

## Appendix D. Intraclass correlation coefficient (ICC) and $R^2$ equations for mixed models.

### Equation to estimate intraclass correlation (ICC) for random intercept model

After Goldstein et al. (2002), we calculate the ICC for a random intercept only model as:

$$ICC_{\gamma|\delta} = \frac{\sigma_{\gamma|\delta}^2}{\sigma_{\gamma|\delta}^2 + \sum_{l=1}^u \sigma_l^2 + \sigma_e^2} \quad \text{Eq. D.1}$$

where  $\sigma_{\gamma|\delta}^2$  is the *Year* or *Cohort* random intercept variance,  $u$  is the number of random effects in the model,  $\sigma_l^2$  is the variance component for the  $l$ th random effect and  $\sigma_e^2$  is the residual variance.

### $R^2$ for mixed effects models

Describing the amount of variance explained by mixed effects models has proven a difficult task due to complex variance structures (see discussion in Nakagawa and Schielzeth 2013). Here we employ and present two  $R^2$  metrics (calculated on models fit with REML) defined for mixed effects models by Nakagawa and Schielzeth (2013). The first, called the marginal  $R^2$ , describes the proportion of variance explained by fixed effects alone:

$$R_{LMM(m)}^2 = \frac{\sigma_F^2}{\sigma_F^2 + \sum_{l=1}^u \sigma_l^2 + \sigma_e^2} \quad \text{Eq. D.2}$$

where  $\sigma_F^2$  is the variance calculated from the fixed effect component of the linear mixed model. The second, called the conditional  $R^2$ , describes the proportion of variance explained by fixed and random effects combined:

$$R_{LMM(c)}^2 = \frac{\sigma_F^2 + \sum_{l=1}^u \sigma_l^2}{\sigma_F^2 + \sum_{l=1}^u \sigma_l^2 + \sigma_e^2} \quad \text{Eq. D.3}$$

Goldstein, H., W. J. Browne, and J. Rasbash. 2002. Partitioning variation in multilevel models. *Understanding Statistics* 1:223-232.

Nakagawa, S., and H. Schielzeth. 2013. A general and simple method for obtaining  $R^2$  from generalized linear mixed-effects models. *Methods in Ecology and Evolution* 4:133-142.