How resource abundance and stochasticity affect animals' space-use requirements

Appendix 1: Concepts and definitions

Stefano Mezzini[1,2] Chris H. Fleming[3,4] E. Patrícia Medici[5,6,7]

Michael J. Noonan[1,2,8]

[1] Okanagan Institute for Biodiversity, Resilience, and Ecosystem Services, The University of British Columbia Okanagan, Kelowna, British Columbia, Canada.

[2] Department of Biology, The University of British Columbia Okanagan, Kelowna, British Columbia, Canada.

[3] Department of Biology, University of Central Florida, Orlando, Florida 32816, United States.

[4] Smithsonian Conservation Biology Institute, National Zoological Park, 1500 Remount Rd., Front Royal, VA 22630, United States.

[5] Lowland Tapir Conservation Initiative (LTCI), Instituto de Pesquisas Ecológicas (IPÊ), Rodovia Dom Pedro I, km 47, Nazaré Paulista, São Paulo 12960-000, Brazil.

[6] IUCN SSC Tapir Specialist Group (TSG), Campo Grande, Brazil.

[7] Escola Superior de Conservação Ambiental E Sustentabilidade (ESCAS/IPÊ), Rodovia Dom Pedro I, km 47, Nazaré Paulista, São Paulo 12960-000, Brazil.

[8] Department of Computer Science, Math, Physics, and Statistics, The University of British Columbia Okanagan, Kelowna, British Columbia, Canada.

Contents

In this appendix, we presents the foundational concepts and terms used in the main manuscript. We introduce each concept without assuming a statistical or quantitative background to maximize accessibility and minimize misunderstandings and misinterpretations.

Resources as a random variable

In statistics, **random variables** indicate random (i.e., unknown) quantities and are indicated with capital letters (e.g., R). Known values, such as realizations of random variables (i.e., known observations or instances), are indicated with lower-case letters (e.g., r). Using this notation, we can write the statement "the probability of random variable R taking the value r" as $P(R = r)$. Resources are often unpredictable (and difficult to quantify), since they depend on various factors which cannot be accounted for easily, including climate (Lindstedt and Boyce 1985; Morellet et al. 2013; Schmidt et al. 2020), weather (Morellet et al. 2013; Fjelldal et al. 2021), competitive pressure (Rich et al. 2012; Tórrez-Herrera et al. 2020), and differences in energetics at the individual (Schmidt et al. 2020) and species level (Jetz et al. 2004). Thus, we can let the random variable R indicate the amount of resources at a given point in space and time. Quantifying resources as a numerical random variable, as opposed to using *ad hoc* qualitative descriptions, provides us with the capacity to leverage techniques from probability theory and statistics.

Probability distributions

Random variables are defined by specifying the **distribution** the variable is assumed to follow (e.g., Gaussian, Gamma, Poisson, Bernoulli). Since the variable is random, it can take multiple possible values, each with different probabilities. The set or range of values which have non-zero probabilities in a distribution is referred to as the distribution's **support**.

There are many distributions we can assign to R depending on how we quantify it. For instance, if we measure R using the Normalized Difference Vegetation Index (**NDVI**, see Pettorelli et al. 2011), we should use a distribution with support over the interval $[-1, 1]$, since NDVI can only take on values between -1 and 1 (extremes included). However, there is no commonly used distribution with that support, so the best option is to rescale NDVI to (0, 1) and use a beta distribution (see the section below on applying this framework). Alternatively, if R is the number of calories an animal is able to access from food in a given location, we can let R follow a distribution with support positive real numbers, such as a Gamma or log-normal distribution. If R is a discrete integer variable, such as the number of prey in a location during a period of time, we can use a Poisson or negative binomial distribution.

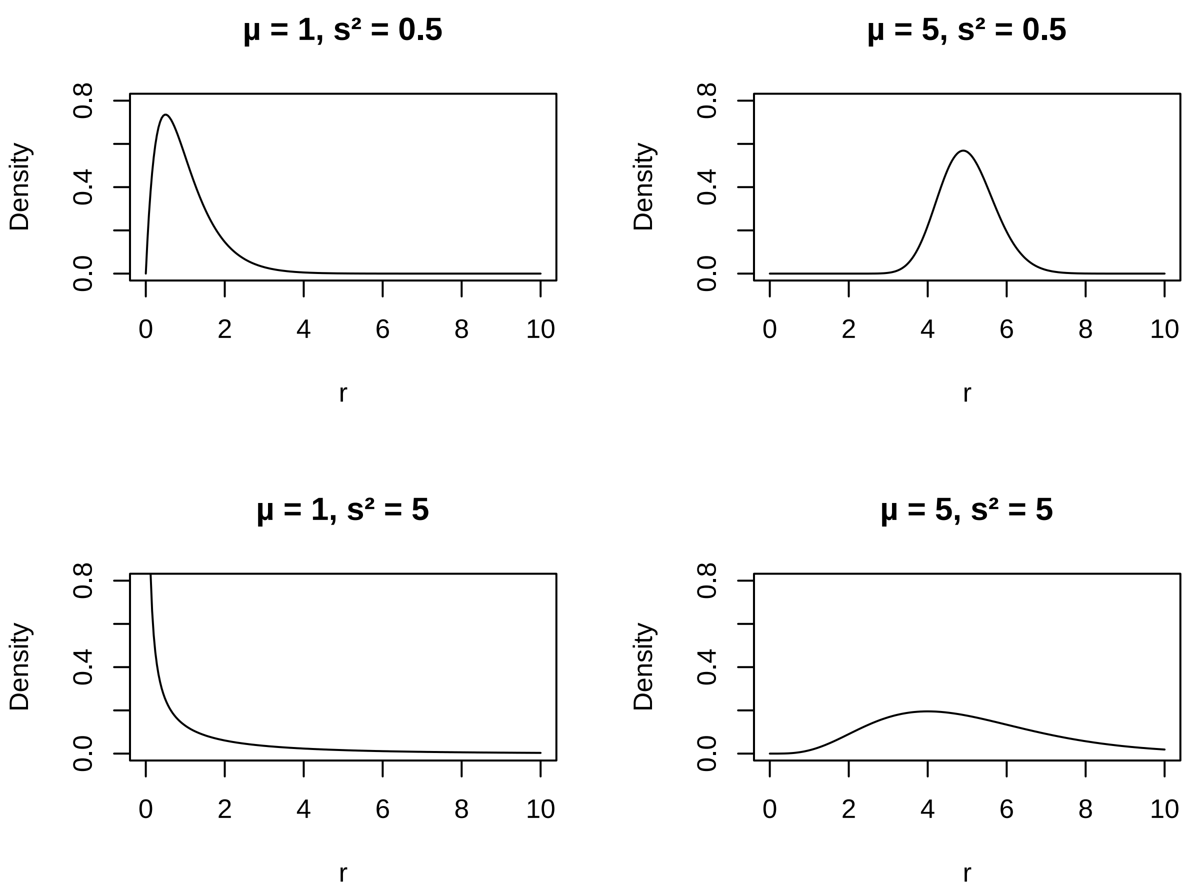
Expected resources, E(R)

Since the exact value of R at a given time and location is unknown, comparing the magnitude in R between two locations or time periods requires a quantitative measure of what value we believe R will take, on average. The **expectation** of a random variable is the value one can *expect* the random variable to take, on average, in the long term. Here we use $\mathrm{E}(R)$ to indicate the expectation of the random variable R. When the mean changes over time, such as in strongly seasonal regions, we explicitly indicate that $\mathrm{E}(R)$ changes over time by writing $\mathrm{E}(R)$ as a function of time, t: $\mathrm{E}(R|t) = \mu(t)$. We indicate the *estimated* average amount of resources over time by adding a caret on the symbol: $\hat{\mu}(t)$. Note, however, that the estimate of $\mu(t)$ and what values it can take depend on what distribution we assume R follows. For a Gamma distribution, $\mu(t)$ can take any positive value, but if we use NDVI as a proxy for R, then $\mu(t)$ is necessarily within the interval $(-1, 1)$. See the section on modeling R in the main manuscript for more information on how to choose probability distributions.

Variance in resources, Var(R)

In viewing resources as a random variable, we not only obtain a formal framework for describing $\mathrm{E}(R)$, but also the spread around $\mathrm{E}(R)$. A random variable's **variance** is a measure of its unpredictability (i.e., variability). We use the notation $\mathrm{Var}(R)$ to indicate the variance in R after accounting for changes in $\mu(t)$, and we use $\sigma^2(t)$ to indicate its function over time (with estimate $\widehat{\sigma^2}(t)$). For example, the time at which berry bushes produce fruit may seem highly stochastic (i.e., unpredictable) to a young bear, but it becomes predictable as it learns to understand and predict how the mean amount of berry changes with the seasons. Still, whether next year will be a good or bad year for berries remains stochastic because it depends on factors the bear cannot predict (e.g., droughts, fires), but the bear can still expect $\sigma^2(t)$ to be lower in the winter since it does not expect to find berries (i.e., $\mu(t) \approx 0$). Also note that, like with $\mu(t)$, the estimate of $\sigma^2(t)$ and what values it can take depend on what distribution we assume R follows.

Below are four examples of Gamma probability distributions with different means and variances:



References

Fjelldal, M. A., J. Wright, and C. Stawski. 2021. Nightly torpor use in response to weather conditions and individual state in an insectivorous bat. Oecologia 197:129–142.

Jetz, W., C. Carbone, J. Fulford, and J. H. Brown. 2004. The scaling of animal space use. Science 306:266–268.

Lindstedt, S. L., and M. S. Boyce. 1985. Seasonality, fasting endurance, and body size in mammals. The American Naturalist 125:873–878.

Morellet, N., C. Bonenfant, L. Börger, F. Ossi, F. Cagnacci, M. Heurich, P. Kjellander, et al. 2013. Seasonality, weather and climate affect home range size in roe deer across a wide latitudinal gradient within europe. (T. Coulson, ed.)Journal of Animal Ecology 82:1326–1339.

Pettorelli, N., S. Ryan, T. Mueller, N. Bunnefeld, B. Jedrzejewska, M. Lima, and K. Kausrud. 2011. The normalized difference vegetation index (NDVI): Unforeseen successes in animal ecology. Climate Research 46:15–27.

Rich, L. N., M. S. Mitchell, J. A. Gude, and C. A. Sime. 2012. Anthropogenic mortality, intraspecific competition, and prey availability influence territory sizes of wolves in montana. Journal of Mammalogy 93:722–731.

Schmidt, N. M., C. Grøndahl, A. L. Evans, J.-P. Desforges, J. Blake, L. H. Hansen, L. T. Beumer, et al. 2020. On the interplay between hypothermia and reproduction in a high arctic ungulate. Scientific Reports 10:1514.

Tórrez-Herrera, L. L., G. H. Davis, and M. C. Crofoot. 2020. Do monkeys avoid areas of home range overlap because they are dangerous? A test of the risk hypothesis in white-faced capuchin monkeys (cebus capucinus). International Journal of Primatology 41:246–264.