# Appendix 2: Modelling Methods and Results USED TO INFORM THE Newell's Shearwater Landscape Strategy 

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## EXECUTIVE SUMMARY

This appendix to the Newell's Shearwater (NESH) Recovery Strategy provides a detailed methodological and technical overview of the modeling used to assess the status, threats and mitigation strategies for NESH. It was developed by the United States Fish and Wildlife Service (USFWS) to determine the degree to which the number of threats affects the overall viability of the species, and to help managers evaluate the efficacy of various mitigation strategies. The assessment relies on information from Day et al. (2003), Ainley et al. (2001), Griesemer and Holmes (2011), and the Kauai Seabird Program.

Using a series of statistical methodologies, a set of geographic layers were developed that either directly or indirectly inform three major features affecting the status of NESH: (1) a geographic projection of the current distribution of NESH; (2) the location and severity of power-line strikes, as projected across monitored transmission lines; and (3) a site based population viability assessment. The NESH model assessment showed that approximately 1,800 birds per year die due to powerline strikes. The assessment also showed an estimated reduction in modeled NESH habitat of approximately $65 \%$ due to current viewable light sources; and that even with a conservative predation estimate, all Kauai colonies will likely be reduced to five or fewer individuals by 2050-2100 unless further conservation efforts are implemented.

Though the decline of NESH is severe, mitigation of the powerline and light based mortalities is possible with the immediate application of landscape scale strategies. These mitigation strategies, when applied strategically, can theoretically prolong the survival of certain NESH colonies past the current mid to end century extinction projection. Mitigation strategies that should be pursued on Kauai are large scale control, removal and exclusion of NESH predators (pigs, cats, rats, and barn owls), translocation to predator free areas, and social attraction in predator free areas. Tools were developed for this assessment, and are reviewed here, that may help managers assess the efficacy of applying the various strategies on both a site specific and landscape scale. This analysis in its current form does not take into account powerline strike or light fallout minimization, a variable that will positively influence the projected population's status. Minimization can be incorporated into the analysis once additional data identifying potential minimization sites and efficacy is available.

This assessment reflects the information known at the time of the modeling (July 2016) however additional data continues to be collected on Kauai's seabirds. Therefore this assessment will be evaluated and modified as needed over time. Adjustments will be made no more frequently than annually and only as needed given any new, significant data received each year. The overall assessment will be made available each time it is formally modified.

## TABLE OF CONTENTS

ACKNOWLEDGMENTS ..... 2
EXECUTIVE SUMMARY ..... 3
TABLE OF CONTENTS ..... 5
APPENDIX 2 TABLES ..... 8
APPENDIX 2 FIGURES ..... 11
SUMMARY ..... 20
Assessment Utility, Need, and Sectional Overview ..... 20
Summarized Results ..... 22

1. Section 1: ENVIRONMENTAL LAYER DEVELOPMENT AND SELECTION ..... 31
1.1 Bioclimatic, Topographic, and Weather Variable Development: Overview ..... 31
1.1.1 Nightlight Viewshed: Development ..... 32
1.1.2 Nightlight Viewshed: Output ..... 33
1.2 Extreme Weather Event Impact Projection: Development ..... 33
1.3 Extreme Weather Event Impact Projection: Output ..... 37
1.4 Variable Selection: Overview ..... 38
1.4.1 Variable Selection Procedure: Development ..... 38
1.4.2 Variable Selection: Output ..... 40
1.5 Section 1: TABLES ..... 42
1.6 Section 1: FIGURES ..... 44
2. Section 2: ENSEMBLE NICH MODEL AND CARRYING CAPACITY ESTIMATION ..... 49
2.1 Ensemble Niche Model Development, Validation and Implementation ..... 49
2.1.1 Species Distribution Model (SDM): Development ..... 49
2.1.2 Ensemble Model: Development ..... 51
2.1.3 Model Validation Statistics and Variable Importance: Development ..... 52
2.1.4 Species Distribution Model Validation and Ensemble Model: Output. ..... 52
2.2 Carrying Capacity Estimate: Development ..... 53
2.3 Carrying Capacity Estimate: Output ..... 54
2.4 Section 2: TABLES ..... 55
2.5 Section 2: FIGURES ..... 56
3. Section 3: FLIGHT PATH MODEL ESTIMATION AND VALIDATION ..... 60
3.1 Flight Path Model Development and Ensemble Compilation. ..... 60
3.1.1 Topographically Modified Flight Path Model: Development ..... 60
3.1.2 Flight Path Ensemble and Threshold Model: Development ..... 62
3.1.3 Flight Path Model: Output ..... 63
3.1.4 Flight Path Model Validation Statistics: Development ..... 64
3.1.5 Flight Path Model Validation Statistics: Output ..... 65
3.2 Section 3: TABLES ..... 67
3.3 Section 3: FIGURES ..... 70
4. Section 4: KIUC STRIKE ASSESSMENT MODEL ..... 75
4.12014 and 2015 Power-line Strike Data Imputation: Development ..... 75
4.22014 and 2015 Power-line Strike Data Imputation: Output ..... 78
4.3 Strike Projection: Development ..... 79
4.4 Strike Projection: Output ..... 83
4.5 Estimating Strike Mortality ..... 84
4.6 Section 4: TABLES ..... 85
4.7 Section 4: FIGURES ..... 95
5. Section 5: SITE BY SITE STOCHASTIC POPULATION VIABILITY ANALYSIS ..... 112
5.1 Colony Size Projection: Overview ..... 114
5.2 Colony Size Projection: Output ..... 118
5.3 NESH Demography as Modified by Predation: Overview ..... 118
5.4 NESH Demography as Modified by Predation: Output. ..... 122
5.5 SbS-PVA Powerline Strike and Light Fallout Estimate: Development ..... 123
5.6 Projecting Temporal Viability with Demographic Stochasticity and Extreme Weather Events: Development ..... 125
5.7 Projecting Temporal Viability with Demographic Stochasticity and Extreme Weather Events: Output ..... 129
5.8 Site Specific Carrying Capacity Estimation and Limitation ..... 130
5.9 Stochastic Site-by-Site Population Viability Assessment (SbS-PVA) per site: Overview ..... 131
5.10 Stochastic Site-by-Site Population Viability Assessment (SbS-PVA) Compilation Assessment: Output ..... 132
5.11 Section 5: TABLES ..... 136
5.12 Section 5: FIGURES ..... 141
6. Section 6: META-POPULATION MITIGATION VIABILITY REPLACEMENT CALCULATOR ..... 176
6.1 Base Population Demography without Mitigation Used in the Replacement Calculator ..... 176
6.2 Mitigation Strategy Implementation ..... 176
6.3 Estimating Mitigation Effect. ..... 178
6.4 Replacement Calculator: Output ..... 179
6.5 Section 6: TABLES ..... 181
6.6 Section 6: FIGURES ..... 187
6.7 Section 6: SUPPLEMENTARY CODE ..... 189
7. Section 7: SITE SPECIFIC PREDATOR EXCLUSION/MITIGATION EFFICACY CONTROL CALCULATOR ..... 218
7.1 Site Specific Mitigation Calculator: Overview ..... 218
7.2 Site Specific Mitigation Calculator: Output ..... 222
7.3 Section 7: TABLES ..... 225
7.4 Section 7: FIGURES ..... 235
7.5 Section 7: SUPPLEMENTARY CODE ..... 237
8. BIBLIOGRAPHY ..... 266

## APPENDIX 2 TABLES

Table 1: Outputs for the five factors (corrected Akaike Information Criterion (AICc), Baysian Information Criterion (BIC), Variance Inflation Factor (VIF), and Adjusted R ${ }^{2}$ (Adj-R ${ }^{2}$ )) used in the variable selection procedure are compiled into this binary variable selection table. This table was compiled using specific rule sets developed per analysis technique. These binary outcomes were then summed across the various techniques employed, and an overall assessment of the variables value (in relation to all other values identified) was given. This analysis helped to define a subset of variables from which to select, serving to inform the selection protocol.

Table 2: ROC, TSS and KAPPA validation statistics ( $\pm$ standard deviation) for each of the modelling approaches used (gbm and maxent) as defined over 500 iterations. Potential ranges are: ROC (range 0 to 1 ), TSS (range -1 to 1 ), and KAPPA (range -1 to 1 ).

Table 3: Average number of radar contacts assessed at each site per day, as well as summary data describing the average distance, direction, and velocity of those compiled contacts. 67

Table 4: Multiple regression outputs comparing either the location of an auditory detection, or a radar detection, to the distance from a projected flight path, and the number of flight paths that overlap. Analyses analyzed here are those that were initially produced to assess flight path variability due to topographic variation. As the significance of topography was varied based on a boxplot assessment of the elevations within each overall polygon assessment (KESRP or ENM), values defined were the minimum (Min), first quartile (1stQ), median (Median), mean (Mean), third quartile (3rdQ), and maximum (Max). Values highlighted in red are those analyses that have a $p$-values $\leq 0.05$. The number of detections used to develop this assessment is identified in the data description. 68

Table 5: Multiple regression outputs that compare the location of radar detections to the distance from a projected flight path, and the number of overlapping flight paths. Projections analyzed here are those that were compiled either using a base average, or a weighted average, where weighting was determined by the adjusted $R^{2}$ values of each individual assessment. For each assessment (i.e. weighted or base average) three thresholds were applied. Values highlighted in red are those analyses that have a p-values $\leq 0.05$. The number of detections used to develop this assessment is identified in the data description. 69

Table 6: Imputation procedures, description of secondary modifications, and a citation to their use.

Table 7: The summed yearly imputed/recorded strike detections over all units (Peak and OffPeak) for both 2014 and 2015. The imputation approaches used depended on whether strikes were detected at the site or not. Two of the highest performing approaches were used to calculate the number of imputed strikes shown here, the expectation maximization arima with Fourier imputation approach without Kahili sites, and copy mean longitudinal imputation approach. Imputed sites with an asterisk were removed from all subsequent analyses. Those sites highlighted in red were identified as potentially having outsized influence on a GLM assessment conducted in 2014 or 2015. As such, all subsequent strike
projections were conducted with and without that subset. Highlighted sites denoted with an ${ }^{\dagger}$ are outliers only identified when running the analysis with a subset of variables. 85

$$
\begin{aligned}
& \text { Table 8: Power-line segment variables used to project line strikes. Environmental variables } \\
& \text { selected to inform the variable subset model using a bootstrapped lasso regularization } \\
& \text { selection procedure are highlighted in red. The year that the covariate was selected is also } \\
& \text { defined. .................................................................................................................... } 90
\end{aligned}
$$

Table 9: Scenarios for estimating Newell's Shearwater power-line strike mortality (2014) ..... 91
Table 10: Scenarios for estimating Newell's Shearwater power-line strike mortality (2015) ..... 93
Table 11: Description and AUC ranking of the variable and data subsets used to derive a prediction of site occupancy. Predicted occupancy was defined primarily for Newell's shearwater (NESH). Those assessments highlighted in red were selected for downstream analyses of burrow occupancy. ..... 136
Table 12: NESH specific Elastic Net GLM variable weighting output for the two assessments that were most predictive of burrow occupancy, as defined using the area under the curve (AUC) validation metric (Table 11). Observed variables are shown that overlap with all analyzed points, and are descriptive of vegetation height and type. ..... 137
Table 13 Adult survivorship $\left(S_{x}\right)$ for proxy Procellariformes and their respective sources. This table represents an update to that of Griesemer and Holmes (2011) (Appendix 5). The species highlighted in red represent an outlier to the overall distribution, and thus was not used to define the standard deviation of survivorship. ..... 138
Table 14: KESRP/HCHCP modified predation estimates that reflect chick survivorship in the absence of nesh adults, as well as the levels of predation as increased from the KESRP/HCHCP estimate to match low, medium and high predation lambdas as estimated by Griesemer and Holmes (2011). Each predation estimate was defined from a population with 100 breeding pairs. Mortality of individuals at the major age classes and the proportion of that mortality, as compared to the overall population, are defined. All mortality estimates are here rounded to the second significant figure, but raw calculated values are used in the SBS-PVA. ..... 140
Table 15: Mitigation effect of each predator reduction scenario used in the replacement calculator. These estimates were modified to reflect the Predation lambda s estimated by KESRP/KSHCP. For the KESRP/KSHCP predation scenario the mitigation estimate and the resulting predator reduction was defined as the number of individuals added to the population from each scenario for a population with 100 breeding pairs. Control (not exclusion) here was estimated to be $\sim 50 \%$ of predation (see Table 16). ..... 181
Table 16: Input parameters used in the replacement calculator. ..... 182
Table 17: Inputs used in the replacement calculator example. Input values used here are only meant to help understand the example outputs. ..... 184
Table 18: Replacement Calculator output legend ..... 185
Table 19: Replacement calculator output of the first 15 years, as estimated for the parametersidentified in Table 17. For an explanation of the columns please see Table 18 in thematerials and methods.186
Table 20: Input parameters for the mitigation efficacy site calculator ..... 225
Table 21: Input values for the example analyses (A and B) used in the presented grahics (Figures$44 \& 45)$ and tables226
Table 22: Fledgling production and mitigation for example A. Here fledgling mitigation is assessed over 30 years. To assess mitigation, the total amount of fledglings produced in the site is subtracted from the total number of birds produced without any protection. This can be partitioned between the different population types within the polygon. Because example A is primarily a social attraction site, this table only shows the partitioned mitigation for the social attraction site (which equals the mitigation for the site as a whole).227
Table 23: Fledgling production and mitigation for example B . Here fledgling mitigation is assessed over 30 years. To assess mitigation, the total amount of fledglings produced in the site is subtracted from the total number of birds produced without any protection. This can be partitioned between the different population types within the polygon. Because example B has both a standing population and social attraction component, both are partitioned from the total to assess mitigation229
Table 24: Adult Production and mitigation at year 30 for Example A. For adult production/mitigation, only the reproductive ages are summed for the year of interest. Multiple years should not be compiled to assess mitigation. As in the fledgling production, mitigations is here assessed by subtracting the total amount of adults produced in the site from the total number of birds produced without any protection. This can be partitioned between the different population types within the polygon. Because example A is primarily a social attraction site, this table only shows the partitioned mitigation for the social attraction site (which equals the mitigation for the site as a whole).231
Table 25: Adult Production and mitigation at year 30 for Example B. For adult production/mitigation, only the reproductive ages are summed for the year of interest. Multiple years should not be compiled to assess mitigation. As in the fledgling production, mitigations is here assessed by subtracting the total amount of adults produced in the site from the total number of birds produced without any protection. This can be partitioned between the different population types within the polygon. Because example B has both a standing population and social attraction component, both are partitioned from the total to assess mitigation. 233

## APPENDIX 2 FIGURES

Figure 1: Boxplot assessments of light impact per site defining: (A) the distribution of seabird presence in relation to night time light intensity, and (B) the percent light visibility (i.e. intensity) at each seabird site. Each metric also compares the outputs to the overall (compiled) Light intensity/visibility of each island.

Figure 2: \% Light visibility analysis for Kauai conducted over 10 viewshed iterations projected over a 250 m DEM. Each iteration was varied by a $10^{\text {th }}$ of the light intensity within the thresholded seabird light contour (blue outline); the outputs were compiled to reflect a percentage scale. The Seabird Light Contour was defined using the upper quartile of light intensities in which seabirds occur (Figure 11A). All areas within the contour were considered to have $100 \%$ visible lights

Figure 3: Using regression, each quadrants periphery was defined. This figure shows an example of the wind speed to 34 knots (i.e. the storm events periphery) for a 100 knot storm. The logistic and exponential plots for each estimate are defined. The exponential equation is given for each quadrant. These analyses were then combined to define the overall storm periphery (inset)

Figure 4: Extreme weather event impact assessments in which wind refugia (due to topographic complexity) was identified (A), historical wind impact from extreme weather events was defined (B), and both combined to beget a topographically enabled extreme weather event probability impact assessment that ranged from 0 (no impact) to 1 (high probability of impact) (C). The wind refugia assessment (A) was considered a conservative estimate in that it was derived from a $5^{\circ}$ hillshade affect projected for every compass degree around Kauai.

Figure 5: Pearson Correlation Coefficient (PCC) of all Environmental Variables initially assessed to describe the distribution of Newell's Shearwater. For descriptions of each variable please see Table 1. Variables selected for the final analysis were bio3 = isothermality , bio15 $=$ precipitation seasonality, slope $=$ slope, tri $=$ topographic roughness index and wind $50 \mathrm{mHI}=$ wind at 50 meters.

Figure 6: Variable importance boxplot for each species distribution model modelling approach (Maxent and GBM). Higher response values for each variable indicate greater importance of that variable to the overall models output. Each variables response is calculated from 500 iterations of each modelling approach used. The presented variables correspond to: bio3 = isothermality, bio15 $=$ precipitation seasonality, slope $=$ slope, tri $=$ topographic roughness index and wind $50 \mathrm{mHI}=$ wind at 50 meters.

Figure 7: Average linear response plots of each variable within each modelling approach over the range of each environmental variables distribution (as rescaled to an overall 0-1 range). Response plots were defined as the average of responses over 500 iterations for both Maxent (A) and GBM (B). The presented variables correspond to: bio3 $=$ isothermality, bio15 = precipitation seasonality, slope $=$ slope, tri $=$ topographic roughness index and wind $50 \mathrm{mHI}=$ wind at 50 meters

Figure 8: GBM and Maxent species distribution ensemble models as cut to define presence/absence by the equal sensitivity and specificity thresholding parameter under the ROC AUC statistic (A). To assess the impact of light on the ensemble model, certain areas were removed due to visible light impingement (B) (Fig. 1\& 2).

Figure 9: NESH cell density boxplot used to approximate the carrying capacity (K) from KESRP auditory collections. To define K, the upper $95 \%$ confidence interval was used. This assessment was mainly applied to define the upper bounds in which any population viability assessment should predict the maximum size of the Kauai meta-population.

Figure 10: Least cost path projections of NESH flight path from ENM projected locations. Elevation was varied based on a boxplot assessment of elevation over all ENM defined polygons. Elevation for each assessment was thresholded by the minimum (A), $1^{\text {st }}$ Quartile, (B), Mean (C), Median (D), $3^{\text {rd }}$ Quartile (E), and Maximum (F) elevation defined by the boxplot. All plots shown describe the least cost path from the polygons (1 point every 250 $\mathrm{m}^{2}$ ), to $1 / 4^{\text {th }}$ of the islands coastal destination, as defined by 1 point approximately every 100 meters. Variations in color (varied numerically from 0-1) describe the degree of flight path overlap for each location in each model.

Figure 11: Least cost path projections of NESH flight path from KESRP defined colony polygons. Elevation was varied based on a boxplot assessment of elevation over all KESRP colony polygons. Elevation for each assessment was thresholded by the minimum (A), 1st Quartile, (B), Mean (C), Median (D), 3rd Quartile (E), and Maximum (F) elevation defined by the boxplot. All plots shown describe the least cost path from the polygons (1 pointe every 250 m 2 ), to $1 / 4$ th of the islands coastal destination, as defined by 1 point approximately every 100 meters. Variations in color (varied numerically from 0-1) describe the degree of flight path overlap for each location in each model.

Figure 12: Ensemble models of the ENM (A\&B) and KESRP (C\&D) flight paths using either the weighted Average (A\&C) or the base average (B\&D) of all assessments. The weighted average was compiled/weighted based on the summed proportion of each adjusted $R^{2}$ value.

Figure 13: Overlapping least cost path projections of NESH flight paths for thresholded and compiled ENM polygon flight path projections, either with a weighted (A, C, \& E) or base $(\mathrm{B}, \mathrm{D}, \& \mathrm{~F})$ average. The averages have been thresholded by either the minimum presence (A\&B), sensitivity equals specificity (C\&D), and maximum sensitivity equals specificity thresholds.

Figure 14: Overlapping least cost path projections of NESH flight paths for thresholded and compiled KESRP polygon flight path projections, either with a weighted (A, C, \& E) or base $(\mathrm{B}, \mathrm{D}, \& \mathrm{~F})$ average. The averages have been thresholded by either the minimum presence (A\&B), sensitivity equals specificity (C\&D), and maximum sensitivity equals specificity ( $\mathrm{E} \& \mathrm{~F}$ ) thresholds. 74

Figure 15: Sorted (high to low) root mean square errors (A) and (low to high) area under the curve (B) for all imputation procedures applied to the 2014 powerline strike dataset. No Kahili points were used in this comparison.

Figure 16: Sorted (high to low) root mean square errors (A) and (low to high) area under the curve (B) for all imputation procedures applied to the 2014 powerline strike dataset. Kahili points were used in this comparison.

Figure 17: Sorted (high to low) root mean square errors (A) and (low to high) area under the curve (B) for all imputation procedures applied to the 2015 powerline strike dataset. No Kahili points were used in this comparison.

Figure 18: Sorted (high to low) root mean square errors (A) and (low to high) area under the curve (B) for all imputation procedures applied to the 2015 powerline strike dataset. Kahili points were used in this comparison.

Figure 19: Sorted (high to low) no strike unit imputed strikes across imputation methodologies that can handle matrices without strikes for both 2014 (A) and 2015 (B).

Figure 20: Compiled recorded/imputed strikes for peak and off peak strike detection units (without Kahili), as summed for each year day in 2014. Inset shows the total number of strikes summed over all units, the total number of peak and off peak summed strikes, check units strikes, and the total number of actual strikes from which the data were imputed. The imputation approach selected and defined here was the expectation maximization arima approach, with a Fourier transformation.

Figure 21: Compiled recorded/imputed strikes for peak and off peak strike detection units (without Kahili), as summed for each year day in 2015. Inset shows the total number of strikes summed over all units, the total number of peak and off peak summed strikes, check units strikes, and the total number of actual strikes from which the data was imputed. The imputation approach selected and defined here was the expectation maximization arima approach, with a Fourier transformation.

Figure 22: 2014 Variable significance jackknife (i.e. leave one out) procedure comparing the change in RMSE of a GLM of that specific variable and a GLM with a least absolute shrinkage and selection operator procedure (GLM/LASSO) projecting all other variables, to a GLM/LASSO projecting ALL variables. This procedure helped to assess the utility of those variables prior to the application of the more computationally intensive elastic net mixing procedure. The assessment was conducted for all variables with (A) and without influential outliers (B).

Figure 23: 2015 Variable significance jackknife (i.e. leave one out) procedure comparing the change in RMSE of a GLM of that specific variable and a GLM with a least absolute shrinkage and selection operator procedure (GLM/LASSO) projecting all other variables, to a GLM/LASSO projecting ALL variables. This procedure helped to assess the utility of those variables prior to the application of the more computationally intensive elastic net mixing procedure. The assessment was conducted for all variables with (A) and without influential outliers (B).

Figure 24: 2014 Powerline Strike Projections using all variables and all strike data (i.e. with outliers). The summed strikes are defined with and without peak and off-peak and detection probability corrections. 104

Figure 25: 2014 Powerline Strike Projections using all variables while removing statistically identified outliers. The summed strikes are defined with and without peak and off-peak and detection probability corrections 105

Figure 26: 2014 Powerline Strike Projections using a statistically significant subset of variables and all strike data (i.e. with outliers). The summed strikes are defined with and without peak and off-peak and detection probability corrections

Figure 27: 2014 Powerline Strike Projections using a statistically significant subset of variables while removing statistically identified outliers. The summed strikes are defined with and without peak and off-peak and detection probability corrections.

107
Figure 28: 2015 Powerline Strike Projections using all variables and all strike data (i.e. with outliers). The summed strikes are defined with and without peak and off-peak and detection probability corrections. 108

Figure 29: 2015 Powerline Strike Projections using all variables while removing statistically identified outliers. The summed strikes are defined with and without peak and off-peak and detection probability corrections. 109

Figure 30: 2015 Powerline Strike Projections using a statistically significant subset of variables and all strike data (i.e. with outliers). The summed strikes are defined with and without peak and off-peak and detection probability corrections.

Figure 31: 2015 Powerline Strike Projections using a statistically significant subset of variables while removing statistically identified outliers. The summed strikes are defined with and without peak and off-peak and detection probability corrections.

Figure 32: Depiction of how variables were developed to predict burrow presence and colony size.

Figure 33: Six of the ten variables used to define burrow occupancy as developed for each $30 \mathrm{~m}^{2}$ pixel within each KESRP polygon describing possible colony sites. These variables are: the aspect of the coastal point (in relation to the aspect of the pixel) as defined by the topographic and Euclidean least cost path from the pixel location (A and B respectively), the difference between the coastal and pixel aspect as defined for the topographic and Euclidean least cost path assessments ( C and D respectively), the difference between the topographic and Euclidean derived aspects (E), and the aspect at the pixel location (F). All variables are expressed in Arc Degrees

Figure 34: Four of the ten variables used to define burrow occupancy as developed for each $30 \mathrm{~m}^{2}$ pixel within each KESRP polygon describing possible colony sites. These variables are: the elevation of each pixel analyzed (A), the slope of each pixel (B), the percent cover of shrubs and trees for each pixel as defined using the Landfire assessment (C and D)..... 143

Figure 35: Density estimates of burrows defined for the Hawaiian Petral (HAPE), Newell's Shearwater (NESH), unknown petrels (UNPE), and sites combined (ALL) as defined using the median nearest neighbor distances. A Tukey's pairwise comparison test was applied to an ANOVA assessment of the data and used to compare the different projections. Significance between projections is indicated by letters placed above the upper whisker. 144

Figure 36: Proportion of the population that each KESRP polygon was projected to contain. This was used in downstream analyses to define the population size at a specific site, given a specific meta-population estimate.

Figure 37: Exponential approximation of cat and ungulate seabird predation reduction defined for the median slope at each site, as inferred from the displayed predation limiting calculation. This calculation was used to derive predation limitations at specific sites from site specific slopes. In this site based assessment; $l$ is the multiplier used to define the effect of slope at site $c, s$ defines the slope at $c, q$ equals the maximum slope at which $l_{c}$ is equal to 1 , and $p$ represents the slope at which predation reduction due to slope begins. 146

Figure 38: Boxplots of compiled Survivorship, Breeding Probability, and Reproductive Success measurements for proxy species. Outliers in each are defined by the species name.

Figure 39: Linear regression of the Adult survivorship ( $S_{x}$ ) versus the log of seabird mass. Regression statistics are shown in the upper left corner of the analysis, and the $95 \%$ confidence and prediction intervals are defined around the regression line. The mass for three Procellaridae (NESH, HAPE and BANP, or Newells Shearwater, Hawaiian Petrel and Band Rumped Storm Petrel) with little to no $S_{x}$ information associated with them are graphed along the line, using the linear equation defined in the graphic inset. Using this information the $S_{x}$ of each can be defined. The standard error of the body mass was transformed into the standard error of the $S_{x}$ to derive both error measurements.

Figure 40: NESH life-cycle diagram (A), Leslie projection matrix key (B), and NESH Leslie projection matrix (C) with the deterministic population growth rate for an optimal population as defined with little to no predation, strikes, or fledgling light fallout.

Figure 41: NESH Leslie projection matrices defined for various predation scenarios used in the analysis. The KESRP predation scenario (A) is equivalent to that predation defined by KESRP/KSHCP per predator. The low (B), medium (C) and high (D) predation Leslie matrices are modifications of the KESRP predation estimates to reflect the population growth rate of the various scenarios as estimated by Griesemer and Holmes (2011). The BASE un-projected, deterministic population growth rates are defined for each scenario. 150

Figure 42: Cory's Shearwater Data from Jenouvrier et al. (2009) for the Mediterranean regions selected to represent extreme weather event effects. The change in survivorship over time (A) identifies extreme weather events in 1990 and 1995. The difference between the average survivorship effects of those time points with extreme weather events, versus the average of those without, (B) per island was used to identify variance in survivorship due to extreme weather event intensity.

Figure 43: Comparisons between the probability of weather events and the predictive survivorship reductions due to these events. An estimate of storm affect was developed by linearizing the Jenouvrier et al. (1997) data over a storm intensity spectrum, and in relation to the prevalence of storms defined around Hawaii.

Figure 44: Projected Population Sizes, and population IDs used in the analsis, each ID correspondes to a separate PVA projection.153

Figure 45: Proportional, scaled Strike Affect per polygon as defined using the projected flight path information. Numbers within each polygon correspond to the polygons identification number. The Transmission Lines on Kauai for which Strikes were projected are shown in grey.

Figure 46: Proportional, scaled Light Affect per polygon as defined using the projected flight path information. Numbers within each polygon correspond to the polygons identification number. The Light Viewshed from which the light affect was defined are shown in various shades of yellow.

Figure 47: Histograms of projected Years to Ecological Extinction as compiled for all light fallout and predation scenarios without strike mortalities applied to the population. Various colors and line markings are used to indicate the specific light fallout scenario in each predation graphic (see legend for details). The projected effect of all four predation scenarios (KSHCP-KESRP (A), Griessemer \& Holmes Low (B), Griessemer \& Holmes Medium (C), Griessemer \& Holmes High (D)) is defined per graphic.

Figure 48: Histograms of projected Years to Ecological Extinction as compiled for all light fallout and predation scenarios with strike mortalities applied to the population. Various colors and line markings are used to indicate the specific light fallout scenario in each predation graphic (see legend for details). The projected effect of all four predation scenarios (KSHCP-KESRP (A), Griessemer \& Holmes Low (B), Griessemer \& Holmes Medium (C), Griessemer \& Holmes High (D)) is defined per graphic. .............................. 157

Figure 49: Histograms of projected lambdas as compiled for all light fallout and predation scenarios without strike mortalities applied to the population. Various colors and line markings are used to indicate the specific light fallout scenario in each predation graphic (see legend fo rdetails). The projected effect of all four predation scenarios (KSHCPKESRP (A), Griessemer \& Holmes Low (B), Griessemer \& Holmes Medium (C), Griessemer \& Holmes High (D)) is defined per graphic.

Figure 50: Histograms of projected lambdas as compiled for all light fallout and predation scenarios with strike mortalities applied to the population. Various colors and line markings are used to indicate the specific light fallout scenario in each predation graphic (see legend fo rdetails). The projected effect of all four predation scenarios (KSHCP-KESRP (A), Griessemer \& Holmes Low (B), Griessemer \& Holmes Medium (C), Griessemer \& Holmes High (D)) is defined per graphic 159

Figure 51: Projected years to Ecological Extinction, as projected for all KESRP polygons susing the KSHCP-KESRP predation scenario without strikes. Each Graphic defines a different
light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 160

Figure 52: Projected years to Ecological Extinction, as projected for all KESRP polygons susing the KSHCP-KESRP predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 161

Figure 53: Projected Lambda, as projected for all KESRP polygons susing the KSHCP-KESRP predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program 162

Figure 54: Projected Lambda, as projected for all KESRP polygons susing the KSHCP-KESRP predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 163

Figure 55: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - Low predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 164

Figure 56: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - Low predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 165

Figure 57: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - Low predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 166

Figure 58: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - Low predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 167

Figure 59: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - Medium predation scenario without strikes. Each

Graphic defines a different light fallout scenario (100\% fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 168

Figure 60: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - Medium predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 169

Figure 61: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - Medium predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 170

Figure 62: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - Medium predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 171

Figure 63: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - High predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 172

Figure 64: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - High predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program 173

Figure 65: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - High predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.

Figure 66 Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - High predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $80 \%$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $50 \%$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program. 175

Figure 67: Figure output for the Replacement Calculator using the parameters defined in table 18. The output shows the trend lines of the overall meta-population (blue), the Social
attraction based population (dotted blue), the accumulated mortalities due to strikes over time (black), the number of mortalities due to predation (red) and the Year to Year (not accumulated) strike mortalities (green). The parameters used to project the assessment are also embedded into the figure, this allows for easy differentiation between different analyses.

Figure 68: Figure output for the Replacement Calculator using the parameters defined in table 18, but with the NoControlScen parameter set to TRUE. Setting this parameter to True turns off all mitigation scenarios and outputs a deterministic Population Viability Assessment for the meta-population using the specified predation estimate. The output shows the trend lines of the overall meta-population (blue), the Social attraction based population (dotted blue), the accumulated mortalities due to strikes over time (black), the number of mortalities due to predation (red) and the Year to Year (not accumulated) strike mortalities (green). The parameters used to project the assessment are also embedded into the figure, this allows for easy differentiation between different analyses

Figure 69: Example output graphic for the KSHCP social attraction site without a standing population (A) and with a standing population (B). Both graphics show the flight path and buffers used for each analysis 235

Figure 70: Example population trend analysis graphic output for the KSHCP social attraction site without a standing population (a) and with a standing population (b) (see table 20). Input parameters, as well as various outputs from the graphic are shown, including final population size, and the added number of adults and fledglings under the various control scenarios with and without a carrying capacity, and partitioned between those added via social attraction, versus those added from the standing population.

## Assessment Utility, Need, and Sectional Overview

The modeling assessments presented here were developed by the United States Fish and Wildlife Service (USFWS) to assess the status of Newell's Shearwater (NESH), and to inform management actions that will promote NESH strategic habitat conservation through a landscapebased recovery strategy on Kauai. Newell's Shearwater has been considered a threatened species by the USFWS since 1975 due to low population numbers. Major threats to NESH include infrastructure development and maintenance, habitat loss, and predation by invasive species. Direct depredation of NESH, or other similarly sized ground nesting birds, have been observed by mongoose (Herpestes javanicus), pigs (Sus scrofa), cats (Felis catus), rats (Rattus spp.), and barn owls (Tyto alba) (Ainley et al. 1997) . It is commonly acknowledged that Kauai likely supports $\sim 90 \%$ of the NESH in the Hawaiian Islands (Griesemer and Holmes 2011; Ainley et al. 1997). As of the writing of this document, Kauai is not thought to have established populations of mongoose, although sightings have recently occurred in lowland areas.

There are two primary anthropogenic threats to NESH: light fallout, and powerline collisions. Light fallout is the attraction of fledgling NESH to light sources followed by collision and death. Powerline collisions occur during daily nocturnal NESH feeding migrations out to sea after sunset and returning before sunrise. It is thought that only a subset of collisions due to power lines, or lights, are mortality events. The technical assessments discussed below were developed to determine the degree to which these threats affect overall viability of NESH, and to help managers evaluate the efficacy of various mitigation strategies.

A new assessment of NESH population viability on Kauai was undertaken using new information on the degree of NESH mortalities associated with powerline collisions. Previously, (Griesemer and Holmes (2011) conducted a population viability analysis (PVA) that assessed light fallout, powerline strikes and predation. The new mortality information led to a need for site-specific PVAs that incorporated variability in mortality and climate change effects in a geographic format that will help support a NESH landscape conservation strategy: this appendix provides a methodological and technical overview of that updated assessment. The modeling
methods and results are grouped in seven sections, each of which corresponds to a set of related analyses, or a single analysis that uses data from previous sections.

- Section 1 - Development and Selection of Environmental Variables: geographicallyenabled variables that include bioclimatic variables for niche modeling (Section 2), light viewshed variables for viewshed projections (Section 2) and site-based viability analyses (Section 5); and extreme weather projection variables used to assess climate change effects on the projected viability of NESH (Section 5).
- Section 2 - Ensemble Niche Model and Carrying Capacity Estimation: model of the current, island-wide NESH habitat (e.g., the current NESH realized niche) based on currently occupied NESH sites. The assessment uses an ensemble model developed from several different modeling approaches. The ensemble model was used in Section 3 to determine flight path, and Section 5 to help determine the proportion of the Kauai NESH meta-population observed by the Kauai Endangered Seabird Recovery Program (KESRP). The viewable light source projections (Section 1) were used to evaluate light effects on the modeled island-wide NESH habitat. An overall assessment of carrying capacity $(\mathrm{K})$ was developed to show the potential for recovery if all threats are effectively controlled.
- Section 3 - Flight Path Model Estimation and Validation: develop, validate and compile flight path models into an ensemble flight path model that is used to characterize the nocturnal movement of seabirds between the colony site and the sea, and is a critical input into the powerline strike model (Section 4). Section 5 uses the flight path model to describe the proportional mortality associated with each site, in relation to power-line strikes and lights. Section 7 uses the site-specific flight path output to subset the Kauai NESH meta-population, which is then used in evaluating site specific mitigation and social attraction efficacy.
- Section 4 - Strike Assessment Model Development: uses the KESRP power-line strike data through July 2016 (collected on a subset of all Kauai transmission lines) to impute and project powerline strikes. The crippling/mortality bias factors applied to the NESH powerline strike evaluation is also reviewed. These mortalities are used to inform the site by site population viability assessment in Section 5.
- Section 5 - Site-by-site Stochastic Population Viability Analysis (SbS-PVA): evaluates geographically-enabled threat and refugia inputs for each identified NESH colony on Kauai, and combines the information into a stochastic site and meta-population population viability analysis. Incorporating these geographically-enabled factor inputs into the SbS-PVA, gives an assessment of their effects on the projected colony viability at each site, and on the overall viability of the entire meta-population.
- Section 6 - Meta-Population Mitigation Viability Replacement Calculator: describes a deterministic tool that gives an overview of the efficacy of mitigation for the entire Kauai NESH meta-population. The user can select a mitigation action and the tool will calculate the modelled impact of the action on the NESH meta-population.
- Section 7 - Site Specific Predator Exclusion/Mitigation Efficacy Control Calculator: describes a tool that assesses the efficacy of the various mitigation strategies at specific sites. This tool was developed for areas without demographic impacts from power-line strikes or light-induced fallout. As with the Replacement Calculator, the user can select a site-specific mitigation action and the tool will calculate the modelled site-specific impact of the action on the NESH.

Although the analyses reviewed here attempt to be comprehensive, its primary use is in building a foundation for evaluating new or updated information on NESH, and providing reproducible projections using explicit and defined parameters. The intent is to modify the model as more data becomes available with routine releases no more than annually when there are significant new findings from model adjustments. Coding this assessment in the R statistical environment provides a recognized set of modeling tools that can be used to develop future projections of NESH mortalities and population viability.

## Summarized Results

The first section of this technical assessment primarily reviews the development of variables and formulation of analyses that are important for use in subsequent sections, and so is a compilation of many distinct assessments. The variables reviewed and/or developed include geographic bioclimatic projections as well as two variables that are important in the Kauai NESH metapopulation analysis: the light viewshed and the extreme weather event variable (Section 1: Fig. 2
\& 4). These two variables show the potential impact of two mortality threats, light fallout, and extreme weather events.

Artificial light sources are a significant mortality factor associated with NESH fledglings (Ainley et al. 2001a; Troy, Holmes, and Green 2011). Because of this mortality effect, light overlap with NESH habitat is an important habitat modifier that may limit the distribution of NESH, and so should be used to adjust any NESH landscape distribution model. The light viewshed assessment developed here first assesses the relationship between NESH and standing light sources, and then uses a threshold developed from the analysis of that relationship to define the intensity of light that most NESH do not occur in. This partitioned light intensity is then used to threshold the standing light sources (Section 1: Fig. 1), and project them into unlit areas across a topographic plane to define the viewshed of light (Section 1: Fig. 2). From these light viewshed assessments the impact of light on both flight paths, and colony development, can be approximated.

Like light sources, extreme weather is another significant mortality factor, especially for reproductive success and survival of ground nesting seabirds (Pratt 1994; Jenouvrier et al. 2009; Wolfaardt, Crofts, and Baylis 2012; Wolf et al. 2009; Frederiksen et al. 2014). On Kauai, hurricanes Iniki and Iwa have been implicated in the extinction of several highly endangered forest birds (Pratt 1994), therefore, a geographic depiction of the probability of storm impact (based on high wind speed events) for Kauai is essential to any future projection of site specific population viability. Using the impact of historic storm events, the analysis presented in SubSection 1.2 and 1.3 estimates a probability of extreme weather event impacts on Kauai (Section 1: Fig. 4A). This impact assessment is then combined with a topographic refugia analysis (Section 1: Fig 4B \& C) to develop a topographically enabled impact probability. In the subsequent site by site Population Viability Assessment these probability assessments, and their impact to NESH, were projected into the future based on the work conducted by Murakami et al. (2013).

Interestingly, both light and extreme weather event projections show decreases in severity in the less disturbed ecosystems definitive of the northwest portion of Kauai, an area known to have the greatest proportion of NESH (see Section 5: Fig. 35 for example). That said, the topographic
complexity of northwest and northeast Kauai is far greater, and, as such, likely greatly influences extreme weather event impact as well (Section 1: Fig. 4C).

To increase our knowledge base regarding NESH, and develop another foundational assessment from which further information can be garnered, a landscape based approach projecting the known locations of NESH across abiotic geographic space was developed. As the realized niche of NESH on Kauai is unknown, and information was available that would help the development and validation of a distribution model for NESH, an ensemble niche model combining two often used presence only machine learning methodologies was developed (Section 2: Fig. 8A). To conduct this assessment many of the abiotic projections described and analyzed in Section 1 were used (see Sub-Section 1.1, and Section 1: Table 1\& Fig. 5).

The ensemble niche model estimated that the current realized niche of NESH, based on available points at the time of development (information and data collected prior to July 2016), encompassed $\sim 341 \mathrm{~km}^{2}(34,100 \mathrm{Ha})$ (Section 2: Fig. 8A). As viewable light sources likely impede the breeding success and establishment of NESH colonies, it was thought that subsetting this model by the light viewshed assessment described above would be more descriptive of available NESH (or at least likely occupied) habitat. When areas with viewable light were removed (Section 2: Fig. 8B) this is reduced potential habitat to $\sim 120 \mathrm{~km}^{2}(12,000 \mathrm{Ha})$. This represents a $\sim 65 \%$ reduction in actual and/or potential habitat (i.e. modeled niche) due directly to viewable light sources.

Although unused in any of the subsequent sections, a carrying capacity (K) estimate was also derived from the data used to develop the Niche Model. It was primarily derived as an initial assessment of what the maximum population on Kauai may be if NESH were to inhabit all currently available projected niche space, with and without viewable light sources. Using the 95\% confidence interval between NESH observations (Section 2: Fig. 9) an initial K was developed ( 4,820 Adult NESH per $\mathrm{km}^{2}$ ) and then projected across the Niche Model with (1,644,912 Adult NESH) and without (578,789 Adult NESH) viewable light sources. Though this projection is admittedly $a d h o c$, it still likely represents a conservative estimate of the density of NESH that may have occupied available habitat on Kauai at one time. For comparison, the current median burrow density of NESH in the most densely occupied habitat on

Kauai was calculated to be 1 burrow every $\sim 17$ ( $95 \%$ CIM: $\sim 12-22$ ) meters $^{2}$ (see Section 5: Fig. 34), or about 3,460 burrows $/ \mathrm{km}^{2}$. In reviewing these assessments it is clear that NESH can occupy sites at much higher densities once various mortality threats are removed.

Understanding the flight path of NESH is critical to projecting the influence of various anthropogenic mortality factors (light and strike impact) imposed on the organism during flight. These flight path assessments are especially important in relation to site based estimates of population viability, projections that are far more revealing than those developed specifically for the meta-population. The ensemble niche model developed in Section 2 was one of two colony estimates used to assess the flight path of NESH on Kauai from colony to coast, and back. The second colony estimate used to project flight paths were those from direct observations of NESH around Kauai collected by KESRP. The multiple estimates of flight path, which take into account topographic complexity, are defined for the ENM (Section 3: Fig.10) and KESRPs NESH polygons (Section 3: Fig. 11). These projections allow an upper and lower bound from which one can infer/project probable flight paths.

Each flight path estimate was validated, ranked and then compiled into an ensemble model of the projected least cost paths from colony to coast, as defined by the modification of topographic influence on the flight path (Section 3: Fig. 12 A-D). The ensembles produced using these approaches were then modified to account for three different statistically derived thresholds (Section 3: Fig. 13 \& 14 A-F). These thresholds are used here to optimize the flight path by the probability of detection, and thus is an attempt to inform biologists looking to increase the probability of in-flight NESH detections. As all analyses were considered equally informative (Section 3: Table 4), the weighted mean as constrained by a minimum presence threshold was used in all subsequent analyses (Section 3: Fig. 14A). The minimum presence threshold was selected because it minimized the flight path projections while accounting for all known NESH in flight. Although flight paths were defined for the niche model defined polygons, subsequent analyses presented here defining site based population viability (Sections $5 \& 6$ ) primarily use the KESRP colonies, and their flight paths, to project the various factors estimated for the colony at each site.

Prior to an innovative, and still ongoing, effort by KESRP to assess powerline strikes little was known regarding the degree to which powerline strikes are impacting Kauai's meta-population. Section 4 uses the data collected by KESRP (through July 2016), and analyzed by Conservation Metrics, to impute and project NESH strikes across the sampled transmission lines on Kauai. Along with other variables, the flight path assessment discussed above was used in Section 4 to develop an estimate of powerline strikes, and subsequent mortalities. This estimate was used to inform the effect of Kauai's infrastructure development and maintenance on the population viability of NESH.

Due to many factors, there is a large degree of variation in the collection of strike information for both 2014 and 2015 data, therefore, it was necessary to develop a predictive imputation approach that best explains and imputes the strike information across dates and times at specific line segments in which samples were not collected (see Section 4: Table 6 \& Fig. 16-21 for a review of approaches tested). From the imputed dataset (Section 4: Table 7) two sets of strike projections were developed. The first set included all of the variables considered potentially significant to line strikes (Section 4: Table $8 \&$ Fig. 22-25, 28-29). The second set of strike projections were developed using a subset of variables that were shown to have significant influence on the projection of strikes across the power lines (Section 4: Table 8 \& Fig.22-23, 2627, 30-31). These assessments were conducted for both 2014 and 2015 projections (Section 4: Table 8 \& Fig. 22-31). Projected strikes ranged from 10,801 to 18,841 in 2014, and 6,491 to 12,053 in 2015 the large variance in projected strikes for each year is the result of the two different sets of correction factors used in the strike assessment."

Using various crippling bias and strike correction estimates, a range of yearly mortality estimates was derived for both years in which the projections were calculated (Section 4: Table 9 for 2014 and Table 10 for 2015). Using the estimates from this assessment the Service set the average year to year NESH mortalities due to power-line strikes, as derived from the inputs in Tables 9 and 10 (mortalities $=1,800$ NESH adults/year). The yearly estimated mortality was derived from the average of the overall projected strikes with acoustic strike detection corrections (reviewed in Section 4: Table 9 for 2014 and Table 10 for 2015), an estimated 4\% direct strike morality, and the lowest published crippling bias (20\%) (Bevanger 1995). This value was used in all subsequent analyses to define the viability of NESH on Kauai.

In Section 5 a Site by Site Population Viability Assessment (PVA) was developed that attempts to compile all available information in order to understand the inherent geographic and demographic stresses of each colony identified on Kauai. To do so the analysis uses a stochastic site and meta-population PVA. Because this PVA incorporates the geographically enabled threat and refugia assessments, it allows a comprehensive assessment of their effect on the projected viability of each site, and the overall meta-population. Secondary variables defined within this section that directly inform the PVA include a comprehensive assessment of projected colony population sizes, theorized slope effects on predation, and projected effects of extreme weather events on the demography of NESH.

As stated previously KESRP has collected extremely valuable polygon information defining a large proportion of the known NESH meta-population. These polygons were used in the PVA to assess the overall NESH meta-population health on Kauai. As the KESRP polygons do not have an estimate of colony size associated with them, and this estimate is important for the development of the PVA, a statistically rigorous assessment (Section 5: Tables $11 \& 12$, Fig. 3537) was developed to proportion out the median meta-population projection of Joyce (2013) per colony (Section 5: Fig. 38). This assessment was followed by the development of a theorized assessment of the effect of slope on predation (essentially a placeholder for new information) (Section 5: Fig. 39), and the projected effect of extreme weather events on the demography of NESH (Section 5: Fig. 40 \& 44-45).

The previously cited variables were all used to inform and modify the demography of NESH, as defined from both proxy organisms (Section 5: Table $13 \&$ Fig. 41) and information collected directly from NESH. The compiled base information, represented in Section 5: Fig. 42, was then modified by various predation estimates (Section 5: Table 14 \& Fig. 43), and further modified in the code by the extreme weather event probabilities, site-based slope, light and strike effect per colony.

The site-based demographic parameters were then incorporated into a site specific PVA for all predation and light fallout scenarios, and projections conducted with and without the estimated strike mortalities. For ease of representation, and review, these assessments were compiled into an overall projection of the meta-population, represented using both the compilation of each population's (i.e. colonies) growth rates (Lambda), and years until ecological extinction.

Compilations of scenarios for both parameters were represented using both a histogramatic (Section 6: Fig. 47 - 50) and geographic (Section 6: Fig. $51-66$ ) representation of the cumulative impact of all sites on the projected outcome of the meta-population. Site specific information can also be gathered from the geographic compilation of the figures.

For the NESH meta-population on Kauai, comparing the overall distribution of the estimated time until ecological extinction (and the population lambda) show significant differences between projections with (Section 5: Figs. 47 and 49; Figs. 51, 53, 55, 57 and 59) and without (Section 5: Figs. 46 and 48; Figs. 50, 52, 54, 56 and 58) the inclusion of line-strike mortalities. This is the case for both the histographic (Section 5: Fig. 47 - 50) and geographic (Section 5: Fig. 51 -66) representations of the compiled meta-population PVAs.

When strike mortalities are accounted for, ecological extinctions are heavily weighted such that more ecological extinctions are projected to occur in the much nearer future (Section 6: Fig. 47 50). Meta-population estimates conducted without and with strikes show meta-populations across all predation and light fallout scenarios have equivalent projected ecological extinction end points, ranging from mid to end century. This is likely because a large subset of the NESH meta-population is projected to be in a strike and light free zone (see Section 5: Fig. 45 \& 46, Section 1: Fig. 2 and Section 4: Fig. $24-31$ ) and as such have equivalent demography's across all light fallout and strike projections.

The overall aspect-based distributions of the power-line strike effect and the light impingement effect are similar (Section 1: Fig. 2 and Section 4: Fig. 24-31) across Kauai's landscape. It follows that increases in these two factors will result in greater effects on a subset of seabird sites that align with the aspect-based distributions of these two factors. This is, in general, what is happening when strike or light mortalities are input into each of the predation projections. As is expected, as light based mortality increases, the geographic distribution of those effects are similar to strike mortalities, with those populations in the North West of Kauai being relatively unaffected by both strike and light mortality.

All predation scenarios, when strikes are incorporated (Section 5: Fig. 52, 56, $60 \& 65$ ), show the Northwest portion of Kauai being the longest lived NESH reservoir. This is not necessarily the case for interior populations due to the greater variance in their projected flight paths to the coast
(Section 3: Fig. $12 \mathrm{C} \& \mathrm{D}$ ). These reservoir populations also show the greatest degree of population growth (Section 5: Fig. 54, 58, $62 \& 66$ ) when compared to other populations impacted by strikes and lights.

Finally, two tools coded in the R statistical environment were developed that may help inform managers regarding both the state of the meta-population, given the specified input variables (as specified by the user), and the effect of various mitigation scenarios on either the metapopulation (Section 6) or a specific site of interest (Section 7). Both tools used the base demographic and predation estimates defined in Section 5.

The first tool, reviewed in Section 6, is a deterministic assessment of the meta-population. The script was developed to allow users to both assess the state of the meta-population, and how various mitigation strategies can be used to replace mortalities caused by the yearly strike estimates projected in Section 4. Currently, this tool is referred to as the "replacement calculator", as it can be used to project the amount of time replacement of strike mortalities would take given the application of various mitigation scenarios. The replacement calculator is meant as a quick and basic overview of the efficacy of mitigation on the population as a whole.

An example of the assessment was conducted to show the potential of the tool, and review the tool's various outputs (Section 6: Tables 15-19 \& Fig. 67-68). The assessment was coded such that the effect of mitigation on the meta-population can be switched on and off, allowing the user to assess projected trends in the meta-population, given the various input variables, with (Section 6: Fig. 67) and without (Section 6: Fig. 68) implementation of the various mitigation scenarios. All input variables needed to run an analysis are defined in Section 6: Table 16. The code for conducting the assessment can be viewed, or copied into an R based integrated development environment, in Sub-Section 6.7.

The second tool, as reviewed in Section 7, is a deterministic assessment of site-based mitigation effect. This script was initially developed to assess social attraction utility at specific sites, but it was subsequently re-coded such that it can be used to assess the utility of management efforts at most sites with and without a standing population size. Although the replacement calculator reviewed in Section 6 accounts for various predator control strategies, as well as social attraction, it is at best a coarse deterministic descriptor of the utility of those methodologies to replace strike
mortalities over the meta-population. This calculator was developed to allow the user to assess the utility of the various control strategies at specific sites. This permits a more tangible and site specific estimate of mitigation efficacy that can be used directly in planning efforts. Because the calculator in this assessment does not account for strike and light mortalities at the colony, it is developed for use only in areas without these demographic impacts.

As in Section 6, an example input set was used to show the potential of the tool, and review the various inputs needed to run the script (Section 7: Tables 20-25 \& Fig. 69-70). Because this assessment is site specific, a suite of input variables are necessary to define the site, the number of burrows at the site, and the potential proportion of the meta-population that may fly over that site (Section 7: Table 20). The tool presented here was coded such that a standing population can be present at a site if social attraction is also conducted at that site (Section 7: Fig. 70). The example assessment (Section 7: Table 21) outputs show the projected population size of the same site, as conducted without (Section 7: Tables 22 and $24 \&$ Fig. 70A) and with (Section 7: Tables 23 and 25 \& Fig. 70B) a standing population. The code can be viewed and accessed in SubSection 7.5.

As in Section 6, the input variables used to project these two toolsets/scripts are meant to be user defined, and as such the reasoning behind the inputs used for the analyses should be itemized and supported via literature reviews and/or statistical assessments. As such, the inputs used in this document are for illustration use only, and should not be applied unless corroborated and endorsed by literature, or established sources.

## 1. SECTION 1: ENVIRONMENTAL LAYER DEVELOPMENT AND SELECTION

In this section the development, projection, and depiction of many of the geographically enabled variables used in subsequent sections to inform directly or indirectly species viability and mitigation are described. Although variables are also developed in other sections, the various metrics reviewed here are foundational to many of those, and subsequent analyses. Various uses of these variables in subsequent sections include:

- The projected geographic distribution of the species in relation to precipitation, temperature, and wind;
- The geographic distribution and analysis of light effects and power-line strikes;
- The effect of climate change on extreme weather events within the Hawaiian Islands.

These three uses correspond to three sets of variables for which the methodological overview and results are given. A secondary analysis of variable selection describes the comparison of variables in relation to species data, and the subsequent selection of those variables that best describe the distribution of NESH. Subsequent analyses that use these assessments and variables are described in Section 2.

### 1.1 Bioclimatic, Topographic, and Weather Variable Development: Overview

Twenty-four continuous abiotic environmental indices, including 19 bioclimatic and 5 topographic variables, were initially developed following the protocol of (Vorsino et al. 2014). These indices were defined for the main eight Hawaiian Islands, excluding Niihau. All variables were calculated using the R statistical environment (Team 2013). The R package 'dismo' provided methods for bioclimatic and topographic variable generation based on rainfall, temperature, and elevation data (R. Hijmans et al. 2010). Raster manipulation was conducted using the 'raster', ‘SDMtools" and dismo packages (R. J. Hijmans 2012; R. Hijmans et al. 2010; VanDerWal et al. 2014). Future climate variables were developed using the methodology of (Vorsino et al. 2014). For all variables in which it is either not possible, or not appropriate, to define future climate variables (i.e., topographic variables or future wind power), the current variable was used.

Two additional abiotic spatial variables were also evaluated: wind power at 50 meters elevation, and the night-light viewshed for Kauai (similar to that of Troy, Holmes, and Green 2011). The 50meter wind power projection was developed by the (National Renewable Energy Laboratory 2004), and was considered biologically relevant given the utility of wind in facilitating a seabird's alightment and ascension (Mueller and Berger 1967). The night-light viewshed variable is used to help assess light impact on NESH habitat.

A third environmental variable was used in the site by site population viability assessment (see Section 5). This covariate assessed the impact and probability of extreme weather events. The viewshed and extreme weather event assessments are reviewed in detail in subsequent sections. All geographic analyses, excepting the extreme weather event impact assessment, were projected and analyzed at $250 \mathrm{~m}^{2}$ landscape resolution.

### 1.1.1 Nightlight Viewshed: Development

Artificial light sources are a significant mortality factor associated with NESH fledglings (D. G. Ainley et al. 2001a; Troy, Holmes, and Green 2011). Light overlap with NESH habitat is an important habitat modifier that may limit the potential future distribution of viable NESH colonies. Light overlap and intensity (15 arc-second Visible Infrared Imaging Radiometer Suite [VIIRS cloud free composite downloaded from the National Geophysical Data Center Earth Observation Group [http://www.ngdc. noaa.gov/dmsp/]) was modeled. To define the projected light impingement, code was developed in R that both maximized the statistical framework of the R statistical environment (http://www.r-project.org), and the efficiency of the object oriented programming environment, Python (www.python.org) using ArcPy (Esri 2014).

In order to project light into un-lit areas, such that they defined regions in which light was viewable and thus may impact seabird populations, a threshold defining the lit and unlit zones was developed specifically using seabird siting's at or around colonies. Light intensity, defined using the VIIRS light map, was initially extracted for all recently collected and geographically oriented seabird localities on the island of Kauai. The locations and meta-data for these sightings were compiled from data collected and previously assembled by the United States Fish \& Wildlife Service (USFWS) and the Kauai Endangered Species Recovery Program (KESRP). A boxplot assessment was applied to the data to assess the distribution of seabird presence in
relation to night time light intensity. These data were also compared to overall light intensities defined for each island for comparison. This boxplot assessment allowed the selection of a lit zone threshold that minimized the number of seabird occurrences and lit area, while maximizing locations known to have high intensity light sources. The $3{ }^{\text {rd }}$ quartile of the boxplot (as extracted from VIIRS) best exemplified seabird siting's, maximized the number of high intensity light source areas present, and minimized indirect sky glow (Chalkias et al. 2006). Ten equal intervals were then defined within this threshold in order to account for viewable light intensity. As coded in R (using Python and ArcPy) the viewshed of these 10 light intensity outlines was then projected across a 10 m digital elevation model (DEM), after elevating them by 100 m (as conducted by(Troy, Holmes, and Green 2011)) to account for possible light detection during fledgling flight. These 10 projected viewshed maps were then combined into an ensemble model that attempts to define viewable light sources, as well as the intensities of the viewable light sources, on a $0-100 \%$ visibility scale. The initial lit/unlit thesholded areas were defined as $100 \%$ visible, and thus do not vary in intensity. Although the threshold was developed from Kauai specific data, it was applied and projected in a similar manner to all of the main Hawaiian Islands.

### 1.1.2 Nightlight Viewshed: Output

The impact of the nightlight viewshed iteration ensemble describing viewable light presence and intensity is analyzed for each island, and the seabird data, in Figure 1A. The upper quartile of the boxplot assessment ( 0.2234 nano-Watts/ $\left(\mathrm{sr}^{*} \mathrm{~cm}^{2}\right)$ ), comparing the seabird presence sites to light intensities, was used to further define light visibiltity using an iterative viewshed analysis. The light visibility results for Kauai (Fig. 2) define areas of low to high light visibility and can be used to infer the area of a no light conservation zone. A similar light visibility assessment was also conducted for all other islands, the results of which are summarized in Figure 1B.

### 1.2 Extreme Weather Event Impact Projection: Development

Although not used directly in the distribution modelling, extreme weather events are likely a significant factor in the reproductive success and survival of ground nesting seabirds (Pratt 1994; Jenouvrier et al. 2009; Wolfaardt, Crofts, and Baylis 2012; Wolf et al. 2009; Frederiksen et al. 2014). On Kauai, hurricanes Iniki and Iwa have already been implicated in the extinction of
several highly endangered forest birds (Pratt 1994), therefore, a geographic depiction of the probability of storm impact (based on high wind speed events) for Kauai was developed. This allowed us to estimate site specific impacts to the seabird's demography by identifying the probability of those storm events at locations known to contain NESH.

The geographic distribution of these storm events was developed from compiled storm track data for the Eastern Pacific downloaded from the National Climate Data Center (http://www.ncdc.noaa.gov/) and outlined in (Gibney et al. 2009). The compiled storm events ranged in date from 1950 to 2014. These data contained identifiers of each storm event, the latitude and longitude of specific points (at specific times) along the storms track, and a definitive wind speed of that storm at that specific point location (as rounded to the nearest 5 knots).

For a subset of recently collected storms in the complete Eastern Pacific database, the distance to 64, 50, and 34 knot winds were defined for the North West (NW), North East (NE), South West (SW), and South East (SE) quadrants of the storm. This subset contained storm events recorded from 2004 to 2013 that ranged (in increments of 5 knots) from 35 to 155 knots. Therefore, it adequately encompassed a large range of the wind speeds in the complete Eastern Pacific storm event dataset, and so can be used to extrapolate these quadrant based measurements to unmeasured storms. Within this subset, multiple storm events were recorded that were categorized at the same wind speed class. These wind speed categories were compiled per quadrant, per distance, using both the maximum and median distances in various iterations of the analysis. Although the similarly classed storm events were compiled using both median and maximum, the median wind speed classifications will be primarily presented (and used in all subsequent analyses) because it was the most realistic projection and depiction of each storm event.

Due to the large amount of data contained in the overall database, and the unlikely impact of storms whose centers occurred $>3000 \mathrm{~km}$ from the Hawaiian Islands on the Hawaiian archipelago, we subset the storm events database by selecting (and further analyzing) only those events with a storm center $\leq 2,185 \mathrm{~km}$ from the Hawaiian Islands. This distance was selected
because it is the maximum peripheral distance to a 34 knot wind defined for a storm quadrant in the dataset.

To project the wind speed in various quadrants, at various distances, a logistic regression analysis was developed from the wind speeds defining that storm event in which quadrant specific information was collected. At most, four points were used to define the wind speed/distance trend line of each storm, the wind speed defining that storm event (which we have used as a proxy for the storm center), and the various distances to the 64,50 , and 34 knot winds of that storm within each quadrant. The wind speed defining the storm event was used as a proxy for the storm center because those wind speeds were supposedly collected on the edge of the eye of the storm (i.e. eye wall), an area definitive of a storms maximum sustained velocity (Willoughby, Darling, and Rahn 2006). Given that some storms were defined by wind speeds that were less than the 64,50 , and/or 34 knot wind speed measurements (even though a distance to one or more of those wind speeds was defined) it seemed reasonable to assume that these measurements were centrally located in the storm. As such, the higher wind speed that the storm was defined at was used to replace an un-measured value (close to 0 knots) that is usually definitive of a storm eye, doing so allowed us to develop an easily calculated linear model that relates wind speed to distance from the storm center per quadrant. This dimensional variance of the storm interior does not alter the model output, given that this analysis is meant to only define the probability of storm impact on the islands and not the exact dimensions of the interior of the storm as the storm impacts the island.

The calculated wind speed-to-distance logistic regression was transformed into a polynomial regression and graphed as a check on the relationship of these wind speeds to distance. Using this approach we were able to develop polynomial regression equations describing the relationship of wind speed from the distance to the center of storm events (ranging in intensity from 35 to 155 knots) to their periphery (defined here as a wind speed of 34 knots) within their respective quadrants.

Because the storm track data in the Eastern Pacific database were only intermittently sampled approximately every 4 hours, it was necessary to relate the distances between storm track point locations to changes in wind speed using a linear approximation. By projecting the wind speed at
various unmeasured points along the selected storm tracks, non-overlap in the periphery of the storms track was reduced. This storm non-overlap is an error caused by intermittent track collections and the quasi-circular/oblong structure of each storm. Using this approach, wind speeds were projected (as rounded to the nearest 5 knots) for every $10^{\text {th }}$ of a kilometer along each storms track.

For each of these newly defined point locations in a specific storms track a wind speed $x$ distance profile was projected using a similar wind speed polynomial regression profile (as defined above). These profiles were projected for each quadrant of the storm track point location. The maximum distance of impact of a storm was defined by the quadrant profile that projected the periphery ( $<34$ knots) of the storm out to the greatest distance. This periphery was used to define the overlap of the storm with Kauai. If the storm periphery did not overlap with Kauai no further analysis was conducted.

If the storm- periphery did overlap with the Kauai, the area of overlap was extracted from a 1 $\mathrm{km}^{2}$ resolution DEM model. For each extracted pixel, its bearing to the storms center was recorded. Each storm quadrant was assigned a bearing $\left(45^{\circ}=\mathrm{NE}, 135^{\circ}=\mathrm{SE}, 225^{\circ}=\mathrm{SW}\right.$, and $\left.325^{\circ}=\mathrm{NW}\right)$. The relationship of the pixel to two of the closest quadrants was evaluated from the pixel bearing data. This relationship (given as percent association) was used to weight the results given by each wind speed assessment. The weighted quadrant results were then summed to define the wind speed at that pixel. Weighting the analysis in this way allowed the connection of quadrants based on wind speeds, if this was not done quadrant peripheries would connect via stepped (rather than gradual) increases and decreases, and less accurately reflected the storms probable pixel overlap. For all storms with a wind speed $\leq 35$ knots (e.g. tropical depressions), the algorithm defined for 35 knot storm events was used. The difference between the wind speed of that storm event and 35 knots was then subtracted from the end result to define realistic wind speeds for that storm.

All of the resulting raster's that were output per storm track point were reclassified to project only those locations with wind speeds $\geq 34$ knots (i.e. tropical storm periphery). Reclassifying the analysis in this way allowed a direct assessment of the storms probable periphery as the storm impacted land. An extreme weather event probability profile for the islands (excluding
any topographically defined refugia, as defined in the next paragraph) was then developed from the summation of these reclassified rasters (as divided by the maximum value defined by this raster summation). The output of this analysis was an extreme weather event projection that varies from 0 (no storm events) to 1 (all storms overlap).

Because topography greatly affects wind speed, and thus impact (Chock and Cochran 2005), it was necessary to understand how the topographic complexity of the Hawaiian Islands could reduce wind impact by developing a wind refugia map (i.e. topographic exposure). A wind refugia assessment was developed following the methodologies of (Mikita and Klimánek 2010). Using the 'raster' package in R, slope and aspect at a $30 \mathrm{~m}^{2}$ resolution was estimated for each pixel for the Hawaiian Islands. Then, for every compass degree a hillshade projection was produced using these slope and aspect profiles combined with a source (e.g. wind) direction angle of $5^{\circ}$. The wind shade projections for the Hawaiian Islands, as developed from sources projecting at various directions around Hawaii, were then summed and divided by the maximum value of their summation to create a wind refugia map that varies from 0 (no wind refuge) to 1 (complete wind refuge). This wind refugia map was then compiled and transformed such that 0 was equivalent to a complete wind refuge and 1 indicated no refuge.

Following the creation of both the transformed wind refugia and extreme weather event probability estimate, the rasters were multiplied by one another. This analysis generated a topographic layer for extreme weather impact probability ranging from 0 (no impact) to 1 (high probability of impact). Combining a topographic projection of wind refugia with a storm probability profile of Kauai yielded a topographic projection of extreme weather impact probabilities that can be applied to NESH habitat and population evaluations.

### 1.3 Extreme Weather Event Impact Projection: Output

The extreme weather impact probability was assessed only when the storm quadrant periphery (i.e. distance from the storm center to reach a wind speed of 34 knots) impacted land. An example of each quadrant's periphery for a 100 knot storm event is shown in Figure 3. All quadrant peripheries used are defined in 5 knot wind speed increments. The trends defined by these estimates were then used to define wind speed at different locations within the storm, and the overall periphery of the storm event.

The wind refugia assessment (Fig. 4A) projected the innermost gullies to be those areas least impacted by high wind events (green), whereas coastal areas were more so. Note that this refugia assessment does not account for topographically directed wind patterns, which may greatly enhance or mitigate localized storm wind impacts. Except for coastal areas with high topographic complexity, coastal areas are equally impacted and receive the highest storm impact.

The compiled, projected, geographic distribution of storm events affecting Kauai is shown in Figure 4B. This analysis represents a compilation of storm tracks and their projected extent (out from the storm center to a 34 knot wind) between 1950 and 2014. As would be expected, the southernmost portion of Kauai seems to be most impacted by storm events, although the regional variation is low; $\sim 6 \%$ between the areas least and most effected ( $\sim$ North and $\sim$ South Kauai, respectively).

The wind impact probability assessment (Fig. 4C) combines the wind refugia and wind impact assessments. The metric shows the primary effect of wind refugia on wind impact, but still encompasses the slight variation, and overall impact, of regionally defined storm events. As in the wind refugia assessment, the areas with the greatest topographic complexity (central and northwest Kauai) are those with the greatest area of wind refugia.

### 1.4 Variable Selection: Overview

A variable selection procedure was developed that identified possible significant subsets of variables to use in the analysis in order to reduce variable collinearity while maximizing the geographic and biological explanatory power of the species distribution model. This procedure does not replace expert opinion regarding the significance or biological relevance of variables to the overall distribution of the species, but rather seeks to inform expert opinion about the selected variables.

### 1.4.1 Variable Selection Procedure: Development

Variable ranking consisted of four parts, defined using specific analysis techniques. These techniques included: Stepwise sample-size corrected Akaiki and Bayesian Information Criteria (AICc and BIC respectively); variable specific polynomial regressions; Pearson's Correlation Coefficient (PCC) analysis, and variance inflation factors (VIF).

The stepwise corrected AICc and BIC were developed from a general linear model comparison of stepwise selected variables to auditory data collected at specific sites (provided by KESRP). This, and other comparisons, assumed that that the larger the colony of seabirds at a specific site, the greater number of auditory collections defined for that site. These model selection criteria are commonly used to define the best fit models with the least number of variables, when multiple variables are employed (Kutner et al. 2004).

A polynomial regression was also conducted in which the variance of each variable was compared to site specific auditory data from which the variable's relevance (adjusted $\mathrm{R}^{2}$ ) and significance ( $p$-value $\leq 0.05$ ) was assessed. These variable specific analyses were particularly important after comparing the correlation of variables and selecting a single correlated variable that best fits the data.

Variance inflation factor estimates were developed from the General Linear Models (GLMs) defined during the stepwise variable selection procedure (Kutner et al. 2004). The VIF was specifically used to quantify the degree of multi-collinearity within the regression analysis. As such it can be seen as a secondary measure of variable collinearity in relation to the PCC. Although the VIF identifies collinear variables, its ability to distinguish related collinear variables is lacking, as such the PCC approach was the primary identifier of collinearity, whereas the VIF was used to further inform the variable selection procedure.

A PCC was applied using the methodology of (Vorsino et al. 2014) and was used to specifically assess correlations between all pairs of abiotic variables. Outputs for these five factors were exported with their analysis specific results, but also compiled into a binary variable selection table. This table was compiled using specific rule sets developed from the analysis technique. If the environmental covariate fulfilled the expectations of the binary rule set it was given a value of 1 ; otherwise a value of 0 was given for that specific comparison. These binary outcomes were then summed across the various techniques employed, and an overall assessment of the variables value (in relation to all other values identified) was given. The rule-sets for this procedure are as follows:

- For both the AIC and BIC stepwise selection procedures, if the environmental covariate used in the model was ranked as significant to the model by the procedure, it was given a rank value of 1 .
- For VIF, Kutner et al. (2004) defined the threshold of multi-collinearity as a covariate with a VIF value $>10$. Variables with a VIF $\leq 10$ were given a rank value of 1 .
- As expressed in (Rissler et al. 2006), a PCC of 0.75 is a common threshold to define the correlation of variables. Variables with a PCC $\leq 0.75$ were given a rank value of 1 .
- Finally, all polynomial regressions (comparing the environmental covariate values defined for each site, to the number of calls defined at that site) that had a significant association were given a value of 1 .

This analysis helped to define a subset of uncorrelated variables that were associated with the number of auditory calls at a site. It primarily served to inform the selection protocol, but it does not directly replace it because once variables were removed from the set of collinear pairs, that selected variable may significantly inform, or influence, the model. As such, the compilation of these four factors helped to identify relevant, uncorrelated variables. A single variable thought to be more relevant to the distribution of the species was selected from correlated variables that were also found to be descriptive of the species distribution.

### 1.4.2 Variable Selection: Output

Outputs for the five factors used in the variable selection procedure are compiled into a binary variable selection table shown in Table 1. In the analysis, those variables that had a compiled score of 3 or greater (greater than half the assessments used identified the variables as potentially significant) were identified (Table 1). These binary outcomes, as summed across the various techniques employed, helped to define a subset of uncorrelated variables for model development. Using this approach it was found that the AICc and BIC selection factors did not vary enough to be useful in this assessment, whereas a large amount of variation was identified in the binary output of the VIF, PCC, and significance of the regression analysis (Table 2). Tables describing the results of the VIF and regression analysis, as well as figures showing the comparison of each environmental covariate to the KESRP auditory collections will be distributed upon request.

Although these secondary variables were taken into account, it was felt that the most significant analysis to help inform the selection of the environmental variables (other than biological relevance) was the PCC (Fig. 5). This was mainly because once variables were removed from the set of collinear pairs, that selected variable may significantly inform, or influence, the model. The PCC, in compilation with the overall binary variable selection criteria and expert opinion, proved to be a powerful approach to select appropriate variables to model the current and future distribution of NESH.

A total of five variables were selected (Table 1; BIO3, BIO15, Slope, TRI, and Wind50m). All but one of these variables had a test value above three and was selected based on their statistical significance and probable biological significance to burrow site selection. Of those variables selected BIO15 did not have a Test value of $\geq 3$. This variable was selected because as a single variable, it was thought to better identify precipitation seasonality than the combination of BIO18 and BIO19. It was also selected because it describes yearly abiotic variation similar to that of BIO3 (Isothermality), another selected variable. Because no other variable correlated ( $\mathrm{PCC} \geq 0.75$ ) to BIO15, it was selected and used in the analysis (Fig. 5), and the corrected test value for this variable would be greater than three if re-run in the testing procedure (Table 3).

### 1.5 Section 1: TABLES

Table 1: Outputs for the five factors (corrected Akaike Information Criterion (AICc), Bayesian Information Criterion (BIC), Variance Inflation Factor (VIF), and Adjusted R ${ }^{\mathbf{2}}$ (Adj- $\mathbf{R}^{2}$ )) used in the variable selection procedure are compiled into this binary variable selection table. This table was compiled using specific rule sets developed per analysis technique. These binary outcomes were then summed across the various techniques employed, and an overall assessment of the variables value (in relation to all other values identified) was given. This analysis helped to define a subset of variables from which to select, serving to inform the selection protocol.

| COVARIATE | DESCRIPTION | AICe | BIC | $\mathrm{VIF} \leq 10$ | PCC $\leq 75$ | $\begin{gathered} \text { Adj-R }{ }^{2} \\ (\mathrm{p} \leq 0.05) \end{gathered}$ | Test |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| BIO1 | Annual Mean Temperature | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO2 | Mean Diurnal Range (Mean of monthly (max temp - min temp)) | 0.5 | 0.5 | 0 | 0 | 0 | 1 |
| $\mathrm{BIO}^{+}$ | Isothermality (BIO2/BIO7) (* 100) | 0.5 | 0.5 | 0 | 1 | 1 | 3 |
| BIO4 | Temperature Seasonality (standard deviation *100) | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO5 | Max Temperature of Warmest Month | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO6 | Min Temperature of Coldest Month | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO7 | Temperature Annual Range (BIO5- BIO6) | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO8 | Mean Temperature of Wettest Quarter | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO9 | Mean Temperature of Driest Quarter | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO10 | Mean Temperature of Warmest Quarter | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO11 | Mean Temperature of Coldest Quarter | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO12 | Annual Precipitation | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO13 | Precipitation of Wettest Month | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO14 | Precipitation of Driest Month | 0.5 | 0.5 | 0 | 1 | 0 | 2 |
| BIO15 ${ }^{\dagger}$ | Precipitation Seasonality (Coefficient of Variation) | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO16 | Precipitation of Wettest Quarter | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO17 | Precipitation of Driest Quarter | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| BIO18 | Precipitation of Warmest Quarter | 0.5 | 0.5 | 1 | 1 | 0 | 3 |
| BIO19 | Precipitation of Coldest Quarter | 0.5 | 0.5 | 1 | 1 | 0 | 3 |
| NORTHNESS | $\cos$ (Aspect) | 0.5 | 0.5 | 1 | 1 | 0 | 3 |
| WESTNESS | sine(Aspect) | 0.5 | 0.5 | 1 | 1 | 0 | 3 |
| NTELTE | VIIRS Satellite Light Imagery | 0.5 | 0.5 | 1 | 1 | 0 | 3 |
| VU_SHED | Night Light Viewshed | 0.5 | 0.5 | 1 | 1 | 0 | 3 |
| ROUGHNESS | - | 0.5 | 0.5 | 0 | 0 | 1 | 2 |
| SLOPE ${ }^{\dagger}$ | - | 0.5 | 0.5 | 1 | 0 | 1 | 3 |
| SLPCOSASPECT | Slope * Northness | 0.5 | 0.5 | 1 | 1 | 0 | 3 |
| SLPSINASPECT | Slope * Westness | 0.5 | 0.5 | 1 | 1 | 0 | 3 |
| TPI | Topographic Position Index | 0.5 | 0.5 | 1 | 1 | 0 | 3 |
| TRASP | TopographicRadiation Index | 0.5 | 0.5 | 1 | 1 | 0 | 3 |


| COVARIATE | DESCRIPTION | AICc | BIC | VIF $\leq \mathbf{1 0}$ | PCC $\leq 75$ | Adj-R <br> $(\mathbf{p} \leq \mathbf{0 . 0 5})$ | Test |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| TRI $^{\dagger}$ | Topographic Roughness Index | 0.5 | 0.5 | 1 | 0 | 1 | 3 |
| ${\text { Wind } 50 \mathrm{~m}^{\dagger}}$ | Wind Speed at 50 m | 0.5 | 0.5 | 1 | 1 | 1 | 4 |

- Red variables had a test factor greater than 3 (greater than $50 \%$ of the tests identified them as potentially informative)
- Blue variables were selected based on prior information, and had a test value greater than 3 when run independently
- Variables with an " $\dagger$ " were those selected for the final analysis


Figure 1: Boxplot assessments of light impact per site defining: (A) the distribution of seabird presence in relation to night time light intensity, and $(B)$ the percent light visibility (i.e. intensity) at each seabird site. Each metric also compares the outputs to the overall (compiled) Light intensity/visibility of each island.


Figure 2: \% Light visibility analysis for Kauai conducted over 10 viewshed iterations projected over a 250m DEM. Each iteration was varied by a $10^{\text {th }}$ of the light intensity within the thresholded seabird light contour (blue outline); the outputs were compiled to reflect a percentage scale. The Seabird Light Contour was defined using the upper quartile of light intensities in which seabirds occur (Figure $1 \mathbf{1 A}$ ). All areas within the contour were considered to have $100 \%$ visible lights.


Figure 3: Using regression, each quadrants periphery was defined. This figure shows an example of the wind speed to 34 knots (i.e. the storm events periphery) for a 100 knot storm. The logistic and exponential plots for each estimate are defined. The exponential equation is given for each quadrant. These analyses were then combined to define the overall storm periphery (inset).
A)

B)
 Figure 4: Extreme weather event impact assessments in which wind refugia (due to topographic complexity) was identified (A), historical wind impact from extreme weather events was defined $(B)$, and both combined to beget a topographically enabled extreme weather event probability impact assessment that ranged from 0 (no impact) to 1 (high probability of impact) ( $C$ ). The wind refugia assessment (A) was considered a conservative estimate in that it was derived from a $5^{\circ}$ hillshade affect projected for every compass degree around Kauai.

C)


## 2. SECTION 2: ENSEMBLE NICH MODEL AND CARRYING CAPACITY ESTIMATION

As the occupied habitat of NESH on Kauai is only partially known, and information was available that would help the development and validation of a distribution model for NESH, an ensemble niche model combining two often used presence only machine learning methodologies was developed. The niche model developed in this section is foundational in understanding the distribution and proportion of the sampled Kauai meta-population. Understanding where NESH may occur, and the suitability of site occupancy around Hawaii, is especially important in relation to the analysis of viewable light source impacts, and the efficacy of mitigation and conservation actions associated with specific colonies.

In order to conduct this assessment the variables selected in Section 1 were combined and projected using the various niche modelling approaches. Each projection was then validated using a subset of species data, and an overall assessment was developed from both models that best describes the relationship of NESH to the various topographic and climatic variables used in the assessment. Subsequent removal of the viewable light source projections described in Section 1 were used to estimate possible light effects on the realized niche (the actual space an organism occupies).

Although described here, the overall assessment of carrying capacity ( K ) within the species distribution model was not used to inform any subsequent analyses. This estimate of K was primarily developed to show the potential for recovery, assuming that the relationship of NESH to the variables used in the model is direct and biologically relevant.

### 2.1 Ensemble Niche Model Development, Validation and Implementation

### 2.1.1 Species Distribution Model (SDM): Development

Two presence-only machine learning SDM methodologies were used to model the distribution of occurrence localities over geographic space, as defined by the selected abiotic variables. These two methodologies, MAXENT (Phillips, Anderson, and Schapire 2006) and Gradient Boosting Model (GBM, Friedman 2001) were selected based on their previously estimated utility (Vorsino et al. 2014) and published predictive accuracy (Caruana and Niculescu-Mizil 2006; Cutler et al. 2007;

Ortega-Huerta and Peterson 2008; Hastie, Tibshirani, and Friedman 2011). MAXENT is a popular SDM tool that models species distributions by comparing the modeled distribution of occurrence localities, as derived from the environmental variables, to a null (random) distribution (as defined by pseudo-absences) of the environmental variables (Jane Elith et al. 2011). A GBM is a classification tree learning methodology that improves the predictive accuracy of decision trees using statistical boosting (J. Elith, Leathwick, and Hastie 2008; Hastie, Tibshirani, and Friedman 2011).. Boosting, as implemented in the 'gbm' R package (Ridgeway 2007), is a machine learning approach that constructs additive ensemble models over many iterations to improve the predictive accuracy of the training data. All analyses were run in R using 'biomod2' (Wilffred Thuiller, Damien Georges, and Robin Engler 2012, 2). See Vorsino et al. (2014) for an extensive review of the methodology and code used.

The presence-only data used in these analyses were acquired from auditory surveys, burrow nesting site location data, and expert opinion polygons for NESH. The Auditory surveys were conducted by the Kauai Endangered Seabird Recovery Project (KESRP) from 2006 to 2012. This extensive dataset was collected around Kauai, and totaled 993 survey locations. The burrow nesting site data were collected from multiple surveys conducted across Kauai from the 1950's to 2008, as compiled in the Pacific Island Fish and Wildlife Office database. If survey points overlapped at a locality, the overlap was reduced to a single point per locality. A total of 28 burrow localities collected across Kauai were used to develop the NESH ecological niche model (ENM).

Because both niche modelling procedures used were presence-only based assessments, there may be some unknown bias in how and where the data was collected. One example of a bias that presence only data can unknowingly exacerbate is accessibility bias; where the data is biased toward more accessible sites (Phillips et al. 2009). In an attempt to de-bias the collections the presence of other similarly collected species (Hawaiian Petrel (HAPE), and Band Rumped Storm Petrel (BANP)) were used in combination with randomly selected pseudo-absence data to define the collection background. This was done because occurrence data for NESH, HAPE and BANP was collected similarly, and thus the presences of BANP and HAPE could be used to help reduce collection bias (Phillips et al. 2009; Hertzog, Besnard, and Jay-Robert 2014). Although the removal of collection bias was attempted using these similarly collected species points, the
number of acquired points was not sufficient to describe the background from which the species occurred, as such a number of pseudo-absences whose localities were randomly distributed throughout Kauai were also selected. The number of pseudo-absence points to select was based on the area (in $\mathrm{km}^{2}$ ) of Kauai such that there was one pseudo-absence generated per $\mathrm{km}^{2}$. Pseudo-absences were also selected such that they did not overlap with either HAPE or BANP presence localities, and so a semblance of collection bias was still incorporated into the ENM background profile. Also, like the presence data, only a single point per $250 \mathrm{~m}^{2}$ grid cell was used to define the collection background.

Many of the default settings, as specified for the specific modeling methodologies, were used and defined directly in biomod2. The GBM procedure used 100 trees with 5 cross validation folds, while the maximum number of iterations in MAXENT was set to 100. A Markov Chain randomization evaluation of 500 runs for each modeling methodology was specified with a 20/80 (test/train) data split such that $20 \%$ of the presence data were used for model evaluation and $80 \%$ were used to calibrate each model. A sensitivity equals specificity threshold, as recommended by (Canran Liu et al. 2005) was used to mask the ensemble suitability model by removing locations from which NESH was statistically defined as absent.

### 2.1.2 Ensemble Model: Development

The two ENM modeling approaches (GBM and MAXENT) were combined as an ensemble model to assess model congruence, and improve model accuracy. All ensembles were developed in 'biomod2' such that an evaluation metric quality threshold of 0.5 was used to define the minimum scores of each model's Receiver Operating Characteristic Area Under the Curve (AUC) value (see Model Validation Statistics below). Values above 0.5 (corresponding to a discriminatory power no better than random) (Thuiller, Georges, and Engler 2012) were used as the minimum model scores to define the final ensemble model.

For all ensemble models, the weighted mean probability of occurrence was reported. The weighted mean probability of occurrence is similar to a standard model mean in that they both define the mean prediction of all models developed for the analysis above the quality threshold evaluation metric (AUC>0.5). However, the weighted mean probability of occurrence metric weights each model according to the value of the evaluation metric (the higher the metric the greater the weight given to the model).

For further analyses all ensemble models were cropped to only include the unlit portions of the light viewshed analysis (see above for methodology). Given the significance of light impact on NESH fledglings, it was felt that this was a more accurate description of the probable distribution of current NESH terrestrial habitat.

### 2.1.3 Model Validation Statistics and Variable Importance: Development

Each model was evaluated using AUC, and the True Skill Statistic (TSS). The AUC validation statistic is a commonly used threshold independent accuracy index that ranges from 0 to $1(1=$ highly accurate prediction). The AUC index defines the probability that an SDM will rank a presence locality higher than an absence (here a pseudo-absence) (C. Liu, White, and Newell 2009). The TSS statistic ranges from -1 to +1 and tests the agreement between the expected and observed distribution, and whether that outcome would be predicted under chance alone (Allouche, Tsoar, and Kadmon 2006; C. Liu, White, and Newell 2009). A TSS value of +1 is considered perfect agreement between the observed and expected distributions, whereas a value $<0$ defines a model which has a predictive performance no better than random (Allouche, Tsoar, and Kadmon 2006; C. Liu, White, and Newell 2009). The TSS statistic is very closely related to Cohens Kappa statistic (KAPPA), in that they both range from -1 to +1 and define accuracy in comparison to chance. Unlike KAPPA, TSS is not affected by point prevalence (Allouche, Tsoar, and Kadmon 2006). As recommended by (Franklin 2010) and (Jane Elith and Leathwick 2009) multiple test statistics were used to allow a more robust assessment of model performance and validate model responses.

To understand a variable's relative importance to each model, response plots and variable importance boxplots were developed for each SDM using 'biomod2'. Response plots for each variable defined the sensitivity of the prediction to variation in the variable while all other variables were held constant. Using these plots allowed inference into the ecological sensitivity and significance of each variable to the organism's distribution, as defined by the variables used in the model (Jane Elith et al. 2005).

### 2.1.4 Species Distribution Model Validation and Ensemble Model: Output

Both modelling outputs used to develop the ENM for NESH (MAXENT and GBM) produced highly predictive and descriptive models, as defined using the three validation metrics employed
(Table 1). Both models were combined to form an ensemble using a weighted mean approach, where differential weighting of each model within the ensemble is based on the validation metric.

The response of each environmental covariate was relatively similar per modelling approach (Fig. $6 \& 7$ ), where topographic roughness (TRI) and wind at 50 m elevation (Wind50m) explained the most variance in response. Of the two main variable responses, there was a juxtaposition in their effect depending on the modelling approach employed (Fig. 6). For each environmental covariate employed, the average response over their range of values was only slightly different between modelling approaches (Fig. 7). Interestingly, although there was some variability depending upon the approach, relatively high slopes, a great degree of roughness, and high wind at 50 m elevation were all associated with a greater response by both models in the NESH ENM predictions (Fig. 7).

Because of the relatively strong concordance between modelling approaches, an ensemble model was developed using a weighted mean approach. This was done by weighting the average of the 500 iterations for each model, by each of the validation statistics employed (Table 2), and combining them to form a consistently scaled metric. As both models, and there validation statistics, are relatively concordant, AUC (see Section 2.1.2) was used to depict the ensemble models output (Fig. 8). The ensemble model depicted here was thresholded (partitioned) by equal sensitivity and specificity to help infer presence/absence. Two variations of the model are depicted, the first is without removing the light-impacted areas (Fig. 8A), and the second is after light-impacted areas have been removed (Fig. 8B). The total area of suitable habitat in the initial thresholded ENM is $341.3 \mathrm{~km}^{2}$ ( $34,130 \mathrm{Ha}$ ) (Fig. 8A). When areas with viewable light are removed (Fig. 8B), the suitable habitat area is reduced to $120.1 \mathrm{~km}^{2}(12,010 \mathrm{Ha})$. This represents a $64.81 \%$ reduction in actual and/or potential habitat (i.e. modeled niche) due directly to viewable light sources.

### 2.2 Carrying Capacity Estimate: Development

Using the compiled presence-only auditory data defined above, an ad hoc estimate of carrying capacity $(\mathrm{K})\left(\right.$ at $1 \mathrm{~km}^{2}$ ) was projected over the ENM. This was done by modifying the ENM raster to project at a resolution of $1 \mathrm{~km}^{2}$, and for each $\mathrm{km}^{2}$ assessing the density of unique
presence points within that cell. The density of points per cell was then analyzed via a boxplot assessment, and the boxplots upper whisker ( $\sim 95 \%$ confidence interval) was used as the projected K per $\mathrm{km}^{2}$.

### 2.3 Carrying Capacity Estimate: Output

Carrying capacity was estimated at 4,820 individuals per $\mathrm{km}^{2}$ (Fig. 9). When projected across the ENM for all NESH habitats (including light-impacted habitat), a maximum K of 1,644,912 individual NESH was estimated to occur over the extent of the thresholded niche model. When light-impacts were removed from the analysis, an estimated maximum K of 578,789 NESH was estimated to occur.

This single estimate does not take into account variation in habitat quality (as estimated by the ENM); just the boundary's predicted by the various ENMs. Consequently, these carrying capacities most likely represent very high estimates of the actual number of NESH that could occur across the habitat

### 2.4 Section 2: TABLES

Table 2: ROC, TSS and KAPPA validation statistics ( $\pm$ standard deviation) for each of the modelling approaches used (gbm and maxent) as defined over 500 iterations. Potential ranges are: ROC (range 0 to 1), TSS (range -1 to 1), and KAPPA (range -1 to 1).

|  | MAXENT $( \pm$ SD $)$ | GBM $( \pm$ SD $)$ |
| :--- | :---: | :---: |
| ROC | $0.8667( \pm 0.0172)$ | $0.8723( \pm 0.0174)$ |
| TSS | $0.5921( \pm 0.0404)$ | $0.6019( \pm 0.0395)$ |
| KAPPA | $0.5405( \pm 0.0409)$ | $0.5437( \pm 0.0405)$ |

### 2.5 Section 2: FIGURES



Figure 6: Variable importance boxplot for each species distribution model modelling approach (Maxent and GBM). Higher response values for each variable indicate greater importance of that variable to the overall models output. Each variables response is calculated from 500 iterations of each modelling approach used. The presented variables correspond to: bio3 $=$ isothermality, bio15 = precipitation seasonality, slope $=$ slope, tri $=$ topographic roughness index and wind $50 \mathrm{mHI}=$ wind at 50 meters.


Figure 7: Average linear response plots of each variable within each modelling approach over the range of each environmental variables distribution (as rescaled to an overall 0-1 range). Response plots were defined as the average of responses over 500 iterations for both Maxent (A) and GBM (B). The presented variables correspond to: bio3 = isothermality, bio15 = precipitation seasonality, slope = slope, tri = topographic roughness index and wind $50 \mathrm{mHI}=$ wind at 50 meters.


Figure 8: GBM and Maxent species distribution ensemble models as cut to define presence/absence by the equal sensitivity and specificity thresholding parameter under the ROC AUC statistic (A). To assess the impact of light on the ensemble model, certain areas were removed due to visible light impingement (B) (Fig. 1\& 2).


Figure 9: NESH cell density boxplot used to approximate the carrying capacity (K) from KESRP auditory collections. To define $K$, the upper $95 \%$ confidence interval was used. This assessment was mainly applied to define the upper bounds in which any population viability assessment should predict the maximum size of the Kauai meta-population.

## 3. SECTION 3: FLIGHT PATH MODEL ESTIMATION AND VALIDATION

In order to inform a site based assessment of NESH viability, based on colonies of NESH around Kauai, it was necessary to understand the passage of seabirds from there colony to the coast, and back. Assuming topography is a highly influential variable defining the path of NESH to and from their natal colony, one can model the flight path of NESH while varying the influence of various elevations to its flight path. In this section the development, validation and compilation of various flight path models are described and projected. Although it is recognized that other factors likely influence the flight path of NESH to and from the coast during their daily nocturnal migration, these factors are currently unknown. As such, this flight path assessment acts as a placeholder until more information is available.

Assessing the flight path of NESH is critical to understanding and projecting the influence of various anthropogenic mortality factors (light fallout and power-line strike impact) imposed on the seabirds during flight. The flight path models developed here are critical for the development of the subsequent sections. For instance, the strike model in Section 4 uses the ensemble flight path model as a variable in the projection of powerline strikes across sampled transmission lines. Also, the proportional mortality information extracted for each colony, for each compilation of the colony's flight paths, is used to inform the site-based projection of colony viability in Section 5. Finally, in Section 7 the overall flight path information extracted for a specific site is used to subset the Kauai NESH meta-population to help inform site specific mitigation and social attraction efficacy.

### 3.1 Flight Path Model Development and Ensemble Compilation

### 3.1.1 Topographically Modified Flight Path Model: Development

Two estimates of the NESH flight paths were developed: a flight-path estimate based on the polygons collected by KESRP outlining possible NESH colonies throughout Kauai (hereafter referred to as KESRP polys); and a flight-path estimate derived from the ensemble Ecological Niche Model (ENM) polygons (described in Section 2). The ENM-derived polygons were converted into presence polygons (hereafter referred to as ENM polys). These two sets of polygons (KESRP polys and ENM polys) of occupied NESH distribution represent two
assessments of known and possible NESH flight origins. The KESRP polys represent the most confined distribution possible, and thus very specifically define flight origins. The ENM polys represent the most expansive distribution of NESH currently possible, and thus represent a more expansive set of flight origins. Neither of these polygons sets are completely representative of the Kauai NESH population (Andre Raines personal communication), as such the actual polygon distribution (and thus NESH flight path/leading lines developed from them) likely falls between these two estimates.

Although there are likely many parameters that may significantly affect the distribution and track of a seabird's flight path, two readily available and likely significant geographic parameters are Topography and Coastal Access (Mueller and Berger 1967). These parameters are not necessarily independent of each other and so were jointly modeled and varied. To define variation in topography on Kauai, a $250 \mathrm{~m}^{2}$ elevation profile was used (see Section 1 for details on the $250 \mathrm{~m}^{2}$ elevation profile). This elevation profile was then thresholded at specific elevations (Minimum, $1^{\text {st }}$ Quartile, Mean, Median, $3^{\text {rd }}$ Quartile, and Maximum) selected from elevation based boxplot assessments of either the ENM or KESRP polys, depending on which flight path model was being defined. These quartile range estimates were selected to define various flight path models in order to develop an iteratively reproducible, data-informed, methodology that evaluates the significance of various topographic profiles on the flight path. Potential flight paths were then projected over these thresholded elevation profiles using the package 'gdistance' in R (Etten 2012). An estimate of topographic friction (i.e., the variance in elevation, and its effect on origin to destination access) was developed in gdistance from these various topographic profiles following the protocols of Etten (2012). A least cost (least topographic friction) path model derived from this friction estimate could then be iteratively developed between specific points (source/sink) on Kauai.

As many of the KESRP polys are overlapping, or in close proximity to one another, it was necessary to compile these polygons into a smaller group such that they still represent the polygon areas, but do not overlap. As such, all of the KESRP polygons that directly intersect, or intersect at a width from there perimeter of 100 meters, were combined into a single polygon: this assumes that a distance of 200 m is adequate to define separate colony sites for modeling flight paths.

A set of source points was selected from within each polygon, where a point was defined for each $250 \mathrm{~m}^{2}$ within the polygon. If the polygon was $\leq 250 \mathrm{~m}^{2}$ only a single point was used to define the flight path from that polygon. A set of destination (sink) coastal points were also developed from a transformation of a linear coastline profile to a point profile, where a point along the coast was demarcated approximately every 100 m . Using a Euclidean distance profile from each source, 500 coastal points were iteratively selected that were the closest to the source points; this analysis assesses the least cost path distance from each point within the polygon to the closest $4^{\text {th }}$ of the island's coast. Paths were developed in this way to increase the likely specificity of the flight paths to the colonies. Limiting the coastal point locations to a $4^{\text {th }}$ of the island assumes that most birds at a colony will use one of the flight paths within that quarter of the island coastline.

Topographic variation was used to test assumptions regarding the specificity of the flight path, as well as to develop an ensemble of flight path models that incorporated model variance. A topographically-enabled least-cost path profile from each source point to each coastal sink point was estimated for each variation of the elevation profile. Graphics were developed that define the relationships per polygon-source point to the friction profile, and all coastal points. Within each of these source-to-coast least cost path assessments, each path was given a value of one, such that the path overlap could be assessed by summing the number of times paths overlapped. The overlap summed values were transformed such that 0 indicated no least-cost path overlap and 1 was the highest number of least-cost path overlaps.

### 3.1.2 Flight Path Ensemble and Threshold Model: Development

No single assessment will accurately predict the flight paths across the landscape; this is because there is likely a great deal of flight-path variability due to biotic (e.g. behavioral) and/or abiotic (e.g. dominant winds) factors. In an attempt to partially account for this variance, this assessment has incorporated two different colony source polygons (KESRP poly and ENM poly), and variance in the significance of topography into the modeled flight lines of NESH.

In order to increase the specificity (low false positive rate) of the assessment, but still maintain an acceptable level of predictive power (low false negative rate), the models (KESRP or ENM) were combined in two different ways. The first method combined all of the topographically
varied flight paths developed from either the KESRP or ENM polygons through summing and averaging the outputs per pixel. This method is valuable in that it is easily understood, but because of the way the variance for the assessment was developed (through attributes of the boxplots), this analysis may be skewed toward the central limit. The second methodology used to compile these assessments employed a weighted average approach. The weight average of each model was defined by the adjusted $\mathrm{R}^{2}$ value of each assessment, as inferred from the multiple regressions described in the Flight Path Model Validation Statistics Development section, below.

A series of statistically derived threshold values were then applied to these weighted averages. The threshold values were the minimum prediction occurrence; sensitivity equals specificity; and maximum sensitivity plus specificity. These thresholds were derived from the direct overlap of the KESRP NESH auditory detections with the averaged flight path overlap values described previously. The minimum occurrence threshold is the minimum averaged overlap of flight paths for a NESH auditory detection location. Sensitivity-equals-specificity is defined as the probability value where a false positive is as likely as a false negative. The maximum sensitivity plus specificity threshold attempts to minimize the false positive and false negative rate of the prediction as much as the input data allow. For these assessments an example of a false positive would be the prediction of a point without a NESH observation that is predicted to have an observation, a false negative is essentially the reverse. These thresholds are used here to optimize the flight path by the probability of detection, and thus is an attempt to inform biologists looking to increase the probability of in-flight NESH detections.

### 3.1.3 Flight Path Model: Output

Least cost paths were projected from two estimates of NESH presence, the ENM (Fig.10) and KESRPs NESH polygons (Fig. 11). The combination of these two estimates allows an upper and lower bound from which one can infer flight paths. Using a weighted (Fig. 12 A\&C) and base (Fig. $12 \mathrm{~B} \& D$ ) average approach, these estimates were compiled into single ensemble models that attempt to account for the variance in flight path of NESH. The ensembles produced using these approaches were then modified to account for three different statistically derived thresholds; minimum prediction occurrence (Figures $13 \& 14$; A\&B), sensitivity equals
specificity (Figures 13\& 14; C\&D), and maximum sensitivity plus specificity (Figures 13\& 14; E\&F).

### 3.1.4 Flight Path Model Validation Statistics: Development

Two validation analyses were conducted for each variation of the ENM and KESRP poly flight path models. Both analyses involved multiple regression, comparing the Euclidean distance of locations with known densities of NESH to the closest flight-path line, and the proportion of lines at that flight path that overlap. The first assessment involved the use of the KESRP auditory data, where the number of NESH calls at each site was used as a proxy of NESH density. This proxy of density (as normalized using a BoxCox transformation (Kutner et al. 2004)) was then compared to the square root (to normalize the dataset) of each collected locations distance to the closest flight path (as defined by the compiled flight path raster) and the number of flight paths that overlap at that NESH location. Flight path overlap was used in the assessment to act as another proxy of NESH density at each location, but because the closest flight path to any point is usually on the exterior of the compiled flight paths per polygon (due to stochastic variation in the actually flight paths of NESH), it was not thought to be likely effective in discriminating an association between NESH calls and flight path overlap. Also, because these auditory points were used to define the ENM, they were not necessarily independent of the ENM poly flight path; as such a secondary assessment using independently collected Radar data was developed.

Radar data were collected by KESRP during the months of June and July as part of a monitoring program developed for NESH and HAPE). Radar surveys were conducted for at least one night (and at some locations 4 nights) on a Furuno FR-1510 MKIII surveillance radar (range $=1.5 \mathrm{~km}$, pulse $=0.07 \mu \mathrm{sec}$ ) starting 15 minutes before sunset and continued for $\sim 3$ hours to cover the peak of evening flights (KESRP work order, 2013). Approximately six surveys were conducted over the 3 hours of collection, each sampling session lasting twenty-five minutes. During these sampling sessions targets were recorded and the speed and flight behavior (erratic, straight line, or circling) of each target was assessed. This dataset could distinguish NESH from other night flying organism (such as Barn Owls, Bats, HAPE, or BANP) using the speed ( $\geq 30 \mathrm{mph}$ ), behavior (straight line), and the monitoring session ( $\geq$ the second monitoring session of the night) of the contact(s) (KESRP personal communication). As such, in R the number of contacts
with a recorded speed $\geq 30 \mathrm{mph}$, a straight line flight path behaviors, and occurrence during or after the second monitoring session, were defined as NESH per site. This discriminative assessment has the potential to be overly specific, but because these assessments are being used as proxies of densities per site, the high specificity of the selection procedure doesn't significantly affect the overall measurement (whereas a procedure with high sensitivity might).

A multiple regression was then conducted in which the normalized Euclidean distance from the collection site to the flight path, and the path overlap at those close sites, were compared to a BoxCox transformed (Kutner et al. 2004) contact estimate (as defined in Table 3). Because some collections were performed at some sites over multiple days, the analysis was conducted for the average number targets detected by the radar data at each site per hour, and there average velocity and direction defined over the complete span of the compiled multi-day monitoring sessions. An overview of the data is given in Table 3.

Validation analyses were conducted over all iterations of the assessment, and for each ensemble modeling approach, using both the auditory and radar data. Because the auditory detection data were used directly to develop the thresholds for the threshold analyses, only radar data were used to attempt validation of the thresholded assessments.

### 3.1.5 Flight Path Model Validation Statistics: Output

Multiple regressions using NESH auditory and radar detections were conducted for each assessment. Initial analyses attempting to assess the correlation of the flight path to the number of calls per location, and the distance of the path lines to those calls were conducted over all uncompiled variations of the flight path, where flight path was varied by topography (Table 4). All analyses for this assessment showed either a significant ( $\mathrm{p} \leq 0.05$ ) or notable ( $\mathrm{p} \leq 0.1$ ) trend. Adjusted- $\mathrm{R}^{2}$ values in these assessments all indicated a positive trend line, but had large differences in values depending on the detection type (i.e. radar or auditory) used. The regression analyses conducted on the ENM flight path profiles using the auditory detections tended to have larger degrees of correlation than those conducted on the KESRP flight path profile. This difference is not necessarily unexpected given that the ENM polygons were derived from the auditory detections. That said, this difference is not maintained when using the radar
data to compare the correlations, in fact the KESRP polygon derived flight paths show a slightly greater degree of correlation than those derived from the ENM polygons.

These same multiple regression analyses were conducted over the ensemble models (weighted and base averages) (Fig. 12), and the threshold modifications applied to them (Fig. 13 \& 14). Table 5 depicts the multiple regression outputs for the ensemble models developed from KESRP and ENM polygons. As these models were developed using the validation statistics derived from the NESH auditory detections, only analyses that included the radar detections were deemed appropriate. Interestingly, and this is likely due to the small number of points used for this assessment, all analyses but the base average assessment showed similar trends within the KESRP or ENM polygon ensemble assessments. Of the ensemble models, both the KESRP and ENM base average assessment showed the greatest degree of correlation to the variables used.

### 3.2 Section 3: TABLES

Table 3: Average number of radar contacts assessed at each site per day, as well as summary data describing the average distance, direction, and velocity of those compiled contacts.

| SITE | MAX. CONTACTS <br> PER SITE | NUMBER OF <br> CONTACTS <br> PER DAY | AVERAGE <br> DIRECTION | AVERAGE <br> DISTANCE | AVERAGE <br> VELOCITY |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Lumahai | 12.00 | 271.33 | 230.21 | 6.29 | 30.76 |
| Waimea | 6.00 | 171.00 | 63.57 | 5.90 | 30.43 |
| Kalihiwai | 5.00 | 104.00 | 240.12 | 5.90 | 31.14 |
| Hanalei | 5.00 | 38.50 | 211.48 | 7.02 | 30.37 |
| Waialua | 4.00 | 169.00 | 263.94 | 5.74 | 30.88 |
| Kalepa Ridge | 3.00 | 305.00 | 262.29 | 7.13 | 31.06 |
| Anahola | 3.00 | 171.00 | 268.13 | 5.14 | 33.00 |
| Kealia | 2.00 | 80.00 | 261.79 | 6.41 | 30.38 |
| Kapaa | 2.00 | 54.00 | 258.42 | 6.46 | 31.29 |
| Eleele | 2.00 | 44.67 | 255.04 | 4.40 | 32.03 |
| Wainiha | 2.00 | 37.00 | 193.43 | 5.94 | 31.29 |
| Waiakalua | 2.00 | 61.00 | 260.50 | 5.28 | 32.00 |
| Lihue Airport | 1.00 | 28.00 | 260.00 | 4.64 | 31.25 |
| Kalaheo | 1.00 | 24.00 | 236.67 | 5.42 | 32.50 |
| Kekaha | 1.00 | 11.00 | 141.21 | 7.97 | 30.30 |

Table 4: Multiple regression outputs comparing either the location of an auditory detection, or a radar detection, to the distance from a projected flight path, and the number of flight paths that overlap. Analyses analyzed here are those that were initially produced to assess flight path variability due to topographic variation. As the significance of topography was varied based on a boxplot assessment of the elevations within each overall polygon assessment (KESRP or ENM), values defined were the minimum (Min), first quartile (1stQ), median (Median), mean (Mean), third quartile (3rdQ), and maximum (Max). Values highlighted in red are those analyses that have a $p$-values $\leq 0.05$. The number of detections used to develop this assessment is identified in the data description.

AUDITORY NESH DETECTION DATA ( $\mathrm{n}=995$ )

| $\mathrm{R}^{2}$ | Adjusted $\mathrm{R}^{2}$ | p -Value (<0.05) | Analysis Name |
| :---: | :---: | :---: | :---: |
| 0.0108 | 0.0088 | 0.00 | KESRP_Min |
| 0.0276 | 0.0256 | 0.00 | KESRP_1stQ |
| 0.0254 | 0.0235 | 0.00 | KESRP_Median |
| 0.0217 | 0.0198 | 0.00 | KESRP_Mean |
| 0.0875 | 0.0857 | 0.00 | KESRP_3rdQ |
| 0.0594 | 0.0575 | 0.00 | KESRP_Max |
| 0.094 | 0.0922 | 0.00 | ENM_Min |
| 0.1358 | 0.1341 | 0.00 | ENM_1stQ |
| 0.1312 | 0.1295 | 0.00 | ENM_Median |
| 0.1613 | 0.1596 | 0.00 | ENM_Mean |
| 0.1453 | 0.1436 | 0.00 | ENM_3rdQ |
| 0.063 | 0.0611 | 0.00 | ENM_Max |

RADAR NESH DETECTION DATA ( $\mathrm{n}=12$ )

| $\mathrm{R}^{2}$ | Adjusted $\mathrm{R}^{2}$ | p-Value $(<0.05)$ | Analysis Name |
| :---: | :---: | :---: | :---: |
| 0.6125 | 0.5479 | 0.00 | KESRP_Min |
| 0.7118 | 0.6637 | 0.00 | KESRP_1stQ |
| 0.7835 | 0.7475 | 0.00 | KESRP_Median |
| 0.6408 | 0.581 | 0.00 | KESRP_Mean |
| 0.7397 | 0.6963 | 0.00 | KESRP_3rdQ |
| 0.4788 | 0.3919 | 0.02 | KESRP_Max |
| 0.4467 | 0.3544 | 0.03 | ENM_Min |
| 0.3697 | 0.2647 | 0.06 | ENM_1stQ |
| 0.6067 | 0.5411 | 0.00 | ENM_Median |
| 0.4029 | 0.3034 | 0.05 | ENM_Mean |
| 0.3947 | 0.2938 | 0.05 | ENM_3rdQ |
| 0.6234 | 0.5606 | 0.00 | ENM_Max |

Table 5: Multiple regression outputs that compare the location of radar detections to the distance from a projected flight path, and the number of overlapping flight paths. Projections analyzed here are those that were compiled either using a base average, or a weighted average, where weighting was determined by the adjusted $R^{2}$ values of each individual assessment. For each assessment (i.e. weighted or base average) three thresholds were applied. Values highlighted in red are those analyses that have a $\mathbf{p}$-values $\leq \mathbf{0 . 0 5}$. The number of detections used to develop this assessment is identified in the data description.

RADAR NESH DETECTION DATA ( $\mathrm{n}=12$ )

| $\mathrm{R}^{2}$ | Adjusted $\mathrm{R}^{2}$ | p -Value (<0.05) | Analysis Name | Threshold Applied |
| :---: | :---: | :---: | :---: | :---: |
| 0.8051 | 0.7726 | 0.00 | KESRP Base Average | None |
| 0.7925 | 0.758 | 0.00 | KESRP Weighted Average | None |
| 0.7925 | 0.758 | 0.00 | KESRP Base Average | Min. Occurrence |
| 0.7925 | 0.758 | 0.00 | KESRP Weighted Average | Min. Occurrence |
| 0.7925 | 0.758 | 0.00 | KESRP Base Average | Sensitivity equals Specificity |
| 0.7925 | 0.758 | 0.00 | KESRP Weighted Average | Sensitivity equals Specificity |
| 0.7925 | 0.758 | 0.00 | KESRP Base Average | Max. Sensitivity plus Specificity |
| 0.7925 | 0.758 | 0.00 | KESRP Weighted Average | Max. Sensitivity plus Specificity |
| 0.7014 | 0.6517 | 0.00 | ENM Base Average | None |
| 0.6271 | 0.5649 | 0.00 | ENM Weighted Average | None |
| 0.6271 | 0.5649 | 0.00 | ENM Base Average | Min. Occurrence |
| 0.6271 | 0.5649 | 0.00 | ENM Weighted Average | Min. Occurrence |
| 0.6271 | 0.5649 | 0.00 | ENM Base Average | Sensitivity equals Specificity |
| 0.6271 | 0.5649 | 0.00 | ENM Weighted Average | Sensitivity equals Specificity |
| 0.6271 | 0.5649 | 0.00 | ENM Base Average | Max. Sensitivity plus Specificity |
| 0.6271 | 0.5649 | 0.00 | ENM Weighted Average | Max. Sensitivity plus Specificity |



Figure 10: Least cost path projections of NESH flight path from ENM projected locations. Elevation was varied based on a boxplot assessment of elevation over all ENM defined polygons. Elevation for each assessment was thresholded by the minimum (A), $1^{\text {st }}$ Quartile, (B), Mean (C), Median (D), $3^{\text {rd }}$ Quartile (E), and Maximum (F) elevation defined by the boxplot. All plots shown describe the least cost path from the polygons ( 1 point every $\mathbf{2 5 0} \mathrm{m}^{\mathbf{2}}$ ), to $1 / 4^{\text {th }}$ of the islands coastal destination, as defined by 1 point approximately every 100 meters. Variations in color (varied numerically from 0-1) describe the degree of flight path overlas for each location in each model.


Figure 11: Least cost path projections of NESH flight path from KESRP defined colony polygons. Elevation was varied based on a boxplot assessment of elevation over all KESRP colony polygons. Elevation for each assessment was thresholded by the minimum (A), 1st Quartile, (B), Mean (C), Median (D), 3rd Quartile (E), and Maximum (F) elevation defined by the boxplot. All plots shown describe the least cost path from the polygons ( 1 pointe every 250 m2), to $1 / 4$ th of the islands coastal destination, as defined by 1 point approximately every 100 meters. Variations in color (varied numerically from 0-1) describe the degree of flight path overlap for each location in each model.


Figure 12: Ensemble models of the ENM (A\&B) and KESRP (C\&D) flight paths using either the weighted Average (A\&C) or the base average (B\&D) of all assessments. The weighted average was compiled/weighted based on the summed proportion of each adjusted $\mathbf{R}^{2}$ value.


Figure 13: Overlapping least cost path projections of NESH flight paths for thresholded and compiled ENM polygon flight path projections, either with a weighted (A, C, \& E) or base (B, D, \& F) average. The averages have been thresholded by either the minimum presence ( $A \& B$ ), sensitivity equals specificity (C\&D), and maximum sensitivity equals specificity thresholds.

Flight Path Model Estimation and Validation


Figure 14: Overlapping least cost path projections of NESH flight paths for thresholded and compiled KESRP polygon flight path projections, either with a weighted (A, C, \& E) or base (B, D, \& F) average. The averages have been thresholded by either the minimum presence (A\&B), sensitivity equals specificity (C\&D), and maximum sensitivity equals specificity ( $E \& F$ ) thresholds.

## 4. SECTION 4: KIUC STRIKE ASSESSMENT MODEL

On Kauai, NESH face major threats from both infrastructure development and maintenance. Little was known regarding the degree to which power-line strikes are impacting Kauai's metapopulation until recent large scale assessments conducted by KESRP, in collaboration with conservation metrics, were conducted. These assessments used innovative applications of sound detection devices on transmission lines, in combination with machine learning algorithms, to determine the probability that a noise made at a specific location on a line was a seabird strike. This section uses the power-line strike data collected by KESRP, and analyzed by conservation metrics, to impute and project NESH strikes across the sampled transmission lines on Kauai.

Due to the large number of power-line strikes identified by KESRP from a small number of collection locations (Travers et al. 2014), a line strike projection was developed for data collected in 2014 and 2015 that attempts to project the number of sites over the season in which strikes occurred, and into locations in which data were not yet collected. Data collection, site information, and analysis procedures of the 2014 and 2015 strike data are thoroughly reviewed in Travers et al. (2014 and 2016). As such, this section will only review the methodology for the imputation of power-line NESH strikes into unmeasured locations and times using data from rover and stationary (static) detection equipment.

### 4.1 2014 and 2015 Power-line Strike Data Imputation: Development

Data collected by KESRP were defined as either a static (stationary) or rover sampling site. Static sites are here defined as units placed at locations over the extent of the seabird breeding season; rover sites are locations that were monitored for brief periods within the same season as the static units. In order to use rover sites for the entire seabird breeding season, data gaps need to be filled by estimating values using statistical imputation (Ding and Simonoff 2010).

Imputation is the process of filling in missing data with reasonably accurate information. This process allows for further data processing and more accurate projections (Moritz et al. 2015). There are currently quite a few methodologies that attempt to impute missing data, all of which have various levels of rigor and accuracy associated with them (Moritz et al. 2015; Engels 2003; Wilson, Lister, and Riemann 2012). As the power-line strike dataset is a multifaceted (e.g.
length of time the various units were deployed, date deployed, and date retrieved, etc.) set of univariate time series from many different locations, it was necessary to develop a data-driven assessment to select the best imputation approach to apply. To conduct such an assessment, a collection of imputation approaches was assembled and applied in the R statistical environment. These imputation approaches are described in Table 6.

Two modifications applied to all imputation procedures were the addition, or removal, of data collected at the Mount Kahili (Kahili) power-line span; and/or the application of a Fourier transformation to improve seasonal trends. Because power-line strike minimization efforts were conducted and monitored at the Kahili site in both 2014 and 2015, it was felt that including these data may bias the results of the overall analysis. Although attempts were made to apply the imputation procedures to strikes recorded at the Kahili power-line span, imputations using this power-line span were not used in the overall projection of power-line strikes due to this potential biasing affect. Though the Kahili site is not used in the finalized strike imputations or projections, the imputation procedures that use the Kahili power-line strikes are shown in all of the imputation graphics for comparison.

A Fourier transformation attempts to partition a function of time into its harmonic (sine/cosine) components (Weisstein 2016; Marks 2009). The application of the Fourier transformation was only applied using two imputation approaches, the expectation maximization algorithm using an Autoregressive Integrated Moving Average (ARIMA); or cubic smoothing spline algorithm (SPLINE). These two imputation algorithms were the only methodologies to which the Fourier transformations were applied. Both of the imputation algorithms employ a moving average assessment appropriate for the Fourier transformed imputation data. The ARIMA and SPLINE expectation maximization techniques require inputs greater than zero due to the need to invert a non-singular matrix. Rover and static sites that did not detect a power-line strike were compiled with the other strike data. Although these sites did not detect a strike, there inclusion in the analyses does affect the variability of strike detection. Whether or not to apply imputed strikes to those locations that did not detect strikes was determined by a comparison of assessments across all non-expectation maximization techniques, with all methodologies applied to strike detection units with strikes.

In order to select an imputation approach, it was necessary to compare approaches using some measurement of predictive accuracy per methodology. To apply these validation and accuracy measurements in a statistically rigorous manner, training and testing data subsets were randomly developed over multiple iterations of each methodology (Ding and Simonoff 2010). This allowed for comparisons between the imputation models. For this cross validation assessment, each model was replicated 200 times. For each iteration, a $1 / 50^{\text {th }}$ subset of all field collected strikes derived from both rover and static sites was randomly selected as the testing data and the remaining training data $\left(49 / 50^{\text {th }}\right)$ were used to establish the predicted site baseline. From this 50fold cross validation, a set of validation/comparison metrics were calculated, comparing the actual site data (testing data) to the projected site data derived from the training data.

Two validation statistics were assessed per iteration, the root mean square error (RMSE) and the receiver operating characteristic area under the curve (AUC). The RMSE uses the difference between the actual (test data) and the predicted (training data) values generated by the model; it assesses the model's ability to predict the occurrence of strikes at static and rover sites. The lower the RMSE value, the better the models predictions. The AUC tests the discriminatory ability of the imputation method. It is a compilation of binary assessments, comparing the testing data subset to site data derived from the imputed data in the training data subset (JiménezValverde 2012). For this assessment the AUC is used to define the ability of the model to predict the presence or absence of a strike at a site. Values above 0.5 indicate prediction ability greater than random; the closer the value is to one the better the predictive accuracy of the assessment.

Although each cross-validation metric produces compiled prediction accuracy (RMSE, AUC) and strike amount metrics for all imputation methodologies, it is only after an imputation procedure is selected, and the procedure is run without being subset, that a strike amount is determined. Re-training the analysis on the complete data after imputation is considered a best practice because it helps remove any bias associated with the subset data (Cawley and Talbot 2010)

### 4.22014 and 2015 Power-line Strike Data Imputation: Output

Initially, imputation strike estimates were developed for strike detection units that detected one or more strikes during its deployment. The imputation procedures were compared for both the 2014 (Fig. 15 \& 16) and 2015 (Figures 17 \& 18) strike detection unit data, with and without the Kahili site. Of those imputation procedures ARIMA was consistently ranked among the top approaches when comparing the AUC and RMSE validation metrics for both 2014 and 2015 datasets. ARIMA can only deal with datasets with at least one strike detected.

A second imputation approach was also selected from among the longitudinal imputation procedures. The imputed strikes for all longitudinal procedures were compared for all units that did not detect a strike and summed overall iterations for 2014 and 2015 (Fig. 19 A\&B, respectively). CopyMean was selected to impute the no-strike-detection data, as it is one of the most consistently ranked longitudinal procedures: when comparing the total number of strikes, CopyMean was consistently close to the ARIMA approach in defining strike total. The CopyMean approach imputes zero strikes at the strike detection units without any strikes; this is consistent with assumptions applied to another strike projection/imputation procedure developed by KESRP (Kauai Endangered Seabird Recovery Project 2015). All imputed and recorded strike detections were rounded to the nearest integer and summed across the year per unit for each imputation approach applied, and for both peak and off-peak units (see below) deployed in 2014 and 2015 (Table 7).

In 2014 at total of 995 strikes were recorded for peak and off-peak units, the yearly distribution of those strikes imputed an additional 2,456 strikes (total 3,451). Of the 3,451 imputed and recorded strikes, 3,074 were defined for units deployed at peak flight times, and 377 for units deployed during off-peak flight times. Figures 20 and 21 show the yearly distribution of the imputed and recorded strikes for both peak and off-peak units (without and with Kahili).

In 2015 a total of 1,017 strikes were recorded for peak, off-peak, check, and diverter units (see Travers et al. (2016) for unit descriptions). As only the peak and off peak unit strike detections were used for further projections, the 111 strikes imputed or recorded by the check units, and 1,534 strikes imputed by the backup unit at site T-48-335 were removed from any further assessment. Sites removed from subsequent analyses are marked with an asterisk in Table 7.

These sites were used in the imputation procedure as they contain valuable intra-seasonal trends. Without the check and backup units the imputation procedure imputed an additional 2,357 strikes (total 3,374). Of the 3,374 imputed/recorded strikes, 2,705 were defined for units deployed at peak flight times, and 669 for units deployed during off-peak flight times.

### 4.3 Strike Projection: Development

Strikes imputed or detected for each site were rounded to the nearest integer and summed (Table 7). For each power-line segment, potentially important environmental variables (measured by KESRP or developed from raster data) were defined. All variables are described in Table 8. In this assessment only the flight path model developed for the KESRP polygons was used, as this is a more conservative and specific model of actual bird locations, and thus likely definitive of actual birds in flight.

Because span length and geographic location have direct influence over the number of strikes per span assessments were initially projected using the estimated strikes per foot for each of the imputed line segments. This unique line-segment approach helps maintain the geographic specificity of the analysis. The overall number of strikes per line segment was then estimated from the unique line segment projections.

For the strike projections, a set of variables was developed to characterize what had been identified as variance in strikes along an aspect gradient (i.e. coastline). This coastal variance in strikes was thought to be due to elevation differences in their orientation along the coast (Travers, Shipley, Harris, et al. 2014). Coastal elevation also seems to influence the flight height at which seabirds cross the coast; for instance flight heights for the northeast coast of Kauai tend to be higher than at other coastal regions. To account for this, the average elevation of each line segment was characterized (termed Elevation in Table 8), and defined in relation to the topographic distance of each line segment to the closest point along the coast (termed Distance in Table 8). The variables were then rescaled (Hastie, Tibshirani, and Friedman 2011) and combined, using a Principle Component Analysis (PCA). The first two most descriptive principle components of line segment elevation and distance to coast, that were selected to be assessed in the analysis, are hereafter referred to as PCAEigen1 and PCAEigen2 (Table 8).

It should be noted that previous power-line strike projections incorporated a power-line exposure variable, and a power-line height variable. Due to the ongoing collection by KESRP of more accurate data defining power-line exposure and height, as well as problems found with the location of certain power-line segments in previous assessments, the power-line segment and pole shapefiles were redeveloped by KESRP and are to be updated in the near future (at the time of writing) with the exposure and height variables defined using high resolution LIDAR. For this reason these variables are not included in this assessment. In previous iterations, the exposure and height variables were found to be predictive of strikes, but were also slightly correlated with powerline distance to vegetation. Given that the distance-to-vegetation covariate is included in this dataset, the projection still may be descriptive of one with the updated variables, but is possibly not as definitive of a strike projection as one conducted with exposure and height.

As there is a great deal of variance associated with the power-line strike data (Table 7), an attempt was made to identify imputed points with any outsized influence on the analysis. Two outlier assessments, as defined using a leave one out deletion procedure, were applied to a General Linear Model (GLM) containing all variables. Data outliers were identified (using DFFITS (the difference in fit statistic) and Cook's distance) to assess the influence of each point on a standard multivariate GLM (Chatterjee and Hadi 2009). Any point that was defined as an outlier by either of these distance measurement tools was identified, and all subsequent analyses were run with and without these potentially influential points.

To assess the utility of these variables in the strike prediction, a jackknife (i.e. leave one out) procedure was applied, comparing the change in RMSE of a GLM derived from that specific variable to a GLM with a least-absolute-shrinkage-and-selection-operator procedure (GLM/LASSO) developed for all other variables, and to a GLM/LASSO projecting all variables. This procedure helped to assess the utility of those variables prior to the application of the more computationally intensive elastic net mixing procedure. These analyses were conducted in R for each year, and each outlier compilation (see previous paragraph), using the package 'glmnet' (Sill et al. 2013).

Given that GLM/LASSO is also a regularization procedure (a procedure that can compare and weight models with variable subsets, like AICc, BIC etc.), a subsequent analysis was conducted across all of the variables using a sequentially derived regularization parameter following the methodology of Guo et al. (2015). The analysis was conducted using the R package 'SparseLearner' (Guo and Hao 2015). The applied regularization procedure develops an optimally sparse subset of variables using a logistic regression with LASSO. The data were modified to reflect a binomial distribution such that the selection procedure selected variables that would predict presence or absence of strikes, and not degree of strikes. The methodology applied selects the most stable variables across an iterative bootstrap selection procedure with cross validation. For this assessment 200 bootstraps were conducted across 5 iterations with a 10 -fold cross validation metric for each year. All variables used in the overall assessment, as well as those selected for each year's subset projection, are highlighted in Table 8.

To develop a multivariate projection of power-line strikes, the lambda value (used in an elastic net mixing procedure to combine the best attributes of ridge-regression and LASSO regularization) was estimated using a leave-one-out-cross-validation (LOOCV) assessment. The number of iterations for each LOOCV assessment was set to be equivalent to the number of strike units imputed for the projection. The alpha values were sequential increased for each LOOCV from zero to one by 0.01 . The alpha with the smallest RMSE was selected to develop a data-specific elastic-net multivariate linear model (Zou and Hastie 2005).

For each assessment either all, or a subset, of the environmental variables were used with either all of the data, or the data with influential outliers removed. A model using all variables was developed for comparison because the elastic-net procedure also conducts internal variable weighting/regularization, and, as such, sub-setting the variables of the assessment may be inconsequential, or potentially detrimental, to the overall assessment. That said, understanding the value of the variables to the distribution was still thought to be important, and so the analysis is still reported on and described.

Two correction factors, peak/off-peak strike correction and detection probability, were either developed within the model or presented by Travers et al. (2016). These correction factors are
incorporated in this step primarily as a depiction of the maximum probable strikes, as such they are further refined in subsequent steps to assess strike mortality.

As peak/off-peak strike occurrence was identified as a potential source of variation (Travers et al. 2014), a deterministic ratio was devised using the imputations from sites that contained both peak and off-peak strike detection units. These ratios were developed for each year the strike projection were calculated (see Travers et al. (2014) for a definition of peak and off-peak units/sites). To conduct this assessment, all of the peak/off-peak ratios were defined per site, and the median of each year was assessed and used in all further calculations.

The detection probability correction factor incorporated into the overall assessment was for power-line strikes that were missed by the standard or updated microphones and algorithms. This assessment was developed for each year that data were collected. For the 2014 strike projection, this assessment uses the detection probability metric of 0.563 to determine the probability of an accurate detection of a strike by a song meter (provided by Conservation Metrics). The 2015 detection probability of 0.656 estimates a $9.5 \%$ increase in accuracy over the old assessment, and is definitive of an updated algorithm used to detect strikes by Conservation Metrics (see Travers et al. 2016 for details). This additional constant is incorporated into various model outputs along with the peak/off-peak assessment, and as explained previously represents a likely maximum number of strikes.

To project strikes onto un-monitored sites an elastic-net multivariate linear regression model was used. Elastic-net regression attempts to combine the attributes of Ridge and LASSO regressions by penalizing the L1 (minimization of absolute differences) and L2 (minimization of sum of square differences) norms to account for both overfitting and for correlation of variables (Zou and Hastie 2005). As described above, the lambda parameters of the elastic net procedure were selected per analysis through LOOCV and applied to each specific projection. All analyses were projected onto all selected power-line sites except for Mt. Kahili. All variables used to project strike number over the various iterations are identified in Table 8.

Finally, as the strike detections/imputations do not differentiate between bird species (NESH, HAPE, or BANP) differentiation of strikes was needed to define that proportion that is associated with NESH. To do this, a ratio of NESH to all other seabirds was developed using
call data collected by KESRP. This assessment measured the proportion of calls associated with NESH to be $\sim 81 \%$ of the seabird data collected. As it is assumed that the power lines are primarily impacting seabirds, and this proportion of NESH is essentially a proxy estimate of comparative abundance, a multiplier of 0.81 was used to estimate the number of strikes associated with NESH.

### 4.4 Strike Projection: Output

Statistical outliers were estimated from the overall projection using either DFFITS or Cook's Distance (Chatterjee and Hadi 2009). For the 2014 strike dataset, two points were defined as strike outliers for both the analysis using all variables, and the analysis using a subset of variables (Table 7). In 2015 five points were defined as outliers for the analysis conducted with all variables, whereas six points were defined when using only a subset of variables in the model (Table 7). Although these points were removed from the overall trend assessment for all analyses that do not use outliers, they were added back in to define that specific powerline segments information, as that information is still derived from real data.

As indicated in Figures 22 and 23 (and implied in Table 8), models performed much differently depending on the variables or the data used in the model. For the 2014 data, the flight path model developed using the KESRP polygons (see previous section for details) seemed to be highly predictive of the strike distributions for both the analysis conducted with (Fig. 22A) and without (Fig. 22B) outliers. For the 2015 strike dataset this trend was maintained, where the KESRP flight path model (when used individually) either improved the overall comparisons (Fig 23A), or was closest to the projection using all variables (Fig. 23B) (as compared to a LASSO developed for all, or all other, variables), depending on the inclusion of statistically derived outliers. The elastic net regularization/variable selection procedure defined two significant variables for 2014 and two for 2015 (see Table 8). In both years the KESRP flight path model was selected as predictive of the power-line strike distributions (Table 8).

For the 2014 uncorrected power-line strike projections ranged from 6,636 to 11,678. When adding in the peak/off-peak and detection probability corrections factors, this range increased from 11,576 to 20,371 (Figures 24 - 27). The peak/off-peak correction factor calculated for 2014 increased the number of strikes by $\sim 31 \%$. When also taking into account the detection
probability correction factor the number of strikes was increased from the base estimate by $\sim 75 \%$. Without any corrections, and using all powerline segments and points, the strike projection estimated 10,801 strikes in 2014 (Fig. 24).

The 2015 uncorrected powerline strike projections ranged from 3,695 to 6,495 , when the correction factors were added these values increased from 6,861 to 12,053 (Figures 28-31). The peak/off-peak correction factor calculated from units monitored in 2015 increased the number of strikes by $\sim 51 \%$. This increased to $\sim 85 \%$ when the detection probability correction was applied. Without any corrections, and using all powerline segments and points to project from, the strike projection estimated 6,491 strikes in 2015 (Fig. 24).

### 4.5 Estimating Strike Mortality

Estimates of power-line strike mortality were derived from data presented in Travers et al. (2016). In this report, 16 of 28 NESH descended with no observed recovery ( $\sim 57 \%$ ); one NESH was observed on the ground ( $\sim 4 \%$ of the total). The remaining 11 birds flew away, seemingly unhindered following the strike.

Using these observations, a set of estimated mortalities were combined with a set of estimated crippling biases. Crippling bias is defined as birds that fly beyond the observed area but do not survive due to injuries sustained during the strike (Faanes 1987; Rioux et al. 2013). Two crippling bias estimates are used to approximate mortality (Table 9). The first (20\%) is that reported by Bevanger (1995), and is considered to be a low crippling bias. The second (80\%) is a crippling bias defined by Rioux et al. (2013). A third crippling bias used in the analyses is the midpoint between the two estimates ( $50 \%$ ). It is recognized that these crippling biases are based on a different avian taxa, and are assessed under different conditions than those on Kauai. However these published crippling rates are provided as important comparative information. Tables 9 and 10 (for 2014 and 2015, respectively) show a compilation of many possible mortality estimates that are based on these crippling biases. Although the strike estimates used in this table include the strike values projected using all variables, and all strike information, they can be replaced with the other estimates depicted in Figures 24-31.

Table 6: Imputation procedures, description of secondary modifications, and a citation to their use.

| ANALYSIS | DESCRIPTION | CITATION |
| :---: | :---: | :---: |
| ARIMA | Expectation Maximization algorithm using an Autoregressive Integrated Moving Average | (Moritz et al. 2015; Junger and Junger 2012) |
| copyMean | Linear interpolation across the assessment is then combined the mean variance to impute missing values | (Genolini, Écochard, and JacqminGadda 2013; Genolini and Falissard 2010) |
| copyMean.bisector | Values surrounding the missing value are joined by a line and then to each imputed value the variance around the mean is added to each imputed value, thus following the shape of the average trajectory | (Genolini, Écochard, and JacqminGadda 2013) |
| trajMean | The mean trajectory is used to impute missing values | (Genolini, Écochard, and JacqminGadda 2013) |
| trajMedian | The median trajectory is used to impute missing values | (Genolini, Écochard, and JacqminGadda 2013 |
| crossMean | Missing values are imputed by the mean of the non-missing values at the time-point | (Genolini, Écochard, and JacqminGadda 2013) |
| crossMedian | Missing values are imputed by the median of the nonmissing values at the time-point | (Genolini, Écochard, and JacqminGadda 2013) |
| crossHotDeck | A non-missing value at that specific time point is used to fill in the missing value | (Genolini, Écochard, and JacqminGadda 2013) |
| spline | Expectation Maximization algorithm using a cubic smoothing spline | (Moritz et al. 2015; Junger and Junger 2012) |
| SECONDARY ASSESSMENT DESCRIPTIONS |  |  |
| Fourier | Fourier Transformation to help inform seasonal trends | (Marks 2009) |
| wKahili | The addition of the Kahili sites (sites that are not selected at random) to assess predictive ability/model stability | - |

Table 7: The summed yearly imputed/recorded strike detections over all units (Peak and OffPeak) for both 2014 and 2015. The imputation approaches used depended on whether strikes were detected at the site or not. Two of the highest performing approaches were used to calculate the number of imputed strikes shown here, the expectation maximization arima with Fourier imputation approach without Kahili sites, and copy mean longitudinal imputation approach. Imputed sites with an asterisk were removed from all subsequent analyses. Those sites highlighted in red were identified as potentially having outsized influence on a GLM assessment conducted in 2014 or 2015 . As such, all subsequent strike projections were conducted with and without that subset. Highlighted sites denoted with an ${ }^{\dagger}$ are outliers only identified when running the analysis with a subset of variables.

| 2014 SUMMED <br> IMPUTED/RECORDED STRIKES PER STRIKE DETECTION UNIT |  | 2015 SUMMED IMPUTED/RECORDED STRIKES PER STRIKE DETECTION UNIT |  |
| :---: | :---: | :---: | :---: |
| 2014 Unit Name | Yearly Summed Strike Number | 2015 Unit Name | Yearly Summed Strike Number |
| CF43OP | 11 | T_144_431_SO_STATIC_OFFPEAK | 390 |
| PLT1380P | 69 | T_140_427_SO_STATIC_OFFPEAK | 56 |
| CF43S | 16 | T_142_429_SO_STATIC_OFFPEAK | 44 |
| PLT144OP | 170 | 135_540_8061_1218_KI_STATIC_OFFPEAK | 12 |
| PLT144S | 100 | T_64_351_LA_STATIC_OFFPEAK | 5 |
| PLT142S | 134 | 125_545_9360_1177_KI_CHECK_CHECK* | 67* |
| CF45OP | 4 | T_43_330_EK_STATIC_OFFPEAK | 157 |
| PLT138S | 94 | T_45_332_EK_STATIC_OFFPEAK | 5 |
| PLT142OP | 44 | 135_535_3160_1246_KI_CHECK_CHECK* | 26* |
| PLT140S | 170 | T_159_446_NO_ROVER_PEAK | 147 |
| PLT1400P | 42 | T_155_442_NO_ROVER_PEAK | 18 |
| CF45S | 18 | T_140_427_SO_STATIC_PEAK | 160 |
| PLT160R | 133 | T_144_431_SO_STATIC_PEAK | 200 |
| KI2460R | 35 | 130_545_2161_1196_KI_DIVERTER_PEAK | 11 |
| KI2062R | 398 | 130_545_2760_1208_KI_DIVERTER_PEAK | 4 |
| CF48R | 193 | L_8_708_LC_ROVER_PEAK | 162 |
| NS174R | 1 | 025_470_8461_502_WW_STATIC_PEAK | 6 |
| PLT134R | 18 | 120_555_7560_1141_NA_ROVER_PEAK | 233 |
| CF50R | 5 | 030_460_5060_246_PK_DIVERTER_PEAK | 3 |
| CF8760R | 10 | T_48_335_EK_STATIC_PEAK | 42 |
| KE8160R | 128 | T_147_434_NO_ROVER_PEAK | 102 |
| KI5760R | 12 | 135_525_5760_1294_KI_STATIC_PEAK | 127 |
| NS162R | 44 | T_104_391_CP_ROVER_PEAK | 27 |
| CF52R | 7 | 130_545_1960_1212_KI_DIVERTER_PEAK | 1 |
| PLT154R | 43 | 020_490_5660_562_EW_ROVER_PEAK | 35 |
| EL1661R | 6 | T_43_330_EK_CHECK_CHECK | 6 |
| PLT136S | 19 | T_165_452_NO_ROVER_PEAK | 31 |
| PLT1360P | 9 | T_138_425_SO_STATIC_PEAK | 359 |
| KI8061R | 10 | T_136_423_SO_STATIC_PEAK | 14 |
| EL8960R | 3 | 050_495_8300_KA_STATIC_PEAK | 7 |
| KL3760 | 5 | T_142_429_SO_STATIC_PEAK | 299 |
| PA3360R | 2 | L_10_710_LC_ROVER_PEAK | 52 |
| PLT146R | 180 | 130_545_2560_1205_KI_CHECK_CHECK* | 3* |
| AN9360R | 435 | 135_540_3060_1234_KI_ROVER_PEAK | 6 |
| PLT158R | 10 | T_109_396_CP_ROVER_PEAK | 43 |


| 2014 SUMMED <br> IMPUTED/RECORDED STRIKES PER STRIKE DETECTION UNIT |  | 2015 SUMMED IMPUTED/RECORDED STRIKES PER STRIKE DETECTION UNIT |  |
| :---: | :---: | :---: | :---: |
| 2014 Unit Name | Yearly Summed Strike Number | 2015 Unit Name | Yearly Summed Strike Number |
| WG8461R | 72 | T_149_436_NO_ROVER_PEAK | 118 |
| PLT150R | 43 | T_151_438_NO_ROVER_PEAK ${ }^{\dagger}$ | $11^{\dagger}$ |
| KI1860R | 20 | T_161_448_NO_ROVER_PEAK | 162 |
| PM3460R | 129 | T_45_332_EK_STATIC_PEAK | 12 |
| PM0860R | 9 | 035_450_4360_210_PK_ROVER_PEAK | 15 |
| LAW68R | 13 | T_48_335_EK_BACKUP_PEAK* | 1534* |
| KI5960R | 275 | 135_530_2960_1272_KI_ROVER_PEAK | 13 |
| PLT170R | 10 | T_123_410_CP_ROVER_PEAK | 18 |
| KE0560R | 47 | 135_540_8061_1218_KI_STATIC_PEAK | 3 |
| AN6460R | 15 | 130_530_6961_1264_KI_CHECK_CHECK* | 5* |
| AN3462R | 9 | T_163_450_NO_ROVER_PEAK | 116 |
| NS6R | 79 | T_152_439_NO_ROVER_PEAK | 32 |
| KI9061R | 15 | T_171_458_NO_ROVER_PEAK | 73 |
| CF9860R | 1 | 065_405_4360_27_PM_CHECK_CHECK* | 4* |
| PLT156R | 71 | T_179_466_HT_ROVER_PEAK | 24 |
| KA3560R | 8 | T_166_453_NO_ROVER_PEAK | 4 |
| PLT172R | 18 | T_173_460_NO_ROVER_PEAK | 15 |
| PM4360R | 11 | UM16RPM5161 | 0 |
| PLTOP139 | 28 | Ump10RKR9561 | 0 |
| UMP10RELET22 | 0 | UMP10RSA1162 | 0 |
| UMP10RLAW66 | 0 | UMP10RSA1961 | 0 |
| UMP11RAN1360 | 0 | UMP11OPK8960 | 0 |
| UMP11RAN8462 | 0 | UMP14REK14 | 0 |
| UMP15RHW5360 | 0 | UMP14RKW5560 | 0 |
| UMP16RNS177 | 0 | UMP15ROC91 | 0 |
| UMP19RKL1560 | 0 | UMP16RCP126 | 0 |
| UMP1RKI2160 | 0 | UMP16RKP13 | 0 |
| UMP1RKI3160 | 0 | UMP16RKW7660 | 0 |
| UMP20RCF3663 | 0 | UMP16SKI9360 | 0 |
| UMP20RPL139 | 0 | UMP18REW1760 | 0 |
| UMP21RKI7060 | 0 | UMP18RKM6060 | 0 |
| UMP21RPO7261 | 0 | UMP18ROC83 | 0 |
| UMP22RHA9760 | 0 | UMP18ROC87 | 0 |
| UMP30SCF41 | 0 | UMP19RPM5261 | 0 |
| UMP40RKE7760 | 0 | UMP19RPM6861 | 0 |


| 2014 SUMMED <br> IMPUTED/RECORDED STRIKES PER STRIKE DETECTION UNIT |  | 2015 SUMMED IMPUTED/RECORDED STRIKES PER STRIKE DETECTION UNIT |  |
| :---: | :---: | :---: | :---: |
| 2014 Unit Name | Yearly Summed Strike Number | 2015 Unit Name | Yearly <br> Summed Strike Number |
| UMP41RK4001 | 0 | UMP1RPM2260 | 0 |
| UMP41RK5300 | 0 | UMP1RPM2360 | 0 |
| UMP42RKA7360 | 0 | UMP1RWW1761 | 0 |
| UMP42RKE1561 | 0 | UMP1RWW4660 | 0 |
| UMP42RPA1550 | 0 | UMP20RKR960 | 0 |
| UMP43RKE4160 | 0 | UMP20RKT9861 | 0 |
| UMP43RKE8560 | 0 | UMP22RNA3861 | 0 |
| UMP43RKE9560 | 0 | UMP22RSA2660 | 0 |
| UMP43RPO9060 | 0 | UMP22RWC4460 | 0 |
| UMP44REL8260 | 0 | UMP23RKI2261 | 0 |
| UMP44RKC6660 | 0 | UMP23RKM2661 | 0 |
| UMP44RPA4560 | 0 | UMP23RKM5760 | 0 |
| UMP45RKE1160 | 0 | UMP23RWC6460 | 0 |
| UMP46RAN2661 | 0 | UMP25REW3762 | 0 |
| UMP46RCF9861 | 0 | UMP26RKP58 | 0 |
| UMP46RWL2260 | 0 | UMP26RKP66 | 0 |
| UMP47RKA1860 | 0 | UMP26RLC27 | 0 |
| UMP48RCF3961 | 0 | UMP26RLC29 | 0 |
| UMP51RELET11 | 0 | UMP27RCP118 | 0 |
| UMP51RKAL58 | 0 | UMP2REW4760 | 0 |
| UMP51RKOT56 | 0 | UMP37RPK2062 | 0 |
| UMP51RLAW62 | 0 | UMP37RPM3360 | 0 |
| UMP52RCF1761 | 0 | Ump390ka8300 | 0 |
| UMP52RKA2062 | 0 | UMP3RHW8160 | 0 |
| UMP53EL1661 | 0 | UMP3RPK6361 | 0 |
| UMP53ELET29S | 0 | UMP3RPK7061 | 0 |
| UMP53RKC6160 | 0 | UMP3RPK7360 | 0 |
| UMP54RCF54 | 0 | UMP42SLA64 | 0 |
| UMP54RKOT60 | 0 | UMP43RKP24 | 0 |
| UMP54RLAW71 | 0 | UMP43RKP6 | 0 |
| UMP55REL7460 | 0 | UMP43RLC31 | 0 |
| UMP55RKA0160 | 0 | UMP46RKP6 | 0 |
| UMP55RKL6960 | 0 | UMP46RKR7562 | 0 |
| UMP56RAN3761 | 0 | UMP46ROC98 | 0 |
| UMP56RKA4109 | 0 | UMP51RHL6262 | 0 |

$\left.\begin{array}{c|cc}\begin{array}{c}\text { 2014 SUMMED } \\ \text { IMPUTED/RECORDED } \\ \text { STRIKES PER STRIKE }\end{array} & \begin{array}{c}\text { 2015 SUMMED IMPUTED/RECORDED STRIKES } \\ \text { DETECTION UNIT }\end{array} & \text { PER STRIKE DETECTION UNIT }\end{array}\right]$

Table 8: Power-line segment variables used to project line strikes. Environmental variables selected to inform the variable subset model using a bootstrapped lasso regularization selection procedure are highlighted in red. The year that the covariate was selected is also defined.

| COVARIATE NAME | DESCRIPTION | SUBSET SELECTION <br> YEAR |
| :---: | :--- | :---: |
| Drainage | Drainage assessment | - |
| Near_Dist | Distance to Vegetation |  |
| Distance | Line segment distance to the coast |  |
| Elevation | Topographic elevation of the line segment | - |
| PCAEigen1 | Principle component 1 describing the principle component <br> analysis between Distance and Elevation | - |
| PCAEigen2 | Principle component 2 describing the principle component <br> analysis between Distance and Elevation | 2015 |
| Flight_Path_KESRP | Flight path metric derived from KESRP polygons | 2014 |
| Length | Length of Line segment | $2014-2015$ |

Table 9: Scenarios for estimating Newell's Shearwater power-line strike mortality (2014)


KIUC Strike Assessment Model Development

Scenarios for estimating Newell's Shearwater power-line strike mortality (2015) - continued

|  |  | Acoustic Strike Detection |  |
| :---: | :---: | :---: | :---: |
|  |  | Uncorrected | Corrected |
| VII. Scenarios used to estimate total mortality; number of birds that strike a power line and are crippled or die (continued): | Sum of (IV, VC, VIA) $=$ | 3,754 | 5,406 |
|  |  | 4,908 | 6,560 |
|  | Sum of (IV, VC, VIB) = | 3,904 | 5,621 |
|  |  | 5,104 | 6,821 |
|  | Sum of (IV, VC, VIC $)=$ | 4,053 | 5,837 |
|  |  | 5,299 | 7,083 |
| Sum of (IV, VC, VID $)=$ |  | 4,951 | 7,130 |
|  |  | 6,389 | 8,652 |
| Sum of (IV, VC, VIE $)=$ |  | 4,502 | 6,483 |
|  |  | 5,886 | 7,867 |
| Sum of (IV, VD, VIA) = |  | 2,448 | 3,526 |
|  |  | 3,201 | 4,278 |
| Sum of (IV, VD, VIB $)=$ |  | 2,598 | 3,741 |
|  |  | 3,397 | 4,540 |
| Sum of (IV, VD, VIC $)=$ |  | 2,748 | 3,956 |
|  |  | 3,592 | 4,801 |
| Sum of (IV, VD, VID) $=$ |  | 3,645 | 5,249 |
|  |  | 4,766 | 6,370 |
| Sum of (IV, VD, VIE) $=$ |  | 3,196 | 4,603 |
|  |  | 4,179 | 5,585 |
| Average of all possible scenarios: |  | 3,374 | 4,665 |
| GRAND AVERAGE: 4,020 |  | deaths in 2014 |  |

Table 10: Scenarios for estimating Newell's Shearwater power-line strike mortality (2015)

| I. Birds observed striking a power line (KESRP) $=28$ | A. Power-line strike birds grounded $=14 \%$ |  |
| :---: | :---: | :---: |
| B. Power-line strike birds that descend $=16 \quad 57 \% \quad$ C. Pow | ine strike birds stil | $=1139 \%$ |
| II. The ALL model uses all sections of the power lines, not just the flight path intersection sections. | All Power-Line Sections |  |
|  | Acoustic Strike Detection |  |
| III. Total number of birds estimated to strike power lines: | Uncorrected | Corrected |
| A. Acoustic strike detection correction multiplier: $\mathbf{1 . 3 4}$ | 6,491 | 8,724 |
| B. Peak-off peak strike correction multipliers: $\mathbf{1 . 5 1}$ | 9,820 | 12,053 |
| IV. Number of birds estimated to be killed by impact with a power line (4\% of IIIA-All or IIIB-All): | 232 | 312 |
|  | 351 | 430 |
| V. Number of birds estimated to strike a power line and descend ( $57 \%$ of IIIA or IIIB): | 3,709 | 4,985 |
|  | 5,611 | 6,887 |
| A. Estimated crippling rate (unobserved mortality) for birds that strike a power line and descend: |  |  |
| 1. Lowest published rate: $20 \%$ Be | r, 1995. J. Applied | Vol. 32: 745-753 |
| 2. Highest published rate (73-82\%): $80 \%$ Rioux | al. 2013. Avian C | . and Ecol. Vol. 8 |
| 3. MIDPOINT crippling rate: |  |  |
| B. $20 \%$ of descending birds that do not survive a power-line impact ( $20 \%$ crippling rate): | 742 | 997 |
|  | 1,122 | 1,377 |
| C. $80 \%$ of descending birds that do not survive a power-line impact ( $80 \%$ crippling rate): | 2,967 | 3,988 |
|  | 4,489 | 5,510 |
| D. $50 \%$ of descending birds that do not survive a power-line impact (50\% crippling rate): | 1,855 | 2,493 |
|  | 2,806 | 3,444 |
| VI. Number or birds estimated to strike a power line and continue flying ( $\mathbf{3 9 \%}$ of IIIA or IIIB); VIA through VIB, below, are arbitrary; other rates are possible: | 2,550 | 3,427 |
|  | 3,858 | 4,735 |
| A. All birds survive a power-line impact: zero crippling rate: | - | - |
|  | - | - |
| B. For birds that do not survive a power-line impact, using $1 / 4$ of lowest crippling rate: | 128 | 171 |
|  | 193 | 237 |
| C. For birds that do not survive a power-line impact, using $1 / 2$ of lowest crippling rate: | 255 | 343 |
|  | 386 | 473 |
| D. Flying birds that do not survive a power-line impact, using $1 / 2$ of highest crippling rate: | 1,020 | 1,371 |
|  | 1,543 | 1,894 |
| E. Flying birds that do not survive a power-line impact, using $1 / 2$ of midpoint crippling rate: | 638 | 857 |
|  | 964 | 1,184 |
| VII. Scenarios used to estimate total mortality; number of birds that strike a power line and are crippled or die: | 974 | 1,309 |
|  | 1,473 | 1,808 |
|  | 1,101 | 1,480 |
|  | 1,666 | 2,045 |
| Sum of (IV, VB, VIC $)=$ | 1,229 | 1,651 |
|  | 1,859 | 2,281 |
| Sum of (IV, VB, VID $)=$ | 1,994 | 2,679 |
|  | 3,016 | 3,702 |
| Sum of (IV, VB, VIE) $=$ | 1,611 | 2,165 |
|  | 2,437 | 2,992 |

KIUC Strike Assessment Model Development

Scenarios for estimating Newell's Shearwater power-line strike mortality (2015) - continued

|  |  | Acoustic Strike Detection |  |
| :---: | :---: | :---: | :---: |
|  |  | Uncorrected | Corrected |
| VII. Scenarios used to estimate total mortality; number of birds that strike a power line and are crippled or die (continued): | Sum of (IV, VC, VIA) = | 3,199 | 4,300 |
|  |  | 4,840 | 5,940 |
|  | Sum of (IV, VC, VIB) = | 3,327 | 4,471 |
|  |  | 5,033 | 6,177 |
| Sum of (IV, VC, VIC) = |  | 3,454 | 4,642 |
|  |  | 5,225 | 6,414 |
| Sum of (IV, VC, VID) = |  | 4,219 | 5,671 |
|  |  | 6,264 | 7,834 |
| Sum of (IV, VC, VIE) = |  | 3,837 | 5,156 |
|  |  | 5,804 | 7,124 |
| Sum of (IV, VD, VIA) $=$ |  | 2,086 | 2,804 |
|  |  | 3,156 | 3,874 |
| Sum of (IV, VD, VIB) = |  | 2,214 | 2,975 |
|  |  | 3,349 | 4,111 |
| Sum of (IV, VD, VIC) $=$ |  | 2,341 | 3,147 |
|  |  | 3,542 | 4,348 |
| Sum of (IV, VD, VID) $=$ |  | 3,106 | 4,175 |
|  |  | 4,699 | 5,768 |
| Sum of (IV, VD, VIE) = |  | 2,724 | 3,661 |
|  |  | 4,121 | 5,058 |
| Average of all possible scenarios: |  | 3,130 | 3,992 |
| GRAND AVERAGE: $\quad 3,561$ |  | deaths in 2015 |  |

### 4.7 Section 4: FIGURES



Figure 15: Sorted (high to low) root mean square errors (A) and (low to high) area under the curve (B) for all imputation procedures applied to the 2014 powerline strike dataset. No Kahili points were used in this comparison.

Sorted (low to high) Root Mean Squared Error (RMSE) for each of the 2014 wKahili Strike Imputation Methodologies


B)

Sorted (high to low) Area Under the Curve (AUC) values for each of the 2014 wKahili Strike Imputation Methodologies As Applied over 200, 50-Fold Cross Validation Iterations with a Binary Threshold of 0.5


Figure 16: Sorted (high to low) root mean square errors (A) and (low to high) area under the curve (B) for all imputation procedures applied to the 2014 powerline strike dataset. Kahili points were used in this comparison.

## KIUC Strike Assessment Model Development

Sorted (low to high) Root Mean Squared Error (RMSE) for each of the 2015 NoKahili Strike Imputation Methodologie



Imputation Methodologies
B)

Sorted (high to low) Area Under the Curve (AUC) values for each of the 2015 NoKahili Strike Imputation Methodologie As Applied over 200, 50-Fold Cross Validation Iterations with a Binary Threshold of 0.5


Figure 17: Sorted (high to low) root mean square errors (A) and (low to high) area under the curve (B) for all imputation procedures applied to the 2015 powerline strike dataset. No Kahili points were used in this comparison.

## KIUC Strike Assessment Model Development



Figure 18: Sorted (high to low) root mean square errors (A) and (low to high) area under the curve (B) for all imputation procedures applied to the 2015 powerline strike dataset. Kahili points were used in this comparison.

## KIUC Strike Assessment Model Development



Figure 19: Sorted (high to low) no strike unit imputed strikes across imputation methodologies that can handle matrices without strikes for both 2014 (A) and 2015 (B).


Figure 20: Compiled recorded/imputed strikes for peak and off peak strike detection units (without Kahili), as summed for each year day in 2014. Inset shows the total number of strikes summed over all units, the total number of peak and off peak summed strikes, check units strikes, and the total number of actual strikes from which the data were imputed. The imputation approach selected and defined here was the expectation maximization arima approach, with a Fourier transformation.


Figure 21: Compiled recorded/imputed strikes for peak and off peak strike detection units (without Kahili), as summed for each year day in 2015. Inset shows the total number of strikes summed over all units, the total number of peak and off peak summed strikes, check units strikes, and the total number of actual strikes from which the data was imputed. The imputation approach selected and defined here was the expectation maximization arima approach, with a Fourier transformation.
A) $\begin{aligned} & \text { ■ LASSO/GLM of all other Covariates } \\ & \text { ■ GLM of Labled Covariate }\end{aligned}$

containing all covariates in the
B)

> ㄷASSO/GLM of all other Covariates
> GLM of Labled Covariate



PCAEigen1

Distance
Q|l||||||||||||||||||||||||1.

Flight Path_KESRP (1)17111.

PCAEigen2


containing all covariates in the
All Variables With No Outliers Analysis

Figure 22: 2014 Variable significance jackknife (i.e. leave one out) procedure comparing the change in RMSE of a GLM of that specific variable and a GLM with a least absolute shrinkage and selection operator procedure (GLM/LASSO) projecting all other variables, to a GLM/LASSO projecting ALL variables. This procedure helped to assess the utility of those variables prior to the application of the more computationally intensive elastic net mixing procedure. The assessment was conducted for all variables with (A) and without influential outliers (B).


Figure 23: 2015 Variable significance jackknife (i.e. leave one out) procedure comparing the change in RMSE of a GLM of that specific variable and a GLM with a least absolute shrinkage and selection operator procedure (GLM/LASSO) projecting all other variables, to a GLM/LASSO projecting ALL variables. This procedure helped to assess the utility of those variables prior to the application of the more computationally intensive elastic net mixing procedure. The assessment was conducted for all variables with (A) and without influential outliers (B).


Figure 24: 2014 Powerline Strike Projections using all variables and all strike data (i.e. with outliers). The summed strikes are defined with and without peak and off-peak and detection probability corrections.


Figure 25: 2014 Powerline Strike Projections using all variables while removing statistically identified outliers. The summed strikes are defined with and without peak and off-peak and detection probability corrections.


Figure 26: 2014 Powerline Strike Projections using a statistically significant subset of variables and all strike data (i.e. with outliers). The summed strikes are defined with and without peak and off-peak and detection probability corrections.


Figure 27: 2014 Powerline Strike Projections using a statistically significant subset of variables while removing statistically identified outliers. The summed strikes are defined with and without peak and off-peak and detection probability corrections.


Figure 28: 2015 Powerline Strike Projections using all variables and all strike data (i.e. with outliers). The summed strikes are defined with and without peak and off-peak and detection probability corrections.


Figure 29: 2015 Powerline Strike Projections using all variables while removing statistically identified outliers. The summed strikes are defined with and without peak and off-peak and detection probability corrections.


Figure 30: 2015 Powerline Strike Projections using a statistically significant subset of variables and all strike data (i.e. with outliers). The summed strikes are defined with and without peak and off-peak and detection probability corrections.


Figure 31: 2015 Powerline Strike Projections using a statistically significant subset of variables while removing statistically identified outliers. The summed strikes are defined with and without peak and off-peak and detection probability corrections.

## 5. SECTION 5: SITE BY SITE STOCHASTIC POPULATION VIABILITY ANALYSIS

Previous Population Viability Analyses (PVAs) have focused on deterministic meta-population models (Ainley et al. 2001; Griesemer and Holmes 2011). These models were developed to assess the overall population viability as it relates directly to average demographic trends without significant stochastic variation (Morris 1999). These deterministic models are useful in identifying demographic parameters sensitive to some form of modification (e.g. predation, collision etc.). This work attempts to build on the outputs and methodologies discussed in Ainley et al. (2001) and Griesemer and Holmes (2011). It does so by incorporating up-to-date geographic and demographic information (much of which is described above), developing a geographic assessment of NESH colony sites, and creating an iteratively reproducible and updatable projection in the R statistical environment.

In this Site by Site PVA (hereafter referred to as SbS-PVA) an attempt is made to understand the inherent geographic and demographic stresses of each colony identified on Kauai, and combine all of the information developed in this assessment and elsewhere, into a stochastic site and meta-population PVA. By conducting this comprehensive assessment, combining all known information and models relevant to the biology of NESH, it is hoped that a better understanding of the geographic and demographic stresses of NESH can be better visualized, and by doing so, better managed. Because this SbS-PVA incorporates the geographically enabled threat and refugia assessments, it allows a comprehensive assessment of their effect on the projected viability of each site, and the overall meta-population. The assessment developed here also permits specific modifications threats to the organism which allows the model to account for future management needs.

The KESRP polys were used in this analysis to define colony sites and expanse. Colony specific geographic and demographic parameters were either extracted or extrapolated from many of the formerly defined models and polygons, and as such affected the model outputs significantly. Colony population sizes were developed per KESRP poly, and are used as the starting population for each SbS-PVA.

For this assessment the model was primarily developed around the KESRP flight path projections described in Section 3. Using this flight path projection, interaction of specific colonies with anthropogenic threats, such as lights and powerlines, could be linked specifically to that colony. For each flight path, from every origin point within the colony, this crossover was assessed and compiled into an overall valuation of both light and transmission line impingement on that colony. To inform the SbS-PVA only light and powerline impingement defined for the KESRP polys was used.

Two refugia estimates were included that help to define both storm impact refugia and predator refugia per site. The storm impact refugia estimate was extracted directly from the extreme weather event probability projection (as discussed in Section 1) per site. This assessment attempted to inform the SbS-PVA about both the probability of an extreme weather event, and that events impact on the specific site. The predator refugia estimate used slope as a proxy for accessibility by pigs and cats (Nelson and Hamer 1995; Marzluff and Sallabanks 1998). It was used in the model to define: A threshold at which point some form of demographic effect would be seen by an increase in slope, the trend at which this demographic effect takes place, and a maximum possible demographic effect seen at (and passed) a specific slope. The utility of this will be discussed.

The NESH Ensemble Niche Model (ENM; see Section 2) was also used to help inform the SbSPVA. Although characterization of the ENM was derived from abiotic elements, recently collected seabird presence locations are likely defined by both biotic and abiotic pressures. As such, the ENM projects these pressures as they are represented over abiotic climatic space, and so may indirectly represent both refugia and area preference. Like the refugia estimates, the NESH ENM was extracted per polygon per site, but unlike the refugia estimate it is not used to modify NESH demography.

A boxplot and spreadsheet describing each variables site specific attributes was then defined per KESRP poly to characterize each site. For all elements in which many measurements were extracted (weather refugia, predator refugia, and the ENM) the median of the measurements was used to describe the elements of each site in the SbS-PVA. Because light and strike impingements were direct compilations of the overlap of the flight path model with each
variable, only a single measurement was defined per KERSP poly and thus used in the SbS-PVA. Detailed descriptions of the development and use of each variable in the SbS-PVA follow.

### 5.1 Colony Size Projection: Overview

In order to project the viability of each colonies population, and compile an accurate depiction of the threats that specific colonies face, it was necessary to develop an estimate of colony population sizes in relation to the KESRP polys described previously. Between 1998 and 2011 NESH were estimated to have a global population size of 27,011 individuals (T. W. Joyce 2013). It is commonly acknowledged that Kauai likely supports $\sim 90 \%$ of the NESH in the Hawaiian islands (Griesemer and Holmes 2011; Ainley et al. 1997), as such the most recent population size estimate for NESH on Kauai approximates 24,310 individuals.

Though we have an overall estimate for the island based meta-population, this cannot be directly applied to the polygons because the KESRP polys likely do not represent the complete metapopulation of birds on Kauai. To address this, a reproducible estimate of the proportion of the birds that the KESRP polys potentially define was developed. This estimate used the light free, thresholded ENM described in Section 2 (Figure 8B) to infer the approximate proportion of the ENM occupied by the KESRP polys. Assuming that (unquantified) prior knowledge was used in the selection of sites in which to search for NESH, and that access to those sites was based on landowner permission, landownership can be used as a proxy to define unsearched but potentially occupied sites. To conduct this analysis landowner information was extracted from the area that KESRP covered in their surveys; the landowners that were identified from this extraction were then removed from the ENM. Once the KESRP polys, KESRP survey coverage, and covered landowners were removed from the ENM, the area left was multiplied by the approximate proportion of the ENM occupied by the KESRP polys to obtain an estimate of the unobserved colony amounts. A percentage was then defined that described the observed colony areas relation to the projected complete area that NESH occupies.

Another approximation that was calculated to better reflect actual population size was the area within each KESRP polygon that could likely host a burrow site. As the polygons were made in a way that was not necessarily reproducible (biologists estimated from a distance the likely area that birds were occupying, based on flight paths and displays), reproducibly subsetting the KESRP polys to inform site occupancy was recommended. To conduct this assessment an
analysis was developed to subset the KESRP polys by likely occupancy, and then estimate the burrow occupancy at that site using an average nearest neighbor distance in relation to area of the "occupied" site. This analysis attempts to project the occupancy from occupied sites onto sites within the KESRP polys that have not been sampled for burrows, essentially defining potential burrow occupancy by pixel. Variables of possible significance to the assessment were evaluated using burrow location information collected since 2010 by KESRP. The location information collected by KESRP included very specific data relevant to the ecosystem and topography occupied by a burrow. These variables are extremely important in developing a detailed understanding of occupancy, but they were only available for surveyed sites. As such, other topographically derived and remotely sensed variables were developed or extracted for each burrow location, and for each 30 m pixel within a raster representation of the KESRP polygons. These other variables allowed for occupancy projections outside of the burrow sites, but within the previously defined KESRP occupied polygons.

Two variables thought to potentially be significant to burrow occupancy were; the burrow aspect in relation to the bearing of a potential coastal entry and exit point, and the burrow aspect of the closest site (from the burrow) in a stream bed in relation to the bearing of a potential coastal entry and exit point (Fig. 32). These two variables hold biological significance in that they define a level of accessibility of the burrow to the coast. It was thought that a point in the stream bed that is closest to a burrow may be significant because it represents a more direct path to the coast. In other words, burrow locations may be present at sites minimally separated by a peak from a stream bed that has a more direct route to the coast then the one with a path that starts at the exact burrow location. These metrics assume that the organism follows either a leading line/least cost path (Mueller and Berger 1967), or straight line path to the coast. In this case the leading line is the least cost path to the coast over a 30 meter digital elevation model (DEM).

To develop these remotely derived variables potentially significant to burrow occupancy, metrics were defined that attempt to infer possible paths from an actual or potential burrow, or stream location, to a coastal point. The first metric used a topographically derived least cost path assessment (similar to the one applied in Section 3) over a 30 meter DEM to define the coastal point that the organism at the burrow would access, while the second used a straight line path to
define a similar coastal access point (Fig. 32). These two assessments were used to define two potential coastal access points for all actual or potential burrow and stream sites.

After identifying the actual or potential burrow, stream, and coastal access sites, bearings were developed for each. A 30 meter topographic projection of bearing and slope were developed from the 30 meter DEM, and used to identify the bearings of the stream and actual/potential burrow site. Bearings associated with the coastal access points were defined using the straightline bearing (i.e. rhumbline) of the identified coastal point, (identified from either the straightline or least cost path assessment) in relation to the bearing of the stream or burrow site. An overview of the assessment process per actual or potential burrow site is shown in Figure 32. Because bearings are here used to describe the accessibility of the coast to a particular site, relating the stream or burrow site bearing to the coastal access site was necessary; this was done by calculating the difference between the bearing of the coastal access site and the bearing of the burrow/stream sites. As the greatest difference in bearing from one aspect to another is $180^{\circ}$ (in a $360^{\circ}$ plane), the difference in coastal versus burrow/stream bearings was assessed from 0 to $180^{\circ}$ per site.

In order to project this assessment beyond the burrow sites and into unknown and potentially occupied sites, these analyses were conducted for all of $30 \mathrm{~m}^{2}$ pixels in a raster defining the KESRP polygons. By projecting the analysis in this way the polygons can be subset by likely occupied sites. Other metrics extracted per burrow point and polygon pixel include the slope at 30 meters, and percent shrub and tree cover as defined using the most updated LandFire Vegetation map (Rollins 2009) (Fig. 33-34). These were thought to be lower resolution assessments of the data collected at each burrow (described above), and so potentially predictive of occupancy.

An elastic net regression was used to assess the correlation between the all dependent and independent variables. As also described in Section 4, the elastic net regression procedure blends the utility of L1 (LASSO regularization) and L2 (Ridge Regression) penalization (Zou and Hastie 2005). By using this hybrid approach, overfitting and collinearity are reduced significantly. As previously mentioned, the amount of L1/L2 penalization is determined using the $\lambda$ parameter. This parameter ranges from 0 to 1 , where a value of 1 is equivalent to ridge regression (only L2 penalization), a value of 0 is equivalent to LASSO regularization (only L1
penalization) and a value of 0.5 (equal L1 and L2 penalization) is considered a pure elastic net model. The $\lambda$ parameter was automatically assigned to each assessment using a cross-validation approach, as recommended in Sill et al. (2013).

Six assessments were conducted using the elastic net variable selection procedure. These assessments were used as comparisons of subsets of the data, specifically to compare different combinations of remotely sensed information with the complete set of variables, and the directly observed and recorded variables. These subsets are described in Table 11. Following these assessments the analyses that only included remotely sensed variables were then projected onto those variables developed for all other potentially occupied sites using the elastic net regression projection in the R package 'glmnet' (Sill et al. 2013).

In order to obtain a metric of colony size it was necessary to use an estimate of projected occupancy in combination with potential colony numbers. Potential site occupancy was assessed using a nearest neighbor analysis conducted in the R statistical environment between all burrow sites. For comparison purposes, the nearest neighbor analysis was conducted for NESH, HAPE BANP and all petrels combined, but only the assessment for NESH was used for any further projections. To conduct this assessment the straight-line distance of every burrow point to all other burrow points was defined and combined into a matrix, the distance to the closest point was then identified and subsequently compiled for all points for each pair of burrows. The distances for each assessment were then compiled and compared using a boxplot analysis. The median value, as defined for NESH densities, was used to project the proportional colony sizes within each KESRP poly as subset by probable occupancy for NESH (Fig. 36).

These proportional colony sizes (Fig. 36) were then used to partition the 2016 estimate of Kauai's meta-population as projected by the various predation estimates from the Joyce (2013) estimate. The base meta-population value used here was developed in 2013 from data assumed collected in 2011 (input: YearPopEstimated). Because there is a differential between when the code is run and when the data were collected to obtain the population estimate (i.e.

YearPopEstimated) the code automatically collects the year in which the assessment is being run, and applies the lambda of the selected predation scenario (see below) to the meta-population size to get a more accurate estimate of the current meta-population size.

### 5.2 Colony Size Projection: Output

As defined in Table 11, the analyses that contained direct observations of the burrow site were more descriptive of occupancy than those primarily using remotely sensed or topographically derived information. This is to be expected given the difference in resolution between the data sources ( $1 \mathrm{~m}^{2}$ versus $30 \mathrm{~m}^{2}$ ) as well as the lack of site specific floral data that occupy that site when not using observer data. Though this is the case the assessments derived from remotely sensed or topographically derived information were the only means of assessing potential occupancy (Table 11), and so were used for occupancy projections. The variables developed specifically for the assessment of potential burrow occupancy for all $30 \mathrm{~m}^{2}$ pixels within each KESRP poly, are shown in Figures 33 and 34. These variables varied in there utility to the model (Table 12). To conduct the colony subset projection, only those variables associated with the stream remotely sensed data were used; this was because it was the least amount of variables that still gave a moderately accurate depiction of occupancy, as defined using AUC (Table 12). This projection identifies $1,066.35$ hectares within the $1,962.17$ hectares defined by the KESRP polygons to be potentially occupied by NESH burrows (<64\%) if invasive species and anthropogenic disturbances were completely removed.

The median density value defined using the nearest neighbor assessment between burrow locations for NESH was one NESH burrow every $\sim 17$ ( $95 \%$ CIM: ~12-22) meters $^{2}$ (Fig. 35). Estimating the overall burrow density and site based burrow density involved dividing the area (in meters ${ }^{2}$ ) of the compiled KESRP polygons (or each individual polygon) by the median to obtain a proportional burrow amount per site. These proportional burrow occupancy estimates projected per site were rescaled such that they summed to 1 . These values were then multiplied by the meta-population size, as projected from 2011, to the current date using each scenarios estimated effect of predation on the demography (and as such lambda) of the organism (see SubSection 5.3 for more details).

### 5.3 NESH Demography as Modified by Predation: Overview

As in Ainley et al. (2001) a Leslie matrix was used to compile the fecundity $\left(m_{x}\right)$ and survivorships ( $\Phi$ ) for each age class (for each iteration of the analysis) to estimate population growth rates. NESH were assumed to live for approximately 36 years, and begin breeding at age

6 ( Ainley et al. 2001). Life cycle demographic characteristics are described in the outputs section.

Many of the demographic parameters used here are derived from Ainley et al. (2001) and Griesemer and Holmes (2011). The Population Modelling section in Ainley et al. (2001), or Table 2-4 in Griesemer and Holmes (2011) (stable), describes these stage based survivorship estimates. Like both of these previously published estimates, we assumed a constant survivorship and fecundity for those individuals that have matured to adulthood (reached their reproductive age). Unlike the aforementioned estimates though, the approach of this analysis initially attempts to define a predator free population that has not reached carrying capacity (i.e. the current population's estimated growth if all terrestrial predation or anthropogenic mortality were removed, or eradicated). From this estimate, mortality factors can sequentially be removed, and demographic stochasticity can be incorporated, to assess the state of the current NESH population on Kauai.

Like Griesemer and Holmes (2011) all life-stage data were unchanged from the initial predator free estimates described by Ainley et al. (2001), except for the breeding probability and reproductive success parameters. These breeding and reproductive estimates were defined using fecundity data recently collected by Raine and McFarland (2014a \& b) as well as similar estimates collected from seabirds in the family Procellaridae. Raine and McFarland (2014a) found in the Upper Limahuli area of Kauai a reproductive success of 0.7838 , and a reproductive probability of 0.9024 . Given that this was only defined from a single year, and that Upper Limahuli has ungulate fencing and predator control (not exclusion); the estimate is somewhat tentative. Yet, the average reproductive probability and breeding success from compiled data of other locations (with some small level of predator control) in a similar assessment (Raine and McFarland 2014b) was also rather high ( 0.88 and 0.75 , respectively) compared to previous estimates (Ainley et al. 2001; Telfer et al. 1987; Griesemer and Holmes 2011). The combination of these parameters with the stable growth model produced a population projection far greater than was previously anticipated for optimal growth, assuming no predation. Therefore, it is safe to assume that fecundity ( $m_{x}=$ breeding probability $x$ reproductive success) is much higher than previously estimated for a predator free population.

Using information compiled by Griesemer and Holmes (2011) (see Griesemer and Holmes (2011); Appendix 1), a boxplot analysis was employed to analyze the proxy Procellarids reproductive success, breeding probability and survivorship data for species without predation. From this assessment, values were selected that seemed to represent both expert opinion, and the current data regarding reproductive success and probability (Raine and McFarland 2014a; Raine and McFarland 2014b; Telfer et al. 1987; Ainley et al. 2001).

As in Ainley et al. (2001) and Griesemer and Holmes (2011) a linear regression of the log of adult body size to survivorship was conducted to determine adult survivorship. This linear equation was used to assess adult survivorship given the mass of the organism. This analysis was conducted using data compiled by Griesemer and Holmes (2011) as well as additional survivorship/adult seabird mass collections mined for this assessment (Table 13) . Outliers identified in the boxplot assessment were removed prior to the regression analysis.

The Kauai Seabird Habitat Conservation Plan (KSHCP) team, with the expertise from biologists of the Kauai Endangered Species Recovery Program (KESRP), developed an initial low predation estimate as defined by dominant predators (Ungulates, Cats, Rats and Barn Owls) for a population with 100 breeding pairs (KSHCP \& KESRP 2014) (see Table 14). Using this estimate, the previously defined reproductive probability, and the stable age distribution; the differential predation mortality of each major age class was assessed. To define the predation effect on different age classes it was necessary to conduct an initial assessment of adult and subadult population proportions. This was accomplished by running an Eigen analysis (a calculator of projecting the change inferred by the population matrix) on the previously defined predator free projection matrices, and dividing the stable age distribution (for age classes $\geq 2$ ) produced by that Eigen analysis by its summation. Using these age class proportions, estimates of individual organism numbers within each age class can be defined, as well as projections of numbers outside of known age class sizes. Therefore, because 100 breeding pairs (or 200 NESH) were initially specified to define predation, the approximate number of adults, subadults, and eggs/chicks can be determined from both the population proportions and demographic parameters (e.g. back projecting reproductive probability) (see Table 14 for details). In applying predation to the previously defined demographic parameters we followed the methodology of Ainley et al. (2001) in which the reproductive success parameters were
modified appropriately to incorporate chick/egg predation. Also, like Griesemer and Holmes (2011) we assumed no direct predation on sub-adults until they returned to their breeding area (years 2-3).

From the initial KESRP/KSHCP predation effects model, three other predation scenarios were developed (Table 14). These scenarios were developed from modifications of the KESRP estimate such that the effect per predator is sequentially increased by a decrease in the number of breeding pairs defining the starting population. These population sizes were decreased to reflect specific population growth rates ( $\lambda$ ) with predation (i.e. Low, Medium and High) defined by Griesemer and Holmes (2011) . Modifying the initial starting population sizes allowed the maintenance of each predator's proportional effect throughout each scenario, while increasing the overall influence of predation. When these modified KESRP /KSHCP estimates are transformed to reflect a population with 100 breeding pairs, the increases in the influence of predation per scenario are apparent. This set of proportional predation effects defined per age class was removed per assessment from each predator free demographic estimate. A SbS-PVA was developed for each predation scenario using the Leslie matrix demographic projections derived from these assessments. The predation levels defined here are thought to encompass the likely depredation levels experienced by NESH on Kauai.

Modifications of the SbS-PVA to define site specific predation effect were conducted using an assessment of average slope of the site. It has long been acknowledged that steep slopes may act as a barrier to predators, and thus predation. Although the authors have been able to find information identifying slopes as a probable barrier to movement (Rayner, Hauber, and Clout 2007; Pye, Swain, and Seppelt 1999; J. K. J E Christie 2006; D. J. B. J. E. Christie 2009; Lingle 2002; Delgado et al. 2007), very little information is available that quantifies the degree to which slope hinders this movement. As such, expert opinion was used to assess the degree to which slope hinders predation, and define which predators are most susceptible. USFWS Biologists identified cats (Felis domesticus) and ungulates (Sus scrofa) as those predators most susceptible to extremes in slope, therefore predation reductions due to slope was only applied to cat and ungulate predation.

In this assessment, the median slope of each site was used to estimate refugia from foraging cats and ungulates. An exponential approximation of slope, as scaled to obtain a $y$-axis ranging from

0 to 1 , was used to define the multiplier from which predation is reduced. A visual approximation of this exponential relationship between slope and this predation reduction multiplier is shown in Figure 37. Each sites multiplier was assessed separately from the median slope for that site. Because it was felt that there was very limited data quantifying the slope/predation affect, the slope at which predation is effected $(p)$ was set at $60^{\circ}$, and the slope at which no predation by cats and ungulates occurs $(q)$ at site $(c)$ was set at $90^{\circ}$. We felt this was a conservative estimate of the slope/refugia effect, and should note that no sites had a compiled median slope (and thus predation limiting effect) above $79^{\circ}$.

To remove the predation slope mitigation effect $(l)$ at each site $(c), l_{c}$ was multiplied by the predation amount defined for $c$ (with cat and ungulate effect removed) for all age classes. This value was then subtracted from the sites overall predation effect to determine the new estimate of predation. All modifications to the demographic data due to predation were incorporated in an updated, site specific, projection matrix. This estimate is meant as a place holder until more accurate information is available.

### 5.4 NESH Demography as Modified by Predation: Output

The outlier assessment of adult survivorship in the absence of predation indicated several outliers in defining adult survivorship (Thalassarche chlororyhnchos and Pelecanoides urinatrix) and reproductive success (Procellaria aequinoctialis) (Fig. 38, Table 13). Values were selected that seemed to represent the current data regarding reproductive success and probability. Using this approach, the upper whisker $\left(0.81=\sim 95^{\text {th }}\right.$ percentile) of the boxplot describing the reproductive success of the compiled data was used to define NESH reproductive success without predation. The upper quartile boundary ( $0.88=\sim 75^{\text {th }}$ percentile) was also selected from a boxplot of the compiled breeding probability for other Procellaridae to represent the likely predator free breeding probability for NESH. These values were selected because they fell near the measurements defined for Upper Limahuli, but produced a fecundity value slightly higher (Upper Limahuli $m_{x}=0.675$ versus Proxy $m_{x}=0.7128$ ). This proxy was far greater than that of Griesemer and Holmes (2011) ( $m_{x}=0.48$ ) and Ainley et al. (2001) $\left(m_{x}=0.361\right)$ in their estimates of a stable predator/anthropogenic/environmental mortality free, population.

The linear regression of the log of adult mass to survivorship was conducted for NESH, HAPE and BANP (Fig. 39). The output to the assessment was quite similar to that of Griesemer and

Holmes (2011) and (D. G. Ainley et al. 2001a) given the prediction interval and standard errors. As such adult survivorship was defined using the median survivorship in the boxplot, and what had been used in the Griesemer and Holmes (2011) work (Adult $S_{x}=0.92$ ). The sub-adult and fledgling survivorship for a population without predation mirrored that of Ainley et al. (2001) . The NESH life-cycle diagram used to model the assessment, and the NESH demographic Leslie matrix (with its deterministic $\lambda$ ) are reviewed in Figure 40.

The no-predation demographic variables were modified by four predation estimates per SbS PVA analysis: the predation estimate defined directly by the KESRP team (termed KESRP Defined Predation), the KESRP/KSHCP predation proportion estimate modified to resemble the low predation scenario described in Griesemer and Holmes (2011) (termed KESRP -G\&H Defined Low Predation), the KESRP/KSHCP predation proportion estimate modified to define the mid-point predation scenario described in Griesemer and Holmes (2011) (termed KESRP G\&H Defined Medium Predation), and the KESRP/KSHCP predation proportion estimate modified to define the high predation scenario also described in Griesemer and Holmes (2011) (termed KESRP -G\&H Defined High Predation). The Leslie matrices defined for each scenario, and the deterministic population growth rate also defined for each scenario, are shown in Figure 41. Each matrix was used as the starting point from which the individuals defined within each polygon were assessed. The abiotic and biotic influences (Light Fallout, Extreme Weather Events, Strike Fallout, Slope) used in the SbS-PVA modified these matrices to better reflect site based variance in the parameters.

The median polygon slope of each of the KESRP polys was used as a proxy for site-specific predation reduction. The median scaled slope metric (rescaled such that $0^{\circ}$ is equal to 0 , and $90^{\circ}$ is equal to 1) over all of the characterized polygons was 0.41 ( $95 \%$ C. I. $0.44-0.39$ ), equivalent to a slope of $46^{\circ}$, represents a negligible survivorship increase at the sites due to slope.

### 5.5 SbS-PVA Powerline Strike and Light Fallout Estimate: Development

NESH mortality from strikes was estimated in Section 4 for 2014 and 2015. The various imputations and the factors associated with their projections are represented in Tables 9 and 10. Internal discussions within the United States Fish and Wildlife Ecological Services, Honolulu Office have been used to select the most likely amount of strike mortalities. The USFWS has tentatively settled on 1800 NESH mortalities occurring per year due to powerline strikes, this is
the rounded average of scenarios IV, VB and VIA for the 2014 and 2015 projections (see Section 4 and Tables $9 \& 10$ for descriptions of the estimates).

These powerline strikes were then separated into the different age classes for further assessment. Like Ainley et al. (2001), a 20:80 (Adult:Sub-Adult) ratio was used estimate mortalities of the various age classes due to powerline strikes. A secondary estimate was also incorporated, that defines chick mortality. Chick mortality was derived by estimating the fecundity (reproductive probability multiplied by reproductive success), and thus chick production, of the stricken adults. As in the predation analysis, it was assumed that the chick would not be able to survive without tending by both parents.

Flight path strike impingement per site was then used as a multiplier to derive the strikes per age classification, per site. This metric evaluates the proportional strike impingement, as defined by powerline overlap with the flight path models defined for that site divided by the overall strike impingement for all sites. As such it varies from 0 (no strike impingement) to 1 (all strike impingement occurs at this site).

The number of adults (age: $6+$ years), sub-adults (age: 2-6 years), and chicks (age: $\leq 1$ year) were then estimated for each site under a stable age distribution (defined by the Eigen analysis). Using these metrics, the proportional reduction in survivorship for each class due to strikes was defined and used to modify the site specific demographic parameters per year.

In order to determine site specific fledgling light fallout it was initially necessary to estimate the number of fledglings at each site. Using an Eigen analysis on the sites projection matrices (with the added predation effect) a stable age distribution was defined. As in Section 5.4, this age distribution was then used to assess the number of fledglings (year 1) at each site.

As in Ainley et al. (2001) four collection and rehabilitation scenarios of fallout were considered per assessment, each derived from the Save Our Shearwaters (SOS) program, a program developed to mitigate the effects of fallout on the Kauai population through resident collection and delivery of downed seabirds (Telfer et al. 1987; Rauzon 1991). These four scenarios (100, 80, 67, and $50 \%$ ) were used as estimates of the proportion of downed NESH recovered and rehabilitated by SOS (Griesemer and Holmes 2011). The number of birds grounded and recovered was defined from the average recovery of NESH by SOS over the last five years ( $\sim 178$
birds). In this analysis all groundings due to fallout, unless they are tended to in some way, were considered a fatality. NESH fallout was calculated for each of the four scenarios by dividing the average NESH collected by that specific scenarios theorized collection estimate, and then multiplied by the proportional, site specific, flight path light impingement. The flight path light impingement evaluates the proportional light impingement defined for each KESRP poly site, as compared to the overall light impingement for all sites. As such it varies form 0 (no light impingement) to 1 (all light impingement occurs at this site). The output of this analysis, the overall fledging light fallout for that site, was then divided by the estimated number of fledging's at that site to obtain the site specific light fallout proportion.

It is theorized that the SOS program reduces mortality due to light fallout through rehabilitation, yet little information exists regarding the survivorship of these seabirds post-release. Because there is no information yet available on the efficacy of the program, it was ultimately left to USFWS to assess the programs utility without information regarding the fledgling's post-release survivorship. The USFWS has tentatively credited the SOS program with reducing the mortality of those NESH released by $30 \%$, thus the mortality of those grounded NESH fledglings found and released is approximately $70 \%$. This mortality estimate is relatively close to the upper bound crippling bias presented in Section 4, and as such is considered a conservative placeholder until more information is available.

To account for the survivorship increase of the SOS rehabilitated fledglings at a site, the average NESH recovery estimate (i.e. NESH discovery for light fallout) was multiplied by the site specific proportional light impingement, and divided by the number of fledglings at that site. This proportion was removed from the overall fledging light fallout for that site to derive the site specific fallout proportions. As in Ainley et al. (2001) and Griesemer and Holmes (2011), fledgling mortality by site due to light fallout was removed from the reproductive success estimate defined for each predation/powerline strike scenario.

### 5.6 Projecting Temporal Viability with Demographic Stochasticity and Extreme Weather Events: Development

A multi-year population viability assessment was conducted for each predation and light fallout scenario. For each projected year of the analyses, an attempt was made to define a realistic estimate of site and meta-population growth/decline using demographic stochasticity, and an
estimate of storm effect (and its projected increase due to climate change (Murakami et al. 2013). These assessments were incorporated directly into the SbS-PVA.

Natural demographic stochasticity is theorized to be an important parameter influencing extinction risk for a small population (Doak et al. 2005; Morris 1999). Given that the population for each site is defined by a rather modest number of individuals, the influence of this natural variance on the meta-population is significant when extrapolated over multiple sites. Population assessments compiled from a large number of individuals spread the demographic variance throughout the population, when the population size is partitioned into sub-units (e.g. metapopulation segments) the demographic variance of each sub-unit is averaged over fewer individuals, and so may result in greater changes in the overall population growth and decline.

Demographic stochasticity of population size was defined by assuming a truncated normal distribution (truncated such that values below zero are not selected) around each pre-defined demographic parameter (i.e. annual survivorship and fecundity), and from these distributions extracting a random survivorship and fecundity quantities for each age class. All distributions developed assumed that the demographic parameter initially input into the Leslie matrix (whether it be the year-to-year survivorship or fecundity) was the average for that site. Once the mean was identified per class, proxy data to define the standard deviation of survivorship were compiled from both Griesemer and Holmes (2011) and other sources (Table 13) . All of the compiled data were incorporated to define the adult and sub-adult standard deviation around the mean ( $\mathrm{sd}=0.03527$ ), except for those species identified as outliers. The mean and standard deviation of breeding probability ( $\overline{\mathrm{x}}=0.8227$, sd $=0.07459$ ) and reproductive success ( $\overline{\mathrm{x}}=$ $0.6089, \mathrm{sd}=0.1152$ ) were calculated from work by both Ainley et al (2001) and Griesemer and Holmes (2011) (Table 2.2 and Appendix 1 in both Ainley et al (2001) and Griesemer and Holmes (2011)) in a similar way. Using the mean and standard deviation of breeding probability and reproductive success a truncated normal distribution of each was projected over one thousand points, and the distributions were combined through multiplication to beget a normal distribution of fecundity. The standard deviation of this fecundity distribution was then used to define the demographic stochasticity of fecundity over multiple iterations. For those proxy estimates used to define the standard deviation of reproductive success, only those collections where non-native predators were absent, eradicated or controlled were used.

In order to incorporate the previously defined demographic stochasticity, model replication over each year the SbS-PVA is projected, was necessary. As such each future projection scenario was replicated 100 times per year and the median and standard deviation of all combined iterations was graphed per scenario. For each iteration it was necessary to integrate the probability forecast of extreme weather events (which projected future increases in extreme weather event likelihood, derived from Murakami et al. (2013)), and include the demographic effect of extreme weather events such that their influence can be averaged over multiple iterations.

Using the Eastern Pacific storm database (downloaded from the National Climate Data Center (http://www.ncdc.noaa.gov/) to define the number of storms that occur within 360 nautical miles ( 666.4 km ) of Hawaii's coast within the period of collection (1950's - 2013), it was estimated that there was a $92.1 \%$ probability of the periphery of a $>34 \mathrm{mph}$ wind storm event (i.e. $\geq$ Tropical Storm) striking Hawaii per year. A buffer of 666.4 km was used to define the probability of these storm events because; the buffer encompassed the most devastating historical extreme weather events to occur in Hawaii, was a central storm quadrant periphery defined in the extreme weather event probability assessment, gave a relatively realistic estimate of extreme weather event probability. The applied buffer was used as a prior risk assessment periphery to define the probability of storm event occurrence (Gilmore and Naval Research Laboratory (U.S.) 1996). On top of this initial year-to-year storm probability estimate, Murakami et al. (2013) projected a $60 \%$ increase in storm events by $\sim 2100$ (from $\sim 2013$ ). Consequently, in any temporal projection of storm events it is necessary to increase the year-to-year storm probability estimate by this rate (i.e. $0.6897 \%$ increase per year). The projected extreme weather event for a given year was then multiplied by this rate, and the base (i.e. starting year) extreme weather event probability was added to define the projected probability per year. Previous estimates of storm event probabilities (Gilmore and Naval Research Laboratory (U.S.) 1996) conducted on data collected between 1994-1995 estimated an $\sim 80 \%$ probability of a storm event (wind speeds $>34 \mathrm{mph}$ ) occurring in Hawaii per year. Although this assessment was significantly higher, when hind-cast from 2013 to 1995 using a probability decrease per year of $0.6897 \%$, the resulting output was comparable ( $79.65 \%$ probability of a storm event). To assess whether an extreme weather event affected the demography of the meta-population, for each year (in each replication of each scenario) an independently defined, randomly selected, integer between 1 and 100 was selected. If an integer matched a sequence of numbers generated per year between 1 and the
yearly projected probability of an extreme weather event, as rounded to the nearest integer, the demographic effects of the extreme weather event was assimilated.

Data defining the demographic effects of extreme weather events on the seabird populations were acquired from the Jenouvrier Seabird Lab at The Woods Hole Oceanographic Institute, these data were presented in Jenouvrier et al. (2009). The data were used in Jenouvrier et al. (2009) to identify reductions in adult survivorship due to extreme weather events for Cory's shearwater (Calonectris diomedea) populations in the Mediterranean. The work by Jenouvrier et al. (2009) assesses the impact of extreme weather events (e.g. cyclones) on various islands, defines a concomitant survivorship reduction, and extrapolates a latitudinal gradient in this survivorship reduction. Although the work collected and used data from 6 Islands in both the Mediterranean and Atlantic to assess this relationship, we identified four Islands (Corsica, Crete, Fioul, and Malta) that best represent the variation in cyclonic activity of the Mediterranean (Bocheva, Georgiev, and Simeonov 2007). Adult survivorship was compiled and compared per year from 1990-1995 for each Island. The study, and the data from the Jenouvrier lab, were used to assess survivorship reductions due to these extreme weather events in Hawaii by correlating specific survivorship reductions identified in the manuscript to wind speed estimates for cyclones occurring in that area.

To assess the degree of survivorship reductions associated with specific extreme weather events in the Jenouvrier et al. (2009) study, the difference between the average of the years displaying the highest levels of adult survivorship (per island) (1991-1994), were subtracted from the average of the lowest levels (1990 and 1995) to define the variance of the changes in survivorship ( $\Delta S_{x}$ ) due to storm events. Since the survivorship reductions in 1990 were equivalent to those in 1995, and because no known cyclone event could be found for 1990, the two $S_{x}$ estimates defined for those years were combined to assess all further effects. The $\Delta S_{x}$ was assessed for all of the selected Islands. The largest $\Delta S_{x}$ assessed for all regions then linked to a wind speed estimate derived from observations of a hurricane like cyclone that occurred in 1995 in the Mediterranean (Pytharoulis, Craig, and Ballard 2000). This cyclone formed on the $13^{\text {th }}$ of January 1995 between Libya and Italy and moved northwards towards Greece with recorded wind speeds at $\sim 84$ knots (Pytharoulis, Craig, and Ballard 2000). It formed and tracked roughly between Crete and Malta, the regions with some of the highest $\Delta S_{x}$.

In order to derive a linear relationship between survivorship reduction and wind speed (an estimate used here to define extreme weather events) it was assumed that the variation in survivorship by island was due to differences in weather intensities, and as such wind speeds. Although tentative, it was felt that this correlation was relatively accurate. It was also assumed that these effects are roughly equivalent throughout all of the islands, given the extensive migratory ability of C. diomedea (González-Solís et al. 2007; Ristow et al. 2000; A. Raine, Borg, and Raine 2011; Ristow et al. 2000). With these assumptions we then derived a linear approximation of the relationship between survivorship and wind speed by using the proportional differences defined by the various $S_{x}$ values. Given that the largest $\Delta S_{x}(0.0885 \pm 0.0428)$ was linked to the greatest wind speed defined for that region during that time period ( $\sim 84$ knots), it was possible to use the proportional differences in $S_{x}$ to define the proportional difference from this wind speed. In this analysis it was also assumed that there was a minimal survivorship loss in winds less than 74 mph ( 64 (knots), as such these proportions were modified by a constant (iteratively selected in the analysis) that minimizes the y-intercept, restricting it to be as close to zero as possible at 74 mph .

For each year (within each iteration) whether or not a storm impacted the islands was assessed using the storm probability output (as described above). If a storm did impact Kauai, the intensity of that storm was randomly selected from the mean and standard deviation of the normal distribution of storm events, and their respective intensities (as defined by Wind Speed) impacting Hawaii. This value was then modified per site using the site specific extreme weather event impact projection. For the site impact projection, a value above 0.5 (as would be predicted by the central limit theorem) was considered an increase in the mean projected intensities, from which a value defining intensities was extracted (a value below 0.5 was defined as a decrease). Using the linear relationship defined by the $S_{x} /$ Wind Speed (e.g. Storm Intensity) linear extrapolation, the site specific storm intensity was used to calculate the $\Delta S_{x}$ by solving for $y$ in the linear equation.

### 5.7 Projecting Temporal Viability with Demographic Stochasticity and Extreme Weather Events: Output

Adult survivorship of Cory's shearwater was characterized from data provided by the Jenouvrier Seabird Lab at the Woods Hole Oceanographic Institute (as presented in Jenouvrier et al. (2009)).

These data were compiled and compared per year from 1990 - 1995 for each Island (Fig. 42A) and the survivorship reductions due to these extreme weather events was assessed by correlating specific survivorship reductions identified in the manuscript to wind speed estimates for cyclones occurring in that area. The variance of the changes in survivorship $\left(\Delta S_{x}\right)$ over the various regions impacted by storm events, were sorted (Fig. 42B) and the largest $\Delta S_{x}$ assessed for all regions (that defined for Malta) was then linked to the wind speed estimate ( 84 knots) derived from observations of a hurricane like cyclone that occurred in 1995 in the Mediterranean (Pytharoulis, Craig, and Ballard 2000)

Assuming that the variation in survivorship by island was due to differences in weather intensities/wind speeds (as supported by Fig. 42), various wind speed estimates were linked with $\Delta S_{x}$. Using the approach described in the in Section 5.6, a linear approximation of the relationship between survivorship and wind speed was defined by using the proportional differences defined by the various $S_{x}$ parameters to project the difference in wind speed (Fig.43).

For each year, within each iteration, whether or not a storm impacted the islands was assessed using the storm probability output (curve in Fig. 43). This value was then modified per site using the site specific extreme weather event impact projection (Section 1, Fig. 4). For the site impact projection, a value above 0.5 (as would be predicted by the central limit theorem) was considered an increase in the mean projected intensities, from which a value defining intensities was extracted (a value below 0.5 was defined as a decrease). Using the linear relationship defined by the $S_{x} /$ Wind Speed (e.g. Storm Intensity) linear extrapolation (as presented in Fig. 43), the site specific storm intensity was then used to calculate the site specific $\Delta S_{x}$ by solving for y in the linear equation in Figure 43.

### 5.8 Site Specific Carrying Capacity Estimation and Limitation

The site specific carrying capacity (K) was estimated in a similar manner as the site specific population size (see Sub-Sections 5.1 and 5.2). Although similar to the population size estimates, the carrying capacity estimate specifically used the areas in the KESRP polygons that have similar characteristics to known burrow locations, projected them on the Lower 95\% Confidence Interval of distance (derived from data in Fig. 35) found between all known NESH burrow locations, and then extrapolated burrow number estimates across the suitable sites.

Because it biologically inappropriate to define an exacting threshold at which the demographic effects of reaching K are specifically defined, which in this modeling approach was defined by the elimination of fecundity until the population is below K , a $5 \%$ reduction in K was used to define the point at which the linear reduction in fecundity was implemented. From this 5\% threshold a linear reduction in fecundity was incorporated until the overall site specific K was reached, at which point fecundity was removed from the overall assessment. If in the following year the population size fell below K , fecundity was incorporated at the appropriate extent. This sinusoidal relationship around K is averaged over all iterations conducted per year of projection.

### 5.9 Stochastic Site-by-Site Population Viability Assessment (SbS-PVA) per site: Overview

The SbS-PVA was developed for each polygon in the KESRP poly shapefile and per predation scenario (4 predation scenarios), with and without the projected powerline strike estimate developed in Section 4. Power-line and light based mortalities were partitioned per site using the flight path ensemble model developed in Section 3, and the methodologies described in SubSection 5.5. In order to project a PVA for a site, an initial starting population size is necessary, the estimated population size per polygon (as reviewed in Section $5.1 \& 5.2$ ) is shown in Fig. 44. The normalized proportional threat effect for each site is projected within each polygon, as partitioned for strike and light impingement (Figures $45 \& 46$ ). This simulation was projected, using a limited number of replicates, to year 2100. Thirty two different scenarios (four predation scenarios per strike estimate, within which are four light fallout scenarios) were developed per site.

In each model, for each site, stochastic variation was enabled using the stochastic variation in survivorship, fecundity, and reproductive success defined in Table 14, and Figures 38, 41 and 43, and those variables defined in Sub-Section 5.3. Stochastic variation was also incorporated into the application of strike mortality per site in an attempt to incorporate the year to year variance in strike mortality. As there were two projections of strike mortalities from which the mean was used (2014 and 2015, see Section 4) the standard deviation of these strike mortality models, along with the projected sites average mortality due to strikes, was used to develop a truncated non-negative normal distribution. From this truncated normal distribution a mortality amount was randomly selected per year. This allowed for a more conservative estimate of population
viability by linking demographic effects identified by the flight path to colonies, and building in significant year to year variation associated with the mortality and fecundity of NESH.

A PVA graphic was produced for each site the assessment was developed for, along with the text file output of many of the base metrics used to produce that graphic. Four graphics (one for each predation scenario) describing the various light fallout scenarios, with and without strike mortalities were developed per polygon, for a total of 304 site specific PVA graphical outputs. Predictions concerning the population viability of those sites can be inferred from these graphics. For ease of use, a Qausi Extinction Threshold (QET) of five individuals per colony (i.e. 380 individuals for the meta-population), was used to define ecological extinction of the colony at the site. The QET, and the date at which it was reached, was given for each for the 304 figures. As the number of figures is disproportionately large, and the information in them is compiled into an ensemble graphic (described below) the PVA figures describing specific sites are not shown here, but can be distributed upon request. Each of the 76 sites was labeled with a number (shown in Fig. 44) which can be used to identify sites of interest for further discussion.

For each of the scenarios analyzed, a set of meta-population graphics were developed attempting to compile all of the information identified in the site based models into a set of histograms, or geographic projections, describing the lambdas, and extinction times for all sites as the metapopulation is projected into the future. The graphics were compiled in this way to show both the structure (geographic, temporal) and variance in population growth rates of the projected metapopulations ecological extinction, as it is projected with and without strike mortalities.

### 5.10 Stochastic Site-by-Site Population Viability Assessment (SbS-PVA) Compilation Assessment: Output

As noted in Sub-Section 5.9, a PVA graphic was produced for each site and each scenario, for a total of 304 site specific PVA graphical outputs. For ease of representation, and review, these graphics were compiled into an overall assessment of the meta-population, represented using both the compilation of each populations growth rates (Lambda), and years until ecological extinction. Compilations of scenarios for both parameters were represented using both a histogramatic (Fig. $47-50$ ) and geographic (Fig. $51-66$ ) representation of the cumulative effect of all sites on the projected outcome of the meta-population. Site specific information can also be gathered from the geographic compilation of the figures.

The histograms shown in Figures 47 - 50 are compilations of all scenarios for the SbS-PVAs conducted without (Fig. $47 \& 48$ ) and with (Fig. 49 \& 50) strike mortalities included in the PVA projections. As such, each of the histogram figures represents either the compiled lambdas, or ecological extinctions of projections, with and without strikes. These figures are partitioned by the four predation scenarios defined in Sub-Sections 5.3 and 5.4 (e.g. Fig. 47 A-D). The variance in light fallout mortality is discretized within each figure using different color or banding schemes. The figures were developed in this way to review the variance in Lambda, and ecological extinction, within and between scenarios. These graphics represent three levels of comparison, overall estimates of the meta-population as projected without and with strikes, and internal comparisons between predation and/or light fallout scenarios.

The overall distribution of the estimated time until ecological extinction between metapopulations of NESH on Kauai without (Fig. 48) and with (Fig. 50) strike mortalities projected on the population is definitively dissimilar. As would be expected from predation effects that are not necessarily geographically derived, the dissemination of site based ecological extinctions is more normally distributed across the years in all scenarios without strike mortalities (see Fig. 47). When strike mortalities are accounted for, ecological extinctions are heavily weighted such that more ecological extinctions are projected to occur in the much nearer future. Metapopulation estimates conducted without and with strikes show meta-populations across all predation and light fallout scenarios that have equivalent projected ecological extinction endpoints, ranging from 2070 to 2100. This is likely because a large subset of the metapopulation is in a strike and light free zone (see Fig. $45 \& 46$, and Section 1, Fig. 2 and Section 4 Fig. $24-31$ ) and as such has equivalent demography's across all light fallout and strike projections.

The greatest variance shown in each of the graphics is that between predation scenarios. In these graphics the higher the predation effect (See Fig. 41) the more recent the projected ecological extinction of the meta-population. Compared to mortalities caused by predation and strikes, light mortalities on the meta-population are relatively negligible. Light mortalities impact the metapopulation in a proportionately similar manner as strike mortalities, but are far from as detrimental due to both the age class at which light mortalities effect the population, and the total amount of mortalities due to light sources.

The histograms of projected lambdas (Fig. 49 \& 50) show similar dissimilarities (similar to the histogram of ecological extinctions) across projections conducted without and with strikes. As would be expected if a large mortality sink were removed from the population, lambdas for the site based projection without strikes (Fig. 49) tend to be closer to 1 (i.e. stable) than when strikes are incorporated. Interestingly, a large subset of the population has extremely low Lambdas in both projections. These lambdas would likely only come about if the amount of mortality in the first year was greater than the population could sustain in subsequent years. Lambdas for the projection in which strike mortalities were incorporated tend to be tending more toward a normal distribution of sites, with stable populations being an outlier.

As would be predicted with the increase in any mortality factor, the increasing effect of predation (Fig. 49 \& $50 \mathrm{~A}-\mathrm{D}$ ) decreases the proportional distribution of lambdas across the metapopulation. Like the figures explaining the ecological extinction of the meta-population, the light mortality effect for both strike projections (Fig. 49-50) is comparatively less than strike or predation mortality, but proportionately similar to the effect of strike mortalities on lambda.

Because the geographic projection of ecological extinctions and lambdas could not be compiled to the degree the histograms were without an extreme loss of information, projections were compiled per predation scenario. Projections were separated such that they are descriptive of the meta-population projections without and with strike mortalities applied (KSHCP-KESRP Fig. 51 - 54, Griessemer \& Holmes - Low Fig. 55 - 58, Griessemer \& Holmes - Medium Fig. 59 - 62, Griessemer \& Holmes - High Fig. 66 - 66). These geographic projections are meant to give a holistic overview of how each site in Kauai's meta-population is affected by the projection of predation, strike mortality and light effect.

As the overall aspect based distribution of power-line strike and light effect (i.e. light fallout) is similar (Section 1, Fig. 2 and Section 4 Fig. 24-31) across Kauai's landscape, it would be expected that as these factors increase, their effect on a subset of sites most impacted by them would also increase. This is, in general, what is happening when strike or light mortalities are input in these projections. For instance, the KSCHP-KESRP predation scenario without strike mortalities shows a marked increase of both times until ecological extinction (Fig. 51) and lambdas (Fig. 53) in the interior and South East periphery of Kauai compared to when strikes are incorporated into the assessment (Fig. 52 for ecological extinction and Fig. 54 for lambdas).

This trend is similar when comparing all of the predation scenarios to their projections without and with strikes. As is expected, as light mortality is increased on the population, the geographic distribution of those effects are similar to strike mortalities, with those populations in the North West of Kauai being relatively unaffected by both strike and light.

All predation scenarios, when strikes (Fig. 52, 56, $60 \& 64$ ) are incorporated, show the North West portion of Kauai being the longest lived NESH reservoir. This is not necessarily the case for interior populations due to the greater variance in there projected flight paths to the coast (See Section 3 Fig. 12 C\&D). These reservoir populations also show the greatest degree of population growth (Fig. 54, 58, $62 \& 66$ ) when compared to other populations impacted by strikes and lights.

### 5.11 Section 5: TABLES

Table 11: Description and AUC ranking of the variable and data subsets used to derive a prediction of site occupancy. Predicted occupancy was defined primarily for Newell's shearwater (NESH). Those assessments highlighted in red were selected for downstream analyses of burrow occupancy.

| TEST | DESCRIPTION | NESH |
| :---: | :---: | :---: |
| Burrow | All variables (remotely sensed, and observer information) were used in the occupancy prediction; this analysis only uses the known burrow locations to describe its aspect relationship to the coast. | 0.99 |
| Burrow Only | Only remotely sensed information was used in this occupancy prediction; this analysis also | 0.71 |
| Remotely Sensed | only uses the known burrow locations to describe its aspect relationship to the coast. All variables (remotely sensed, and observer |  |
| Stream and Burrow | information) were used in the occupancy prediction, this analysis uses known burrow and stream locations to describe the burrows aspect relationship to the coast. | 0.99 |
| Stream and <br> Burrow Only <br> Remotely Sensed | Only remotely sensed information was used in this occupancy prediction, this analysis uses burrow and stream locations to describe the burrows aspect relationship to the coast. | 0.75 |
| Stream | All variables (remotely sensed, and observer information) were used in the occupancy prediction but this analysis only uses the stream locations to describe the burrows aspect relationship to the coast. | 0.99 |
| Stream Only <br> Remotely Sensed | Only remotely sensed information was used in this occupancy prediction, this analysis also only uses the stream locations to describe the burrows aspect relationship to the coast. | 0.73 |

Table 12：NESH specific Elastic Net GLM variable weighting output for the two assessments that were most predictive of burrow occupancy，as defined using the area under the curve （AUC）validation metric（Table 11）．Observed variables are shown that overlap with all analyzed points，and are descriptive of vegetation height and type．

|  | VARIABLE DESCRIPTION | STREAM | STREAM ONLY REMOTELY SENSED |
| :---: | :---: | :---: | :---: |
|  | （Intercept） | －1．6357 | －15．0840 |
|  | Burrow Length | 0.0000 | － |
|  | Burrow Mouth Aspect | 0.0000 | － |
|  | Burrow Mouth Bearing | 0.0007 | － |
|  | Burrow Mouth Height | 0.0044 | － |
|  | Burrow Mouth Width | 0.0043 | － |
|  | Burrow Openings | 0.2990 | － |
|  | Burrow Slope Bearing | －0．0011 | － |
| W | Canopy Percent Cover | 0.0045 | － |
| ＊ | Greater than 2 meter Vegetation：Kopiko（Psychotria hexandra） | 0.0003 | － |
| 宏 | Greater than 2 meter Vegetation：Lapalapa（Cheirodendron platyphyllum） | 0.0019 | － |
| ＞ | Greater than 2 meter Vegetation：Ohia（Meterosideros polymorpha） | 0.0024 | － |
| 易 | Greater than 2 meter Vegetation：Olapa（Cheirodendron trigynum） | 0.0214 | － |
| 采 | Less than 2 meter Vegetation ：Uluhe（Dicranopteris linearis） | －0．1657 | － |
| $\stackrel{\mathscr{N}}{\hat{e}}$ | Less than 2 meter Vegetation ：Uluhe（Dicranopteris spp．） | 0.1726 | － |
| O | Less than 2 meter Vegetation：Kopiko（Psychotria hexandra） | －0．0166 | － |
|  | Less than 2 meter Vegetation：Lapalapa（Cheirodendron platyphyllum） | －0．0316 | － |
|  | Less than 2 meter Vegetation：Ohia（Meterosideros polymorpha） | 0.0081 | － |
|  | Less than 2 meter Vegetation：Olapa（Cheirodendron trigynum） | －0．0528 | － |
|  | Maximum Vegetation Height | －0．0516 | － |
|  | Percent Native Vegetation Cover | 0.0116 | － |
|  | Substrate Slope of Burrow | －0．0006 | － |
| REMOTELY SENSED VARIABLES | Burrow Aspect | 0.0012 | 0.0009 |
|  | Difference between the Euclidean Distance Defined Coastal Aspect and Stream Burrow Aspect | 0.0035 | 0.0107 |
|  | Difference between the Topographic Distance Defined Coastal Aspect and Stream Burrow Aspect | －0．0025 | －0．0087 |
|  | Difference between Topographic and Euclidean Defined Coastal Aspects | 0.0110 | 0.0098 |
|  | Elevation | －0．0017 | －0．0052 |
|  | Euclidean Distance Defined Coastal Aspect | 0.0010 | 0.0480 |
|  | Percent Shrub Cover | 0.0067 | 0.0145 |
|  | Percent Tree Cover | 0.0043 | 0.0116 |
|  | Slope | 0.0035 | 0.0458 |
|  | Topographic Distance Defined Coastal Aspect | 0.0032 | 0.0034 |

Site by Site Stochastic Population Viability Analysis
Table 13 Adult survivorship ( $S_{x}$ ) for proxy Procellariformes and their respective sources. This table represents an update to that of Griesemer and Holmes (2011) (Appendix 5). The species highlighted in red represent an outlier to the overall distribution, and thus was not used to define the standard deviation of survivorship.

| Bulweria bulweria | 0.95 | Warham 1999 |
| :---: | :---: | :---: |
| Calonectris diomedea | 0.95 | Warham 1996 |
| Calonectris diomedea | 0.93 | Mougin et al 2000; Skira 1991 |
| Calonectris diomedea | 0.87 | Jenouvrier et al., 2008 |
| Daption capense | 0.95 | Warham 1997 |
| Daption capense | 0.93 | Warham 1996 |
| Diomedea epomorpha | 0.94 | Warham 1996 |
| Diomedea epomorpha | 0.97 | Warham 1996 |
| Diomedea epomorpha | 0.92 | Robertson 1993 |
| Diomedea exulans | 0.97 | Warham 1996 |
| Fulmarus glacialis | 0.97 | Warham 1996 |
| Fulmarus glaciodes | 0.9 | Warham 1996 |
| Fulmarus glaciodes | 0.95 | Warham 1996 |
| Hydrobates pelagicus | 0.88 | Warham 1996 |
| Macronectes giganteus | 0.9 | Warham 1996 |
| Macronectes halli | 0.9 | Warham 1996 |
| Oceanites oceanicus | 0.91 | Warham 1997 |
| Oceanodroma leucorhoa | 0.86 | Warham 1998 |
| Pachyptila turtur | 0.84 | Warham 2000 |
| Pagodroma nivea | 0.93 | Chastel et al. 1993 |
| Pelecanoides urinatrix | 0.67 | Warham 2001 |
| Phoebastria immutabilis | 0.95 | Sagar et al. 2000 |
| Phoebatria fusca | 0.95 | Warham 1996 |
| Phoebatria irrorata | 0.96 | Warham 1996 |
| Phoebatria palpebrata | 0.97 | Warham 1996 |
| Procellaria aequinoctialis | 0.9 | Barbraud et al. 2008 |
| Procellaria aequinoctialis | 0.9 | Barbraud et al., 2008 |
| Procellaria westlandica | 0.97 | Waugh et al 2006 |
| Pterodroma macoptera gouldii | 0.88 | Jones et al., 2011 |
| Pterodroma sandiwichensis | 0.93 | Warham 1998 |
| Puffinus carneipes | 0.92 | Reid et al. 2013 |
| Puffinus griseus | 0.93 | Warham 1996 |
| Puffinus griseus | 0.92 | Clucas et al. 2008 |
| Puffinus griseus | 0.95 | Clucas et al. 2008 |
| Puffinus griseus | 0.97 | Clucas et al. 2008 |
| Puffinus griseus | 0.91 | Richdale in Scofield et al. 2001 |
| Puffinus huttoni | 0.93 | Cuthbert and Davis 2002 |

Site by Site Stochastic Population Viability Analysis

| SPECIES | $\boldsymbol{S}_{\boldsymbol{X}}$ | $\boldsymbol{S}_{\boldsymbol{X}}$ CITATION |
| :---: | :---: | :---: |
| Puffinus puffinus | 0.91 | Brooke 1990 |
| Puffinus tenuirostris | 0.92 | Warham 1996 |
| Puffinus tenuirostris | 0.91 | Hunter et al. 2000 |
| Thalasarche impavida | 0.92 | Cuthbert et al., 2003 |
| Thalassarche bulleri | 0.89 | Warham 1996 |
| Thalassarche bulleri | 0.95 | Sagar et al. 2000 |
| Thalassarche bulleri | 0.89 | Warham 1996 |
| Thalassarche bulleri | 0.95 | Warham 1996 |
| Thalassarche chlororyhnchos | 0.87 | Weimerskirch et al., 2001 |
| Thalassarche chlororyhnchos | 0.78 | Weimerskirch et al., 2001 |
| Thalassarche chlororyhnchos | 0.86 | Weimerskirch et al., 2001 |
| Thalassarche chlororyhnchos | 0.82 | Weimerskirch et al., 2001 |
| Thalassarche chlororyhnchos | 0.91 | Weimerskirch et al., 2001 |
| Thalassarche chlororyhnchos | 0.88 | Weimerskirch et al., 2001 |
| Thalassarche chlororyhnchos | 0.92 | Weimerskirch et al., 2001 |
| Thalassarche chlororyhnchos | 0.91 | Warham 1996 |
| Thalassarche chrysotoma | 0.95 | Warham 1996 |
| Thalassarche melanophrys | 0.93 | Warham 1996 |
| Thalassarche melanophrys | 0.88 | Warham 1996 |

Table 14: KESRP/HCHCP modified predation estimates that reflect chick survivorship in the absence of nesh adults, as well as the levels of predation as increased from the KESRP/HCHCP estimate to match low, medium and high predation lambdas as estimated by Griesemer and Holmes (2011). Each predation estimate was defined from a population with 100 breeding pairs. Mortality of individuals at the major age classes and the proportion of that mortality, as compared to the overall population, are defined. All mortality estimates are here rounded to the second significant figure, but raw calculated values are used in the SBS-PVA.

|  | Predator | Year 0-1 Mortality | Sub-Adult (2-5) Mortality | Adult (6+) Mortality | Year 0-1 <br> Mortality <br> Proportion | Sub-Adult (2- <br> 5) Mortality <br> Proportion | Adult (6+) <br> Mortality <br> Proportion |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Ungulate | 12 | 3.8 | 4.2 | 0.12 | 0.021 | 0.021 |
|  | Cat | 12 | 3.8 | 4.2 | 0.12 | 0.021 | 0.021 |
|  | Rat | 12 | 0 | 0 | 0.12 | 0 | 0 |
|  | Barn Owl | 0.96 | 0.48 | 0.52 | 0.0096 | 0.0026 | 0.0026 |
|  | Ungulate | 13 | 4.4 | 4.8 | 0.13 | 0.024 | 0.024 |
|  | Cat | 13 | 4.4 | 4.8 | 0.13 | 0.024 | 0.024 |
|  | Rat | 14 | 0 | 0 | 0.14 | 0 | 0 |
|  | Barn Owl | 1.1 | 0.55 | 0.60 | 0.011 | 0.0030 | 0.0030 |
|  | Ungulate | 16 | 5.3 | 5.8 | 0.16 | 0.029 | 0.029 |
|  | Cat | 16 | 5.3 | 5.8 | 0.16 | 0.029 | 0.029 |
|  | Rat | 17 | 0 | 0 | 0.17 | 0 | 0 |
|  | Barn Owl | 1.3 | 0.66 | 0.72 | 0.013 | 0.0036 | 0.0036 |
|  | Ungulate | 18 | 6 | 6.6 | 0.18 | 0.033 | 0.033 |
|  | Cat | 18 | 6 | 6.6 | 0.18 | 0.033 | 0.033 |
|  | Rat | 19 | 0 | 0 | 0.19 | 0 | 0 |
|  | Barn Owl | 1.5 | 0.75 | 0.82 | 0.015 | 0.0041 | 0.0041 |



Figure 32: Depiction of how variables were developed to predict burrow presence and colony size.


Figure 33: Six of the ten variables used to define burrow occupancy as developed for each $\mathbf{3 0 m}{ }^{\mathbf{2}}$ pixel within each KESRP polygon describing possible colony sites. These variables are: the aspect of the coastal point (in relation to the aspect of the pixel) as defined by the topographic and Euclidean least cost path from the pixel location ( $A$ and $B$ respectively), the difference between the coastal and pixel aspect as defined for the topographic and Euclidean least cost path assessments ( $C$ and $D$ respectively), the difference between the topographic and Euclidean derived aspects ( E ), and the aspect at the pixel location (F). All variables are expressed in Arc Degrees.


Figure 34: Four of the ten variables used to define burrow occupancy as developed for each $30 \mathrm{~m}^{2}$ pixel within each KESRP polygon describing possible colony sites. These variables are: the elevation of each pixel analyzed (A), the slope of each pixel (B), the percent cover of shrubs and trees for each pixel as defined using the Landfire assessment ( $C$ and $D$ ).


Figure 35: Density estimates of burrows defined for the Hawaiian Petral (HAPE), Newell's Shearwater (NESH), unknown petrels (UNPE), and sites combined (ALL) as defined using the median nearest neighbor distances. A Tukey's pairwise comparison test was applied to an ANOVA assessment of the data and used to compare the different projections. Significance between projections is indicated by letters placed above the upper whisker.


Figure 36: Proportion of the population that each KESRP polygon was projected to contain. This was used in downstream analyses to define the population size at a specific site, given a specific meta-population estimate.


Figure 37: Exponential approximation of cat and ungulate seabird predation reduction defined for the median slope at each site, as inferred from the displayed predation limiting calculation. This calculation was used to derive predation limitations at specific sites from site specific slopes. In this site based assessment; $l$ is the multiplier used to define the effect of slope at site $c, s$ defines the slope at $c, q$ equals the maximum slope at which $l_{c}$ is equal to 1 , and $p$ represents the slope at which predation reduction due to slope begins.


Figure 38: Boxplots of compiled Survivorship, Breeding Probability, and Reproductive Success measurements for proxy species. Outliers in each are defined by the species name.


Figure 39: Linear regression of the Adult survivorship ( $S_{x}$ ) versus the $\log$ of seabird mass. Regression statistics are shown in the upper left corner of the analysis, and the $\mathbf{9 5 \%}$ confidence and prediction intervals are defined around the regression line. The mass for three Procellaridae (NESH, HAPE and BANP, or Newells Shearwater, Hawaiian Petrel and Band Rumped Storm Petrel) with little to no $S_{x}$ information associated with them are graphed along the line, using the linear equation defined in the graphic inset. Using this information the $S_{x}$ of each can be defined. The standard error of the body mass was transformed into the standard error of the $S_{x}$ to derive both error measurements.

B. $\quad\left(\begin{array}{cccccccc}0 & 0 & 0 & 0 & 0 & 0 & \Phi_{A 1} m_{\times 1} & \Phi_{A . .} m_{\times . .} \\ \Phi_{F} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \Phi_{S A 1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \Phi_{S A 2} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \Phi_{S A 3} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \Phi_{S A A} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \Phi_{S A 5} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \Phi_{A 1} & \Phi_{A .1}\end{array}\right)$

$$
\begin{aligned}
& \text { NO PREDATION } \\
& \text { C. } \quad\left(\begin{array}{cccccccc}
0 & 0 & 0 & 0 & 0 & 0 & 0.7128 & 0.7128 \\
0.654 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0.78 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0.89 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0.905 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0.905 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0.905 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.92 & 0.92
\end{array}\right)
\end{aligned}
$$

Figure 40: NESH life-cycle diagram (A), Leslie projection matrix key (B), and NESH Leslie projection matrix (C) with the deterministic population growth rate for an optimal population as defined with little to no predation, strikes, or fledgling light fallout.
A.

KESRP DEFINED PREDATION
(Population Growth Rate $(\lambda)=0.9889$ )
$\left(\begin{array}{cccccccc}0 & 0 & 0 & 0 & 0 & 0 & 0.4539 & 0.4539 \\ 0.654 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.78 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.89 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.905 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.8161 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.8161 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.8311 & 0.8311\end{array}\right)$
B.

## KESRP-G\&H LOW PREDATION

(Population Growth Rate $(\lambda)=0.9730$ )
$\left(\begin{array}{cccccccc}0 & 0 & 0 & 0 & 0 & 0 & 0.4168 & 0.4168 \\ 0.654 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.78 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.89 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.905 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.8034 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.8034 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.8184 & 0.8184\end{array}\right)$

KESRP-G\&H MEDIUM PREDATION
C.
(Population Growth Rate $(\lambda)=0.9450$ )
$\left(\begin{array}{cccccccc}0 & 0 & 0 & 0 & 0 & 0 & 0.3545 & 0.3545 \\ 0.654 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.78 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.89 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.905 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & & 0.782 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.782 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.797 & 0.797\end{array}\right)$

## KESRP-G\&H HIGH PREDATION

D. $\left(\right.$| (Population Growth Rate $(\boldsymbol{\lambda})=0.921)$ |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 0 | 0 | 0 | 0 | 0 | 0.3044 | 0.3044 |
| 0.654 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0.78 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0.89 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0.905 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0.7648 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0.7648 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0.7798 | 0.7798 |$)$

Figure 41: NESH Leslie projection matrices defined for various predation scenarios used in the analysis. The KESRP predation scenario $(\mathrm{A})$ is equivalent to that predation defined by KESRP/KSHCP per predator. The low (B), medium (C) and high (D) predation Leslie matrices are modifications of the KESRP predation estimates to reflect the population growth rate of the various scenarios as estimated by Griesemer and Holmes (2011). The BASE un-projected, deterministic population growth rates are defined for each scenario.


Figure 42: Cory's Shearwater Data from Jenouvrier et al. (2009) for the Mediterranean regions selected to represent extreme weather event effects. The change in survivorship over time (A) identifies extreme weather events in 1990 and 1995. The difference between the average survivorship effects of those time points with extreme weather events, versus the average of those without, (B) per island was used to identify variance in survivorship due to extreme weather event intensity.


Figure 43: Comparisons between the probability of weather events and the predictive survivorship reductions due to these events. An estimate of storm affect was developed by linearizing the Jenouvrier et al. (1997) data over a storm intensity spectrum, and in relation to the prevalence of storms defined around Hawaii.

Projected Population Sizes and Population ID


Figure 44: Projected Population Sizes, and population IDs used in the analsis, each ID correspondes to a separate PVA projection.

Strike Affect per Polygon for Ka:
Derived from Topographic Distance Flight paths from multiple points from Origin to Coast


Figure 45: Proportional, scaled Strike Affect per polygon as defined using the projected flight path information. Numbers within each polygon correspond to the polygons identification number. The Transmission Lines on Kauai for which Strikes were projected are shown in grey.

Normalized Light Affect per Polygon:
Derived from Topographic Distance Flight paths from multiple points from Origin to Coast


Figure 46: Proportional, scaled Light Affect per polygon as defined using the projected flight path information. Numbers within each polygon correspond to the polygons identification number. The Light Viewshed from which the light affect was defined are shown in various shades of yellow.

Compiled Histograms of Years to Extirpation showing all Scenarios: No Strikes


Figure 47: Histograms of projected Years to Ecological Extinction as compiled for all light fallout and predation scenarios without strike mortalities applied to the population. Various colors and line markings are used to indicate the specific light fallout scenario in each predation graphic (see legend for details). The projected effect of all four predation scenarios (KSHCP-KESRP (A), Griessemer \& Holmes Low (B), Griessemer \& Holmes Medium (C), Griessemer \& Holmes High (D)) is defined per graphic.


Figure 48: Histograms of projected Years to Ecological Extinction as compiled for all light fallout and predation scenarios with strike mortalities applied to the population. Various colors and line markings are used to indicate the specific light fallout scenario in each predation graphic (see legend for details). The projected effect of all four predation scenarios (KSHCP-KESRP (A), Griessemer \& Holmes Low (B), Griessemer \& Holmes Medium (C), Griessemer \& Holmes High (D)) is defined per graphic.


Figure 49: Histograms of projected lambdas as compiled for all light fallout and predation scenarios without strike mortalities applied to the population. Various colors and line markings are used to indicate the specific light fallout scenario in each predation graphic (see legend fo rdetails). The projected effect of all four predation scenarios (KSHCP-KESRP (A), Griessemer \& Holmes Low (B), Griessemer \& Holmes Medium (C), Griessemer \& Holmes High (D)) is defined per graphic.


Figure 50: Histograms of projected lambdas as compiled for all light fallout and predation scenarios with strike mortalities applied to the population. Various colors and line markings are used to indicate the specific light fallout scenario in each predation graphic (see legend fo rdetails). The projected effect of all four predation scenarios (KSHCP-KESRP (A), Griessemer \& Holmes Low (B), Griessemer \& Holmes Medium (C), Griessemer \& Holmes High (D)) is defined per graphic.


Figure 51: Projected years to Ecological Extinction, as projected for all KESRP polygons susing the KSHCP-KESRP predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 52: Projected years to Ecological Extinction, as projected for all KESRP polygons susing the KSHCP-KESRP predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 53: Projected Lambda, as projected for all KESRP polygons susing the KSHCP-KESRP predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 54: Projected Lambda, as projected for all KESRP polygons susing the KSHCP-KESRP predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 55: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - Low predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 56: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - Low predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 57: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - Low predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 58: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - Low predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 59: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - Medium predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 60: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - Medium predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0}$ \% fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), 67 \% fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 61: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes Medium predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 62: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes Medium predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 63: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - High predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0}$ \% fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 64: Projected Years to Ecological Extinction, as projected for all KESRP polygons susing the Griessemer \& Holmes - High predation scenario with strikes. Each Graphic defines a different light fallout scenario ( $\mathbf{1 0 0 \%}$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $\mathbf{6 7 \%}$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 65: Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - High predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.


Figure 66 Projected Lambda, as projected for all KESRP polygons susing the Griessemer \& Holmes - High predation scenario without strikes. Each Graphic defines a different light fallout scenario ( $100 \%$ fledgeling fallout (a), $\mathbf{8 0 \%}$ fledgling fallout (B), $67 \%$ fledgeling fallout (C), $\mathbf{5 0 \%}$ fledgling fallout (D)). These scenarios were defined in relation to the birds collected by the Save our Shearwaters program.

## 6. SECTION 6: META-POPULATION MITIGATION VIABILITY REPLACEMENT CALCULATOR

The replacement calculator is meant as a quick and basic overview of the efficacy of mitigation on the population as a whole. It does not account for potential site-specific demographic variance, stochastic variation, or carrying capacities. As such, the tool is meant to act as a quick assessment for any proposed mitigation strategy. Though it uses proportions of the types of mitigation to determine the efficacy of each mitigation strategy, it does not assess this on a site specific basis. Estimates of line strikes, predation, and light fallout are used to modify the base population demographic information to assess population growth or decline. Although the replacement calculator is useful in ranking different mitigation actions, and as a general forecast of production, there are drawbacks to this approach. One major drawback is that it gives a single number (i.e., Adult mitigation number or Population number) as its output for each year, implying an unsubstantiated level of accuracy. Although the SbS-PVA can also incorporate these mitigation estimates, the replacement calculator is an initial deterministic assessment, and so can be used to quickly evaluate any proposed mitigation strategy on the overall metapopulation.

### 6.1 Base Population Demography without Mitigation Used in the Replacement Calculator

Like the SbS-PVA many of the demographic parameters used here are derived from (and reviewed extensively in) Ainley et al. (2001) and Griesemer and Holmes (2011). Prior to incorporating mitigation effects, the initial deterministic assessment of population growth followed the same methodology as the SbS-PVA. Because the Upper Limahule (ULM) area currently has ungulate fencing and predator control, mitigation provided by ULM is automatically added to any projection from the point at which the calculator is run, into perpetuity.

### 6.2 Mitigation Strategy Implementation

Eight mitigation control strategies were used in the replacement calculator. These strategies were considered to be potentially significant in the mitigation of powerline strike and light fallout. The control strategies, and their respective inputs, are presented in Table 15, as
calculated using the KESRP predation estimate, and control (rather than eradication) at levels equivalent to $50 \%$ of the complete effects of predation eradication (see Tables 16 and 17) . Barn owl control was considered a strategy that could be implemented for each scenario, and over the complete population, this was due to the mobility of barn owls as compared to the other organisms, and thus the control mechanisms long range impact. Parameter inputs for each control strategy are specifically described in Table 16. Each control estimate was derived from variations in Table 14 that represented the proportional effect mitigation of the various predators would have on a population of 100 breeding adults when various control strategies are applied. In other words, it represents the increase in population due to each mitigation strategy for a colony with 100 breeding pairs.

To use this calculator it is initially necessary to define the total area of occupied sites. The scenario defined here (Table 17) is an initial projection defined from the summation of all the areas of the known occupied sites divided by the percentage these sites that were thought to make up of the total known and potential NESH sites ( $\sim 81 \%$ ). Then, for each mitigation control strategy (except the social attraction sites) the proportional area occupied by that strategy (specified by the user), as compared to the area of occupied sites (known and unknown), was determined. In the calculator, these areas are used to define the influence of each mitigation strategy on the overall population. The Barn Owl control strategy was applied throughout the population over all mitigation strategies. It is strongly recommended that the user of the calculator define and support their own inputs, independent of any assessed here, as those defined here are only used as an example.

Mitigation start times and the mitigation sequential effect are also variables that can be specifically modified. The mitigation start times (Table 16, code: CntrlStart) is the time it takes for any proposed work to start, whereas the mitigations sequential affect (Table 16, code: MitYrs) estimates the number of years it takes to completely implement the proposed mitigation strategies. The mitigation sequential effect modification essentially linearizes the effect of the proposed mitigation strategies, from the point at which mitigation starts to the point at which it is completed (e.g. fences are done etc.). The complete effect of each mitigation control strategy implemented is assessed at the end of the number of years defined until complete implementation
(MitYrs), and into perpetuity. This is applied similarly to all strategies except the social attraction mitigation factor.

Because there is very little information regarding the efficacy and population increase brought about by Social Attraction, it was left to the user of the replacement calculator to define the number of burrows that would be produced after a certain number of years of mitigation implementation (and attraction of NESH to the site). The parameter the user must modify to do so is termed the Bdivisore in Table 16. Examples of some variations that the user can apply are identified in the calculator code and Table 16. The effect of predator removal and fencing on these sites is comparable to that of the Predator exclusion with Barn owl control strategy (Table 15).

Unlike the other strategies where the proportion of the total area was identified, users are requested to input the total area (in Hectares) to be occupied by the social attraction mitigation strategy. Since this strategy, by definition, expands the total area occupied, it was necessary to initially separate the population growth defined by this strategy from the other assessments and as such separate the area. To derive an easy to use proportional constant, the area for social attraction was then divided by the total area NESH occupy (Tot_HA), with the area of social attraction added. This constant was a necessary input in order to modify the efficacy of the strategy appropriately.

Implementation for social attraction involves complete predator removal (and Barn Owl control) within fenced areas, as well as attraction unit positioning and activation. It was theorized that the implementation of all of these would take the extent of MitYrs (i.e. no radio units active after MitYrs) consequently only the effect of the predator free fence is estimated for the colony (attracted by the radio units) after MitYrs and into perpetuity.

### 6.3 Estimating Mitigation Effect

To estimate mitigation effect over time it was first necessary to define the current number of burrows per hectare, and with that, the number of breeding adults. This was accomplished by estimating the total number of adults using an Eigen analysis of a stable age distribution and summing those ages that are reproductively active ( $>6$ ). The number of reproductive adults was then estimated by multiplying the number of adults by the reproductive probability estimated for
the predation estimate. To derive burrows per hectare, the estimated value for the number of reproductive adults was then divided by two (assuming an equal sex ratio), and further divided by the total number of hectares estimated to be on Kauai (as characterized by Tot_HA).

As stated above, only those estimates of mitigation defined in Table 15, combined with the user defined control estimates in Table 16, were used to estimate the efficacy of each mitigation strategy. This efficacy was expressed in the calculator by defining the proportional survivorship increases per age class that the compiled mitigation strategies represent. For all strategies, but social attraction, this compiled mitigation effect was estimated prior to the yearly projection, and then added to the base predation estimate after CntrlStart. This was done either in increments of (CntrlStart+t)/MitYears (where time ( $t$ ) starts at 1+CntrlStart, and continues over MitYears), or completely after MitYears. A similar assessment of mitigation was also conducted for social attraction, but because social attraction involves adding individuals to the population it was assessed separately and added to the overall analysis each year.

The replacement calculator outputs a table per projected year defining various trends in the population. An overview and description of each output is shown in Table 18.

### 6.4 Replacement Calculator: Output

Though the replacement calculator uses acreage of the types of mitigation to determine the efficacy of each mitigation strategy, it does not assess this on a site specific basis. For a more indepth description of the analysis, and the caveats concerning this assessment, please see Section 6.3.

As an example of the replacement calculator output and utility, the input variables were set such that each of the mitigation procedures was conducted over an equal area $\left(1 / 7^{\text {th }}\right.$ of the total area each), and 100 hectares of social attraction sites were added to the total area of the polygons. The strike mortality defined in Section 5 was used in this assessment as the strike mortality input, from which years until replacement was assessed. In this run, control was set to start at year two, and the number of available hectares was derived from the KESRP polygons (see Table 17 for input variables).

Using these input variables, which are used here only for descriptive purposes, the results indicate that strike replacement through these mitigation efforts is likely not to occur (see Table

19 for an example output, and Figure 67 for the results of the run). In the graphic output with each assessment, the year at which the meta-population of NESH is equivalent to when the population was run is also defined. This point has been implicated as a potential point of interest in helping to define mitigation success. The scenario used for this depiction is only for descriptive and demonstration purposes.

As defined in table 16, there is also an input parameter that allows the user to assess the current meta-populations viability (NoControlScen) given the predation estimate defined by the user (PredationEst). Setting NoControlScen to "True" creates a projection of the meta-population without any mitigation. When applying this to the example inputs defined in Table 17, the projected population without mitigation is shown in Figure 68.

Scenarios selected for further assessment should take into account available habitat (especially given the potential of landowner issues), minimize cost, and maximize mitigation that can be conducted in a timely manner. The R script for the replacement calculator, as initially defaulted to this scenario, can be accessed in the supplementary code Section 6.7.

### 6.5 Section 6: TABLES

Table 15: Mitigation effect of each predator reduction scenario used in the replacement calculator. These estimates were modified to reflect the Predation lambda sestimated by KESRP/KSHCP. For the KESRP/KSHCP predation scenario the mitigation estimate and the resulting predator reduction was defined as the number of individuals added to the population from each scenario for a population with 100 breeding pairs. Control (not exclusion) here was estimated to be $\mathbf{\sim 5 0 \%}$ of predation (see Table 16).

|  | Ungulate Predation Reduction |  |  | Cat Predation Reduction |  |  | Rat Predation Reduction |  |  | Barn Owl Predation Reduction |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (0-1) | (1-5) | (6+) | (0-1) | (1-5) | (6+) | (0-1) | (1-5) | (6+) | (0-1) | (1-5) | (6+) |
| Predator exclusion fence with Barn owl control | 11.68 | 3.82 | 4.18 | 11.68 | 3.82 | 4.18 | 12 | 0 | 0 | 0.96 | 0.52 | 0.48 |
| Ungulate exclusion fence with Cat and Barn Owl control | 11.68 | 3.82 | 4.18 | 5.84 | 1.91 | 2.09 | 0 | 0 | 0 | 0.96 | 0.52 | 0.48 |
| ALL predator control (i.e. not exclusion) | 5.84 | 1.91 | 2.09 | 5.84 | 1.91 | 2.09 | 6 | 0 | 0 | 0.96 | 0.52 | 0.48 |
| Ungulate exclusion and predator control | 11.68 | 3.82 | 4.18 | 5.84 | 1.91 | 2.09 | 6 | 0 | 0 | 0.96 | 0.52 | 0.48 |
| Ungulate and Cat exclusion fence, all other predators controlled | 11.68 | 3.82 | 4.18 | 11.68 | 3.82 | 4.18 | 6 | 0 | 0 | 0.96 | 0.52 | 0.48 |
| Barn Owl and Cat control only | 0 | 0 | 0 | 5.84 | 1.91 | 2.09 | 0 | 0 | 0 | 0.96 | 0.52 | 0.48 |
| Barn Owl control only | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.96 | 0.52 | 0.48 |
| Social Attraction in exclusion fence | 11.68 | 3.82 | 4.18 | 11.68 | 3.82 | 4.18 | 12 | 0 | 0 | 0.96 | 0.52 | 0.48 |

Table 16: Input parameters used in the replacement calculator

| INPUT | USER INPUT DESCRIPTION |
| :---: | :---: |
| PredationEst | Predation estimate to be used (1, 2, 3 or 4). Values correspond to the <br> KSHCP/KESRP (1), and Greissemer and Holmes (2011) low (2) and <br> medium (3) and high (4) predation estimates respectively. |
| MetaPopSize | The estimated Kauai meta-population size for the year at which the <br> estimator was run. |
| KCap | The NESH Carrying Capacity (per Hectare) estimate for adult birds <br> The year that the data used to define the meta-population size was <br> obtained. This is used to calculate the meta-population size at the <br> time the calculator was run. |
| YearPopEstimated |  |


| INPUT | USER INPUT DESCRIPTION |
| :---: | :---: |
| Bdivisore | Divisor to defining how many burrows at the end of building fences (MitYrs) will be in a social attraction predator exclusion enclosure. <br> So, when "MitYrs" equals 10, after 10 years of mitigation: <br> - a "Bdivisore" value of $2.9754449=100$ birds/ 100 hectares <br> - a "Bdivisore" value of 5.95089 (2.9754449*2)=50 birds/100 hectares <br> - $\quad a$ "Bdivisore" value of $14.87722(2.9754449 * 5)=20$ birds/100 hectares <br> - $\quad$ "Bdivisore" value of $29.75445(2.9754449 * 10)=10$ birds/100 hectares |
| DCN | Desktop computer user name |
| THESE VALUES MUST SUM TO ONE |  |
| PercExclusion | The proportional area of predator exclusion mitigation with Barn owl control |
| PercUngulate | The proportional area of only Ungulate fencing with Cat and Barn Owl control |
| PercPrCntrl | The proportional area of all predator control (not exclusion) |
| PercUngPrCntrl | The proportional area of ungulate exclusion and predator control |
| PercUngPrCntrlNoCats | The proportional area of ungulate and cat exclusion with other predators controlled |
| PercBarnOwlCatOnly | The proportional area of Barn Owl and Cat control |
| PercBarnOwlOnly | The proportional area of Barn Owl control |

Table 17: Inputs used in the replacement calculator example. Input values used here are only meant to help understand the example outputs.

| INPUT | USER INPUT DESCRIPTION |
| :---: | :---: |
| PredationEst | 1 |
| MetaPopSize | $27011^{*} 0.9$ |
| YearPopEstimated | 2011 |
| KCap | 1000 |
| CntrlStart | 2 |
| MitYrs | 10 |
| Tot_HA | 1122.7 |
| popPercEx | 0.81 |
| year | 100 |
| TotStrk | 1800 |
| TotLight | 0 |
| NoControlScen | FALSE |
| PercExclusion | $1 / 7=0.1428571$ |
| PercUngulate | $1 / 7=0.1428571$ |
| PercPrCntrl | $1 / 7=0.1428571$ |
| PercUngPrCntrl | $1 / 7=0.1428571$ |
| PercUngPrCntrlNoCats | $1 / 7=0.1428571$ |
| PercBarnOwlCatOnly | $1 / 7=0.1428571$ |
| PercBarnOwlOnly | $1 / 7=0.1428571$ |
| CntrlUngulate | 0.5 |
| CntrlCat | 0.5 |
| CntrlRat | 0.5 |
| CntrlBarnOwl | 0.5 |
| HAExlcusion | 10 |
| Bdivisore | 29.754449 |
| DCN | 'avorsino' |

## Table 18: Replacement Calculator output legend

OUTPUT
DESCRIPTION

| Year | HCP implementation year. For example, this could be year 2015 under the KIUC Short-term HCP. |
| :---: | :---: |
| Burrow | Multiplying the total number of reproductive adults by their probability of reproduction, and dividing by two (assuming a $50: 50$ sex ratio) to obtain the number of burrows. |
| Birds | Number of reproductive adults estimated to be receiving some form of management. This is based on a stable age distribution, where $86 \%$ of the population is age 6 or older, and the managed/known subpopulation is receiving a constant level of predation, light attraction fallout, and power-line strike collisions. Please, note the Replacement calculator currently assumes that the entire population (known or unknown) will receive barn owl control. |
| Adult Mitigation | Number of adults produced. The Replacement calculator adds mitigation achieved to date from Upper Limahuli Preserve into Year 1. |
| Juvenile Mitigation | Number of juveniles/fledglings produced. |
| Deficit | Total deficit due to the strikes per year and the mitigation available/planned to reduce that deficit, influenced by the six-year breeding age delay. |
| Deficit Adult | Adult deficit, assumes that of the total strikes $20 \%$ are adults. |
| Deficit Sub-Adults | Sub-adult deficit, assumes that of the total strikes $80 \%$ are sub-adults. |
| Population | Population of NESH on Kauai at each time point |
| Predation | Predation and fallout impacts are estimated as changes to the demographic parameters. |
| Demographic Lambda | Population growth rate as defined from an Eigen analysis of the demographic data per projected year. |
|  | Characterizes population increase using year to year growth/decline. It is characterized by the following equation: $P L_{t}=\frac{N_{t}}{N_{t-1}}$ |
| Population Lambda | Here $P L_{t}$ represents the population growth rate at year $t$, and $N$ defines the number of individuals in $t$. This metric was used in concert with the Demographic Lambda to more accurately characterize the effect of population growth rate from social attraction sites. It was necessary to do so because very little information is available concerning the efficacy of social attraction, and thus user input greatly influences the effect of this mitigation strategy. |
| Birds Not In Polygons | Number of individual birds estimated to be elsewhere in unknown locations (e.g., Private land), outside of the total hectares estimated. |
| Strike Mortalities | Assumes line strikes affect the entire NESH population and not just the known colonies. The current Replacement calculator does not include any reductions in strikes due to minimization efforts, but once information is available about the efficacy of line strike reduction efforts, future iterations are capable of incorporating these minimization efforts. |

Table 19: Replacement calculator output of the first 15 years, as estimated for the parameters identified in Table 17. For an explanation of the columns please see Table 18 in the materials and methods.

VALUES FOR EACH ITEM DEFINED FOR EACH PROJECTED YEAR

| Year | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Burrow | 4189.35 | 3763.94 | 3381.72 | 3382.06 | 3057.09 | 2798.56 | 2594.77 | 2436.95 | 2318.64 | 2235.19 | 2183.45 | 2161.53 | 2167.82 | 2196.76 | 2226.85 | 2258.16 |
| Birds | 9521.26 | 8554.40 | 7685.72 | 6945.69 | 6355.94 | 5889.80 | 5527.31 | 5253.70 | 5058.32 | 4933.88 | 4875.98 | 4880.83 | 4944.34 | 5010.34 | 5078.98 | 5150.36 |
| Adult Mitigation | 0.00 | 0.00 | 0.00 | 33.57 | 61.45 | 85.43 | 106.93 | 127.11 | 146.95 | 167.36 | 189.19 | 213.26 | 240.31 | 243.57 | 246.96 | 250.48 |
| Juvenile Mitigation | 0.00 | 0.00 | 0.00 | 43.34 | 78.38 | 107.66 | 133.17 | 156.45 | 178.81 | 201.35 | 225.12 | 251.13 | 280.37 | 284.21 | 288.20 | 292.35 |
| Deficit | 1800.00 | 3414.07 | 4863.91 | 6100.01 | 7161.70 | 8082.01 | 8886.81 | 9596.47 | 10227.09 | 10791.41 | 11299.44 | 11758.70 | 12174.32 | 12596.00 | 13023.98 | 13458.52 |
| Deficit Adult | 360.00 | 682.81 | 972.78 | 1220.00 | 1432.34 | 1616.40 | 1777.36 | 1919.29 | 2045.42 | 2158.28 | 2259.89 | 2351.74 | 2434.86 | 2519.20 | 2604.80 | 2691.70 |
| Deficit Sub-Adults | 1440.00 | 2731.26 | 3891.13 | 4880.00 | 5729.36 | 6465.61 | 7109.45 | 7677.18 | 8181.67 | 8633.13 | 9039.55 | 9406.96 | 9739.46 | 10076.80 | 10419.18 | 10766.82 |
| Population | 22990.63 | 20656.00 | 18558.44 | 16770.42 | 15346.45 | 14221.03 | 13346.06 | 12686.04 | 12215.50 | 11917.11 | 11780.59 | 11797.51 | 11959.00 | 12126.97 | 12301.72 | 12483.59 |
| Predation | 4503.23 | 4045.94 | 3635.08 | 3192.58 | 2740.33 | 2371.45 | 2066.96 | 1812.06 | 1595.59 | 1408.81 | 1244.54 | 1100.98 | 978.62 | 971.97 | 969.03 | 967.98 |
| Demographic Lambda | 0.90 | 0.90 | 0.90 | 0.90 | 0.91 | 0.92 | 0.93 | 0.94 | 0.95 | 0.96 | 0.97 | 0.98 | 0.99 | 0.99 | 0.99 | 0.99 |
| Population Lambda | 0.00 | 0.90 | 0.90 | 0.90 | 0.92 | 0.93 | 0.94 | 0.95 | 0.96 | 0.98 | 0.99 | 1.00 | 1.01 | 1.01 | 1.01 | 1.01 |
| Birds Not In Polygons | 4368.22 | 4368.22 | 4368.22 | 3924.64 | 3526.10 | 3168.04 | 2846.33 | 2557.29 | 2297.61 | 2064.29 | 1854.67 | 1666.33 | 1497.12 | 1345.09 | 1208.50 | 1085.78 |
| Strikes Mortalities | 1800.00 | 1617.22 | 1452.99 | 1313.00 | 1201.52 | 1113.40 | 1044.90 | 993.22 | 956.39 | 933.02 | 922.33 | 923.66 | 936.30 | 949.45 | 963.14 | 977.37 |

### 6.6 Section 6: FIGURES

## Projected Mitigation and Mortality Effects



Figure 67: Figure output for the Replacement Calculator using the parameters defined in table 18. The output shows the trend lines of the overall meta-population (blue), the Social attraction based population (dotted blue), the accumulated mortalities due to strikes over time (black), the number of mortalities due to predation (red) and the Year to Year (not accumulated) strike mortalities (green). The parameters used to project the assessment are also embedded into the figure, this allows for easy differentiation between different analyses.


Figure 68: Figure output for the Replacement Calculator using the parameters defined in table 18, but with the NoControlScen parameter set to TRUE. Setting this parameter to "True" turns off all mitigation scenarios and outputs a deterministic Population Viability Assessment for the meta-population using the specified predation estimate. The output shows the trend lines of the overall meta-population (blue), the Social attraction based population (dotted blue), the accumulated mortalities due to strikes over time (black), the number of mortalities due to predation (red) and the Year to Year (not accumulated) strike mortalities (green). The parameters used to project the assessment are also embedded into the figure, this allows for easy differentiation between different analyses.

# Code 1: Replacement Calculator for NESH Strategy.R 

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Tue Sep 14 13:20:26 2016

## \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#NESH STRIKE REPLACEMENT CALCULATOR TO ASSESS OVERALL MITIGATION AFFE CTS ON THE META-POPULATIUON\# <br> \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#

```
rm(list = ls())
# For further information about this calculator please contact the author at:
#
# Adam E. Vorsino, Ph.D.
# Strategic Habitat Conservation Division
# Pacific Island Fish and Wildlife Office
# 300 Ala Moana Blvd. Ste. 3-122
# adam_vorsino@fws.gov
# (808)792-9431
#
#
# Disclaimer:This calculator was developed to assess the potential for certain mitigation tec# hniques to mitigate p
owerline strikes on Newell's Shearwater. To do this, the assessment us# es various predator control mitigation tech
niques/scenarios. The information used to devel# op this assessment is specific to Newell's shearwater and so should
not be used to assess effe# cts at sites that are not suitable for this species. The population information is up-to-date
as # of 3/7/2016. Please use and review the input and output car fully. The user of this tool is so# lely responsiblef
or the input and output of the assessment. This calculator is provided as te# chnical assistance and does not represe
nt USFWS/Service policy. It should be used only if it # c onstitutes the best available scientific information on a cas
e-by-case basis.
```

```
#################################################################
##### INPUT PARAMETERS FOR SOCIAL ATTRACTION SITE CALCULATOR ########
##
```

\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\# PREDATOIN ESTIMATE
\# Can use 1, 2, 3 or 4 this corresponds to the KSHCP predation estimate (1),
\# and Greissemer and Holmes (2011) low (2) and medium (3) and high (4) predation
\# estimates respectively. It is a good practice to look at all four...
PredationEst <-1\#UserSpecified\# inpute 1, 2, 3, or 4 (as defined above) to define the predation $e$
stimates

# \#POPULATION <br> MetaPopSize <- 27011 * 0.9\#UserSpecified\# \# Estimated Population on Kauai 

\# The Year the population estimate data were collected (or if unknown the year it was defined)
YearPopEstimated <- 2011\#UserSpecified\#
\#CARRYING CAPACITY
KCap <- 1000\#UserSpecified\# \# Define a Carrying Capacity (per Hectare) estimate for adult bir ds for the areas being estimated

## \#\# MITIGATION START YEAR

CntrlStart <-2\#UserSpecified\# \# Year at which Control would Start. Upper Limahule control a dded to population at year 1

```
# The following defines the time it takes for mitigation (i.e. fenceing etc.) to be completed.
# It essentially Defines a gradual increase in control until asymptoting at year X after the start of control
MitYrs <- 10#UserSpecified# # years until complete mitigation takes place, where the start is at
"CntrlStart" (must be a number > or =2 b/c it accounts for the year started and the next year in
which it was implemented)
```


## \#AREA IN QUESTION

```
Tot_HA <- 1122.7 \#UserSpecified\# \# Total Number of Hectares estimated to be breeding habita \(t\)
popPercEx <- 0.81 \#UserSpecified\# \# How much of the population (Proportion between 0 to 1) \(i\) s accounted for by the Hectares estimate (Tot_HA) above
```


## \# YEARS TO RUN ANALYSYS

year <- 100 \#UserSpecified\# \# number of years to project to

## \#\#\#\#STRIKE MORTALITIES\#\#\#\#

TotStrk<-1800 \# Estimate yearly strikes to be used to assess when replacement occurs

## \#\#\#LIGHT MORTALITIES\#\#\#

TotLight <- 0 \# Estimate of yearly fledgling light fallout mortalities that can be added to the over all assessment

## \#\#\#\#\#\#\# CONTROL SCENARIOS \#\#\#\#\#

\# If a Deterministic assessement of the status of the meta-population is wanted without any control metrics appliedIf 'TRUE' no control scenario will be applied (all control metrics are equal to 0) If false, all those defined below will ap ply.

## NoControlScen <- FALSE \#

## \#\#\#\#\#\#\# CONTROL SCENARIOS \#\#\#\#\#

\# Proportion of each control metric (OTHER THAN SOCIAL ATTRACTION) to be appl\# ied to the overall HA to conserve, sum to 1 (ALL BUT PercUngulate HAVE BARN \# OWL AND CAT CONTROL)

PercExclusion <- 1/7\#UserSpecified\# \# Defines Proportional area of predator exclusion mitigati on with Barn owl control
PercUngulate <- 1/7\#UserSpecified\# \# Defines Proportional area of only Ungulate fenceing with Cat and Barn Owl control
PercPrCntrl <- 1/7\#UserSpecified\# \# Defines Proportional area of ALL predator Control (not ex clusion)
PercUngPrCntrl <- 1/7\#UserSpecified\# \# Defines Proportional area of ungulate exclusion and p redator control
PercUngPrCntrlNoCats <- 1/7\#UserSpecified\# \# Defines Proportional area of ungulate and cat exclusion with other predators controled
PercBarnOwlCatOnly <- 1/7\#UserSpecified\# \# Defines Proportional area of Barn Owl and Cat control only
PercBarnOwlOnly <-1/7\#UserSpecified\# \# Defines Proportional area of Barn Owl control only

```
# CONTROL LEVELS FOR SCENARIOS THAT DO NOT DEPEND ON EXCLUSION
# Used to define the levels that define control of the various organisms.
# This metric is used in combination with the above control scenario percentages to define the
# level of control to acheive that specific scenario. As this is a proportion (range from 0 to 1),
# a value of 1 defined complete control of that organism. This level of control only applies to the
# specific control scenario area amount defined above. For instance in the Exclusion area, only
# the Barn owl control metric is used.
CntrlUngulate <- 0.5#UserSpecified#
CntrlCat <- 0.5#UserSpecified#
CntrlRat <- 0.5#UserSpecified#
CntrlBarnOwl <- 0.5#UserSpecified#
```

\# AREA OF SITE TO BE USED FOR SOCIAL ATTRACTION (in HA)
HAExclusion <- 10\#UserSpecified\# \# Hectares to be used for Social Attraction Sites

## \#\#\# DIVISORE FOR SOCIAL EXCLUSION PARAMETERS \#\#\#

\# Divisore to define how many burrows at the end of building fences (MitYrs) will be in the exclosure \# So, when "MitYrs" equals 10 after 10 years of mitigation \# a "Bdivisore" value of $2.9754449=100$ birds $/ 100$ hectares; \# a "Bdivisore" value of 5.95089 (2.9754449*2)= 50 birds/100 hectares;
\# a "Bdivisore" value of $14.87722(2.9754449 * 5)=20$ birds/ 100 hectares;
\# a "Bdivisore" value of $29.75445(2.9754449 * 10)=10$ birds 100 hectares
Bdivisore <- 29.75445
\#Put Desktop Computer User Name here or (if not a federal computer that needs admin privileg es) use "Public"
DCN <- 'avorsino'\#UserSpecified\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#\#\#\#DO NOT MODIFY PAST THIS SECTION \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#

```
if(NoControlScen == T){
    errortest<-1
```

```
    PercExclusion <- 0
    PercUngulate <- 0
    PercPrCntrl <- 0
    PercUngPrCntrl <- 0
    PercUngPrCntrlNoCats <- 0
    PercBarnOwlCatOnly <- 0
    PercBarnOwlOnly <- 0
    HAExclusion <- 0
}else{
    errortest<-signif(sum(PercExclusion+PercUngulate+PercPrCntrl+PercUngPrCntrl+PercUn
gPrCntrlNoCats+PercBarnOwlCatOnly+PercBarnOwlOnly),4)
}
if (errortest!=1){
    cat(" !CONTROL SCENARIOS (EXCEPT FOR SOCIAL ATTRACTION) MUST SUM TO 1!
")
}else{
    Dir<-paste0('C:/Users/', DCN, '/Desktop/KESRP_Mit_Start_Yr_', CntrlStart,'_with_', MitYrs,
'_Yr_Imp/')
    if(file.exists(Dir) == F){
        dir.create(Dir)
    }
    if ((is.na(installed.packages()[,"Package"]["popbio"]))==T){
    install.packages("popbio", dependencies = T)
    }
    library(popbio)
    HA <- (Tot_HA/popPercEx)
```

\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#MAKEING THE LIFE TABLE AND PROJECTION MATRIX USING Qx AND Px\#\#\#
\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#
PercSocialExclusion <- HAExclusion/((Tot_HA/popPercEx) + HAExclusion)
HA2 <- ((Tot_HA/popPercEx) + HAExclusion)
\#\#\#\#\#\#\#\#\#\#Defining carrying capacity for Social Attraction Sites\#\#\#\#\#\#\#\#\#\#\#
SE_K <- KCap \#
\#\#\#\#\#\#\#\#\#\#\#\#\# Defined from Breeding Success and Reproductive Success of Procelarif
orms (with not predation) to get Standard Deviations\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#Calculation of Breeding Probability from G\&H 2011 and KESRP 2013 data
BrProb<-c(0.87, 0.90, 0.80, 0.72, 0.81, 0.75, 0.83, 0.95, 0.89, 0.90, 0.86, 0.80, 0.74, 0.83, 0.6
9)
\#\#\#\#\#\#\#Calculation of Reproductive Success from G\&H 2011 (no predators present (<= \#11) or eradicated (> \#11))
ReproSucc<-c(0.52, 0.51, $0.63,0.35,0.76,0.61,0.52,0.58,0.70,0.62,0.61,0.81,0.51,0.76$, 0.7,

$$
0.62,0.67,0.31,0.53,0.66,0.38,0.47,0.59,0.73,0.75,0.68,0.56,0.60,0.77,0.72
$$ $0.59,0.64,0.75,0.60,0.59,0.64,0.54,0.56)$ \# removed outlier Procellaria aequinocti

alis $=0.22$

NESH_age<-36 \# age of oldest probable NESH
NESHfirst_rep<-6 \# age reproduction occurs for NESH
Age<-c(0, seq(1, NESH_age, 1))

```
Lx<-c(1)
for (ti in 1:NESH_age){
    if (ti== 1){
        Lx<-cbind(Lx, Lx*0.654)
    }
    if (ti == 2){
        Lx<-cbind(Lx, Lx[length(Lx)]*0.78)
    }
    if (ti== 3){
        Lx<-cbind(Lx, Lx[length(Lx)]*0.89)
    }
    if (ti== 4){
        Lx<-cbind(Lx, Lx[length(Lx)]*0.905)
    }
    if (ti== 5){
        Lx<-cbind(Lx, Lx[length(Lx)]*0.905)
    }
    if (ti== 6){
    Lx<-cbind(Lx, Lx[length(Lx)]*0.905)
    }
    if (ti > 6){
    Lx<-cbind(Lx, Lx[length(Lx)]*0.92)
    }
}
Lx<-as.numeric(as.character(Lx))
```

\# No PRedators
\# Used these estimates for reproductive success without predators because the average foun
$d$ for NESH with some level of control was
\# 0.88 NESH repro prob, and 0.75 NESH repro. success (max $=0.95$ and 0.81 respectively). F
or an area with some level of control (Upper limahule) repro. succes was estimated
\# at 0.902439 and repro. prob was 0.7837838 . Given that ULM has ungulate fenceing and pr
edator control (not exclusion), it is
\# definitive that these numbers are probably even higher for an area with predator exclusion
, as such these numbers were selected
Ex_JuviSucc<-boxplot(ReproSucc, plot=F)\$stats[5,]\# the upper whisker of reproductive suc cess ( $=0.81$ )
Ex_ReproProb<-boxplot(BrProb, plot=F)\$stats[4,]\# the 3rd Quantile of reproductive succe ss ( $=0.88$ ) \# 0.91

Mx<-c(rep(0, (NESHfirst_rep)), rep(Ex_JuviSucc*Ex_ReproProb, (NESH_age-NESHfirst_rep $+1)$ )
life_table<-data.frame(cbind(Age, Lx, Mx))
\#Calculating Qx and Px to define the population wihout predation (Leslie Matrix) (original G \&H 2011 growth estimates)
proj_mat<-matrix(rep(0,NESH_age*NESH_age),nrow=NESH_age) \#NEED TO CHANGE THI S TO MAKE SEABIRD SPECIFIC for (i in 1:nrow(life_table))\{
if $((\mathrm{i}==$ nrow(life_table) $)==\mathrm{T})\{$
life_table[i,'Qx']<-1.0000
\}else\{
life_table[i,'Qx']<-round((life_table[i, 'Lx']-life_table[i+1, 'Lx'])/life_table[i, 'Lx'], digits = 4) \}
life_table[i,'Px']<-(1-life_table[i, 'Qx']) \# this is the stable projection for comparison
for (ii in 1:nrow(life_table))\{
try(proj_mat[ii, ii]<-life_table[ii,'Px'], T) \# subtract by -0.038907 for completely stable po
p (lambda exactly ==1)
\}
\} \# end of "i"loop
proj_mat<-proj_mat[1:(NESH_age-1),]
jk<-proj_mat
\# The Growth Population Projection Matrix
\# from $G$ and $H$
Stable_Proj_mat<-as.matrix(rbind(Mx, jk), rownames.force= F) \#make sure it is a square matrix
colnames(Stable_Proj_mat)<-NULL
eigenNP<-eigen.analysis(Stable_Proj_mat, zero=TRUE) \# without strikes and without pred ation
Stable_Proj_matNP<-jk
MxNP<-Mx
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#

```
########### STEP 1 ESTIMATING AFFECTS OF PREDATION ############
###############################################################
#
    ############# Raw data from 2013 Raines North Bog, Pihea, Pohakea, and Upper Lim
ahule
    #############to define Breeding Success and Probability
    NESH_Monitord<-c(9,41) # # Active Burrows for Adult Estimate
    NESH_MonWBrd<-c(7, 37)
    NESH_MonWSuc<-c(4, 29)
    NESH_over_BrProb<-median(NESH_MonWBrd)/median(NESH_Monitord)
    NESH_over_BrSucc<-median(NESH_MonWSuc)/median(NESH_MonWBrd)
NESHReproProb<-0.547 # Ainley Average Reproductive Probability
```

```
##############################################################
```

\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\# KESRP ESTIMATED PREDATION AFFECTS FOR X BREEDING PAIRS PER PRE
\#\#\#\#\#\#\#\#\# KESRP ESTIMATED PREDATION AFFECTS FOR X BREEDING PAIRS PER PRE
DATOR \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
DATOR \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
if(PredationEst == 1){
LMH<-100
LMHName<-'KSHCP_KESRP' \# DEFINED BY KSHCP
}else{
if(PredationEst == 2){
LMH<-87.4675
LMHName<-'GH_Low' \# DEFININD IN G\&H
}else{
if(PredationEst==3){
LMH<-72.2599
LMHName<-'GH_Medium' \# DEFININD IN G\&H
}else{
LMH <-63.396
LMHName<-'GH_High' \# DEFINED IN G\&H
}
}
}
KESRPBreedingPairs<-LMH \#
AdultSubAdultSS<-eigenNP$stable.stage[3:length(eigenNP$stable.stage)]/sum(eigenNP\$
stable.stage[3:length(eigenNP$stable.stage)]) # start at stage 3 (2-3 y/o survivorship) b/c it
is when predation mortality starts
    NumAdults<-2*KESRPBreedingPairs
    AdultSubAdultForSANum<-eigenNP$stable.stage[2:length(eigenNP$stable.stage)]/sum(e
igenNP$stable.stage[2:length(eigenNP\$stable.stage)])

```
```

    # NumSubAdults<-sum(AdultSubAdultSS[1:4])*((KESRPBreedingPairs*2)/sum(AdultSubAd
    ultSS[5:length(AdultSubAdultSS)]))
\# NumSubAdultsTot<-sum(AdultSubAdultForSANum[1:(NESHfirst_rep-1)]*((KESRPBreedin
gPairs*2)/sum(AdultSubAdultForSANum[NESHfirst_rep:length(AdultSubAdultForSANum)])])
NumSubAdults<- sum(AdultSubAdultSS[1:(NESHfirst_rep-2)]*((KESRPBreedingPairs*2)/
sum(AdultSubAdultSS[(NESHfirst_rep-1):length(AdultSubAdultSS)]))) \# number of sub-ad
ults predated (i.e. after year 2)
numChicks<-KESRPBreedingPairs \# breeding pairs count assumes 100% breeding prob.
\#\#\#\#\#\#\#\# Overall Predation \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#Ungulate Predation
UngAdultPredation<-sum((8*AdultSubAdultSS[(NESHfirst_rep-1):length(AdultSubAdultS
S)])) \# adults >=6
UngSubAdultPredation<-sum((8*AdultSubAdultSS[1:(NESHfirst_rep-2)])) \# subadults fro
m age 2-5
UngChickPredation<-8+(UngAdultPredation*Ex_ReproProb)\#NESHReproProb) \# added al
l predated breeding adults to estimate chick predation due to parental death, estimated breed
ing probability to establish which to remove
PercUngPredAdults<- UngAdultPredation/NumAdults\#divide Adult \# by 2 to account for n
octurnal/crepuscular predation= when only 1 individual of pair at nest at that time
PercUngPredSubAdults<-UngSubAdultPredation/NumSubAdults
PercUngPredChick<-UngChickPredation/numChicks\# Any predation of adults would be a p
redation of chick as well...did not include breeding prob because this was already esimtated he
re

```

Ung_NESHReproProb<-0\#(UngAdultPredation*4)/NumAdults \# quadruples time until repr oduction so used it to modify repro. probability
\#Cat Predation
CatAdultPredation<-sum((8*AdultSubAdultSS[(NESHfirst_rep-1):length(AdultSubAdultS S)])) \# adults >=6

CatSubAdultPredation<-sum((8*AdultSubAdultSS[1:(NESHfirst_rep-2)])) \# subadults fro m age 2-5
CatChickPredation<-8+(CatAdultPredation*Ex_ReproProb)\#NESHReproProb) \# added all predated breeding adults to estimate chick predation due to parental death, estimated breedi ng probability to establish which to remove
PercCatPredAdults<- CatAdultPredation/NumAdults\#divide Adult \# by 2 to account for no cturnal/crepuscular predation= when only 1 individual of pair at nest at that time
PercCatPredSubAdults<-CatSubAdultPredation/NumSubAdults
PercCatPredChick<-CatChickPredation/numChicks\# Any predation of adults would be a pr edation of chick as well...did not include breeding prob because this was already esimtated her \(e\)

\section*{Cat_NESHReproProb<-0}
\#Rat Predation

RatAdultPredation<-0 \# adults >=6
RatSubAdultPredation<-0 \# subadults from age 2-5
RatChickPredation<-12+(RatAdultPredation*Ex_ReproProb)\#NESHReproProb) \# added al l predated breeding adults to estimate chick predation due to parental death, estimated breed ing probability to establish which to remove
PercRatPredAdults<- RatAdultPredation/NumAdults\#divide Adult \# by 2 to account for no cturnal/crepuscular predation= when only 1 individual of pair at nest at that time
PercRatPredSubAdults<-RatSubAdultPredation/NumSubAdults
PercRatPredChick<-RatChickPredation/numChicks\# Any predation of adults would be a pr edation of chick as well...did not include breeding prob because this was already esimtated her \(e\)

\section*{Rat_NESHReproProb<-0}

\section*{\#Barn Owl Predation}

BrOwlAdultPredation<-sum((1*AdultSubAdultSS[(NESHfirst_rep-1):length(AdultSubAdu ltSS)])) \# adults >=6
BrOwlSubAdultPredation<-sum((1*AdultSubAdultSS[1:(NESHfirst_rep-2)]), na.rm = T) \# subadults from age 2-5
BrOwlChickPredation<-0.5+(BrOwlAdultPredation*Ex_ReproProb)\#NESHReproProb) \# a dded all predated breeding adults to estimate chick predation due to parental death, estimate d breeding probability to establish which to remove
PercBrOwlPredAdults<- BrOwlAdultPredation/NumAdults\#divide Adult \# by 2 to account for nocturnal/crepuscular predation= when only 1 individual of pair at nest at that time
PercBrOwlPredSubAdults<-BrOwlSubAdultPredation/NumSubAdults
PercBrOwlPredChick<-BrOwlChickPredation/numChicks\# Any predation of adults would \(b\) e a predation of chick as well... did not include breeding prob because this was already esimtat ed here
```

    BrOwl_NESHReproProb<-0
    # making projection matrix bottom (not mortality/fertility information yet)
    ad_RatsOwl<-PercRatPredAdults+PercBrOwlPredAdults
    sa_RatsOwl<-PercRatPredSubAdults+PercBrOwlPredSubAdults
    ad_All<-PercUngPredAdults+PercCatPredAdults+PercRatPredAdults+PercBrOwlPredAdul
    ts
sa_All<-PercUngPredSubAdults+PercCatPredSubAdults+PercRatPredSubAdults+PercBrO
wlPredSubAdults

```
```

\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\# ALL PREDATORS ESTIMATES\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#

# Base Estimate all predators

Ex_AllPredAdults<-(((PercUngPredAdults+PercUngPredSubAdults)+
(PercCatPredAdults+PercCatPredSubAdults)+
(PercRatPredAdults+PercRatPredSubAdults)+

```
(PercBrOwlPredAdults+PercBrOwlPredSubAdults)))
Ex_APredJuviSucc<-Ex_JuviSucc-((Ex_JuviSucc*PercRatPredChick)+(Ex_JuviSucc*PercCatP redChick)+
(Ex_JuviSucc*PercBrOwlPredChick)+(Ex_JuviSucc*PercUngPredChick))
Ex_APredReproProb<-Ex_ReproProb-((Ex_ReproProb*BrOwl_NESHReproProb)+(Ex_Repr oProb*Rat_NESHReproProb)+
(Ex_ReproProb*Cat_NESHReproProb)+(Ex_ReproProb*Ung_NESHRepro
Prob)
proj_MatPred<-proj_mat
for (ii in (NESHfirst_rep-1):(nrow(life_table)-1))\{
try(proj_MatPred[ii, ii]<-proj_MatPred[ii, ii]-Ex_AllPredAdults, T)
\} \# end of ii
Bred<-Ex_APredJuviSucc
Rep<-Ex_APredReproProb
```

Mx<-c(rep(0, (NESHfirst_rep-1)), rep(Bred*Rep, (NESH_age-NESHfirst_rep+1)))
jk<-proj_MatPred[1:(NESH_age-1),]
RunTme <- year
dfMitSoc<-data.frame(matrix(nrow=13, ncol= RunTme))
proj_mat2<-jk

# Adding to the The Growth Projection Matrix (actually Lamda is not exactly ~ 1.04)

# from G and H

Stable_Proj_mat<-as.matrix(rbind(Mx, jk), rownames.force= F) \#make sure it is a square
matrix
colnames(Stable_Proj_mat)<-NULL
rownames(Stable_Proj_mat)<-NULL
eigen<-eigen.analysis(Stable_Proj_mat, zero=TRUE) \# with predation without strikes
eigen\$lambda1

```
    CurrYear<-as.numeric(as.character(format(Sys.time(), "\%Y"))) \# Defining the year at w
hich the tool was run
    \# Because the initial meta-population size was defined for 2011 (by Trevor Joyce in 2013) a
m updating to estimate the Meta-popSize during
    \# the current time period using the predation estimate defined int he parameters
    MetaPopSize<- MetaPopSize*(eigen\$lambda1 ^(CurrYear-YearPopEstimated))
    \# Stable Stage distribution developed from Eigen analysis of the base model
    stable.stage<-eigen\$stable.stage
```

pop.each<-MetaPopSize*stable.stage
TotAadult.sum<-sum(pop.each[6:length(pop.each)])
TotSAadult.sum<-sum(pop.each[2:5])
TotAll<-TotAadult.sum+TotSAadult.sum
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#Defining the Scenarios For Predator Control\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#

```
    \#Scenarios are to be combined with the all predation, strike and light fallout metrics
    \#!!!!!!!!!!!!!!!!!!!!! EXCLUSION
    Ex_Adults<-((Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*(PercUngPredAdults+Per
cUngPredSubAdults))+
    (Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*(PercCatPredAdults+PercCatPr
edSubAdults))+
    (Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*(PercRatPredAdults+PercRatPr
edSubAdults))+
    (Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]* \({ }^{*}(\) PercBrOwlPredAdults+PercB
rOwlPredSubAdults)*CntrlBarnOwl))
Ex_Juvi<-(Ex_JuviSucc*PercUngPredChick)+
    (Ex_JuviSucc*PercCatPredChick)+
    (Ex_JuviSucc*PercRatPredChick)+
    (Ex_JuviSucc*PercBrOwlPredChick*CntrlBarnOwl)
    Ex_ReproProbScen<-(Ex_ReproProb*Ung_NESHReproProb)+
    (Ex_ReproProb*Cat_NESHReproProb)+
    (Ex_ReproProb*Rat_NESHReproProb)+
    (Ex_ReproProb*BrOwl_NESHReproProb*CntrlBarnOwl)
    \#!!!!!!!!!!!!!!!!!!!!!! UNGULATE FENCED AREA with Cat and Barn owl control
    Ung_Adults<-(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*(PercUngPredAdults+Pe
rcUngPredSubAdults)+
    (Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*((PercCatPredAdults+PercCat
PredSubAdults)*CntrlCat))+
    (Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*((PercBrOwlPredAdults+Perc
BrOwlPredSubAdults)*CntrlBarnOwl))
    Ung_Juvi<-((Ex_JuviSucc*PercUngPredChick)+
    (Ex_JuviSucc*(PercCatPredChick*CntrlCat))+
    (Ex_JuviSucc*PercBrOwlPredChick*CntrlBarnOwl))
Ung_ReproProb<-((Ex_ReproProb*Ung_NESHReproProb)+
            (Ex_ReproProb*(Cat_NESHReproProb*CntrlCat))+
(Ex_ReproProb*(BrOwl_NESHReproProb*CntrlBarnOwl)))

\section*{\#!!!!!!!!!!!!!!!!!!!!!! PREDATOR CONTROL AREA}

PrCntrl_Adults<-((Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*((PercUngPredAdult s+PercUngPredSubAdults) * CntrlUngulate)) + \# used \(4 \mathrm{~b} / \mathrm{c}\) defined by KESRP
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*((PercCatPredAdults+PercC atPredSubAdults) * CntrlCat) \()+\)
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]* ((PercRatPredAdults+PercR atPredSubAdults) * CntrlRat))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*((PercBrOwlPredAdults+Per cBrOwlPredSubAdults) * CntrlBarnOwl))
```

PrCntrl_Juvi<-((Ex_JuviSucc*(PercUngPredChick * CntrlUngulate))+
(Ex_JuviSucc*(PercCatPredChick * CntrlCat))+
(Ex_JuviSucc*(PercRatPredChick * CntrlRat))+
(Ex_JuviSucc*(PercBrOwlPredChick * CntrlBarnOwl)))
PrCntrl_ReproProb<-((Ex_ReproProb*(Ung_NESHReproProb * CntrlUngulate))+
(Ex_ReproProb*(Cat_NESHReproProb * CntrlCat))+
(Ex_ReproProb*(Rat_NESHReproProb * CntrlRat))+
(Ex_ReproProb*(BrOwl_NESHReproProb * CntrlBarnOwl)))

```
\#!!!!!!!!!!!!!!!!!!!!!!!! UPPER LIMAHULE EQUIVALENT (PREDATOR CONTROL WITH NO UNGULA TES)
UpLim_Adults<-((Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*(PercUngPredAdults +PercUngPredSubAdults))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]* ((PercCatPredAdults+PercCat PredSubAdults) * CntrlCat))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]* \((\) (PercRatPredAdults+PercRa tPredSubAdults) * CntrlRat) \()+\)
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]* ((PercBrOwlPredAdults+Perc BrOwlPredSubAdults) * CntrlBarnOwl))) \# Ainley Juvi Survivorship versus Upp. Lim Juvi Surv ivorship
```

UpLim_Juvi<-((Ex_JuviSucc*(PercUngPredChick))+
(Ex_JuviSucc*(PercCatPredChick * CntrlCat))+
(Ex_JuviSucc*(PercRatPredChick * CntrlRat))+
(Ex_JuviSucc*(PercBrOwlPredChick * CntrlBarnOwl)))
UpLim_ReproProb<-((Ex_ReproProb*(Ung_NESHReproProb))+
(Ex_ReproProb*(Cat_NESHReproProb * CntrlCat))+
(Ex_ReproProb*(Rat_NESHReproProb * CntrlRat))+
(Ex_ReproProb*(BrOwl_NESHReproProb * CntrlBarnOwl)))

```
\#!!!!!!!!!!!!!!!!!!!!!!! UPPER LIMAHULE EQUIVALENT (PREDATOR CONTROL WITH NO UNGULA TES)!!!!! WITHOUT ANY CATS !!!!!

UpLimNC_Adults<-((Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*(PercUngPredAdu lts+PercUngPredSubAdults))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*(PercCatPredAdults+PercCa tPredSubAdults))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*((PercRatPredAdults+PercR atPredSubAdults) * CntrlRat))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*((PercBrOwlPredAdults+Per cBrOwlPredSubAdults) * CntrlBarnOwl) )) \# Ainley Juvi Survivorship versus Upp. Lim Juvi Sur vivorship

UpLimNC_Juvi<-((Ex_JuviSucc*(PercUngPredChick))+
(Ex_JuviSucc*(PercCatPredChick))+
(Ex_JuviSucc*(PercRatPredChick * CntrlRat))+
(Ex_JuviSucc*(PercBrOwlPredChick * CntrlBarnOwl)))

UpLimNC_ReproProb<-((Ex_ReproProb*(Ung_NESHReproProb))+
(Ex_ReproProb*(Cat_NESHReproProb))+
(Ex_ReproProb*(Rat_NESHReproProb * CntrlRat))+ (Ex_ReproProb*(BrOwl_NESHReproProb * CntrlBarnOwl))
\#!!!!!!!!!!!!!!!!!!!!!!!! SOCIAL ATTRACTION (STARTING FROM SCRATCH) WITH EXCLUSION
SocEx_Adults<-Ex_Adults
SocEx_Juvi<-Ex_Juvi
SocEx_ReproProb<-Ex_ReproProbScen
\#!!!!!!!!!!!!!!!!!!!!!!!! BARN OWL AND CAT CONTROL ONLY
CatandBrCntrl_Adults<-((Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*((PercCatPre dAdults+PercCatPredSubAdults) * CntrlCat))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]*((PercBrOwlPredAdults+ PercBrOwlPredSubAdults) * CntrlBarnOwl) ))

CatandBrCntrl_Juvi<-((Ex_ReproProb*(Cat_NESHReproProb * CntrlCat))+ (Ex_ReproProb*(BrOwl_NESHReproProb * CntrlBarnOwl)))

CatandBrCntrl_ReproProb<-((Ex_ReproProb*(Cat_NESHReproProb * CntrlCat))+ (Ex_ReproProb*(BrOwl_NESHReproProb * CntrlBarnOwl)))

\section*{\#!!!!!!!!!!!!!!!!!!!!!! BARN OWLONLY}

BrCntrl_Adults<-(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep]* \((\) (PercBrOwlPredAdu lts+PercBrOwlPredSubAdults) * CntrlBarnOwl))

BrCntrl_Juvi<-(Ex_ReproProb*(BrOwl_NESHReproProb * CntrlBarnOwl))
BrCntrl_ReproProb<-(Ex_ReproProb*(BrOwl_NESHReproProb * CntrlBarnOwl))
```

\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#
\#Defining the percentage of each control methodology in the overall plan an \# d adding it
up to define the mitigation strategy \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# For all BUT Social Attraction
ratioCntrlAdults<-((Ex_Adults*PercExclusion)+(Ung_Adults*PercUngulate)+(UpLim_Adult s*PercUngPrCntrl)+ (PrCntrl_Adults*PercPrCntrl)+(PercUngPrCntrlNoCats*UpLimNC_Adults)+ (CatandBrCntrl_Adults*PercBarnOwlCatOnly)+(BrCntrl_Adults*PercBarnOwlO nly))

```
ratioCntrlJuvi<-((Ex_Juvi*PercExclusion)+(Ung_Juvi*PercUngulate)+(UpLim_Juvi*PercUng PrCntrl)+
(PrCntrl_Juvi*PercPrCntrl)+(PercUngPrCntrlNoCats*UpLimNC_Juvi)+ (CatandBrCntrl_Juvi*PercBarnOwlCatOnly)+(BrCntrl_Juvi*PercBarnOwlOnly))
ratioReproRate<-((Ex_ReproProbScen*PercExclusion)+(Ung_ReproProb*PercUngulate)+( UpLim_ReproProb*PercUngPrCntrl)+
(PrCntrl_ReproProb*PercPrCntrl)+(UpLimNC_ReproProb*PercUngPrCntrlNoCat s)+
(PercBarnOwlCatOnly*CatandBrCntrl_ReproProb)+(PercBarnOwlOnly*BrCntrl_ ReproProb))
```

\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# For Social Attraction
ratioCntrlAdults_SocEx<-(SocEx_Adults)
ratioCntrlJuvi_SocEx<-(SocEx_Juvi)
ratioReproRate_SocEx<-(SocEx_ReproProb)
if(PercSocialExclusion==0){
ratioCntrlAdults_SocEx<-0
ratioCntrlJuvi_SocEx<-0
ratioReproRate_SocEx<-0
}
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#MAIN ASSESSMENT SECTION\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# Defines number of burrows per HA if Andres Colonies
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# account for between all to 1/2 of the NESH population
\# Multiplying the total number of reproductive adults by thier probability of
\# reproduction with all predators, and dividing by two (assuming a 50:50 sex ratio) to obtai
n the number of burrows

```

TotBurrows<-(((sum(TotAadult.sum)*popPercEx)*Ex_APredReproProb)/2)/Tot_HA TotAdults<-(sum(TotAadult.sum)*popPercEx)/Tot_HA

Burrfence_half<-TotBurrows*HA
Adultfence_half<-TotAdults*HA
Burrow<-Burrfence_half
StrikeEst<-TotStrk
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#
dfMit<-data.frame(matrix(nrow=13, ncol= year))
names(dfMit)<-seq(1, year)
rownames(dfMit)<-c('Burrow', 'Birds', 'Adult_Mitigation', 'Juvenile_Mitigation','Deficit', 'D eficit_Adult',
'Deficit_SubAdults', 'Population', 'Predation', 'Demographic Lambda', 'Population Lambda', "Birds_Not_In_Polygons", 'Strikes_Mortalities')
dfMitSoc<-data.frame(matrix(nrow=13, ncol= year))
names(dfMitSoc)<-seq(1, year)
rownames(dfMitSoc)<-c('Burrow', 'Birds', 'Adult_Mitigation', 'Juvenile_Mitigation', 'Defici t', 'Deficit_Adult',
'Deficit_SubAdults', 'Population', 'Predation', 'Demographic Lambda', 'Populati on Lambda', "Birds_Not_In_Polygons", 'Strikes_Mortalities')
\#\#\#\#\#\#\#\# Percent Survivorship Increase Due to Above Scenarios \#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\# Credit Given to Upper Limahule (current control)
UpperLimACredit<-UpLim_Adults*(((NESH_Monitord[2]*2)/(Ex_APredReproProb+UpLim _ReproProb)) \# defined the number of adults at the site by div by repro prob
/sum((MetaPopSize*stable.stage[6:length(stable.stage)]))) \# defines the proportion of ULM adults compared to all adults (96/10354)
UpperLimJCredit<-UpLim_Juvi*(((NESH_MonWBrd[2])*(Ex_APredJuviSucc+UpLim_Juvi)) \# number of burrows times juv success at upper limahule
/sum((MetaPopSize*stable.stage[1]))) \# defines proportion (as above) (27/ 4597)

Overview<-paste0('Exc_', round(PercExclusion, 2), '_UngCntrl_', round(PercUngulate, 2),
'_PrdCntrl_', round(PercPrCntrl, 2), '_ULM_', round(PercUngPrCntrl, 2),
'_ULMNoCat_', round(PercUngPrCntrlNoCats, 2), '_SocAt_', round(PercSocialExcl usion, 2),
'_BOCatCntrl_', round(PercBarnOwlCatOnly, 2), '_BOCntrl_', round(PercBarnOwl Only, 2))

CurrYearFile<-as.character(format(Sys.time(), "Day-\%Y_\%m_\%d Time-\%H_\%M_\%S"))

\section*{\# Defining the year at which the tool was run}
```

Dir2<-paste0(Dir, CurrYearFile, '/')
if(file.exists(Dir2) == F){
dir.create(Dir2)
}
\# Mitigation Estimator

```
```

\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\# MAKEING A DETERMINISTIC MODEL WITH STRIKES AND PREDATION \#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
Adults<-(eigen$stable.stage * (MetaPopSize))[NESHfirst_rep:length(eigen$stable.stage)]
SAs<-(eigen$stable.stage * (MetaPopSize))[2:(NESHfirst_rep-1)]
Chicks<-(eigen$stable.stage * (MetaPopSize))[1]
NumAdults<-sum(Adults)
NumSAs<-sum(SAs)

```
\# this uses Ainley's 20/80 estimate of strikes
AdultStrike<-sum(StrikeEst*0.2)
SAStrike<-sum(StrikeEst*0.8)
\# The following will use the proportion of adults and sub-adults (assuming a stable age distri
bution) to the total population to define adult and sub-adult strikes
    \# AdultStrike<-sum(get(est)*(sum(eigen\$stable.stage[NESHfirst_rep:NESH_age]*pop)/su
m(eigen\$stable.stage[1:NESH_age]*pop))
    \# SAStrike<-sum(get(est)*(sum(eigen\$stable.stage[1:(NESHfirst_rep-1)]*pop)/sum(eigen\$
stable.stage[1:NESH_age]*pop)))
    \# Mortality due to chick loss
    ChicksStrike<-(sum((AdultStrike*Ex_APredReproProb))/2)*Ex_APredJuviSucc + TotLight
\#Stable_Proj_mat[1, NESHfirst_rep] \# Divide adult strike by two to estimate pairs (affective l
oss of chicks due to strikes)
    PercRemove_Adults<-AdultStrike/NumAdults
    PercRemove_SAs<-SAStrike/NumSAs
    PercRemove_Chicks<-ChicksStrike/Chicks
    proj_mat2<-jk
    \#\#\#\# Adding seabird strike scenarios if applicable
    for (ii in 2:(nrow(life_table)-1))\{
    if ((ii < NESHfirst_rep)==T)\{
        try(proj_mat2[ii, ii]<-jk[ii,ii]-PercRemove_SAs, T) \#(PercRemove_SAs*jk[ii,ii]), T) \# remov
ing sub-adults
    \}else\{
        try(proj_mat2[ii, ii]<-jk[ii,ii]-PercRemove_Adults, T) \#(PercRemove_Adults*jk[ii,ii]), T) \#
```

removing adults
} \#end if/else
try(if((proj_mat2[ii,ii]<0)==T){
proj_mat2[ii,ii]<-0.000000001\# makeing as close to zero as possible
},T)
} \# end ii
Bred<-Ex_APredJuviSucc-(PercRemove_Chicks)\#*Ex_APredJuviSucc)
Rep<-Ex_APredReproProb
Mx<-c(rep(0, (NESHfirst_rep-1)), rep(Bred*Rep, (NESH_age-NESHfirst_rep+1)))
jk2<-proj_mat2[1:NESH_age-1,]
Stable_Proj_mat<-as.matrix(rbind(Mx, jk2), rownames.force= F) \#make sure it is a square
matrix
colnames(Stable_Proj_mat)<-NULL
rownames(Stable_Proj_mat)<-NULL
eigenAllMort<-eigen.analysis(Stable_Proj_mat, zero=0)
CurrLambda<-eigenAllMort$lambda1
    sum(eigenAllMort$stable.stage[1:5])
PopLambda<-0
strikes<-StrikeEst
\# This section is for the first year estimates
pop1<-MetaPopSize
unmitPop<-MetaPopSize*(1-popPercEx)
\# Predation<-0
Predation<-(MetaPopSize*abs(eigenNP\$lambda1-CurrLambda))/CurrLambda \#estimatin
g amount of predation using difference b/t lambda without strikes/predation and with predat
ion and without strikes
dfMit[, 1]<-c(Burrow, Adultfence_half, 0, 0,
StrikeEst, StrikeEst*0.2, StrikeEst*0.8,
pop1, Predation, CurrLambda, PopLambda, unmitPop, strikes) \# starting populatio
n with all but Social attraction
dfMitSoc[, 1]<-c(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) \# social attraction/exclusion starting popul
ation size
for (i in seq(2, year+1)){
\# estimates the strike removal from the population prior to the start of control
\# Everything with Soc in it's name has to do with the social attraction population

```
if(i \%in\% c(seq(2, CntrlStart+1, 1)))\{
CurrLambda<-eigenAllMort\$lambda1
pop1<-(dfMit[8, i-1] * eigenAllMort\$lambda1)\#-dfMit[5, i-1] \# estimating population size given lambda with all mortality

PopLambda<-pop1/dfMit[8, i-1]
unmitPop<-MetaPopSize*(1-popPercEx)
Predation<-dfMit[8, i-1] * abs(eigenNP\$lambda1-CurrLambda) \#estimating amount of p redation using difference b/t lambda without strikes/predation and with predation and witho ut strikes

Birds1<-dfMit[2, i-1]*eigenAllMort\$lambda1
SocBirds<-0
Burrows1<-(Birds1*Ex_APredReproProb)/2
SocBurrows<-0

Adults_Saved1<-0\#Birds* ((ratioCntrlAdults*-1)+UpperLimACredit)
SocAdults_Saved1<-0
Juvi_Saved1<-0\#Burrows*((ratioCntrlJuvi*-1)+UpperLimJCredit)*Ex_APredReproProb SocJuvi_Saved1<-0

UpLimCreditA<-UpperLimACredit*StrikeEst
UpLimCreditJ<-UpperLimJCredit*StrikeEst
strikes<-(dfMit[13, i-1]*PopLambda)
Deficit1<-(dfMit[5, i-1]+(strikes-(UpLimCreditA+UpLimCreditJ)))
Deficit_Adult<-Deficit1*0.2
Deficit_SubAdults<-Deficit1*0.8
\# Output has: 'Burrow', 'Birds', 'Adults', 'Juveniles', 'Deficit', 'Deficit_Adult', 'Deficit_SubAdu lts', 'Population', 'Predation', 'Strikes'
dfMit[, i]<-c(Burrows1, Birds1, Adults_Saved1, Juvi_Saved1, Deficit1, Deficit_Adult, Defic it_SubAdults, pop1, Predation, CurrLambda, PopLambda, unmitPop, strikes)
dfMitSoc \([\mathrm{i}]<-\mathrm{c}(0,0,0,0,0,0,0,0,0,0,0,0,0)\) \# Because the Social Attraction sites don't
add anything until they're made \(=\) no additional protection or reduction
\}else\{
\# estimates the strike removal from the population after control starts
\# but durring years in which it takes to implement the complete program
plus2<-2
```

    plus1<-1
    if(i %in% c(seq(CntrlStart+plus2, (plus2+CntrlStart)+(MitYrs-plus1), 1))){ # mitigation
    scenario years
\# Adult Mitigation
RegAdMit<-((ratioCntrlAdults/MitYrs)
*which(c(seq(CntrlStart+plus2, (plus2+CntrlStart)+(MitYrs-plus1), 1)[1:MitYrs]
)==i)) \# 0.21 is a constant to make sure exclusion of predation = adult survivorship of 0.92
SocAdMit<-((ratioCntrlAdults_SocEx/MitYrs)
*which(c(seq(CntrlStart+plus2, (plus2+CntrlStart)+(MitYrs-plus1), 1)[1:MitYrs]
)==i)(
\# Sub-adult Mitigation
RegJuvMit<-((ratioCntrlJuvi/MitYrs)
*which(c(seq(CntrlStart+plus2, (plus2+CntrlStart)+(MitYrs-plus1), 1)[1:MitYrs]
)==i)(
SocJuvMit<-((ratioCntrlJuvi_SocEx/MitYrs)
*which(c(seq(CntrlStart+plus2, (plus2+CntrlStart)+(MitYrs-plus1), 1)[1:MitYrs]
)==i)(
\# Reproductive probability Mitigation
RegRepr<- Ex_APredReproProb + (((ratioReproRate)/MitYrs)
* which(c(seq(CntrlStart+plus2, (plus2+CntrlStart)+(MitYrs-plus1), 1)
[1:MitYrs])==i))
SocRepr<- Ex_APredReproProb + (((ratioReproRate_SocEx)/MitYrs)
* which(c(seq(CntrlStart+plus2, (plus2+CntrlStart)+(MitYrs-plus1), 1)
[1:MitYrs])==i))
\# Reproductive Success Mitigation
RegSucc<- Ex_APredJuviSucc + (((ratioCntrlJuvi)/MitYrs)
* which(c(seq(CntrlStart+plus2, (plus2+CntrlStart)+(MitYrs-plus1), 1)
[1:MitYrs])==i)) \# constant used to make equal to maxium possible (0.81) when exclusion is u
sed
SocSucc<- Ex_APredJuviSucc + (((ratioCntrlJuvi_SocEx)/MitYrs)
* which(c(seq(CntrlStart+plus2, (plus2+CntrlStart)+(MitYrs-plus1), 1)
[1:MitYrs])==i))

```

\section*{\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\# \\ \# Deterministic model to assess increase in levels of mitigation effort for both Social \# \#\#\#\#\#\#\#\#\#\#\#\#\# attraction (Soc) and regular (Reg) mitigation strategies}
for (mitty in c('Reg', 'Soc'))\{ proj_mat3<-proj_mat2
for (ii in 2:(nrow(life_table)-1))\{
```

    if ((ii > NESHfirst_rep)==T){
        try(proj_mat3[ii, ii]<-proj_mat3[ii,ii]+get(paste0(mitty, "AdMit")), T) #
        try(if(proj_mat3[ii,ii]>Stable_Proj_matNP[ii,ii]){
        proj_mat3[ii,ii]<-Stable_Proj_matNP[ii,ii]
        },T)
    }else{
try(proj_mat3[ii, ii]<-proj_mat3[ii,ii]+get(paste0(mitty, "JuvMit")), T) \#
try(if(proj_mat3[ii,ii]>Stable_Proj_matNP[ii,ii]){
proj_mat3[ii,ii]<-Stable_Proj_matNP[ii,ii]
}, T)
} \#end if/else
try(if((proj_mat3[ii,ii]<0)==T){
proj_mat3[ii,ii]<-0.000000001\# makeing as close to zero as possible
},T)
} \# end ii
MxMit<-c(rep(0, (NESHfirst_rep-1)), rep(get(paste0(mitty, "Repr"))*get(paste0(mit
ty, "Succ")), (NESH_age-NESHfirst_rep+plus1)))
for (xi in 1:length(MxMit)){
if (MxMit[xi] > MxNP[xi]){
MxMit[xi] <- MxNP[xi]
}
}
jk2Mit<-proj_mat3[1:NESH_age-1,]
Stable_Proj_mat<-as.matrix(rbind(MxMit, jk2Mit), rownames.force= F) \#make sure it
is a square matrix
colnames(Stable_Proj_mat)<-NULL
rownames(Stable_Proj_mat)<-NULL
eigenMit<-eigen.analysis(Stable_Proj_mat, zero=0)
assign(paste0(mitty, 'eigenMit'), eigenMit)
} \# end Reg/Soc loop (defined matrices for all but social attraction (Reg), and social attra
ction (Soc))
SocLambda<-SoceigenMit\$lambda1
SocBurrows<-(dfMitSoc[1, i-1] * SocLambda) + which(c(seq(CntrlStart+plus2, (CntrlSt art+MitYrs+plus1), 1))==i) * ((HA2 * PercSocialExclusion)/Bdivisore) \#essentially addition of 1 active burrow for every 10 HA fenced
SocBirds<-(SocBurrows*2)/SocRepr
RegPop1<-(dfMit[8, i-1] * RegeigenMit\$lambda1)\#-dfMit[5, i-1] \# estimating population size given lambda with all mortality
if (SocBirds == 0)\{
SocPop1<-0

```
```

    }else{
    if (i == CntrlStart+plus2){
        SocPop1<-SocBirds
    }else{
        SocPop1<-SocBirds/sum(SoceigenMit$stable.stage[NESHfirst_rep:length(Soceigen
    Mit$stable.stage)])
    }
    }
    Population<-RegPop1+SocPop1
    CurrLambda<-((SocLambda*(SocPop1/Population)) + (RegeigenMit$lambda1)*(1-(So
cPop1/Population)))
unmitPop<-dfMit[12, i-1]*eigenAllMort$lambda1
    CurrLambda<-(CurrLambda*(1-unmitPop/Population))+(eigenAllMort$lambda1*unm
itPop/Population) \# 25% of the lambda has all predation on it
if (CurrLambda>eigenNP$lambda1){
    CurrLambda<-eigenNP$lambda1
}
PopLambda<-Population/dfMit[8, i-1]
\# i=3
Predation<-(dfMit[8, i-1] - dfMitSoc[8, i-1])* abs(eigenNP$lambda1-CurrLambda) #esti
mating amount of predation using difference b/t lambda without strikes/predation and with
predation and without strikes
    # Pedation for social attraction sites is "0"
    RegBirds<-dfMit[2, i-1]*RegeigenMit$lambda1
RegBurrows<-(dfMit[2, i-1]*RegRepr)/2
RegAdults_Saved<-RegBirds*RegAdMit
SocAdults_Saved<-SocBirds*SocAdMit
RegJuvi_Saved<-RegBurrows*RegJuvMit*RegRepr
SocJuvi_Saved<-SocBurrows*SocJuvMit*SocRepr
Adults_Saved<-RegAdults_Saved+SocAdults_Saved
Juvi_Saved<-RegJuvi_Saved+SocJuvi_Saved
strikes<-(dfMit[13, i-1]*PopLambda)
Deficit<-(dfMit[5, i-1]+(strikes-(Adults_Saved+Juvi_Saved)))
Deficit_Adult<-Deficit*0.2
Deficit_SubAdult<-Deficit*0.8
Burrows<-RegBurrows+SocBurrows
Birds<-RegBirds+SocBirds

```
```

    # Output has: 'Burrow', 'Birds', 'Adults', 'Juveniles', 'Strikes', 'Deficit', 'Deficit_Adult', 'Defic
    it_SubAdults', 'Population', 'Predation'
dfMit[, i]<-c(Burrows, Birds, Adults_Saved, Juvi_Saved, Deficit, Deficit_Adult, Deficit_Su
bAdult, Population, Predation, CurrLambda, PopLambda, unmitPop, strikes)
dfMitSoc[i]<-c(SocBurrows, SocBirds, SocAdults_Saved, SocJuvi_Saved, 0, 0, 0, SocPop
1, 0, 0, 0, 0, 0)
}else{ \# time at which complete mitigation is reached
\# estimates the strike removal from the population after control starts
\# from complete implimentation of the program
\# Adult Mitigation
RegAdMit<-ratioCntrlAdults
SocAdMit<-ratioCntrlAdults_SocEx
\# Sub-adult Mitigation
RegJuvMit<-ratioCntrlJuvi
SocJuvMit<-ratioCntrlJuvi_SocEx
\# Reproductive probability Mitigation
RegRepr<- Ex_APredReproProb + abs(ratioReproRate)
SocRepr<- Ex_APredReproProb + abs(ratioReproRate_SocEx)
\# Reproductive Success Mitigation (essentially linked with Reproductive probability, bec
ause it was not defined by the KESRP)
RegSucc<- Ex_APredJuviSucc + abs(ratioCntrlJuvi)
SocSucc<- Ex_APredJuviSucc + abs(ratioCntrlJuvi_SocEx)
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\# Deterministic model to assess overall mitigation effort for both Social \#\#\#\#

#### 

    ############# attraction (Soc) and regular (Reg) mitigation strategies ########
    \#\#\#\#\#\#\#\#\#
for (mitty in c('Reg', 'Soc')){
proj_mat3<-proj_mat2
for (ii in 2:(nrow(life_table)-1)){
if ((ii > NESHfirst_rep)==T){
try(proj_mat3[ii, ii]<-proj_mat3[ii,ii]+get(paste0(mitty, "AdMit")), T) \# removing su
b-adults
try(if(proj_mat3[ii,ii]>Stable_Proj_matNP[ii,ii]){
proj_mat3[ii,ii]<-Stable_Proj_matNP[ii,ii]
},T)
}else{

```
try(proj_mat3[ii, ii]<-proj_mat3[ii,ii]+get(paste0(mitty, "JuvMit")), T) \# removing a dults
try(if(proj_mat3[ii,ii]>Stable_Proj_matNP[ii,ii])\{
proj_mat3[ii,ii]<-Stable_Proj_matNP[ii,ii]
\}, T)
\} \#end if/else
try(if([proj_mat3[ii,ii]==0)==T)\{
proj_mat3[ii,ii]<-0.000000001\# makeing as close to zero as possible
\}, T)
\} \# end ii

MxMit<-c(rep(0, (NESHfirst_rep-1)), rep(get(paste0(mitty, "Repr"))*get(paste0(mit
ty, "Succ")), (NESH_age-NESHfirst_rep+plus1)))
for (xi in 1:length(MxMit))\{
if (MxMit[xi] > MxNP[xi]) \{
MxMit[xi] <- MxNP[xi]
\}
\}
jk2Mit<-proj_mat3[1:NESH_age-1,]
Stable_Proj_mat<-as.matrix(rbind(MxMit, jk2Mit), rownames.force= F) \#make sure it is a square matrix
colnames(Stable_Proj_mat)<-NULL
rownames(Stable_Proj_mat)<-NULL
eigenMit<-eigen.analysis(Stable_Proj_mat, zero=0)
assign(paste0(mitty, 'eigenMit'), eigenMit)
\}
SocLambda <-SoceigenMit\$lambda1
\# cat('\n', SocLambda)
SocBurrows<-(dfMitSoc[1, i-1]*SocLambda) \#stopped social attraction
SocBirds<-(SocBurrows*2)/SocRepr
RegPop1<-(dfMit[8, i-1] * RegeigenMit\$lambda1)\#-dfMit[5, i-1] \# estimating population size given lambda with all mortality
if (SocBirds \(==0\) ) \{
SocPop1<-0
\}else\{
SocPop1<-SocBirds/sum(SoceigenMit\$stable.stage[NESHfirst_rep:length(SoceigenMi t\$stable.stage)]) \#
\}
if (SocBirds >= (SE_K * HAExclusion))\{ \# used adult rather than SocPop1 (overall popula

\section*{tion) because the ad hoc \(K\) is based on the adult estimate}

SocLambda <-1
SocBurrows<-(dfMitSoc[1, i-1]*SocLambda) \#stopped social attraction
SocBirds<-(SocBurrows*2)/SocRepr
SocPop1<-SocBirds/sum(SoceigenMit\$stable.stage[NESHfirst_rep:length(SoceigenMi t\$stable.stage)]) \#
\}
Population<-RegPop1+SocPop1
CurrLambda<-((SocLambda*(SocPop1/Population)) +(RegeigenMit\$lambda1)*(1-(Soc Pop1/Population)))\#(RegeigenMit\$lambda1))
unmitPop<-dfMit[12, i-1]*eigenAllMort\$lambda1
CurrLambda<-(CurrLambda*(1-(unmitPop/Population)))+(eigenAllMort\$lambda1*un mitPop/Population) \# 25\% of the lambda has all predation on it

PopLambda<-Population/dfMit[8, i-1]
Predation<-(dfMit[8, i-1] - dfMitSoc[8, i-1])* abs(eigenNP\$lambda1-CurrLambda) \#esti mating amount of predation using difference b/t lambda without strikes/predation and with predation and without strikes

RegBirds<-dfMit[2, i-1]*RegeigenMit\$lambda1
RegBurrows<-(dfMit[2, i-1]*RegRepr)/2
RegAdults_Saved<-RegBirds*RegAdMit
SocAdults_Saved<-SocBirds*SocAdMit
RegJuvi_Saved<-RegBurrows*RegJuvMit*RegRepr
SocJuvi_Saved<-SocBurrows*SocJuvMit*SocRepr
Adults_Saved<-RegAdults_Saved+SocAdults_Saved
Juvi_Saved<-RegJuvi_Saved+SocJuvi_Saved
strikes<-(dfMit[13, i-1]*PopLambda)
Deficit<-(dfMit[5, i-1]+(strikes-(Adults_Saved+Juvi_Saved)))
Deficit_Adult<-Deficit*0.2
Deficit_SubAdult<-Deficit*0.8
Burrows<-RegBurrows+SocBurrows
Birds<-RegBirds+SocBirds
if (Population >= (SE_K * Tot_HA))\{ \# used adult rather than SocPop1 (overall populatio n) because the ad hoc \(K\) is based on the adult estimate
```

    CurrLambda <- 1
    RegBirds<-(dfMit[2, i-1]*CurrLambda) - SocBirds
    RegBurrows<-((RegBirds*RegRepr)/2) - SocBurrows
    RegBurrows<-(dfMit[1, i-1]*CurrLambda) #stopped social attraction
    RegBirds<-(RegBurrows*2)/RegRepr
    Population<-RegBirds/sum(eigenMit$stable.stage[NESHfirst_rep:length(eigenMit$st
    able.stage)]) + SocPop1\#
Burrows<-RegBurrows+SocBurrows
Birds<-RegBirds+SocBirds

```
    \}
    \# Output has: 'Burrow', 'Birds', 'Adults', 'Juveniles', 'Deficit', 'Deficit_Adult', 'Deficit_SubAd
ults', 'Population', 'Predation', 'Strikes'
    dfMit[, i]<-c(Burrows, Birds, Adults_Saved, Juvi_Saved, Deficit, Deficit_Adult, Deficit_Su
bAdult, Population, Predation, CurrLambda, PopLambda, unmitPop, strikes)
    dfMitSoc[i]<-c(SocBurrows, SocBirds, SocAdults_Saved, SocJuvi_Saved, 0, 0, 0, SocPop1
, 0, 0, 0, 0, 0)
    \}
    \}
\} \# end year loop
YrAt0<-which(dfMit[5,]<=0)[1]-1
names(dfMit)<-paste0('year_', (seq(1, year+1)-1))
write.csv(dfMit, paste0(Dir2, StrikeEst, "_Strike_Replacement_YearAtZero_", YrAt0, '_Pre
dation_', LMHName, ".csv"))
    cat(paste0('\nfor the ', StrikeEst, ' estimate of strike mortalities,
        replacement occurs at year ', YrAt0, ', given ', Burrow, ' burrows'))
\# \# CONTROL LEVELS FOR SCENARIOS THAT DO NOT DEPEND ON EXCLUSION
\# \# Used to define the levels that define control of the various organisms.
\# \# This metric is used in combination with the above control scenario percentages to define
the
\# \# level of control to acheive that specific scenario. As this is a proportion (range from 0 to
1),
\# \# a value of 1 defined complete control of that organism. This level of control only applies
to the
\# \# specific control scenario area amount defined above. For instance in the Exclusion area,
only
\# \# the Barn owl control metric is used.
\# CntrlUngulate <- 0.5\#UserSpecified\#
\# CntrlCat <- 0.5\#UserSpecified\#
\# CntrlRat <- 0.5\#UserSpecified\#
\# CntrlBarnOwl <- 0.5\#UserSpecified\#
```


# 

# \# AREA OF SITE TO BE USED FOR SOCIAL ATTRACTION (in HA)

# HAExclusion <- 10\#UserSpecified\# \# Hectares to be used for Social Attraction Sites

# 

# \#\#\# DIVISORE FOR SOCIAL EXCLUSION PARAMETERS

# \# Divisore to define how many burrows at the end of building fences (MitYrs) will be in the

exclosure

# \# So, when "MitYrs" equals 10 after 10 years of mitigation

# \# a "Bdivisore" value of 2.9754449 = 100 birds/100 hectares;

# \# a "Bdivisore" value of 5.95089 (2.9754449*2)= 50 birds/100 hectares;

# \# a "Bdivisore" value of 14.87722 (2.9754449*5) = 20 birds/100 hectares;

# \# a "Bdivisore" value of 29.75445 (2.9754449*10) = 10 birds/100 hectares

# Bdivisore <- 29.75445

```

Metadata<-round(rbind(PredationEst, MetaPopSize, YearPopEstimated, KCap, CntrlStart, MitYrs, Tot_HA, popPercEx, RunTme,

TotStrk, PercExclusion*100, PercUngulate*100, PercPrCntrl*100, PercUngPrCntrl *100, PercUngPrCntrlNoCats*100,

PercBarnOwlCatOnly*100, PercBarnOwlOnly*100, CntrlUngulate, CntrlCat, CntrlR at, CntrlBarnOwl, HAExclusion,

Bdivisore), 2)
rownames(Metadata)<-c('Predation Estimate = ', 'Meta-Pop Size = ', 'Year Population was Estimated = ',
'Carrying Capacity (per Ha) = ', 'Year Fencing/Predator Control Starts = ',
'Year Fencing and Control implementation is complete = ', 'Total Estimated Hec tares of NESH habitat = ',
'Proportion of the Population Explained by the Tot_Ha = ', 'The Run length (in Y ears) = ', 'Total Number of Powerline Strikes = ', '\% Exclusion = ', 'Percent Ungulate Fencing \(=\) ',
'\% Predator Control = ', '\% Ungulate Fencing and Predator Control = ', '\% Ungu late and Cat Fencing with Predator Control = ',
'\% BarnOwl and Cat Control = ', '\% Barn Owl Control (Only) = ', 'Control level o f Ungulates = ', 'Control level fo Cats = ',
'Control level of Rats = ', 'Control level of Barn Owls = ', 'Number of Hectares fo r Social Attraction = ', 'Social Attraction Efficacy = ')
colnames(Metadata)<- 'MetaData of Analysis'
png(filename = paste0(Dir2, " Projected Mitigation, Mortality Effects, and Strike Deficit.pn g"), width = 1000, height \(=1000\), pointsize \(=18\), type="cairo")
plot(seq(1, length(dfMit), 1), as.numeric(dfMit['Deficit',]), type = 'l', ylim = c(0, max(as.n
umeric(dfMit['Population',]))*2),
xlab = 'Year', ylab = 'Number of Individuals', main = 'Projected Mitigation and Mortality Effects')
\# plot(seq(1, length(dfMit), 1), as.numeric(dfMit['Birds',]), type = 'l')
\# lines(as.numeric(dfMit['Birds',]), col = 'red')
lines(as.numeric(dfMit['Population',]), col = 'blue')
lines(as.numeric(dfMitSoc['Population',]), col = 'blue', lty = 2)
lines(as.numeric(dfMit['Predation',]), col = 'red')
lines(as.numeric(dfMit['Strikes_Mortalities',]], col = 'green')
lines(rep(as.numeric(dfMit['Population',1]), year), col = 'darkgrey', lty = 3)
text(year/2, dfMit['Population',1], paste0('Projected population Size at Run (', CurrYear , ' )'), cex = 0.7)

WhenPopIsNow<-dfMit['Population',][which.min(abs(dfMit['Population',-c(1:4)]-dfMit[' Population',1]))+4]

\section*{if(NoControlScen \(==\) F) \{}
arrows(which.min(abs(dfMit['Population',-c(1:4)]-dfMit['Population',1]))+4, dfMit['Popu lation',1] + max(as.numeric(dfMit['Population',]/8)),
which.min(abs(dfMit['Population',-c(1:4)]-dfMit['Population',1]))+4, dfMit['Populatio n',1],
\[
\text { length }=0.1, \text { lty }=2 \text { ) }
\]
text(which.min(abs(dfMit['Population',-c(1:4)]-dfMit['Population',1]))+4, dfMit['Populati on',1] + max(as.numeric(dfMit['Population',]/7)),
paste 0 ('Year at which the population is equivalent \(\backslash\) nto when the assessment was run (Year ',
which.min(abs(dfMit['Population',-c(1:4)]-dfMit['Population',1]))+4, ')'),
```

cex =0.6)

```
\}
legend('top', c('Accumulated Deficit of Strikes', 'Meta-Population Size (Including Social At traction Site Population)', 'Social Attraction Site Population Size', 'Predation', 'Year to Year Strike Mortalities'),
```

    col = c('black', 'blue', 'blue','red', 'green'), lty = c(1,1,2,1,1), bty = 'n')
    ```
upway <--6
adjVal <- 0.01
mtext(bquote(underline('Various Parameters Used in the Analysis')), cex = 0.7, col = 're d', line = -5 + upway, adj = adjVal, side = 3, font = 2)
mtext(paste0(rownames(Metadata)[1], (Metadata[1,])), cex = 0.6,line =-5.5+ upway, adj
= adjVal, side = 3)
mtext(paste0(rownames(Metadata)[2], Metadata[2,]), cex = 0.6,line \(=-6+\) upway, \(\operatorname{adj}=\mathrm{a}\) djVal, side = 3)
mtext(paste0(rownames(Metadata)[3], Metadata[3,]), cex = 0.6,line \(=-6.5+\) upway, \(\operatorname{adj}=\) adjVal, side = 3)
mtext(paste0(rownames(Metadata)[4], (Metadata[4,])), cex = 0.6,line \(=-7+\) upway, adj \(=\) adjVal, side \(=3\) )
mtext(paste0(rownames(Metadata)[5], (Metadata[5,])), cex = 0.6,line =-7.5+ upway, adj \(=\) adjVal, side = 3)
mtext(paste0(rownames(Metadata)[6], (Metadata[6,])), cex \(=0.6\), line \(=-8+\) upway, \(\operatorname{adj}=\) adjVal, side = 3)
mtext(paste0(rownames(Metadata)[7], (Metadata[7,])), cex \(=0.6\),line \(=-8.5+\) upway, adj = adjVal, side = 3)
mtext(paste0(rownames(Metadata)[8], (Metadata[8,])), cex = 0.6,line =-9+ upway, adj = adjVal, side = 3)
mtext(paste0(rownames(Metadata)[9], (Metadata[9,])), cex = 0.6,line = -9.5+ upway, adj = adjVal, side = 3)
mtext(paste0(rownames(Metadata)[10], (Metadata[10,])), cex = 0.6,line =-10+ upway, a dj = adjVal, side \(=3\) )
mtext(paste0(rownames(Metadata)[11], (Metadata[11,])), cex \(=0.6\), line \(=-10.5+\) upway, adj = adjVal, side = 3)
mtext(paste0(rownames(Metadata)[12], (Metadata[12,])), cex = 0.6,line =-11+ upway, a dj = adjVal, side \(=3\) )
mtext(paste0(rownames(Metadata)[13], (Metadata[13,])), cex = 0.6,line =-11.5+ upway, adj \(=\) adjVal, side \(=3\) )
mtext(paste0(rownames(Metadata)[14], (Metadata[14,])), cex \(=0.6\), line \(=-12+\) upway, a dj \(=\operatorname{adjVal}\), side \(=3\) )
mtext(paste0(rownames(Metadata)[15], (Metadata[15,])), cex = 0.6,line = -12.5+ upway, adj \(=\) adjVal, side \(=3\) )
mtext(paste0(rownames(Metadata)[16], (Metadata[16,])), cex \(=0.6\), line \(=-13+\) upway, a dj = adjVal, side = 3)\#\} \# end "est" loop
mtext(paste0(rownames(Metadata)[17], (Metadata[17,])), cex \(=0.6\), line \(=-13.5+\) upway, adj \(=\) adjVal, side \(=3\) )
mtext(paste0(rownames(Metadata)[18], (Metadata[18,])), cex \(=0.6\), line \(=-14+\) upway, a \(\mathrm{dj}=\operatorname{adjVal}\), side \(=3\) )
mtext(paste0(rownames(Metadata)[19], (Metadata[19,])), cex = 0.6,line = -14.5+ upway, adj \(=\) adjVal, side \(=3\) )
mtext(paste0(rownames(Metadata)[20], (Metadata[20,])), cex = 0.6,line = -15+ upway, a dj = adjVal, side = 3)
mtext(paste0(rownames(Metadata)[21], (Metadata[21,])), cex = 0.6,line = -15.5+ upway, adj \(=\) adjVal, side \(=3\) )
mtext(paste0(rownames(Metadata)[22], (Metadata[22,])), cex \(=0.6\), line \(=-16+\) upway, a dj = adjVal, side = 3)
mtext(paste0(rownames(Metadata)[23], (Metadata[23,])), cex = 0.6,line = -16.5+ upway, adj = adjVal, side = 3)
graphics.off()
\} \# end of if/else for error test
\#\# Warning in dir.create(Dir): 'C:\Users\avorsino\Desktop
\#\# \KESRP_Mit_Start_Yr_2_with_10_Yr_Imp' already exists
\#\# Warning: package 'popbio' was built under R version 3.2.4
\#\# Warning in rbind( \(\mathrm{Mx}, \mathrm{jk}\) ): number of columns of result is not a multiple of \#\# vector length (arg 1)
\#\#
\#\# for the 1800 estimate of strike mortalities,
\#\# replacement occurs at year NA, given 4189.35328591272 burrows

\section*{\# dfMitSoc}

\section*{7. SECTION 7: SITE SPECIFIC PREDATOR EXCLUSION/MITIGATION EFFICACY CONTROL CALCULATOR}

Although the replacement calculator reviewed in Section 6 accounts for various predator control strategies, as well as social attraction, it is at best a coarse deterministic descriptor of the utility of those methodologies to replace strike mortalities over the meta-population. As such, a secondary calculator was developed that allows the user to assess the utility of the various control strategies at specific sites. This permits a more tangible and site specific estimate of mitigation efficacy that can be used directly in planning efforts. Because the calculator in this assessment does not account for power-line strike and light fallout/impingement mortalities at the colony, it is developed for use only in areas without these demographic impacts.

This mitigation calculator was developed for the Kauai Seabird Habitat Conservation Program. The information used to develop this assessment is specific to Newell's shearwater and so should not be used to assess social attraction at sites that are not suitable for this species. The population and flight path overlap information used here is up-to-date as of \(3 / 7 / 2016\).. This calculator should be used only if it constitutes the best available scientific information on a case-by-case basis.

\subsection*{7.1 Site Specific Mitigation Calculator: Overview}

The site specific mitigation calculator is divided into two sections, the first is primarily for user modification, and the second uses this information to model the inputs, and sites, efficacy. As implied here, command modifications to the first section should be modified as the user sees fit, whereas the third section should only be modified if the user completely understands the effect of that modification on the input and output. All modifications should be noted when presenting the results of the calculator. The base of this assessment is given in Section 7.4.

User specified inputs for the analysis are defined in Table 19. Although the meta-population size (coded MetaPopSize ) is left for the user to define, a suggestion is given in the code using the most recent abundance estimate by Joyce (2013) of approximately 27, 011 NESH, of which 90\% are estimated to occur on Kauai (Griesemer and Holmes 2011; Ainley et al. 1997). An initial estimate of 0.81 , (an attempt to estimate the searched habitat on Kauai represented by the

KESRP polygons) was approximated from the area searched by landowner in relation to suitable habitat in unsearched areas. This estimate assumes that \(19 \%\) of suitable NESH habitat is unsearched. The approximation is a very general estimate and should be updated as more information becomes available. The base meta-population value used here was developed in 2013 from data with finalized collections in 2011 (Table 20, input: YearPopEstimated). Because there is a differential between when the code is run, and when these data were collected to obtain the population estimate (i.e. YearPopEstimated) the code automatically collects the year in which the assessment is being run, and applies the lambda of the selected predation scenario (see below) to the meta-population size to get a more accurate estimate of the current meta-population size.

The input parameter in this assessment, coded as the \(S P S\), is used here to indicate the standing population size. Although the calculator was initially developed as a social attraction site estimator, interest in developing social attraction and predator mitigation in areas that have a standing population size were expressed. As such the capability of implementing any of the commonly expressed mitigation techniques on a site with and without a standing population was coded into the calculator, along with variance in the efficacy of each of the mitigation techniques.

Mitigation technique efficacy is another parameter input by the user of the tool (Table 20, coded: Ungulate_Cntrl, Rat_Cntrl, Cat_Cntrl, BrOwl_Cntrl, or for the social attraction site SitFid). Except for the site fidelity, each of the predator control parameters is expressed as a proportion, where a value of 1 infers complete eradication of the predator in the specified site. Maintenance of this predator control efficacy is defined from the point at which control at the site is completely implemented (Table 20, input: Fence_Fin or Broad_Strt, whichever is greater), until the last year that the assessment is run for (Table 20, input: RunTme). Complete efficacy of control throughout the time span of the assessment effectively implies fencing of the site for that predator. As such, the input naming scheme "Fence_Fin" (Table 20) was used as the input parameter that implies completion of the control implementation.

The proportional effect that each of the predator control mitigation percentages have on the population is directly related to the predation scenario used. Four predation scenarios (Table 20, input: PredationEst) were defined for this calculator, allowing the user to assess the effect the
control scenario has on varying degrees of predator control. The first three scenarios are equivalent to that defined in Table 13, whereas the fourth has a proportional predation effect distributed among the different age classes, similar to those in Table 13, but with a lambda equivalent to that of the highest predation scenario defined by (Griesemer and Holmes 2011).

The social attraction site fidelity metrics (Table 20, input, SitFidIn and SitFidOut), are somewhat different from the control efficacy estimates. These two metrics allow the user to estimate the site fidelity to their natal population of juveniles/sub-adults (2-5 year old NESH) in and around the specified site (input SitFidOut), as well as within the control site (input SitFidIn). These inputs are expressed as a proportion on a scale of 0 to 1 ; where 1 assumes that all juveniles return to their natal population (and as such social attraction will not work), and 0 assumes that all juveniles will not return to the natal population. From this value, the efficacy of social attraction at the specified site is obtained using the estimated flight path defined for all known populations in the meta-population (Table 20, input: FlightPath) and the attraction distance of the social attraction cues used (Table 20, input: ExclusBuffer, as implemented on the site shapefile SASiteFile/ ShapeName), in relation to the sites perimeter. Using the flight path and attraction distance, the calculator subsets the proportion of the meta-population that flies within the distance that juveniles/sub-adults would be attracted to the site after whatever social attraction method is applied (Table 20, input: Broad_Start). The site fidelity metric "SitFidIn" (Table 20) is then used to obtain the proportion of those juveniles/sub-adults that would select the social attraction site over their natal site. This contrasts with the use of the site fidelity metric "SitFidOut" (Table 20), which is used define the proportion of those juveniles/sub-adults within the control site that select a location without applied social attraction that is outside of the natal site.

The calculator also requires the user to either define carrying capacity for the site directly, as expressed in burrow number (Table 20, input: Burrow_Cap), or allow the calculator to estimate the carrying capacity using slope and the estimated number of burrows per square meter to determine likely maximum burrow occupancy. If selected to run (by using the 'none' command in the Burrow_Cap input) the latter estimate of carrying capacity (Table 20, input: Slope_Of_Occupancy combined with the input Num_Per_Meter ) uses various slopes estimated either via GIS or directly from burrow site information collected by KESRP (see Section 5.1 and

Table 11 and 12 for a review of the burrow site information used) to estimate the probable area in the site that can be used by NESH (Table 20, input: Slope_Of_Occupancy), and the number of NESH in that site from that area (Table 20, input: Num_Per_Meter). There are five potential inputs for the Slope_Of_Occupancy parameter, all of which are based on boxplot quantiles of slopes derived either directly from a \(1 \mathrm{~m}^{2}\) area at each burrow site, or indirectly for each burrow using a \(30 \mathrm{~m}^{2}\) digital elevation model (DEM). Input character names for Slope_Of_Occupancy include 'min', '1stQ', 'median', '3rdQ', and 'max', all of which correspond to the minimum, first, second and third quartiles, and maximum slope in the assessment.

The value of each Slope_Of_Occupancy input is dependent on the resolution of the DEM (input \(D E M\) ) used in the assessment. There are currently two values for each input, if the resolution of the DEM is less then \(30 \mathrm{~m}^{2}\), then values associated with slopes derived directly from the burrow site will be used. If the resolution of the DEM is \(\geq 30 \mathrm{~m}^{2}\), slope values derived from a \(30 \mathrm{~m}^{2}\) DEM will be used. The values were defined in this way because as the resolution decreases the variance expands and so the slope variables change in each parameter by an amount that is site dependent, and may or may not be linear. One way to modify this is to have the user input the location of all burrow information, but because an attempt was made here to minimize the amount of input by the user, the \(30 \mathrm{~m}^{2}\) resolution threshold was selected as it is the maximum resolution at which the burrow slopes have been calculated.

As noted above, because the calculator does not account for light impingement, light fallout and power-line strike demographic impacts, this assessment is only appropriate for areas that do not have these impacts. Although the calculator accounts for the complete meta-population, it only applies the predation effects to the meta-population. Not accounting for the light and strike mortality factors is appropriate because the subset of the population that the calculator is projecting should not have these factors associated with them.

A caveat to the overall assessment is that in order to obtain an easy to use and run estimate of predator control efficacy an assumption was made that the flight paths are proportional to whatever meta-population amount is used. This essentially assumes that the polygon sizes of the KESRP polygons used to assess the flight path is proportional to the population size within each polygon. This is different from the stochastic site by site PVA presented in Section 5, in that assessment the flight paths in Section 5 lead back to a colony in which the population has been
projected, and the population size of that site is defined using a more in depth analysis. The latter methodology is likely more accurate in its estimate, but also requires far more file inputs to the analysis, and analysis time. Future iterations of the calculator may be updated to better reflect this value, while maintaining ease of use. Like the calculator defined in Section 6, this deterministic assessment is meant to act as a quick evaluation tool for any proposed mitigation strategy

\subsection*{7.2 Site Specific Mitigation Calculator: Output}

An example is used in this section to illustrate the outputs, utility and shortcomings of the site specific mitigation calculator. Here, a site will be used that has been selected by the KSHCP team as one in which proposed mitigation could be conducted in, and that has a surrounding population that would not be influenced by strikes or lights. Two analyses were conducted for the site, one with a standing population, and one without, the various input parameters used for each assessment (as described above) are given in Table 20. As this is just a meant as an example, input values were chosen \(a d h o c\), and thus there was no biological or geographic basis for selection.

The mitigation calculator outputs two graphics, the first is a figure showing the buffer size around the site of interest, and the flight paths within the area of interest (Fig. \(69 \mathrm{~A} \& \mathrm{~B}\) for examples A \& B respectively). It is mainly used to help the user understand how the output is being derived, especially for the social attractions site. The second figure output by the calculator is a deterministic population trend analysis that has itemized within it most of the parameters used in the analysis (Fig. 70 A \& B for examples A \& B respectively). Within this figure the results up to year 30 are presented and partitioned by whether a carrying capacity was applied, by the different population types (Social Attraction versus Standing populations) and by fledgling and adult production. Production of fledglings and adults for the site is estimated in the calculator by comparing the site with the various predator mitigation parameters, to a site without those inputs. The social attraction inputs would be applied to both sites, as it is assumed that a social attraction site without mitigation would essentially be equivalent to the natal population's predation. These metrics allow the estimation of site and mitigation efficacy.

Lambdas for the social attraction populations defined in Figure 70 are calculated differently from the lambda of the standing population size, which is calculated from an Eigen analysis. Because the social attraction population is impacted by any decrease in the meta-population, but always adds birds to the population, its impact on the overall population must be compared with that of the social attraction site without any mitigation. Therefore, the lambda defined for the social attraction population is calculated by subtracting the total number of birds within each year in the controlled site \((x)\), by the total number of birds in that same year that had no mitigation applied (y), and then dividing by \(x\). This gives a lambda for all years calculated. The median of all years is then reported in Figure 70.

Although the calculation of fledglings and adults produced by mitigation is conducted in Figure 53 for examples A and B , it is important to understand how those calculations were derived. Spreadsheets with all necessary information for the population, with and without a carrying capacity, are output for each analysis. These spreadsheets define the population growth, either compiled or discretized by the different population types, for a site with and without the specified levels of predator mitigation and social attraction. Table 21, an output derived from these spreadsheets, shows the number of fledglings produced over a 30 year period for both a protected and unprotected site with no standing population (inputs are defined in Table 20 Example A). As shown in Table 21, a comparison between the total population and those individuals derived from social attraction are conducted. The fledgling production estimates are equivalent because this example is definitive of a social attraction site without a standing population. Table 23 shows the adult production estimate, derived similarly to fledgling production. As adults are not produced, except between the transition between non-reproductive five year olds, and reproductive six year olds, it is important that only a single year is used to estimate adult production. Mitigation outputs for example B (Tables 22 \& 24) are derived similarly to those in example A, but because multiple population types are defined they are discretized to assess the proportion of fledgling (Table 22) and adult (Table 24) production due to mitigation in each.

The output for example B is particularly interesting, as it defines a net increase in production due to mitigation while the sites population trend shows a decrease. This decrease is likely due to multiple factors, the first being that the site fidelity metric used (0.9) is applied to both the
population at the site, and the subset of the population flying over the site. As such, as the metapopulation decreases in size the proportional effect of the site fidelity on birds in the site increases, which decreases the available juveniles for future production. Those birds that move outside the protected site are subject to the same predation as that of the meta-population. Also, the level of mitigation in general may not be capable of supporting the population at the site over the long term. These two factors combined create something of a \(U\) shaped site population projection, where there is still a net benefit, but a general trend line of the sites population initially increases, but then declines.

\subsection*{7.3 Section 7: TABLES}

Table 20: Input parameters for the mitigation efficacy site calculator
\begin{tabular}{cc}
\hline INPUT SECTION 1 & USER INPUT DESCRIPTION \\
\hline MetaPopSize & \begin{tabular}{c} 
The estimated Kauai meta-population size for the year at which the \\
estimator was run (based off of Joyce (2013) estimate) defined in table \\
20.
\end{tabular} \\
YearPopEstimated & \begin{tabular}{c} 
The year that the data used to define the meta-population size was \\
obtained. This is used to calculate the current meta-population size. \\
SPS
\end{tabular} \\
\begin{tabular}{c} 
The standing population size of the site to be calculated (if none put 0)
\end{tabular} \\
Ungulate_Cntrl & Percent ungulate control to be conducted at the specified site \\
Rat_Cntrl & Percent rat control to be conducted at the specified site \\
Cat_Cntrl & Percent cat control to be conducted at the specified site \\
BrOwl_Cntrl & Percent barn owl control to be conducted at the specified site \\
Fence_Fin & Fencing completion year \\
Broad_Strt & Year at which social attraction will start \\
Burrow_Cap & The burrow capacity of the social attraction site
\end{tabular}

Table 21: Input values for the example analyses (A and B) used in the presented grahics (Figures 44 \& 45) and tables .
\begin{tabular}{ccc}
\hline INPUT SECTION 1 & \begin{tabular}{c} 
EXAMPLE A INPUT \\
(Social Attraction Site)
\end{tabular} & \begin{tabular}{c} 
EXAMPLE B INPUT \\
(Social Attraction Site \\
with a Standing \\
Population)
\end{tabular} \\
\hline MetaPopSize & \(27011 * 0.9 * 0.81\) & \(27011^{*} 0.9 * 0.81\) \\
YearPopEstimated & 2011 & 2011 \\
SPS & 0 & 500 \\
Ungulate_Cntrl & \(100 \%(1)\) & \(100 \%(1)\) \\
Rat_Cntrl & \(100 \%(1)\) & \(50 \%(0.5)\) \\
Cat_Cntrl & \(100 \%(1)\) & \(50 \%(0.5)\) \\
BrOwl_Cntrl & \(50 \%(0.5)\) & \(50 \%(0.5)\) \\
Fence_Fin & 2 & 2 \\
Broad_Strt & 2 & 2 \\
Burrow_Cap & - & 5000 \\
Slope_Of_Occupancy & 0.037 & - \\
Num_Per_Meter & 4 & - \\
PredationEst & 50 & 4 \\
RunTme & 1000 meters & 50 \\
ExclusBuffer & 0.95 & 3000 meters \\
SitFidIn & 0.95 & 0.90 \\
SitFidOut & min & 0.90 \\
SHAPEFILE AND RASTER INPUT AND DESCRIPTIONS AS USED FOR BOTH \\
PRIMARY AND SECONDARY ASSESSMENTS
\end{tabular}

Table 22: Fledgling production and mitigation for example A. Here fledgling mitigation is assessed over 30 years. To assess mitigation, the total amount of fledglings produced in the site is subtracted from the total number of birds produced without any protection. This can be partitioned between the different population types within the polygon. Because example \(A\) is primarily a social attraction site, this table only shows the partitioned mitigation for the social attraction site (which equals the mitigation for the site as a whole).

Fledgling Production Example A
\begin{tabular}{c|cc|c|c|}
\cline { 2 - 5 } \multicolumn{1}{c|}{} & \begin{tabular}{c} 
Predator \\
Exclusion
\end{tabular} & All Predators & \begin{tabular}{c} 
Predator \\
Exclusion, Social \\
Attraction
\end{tabular} & \begin{tabular}{c} 
All Predators, \\
Social Attraction
\end{tabular} \\
\cline { 2 - 6 } \multicolumn{1}{c|}{} & \multicolumn{4}{c|}{ 1 YEAR OLDS (FLEDGELINGS) }
\end{tabular}

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
\begin{tabular}{|c|cc|cc|} 
Year 27 & 1.13 & 0.07 & 1.13 & 0.07 \\
Year 28 & 1.15 & 0.07 & 1.15 & 0.07 \\
Year 29 & 1.17 & 0.06 & 1.17 & 0.06 \\
Year 30 & 1.19 & 0.06 & 1.19 & 0.06 \\
\hline \hline Total Production & 20.61 & 2.72 & 20.61 & 2.72 \\
\hline Total Mitigation & & \(\mathbf{1 8}\) & \(\mathbf{1 8}\) \\
\hline \hline
\end{tabular}

Table 23: Fledgling production and mitigation for example B. Here fledgling mitigation is assessed over 30 years. To assess mitigation, the total amount of fledglings produced in the site is subtracted from the total number of birds produced without any protection. This can be partitioned between the different population types within the polygon. Because example \(B\) has both a standing population and social attraction component, both are partitioned from the total to assess mitigation.
\begin{tabular}{|c|c|c|c|c|c|c|c|}
\hline \multicolumn{2}{|l|}{\multirow[t]{3}{*}{}} & \multicolumn{6}{|c|}{Fledgling Production Example B} \\
\hline & & Predator Exclusion & \begin{tabular}{l}
All \\
Predators
\end{tabular} & Predator Exclusion, Social Attraction & All Predators, Social Attraction & Predator Exclusion, Standing Population & All Predators, Standing Population \\
\hline & & \multicolumn{6}{|c|}{1 YEAR OLDS (FLEDGELINGS)} \\
\hline & Year 1 & 32.68 & 32.68 & 0.00 & 0.00 & 32.68 & 32.68 \\
\hline & Year 2 & 30.10 & 30.10 & 0.00 & 0.00 & 30.10 & 30.10 \\
\hline & Year 3 & 58.66 & 27.72 & 0.00 & 0.00 & 58.66 & 27.72 \\
\hline & Year 4 & 60.29 & 25.87 & 0.72 & 0.34 & 59.57 & 25.53 \\
\hline & Year 5 & 61.58 & 24.37 & 1.87 & 0.85 & 59.71 & 23.51 \\
\hline & Year 6 & 58.62 & 21.26 & 3.27 & 1.44 & 55.34 & 19.82 \\
\hline & Year 7 & 56.11 & 18.88 & 4.77 & 2.02 & 51.34 & 16.86 \\
\hline & Year 8 & 56.65 & 16.84 & 5.91 & 2.40 & 50.73 & 14.43 \\
\hline & Year 9 & 57.07 & 15.09 & 6.83 & 2.65 & 50.24 & 12.44 \\
\hline & Year 10 & 57.40 & 13.59 & 7.58 & 2.79 & 49.82 & 10.80 \\
\hline ¢ & Year 11 & 57.22 & 12.20 & 8.21 & 2.87 & 49.01 & 9.34 \\
\hline E & Year 12 & 56.65 & 10.96 & 8.75 & 2.89 & 47.90 & 8.06 \\
\hline * & Year 13 & 56.08 & 9.83 & 9.20 & 2.88 & 46.88 & 6.95 \\
\hline 3 & Year 14 & 55.49 & 8.83 & 9.56 & 2.83 & 45.93 & 6.00 \\
\hline  & Year 15 & 54.89 & 7.93 & 9.84 & 2.76 & 45.05 & 5.18 \\
\hline 㤑 & Year 16 & 54.25 & 7.13 & 10.05 & 2.67 & 44.21 & 4.47 \\
\hline \% & Year 17 & 53.54 & 6.42 & 10.19 & 2.56 & 43.35 & 3.85 \\
\hline \(\stackrel{3}{ \pm}\) & Year 18 & 52.78 & 5.78 & 10.28 & 2.45 & 42.50 & 3.33 \\
\hline \% & Year 19 & 51.98 & 5.20 & 10.32 & 2.33 & 41.65 & 2.87 \\
\hline \(\stackrel{\text { ¢ }}{\sim}\) & Year 20 & 51.15 & 4.69 & 10.32 & 2.21 & 40.83 & 2.47 \\
\hline & Year 21 & 50.30 & 4.23 & 10.29 & 2.09 & 40.02 & 2.13 \\
\hline & Year 22 & 49.43 & 3.81 & 10.21 & 1.97 & 39.22 & 1.84 \\
\hline & Year 23 & 48.55 & 3.44 & 10.11 & 1.85 & 38.43 & 1.59 \\
\hline & Year 24 & 47.65 & 3.11 & 9.99 & 1.74 & 37.66 & 1.37 \\
\hline & Year 25 & 46.74 & 2.81 & 9.84 & 1.63 & 36.89 & 1.18 \\
\hline & Year 26 & 45.82 & 2.54 & 9.68 & 1.52 & 36.14 & 1.02 \\
\hline & Year 27 & 44.90 & 2.30 & 9.50 & 1.42 & 35.40 & 0.88 \\
\hline & Year 28 & 43.98 & 2.08 & 9.30 & 1.33 & 34.67 & 0.75 \\
\hline & Year 29 & 43.05 & 1.88 & 9.10 & 1.23 & 33.95 & 0.65 \\
\hline & Year 30 & 42.13 & 1.71 & 8.89 & 1.15 & 33.24 & 0.56 \\
\hline
\end{tabular}

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
\begin{tabular}{|c|c|cc|c|}
\hline \hline \begin{tabular}{c} 
Total \\
Production
\end{tabular} & \(1535.73 \quad 333.26\) & 224.59 & 54.89 & 1311.14
\end{tabular}

Table 24: Adult Production and mitigation at year 30 for Example A. For adult production/mitigation, only the reproductive ages are summed for the year of interest. Multiple years should not be compiled to assess mitigation. As in the fledgling production, mitigations are here assessed by subtracting the total amount of adults produced in the site from the total number of birds produced without any protection. This can be partitioned between the different population types within the polygon. Because example \(A\) is primarily a social attraction site, this table only shows the partitioned mitigation for the social attraction site (which equals the mitigation for the site as a whole).
\begin{tabular}{|c|c|c|c|c|c|}
\hline \multicolumn{2}{|l|}{\multirow[t]{2}{*}{}} & \multicolumn{4}{|c|}{Adult Production Example A} \\
\hline & & \begin{tabular}{l}
Predator \\
Exclusion
\end{tabular} & \begin{tabular}{l}
All \\
Predators
\end{tabular} & Predator Exclusion, Social Attraction & All Predators, Social Attraction \\
\hline \multirow{24}{*}{cis} & 6 Year Old & 0.37 & 0.07 & 0.37 & 0.07 \\
\hline & 7 Year Old & 0.33 & 0.05 & 0.33 & 0.05 \\
\hline & 8 Year Old & 0.30 & 0.05 & 0.30 & 0.05 \\
\hline & \[
9 \text { Year Old }
\] & 0.26 & 0.04 & 0.26 & 0.04 \\
\hline & 10 Year Old & 0.24 & 0.03 & 0.24 & 0.03 \\
\hline & 11 Year Old & 0.21 & 0.03 & 0.21 & 0.03 \\
\hline & 12 Year Old & 0.19 & 0.02 & 0.19 & 0.02 \\
\hline & 13 Year Old & 0.17 & 0.02 & 0.17 & 0.02 \\
\hline & 14 Year Old & 0.15 & 0.02 & 0.15 & 0.02 \\
\hline & \[
15 \text { Year Old }
\] & 0.14 & 0.01 & 0.14 & 0.01 \\
\hline & 16 Year Old & 0.12 & 0.01 & 0.12 & 0.01 \\
\hline & 17 Year Old & 0.11 & 0.01 & 0.11 & 0.01 \\
\hline & 18 Year Old & 0.10 & 0.01 & 0.10 & 0.01 \\
\hline & 19 Year Old & 0.09 & 0.01 & 0.09 & 0.01 \\
\hline & 20 Year Old & 0.08 & 0.01 & 0.08 & 0.01 \\
\hline & 21 Year Old & 0.07 & 0.00 & 0.07 & 0.00 \\
\hline & 22 Year Old & 0.06 & 0.00 & 0.06 & 0.00 \\
\hline & 23 Year Old & 0.06 & 0.00 & 0.06 & 0.00 \\
\hline & 24 Year Old & 0.05 & 0.00 & 0.05 & 0.00 \\
\hline & 25 Year Old & 0.04 & 0.00 & 0.04 & 0.00 \\
\hline & 26 Year Old & 0.04 & 0.00 & 0.04 & 0.00 \\
\hline & 27 Year Old & 0.04 & 0.00 & 0.04 & 0.00 \\
\hline & 28 Year Old & 0.03 & 0.00 & 0.03 & 0.00 \\
\hline & 29 Year Old & 0.03 & 0.00 & 0.03 & 0.00 \\
\hline
\end{tabular}

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
\begin{tabular}{|c|cc|cc|}
\hline \hline 30 Year Old & 0.03 & 0.00 & 0.03 & 0.00 \\
31 Year Old & 0.02 & 0.00 & 0.02 & 0.00 \\
32 Year Old & 0.01 & 0.00 & 0.01 & 0.00 \\
33 Year Old & 0.00 & 0.00 & 0.00 & 0.00 \\
34 Year Old & 0.00 & 0.00 & 0.00 & 0.00 \\
35 Year Old & 0.00 & 0.00 & 0.00 & 0.00 \\
36 Year Old & 0.00 & 0.00 & 0.00 & 0.00 \\
\hline \hline \begin{tabular}{c} 
Total \\
Production
\end{tabular} & 3.35 & 0.39 & 3.35 & 0.39 \\
\hline \begin{tabular}{c} 
Total \\
Mitigation
\end{tabular} & \(\mathbf{2 . 9 6}\) & \(\mathbf{2 . 9 6}\) \\
\hline \hline
\end{tabular}

Table 25: Adult Production and mitigation at year 30 for Example B. For adult production/mitigation, only the reproductive ages are summed for the year of interest. Multiple years should not be compiled to assess mitigation. As in the fledgling production, mitigations are here assessed by subtracting the total amount of adults produced in the site from the total number of birds produced without any protection. This can be partitioned between the different population types within the polygon. Because example \(B\) has both a standing population and social attraction component, both are partitioned from the total to assess mitigation.
\begin{tabular}{|c|c|c|c|c|c|c|c|}
\hline \multicolumn{2}{|l|}{\multirow[t]{2}{*}{}} & \multicolumn{6}{|c|}{Adult Production Example B} \\
\hline & & \begin{tabular}{l}
Predator \\
Exclusion
\end{tabular} & \begin{tabular}{l}
All \\
Predators
\end{tabular} & Predator Exclusion, Social Attraction & All Predators, Social Attraction & Predator Exclusion, Standing Population & All Predators, Standing Population \\
\hline & 6 Year Old & 16.30 & 1.61 & 3.29 & 1.24 & 13.01 & 0.37 \\
\hline & 7 Year Old & 14.32 & 1.35 & 2.93 & 1.02 & 11.39 & 0.33 \\
\hline & 8 Year Old & 12.82 & 1.16 & 2.65 & 0.86 & 10.17 & 0.30 \\
\hline & 9 Year Old & 11.48 & 1.00 & 2.40 & 0.73 & 9.08 & 0.27 \\
\hline & 10 Year Old & 10.28 & 0.85 & 2.17 & 0.61 & 8.10 & 0.24 \\
\hline & 11 Year Old & 9.20 & 0.73 & 1.97 & 0.51 & 7.23 & 0.22 \\
\hline & 12 Year Old & 8.23 & 0.63 & 1.78 & 0.43 & 6.45 & 0.20 \\
\hline & 13 Year Old & 7.36 & 0.54 & 1.61 & 0.36 & 5.76 & 0.18 \\
\hline ले & 14 Year Old & 6.59 & 0.47 & 1.45 & 0.30 & 5.14 & 0.16 \\
\hline ฐ & 15 Year Old & 5.89 & 0.40 & 1.31 & 0.26 & 4.58 & 0.15 \\
\hline \(\sigma\) & 16 Year Old & 5.26 & 0.35 & 1.18 & 0.21 & 4.08 & 0.13 \\
\hline W & 17 Year Old & 4.70 & 0.30 & 1.06 & 0.18 & 3.64 & 0.12 \\
\hline \(\underset{4}{7}\) & 18 Year Old & 4.20 & 0.26 & 0.95 & 0.15 & 3.25 & 0.11 \\
\hline 品 & 19 Year Old & 3.76 & 0.22 & 0.86 & 0.12 & 2.90 & 0.10 \\
\hline \(\bigcirc\) & 20 Year Old & 3.37 & 0.19 & 0.77 & 0.10 & 2.60 & 0.09 \\
\hline \(\stackrel{\text { U }}{ }\) & 21 Year Old & 3.00 & 0.17 & 0.69 & 0.09 & 2.31 & 0.08 \\
\hline - & 22 Year Old & 2.66 & 0.14 & 0.62 & 0.07 & 2.04 & 0.07 \\
\hline  & 23 Year Old & 2.35 & 0.12 & 0.55 & 0.06 & 1.80 & 0.06 \\
\hline & 24 Year Old & 2.08 & 0.11 & 0.49 & 0.05 & 1.59 & 0.06 \\
\hline & 25 Year Old & 1.93 & 0.09 & 0.43 & 0.04 & 1.50 & 0.05 \\
\hline & 26 Year Old & 1.80 & 0.08 & 0.38 & 0.03 & 1.42 & 0.05 \\
\hline & 27 Year Old & 1.58 & 0.07 & 0.35 & 0.03 & 1.24 & 0.04 \\
\hline & 28 Year Old & 1.38 & 0.06 & 0.32 & 0.02 & 1.07 & 0.04 \\
\hline & 29 Year Old & 0.78 & 0.05 & 0.30 & 0.02 & 0.48 & 0.03 \\
\hline & 30 Year Old & 0.68 & 0.04 & 0.23 & 0.01 & 0.45 & 0.03 \\
\hline & 31 Year Old & 1.09 & 0.05 & 0.15 & 0.01 & 0.94 & 0.05 \\
\hline
\end{tabular}

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
\begin{tabular}{|c|cc|cc|c|}
\hline \hline 32 Year Old & 0.96 & 0.04 & 0.08 & 0.00 & 0.89 \\
33 Year Old & 0.84 & 0.03 & 0.00 & 0.00 & 0.84 \\
34 Year Old & 0.71 & 0.03 & 0.00 & 0.00 & 0.71 \\
35 Year Old & 0.61 & 0.02 & 0.00 & 0.00 & 0.61 \\
36 Year Old & 0.51 & 0.02 & 0.00 & 0.00 & 0.03 \\
\hline \hline \begin{tabular}{c} 
Total \\
Production
\end{tabular} & 146.74 & 11.21 & 30.95 & 7.54 & 0.03 \\
\hline \begin{tabular}{c} 
Total \\
Mitigation
\end{tabular} & \(\mathbf{1 3 5 . 5 2}\) & \(\mathbf{2 3 . 4 1}\) & 115.78 & 0.02 \\
\hline \hline
\end{tabular}

\subsection*{7.4 Section 7: FIGURES}


Figure 69: Example output graphic for the KSHCP social attraction site without a standing population (A) and with a standing population (B). Both graphics show the flight path and buffers used for each analysis.


Figure 70: Example population trend analysis graphic output for the KSHCP social attraction site without a standing population (a) and with a standing population (b) (see table 20). Input parameters, as well as various outputs from the graphic are shown, including final population size, and the added number of adults and fledglings under the various control scenarios with and without a carrying capacity, and partitioned between those added via social attraction, versus those added from the standing population.

\subsection*{7.5 Section 7: SUPPLEMENTARY CODE}

\title{
Code 2: SITE SPECIFIC PREDATOR EXCLUSION/MITIGATION EFFICACY CONTROL CALCULATOR.R
}

\author{
Adam E. Vorsino, Ph.D. Strategic Habitat Conservation Division Pacific Island Fish and Wildlife Office 300 Ala Moana Blvd. Ste. 3-122 \\ adam_vorsino@fws.gov \\ (808)792-9431
}
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#SOCIAL ATTRACTION SITE ESTIMATOR FOR A SITE WITH A STANDING POPULATION\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
```

rm(list = ls())

# For further information about this calculator please contact the author at:

# 

# Adam E. Vorsino, Ph.D.

# Strategic Habitat Conservation Division

# Pacific Island Fish and Wildlife Office

# 300 Ala Moana Blvd. Ste. 3-122

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# (808)792-9431

# 

# 

# Disclaimer: This calculator was developed for the Kauai Seabird Habitat Conservation Program.

# The information used to develop this assessment is specific to Newell's shearwater and so should

# not be used to assess social attraction at sites that are not suitable for this species.

# The population and flight path overlap information is up-to-date as of 3/7/2016. Please use

# and review the input and output carefully. If used to assess the utility of a site for social

# attraction, the user of this tool is solely responsible for the input and output of the assessment.

# This calculator is provided as technical assistance and does not represent Service policy. It

# should be used only if it constitutes the best available scientific information on a case-by-case basis.

\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#INPUT PARAMETERS FOR SOCIAL ATTRACTION SITE CALCULATOR \#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#

```
```


# META-POPULATION SIZE (TO ASSESS SUB-ADULT FLYOVER)

# 27011*0.9 uses Trevor Joice Estimate multiplied by 0.9 (for Kauai Meta-pop) and multiplied by 0.81

# to estimate the amount of population explained by the KESRP colony polygons

# These numbers will be modified using the selected predation estimate to reflect the current meta-population

MetaPopSize <- 27011*0.9*0.81

```

\footnotetext{
\# The year that the data used to define the meta-population size were obtained. From this a current estimate of the m\# eta-population (without light or strike impact)is derived by applying the predation estimate to all years between \(t\) \(h \# e\) and the current year. The current year is defined by the computer and uses the year in which the calculator wa s \# run. A Year must be defined.
}

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator

\section*{YearPopEstimated <- \#UserSpecified\# 2011}
```


# STARTING POPULATION SIZE OF THE ASSESSED SITE

# This metric is meant to inform the population growth at a site with a standing population while

# social attraction is also being conducted at that site

# If SPS is 0 the calculator will develop an assessment that only defines a Social Attraction Site

# Please note, this is meant to be an estimate of the Total Population Size at the site, not just adults

# or burrows.

```
SPS <- \#UserSpecified\#
```


# FENCE EFFICACY

# Can use this section to assess either "leaky fence" or specific fence type scenarios,

# values range from 0 to 1, where 1 is complete control, and 0 is no control.

Ungulate_Cntrl <- 1 \# Ungulate Control
Rat_Cntrl <- 1 \# Rat Control
Cat_Cntrl <- 1 \# Cat Control
BrOwl_Cntrl <- 1 \# Barn Owl Control

# FENCING COMPLETION YEAR

Fence_Fin <- \#UserSpecified\#

```
\# START OF SOCIAL ATTRACTION SITE BROADCASTING YEAR
Broad_Strt <- \#UserSpecified\#
\# BURROW CAPACITY OF SOCIAL ATTRACTION SITE
\# Define the number of burrows in the location specified (either artificial or naturaly produced)
\# If unknown use the SLOPE OF OCCUPANCY FOR BURROW CAPACITY and put "None"
Burrow_Cap <-'None'
\# SLOPE OF OCCUPANCY FOR BURROW CAPACITY
\# If burrow capacity is not given (i.e. it is set to "none") then the code will use various slopes defined by burrow coll ections (as collected by KESRP) to estimate the area that can be used by NESH. Can use 'min', '1stQ', 'median', '3 \({ }^{\text {rd }}\) \# Q', an d 'max') these are minimum, first quartile, median, third quartile, maximum,
\# If using a DEM with a resolution of 30 m or greater the burrow slope esitmates were approximated at a 30 m slope.
\# If using a higher resolution DEM the burrow slope estimates collected at the burrow will be used.
\# if not in use please put 'None'
Slope_Of_Occupancy <- \#UserSpecified\# \#None'

\section*{\#NUMBER OF BURROWS PER METER SQUARED}
\# only specify if using 'Slope_Of_Occupancy' to define burrow occupancy for a site
\# otherwise specify 'None'
Num_Per_Meter <- 0.037 \# Value defined by KSHCP/KESRP

\section*{\# PREDATOIN ESTIMATE}
\# Can use 1, 2, 3 or 4 this corresponds to the KSHCP predation estimate (1),
\# and Greissemer and Holmes (2011) low (2) and medium (3) and high (4) predation estimates respectively.
\# It is a good practice to look at all four...
PredationEst <- \#UserSpecified\#
\# RUN TIME OF CALCULATOR (IN YEARS),
```


# Run for > or = 50 years for best results

RunTme <- \#UserSpecified\#

```
```


# BUFFER AREA AROUND THE SOCIAL ATTRACTION SITE FROM WHICH BIRDS WILL B

E CALLED INTO

# DO NOT CHANGE UNLESS THE OPTIONAL AREA (BELOW) HAS ALL OF THE SPECIFIED INFORMATION

# IN IT

# Buffer should be in meters. It represents the distance from the fenceline that the calling units are effective

ExclusBuffer <- \#UserSpecified\#

```
\# SITE FIDELITY OF JUVENILES (SUB ADULTS)
\# constant is used to derive an estimate of attraction to a newly enclosed site (SitFidIn)
\# or the natal population (SitFidOut)a value of 0.95 indicates that juveniles/sub-adults
\# have a \(95 \%\) probability of returning to their breeding area. Make sure the value is
\# greater than 0 and less than or equal to 1
SitFidIn <- \#UserSpecified\#
SitFidOut <- \#UserSpecified\#
\#Put Desktop Computer User Name here or (if not a federal computer or other that needs admin privileges) use "Public"
DCN <- \#UserName\#
\#(DO NOT ADD OR MODIFY UNLESS THE INFORMATION IS SPECIFICALLY KNOWN, SE E BUFFER ESTIMATE ABOVE)\#
\# PUT THE FILE NAME !!!!!CONTAINING!!!!! THE SOCIAL ATTRACTION SITE SHAPEFIL E
\# please make sure this is in quotes and forward slasshes are used Instead of backslashes (see example)
\# on my computer (Adam Vorsino) this looks like
\#' J:/PIOGISI2/APPS/SH_CC/Adam/KSHCP Social Attraction Site'\#
\# If no file is specified please put "None" \#
SASiteFile <- "None" \#'J:/PIOGIS12/APPS/SH_CC/Adam/KSHCP Social Attraction Site'\#
\# PUT THE NAME OF THE SHAPEFILE TO USE IN THE ANALYSIS (THAT WHICH SASiteFi le IS LEADING TO)
\# If no file is specified please put "None" "Exocarpos_SAS"\#
ShapeName <- "None" \#"Exocarpos_SAS"\#"None"\#
```


# PUT THE RASTER LOCATION CONTAINING THE FLIGHT PATH ESTIMATES FOR THE

AREA

# please make sure this is in quotes and forward slasshes are used Instead of backslashes (see example)

# on my computer (Adam Vorsino) this looks like

# J:/PIOGIS12/APPS/SH_CC/Adam/NESH_Analysis/Andre_LCP_AroundIsle/NESH_WeightedAvg_ForKa.tif

# If no file is specified please put "None"

```

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator

FlightPath <- "None" \#'J:/PIOGIS12/APPS/SH_CC/Adam/NESH_Analysis/Andre_LCP_AroundI sle/NESH_WeightedAvg_ForKa.tif"\#"None"\#
\# PUT THE RASTER LOCATION CONTAINING THE ELEVATION PROFILE (DIGITAL ELEV ATION MODEL)
\# please make sure this is in quotes and forward slashes are used Instead of backslashes (see example)
\# on my computer (Adam Vorsino) this looks like \# J:/PIOGIS12/APPS/SH_CC/Adam/NESH_Analysis/Andre_LCP_AroundIsle/ka_DEM.tif \# It is recomended to use a DEM with a resolution of 30 m or less. \# If no file is specified please put "None"
DEM <- "None" \#'J:/PIOGIS12/APPS/SH_CC/Adam/NESH_Analysis/Andre_LCP_AroundIsle/k a_DEM.tif'\#"None"\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#DO NOT MODIFY PAST THIS SECTION \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#TESTING FOR ERRORS OR LACK OF INFORMATION
ertest1<-cbind(MetaPopSize, Fence_Fin, Broad_Strt, Burrow_Cap, RunTme)
ertest1A<-apply(ertest1, 2, function(x)\{length(unique(x))\})
ErrMessages<-c('META-POPULATION SIZE THAT HAS POTENTIAL FOR RECRUITMEN T INTO THE SITE', 'YEAR IN WHICH THE FENCE FOR THE SOCIAL ATTRACTION SITE IS TO BE
COMPLETED',
'YEAR IN WHICH THE SOCIAL ATTRACTION BROADCASTING STARTS', 'BURROW CAPACITY OF THE SOCIAL ATTRACTION SITE', 'THE NUMBER OF YEARS THE ANALYSIS RUNS FOR')
if(TRUE \%in\% c(unique(ertest1A \(!=\mathbf{c}(1,1,1,1,1))))\{\)
Msg1<-ErrMessages[which((ertest1A !=c(1, 1, 1, 1, 1))==T)]
cat(paste0(" !PLEASE PUT A SINGLE VALUE DESCRIBING THE ", Msg1, "! "))
\(\operatorname{try}(\operatorname{stop}(), \mathrm{T})\)
\}else\{
if(length(which((c(1,2,3,4) \%in\% PredationEst)==T))!=1)\{ cat(" !PLEASE PUT A SINGLE VALUE (1,2 or 3) DESCRIBING PREDATION ESTIM
ATE TO BE USED! ")
\(\operatorname{try}(\operatorname{stop}(), \mathrm{T})\)
\}else\{
if(SitFidIn>1)\{
cat(" !PLEASE PUT A SINGLE VALUE (LESS THAN OR EQUAL TO 1) DESCRIBI
NG THE SITE FIDELITY OF JUVENILE (PRE-BREEDING) SEABIRDS! ")
try(stop(), T)
\}else\{
if(SitFidIn<=0) \{
cat(" !PLEASE PUT A SINGLE VALUE (GREATER THAN 0) DESCRIBING THE S
ITE FIDELITY OF JUVENILE (PRE-BREEDING) SEABIRDS! ") try(stop(), T)
\}else \{
```

    Dir<-paste0('C:/Users/', DCN, '/Desktop/KIUC_SPS-SA_FenceYr_', Fence_Fin,'_CallYr_',
    Broad_Strt, '_RunTime_', RunTme, '/')
if(file.exists(Dir) == F){
dir.create(Dir)
}
if ((is.na(installed.packages()[,"Package"]["popbio"]))==T){
install.packages("popbio", dependencies = T)
}
if ((is.na(installed.packages()[,"Package"]["stringr"]))==T){
install.packages("stringr", dependencies = T)
}
if ((is.na(installed.packages()[,"Package"]["raster"]))==T){
install.packages("raster", dependencies = T)
}
if ((is.na(installed.packages()[,"Package"]["rgdal"]))==T){
install.packages("rgdal", dependencies = T)
}
if ((is.na(installed.packages()[,"Package"]["rgeos"]))==T){
install.packages("rgeos", dependencies = T)
}
library(rgdal)
library(raster)
library(rgeos)
library(stringr)
library(popbio)
if(ExclusBuffer>0){
\#\#\#\#\#\#\#\#\#\#Defining carrying capacity for Social Attraction Sites\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
if(unique(file.exists(SASiteFile, FlightPath))==T){
WgtAvg_FP<-raster(FlightPath)/cellStats(raster(FlightPath), stat = 'sum')
coordSys <- '+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0'
utmSys<-"+proj=utm +zone=4 +ellps=WGS84"
KSHCP_AAS<-readOGR(SASiteFile, ShapeName)
KSHCP_AAS_WGS<-spTransform(KSHCP_AAS, coordSys)
KSHCP_AAS_UTM<-spTransform(KSHCP_AAS_WGS, utmSys)
KSHCP_AAS_UTMBuff<-gBuffer(KSHCP_AAS_UTM, byid = T, width = ExclusBuff
er)
Overlap<-sum(unlist(raster:::extract(WgtAvg_FP, KSHCP_AAS_UTMBuff)), na.rm =
T)
}else{
cat(" !IF A BUFFER GREATER THAN 0 IS USED THE FLIGHT PATH RASTER
AND SOCIAL ATTRACTION SITE SHAPEFILE LOCATION (AND NAME)

```
\}else\{
if(unique(file.exists(SASiteFile, FlightPath))==T) \(\{\)
WgtAvg_FP<-raster(FlightPath)/cellStats(raster(FlightPath), stat = 'sum')
coordSys <- '+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0' utmSys<-"+proj=utm +zone=4 +ellps=WGS84"

KSHCP_AAS<-readOGR(SASiteFile, ShapeName)
KSHCP_AAS_WGS<-spTransform(KSHCP_AAS, coordSys)
KSHCP_AAS_UTM<-spTransform(KSHCP_AAS_WGS, utmSys)
\# KSHCP_AAS_UTMBuff<-gBuffer(KSHCP_AAS_UTM, byid \(=\) T, width \(=\) ExclusBuffer
)
Overlap<-sum(unlist(raster:::extract(WgtAvg_FP, KSHCP_AAS_UTM)), na.rm = T)
\}else\{
Overlap<-0.14
\}
\}
cat('\n Flight Path Overlap Value Used = ', Overlap)
if(Burrow_Cap == 'None')\{
if((DEM != 'None')==T) \(\{\)

DEMRas<-raster(DEM)
DEMRas_UTM<- projectRaster(DEMRas, crs = utmSys)

SiteSlope <- raster:::extract(terrain(DEMRas_UTM, opt = 'slope', unit = 'degrees'), KS HCP_AAS_UTM)

SofORange<-c('min', '1stQ', 'median', '3rdQ', 'max')
resRas<-res(DEMRas_UTM)[1]
if(resRas >=30) \{
SofONum<-c(0.62, 14.93, 21.64, 29.94, 45) \# burrow slopes derived from 30m DEM
\}else\{
SofONum<-c(5, 30, 45, 65, 90)
\}
SofO1<-SofONum[which(SofORange == Slope_Of_Occupancy)]
```

NumBurrows<-(length(SiteSlope[which(SiteSlope[[1]]>=SofO1)])*(resRas^2))*Num_P
er_Meter
Burrow_Cap<-NumBurrows
}else{
cat(" !IF NO BURROW CAPACITY IS SPECIFIED A 'Slope_Of_Occupancy' AND
'DEM' FILE MUST BE SPECIFIED! ')
}
}else{
Burrow_Cap <-Burrow_Cap
}
cat('In Burrow Capacity of Site = ', Burrow_Cap)
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#MAKEING THE LIFE TABLE AND PROJECTION MATRIX USING Qx AND
Px\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#

```
\#\#\#\#\#\#\#\#\#\#\#\#\#\# Defined from Breeding Success and Reproductive Success of Procelarifor ms (with not predation) to get Standard Deviations\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#Calculation of Breeding Probability from G\&H 2011 and KESRP 2013 data
BrProb<-c(0.87, 0.90, 0.80, 0.72, 0.81, 0.75, 0.83, 0.95, 0.89, 0.90, 0.86, 0.80, 0.74, 0.83, 0. 69)
\#\#\#\#\#\#\#Calculation of Reproductive Success from G\&H 2011 (no predators present (<= \#1 1) or eradicated (> \#11))

ReproSucc<-c( \(0.52,0.51,0.63,0.35,0.76,0.61,0.52,0.58,0.70,0.62,0.61,0.81,0.51,0.7\) 6, 0.7,
\(0.62,0.67,0.31,0.53,0.66,0.38,0.47,0.59,0.73,0.75,0.68,0.56,0.60,0.77,0.72\), \(0.59,0.64,0.75,0.60,0.59,0.64,0.54,0.56)\) \# removed outlier Procellaria aequino ctialis \(=0.22\)

NESH_age<-36 \# age of oldest probable NESH
NESHfirst_rep<-6 \# age reproduction occurs for NESH
Age<-c(0, seq(1, NESH_age, 1))
```

Lx<-c(1)
for (ti in 1:NESH_age){
if (ti == 1){
Lx<-cbind(Lx, Lx*0.654)
}
if (ti== 2){

```
```

        Lx<-cbind(Lx, Lx[length(Lx)]*0.78)
    }
    if (ti== 3){
    Lx<-cbind(Lx, Lx[length(Lx)]*0.89)
    }
    if (ti == 4){
        Lx<-cbind(Lx, Lx[length(Lx)]*0.905)
    }
    if (ti== 5){
        Lx<-cbind(Lx, Lx[length(Lx)]*0.905)
    }
    if (ti== 6){
        Lx<-cbind(Lx, Lx[length(Lx)]*0.905)
    }
    if (ti> 6){
Lx<-cbind(Lx, Lx[length(Lx)]*0.92)
}
}
Lx<-as.numeric(as.character(Lx))

```

\section*{\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#}
\#\#\#\#\#\#\#\#\#\#\#\# NO PREDATOR ESTIMATES\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\# Used these estimates for reproductive success without predators because the average foun d for NESH with some level of control was
\# 0.88 NESH repro prob, and 0.75 NESH repro. success ( \(\max =0.95\) and 0.81 respectively) . For an area with some level of control (Upper limahule) repro. succes was estimated
\# at 0.902439 and repro. prob was 0.7837838 . Given that ULP has ungulate fenceing and predator control (not exclusion), it is
\# definitive that these numbers are probably even higher for an area with predator exclusio \(n\), as such these numbers were selected

Ex_JuviSucc<-boxplot(ReproSucc, plot=F)\$stats[5,]\# the upper whisker of reproductive su ccess ( \(=0.81\) )

Ex_ReproProb<-boxplot(BrProb, plot=F)\$stats[4,]\# the 3rd Quantile of breeding probabilit \(y(=0.88)\)

Mx<-c(rep(0, (NESHfirst_rep)), rep(Ex_JuviSucc*Ex_ReproProb, (NESH_age-NESHfirst _rep+1)))
life_table<-data.frame(cbind(Age, Lx, Mx))
\#Calculating Qx and Px to define the population wihout predation (Leslie Matrix) (original G\&H 2011 growth estimates)
proj_mat<-matrix(rep(0,NESH_age*NESH_age),nrow=NESH_age)
for (i in 1:nrow(life_table))\{
```

    if ((i == nrow(life_table))==T){
    life_table[i,'Qx']<-1.0000
    }else{
    life_table[i,'Qx']<-round((life_table[i, 'Lx']-life_table[i+1, 'Lx'])/life_table[i, 'Lx'], digits
    =4)
}
life_table[i,'Px']<-(1-life_table[i, 'Qx']) \# this is the stable projection for comparison
for (ii in 1:nrow(life_table)){
try(proj_mat[ii, ii]<-life_table[ii,'Px'], T) \# subtract by -0.038907 for completely stable p
op (lambda exactly == 1)
}
} \# end of "i"loop
proj_mat<-proj_mat[1:(NESH_age-1),]
jk<-proj_mat
\# The Growth Population Projection Matrix
\# from G and H
Stable_Proj_mat<-as.matrix(rbind(Mx, jk), rownames.force= F) \#make sure it is a square
matrix
colnames(Stable_Proj_mat)<-NULL
eigenNP<-eigen.analysis(Stable_Proj_mat, zero=TRUE) \# without strikes and without pred
ation
Stable_Proj_matNP<-jk
MxNP<-Mx

# 

# \#\#\#\#\#\#\#\#\#\#\# STEP 1 ESTIMATING AFFECTS OF PREDATION

# 

# \#\#\#\#\#\#\#\#\#\#\#\#\# Raw data from 2013 Raines North Bog, Pihea, Pohakea, and Upper Lim

ahule

# \#\#\#\#\#\#\#\#\#\#\#\#\#to define Breeding Success and Probability

# 

# NESH_Monitord<-c(9, 41) \# \# Active Burrows for Adult Estimate

# NESH_MonWBrd<-c(7, 37)

# NESH_MonWSuc<-c(4, 29)

# 

# NESH_over_BrProb<-median(NESH_MonWBrd)/median(NESH_Monitord)

# NESH_over_BrSucc<-median(NESH_MonWSuc)/median(NESH_MonWBrd)

# 

# NESHReproProb<-0.547 \# Ainley Average Reproductive Probability

```
```

    ############################################################################
    ```
    ############################################################################
#############################
#############################
    ############# KESRP ESTIMATED PREDATION AFFECTS FOR X BREEDING PAI
```

    ############# KESRP ESTIMATED PREDATION AFFECTS FOR X BREEDING PAI
    ```

\section*{Site Specific Predator Exclusion/Mitigation Efficay Control Calculator}

\section*{RS PER PREDATOR\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#}
```

if(PredationEst == 1){
LMH<-100
LMHName<-'KSHCP_KESRP' \# DEFINED BY KSHCP
}else{
if(PredationEst == 2){
LMH<-87.4675
LMHName<-'GH_Low' \# DEFININD IN G\&H
}else{
if(PredationEst==3){
LMH<-72.2599
LMHName<-'GH_Medium' \# DEFININD IN G\&H
}else{
LMH <-63.396
LMHName<-'GH_High' \# DEFINED IN G\&H
}
}
}
KESRPBreedingPairs<-LMH \#

```

AdultSubAdultSS<-eigenNP\$stable.stage[3:length(eigenNP\$stable.stage)]/sum(eigenNP\$s table.stage[3:length(eigenNP\$stable.stage)]) \# start at stage 3 (2-3 y/o survivorship) b/c it is whe n predation mortality starts

NumAdults<-2*KESRPBreedingPairs
AdultSubAdultForSANum<-eigenNP\$stable.stage[2:length(eigenNP\$stable.stage)]/sum(ei genNP\$stable.stage[2:length(eigenNP\$stable.stage)])
\# NumSubAdults<-sum(AdultSubAdultSS[1:4])*((KESRPBreedingPairs*2)/sum(AdultSub AdultSS[5:length(AdultSubAdultSS)]))
\# NumSubAdultsTot<-sum(AdultSubAdultForSANum[1:(NESHfirst_rep-1)]*((KESRPBree dingPairs*2)/sum(AdultSubAdultForSANum[NESHfirst_rep:length(AdultSubAdultForSANum)]) ))

NumSubAdults<- sum(AdultSubAdultSS[1:(NESHfirst_rep-2)]*((KESRPBreedingPairs*2) /sum(AdultSubAdultSS[(NESHfirst_rep-1):length(AdultSubAdultSS)]))) \# number of sub-adults predated (i.e. after year 2)
numChicks<-KESRPBreedingPairs \# breeding pairs count assumes \(100 \%\) breeding prob.
\#\#\#\#\#\#\#\# Overall Predation \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#Ungulate Predation
UngAdultPredation<-sum((8*AdultSubAdultSS[(NESHfirst_rep-1):length(AdultSubAdult SS)])) \# adults > =6

UngSubAdultPredation<-sum((8*AdultSubAdultSS[1:(NESHfirst_rep-2)])) \# subadults fro \(m\) age 2-5

UngChickPredation<-8+(UngAdultPredation*Ex_ReproProb)\#NESHReproProb) \# added a ll predated breeding adults to estimate chick predation due to parental death, estimated breeding

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
probability to establish which to remove
PercUngPredAdults<- UngAdultPredation/NumAdults\#divide Adult \# by 2 to account for \(n\) octurnal/crepuscular predation = when only 1 individual of pair at nest at that time

PercUngPredSubAdults<-UngSubAdultPredation/NumSubAdults
PercUngPredChick<-UngChickPredation/numChicks\# Any predation of adults would be a p redation of chick as well...did not include breeding prob because this was already esimtated here

Ung_NESHReproProb<-0\#(UngAdultPredation*4)/NumAdults \# quadruples time until repr oduction so used it to modify repro. probability
\#Cat Predation
CatAdultPredation<-sum((8*AdultSubAdultSS[(NESHfirst_rep-1):length(AdultSubAdultS S)])) \# adults >=6

CatSubAdultPredation<-sum((8*AdultSubAdultSS[1:(NESHfirst_rep-2)])) \# subadults fro \(m\) age 2-5

CatChickPredation<-8+(CatAdultPredation*Ex_ReproProb)\#NESHReproProb) \# added all predated breeding adults to estimate chick predation due to parental death, estimated breeding \(p\) robability to establish which to remove

PercCatPredAdults<- CatAdultPredation/NumAdults\#divide Adult \# by 2 to account for noc turnal/crepuscular predation= when only 1 individual of pair at nest at that time

PercCatPredSubAdults<-CatSubAdultPredation/NumSubAdults
PercCatPredChick<-CatChickPredation/numChicks\# Any predation of adults would be a pr edation of chick as well...did not include breeding prob because this was already esimtated here

\section*{Cat_NESHReproProb<-0}
\#Rat Predation
RatAdultPredation<-0 \# adults >=6
RatSubAdultPredation<-0 \# subadults from age 2-5
RatChickPredation<-12+(RatAdultPredation*Ex_ReproProb)\#NESHReproProb) \# added al \(l\) predated breeding adults to estimate chick predation due to parental death, estimated breeding probability to establish which to remove

PercRatPredAdults<- RatAdultPredation/NumAdults\#divide Adult \# by 2 to account for noc turnal/crepuscular predation= when only 1 individual of pair at nest at that time

PercRatPredSubAdults<-RatSubAdultPredation/NumSubAdults
PercRatPredChick<-RatChickPredation/numChicks\# Any predation of adults would be a pr edation of chick as well...did not include breeding prob because this was already esimtated here

Rat_NESHReproProb<-0
\#Barn Owl Predation
BrOwlAdultPredation<-sum((1*AdultSubAdultSS[(NESHfirst_rep-1):length(AdultSubAd ultSS)])) \# adults > = 6

BrOwlSubAdultPredation<-sum((1*AdultSubAdultSS[1:(NESHfirst_rep-2)]), na.rm = T)
\# subadults from age 2-5
BrOwlChickPredation<-0.5+(BrOwlAdultPredation*Ex_ReproProb)\#NESHReproProb) \# a

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
dded all predated breeding adults to estimate chick predation due to parental death, estimated br eeding probability to establish which to remove

PercBrOwlPredAdults<- BrOwlAdultPredation/NumAdults\#divide Adult \# by 2 to account \(f\) or nocturnal/crepuscular predation = when only 1 individual of pair at nest at that time

PercBrOwlPredSubAdults<-BrOwlSubAdultPredation/NumSubAdults
PercBrOwlPredChick<-BrOwlChickPredation/numChicks\# Any predation of adults would be a predation of chick as well...did not include breeding prob because this was already esimtate \(d\) here

BrOwl_NESHReproProb<-0
\# making projection matrix bottom (not mortality/fertility information yet)
\# Adding \% adults removed by predators
\# a_Ungulates<-PercUngPredAdults+PercUngPredSubAdults
\# a_Cats<-PercCatPredAdults+PercCatPredSubAdults
\# a_Rats<-PercRatPredAdults+PercRatPredSubAdults
\# a_Owl<-PercBrOwlPredAdults+PercBrOwlPredSubAdults
\# a_RatsCats<-a_Cats+a_Rats
\# a_RatsOwl<-a_Cats+a_Owl
ad_RatsOwl<-PercRatPredAdults+PercBrOwlPredAdults
sa_RatsOwl<-PercRatPredSubAdults+PercBrOwlPredSubAdults
\# a_All<-a_Ungulates+a_Cats+a_Rats+a_Owl
ad_All<-PercUngPredAdults+PercCatPredAdults+PercRatPredAdults+PercBrOwlPredAdul ts
sa_All<-PercUngPredSubAdults+PercCatPredSubAdults+PercRatPredSubAdults+PercBrO wlPredSubAdults

> \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
> \#\#\#\#\#\#\#\#\#\#\# ALL PREDATORS ESTIMATES \#\#\#\#\#\#\#\#\#\#\#\#\#\#
> \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
> \# Base Estimate all predators
> Ex_AllPredAdults<-(((PercUngPredAdults+PercUngPredSubAdults)+
> (PercCatPredAdults+PercCatPredSubAdults)+ (PercRatPredAdults+PercRatPredSubAdults)+ (PercBrOwlPredAdults+PercBrOwlPredSubAdults)))

Ex_APredJuviSucc<-Ex_JuviSucc-((Ex_JuviSucc*PercRatPredChick)+(Ex_JuviSucc*Perc CatPredChick)+
(Ex_JuviSucc*PercBrOwlPredChick)+(Ex_JuviSucc*PercUngPredChi ck))

\footnotetext{
Ex_APredReproProb<-Ex_ReproProb-((Ex_ReproProb*BrOwl_NESHReproProb)+(Ex_Re proProb*Rat_NESHReproProb)+
}
proj_MatPred<-proj_mat
for (ii in (NESHfirst_rep-1):(nrow(life_table)-1))\{
try(proj_MatPred[ii, ii]<-proj_MatPred[ii, ii]-Ex_AllPredAdults, T)
\} \# end of ii
Bred<-Ex_APredJuviSucc
Rep<-Ex_APredReproProb
Mx<-c(rep(0, (NESHfirst_rep-1)), rep(Bred*Rep, (NESH_age-NESHfirst_rep+1)))
jk<-proj_MatPred[1:(NESH_age-1),]
dfMitSoc<-data.frame(matrix(nrow=13, ncol= RunTme))
proj_mat2<-jk

\section*{\# Adding to the The Growth Projection Matrix}
\# from \(G\) and \(H\)
Stable_Proj_mat<-as.matrix(rbind(Mx, jk), rownames.force= F) \#make sure it is a square matrix
colnames(Stable_Proj_mat)<-NULL
rownames(Stable_Proj_mat)<-NULL
eigen<-eigen.analysis(Stable_Proj_mat, zero=TRUE) \# with predation without strikes
\# Stable Stage distribution developed from Eigen analysis of the base model
stable.stage<-eigen\$stable.stage
PredLamb<-eigen\$lambda1
PredLamb
\# Population Size at year 1 (now)
StanPopSizeYr1<-SPS*eigen\$stable.stage \# standing population size at year I
\# NonBreedOverlap<-MetaPopSize*stable.stage[c(2:5)]*Overlap
\(M x<-c\left(r e p\left(0,\left(N E S H f i r s t \_r e p-1\right)\right), \mathbf{r e p}\left(B r e d * R e p,\left(N E S H \_a g e-N E S H f i r s t \_r e p+1\right)\right)\right)\)
jk2<-proj_mat2[1:(NESH_age-1),]
Stable_Proj_mat<-as.matrix(rbind(Mx, jk2), rownames.force= F) \#make sure it is a squar e matrix
colnames(Stable_Proj_mat)<-NULL
rownames(Stable_Proj_mat)<-NULL
eigenAllMort<-eigen.analysis(Stable_Proj_mat, zero=0)

CurrLambda<-eigenAllMort\$lambda1
dfMitSoc[, 1]<-c( \(0,0,0,0,0,0,0,0,0,0,0,0,0) \#\) social attraction/exclusion starting pop ulation size
numBirdsAllprd<-c()\#rep(0, NESH_age) \# Social Attraction birds
NmBrdStPopAllPred<-c()\# Birds already at site
CurrYear<-as.numeric(as.character(format(Sys.time(), "\%Y"))) \# Defining the year at w hich the tool was run
\# Because the initial meta-population size was defined for 2011 (by Trevor Joyce in 2013) a \(m\) updating to estimate the Meta-popSize during
\# the current time period using the predation estimate defined int he parameters
MetaPopSize<- MetaPopSize*(CurrLambda ^(CurrYear-YearPopEstimated))
cat('\n', CurrYear, "Meta-Population Size Using the Predation Estimate", PredationEst, " =", MetaPopSize)
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#MAIN ASSESSMENT SECTION\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\# Deterministic model to assess what happens without a fenced site \#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
```

\# Deterministic model to assess what happens without a fenced site

``` \(\qquad\)
for (i in seq(1, RunTme, 1)) \{ \#RunTme
NmBrdStPopAllPred<-c()\#!!!!!!!!!!!
for(i in \(\operatorname{seq}(1,2,1))\{\) \#!!!!!!!!!!!!
numBirds1<-rep(0, NESH_age)
Choices1<-c(Broad_Strt, Fence_Fin)
Choices2<-which.max(c(Broad_Strt, Fence_Fin))
if(i \%in\% c(seq(1, Choices1[Choices2], 1)))\{
\#\#\#\#\#\#\#\#\#\#\#\#\#Standing Population Estimates
if( \(\mathrm{i}==1)\{\)
SPSJ<-SPS*eigenAllMort\$stable.stage
\}else\{
SPSJ<-NmBrdStPopAllPred[i-1,]
\}
AdSubAdSurv<-c(0,SPSJ*c(diag(jk2), 0))
jnkSP<-Ex_APredJuviSucc*Ex_APredReproProb

FledgSameYr<-sum(AdSubAdSurv[NESHfirst_rep:NESH_age], na.rm = T)*jnkSP/2
NmBrdStPopSize<-c(FledgSameYr,AdSubAdSurv[-1])[-(NESH_age+1)]
NmBrdStPopAllPred<-rbind(NmBrdStPopAllPred, NmBrdStPopSize)
\# \}\}
\#\#\#\#\#\#\#\#\#\#\#\#\# Social Attraction Site Estimates
CurrLambda<-eigenAllMort\$lambda1
SocBirds<-0
SocBurrows<-0
SocAdults_Saved1<-0
SocJuvi_Saved1<-0
dfMitSoc[,i]<-c(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) \# Because the Social Attraction sites do
n't add anything until they're made \(=\) no additional protection or reduction
numBirds1<-rep( 0, NESH_age)
numBirdsAllprd<-rbind(numBirdsAllprd, numBirds1)
\}else\{
\# estimates after control starts = complete implimentation of the program
NoSocAdMit<-Ex_AllPredAdults\#ratioCntrlAdults_SocEx\#+(0.2191627*PercSocialExc
lusion)
NoSocJuvMit<-Ex_APredJuviSucc\#ratioCntrlJuvi_SocEx
NoSocRepr<- Ex_APredReproProb\#Ex_APredReproProb + abs(ratioReproRate_SocEx)
NoSocSucc<- Ex_APredJuviSucc\#Ex_APredJuviSucc + abs(ratioCntrlJuvi_SocEx)
Bred<-Ex_APredJuviSucc
Rep<-Ex_APredReproProb
plus2<-2
plus1<-1
NonBreedOverlap<-(MetaPopSize*(PredLamb^i))*stable.stage[c(2:5)]*Overlap
NonBreedOverlapAP<-NonBreedOverlap
\# cat ('n Non-breeders in year ', \(i\), ' (years 2:5) that have the potential to get called in:', \(N\) onBreedOverlap)

Attraction<-NonBreedOverlap*(1-SitFidIn)
\# Attraction profile of site
if( \(\mathrm{i}==(\) Choices \(1[\) Choices2]+1) \()\{\#\) if \(i\) is equal to the year after start
\#\#\#\#\#\#\#\#\#\#\#\#\#Standing Population Estimates
\#\#\#\#\#\#\#\#\#\#\#\#\#Standing Population Estimates
if( \(\mathrm{i}==1\) ) \(\{\)
SPSJ<-SPS*eigenAllMort\$stable.stage
\}else\{
SPSJ<-NmBrdStPopAllPred[i-1,]
\}
```

AdSubAdSurv<-c(0,SPSJ*c(diag(jk2), 0))
jnkSP<-Ex_APredJuviSucc*Ex_APredReproProb
FledgSameYr<-(sum(AdSubAdSurv[NESHfirst_rep:NESH_age], na.rm = T)*jnkSP)/2
NmBrdStPopSize<-c(FledgSameYr,AdSubAdSurv[-1])[-(NESH_age+1)]
NmBrdStPopAllPred<-rbind(NmBrdStPopAllPred, NmBrdStPopSize)
\#\#\#\#\#\#\#\#\#\#\#\#\#Social Attraction Site Estimates

# adding the number that are attracted via microphones

Juvis<-Attraction
numBirds 1[2:(NESHfirst_rep-1)]<-Attraction
numBirdsAllprd<-rbind(numBirdsAllprd, numBirds1)
}else{
\#\#\#\#\#\#\#\#\#\#\#\#\#Standing Population Estimates
if(i== 1){
SPSJ<-SPS*eigenAllMort\$stable.stage
}else{
SPSJ<-NmBrdStPopAllPred[i-1,]
}
AdSubAdSurv<-c(0,SPSJ*c(diag(jk2), 0))
jnkSP<-Ex_APredJuviSucc*Ex_APredReproProb
FledgSameYr<-(sum(AdSubAdSurv[NESHfirst_rep:NESH_age], na.rm = T)*jnkSP)/2
NmBrdStPopSize<-c(FledgSameYr,AdSubAdSurv[-1])[-(NESH_age+1)]
NmBrdStPopAllPred<-rbind(NmBrdStPopAllPred, NmBrdStPopSize)
\#\#\#\#\#\#\#\#\#\#\#\#\#\#Social Attraction Site Estimates

# DEFINGING THE YEAR TO YEAR POPULATION GROWTH

# adding the number that are attracted via microphones

numBirds1[2:(NESHfirst_rep-1)]<-Attraction \# adding the number that come in to the y

```
ear
\# Adding the number that reproduce based on the previous years attraction via microph
\#\#\# the Number to add to reproduction
PrevYearSurv<-numBirdsAllprd[i-1,]*e(diag(jk2), 0)\#(Broad_Strt+1)
\# adding two zeros the first because the assessment starts
\# at year 0 and the second to move it up a year
PrevYearSurvA <-c (0, PrevYearSurv) \#O,
PrevYearSurvB<-PrevYearSurvA[-length(PrevYearSurvA)]
\#\#\#Reproduction
ReproYr<-c(Stable_Proj_mat[1,]) \# adding 0 because starts at year 0
\# NumBabies<-sum((numBirdsAllprd[i-1,1]/2)*ReproYr)\#ReproYr)\#
NumBabies<-sum(PrevYearSurvB/2*ReproYr, na.rm = T)

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
```

PrevYearSurvB[2:(NESHfirst_rep-1)]<-PrevYearSurvB[2:(NESHfirst_rep-1)]*(SitFidO ut)
PrevYearSurvC<-PrevYearSurvB+numBirds1 \#Removing year 0 and adding the numbe r attracted[-1]
PrevYearSurvC[1]<-NumBabies
numBirdsAllprd<-rbind(numBirdsAllprd, PrevYearSurvC)
test1<-try ((numBirdsAllprd[i,1]/(sum(numBirdsAllprd[i,NESHfirst_rep:NESH_age], n a.rm $=\mathrm{T}) / 2)) / \operatorname{ReproYr}[$ length $($ ReproYr $)], \mathrm{T})$
if(class(test1) $==$ 'try-error') $\{$
test1<-"out of bounds"
\}
cat('InTESTA (should equal 1)', test1, ':Number of Fledglings = ', (sum((numBirdsAllpr d[i,NESHfirst_rep:NESH_age]), na.rm = T)/2)*ReproYr[length(ReproYr)])

```
```

        }
        }
    } \# end runtime in years

# Birds at Site (With all predation)

```

AllPredSiteBirds<-data.frame(NmBrdStPopAllPred)
rownames(AllPredSiteBirds)<-paste0('Year ', seq(1, RunTme, 1))
colnames(AllPredSiteBirds)<-paste0(seq(1, ncol(AllPredSiteBirds)), ' Years Old')

\section*{\# Social Attraction Birds}
numBirdsDataAllPred<-data.frame(numBirdsAllprd)
rownames(numBirdsDataAllPred)<-paste0('Year ', seq(1, RunTme, 1))
colnames(numBirdsDataAllPred)<-paste0(seq(1, ncol(numBirdsDataAllPred)), ' Years Old ')

\section*{\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#}
\#\#DEFINING A PREDATOR EXCLUSION FENCE SITE TO INFORM SOCIAL
ATTRACTION \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#
\# Ages 7 and up adults have greater survivorship
Ex_Adults7up<-((Stable_Proj_matNP[NESHfirst_rep+1, NESHfirst_rep+1]*((PercUngPre dAdults+PercUngPredSubAdults)* Ungulate_Cntrl))+
(Stable_Proj_matNP[NESHfirst_rep+1, NESHfirst_rep+1]*((PercCatPredAdults+ PercCatPredSubAdults)* Cat_Cntrl))+
(Stable_Proj_matNP[NESHfirst_rep+1, NESHfirst_rep+1]*((PercRatPredAdults+ PercRatPredSubAdults)* Rat_Cntrl)))+
(Stable_Proj_matNP[NESHfirst_rep+1, NESHfirst_rep+1]*((PercBrOwlPredAdult s+PercBrOwlPredSubAdults)* BrOwl_Cntrl))

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator

\section*{\# Ages 5-6 has lower survivorship for adults}

Ex_Adults <- ((Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep] * ((PercUngPredAdult s+PercUngPredSubAdults) * Ungulate_Cntrl))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep] * ((PercCatPredAdults+Perc CatPredSubAdults) * Cat_Cntrl))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep] * ((PercRatPredAdults+Perc RatPredSubAdults) * Rat_Cntrl))+
(Stable_Proj_matNP[NESHfirst_rep, NESHfirst_rep] * ((PercBrOwlPredAdults+P ercBrOwlPredSubAdults) * BrOwl_Cntrl)))

Ex_Juvi <- ((Ex_JuviSucc*PercUngPredChick)* Ungulate_Cntrl)+ ((Ex_JuviSucc*PercCatPredChick)* Cat_Cntrl)+ ((Ex_JuviSucc*PercRatPredChick)* Rat_Cntrl)+ ((Ex_JuviSucc*PercBrOwlPredChick)* BrOwl_Cntrl)

Ex_ReproProbScen <- ((Ex_ReproProb*Ung_NESHReproProb)* Ungulate_Cntrl)+ ((Ex_ReproProb*Cat_NESHReproProb)* Cat_Cntrl)+ ((Ex_ReproProb*Rat_NESHReproProb)* Rat_Cntrl)+ ((Ex_ReproProb*BrOwl_NESHReproProb)* BrOwl_Cntrl)
\# SOCIAL ATTRACTION (STARTING FROM SCRATCH) WITH EXCLUSION
SocEx_Adults7up <- Ex_Adults7up
SocEx_Adults <- Ex_Adults
SocEx_Juvi <- Ex_Juvi
SocEx_ReproProb <- Ex_ReproProbScen
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# For Social Attraction
ratioCntrlAdults_SocEx7up <- (SocEx_Adults7up)\#*PercSocialExclusion)
ratioCntrlAdults_SocEx <- (SocEx_Adults)\#*PercSocialExclusion)
ratioCntrlJuvi_SocEx <- (SocEx_Juvi)\#*PercSocialExclusion)
ratioReproRate_SocEx <- (SocEx_ReproProb)\#*PercSocialExclusion)

\section*{\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\# \\ \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \\ \#\#\#\#\#\#\#\# MAKEING A DETERMINISTIC MODEL WITH PREDATION \#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \\ \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#}

Bred<-Ex_APredJuviSucc
Rep<-Ex_APredReproProb

Mx<-c(rep(0, (NESHfirst_rep-1)), \(\left.\boldsymbol{r e p}\left(B r e d * R e p,\left(N E S H \_a g e-N E S H f i r s t \_r e p+1\right)\right)\right) ~\)
jk2<-proj_mat2[1:(NESH_age-1),]
Stable_Proj_mat<-as.matrix(rbind(Mx, jk2), rownames.force= F) \#make sure it is a squar e matrix
colnames(Stable_Proj_mat)<-NULL
rownames(Stable_Proj_mat)<-NULL
eigenAllMort<-eigen.analysis(Stable_Proj_mat, zero=0)
CurrLambda<-eigenAllMort\$lambda1
dfMitSoc[, 1]<-c( \(0,0,0,0,0,0,0,0,0,0,0,0,0) \#\) social attraction/exclusion starting pop ulation size
numBirds<-c()\#rep(0, NESH_age)
StPopAllPred<-c() \# Birds at site
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\#\#\#\#\#\#\# Deterministic model to assess what happens with a fenced site, \#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#
\#\#\#\#\#\#\# a standing population, and Social Attraction\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\# Deterministic model to assess overall mitigation effort for Soci --------
for (i in seq(1, RunTme, 1\()\) ) \{
\# numBirds1<-rep(0, NESH_age)
\# estimates the strike removal from the population prior to the start of control
\# Everything with Soc in it's name has to do with the social attraction population
Choices1<-c(Broad_Strt, Fence_Fin)
Choices2<-which.max(c(Broad_Strt, Fence_Fin))
\# StPopAllPred<-c()
\# for \((\operatorname{in} \operatorname{in} \operatorname{seq}(1,2,1))\) )
\#
\# \(\quad i=1\)
if(i \%in\% c(seq(1, Choices1[Choices2], 1))) \{ \# Prior to Fencing
\#\#\#\#\#\#\#\#\#\#\#\#\#\#Standing Population Estimates
if( \(\mathrm{i}==1)\{\)
SPSJ<-SPS*eigenAllMort\$stable.stage
\}else\{
```

    SPSJ <- StPopAllPred[i-1,]
    }
AdSubAdSurv<-c(0,SPSJ*c(diag(jk2), 0))
jnkSP<-Ex_APredJuviSucc*Ex_APredReproProb
FledgSameYr<-sum(AdSubAdSurv[NESHfirst_rep:NESH_age], na.rm = T)*jnkSP/2
SPSii1<-c(FledgSameYr,AdSubAdSurv[-1])[-(NESH_age+1)]
StPopAllPred<-rbind(StPopAllPred, SPSii1)
\#\#\#\#\#\#\#\#\#\#\#\#\#Social Attraction Site Estimates
CurrLambda<-eigenAllMort\$lambda1
SocBirds<-0
SocBurrows<-0
SocAdults_Saved1<-0
SocJuvi_Saved1<-0
dfMitSoc[,i]<-c(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) \# Because the Social Attraction sites do
n't add anything until they're made = no additional protection or reduction
numBirds1<-rep(0, NESH_age)
numBirds<-rbind(numBirds, numBirds1)
}else{

# estimates after control starts = complete implimentation of the program

SocAdMit7up<-ratioCntrlAdults_SocEx7up\#+(0.2191627*PercSocialExclusion)
SocAdMit<-ratioCntrlAdults_SocEx\#+(0.2191627*PercSocialExclusion)
SocJuvMit<-ratioCntrlJuvi_SocEx \# Only used for chick/fledgeing success
SocRepr<- Ex_APredReproProb + abs(ratioReproRate_SocEx)
SocSucc<- Ex_APredJuviSucc + abs(ratioCntrlJuvi_SocEx)

# Stable_Proj_matNP

plus2<-2
plus1<-1
for (mitty in c('Soc')){
proj_mat3<-proj_mat2
for (ii in life_table[2:nrow(life_table), 'Age']){
if ((ii >= NESHfirst_rep-1)==T){ \# Start at year 5 prospectors
if(ii %in% c(5, 6)){
try(proj_mat3[ii, ii]<-proj_mat2[ii,ii]+get(paste0(mitty, "AdMit")), T) \# removing s
ub-adults
}
if(ii >= 7){
try(proj_mat3[ii, ii]<-proj_mat2[ii,ii]+get(paste0(mitty, "AdMit7up")), T) \# removi
ng sub-adults
}

```
\}else\{
try(proj_mat3[ii, ii]<-proj_mat2[ii,ii], T)\#+get(paste0(mitty, "JuvMit")), T) \# removi
ng sub-adults
\}
\(\operatorname{try}(\mathrm{if}((\) proj_mat3[ii,ii]==0)==T)\{
proj_mat3[ii,ii]<-0.000000001\# makeing as close to zero as possible
\}, T)
\} \# end ii
MxMit<-c(rep(0, (NESHfirst_rep-1)), rep(get(paste0(mitty, "Repr"))*get(paste0(mitty , "Succ")), (NESH_age-NESHfirst_rep+plus1)))
jk2Mit<-proj_mat3[1:(NESH_age-1),]
Stable_Proj_mat<-as.matrix(rbind(MxMit, jk2Mit), rownames.force= F ) \#make sure it is a square matrix
colnames(Stable_Proj_mat)<-NULL
rownames(Stable_Proj_mat)<-NULL
eigenMit<-eigen.analysis(Stable_Proj_mat, zero=0)
assign(paste0(mitty, 'eigenMit'), eigenMit)
\}
NonBreedOverlap<-(MetaPopSize*(PredLamb^i) \({ }^{\wedge}\) *stable.stage[c(2:5)]*Overlap
NonBreedOverlapNP<-NonBreedOverlap
\# cat( 'n Non-breeders in year ', i, ' (years 2:5) that have the potential to get called in:', N onBreedOverlap)

Attraction<-NonBreedOverlap*(1-SitFidIn)
\# Attraction profile of site
if(i \(==(\) Choices1[Choices2]+1)) \{\# if i is equal to the year after start
\#\#\#\#\#\#\#\#\#\#\#\#\#\#Standing Population Estimates
if \((\mathrm{i}==1)\{\)
SPSJ<-SPS*eigenMit\$stable.stage
\}else\{
SPSJ<-StPopAllPred[i-1,]
\}
AdSubAdSurv<-c(0,SPSJ*c(diag(jk2Mit), 0))
jnkSP<-SocRepr*SocSucc
FledgSameYr<-(sum(AdSubAdSurv[NESHfirst_rep:NESH_age], na.rm = T)*jnkSP)/2
SPSii2<-c(FledgSameYr,AdSubAdSurv[-1])[-(NESH_age+1)]
StPopAllPred<-rbind(StPopAllPred, SPSii2)
\#\#\#\#\#\#\#\#\#\#\#\#\#\#Social Attraction Site Estimates
\# adding the number that are attracted via microphones
```

    Juvis<-Attraction
    numBirds 1[2:(NESHfirst_rep-1)]<-Attraction
    numBirds<-rbind(numBirds, numBirds1)
    }else{
\#\#\#\#\#\#\#\#\#\#\#\#\#\#Standing Population Estimates
if(i == 1){
SPSJ<-SPS*eigenMit\$stable.stage
}else{
SPSJ<-StPopAllPred[i-1,]
}

```

AdSubAdSurv<-c(0,SPSJ*c(diag(jk2Mit), 0)) jnkSP<-SocRepr*SocSucc
FledgSameYr<-sum(AdSubAdSurv[NESHfirst_rep:NESH_age], na.rm = T)*jnkSP/2 SPSii3<-c(FledgSameYr,AdSubAdSurv[-1])[-(NESH_age+1)]

StPopAllPred<-rbind(StPopAllPred, SPSii3)
\#\#\#\#\#\#\#\#\#\#\#\#\#Social Attraction Site Estimates
\# adding the number that are attracted via microphones
numBirds 1[2:(NESHfirst_rep-1)]<-Attraction \# adding the number that come in to the \(y\)
\# Adding the number that reproduce based on the previous years attraction via microph
\#\#\# the Number to add to reproduction
PrevYearSurv<-numBirds[i-1,]*e(diag(jk2Mit), 0)\#(Broad_Strt+1)
\# adding two zeros the first because the assessment starts
\# at year 0 and the second to move it up a year
PrevYearSurvA<-c(0, PrevYearSurv)
PrevYearSurvB<-PrevYearSurvA[-length(PrevYearSurvA)]
\#\#\#Reproduction
ReproYr<-c(Stable_Proj_mat[1,]) \# adding 0 because starts at year 0
\# NumBabies<-sum((numBirds[i,]/2)*ReproYr)\#ReproYr)\#
NumBabies<-sum(PrevYearSurvB/2*ReproYr, na.rm = T)
\# [NESHfirst_rep:NESH_age]
\# Total added
PrevYearSurvB[2:(NESHfirst_rep-1)]<-PrevYearSurvB[2:(NESHfirst_rep-1)]*(SitFidO
PrevYearSurvC<-PrevYearSurvB+numBirds1 \#Removing year 0 and adding the numbe \(r\) attracted[-1]

PrevYearSurvC[1]<-NumBabies
numBirds<-rbind(numBirds, PrevYearSurvC)
\(\# i=10\)
test2<-try ((numBirds[i,1]/(sum(numBirds[i,NESHfirst_rep:NESH_age], na.rm = T)/2)) /ReproYr[length(ReproYr)], T)
if(class(test2) == 'try-error')\{
test2<-"out of bounds"
\}
cat(' \(\ln\) TESTB (should equal 1)', test2, ':Number of Fledglings = ', (sum((numBirdsAllpr d[i,NESHfirst_rep:NESH_age]))/2)*ReproYr[length(ReproYr)])
\}
\}
\}
Overview<-paste0('SAS_Using_PredEst_', PredationEst, '_with_Site Fid_of_', SitFidIn)
Metadata<-rbind(MetaPopSize, Fence_Fin, Broad_Strt, Burrow_Cap, RunTme, PredationE st, SitFidIn, SitFidOut)
rownames(Metadata)<-c('Meta-Pop Size = ', 'Year Fencing is Complete = ', 'Year Broadcas ting Starts= ', 'Burrow Capacity of the Site = ',
"Years the Analysis is Run For = ", 'Predation Estimate = ', 'Juvenile Site Fide lity Value Within the Site= ',
'Juvenile Site Fidelity Value Outside of the Site= ')
colnames(Metadata)<- 'MetaData of Analysis'

Dir2<-paste0(Dir, Overview, '/')
if(file.exists(Dir2) == F) \(\{\) dir.create(Dir2)
\}
StPopAllPredData<-data.frame(StPopAllPred)
rownames(StPopAllPredData)<-paste0('Year ', seq(1, RunTme, 1))
colnames(StPopAllPredData)<-paste0(seq(1, ncol(StPopAllPredData)), ' Years Old')
\# write.csv(Metadata, paste0(Dir2, 'MetaData.csv'))
numBirdsData<-data.frame(numBirds)
rownames(numBirdsData)<-paste0('Year ', seq(1, RunTme, 1))
colnames(numBirdsData)<-paste0(seq(1, ncol(numBirdsData)), ' Years Old')
\# Lambda for the social attraction site is calculated differentily. Because the social attracti on site is
\# affected by the decrease in the meta-population, but always adds birds to the population, \(i\) ts growth must

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
\# be compared with that of the social attraction site without any mitigation. That is what is done here.
tunction1<-apply(numBirdsData, 1, function(x)\{
xrow <- which(sum(x) == apply(numBirdsData, 1 , sum))
round \((1+((\operatorname{sum}(x)-s u m(n u m B i r d s D a t a A l l P r e d[x r o w]),) / \operatorname{sum}(x)), 2)\)
\})
lambda <- median(tunction1, na.rm = T)
\# lambda<-round(1+abs((sum(numBirdsData[nrow(numBirdsData),])-sum(numBirdsData [nrow(numBirdsData)-1,]))/sum(numBirdsData[nrow(numBirdsData),])), 2)
lambdaSP <- round(eigenMit\$lambda1, 2)
write.csv(numBirdsDataAllPred, paste0(Dir2, 'All Predators Social Attraction Birds.csv'))
write.csv(AllPredSiteBirds, paste0(Dir2, 'All Predators for Standing Population.csv'))
write.csv(AllPredSiteBirds+numBirdsDataAllPred, paste0(Dir2, 'All Predators for ALL BI RDS.csv'))
write.csv(numBirdsData, paste0(Dir2, 'Predator Exclusion Social Attraction Birds NO CA RRYING CAPACITY.csv'))
write.csv(StPopAllPredData, paste0(Dir2, 'Predator Exclusion For Standing Population NO CARRYING CAPACITY.csv'))
write.csv(StPopAllPredData+numBirdsData, paste0(Dir2, 'Predator Exclusion for ALL BI RDS NO CARRYING CAPACITY.csv'))

AllBirds<-StPopAllPredData+numBirdsData
PropSPS<-StPopAllPredData/AllBirds \# Proportion that is the standing population size
PropSA<-numBirdsData/AllBirds \# Proportion that is the Social Attraction birds
png(filename = paste0(Dir2, " Social Attraction Site Population Site with a Standing Popul ation Size Analysis.png"), width = 1000,
height \(=1000\), pointsize \(=18\), type="cairo")
\#\#\#\#\#\#\#\#\#\#Defining carrying capacity for Social Attraction Sites\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
SE_K<-(Burrow_Cap/Rep)*2\#PercSocialExclusion*1644912 \# Social attraction Site Carry ing Capacity ( = percent area defined by social attraction, multiplied by total K for ENM)
\# SE_K<- KCap*HAExclusion \# 48.2 individuals per ha, ad hoc K defined in M\&M for NE SH strategy write up

OverSum<-apply(AllBirds, 1, sum)
OverSum2<-OverSum
OverSum2[which(OverSum2>SE_K)]<-SE_K
\# applying \(K\) to the csv file
numBirdsDataTK<-AllBirds
for (Ni in which(OverSum>SE_K))\{

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
```

if(Ni < NESH_age) $\{$

```
\# Ni \(=22\)

SSgd<-SoceigenMit\$stable.stage[1:(Ni+2)]/sum(SoceigenMit\$stable.stage[1:(Ni+2)], na.
\(\mathrm{rm}=\mathrm{T}\) )
    ToApp<-SE_K*SSgd
    numBirdsDataTK[Ni,]<-c(ToApp, rep(0, NESH_age-Ni))
    \}else\{
    SSgd<-SoceigenMit\$stable.stage
    ToApp<-SE_K*SSgd
    numBirdsDataTK[Ni,]<-ToApp
    \}
    \}
\# numBirdsDataTK[21:22,]
write.csv(numBirdsDataTK*PropSA, paste0(Dir2, 'Predator Exclusion Social Attraction Bi rds WITH CARRYING CAPACITY.csv'))
write.csv(numBirdsDataTK*PropSPS, paste0(Dir2, 'Predator Exclusion For Standing Popu lation WITH CARRYING CAPACITY.csv'))
write.csv(numBirdsDataTK, paste0(Dir2, 'Predator Exclusion for ALL BIRDS WITH CAR RYING CAPACITY.csv'))
\# ((apply((numBirdsDataTK*PropSPS)[,6:36], 1, sum)*get(paste0(mitty, "Repr")))/2)*get( pasteO(mitty, "Succ"))
\# write.csv(numBirdsDataTK, pasteO(Dir2, 'Analysis Output per Age Class and Per Year W ITH CARRYING CAPACITY.csv'))
plot(apply(numBirdsDataTK, 1, sum), type = 'l', bty = 'l', ylab = "Number of Birds (All Ag e Classes)", xlab = 'Year', lty = 1)
mtext('Social Attraction Site with Standing Population Analysis')
mtext('(the rate of site occupancy from Social Attraction is estimated \nusing the overlap of the flight path with a Inproposed Social Attraction Site)',
\[
\text { line }=-2.5, \operatorname{cex}=0.8)
\]
mtext(paste0('Population Size at Year ', RunTme, ' = ', round(apply(numBirdsDataTK, 1, sum)[paste0('Year ',RunTme)], 2)),
\[
\text { line }=-4, \text { cex }=0.6)
\]
upway <--2
mtext(bquote(underline('Various Parameters Used in the Analysis')), cex = 0.7, col = 'red', line \(=-10+\) upway, adj \(=1\), side \(=3\), font \(=2\) )
mtext(paste0(rownames(Metadata)[1], round(Metadata[1,])), cex \(=0.6\),line \(=-10.5+\) upw ay, \(\operatorname{adj}=1\), side \(=3\) )
mtext(paste0(rownames(Metadata)[2], Metadata[2,]), cex \(=0.6\) line \(=-11+\) upway, adj \(=1\)
```

, side = 3)

```
mtext(paste0(rownames(Metadata)[3], Metadata[3,]), cex \(=0.6\), line \(=-11.5+\) upway, adj \(=\) 1 , side \(=3\) )
mtext(paste0(rownames(Metadata)[4], round(Metadata[4,])), cex \(=0.6\), line \(=-12+\) upway , \(\operatorname{adj}=1\), side \(=3\) )
\(\boldsymbol{m t e x t}(\boldsymbol{p a s t e} \mathbf{0}\) ('Carrying Capacity of the Site \(=\) ', round(SE_K, 0)), cex \(=0.6\), line \(=-12.5+\mathrm{u}\) pway, \(\operatorname{adj}=1\), side \(=3\) )
mtext(paste0(rownames(Metadata)[5], Metadata[5,]), cex \(=0.6\), line \(=-13+\) upway, adj \(=1\) , side \(=3\) )
mtext(paste0(rownames(Metadata)[6], Metadata[6,]), cex \(=0.6\), line \(=-13.5+\) upway, \(\operatorname{adj}=\) 1 , side \(=3\) )
mtext(paste0(rownames(Metadata)[7], Metadata[7,]), cex \(=0.6\), line \(=-14+\) upway, adj \(=1\) , side \(=3\) )
mtext(paste0(rownames(Metadata)[8], Metadata[8,]), cex \(=0.6\), line \(=-14.5+\) upway, adj \(=\) 1 , side \(=3\) )
mtext(paste0('Flight Path Overlap Value Used = ', round(Overlap,4)), cex = 0.6, line = -15 + upway, \(\operatorname{adj}=1\), side \(=3\) )
```


# SPS <- 500 \#UserSpecified\#

# 

# \# FENCE EFFICACY

# \# Can use this section to assess either "leaky fence" or specific fence type scenarios,

# \# values range from 0 to 1, where 1 is complete control, and 0 is no control.

# Ungulate_Cntrl <- I \# Ungulate Control

# Rat_Cntrl <- 1 \# Rat Control

# Cat_Cntrl <-1 \# Cat Control

# BrOwl_Cntrl <- l \# Barn Owl Control

    mtext(paste0('Starting Population Size at Site = ', SPS), cex = 0.6, line = -15.5+ upway, adj
    = 1, side = 3)
mtext(paste0('Percent Ungulate Control = ', Ungulate_Cntrl*100, '%'), cex = 0.6, line = -16

+ upway, adj = 1, side = 3)
mtext(paste0('Percent Cat Control = ', Cat_Cntrl*100, '%'), cex = 0.6, line = -16.5+ upway,
adj = 1, side = 3)
mtext(paste0('Percent Rat Control = ', Rat_Cntrl*100, '%'), cex = 0.6, line = -17+ upway, a
dj = 1, side = 3)
mtext(paste0('Percent Barn Owl Control = ', BrOwl_Cntr1*100,'%'), cex = 0.6, line = -17.5
+ upway, adj = 1, side = 3)
upway <- upway + -6
SAFenceFledgeProd <- round(sum(numBirdsData[1:30, 1], na.rm = T) - sum(numBirdsDa
taAllPred[1:30, 1], na.rm = T))
SAFenceAdultProd <- round(sum(numBirdsData[30, 6:36], na.rm = T) - sum(numBirdsDa
taAllPred[30, 6:36], na.rm = T))

```

SPFenceFledgeProd <- round(sum(StPopAllPredData[1:30, 1], na.rm = T) - sum(AllPredS

Site Specific Predator Exclusion/Mitigation Efficay Control Calculator
iteBirds [1:30, 1], na.rm = T))
SPFenceAdultProd <- round(sum(StPopAllPredData[30, 6:36], na.rm = T) - sum(AllPredS iteBirds[30, 6:36], na.rm = T))

AddFled <- round(SAFenceFledgeProd + SPFenceFledgeProd)
AddAdult <- round(SAFenceAdultProd + SPFenceAdultProd)
AddFledCC <- round(sum(numBirdsDataTK[1:30, 1]) - sum((AllPredSiteBirds+numBirds DataAllPred)[1:30, 1]))

AddAdultCC <- round(sum(numBirdsDataTK[30, 6:36]) - sum((AllPredSiteBirds+numBir dsDataAllPred)[30, 6:36]))
```

\# PropSPS<-StPopAllPredData/AllBirds \# Proportion that is the standing population size \# PropSA<-numBirdsData/AllBirds \# Proportion that is the Social Attraction birds

```

CCSPS <- (numBirdsDataTK*PropSPS)-(AllPredSiteBirds)
CCSPSFledge<-round(sum(CCSPS[1:30, 1], na.rm = T))
CCSPSAdult<-round(sum(CCSPS[30, 6:36], na.rm = T))
CCSA <- (numBirdsDataTK*PropSA - (numBirdsDataAllPred))
CCSAFledge<-round(sum(CCSA[1:30, 1], na.rm = T))
CCSAAdult<-round(sum(CCSA[30, 6:36], na.rm = T))
mtext(bquote(underline('Various Outputs From the Calculator')), cex \(=0.7, \mathrm{col}=\) 'red', lin \(e=-16+\) upway, \(\operatorname{adj}=1\), side \(=3\), font \(=2\) )
mtext('Outputs Define the Difference Between Predated \nand Controled Populations', cex \(=0.5, \mathrm{col}=\) 'red', line \(=-17+\) upway, \(\operatorname{adj}=1\), side \(=3\) )
mtext('With Carrying Capacity', cex \(=0.6, \operatorname{col}=\) 'blue', line \(=-18+\) upway, \(\operatorname{adj}=1\), side \(=3\), font \(=2\) )
mtext(paste0("Added Adults at Year 30: ", AddAdultCC), cex \(=0.6\), line \(=-18.5+\) upway, a \(\mathrm{dj}=1\), side \(=3\), font \(=2\) )
mtext(paste0("---from Social Attraction: ", CCSAAdult), cex \(=0.6\),line \(=-19+\) upway, adj \(=1\), side \(=3\) )
mtext(paste0("---from Standing Population: ", CCSPSAdult), cex \(=0.6\),line \(=-19.5+\) upwa \(y, \operatorname{adj}=1\), side \(=3)\)
mtext(paste0("Added Fledgelings until Year 30: ", AddFledCC), cex = 0.6,line = -20+ upw ay, \(\operatorname{adj}=1\), side \(=3\), font \(=2\) )
mtext(paste0("---from Social Attraction: ", CCSAFledge), cex \(=0.6\), line \(=-20.5+\) upway, \(\operatorname{adj}=1\), side \(=3)\)
mtext(paste0("---from Standing Population: ", CCSPSFledge), cex \(=0.6\), line \(=-21+\) upway , \(\operatorname{adj}=1\), side \(=3\) )
mtext('Without Carrying Capacity', cex \(=0.6, \mathrm{col}=\) 'blue', line \(=-21.5+\) upway, adj \(=1\), sid \(\mathrm{e}=3\), font \(=2\) )
mtext(paste0("Added Adults at Year 30: ", AddAdult), cex \(=0.6\), line \(=-22+\) upway, adj \(=\) 1 , side \(=3\), font \(=2\) )
mtext(paste0("---from Social Attraction: ", SAFenceAdultProd), cex \(=0.6\),line \(=-22.5+\) up way, \(\operatorname{adj}=1\), side \(=3\) )
mtext(paste0("---from Standing Population: ", SPFenceAdultProd ), cex \(=0.6\), line \(=-23+u\) pway, \(\operatorname{adj}=1\), side \(=3\) )
mtext(paste0("Added Fledgelings until Year 30: ", AddFled), cex \(=0.6\),line \(=-23.5+\) upwa \(y, \operatorname{adj}=1\), side \(=3\), font \(=2\) )
mtext(paste0("---from Social Attraction: ", SAFenceFledgeProd), cex \(=0.6\),line \(=-24+\) up way, \(\operatorname{adj}=1\), side \(=3\) )
mtext(paste0("---from Standing Population: ", SPFenceFledgeProd ), cex \(=0.6\),line \(=-24.5\) + upway, \(\operatorname{adj}=1\), side \(=3\) )
text(RunTme/4+10, apply(numBirdsData+StPopAllPredData, 1, sum)[RunTme/4], paste0 ('LAMBDA = Soc. Att.: ', lambda, ' / Stand. Pop.: ', lambdaSP), cex = 0.6)
arrows(RunTme/4+10, apply(numBirdsData+StPopAllPredData, 1, sum)[RunTme/4], as.n umeric(str_replace(names(apply(numBirdsData, 1, sum)[round(RunTme-30)]), 'Year ', "')), apply(numBirdsData+StPopAllPredData, 1, sum)[round(RunTme-30)], lty = 2, length \(=0.1\) )
graphics.off()
cat('InEnd Metapopulation Size = ', (MetaPopSize* \((\) PredLamb^i \()\) ), ':BurrowCapacity = ', Burrow_Cap, ' :Predation Lambda = ', PredLamb, ' :SA Lambda = ', lambda, ': SA Reproductive Success = ', ReproYr[6])
if((DEM != 'None')==T \()\{\)

DEMRas<-raster(DEM)
DEMRas_UTM<- projectRaster(DEMRas, crs = utmSys)
DEM_UTM <-DEMRas_UTM
Slope<-terrain(DEM_UTM, opt = 'slope')
Aspect<-terrain(DEM_UTM, opt = 'aspect')
HShade \(<-\) hillShade \((\) Slope, Aspect, angle \(=215\), direction \(=315\) )
col4<-colorRampPalette(c("antiquewhite1", 'yellow', 'orange', 'brown', 'grey10', 'red', 'pur ple', "blue", "green"))\#c("antiquewhitel", "purple", "orangered", "gray", "blue", "yellowgreen", "darkgreen"))
ourcolors<-col4(400)
graphics.off()
png(filename = paste0(Dir2, "Plot of the Social Attraction Site and Buffer.png"), width = 1000,
```

        height =1000, pointsize = 18, type="cairo")
    par(las = 0, cex.axis = 0.8, bty =c("L"), cex.lab = 1, mar=c(5, 4, 4,4) + 0.1)
    plot(HShade,col=gray(c(100:0/100)), legend = F, alpha = 0.35, bty = 'L',
    main = paste0('Social Attraction Site with an Attraction Buffer of ', ExclusBuffer, ' met
    ers'))
plot(raster(FlightPath), add= T, alpha = 0.5, col = ourcolors,
cex.axis= 0.75,
legend.width }=0.75\mathrm{ , legend.shrink=0.65,
legend.args=list(text='Scaled (0-1) Flight Path Overlap',\#str_replace(int, '_BurrowSite
Raster', '')
side=4, font=1, line=2.5, cex=0.8, las = 3))
plot(KSHCP_AAS_UTMBuff, add = T, lty = 3)
plot(KSHCP_AAS_UTM, col = 'blue', add = T)
legend('bottom', legend = c('Social Attraction Site Buffer Perimeter'), bty = 'n', lty = 3)
dev.off()
}
cat('\n Predation Reproductive Success:', Ex_APredJuviSucc)
SAFenceFledgeProd <- round(sum(numBirdsData[1:30, 1]) - sum(numBirdsDataAllPred[ 1:30, 1]))
SAFenceAdultProd <- round(sum(numBirdsData[30, 6:36]) - sum(numBirdsDataAllPred[ 30, 6:36]))

```

SPFenceFledgeProd <- round(sum(StPopAllPredData[1:30, 1]) - sum(AllPredSiteBirds[1: 30, 1]))

SPFenceAdultProd <- round(sum(StPopAllPredData[30, 6:36]) - sum(AllPredSiteBirds[30 , 6:36]))
cat('In \(\ln\) Total Number of Fledgleings Produced prior to year 30: ', SAFenceFledgeProd + SPFenceFledgeProd)
cat('In \(\ln\) Total Number of Adults Produced at year 30: ', SAFenceAdultProd + SPFenceAd ultProd)
```

            # error testing if/thens after this
        }
    }
    }
}

## !PLEASE PUT A SINGLE VALUE (1,2 or 3) DESCRIBING PREDATION ESTIMATE

TO BE USED!

```

\section*{8. BIBLIOGRAPHY}

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