

New, L. F., Buckland, S. T., Redpath, S. and Matthiopoulos, J. 2012. Modelling the impact of hen harrier management measures on a red grouse population in the UK. – Oikos 121: 1061–1072.

Appendix 1

Table A1.1. Additional equations for the hen harrier and red grouse models.

$a_t = \frac{\exp\{\xi_0 + \xi_1 0.5G_{f,t} + \xi_2 0.5G_{f,t-1}\}}{1 + \exp\{\xi_0 + \xi_1 0.5G_{f,t} + \xi_2 0.5G_{f,t-1}\}} *$	<p>Aggression of male red grouse, where ξ_0, ξ_1 and ξ_2 relate grouse density prior to hunting and recruitment (G_f) in years t and $t-1$ to aggression (a_t).</p>
$\lambda_t = \exp\{\gamma_0 - \gamma_1 W_t\} *$	<p>Rearing rate of red grouse (λ_t), where γ_0 is the natural log of brood size and γ_1 measures the effect of average worm burden (W_t) on reducing rearing rate.</p>
$W_{t+1} = W_{a,t} \phi_{w,t} + A_t \phi_{l,t} ** \dagger$	<p>Change in parasite burdens from time t to time $t-1$, where W_a is the autumn parasite burden, A_t is the arrested larvae in autumn of time t, and $\phi_{w,t}$ and $\phi_{l,t}$ are the over-winter survival of adult worms and arrested larvae, respectively.</p>
$\eta_t = \exp(\beta_0 V_t + \beta_1 P_t - \beta_2 H_{Obs,t-1} \phi_{t-1}) \dagger$	<p>Net movement of hen harriers (η_t), where β_0, and β_1 measure the effect of vole (V_t) and pipit (P_t) density on net movement and β_2 measures the effect of harriers surviving from the previous year ($H_{Obs,t-1} \phi_{t-1}$) on net movement.</p>
$\phi_t = \frac{\exp(\alpha_0 + \alpha_1 P_t)}{1 + \exp(\alpha_0 + \alpha_1 P_t)} \dagger$	<p>Harrier survival (ϕ_t), where α_0 incorporates all other sources of mortality and α_1 measures the effect of pipit density on harrier survival.</p>

* equations from New et al. (2009)

† equations from New et al. (2011)

‡ values for these parameters were taken from previously published literature (New et al. 2009)

Table A1.2. Parameter values for the MSFR for each species, j .

Parameters	m	k	h
Grouse	4.51	1.89×10^{-6}	2.16
Vole	1.04	2.52×10^{-2}	1.24
Pipit	1.14	1.33	1.85

Table A1.3. Priors for the harrier-grouse interaction model.

Θ	Prior
α_0	N(0,1)
α_1	LN(-5.29,0.833)
β_0	$\Gamma(1,50)$
β_1	$\Gamma(1,50)$
β_2	$\Gamma(1,5)$
γ_0	N(0,1)
γ_1	$\Gamma(1,50)$
ϕ_a	$\beta(1,1)$
ξ_0	U(-4,-2)
ξ_1	U(0,0.02)
ξ_2	U(0.005,0.04)
τ_c	$\Gamma(2.5,0.1)$
c	$\Gamma(15,2)$

Table A1.4. Parameter estimates and 95% credible intervals for the hen harrier parameters for all four scenarios.

Θ	Predation	Prediction	Partial	Full
α_0	0.37 (-0.65, 1.25)	0.06 (-1.45, 1.45)	0.37 (-0.65, 1.25)	0.37 (-0.66, 1.25)
α_1	2.6×10^{-3} (6.6×10^{-4} , 6.2×10^{-3})	3.0×10^{-3} (7.6×10^{-4} , 7.1×10^{-3})	2.7×10^{-3} (7.1×10^{-4} , 6.2×10^{-3})	2.7×10^{-3} (6.8×10^{-4} , 6.1×10^{-3})
β_0	1.3×10^{-3} (5.7×10^{-4} , 1.9×10^{-3})	1.3×10^{-3} (5.5×10^{-4} , 1.9×10^{-3})	1.3×10^{-3} (5.8×10^{-4} , 1.9×10^{-3})	1.3×10^{-3} (5.8×10^{-4} , 1.9×10^{-3})
β_1	1.1×10^{-3} (7.4×10^{-5} , 2.6×10^{-3})	1.1×10^{-3} (7.9×10^{-5} , 2.6×10^{-3})	1.1×10^{-3} (7.6×10^{-5} , 2.6×10^{-3})	1.1×10^{-3} (7.4×10^{-5} , 2.6×10^{-3})
β_2	0.031 (9.8×10^{-4} , 0.10)	0.031 (9.0×10^{-4} , 0.1)	0.031 (9.6×10^{-4} , 0.097)	0.031 (9.2×10^{-4} , 0.097)
ξ_0	-2.2 (-2.6, -2.0)	-2.2 (-2.6, -2.0)	-2.2 (-2.6, -2.0)	-2.2 (-2.6, -2.0)
ξ_1	0.013 (0.0016, 0.019)	0.013 (0.002, 0.019)	0.013 (0.002, 0.019)	0.013 (0.002, 0.019)
ξ_2	0.024 (0.006, 0.039)	0.026 (0.006, 0.039)	0.023 (0.006, 0.039)	0.023 (0.006, 0.040)

Table A1.5. Parameter estimates and 95% credible intervals for the red grouse parameters for all for scenarios.

Θ	Predation	Prediction	Partial	Full
$\gamma_{0,LC}$	1.8 (1.1, 2.3)	1.9 (1.3, 2.4)	1.8 (1.1, 2.3)	1.8 (1.2, 2.3)
$\gamma_{0,LD}$	2.2 (1.5, 2.8)	2.3 (1.7, 2.9)	2.2 (1.5, 2.8)	2.2 (1.6, 2.8)
$\gamma_{0,LM}$	1.7 (1.1, 2.3)	1.9 (1.2, 2.6)	1.7 (1.1, 2.3)	1.7 (1.1, 2.3)
$\gamma_{0,LR}$	1.6 (0.94, 2.3)	1.7 (1.0, 2.3)	1.6 (0.96, 2.3)	1.6 (1.0, 2.2)
$\gamma_{1,LC}$	9.6×10^{-5} (7.7×10^{-7} , 6.1×10^{-4})	9.9×10^{-5} (8.6×10^{-7} , 6.5×10^{-4})	9.1×10^{-5} (7.8×10^{-7} , 5.6×10^{-4})	8.4×10^{-5} (8.1×10^{-7} , 5.1×10^{-4})
$\gamma_{1,LD}$	1.2×10^{-3} (9.3×10^{-6} , 7.2×10^{-3})	1.5×10^{-3} (1.2×10^{-5} , 7.9×10^{-3})	1.1×10^{-3} (9.3×10^{-6} , 6.6×10^{-3})	1.2×10^{-3} (1.1×10^{-5} , 6.6×10^{-3})
$\gamma_{1,LM}$	8.7×10^{-5} (4.9×10^{-7} , 4.9×10^{-4})	1.0×10^{-4} (7.3×10^{-7} , 5.9×10^{-4})	8.8×10^{-5} (5.3×10^{-7} , 5.0×10^{-4})	8.6×10^{-5} (3.8×10^{-7} , 5.1×10^{-4})
$\gamma_{1,LR}$	9.5×10^{-5} (2.4×10^{-8} , 6.1×10^{-4})	1.0×10^{-4} (9.0×10^{-8} , 6.4×10^{-4})	8.8×10^{-5} (3.4×10^{-8} , 5.8×10^{-4})	9.6×10^{-5} (4.5×10^{-8} , 6.5×10^{-4})
$\phi_{a,LC}$	0.32 (0.04, 0.56)	0.34 (0.06, 0.58)	0.31 (0.03, 0.57)	0.32 (0.03, 0.56)
$\phi_{a,LD}$	0.51 (0.23, 0.69)	0.57 (0.34, 0.72)	0.51 (0.23, 0.70)	0.52 (0.23, 0.70)
$\phi_{a,LM}$	0.32 (0.03, 0.60)	0.36 (0.06, 0.61)	0.32 (0.03, 0.60)	0.32 (0.03, 0.59)
$\phi_{a,LR}$	0.51 (0.16, 0.74)	0.57 (0.28, 0.76)	0.50 (0.17, 0.73)	0.52 (0.15, 0.75)
τ_c	11.3 (2.1, 35.3)	18.5 (4.5, 47.6)	10.5 (2.0, 32.3)	8.6 (1.9, 25.3)
c_{LC}	6.6 (4.6, 9.2)	6.7 (4.6, 9.2)	6.7 (4.6, 9.1)	6.7 (4.6, 9.2)
c_{LD}	10.0 (6.6, 14.2)	10.6 (7.2, 14.5)	10.1 (6.6, 14.1)	10.1 (6.5, 14.2)
c_{LM}	5.6 (3.6, 7.9)	5.8 (3.7, 8.4)	5.8 (3.7, 8.0)	5.8 (3.6, 8.0)
c_{LR}	5.2 (3.2, 7.7)	5.6 (3.4, 8.5)	5.1 (3.2, 7.6)	5.2 (3.2, 7.7)

Appendix 2

Posterior–prior plots

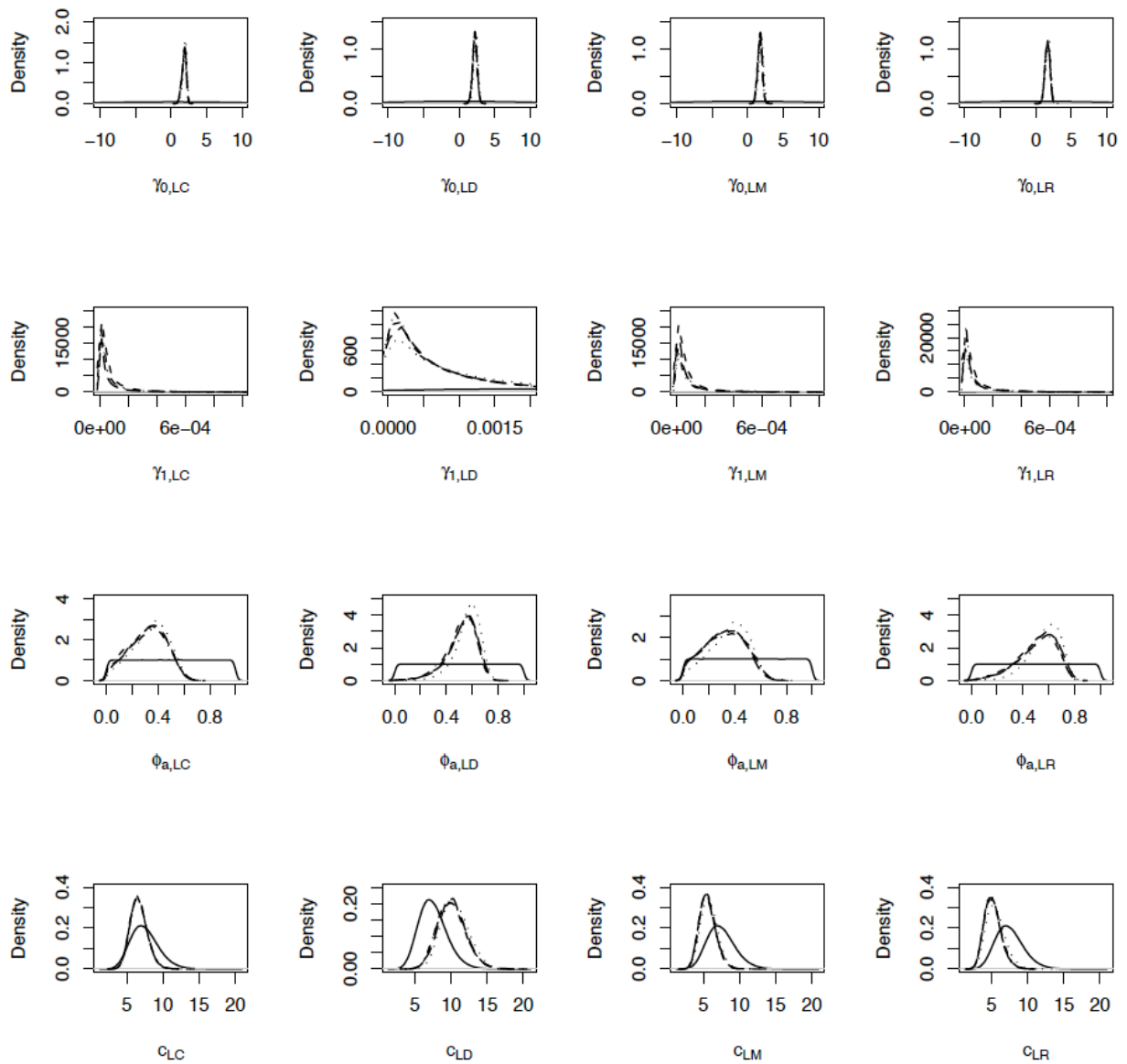
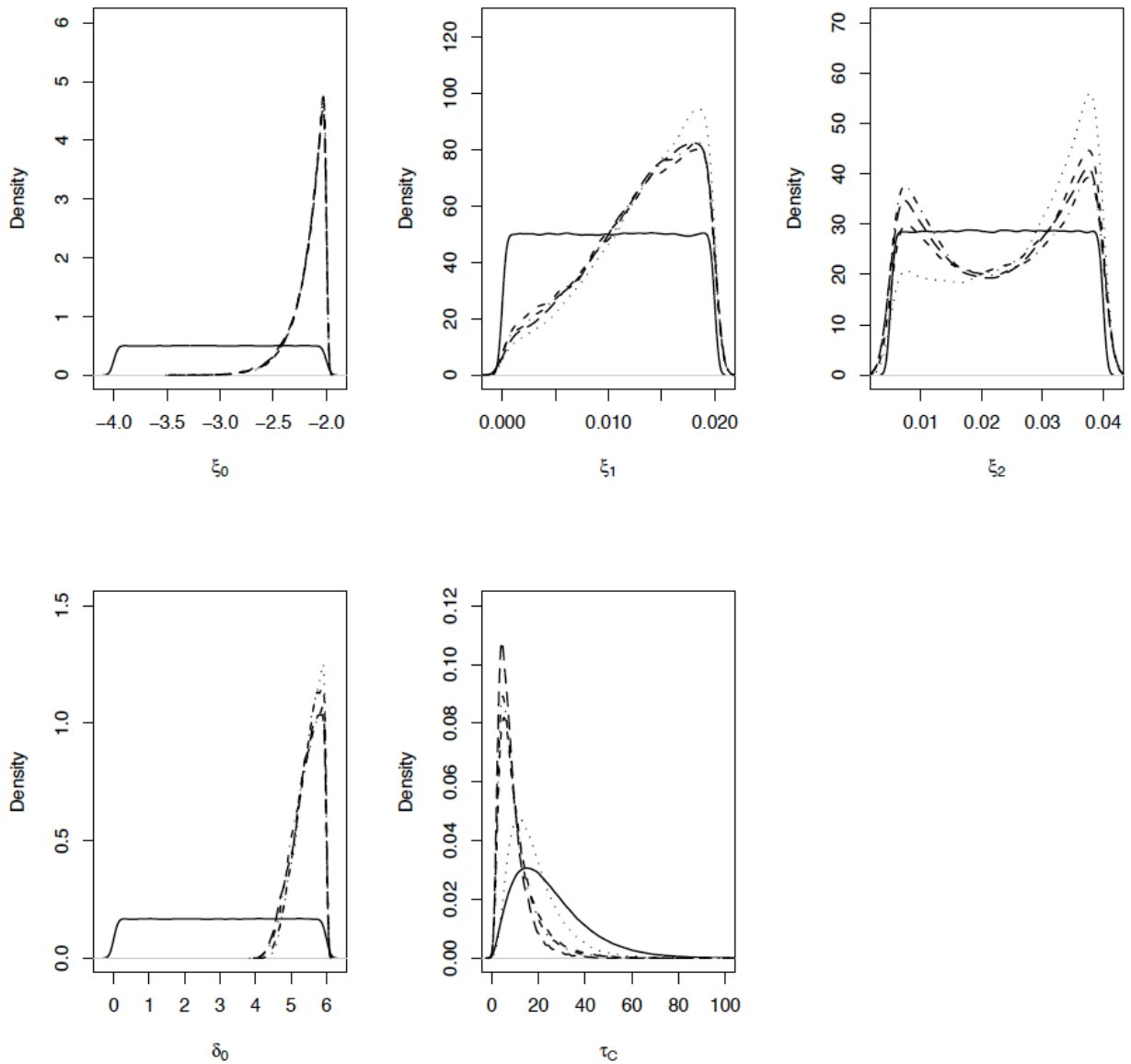
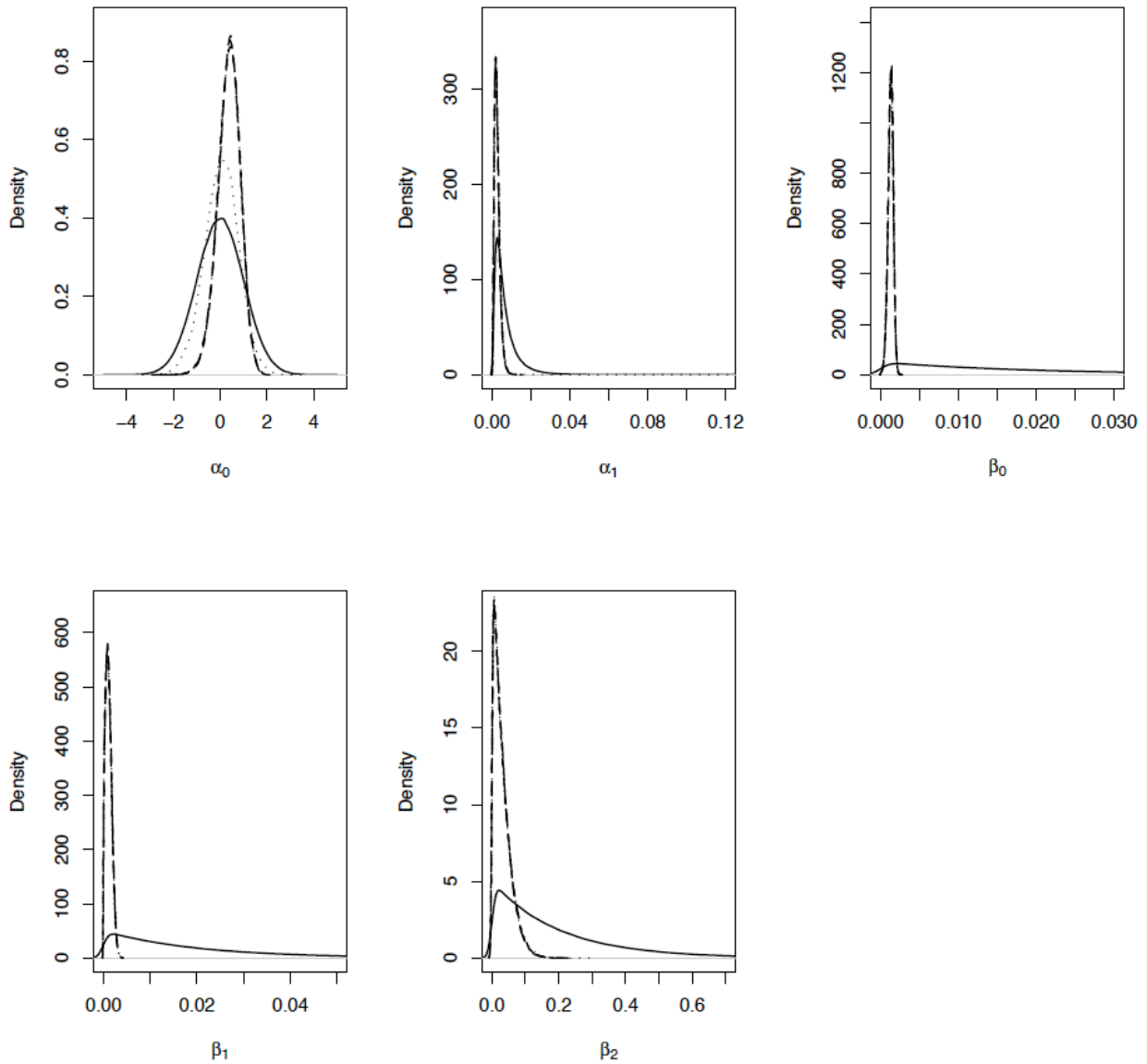


Figure A2.1. Plots of the posterior distributions for the beat-specific grouse parameters (γ_0 , γ_1 , ϕ_a , c) for the predation (dash), prediction (dot) and partial (dot-dash) and full (long dash) diversionary feeding scenarios for grouse–harrier population dynamics, compared to each parameter’s prior distribution (solid).



1
2 Figure A2.2. Plots of the posterior distributions for the beat-independent grouse parameters
3 ($\xi_0, \xi_1, \xi_2, \tau_c$) for the predation (dash), prediction (dot) and partial (dot-dash) and full (long
4 dash) diversionary feeding scenarios for grouse–harrier population dynamics, compared to
5 each parameter’s prior distribution (solid).
6



7
8 Figure A2.3. Plots of the posterior distributions for the hen harrier parameters
9 ($\alpha_0, \alpha_1, \beta_0, \beta_1, \beta_2$) for the predation (dash), prediction (dot) and partial (dot-dash) and full
10 (long dash) diversionary feeding scenarios for grouse–harrier population dynamics,
11 compared to each parameter’s prior distribution (solid).

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15 Appendix 3

16 Asseburg (2005) Abstract

17 Multi-species functional response models are required to model the predation of generalist
18 predators, which consume more than one prey species. In chapter 2, a new model for the
19 multi-species functional response is presented. This model can describe generalist predators
20 that exhibit functional responses of Holling type II to some of their prey and of type III to
21 other prey. In chapter 3, I review some of the theoretical distinctions between Bayesian and
22 frequentist statistics and show how Bayesian statistics are particularly well-suited for the
23 fitting of functional response models because uncertainty can be represented
24 comprehensively. In chapters 4 and 5, the multi-species functional response model is fitted
25 to field data on two generalist predators: the hen harrier *Circus cyaneus* and the harp seal
26 *Phoca groenlandica*. I am not aware of any previous Bayesian model of the multi-species
27 functional response that has been fitted to field data. The hen harrier's functional response
28 fitted in chapter 4 is strongly sigmoidal to the densities of red grouse *Lagopus lagopus*
29 *scoticus*, but no type III shape was detected in the response to the two main prey species,
30 field vole *Microtus agrestis* and meadow pipit *Anthus pratensis*. The impact of using
31 Bayesian or frequentist models on the resulting functional response is discussed. In chapter
32 5, no functional response could be fitted to the data on harp seal predation. Possible reasons
33 are discussed, including poor data quality or a lack of relevance of the available data for
34 informing a behavioural functional response model. I conclude with a comparison of the role
35 that functional responses play in behavioural, population and community ecology and
36 emphasise the need for further research into unifying these different approaches to
37 understanding predation with particular reference to predator movement. In an appendix, I
38 evaluate the possibility of using a functional response for inferring the abundances of prey
39 species from performance indicators of generalist predators feeding on these prey. I argue
40 that this approach may be futile in general, because a generalist predator's energy intake does
41 not depend on the density of any single of its prey, so that the possibly unknown densities of
42 all prey need to be taken into account.

43

44 Asseburg, C. 2005. Modelling uncertainty in multi-species predator-prey interactions. PhD
45 Thesis, University of St Andrews. URI: <http://hdl.handle.net/10023/174>.