A303 Amesbury to Berwick Down

Applicant's provision of technical reports supporting the Environmental Information Review

Bat Landscape Scale Report (2020)

Document reference: Redetermination 2.9

Planning Act 2008

The Infrastructure Planning (Examination Procedure) Rules 2010

February 2022

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1 Introduction

1.1.1 To inform the baseline of the local bat population for the A303 Amesbury to Berwick Down Scheme (hereafter referred to as the 'Scheme'), a suite of bat surveys was undertaken. These surveys included bat roosting surveys, bat activity surveys, using walked transects, bat crossing point surveys, automated static recording, and advanced licence bat survey techniques, including bat trapping and radio-tracking activities. These bat surveys informed the environmental assessment for the Scheme and were reported in the Environmental Statement (ES) in 2018[1]

1.1.2 In order to provide an update to the baseline presented in the ES and in accordance with current best practice[2] additional bat landscape scale surveys were undertaken over two survey seasons in 2019 and 2020. This method is designed to monitor bat activity at pre-defined distances from linear infrastructure (proposed Scheme) at a landscape scale. It differs from the crossing-point surveys undertaken previously which are used to address bat activity at a more local scale. This approach will allow a comparison to be made of the current bat activity baseline against the future monitoring surveys (informed by using repeated monitoring both during and post-construction. The monitoring will aim to identify changes in bat activity and correlate with various recorded variable. This monitoring of changes over time will specifically focus on species diversity and bat activity levels at a landscape scale, against which the effectiveness of the mitigation/compensation measures will be measured.

1.1.3 This report presents the results of the 2019 and 2020 bat landscape scale surveys, subsequent analysis for the individual years and provides a robust, two-year baseline. The aim of the subsequent monitoring surveys is to identify any statistically significant changes in bat activity and species diversity that can be attributed to the Scheme. The results would be used to assess the effect of the Scheme on the bat populations at a landscape scale.

[1] Highways England (2018) A303 Amesbury to Berwick Down TR010025 6.1 Environmental Statement Chapter 8: Biodiversity [Online] https://infrastructure.planninginspectorate.gov.uk/wp-content/ipc/uploads/projects/TR010025/TR010025-000199-6-1_ES_Chapters_08_Biodiversity.pdf

2 Methods

2.1.1 All of the bat landscape scale surveys were carried out in accordance with current best practice[2].

2.2 Scoping of transect locations

2.2.1 Transects were selected using desk-based applications such as OS maps and Google maps, with the aim of selecting an equal number of transects either side of the Scheme. To ensure continued future access transects were located along public rights of way, including: footpaths, bridleways, byways or minor roads. The transects were 1km in length and ran perpendicular to the Scheme.

2.2.2 Due to a lack of availability of public rights of way perpendicular to the Scheme, as well as health and safety issues related to transects on public roads, it was not possible to survey one of the identified transect (See Appendix B, Figure 1). Therefore, nine individual transect routes were surveyed. To ensure that ten transects were undertaken "Transect 2" was walked twice in opposite directions on separate nights, during both the 2019 and 2020 surveys in line with current best practice[1].

2.2.3 The transects were designed to sample typical habitats within the general landscape, to avoid any habitat extremes that might hide or over emphasise any potential impacts of the proposed Scheme. Wherever possible, transects were located over 500m apart, to avoid pseudo-replication. In two instances, two transects were located within 500m of each other, see limitations Section 2.5.

2.2.4 Spot check locations were measured and marked along the transects (Appendix B, Figure 1), these were located every 100m (i.e. shortest perpendicular distance) from the Scheme between 0 and 1km. The first spot check "0m" was located as close to the Scheme as possible (considering health and safety precautions of working near a busy A road) and "1km" was the last spot check 1km perpendicular from the Scheme. In total eleven spot checks were marked along the transect.

2.3 Survey methods

2.3.1 All surveys were undertaken during suitable weather conditions (>7°C, wind <20km/h, ~12 mph). The weather conditions were recorded at every 10 minute spot check location, along with the number of bat passes, start time, stop time, habitat grade, path type and any additional notes regarding activity. The habitat grades that were recorded at each spot check are categorised below (Table 2-1). These provide a qualitative scale of increasing suitability of habitat for bats (from low (grade 1) to high (grade 5). These were then included within the analysis to determine whether habitat type was a significant variable. The bat detectors were

[2] Berthinussen, A. & Altringham J. (2015) WC1060: Development of a cost-effective method for monitoring the effectiveness of mitigation for bats crossing linear transport infrastructure. Final report to Defra. Appendix E. Landscape scale effects of transport infrastructure: Best practice survey protocol and data analysis.

always held at approximately waist height, pointing upwards and away from the surveyor.

Table 2-1: Habitat grade descriptions

Grade	Description
1	Fence or wall lining road/ path and open fields beyond
2	Hedges/ shrubby verges lining road/ path and open fields beyond
3	Intermittent medium trees/ bushes lining road/ paths and open fields beyond
4	Intermittent tall trees lining road/ path and open fields beyond
5	Continuous tall tree cover lining road/ path with woodland and or open fields beyond

2.3.2 Natural peaks in bat activity occur at certain times after sunset. To reduce any bias in the results through differing bat activity throughout the evening, transects were walked in both directions (towards and away from the Scheme). During the 2019 surveys, five transects were walked away from the Scheme and five transects were walked towards the Scheme, "Transect 2" was repeated on different nights (once away and once towards the Scheme). During the 2020 surveys six transects were walked away from the Scheme and four transects were walked towards the Scheme, "Transect 2" was repeated on different nights (once away and once towards the Scheme).

2.3.3 Survey dates and weather conditions are outlined in Table 2-2.

Table 2-2: Survey dates and weather conditions for all surveys

Date	Direction walked	Transect No.	Sunset	Start time	End time	Range temp (°C)	Rain (0-5)[1]	Cloud cover (0-8)[2]	Wind speed (Beaufort scale)[3]
05/08/19	Away	1	20:48	21:13	23:22	15-18	0	4	2-3
07/08/19	Towards	2	20:43	21:16	23:26	14-16	0	6	1-2
19/08/19	Away	3	20:21	20:49	22:58	11-16	0	1	0-1
20/08/19	Away	4	20:19	20:51	22:55	12-13	0	2	0-1
27/08/19	Towards	5	20:05	20:45	22:51	16-21	0-1	7	-
06/08/19	Towards	6	20:48	21:13	23:19	14-15	0-1	4	2-3
14/08/19	Towards	7	20:31	21:06	23:15	17	0-1	7	2-3
14/08/19	Towards	8	20:31	21:04	23:09	16-19	0-1	7	0-3
15/08/19	Away	9	20:29	20:59	23:10	10-16	0	1	0-1
29/08/19	Away	2 (repeat)	20:00	20:29	22:43	13-18	0	0	0-2
18/08/20	Away	1	20:20	20:50	22:55	17	0	7	2-3
15/09/20	Away	2	19:21	19:56	22:10	13-20	0	0	0
26/08/20	Away	3	20:05	20:35	22:45	15-17	0	6	2
14/09/20	Away	4	19:22	20:01	22:02	15-16	0	0	0
11/08/2020	Towards	5	20:30	21:00	23:02	14-16	0	3	1
04/08/2020	Towards	6	20:48	21:15	23:30	15-16	0	6	2
18/08/20	Away	7	20:21	20:21	23:04	17	0	7	2-3
04/08/2020	Towards	8	20:48	20:48	23:22	15-16	0	6	2

Date	Direction walked	Transect No.	Sunset	Start time	End time	Range temp (°C)	Rain (0-5)[1]	Cloud cover (0-8)[2]	Wind speed (Beaufort scale)[3]
11/08/20	Away	9	20:30	21:00	23:06	14-16	0	3	1
17/09/20	Towards	2 (repeat)	19:15	19:43	21:33	17	0	2	2
[1] Rain scale: 0 = none, 1 = drizzle, 2 = shower, 3 = rain, 4 = downpour, 5 = flood [2] Estimate of cloud cover: 0= sky completely clear, 4= sky half clouded, 8=sky fully clouded [3] Beaufort scale: 0 = calm (<2 km/h), 1= light air (2 - 5 km/h), 2 = light breeze (6 - 11 km/h), 3 = gentle breeze (12 - 19 km/h), 4 = moderate breeze (20 - 28 km/h).									

2.4 Data analysis

2.4.1 Bat calls recorded during the surveys were analysed automatically using BatClassify[3]. Bat species were assigned to all bat call recordings where the bat species probability was greater than an 80% probability threshold. Each bat call recorded was defined as a single bat pass. All bat passes were checked visually using bat explorer[4] as a general quality assurance process (all files were checked against the corresponding sonogram, although not labelled if they had not met the 80% threshold). Each bat pass was then assigned to a spot check location (distance from the Scheme) if applicable. All bat passes recorded outside of the spot checks were omitted from analysis.

2.4.2 The final data spreadsheet for analysis included the following data for each spot check: transect identifier, distance from the proposed Scheme, time after sunset, total number of bat passes, total number of bat species, number of bat passes for each individual species and habitat.

2.4.3 Multiple regression models were used to investigate the relationship between bat activity and distance from the proposed Scheme and examine the effects of other variables (time and habitat) that could influence bat activity and hence the relationship. The analysis was carried out using Generalised Estimating Equations (GEE) using the *geeglm* function from the library *geepack* in the statistical software program R[5], following the DEFRA guidance[6].

2.4.4 Explanatory variables used in the model were distance from the Scheme, habitat grade, and time after sunset as either a linear or quadratic term. A linear term is used to describe a linear relationship between time after sunset and the number of bat passes (e.g. bat activity either increasing or decreasing throughout the evening), and a quadratic term is used to describe a curved relationship (e.g. to show peaks or troughs of bat activity over time). Habitat and time variables are included in the analysis to account for associated variations in bat activity and produce accurate models with unbiased predictions of road/rail effects

[3] [redacted]/ Accessed December 2020 (Version 2014-07-15)
[4] [redacted])
[5] [redacted]/ Accessed December 2020 (Version 3.6.3)
[6] Berthinussen, A. & Altringham J. (2015) WC1060: Development of a cost-effective method for monitoring the effectiveness of mitigation for bats crossing linear transport infrastructure. Final report to Defra. Appendix E. Landscape scale effects of transport infrastructure: Best practice survey protocol and data analysis.

2.4.5 The following information is reported for all GEE model outputs, the estimate, standard error, and the significance of the distance from the Scheme, plus other variables in the final models are tabulated, along with the Scale and Correlation Parameters. The Wald statistic and significance level are reported individually for each variable in the results section, along with the effect size expressed as a percentage.

2.4.6 QICu statistics were used to test for the model with the best subset of co-variants (to show which predictors best explain the responses), with the model with the smallest QICu chosen as the final model. Distance from the Scheme was retained in all models so that the magnitude and standard error of the effect could be inspected regardless of statistical significance.

2.4.7 Species-specific analyses were carried out using the same methods as above for species that were present at more than 30% of spot checks.

2.4.8 The predicted percentage change in bat activity between 0 and 1000m from the proposed Scheme (presented as the effect size %) was calculated using the following formula:

$$\left(\frac{\textit{predicted no. of bat passes at } 1000\ m - \textit{predicted no. of bat passes at } 0\ m}{\textit{predicted no. of bat passes at } 0\ m}\right) \times 100$$

2019 Data Analysis

2.4.9 QICu values identified that distance and time predictors best explain the response variable in the model. As such, plots of predictions were created for the 2019 survey data to display the effect of distance from the proposed Scheme and time after sunset for all bat species passes and number of species.

2.4.10 The following species were present at more than 30% of spot checks and were therefore taken forward to species-specific analysis: common pipistrelle and soprano pipistrelle.

2.4.11 To investigate the effect of the proposed Scheme on bat diversity, the number of species detected at each spot check was converted to a proportion of the total number of species detected across the whole of the study area. GEEs were then fit to the data using the methods outlined above but with a binomial link.

2020 Data Analysis

2.4.12 The QICu values identified that the distance predictor best explains the response variable in the model. As such, plots of predictions were created for the 2020 survey data to display the effect of distance from the proposed Scheme for all bat species passes and number of species.

2.4.13 The following species were present at more than 30% of spot checks and were therefore taken forward to species-specific analysis: common pipistrelle, soprano pipistrelle and *Nyctalus* species. The *Nyctalus* species recorded were mainly noctule, but Leisler's bat has also been recorded in the area in bat activity surveys[7] As the calls of these species cannot always be distinguished, they were aggregated here.

2.4.14 To investigate the effect of the proposed Scheme on bat diversity, the number of species detected at each spot check was converted to a proportion of the total number of species detected across the whole of the study area. GEEs were then fit to the data using the methods outlined above but with a binomial link.

2019 2020 Comparison

2.4.15 In accordance with best practice[8], the data from each year were analysed separately. Comparing the magnitude of current effects between two years of survey is not sufficient to draw reliable conclusions as to whether effect sizes have changed, as the effect size predicted by the model may vary due to other factors. It was however possible to undertake a t-Test (two-sample assuming unequal variances) to compare levels of bat activity over the two seasons and graphs to illustrate the bat activity levels and species abundance between the two years.

2.5 Limitations and assumptions

2.5.1 As detailed above, due to the limited availability of public rights of way perpendicular to the Scheme, and the health and safety risks associated with transects along the roads perpendicular to the Scheme, it was only possible to select nine individual transects. This is not seen as a substantive limitation as one of the transects was walked twice in opposite directions on separate nights, as such, a full suite of surveys has been completed in line with best practice2.

2.5.2 During four of the 2019 transects, a slight drizzle was recorded, and lasted between 15-20 minutes. This was not seen as a limitation as bats were still seen to be active and the rain was very light and only affected a maximum of two spot checks.

2.5.3 Two pairs of transects (Transect 2 and 4, and Transect 5 and 6) were separated by less than 500m for part of their length, about 350m apart at the closest point on the transects. This proximity is unlikely to affect the validity of the results as the surveys were undertaken on separate nights and the transects were located on unconnected linear features. As such, the surveys were considered to be independent.

2.5.4 During the 2019 surveys a total of 763 bat passes were recorded at the spot counts. During the 2020 surveys a total of 636 bat passes were recorded at the spot counts. The sample size is considered suitable to ensure a valid result using the bat landscape survey method.

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[7] Highways England 2018 A303 Amesbury to Berwick Down TR010025 6.3 Environmental Statement Appendices Appendix 8.17 Bat activity report. https://infrastructure.planninginspectorate.gov.uk/wp-content/ipc/uploads/projects/TR010025/TR010025-000412-6-3_ES-Appendix_8.18_BatCrossingPointSurvey.pdf

[8] Berthinussen, A. & Altringham J. (2015) WC1060: Development of a cost-effective method for monitoring the effectiveness of mitigation for bats crossing linear transport infrastructure. Final report to Defra. Appendix E. Landscape scale effects of transport infrastructure: Best practice survey protocol and data analysis.

3 Results

3.1 2019 Results

3.1.1 A total of 763 bat passes including a minimum of eight species were recorded. Common pipistrelle (*Pipistrellus pipistrellus*) was the most abundant species, making up ~53% (n=401) of the total bat passes. The other species or species groups recorded in order of abundance were:

- Soprano pipistrelle (*Pipistrellus pygmaeus*) (27%, n=206);
- *Nyctalus* species and serotine (*Nyctalus* sp. and *Eptesicus* sp.) (~17%, n=128);
- Barbastelle (*Barbastella barbastellus*) (~1%, n=9),
- Daubenton's bat (*Myotis daubentonii*) (~1%, n=7),
- Brown long-eared bat (*Plecotus auritus*) (~1%, n=6),
- Brandt's bat or whiskered bat (*Myotis brandtii* or *Myotis mystacinus*) (~1%, n=5); and,
- Natterer's bat (*Myotis nattereri*) (<1%, n=1).

3.1.2 The QICu analyses indicated that Model 3, containing time and distance as co-variants, was the most appropriate model for both total bat activity and number of bat species analyses, due to the low QICu number.

3.1.3 The GEE analyses of Model 3 identified that the distance from the Scheme was not significant for total bat activity (GEE, Wald $\chi2= 0.279$, $P > 0.05$, effect size = 15%; Table 3-1, Figure 3-1), or the number of bat species (GEE, Wald $\chi2= 0.13$, $P =0.72$; effect size = 13%; Table 3-1, Figure 3-1). As such, the result indicated that there is no significant difference in the number of bat species within the landscape relative to the alignment of the Scheme, despite six of nine different transects starting on or close to the existing A303 (Figure 1). The other three (Transect 2,3 and 4) are on the offline section of the Scheme near Winterbourne Stoke, Transect 3 is offset from the existing A303 by approximately 400m, Transect 2 and 4 do not intersect the existing A303, but at approximately 200m and 400m distant they are both within the potential zone of influence of the existing A303.

3.1.4 Time after sunset was seen to have a significant negative effect on the number of bat passes (GEE, Wald $\chi^2= 6.448$, $P<0.05$; Table 3-1, Figure 3-2), but not on the number of bat species (GEE, Wald $\chi^2= 2.29$, $P>0.05$; Table 3-1, Figure 3-2). This suggests that bat activity reduces towards the end of the survey period.

3.1.5 The correlation between the spot checks conducted along the same route on the same night was moderate for total bat activity (0.465) and the number of bat species (0.406).

Table 3-1: GEE results for total bat activity (log (1+ number of bat passes)) and the number of bat species (proportion of species present per spot check), as a function of the distance from the proposed Scheme and time after sunset (30-150 min)

Coefficients	Bat passes (all species)		No. bat species	
	Estimate	Standard Error	Estimate	Standard Error
Intercept	2.146***	0.316	-0.9088	0.4141
Distance (m)	0.0002	0.0004	0.000160	0.0004
Time	-0.009*	0.003	-0.0059	0.0039
Correlation parameter‡	0.465	0.114	0.406	0.0874
Scale parameter	1.02	0.162	0.128	0.0246
* P < 0.05, ** P< 0.01, *** P< 0.001, . 0.1 (Wald test) ‡ Correlation (on a scale of 0 to 1) between two sequential spot checks along the same transect route on the same night				

3.1.6 Two species were recorded at more than 30% of spot checks allowing individual statistical analyses: common pipistrelle (at 53% of spot checks) and soprano pipistrelle (at 48%). As such, analyses were undertaken individually on these species.

3.1.7 The QICu indicated that Model 3, containing time and distance as co-variants, was the most appropriate model for both these species due to the low QICu number.

3.1.8 The GEE analyses of Model 3 identified that currently distance from the proposed Scheme did not have a significant effect on the bat activity (in the absence of the proposed Scheme) of either common pipistrelle (GEE, Wald χ^2=0.01, P =0.918, effect size = -4%; Table 3-2, Figure 3-1) or soprano pipistrelle (GEE, Wald χ^2= 2.70, P = 0.1006, effect size = 80%; Table 3-2, Figure 3-1). As such, the result indicates that the existing A303 has a limited / negligible effect on the number of common or soprano pipistrelle species within the landscape.

3.1.9 Time after sunset was seen to have a significant negative effect on the number of soprano pipistrelle passes shown (GEE, Wald χ^2= 9.47, P<0.001,Table 3-2, Figure 3-2). This suggests that soprano pipistrelle activity reduces towards the end of the survey period, whereas there was no significant effect of time after sunset for common pipistrelle.

3.1.10 The correlation between the spot checks conducted along the same route on the same night was moderate for common pipistrelle (0.616) and low for soprano pipistrelle (0.246).

Table 3-2: GEE results for common pipistrelle and soprano pipistrelle (log (1+ number of bat passes)), as a function of the distance from the proposed Scheme and time after sunset (30-150 min)

Coefficients	Common pipistrelle		Soprano pipistrelle	
	Estimate	Standard Error	Estimate	Standard Error
Intercept	1.35e+00 ***	3.19e-01	0.9282***	0.1698
Distance (m)	-4.19e-05	4.09e-04	0.0004	0.000263
Time	-5.69e-03	3.31e-03	-0.0064**	0.0020
Correlation parameter‡	0.616	0.0652	0.246	0.187
Scale parameter	1.04	0.148	0.512	0.127

* P < 0.05, ** P< 0.01, *** P< 0.001 (Wald test)

‡ Correlation (on a scale of 0 to 1) between two sequential spot checks along the same transect route on the same night

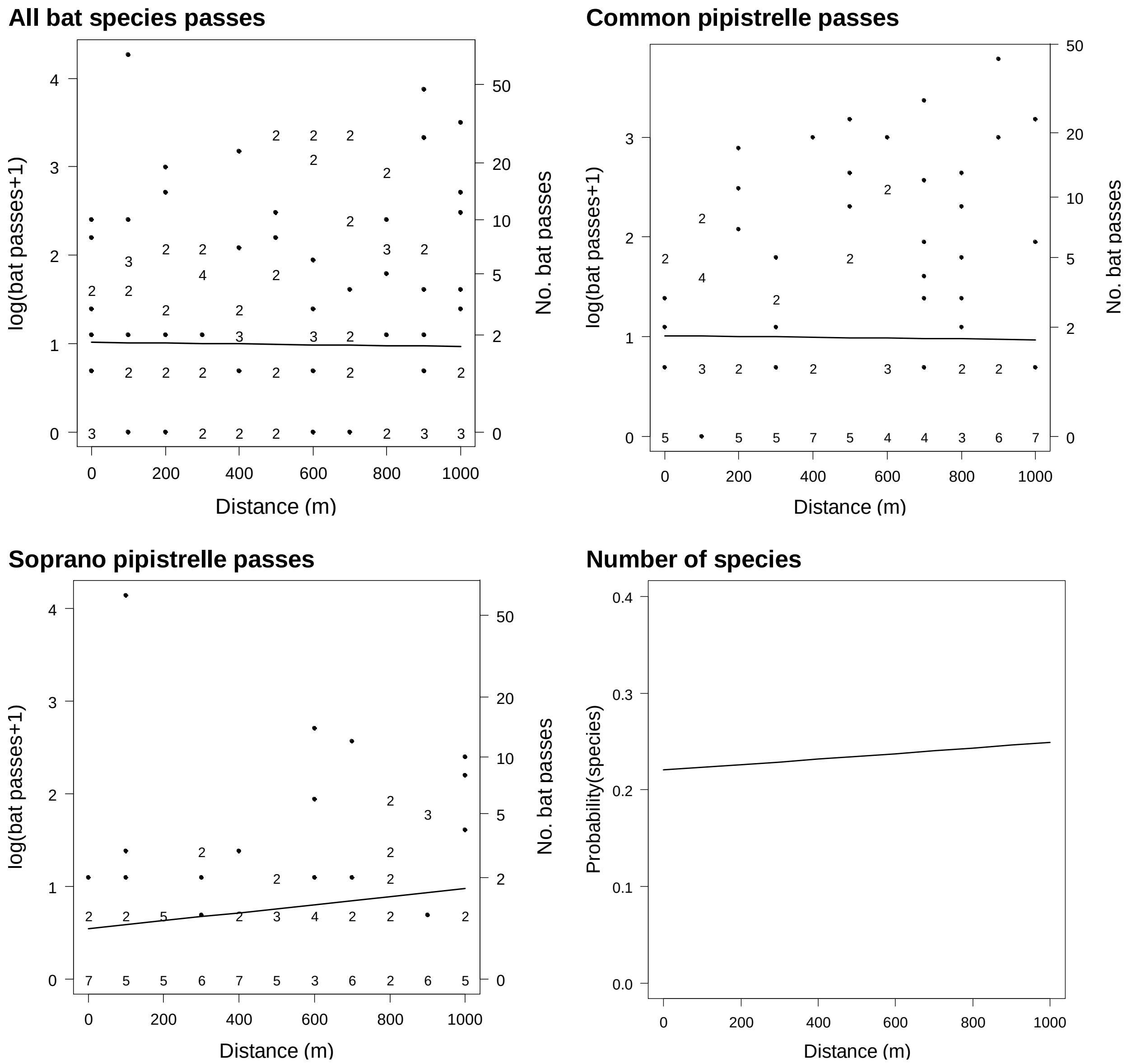


Figure 3-1: Bat activity (bat passes) and bat diversity (number of species) with distance from the proposed Scheme (2019 data).

Plots show the full range of data points on a log scale (numbers represent replicate points, right y axes show the original scale for reference). Lines show the effect of distance from the Scheme as predicted by the final GEE model. Other variables are held constant.

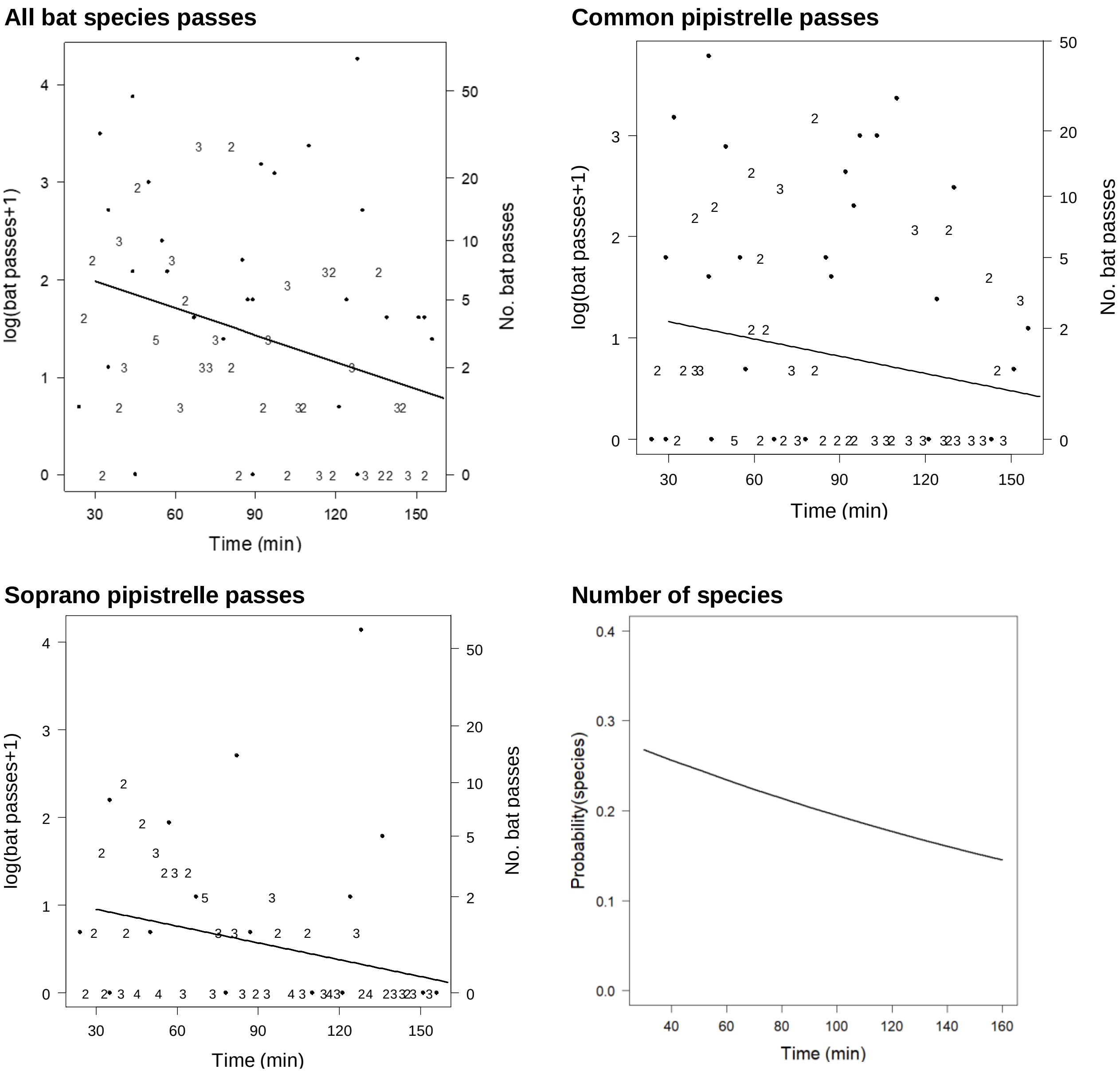


Figure 3-2: Bat activity (bat passes) and bat diversity (number of species) with time after sunset (2019 data).

Plots show the full range of data points on a log scale (numbers represent replicate points, right y axes show the original scale for reference). Lines show the effect of time after sunset as predicted by the final GEE model. Other variables are held constant.

3.2 2020 Results

3.2.1 A total of 636 bat passes including a minimum of eight species were recorded. Common pipistrelle (*Pipistrellus pipistrellus*) was the most abundant species, making up ~45% (n=287) of the total bat passes. The other species or species groups recorded in order of abundance were:

- Soprano pipistrelle (*Pipistrellus pygmaeus*) (22%, n=142);
- *Nyctalus* species and serotine (*Nyctalus* sp. and *Eptesicus* sp.) (~30%, n=193);
- Barbastelle (*Barbastella barbastellus*) (~1%, n=6);
- Daubenton's bat (*Myotis daubentonii*) (~1%, n=7); and
- Brown long-eared bat (*Plecotus auritus*) (<1%, n=1).

3.2.2 It should be noted that the majority of *Nyctalus* species and serotine passes recorded were identified as serotine during the surveys. They are however not differentiated during the bat analysis and are aggregated with the *Nyctalus* species (most of which were identified as noctule) as these species are likely to be unaffected by roads.

3.2.3 The QICu analyses indicated that Model 6, containing distance as a variant, was the most appropriate model for both total bat activity and number of bat species analyses, due to the low QICu result (109.856).

3.2.4 The GEE analyses of Model 6 identified that the distance from the Scheme was not significant for total bat activity (GEE, Wald χ^2= 0.08, $P>0.05$, effect size=6%, Table 3-3, Figure 3-3), or the number of bat species (GEE, Wald χ^2= 0.08, P >0.05, effect size = 8%; Table 3-3, Figure 3-1). As such, the result indicated that the existing A303 has a limited / negligible effect on bat activity or the number of bat species within the landscape.

3.2.5 The correlation between the spot checks conducted along the same route on the same night was moderate for total bat activity (0.366) and the number of bat species (0.395).

Table 3-3: 2020 GEE results for total bat activity (log (1+ number of bat passes)) and the number of bat species (proportion of species present per spot check), as a function of the distance from the proposed Scheme (30-150 min)

Coefficients	Bat passes (all species)		No. bat species	
	Estimate	Standard Error	Estimate	Standard Error
Intercept	0.0154	0.19	-0.158295	0.231072
Distance (m)	-0.00000936	0.000325	0.000112	0.000399
Correlation parameter‡	0.366	0.0859	0.395	0.0121
Scale parameter	0.962	0.105	0.152	0.0183

* P < 0.05, ** P< 0.01, *** P< 0.001, . P<0.1, P =1(Wald test)

‡ Correlation (on a scale of 0 to 1) between two sequential spot checks along the same transect route on the same night

3.3 2020 Species-specific effects

3.3.1 Three species were recorded at more than 30% of spot checks allowing individual statistical analyses: common pipistrelle (at 53% of spot checks), soprano pipistrelle (at 50% of spot checks), *Nyctalus* species and serotine (at 36%). As such, analyses were undertaken individually on these species.

3.3.2 The QICu indicated that Model 6, containing time and distance as co-variants, was the most appropriate model for all species due to the low QICu number.

3.3.3 The GEE analyses of Model 6 identified that distance from the proposed Scheme did not have a significant effect on the bat activity of *Nyctalus* species and serotine (GEE, Wald χ^2=1.41, $P>0.05$, effect size = -41%; Table 3-4, Figure 3-3), common pipistrelle (GEE, Wald χ^2= <0.00, $P>0.05$, effect size = 7%; Table 3-4, Figure 3-3), and soprano pipistrelle (GEE, Wald χ^2= 0.18, $P>0.05$, effect size = 18%; Table 3-4, Figure 3-3). As such, the result indicates that the existing A303 has a limited / negligible effect on the number of common pipistrelle, soprano pipistrelle, or *Nyctalus* species and serotine species within the landscape.

3.3.4 The correlation between the spot checks conducted along the same route on the same night was moderate for *Nyctalus* species and serotine species (0.449) and common pipistrelle (0.363) and low for soprano pipistrelle (0.173).

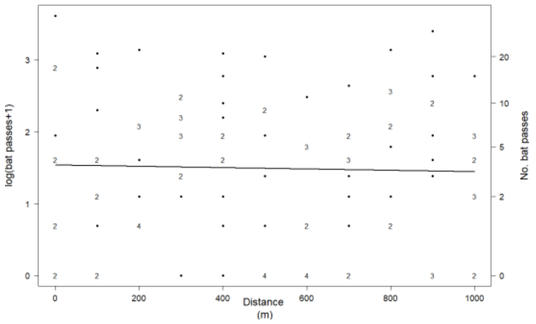
Table 3-4: GEE results for common pipistrelle, soprano pipistrelle and *Nyctalus* species and serotine (log (1+ number of bat passes)), as a function of the distance from the proposed Scheme and time after sunset (30-150 min)

Coefficients	Common pipistrelle		Soprano pipistrelle		*Nyctalus* species and serotine	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Intercept	0.743	0.83	0.51	0.35	0.931088	0.157730
Distance (m)	0.0000173	0.000284	0.0000935	0.00022	-0.000389	0.000327
Correlation parameter‡	0.363	0.148	0.173	0.128	0.449	0.108
Scale parameter	0.889	0.122	0.442	0.0479	0.462	0.07

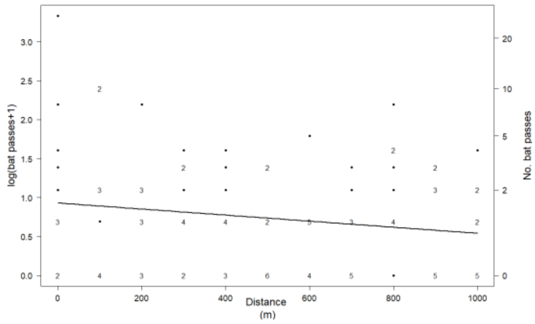
* P < 0.05, ** P< 0.01, *** P< 0.001 (Wald test)

‡ Correlation (on a scale of 0 to 1) between two sequential spot checks along the same transect route on the same night

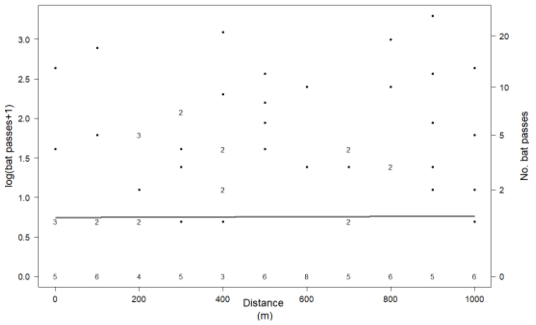
All bat species passes



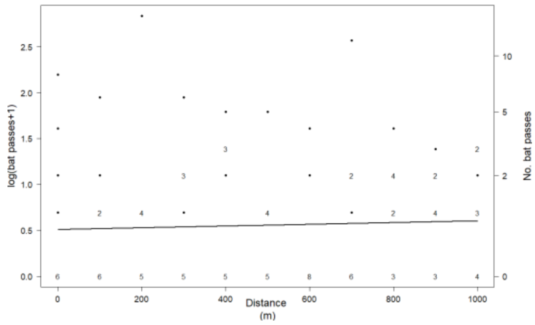
Nyctalus species and serotine passes



Common pipistrelle passes



Soprano pipistrelle passes



Number of species

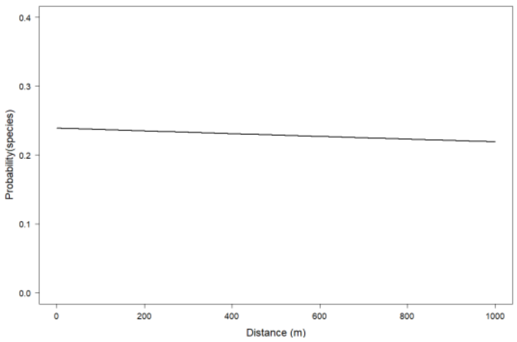


Figure 3-3: Bat activity (bat passes) and bat diversity (number of species) with distance from the proposed Scheme.
Plots show the full range of data points on a log scale (numbers represent replicate points, right y axes show the original scale for reference). Lines show the effect of distance from the Scheme as predicted by the final GEE model. Other variables are held constant.

3.4 2019 2020 Comparison

3.4.1 During the 2019 surveys a total of 763 bat passes were recorded at the spot counts from a minimum of eight species (Figure 3-4). During the 2020 surveys a total of 636 bat passes were recorded at the spot counts from a minimum of six different species (Figure 3-4). The levels of bat activity were compared across the years using a t-test with unequal variance, (t Stat-0.93, df=183, P>0.05), the result was not significant, meaning that the bat activity levels recorded in 2019 were not significantly different from the 2020 bat activity levels.

3.4.2 During both the 2019 and 2020 surveys, the most commonly recorded species were common pipistrelle, soprano pipistrelle and *Nyctalus* species and serotine (Figure 3-4). Although not significantly different, bat activity levels across the transects and years, have small differences, with more bat activity recorded during the 2020 surveys at Transect 1 and 2, and less bat activity being recorded in 2020 at Transect 6 to 8 (Figure 3-5).

2019 **2020**

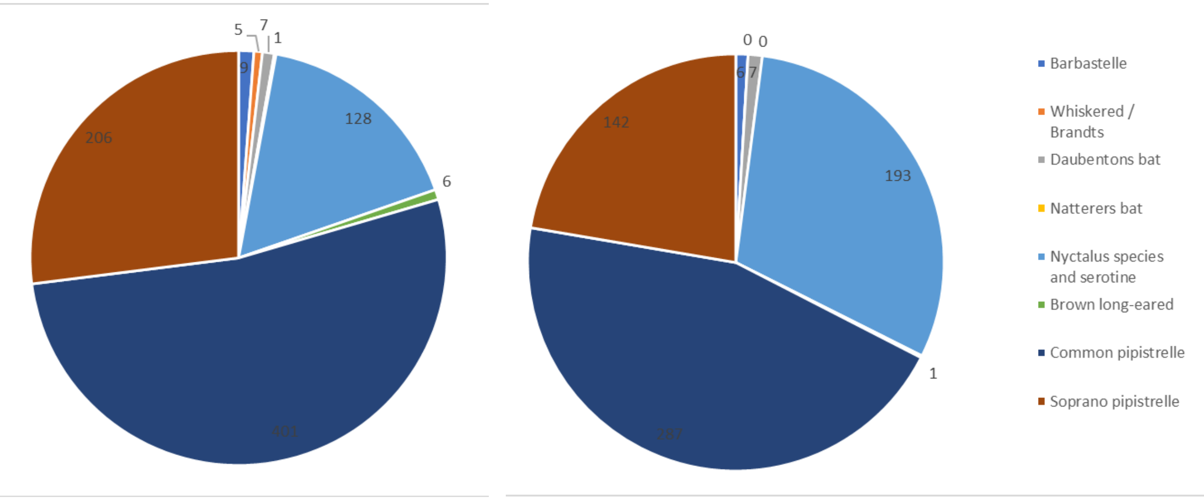
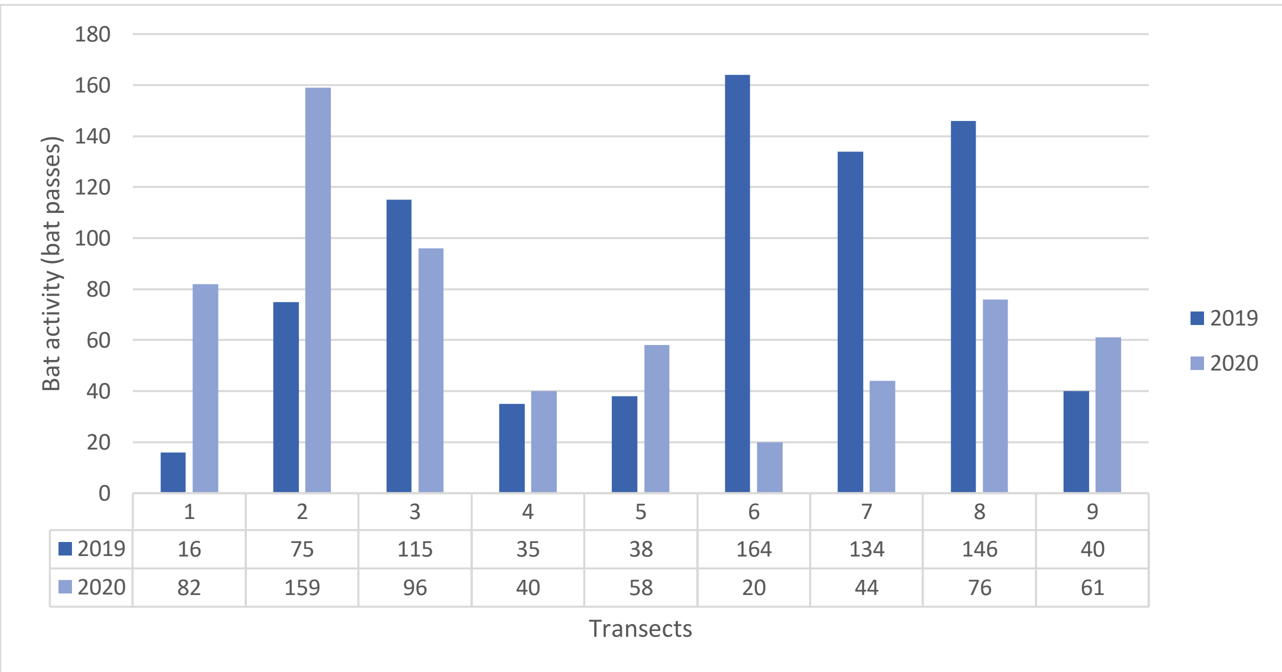


Figure 3-4: Bat species composition / abundance during the 2019 – 2020 surveys



	1	2	3	4	5	6	7	8	9
2019	16	75	115	35	38	164	134	146	40
2020	82	159	96	40	58	20	44	76	61

Figure 3-5: Bat activity along the transect of the 2019 – 2020 surveys

4 Conclusions

4.1.1 There was no significant difference in species abundance of bats at various distances from the existing A303 and / or the route of the proposed Scheme during both the 2019 and 2020 surveys (there is no correlation of distance along transects and species abundance). The bat landscape surveys were not intended to assess the effects of the existing A303 alignment – they are intended to inform future monitoring of the Scheme. It should be noted that the surveys are based on the route of the Scheme, which is up to 400m from the existing A303 alignment, at Winterbourne Stoke, where the Scheme will provide a bypass north of the village (evident in Transect 2 and 3, which together cross both the existing A303 and the Scheme and to a lesser extent Transect 4, which starts about 200m north of the existing A303). Despite this, as the other five transects are much closer to the existing A303 that it is likely that if the highway was having a significant effect on bat activity at landscape scale it would be apparent as a trend in the 2019 and 2020 data.

4.1.2 The data suggests that time had a significant effect on all species bat activity and a species-specific effect on soprano pipistrelle activity during the 2019 surveys. Time was negatively correlated with bat activity, indicating that bat activity declines during the first two hours after sunset. The 2020 results and analysis did not indicate that time had an impact on bat activity or specific species that were analysed (common pipistrelle, soprano pipistrelle and *Nyctalus* species and serotine species).

4.1.3 Habitat grade and distance did not show either a positive or negative effect on the species abundance or diversity.

4.1.4 It should be noted that the landscape is very open and exposed, this is reflected in the relatively low total number of bat passes and species present across the Scheme.

4.1.5 The results within this report provide a baseline for further monitoring both during and post-construction. The methodology within this report will be repeated to allow a comparison to be made between the current baseline and the future baseline. This comparison will indicate whether a change in bat activity has occurred at a landscape scale and whether that change is likely to be attributable to the Scheme.

Appendix A Raw Data spreadsheets

A.1 2019 Raw Data

Route	Direction	Date	Distance (m)	Sunset	Spot start time	Time after sunset (mins)	No. bat passes	No. bat species	Bbar	Malc	Mbec	Mbra Mmys	Mdau	Mnat	NSL	Paur	Ppip	Ppyg	Rfer	Rhip	Habitat grade
1	away	05/08/2019	0	20:48:00	21:15:00	26	4	2	0	0	0	0	0	0	3	0	1	0	0	0	1
1	away	05/08/2019	100	20:48:00	21:28:00	39	1	1	0	0	0	0	0	0	0	0	1	0	0	0	1
1	away	05/08/2019	200	20:48:00	21:42:00	53	3	1	0	0	0	0	0	0	3	0	0	0	0	0	1
1	away	05/08/2019	300	20:48:00	21:51:00	62	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1
1	away	05/08/2019	400	20:48:00	22:02:00	73	2	2	0	0	0	0	0	0	1	0	1	0	0	0	1
1	away	05/08/2019	500	20:48:00	22:13:00	84	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
1	away	05/08/2019	600	20:48:00	22:24:00	95	3	2	0	0	0	0	0	0	1	0	0	2	0	0	1
1	away	05/08/2019	700	20:48:00	22:35:00	106	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1
1	away	05/08/2019	800	20:48:00	22:47:00	119	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
1	away	05/08/2019	900	20:48:00	22:59:00	131	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
1	away	05/08/2019	1000	20:48:00	23:11:00	143	1	1	0	0	0	0	0	1	0	0	0	0	0	0	1
2	towards	07/08/2019	0	20:43:00	23:16:00	153	4	2	1	0	0	0	0	0	0	0	3	0	0	0	2
2	towards	07/08/2019	100	20:43:00	23:05:00	142	4	1	0	0	0	0	0	0	0	0	4	0	0	0	2
2	towards	07/08/2019	200	20:43:00	22:53:00	130	14	3	1	0	0	0	0	0	2	0	11	0	0	0	2
2	towards	07/08/2019	300	20:43:00	22:42:00	119	7	3	0	0	0	0	0	0	1	0	3	3	0	0	2
2	towards	07/08/2019	400	20:43:00	22:31:00	108	1	1	0	0	0	0	0	0	0	0	0	1	0	0	2
2	towards	07/08/2019	500	20:43:00	22:19:00	96	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1
2	towards	07/08/2019	600	20:43:00	22:07:00	84	1	1	0	0	0	0	0	0	1	0	0	0	0	0	3
2	towards	07/08/2019	700	20:43:00	21:53:00	70	2	1	0	0	0	0	0	0	0	0	0	2	0	0	2
2	towards	07/08/2019	800	20:43:00	21:40:00	57	7	2	0	0	0	0	0	0	0	0	1	6	0	0	1
2	towards	07/08/2019	900	20:43:00	21:28:00	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	towards	07/08/2019	1000	20:43:00	21:16:00	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2

Route	Direction	Date	Distance (m)	Sunset	Spot start time	Time after sunset (mins)	No. bat passes	No. bat species	Bbar	Malc	Mbec	Mbra Mmys	Mdau	Mnat	NSL	Paur	Ppip	Ppyg	Rfer	Rhip	Habitat grade
2	away	29/08/2019	0	20:00:00	20:29:00	29	8	3	0	0	0	0	0	0	2	0	5	1	0	0	2
2	away	29/08/2019	100	20:00:00	20:40:00	40	6	3	0	0	0	0	0	0	1	0	4	1	0	0	2
2	away	29/08/2019	200	20:00:00	20:52:00	52	7	6	1	0	0	1	2	0	1	0	1	1	0	0	2
2	away	29/08/2019	300	20:00:00	21:03:00	63	6	3	0	0	0	0	0	0	2	0	3	1	0	0	2
2	away	29/08/2019	400	20:00:00	21:14:00	74	7	3	1	0	0	0	0	0	3	0	0	3	0	0	3
2	away	29/08/2019	500	20:00:00	21:29:00	89	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	away	29/08/2019	600	20:00:00	21:42:00	102	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	away	29/08/2019	700	20:00:00	21:54:00	114	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	away	29/08/2019	800	20:00:00	22:08:00	128	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	away	29/08/2019	900	20:00:00	22:20:00	140	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	away	29/08/2019	1000	20:00:00	22:33:00	153	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
3	away	19/08/2019	0	20:21:00	20:49:00	27	10	2	0	0	0	0	0	0	6	0	4	0	0	0	2
3	away	19/08/2019	100	20:21:00	21:01:00	39	10	2	0	0	0	0	0	0	0	0	8	2	0	0	2
3	away	19/08/2019	200	20:21:00	21:12:00	50	19	3	0	0	0	0	0	0	0	1	17	1	0	0	2
3	away	19/08/2019	300	20:21:00	21:24:00	62	5	1	0	0	0	0	0	0	0	0	5	0	0	0	1
3	away	19/08/2019	400	20:21:00	21:36:00	74	2	1	0	0	0	0	0	0	2	0	0	0	0	0	1
3	away	19/08/2019	500	20:21:00	21:47:00	85	8	3	0	0	0	0	0	0	2	0	5	1	0	0	1
3	away	19/08/2019	600	20:21:00	21:59:00	97	21	3	0	0	0	0	0	0	1	0	19	1	0	0	1
3	away	19/08/2019	700	20:21:00	22:12:00	110	28	1	0	0	0	0	0	0	0	0	28	0	0	0	1
3	away	19/08/2019	800	20:21:00	22:25:00	124	5	2	0	0	0	0	0	0	0	0	3	2	0	0	4
3	away	19/08/2019	900	20:21:00	22:37:00	136	7	2	0	0	0	0	0	0	2	0	0	5	0	0	1
3	away	19/08/2019	1000	20:21:00	22:48:00	147	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
4	away	20/08/2019	0	20:19:00	20:51:00	32	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1
4	away	20/08/2019	100	20:19:00	21:03:00	44	7	2	0	0	0	0	0	0	0	0	4	3	0	0	3
4	away	20/08/2019	200	20:19:00	21:14:00	54	1	1	0	0	0	0	0	0	0	0	0	1	0	0	2
4	away	20/08/2019	300	20:19:00	21:27:00	67	4	2	0	0	0	0	0	0	2	0	0	2	0	0	2
4	away	20/08/2019	400	20:19:00	21:38:00	78	3	2	0	0	0	0	0	0	1	2	0	0	0	0	1

Route	Direction	Date	Distance (m)	Sunset	Spot start time	Time after sunset (mins)	No. bat passes	No. bat species	Bbar	Malc	Mbec	Mbra Mmys	Mdau	Mnat	NSL	Paur	Ppip	Ppyg	Rfer	Rhip	Habitat grade
4	away	20/08/2019	500	20:19:00	21:49:00	89	5	2	0	0	0	0	0	0	3	2	0	0	0	0	2
4	away	20/08/2019	600	20:19:00	22:01:00	102	6	2	0	0	0	0	0	0	5	0	1	0	0	0	2
4	away	20/08/2019	700	20:19:00	22:14:00	115	2	2	0	0	0	0	0	0	1	0	1	0	0	0	1
4	away	20/08/2019	800	20:19:00	22:25:00	126	2	2	0	0	0	0	0	0	1	0	0	1	0	0	1
4	away	20/08/2019	900	20:19:00	22:36:00	137	1	1	0	0	0	0	0	0	0	1	0	0	0	0	3
4	away	20/08/2019	1000	20:19:00	22:45:00	146	3	2	2	0	0	0	0	0	0	0	0	1	0	0	3
5	towards	27/08/2019	0	20:05:00	22:41:00	156	3	2	0	0	0	0	0	0	1	0	2	0	0	0	1
5	towards	27/08/2019	100	20:05:00	22:30:00	145	1	1	0	0	0	0	0	0	0	0	1	0	0	0	1
5	towards	27/08/2019	200	20:05:00	22:17:00	132	3	3	0	0	0	0	1	0	0	0	1	1	0	0	1
5	towards	27/08/2019	300	20:05:00	22:06:00	121	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1
5	towards	27/08/2019	400	20:05:00	21:53:00	108	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
5	towards	27/08/2019	500	20:05:00	21:38:00	93	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1
5	towards	27/08/2019	600	20:05:00	21:26:00	81	2	2	0	0	0	0	0	0	0	0	1	1	0	0	1
5	towards	27/08/2019	700	20:05:00	21:15:00	70	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1
5	towards	27/08/2019	800	20:05:00	21:04:00	59	8	3	0	0	0	0	0	0	3	0	2	3	0	0	1
5	towards	27/08/2019	900	20:05:00	20:57:00	52	7	2	0	0	0	0	0	0	3	0	0	4	0	0	1
5	towards	27/08/2019	1000	20:05:00	20:45:00	40	11	2	0	0	0	0	0	0	1	0	0	10	0	0	1
6	towards	06/08/2019	0	20:48:00	23:08:00	140	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
6	towards	06/08/2019	100	20:48:00	22:56:00	128	70	3	0	0	0	0	0	0	1	0	7	62	0	0	2
6	towards	06/08/2019	200	20:48:00	22:45:00	116	7	1	0	0	0	0	0	0	0	0	7	0	0	0	1
6	towards	06/08/2019	300	20:48:00	22:34:00	105	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
6	towards	06/08/2019	400	20:48:00	22:21:00	92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
6	towards	06/08/2019	500	20:48:00	22:10:00	81	28	3	0	0	0	0	0	0	4	0	23	1	0	0	1
6	towards	06/08/2019	600	20:48:00	21:58:00	69	28	3	0	0	0	0	0	0	11	0	11	6	0	0	1
6	towards	06/08/2019	700	20:48:00	21:48:00	59	10	3	0	0	0	0	0	0	6	0	3	1	0	0	1
6	towards	06/08/2019	800	20:48:00	21:35:00	46	18	3	0	0	0	0	0	0	8	0	9	1	0	0	1
6	towards	06/08/2019	900	20:48:00	21:24:00	35	2	2	0	0	0	0	0	0	1	0	1	0	0	0	1

Route	Direction	Date	Distance (m)	Sunset	Spot start time	Time after sunset (mins)	No. bat passes	No. bat species	Bbar	Malc	Mbec	Mbra Mmys	Mdau	Mnat	NSL	Paur	Ppip	Ppyg	Rfer	Rhip	Habitat grade
6	towards	06/08/2019	1000	20:48:00	21:13:00	24	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1
7	towards	14/08/2019	0	20:31:00	23:05:00	154	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
7	towards	14/08/2019	100	20:31:00	22:53:00	142	5	1	0	0	0	0	0	0	0	0	5	0	0	0	1
7	towards	14/08/2019	200	20:31:00	22:41:00	130	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1
7	towards	14/08/2019	300	20:31:00	22:29:00	118	2	2	0	0	0	0	0	0	1	0	1	0	0	0	1
7	towards	14/08/2019	400	20:31:00	22:17:00	106	2	2	0	0	0	0	0	0	1	0	1	0	0	0	1
7	towards	14/08/2019	500	20:31:00	22:06:00	95	11	2	0	0	0	0	0	0	0	0	9	2	0	0	1
7	towards	14/08/2019	600	20:31:00	21:53:00	82	24	2	0	0	0	0	0	0	0	0	10	14	0	0	1
7	towards	14/08/2019	700	20:31:00	21:41:00	70	26	3	0	0	0	0	0	0	2	0	12	12	0	0	1
7	towards	14/08/2019	800	20:31:00	21:30:00	59	22	3	0	0	0	0	0	0	2	0	13	7	0	0	1
7	towards	14/08/2019	900	20:31:00	21:18:00	47	27	3	0	0	0	0	0	0	2	0	19	6	0	0	1
7	towards	14/08/2019	1000	20:31:00	21:06:00	35	14	2	0	0	0	0	0	0	0	0	6	8	0	0	1
8	towards	14/08/2019	0	20:31:00	22:59:00	148	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
8	towards	14/08/2019	100	20:31:00	22:48:00	137	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
8	towards	14/08/2019	200	20:31:00	22:37:00	126	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
8	towards	14/08/2019	300	20:31:00	22:26:00	115	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
8	towards	14/08/2019	400	20:31:00	22:15:00	103	23	2	0	0	0	0	0	0	4	0	19	0	0	0	3
8	towards	14/08/2019	500	20:31:00	22:04:00	92	23	3	0	0	0	0	0	0	8	0	13	2	0	0	1
8	towards	14/08/2019	600	20:31:00	21:53:00	81	2	2	0	0	0	0	0	0	0	0	1	1	0	0	4
8	towards	14/08/2019	700	20:31:00	21:41:00	69	9	3	0	0	0	0	0	0	2	0	6	1	0	0	4
8	towards	14/08/2019	800	20:31:00	21:27:00	55	10	3	0	0	0	0	0	0	2	0	5	3	0	0	1
8	towards	14/08/2019	900	20:31:00	21:16:00	44	47	3	0	0	0	1	0	0	3	0	43	0	0	0	5
8	towards	14/08/2019	1000	20:31:00	21:04:00	32	32	3	0	0	0	0	0	0	5	0	23	4	0	0	5
9	away	15/08/2019	0	20:29:00	20:59:00	29	2	1	0	0	0	0	0	0	0	0	0	2	0	0	5
9	away	15/08/2019	100	20:29:00	21:10:00	41	2	2	0	0	0	0	0	0	0	0	1	1	0	0	4
9	away	15/08/2019	200	20:29:00	21:21:00	52	2	2	0	0	0	0	0	0	1	0	0	1	0	0	2
9	away	15/08/2019	300	20:29:00	21:33:00	64	5	2	0	0	0	0	0	0	0	0	2	3	0	0	2

Route	Direction	Date	Distance (m)	Sunset	Spot start time	Time after sunset (mins)	No. bat passes	No. bat species	Bbar	Malc	Mbec	Mbra Mmys	Mdau	Mnat	NSL	Paur	Ppip	Ppyg	Rfer	Rhip	Habitat grade
9	away	15/08/2019	400	20:29:00	21:44:00	75	3	2	0	0	0	0	0	0	2	0	0	1	0	0	2
9	away	15/08/2019	500	20:29:00	21:56:00	87	5	2	0	0	0	0	0	0	0	0	4	1	0	0	2
9	away	15/08/2019	600	20:29:00	22:12:00	103	2	2	0	0	0	0	0	0	1	0	0	1	0	0	3
9	away	15/08/2019	700	20:29:00	22:25:00	116	4	1	0	0	0	0	0	0	0	0	4	0	0	0	3
9	away	15/08/2019	800	20:29:00	22:36:00	127	7	5	0	0	0	2	1	0	1	0	1	2	0	0	3
9	away	15/08/2019	900	20:29:00	22:48:00	139	4	3	0	0	0	0	2	0	0	0	1	1	0	0	3
9	away	15/08/2019	1000	20:29:00	23:00:00	151	4	4	1	0	0	1	1	0	0	0	1	0	0	0	3

A.2 2020 Raw Data

Route	Direction	Date	Dist	Sunset	Spot start time (min)	Time After sunset	Pass	Species	Bbar	Mbra / Mmys	Mdau	Mnat	NSL	Paur	Ppip	Ppyg	Rfer	Rhip	Habitat grade
1	AWAY	18/08/2020	0	20:20	20:50	30	4	2	0	0	0	0	3	0	1	0	0	0	1
1	AWAY	18/08/2020	100	20:20	21:01	41	0	0	0	0	0	0	0	0	0	0	0	0	1
1	AWAY	18/08/2020	200	20:20	21:12	52	7	3	0	0	0	0	1	0	5	1	0	0	1
1	AWAY	18/08/2020	300	20:20	21:24	64	0	0	0	0	0	0	0	0	0	0	0	0	1
1	AWAY	18/08/2020	400	20:20	21:36	76	2	0	0	0	0	0	0	0	2	0	0	0	1
1	AWAY	18/08/2020	500	20:20	21:47	87	0	0	0	0	0	0	0	0	0	0	0	0	1
1	AWAY	18/08/2020	600	20:20	21:56	96	0	0	0	0	0	0	0	0	0	0	0	0	1
1	AWAY	18/08/2020	700	20:20	22:07	107	3	2	0	0	0	0	2	0	1	0	0	0	1
1	AWAY	18/08/2020	800	20:20	22:18	118	22	3	0	0	0	0	1	0	19	2	0	0	1
1	AWAY	18/08/2020	900	20:20	22:29	129	29	3	0	0	0	0	2	0	26	1	0	0	1
1	AWAY	18/08/2020	1000	20:20	22:42	142	15	2	0	0	0	0	0	0	13	2	0	0	1

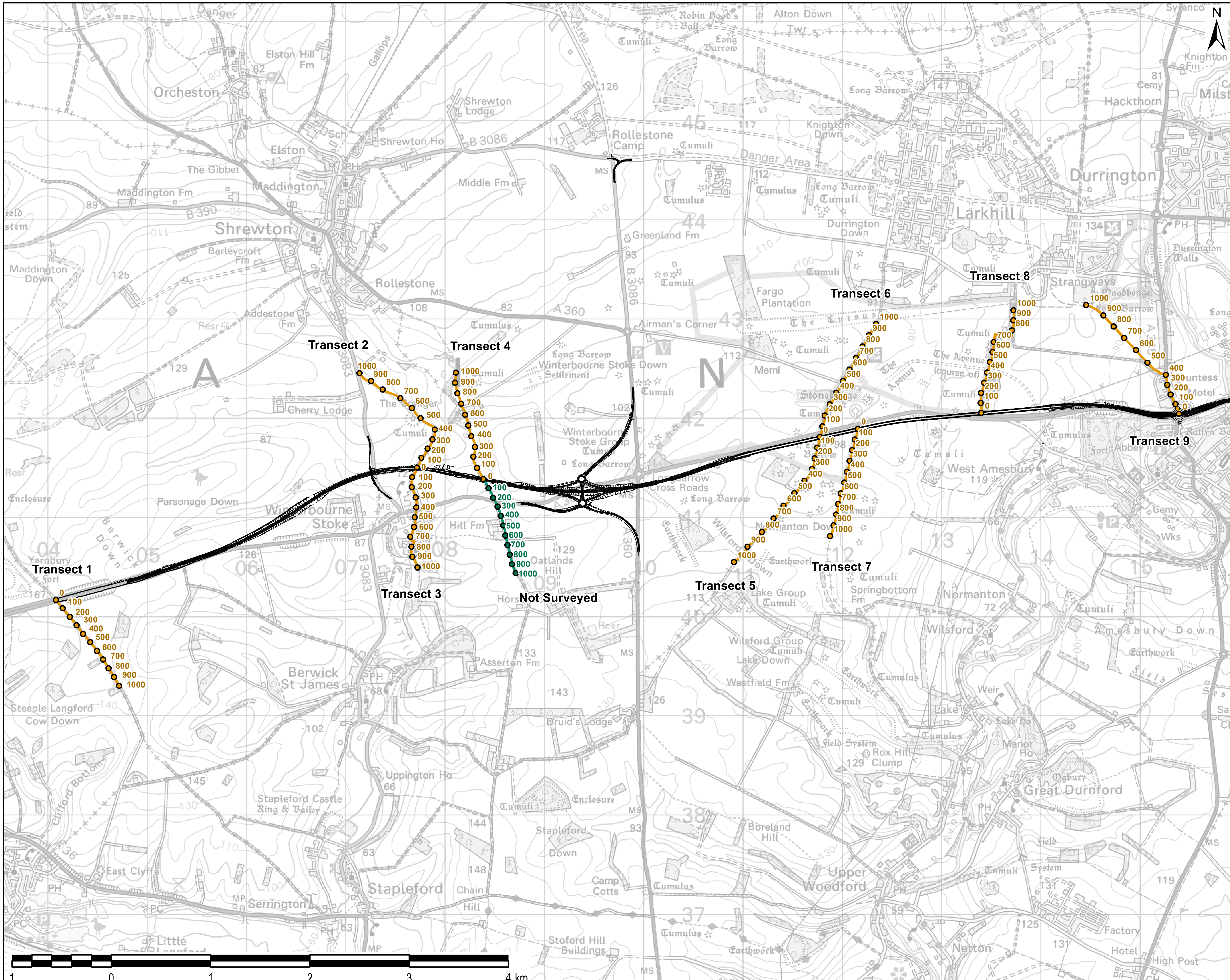
2	AWAY	15/09/2020	0	19:21	19:56	35	36	3	0	0	0	0	27	0	1	8	0	0	**2**
2	AWAY	15/09/2020	100	19:21	20:09	48	21	3	0	0	0	0	10	0	5	6	0	0	**2**
2	AWAY	15/09/2020	200	19:21	20:21	60	2	1	0	0	0	0	0	0	2	0	0	0	**2**
2	AWAY	15/09/2020	300	19:21	20:33	72	11	4	1	0	0	0	2	0	7	1	0	0	**2**
2	AWAY	15/09/2020	400	19:21	20:45	84	6	3	0	0	0	0	1	0	2	3	0	0	**2**
2	AWAY	15/09/2020	500	19:21	20:57	96	0	0	0	0	0	0	0	0	0	0	0	0	2
2	AWAY	15/09/2020	600	19:21	21:07	106	0	0	0	0	0	0	0	0	0	0	0	0	**3**
2	AWAY	15/09/2020	700	19:21	21:14	113	4	0	0	0	0	0	0	0	4	0	0	0	**2**
2	AWAY	15/09/2020	800	19:21	21:26	125	5	2	0	0	0	0	0	0	3	2	0	0	**1**
2	AWAY	15/09/2020	900	19:21	21:41	140	0	0	0	0	0	0	0	0	0	0	0	0	**1**
2	AWAY	15/09/2020	1000	19:21	21:56	155	6	2	0	0	0	0	0	0	5	1	0	0	**2**
2	TOWARDS	17/09/2020	0	19:15	21:33	138	1	1	0	0	0	0	1	0	0	0	0	0	**2**
2	TOWARDS	17/09/2020	100	19:15	21:22	127	0	0	0	0	0	0	0	0	0	0	0	0	**2**
2	TOWARDS	17/09/2020	200	19:15	21:10	115	1	1	0	0	0	0	0	0	1	0	0	0	**2**
2	TOWARDS	17/09/2020	300	19:15	20:58	103	6	3	0	0	1	0	1	0	4	0	0	0	**2**
2	TOWARDS	17/09/2020	400	19:15	20:47	92	21	1	0	0	0	0	0	0	21	0	0	0	**2**
2	TOWARDS	17/09/2020	500	19:15	20:40	85	0	0	0	0	0	0	0	0	0	0	0	0	**1**
2	TOWARDS	17/09/2020	600	19:15	20:31	76	0	0	0	0	0	0	0	0	0	0	0	0	**3**
2	TOWARDS	17/09/2020	700	19:15	20:22	67	4	0	0	0	0	0	0	0	4	0	0	0	**2**
2	TOWARDS	17/09/2020	800	19:15	20:09	54	1	1	0	0	0	0	1	0	0	0	0	0	**1**
2	TOWARDS	17/09/2020	900	19:15	19:56	41	0	0	0	0	0	0	0	0	0	0	0	0	**1**
2	TOWARDS	17/09/2020	1000	19:15	19:43	28	0	0	0	0	0	0	0	0	0	0	0	0	**2**
3	AWAY	26/08/2020	0	20:05	20:35	30	17	3	0	0	0	0	2	0	13	2	0	0	2
3	AWAY	26/08/2020	100	20:05	20:46	41	17	1	0	0	0	0	0	0	17	0	0	0	2
3	AWAY	26/08/2020	200	20:05	20:57	52	8	3	0	0	0	0	2	0	5	1	0	0	2
3	AWAY	26/08/2020	300	20:05	21:09	64	9	3	0	0	0	0	1	0	6	2	0	0	1
3	AWAY	26/08/2020	400	20:05	21:21	76	8	2	0	0	0	0	4	0	4	0	0	0	1
3	AWAY	26/08/2020	500	20:05	21:32	87	20	3	0	0	0	0	3	0	12	5	0	0	1
3	AWAY	26/08/2020	600	20:05	21:44	99	11	2	0	0	0	0	1	0	10	0	0	0	1

3	AWAY	26/08/2020	700	20:05	21:57	112	6	3	0	0	0	0	1	0	3	2	0	0	1
3	AWAY	26/08/2020	800	20:05	22:09	124	12	2	0	0	0	0	2	0	10	0	0	0	4
3	AWAY	26/08/2020	900	20:05	22:21	136	10	3	0	0	0	0	2	0	6	2	0	0	1
3	AWAY	26/08/2020	1000	20:05	22:32	147	2	2	0	0	0	0	1	0	0	1	0	0	1
4	AWAY	14/09/2020	0	19:22	20:01	39	6	3	0	0	0	0	1	0	1	4	0	0	1
4	AWAY	14/09/2020	100	19:22	20:12	50	4	3	0	0	0	0	2	0	1	1	0	0	3
4	AWAY	14/09/2020	200	19:22	20:24	62	4	3	0	0	0	0	2	0	1	1	0	0	2
4	AWAY	14/09/2020	300	19:22	20:36	74	5	3	1	0	0	0	3	0	1	0	0	0	2
4	AWAY	14/09/2020	400	19:22	20:47	85	4	2	0	0	0	0	1	0	1	2	0	0	1
4	AWAY	14/09/2020	500	19:22	20:58	96	0	0	0	0	0	0	0	0	0	0	0	0	2
4	AWAY	14/09/2020	600	19:22	21:10	108	1	1	0	0	0	0	1	0	0	0	0	0	2
4	AWAY	14/09/2020	700	19:22	21:21	119	0	0	0	0	0	0	0	0	0	0	0	0	1
4	AWAY	14/09/2020	800	19:22	21:34	132	2	2	0	0	0	0	1	0	0	1	0	0	1
4	AWAY	14/09/2020	900	19:22	21:46	144	3	1	0	0	0	0	0	0	0	3	0	0	3
4	AWAY	14/09/2020	1000	19:22	21:50	148	4	2	0	0	0	0	0	1	0	3	0	0	3
5	TOWARDS	11/08/2020	0	20:30	23:01	151	15	5	1	0	1	0	8	0	4	1	0	0	1
5	TOWARDS	11/08/2020	100	20:30	22:50	140	2	2	0	0	0	0	1	0	0	1	0	0	1
5	TOWARDS	11/08/2020	200	20:30	22:37	127	1	1	0	0	0	0	1	0	0	0	0	0	1
5	TOWARDS	11/08/2020	300	20:30	22:26	116	3	2	0	0	0	0	1	0	0	2	0	0	1
5	TOWARDS	11/08/2020	400	20:30	22:12	102	15	2	0	0	0	0	3	0	9	3	0	0	1
5	TOWARDS	11/08/2020	500	20:30	22:00	90	1	1	0	0	0	0	0	0	0	1	0	0	1
5	TOWARDS	11/08/2020	600	20:30	21:49	79	5	1	0	0	0	0	5	0	0	0	0	0	1
5	TOWARDS	11/08/2020	700	20:30	21:35	65	13	2	0	0	0	0	1	0	0	12	0	0	1
5	TOWARDS	11/08/2020	800	20:30	21:24	54	10	2	0	0	0	0	8	0	0	2	0	0	1
5	TOWARDS	11/08/2020	900	20:30	21:12	42	4	2	0	0	0	0	3	0	0	1	0	0	1
5	TOWARDS	11/08/2020	1000	20:30	21:00	30	5	2	0	0	0	0	4	0	0	1	0	0	1
6	TOWARDS	04/08/2020	0	20:48	23:15	147	0	0	0	0	0	0	0	0	0	0	0	0	1
6	TOWARDS	04/08/2020	100	20:48	23:04	136	1	1	0	0	0	0	0	0	1	0	0	0	2
6	TOWARDS	04/08/2020	200	20:48	22:52	124	1	1	0	0	0	0	0	0	0	1	0	0	1

6	TOWARDS	04/08/2020	300	20:48	22:38	110	2	1	0	0	0	0	0	0	0	2	0	0	1
6	TOWARDS	04/08/2020	400	20:48	22:26	98	1	1	0	0	0	0	1	0	0	0	0	0	1
6	TOWARDS	04/08/2020	500	20:48	22:14	86	9	2	0	0	0	0	0	0	8	1	0	0	1
6	TOWARDS	04/08/2020	600	20:48	22:02	74	0	0	0	0	0	0	0	0	0	0	0	0	1
6	TOWARDS	04/08/2020	700	20:48	21:51	63	1	1	0	0	0	0	0	0	1	0	0	0	1
6	TOWARDS	04/08/2020	800	20:48	21:39	51	1	1	0	0	0	0	1	0	0	0	0	0	1
6	TOWARDS	04/08/2020	900	20:48	21:26	38	0	0	0	0	0	0	0	0	0	0	0	0	1
6	TOWARDS	04/08/2020	1000	20:48	21:15	27	0	0	0	0	0	0	0	0	0	0	0	0	1
7	AWAY	18/08/2020	0	20:21	20:52	31	1	1	0	0	0	0	1	0	0	0	0	0	1
7	AWAY	18/08/2020	100	20:21	21:03	42	4	2	0	0	0	0	2	0	0	2	0	0	1
7	AWAY	18/08/2020	200	20:21	21:14	53	8	1	0	0	0	0	8	0	0	0	0	0	1
7	AWAY	18/08/2020	300	20:21	21:26	65	7	2	0	0	0	0	4	0	3	0	0	0	1
7	AWAY	18/08/2020	400	20:21	21:32	71	5	2	0	0	0	0	2	0	0	3	0	0	1
7	AWAY	18/08/2020	500	20:21	21:44	83	3	1	0	0	0	0	3	0	0	0	0	0	1
7	AWAY	18/08/2020	600	20:21	22:01	100	1	1	0	0	0	0	1	0	0	0	0	0	1
7	AWAY	18/08/2020	700	20:21	22:13	112	0	0	0	0	0	0	0	0	0	0	0	0	1
7	AWAY	18/08/2020	800	20:21	22:35	134	7	2	0	0	0	0	3	0	0	4	0	0	1
7	AWAY	18/08/2020	900	20:21	22:37	136	9	3	0	0	4	0	0	0	3	2	0	0	1
7	AWAY	18/08/2020	1000	20:21	22:50	149	2	1	0	0	0	0	2	0	0	0	0	0	1
8	TOWARDS	04/08/2020	0	20:48	23:22	154	0	0	0	0	0	0	0	0	0	0	0	0	5
8	TOWARDS	04/08/2020	100	20:48	23:11	143	2	1	0	0	0	0	2	0	0	0	0	0	4
8	TOWARDS	04/08/2020	200	20:48	22:59	131	1	1	0	0	0	0	1	0	0	0	0	0	4
8	TOWARDS	04/08/2020	300	20:48	22:47	119	8	3	1	0	0	0	1	0	0	6	0	0	4
8	TOWARDS	04/08/2020	400	20:48	22:35	107	10	2	0	0	0	0	1	0	4	5	0	0	3
8	TOWARDS	04/08/2020	500	20:48	22:23	95	8	2	0	0	0	0	1	0	6	1	0	0	1
8	TOWARDS	04/08/2020	600	20:48	22:11	83	5	2	0	0	0	0	1	0	0	4	0	0	4
8	TOWARDS	04/08/2020	700	20:48	21:59	71	2	2	0	0	0	0	1	0	0	1	0	0	4
8	TOWARDS	04/08/2020	800	20:48	21:47	59	7	3	1	0	0	0	4	0	0	2	0	0	1
8	TOWARDS	04/08/2020	900	20:48	21:32	44	15	3	0	0	0	0	2	0	12	1	0	0	5

8	TOWARDS	04/08/2020	1000	20:48	21:20	32	7	3	0	0	0	0	2	0	2	3	0	0	5
9	AWAY	11/08/2020	0	20:30	21:00	30	4	1	0	0	0	0	4	0	0	0	0	0	5
9	AWAY	11/08/2020	100	20:30	21:11	41	9	1	0	0	0	0	9	0	0	0	0	0	4
9	AWAY	11/08/2020	200	20:30	21:21	51	22	2	0	0	0	0	2	0	4	16	0	0	2
9	AWAY	11/08/2020	300	20:30	21:32	62	3	1	0	0	0	0	3	0	0	0	0	0	2
9	AWAY	11/08/2020	400	20:30	21:43	73	0	0	0	0	0	0	0	0	0	0	0	0	2
9	AWAY	11/08/2020	500	20:30	21:56	86	6	3	0	0	0	0	1	0	4	1	0	0	2
9	AWAY	11/08/2020	600	20:30	22:08	98	6	2	0	0	0	0	1	0	3	2	0	0	3
9	AWAY	11/08/2020	700	20:30	22:20	110	5	2	0	0	0	0	3	0	0	2	0	0	3
9	AWAY	11/08/2020	800	20:30	22:32	122	11	4	1	0	1	0	5	0	3	1	0	0	3
9	AWAY	11/08/2020	900	20:30	22:44	134	6	2	0	0	0	0	3	0	2	1	0	0	3
9	AWAY	11/08/2020	1000	20:30	22:55	145	2	2	0	0	0	0	1	0	1	0	0	0	3

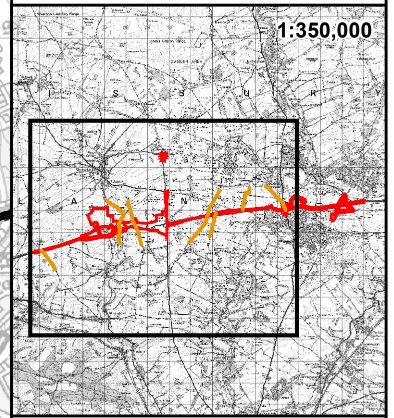
Appendix B Figure 1



Filename: pw:\\UKLON3AP114.aecomonline.local:PWAECOM_EU\Documents\60541439-A303 Stonehenge Technical Partner\0300 Non Deliverables\0330 Environmental Management Team\GIS\Figures\HE551506-AMW-DR-GI-00642.mxd

NOTES / LEGEND

- Bat Landscape Transect Waymarks
- Bat Landscape Transect Waymarks - Not Surveyed
- Bat Landscape Transect
- Bat Landscape Transect - Not Surveyed (H&S issues)
- Scheme Wide Alignment - ES 03/10/18



Revision Details	By / Check	Date	Suffix

Purpose of issue: FINAL

Client: Highways England

Working on behalf of highways england

Project Title: A303 AMESBURY TO BERWICK DOWN

Drawing Title: Bat Landscape Scale Survey Transects

Designed	Drawn	Checked	Approved	Date
HM	BM	AM	HM	25/02/20

Internal Project No. 60598638

Scale @ A3: 1:35,000 | Zone: SW

Highways England
Temple Quay House
2 Temple Quay
Bristol
BS1 6PN

AmW
AECOM + mace + WSP

Drawing Number				Rev
Highways England PIN	Originator	Volume		
HE551506	AMW	GEN		02
SCHEME WIDE	DR	GI	00642	
Location	Type	Role	Number	

Appendix C R outputs and codes

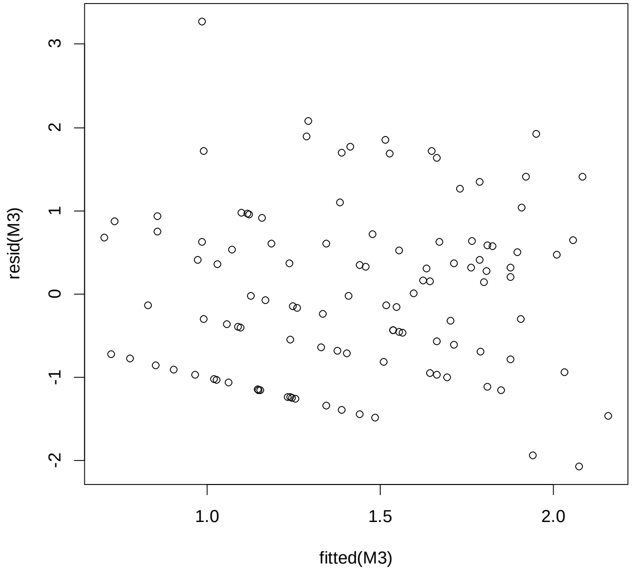
C.1 2019 R Outputs and Codes

```
> #input csv file
> site1<-read.csv("C:\\Users\\hannah.mitchell\\Documents\\batlandscapedata2019.csv", header=T)
> attach(site1)
>
> #tell R what each variable is
> site1$Route<-as.factor(site1$Route)
> site1$Day<-as.factor(site1$Day)
> site1$Dist<-as.numeric(site1$Dist)
> site1$Time<-as.numeric(site1$Time)
> site1$Pass<-as.numeric(site1$Pass)
> site1$Species<-as.numeric(site1$Species)
> site1$Bbar<-as.numeric(site1$Bbar)
> site1$Malc<-as.numeric(site1$Malc)
> site1$Mbec<-as.numeric(site1$Mbec)
> site1$MbraMmys<-as.numeric(site1$MbraMmys)
> site1$Mdau<-as.numeric(site1$Mdau)
> site1$Mnat<-as.numeric(site1$Mnat)
> site1$NSL<-as.numeric(site1$NSL)
> site1$Paur<-as.numeric(site1$Paur)
> site1$Ppip<-as.numeric(site1$Ppip)
> site1$Ppyg<-as.numeric(site1$Ppyg)
> site1$Rfer<-as.numeric(site1$Rfer)
> site1$Rhip<-as.numeric(site1$Rhip)
> site1$Hab<-as.factor(site1$Hab)
>
> #create new variable for transects walked twice
> site1$RouteNight<-factor(ifelse(site1$Day=="1",paste(site1$Route,".1",sep=""), paste(site1$Route, ".2",sep="")))
```

```
> #Displays the structure of the data and variable types:
> str(site1)
'data.frame':	110 obs. of  20 variables:
 $ Route     : Factor w/ 9 levels "A","B","C","D",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ Day       : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 1 ...
 $ Dist      : num  0 100 200 300 400 500 600 700 800 900 ...
 $ Time      : num  26 39 53 62 73 84 95 106 119 131 ...
 $ Pass      : num  4 1 3 1 2 0 3 1 0 0 ...
 $ Species   : num  2 1 1 1 2 0 2 1 0 0 ...
 $ Bbar      : num  0 0 0 1 0 0 0 1 0 0 ...
 $ Malc      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Mbec      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ MbraMmys  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Mdau      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Mnat      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ NSL       : num  3 0 3 0 1 0 1 0 0 0 ...
 $ Paur      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Ppip      : num  1 1 0 0 1 0 0 0 0 0 ...
 $ Ppyg      : num  0 0 0 0 0 0 2 0 0 0 ...
 $ Rfer      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Rhip      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Hab       : Factor w/ 5 levels "1","2","3","4",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ RouteNight: Factor w/ 10 levels "A.1","B.1","B.2",..: 1 1 1 1 1 1 1 1 1 1 ...
>
> #install relevant packages
> #install.packages("geepack")
> #install.packages("MESS")
> #install.packages("plotrix")
>
> #input packages from library
> library(geepack)
> library(MESS)
> library(plotrix)
>
> #log passes
> LPass<-log(Pass+1)
```

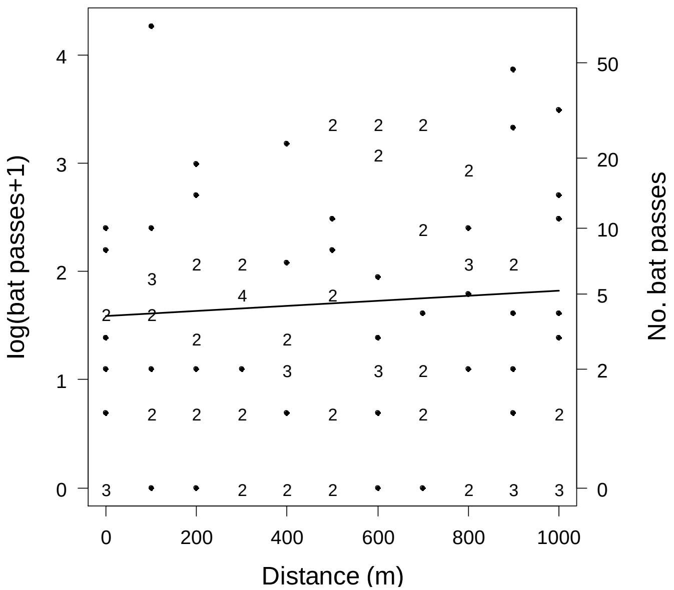
```
> #Run models with different combinations of variable
> M1<-geeglm(LPass ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M2<-geeglm(LPass ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M3<-geeglm(LPass ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M4<-geeglm(LPass ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight, corstr="ar1", std.err="fij")
> M5<-geeglm(LPass ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M6<-geeglm(LPass ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
>
> #Use QIC model selection, choose model with lowest QICu
> print(QIC(M1),digits=5)
      QIC      QICu Quasi Lik       CIC    params      QICC
 123.8691  123.3560  -54.6780    7.2566    7.0000  125.2948
> print(QIC(M2),digits=5)
      QIC      QICu Quasi Lik       CIC    params      QICC
 123.8808  123.0190  -53.5095    8.4309    8.0000  125.6808
> print(QIC(M3),digits=5)
      QIC      QICu Quasi Lik       CIC    params      QICC
 119.9017  118.5859  -56.2929    3.6579    3.0000  120.2826
> print(QIC(M4),digits=5)
      QIC      QICu Quasi Lik       CIC    params      QICC
 120.6568  119.7746  -55.8873    4.4411    4.0000  121.2337
> print(QIC(M5),digits=5)
      QIC      QICu Quasi Lik       CIC    params      QICC
 134.1671  132.9006  -60.4503    6.6332    6.0000  135.2651
> print(QIC(M6),digits=5)
      QIC      QICu Quasi Lik       CIC    params      QICC
 131.2465  130.2993  -63.1496    2.4736    2.0000  131.4729
>
> #Compare Models
> anova(M3,M4)
Analysis of 'Wald statistic' Table

Model 1 LPass ~ Dist + poly(Time, 2, raw = TRUE)
Model 2 LPass ~ Dist + Time
  Df     X2 P(>|Chi|)
1  1 3.3162    0.0686 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> #View the model output
> summary(M3)

Call:
geeglm(formula = LPass ~ Dist + Time, family = gaussian, data = site1,
    id = RouteNight, corstr = "ar1", std.err = "fij")

 Coefficients:
              Estimate    Std.err   Wald Pr(>|W|)
(Intercept)  2.1457190  0.3163521 46.005 1.18e-11 ***
Dist         0.0002337  0.0004422  0.279   0.5971
Time        -0.0092359  0.0036372  6.448   0.0111 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Estimated Scale Parameters:
            Estimate Std.err
(Intercept)    1.024  0.1618

Correlation: Structure = ar1  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha   0.4651  0.1136
Number of clusters:   10   Maximum cluster size: 11
```



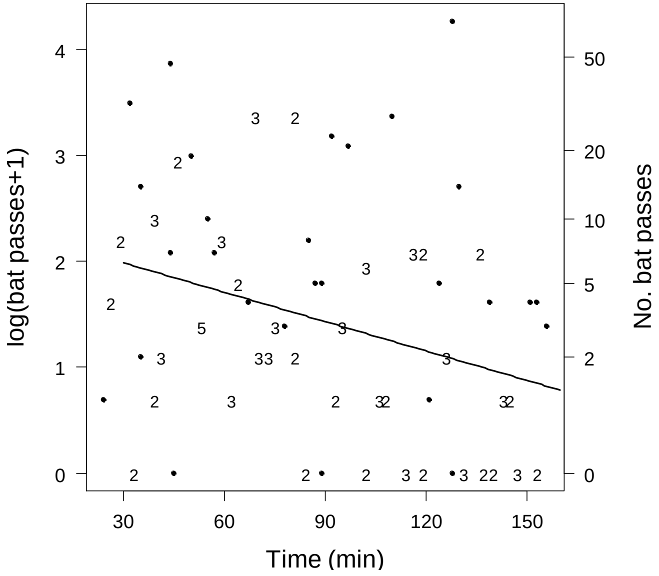

```
> #view plots of residuals
> plot(resid(M3))
> plot(fitted(M3), resid(M3))
```

```
> #Plot model predictions(distance):
> All_new_Dist<-data.frame(Dist=seq(0,1000,length=11),Hab=c("5"),Time=c(60))
> logPass_pred<-predict(M3,newdata=All_new_Dist,type="response")
>
> par(mar=c(4,4,4,4.5))
> count.overplot(Dist,LPass, cex.axis=1.2, pch=20,tol=0.2,xlab="Distance (m)",ylab ="log(bat passes+1)",cex.lab=1.5,font=1,las=2,xaxt="n")
> xax<-c(0,200,400,600,800,1000)
> axis(1,at=xax,cex.axis=1.2,font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale, cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(All_new_Dist$Dist, logPass_pred,lwd=2, lty=1)
```




```
> #Shows predictions (with habitat held constant at grade 5)
> Allpred_table_Dist<-cbind(All_new_Dist,logPass_pred)
> Allpred_table_Dist
   Dist Hab Time logPass_pred
1     0   5   60         1.59
2   100   5   60         1.61
3   200   5   60         1.64
4   300   5   60         1.66
5   400   5   60         1.69
6   500   5   60         1.71
7   600   5   60         1.73
8   700   5   60         1.76
9   800   5   60         1.78
10  900   5   60         1.80
11 1000   5   60         1.83
```

```
> #Plot model predictions(time):
> All_new_Time<-data.frame(Dist=c(500),Hab=c("5"),Time=seq(30,160,length=140))
> logPass_pred<-predict(M3,newdata=All_new_Time,type="response")
>
> par(mar=c(4,4,4,4.5))
> count.overplot(Time,LPass, cex.axis=1.2, pch=20,tol=1.5,xlab="Time (min)",ylab ="log(bat passes+1)",cex.lab=1.5,font=1,las=2,xaxt="n"
> xax<-c(30,60,90,120,150)
> axis(1,at=xax,labels=c("30","60","90","120","150"),cex.axis=1.2,font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale,cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(All_new_Time$Time, logPass_pred,lwd=2, lty=1)
```



```
> #Plot model predictions(time):
> All_new_Time<-data.frame(Dist=c(500),Hab=c("5"),Time=seq(30,160,length=140))
> logPass_pred<-predict(M3,newdata=All_new_Time,type="response")
>
> par(mar=c(4,4,4,4.5))
> count.overplot(Time,LPass, cex.axis=1.2, pch=20,tol=1.5,xlab="Time (min)",ylab ="log(bat passes+1)",cex.lab=1.5,font=1,las=2,xaxt="n")
> xax<-c(30,60,90,120,150)
> axis(1,at=xax,labels=c("30","60","90","120","150"),cex.axis=1.2,font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale,cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(All_new_Time$Time, logPass_pred,lwd=2, lty=1)
>
> #Shows predictions (with habitat held constant at grade 5)
> Allpred_table_Time<-cbind(All_new_Time,logPass_pred)
> Allpred_table_Time
```

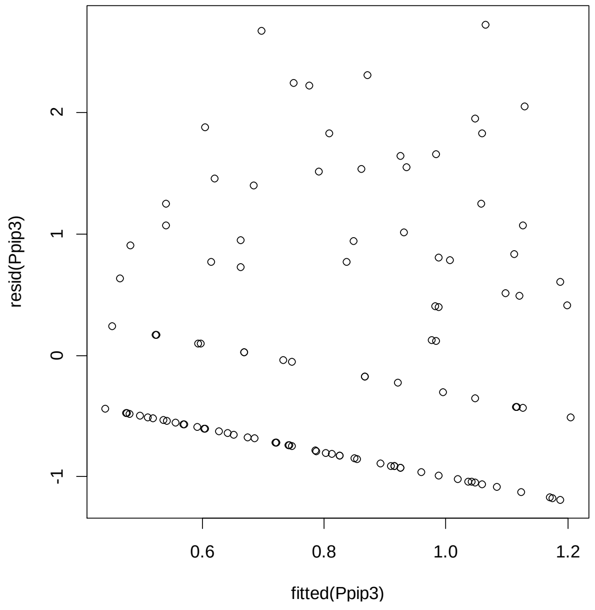
	Dist	Hab	Time	logPass_pred
1	500	5	30.0	1.985
2	500	5	30.9	1.977
3	500	5	31.9	1.968
4	500	5	32.8	1.960
5	500	5	33.7	1.951
6	500	5	34.7	1.942
7	500	5	35.6	1.934
8	500	5	36.5	1.925
9	500	5	37.5	1.916
10	500	5	38.4	1.908
11	500	5	39.4	1.899
12	500	5	40.3	1.890
13	500	5	41.2	1.882
14	500	5	42.2	1.873
15	500	5	43.1	1.865
16	500	5	44.0	1.856
17	500	5	45.0	1.847
18	500	5	45.9	1.839
19	500	5	46.8	1.830
20	500	5	47.8	1.821
21	500	5	48.7	1.813
22	500	5	49.6	1.804
23	500	5	50.6	1.795
24	500	5	51.5	1.787
25	500	5	52.4	1.778
26	500	5	53.4	1.770
27	500	5	54.3	1.761
28	500	5	55.3	1.752
29	500	5	56.2	1.744
30	500	5	57.1	1.735
31	500	5	58.1	1.726
32	500	5	59.0	1.718
33	500	5	59.9	1.709
34	500	5	60.9	1.700
35	500	5	61.8	1.692
36	500	5	62.7	1.683
37	500	5	63.7	1.675
38	500	5	64.6	1.666
39	500	5	65.5	1.657
40	500	5	66.5	1.649
41	500	5	67.4	1.640
42	500	5	68.3	1.631
43	500	5	69.3	1.623
44	500	5	70.2	1.614
45	500	5	71.2	1.605
46	500	5	72.1	1.597
47	500	5	73.0	1.588
48	500	5	74.0	1.580
49	500	5	74.9	1.571
50	500	5	75.8	1.562
51	500	5	76.8	1.554
52	500	5	77.7	1.545
53	500	5	78.6	1.536
54	500	5	79.6	1.528
55	500	5	80.5	1.519
56	500	5	81.4	1.510
57	500	5	82.4	1.502
58	500	5	83.3	1.493
59	500	5	84.2	1.485
60	500	5	85.2	1.476
61	500	5	86.1	1.467
62	500	5	87.1	1.459
63	500	5	88.0	1.450
64	500	5	88.9	1.441
65	500	5	89.9	1.433
66	500	5	90.8	1.424
67	500	5	91.7	1.415
68	500	5	92.7	1.407
69	500	5	93.6	1.398
70	500	5	94.5	1.389
71	500	5	95.5	1.381
72	500	5	96.4	1.372
73	500	5	97.3	1.364
74	500	5	98.3	1.355
75	500	5	99.2	1.346
76	500	5	100.1	1.338
77	500	5	101.1	1.329
78	500	5	102.0	1.320
79	500	5	102.9	1.312
80	500	5	103.9	1.303
81	500	5	104.8	1.294
82	500	5	105.8	1.286
83	500	5	106.7	1.277
84	500	5	107.6	1.269
85	500	5	108.6	1.260
86	500	5	109.5	1.251
87	500	5	110.4	1.243
88	500	5	111.4	1.234
89	500	5	112.3	1.225
90	500	5	113.2	1.217
91	500	5	114.2	1.208
92	500	5	115.1	1.199
93	500	5	116.0	1.191
94	500	5	117.0	1.182
95	500	5	117.9	1.174
96	500	5	118.8	1.165
97	500	5	119.8	1.156
98	500	5	120.7	1.148
99	500	5	121.7	1.139
100	500	5	122.6	1.130
101	500	5	123.5	1.122
102	500	5	124.5	1.113
103	500	5	125.4	1.104
104	500	5	126.3	1.096
105	500	5	127.3	1.087
106	500	5	128.2	1.079
107	500	5	129.1	1.070
108	500	5	130.1	1.061
109	500	5	131.0	1.053
110	500	5	131.9	1.044
111	500	5	132.9	1.035
112	500	5	133.8	1.027
113	500	5	134.7	1.018
114	500	5	135.7	1.009
115	500	5	136.6	1.001
116	500	5	137.6	0.992
117	500	5	138.5	0.984
118	500	5	139.4	0.975
119	500	5	140.4	0.966
120	500	5	141.3	0.958
121	500	5	142.2	0.949
122	500	5	143.2	0.940
123	500	5	144.1	0.932
124	500	5	145.0	0.923
125	500	5	146.0	0.914

```
126  500   5 146.9        0.906
127  500   5 147.8        0.897
128  500   5 148.8        0.888
129  500   5 149.7        0.880
130  500   5 150.6        0.871
131  500   5 151.6        0.863
132  500   5 152.5        0.854
133  500   5 153.5        0.845
134  500   5 154.4        0.837
135  500   5 155.3        0.828
136  500   5 156.3        0.819
137  500   5 157.2        0.811
138  500   5 158.1        0.802
139  500   5 159.1        0.793
140  500   5 160.0        0.785
> #Calculate the percentage of zero counts per species
> Bbar0<-((sum(Bbar==0))/(nrow(site1))*100)
> Malc0<-((sum(Malc==0))/(nrow(site1))*100)
> Mbec0<-((sum(Mbec==0))/(nrow(site1))*100)
> MbraMmys0<-((sum(MbraMmys==0))/(nrow(site1))*100)
> Mdau0<-((sum(Mdau==0))/(nrow(site1))*100)
> Mnat0<-((sum(Mnat==0))/(nrow(site1))*100)
> NSL0<-((sum(NSL==0))/(nrow(site1))*100)
> Paur0<-((sum(Paur==0))/(nrow(site1))*100)
> Ppip0<-((sum(Ppip==0))/(nrow(site1))*100)
> Ppyg0<-((sum(Ppyg==0))/(nrow(site1))*100)
> Rhip0<-((sum(Rhip==0))/(nrow(site1))*100)
> Rfer0<-((sum(Rfer==0))/(nrow(site1))*100)
>
> #combine as a table with the total counts
> percent_zero<-rbind(Bbar0,Malc0,Mbec0,MbraMmys0,Mdau0,Mnat0,NSL0,Paur0,Ppip0,Ppyg0,Rhip0,Rfer0,c("Total"))
> no_passes<-rbind(sum(Bbar),sum(Malc),sum(Mbec),sum(MbraMmys),sum(Mdau),sum(Mnat),sum(NSL),sum(Paur),sum(Ppip),sum(Ppyg),sum(Rhip),sum(Rfer),sum(Pass))
>
> Species_counts<-data.frame(percent_zero,no_passes)
> capture.output(Species_counts,file="C:\\Users\\hannah.mitchell\\Desktop\\Species_counts.txt")
>
> #Run species-specific GEE models e.g. Ppip
> LPpip<-log(Ppip+1)
> Ppip1<-geeglm(LPpip ~ Dist + Hab + Time, family=gaussian, data=site1,id=RouteNight, corstr="ar1", std.err="fij")
> Ppip2<-geeglm(LPpip ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian,data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Ppip3<-geeglm(LPpip ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Ppip4<-geeglm(LPpip ~ Dist + poly(Time,2,raw=TRUE), family=gaussian,data=site1,id =RouteNight, corstr="ar1", std.err="fij")
> Ppip5<-geeglm(LPpip ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight,corstr="ar1", std.err="fij")
> Ppip6<-geeglm(LPpip ~ Dist, family=gaussian, data=site1, id=RouteNight,corstr="ar1", std.err="fij")
```

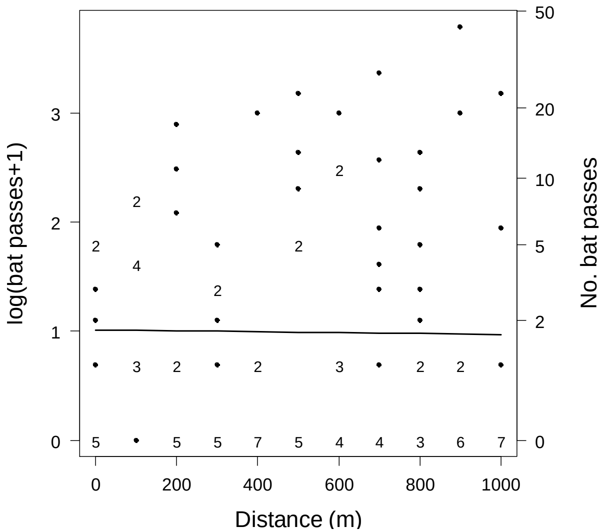
```
> #QICu values
> print(QIC(Ppip1),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
130.9387  128.7475  -57.3738    8.0956    7.0000  132.3645
> print(QIC(Ppip2),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
131.8893  129.5400  -56.7700    9.1746    8.0000  133.6893
> print(QIC(Ppip3),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
120.3001  120.2993  -57.1497    3.0004    3.0000  120.6811
> print(QIC(Ppip4),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
121.8382  122.2487  -57.1243    3.7948    4.0000  122.4151
> print(QIC(Ppip5),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
 133.573   131.371   -59.686     7.101     6.000   134.671
> print(QIC(Ppip6),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
124.2506  124.1177  -60.0589    2.0664    2.0000  124.4770
```

```
> #View model output
> summary(Ppip3)

Call:
geeglm(formula = LPpip ~ Dist + Time, family = gaussian, data = site1,
    id = RouteNight, corstr = "ar1", std.err = "fij")

 Coefficients:
             Estimate   Std.err  Wald Pr(>|W|)
(Intercept)  1.35e+00  3.19e-01 17.98  2.2e-05 ***
Dist        -4.19e-05  4.09e-04  0.01    0.918
Time        -5.69e-03  3.31e-03  2.96    0.085 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Estimated Scale Parameters:
            Estimate Std.err
(Intercept)     1.04   0.148

Correlation: Structure = ar1  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha    0.616  0.0652
Number of clusters:   10   Maximum cluster size: 11
```

```
> #Plot residuals
> plot(resid(Ppip3))
> plot(fitted(Ppip3),resid(Ppip3))
```



```
> #Plot model predictions(distance):
> Ppip_new_dist<-data.frame(Dist=seq(0,1000,length=11),Hab=c("5"),Time=c(60))
> logPpip_predict_dist<-predict(Ppip3,newdata=Ppip_new_dist,type="response")
>
> Predict_dist_Ppip<-cbind(Ppip_new_dist,logPpip_predict_dist)
> Predict_dist_Ppip
   Dist Hab Time logPpip_predict_dist
1     0   5   60                1.011
2   100   5   60                1.007
3   200   5   60                1.003
4   300   5   60                0.999
5   400   5   60                0.995
6   500   5   60                0.991
7   600   5   60                0.986
8   700   5   60                0.982
9   800   5   60                0.978
10  900   5   60                0.974
11 1000   5   60                0.970
> capture.output(Predict_dist_Ppip, file="C:\\Users\\hannah.mitchell\\Desktop\\Predict_dist_Ppip.txt")
> par(mar=c(4,4,4,4.5))
> count.overplot(Dist,LPpip, cex.axis=1.2, pch=20,tol=0.2,xlab="Distance (m)", ylab ="log(bat passes+1)",cex.lab=1.5,font=1,las=2,xaxt="n")
> xax<-c(0,200,400,600,800,1000)
> axis(1,at=xax,cex.axis=1.2,font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale, cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(Ppip_new_dist$Dist, logPpip_predict_dist,lwd=2, lty=1)
```

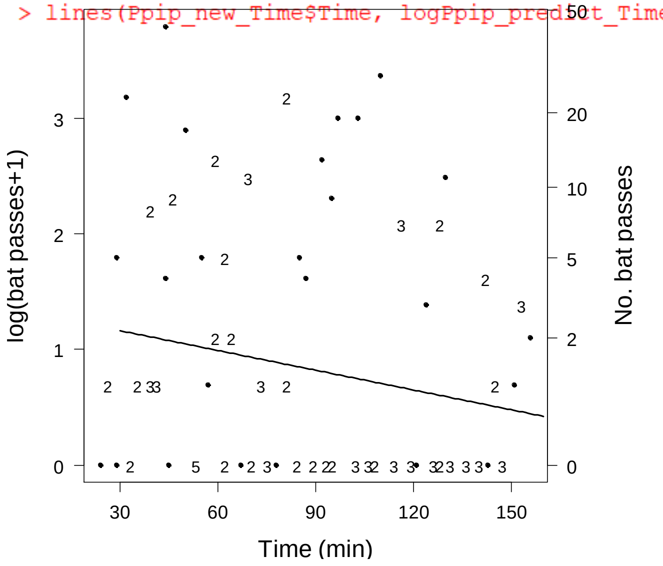

log(bat passes+1)
No. bat passes
Distance (m)
0
200
400
600
800
1000
0
1
2
3
0
2
5
10
20
50

```
> #Plot model predictions(time):
> Ppip_new_Time<-data.frame(Dist=c(500),Hab=c("5"),Time=seq(30,160,length=140))
> logPpip_predict_Time<-predict(Ppip3,newdata=Ppip_new_Time,type="response")
> Predict_Time_Ppip<-cbind(Ppip_new_Time,logPpip_predict_Time)
> Predict_Time_Ppip
```

```
   Dist Hab  Time logPpip_predict_Time
1   500   5  30.0                1.161
2   500   5  30.9                1.156
3   500   5  31.9                1.151
4   500   5  32.8                1.145
5   500   5  33.7                1.140
6   500   5  34.7                1.135
7   500   5  35.6                1.129
8   500   5  36.5                1.124
9   500   5  37.5                1.119
10  500   5  38.4                1.113
11  500   5  39.4                1.108
12  500   5  40.3                1.103
13  500   5  41.2                1.097
14  500   5  42.2                1.092
15  500   5  43.1                1.087
16  500   5  44.0                1.081
17  500   5  45.0                1.076
18  500   5  45.9                1.071
19  500   5  46.8                1.065
20  500   5  47.8                1.060
21  500   5  48.7                1.055
22  500   5  49.6                1.049
23  500   5  50.6                1.044
24  500   5  51.5                1.039
25  500   5  52.4                1.034
26  500   5  53.4                1.028
27  500   5  54.3                1.023
28  500   5  55.3                1.018
29  500   5  56.2                1.012
30  500   5  57.1                1.007
31  500   5  58.1                1.002
32  500   5  59.0                0.996
33  500   5  59.9                0.991
34  500   5  60.9                0.986
35  500   5  61.8                0.980
36  500   5  62.7                0.975
37  500   5  63.7                0.970
38  500   5  64.6                0.964
39  500   5  65.5                0.959
40  500   5  66.5                0.954
41  500   5  67.4                0.948
```

42	500	5	68.3	0.943	84	500	5	107.6	0.719					
43	500	5	69.3	0.938	85	500	5	108.6	0.714					
44	500	5	70.2	0.932	86	500	5	109.5	0.709					
45	500	5	71.2	0.927	87	500	5	110.4	0.703					
46	500	5	72.1	0.922	88	500	5	111.4	0.698					
47	500	5	73.0	0.916	89	500	5	112.3	0.693					
48	500	5	74.0	0.911	90	500	5	113.2	0.687					
49	500	5	74.9	0.906	91	500	5	114.2	0.682					
50	500	5	75.8	0.900	92	500	5	115.1	0.677					
51	500	5	76.8	0.895	93	500	5	116.0	0.671					
52	500	5	77.7	0.890	94	500	5	117.0	0.666					
53	500	5	78.6	0.884	95	500	5	117.9	0.661					
54	500	5	79.6	0.879	96	500	5	118.8	0.656					
55	500	5	80.5	0.874	97	500	5	119.8	0.650					
56	500	5	81.4	0.868	98	500	5	120.7	0.645					
57	500	5	82.4	0.863	99	500	5	121.7	0.640					
58	500	5	83.3	0.858	100	500	5	122.6	0.634					
59	500	5	84.2	0.853	101	500	5	123.5	0.629					
60	500	5	85.2	0.847	102	500	5	124.5	0.624					
61	500	5	86.1	0.842	103	500	5	125.4	0.618					
62	500	5	87.1	0.837	104	500	5	126.3	0.613					
63	500	5	88.0	0.831	105	500	5	127.3	0.608					
64	500	5	88.9	0.826	106	500	5	128.2	0.602					
65	500	5	89.9	0.821	107	500	5	129.1	0.597					
66	500	5	90.8	0.815	108	500	5	130.1	0.592					
67	500	5	91.7	0.810	109	500	5	131.0	0.586					
68	500	5	92.7	0.805	110	500	5	131.9	0.581					
69	500	5	93.6	0.799	111	500	5	132.9	0.576	126	500	5	146.9	0.496
70	500	5	94.5	0.794	112	500	5	133.8	0.570	127	500	5	147.8	0.490
71	500	5	95.5	0.789	113	500	5	134.7	0.565	128	500	5	148.8	0.485
72	500	5	96.4	0.783	114	500	5	135.7	0.560	129	500	5	149.7	0.480
73	500	5	97.3	0.778	115	500	5	136.6	0.554	130	500	5	150.6	0.475
74	500	5	98.3	0.773	116	500	5	137.6	0.549	131	500	5	151.6	0.469
75	500	5	99.2	0.767	117	500	5	138.5	0.544	132	500	5	152.5	0.464
76	500	5	100.1	0.762	118	500	5	139.4	0.538	133	500	5	153.5	0.459
77	500	5	101.1	0.757	119	500	5	140.4	0.533	134	500	5	154.4	0.453
78	500	5	102.0	0.751	120	500	5	141.3	0.528	135	500	5	155.3	0.448
79	500	5	102.9	0.746	121	500	5	142.2	0.522	136	500	5	156.3	0.443
80	500	5	103.9	0.741	122	500	5	143.2	0.517	137	500	5	157.2	0.437
81	500	5	104.8	0.735	123	500	5	144.1	0.512	138	500	5	158.1	0.432
82	500	5	105.8	0.730	124	500	5	145.0	0.506	139	500	5	159.1	0.427
83	500	5	106.7	0.725	125	500	5	146.0	0.501	140	500	5	160.0	0.421

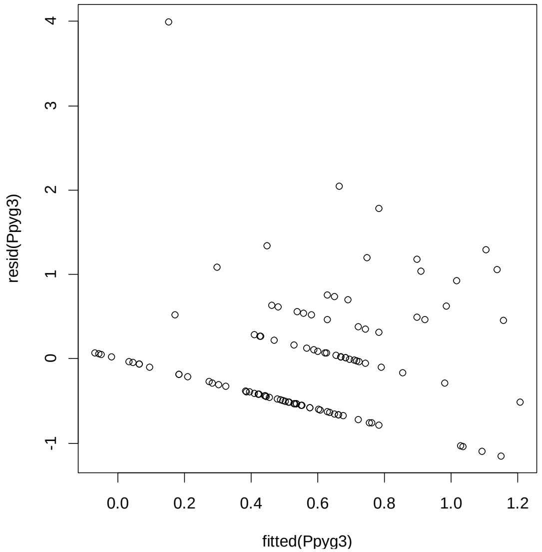
```
> par(mar=c(4,4,4,4.5))
> count.overplot(Time,LPpip, cex.axis=1.2, pch=20,tol=1.5,xlab="Time (min)",ylab ="log(bat passes+1)",cex.lab=1.5,font=1,las=2,xaxt="n")
> xax<-c(30,60,90,120,150)
> axis(1,at=xax,labels=c("30","60","90","120","150"),cex.axis=1.2,font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale,cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(Ppip_new_Time$Time, logPpip_predict_Time,lwd=2, lty=1)
```



```
> #Run species-specific GEE models e.g. Ppyg
> LPpyg<-log(Ppyg+1)
> Ppyg1<-geeglm(LPpyg ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Ppyg2<-geeglm(LPpyg ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Ppyg3<-geeglm(LPpyg ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Ppyg4<-geeglm(LPpyg ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight, corstr="ar1", std.err="fij")
> Ppyg5<-geeglm(LPpyg ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Ppyg6<-geeglm(LPpyg ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
>
> #QICu values
> print(QIC(Ppyg1),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
 70.6522   69.3619  -27.6809    7.6452    7.0000   72.0780
> print(QIC(Ppyg2),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
 71.6930   71.1856  -27.5928    8.2537    8.0000   73.4930
> print(QIC(Ppyg3),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
 63.0637   62.3155  -28.1578    3.3741    3.0000   63.4446
> print(QIC(Ppyg4),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
 63.5473   64.1759  -28.0879    3.6857    4.0000   64.1242
> print(QIC(Ppyg5),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
 75.4941   72.4716  -30.2358    7.5112    6.0000   76.5921
> print(QIC(Ppyg6),digits=5)
     QIC      QICu Quasi Lik       CIC    params      QICC
  67.573    66.503   -31.251     2.535     2.000    67.799
```

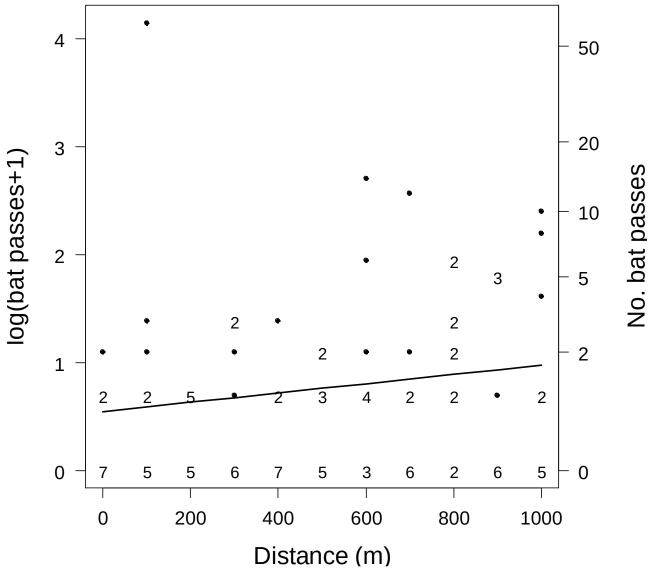
```
> #View model output
> summary(Ppyg3)

Call:
geeglm(formula = LPpyg ~ Dist + Time, family = gaussian, data = site1,
    id = RouteNight, corstr = "ar1", std.err = "fij")

 Coefficients:
             Estimate   Std.err  Wald Pr(>|W|)
(Intercept)  0.928187  0.169798 29.88  4.6e-08 ***
Dist         0.000432  0.000263  2.70   0.1006
Time        -0.006398  0.002080  9.47   0.0021 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Estimated Scale Parameters:
            Estimate Std.err
(Intercept)    0.512   0.127

Correlation: Structure = ar1  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha    0.246   0.187
Number of clusters:   10   Maximum cluster size: 11
```

```
> #Plot residuals
> plot(resid(Ppyg3))
> plot(fitted(Ppyg3),resid(Ppyg3))
```




```
> Predict_Dist_Ppyg<-cbind(Ppyg_new_Dist,logPpyg_pred_Dist)
> Predict_Dist_Ppyg
   Dist Hab Time logPpyg_pred_Dist
1     0   5   60             0.544
2   100   5   60             0.588
3   200   5   60             0.631
4   300   5   60             0.674
5   400   5   60             0.717
6   500   5   60             0.761
7   600   5   60             0.804
8   700   5   60             0.847
9   800   5   60             0.890
10  900   5   60             0.933
11 1000   5   60             0.977
> capture.output(Predict_Dist_Ppyg,file="C:\\Users\\hannah.mitchell\\Desktop\\Predict_Dist_Ppyg.txt")
```

```
> par(mar=c(4,4,4,4.5))
> count.overplot(Dist,LPpyg, cex.axis=1.2, pch=20,tol=0.2,xlab="Distance (m)",ylab ="log(bat passes+1)",cex.lab=1.5,font=1,las=2,xaxt="n")
> xax<-c(0,200,400,600,800,1000)
> axis(1,at=xax,cex.axis=1.2,font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale, cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(Ppyg_new_Dist$Dist,logPpyg_pred_Dist,lwd=2, lty=1)
```

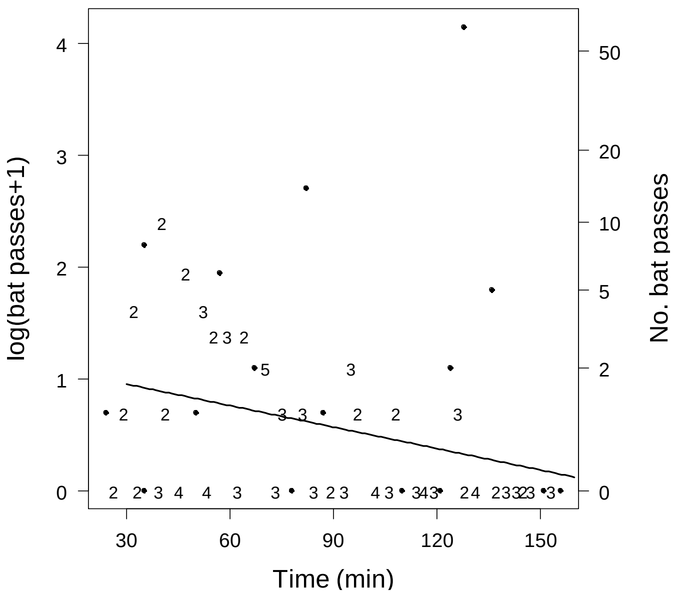


```
> #Plot model predictions(time):
> Ppyg_new_Time<-data.frame(Dist=c(500),Hab=c("5"),Time=seq(30,160,length=140))
> logPpyg_pred_Time<-predict(Ppyg3,newdata=Ppyg_new_Time,type="response")
>
> Predict_Time_Ppyg<-cbind(Ppyg_new_Time,logPpyg_pred_Time)
> Predict_Time_Ppyg
```

	Dist	Hab	Time	logPpyg_pred_Time
1	500	5	30.0	0.952
2	500	5	30.9	0.946
3	500	5	31.9	0.940
4	500	5	32.8	0.934
5	500	5	33.7	0.929
6	500	5	34.7	0.923
7	500	5	35.6	0.917
8	500	5	36.5	0.911
9	500	5	37.5	0.905
10	500	5	38.4	0.899
11	500	5	39.4	0.893
12	500	5	40.3	0.887
13	500	5	41.2	0.881
14	500	5	42.2	0.875
15	500	5	43.1	0.869
16	500	5	44.0	0.863
17	500	5	45.0	0.857
18	500	5	45.9	0.851
19	500	5	46.8	0.845
20	500	5	47.8	0.839
21	500	5	48.7	0.833
22	500	5	49.6	0.827
23	500	5	50.6	0.821
24	500	5	51.5	0.815
25	500	5	52.4	0.809
26	500	5	53.4	0.803
27	500	5	54.3	0.797
28	500	5	55.3	0.791
29	500	5	56.2	0.785
30	500	5	57.1	0.779
31	500	5	58.1	0.773
32	500	5	59.0	0.767
33	500	5	59.9	0.761
34	500	5	60.9	0.755
35	500	5	61.8	0.749
36	500	5	62.7	0.743
37	500	5	63.7	0.737
38	500	5	64.6	0.731
39	500	5	65.5	0.725
40	500	5	66.5	0.719
41	500	5	67.4	0.713

42	500	5	68.3	0.707
43	500	5	69.3	0.701
44	500	5	70.2	0.695
45	500	5	71.2	0.689
46	500	5	72.1	0.683
47	500	5	73.0	0.677
48	500	5	74.0	0.671
49	500	5	74.9	0.665
50	500	5	75.8	0.659
51	500	5	76.8	0.653
52	500	5	77.7	0.647
53	500	5	78.6	0.641
54	500	5	79.6	0.635
55	500	5	80.5	0.629
56	500	5	81.4	0.623
57	500	5	82.4	0.617
58	500	5	83.3	0.611
59	500	5	84.2	0.605
60	500	5	85.2	0.599
61	500	5	86.1	0.593
62	500	5	87.1	0.587
63	500	5	88.0	0.581
64	500	5	88.9	0.575
65	500	5	89.9	0.569
66	500	5	90.8	0.563
67	500	5	91.7	0.558
68	500	5	92.7	0.552
69	500	5	93.6	0.546
70	500	5	94.5	0.540
71	500	5	95.5	0.534
72	500	5	96.4	0.528
73	500	5	97.3	0.522
74	500	5	98.3	0.516
75	500	5	99.2	0.510
76	500	5	100.1	0.504
77	500	5	101.1	0.498
78	500	5	102.0	0.492
79	500	5	102.9	0.486
80	500	5	103.9	0.480
81	500	5	104.8	0.474
82	500	5	105.8	0.468
83	500	5	106.7	0.462
84	500	5	107.6	0.456
85	500	5	108.6	0.450
86	500	5	109.5	0.444
87	500	5	110.4	0.438
88	500	5	111.4	0.432
89	500	5	112.3	0.426
90	500	5	113.2	0.420
91	500	5	114.2	0.414
92	500	5	115.1	0.408
93	500	5	116.0	0.402
94	500	5	117.0	0.396
95	500	5	117.9	0.390
96	500	5	118.8	0.384
97	500	5	119.8	0.378
98	500	5	120.7	0.372
99	500	5	121.7	0.366
100	500	5	122.6	0.360
101	500	5	123.5	0.354
102	500	5	124.5	0.348
103	500	5	125.4	0.342
104	500	5	126.3	0.336
105	500	5	127.3	0.330
106	500	5	128.2	0.324
107	500	5	129.1	0.318
108	500	5	130.1	0.312
109	500	5	131.0	0.306
110	500	5	131.9	0.300
111	500	5	132.9	0.294
112	500	5	133.8	0.288
113	500	5	134.7	0.282
114	500	5	135.7	0.276
115	500	5	136.6	0.270
116	500	5	137.6	0.264
117	500	5	138.5	0.258
118	500	5	139.4	0.252
119	500	5	140.4	0.246
120	500	5	141.3	0.240
121	500	5	142.2	0.234
122	500	5	143.2	0.228
123	500	5	144.1	0.222
124	500	5	145.0	0.216
125	500	5	146.0	0.210
126	500	5	146.9	0.204
127	500	5	147.8	0.198
128	500	5	148.8	0.193
129	500	5	149.7	0.187
130	500	5	150.6	0.181
131	500	5	151.6	0.175
132	500	5	152.5	0.169
133	500	5	153.5	0.163
134	500	5	154.4	0.157
135	500	5	155.3	0.151
136	500	5	156.3	0.145
137	500	5	157.2	0.139
138	500	5	158.1	0.133
139	500	5	159.1	0.127
140	500	5	160.0	0.121

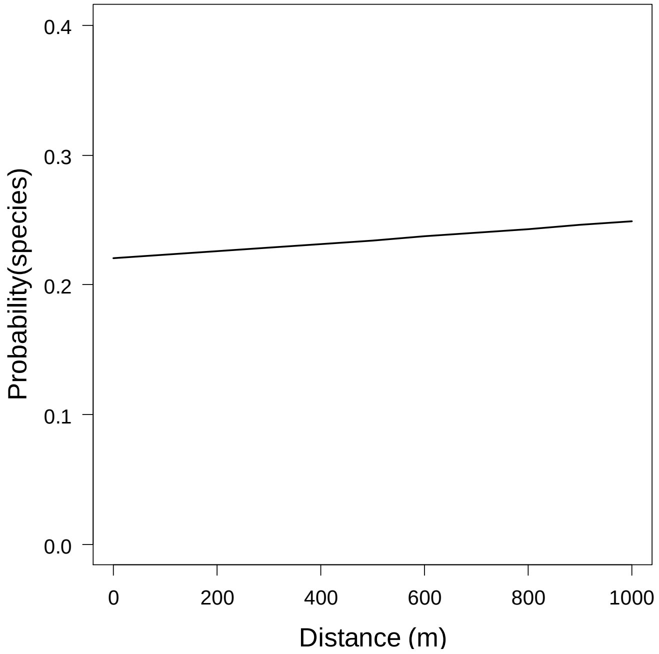
```
> capture.output(Predict_Time_Ppyg, file="C:\\Users\\hannah.mitchell\\Desktop\\Predict_Time_Ppyg.txt")
>
> par(mar=c(4,4,4,4.5))
> count.overplot(Time,LPpyg, cex.axis=1.2, pch=20,tol=1.5,xlab="Time (min)",ylab ="log(bat passes+1)",cex.lab=1.5,font=1,las=2,xaxt="n")
> xax<-c(30,60,90,120,150)
> axis(1,at=xax,labels=c("30","60","90","120","150"),cex.axis=1.2,font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale,cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(Ppyg_new_Time$Time, logPpyg_pred_Time,lwd=2, lty=1)
```



```
>  #model for number of species
> site1$Species_fail<-8-site1$Species
> site1$Sp<-cbind(site1$Species, site1$Species_fail)
>
> Sp1<-geeglm(Sp ~ Dist + Hab + Time, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Sp2<-geeglm(Sp ~ Dist + Hab + poly(Time,2,raw=TRUE), family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Sp3<-geeglm(Sp ~ Dist + Time, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Sp4<-geeglm(Sp ~ Dist + poly(Time,2,raw=TRUE), family=binomial, data=site1,id =RouteNight, corstr="ar1", std.err="fij")
> Sp5<-geeglm(Sp ~ Dist + Hab, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> Sp6<-geeglm(Sp ~ Dist, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
>
> print(QIC(Sp1),digits=5)
      QIC       QICu Quasi Lik       CIC     params      QICC
  222.963   124.694    -55.347    56.134      7.000   224.388
> print(QIC(Sp2),digits=5)
      QIC       QICu Quasi Lik       CIC     params      QICC
  244.996   126.603    -55.301    67.197      8.000   246.796
> print(QIC(Sp3),digits=5)
      QIC       QICu Quasi Lik       CIC     params      QICC
  188.627   118.328    -56.164    38.150      3.000   189.008
> print(QIC(Sp4),digits=5)
      QIC       QICu Quasi Lik       CIC     params      QICC
  202.565   120.275    -56.138    45.145      4.000   203.142
> print(QIC(Sp5),digits=5)
      QIC       QICu Quasi Lik       CIC     params      QICC
  203.669   123.872    -55.936    45.899      6.000   204.767
> print(QIC(Sp6),digits=5)
      QIC       QICu Quasi Lik       CIC     params      QICC
  156.046   117.439    -56.720    21.303      2.000   156.272
```

```
> summary(Sp3)

Call:
geeglm(formula = Sp ~ Dist + Time, family = binomial, data = site1,
    id = RouteNight, corstr = "ar1", std.err = "fij")

 Coefficients:
             Estimate   Std.err Wald Pr(>|W|)
(Intercept) -0.908829  0.414172 4.82    0.028 *
Dist         0.000160  0.000447 0.13    0.720
Time        -0.005905  0.003904 2.29    0.130
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Estimated Scale Parameters:
            Estimate Std.err
(Intercept)    0.128  0.0246

Correlation: Structure = ar1  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha    0.406  0.0874
Number of clusters:   10   Maximum cluster size: 11
```

```
> Sp_new_Dist<-data.frame(Dist=seq(0,1000,length=11),Hab=c("5"),Time=c(60))
> Sp_pred_Dist<-predict(Sp3,newdata=Ppyg_new_Dist,type="response")
>
> Sp_Predict_Dist<-cbind(Sp_new_Dist,Sp_pred_Dist)
> Sp_Predict_Dist
   Dist Hab Time Sp_pred_Dist
1     0   5   60        0.220
2   100   5   60        0.223
3   200   5   60        0.226
4   300   5   60        0.229
5   400   5   60        0.232
6   500   5   60        0.235
7   600   5   60        0.237
8   700   5   60        0.240
9   800   5   60        0.243
10  900   5   60        0.246
11 1000   5   60        0.249
> capture.output(Sp_Predict_Dist,file="C:\\Users\\hannah.mitchell\\Desktop\\Sp_Predict_Dist.txt")
>
> par(mar=c(4,4.1,2,2))
> plot(Sp_new_Dist$Dist, Sp_pred_Dist, type="l", lwd=2, ylim=c(0,0.4), xlab="Distance (m)", ylab="Probability(species)", cex.lab=1.5, cex.axis=1.2, yaxt="n")
> axis(side=2,cex.axis=1.2,las=2)
>
> rm(list = ls())
> detach(site1)
```



C.2 2020 R Outputs and Codes

Output

```
site1$Mbec<-as.numeric(site1$Mbec)
> site1$MbraMmys<-as.numeric(site1$MbraMmys)
> site1$Mdau<-as.numeric(site1$Mdau)
> site1$Mnat<-as.numeric(site1$Mnat)
> site1$NSL<-as.numeric(site1$NSL)
> site1$Paur<-as.numeric(site1$Paur)
> site1$Ppip<-as.numeric(site1$Ppip)
> site1$Ppyg<-as.numeric(site1$Ppyg)
> site1$Rfer<-as.numeric(site1$Rfer)
> site1$Rhip<-as.numeric(site1$Rhip)
> site1$Hab<-as.factor(site1$Hab)
> site1$RouteNight<-factor(ifelse(site1$Day=="1",paste(site1$Route,".1",sep=""), paste(site1$Route, ".2",sep="")))
```

```
> #Displays the structure of the data and variable types:
> str(site1)
'data.frame':	110 obs. of  21 variables:
 $ ï..Blank_cell: logi  NA NA NA NA NA NA ...
 $ Route        : Factor w/ 9 levels "1","2","3","4",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ Day          : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 1 ...
 $ Dist         : num  0 100 200 300 400 500 600 700 800 900 ...
 $ Time         : num  30 41 52 64 76 87 96 107 118 129 ...
 $ Pass         : num  4 0 7 0 2 0 0 3 22 29 ...
 $ Species      : num  2 0 3 0 0 0 0 2 3 3 ...
 $ Bbar         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Malc         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Mbec         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ MbraMmys     : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Mdau         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Mnat         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ NSL          : num  3 0 1 0 0 0 0 2 1 2 ...
 $ Paur         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Ppip         : num  1 0 5 0 2 0 0 1 19 26 ...
 $ Ppyg         : num  0 0 1 0 0 0 0 0 2 1 ...
 $ Rfer         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Rhip         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Hab          : Factor w/ 5 levels "1","2","3","4",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ RouteNight   : Factor w/ 10 levels "1.1","2.1","2.2",..: 1 1 1 1 1 1 1 1 1 1 ...
> #Load the packages required for the analysis
> install.packages("geepack")
Error in install.packages : Updating loaded packages
> library(geepack)
> library(MESS)
> library(xlsx)
> library(plotrix)
> #Log the number of bat passes:
> LPass<-log(Pass+1)
> #Run models with different combinations of variables:
> M1<-geeglm(LPass ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M2<-geeglm(LPass ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
> M3<-geeglm(LPass ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M4<-geeglm(LPass ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight, corstr="ar1", std.er
r="fij")
> M5<-geeglm(LPass ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M6<-geeglm(LPass ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> #Use QIC model selection, choose model with lowest QICu:
> print(QIC(M1),digits=7)
      QIC       QICu  Quasi Lik        CIC      params       QICC
```

```
116.936174 120.651578 -53.325789   5.142298   7.000000 118.361916
> print(QIC(M2),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
119.708450 122.719215 -53.359607   6.494618   8.000000 121.508450
> print(QIC(M3),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
112.629768 111.946279 -52.973140   3.341744   3.000000 113.010720
> print(QIC(M4),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
115.020496 113.962744 -52.981372   4.528876   4.000000 115.597419
> print(QIC(M5),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
115.535515 118.485224 -53.242612   4.525145   6.000000 116.633554
> print(QIC(M6),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
110.589235 109.855765 -52.927883   2.366735   2.000000 110.815651
> #check which are lower if similar QICu
> anova(M3,M6)
Analysis of 'Wald statistic' Table

Model 1 LPass ~ Dist + Time
Model 2 LPass ~ Dist
  Df   X2 P(>|Chi|)
1  1 2.07      0.15
> summary(anova(M3,M6))
       Df          X2           P(>|Chi|)
 Min.   :1   Min.   :2.07   Min.   :0.15
 1st Qu.:1   1st Qu.:2.07   1st Qu.:0.15
 Median :1   Median :2.07   Median :0.15
 Mean   :1   Mean   :2.07   Mean   :0.15
 3rd Qu.:1   3rd Qu.:2.07   3rd Qu.:0.15
 Max.   :1   Max.   :2.07   Max.   :0.15
> #View the model output:
> summary(M6)

Call:
geeglm(formula = LPass ~ Dist, family = gaussian, data = site1,
    id = RouteNight, corstr = "ar1", std.err = "fij")

 Coefficients:
             Estimate   Std.err  Wald Pr(>|W|)
(Intercept)  1.54e+00  1.90e-01 65.31  6.7e-16 ***
Dist        -9.36e-05  3.25e-04  0.08     0.77
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Correlation structure = ar1
Estimated Scale Parameters:

            Estimate Std.err
(Intercept)    0.962   0.105
  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha    0.366  0.0859
Number of clusters:   11  Maximum cluster size: 11
> capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script//S
ummary2020.txt")
> #view plots
> plot(resid(M6))
> plot(fitted(M6), resid(M6))
> #Model predictions for distance with other variables held constant:
> New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
+                          c(60))
> logPass_predict_dist<-predict(M6,newdata=New_dist,type="response")
> Predict_dist<-cbind(New_dist,logPass_predict_dist)
> Predict_dist
   Dist Hab Time logPass_predict_dist
1     0   5   60                 1.54
2    10   5   60                 1.54
3    20   5   60                 1.54
4    30   5   60                 1.53
5    40   5   60                 1.53
6    50   5   60                 1.53
7    60   5   60                 1.53
8    70   5   60                 1.53
9    80   5   60                 1.53
10   90   5   60                 1.53
11  100   5   60                 1.53
12  110   5   60                 1.53
13  120   5   60                 1.53
14  130   5   60                 1.52
15  140   5   60                 1.52
16  150   5   60                 1.52
17  160   5   60                 1.52
18  170   5   60                 1.52
19  180   5   60                 1.52
20  190   5   60                 1.52
21  200   5   60                 1.52
```

22	210	5	60	1.52
23	220	5	60	1.52
24	230	5	60	1.52
25	240	5	60	1.51
26	250	5	60	1.51
27	260	5	60	1.51
28	270	5	60	1.51
29	280	5	60	1.51
30	290	5	60	1.51
31	300	5	60	1.51
32	310	5	60	1.51
33	320	5	60	1.51
34	330	5	60	1.51
35	340	5	60	1.51
36	350	5	60	1.50
37	360	5	60	1.50
38	370	5	60	1.50
39	380	5	60	1.50
40	390	5	60	1.50
41	400	5	60	1.50
42	410	5	60	1.50
43	420	5	60	1.50
44	430	5	60	1.50
45	440	5	60	1.50
46	450	5	60	1.49
47	460	5	60	1.49
48	470	5	60	1.49
49	480	5	60	1.49
50	490	5	60	1.49
51	500	5	60	1.49
52	510	5	60	1.49
53	520	5	60	1.49
54	530	5	60	1.49
55	540	5	60	1.49
56	550	5	60	1.49
57	560	5	60	1.48
58	570	5	60	1.48
59	580	5	60	1.48
60	590	5	60	1.48
61	600	5	60	1.48
62	610	5	60	1.48
63	620	5	60	1.48
64	630	5	60	1.48
65	640	5	60	1.48
66	650	5	60	1.48

```
67   660   5   60                   1.48
68   670   5   60                   1.47
69   680   5   60                   1.47
70   690   5   60                   1.47
71   700   5   60                   1.47
72   710   5   60                   1.47
73   720   5   60                   1.47
74   730   5   60                   1.47
75   740   5   60                   1.47
76   750   5   60                   1.47
77   760   5   60                   1.47
78   770   5   60                   1.46
79   780   5   60                   1.46
80   790   5   60                   1.46
81   800   5   60                   1.46
82   810   5   60                   1.46
83   820   5   60                   1.46
84   830   5   60                   1.46
85   840   5   60                   1.46
86   850   5   60                   1.46
87   860   5   60                   1.46
88   870   5   60                   1.46
89   880   5   60                   1.45
90   890   5   60                   1.45
91   900   5   60                   1.45
92   910   5   60                   1.45
93   920   5   60                   1.45
94   930   5   60                   1.45
95   940   5   60                   1.45
96   950   5   60                   1.45
97   960   5   60                   1.45
98   970   5   60                   1.45
99   980   5   60                   1.45
100  990   5   60                   1.44
101 1000   5   60                   1.44
> write.xlsx(Predict_dist, "C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Prediction
s_distance.xlsx")
> #Plot model predictions (distance):
> par(mar=c(4,4,4,4.5))
> count.overplot(Dist,LPass, cex.axis=1.2, pch=20, tol=0.2, xlab="Distance
+ (m)", ylab ="log(bat passes+1)", cex.lab=1.5, font=1, las=2, xaxt="n")
> xax<-c(0,200,400,600,800,1000)
> axis(1, at=xax, cex.axis=1.2, font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
```

```
> axis(side=4,at=original_scale_position,labels=original_scale,
+      cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(New_dist$Dist, logPass_predict_dist, lwd=2, lty=1)
> #which species are abundant enough for individual analyses
> Bbar0<-((sum(Bbar==0))/(nrow(site1))*100)
> Malc0<-((sum(Malc==0))/(nrow(site1))*100)
> Mbec0<-((sum(Mbec==0))/(nrow(site1))*100)
> MbraMmys0<-((sum(MbraMmys==0))/(nrow(site1))*100)
> Mdau0<-((sum(Mdau==0))/(nrow(site1))*100)
> Mnat0<-((sum(Mnat==0))/(nrow(site1))*100)
> NSL0<-((sum(NSL==0))/(nrow(site1))*100)
> Paur0<-((sum(Paur==0))/(nrow(site1))*100)
> Ppip0<-((sum(Ppip==0))/(nrow(site1))*100)
> Ppyg0<-((sum(Ppyg==0))/(nrow(site1))*100)
> Rhip0<-((sum(Rhip==0))/(nrow(site1))*100)
> Rfer0<-((sum(Rfer==0))/(nrow(site1))*100)
> #total counts for each species
> percent_zero<-rbind(Bbar0, Malc0, Mbec0, MbraMmys0, Mdau0, Mnat0, NSL0,
+                     Paur0, Ppip0, Ppyg0, Rhip0, Rfer0, c("Total"))
> no_passes<-rbind(sum(Bbar), sum(Malc), sum(Mbec), sum(MbraMmys),
+                  sum(Mdau), sum(Mnat), sum(NSL), sum(Paur), sum(Ppip), sum(Ppyg),
+                  sum(Rhip), sum(Rfer), sum(Pass))
> Species_counts<-data.frame(percent_zero,no_passes)
> Species_counts
             percent_zero no_passes
Bbar0     94.5454545454545         6
Malc0                  100         0
Mbec0                  100         0
MbraMmys0              100         0
Mdau0     96.3636363636364         7
Mnat0                  100         0
NSL0      36.3636363636364       193
Paur0     99.0909090909091         1
Ppip0     53.6363636363636       287
Ppyg0     50.9090909090909       142
Rhip0                  100         0
Rfer0                  100         0
                     Total       636
> write.xlsx(Species_counts, "C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Species_
counts.xlsx")
> #Log the number of NSL passes:
> LNSL<-log(NSL+1)
> #Run models with different combinations of variables:
> M1<-geeglm(LNSL ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
```

```
> M2<-geeglm(LNSL ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1, id=RouteNight, corstr="ar1", s
td.err="fij")
> M3<-geeglm(LNSL ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M4<-geeglm(LNSL ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight, corstr="ar1", std.err
="fij")
> M5<-geeglm(LNSL ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M6<-geeglm(LNSL ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> #Use QIC model selection, choose model with lowest QICu:
> print(QIC(M1),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
 64.353695  63.574712 -24.787356   7.389492   7.000000  65.779438
> print(QIC(M2),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
 66.925379  65.540360 -24.770180   8.692509   8.000000  68.725379
> print(QIC(M3),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
 58.805950  54.371803 -24.185902   5.217073   3.000000  59.186902
> print(QIC(M4),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
 59.524291  55.672283 -23.836142   5.926004   4.000000  60.101214
> print(QIC(M5),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
 64.069066  64.007003 -26.003501   6.031032   6.000000  65.167105
> print(QIC(M6),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
 57.855349  54.848836 -25.424418   3.503256   2.000000  58.081764
> #check which are lower if similar QICu
> anova(M3,M6)
Analysis of 'Wald statistic' Table

Model 1 LNSL ~ Dist + Time
Model 2 LNSL ~ Dist
  Df   X2 P(>|Chi|)
1  1 3.38     0.066 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> #View the model output:
> summary(M6)

Call:
geeglm(formula = LNSL ~ Dist, family = gaussian, data = site1,
    id = RouteNight, corstr = "ar1", std.err = "fij")

 Coefficients:
             Estimate   Std.err  Wald Pr(>|W|)
```

```
(Intercept)  0.931088  0.157730 34.85   3.6e-09 ***
Dist        -0.000389  0.000327  1.41     0.23
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation structure = ar1
Estimated Scale Parameters:

            Estimate Std.err
(Intercept)    0.462    0.07
  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha    0.449   0.108
Number of clusters:   11  Maximum cluster size: 11
> capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Su
mmary.txt")
> #view plots
> plot(resid(M6))
> plot(fitted(M6), resid(M6))
> #distance predictions
> New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
+                        c(60))
> logNSL_predict_dist<-predict(M6,newdata=New_dist,type="response")
> Predict_dist<-cbind(New_dist,logNSL_predict_dist)
> Predict_dist
    Dist Hab Time logNSL_predict_dist
1      0   5   60               0.931
2     10   5   60               0.927
3     20   5   60               0.923
4     30   5   60               0.919
5     40   5   60               0.916
6     50   5   60               0.912
7     60   5   60               0.908
8     70   5   60               0.904
9     80   5   60               0.900
10    90   5   60               0.896
11   100   5   60               0.892
12   110   5   60               0.888
13   120   5   60               0.884
14   130   5   60               0.881
15   140   5   60               0.877
16   150   5   60               0.873
17   160   5   60               0.869
```

18	170	5	60	0.865
19	180	5	60	0.861
20	190	5	60	0.857
21	200	5	60	0.853
22	210	5	60	0.849
23	220	5	60	0.846
24	230	5	60	0.842
25	240	5	60	0.838
26	250	5	60	0.834
27	260	5	60	0.830
28	270	5	60	0.826
29	280	5	60	0.822
30	290	5	60	0.818
31	300	5	60	0.814
32	310	5	60	0.811
33	320	5	60	0.807
34	330	5	60	0.803
35	340	5	60	0.799
36	350	5	60	0.795
37	360	5	60	0.791
38	370	5	60	0.787
39	380	5	60	0.783
40	390	5	60	0.779
41	400	5	60	0.776
42	410	5	60	0.772
43	420	5	60	0.768
44	430	5	60	0.764
45	440	5	60	0.760
46	450	5	60	0.756
47	460	5	60	0.752
48	470	5	60	0.748
49	480	5	60	0.744
50	490	5	60	0.741
51	500	5	60	0.737
52	510	5	60	0.733
53	520	5	60	0.729
54	530	5	60	0.725
55	540	5	60	0.721
56	550	5	60	0.717
57	560	5	60	0.713
58	570	5	60	0.709
59	580	5	60	0.706
60	590	5	60	0.702
61	600	5	60	0.698
62	610	5	60	0.694

```
63   620   5   60              0.690
64   630   5   60              0.686
65   640   5   60              0.682
66   650   5   60              0.678
67   660   5   60              0.674
68   670   5   60              0.671
69   680   5   60              0.667
70   690   5   60              0.663
71   700   5   60              0.659
72   710   5   60              0.655
73   720   5   60              0.651
74   730   5   60              0.647
75   740   5   60              0.643
76   750   5   60              0.639
77   760   5   60              0.636
78   770   5   60              0.632
79   780   5   60              0.628
80   790   5   60              0.624
81   800   5   60              0.620
82   810   5   60              0.616
83   820   5   60              0.612
84   830   5   60              0.608
85   840   5   60              0.604
86   850   5   60              0.601
87   860   5   60              0.597
88   870   5   60              0.593
89   880   5   60              0.589
90   890   5   60              0.585
91   900   5   60              0.581
92   910   5   60              0.577
93   920   5   60              0.573
94   930   5   60              0.569
95   940   5   60              0.566
96   950   5   60              0.562
97   960   5   60              0.558
98   970   5   60              0.554
99   980   5   60              0.550
100  990   5   60              0.546
101 1000   5   60              0.542
> write.xlsx (Predict_dist, file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Pred
ictions_distanceNSL.xlsx")
> #Create plot
> par(mar=c(4,4,4,4.5))
> count.overplot(Dist,LNSL, cex.axis=1.2, pch=20, tol=0.2, xlab="Distance
+ (m)", ylab ="log(bat passes+1)", cex.lab=1.5, font=1, las=2, xaxt="n")
```

```
> xax<-c(0,200,400,600,800,1000)
> axis(1, at=xax, cex.axis=1.2, font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale,
+      cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(New_dist$Dist, logNSL_predict_dist, lwd=2, lty=1)
> #Log the number of Ppip passes:
> LPpip<-log(Ppip+1)
> #Run models with different combinations of variables:
> M1<-geeglm(LPpip ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M2<-geeglm(LPpip ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
> M3<-geeglm(LPpip ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M4<-geeglm(LPpip ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight, corstr="ar1", std.er
r="fij")
> M5<-geeglm(LPpip ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M6<-geeglm(LPpip ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> #Use QIC model selection, choose model with lowest QICu:
> print(QIC(M1),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
103.438478 106.676188 -46.338094   5.381145   7.000000 104.864220
> print(QIC(M2),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
104.785813 107.626937 -45.813468   6.579438   8.000000 106.585813
> print(QIC(M3),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
103.949601 103.927216 -48.963608   3.011193   3.000000 104.330554
> print(QIC(M4),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
104.721578 105.035925 -48.517963   3.842827   4.000000 105.298501
> print(QIC(M5),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
102.469361 104.785807 -46.392904   4.841777   6.000000 103.567401
> print(QIC(M6),digits=7)
       QIC       QICu  Quasi Lik        CIC     params       QICC
102.619228 101.800701 -48.900350   2.409263   2.000000 102.845643
> #View the model output:
> summary(M6)

Call:
geeglm(formula = LPpip ~ Dist, family = gaussian, data = site1,
    id = RouteNight, corstr = "ar1", std.err = "fij")
```

```
 Coefficients:
             Estimate  Std.err Wald Pr(>|W|)
(Intercept) 7.43e-01 1.83e-01 16.4  5.1e-05 ***
Dist        1.73e-05 2.84e-04  0.0     0.95
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation structure = ar1
Estimated Scale Parameters:

             Estimate Std.err
(Intercept)    0.889   0.122
  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha    0.363   0.148
Number of clusters:   11  Maximum cluster size: 11
> capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Su
mmaryPpipM6.txt")
> #view plots
> plot(resid(M6))
> plot(fitted(M6), resid(M6))
> #distance predictions
> New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
+                          c(60))
> logPpip_predict_dist<-predict(M6,newdata=New_dist,type="response")
> Predict_dist<-cbind(New_dist,logPpip_predict_dist)
> Predict_dist
    Dist Hab Time logPpip_predict_dist
1      0   5   60                0.743
2     10   5   60                0.743
3     20   5   60                0.743
4     30   5   60                0.743
5     40   5   60                0.744
6     50   5   60                0.744
7     60   5   60                0.744
8     70   5   60                0.744
9     80   5   60                0.744
10    90   5   60                0.744
11   100   5   60                0.745
12   110   5   60                0.745
13   120   5   60                0.745
14   130   5   60                0.745
15   140   5   60                0.745
```

16	150	5	60	0.746
17	160	5	60	0.746
18	170	5	60	0.746
19	180	5	60	0.746
20	190	5	60	0.746
21	200	5	60	0.746
22	210	5	60	0.747
23	220	5	60	0.747
24	230	5	60	0.747
25	240	5	60	0.747
26	250	5	60	0.747
27	260	5	60	0.747
28	270	5	60	0.748
29	280	5	60	0.748
30	290	5	60	0.748
31	300	5	60	0.748
32	310	5	60	0.748
33	320	5	60	0.748
34	330	5	60	0.749
35	340	5	60	0.749
36	350	5	60	0.749
37	360	5	60	0.749
38	370	5	60	0.749
39	380	5	60	0.750
40	390	5	60	0.750
41	400	5	60	0.750
42	410	5	60	0.750
43	420	5	60	0.750
44	430	5	60	0.750
45	440	5	60	0.751
46	450	5	60	0.751
47	460	5	60	0.751
48	470	5	60	0.751
49	480	5	60	0.751
50	490	5	60	0.751
51	500	5	60	0.752
52	510	5	60	0.752
53	520	5	60	0.752
54	530	5	60	0.752
55	540	5	60	0.752
56	550	5	60	0.752
57	560	5	60	0.753
58	570	5	60	0.753
59	580	5	60	0.753
60	590	5	60	0.753

```
61   600   5   60                 0.753
62   610   5   60                 0.753
63   620   5   60                 0.754
64   630   5   60                 0.754
65   640   5   60                 0.754
66   650   5   60                 0.754
67   660   5   60                 0.754
68   670   5   60                 0.755
69   680   5   60                 0.755
70   690   5   60                 0.755
71   700   5   60                 0.755
72   710   5   60                 0.755
73   720   5   60                 0.755
74   730   5   60                 0.756
75   740   5   60                 0.756
76   750   5   60                 0.756
77   760   5   60                 0.756
78   770   5   60                 0.756
79   780   5   60                 0.756
80   790   5   60                 0.757
81   800   5   60                 0.757
82   810   5   60                 0.757
83   820   5   60                 0.757
84   830   5   60                 0.757
85   840   5   60                 0.757
86   850   5   60                 0.758
87   860   5   60                 0.758
88   870   5   60                 0.758
89   880   5   60                 0.758
90   890   5   60                 0.758
91   900   5   60                 0.759
92   910   5   60                 0.759
93   920   5   60                 0.759
94   930   5   60                 0.759
95   940   5   60                 0.759
96   950   5   60                 0.759
97   960   5   60                 0.760
98   970   5   60                 0.760
99   980   5   60                 0.760
100  990   5   60                 0.760
101 1000   5   60                 0.760
> write.xlsx (Predict_dist, file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Pred
ictions_distancePpip.xlsx")
> #Create plot
> par(mar=c(4,4,4,4.5))
```

```
> count.overplot(Dist,LPpip, cex.axis=1.2, pch=20, tol=0.2, xlab="Distance
+ (m)", ylab ="log(bat passes+1)", cex.lab=1.5, font=1, las=2, xaxt="n")
> xax<-c(0,200,400,600,800,1000)
> axis(1, at=xax, cex.axis=1.2, font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale,
+      cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(New_dist$Dist, logPpip_predict_dist, lwd=2, lty=1)
> #Log the number of Ppyg passes:
> LPpyg<-log(Ppyg+1)
> #Run models with different combinations of variables:
> M1<-geeglm(LPpyg ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M2<-geeglm(LPpyg ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
> M3<-geeglm(LPpyg ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M4<-geeglm(LPpyg ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight, corstr="ar1", std.er
r="fij")
> M5<-geeglm(LPpyg ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M6<-geeglm(LPpyg ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> #Use QIC model selection, choose model with lowest QICu:
> print(QIC(M1),digits=7)
      QIC      QICu  Quasi Lik       CIC    params      QICC
 60.069010  61.719438 -23.859719   6.174786   7.000000  61.494752
> print(QIC(M2),digits=7)
      QIC      QICu  Quasi Lik       CIC    params      QICC
 62.152808  63.712106 -23.856053   7.220351   8.000000  63.952808
> print(QIC(M3),digits=7)
     QIC     QICu Quasi Lik      CIC   params     QICC
 55.58323  54.66545 -24.33272   3.45889   3.00000  55.96418
> print(QIC(M4),digits=7)
      QIC      QICu  Quasi Lik       CIC    params      QICC
 57.493832  56.655431 -24.327715   4.419201   4.000000  58.070755
> print(QIC(M5),digits=7)
      QIC      QICu  Quasi Lik       CIC    params      QICC
 58.858366  59.848798 -23.924399   5.504784   6.000000  59.956406
> print(QIC(M6),digits=7)
      QIC      QICu  Quasi Lik       CIC    params      QICC
 53.842294  52.653202 -24.326601   2.594546   2.000000  54.068709
> #View the model output:
> summary(M6)

Call:
geeglm(formula = LPpyg ~ Dist, family = gaussian, data = site1,
```

```
    id = RouteNight, corstr = "ar1", std.err = "fij")

 Coefficients:
            Estimate  Std.err  Wald Pr(>|W|)    
(Intercept) 5.10e-01 1.35e-01 14.34  0.00015 ***
Dist        9.35e-05 2.20e-04  0.18  0.67109    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation structure = ar1 
Estimated Scale Parameters:

            Estimate Std.err
(Intercept)    0.442  0.0479
  Link = identity 

Estimated Correlation Parameters:
      Estimate Std.err
alpha    0.173   0.128
Number of clusters:   11  Maximum cluster size: 11 
> capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Su
mmaryPpygM6.txt")
> #view plots
> plot(resid(M6))
> plot(fitted(M6), resid(M6))
> #distance predictions
> New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
+                          c(60))
> logPpyg_predict_dist<-predict(M6,newdata=New_dist,type="response")
> Predict_dist<-cbind(New_dist,logPpyg_predict_dist)
> Predict_dist
    Dist Hab Time logPpyg_predict_dist
1      0   5   60                0.510
2     10   5   60                0.510
3     20   5   60                0.511
4     30   5   60                0.512
5     40   5   60                0.513
6     50   5   60                0.514
7     60   5   60                0.515
8     70   5   60                0.516
9     80   5   60                0.517
10    90   5   60                0.518
11   100   5   60                0.519
12   110   5   60                0.520
13   120   5   60                0.521
```

14	130	5	60	0.522
15	140	5	60	0.523
16	150	5	60	0.524
17	160	5	60	0.525
18	170	5	60	0.525
19	180	5	60	0.526
20	190	5	60	0.527
21	200	5	60	0.528
22	210	5	60	0.529
23	220	5	60	0.530
24	230	5	60	0.531
25	240	5	60	0.532
26	250	5	60	0.533
27	260	5	60	0.534
28	270	5	60	0.535
29	280	5	60	0.536
30	290	5	60	0.537
31	300	5	60	0.538
32	310	5	60	0.539
33	320	5	60	0.539
34	330	5	60	0.540
35	340	5	60	0.541
36	350	5	60	0.542
37	360	5	60	0.543
38	370	5	60	0.544
39	380	5	60	0.545
40	390	5	60	0.546
41	400	5	60	0.547
42	410	5	60	0.548
43	420	5	60	0.549
44	430	5	60	0.550
45	440	5	60	0.551
46	450	5	60	0.552
47	460	5	60	0.553
48	470	5	60	0.553
49	480	5	60	0.554
50	490	5	60	0.555
51	500	5	60	0.556
52	510	5	60	0.557
53	520	5	60	0.558
54	530	5	60	0.559
55	540	5	60	0.560
56	550	5	60	0.561
57	560	5	60	0.562
58	570	5	60	0.563

```
59   580   5   60                  0.564
60   590   5   60                  0.565
61   600   5   60                  0.566
62   610   5   60                  0.567
63   620   5   60                  0.568
64   630   5   60                  0.568
65   640   5   60                  0.569
66   650   5   60                  0.570
67   660   5   60                  0.571
68   670   5   60                  0.572
69   680   5   60                  0.573
70   690   5   60                  0.574
71   700   5   60                  0.575
72   710   5   60                  0.576
73   720   5   60                  0.577
74   730   5   60                  0.578
75   740   5   60                  0.579
76   750   5   60                  0.580
77   760   5   60                  0.581
78   770   5   60                  0.582
79   780   5   60                  0.582
80   790   5   60                  0.583
81   800   5   60                  0.584
82   810   5   60                  0.585
83   820   5   60                  0.586
84   830   5   60                  0.587
85   840   5   60                  0.588
86   850   5   60                  0.589
87   860   5   60                  0.590
88   870   5   60                  0.591
89   880   5   60                  0.592
90   890   5   60                  0.593
91   900   5   60                  0.594
92   910   5   60                  0.595
93   920   5   60                  0.596
94   930   5   60                  0.596
95   940   5   60                  0.597
96   950   5   60                  0.598
97   960   5   60                  0.599
98   970   5   60                  0.600
99   980   5   60                  0.601
100  990   5   60                  0.602
101 1000   5   60                  0.603
> write.xlsx (Predict_dist, file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Pred
ictions_distancePpyg.xlsx")
```

```
> #Create plot
> par(mar=c(4,4,4,4.5))
> count.overplot(Dist,LPpyg, cex.axis=1.2, pch=20, tol=0.2, xlab="Distance
+ (m)", ylab ="log(bat passes+1)", cex.lab=1.5, font=1, las=2, xaxt="n")
> xax<-c(0,200,400,600,800,1000)
> axis(1, at=xax, cex.axis=1.2, font=1)
> original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
> original_scale_position<-log(original_scale+1)
> axis(side=4,at=original_scale_position,labels=original_scale,
+      cex.axis=1.2,las=2)
> mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
> lines(New_dist$Dist, logPpyg_predict_dist, lwd=2, lty=1)
> #Convert the ‘Species’ variable to proportion data by creating and combining two new variables
> site1$Species_fail<-7-site1$Species
> site1$Sp<-cbind(site1$Species, site1$Species_fail)
> M1<-geeglm(Sp ~ Dist + Hab + Time, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M2<-geeglm(Sp ~ Dist + Hab + poly(Time,2,raw=TRUE), family=binomial, data=site1, id=RouteNight, corstr="ar1", std
.err="fij")
> M3<-geeglm(Sp ~ Dist + Time, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M4<-geeglm(Sp ~ Dist + poly(Time,2,raw=TRUE), family=binomial, data=site1,id =RouteNight, corstr="ar1", std.err="
fij")
> M5<-geeglm(Sp ~ Dist + Hab, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> M6<-geeglm(Sp ~ Dist, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
> #Use QIC model selection, choose model with lowest QICu:
> print(QIC(M1),digits=7)
      QIC      QICu Quasi Lik       CIC    params      QICC
204.26189 132.35587 -59.17793  42.95301   7.00000 205.68763
> print(QIC(M2),digits=7)
      QIC      QICu Quasi Lik       CIC    params      QICC
215.16055 134.33491 -59.16745  48.41282   8.00000 216.96055
> print(QIC(M3),digits=7)
      QIC      QICu Quasi Lik       CIC    params      QICC
175.47447 124.01539 -59.00770  28.72954   3.00000 175.85542
> print(QIC(M4),digits=7)
      QIC      QICu Quasi Lik       CIC    params      QICC
185.02851 125.97044 -58.98522  33.52903   4.00000 185.60543
> print(QIC(M5),digits=7)
      QIC      QICu Quasi Lik       CIC    params      QICC
194.98632 130.19752 -59.09876  38.39440   6.00000 196.08436
> print(QIC(M6),digits=7)
      QIC      QICu Quasi Lik       CIC    params      QICC
162.95867 121.89244 -58.94622  22.53311   2.00000 163.18509
> #View the model output:
> summary(M6)
```

```
Call:
geeglm(formula = Sp ~ Dist, family = binomial, data = site1,
    id = RouteNight, corstr = "ar1", std.err = "fij")

 Coefficients:
             Estimate   Std.err  Wald Pr(>|W|)
(Intercept) -1.158295  0.231072 25.13  5.4e-07 ***
Dist        -0.000112  0.000399  0.08     0.78
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation structure = ar1
Estimated Scale Parameters:

            Estimate Std.err
(Intercept)    0.152  0.0183
  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha    0.395   0.121
Number of clusters:   11  Maximum cluster size: 11
> capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Su
mmarySpM6.txt")
> #view plots
> plot(resid(M6))
> plot(fitted(M6), resid(M6))
> #distance predictions
> New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
+                        c(60))
> New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
+                        c(60))
> Sp_predict_dist<-predict(M6,newdata=New_dist,type="response")
> Species_predict_dist<-cbind(New_dist,Sp_predict_dist)
> Species_predict_dist
    Dist Hab Time Sp_predict_dist
1      0   5   60           0.239
2     10   5   60           0.239
3     20   5   60           0.239
4     30   5   60           0.238
5     40   5   60           0.238
6     50   5   60           0.238
7     60   5   60           0.238
8     70   5   60           0.238
9     80   5   60           0.237
```

10	90	5	60	0.237
11	100	5	60	0.237
12	110	5	60	0.237
13	120	5	60	0.237
14	130	5	60	0.236
15	140	5	60	0.236
16	150	5	60	0.236
17	160	5	60	0.236
18	170	5	60	0.236
19	180	5	60	0.235
20	190	5	60	0.235
21	200	5	60	0.235
22	210	5	60	0.235
23	220	5	60	0.235
24	230	5	60	0.234
25	240	5	60	0.234
26	250	5	60	0.234
27	260	5	60	0.234
28	270	5	60	0.234
29	280	5	60	0.233
30	290	5	60	0.233
31	300	5	60	0.233
32	310	5	60	0.233
33	320	5	60	0.233
34	330	5	60	0.232
35	340	5	60	0.232
36	350	5	60	0.232
37	360	5	60	0.232
38	370	5	60	0.232
39	380	5	60	0.231
40	390	5	60	0.231
41	400	5	60	0.231
42	410	5	60	0.231
43	420	5	60	0.231
44	430	5	60	0.230
45	440	5	60	0.230
46	450	5	60	0.230
47	460	5	60	0.230
48	470	5	60	0.230
49	480	5	60	0.229
50	490	5	60	0.229
51	500	5	60	0.229
52	510	5	60	0.229
53	520	5	60	0.229
54	530	5	60	0.228

55	540	5	60	0.228
56	550	5	60	0.228
57	560	5	60	0.228
58	570	5	60	0.228
59	580	5	60	0.227
60	590	5	60	0.227
61	600	5	60	0.227
62	610	5	60	0.227
63	620	5	60	0.227
64	630	5	60	0.226
65	640	5	60	0.226
66	650	5	60	0.226
67	660	5	60	0.226
68	670	5	60	0.226
69	680	5	60	0.225
70	690	5	60	0.225
71	700	5	60	0.225
72	710	5	60	0.225
73	720	5	60	0.225
74	730	5	60	0.224
75	740	5	60	0.224
76	750	5	60	0.224
77	760	5	60	0.224
78	770	5	60	0.224
79	780	5	60	0.223
80	790	5	60	0.223
81	800	5	60	0.223
82	810	5	60	0.223
83	820	5	60	0.223
84	830	5	60	0.222
85	840	5	60	0.222
86	850	5	60	0.222
87	860	5	60	0.222
88	870	5	60	0.222
89	880	5	60	0.221
90	890	5	60	0.221
91	900	5	60	0.221
92	910	5	60	0.221
93	920	5	60	0.221
94	930	5	60	0.221
95	940	5	60	0.220
96	950	5	60	0.220
97	960	5	60	0.220
98	970	5	60	0.220
99	980	5	60	0.220

```
100  990   5   60           0.219
101 1000   5   60           0.219
> write.xlsx (Predict_dist, file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Spec
iesredictions_distanceSpecies.xlsx")
> #Create plot
> par(mar=c(4,4.1,2,2))
> plot(New_dist$Dist, Sp_predict_dist, type="l", lwd=2, ylim=c(0,0.4),
+      xlab="Distance (m)", ylab="Probability(species)", cex.lab=1.5,
+      cex.axis=1.2, yaxt="n")
> axis(side=2,cex.axis=1.2,las=2)
> detach(site1)
> rm(list = ls())
> rm(list = ls())
> detach(site)
```

Code

```
#Open the csv file
setwd("c:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script")
site1<-read.csv('2020.csv')

#bats<-read.csv(C:Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script//2020.csv,header=TRUE)

#Attach the data:
attach(site1)

#Tell R about the variables (numeric or factors):
site1$Route<-as.factor(site1$Route)
site1$Day<-as.factor(site1$Day)
site1$Dist<-as.numeric(site1$Dist)
site1$Time<-as.numeric(site1$Time)
site1$Pass<-as.numeric(site1$Pass)
site1$Species<-as.numeric(site1$Species)
site1$Bbar<-as.numeric(site1$Bbar)
site1$Malc<-as.numeric(site1$Malc)
site1$Mbec<-as.numeric(site1$Mbec)
site1$MbraMmys<-as.numeric(site1$MbraMmys)
site1$Mdau<-as.numeric(site1$Mdau)
site1$Mnat<-as.numeric(site1$Mnat)
site1$NSL<-as.numeric(site1$NSL)
site1$Paur<-as.numeric(site1$Paur)
site1$Ppip<-as.numeric(site1$Ppip)
site1$Ppyg<-as.numeric(site1$Ppyg)
site1$Rfer<-as.numeric(site1$Rfer)
site1$Rhip<-as.numeric(site1$Rhip)
site1$Hab<-as.factor(site1$Hab)
site1$RouteNight<-factor(ifelse(site1$Day=="1",paste(site1$Route,".1",sep=""), paste(site1$Route,
".2",sep="")))


#Displays the structure of the data and variable types:
str(site1)

#Load the packages required for the analysis
install.packages("geepack")
install.packages("MESS")
install.packages("polyclip")
install.packages("xlsx")
install.packages("plotrix")
library(geepack)
library(MESS)
library(xlsx)
library(plotrix)


#Log the number of bat passes:
LPass<-log(Pass+1)

#Run models with different combinations of variables:
M1<-geeglm(LPass ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M2<-geeglm(LPass ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1,
id=RouteNight, corstr="ar1", std.err="fij")
```

```
M3<-geeglm(LPass ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M4<-geeglm(LPass ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight,
corstr="ar1", std.err="fij")
M5<-geeglm(LPass ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M6<-geeglm(LPass ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")

#Use QIC model selection, choose model with lowest QICu:
print(QIC(M1),digits=7)
print(QIC(M2),digits=7)
print(QIC(M3),digits=7)
print(QIC(M4),digits=7)
print(QIC(M5),digits=7)
print(QIC(M6),digits=7)

#check which are lower if similar QICu
anova(M3,M6)
summary(anova(M3,M6))

#View the model output:
summary(M6)
capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script//Summary2020.txt")

#view plots
plot(resid(M6))
plot(fitted(M6), resid(M6))


#Model predictions for distance with other variables held constant:
New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
                  c(60))
logPass_predict_dist<-predict(M6,newdata=New_dist,type="response")
Predict_dist<-cbind(New_dist,logPass_predict_dist)
Predict_dist

write.xlsx(Predict_dist, "C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script/Predictions_distance.xlsx")


#Plot model predictions (distance):
par(mar=c(4,4,4,4.5))
count.overplot(Dist,LPass, cex.axis=1.2, pch=20, tol=0.2, xlab="Distance
(m)", ylab ="log(bat passes+1)", cex.lab=1.5, font=1, las=2, xaxt="n")
xax<-c(0,200,400,600,800,1000)
axis(1, at=xax, cex.axis=1.2, font=1)
original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
original_scale_position<-log(original_scale+1)
axis(side=4,at=original_scale_position,labels=original_scale,
   cex.axis=1.2,las=2)
mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
lines(New_dist$Dist, logPass_predict_dist, lwd=2, lty=1)


#which species are abundant enough for individual analyses
Bbar0<-((sum(Bbar==0))/(nrow(site1))*100)
Malc0<-((sum(Malc==0))/(nrow(site1))*100)
Mbec0<-((sum(Mbec==0))/(nrow(site1))*100)
MbraMmys0<-((sum(MbraMmys==0))/(nrow(site1))*100)
```

```
Mdau0<-((sum(Mdau==0))/(nrow(site1))*100)
Mnat0<-((sum(Mnat==0))/(nrow(site1))*100)
NSL0<-((sum(NSL==0))/(nrow(site1))*100)
Paur0<-((sum(Paur==0))/(nrow(site1))*100)
Ppip0<-((sum(Ppip==0))/(nrow(site1))*100)
Ppyg0<-((sum(Ppyg==0))/(nrow(site1))*100)
Rhip0<-((sum(Rhip==0))/(nrow(site1))*100)
Rfer0<-((sum(Rfer==0))/(nrow(site1))*100)


#total counts for each species
percent_zero<-rbind(Bbar0, Malc0, Mbec0, MbraMmys0, Mdau0, Mnat0, NSL0,
              Paur0, Ppip0, Ppyg0, Rhip0, Rfer0, c("Total"))
no_passes<-rbind(sum(Bbar), sum(Malc), sum(Mbec), sum(MbraMmys),
            sum(Mdau), sum(Mnat), sum(NSL), sum(Paur), sum(Ppip), sum(Ppyg),
            sum(Rhip), sum(Rfer), sum(Pass))
Species_counts<-data.frame(percent_zero,no_passes)
Species_counts

write.xlsx(Species_counts, "C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script/Species_counts.xlsx")

#Log the number of NSL passes:
LNSL<-log(NSL+1)

#Run models with different combinations of variables:
M1<-geeglm(LNSL ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M2<-geeglm(LNSL ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1,
id=RouteNight, corstr="ar1", std.err="fij")
M3<-geeglm(LNSL ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M4<-geeglm(LNSL ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight,
corstr="ar1", std.err="fij")
M5<-geeglm(LNSL ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M6<-geeglm(LNSL ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")

#Use QIC model selection, choose model with lowest QICu:
print(QIC(M1),digits=7)
print(QIC(M2),digits=7)
print(QIC(M3),digits=7)
print(QIC(M4),digits=7)
print(QIC(M5),digits=7)
print(QIC(M6),digits=7)

#check which are lower if similar QICu
anova(M3,M6)

#View the model output:
summary(M6)

capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script/Summary.txt")

#view plots
plot(resid(M6))
plot(fitted(M6), resid(M6))

#distance predictions
```

```
New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
                   c(60))
logNSL_predict_dist<-predict(M6,newdata=New_dist,type="response")

Predict_dist<-cbind(New_dist,logNSL_predict_dist)
Predict_dist

write.xlsx (Predict_dist, file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script/Predictions_distanceNSL.xlsx")

#Create plot
par(mar=c(4,4,4,4.5))
count.overplot(Dist,LNSL, cex.axis=1.2, pch=20, tol=0.2, xlab="Distance
(m)", ylab ="log(bat passes+1)", cex.lab=1.5, font=1, las=2, xaxt="n")
xax<-c(0,200,400,600,800,1000)
axis(1, at=xax, cex.axis=1.2, font=1)
original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
original_scale_position<-log(original_scale+1)
axis(side=4,at=original_scale_position,labels=original_scale,
    cex.axis=1.2,las=2)
mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
lines(New_dist$Dist, logNSL_predict_dist, lwd=2, lty=1)


#Log the number of Ppip passes:
LPpip<-log(Ppip+1)

#Run models with different combinations of variables:
M1<-geeglm(LPpip ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M2<-geeglm(LPpip ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1,
id=RouteNight, corstr="ar1", std.err="fij")
M3<-geeglm(LPpip ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M4<-geeglm(LPpip ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight,
corstr="ar1", std.err="fij")
M5<-geeglm(LPpip ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M6<-geeglm(LPpip ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")

#Use QIC model selection, choose model with lowest QICu:
print(QIC(M1),digits=7)
print(QIC(M2),digits=7)
print(QIC(M3),digits=7)
print(QIC(M4),digits=7)
print(QIC(M5),digits=7)
print(QIC(M6),digits=7)


#View the model output:
summary(M6)

capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script/SummaryPpipM6.txt")

#view plots
plot(resid(M6))
plot(fitted(M6), resid(M6))

#distance predictions
```

```
New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
                    c(60))
logPpip_predict_dist<-predict(M6,newdata=New_dist,type="response")

Predict_dist<-cbind(New_dist,logPpip_predict_dist)
Predict_dist

write.xlsx (Predict_dist, file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script/Predictions_distancePpip.xlsx")

#Create plot
par(mar=c(4,4,4,4.5))
count.overplot(Dist,LPpip, cex.axis=1.2, pch=20, tol=0.2, xlab="Distance
(m)", ylab ="log(bat passes+1)", cex.lab=1.5, font=1, las=2, xaxt="n")
xax<-c(0,200,400,600,800,1000)
axis(1, at=xax, cex.axis=1.2, font=1)
original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
original_scale_position<-log(original_scale+1)
axis(side=4,at=original_scale_position,labels=original_scale,
    cex.axis=1.2,las=2)
mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
lines(New_dist$Dist, logPpip_predict_dist, lwd=2, lty=1)


#Log the number of Ppyg passes:
LPpyg<-log(Ppyg+1)

#Run models with different combinations of variables:
M1<-geeglm(LPpyg ~ Dist + Hab + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M2<-geeglm(LPpyg ~ Dist + Hab + poly(Time,2,raw=TRUE), family=gaussian, data=site1,
id=RouteNight, corstr="ar1", std.err="fij")
M3<-geeglm(LPpyg ~ Dist + Time, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M4<-geeglm(LPpyg ~ Dist + poly(Time,2,raw=TRUE), family=gaussian, data=site1,id =RouteNight,
corstr="ar1", std.err="fij")
M5<-geeglm(LPpyg ~ Dist + Hab, family=gaussian, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M6<-geeglm(LPpyg ~ Dist, family=gaussian, data=site1, id=RouteNight, corstr="ar1", std.err="fij")

#Use QIC model selection, choose model with lowest QICu:
print(QIC(M1),digits=7)
print(QIC(M2),digits=7)
print(QIC(M3),digits=7)
print(QIC(M4),digits=7)
print(QIC(M5),digits=7)
print(QIC(M6),digits=7)

#View the model output:
summary(M6)

capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script/SummaryPpygM6.txt")

#view plots
plot(resid(M6))
plot(fitted(M6), resid(M6))

#distance predictions
New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
```

```
                    c(60))
logPpyg_predict_dist<-predict(M6,newdata=New_dist,type="response")

Predict_dist<-cbind(New_dist,logPpyg_predict_dist)
Predict_dist

write.xlsx (Predict_dist, file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script/Predictions_distancePpyg.xlsx")

#Create plot
par(mar=c(4,4,4,4.5))
count.overplot(Dist,LPpyg, cex.axis=1.2, pch=20, tol=0.2, xlab="Distance
(m)", ylab ="log(bat passes+1)", cex.lab=1.5, font=1, las=2, xaxt="n")
xax<-c(0,200,400,600,800,1000)
axis(1, at=xax, cex.axis=1.2, font=1)
original_scale<-c(0,2,5,10,20,50,100,200,500,1000)
original_scale_position<-log(original_scale+1)
axis(side=4,at=original_scale_position,labels=original_scale,
    cex.axis=1.2,las=2)
mtext(side = 4, line = 3.5, "No. bat passes",cex=1.5)
lines(New_dist$Dist, logPpyg_predict_dist, lwd=2, lty=1)

#Convert the ‘Species’ variable to proportion data by creating and combining two new variables
site1$Species_fail<-7-site1$Species
site1$Sp<-cbind(site1$Species, site1$Species_fail)

#Run models with different combinations of variables:

M1<-geeglm(Sp ~ Dist + Hab + Time, family=binomial, data=site1, id=RouteNight, corstr="ar1",
std.err="fij")
M2<-geeglm(Sp ~ Dist + Hab + poly(Time,2,raw=TRUE), family=binomial, data=site1, id=RouteNight,
corstr="ar1", std.err="fij")
M3<-geeglm(Sp ~ Dist + Time, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
M4<-geeglm(Sp ~ Dist + poly(Time,2,raw=TRUE), family=binomial, data=site1,id =RouteNight,
corstr="ar1", std.err="fij")
M5<-geeglm(Sp ~ Dist + Hab, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")
M6<-geeglm(Sp ~ Dist, family=binomial, data=site1, id=RouteNight, corstr="ar1", std.err="fij")

#Use QIC model selection, choose model with lowest QICu:
print(QIC(M1),digits=7)
print(QIC(M2),digits=7)
print(QIC(M3),digits=7)
print(QIC(M4),digits=7)
print(QIC(M5),digits=7)
print(QIC(M6),digits=7)

#View the model output:
summary(M6)

capture.output(summary(M6), file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale
surveys/R_Script/SummarySpM6.txt")

#view plots
plot(resid(M6))
plot(fitted(M6), resid(M6))

#distance predictions
New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
                    c(60))
New_dist<-data.frame(Dist = seq(0,1000, length = 101), Hab = c("5"), Time =
```

```
                    c(60))
Sp_predict_dist<-predict(M6,newdata=New_dist,type="response")
Species_predict_dist<-cbind(New_dist,Sp_predict_dist)
Species_predict_dist

write.xlsx (Predict_dist, file="C:/Users/marianne.curtis/Documents/A303/Bat_Landscape scale surveys/R_Script/Speciesredictions_distanceSpecies.xlsx")

#Create plot
par(mar=c(4,4.1,2,2))
plot(New_dist$Dist, Sp_predict_dist, type="l", lwd=2, ylim=c(0,0.4),
    xlab="Distance (m)", ylab="Probability(species)", cex.lab=1.5,
    cex.axis=1.2, yaxt="n")
axis(side=2,cex.axis=1.2,las=2)


detach(site1)
```

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