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Wildlife Research

Supplementary Material

Population dynamics of chital deer (*Axis axis*) in northern Queensland: effects of drought and culling

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Table S1. (a) Model selection statistics and parameter estimates for the mark-recapture component of mark-recapture distance sampling (MRDS; n = 23 observations by one or both left side observers) used to estimate detection probability of deer clusters on the transect line $g(0)$ on aerial surveys in July 2014. Shown for each model are the number of estimated parameters (K), AICc, AICc differences (ΔAICc) and AICc weights. AICc weights can be interpretated as the probability of a model being the best in the set of candidate models (Burnham and Anderson 1998). All models used a half normal key function for the distance sampling component with no covariates.

The effect size (± standard error) for perpendicular distance was small and non-significant (-0.01 ± 0.01) and so the third-ranked model was not considered plausible (Laake *et al*. 2008). The parameter estimate for observer position was also non-significant (0.85 ± 0.69). Therefore, only the model with the smallest AICc was considered.

Model	K	AICc	ΔAICc	AICc weight
No covariates	2	47.96	0.00	0.49
Observer position	3	48.97	1.01	0.30
Perpendicular distance	3	49.63	1.67	0.21

Parameter estimates and detection probability for the preferred model (no covariates).

Parameter	Estimate	Standard error
Intercept	0.96	0.42
Detection probability ($g(0)$)	0.72	0.08

(b) Model selection statistics and parameter estimates for multiple covariate distance sampling (MCDS) used to estimate deer density (n = 171 observations by two rear observers) on aerial surveys in July 2014. Shown for each model are the number of estimated parameters (K), AICc, AICc differences (ΔAICc) and AICc weights. AICc weights can be interpretated as the probability of a model being the best in the set of candidate models (Burnham and Anderson 1998). Four locations include Spyglass, Maryvale Creek, Niall and region as factor levels. Two locations include region and the two properties and Maryvale Creek combined as factor levels. All models used a half-normal key function with no series expansion.

Detection probability P_w is the probability of detecting a cluster within the strip width (w = 150 m). Deer density is estimated as $D = cs \times n/(2wLP_w) \times 1/g(0)$, where cs is average cluster size, L is line length and $g(0)$ is estimated from MRDS (Table S1a; Buckland *et al*. 2015).

Model	K	AICc	ΔAICc	AICc weight
Four locations	5	549.56	0.00	0.70
Two locations	3	552.59	3.03	0.15
No covariates	2	552.75	3.19	0.14

Parameter estimates and detection probability for the preferred model (four locations).

Parameter	Estimate	Standard error
Intercept	42.77	2.01
Maryvale Creek	0.51	0.21
Niall	0.58	0.27
Region	0.19	0.21
Detection probability (P_w)	0.49	0.03

Table S2. Model selection statistics and parameter estimates for MCDS used to estimate deer density on (a) Spyglass (n = 585) and (b) Niall (n = 426) using vehicle ground surveys. Shown for each model are the number of estimated parameters (K), AICc, AICc differences (ΔAICc) and AICc weights. AICc weights can be interpretated as the probability of a model being the best in the set of candidate models (Burnham and Anderson 1998). For Spyglass, two or four levels of vegetation density (open, light, medium or dense) were included as covariates. For Niall, vegetation type (creek or woodland) was included as a covariate. All models used a hazard-rate key function with no series expansion.

Detection probability P_w is the probability of detecting a cluster within the strip width (w = 200 m). Deer density is estimated as $D = cs \times n/(2wLP_w)$, where cs is average cluster size and L is line length (Buckland *et al*. 2015).

(a) Spyglass

Model	K	AICc	ΔAICc	AICc weight
Vegetation density (two levels)	3	2038.7	0.0	0.88
Vegetation density (four levels)	5	2042.6	3.9	0.12
No covariates	1	2071.0	32.3	0.00

Parameter estimates and detection probability for the preferred model (vegetation density (two levels)).

Parameter	Estimate	Standard error
Intercept	119.80	0.96
Power parameter	6.80	9.63
Light vegetation density	0.30	0.05
Detection probability (P_w)	0.74	0.02

(b) Niall

Model	*K*	AICc	ΔAICc	AICc weight
No covariates	1	1502.6	0.0	1.00
Vegetation type (two levels)	3	1503.0	0.4	0.82

Parameter estimates and detection probability for the preferred model (no covariates).

Parameter	Estimate	Standard error
Intercept	119.8	0.96
Power parameter	6.80	9.63
Detection probability (P_w)	0.72	0.03

Table S3. Summary statistics for Pearson's product-moment correlations between annual exponential rate of increase on Spyglass (2013-2022) and Niall (2014-2020) and different periods of rainfall (rain) and total standing dry matter (TSDM; kg ha^{-1}) at varying time lags. Rainfall is coded rain.*x*.*y* and TSDM is coded TSDM.*y*, where *x* is the interval of rainfall (six- or 12-months) falling prior to the second of two consecutive density estimates used to calculate the rate of increase at a lag of *y* months. The strongest relationships for rainfall and TSDM are shown in bold. Degrees of freedom = 13.

Variable	Correlation coefficient	*t*-value	*P*
Rain.6.0	0.664	3.200	0.007
Rain.12.0	**0.714**	**3.674**	**0.002**
Rain.12.6	0.518	2.182	0.048
Rain.12.12	0.267	0.997	0.337
TSDM.0	**0.707**	**3.603**	**0.003**
TSDM.6	0.358	1.382	0.190
TSDM.12	-0.017	-0.061	0.952

Table S4. Model selection statistics and parameter estimates for MCDS used to estimate deer density on six properties, Niall, Maryvale, Felspar, Gainsford, Toomba and Lowholm, on aerial surveys over 2016-2018. Two analyses were undertaken as Lowholm had too few sightings (n = 2) to be included as a factor level: (a) excluding Lowholm (n = 143) and so including property as a covariate and (b) including Lowholm (n = 145) without property as a covariate. Observer team refers to the combination of two rear seat observers. Shown for each model are the number of estimated parameters (K), AICc, AICc differences (ΔAICc) and AICc weights. AICc weights can be interpretated as the probability of a model being the best in the set of candidate models (Burnham and Anderson 1998). All models used a hazard-rate key function with no series expansion.

Detection probability P_w is the probability of detecting a cluster within the strip width (w = 150 m). Deer density is estimated as $D = cs \times n/(2wLP_w) \times 1/g(0)$, where cs is average cluster size, L is line length and $g(0)$ is estimated from MRDS (Table S1a; Buckland *et al*. 2015).

(a) Excluding Lowholm

Model	*K*	AICc	ΔAICc	AICc weight
Year	4	404.21	0.00	0.80
Property	6	408.32	4.11	0.10
Year + observer team	6	409.30	5.09	0.06
Observer team	3	412.15	7.94	0.02
Property + observer team	8	412.57	8.36	0.01
Year + property	8	415.47	11.26	0.00
No covariates	2	419.40	15.19	0.00

Parameter estimates and detection probability for the preferred model (year).

Parameter	Estimate	Standard error
Intercept	54.10	0.93
Power parameter	5.78	12.34
2016	0.65	0.13
2017	0.29	0.16
Detection probability (*Pw*)	0.48	0.03

(b) Including Lowholm

Model	K	AICc	ΔAICc	AICc weight
Year	4	442.18	0.00	0.92
Year + observer team	6	447.54	5.36	0.06
Observer team	3	450.78	8.60	0.01
No covariates	2	460.62	18.44	0.00

Parameter estimates and detection probability for the preferred model (year).

Parameter	Estimate	Standard error
Intercept	54.90	0.95
Power parameter	5.80	11.87
2016	0.65	0.12
2017	0.27	0.16
Detection probability (P_w)	0.50	0.03

Table S5. (a) Model selection statistics and parameter estimates for the mark-recapture component of MRDS (*n* = 106 observations by one or both left side observers) used to estimate detection probability of deer clusters on the transect line *g*(0) on aerial surveys in August 2020. Data were truncated at 100 m. Shown for each model are the number of estimated parameters (*K*), AICc, AICc differences (ΔAICc) and AICc weights. All models used a half normal key function for the distance sampling component with no covariates. AICc weights can be interpretated as the probability of a model being the best in the set of candidate models (Burnham and Anderson 1998). The parameter estimate (± standard error) for perpendicular distance was small and non-significant (-0.002 ± 0.008) and so the third-ranked model was not considered plausible (Laake *et al*. 2008). The parameter estimate for observer position was also non-significant (-0.06 ± 0.24). Therefore, only the model with the smallest AICc was considered.

Model	*K*	AICc	ΔAICc	AICc weight
No covariates	2	234.73	0.00	0.58
Observer position	3	236.78	2.06	0.21
Perpendicular distance	3	236.79	2.06	0.21

Parameter estimates and detection probability for the preferred model (no covariates).

Parameter	Estimate	Standard error
Intercept	0.11	0.20
Detection probability (*g*(0))	0.53	0.05

(b) Model selection statistics and parameter estimates for MCDS (n = 146) used to estimate deer density on aerial surveys in August 2020. Data were truncated at 100 m. This estimate was divided by $g(0)$ estimated by MRDS (Table S5a). Shown for each model are the number of estimated parameters (K), AICc, AICc differences (ΔAICc) and AICc weights. AICc weights can be interpretated as the probability of a model being the best in the set of candidate models (Burnham and Anderson 1998). Four locations include Rita Island, Toomba, Spyglass and other properties as factor levels. Two locations include Rita Island and properties as factor levels. All models used a half-normal key function with no series expansion. The top two ranked models returned almost identical density estimates. The parameter estimate for two locations in the second-ranked model was non-significant (0.10 ± 0.17). Only the simpler top-ranked model was therefore used.

Detection probability P_w is the probability of detecting a cluster within the strip width (w = 100 m). Deer density is estimated as $D = cs \times n/(2wLP_w) \times 1/g(0)$, where cs is average cluster size, L is line length and $g(0)$ is estimated from MRDS (Table S5a; Buckland *et al*. 2015).

Model	K	AICc	ΔAICc	AICc weight
No covariates	1	1268.4	0.00	0.53
Two locations	2	1270.0	1.63	0.23
Four locations	4	1271.9	3.49	0.09
Observer team	3	1272.0	3.59	0.09
Four locations + observer team	6	1274.0	5.59	0.03
Two locations + observer team	4	1274.1	5.70	0.03

Parameter estimates and detection probability for the preferred model (no covariates).

Parameter	Estimate	Standard error
Intercept	38.81	2.59
Detection probability (P_w)	0.48	0.03

Table S6. (a) Model selection statistics for assessing the proportion of females breeding to full potential (BFP) on Spyglass and Niall in wet and dry seasons over 2014-2016 using logistic regression (*n* = eight property-occasion samples comprising 85 animals). BFP is the response variable with the following explanatory variables: property, season, property × season, rainfall in the six (rain.6.0) and 12 months (rain.12.0) prior to sampling and total standing dry matter (TSDM) at the time of sampling. Shown for each model are the number of estimated parameters (*K*), AICc, AICc differences (ΔAICc) and AICc weights. AICc weights can be interpretated as the probability of a model being the best in the set of candidate models (Burnham and Anderson 1998).

Model	*K*	AICc	ΔAICc	AICc weight
Season	2	36.94	0.00	0.60
Rain.6.0	2	39.64	2.70	0.16
Intercept only	1	40.58	3.64	0.10
Property + season	3	41.30	4.36	0.07
Property	2	42.98	6.03	0.03
Rain.12.0	2	43.70	6.76	0.02
TSDM	2	43.81	6.87	0.02
Property × season	4	44.93	7.99	0.01

(b) Parameter estimates for the preferred model (season) in Table S6a.

Parameter	Estimate	Standard error
Intercept	0.762	0.324
Season (wet)	-1.208	0.455

Table S7. (a) Model selection statistics for assessing the sex ratio of culled samples on six culled properties over 2016-2018 using logistic regression (n = 11 property-year samples comprising 163 animals). Sex ratio is the response variable with year as an explanatory variable. Quasi-likelihood AICc (QAICc) was used as data were overdispersed (Burnham and Anderson 1998; Crawley 2013). QAICc was calculated using package *AICcmodavg* (Mazerolle 2020) in R 4.0.5 (R Core Team 2021). Shown for each model are the number of estimated parameters (K), QAICc, QAICc differences (ΔQAICc) and QAICc weights. QAICc weights can be interpretated as the probability of a model being the best in the set of candidate models (Burnham and Anderson 1998).

Model	K	QAICc	ΔQAICc	QAICc weight
Intercept only	2	30.85	0.00	0.98
Year	4	39.04	8.18	0.02

(b) Parameter estimates for the preferred model (intercept only) in Table S7a.

Parameter	Estimate	Standard error
Intercept	0.411	0.215

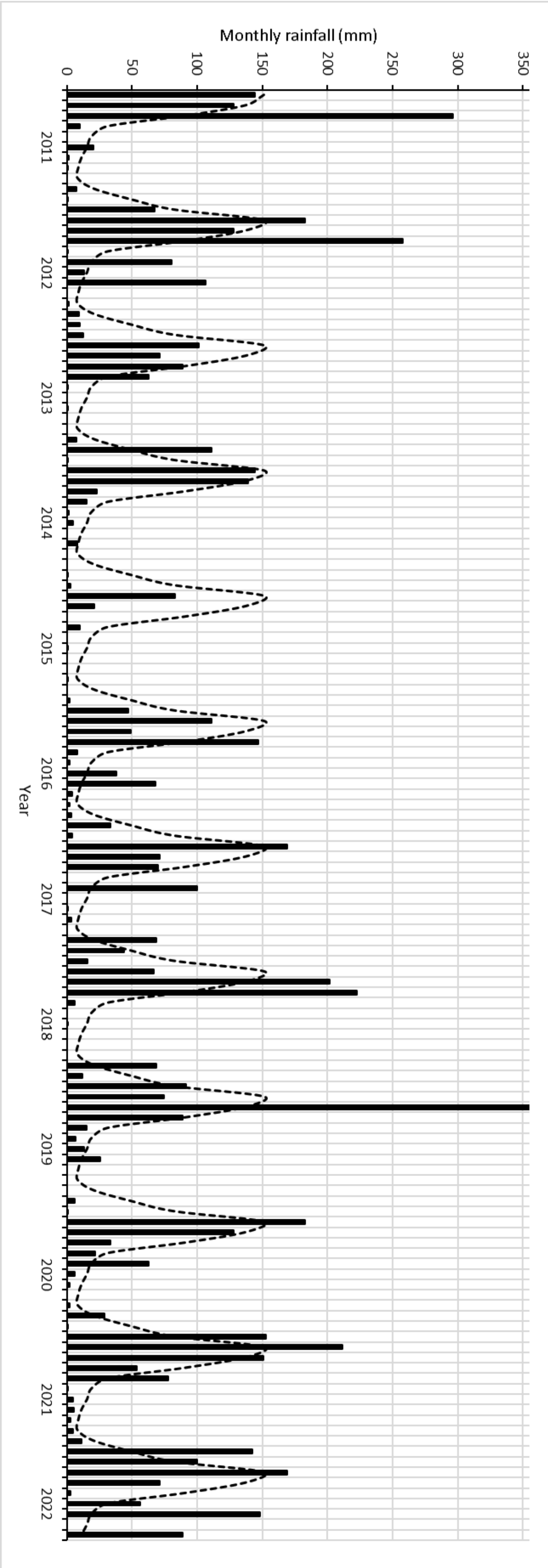
Table S8. Asymptotic exponential coefficients (± standard error), R0 and residual standard error for the numerical response model predicting annual exponential rate of increase of chital deer to 12-months rainfall with no time lag using data combined from Niall and Spyglass. The model takes the form: $r = a - b \times e^{-cx}$, where x is rainfall and $b = a - \mathrm{R0}$.

***, $p < 0.001$. See text for details.

Coefficients or statistic	**Estimate**
a	0.18 ± 0.13
b	87.57 ± 111.77
c	-3.68 ± 0.39***
R0	-87.40
Residual standard error	0.47

Figure S1. (a) Monthly rainfall (bars) and mean monthly rainfall (dashed line) on Niall from January 2011 to April 2022 (https://www.longpaddock.qld.gov.au/, accessed 23 June 2022). Average annual rainfall on Niall during 1889-2021 was 630 mm but was highly variable (coefficient of variation (CV) = 42%, median annual rainfall = 592 mm) (spatially interpolated rainfall, https://www.longpaddock.qld.gov.au/, accessed 23 June 2022; Jeffrey *et al*. 2001).

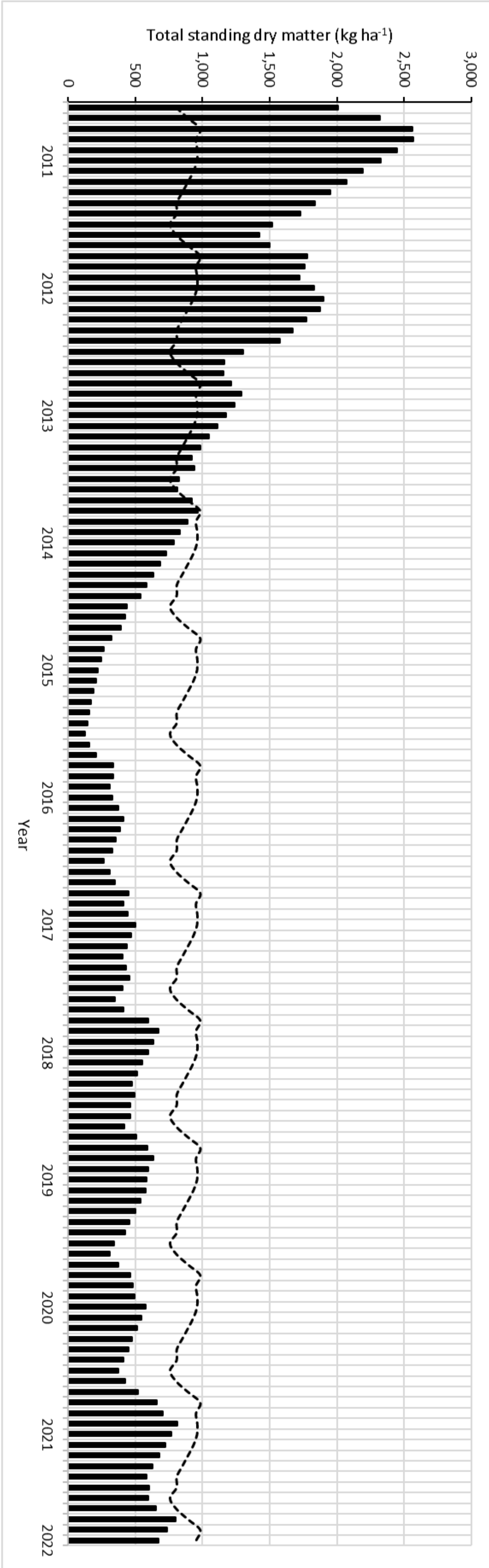
Fig. S1. (a)



Monthly rainfall (mm)
0
50
100
150
200
250
300
350
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Year

Figure S1. (b) Total standing dry matter (TSDM kg ha^{-1}; bars) and mean TSDM (dashed line) on Niall from January 2011 to April 2022 (https://www.longpaddock.qld.gov.au/forage/, accessed 18 October 2022). Average monthly TSDM on Niall during 1975-2021 was 883 kg ha^{-1} and highly variable (CV = 65%; median monthly TSDM = 708 kg ha^{-1}).

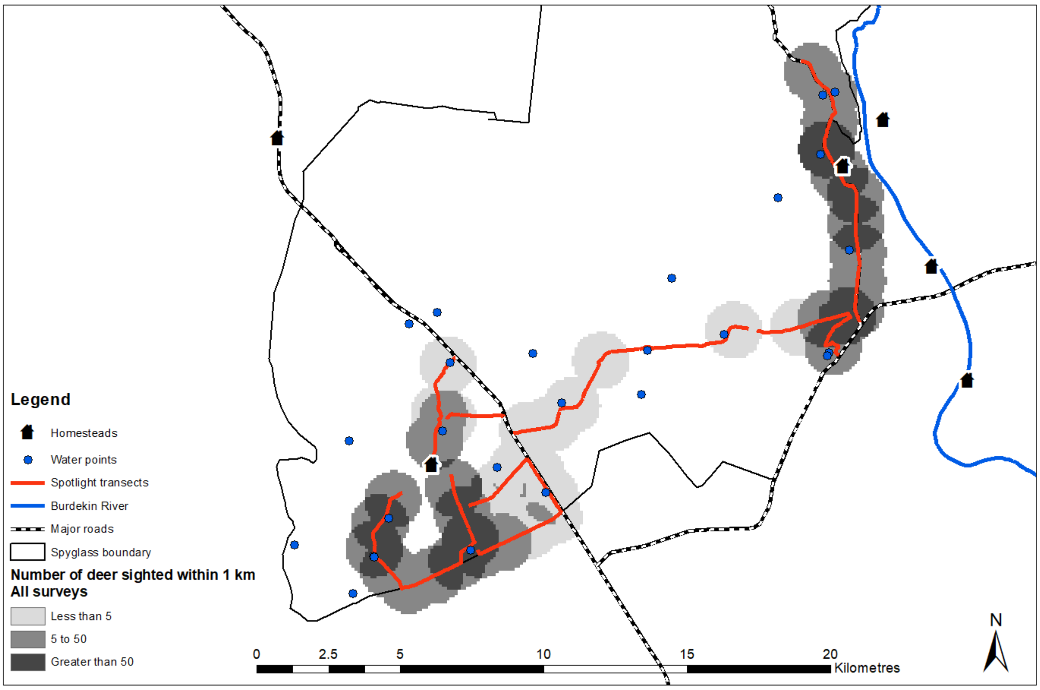
Fig. S1. (b)



Total standing dry matter (kg ha-1)
0
500
1,000
1,500
2,000
2,500
3,000
Year
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022

Figure S2. Vehicle ground survey transects (solid red lines) on (a) Spyglass and (b) Niall. Shaded circles (1 km radius) indicate the total number of deer seen in 1 km segments along transects over all 21 surveys on Spyglass and 14 surveys on Niall.

(a)



(b)

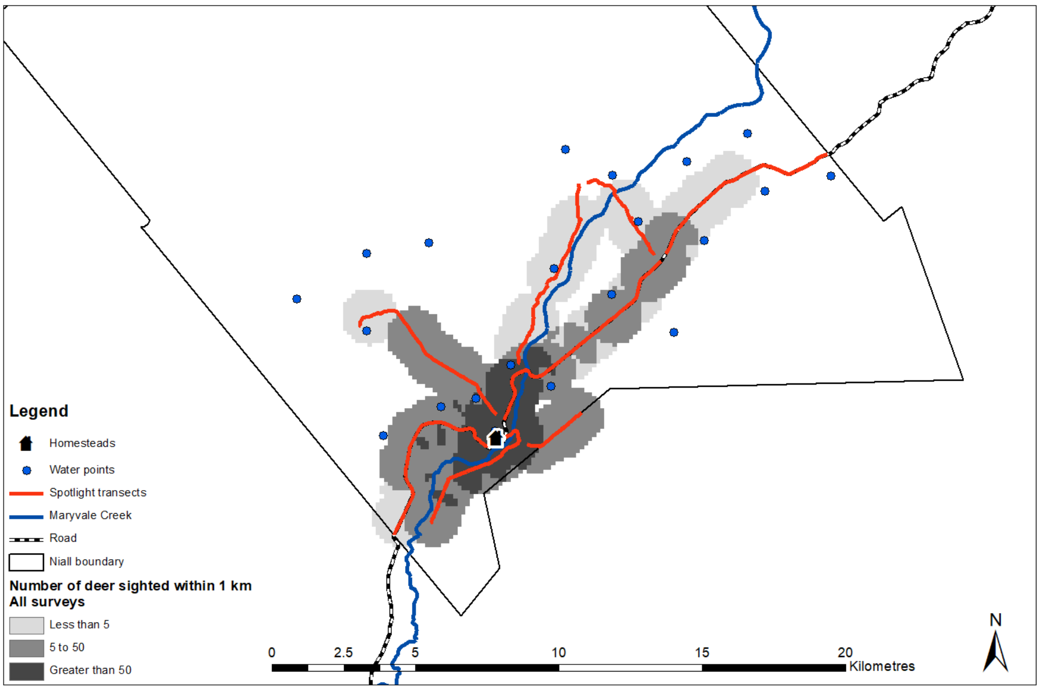
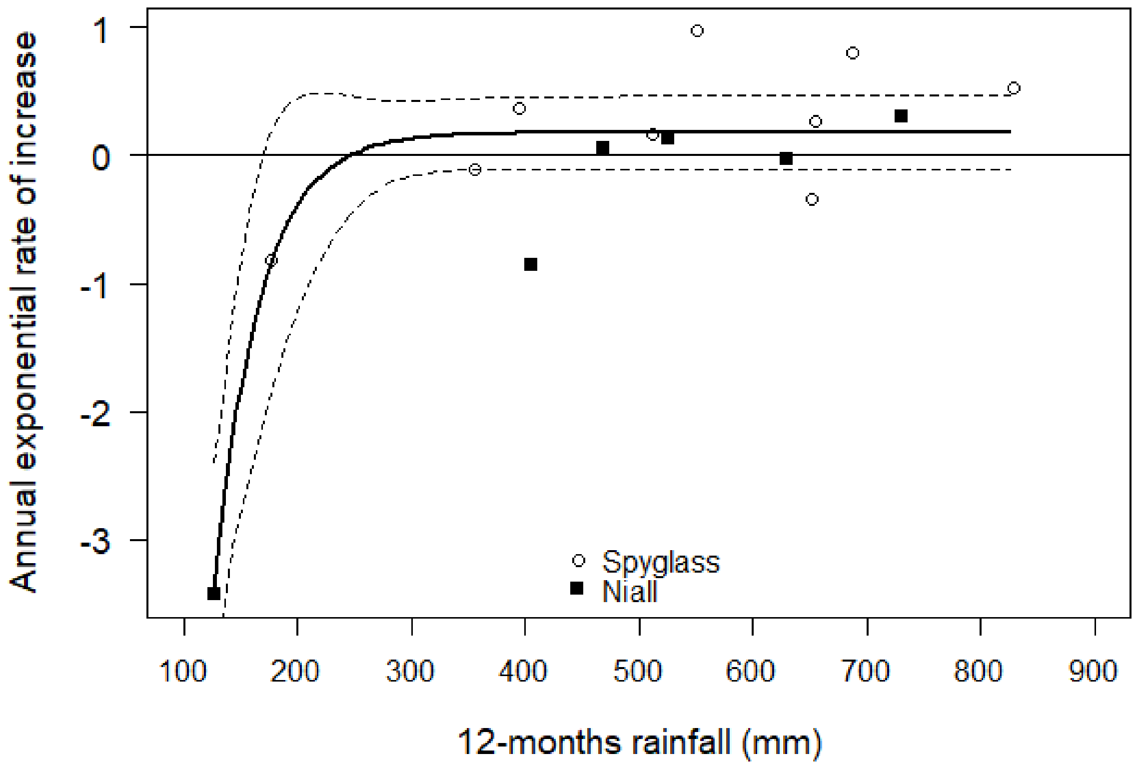


Figure S3. Annual exponential rates of increase of chital deer on Spyglass (open circles, 2013-2022) and Niall (closed squares, 2014-2020) plotted against 12-months rainfall with no lag. The solid line is a fitted asymptotic regression. The dashed lines are the 95% confidence interval fitted using package *investr* (Greenwell and Kabban 2014) in R 4.0.5. See text for details and Table S8 for model parameters.



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