A Gnu Approach: Bayesian Analysis of 20th Century Serengeti Wildebeest

Muntasir Akash, Misha Tseitlin

20 November 2023

Project 2: State-Space Model for Wildebeest Population Dynamics

Contribution Statement

This report jointly involved collaborative discussion, coding, and writing by MA and MT. MT coded four models, and MA coded one model; one of MT's models was selected for this report. MA drove report content, model evaluation, and model selection. An unbiased £1 coin mediated all disputes. For more detail on individual contributions, please reference the GitHub.

University of St Andrews

School of Mathematics and Statistics

in partial fulfilment of the requirements for
MT5767: Modelling Wildlife Population Dynamics

Introduction

Travelling throughout the Tanzanian Serengeti, the blue wildebeest (Connochaetes taurinus) is a keystone species that defines the African grasslands motivates study among ecologists, land managers, and governments. In their travels, wildebeest must contend with threats like rinderpest and poaching while also depending on environmental and ecological processes, from rain to birth rates. Looking back to historical trends, this report uses 1960–1989 measures of wildebeest populations for estimating a Bayesian state space model to understand population sizes, growth rates, and relationships to factors like rainfall while accounting for poaching.

Methodology

Model Formulation A Bayesian state space model (SSM) consists of two components: an unobserved "true" population process N_t and the flawed human observation process y_t. Here, true wildebeest population N_t depends only on the population growth rate λ_t and accounts for estimates of poaching c_t. To account for random variation common in natural systems, large N_{t+1}s take a normal distribution consistent with the thousands of wildebeest observed.

$$N_{t+1} \sim N(\lambda_t(N_t - c_t), \sigma_t^2)$$

λ_t, the wildebeest population growth rate $\frac{N_{t+1}}{N_t}$, may depend on rainfall R_t that impacts food available to the large African herbivores. To test this relation, β_0 and β_1 estimate $log(\lambda_t)$, which is transformed with a logarithm to (1) require positive λ values, (2) allow estimation of the per-capita growth rate $r_t = log_e(\lambda_t) = \frac{\Delta N}{N \Delta t}$, and (3) more easily interpret the relationship with βs.

$$log(\lambda_t) = \beta_0 + \beta_1 R_t$$

Finally, the observation wiildebeest y_t are treated as unbiased with known spread se_t. Measured by skilled surveyors and with a clear sampling strategy, y_t is expressed as a simple stochastic normal distribution dependent centred on the true population N_t with a known spread.

$$y_t \sim N(N_t, se_t^2)$$

Maybe add some more info about why normality? Cite some papers on why it's not Poisson (https://besjournals.onlinelibrary.wiley.com/doi/full/10.1111/2041-210X.13941), negative binomial (https://besjournals.onlinelibrary.wiley.com/doi/full/10.1111/1365-2664.12921), or truncated/half/lognormal (https://onlinelibrary.wiley.com/doi/full/10.1111/aje.12398)

Model Implementation The SSM uses well-studied data with t = [1960, 1989]; measures include rainfall R_t and poaching c_t for all years as well as population estimates y_t and associated error se_t for 12 years.

Explain MCMC. Initial values. Mention JAGS in R. Data source, processing, cleaning.

Results and Discussion

Without looking at the model output, a clear decrease in animal density occurs over the survey period (Figure **??**). The GLS model confirms these results at a high precision (Table **??**)—the probability of no impact from construction is ~0% given the data—with 0.009 fewer animals per km^2 after construction. With in the survey area, a total drop of 213 animals can be linked to wind turbine construction. The remaining three variables were all highly significant (less than 3% probability of seeing our data if there was no relationship with), but their effects on animal density were smaller than windfarm construction. Having attempted several linear and GLS models, Table **??**'s model ultimately shows the lowest error and best-suited information criteria.

Appendix

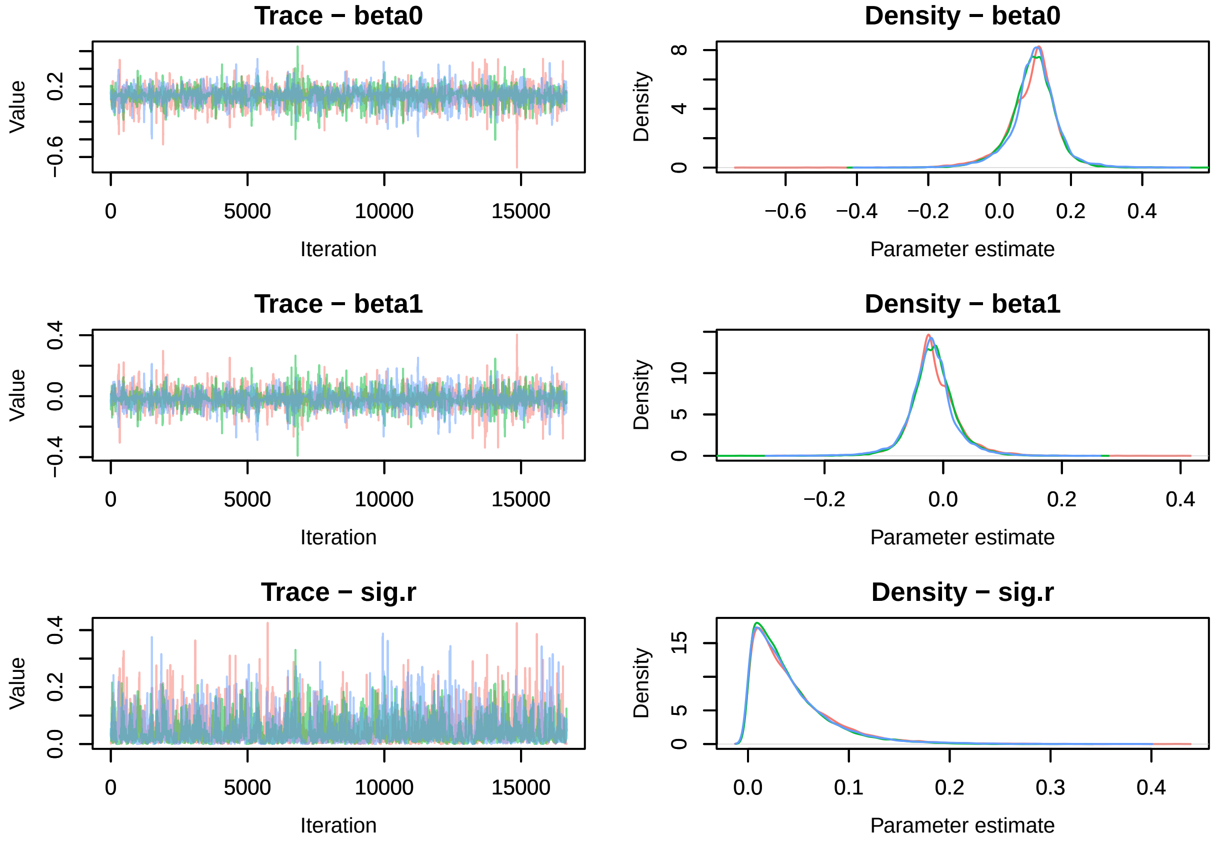

Figure 1: Latent parameter trace plots; derived hierarchical parameters not shown but also converged

	mean	sd	2.5%	50%	97.5%	Rhat	n.eff
beta0	0.0943145	0.0685582	-0.0587840	0.0990302	0.2221599	1	1191
beta1	-0.0172568	0.0404457	-0.0961883	-0.0191346	0.0702762	1	1140
sig.r	0.0416597	0.0392178	0.0013780	0.0305969	0.1457523	1	1573

Code Supplement

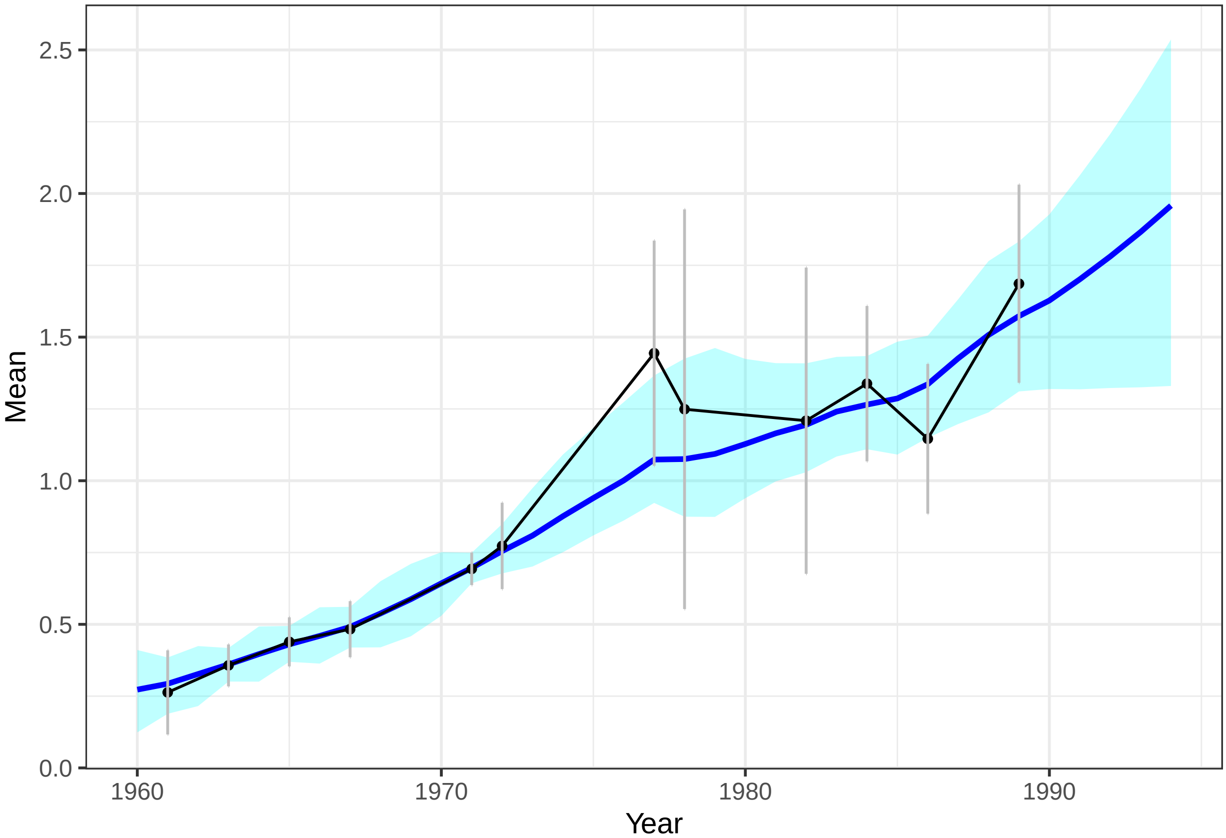

Figure 2: Projected values for true and estimated wildebeest population sizes