Appendix A. Comparison of observation models used in the Gompertz state-space model with extractions.

Before implementing the climate covariates, we compared three potentially relevant observation models for use in eqn 4b (main text) using a plural approach to scientific inference (Scheiner 2004). This included the use of the Deviance Information Criterion (DIC; Spiegelhalter et al. 2002) to compare observation models, but recognizing that DIC is not optimal for models with latent processes like ours (Celeux et al. 2006), we also considered the effect size and precision of key parameters in the observation models when DIC values were similar.

We began by fitting the commonly used log-normal observation model with $\log(y_t) = x_t + \eta_t$, $\eta_t \sim N\left(0, \sigma_o^2\right)$, and $\sigma_o^2 \sim IG(0.001, 0.001)$. Second, we fit a Poisson model that is naturally suited for discrete random variables like population counts, where $y_t \sim Pois\left(\exp(x_t)\right)$. Here, η_t is implicitly estimated by the Poisson distribution where the variance equals and increases with the mean. A drawback of this constraint is that it may offer a poor fit to count data that are over-dispersed relative to the Poisson assumption (Zuur et al. 2009). Similar to Geremia et al. (2014) who modeled aerial counts of bison in Yellowstone National Park, we also considered a negative binomial observation model with $y_t \sim NB\left(\exp(x_t), \alpha\right)$, where α is the over-dispersion parameter to be estimated.

We found that the Poisson observation model offered a superior fit to the bison counts relative to the commonly used log-normal model (ΔDIC = 839.7). Compared to the model of Poisson distributed abundance and observation errors, the negative binomial model was equally supported (only a 0.7 improvement in DIC), but the large and imprecise estimate of α (4706.4;

95% BCI: 139.9 to 19,576.9) indicated that there was essentially no over-dispersion in the data. Thus, we used the more parsimonious Poisson observation model in all analyses presented in the main text.

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