## $R^2$ s for Correlated Data: Phylogenetic Models, LMMs, and GLMMs

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## Appendix 2: More comparisons among the $R^2$ s.

To give a comprehensive assessment of the  $R^2$ s, this supplement discusses and plots a complete set of simulations, from which a subset was presented in the main text. The different models (LMM, PGLS, GLMM, and PLOG) are presented in turn.

For the comparisons,  $R_{glmm}^2$  and  $R_{ols}^2$  are included where applicable. Nakagawa and Schielzeth (2013) present two  $R^2$ s. The conditional  $R_{glmm(c)}^2$  is the total  $R^2$  that includes the "explained" variance by both fixed and random effects. The marginal  $R_{glmm(m)}^2$  give that component of the total variance that is attributed to the fixed effects. Note that  $R_{glmm(m)}^2$  is not a partial  $R^2$ , but instead is given as

$$R_{glmm(m)}^{2} = 1 - \frac{\sigma_d^2 + \hat{\sigma}_l^2}{\hat{\sigma}_f^2 + \hat{\sigma}_l^2 + \sigma_d^2}$$

To give a comparable measure for the contribution of the random effects, I define

$$R_{glmm(v)}^2 = 1 - \frac{\sigma_d^2 + \hat{\sigma}_f^2}{\hat{\sigma}_f^2 + \hat{\sigma}_l^2 + \sigma_d^2}$$

In the comparisons for LMMs and GLMMs, I compare the partial  $R^2$ s of  $R^2_{ls}$ ,  $R^2_{lr}$  and  $R^2_{ce}$  for the fixed effect to  $R^2_{glmm(m)}$  and the partial  $R^2$ s for the random effect to  $R^2_{glmm(v)}$ . This illustrates the differences between using partial  $R^2$ s and marginal  $R^2$ s.

## **Figure Captions**

Figure A2.1: Simulation results for a Linear Mixed Model (LMM) giving  $R^2_{ls}$ ,  $R^2_{lr}$ ,  $R^2_{ce}$ ,  $R^2_{glmm}$ , and  $R^2_{ols}$  versus the log likelihood ratio (LLR) between full and reduced models. The simulation model (equation (7)) contained both a fixed effect  $\beta$  for a continuous variable *x* and a random effect *b* for a categorical variable *u*. For (a), (b) and (c), data were simulated without the random

effect ( $\beta = 1$ ,  $\sigma = 0$ ), and for (d), (e) and (f), data were simulated without the fixed effect ( $\beta = 0$ ,  $\sigma = 1.5$ ). Simulations for (g), (h), and (i) contained both fixed and random effects. Columns give different partial  $R^2$ s for each method. Specifically, (a), (d), and (g) give the partial  $R^2$ s in which the reduced model removes the fixed effect for *x*: therefore, these give partial  $R^2$ s for the fixed effect. Panels (b), (e), and (h) give the partial  $R^2$ s in which the reduced model removes the random effect for *u*: therefore, these give partial  $R^2$ s for the random effect. In panels (c), (f) and (i), the reduced model removes both fixed and random effects, giving the total  $R^2$ s. Each data set consisted of 100 simulated points, *x* was simulated as a normal (0, 1) random variable, and *u* had 10 levels with *b* is simulated as a normal (0,  $\sigma$ ). All analyses were performed with the function lmer().

Figure A2.2: Simulation results for a Linear Mixed Model (LMM) giving associations between  $R_{ls}^2$ ,  $R_{lr}^2$ ,  $R_{ce}^2$ ,  $R_{glmm}^2$ , and  $R_{ols}^2$ . Data are the same as presented in figure A2.1.

Figure A2.3: Simulation results for a Linear Mixed Model (LMM) showing means and standard deviations of  $R_{ls}^2$ ,  $R_{lr}^2$ ,  $R_{ce}^2$ ,  $R_{glmm}^2$ , and  $R_{ols}^2$  versus sample size. The simulation model (equation (7)) contained both a fixed effect  $\beta$  for a continuous variable *x* and a random effect *b* for a categorical variable *u*. For each level of *u*, from 4 to 16 replicates were simulated. (a), (b), and (c) give means of each  $R^2$  were calculated for 500 simulations at each sample, and (d), (e), and (f) give standard deviations. Columns give different partial  $R^2$ s, with (a) and (d) giving the partial  $R^2$ s for the fixed effect, (b) and (e) giving the partial  $R^2$ s for the random effect, and (c) and (f) giving the total  $R^2$ s. In the simulations, *x* is simulated as a normal (0, 1) random variable with  $\beta$  = 1; *u* has 10 levels and *b* is simulated as a normal (0,  $\sigma$  = 1.5) random variable; and residuals *e* are independent (0, 1) random variables. All analyses were performed with the function lmer().

Figure A2.4: Simulation results for the phylogenetic model with a continuous predictor variable *x* giving  $R_{ls}^2$ ,  $R_{lr}^2$ , and  $R_{ce}^2$  versus the log likelihood ratio (LLR) between full and reduced models. For each simulation, a phylogenetic tree was first simulated, and the values of *x* were simulated up the phylogeny assuming Brownian Motion evolution. Data were simulated using equation (7) with *b* = 0, and residuals  $e_i$  were simulated from a multivariate normal distribution with mean zero and covariance matrix  $\Sigma(\lambda) = (1 - \lambda)\mathbf{I} + \lambda \Sigma_{BM}$ . For (a), (b) and (c), data were simulated without phylogenetic signal ( $\lambda = 0, \beta = 1$ ), and for (d), (e) and (f), data were simulated without the fixed effect ( $\lambda = 0.5, \beta = 0$ ). Simulations for (g), (h), and (i) contained both fixed and phylogenetic effects ( $\beta = 1, \lambda = 0.5$ ). (a), (d), and (g) give the partial  $R^2$ s for the fixed effect. Panels (b), (e), and (h) give the partial  $R^2$ s for the phylogenetic effect. In panels (c), (f) and (i), the reduced model removes both fixed and phylogenetic effects, giving the total  $R^2$ s. All analyses were performed with the function phylolm().

Figure A2.5: Simulation results for a PGLS model giving associations between  $R^2_{ls}$ ,  $R^2_{lr}$ , and  $R^2_{ce}$ . Data are the same as presented in figure A2.3.

Figure A2.6: Simulation results for the phylogenetic model with a continuous response variable showing means and standard deviations of  $R_{ls}^2$ ,  $R_{lr}^2$ , and  $R_{ce}^2$  versus sample size. For each simulation, a phylogenetic tree was first simulated, and the values of the predictor variable *x* were simulated up the phylogeny assuming Brownian Motion evolution. In equation 9, residuals  $e_i$  were simulated from a multivariate normal distribution with mean zero and covariance matrix  $\Sigma(\lambda) = (1 - \lambda)\mathbf{I} + \lambda\Sigma_{BM}$ , and the parameter values were  $\lambda = 0.5$ ,  $\beta = 1$ , and b = 0. (a), (b), and (c) give means of each  $R^2$  were calculated for 500 simulations at each sample, and (d), (e), and (f) give standard deviations. Columns give different partial  $R^2$ s, with (a) and (d) giving the partial  $R^2$ s for *x*, (b) and (e) giving the partial  $R^2$ s for phylogenetic signal  $\lambda$ , and (c) and (f) giving the total  $R^2$ s. All analyses were performed with the function phylolm().

Figure A2.7: Simulation results for a binary Generalized Linear Mixed Model (GLMM) giving  $R_{ls}^2 R_{lr}^2 R_{ce}^2 R_{glmm}^2$ , and  $R_{ols}^2$  versus the log likelihood ratio (LLR) between full and reduced models. The simulation model (equation (7)) contained both a fixed effect  $\beta$  for a continuous variable *x* and a random effect *b* for a categorical variable *u*. For (a), (b) and (c), data were simulated without the random effect ( $\beta = 1.8$ ,  $\sigma = 0$ ), and for (d), (e) and (f), data were simulated without the fixed effect ( $\beta = 0$ ,  $\sigma = 1.8$ ). Simulations for (g), (h), and (i) contained both fixed and random effects. (a), (d), and (g) give the partial  $R^2$ s for the fixed effect, and panels (b), (e), and (h) give the partial  $R^2$ s for the random effect. In panels (c), (f) and (i) give total  $R^2$ s. In the simulations, *x* is simulated as a normal (0, 1) random variable and *u* has 10 levels and *b* is simulated as a normal (0,  $\sigma$ ). All analyses were performed with the function glmer().

Figure A2.8: Simulation results for a Generalized Linear Mixed Model (GLMM) giving associations between  $R_{ls}^2$ ,  $R_{lr}^2$ ,  $R_{ce}^2$ ,  $R_{glmm}^2$ , and  $R_{ols}^2$ . Data are the same as presented in figure A2.7.

Figure A2.9: Simulation results for a binary Generalized Linear Mixed Model (GLMM) showing means and standard deviations of  $R_{ls}^2$ ,  $R_{lr}^2$ ,  $R_{ce}^2$ ,  $R_{glmm}^2$ , and  $R_{ols}^2$  versus sample size. The simulation model (equation (7)) contained both a fixed effect  $\beta$  for a continuous variable *x* and a random effect *b* for a categorical variable *u*. For each level of *u*, from 4 to 16 replicates were simulated. (a), (b), and (c) give means of each  $R^2$  were calculated for 1000 simulations at each sample, and (d), (e), and (f) give standard deviations. Columns give different partial  $R^2$ s, with (a) and (d) giving the partial  $R^2$ s for the fixed effect, (b) and (e) giving the partial  $R^2$ s for the random effect, and (c) and (f) giving the total  $R^2$ s. In the simulations, *x* is simulated as a normal (0, 1) random variable with  $\beta = 1.8$  and *u* has 10 levels and *b* is simulated as a normal (0,  $\sigma = 1.8$ ) random variable. All analyses were performed with the function glmer().

Figure A2.10: Simulation results for the phylogenetic model with a continuous predictor variable *x* giving  $R_{ls}^2$ ,  $R_{lr}^2$ , and  $R_{ce}^2$  versus the log likelihood ratio (LLR) between full and reduced models. For each simulation, a phylogenetic tree was first simulated, and the values of *x* were simulated up the phylogeny assuming Brownian Motion evolution. Data were simulated using equation (7) with b = 0, and residuals  $e_i$  were simulated from a multivariate normal distribution with mean zero and covariance matrix  $\Sigma(\lambda) = (1 - \lambda)\mathbf{I} + \lambda \Sigma_{BM}$ . For (a), (b) and (c), data were simulated without phylogenetic signal ( $\lambda = 0$ ,  $\beta = 1.5$ ), and for (d), (e) and (f), data were simulated without the fixed effect ( $\lambda = 2$ ,  $\beta = 0$ ). Simulations for (g), (h), and (i) contained both fixed and phylogenetic effects ( $\lambda = 2$ ,  $\beta = 1.5$ ). (a), (d), and (g) give the partial  $R^2$ s for the fixed effect. Panels (b), (e), and (h) give the partial  $R^2$ s for the phylogenetic effects. In panels (c), (f) and (i), the reduced model removes both fixed and phylogenetic effects, giving the total  $R^2$ s. All analyses were performed with the function phylolm().

Figure A2.11: Simulation results for a phylogenetic logistic regression model giving associations between  $R_{ls}^2$ ,  $R_{lr}^2$ , and  $R_{ce}^2$ . Data are the same as presented in figure A2.10.

Figure A2.12: Simulation results for the phylogenetic model with a binary response variable showing means and standard deviations of  $R_{ls}^2$ ,  $R_{lr}^2$ , and  $R_{ce}^2$  versus sample size. For each simulation, a phylogenetic tree was first simulated, and residuals  $e_i$  (equation (7)) were simulated from a multivariate normal distribution with mean zero and covariance matrix  $\Sigma(\lambda) = \lambda \Sigma_{BM}$ . Values of the predictor variable *x* were assumed to be independently distributed by a (0,1) normal distribution, and the parameter values were  $\lambda = 2$ ,  $\beta = 1.5$ , and b = 0. (a), (b), and (c) give means of each  $R^2$  were calculated for 500 simulations at each sample, and (d), (e), and (f) give standard deviations. Columns give different partial  $R^2$ s, with (a) and (d) giving the partial  $R^2$ s for *x*, (b) and (e) giving the partial  $R^2$ s for phylogenetic signal  $\lambda$ , and (c) and (f) giving the total  $R^2$ s. Calculations of  $R_{lr}^2$  were performed with a modified version of the function phyloglm() and the function glm(). Calculations of  $R_{ls}^2$  and  $R_{ce}^2$  were performed with the function binaryPGLMM().



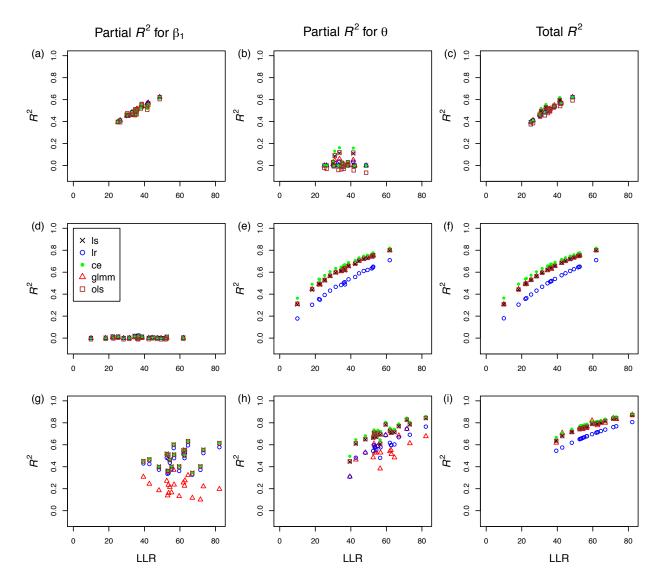
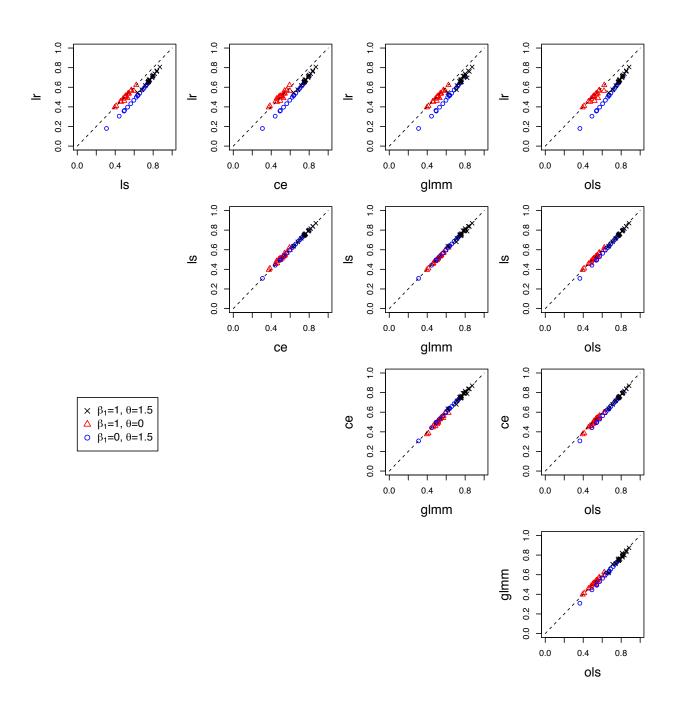
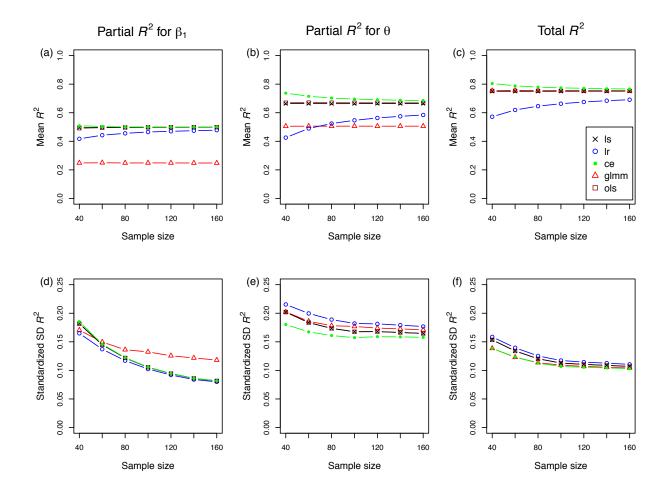


Fig. A2.2







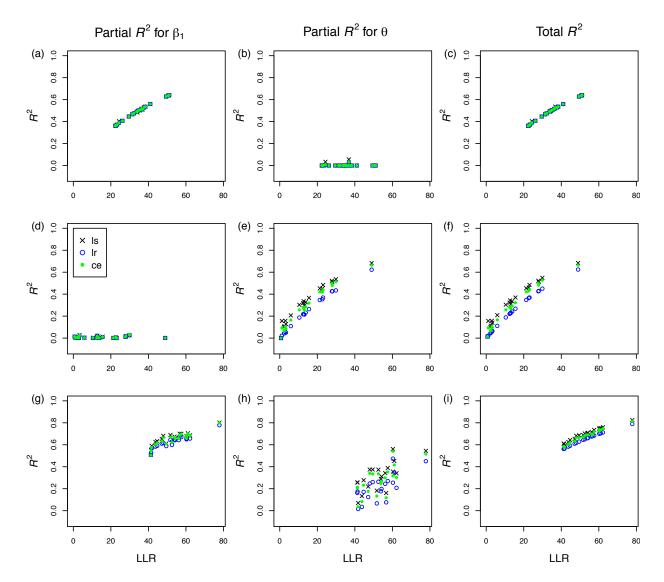
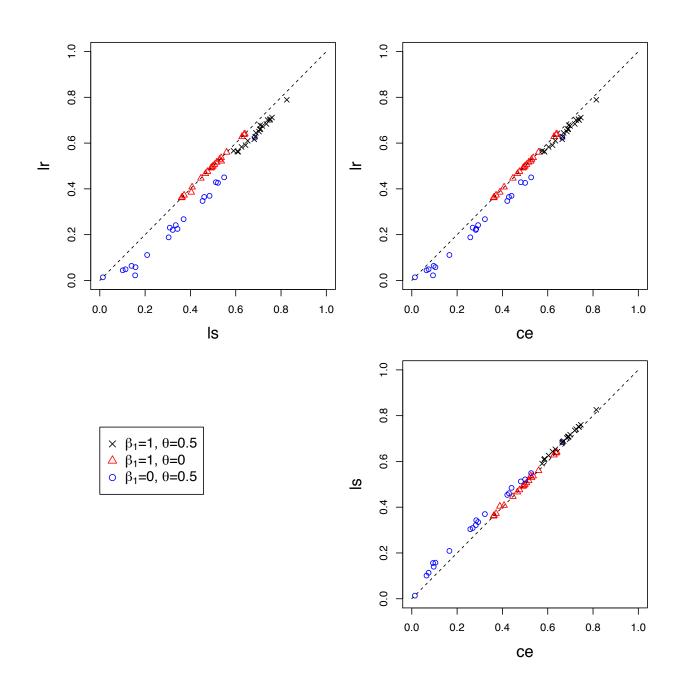
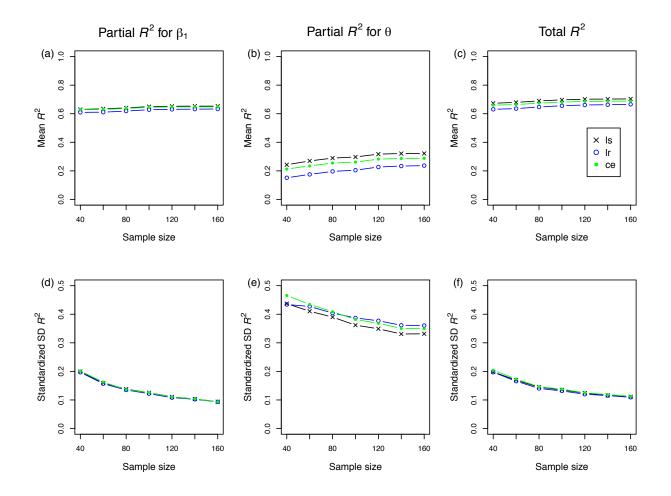


Fig. A2.5





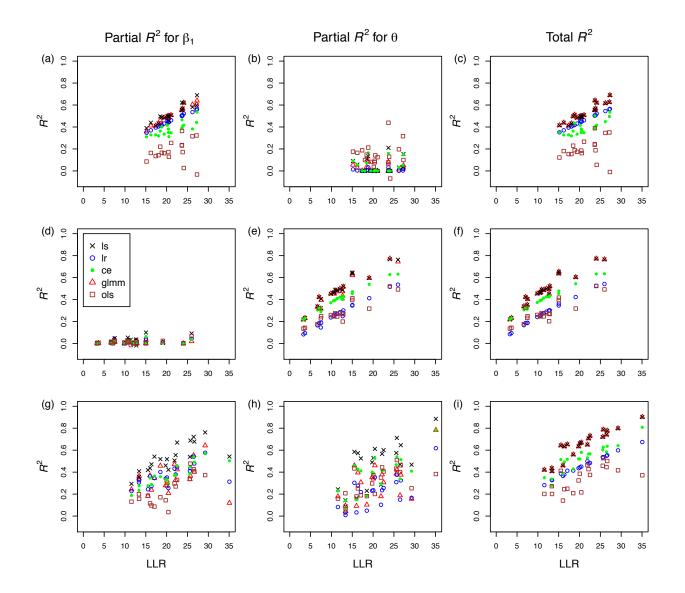
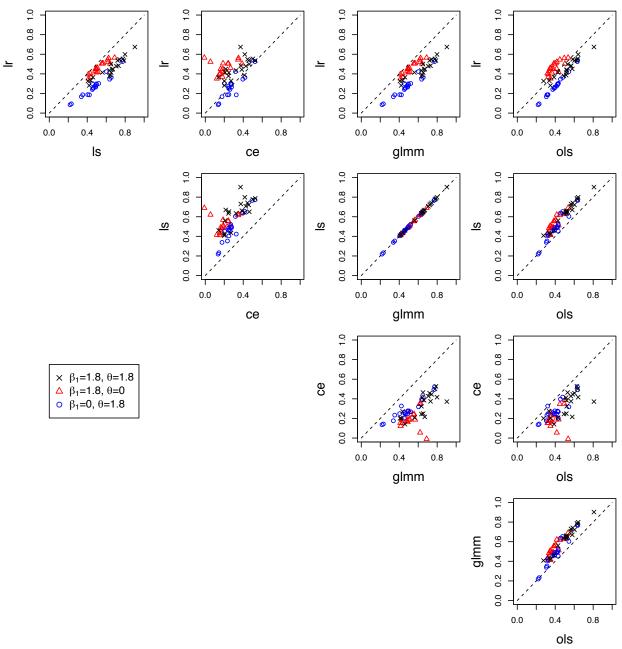
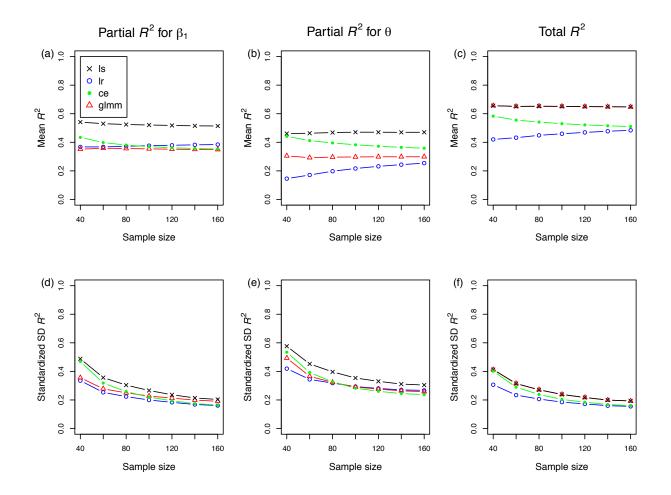


Fig. A2.8





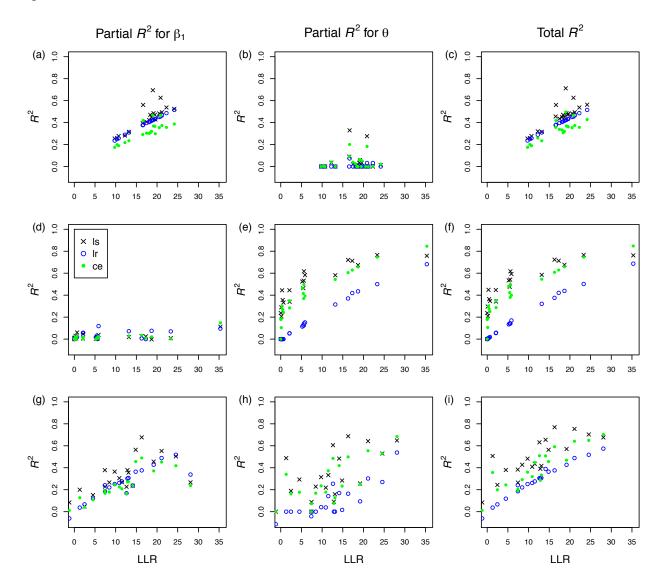


Fig. A2.11

