S2 Appendix. Choice of process error standard deviation

Most of the earliest applications of state-space models in ecology were in fisheries (e.g. [1,2]), where a value of 0.05 for the standard deviation in process error, σ_p, is considered low and a value of 0.20 for σ_p is considered high for annual time steps [3]. Intuitively, terrestrial systems are subject to higher levels of process variability compared to marine systems because the environment is less stable and human actions cause additional variability. We compiled estimates of σ_p from terrestrial state-space modelling applications (Table A), with estimates larger than 0.20 seemingly common in populations of mammal and bird species (e.g. [4,5]).

These state-space models estimated process errors on annual time-steps because they were modelling recruitment-only and not immigration. Because of the multiplicative nature of lognormal process error, two-weekly values of σ_p must be smaller than for annual time-step models. But modelling immigration as well as recruitment in our model potentially increases the process variation. Our model assumes a constant immigration rate, but realistically the number of foxes moving onto or off the culling area may vary substantially around this rate from one time-step to the next. At the upper extreme, during the post-weaning period, vixens may move with family groups onto or off an estate. This degree of variation would not be allowed if σ_p was fixed at too small a value. An additional reason to expect higher process variation in a restricted-area fox population is relatively low population numbers. Given a density of 2 fox km^{-2} across an estate of 5 km^{2}, the number of foxes is small enough that loss or gain of a single fox results in a large (10%) proportional change in density, a considerable change highlighting how noisy fox population processes are at this scale.

The most taxonomically relevant estimate of σ_p=0.08 was from a model of the Scandinavian wolf population [6], except that these authors modelled recruitment-only on an annual time-step, and the wolf population considered was >200 individuals. An estimate of σ_p=0.15 on a monthly time-step from an Australian population of the spectacled flying-fox (*Pteropus conspicillatus*) was more temporally relevant, but also came from a recruitment-only model where the population numbered >100,000 individuals [7]. We expected process variation in our fox population data to be higher, so fixed σ_p=0.2 on a two-weekly time step and examined the sensitivity to this choice.

Table A. Mean estimates of annual process error standard deviation σ_p from terrestrial species. Ranges of values indicate estimates obtained either from more than one population or from using alternative estimation methods

Species	σ_p	Reference
Mammals		
Red deer/Elk *Cervus elaphus*	0.0003-0.14	[8]
Reindeer/Caribou *Rangifer tarandus*	0.003-0.25	[8]
Wolf *Canis lupus*	0.08	[6]
Desert bighorn sheep *Ovis canadensis*	0.14-0.21	[9]
Sika deer *Cervus nippon*	0.22	[10]
Red kangaroo *Macropus rufus*	0.28	[4]
Birds		
Eurasian sparrowhawk *Accipiter nisus*	0.07	[11]
Greater snow goose *Chen caerulescens atlantica*	0.10-0.14	[12]
Ovenbird *Seiurus aurocapilla*	0.11-0.18	[13]
Puerto-Rican parrot *Amazona vittata*	0.12	[11]
Canvasback *Aythya valisineria*	0.14	[14]
California condor *Gymnogyps californianus*	0.21-0.30	[11]
Scaly-naped pigeon *Patagioenas squamosa*	0.25	[15]
Greater sage grouse *Centrocercus urophasianus*	0.55	[5]
Greater sage grouse *Centrocercus urophasianus*	0.62	[16]

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