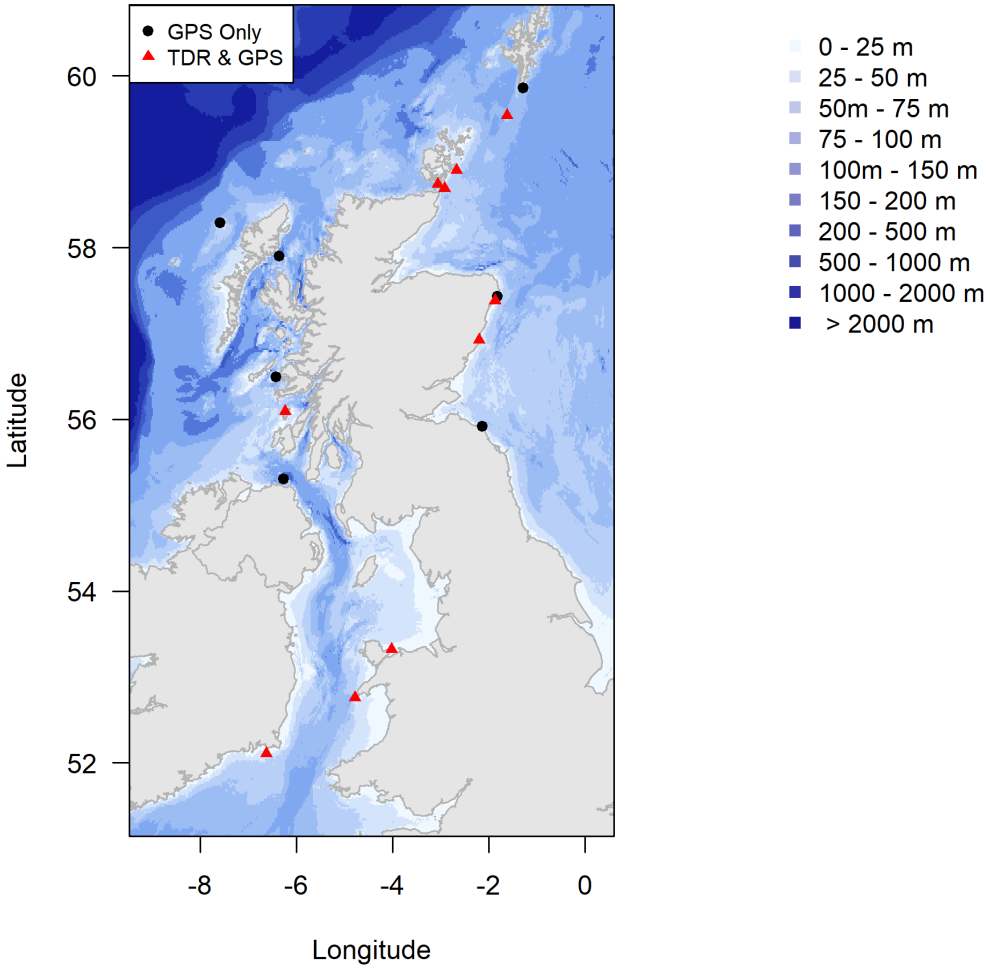
Table S1. Details of seabird colonies in which birds were tracked with the tandem GPS-TDR instrumentation or solely with GPS units. Sample sizes refer to number of individuals used to construct machine learning models of diving behaviour (No. tracked with GPS-TDR) and number of individuals used in species distribution modelling (Total No. Birds Tracked).

Species	Colony	No. Birds Tracked with GPS-TDR	No. Birds Tracked with GPS only	Total No. Birds Tracked
Common Guillemot	Bullers of Buchan	0	2	2
	Colonsay	29	46	75
	Copinsay - Orkney	2	7	9
	Fair Isle	7	7	14
	Fowlsheugh	7	3	10
	Lunga	0	3	3
	Puffin Island	0	15	15
	Shiant Isles	0	1	1
	St Abbs	0	1	1
	Whinnyfold	4	1	5
Razorbill	Bardsey Island	9	10	19
	Colonsay	24	18	42
	Copinsay – Orkney	2	12	14
	Fair Isle	25	40	65
	Flannan Isles	0	4	4
	Lunga	0	7	7
	Muckle Skerry – Orkney	10	23	33
	Puffin Island	0	34	34
	Rathlin Island	0	1	1
	Shiant Isles	0	4	4
	Swona – Orkney	13	16	29
European Shag	Colonsay	7	34	41
	Copinsay – Orkney	3	12	15
	Fair Isle	2	9	11
	Great Saltee	2	3	5
	Lunga	0	11	11
	Muckle Skerry – Orkney	5	19	24
	Rathlin Island	1	0	1
	Sumburgh Head	0	2	2

Fig. S1. Map showing the location of tracked colonies in the current study. Colonies marked with a black circle were tracked using GPS units only. Colonies marked with red triangles included birds that were tracked with a GPS-TDR combination for at least one of the three species in the study (Guillemot, Razorbill, European Shag). More details on sample sizes in Table S1. Different water depth contours also displayed (Bathymetry data from EMODnet Bathymetry Consortium 2020).



Text S1. Assessment of device effects – Comparing behaviour of birds tagged with GPS-TDR versus GPS units only

In the current study, birds were fitted with modified i-GotU GT-120 (Mobile Action Technology, Taipei, Taiwan) GPS logger to their backs (Wakefield et al. 2017). During the FAME / STAR project two different IgotU GPS units were used a 'regular' i-GotU with a mean mass 17.4 g and a 'light' I-gotU with a mean mass of 15 g (Cleasby et al. 2020). In addition, a subset of birds were fitted with Time-Depth recorders (Cefas G5 TDR, Cefas Technology Ltd) together with GPS loggers. Based on manufacturers specifications, TDR devices weigh 2.7 g in air (1.3 g in water) and have a diameter of 8 mm and length of 31 mm. Therefore, the maximum possible mass carried by an individual bird would be 20.1 g (a regular i-GotU with a TDR). The mean mass of birds tagged during the FAME / STAR project was: Guillemot – 907.79 g, SE = 3.59, n = 388 birds; Razorbill – 623.91 g, SE = 1.75, n = 521 birds; European Shag – 1781.23 g, SE = 12.25, n = 285 birds. Note sample size refers to all birds measured during the FAME / STAR project not just individuals fitted with devices.

To examine the potential effect of tagging on birds in the current study, we compared foraging trip metrics (trip duration, maximum distance from colony, total distance travelled per trip) and change in body mass across individuals that were tagged with a GPS to those fitted with a GPS-TDR combination. Foraging trips were defined as any occasion where a tracked individual travelled a minimum specified time and distance from the colony (Lascelles et al. 2016). In the case of Guillemot and Razorbill, trips were defined using a 1 km buffer around the colony and had to last at least 15 minutes. For Shag, the distance buffer was set at 250 m and trips had to last at least 10 minutes. Mass change was assessed as the change in body mass from the time (t_1) when a bird was first tagged to time (t_2) when tags were retrieved, and the bird re-weighed.

Tag effects on foraging trip metrics and mass change

To examine the effects of tagging on foraging trips metrics and mass change for each species we used Bayesian mixed models using the R package MCMCglmm (Hadfield 2010) in which foraging trip duration (hours), maximum distance travelled from the colony (km), total distance travelled during a trip (km) or change in mass between deployment and retrieval were fitted as the response variable in separate models. Trip duration, maximum distance from the colony and total distance travelled were log transformed prior to running models due to the skewed distribution of the raw data and to avoid models predicting negative values. As random effects in these models we included individual identity nested within colony identity.

To estimate an effect size for the effect of tagging we first ran models in which the only covariate was tag type defined as a binary indicator indicating whether birds were tagged with a GPS only (0) or a TDR-GPS combination (1). Thus, effects sizes from these models are not conditioned on any additional covariates. Effect sizes were extracted from these models using the formula

$$d_r = \frac{\beta}{\sigma}$$

where β is the coefficient from the model denoting the mean difference between birds in the GPS only group and birds in the TDR-GPS group and σ is the residual standard deviation from the model (Rouder et al. 2012).

Next, we ran models in which tag effects were included alongside a suite of other covariates which included: mass at deployment (g), deployment duration (days), time of day (hours from sunrise), whether a bird was incubating or feeding chicks and year (coded as a numeric variable with the first year of the study denoted as 0). Prior to running models, total distance travelled, maximum distance from the colony and trip duration were log-transformed. In addition, mass at deployment and deployment duration were standardized (Gelman & Hill 2007). Due to missing values in some of the covariates we used data imputation (Nakagawa & Freckleton 2008) to fill in missing data with imputed values. Missing data was imputed using the missForest R package (Stekhoven 2016). The missForest package is a non-parametric imputation method that uses random forest algorithms to predict missing values for a given variable by fitting random forest on the data that was observed to predict missing values. Random forests for each covariate in our model were built using the remaining covariates listed above together with our outcome variables (trip duration, max. distance travelled etc.).

To perform model selection, we began by fitting a full model for each response variable in which all covariates were included along with all possible two-way interactions involving tag type and deployment duration. Models were first fitted using the R package glmmLasso package (Groll 2017). The glmmLasso packages fits generalized mixed models while incorporating variable selection using L1-penalized estimation that shrinks fixed effect coefficients to 0 if they are not important (Groll & Tutz 2014). After identifying which covariates should be retained (non-zero coefficients) we re-ran models in MCMCglmm (Hadfield 2010) containing only these selected covariates.

Results

The effect sizes calculated from a model in which only tag type was included as a covariate indicated that tagging Razorbill with a combined GPS-TDR set up was associated with small increases in mass gain (Table S2). All the remaining 95% CRI calculated spanned zero, but in certain cases the 95% CRI only just crossed zero. For instance, the negative effects of GPS-TDR on maximum distance from the colony and total distance travelled seen in both Razorbill and Shag are suggestive of tag effects on these measures even though the upper 95% CRI crosses zero. Full results from individual models of device effects are also presented for each species with details of all moderator variables considered (Tables S3 – S5). Even with the inclusion of moderator variables we found little clear evidence that dual GPS-TDR tagging influence bird behaviour. In general, 95% CRI associated with the effect of carrying GPS-TDR instrumentation versus GPS-only spanned 0. That said, coefficients estimating the effect of dual GPS-TDR tagging on traits such as maximum distance travelled and total distance travelled were generally in the negative direction. We also noted slight increases in trip duration and total distance travelled associated with the length a device was deployed on an individual in Razorbill. Such a result may be due to the effect of attaching devices in general, rather to a specific effect of the dual GPS-TDR instrumentation.

Table S2. Effect sizes calculated for each of the variables for which tag effects were examined.

Variable	Effect Size, d_r	Lower 95% CRI	Upper 95% CRI	Species
Trip Duration	0.045	-0.096	0.19	EUSH
Max Distance	-0.087	-0.22	0.042	EUSH
Total Distance	-0.096	-0.23	0.047	EUSH
Mass Change	-0.032	-0.46	0.37	EUSH
Trip Duration	0.064	-0.15	0.27	COGU
Max Distance	-0.016	-0.23	0.19	COGU
Total Distance	0.026	-0.18	0.23	COGU
Mass Change	-0.08	-0.39	0.23	COGU
Trip Duration	-0.034	-0.20	0.13	RAZO
Max Distance	-0.13	-0.29	0.029	RAZO
Total Distance	-0.11	-0.25	0.05	RAZO
Mass Change	**0.23**	**0.033**	**0.49**	RAZO

Table S3. Results of tag effects modelling for Common Guillemot.

Model	Variable	Coefficient	Lower 95% CRI	Upper 95% CRI
log (trip duration)	Intercept	1.86	1.50	2.20
n = 580 observations, 10 Colonies, 135 individuals	Tag type: (TDR-GPS)	0.17	-0.056	0.39
	Deployment duration	0.057	-0.021	0.14
	Incubation: Yes	0.71	0.46	0.94
	Year	-0.036	-0.11	0.033
	σ Individual in Colony	0.24	0.0048	0.35
	σ Colony	0.35	0.031	0.56
log (max. distance from the colony)	Intercept	2.67	2.02	3.29
n = 580 observations, 10 Colonies, 135 individuals	Tag type: (TDR-GPS)	-0.067	-0.33	0.19
	Deployment duration	0.0085	-0.091	0.099
	Incubation: Yes	0.27	-0.021	0.56
	Year	-0.15	-0.24	-0.061

	σ Individual in Colony	0.41	0.29	0.51
	σ Colony	0.88	0.35	1.33
log (total distance travelled) *n* = 580 observations, 10 Colonies, 135 individuals	Intercept	3.65	3.05	4.33
	Tag type: (TDR-GPS)	0.021	-0.25	0.31
	Deployment duration	0.035	-0.065	0.14
	Incubation: Yes	0.44	0.13	0.75
	Year	-0.15	-0.24	-0.051
	σ Individual in Colony	0.39	0.26	0.49
	σ Colony	0.78	0.33	1.19
Mass Change *n* = 150 observations, 10 Colonies, 135 individuals	Intercept	-42.88	-59.51	-27.12
	Tag type: (TDR-GPS)	-6.53	-20.33	7.51
	Deployment duration	-1.60	-8.87	6.13
	Incubation: Yes	13.93	-1.14	28.04
	Mass at deployment	-22.15	-28.80	-15.15
	σ Individual in Colony	25.02	0.0026	38.53
	σ Colony	19.01	0.017	31.05

Table S4. Results of tag effects modelling for Razorbill.

Model	Variable	Coefficient	Lower 95% CRI	Upper 95% CRI
log (trip duration)	Intercept	1.68	1.38	1.99
n = 992 observations, 11 Colonies, 215 individuals	Tag type: (TDR-GPS)	-0.072	-0.25	0.087
	Deployment duration	0.10	0.024	0.18
	Incubation: Yes	0.44	0.29	0.59
	Time of Day	0.015	-0.049	0.081
	σ Individual in Colony	0.37	0.28	0.45
	σ Colony	0.47	0.22	0.69
log (max. distance from the colony)	Intercept	2.81	2.32	3.32
n = 992 observations, 11 Colonies, 215 individuals	Tag type: (TDR-GPS)	-0.20	-0.42	0.010
	Deployment duration	0.076	-0.021	0.17
	Incubation: Yes	0.18	-0.0021	0.36
	Time of Day	0.013	-0.065	0.091
	σ Individual in Colony	0.49	0.40	0.59
	σ Colony	0.88	0.39	1.20
log (total distance travelled)	Intercept	3.85	3.31	4.37
n = 992 observations, 11 Colonies, 215 individuals	Tag type: (TDR-GPS)	-0.15	-0.37	0.061
	Deployment duration	0.10	0.0044	0.20
	Incubation: Yes	0.25	0.074	0.46
	Year	-0.056	-0.13	0.091
	Time of Day	0.013	-0.069	0.091
	σ Individual in Colony	0.48	0.37	0.57
	σ Colony	0.77	0.35	1.11
Mass Change	Intercept	-42.74	-50.76	-34.57
n = 254 observations, 11 Colonies, 215 individuals	Tag type: (TDR-GPS)	7.65	0.92	14.63
	Deployment duration	-1.98	-5.39	1.60

	Incubation: Yes	18.57	10.74	25.68
	Mass at deployment	-14.44	-17.86	-11.41
	σ Individual in Colony	5.87	0.0051	11.75
	σ Colony	8.88	0.19	15.01

Table S5. Results of tag effects modelling for European Shag.

Model	Variable	Coefficient	Lower 95% CRI	Upper 95% CRI
log (trip duration)	Intercept	0.93	0.80	1.07
n = 1669 observations, 8 Colonies, 99 individuals	Tag type: (TDR-GPS)	0.022	-0.063	0.10
	Mass at deployment	-0.019	-0.059	0.016
	Incubation: Yes	0.23	0.13	0.33
	Time of Day	-0.042	-0.079	-0.0091
	σ Individual in Colony	0.25	0.21	0.29
	σ Colony	0.18	0.061	0.29
log (max. distance from the colony)	Intercept	0.68	0.18	1.15
n = 1669 observations, 8 Colonies, 99 individuals	Tag type: (TDR-GPS)	-0.11	-0.31	0.11
	Mass at deployment	-0.085	-0.18	0.0056
	Time of Day	-0.21	-0.28	-0.12
	σ Individual in Colony	0.73	0.65	0.83
	σ Colony	0.73	0.33	1.09
log (total distance travelled)	Intercept	1.72	1.29	2.16
n = 1669 observations, 8 Colonies, 99 individuals	Tag type: (TDR-GPS)	-0.14	-0.32	0.064
	Deployment duration	0.069	-0.023	0.16
	Incubation: Yes	0.18	-0.069	0.43
	Mass at deployment	-0.071	-0.17	0.015
	Time of Day	-0.17	-0.25	-0.094
	σ Individual in Colony	0.71	0.61	0.79
	σ Colony	0.64	0.25	0.96
Mass Change	Intercept	-14.71	-59.54	33.39
n = 102 observations, 7 Colonies, 88 individuals	Tag type: (TDR-GPS)	-5.33	-64.82	51.25
	Deployment duration	20.28	-4.43	43.52
	Incubation:	-8.45	-54.07	37.85

	Yes			
	Mass at deployment	-99.47	-121.51	-76.65
	σ Individual in Colony	94.11	0.32	119.65
	σ Colony	42.95	0.0071	87.68

Text S2. Machine Learning Model Performance

To assess the performance of our selected machine learning models we provide details on the same suite of measures used by Browning et al. (2018) to allow for direct comparison between these studies. All measures of performance here are based on model predictions from our testing dataset which was held out during model training and has therefore not been seen by the machine learning models that were developed. The measures we report are area under the receiving operator curve (AUC), sensitivity, specificity, positive predicted value (PPV) and the negative predictive value (NPV). AUC ranges from 0.5 for a classifier with no predictive value to 1.0 for a perfect classifier. Sensitivity (also called true positive rate) measures the proportion of positive examples correctly classified whereas specificity (true negative rate) measures the proportion of negative examples correctly identified. PPV (also called precision) is defined as the proportion of positive examples that were truly positive. A precise model with high PPV will only predict the positive class in cases very likely to be positive and is therefore more trustworthy. NPV is defined as the proportion of negative examples that were correctly identified. The best models are therefore expected to have high AUC, sensitivity, specificity, PPV and NPV. Alongside these results we also report confusion matrices.

Machine learnings models performed well when predicting diving behaviour in each of the three species examined (Table S6). High values of specificity (all above 95%) indicated that the models were able to predict and classify non-diving behaviour accurately. Models also predicted diving behaviour well with sensitivity values exceeding 85%. Error rates when classifying non-diving behaviour and diving behaviour were low. However, error rates when classifying diving behaviour were higher than when predicting non-diving behaviour. In Guillemot and Razorbill error rates for diving behaviour were 0.12 and 0.13 respectively, whereas the corresponding values for predicting non-diving behaviour were 0.028 and 0.025 (Tables S7-S9). In Shags, error rates for diving and non-diving behaviour were similar. The models presented here represent a slight improvement in performance from those reported in Browning et al. (2018). For example, AUC values in Browning et al. (2018) were 0.96 for Guillemot, 0.95 for Razorbill and 0.97 for Shag, which compare with AUC values of 0.98 for Guillemot and Razorbill and 0.99 for Shag in the current work. In addition, all other performance measures listed in Table S6 either matched or

slightly exceeded those reported in Browning et al. (2018).

Table S6. Measures of performance for machine learning models developed to predict diving behaviour. All measures are based on predictive performance when models were applied to a test dataset that was previously unseen and was not used for model development.

Species	AUC	Sensitivity	Specificity	PPV	NPV
Common Guillemot	0.984	87.31%	97.19%	0.88	0.97
Razorbill	0.987	86.64%	97.82%	0.85	0.98
European Shag	0.993	95.69%	97.47%	0.89	0.99

Table S7. Confusion matrix for random forest machine learning models predicting diving behaviour in Common Guillemot. Values are based on predictive performance on a test dataset that was previously unseen. Error gives the proportion of values wrongly classified in each row and is calculated using the values in the Rate column.

	Predicted: 0 (Not a dive)	Predicted: 1 (A dive)	Rate	Error
Actual: 0 (Not a dive)	16755	485	485 / 17240	0.0281
Actual: 1 (A dive)	515	3542	515 / 4057	0.1269
Total	17270	4027	1000 / 21297	0.04695

Table S8. Confusion matrix for gradient boosting machine learning models predicting diving behaviour in Razorbill. Values are based on predictive performance on a test dataset that was previously unseen. Error gives the proportion of values wrongly classified in each row and is calculated using the values in the Rate column.

	Predicted: 0 (Not a dive)	Predicted: 1 (A dive)	Rate	Error
Actual: 0 (Not a dive)	40299	1045	1045 / 41334	0.0253
Actual: 1 (A dive)	938	6081	938 / 7019	0.1336
Total	41237	7126	1983 / 48363	0.04100

Table S9. Confusion matrix for random forest machine learning models predicting diving behaviour in European Shag. Values are based on predictive performance on a test dataset that was previously unseen. Error gives the proportion of values wrongly classified in each row and is calculated using the values in the Rate column.

	Predicted: 0 (Not a dive)	Predicted: 1 (A dive)	Rate	Error
Actual: 0 (Not a dive)	11121	248	248 / 11369	0.0218
Actual: 1 (A dive)	93	2066	93 / 2159	0.0404
Total	11214	2314	341 / 13528	0.0252

Text S3. Species Distribution Models

Results

Across all species, addition of a covariate for distance from the colony improved model predictions (Table S10). Coefficients for the main effect of distance from the colony were negative in each case and relatively large. However, because distance from the colony is involved in higher order interactions in the models its influence is conditional upon other variables. Another variable that was included in all three models was log(Cumulative Area), which was designed to represent density dependant competition at sea in relation to coastal geography (i.e. colonies with more restricted access to sea may face greater competition as less sea area is available to them). These findings mirror the results from Wakefield et al. (2017) in which these two variables were also included in every species distribution model.

Further comparison of the species distribution models presented here for each species with those of Wakefield et al. (2017) reveals that while some variables are included in both models, others are not. In Guillemot, distance from the coast, thermal front gradient (TFGD) and proportion of gravel were identified as important in the models presented here and in Wakefield et al. (2017), but water depth and sea surface temperature (SST) were only included in models based solely upon diving behaviour. In contrast, variables representing sympatric and parapatric competition were included in the models of Wakefield et al. (2017) but not in models solely using diving behaviour. In Razorbill, the variables seabed slope and sand to mud ratio were included in species distribution models based upon all GPS locations as well as those based on diving locations only. However, Razorbill SDM based on diving only behaviour included primary productivity (NPP) which was not included in the models of Wakefield et al. (2017). Conversely, the Razorbill models presented in Wakefield et al. (2017) included a term for SST which was not included in Razorbill SDM in the current work. In Shag, the Potential Energy Anomaly (PEA) and proportion of gravel in seabed sediment were identified as important covariates for distribution models focussed upon diving behaviour and those constructed by Wakefield et al. (2017) using all GPS locations. However, whereas Wakefield et al. (2017) included a term to capture sympatric competition between birds from the same colony SDMs based on diving behaviour did not but instead included a term for parapatric competition that was not included in Wakefield et al. (2017). Two other variables that were included within best fitting SDM models based on Shag diving behaviour but not in Wakefield et al. (2017) were distance from the coast and NPP. Cross-validation results show that the final selected models for Guillemot, Razorbill and Shag performed similarly well ($\overline{BA}$ = 0.41, 0.43 and 0.47 respectively). $\overline{BA}$ scores for SDM based on diving behaviour were slightly lower for Guillemot and Shag than the corresponding models in Wakefield et al. (2017). However, model performance for Razorbill was slightly higher than the corresponding model in Wakefield et al. (2017).

Table S10. Results from the best predictive SDMs based solely upon diving or predicted diving behaviour for each species.

Model and Covariate	Estimate	SE	*z* score
Common Guillemot (*n* = 663088, BA = 0.41)			
Intercept	-2.14	0.47	-7.16
Distance From Colony	-1.80	0.043	-41.65
Distance From Coast	0.34	0.033	10.19
$\overline{\text{Distance From Coast}}$	-0.91	0.61	-1.48
Proportion of Gravel	-0.31	0.0071	-44.62
Thermal Front Gradient	0.51	0.086	58.64
Depth	-1.81	0.16	-11.04
log (Cumulative Area)	-0.53	0.0045	-117.38
SST	-3.01	0.056	-53.78
Distance From Colony × Distance From Coast	0.98	0.021	44.78
Distance From Colony × SST	-1.51	0.031	-48.93
Distance From Coast × $\overline{\text{Distance From Coast}}$	0.41	0.081	5.10
σ Site	0.79		
Razorbill (*n* = 439745, BA = 0.43)			
Intercept	-103.38	0.91	-142.5
Distance From Colony	-65.46	0.42	-156.70
Distance From Colony^2	-1.78	0.017	-107.06
log (Cumulative Area)	9.30	0.065	142.32
log (Cumulative Area)^2	0.18	0.0021	88.54
NPP	4.23	0.26	16.06
Seabed Slope	-0.88	0.013	-66.08
Sand to Mud Ratio	-0.0078	0.0042	-1.84
Distance From Colony × NPP	2.017	0.12	17.31
Distance From Colony × log(Cumulative Area)	4.64	0.029	156.25
log(Cumulative Area) × NPP	-0.31	0.023	-13.69
Distance From Colony × log(Cumulative Area) × NPP	-0.12	0.0087	-13.60
σ Site	1.19		
European Shag (*n* = 140870, BA = 0.47)			
Intercept	-42.22	0.54	-78.75
Distance From Colony	-1.34	0.033	-41.42
Distance From Coast	-2.65	0.046	-65.76
log(Cumulative Area)	-0.64	0.0061	-105.84

$\sqrt{\rho}$ (parapatric competition)	-1.35	0.030	-45.07
Proportion of Gravel	-0.28	0.024	-11.65
NPP	3.11	0.32	9.73
PEA	-76.75	0.77	-99.77
Distance From Colony × Distance From Coast	-0.38	0.041	-9.26
Distance From Colony × Proportion of Gravel	-0.76	0.023	-33.34
Distance From Coast × Proportion of Gravel	-0.90	0.029	-31.56
NPP × PEA	6.22	0.54	11.51
Distance From Colony × Distance From Coast × Proportion of Gravel	-1.11	0.025	-46.49
σ Site	1.75		

Text S4. Hotspot Mapping Results

Seabird density

Hotspots maps for common Guillemot and Razorbill were broadly similar (Fig. S2a, b) with hotspots covering the majority of Scottish inshore waters and extending into Northern Irish waters encompassing areas around Rathlin Island. For both species, hotspots were also identified on the North Yorkshire coast, close to Bempton cliffs and the Pembrokeshire coast around Skomer island. For Shag, the distribution of hotspots was more localised and constrained to areas close to the shore and in the vicinity of the largest UK Shag colonies (Fig. S2c).

Fishing effort

At the scale of Breen et al. (2015), which was restricted to the inshore waters of England and Wales, a variety of inshore fishing hotspots were identified (Fig. S3). In the north of England hotspots were identified along the North Yorkshire coast to the south of Bempton cliffs, along the Northumbrian coast from Berwick-upon-Tweed to Alnmouth, and off the coast of Walney Island. In southern England hotspots were identified on the east Devon coast, the Jurassic coast and the Sussex coast.

Fig. S2. Map showing areas identifed as hotspots of seabird density using the statistical significance of Gi* scores. Hotspots displayed in red for Common Guillemot (a), Razorbill (b) and European Shag (c).

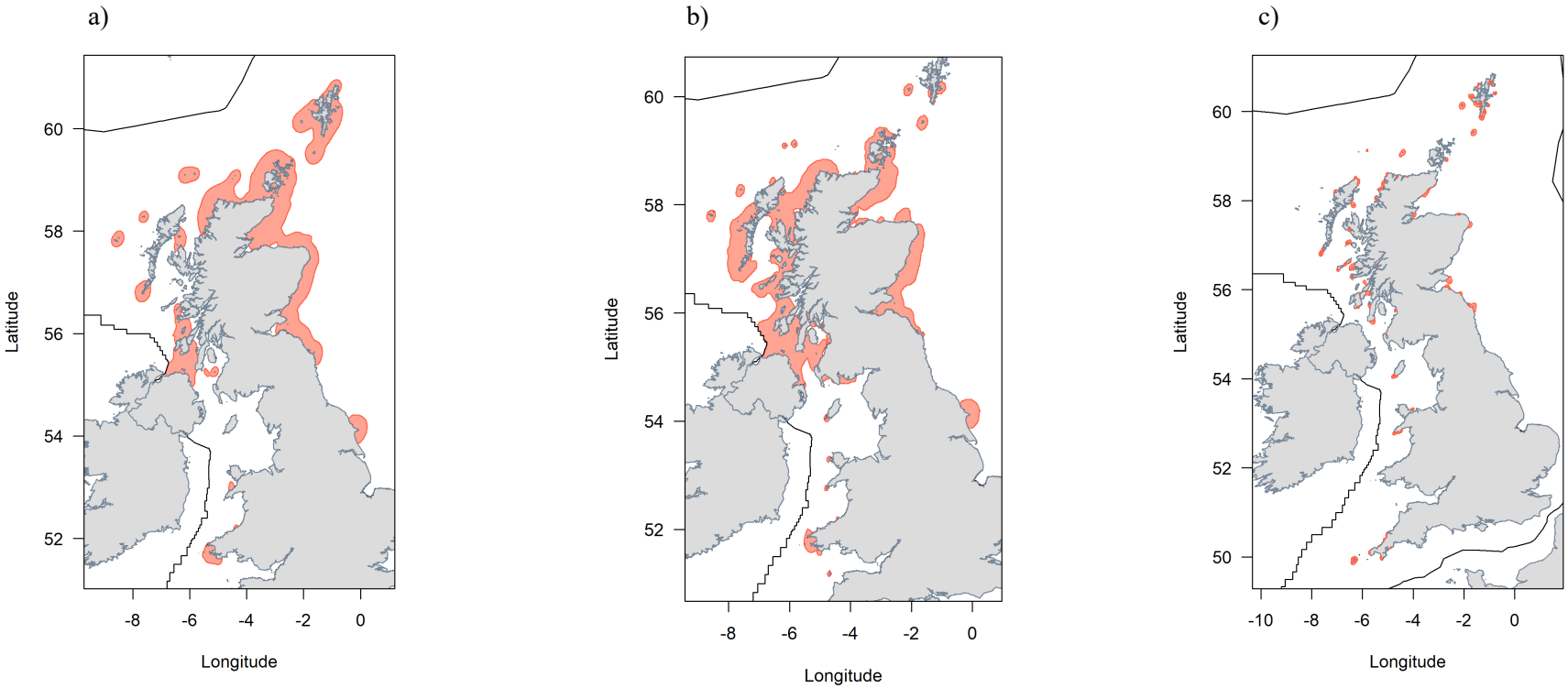


Fig. S3. Map showing areas identifed as hotspots of fishing effort using the statistical significance of Gi* scores using data from Breen et al. (2015).

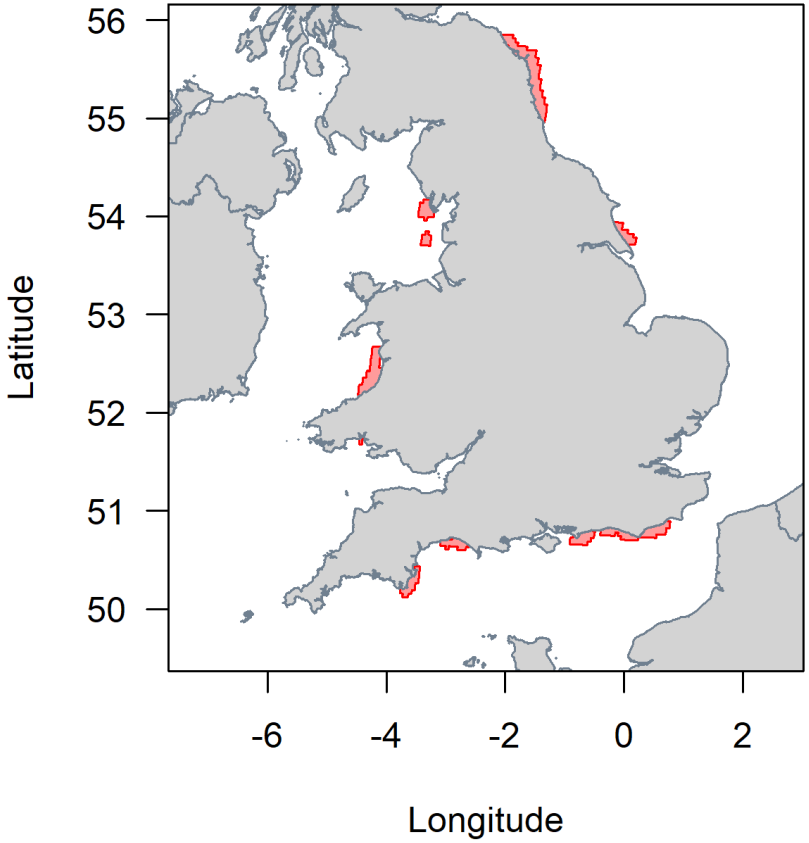
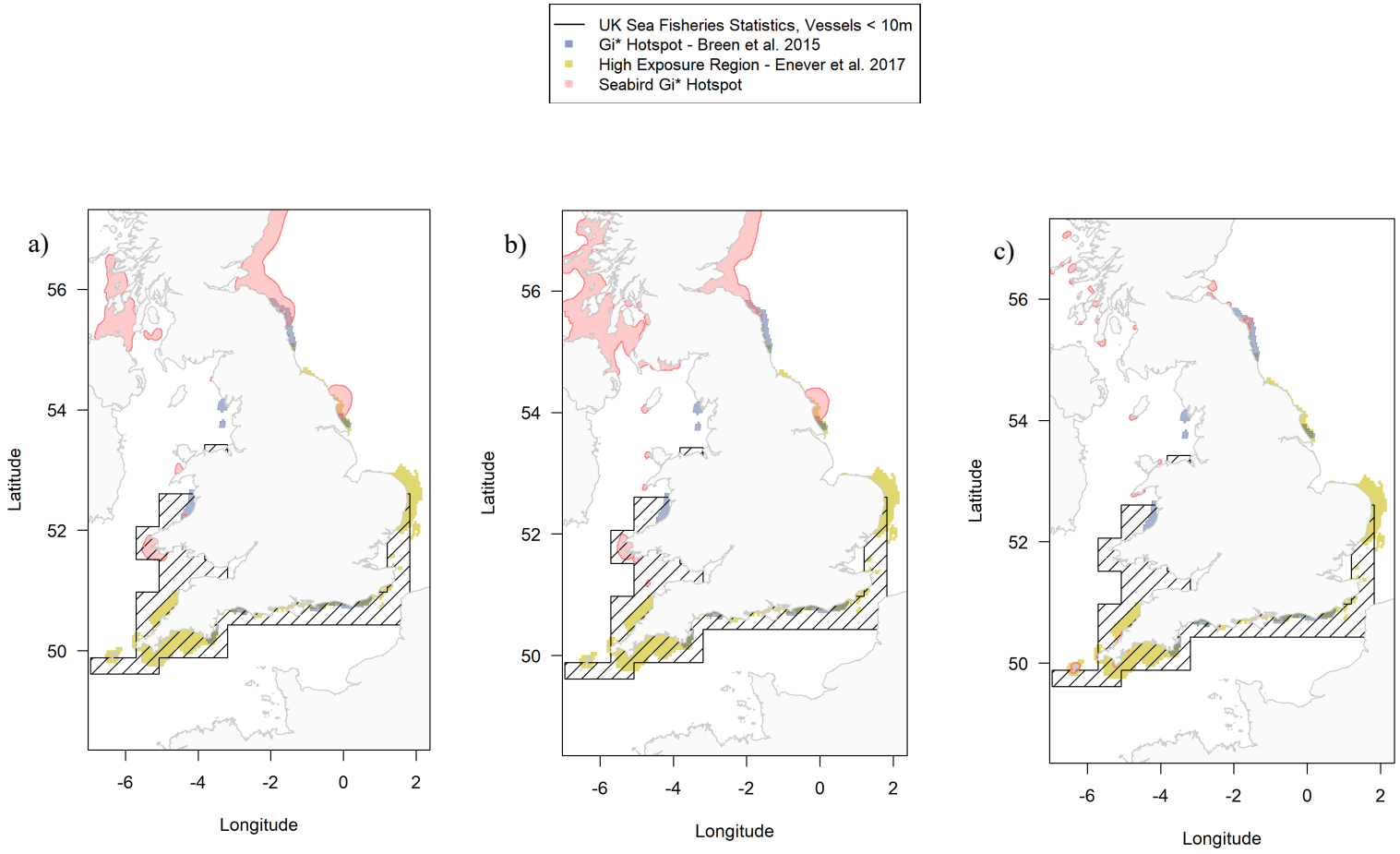


Fig. S4. Plot showing the overlap of seabird density hotspots for a) Guillemot, b) Razorbill and c) European Shag identified using Getis-Ord hotspot analysis with hotspots of fishing effort from vessels with fixed or static gear. Based on fishing effort data incorporating data information from smaller vessels. Plot restricted to inshore waters of England and Wales due to coverage of fishing data and represents inset used in Figs. 2 – 4 in main text.



GAM Model Selection Tables – Diel Diving Activity

Table S11. GAM model selection for tables modelling dive activity for Common Guillemots, Razorbill and European Shag. Comparison is between a model with one of time of day smoother across colonies versus a model with separate time of day smoothers fitted to each colony. Model selection based on Dawid-Sebastiani scores (DSS) calculated using 10-fold cross-validation. Lower DSS scores are preferred with best performing model for each species highlighted in bold.

GAM Model Formula	DSS	Species
~ s(Time of Day, by = Site, bs = 'cc')	**16.41**	Common Guillemot
~ s(Time of Day, bs = 'cc')	17.17	
~ s(Time of Day, by = Site, bs = 'cc')	**25.29**	Razorbill
~ s(Time of Day, bs = 'cc')	45.52	
~ s(Time of Day, by = Site, bs = 'cc')	**17.44**	European Shag
~ s(Time of Day, bs = 'cc')	66.12	

GAM Results Tables – Diel Diving Activity

Table S12. Details on fitted GAM smoothers modelling the influence of time of day on diving activity for Guillemot, Razorbill and European Shag. Different smoothers fitted for each colony. Deviance explained is the % deviance explained for data from each specific colony. *F* and *p* values associated with each smoother also provided.

Species	Smoother			
Common Guillemot	Colony - CSY s(Time of Day)	edf = 6.35	Deviance Explained: 60.1%	F= 6.1, p = <0.001, n = 29 individuals
	Colony - FAI s(Time of Day)	edf = 0.001	Deviance Explained: 0.1%	F= 0, p = 0.45, n = 7 individuals
	Colony - FOW s(Time of Day)	edf = 5.27	Deviance Explained: 59.3%	F= 7.1, p = <0.001, n = 7 individuals
	Colony - WIN s(Time of Day)	edf = 5.94	Deviance Explained: 49.4%	F= 4.4, p = <0.001, n = 4 individuals
Razorbill	Colony - BAR s(Time of Day)	edf = 6.68	Deviance Explained: 84.1%	F= 10.6, p = <0.001, n = 9 individuals
	Colony - CSY s(Time of Day)	edf = 6.76	Deviance Explained: 85.2%	F= 16.5, p = <0.001, n = 24 individuals
	Colony - FAI s(Time of Day)	edf = 6.82	Deviance Explained: 86.9%	F= 15.5, p = <0.001, n = 24 individuals
	Colony - ORK s(Time of Day)	edf = 5.75	Deviance Explained: 86.9%	F= 14.4, p = <0.001, n = 25 individuals
European Shag	Colony – CSY s(Time of Day)	edf = 6.35	Deviance Explained: 95.1%	F= 35.7, p = <0.001, n = 7 individuals
	Colony - ORK s(Time of Day)	edf = 6.35	Deviance Explained: 79.8%	F= 4.8, p = <0.001, n = 8 individuals

GAM Diel Diving Activity Plots At Each Colony

Fig. S5. Diel patterns in diving activity throughout the day for birds tracked at Bardsey Island. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAM with a smoother for time of day. Raw data displayed as black circles. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.

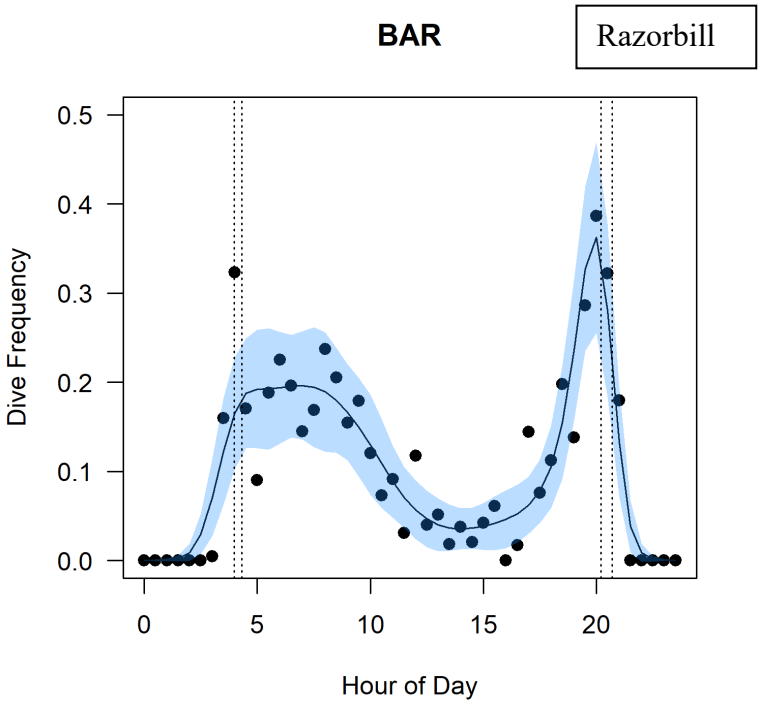


Fig. S6. Diel patterns in diving activity throughout the day for birds tracked at Fair Isle. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAM with a smoother for time of day. Raw data displayed as black circles. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.

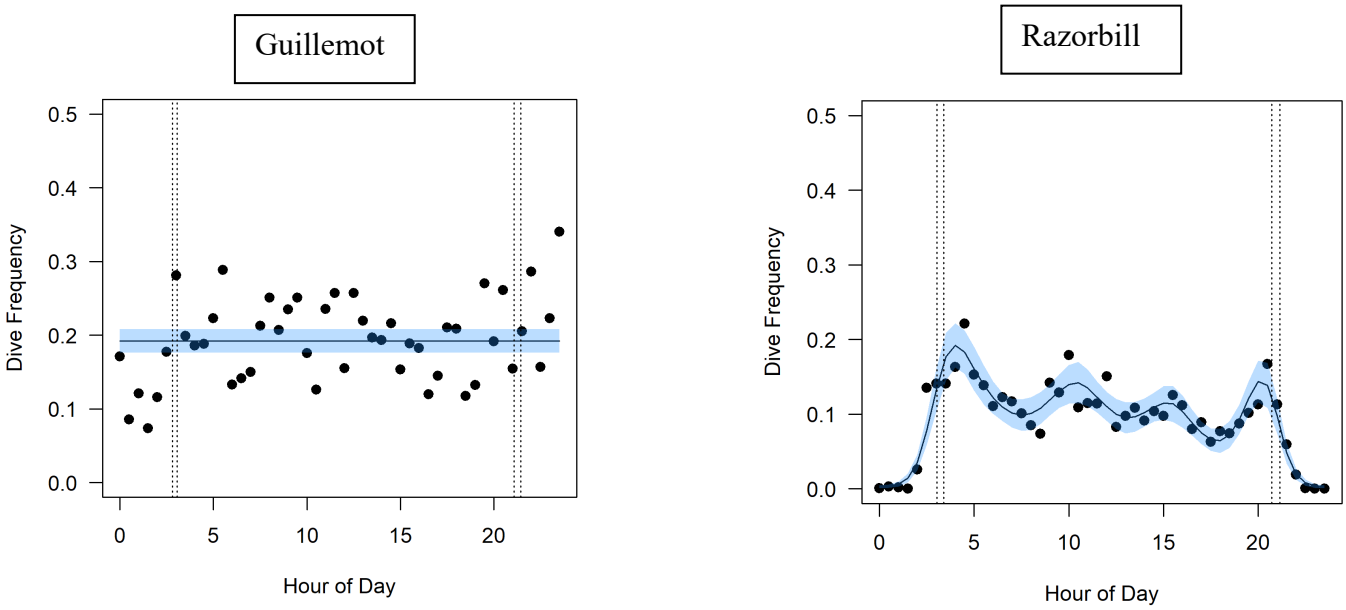


Fig. S7. Diel patterns in diving activity throughout the day for birds tracked at Fowlsheugh. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAM with a smoother for time of day. Raw data displayed as black circles. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.

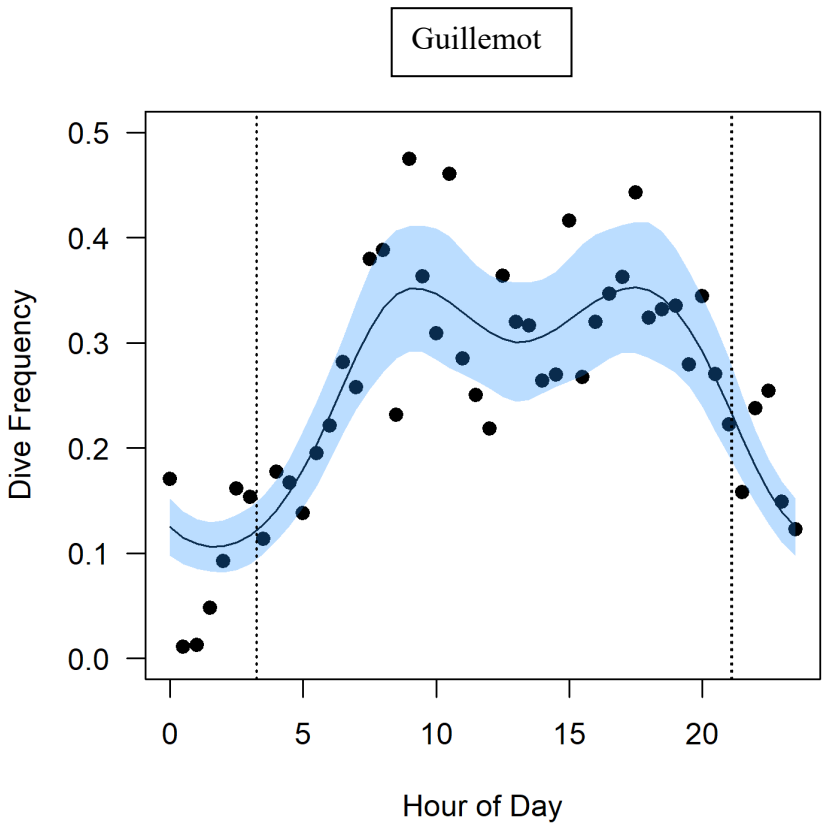


Fig. S8. Diel patterns in diving activity throughout the day for birds tracked at Orkney. Note data from Orkney combines data on birds from the neighbouring islands of Copinsay, Muckle Skerry and Swona. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAM with a smoother for time of day. Raw data displayed as black circles. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.

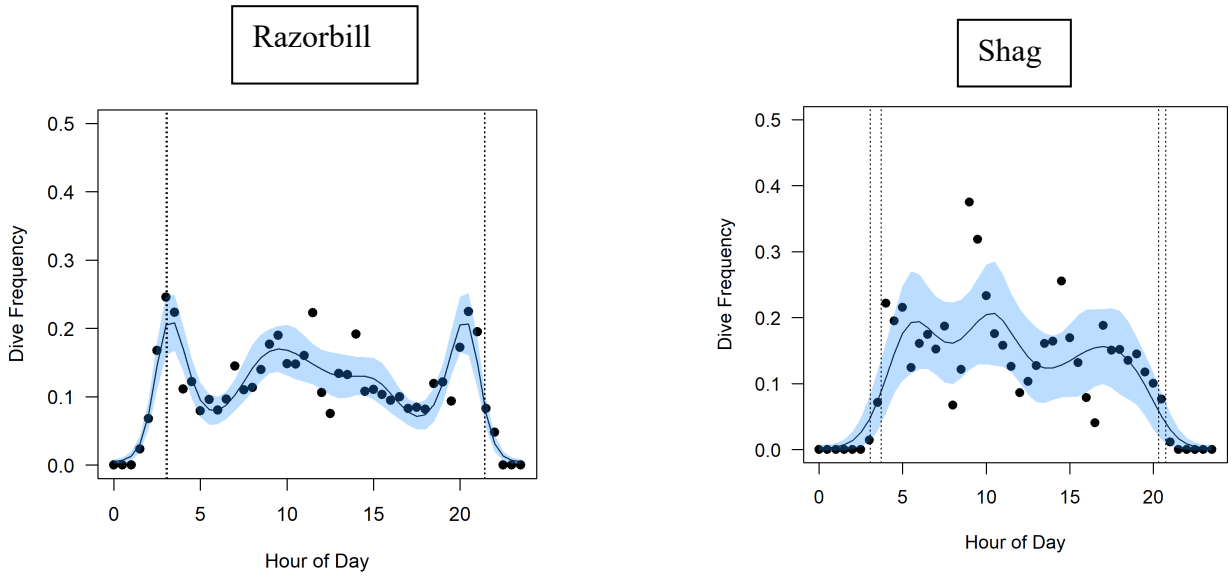
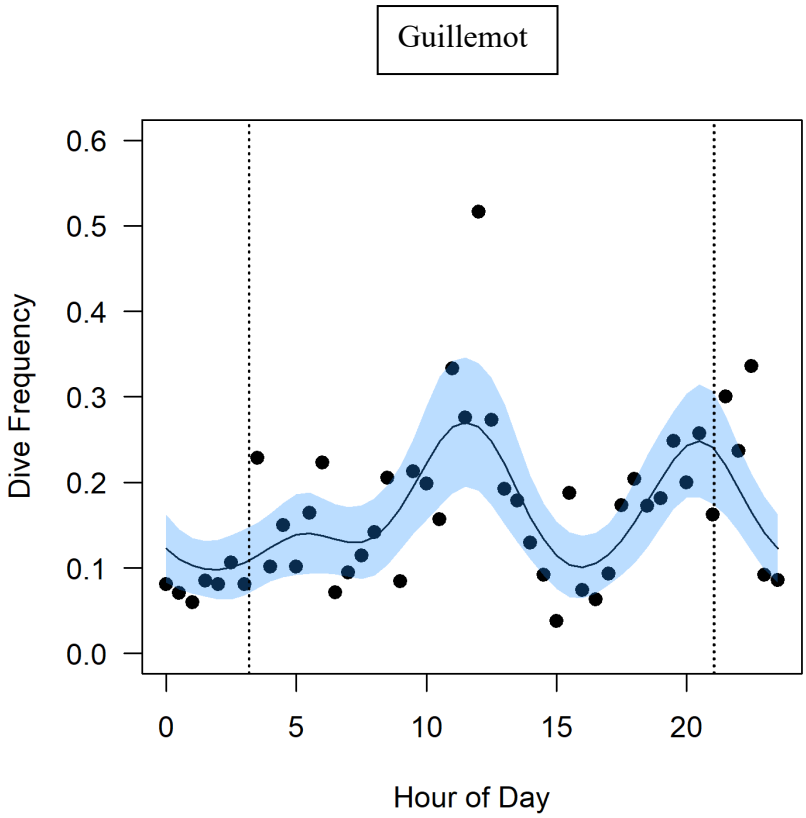


Fig. S9. Diel patterns in diving activity throughout the day for birds tracked at Whinnyfold. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAM with a smoother for time of day. Raw data displayed as black circles. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.



GAM Model Selection Tables – Diel Variation in Dive Depth

Table S13. GAM model selection for tables modelling dive depth for each species. Model selection based on RMSE scores calculated using 10-fold cross-validation. Lower RMSE scores are preferred, top-performing model highlighted in bold text.

GAM Model Formula	RMSE	Species
~s(TimeOfDay, bs = "cc", by = Site) + s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.725	**Common Guillemot**
~ s(TimeOfDay, bs = "cc", by = Site) + s(TimeInTidalCycle, bs = "cc", by = Site) + s(WaterDepth, bs = "cs", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.729	
~ s(TimeOfDay, bs = "cc", by = Site) + s(TimeInTidalCycle, bs = "cc", by = Site) + s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.733	
~ s(TimeOfDay, bs = "cc") + s(WaterDepth, bs = "cs" , by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.738	
~ s(TimeOfDay, bs = "cc") + s(TimeInTidalCycle, bs = "cc") + s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.743	
~ s(TimeOfDay, bs = "cc", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.747	
~ s(WaterDepth, bs = "cs", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.756	
~ s(TimeOfDay, bs = "cc") + s(id, bs = "re") + s(Longitude, Latitude)	0.759	
~ s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.760	
~ s(TimeInTidalCycle, bs = "cc", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.767	
~ s(TimeInTidalCycle, bs = "cc") + s(id, bs = "re") + s(Longitude, Latitude)	0.775	
~ s(id, bs = "re") + s(Longitude, Latitude)	0.775	
~ s(TimeOfDay, bs = "cc", by = Site) + s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.307	**Razorbill**
~ s(TimeOfDay, bs = "cc", by = Site) + s(TimeInTidalCycle, bs = "cc", by = Site) + s(WaterDepth, bs = "cs", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.309	
~ s(TimeOfDay, bs = "cc", by = Site) + s(TimeInTidalCycle, bs = "cc", by = Site) + s(WaterDepth, bs = "cs" + s(id, bs = "re") + s(Longitude, Latitude)	0.312	
~ s(TimeOfDay, bs = "cc", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.313	
~ s(TimeOfDay, bs = "cc") + s(WaterDepth, bs = "cs", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.315	
~ s(TimeOfDay, bs = "cc") + s(TimeInTidalCycle, bs = "cc") + s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.317	
~ s(TimeOfDay, bs = "cc") + s(id, bs = "re") + s(Longitude, Latitude)	0.319	
~ s(WaterDepth, bs = "cs", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.329	
~ s(TimeInTidalCycle, bs = "cc", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.330	
~ s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.331	
~ s(TimeInTidalCycle, bs = "cc") + s(id, bs = "re") + s(Longitude, Latitude)	0.331	
~ s(id, bs = "re") + s(Longitude, Latitude)	0.332	
~ s(TimeOfDay, bs = "cc", by = Site) + s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.192	**European Shag**
~ s(TimeOfDay, bs = "cc", by = Site) + s(TimeInTidalCycle, bs = "cc", by = Site) + s(WaterDepth, bs = "cs", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.193	
~ s(TimeOfDay, bs = "cc", by = Site) + s(TimeInTidalCycle, bs = "cc", by = Site)	0.198	

+ s(WaterDepth, bs = "cs" + s(id, bs = "re") + s(Longitude, Latitude)	
~ s(TimeOfDay, bs = "cc") + s(TimeInTidalCycle, bs = "cc") + s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.202
~ s(TimeOfDay, bs = "cc") + s(WaterDepth, bs = "cs", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.203
~ s(WaterDepth, bs = "cs", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.204
~ s(WaterDepth, bs = "cs") + s(id, bs = "re") + s(Longitude, Latitude)	0.206
~ s(TimeOfDay, bs = "cc", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.308
~ s(TimeInTidalCycle, bs = "cc", by = Site) + s(id, bs = "re") + s(Longitude, Latitude)	0.310
~ s(TimeOfDay, bs = "cc") + s(id, bs = "re") + s(Longitude, Latitude)	0.322
~ s(TimeInTidalCycle, bs = "cc") + s(id, bs = "re") + s(Longitude, Latitude)	0.327
~ s(id, bs = "re") + s(Longitude, Latitude)	0.331

Table S14. Coefficients from a GAM of log-transformed dive depth for Common Guillemot. Separate Time of Day smoothers were run for each colony. The parameter σ Bird ID denotes the standard deviation associated with a random intercept for bird identity. The parameter ø corresponds to the temporal autocorrelation in dive depth within birds. δ1 and δ2 correspond to the parameters in a variance function that includes a constant (δ1) and a power function (δ2). N = 17233 dives from 47 birds. Model R^2 was 0.19.

Coefficient		
Intercept	$\beta_0 = 2.77$	SE = 0.051
GAM Smoothers		
s(Time of Day, CSY)	edf = 6.85	$F = 37.10$, $p = <0.001$
s(Time of Day, FAI)	edf = 6.27	$F = 11.13$, $p = <0.001$
s(Time of Day, FOW)	edf = 6.42	$F = 72.91$, $p = <0.001$
s(Time of Day, WIN)	edf = 6.71	$F = 71.05$. $p = <0.001$
s(Water Depth)	edf = 3.98	$F = 40.13$, $p = <0.001$
s(Longitude, Latitude)	edf = 28.31	$F = 42.34$, $p = <0.001$
Variance Parameters		
σ Bird ID	0.34	
ø Temporal auto-correlation in dive depth	0.76	
δ1	0.0049	
δ2	0.23	

Table S15. Coefficients from a GAM of log-transformed dive depth for Razorbill. Separate Time of Day smoothers were run for each colony. The parameter σ Bird ID denotes the standard deviation associated with a random intercept for bird identity. The parameter ø corresponds to the temporal autocorrelation in dive depth within birds. δ1 and δ2 correspond to the parameters in a variance function that includes a constant (δ1) and a power function (δ2). $N = 24590$ dives from 82 birds. Model R^2 was 0.38.

Coefficient		
Intercept	$\beta_0 = 1.82$	SE = 0.029
GAM Smoothers		
s(Time of Day, BAR)	edf = 7.13	$F = 53.08$, $p = <0.001$
s(Time of Day, CSY)	edf = 6.68	$F = 78.19$, $p = <0.001$
s(Time of Day, FAI)	edf = 6.77	$F = 154.73$, $p = <0.001$
s(Time of Day, ORK)	edf = 6.81	$F = 30.69$. $p = <0.001$
s(Water Depth)	edf = 3.92	$F = 47.84$, $p = <0.001$
s(Longitude, Latitude)	edf = 27.01	$F = 42.93$, $p = <0.001$
Variance Parameters		
σ Bird ID	0.24	
ø Temporal auto-correlation in dive depth	0.68	
δ1	0.039	
δ2	-1.89	

Table S16. Coefficients from a GAM of log-transformed dive depth for European Shag. Separate Time of Day smoothers were run for each colony. The parameter σ Bird ID denotes the standard deviation associated with a random intercept for bird identity. The parameter ø corresponds to the temporal autocorrelation in dive depth within birds. δ1 and δ2 correspond to the parameters in a variance function that includes a constant (δ1) and a power function (δ2). $N = 3974$ dives from 15 birds. Model R^2 was 0.79.

Coefficient		
Intercept	$\beta_0 = 2.92$	SE = 0.030
GAM Smoothers		
s(Time of Day, CSY)	edf = 1.10	$F = 0.40$, $p = 0.041$
s(Time of Day, ORK)	edf = 8.89	$F = 45.85$, $p = <0.001$
s(Water Depth)	edf = 3.98	$F = 648.85$, $p = <0.001$
s(Longitude, Latitude)	edf = 26.52	$F = 38.23$, $p = <0.001$
Variance Parameters		
σ Bird ID	0.11	
ø Temporal auto-correlation in dive depth	0.85	
δ1	27.35	
δ2	3.63	

Fig. S10. Diel patterns in dive depth throughout the day for birds tracked at Bardsey Island. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAMM with a smoother for time of day. Raw data also displayed as grey points. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.

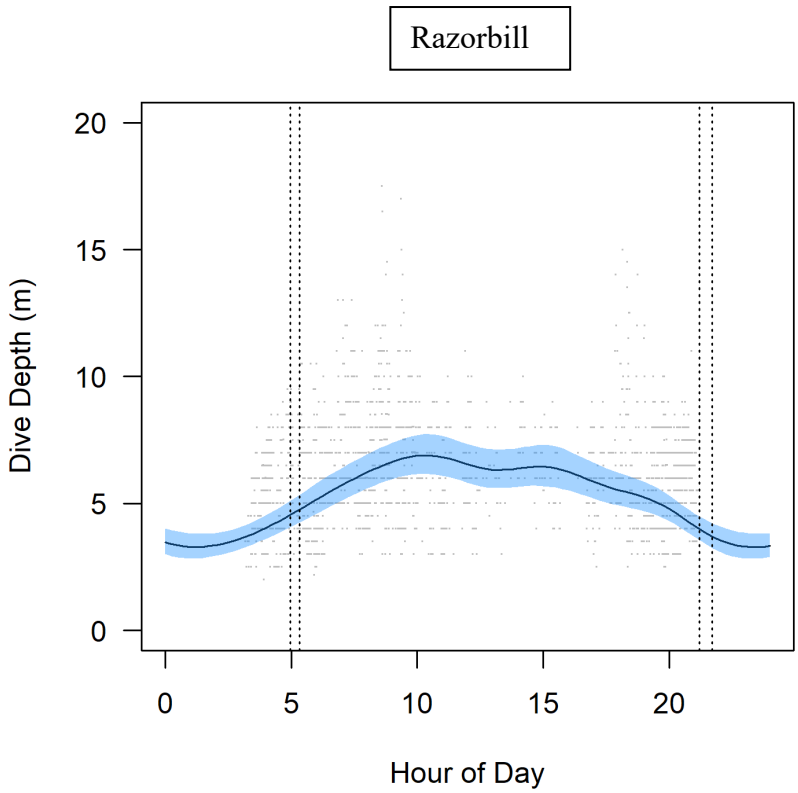


Fig. S11. Diel patterns in dive depth throughout the day for birds tracked at Fair Isle. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAMM with a smoother for time of day. Raw data also displayed as grey points. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.

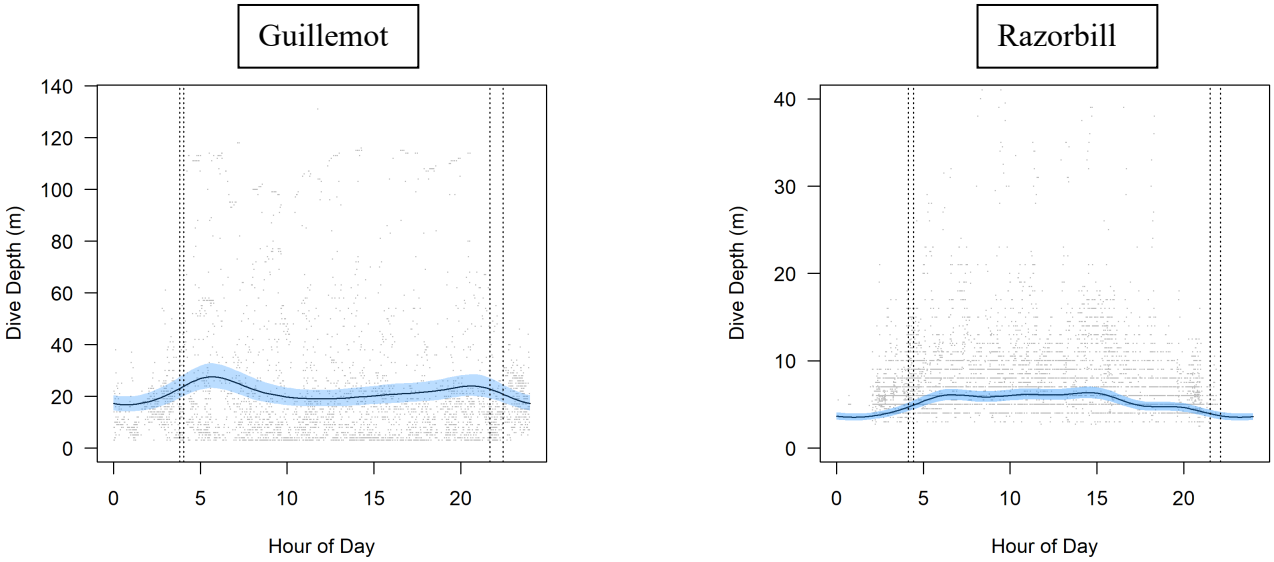


Fig. S12. Diel patterns in dive depth throughout the day for birds tracked at Fowlsheugh. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAMM with a smoother for time of day. Raw data also displayed as grey points. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.

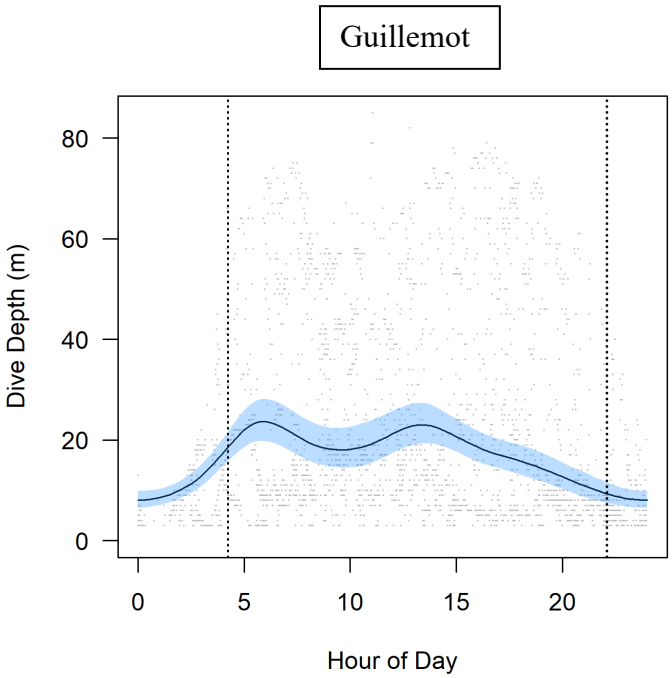


Fig. S13. Diel patterns in dive depth throughout the day for birds tracked at Orkney. Note data from Orkney combines data on birds from the neighbouring islands of Copinsay, Muckle Skerry and Swona. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAMM with a smoother for time of day. Raw data also displayed as grey points. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.

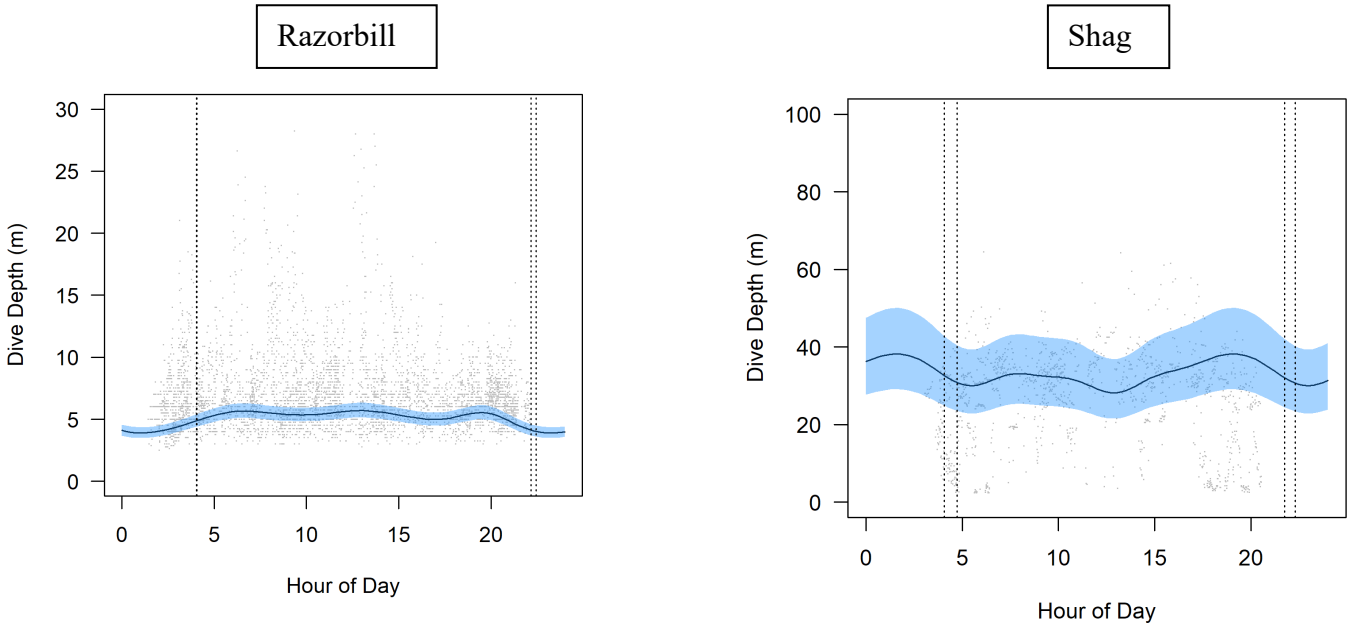
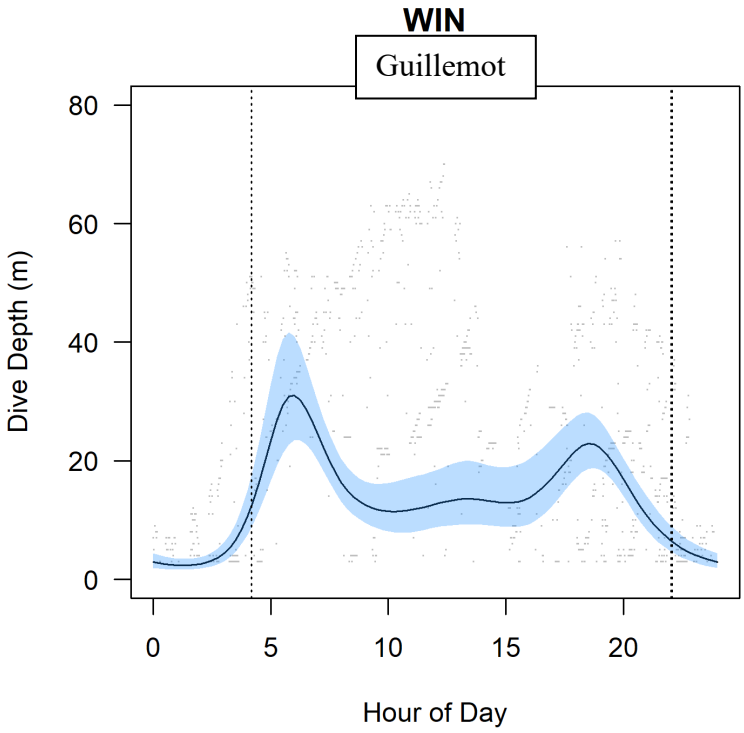


Fig. S14. Diel patterns in dive depth throughout the day for birds tracked at Whinnyfold. Plots show predicted curves and 95% confidence intervals (blue shaded area) from a GAMM with a smoother for time of day. Raw data also displayed as grey points. Dashed vertical lines represents the range of sunrise and sunset times observed over the period birds were tracked.



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