

plants to be followed. Finally, estimating recruitment rates generally requires setting up further experimental plots (i.e. seed addition experiments)

7.1.1 A Genealogy of Count-Based PVA

The construction and use of population dynamic models has long history

with many mathematicians and ecologists contributing advances and techniques that have enabled the development of diffusion-based extinction time

Jande and Orzack (1988) used these more biologically realistic age-struct-

tured models to test how well unstructured diffusion process models represent the dynamics of populations with complex life histories. In particular,

erated by first transforming census data (dates and population counts) so that



FIGURE 1. The distribution of the number of censuses in which the population growth rate is less than or equal to 4.

formation of population growth between two censuses, and x is a transformation of time between censuses (equations given in text). The slope of the regression line gives an estimate of μ for the population, and the scatter of points about this line gives σ^2 ; these values are used for further calculations in the diffusion approximation (DA) method.

Table 7.2. Examples of uses of the diffusion approximation (DA) method of population viability analysis (PVA) in recent studies

Species	Years of data	Source
Alabama beach mouse (2 populations)	7-11	Oli et al. (2001)
Blue wildebeest	10	Nicholls et al. (1996)
Cricetidae rodent (<i>Akodon olivaceus</i>)	5	Lima et al. (1998)
Cricetidae rodent (<i>Phyllotis darwini</i>)	5	Lima et al. (1998)
Didelphidae marsupial (<i>Thylamys elegans</i>)	5	Lima et al. (1998)
Eland	10	Nicholls et al. (1996)
Firefly	10	Nicholls et al. (1996)
Grizzly bear	29	Dennis et al. (1991)
Impala	10	Nicholls et al. (1996)
Kudu	10	Nicholls et al. (1996)
North Pacific gray whale	19	Gerber et al. (1999)
Perdido Key beach mouse (2 populations)	7	Oli et al. (2001)
Sable antelope	10	Nicholls et al. (1996)
Tennessee	10	Nicholls et al. (1996)

approaches simplify the real complexity of population dynamics, but this does not necessarily make them less useful. However, more fundamental aspects of the DA model have recently received criticism, calling into question the general usefulness of this method for predicting extinction risk. As Ludwig (1996, 1999) pointed out, it is difficult to know how much variation in

and Ellner's for populations with low r and low σ values, they found more positive results for other scenarios. In addition, Meir and Fagan only explored the effects of observation error on relative predictive power, and did not examine the absolute accuracy of extinction predictions (with or without observation

7.2 Methods

To examine whether the DA approach can provide useful information when based upon a reasonable amount of data, we constructed a simulation model to compare DA predictions with a known population process. This modeled or “true” population is stage-structured and is governed by a density-independent stochastic transition matrix. All simulations were initiated with 500 individuals arranged in the stable stage class vector for the mean matrix of that population. Both survival and fecundity rates were allowed to vary

between years according to assigned means and variances. Matrix elements involving growth and survival were drawn from a beta distribution (i.e., a probability distribution bounded by 0 and 1), and fecundity rates from a log-

Table 7.3. The average matrix(± 1 standard deviation) for *Calochortus obispoensis* derived from Fielder (1987). The mean and variance of the $a_{2,2}$ matrix element (in **bold**) were varied away from these estimated values to create simulations with differing

future parts of the simulations (i.e., the initial population size for predictions of future viability), regardless of the census interval, we always simulated 50 *past years* as noted above. Census data were collected for the appropriate

7.3 Results

7.3.1 Predictions of Population Growth

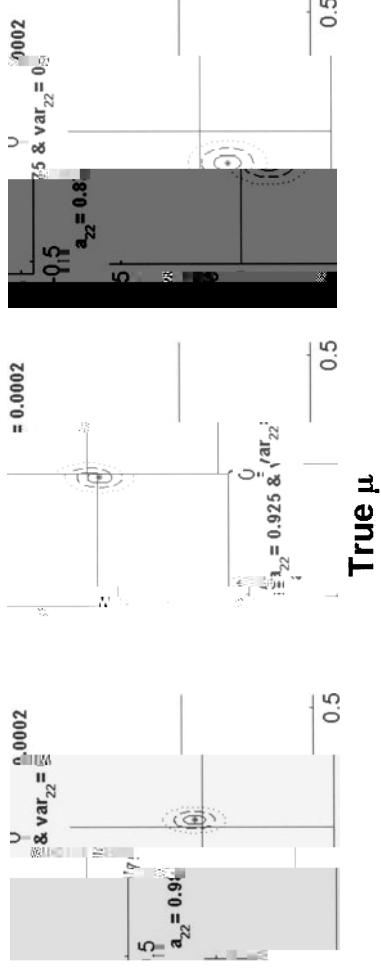
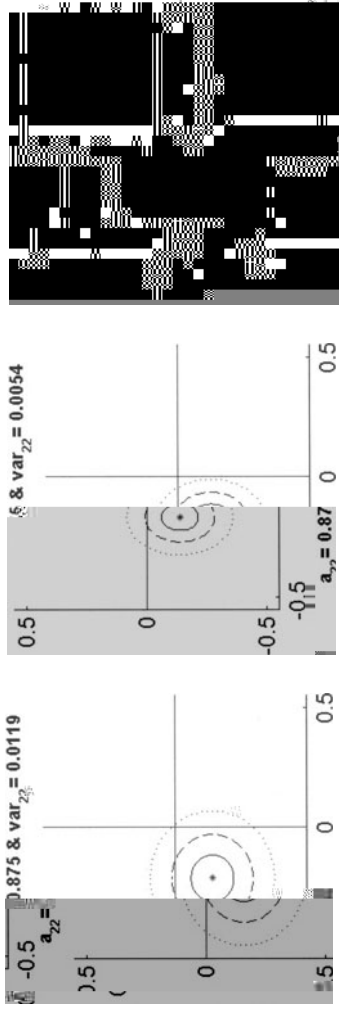
We first asked whether the DA method would usually provide the correct

qualitative prediction of population growth or decline. For most simulations,



elliptical), 80% (solid line), 90% (dotted line), and 95% (dashed line) confidence intervals (CI) for μ compared to the true μ (dotted line) in a 10-year simulation. The same parameters were used in

Approximation of μ

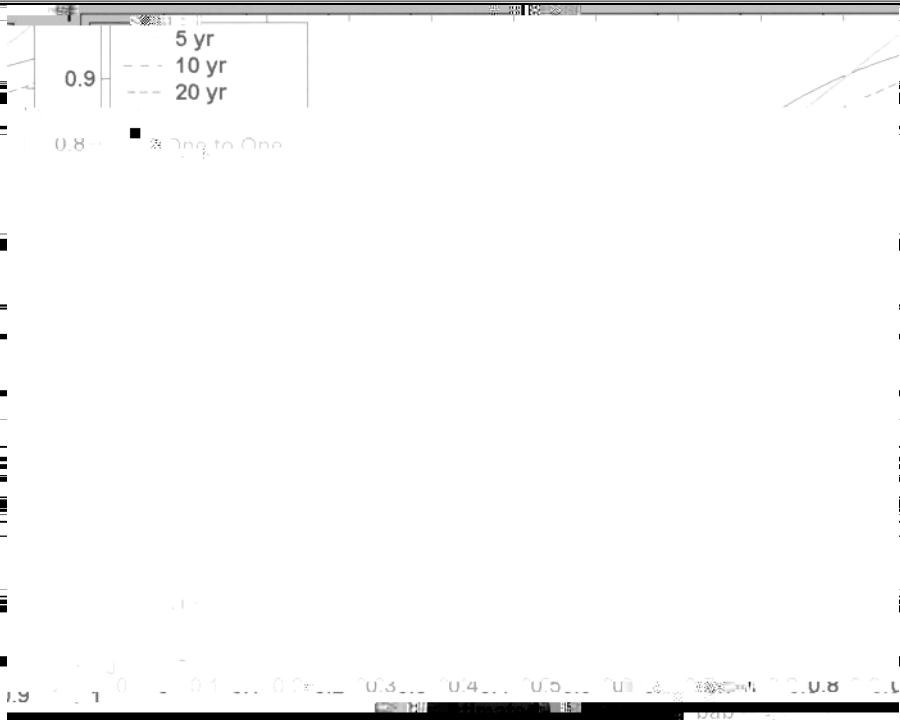


True μ

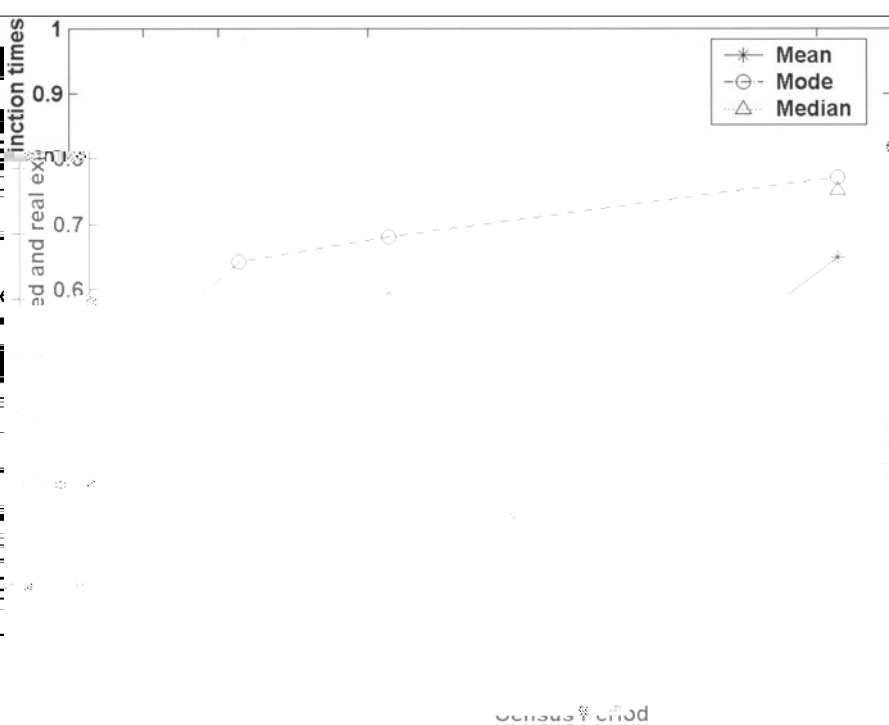
population should be growing; whereas the population was actually declining). Over the 5,000 realizations runs for all demographic and variance rates

used the mean predicted μ and the mean true (or realized) μ for the 50

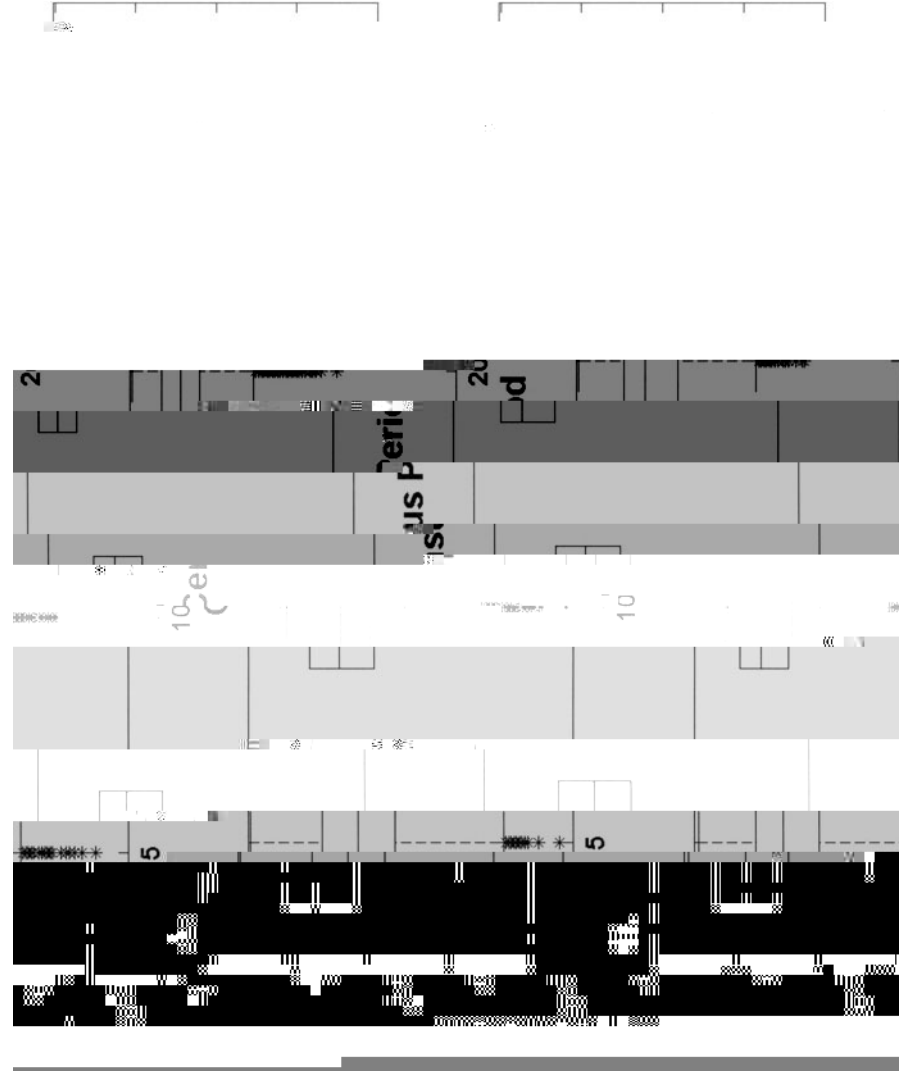
“future” years of the simulations, were almost identical (Fig. 7.4). Furthermore, the degree of uncertainty (difference in upper and lower confidence



Since the DA can, on average, give realistic estimates of extinction probabilities, how well did it predict extinction times? To answer this, we regressed the mean, median, and modal times to extinction for all populations that went



mates, and the mode underestimates time to extinction. This is not surpris-

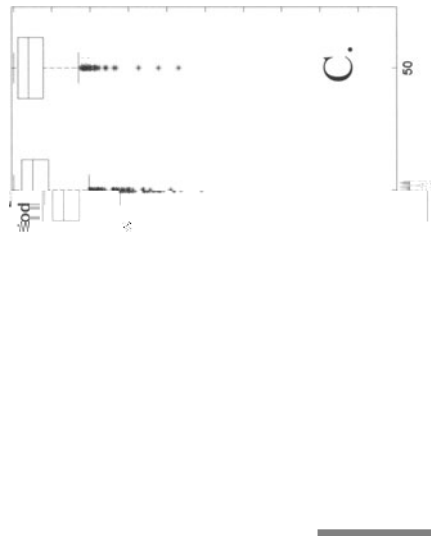
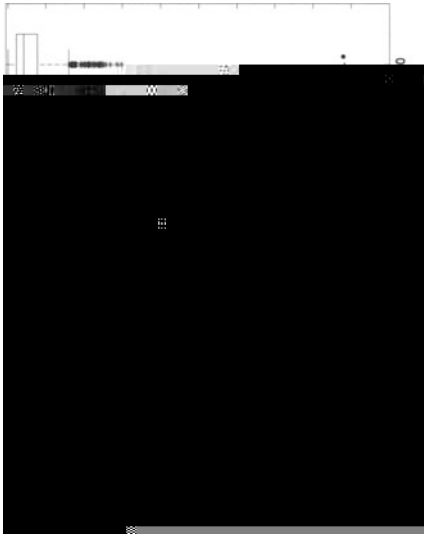
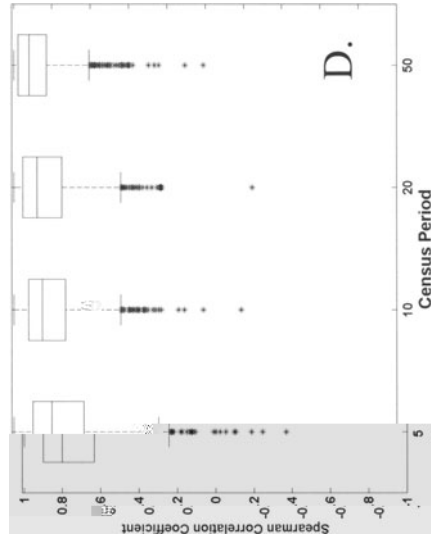
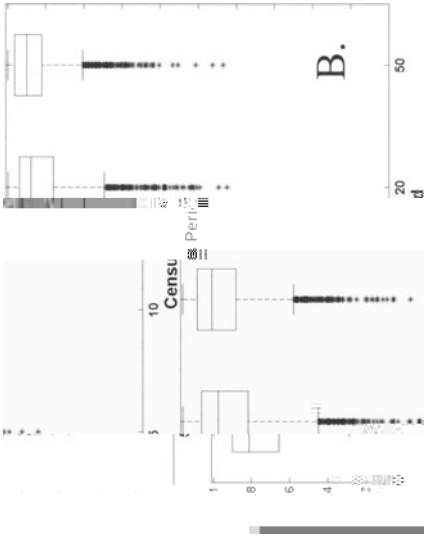


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7.3.4 Effects of an Unseen Stage

For all of the simulations of different life history variations, the predictive

this poor predictive power arises from the inherent uncertainty of short-term outcomes when environmental variability is large. The key question to ask in

rather what the range of likely outcomes is over a defined time horizon. With μ close to zero, these outcomes can span a wide range of values, just as can the estimated values (Fig. 7.5)

The DA method also does a reasonable job of predicting extinction risk

field data for parameterizing the more complex models is not necessarily

available. The DA method employs a relatively simple technique to use count data to estimate population growth and extinction risk. For plants in particular, basic counts of individuals are easy and inexpensive to acquire, making

DA methods an especially appealing way to utilize past data as well as current

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