**Electronic Supplementary Material 5.**

**Estimation of the posterior model probability using Gibbs Variable Selection (GVS)**

The MR model was simultaneously fitted to the covariates ‘sst\_anomaly\_austral’ and ‘days\_wind\_gusts\_33\_annual’ for chick survival (Table 2 in main text) and covariates ‘sst\_anomaly\_austral’ and ‘mean\_air\_temp\_annual’ for adult survival . We assessed the posterior model probability (p(Mi|y)) for each combination of these four covariates using Gibbs variable selection (GVS) (Ntzoufras 2002; Tenan et al. 2014; Hooten and Hobbs 2015). For this purpose we modeled survival in stage *k* at time *t* as:

$logit\left(η\_{k,t}\right)= μ\_{k}+ \sum\_{j=0}^{w}γ\_{j}X\_{j,t}β\_{k,j}$ + εk,t [E5.1]

where Xj,t and βk,j denote the design matrix of covariate *j* in year *t* and the slope parameter *j* for stage *k*, respectively (*w* is the maximum number of covariates considered). $μ\_{k}$ and εk,t reflect the stage-specific mean survival and random effects (see ESM1 eq. E1.1 and eq. E1.2). γj denotes the auxiliary indicator variable and is a binary response variable that indicates whether covariate *βk,j* is present (γj = 1) or absent (γj = 0) in the model. We assumed that the chance that γj = 1 follows a Bernoulli trial with probability 0.5. To ensure good mixing for indicator γj and effect variable *βk,j* we assumed that both variables depend on each other (Ntzoufras 2002; Tenan et al. 2014) by modeling the prior for *βk,j* |(γj = 1) and a pseudoprior for *βk,j* |(γj = 0) using a mixture prior:

$p\left(γ\_{j}\right)=\left(1- γ\_{j}\right)Normal\left(κ\_{j}, S\_{j}\right)+γ\_{j}Normal(0, Σ\_{j})$ [E5.2]

where $κ$*j* and *Sj* are user-defined tuning parameters and Σj denotes the fixed prior variance for *βk,j*. The posterior model probability p(Mi|y) for each model Mi (i = 16 possible models for each combination of the considered covariates) is given by:

p(Mi|y) = Number of occurrences of M = *i* / Total number of iterations

We followed Tenan *et al.* (2014) and checked whether p(Mi|y) is sensitive to the mixture prior by repeating the analysis with different priors for $Normal\left(κ\_{j}, S\_{j}\right)$:(1) $Normal\left(\overbar{β\_{k,j}}, SD(β\_{k,j})\right)$, which is a normal prior for *βk,j* with mean and standard deviation taken from the posterior distribution of each *βk,j* of separate model runs; (2) N(0, 10); (3) N(0, 100); (4) N(0, 1000); (5) N(0, 106); (6) N(0.2, 100) (Tenan *et al.* 2014).

The burn-in was 1,400,000 iterations followed by 1,500,000 iterations and posterior samples were drawn using a thinning interval 3. We computed the potential scale reducing factor (Gelman and Rubin 1992) using the output of three MCMC chains and assumed convergence if was near to 1. For all estimated parameters was smaller than or equal to 1.01. Overall there exist no sensitivity of the estimated posterior model probability to the set of prior distributions used (Table E5.1-Table E5.6). Prior set (5) did not fully converge, but produced similar results to all other prior configurations (Table E5.5).

**Table E5.1** Posterior model probability p(Mi|y) using actual posterior distributions estimated for each βk. Column A: The MR model considers the covariate sst\_anomaly\_austral for chick survival; Column B: The MR model considers the covariate days\_wind\_gusts\_33\_annual for chick survival; Column C: The MR model considers the covariate sst\_anomaly\_austral for adult survival; Column D: The MR model considers the covariate mean\_air\_temp\_annual for adult survival.

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| --- | --- | --- |
|   | **Model configuration**  |   |
| **Mi**  | **A**  | **B**  | **C**  | **D**  | **p(Mi|y)**  |
| 1  | 1  | 0  | 1  | 0  | 0.42 |
| 2  | 0  | 1  | 1  | 0  | 0.13 |
| 3  | 1  | 1  | 1  | 0  | 0.12 |
| 4  | 1  | 0  | 0  | 1  | 0.09 |
| 5  | 0  | 1  | 0  | 1  | 0.06 |
| 6  | 0  | 0  | 0  | 0  | 0.04 |
| 7  | 1  | 0  | 0  | 0  | 0.03 |
| 8  | 0  | 1  | 0  | 0  | 0.03 |
| 9  | 1  | 1  | 0  | 0  | 0.02 |
| 10  | 0  | 0  | 1  | 0  | 0.01 |
| 11  | 0  | 0  | 0  | 1  | 0.01 |
| 12  | 1  | 1  | 0  | 1  | 0.01 |
| 13  | 0  | 0  | 1  | 1  | 0.00 |
| 14  | 1  | 0  | 1  | 1  | 0.00 |
| 15  | 0  | 1  | 1  | 1  | 0.00 |
| 16  | 1  | 1  | 1  | 1  | 0.00 |

**Table E5.2** Posterior model probability p(Mi|y) using a normally distributed prior for βk: N(0, 10). See Column A: The MR model considers the covariate sst\_anomaly\_austral for chick survival; Column B: The MR model considers the covariate days\_wind\_gusts\_33\_annual for chick survival; Column C: The MR model considers the covariate sst\_anomaly\_austral for adult survival; Column D: The MR model considers the covariate mean\_air\_temp\_annual for adult survival.

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| --- | --- | --- |
|   | **Model configuration**  |   |
| **Mi**  | **A**  | **B**  | **C**  | **D**  | **p(Mi|y)**  |
| 1  | 1  | 0  | 1  | 0  | 0.35 |
| 2  | 1  | 0  | 0  | 1  | 0.17 |
| 3  | 0  | 1  | 1  | 0  | 0.15 |
| 4  | 1  | 1  | 1  | 0  | 0.07 |
| 5  | 0  | 1  | 0  | 1  | 0.05 |
| 6  | 0  | 0  | 0  | 0  | 0.04 |
| 7  | 1  | 0  | 0  | 0  | 0.04 |
| 8  | 0  | 1  | 0  | 0  | 0.03 |
| 9  | 1  | 1  | 0  | 0  | 0.03 |
| 10  | 0  | 0  | 1  | 0  | 0.02 |
| 11  | 0  | 0  | 0  | 1  | 0.01 |
| 12  | 1  | 1  | 0  | 1  | 0.01 |
| 13  | 0  | 0  | 1  | 1  | 0.00 |
| 14  | 1  | 0  | 1  | 1  | 0.00 |
| 15  | 0  | 1  | 1  | 1  | 0.00 |
| 16  | 1  | 1  | 1  | 1  | 0.00 |

**Table E5.3** Posterior model probability p(Mi|y) using a normally distributed prior for βk: N(0, 100). Column A: The MR model considers the covariate sst\_anomaly\_austral for chick survival; Column B: The MR model considers the covariate days\_wind\_gusts\_33\_annual for chick survival; Column C: The MR model considers the covariate sst\_anomaly\_austral for adult survival; Column D: The MR model considers the covariate mean\_air\_temp\_annual for adult survival.

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|   | **Model configuration**  |   |
| **Mi**  | **A**  | **B**  | **C**  | **D**  | **p(Mi|y)**  |
| 1  | 1  | 0  | 1  | 0  | 0.43 |
| 2  | 1  | 0  | 0  | 1  | 0.19 |
| 3  | 0  | 1  | 1  | 0  | 0.11 |
| 4  | 1  | 1  | 1  | 0  | 0.06 |
| 5  | 0  | 1  | 0  | 1  | 0.05 |
| 6  | 0  | 0  | 0  | 0  | 0.05 |
| 7  | 1  | 0  | 0  | 0  | 0.04 |
| 8  | 0  | 1  | 0  | 0  | 0.02 |
| 9  | 1  | 1  | 0  | 0  | 0.02 |
| 10  | 0  | 0  | 1  | 0  | 0.01 |
| 11  | 0  | 0  | 0  | 1  | 0.01 |
| 12  | 1  | 1  | 0  | 1  | 0.00 |
| 13  | 0  | 0  | 1  | 1  | 0.00 |
| 14  | 1  | 0  | 1  | 1  | 0.00 |
| 15  | 0  | 1  | 1  | 1  | 0.00 |
| 16  | 1  | 1  | 1  | 1  | 0.00 |

**Table E5.4** Posterior model probability p(Mi|y) using a normally distributed prior for βk: N(0, 1000). Column A: The MR model considers the covariate sst\_anomaly\_austral for chick survival; Column B: The MR model considers the covariate days\_wind\_gusts\_33\_annual for chick survival; Column C: The MR model considers the covariate sst\_anomaly\_austral for adult survival; Column D: The MR model considers the covariate mean\_air\_temp\_annual for adult survival.

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| --- | --- | --- |
|   | **Model configuration**  |   |
| **Mi**  | **A**  | **B**  | **C**  | **D**  | **p(Mi|y)**  |
| 1  | 1  | 0  | 1  | 0  | 0.42 |
| 2  | 1  | 0  | 0  | 0  | 0.14 |
| 3  | 0  | 1  | 1  | 0  | 0.13 |
| 4  | 1  | 1  | 1  | 0  | 0.09 |
| 5  | 1  | 0  | 0  | 1  | 0.05 |
| 6  | 0  | 0  | 0  | 0  | 0.04 |
| 7  | 0  | 1  | 0  | 0  | 0.04 |
| 8  | 1  | 1  | 0  | 0  | 0.03 |
| 9  | 0  | 0  | 1  | 0  | 0.02 |
| 10  | 0  | 0  | 0  | 1  | 0.01 |
| 11  | 0  | 1  | 0  | 1  | 0.01 |
| 12  | 1  | 1  | 0  | 1  | 0.01 |
| 13  | 0  | 0  | 1  | 1  | 0.01 |
| 14  | 1  | 0  | 1  | 1  | 0.00 |
| 15  | 0  | 1  | 1  | 1  | 0.00 |
| 16  | 1  | 1  | 1  | 1  | 0.00 |

**Table E5.5** Posterior model probability p(Mi|y) using a normally distributed prior for βk: N(0, 106). See Column A: The MR model considers the covariate sst\_anomaly\_austral for chick survival; Column B: The MR model considers the covariate days\_wind\_gusts\_33\_annual for chick survival; Column C: The MR model considers the covariate sst\_anomaly\_austral for adult survival; Column D: The MR model considers the covariate mean\_air\_temp\_annual for adult survival.

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|   | **Model configuration**  |   |
| **Mi**  | **A**  | **B**  | **C**  | **D**  | **p(Mi|y)**  |
| 1  | 1  | 0  | 1  | 0  | 0.43 |
| 2  | 1  | 0  | 0  | 1  | 0.13 |
| 3  | 0  | 1  | 1  | 0  | 0.12 |
| 4  | 1  | 1  | 1  | 0  | 0.08 |
| 5  | 0  | 0  | 0  | 0  | 0.06 |
| 6  | 1  | 0  | 0  | 0  | 0.05 |
| 7  | 0  | 1  | 0  | 0  | 0.04 |
| 8  | 1  | 1  | 0  | 0  | 0.03 |
| 9  | 0  | 0  | 1  | 0  | 0.02 |
| 10  | 0  | 0  | 0  | 1  | 0.01 |
| 11  | 0  | 1  | 0  | 1  | 0.01 |
| 12  | 1  | 1  | 0  | 1  | 0.01 |
| 13  | 0  | 0  | 1  | 1  | 0.01 |
| 14  | 1  | 0  | 1  | 1  | 0.00 |
| 15  | 0  | 1  | 1  | 1  | 0.00 |
| 16  | 1  | 1  | 1  | 1  | 0.00 |

**Table E5.6** Posterior model probability p(Mi|y) using a normally distributed prior for βk: N(0.2, 100). Column A: The MR model considers the covariate sst\_anomaly\_austral for chick survival; Column B: The MR model considers the covariate days\_wind\_gusts\_33\_annual for chick survival; Column C: The MR model considers the covariate sst\_anomaly\_austral for adult survival; Column D: The MR model considers the covariate mean\_air\_temp\_annual for adult survival.

|  |  |  |
| --- | --- | --- |
|   | **Model configuration**  |   |
| **Mj**  | **A**  | **B**  | **C**  | **D**  | **p(Mi|y)**  |
| 1  | 1  | 0  | 1  | 0  | 0.47 |
| 2  | 1  | 0  | 0  | 0  | 0.16 |
| 3  | 0  | 1  | 1  | 0  | 0.11 |
| 4  | 1  | 1  | 1  | 0  | 0.10 |
| 5  | 1  | 0  | 0  | 1  | 0.04 |
| 6  | 0  | 0  | 0  | 0  | 0.03 |
| 7  | 0  | 1  | 0  | 0  | 0.03 |
| 8  | 1  | 1  | 0  | 0  | 0.02 |
| 9  | 0  | 0  | 1  | 0  | 0.02 |
| 10  | 0  | 0  | 0  | 1  | 0.01 |
| 11  | 0  | 1  | 0  | 1  | 0.01 |
| 12  | 1  | 1  | 0  | 1  | 0.00 |
| 13  | 0  | 0  | 1  | 1  | 0.00 |
| 14  | 1  | 0  | 1  | 1  | 0.00 |
| 15  | 0  | 1  | 1  | 1  | 0.00 |
| 16  | 1  | 1  | 1  | 1  | 0.00 |

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