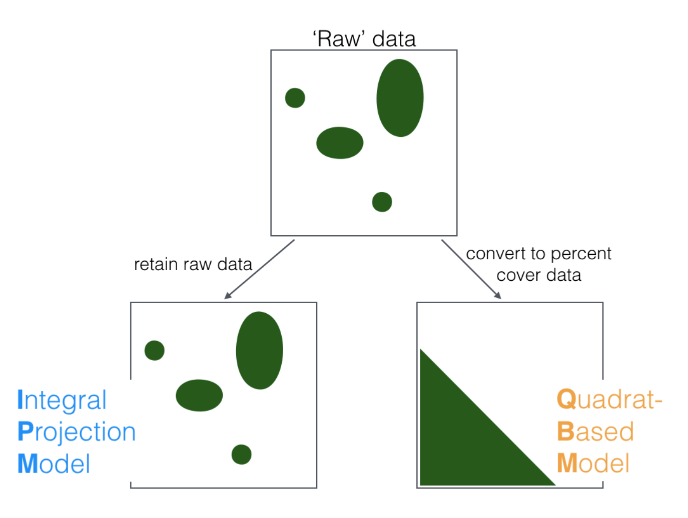
OBJECTIVES

1. Determine if population-level data contains similar climate signal as individual-level data.
2. Compare model accuracy and precision using out-of-sample validation.

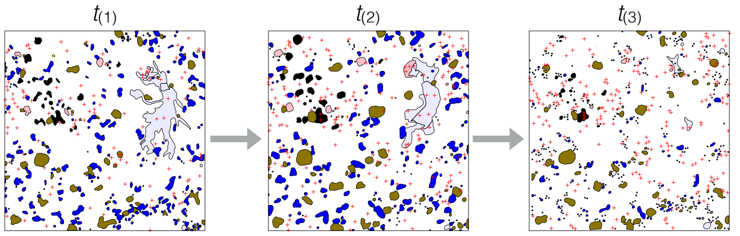
14-YEAR TIME SERIES FROM MONTANA



TWO TYPES OF MODELS

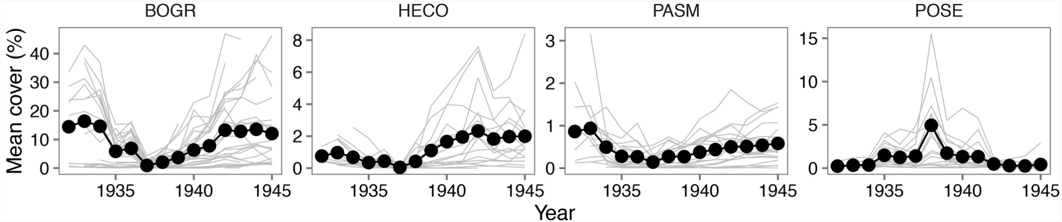


INTEGRAL PROJECTION MODEL



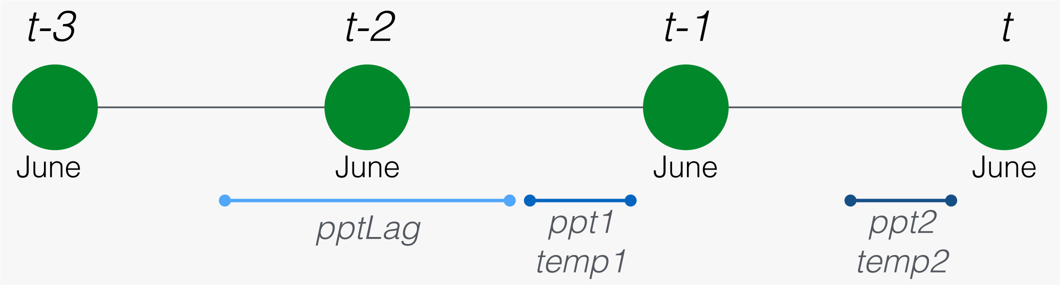
$$\left.\begin{array}{r}\text{survival}(t+1)\\ \text{growth}(t+1)\\ \text{recruitment}(t+1)\end{array}\right. = f\left(\text{size}(t), \text{location}, \text{crowding}(t), \text{year}(t), \text{climate}(t)\right)$$

QAUDRAT(COVER)-BASED MODEL

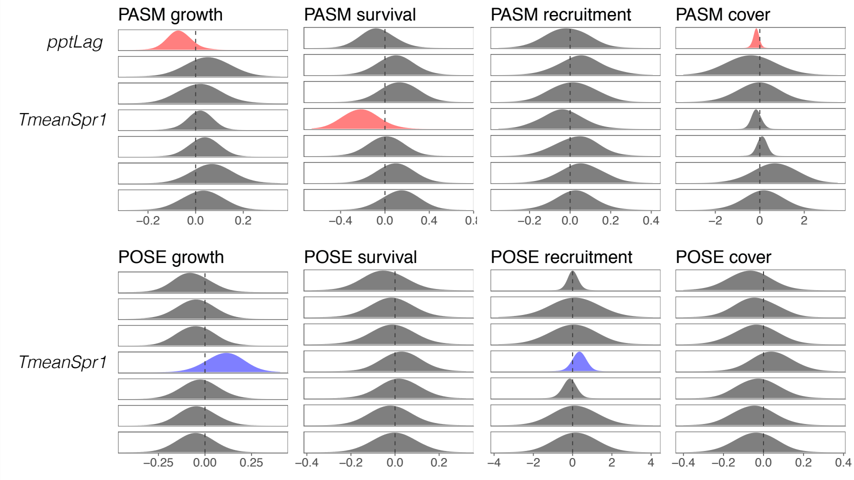


$$\text{cover}(t+1) = f(\text{cover}(t), \text{location}, \text{year}(t), \text{climate}(t))$$

CLIMATE COVARIATES

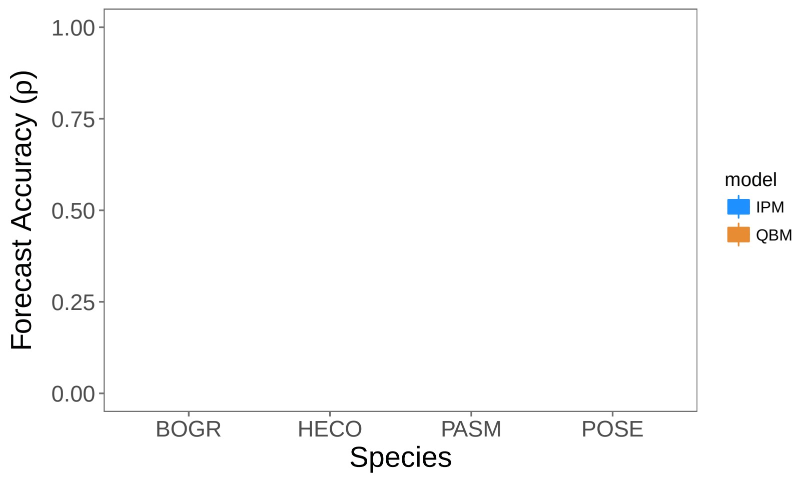


CLIMATE EFFECTS BY VITAL RATES



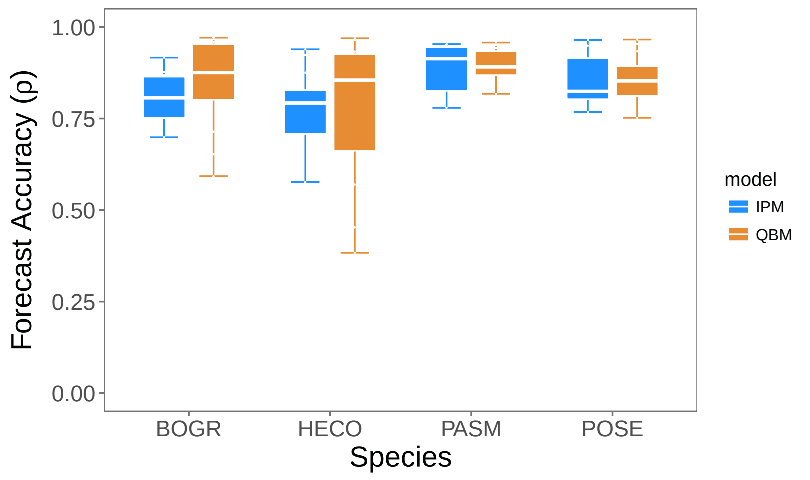
Tredennick et al., 2017, *Methods in Ecol. Evol.*

MODEL COMPARISON



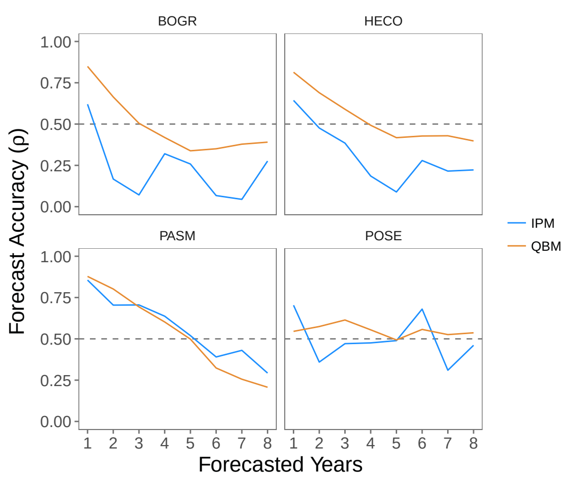
Tredennick et al., 2017, *Methods in Ecol. Evol.*

MODEL COMPARISON



Tredennick et al., 2017, *Methods in Ecol. Evol.*

FORECAST HORIZONS



Tredennick et al., 2017, *Methods in Ecol. Evol.*

DO WE NEED DEMOGRAPHIC DATA?

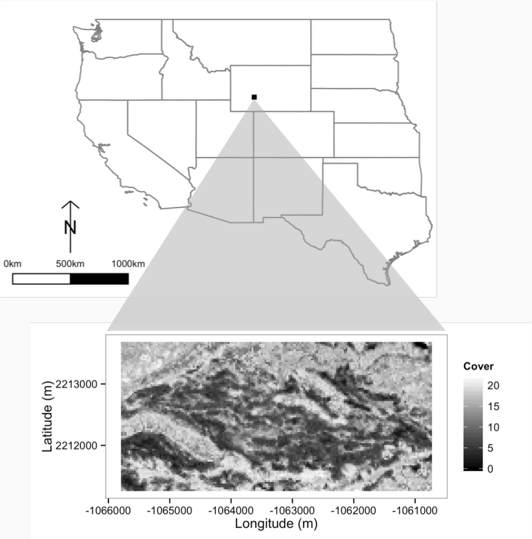
Maybe not.

§ 2

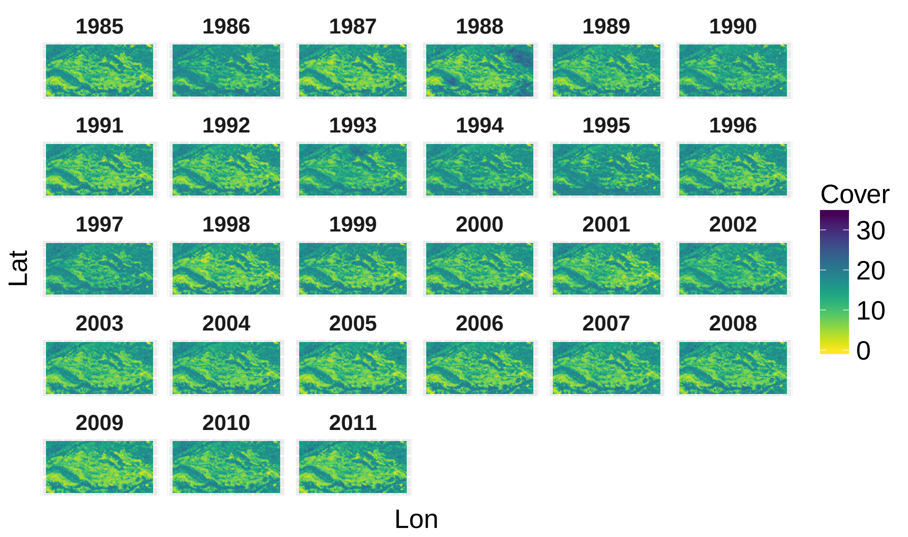
Scaling up plant population forecasts

SAGEBRUSH SEA IN WYOMING

STUDY AREA


N
0km
500km
1000km
Cover
20
15
10
5
0
2213000
2212000
Latitude (m)
-1066000
-1065000
-1064000
-1063000
-1062000
-1061000
Longitude (m)

LANDSAT TIME SERIES

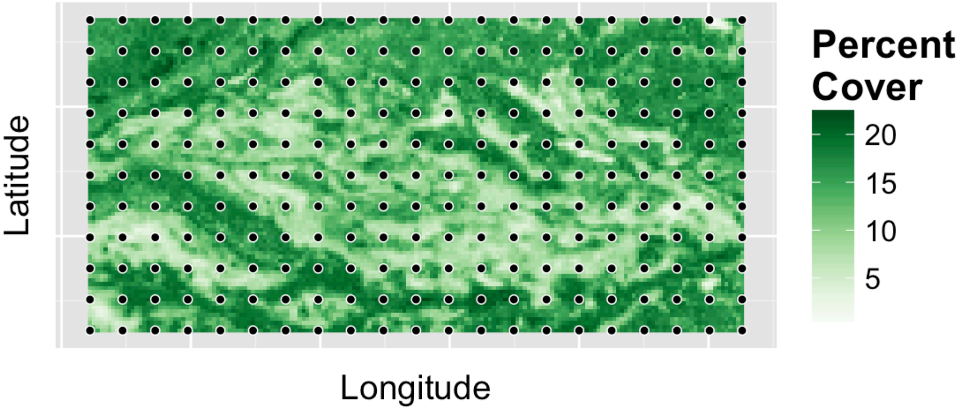


DYNAMIC COVER MODEL

$$y_{i,t} \sim \text{Poisson}(\mu_{i,t})$$

$$\log(\mu_{i,t}) = \underbrace{\beta_{0,t} + \beta_1 y_{i,t-1}}_{\text{temporal + dens. dep}} + \underbrace{\mathbf{x}_t'\varphi}_{\text{climate}} + \underbrace{\eta_i}_{\text{spatial}}$$

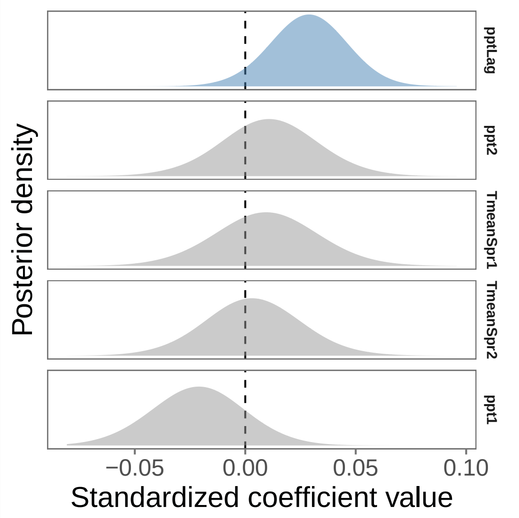
DIMENSION REDUCTION FOR SPATIAL EFFECT



DYNAMIC COVER MODEL

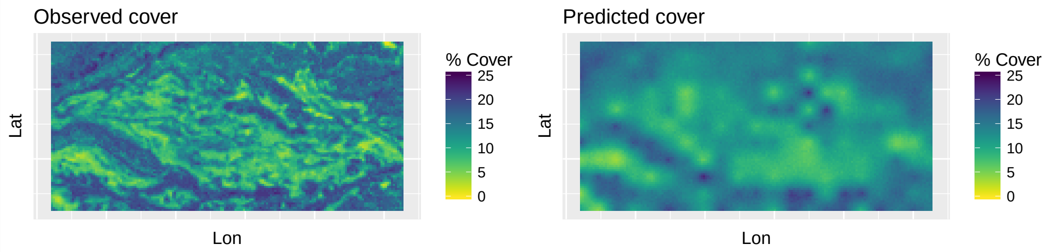
$$
\begin{aligned}
y_{i,t} &\sim \text{Poisson}(\mu_{i,t}) \\
\log(\mu_{i,t}) &= \underbrace{\beta_{0,t} + \beta_1 y_{i,t-1}}_{\text{temporal + dens. dep}} + \underbrace{\mathbf{x}_t' \varphi}_{\text{climate}} + \underbrace{\eta_i}_{\text{spatial}} \\
\eta &\approx \mathbf{K}\alpha, \\
\alpha_m &\sim \text{Normal}(0, \sigma_\eta^2)
\end{aligned}
$$

CLIMATE EFFECTS



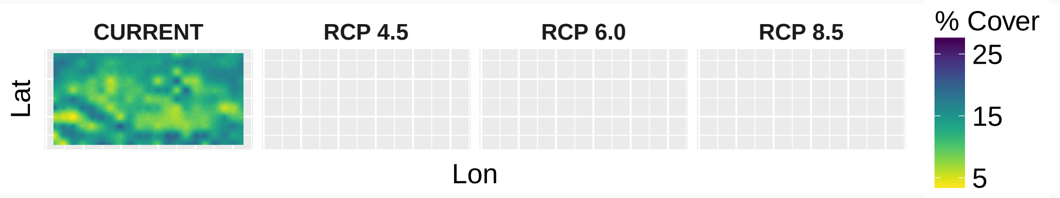
MODEL PERFORMANCE

RMSE $\approx$ 4%



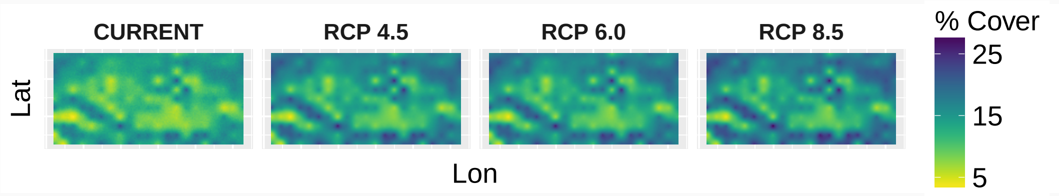
Tredennick et al., 2016, *Ecosphere*

FORECASTS UNDER CLIMATE CHANGE: SPATIAL



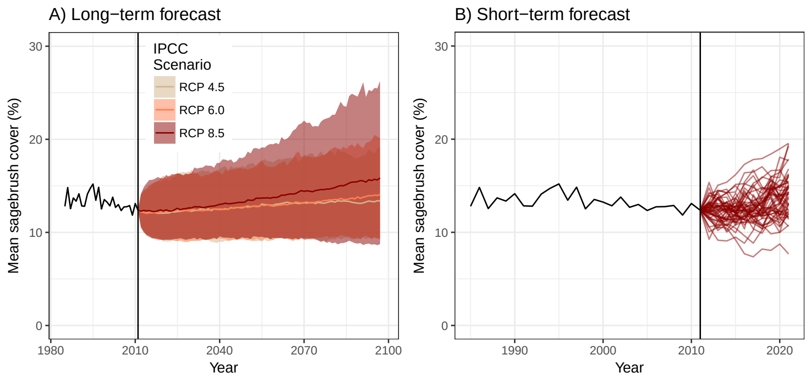
Tredennick et al., 2016, *Ecosphere*

FORECASTS UNDER CLIMATE CHANGE: SPATIAL



Tredennick et al., 2016, *Ecosphere*

FORECASTS UNDER CLIMATE CHANGE: TEMPORAL



Tredennick et al., 2016, *Ecosphere*

§ 3

Partitioning forecast uncertainty

FORECAST VARIANCE...TO A FIRST APPROXIMATION

$$y_{t+1} = f\left(y_t, x_t \middle| \theta\right) + \varepsilon_{t+1}$$

FORECAST VARIANCE...TO A FIRST APPROXIMATION

$$y_{t+1} = f(y_t, x_t|\theta) + \varepsilon_{t+1}$$

$$Var[y_{t+1}] \approx \underbrace{\left(\frac{\delta f}{\delta y}\right)^2}_{\text{stability}} \underbrace{Var[y_t]}_{\text{IC uncert.}} + \underbrace{\left(\frac{\delta f}{\delta x}\right)^2}_{\text{driver sens.}} \underbrace{Var[x_t]}_{\text{driver uncert.}} + \underbrace{\left(\frac{\delta f}{\delta \theta}\right)^2}_{\text{param sens.}} \underbrace{Var[\theta]}_{\text{param. uncert.}} + \underbrace{Var[\varepsilon]}_{\text{process error}}$$

Dietze, 2017, *Ecological Applications*; Cariboni et al., 2007, *Ecological Modeling*

FORECAST VARIANCE...TO A FIRST APPROXIMATION

$$y_{t+1} = f(y_t, x_t | \theta) + \varepsilon_{t+1}$$

$$Var[y_{t+1}] \approx \underbrace{\left(\frac{\delta f}{\delta y}\right)^2}_{\text{stability}} \underbrace{Var[y_t]}_{\text{IC uncert.}} + \underbrace{\left(\frac{\delta f}{\delta x}\right)^2}_{\text{driver sens.}} \underbrace{Var[x_t]}_{\text{driver uncert.}} + \underbrace{\left(\frac{\delta f}{\delta \theta}\right)^2}_{\text{param sens.}} \underbrace{Var[\theta]}_{\text{param. uncert.}} + \underbrace{Var[\varepsilon]}_{\text{process error}}$$

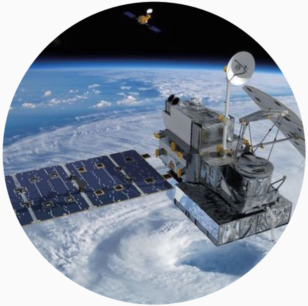
$$Var[y_{t+1}] \approx \text{Internal} + \text{External} + \text{Parameters} + \text{Process Error}$$

Dietze, 2017, *Ecological Applications*; Cariboni et al., 2007, *Ecological Modeling*

THIS IS WHY WE HAVE WEATHER SATELLITES

$$Var[y_{t+1}] \approx \underbrace{\left(\frac{\delta f}{\delta y}\right)^2}_{\text{stability}} \underbrace{Var[y_t]}_{\text{IC uncert.}}$$

$$Var[y_{t+1}] \approx \text{Internal}$$



YELLOWSTONE BISON (*BISON BISON*)

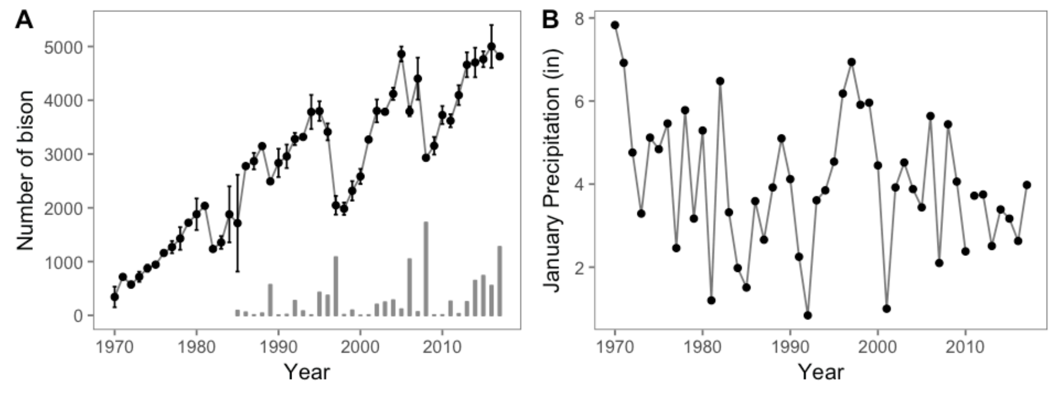
YELLOWSTONE BISON (*BISON BISON*)

Photo credit: Yellowstone National Park

TIME SERIES OF BISON COUNTS (1970 - 2017)

Response Bison counts

Covariate January precipitation



GOMPERTZ POPULATION GROWTH

$$mu_{(t)} = \log(z_{(t-1)}) + e_{(t)} + r + b_0 \log(z_{(t-1)} + e_{(t)}) + b_1 x_{(t)}$$

$$\log(z_{(t)}) \sim \text{Normal}\left(\mu_{(t)}, \sigma^2_{\text{p}}\right)$$

- z_t latent population abundance in year t
- e_t log of harvested animals between $t-1$ and t
- r per capita growth rate
- b_0 density dependence
- b_1 effect of January precipitation
- x_t January precipitation in year t
- $\sigma^2_{\mathbf{p}}$ process variance

LIKELIHOOD AND FULLY SPECIFIED MODEL

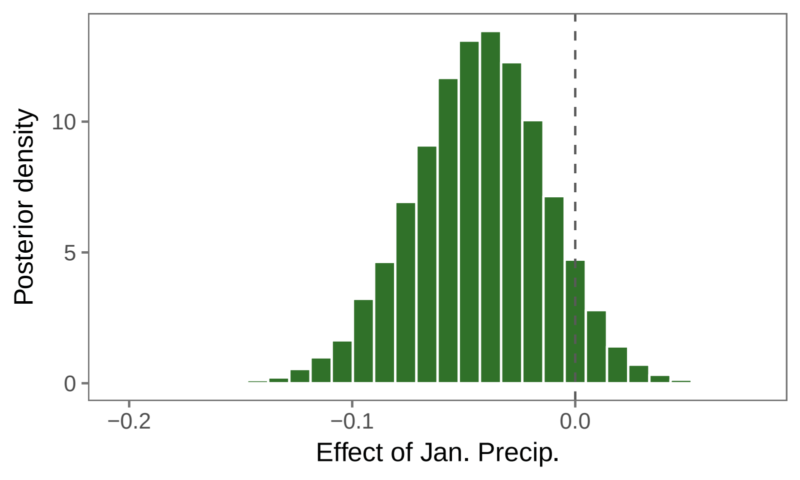
Likelihood

$$y_{(t)} \sim \mathrm{NB}\left(z_{(t)}, \kappa\right)$$

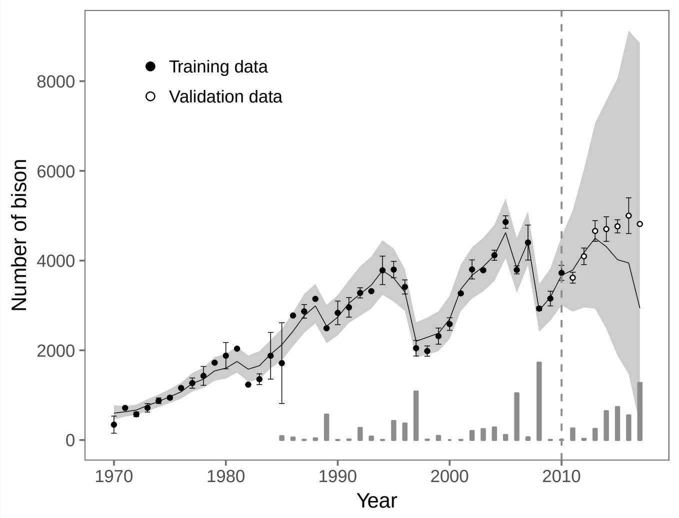
Full model

$$\left[\theta_{\mathrm{p}}, \kappa, z_{(t)}, z_{(t-1)} \middle| y_{(t)}, x_{(t)}\right] \propto \prod_{t=2}^{48} \underbrace{\left[z_{(t)} \middle| \theta_{\mathrm{p}}, z_{(t-1)}, x_{(t)}\right]}_{\text{process}} \prod_{t=1}^{41} \underbrace{\left[y_{(t)} \middle| \kappa, z_{(t)}\right]}_{\text{data}} \underbrace{\left[\theta_{\mathrm{p}}, \kappa, z_{(t=1)}\right]}_{\text{parameters}}$$

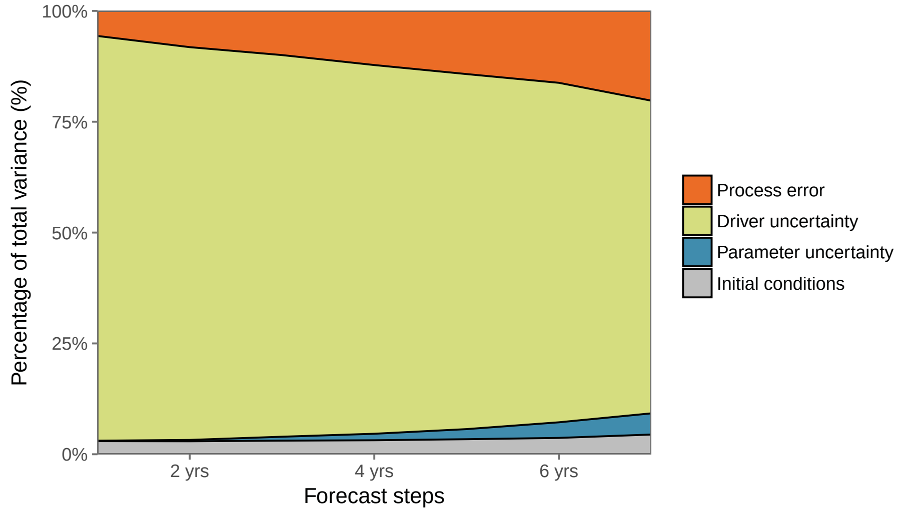
POSTERIOR DISTRIBUTION OF CLIMATE EFFECT



MODEL FIT AND FORECAST



FORECAST PARTITION



CLIMATE PROJECTIONS ARE UNCERTAIN

§ 4

Closing thoughts

CLOSING THOUGHTS

1. We have the tools and the data streams to start forecasting.
2. The time to start is now.
3. Embrace our failures.
4. Generate meaningful forecasts – forecasts that someone wants.