

Data Collection Techniques and Detection Probability:
Population Models and Estimates of Rare and Fragile Invertebrates

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Abstract

The number of described species of insects constitutes more than half of all known organisms on Earth. Throughout the world, scientists monitor Butterflies (Lepidoptera) extensively to determine both the status of a butterfly population and as an indicator of ecosystem health. A common method of data collection is a Pollard walk. Pollard *et al.* (1975) introduced a statistically rigorous method of transect walks to determine an index of abundance for a butterfly species. The less invasive method of transect walks has become prevalent in the study of butterflies and other invertebrates. Zonneveld (1991) determined a method for estimating mortality rate as well from transect walks, although some model assumptions are questionable. The commonly contested assumption of the Zonneveld (1991) model is that detection probability is constant across sample time. For the Saint Francis' Satyr (SFS) and other butterflies, this assumption is not biologically plausible. I shall use a simulation experiment to compare a population distribution selected from samples with varying detection probability to a population distribution selected from samples with a constant (average) detection probability. This experiment will provide insight into the effect of varying detection probability on estimates of the abundance index from the Zonneveld (1991) model. The non-invasive sampling method of count data is an attractive reason to explore the Zonneveld (1991) model, especially when sampling rare and fragile species.

Note: The simulation experiments used in this study were done with the help of Dr. Kevin Gross.

Key words: transect walks, detection probability, population models, butterflies

Table of Contents

Introduction.....	4
Why not Mark-Release-Recapture?.....	5
Life History Traits of Butterflies Relevant Population Models.....	5
Transect (Pollard) Walks.....	7
Saint Francis' Satyr.....	9
INsect Count Analyzer (INCA).....	10
The Zonneveld Model.....	10
Simulation Study.....	12
Methods of Statistical Analysis.....	13
Simulation Experiment 1: Fixed good/bad day probabilities.....	14
Results.....	14
Simulation Experiment 2: High autocorrelation between similar days.....	15
Results.....	16
Conclusion.....	16
Literature Cited.....	18
Appendix I.....	20
Algorithm Simulation Experiment 1.....	20
Table 1: Results of Individual Simulations for Fixed Probabilities.....	20
Appendix II.....	21
Algorithm for Simulation Experiment 2.....	21
Table 2: Results for Individual Simulations for Markov Chain Probabilities.....	21

Introduction

The number of described species of insects comprises more than half of all known organisms on Earth (Thomas 2005). Throughout the world, scientists monitor butterflies (Lepidoptera) extensively to determine both the status of butterfly populations and as an indicator of ecosystem health (Thomas 2005). Innovations in data collection techniques specific to butterflies date back to the early 1970s. Mark-Release-Recapture (MRR) methods are still the common method of data collection of butterfly population dynamics (Morton 1982; Murphy 1987). In 1973, Pollard *et al.* (1975) introduced the statistically rigorous method of transect (Pollard) walks to determine and index of abundance for a butterfly species. The less invasive method of transect walks has become prevalent in the study of butterflies and other invertebrates.

The use of butterflies as an indicator species as a biological measure of ecosystem health (Thomas 2005) motivates the quest to determine the best data collection methods and models of population dynamics to aid in conservation and management of butterflies. Specifically, the Zonneveld (1991) model, which estimates index of abundance, is of interest because it utilizes transect count data instead of invasive MRR data. The model has many assumptions based on general insect life history traits but the assumption that detection probability is constant is of particular interest to Lepidopterists. Instinctively, constant detection probability is a questionable assumption for most butterflies. I shall use a simulation study to test the validity of the assumption of constant detection probability for butterflies and the effect varying detection rate has on index of abundance estimates from the program INsect Count Analyzer (INCA) (<http://www.urbanwildlands.org/INCA>) based on the Zonneveld (1991) model. The assumption that mortality is constant is also questionable, but will not be explored in this paper. The motivation for this study is the Saint Francis' Satyr butterfly, an endangered butterfly found only on Ft. Bragg in the North Carolina Sandhills.

Why not Mark-Release-Recapture?

The MRR technique is widely used, but it is only useful for a limited number of butterfly species (Pollard and Yates 1993). For small, more fragile and rare butterflies, MRR may damage wings and legs, cause reduction of ovipositing efficiency, and cause the modification of behavior (Singer and Wedlake 1981; Morton 1982; Murphy 1988; Mattoni *et al.* 2001). Some behavioral responses of butterflies may be due to displacement upon release and avoidance of capture sites after the first capture (Singer and Wedlake 1981). It is often difficult to both document and quantify the effects of handling on the behavior and mortality of butterflies and incorporate the effects into the model (Murphy 1988). If capture and handling affects the probability of recapture, then a measure of this effect is necessary in order to determine accurate survivability and detectability rates from MRR studies. Another disadvantage of MRR experiments is that the standard error of an estimate is often as large as the estimate, and the standard error will only decrease with more capture experiments (Murphy 1988). Immigration and emigration rates may also affect estimates from MRR. Even with no net migration, estimates of death rate from MRR may be biased (Zonneveld 1991). Despite the shortcomings of MRR for butterflies, it is still a common practice to determine vital rates for rare and fragile species.

Life History Traits of Butterflies Relevant Population Models

Butterflies are an important taxonomic group for conservation in both the United States and Britain (Murphy *et al.* 1990). There are 26 federally listed endangered or threatened species of butterfly in the United States alone (USFWS). Common causes of reduced butterfly population size are habitat reduction and destruction, loss of host plant, microclimatic changes in

over-wintering habitat, solar exposure and wind shelter, and over-collection. Many rare butterflies are isolated to a specific habitat location due to highly specific niche requirements and the loss of that habitat exacerbates the already fragile situation (Pollard and Yates 1993). In a specific niche, changes in habitat can disrupt flight patterns and will affect data collection. Host plant restrictions for a specialized butterfly will also affect larval survivability. Although reduction of habitat will reduce population sizes, most often an extreme weather event causes the extinction of a rare and localized butterfly (Murphy *et al.* 1990). Environmental stochasticity is, therefore, highly influential on the viability of rare butterflies. Demographic stochasticity also affects butterfly viability, especially for small population sizes, although not to the extent of environmental stochasticity (Murphy *et al.* when calculating the detection rates).

The number and overlap of generations are important factors to consider for population analysis. Butterflies have one to three generations per flight season, varying both within and among species. Generations may be distinct or overlap. A special case in butterfly generation is the phenomenon of protandry; where males emerge earlier than females, in which case the males and females should be considered separately (Mattoni *et al.* 2001; Zonneveld 1991). The time of generation is also an important factor to consider in experiment structure in order to acquire a comprehensive data set. The butterfly species' unique generation pattern should be the basis of the determined emergence curve in the model. Zonneveld (1991) based the model on fitting an emergence curve to the count data. Therefore, one should consider the number of generations and protandry when collecting data and inputting data into INCA.

The above summary of life history traits relevant to data collection and model selection is obviously not comprehensive, but for rare and localized butterflies the above characteristics are prevalent in the literature (Pollard 1975, 1977; Zonneveld 1991; Pollard and

Yates 1993; Mattoni *et al.* 2001; Schultz and Hammond 2003; Gross *et al.*, Unpublished manuscript; Murphy *et al.* 1990). Zonneveld (1991) constructs a model of the emergence curve of butterflies in order to estimate the index of abundance based on the general assumptions of butterfly life history and transect walk sampling design.

Transect (Pollard) Walks

Pollard (1975, 1977) popularized the use of transect walks in the British Butterfly Monitoring Scheme. Since its establishment for butterfly monitoring, multiple models have been developed and fitted to data from transect counts (Manly 1974; Zonneveld 1991; Pollard and Yates 1993; Mattoni *et al.* 2001). Data collected from a transect walk provide an index of abundance based on time of peak emergence, the variation in appearance rate, and the death rate (Zonneveld 1991; Pollard and Yates 1993). An estimate for the total population size cannot be determined from transect walk data alone (Pollard and Yates 1993), but an absolute population size is not necessary to develop conservation plans (Murphy 1988). To determine an estimate of total population size, MRR is often used in conjunction with transect walks (see Zonneveld 1991; Mattoni *et al.* 2001; Gross *et al.*, Unpublished manuscript).

Transect walks occur along fixed routes throughout butterfly flight periods. The length of the flight period indicates the length of the data collection period for the count. Since the paths are fixed throughout the experiment, each walkway should be determined by the environmental factors that affect the butterflies' movement, such as host plant dispersal, movement routes, etc (Thomas 1983; Pollard and Yates 1993; Mattoni *et al.* 2001). The observer will walk the determined path at a steady pace counting all butterflies seen within the band and approximately 5 meters ahead. Surveyors should make no extra effort to count the

butterflies (i.e., looking up for flying butterflies or moving vegetation) and an assumption is made that an observer will be able to recognize a previously counted butterfly based on morphological differences (Thomas 1983; Pollard and Yates 1993). In order to determine reliable death rates from transect walks, surveying must occur frequently and occur both prior to the expected time of flight and well after the peak flight period (Mattoni *et al.* 2001). Aside from the butterfly count data, temperature and wind speed should be recorded and any other environmental factors that may affect butterfly counts, relative to the species of study.

The benefit of transect walks is that it is non-invasive; therefore no harm to the butterfly or changes in butterfly behavior will occur. Since the transect walks are fixed, transect walks can also provide means of subsequent and concurrent study of multiple factors, such as vegetation changes (Pollard and Yates 1993), that may affect butterfly movement and population size (see Mattoni *et al.* 2001).

Since the walks are fixed, we cannot account for natural changes in butterfly behavior over time (changes in flight pattern due to changes in vegetation, dispersal of host plants) within models for transect walks (Pollard and Yates 1993; Mattoni *et al.* 2001). The greatest benefit of the use of transect walks is that fixed routes allow for replication and more statistically rigorous methods of quantifying the butterfly index of abundance (Pollard and Yates 1993). Other parameters estimated from transect walks include time of maximal appearance rate, a measure for the dispersion of the appearance rate and the death rate. Models that incorporate transect walk data are now more rigorous and robust and continue to be important in butterfly conservation.

Saint Francis' Satyr

As mentioned previously, the motivation for this study stems from the efforts to monitor the endangered North Carolina Sandhills butterfly, the Saint Francis' Satyr (SFS) (*Neonympha Mitchellii Francisi*). The SFSs' habitat is the wet meadows formed behind abandoned beaver dams. The SFS sites vary in vegetation density depending on stage of succession. The SFS is a generally sedentary species and flies low among the vegetation, therefore, we use swishing techniques in order to detect the butterflies. The species tends to be more active in high temperatures ($>30^{\circ}$ C) with significant cloud coverage (personal observation and communication). The SFS is also small and dark brown, with little coloring to make it stand out from the vegetation. Sampling occurs at least 5 days a week throughout each flight period regardless of weather conditions in order to both monitor the population and butterfly behavior. Due to the rarity of the species, we desire to perform as many counts as possible in order to achieve accurate estimates for Population Viability Analysis. (Pollard counts are another method to estimate the abundance index from transect count data and provides more accurate estimates compared to MRR estimates.)

Each of these factors indicates that the assumption of constant detectability during surveys may not be valid and, therefore, affects INCA estimates of population size. In recent analysis of SFS count and MRR data, abundance index estimates for SFS from INCA were not correlated with MRR estimates of population size (Haddad *et al.* 2005). Assuming MRR estimates are an accurate measure of population size, this indicates that INCA does not provide plausible estimates for the SFS abundance index.

INsect Count Analyzer (INCA)

I chose to focus on the INCA program method to analyze count data for several reasons. INCA is a free software package available from The Urban Wildlands Group online. The software utilizes the model in Zonneveld (1991) to calculate the index of abundance for an insect species based on count data. In addition, the program only necessitates the collection of count data taken over the entire flight period (at frequent intervals, so it is a very simple method to calculate index of abundance with minimal difficulty. Since INCA is free and simple to use, it is advantageous to know the limits of the program when designing a butterfly-monitoring scheme.

The Zonneveld Model

As mentioned previously, INCA is based on the model of Zonneveld (1991). To obtain an estimate of the index of abundance, Zonneveld (1991) used transect count data to determine time of maximal appearance rate, a measure for the dispersion of the appearance rate and the death rate. The index of abundance, N^* , is assumed a constant fraction, c , of the actual total population size, N ($N^* = cN$). The basic assumptions of the Zonneveld (1991) model are:

- (1) Absence of net migration,
- (2) A specific emergence curve,
- (3) A constant death rate, and
- (4) Demographic stochasticity is negligible.

To determine parameter estimates from transect count data we must additionally assume:

- (i) Poisson distribution for the observed number of insects at each time and that insects move independently of the observer,
- (ii) A constant fraction of the total population is observed,

(iii) The transect covers a certain area A .

The resultant model based on the assumptions is:

$$\frac{dX(t)}{dt} = N \frac{b}{\beta(1+b)} - \alpha X(t), \text{ where } b = e^{(t-\mu)/\beta}$$

1. Index density, $X(t)$: This is the total number of insects alive at time t .
2. Total population density, N : This is the total number of insects that emerge from pupae in a certain area.
3. Time of peak emergence, μ : At this time, the rate at which fresh butterflies emerge is maximal.
4. Spread in emergence times, β : Related to the standard deviation of emergence times according to $\sigma = 1.81 \beta$.
5. Death rate, α : The inverse of average longevity (Zonneveld 1991, INCA).

There are several assumptions made in the Zonneveld (1991) model that are questionable. In a recent study, Gross *et al.* (unpublished manuscript), tested the assumption that observed butterfly numbers follow a Poisson distribution. The results showed that the Poisson distribution assumption, although possibly not accurate, does not significantly affect parameter estimates in comparison with other, more realistic distributions. In addition, the model does not incorporate the possibility of demographic stochasticity, which affects parameter estimation. Gross *et al.* (unpublished manuscript) developed two methods of compensating for the demographic stochasticity of a population in the model; therefore one can now incorporate the possibility of varying demographic rates into the model. Thus, one can slacken several of the assumptions of the model. Unfortunately, there are still several assumptions that remain questionable

Assumption (ii) is valid only if surveyors conduct counts during specific weather conditions to account for changes in flight due to temperature and cloud coverage (outlined in Pollard and Yates 1993). In the case of the Saint Francis' Satyr and other endangered butterflies, detectability is subject to many factors including vegetation coverage and weather. I shall further explore the issue of varying detectability and weather through simulation experiments to determine the effect it has on INCA estimates.

Simulation Study

To study how varying detection probability affects INCA estimates of index of abundance, I designed two simulation studies (coded in R 2.3.1). I based the experiments on the concept that there are “good days” and “bad days” for a butterfly to fly. For example, our species of interest, the SFS, moves more frequently in cloudy conditions with temperatures greater than 30° C, increasing its detectability. For each day type, I fixed the probability that a surveyor would count an individual butterfly zero, one, or two times along a transect. I did not consider the possibility that a surveyor would count a butterfly more than twice due to the sedentary nature of the SFS and that SFS surveyors assume that over-counting mistakes would balance with under-counting mistakes on average (personal observation and communication). On a “good day”, the probability of counting a butterfly once or twice was much higher than on a “bad day”. I simulated 200 data sets for each probability parameter set. I then analyzed the “good/bad day” data in INCA and compared the distribution of the abundance index estimates to the distribution of the abundance index estimates simulated from the weighted average of probabilities for zero, one or two observations.

For each simulated butterfly population I assumed the following population parameter values:

1. Total population density, $N = 100$
2. Time of peak emergence, $\mu = 10$
3. Spread in emergence times, $\beta = 1.5$
4. Death rate, $\alpha = 0.25$.

These parameter values are biologically realistic for our species of interest, the SFS.

(See Appendix I and II for the algorithms and individual simulation results)

Methods of Statistical Analysis

I generated INCA parameter estimates for 200 datasets simulated under both good/bad day conditions and average conditions. The distribution of the estimates for N^* under both varying and average conditions were analyzed using the Kolmogorov-Smirnov test. The K-S test seeks differences between two datasets; it is non-parametric and distribution free. All hypothesis tests were at a 0.05 significance level. All data sets were non-parametric so K-S is the logical choice to test the hypothesis that there is not difference between counts with average probability of detection and counts with varying detection probability. Comparison of the two distributions requires the assumption that INCA will provide reasonable results when detection probability is constant. I could not analyze the coverage probability of the confidence intervals because closed confidence intervals do not exist for nonparametric data. (I considered both bootstrapping and Bayesian analysis of the variance, but decided that it was outside the scope of this paper).

Simulation Experiment 1: Fixed good/bad day probabilities

The first simulation experiment there was a fixed probability of occurrence for a good/bad day.

Times Counted i	Pr{good}=p	Pr{bad}=$1-p$	Average
Pr{$i=0$}	G_0	B_0	$pG_0+(1-p)B_0$
Pr{$i=1$}	G_1	B_1	$pG_1+(1-p)B_1$
Pr{$i=2$}	G_2	B_2	$pG_2+(1-p)B_2$

I simulated count data from simulated index densities in R (see Appendix I) and then input into INCA to obtain parameter estimates for index of abundance, N^* , death rate, peak emergence day, and spread in emergence times. I shall focus on the estimate for the index of abundance in this paper since that is of the most interest to most lepidopterists.

Results:

The Kolmogorov-Smirnov test found no difference between distributions of good/bad counts and average counts. The only exception was a case in which extreme values that were not realistic of detection probability. Even when considering extreme weather conditions (example: Pr{good} = 0.90, Pr{bad} = 0.10), no significant difference occurred between the distributions. Therefore, INCA estimates on average yield accurate estimates of the index of abundance.

Although this simulation experiment yielded no significant results, there are several things to note about the experiment in general. First, upon observation of the actual abundance index estimates, one sees that the variance between estimates and the standard errors associated with each estimate are very large. Second, I compared 200 simulations, which is a highly unlikely number of transect counts. Therefore, I would caution confidence in the estimates. The realism of this simulation experiment is obviously questionable. Weather is often highly

correlated. Therefore, my next simulation experiment uses a Markov chain to simulate high autocorrelation between the same day types, a more realistic situation.

Simulation Experiment 2: High autocorrelation between similar days

For the second simulation experiment, I used a Markov Chain design for good/bad day selection so that high autocorrelation between 2-day types would create strings of good days and strings of bad days during the count simulation. The transition matrix, \mathbf{P} , for the day type sequence was a 4x4 matrix:

$$P = \begin{matrix} & \begin{matrix} Good & Bad \end{matrix} \\ \begin{matrix} Good \\ Bad \end{matrix} & \begin{bmatrix} g & 1-g \\ 1-b & b \end{bmatrix} \end{matrix}$$

where $b, g \in (0.5, 1.0)$ (high autocorrelations between similar day types).

To calculate the average detection probability, I determined the stationary distribution of the Markov Chain, by solving the following system of equations:

$$\begin{cases} \pi_g = g\pi_g + (1-b)\pi_b \\ \pi_b = (1-g)\pi_g + b\pi_b \\ \pi_g + \pi_b = 1 \end{cases}$$

Therefore, we sample the population with the following detection regime:

Times Counted i	$\Pr\{\text{good}\} = \pi_g$	$\Pr\{\text{bad}\} = \pi_b$	Average
$\Pr\{i=0\}$	G_0	B_0	$\pi_g G_0 + \pi_b B_0$
$\Pr\{i=1\}$	G_1	B_1	$\pi_g G_1 + \pi_b B_1$
$\Pr\{i=2\}$	G_2	B_2	$\pi_g G_2 + \pi_b B_2$

Markov chains are often used to model weather patterns, so it is justified to use them here (Ross 2002). Markov chains allow for the incorporation of weather events such as tropical storms (rain can last several days) and heat waves, a common occurrence in the North Carolina Sandhills.

Results:

The second simulation experiment yielded varying results. For some autocorrelation values, there were significant differences between the two distributions, for others none. Therefore, INCA will incorrectly estimate the abundance index under several situations. Obviously, the results of this study do not completely discredit INCA as a method of analyzing count data, but the results do not support reliance on the program completely. The fact that INCA does fail in certain situations may imply that data collection cannot simply include counts, but should also incorporate site data such as humidity, temperature, cloud coverage, and vegetation coverage may be necessary to determine if the data is suitable for INCA to analyze. Therefore, the assumption that the detection probability is constant does affect INCA and must be taken under serious consideration before using INCA to estimate insect abundance indexes.

Conclusion

The U.S. Endangered Species Act (ESA) requires that within recovery plans, quantitative measures of recovery are necessary to base listing decisions (U.S. Code 2001, 16 U.S.C. S1533 (f)(1)(B)(ii)). Therefore, the establishment of a data collection method that is both quantitatively rigorous and plausible within the context of a recovery plan is vital to attain the goals of the ESA. A program such as INCA is a valuable tool for conservationists, but reliability and accuracy must be guaranteed to be truly useful for the conservation of butterflies. Obviously, the results of this study show that under certain sampling circumstances, when one cannot

realistically assume that the detection probability is constant, INCA is not the best choice for data analysis. Further analysis of the program is necessary to determine when the program fails and when it is suitable.

In order for INCA to be a valuable tool for butterfly conservation, the model must be improved and the stringent assumptions it is based on slackened. If improvements could be made to INCA or a similar program, then reliance on MRR techniques to estimate butterfly population size would be reduced. The development of a model that depends on noninvasive sampling techniques to estimate butterfly abundance will spur conservation efforts and provide the groundwork to determine viable recovery plans for endangered butterflies.

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Appendix I

Algorithm Simulation Experiment 1

1. Simulate population density for each day i
 - a. Generate $B^{(l)}$ (birth time), $L^{(l)}$ (length of life), $D^{(l)}$ (death time), $l=1, \dots, N$

$$B^{(l)} \sim Logistic(\mu, \beta)$$

$$L^{(l)} \sim Exp(\alpha)$$

$$D^{(l)} = B^{(l)} + L^{(l)}$$
 - b. Population at day i , $X[i] = \text{Sum}(\# \text{ of Butterflies } B^{(l)} < \text{day } i \text{ and } D^{(l)} > \text{day } i)$
 - c. Stop when $E(\text{Population Density at day } i) < 1$
2. Simulate count data for each day i
 - a. Set $\text{Pr}\{\text{Good day}\} = p$
 - b. Generate $u \sim U(0,1)$
 - i. If $u < p$, then $\text{Pr}\{\text{detection}\} = \text{good day}$, else $\text{Pr}\{\text{detection}\} = \text{bad day}$
 - c. Generate $N[k] \sim \text{Multinomial}(1, X[i], \text{Pr}\{\text{detection}\})$ ($N[k]$ is number of times k th butterfly is counted)
 - d. Count for day $i = (\# \text{ of butterflies counted once}) + 2 * (\# \text{ counted twice})$
 - e. Stop when counts for day $i, i+1, i+2$ are zero

Table 1: Results of Individual Simulations for Fixed Probabilities

Description	Good	g0	g1	g2	Bad	b0	b1	b2	avg0	avg1	avg2	Difference
Simulation 1	0.5	0.45	0.45	0.1	0.5	0.55	0.45	0	0.5	0.45	0.05	No (D=0.0468 P=0.979)
Simulation 2	0.7	0.3	0.6	0.1	0.3	0.6	0.25	0.15	0.39	0.495	0.115	No (D=0.0707 P=0.690)
Simulation 3	0.4	0.4	0.5	0.1	0.6	0.6	0.4	0	0.52	0.44	0.04	No (D=0.0971 P=0.304)
EXTREME												Yes (D= 0.1899 P= 0.002)
Simulation 50/50	0.5	0.35	0.5	0.15	0.5	0.65	0.3	0.05	0.5	0.4	0.1	No (D=0.0924 P= 0.350)
Simulation 60/40	0.6	0.35	0.5	0.15	0.4	0.65	0.3	0.05	0.47	0.42	0.11	No (D= 0.0620 P= 0.830)
Simulation 40/60	0.4	0.35	0.5	0.15	0.6	0.65	0.3	0.05	0.53	0.38	0.09	No (D=0.1235 P=0.096)
Simulation 70/30	0.7	0.35	0.5	0.15	0.3	0.65	0.3	0.05	0.44	0.44	0.12	No (D=0.1010 P= 0.251)
Simulation 30/70	0.3	0.35	0.5	0.15	0.7	0.65	0.3	0.05	0.56	0.36	0.08	No (D=0.1290 P= 0.072)
Simulation 80/20	0.8	0.35	0.5	0.15	0.2	0.65	0.3	0.05	0.41	0.46	0.13	No (D= 0.0720 P=0.669)
Simulation 20/80	0.2	0.35	0.5	0.15	0.8	0.65	0.3	0.05	0.59	0.34	0.07	No (D=0.1103 P=0.177)
Simulation 90/10	0.9	0.35	0.5	0.15	0.1	0.65	0.3	0.05	0.38	0.48	0.14	No (D=0.0634 P=0.808)
Simulation 10/90	0.1	0.35	0.5	0.15	0.9	0.65	0.3	0.05	0.62	0.32	0.06	No (D=0.1025 P=0.243)

Appendix II

Algorithm for Simulation Experiment 2

1. Simulate population density for each day i
 - f. Generate $B^{(l)}$ (birth time), $L^{(l)}$ (length of life), $D^{(l)}$ (death time), $l=1, \dots, N$

$$B^{(l)} \sim \text{Logistic}(\mu, \beta)$$

$$L^{(l)} \sim \text{Exp}(\alpha)$$

$$D^{(l)} = B^{(l)} + L^{(l)}$$
 - g. Population at day i , $X[i] = \text{Sum}(\# \text{ of Butterflies } B^{(l)} < \text{day } i \text{ and } D^{(l)} > \text{day } i)$
 - h. Stop when $E(\text{Population Density at day } i) < 1$
2. Simulate count data
 - a. Choose initial $\text{Pr}\{\text{detection}\}$
 - i. Generate $u \sim U(0,1)$
 - ii. If $u < .5$, then $\text{Pr}\{\text{detection}\} = \text{good day}$, else $\text{Pr}\{\text{detection}\} = \text{bad day}$
 - b. Markov Chain Simulation
 - i. If $\text{Pr}\{\text{detection}\} = \text{good day}$, generate $u \sim U(0,1)$
 1. If $u < \text{Pr}\{\text{good day} | \text{good day}\}$, then $\text{Pr}\{\text{detection}\} = \text{good day}$
Else $\text{Pr}\{\text{detection}\} = \text{bad day}$
 - ii. Else ($\text{Pr}\{\text{detection}\} = \text{bad day}$), generate $u \sim U(0,1)$
 1. If $u < \text{Pr}\{\text{bad day} | \text{bad day}\}$, then $\text{Pr}\{\text{detection}\} = \text{bad day}$
Else $\text{Pr}\{\text{detection}\} = \text{good day}$
 - c. Generate $N[k] \sim \text{Multinomial}(1, X[i], \text{Pr}\{\text{detection}\})$ ($N[k]$ is number of times k th butterfly is counted)
 - d. Count for day $i = (\# \text{ of butterflies counted once}) + 2 * (\# \text{ counted twice})$
 - e. Stop when counts for day $i, i+1, i+2$ are zero

Table 2: Results for Individual Simulations for Markov Chain Probabilities

Description	G/G	g0	g1	g2	B/B	b0	b1	b2	LPg	LPb	avg0	avg1	avg2	Difference
MC 60/70	0.7	0.35	0.5	0.15	0.6	0.65	0.3	0.05	0.57	0.43	0.479	0.414	0.107	$D=0.1021$ $P=0.241$
MC 65/45	0.65	0.35	0.5	0.15	0.45	0.65	0.3	0.05	0.61	0.389	0.4664	0.422	0.111	$D=0.1246$ $P=0.087$
MC 75/40	0.75	0.35	0.5	0.15	0.4	0.65	0.3	0.05	0.294	0.706	0.5618	0.359	0.0794	$D=0.4015$ $P=0.000$
MC 75/75	0.75	0.35	0.5	0.15	0.75	0.65	0.3	0.05	0.5	0.5	0.5	0.4	0.1	$D=0.1675$ $P=0.007$
MC 30/80	0.3	0.35	0.5	0.15	0.8	0.65	0.3	0.05	0.222	0.778	0.5834	0.344	0.0722	$D=0.1446$ $P=0.031$
MC 65/65	0.65	0.45	0.45	0.1	0.65	0.55	0.45	0	0.5	0.5	0.5	0.45	0.05	$D=0.0715$ $P=0.679$
MC 55/75	0.55	0.3	0.6	0.1	0.75	0.6	0.25	0.15	0.357	0.643	0.4929	0.375	0.1322	$D=0.0603$ $P=0.852$
MC 75/55	0.75	0.4	0.5	0.1	0.55	0.6	0.4	0	0.643	0.357	0.4714	0.464	0.0643	$D=0.1098$ $P=0.173$