



Need for transparent and repeatable conservation frameworks: reply to Child et al. 2019

Matthew J. Grainger * and Erlend B. Nilsen 

Norwegian Institute for Nature Research, P.O. Box 5685 Torgard, 7485, Trondheim, Norway

Managers frequently rely on models to help support decision making. For such models to serve as robust decision-making tools, they should be both valid and useful (Eker et al. 2019). A model or framework has validity only if it adequately measures what it claims to measure (Schwanitz 2013). A model's usefulness can be described as how well a model fits its given purpose. When models are conceptual and the phenomena of interest are unobservable quantities, adequate assessment of validity is challenging. In general, the validation of nonstatistical models is poorly described (Eker et al. 2019), even though this aspect is crucial if managers are to adopt frameworks and decision-support tools and thus close the knowing-doing gap (Knight et al. 2008). Recently, Child et al. (2019) proposed a framework to measure the "wildness" of managed vertebrate populations. *Wildness* as they define it is an unobservable (i.e., latent) variable and therefore hard to validate. Their framework builds on previous frameworks, including work by Aplet et al. (2000) and Mallon and Stanley Price (2013) and most notably on Redford et al. (2011). Child et al. suggest that refinements to the previous frameworks are needed because the attributes of Redford et al. (2011) are qualitative and not based on species-specific measurable thresholds that allow objective distinction between states and because they apply to species and not to local populations—which is the unit of most management. Child et al. aimed to create a tool to both "... articulate and measure wildness of populations by quantifying management interventions that impact on the evolutionary and ecological dynamics of species." In their study, they apply the framework to game ranches in South Africa.

In the Child et al. framework, wildness is constructed by 6 interlinked attributes (that are also latent variables underpinned by several measured key indicator variables [Fig. 1]) that relate to the evolutionary and ecological dynamics of populations. These attributes are "space," "disease and parasite resistance," "exposure to natural predation," "exposure to natural food limitations and fluctuations," "exposure to natural water limitations and fluctuations," and "reproduction." The conceptual model describes measurable variables that form the basis for the 6 attributes (table 1 in Child et al.). For example, the space attribute is determined by 2 variables: home range size of the species in relation to the estate size and presence of fences along the estate perimeter. A combination of these 2 measurable quantities is transformed to a score between 1 and 5, which represents the value for the space attribute.

Based on the information given in the article, it is hard to disentangle how empirical data are combined to construct the attribute scores. For example, it is not clear if the different components of each of the attributes are additive or if some are given greater weight in the calculation of the attribute scores. Child et al. do suggest that managers should apply their own weightings to the attributes when adapting the framework, but do not provide a clear indication of how they (Child et al.) weighted the attributes in their example. This lack of detail prevents efficient, transparent, and reproducible use of the framework, but the problem can be relatively easily solved by providing an update to the published framework. Our comments below cover more fundamental concerns regarding the validity of the model framework.

*Address correspondence to M. J. Grainger, email matthew.grainger@nina.no

Article impact statement: Without consideration of the validity of conservation frameworks and models to assist managers, efforts of conservation scientists are wasted.

Paper submitted April 3, 2019; revised manuscript accepted July 17, 2019.

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes.

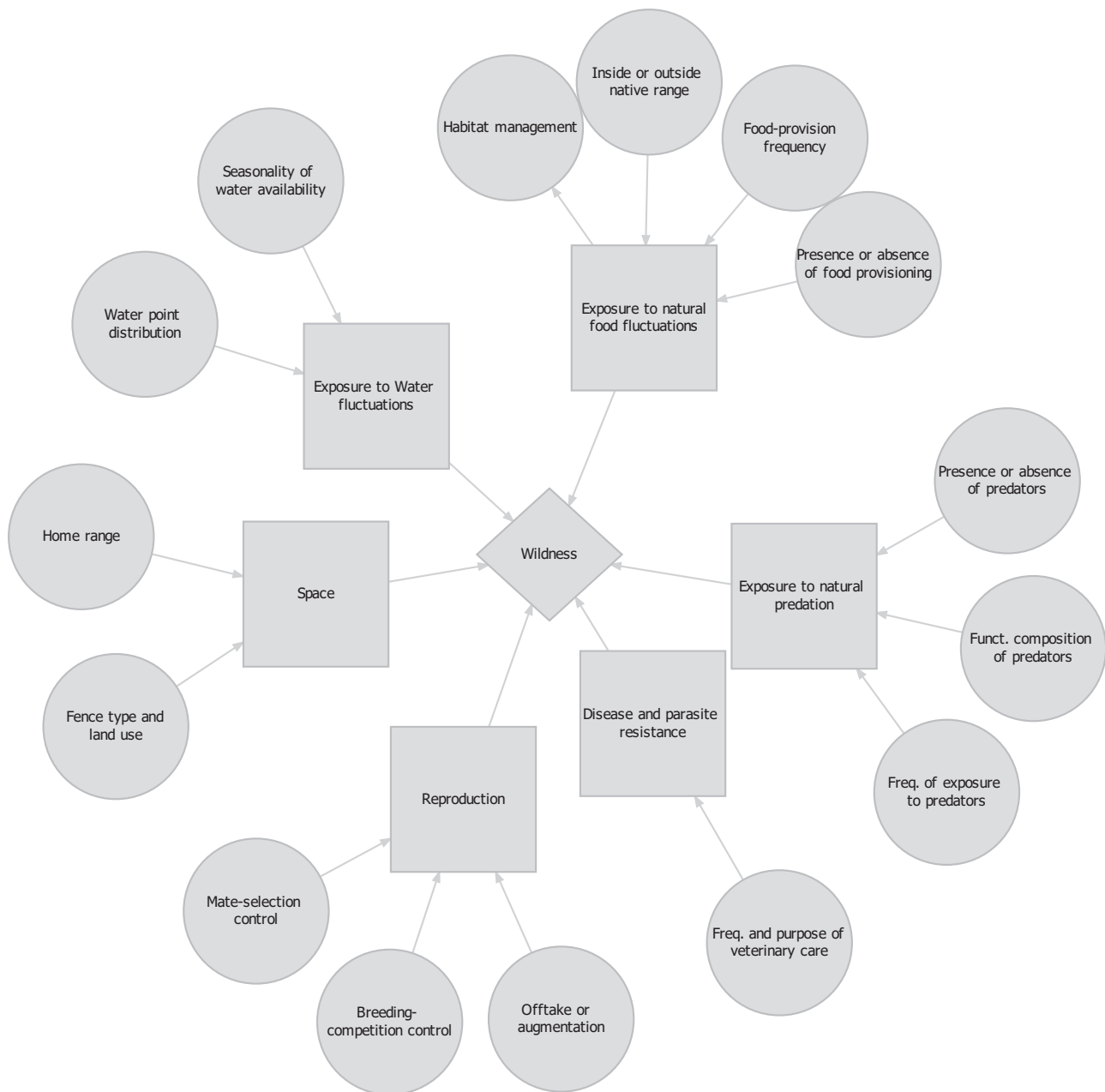


Figure 1. Model of Child et al.'s (2019) framework to measure the wildness of managed vertebrate populations (circles, observed variables; squares, unobserved [latent] variables; diamond, composite unobserved wildness variable).

Estimation of Wildness from Individual Attribute Scores

Based on the individual scores for all 6 attributes, Child et al. define the overall wildness score as the median of the attribute scores. Based on this value, wildness is categorized as 1 of 5 states, forming a gradient of human interference from a “captive managed” to a “self-sustaining” population. Although we value the approach for its simplicity, we see at least 3 problems that could prevent it from being widely adopted.

First, it is well known that a common mistake made in conservation decision making is to combine ordinal scores as if they were truly numerical (Game et al. 2013). Humans interpret ordinal scores inconsistently between different users and often interpret these scores as ratios. Rather than accepting that 4 is greater than 2 on an undefined scale, one typically perceives 4 as twice as great as 2 (Hubbard & Evans 2010). The effect of this is that different managers may interpret scores differently, reducing the reproducibility of decisions. Child et al. go some way to mitigate this problem by using the median score across

attributes to form the wilderness score. However, a single index of combined ordinal scores cannot adequately represent complex natural systems as we show below (“Uncertainty in Model Behavior”).

Second, in the Child et al. framework, there is no explicit estimation or propagation of uncertainty in the individual variables. The interquartile range (provided by Child et al.) will give some information about the variation in the attribute scores, but not any information about uncertainty in those 6 attributes and how that was dealt with. There will often be considerable uncertainty related to empirical data (e.g., related to home range size, which is known to vary in time and space [Duncan et al. 2015]). By not including such uncertainty or variation in the final wilderness score, the quality of the empirical data is given no weight, and there are no incentives to improve the empirical basis for the assessment.

Third, Child et al. refer to the 6 attributes as related, but the extent of this relationship is not quantified. When correlation or additive effects of variables are not accounted for, one is likely to make inferential errors in the overall assessment (Hubbard & Evans 2010). For example, if the attribute scores for space and predators were correlated (which they are in the applied example in Child et al.), the assessment of scores for each attribute is not independent, although they are treated as such in the framework. Predation, space, and breeding are in effect given more weight in the framework by virtue of the underlying covariance structure.

Uncertainty in Model Behavior

The conceptual and structural issues addressed above could lead to unexpected model behavior and a risk of spurious or incorrect inference (Oberkampf & Roy 2010). For example, all the attributes in the framework are given equal weight in the wilderness score, regardless of the uncertainty associated with the attribute score. This means that a species on a property that scores low on 2 of the attributes can still achieve the maximum wilderness score simply by scoring high on other attributes that might be measured with high uncertainty.

Another surprising effect of the conceptual design of the framework (Fig. 1) is that local population size is not related to the wilderness score. This may hold in the specific situation in which Child et al. tested their framework (South African game ranching). However, in a wider geographic context, population size will often itself be a good proxy for wilderness. It is therefore somewhat worrying that species with a small population size (5 individuals in the case of the first property listed in Child et al. data set) can be given a high wilderness score. Most conservation scientists might consider this a population in need of conservation due to the nature of stochastic events that may remove individuals through natural hazards or disease

(Caughley 1994). An isolated population would not be able to maintain itself at such low levels, but it could still in Child et al.’s framework obtain a high wilderness score.

It is clear that Child et al. assessed the validity of the conceptual basis of the framework (in 2 expert workshops); however, in some aspects, the model appears to have logical frailties. For example, a self-sustaining population is defined as being free from “deliberate human interference” but still encompasses direct human-induced mortalities in its threshold definitions. This apparent contradiction undoubtedly also stems from the specific situation of South African game ranching but does not necessarily reflect values of conservation globally and makes it difficult to apply this framework to other contexts.

Conclusions

As suggested by Pitchforth and Mengersen (2013), model validity should not be restricted to a test of how well a model fits with a set of data; rather, it needs to describe how well the model describes the system of interest. Based on the above arguments, we are not fully convinced that the framework as presented by Child et al. measures what it was designed to measure and therefore question whether it will have broad applicability.

There are a variety of ways one can build and validate frameworks and models. For example, in social and psychological sciences, where latent constructs are commonplace, factor analysis is used to reduce observable variables into fewer latent variables. (See Yong and Pearce [2013] for an introduction to factor analysis.) Such an approach applied to the Child et al. framework would reduce the reliance on ordinal scores.

Bayesian networks provide an ideal methodological approach for addressing uncertainty in a decision context. They mathematically address uncertainty, allow the combination of empirical data and expert opinion, and, because they are graphical models, they are easy to communicate to stakeholders (Marcot et al. 2006). The wilderness state of a population is conditional on the state of the attributes, which are in turn conditional on the components of the attribute. The state of each attribute will contain information about the uncertainty in the data underlying its components. Uncertainty can therefore be considered explicitly when determining the wilderness score of each population.

Literature Cited

- Aplet G, Thomson J, Wilbert M. 2000. Indicators of wilderness: using attributes of the land to assess the context of wilderness. Pages 89–98 in McCool SF, Cole DN, Borrie WT, O’Loughlin J, editors. Proceedings RMRS-P-15-VOL-215. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Ogden, Utah.
- Caughley G. 1994. Directions in conservation biology. *Journal of Animal Ecology* 63:215–244.

- Child MF, et al. 2019. A framework to measure the wildness of managed large vertebrate populations. *Conservation Biology* **33**: 1106–1119.
- Duncan C, Nilsen EB, Linnell JDC, Pettorelli N. 2015. Life-history attributes and resource dynamics determine intraspecific home-range sizes in carnivora. *Remote Sensing in Ecology and Conservation* **1**:39–50.
- Eker S, Rovenskaya E, Obersteiner M, Langen S. 2019. Practice and perspectives in the validation of resource management models. *Nature Communications* **9**:5359.
- Game E, Kareiva P, Possingham HP. 2013. Six common mistakes in conservation priority setting. *Conservation Biology* **27**:480–485.
- Hubbard D, Evans D. 2010. Problems with scoring methods and ordinal scales in risk assessment. *IBM Journal of Research and Development* **54**:1–10.
- Knight AT, Cowling RM, Rouget M, Balmford A, Lombard AT, Campbell BM. 2008. Knowing but not doing: selecting priority conservation areas and the research–implementation gap. *Conservation Biology* **22**:610–617.
- Mallon DP, Stanley Price MR. 2013. The fall of the wild. *Oryx* **47**:467–468.
- Marcot BG, Steventon JD, Sutherland GD, McCann RK. 2006. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. *Canadian Journal of Forest Research* **36**:3063–3074.
- Oberkampf WL, Roy CJ. 2010. *Verification and validation in scientific computing*. Cambridge University Press, Cambridge, United Kingdom.
- Pitchforth J, Mengersen K. 2013. A proposed validation framework for expert elicited Bayesian networks. *Expert Systems with Application* **40**:162–167.
- Redford KH, et al. 2011. What does it mean to successfully conserve a (vertebrate) species? *BioScience* **61**:39–48.
- Schwanitz VJ. 2013. Evaluating integrated assessment models of global climate change. *Environmental Modelling and Software* **50**:120–131.
- Yong AG, Pearce S. 2013. A beginner's guide to factor analysis: focusing on exploratory factor analysis. *Tutorials in Quantitative Methods for Psychology* **9**:79–94.

