

Learning from single extreme events. *Philos. Trans. R. Soc. B Biol. Sci.*, 2017,  
<http://dx.doi.org/10.1098/rstb.2016.0141>

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## Appendix S2: Statistical methods used for the meta-analyses in Box 3

### European heatwave of 2003

We adopted a Bayesian approach similar to that of McCarthy and Masters [1] to estimate the mean effect sizes in the three types of response, fecundity, growth and survival. The basic structure of the model was similar to a linear mixed effects model with response type as a fixed effect, study as a random effect and normally distributed residuals. However, we accounted for the fact that each response was estimated with uncertainty, given by the associated standard error. We used non-informative priors ( $Normal(0, 10^7)$  for the mean of each response type – fecundity, growth and survival – and  $Uniform(0, 100)$  for the standard deviation of the study effects and the residual standard deviation). We ran three MCMC chains of 40,000 iterations, discarding the first 20,000 as burn-in, in JAGS 4.2.0 [2] using the package rjags [3] in R 3.3.2 [4]. The Gelman-Rubin diagnostic indicated that these models converged quickly and all R-hat values were below 1.01.

The data are provided as Table S2 in a separate file.

BUGS code used to fit the model for the meta-analysis of different response types to the 2003 heatwave in Europe:

```
model {  
  
  # The data are percent change ('pchange')  
  #           and their standard errors ('se')  
  # 'group' indicates the type of response
```

```

# 'l' is the number of response types (3 in this case)
# 'n' is the number of observations
# 'k' is the number of studies

# Priors
for (j in 1:l) {
  beta[j] ~ dnorm(0, 0.0000001)T(-100,) # mean for each response;
                                         # can't be less than -100%
}
tau.resp <- pow(sd.resp, -2)
sd.resp ~ dunif(0, 100) # residual variability in responses
tau.study <- pow(sd.study, -2)
sd.study ~ dunif(0,100) # study effect

# Likelihood
for (i in 1:k) { # for each of the k studies
  st[i] ~ dnorm(0, tau.study) # random study effect
}

for (i in 1:n) {
  pchange[i] ~ dnorm(mu[i], tau.error[i])
  mu[i] ~ dnorm(mu.a[i], tau.resp)
  mu.a[i] <- beta[resp[i]] + st[study[i]] # mean for each response type
  tau.error[i] <- pow(se[i], -2)
}
} # end model

```

## Effects of extreme heat waves on survival

In this meta-analysis, we had to ignore the uncertainty in the estimates and decided to treat them like regular observations. We used regular linear mixed effects models in the R package ‘nlme’ [4,5] to estimate the relationship between change in survival and extremeness. We entered study as a random effect to account for possible non-independence between estimates reported by the same study.

The data are provided as Table S3 in a separate file.

## References

1. McCarthy, M. A. & Masters, P. 2005 Profiting from prior information in Bayesian analyses of ecological data. *J. Appl. Ecol.* **42**, 1012–1019.  
(doi:10.1111/j.1365-2664.2005.01101.x)
2. Plummer, M. 2003 JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. *Proc. 3rd Int. Work. Distrib. Stat. Comput. (DSC 2003)*, March 20–22, Vienna, Austria. ISSN 1609–395X.
3. Plummer, M. 2016 rjags: Bayesian Graphical Models using MCMC. R package version 4-6. <https://CRAN.R-project.org/package=rjags>
4. R Core Team 2016 *R: A language and environment for statistical computing*. 3.3.2. Vienna, Austria: R Foundation for Statistical Computing.
5. Pinheiro, J. C. & Bates, D. M. 2000 *Mixed-effects models in S and S-PLUS*. New York: Springer-Verlag.