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# A comparison of theoretical and empirical results for some stochastic population models* 

By M. S. Bartlett, J. C. GOWER and P. H. LesLie<br>Statistical Laboratory, University of Manchester; Statistical Department, Rothamsted Experimental Station ; Bureau of Animal Population, Department of Zoological Field Studies, Oxford

## 1. General remarks

In recent papers Bartlett (1957), Leslie (1958) and Leslie \& Gower (1958) have illustrated by means of artificial series the properties of various idealized models of biological systems, including the single-species logistic stochastic process and two-species extensions. While these artificial series are always useful in an auxiliary qualitative sense, the theoretical intractability of many of these models has given the artificial series a somewhat more important role than they might otherwise have had. Nevertheless, what theoretical results there are should not be neglected, and indeed some of these were compared with empirical results from series in the last two of the papers mentioned above. It is the purpose of the present paper to indicate somewhat more systematically where theoretical results, even when only approximate, may be useful, and to make some further comparisons with the empirical results available.

## PART I. THEORETICAL RESULTS

## 2. Single-Species models (continuous time)

Consider first a stochastic population model for a single species, with transition probabilities (in continuous time during the infinitesimal interval $d t$ ) $\lambda_{n} d t$ of a 'birth', and $\mu_{n} d t$ of a 'death', where $n$ is the total population size. A 'death' may include emigration, but unless a 'birth' can include immigration, $\lambda_{0}=0$. If $\lambda_{0}=0$, an ultimate stationary distribution for $n$ cannot strictly exist, but may effectively exist over all realizable timeintervals (see §5; also Leslie (1958), Bartlett (1960)). Under conditions for which a stationary (or quasi-stationary) distribution does exist, the probability distribution for it must satisfy the recurrence relation

$$
\begin{equation*}
\mu_{n} P(n)=\lambda_{n-1} P(n-1) \tag{1}
\end{equation*}
$$

(see, for example, Bartlett, 1960), from which relation the exact distribution $P(n)$ may always be calculated numerically, as will be illustrated below (§6). Under some further conditions which include $m, m / \sigma \gg 1$, we have asymptotically

$$
\begin{equation*}
P(n) \sim C \exp \left\{-\frac{1}{2}(n-m)^{2} / \sigma^{2}\right\}, \tag{2}
\end{equation*}
$$

where $m$ is the relevant solution of $\lambda_{m}=\mu_{m}$, and

$$
\begin{equation*}
\sigma^{2}=-1 /\left[\frac{d\left(\lambda_{n} / \mu_{n}\right)}{d n}\right]_{n=m} . \tag{3}
\end{equation*}
$$

[^0]If alternatively the properties of small fluctuations about the mean of the stationary distribution are investigated directly, the results obtained to the first approximation will be equivalent to the normal approximation above. As the first mention of this approach (Bartlett, 1956) was rather brief, it seems worth while showing how it may be developed to include second-stage (or even higher order) corrections. The procedure is sufficier.tly illustrated by means of the logistic model

$$
\begin{equation*}
\lambda_{n}=a_{1} n-b_{1} n^{2}, \quad \mu_{n}=a_{2} n+b_{2} n^{2} \tag{4}
\end{equation*}
$$

where $\lambda_{n}$ remains zero when $n>a_{1} / b_{1},\left(a_{1}, b_{1}, a_{2}, b_{2}>0\right)$. The stochastic equation (cf. Bartlett, 1957) :s
or

$$
\begin{gather*}
d N_{t}=\left(\lambda_{N}-\mu_{N}\right) d t+d Z_{1}-d Z_{2}  \tag{5}\\
N_{l+d t}=N_{l}+\left(\lambda_{N}-\mu_{N}\right) d t+d Z_{1}-d Z_{2} . \tag{6}
\end{gather*}
$$

Averaging (6) on the assumption that a stationary distribution has been reached, we have (from the coefficient of $d t$ )

$$
\begin{equation*}
\left(a_{1}-a_{2}\right) m-\left(b_{1}+b_{2}\right)\left(\sigma^{2}+m^{2}\right)=0, \tag{7}
\end{equation*}
$$

where $m \equiv E\{N\}, \sigma^{2} \equiv E\left\{(N-m)^{2}\right\}$. Write further $\delta N_{t}=N_{t}-m$; then

$$
\begin{equation*}
\delta N_{l+d l}=\delta N_{l}+\left(\lambda_{N}-\mu_{N}\right) d t+d Z_{1}-d Z_{2} . \tag{8}
\end{equation*}
$$

Squaring and averaging this equation, we have exactly

$$
2\left[\left(a_{1}-a_{2}\right) \sigma^{2}-\left(b_{1}+b_{2}\right) \mu_{3}\right]+\left[\left(a_{1}+a_{2}\right) m-\left(b_{1}-b_{2}\right)\left(m^{2}+\sigma^{2}\right)\right]=0,
$$

where $\mu_{3} \equiv E\left\{(\delta N)^{3}\right\}$. Hence to the first order of approximation (noting that
to this order)

$$
\begin{gather*}
m \sim\left(a_{1}-a_{2}\right) /\left(b_{1}+b_{2}\right), \quad \mu_{3} \sim 0 \\
\sigma^{2} \sim\left(a_{1}-b_{1} m\right) /\left(b_{1}+b_{2}\right) . \tag{9}
\end{gather*}
$$

Similarly from the cube of (8) we obtain, noting that the averaged cube of $d Z_{1}-d Z_{2}$ is strictly zero at $N=m$,

$$
3 E\left\{\left(\lambda_{N}-\mu_{N}\right) d t(\delta N)^{2}\right\}+3 E\left\{\left(d Z_{1}-d Z_{2}\right)^{2} \delta N\right\}=0
$$

From the normality approximation, we can to the second order of approximation write in this equation $\mu_{4} \equiv E\left\{(\delta N)^{4}\right\}=3 \sigma^{4}$. We thus obtain

$$
\left(a_{1}-a_{2}\right)\left(\mu_{3}+m \sigma^{2}\right)-\left(b_{1}+b_{2}\right)\left(m^{2} \sigma^{2}+2 m \mu_{3}+3 \sigma^{4}\right)=-\left(a_{1}+a_{2}\right) \sigma^{2}+\left(b_{1}-b_{2}\right)\left(2 m \sigma^{2}+\mu_{3}\right),
$$

whence to the same order, as $m \gg 1$,

$$
\mu_{3} m\left(b_{1}+b_{2}\right) \sim \sigma^{2} m\left(b_{2}-b_{1}\right),
$$

that is

$$
\begin{equation*}
\mu_{\mathrm{a}} \sim \sigma^{2}\left(b_{2}-b_{1}\right) /\left(b_{2}+b_{1}\right) \tag{10}
\end{equation*}
$$

It will be seen that $\mu_{3}$ is only zero to this order if $b_{1}=b_{2}$; and it changes sign as we move from a constant birth-rate ( $b_{1}=0$ ) to a constant death-rate ( $b_{2}=0$ ).

## 3. Single-SPecies models (discrete time)

Before, however, we consider comparing any of these results with empirical results obtained from Leslie's artificial series, we must recall tnat the latter were obtained on the basis of a discrete-time model (Leslie, 1958), which has its own theoretical distribution. Whilst its exact form would be complicated, the investigation of approximative moment
formulae proceeds very similarly, as was noted by Leslie \& Gower (1958) in the case of a two-species model. We shall illustrate the procedure here for a single-species model, taking it to the next stage of approximation.

The transitions in Leslie's model are obtained from the recurrence formulae

$$
\left.\begin{array}{l}
E\left\{N_{l+1}\right\}=e^{b_{t}-d_{\nu}} N_{t},  \tag{11}\\
\sigma^{2}\left\{N_{t+1}\right\}=\frac{b_{t}+d_{t}}{b_{t}-d_{l}}\left(e^{b_{r}-d_{t}}-1\right) e^{b_{t}-d_{t}} N_{l},
\end{array}\right\}
$$

treating $b_{t}$ and $d_{t}$ constant from $t$ to $t+1$, and assuming also $\Delta N_{t}$ normal (with the restriction $\left.N_{t+1}>0\right)$. Putting $b_{l}-d_{t}=\log \lambda_{t}$, we have in the recurrence relation

$$
\begin{equation*}
N_{t+1}=f\left(N_{t}\right)+Z_{t+1}, \tag{12}
\end{equation*}
$$

$f\left(N_{t}\right)=\lambda_{t} N_{t}$ in this case, where $\lambda_{t}$ for the logistic model is of the form $\lambda /\left(1+\alpha N_{t}\right)$. Putting $\delta N_{t}=N_{t}-m$, where $m=E\left\{N_{t}\right\}$ under stationary conditions, and writing

$$
f\left(N_{t}\right)=f(m)+\delta N_{t} \frac{\partial f}{\partial m}+\frac{1}{2}\left(\delta N_{t}\right)^{2} \frac{\partial^{2} f}{\partial m^{2}}+\ldots,
$$

where $\partial f / \partial m$ denotes $\partial f / \partial N_{t}$ at the value $N_{l}=m$, etc., we have in the first approximation

$$
\left.\begin{array}{rl} 
& m=f(m)=(\lambda-1) / \alpha \\
\sigma^{2}= & \frac{\sigma_{Z}^{2}}{1-(\partial f / \partial m)^{2}}=\frac{\sigma_{Z}^{2}}{1-(1 / \lambda)^{2}},  \tag{14}\\
\mu_{\mathrm{z}}= & 0
\end{array}\right\}
$$

To the next approximation

$$
f(m)-m+\frac{1}{2} \frac{\partial^{2} f}{\partial m^{2}} \sigma^{2}=0
$$

where $\partial f / \partial m=1 / \lambda, \partial^{2} f / \partial m^{2}=-2 \alpha / \lambda^{3}$; and

$$
\begin{aligned}
& \mu_{3}=E\left\{\left(\delta N_{t} \frac{\partial f}{\partial m}+\frac{1}{2}\left[\left(\delta N_{t}\right)^{2}-\sigma^{2}\right] \frac{\partial^{2} f}{\partial m^{2}}+Z_{l+1}\right)^{3}\right\} \sim \mu_{3}(Z)+\left(\frac{\partial f}{\partial m}\right)^{8} \mu_{3} \\
&+\frac{3}{2}\left(\frac{\partial f}{\partial m}\right)^{2} \frac{\partial^{2} f}{\partial m^{2}}\left(\mu_{4}-\sigma^{4}\right)+3 E\left\{\sigma^{2}\left(Z_{l+1} \mid N_{t}\right)\left(\delta N_{i} \frac{\partial f}{\partial m}+\frac{1}{8}\left[\left(\delta N_{t}\right)^{2}-\sigma^{2}\right] \frac{\partial^{2} f}{\partial m^{2}}\right)\right\} .
\end{aligned}
$$

Now $\mu_{3}(Z)=0, \mu_{4} \sim 3 \sigma^{4}$, and it only remains to evaluate such terms as $E\left\{\sigma^{2}\left(Z_{t+1} \mid N_{t}\right) \delta N_{t}\right\}$. It should be noted that the value of this expression may depend on the precise numerical procedure adopted in obtaining the artificial series. Thus if $\sigma^{2}\left(Z_{t+1} \mid N_{t}\right)$ were taken constant, say at the value $\sigma^{2}\left(Z_{l+1} \mid m\right)$, the whole of the last term in the expression above for $\mu_{3}$ would be zero. However, if, more accurately, we expand $\sigma^{2}\left(Z_{t+1} \mid N_{t}\right)$ in (11) in the neighbourhood of $N_{t}=m$ (where $b_{t} \sim d_{t}$ ), we find

$$
\begin{equation*}
\sigma^{2}\left(Z_{t+1} \mid N_{t}\right) \sim\left(2 b-(3 b-1) \alpha \delta N_{t} / \lambda\right) N_{t} \tag{15}
\end{equation*}
$$

when the birth-rate is constant (b), and

$$
\begin{equation*}
\sigma^{2}\left(Z_{t+1} \mid N_{t}\right) \sim\left(2 d-(3 d+1) \alpha \delta N_{t} / \lambda\right) N_{t} \tag{16}
\end{equation*}
$$

when the death-rate is constant ( $d$ ). These results, incidentally, may be useful as approximations for $\sigma^{2}\left(Z_{\ell+1}\right)$ when artificial series are being constructed. Thus, retaining terms of the appropriate order, we find for $b_{b} \equiv b$,

$$
\begin{equation*}
\mu_{3}\left(1-(1 / \lambda)^{3}\right) \sim \frac{3 \sigma^{2}(\lambda-1)}{\lambda^{2}}\left\{\frac{(2 b)(\lambda+2)}{\lambda+1}-(3 b-1)\right\} . \tag{17}
\end{equation*}
$$

Similarly in the case of constant death-rate (d),

$$
\begin{equation*}
\mu_{3}\left(1-(1 / \lambda)^{3}\right) \sim \frac{3 \sigma^{2}}{\frac{\lambda}{\lambda^{2}}}\left\{\frac{(2 d)(\lambda+2)}{\lambda+1}-(3 d+1)\right\} . \tag{18}
\end{equation*}
$$

It may be useful to summarize the formulae derived in $\S \S 2$ and 3.

## Logistic model; continuous time

$\lambda_{n}=a_{1} n-b_{1} n^{8} ; \mu_{n}=a_{2} n+b_{2} n^{8}$.
Variance (lst approx.) $\sigma^{2} \sim\left(a_{1}-b_{1} m\right) /\left(b_{1}+b_{\mathrm{g}}\right)$.
Mean (2nd approx.) $m^{\prime} \sim m-\sigma^{2} / m$, where $m=\left(a_{1}-a_{2}\right) /\left(b_{1}+b_{8}\right)$.
Skewness (2nd approx.) $\mu_{3} \sim \sigma^{2}\left(b_{2}-b_{1}\right) /\left(b_{2}+b_{1}\right)$.

## Discrete time

$\lambda_{t}=\lambda /\left(1+\alpha N_{t}\right)$, (i) birth-rate constant, $b$; (ii) death-rate constant, $d$.
(i) Variance (lst approx.) $\sigma^{2} \sim 2 b m /\left\{1-(1 / \lambda)^{2}\right\}$, where $m=(\lambda-1) / \alpha$. Mean (2nd approx.) $m^{\prime} \sim m-\sigma^{2} /(\lambda m)$.
Skewness (2nd approx.)

$$
\mu_{3} \sim \frac{3 \sigma^{2} \lambda(\lambda-1)}{\lambda^{8}-1}\left\{\frac{2 b(\lambda+2)}{\lambda+1}-(3 b-1)\right\} .
$$

(ii) Variance (lst approx.) $\sigma^{2} \sim 2 d m /\left\{1-(1 / \lambda)^{2}\right\}$. Mean (2nd approx.) $m^{\prime} \sim m-\sigma^{2} /(\lambda m)$.
Skewness (2nd approx.)

$$
\mu_{3} \sim \frac{3 \sigma^{2} \lambda(\lambda-1)}{\lambda^{3}-1}\left\{\frac{2 d(\lambda+2)}{\lambda+1}-(3 d+1)\right\} .
$$

## 4. Models with two species

Whilst the above methods are available for models with two (or more) species, the formulae get rather complicated; as the first approximation results in the case of a quasistationary distribution for two species have already been indicated by Leslie \& Gower (1958), they will not be listed here. With regard to the exact recurrence relation (1) for the distribution $P(n)$, the corresponding relation for two species is easy to write down, but has no simple method of solution. However, under conditions for which a well-defined stationary (or quasi-stationary) distribution exists with $m_{i}, m_{i} / \sigma_{i} \gg 1$, the distribution will be approximately bivariate normal, with its moments given by the approximate formulae already referred to.

In the case of models for which one species will become extinct, it is also easy to write down the equation satisfied by the extinction probability, say, $p\left(n, n^{\prime}\right)$ for the first species, if $n$ and $n^{\prime}$ are the initial numbers of the two species. Thus consider a continuous time model with birth- and death-rates:

1st species

$$
\begin{aligned}
& \lambda\left(n, n^{\prime}\right)=a_{1}-b_{1} n-c_{1} n^{\prime} \\
& \mu\left(n, n^{\prime}\right)=a_{2}+b_{2} n+c_{2} n^{\prime}
\end{aligned}
$$

2nd species
$\lambda^{\prime}\left(n, n^{\prime}\right)=a_{1}^{\prime}-b_{1}^{\prime} n^{\prime}-c_{1}^{\prime} n$
$\mu^{\prime}\left(n, n^{\prime}\right)=a_{\mathbf{n}}^{\prime}+b_{\mathbf{2}}^{\prime} n^{\prime}+c_{\mathbf{2}}^{\prime} n$

The equation for $p\left(n, n^{\prime}\right)$ is obtained from the differential equation for the chance of extinction $p_{t}\left(n, n^{\prime}\right)$ by time $t$, and letting $t \rightarrow \infty$; this equation for $p_{t}\left(n, n^{\prime}\right)$ is readily derived from the possible transitions in the first infinitesimal interval $d t$. We obtain

$$
\begin{align*}
n \lambda\left(n, n^{\prime}\right) & {\left[p\left(n+1, n^{\prime}\right)-p\left(n, n^{\prime}\right)\right]+n \mu\left(n, n^{\prime}\right)\left[p\left(n-1, n^{\prime}\right)-p\left(n, n^{\prime}\right)\right] } \\
& +n^{\prime} \lambda^{\prime}\left(n, n^{\prime}\right)\left[p\left(n, n^{\prime}+1\right)-p\left(n, n^{\prime}\right)\right]+n^{\prime} \mu^{\prime}\left(n, n^{\prime}\right)\left[p\left(n, n^{\prime}-1\right)-p\left(n, n^{\prime}\right)\right]=0, \tag{19}
\end{align*}
$$

with boundary conditions $p(n, 0)=0, p\left(0, n^{\prime}\right)=1$. While it is possible to solve this equation, for example, by iteration, in any actual example, it seems quicker to obtain approximate answers by Monte Carlo methods, as shown by Leslie \& Gower (1958).

## 5. Recurrenoe times

If it is desired to check recurrence times to any state $S$ in a stationary process with a finite number of states, the relevant formulae have been given by Bartlett (1955, §6.41). Thus in the case of discrete time, the mean recurrence time is

$$
\begin{equation*}
\Theta_{1}=\frac{1-P(S)}{P(S)[1-P(S \mid S)]}, \tag{20}
\end{equation*}
$$

where $P(S \mid S)$ denotes the conditional probability of $S$ at one instant, given $S$ at the previous instant. In the case of continuous time, if $P(S \mid S)$ for times separated by an interval $\delta t$ is $1-\epsilon \delta t+o(\delta t)$, then

$$
\begin{equation*}
\Theta_{1}=\frac{1-P(S)}{\epsilon \bar{P}(S)} . \tag{21}
\end{equation*}
$$

This formulae is relevant in assessing the passage-time to the zero state $S$ for population processes with an 'absorbing barrier' at this state, for if we insert a fictitious escape probability $\epsilon \delta t$ in $\delta t$, we have from the equilibrium for the state $N=1$,
whence

$$
\begin{gather*}
\mu_{1} P(1)=\epsilon P(0)  \tag{22}\\
\Theta_{1}=\frac{1-P(0)}{\mu_{1} P(1)} \tag{23}
\end{gather*}
$$

Under conditions for which $P(0)$ is small, the quasi-stationary distribution $P(n),(n>0)$, exists approximately independently of $\epsilon$, and under such conditions the mean recurrence time $\Theta_{1} \sim 1 /\left[\mu_{1} P(1)\right]$ gives the order of magnitude of the passage-time to zero. For processes of the type discussed in $\S 2$ such passage-times may be so large as to be considered infinite (cf. Leslie, 1958).

## PART II. NUMERICAL RESULTS

## 6. Example of distribution $P(n)$

It was noted in §2 that the recurrence relation for $P(n)$ enabled $P(n)$ to be calculated exactly. This is strictly true only if the zero state is not absorbing, but from the last section $P(n)$ is effectively defined in quasi-stationary cases also. Whilst it is still a purely theoretical result, we give a numerical example of $P(n)$ in this last case, for the logistic model

$$
\begin{array}{ll}
a_{1}=0.8077, & b_{1}=0.008932, \\
a_{2}=0.1145, & b_{2}=0 .
\end{array}
$$

$P(n)$, standardized to a total of 4975 , was found to have the values given in Table 1.

Table 1 (giving $f=4975 P(n)$ )

| $n=81$ | $f=0.1$ | $n=93$ | $f=118.3$ | $n=105$ | $f=236 \cdot 7$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 82 | 0.2 | 94 | 166.7 | 106 | $183 \cdot 4$ |
| 83 | $0 \cdot 5$ | 95 | 224.7 | 107 | 103.1 |
| 84 | $1 \cdot 0$ | 96 | $289 \cdot 7$ | 108 | 58.8 |
| 85 | $1 \cdot 9$ | 97 | $358 \cdot 0$ | 109 | $30 \cdot 1$ |
| 88 | $3 \cdot 7$ | 98 | 416.3 | 110 | $13 \cdot 5$ |
| 87 | $8 \cdot 7$ | 99 | $461 \cdot 8$ | 111 | $5 \cdot 3$ |
| 88 | 11.8 | 100 | $484 \cdot 8$ | 112 | $1 \cdot 7$ |
| 89 | $20 \cdot 2$ | 101 | $480 \cdot 1$ | 113 | 0.5 |
| 90 | $33 \cdot 2$ | 102 | $446 \cdot 8$ | 114 | $0 \cdot 1$ |
| 91 | 52.7 | 103 | $388 \cdot 9$ |  |  |
| 92 | $80 \cdot 6$ | 104 | $315 \cdot 1$ |  | $4975 \cdot 0$ |

The constants of this distribution as calculated by the approximate formulae of $\S 2$ agree very well with the exact results:

| Exact |  | Approximation |
| :--- | ---: | ---: |
| $m:$ | 99.83 | 99.83 (2nd approx.) |
| $\sigma^{2}:$ | 16.71 | 16.52 (lst approx.) |
| $\mu_{3}:$ | -16.61 | -16.52 (2nd approx.) |

## 7. Comparison of approximate moments for discrete-time MODEL WITH EMPIRICAL RESULTS

Four empirical distributions for a logistic process in the region of the stationary state were built up on the Elliott-N.R.D.C. 401 computer at Rothamsted Experimental Station, taking the values of the parameters in the discrete-time model

$$
E\left\{N_{t+1} \mid N_{t}\right\}=\frac{\lambda}{1+\alpha N_{l}} N_{t}=\lambda_{l} N_{t} \quad\left(\lambda=e^{b-d}\right)
$$

given in Table 2. In each case $m=(\lambda-1) / \alpha=100$, and it will be noted that the unit of time in $I b$ is $\frac{1}{5}$ th of that adopted in the remaining three models.

Table 2

| Model |  | $a$ | Constant <br> birth-rate $(b)$ | Constant <br> death-rate $(d)$ |
| :---: | :--- | :--- | :---: | :---: |
| I $a$ | 2.0 | 0.01 | 1.0083 | - |
| $\mathrm{I} b$ | 1.1487 | 0.001487 | 0.2017 | - |
| II $a$ | 2.0 | 0.01 | - | 0.1145 |
| II $b$ | 2.0 | 0.01 | - | 0.3151 |

The programmes used for computing $I a, \amalg a$ and $I I b$ were originally written for a system of two competing species (Leslie \& Gower, 1958), but by putting two of the parameters equal to zero (cf. the equations given later in § 8), these could be used for computing simultaneously a pair of logistic processes. In order to simplify these programmes, however, certain approximations had been made to $\operatorname{var}\left(N_{t+1} \mid N_{t}\right)$. Thus, if the expression for the variance in (11) is written as

$$
\sigma^{2}\left\{N_{t+1}\right\}=\phi E\left\{N_{t+1}\right\}
$$

where, when the birth-rate (b) remains constant (BRC model),

$$
\begin{equation*}
\phi=\left(\frac{2 b}{r_{1}}-1\right)\left(\lambda_{1}-1\right) \tag{24}
\end{equation*}
$$

and when the death-rate ( $d$ ) remains constant (DRC model),

$$
\begin{equation*}
\phi=\left(\frac{2 d}{r_{t}}+1\right)\left(\lambda_{t}-1\right) \tag{25}
\end{equation*}
$$

then it may be shown empirically (Leslie, 1958), by tabulating $\phi$ over a relatively wide range of possible values of $\lambda_{l}$ (or $\log _{e} \lambda_{l}=r_{t}$ ), that in the BRC model we have, when $\lambda=2.0$ and constant $(b)=1 \cdot 0083$,

$$
\begin{equation*}
\sigma^{2}\left\{N_{l+1}\right\} \sim 2 E\left\{N_{l+1}\right\} \tag{26}
\end{equation*}
$$

and in the DRC model for

$$
\left.\begin{array}{ll}
\text { constant }(d)=0.1145: & \sigma^{2}\left\{N_{t+1}\right\} \sim\left(-0.87+1 \cdot 10 \lambda_{t}\right) E\left\{N_{t+1}\right\},  \tag{27}\\
\text { constant }(d)=0.3151: & \sigma^{2}\left\{N_{t+1}\right\} \sim\left(-0.66+1 \cdot 29 \lambda_{t}\right) E\left\{N_{t+1}\right\}
\end{array}\right\}
$$

These empirical approximations, which should hold over the entire development of any process with the given parameters, are closely related to (15) and (16) for systems in the neighbourhood of the stationary mean. For, expressing the latter in terms of $E\left\{N_{t+1} \mid N_{i}\right\}$, we have in the region of $N_{t} \sim m$,

$$
N_{t} \sim\left(1+\frac{\alpha}{\lambda} \delta N_{t}\right) E\left\{N_{l+1}\right\}, \quad \lambda_{t} \sim 1-\frac{\alpha}{\lambda} \delta N_{t}
$$

and (15) and (16) can be written, respectively, as

$$
\begin{gather*}
\sigma^{2}\left\{Z_{t+1} \mid N_{t}\right\} \sim\left[(b+1)+(b-1) \lambda_{t}\right] E\left\{N_{t+1}\right\},  \tag{28}\\
\sigma^{2}\left\{Z_{t+1} \mid N_{t}\right\} \sim\left[(d-1)+(d+1) \lambda_{t}\right] E\left\{N_{t+1}\right\} . \tag{29}
\end{gather*}
$$

Thus, in the BRC model, when $b \sim 1$,

$$
\sigma^{2}\left\{Z_{t+1} \mid N_{t}\right\} \sim 2 E\left\{N_{t+1}\right\}
$$

while in the DRC model, for $d=0.1145$,

$$
\sigma^{2}\left\{Z_{t+1} \mid N_{l}\right\} \sim\left[-0.8855+1 \cdot 1145 \lambda_{t}\right] E\left\{N_{t+1}\right\}
$$

and for $d=0.3151$

$$
\sigma^{2}\left\{Z_{t+1} \mid N_{l}\right\} \sim\left[-0.6849+1.3151 \lambda_{t}\right] E\left\{N_{t+1}\right\}
$$

which correspond very closely to (27).
In the remaining model ( $\mathrm{I} b$ ), a programme was used in which the 'exact' expression (24) for $\phi$ was incorporated. This has the advantage that the choice of the constant birth-rate (b) is not restricted to only a very limited range of values, as in the case of the approximation (26).

The observed moments of these computed distributions, together with those expected from the theoretical approximations for the discrete-time (D-T) and equivalent continuoustime (C-T) models, are shown in Table 3.

The agreement between the observed moments and the theoretical approximations for the discrete-time model seems very satisfactory, considering the errorsinvolvedin estimating the former, even in samples of this size. The standard errors quoted are in general classical values, ignoring the serial correlations between the successive observations, and representing lower limits to the correct values. The correlation $\rho_{1}$ between successive observations is to the first approximation $1 / \lambda$, and the correcting factors to the standard errors of the mean and standard deviation are respectively $\sqrt{ }\left\{\left(1+\rho_{1}\right) /\left(1-\rho_{1}\right)\right\}$ and $\sqrt{ }\left\{\left(1+\rho_{1}^{2}\right) /\left(1-\rho_{1}^{2}\right)\right\}$. Where the differences between the observed and theoretical means or standard deviations
exceed twice the classical standard error, the corrected standard error is shown in brackets, and it will be seen that the one such difference no longer appears anomalous. The corrections to the standard errors of moments to allow for dependence become more complicated for the higher moments, but are not needed for the $\gamma_{1}$ values in Table 3 (formulae for them may be ascertained if required from Chanda (1958)).

| Model | No. of observations | Moment | Approximations |  | Observed (D.T) model |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | $(\overparen{C \cdot T})_{\text {model }}$ | (D-T) model |  |
| $\mathrm{I} a$ | 9950 | Mean | 98.54 | 98.68 | $98.80 \pm 0.18$ |
|  |  | $\sigma$ | 12.06 | 16.40 | $18 \cdot 47 \pm 0 \cdot 12$ |
|  |  | $\gamma_{1}$ | 0.083 | 0.035 | $0.072 \pm 0.025$ |
| I $b$ | 5240 | Mean | 98.54 | 98.55 | $98.63 \pm 0.17$ |
|  |  | $\sigma$ | 12.06 | 12.90 | $12.53 \pm 0.12$ (0.33) |
|  |  | $\gamma_{1}$ | 0.083 | 0.076 | $0.053 \pm 0.034$ |
| II $a$ | 4975 | Mean | 99.83 | 99.85 | $99.97 \pm 0.08$ |
|  |  | $\sigma$ | $4 \cdot 06$ | $5 \cdot 53$ | $5.51 \pm 0.06$ |
|  |  | $\gamma_{1}$ | $-0.246$ | -0.161 | $-0.182 \pm 0.035$ |
| II $b$ | 4975 | Mean | 99.55 | 99.58 | $99.44 \pm 0.13$ |
|  |  | $\sigma$ | 6.74 | $9 \cdot 17$ | $9.16 \pm 0.09$ |
|  |  | $\gamma_{1}$ | -0.148 | $-0.103$ | $-0.103 \pm 0.035$ |

Table 4

| V | $f(N)$ | $N$ | $f(N)$ | $N$ | $f(N)$ |
| :--- | :---: | :---: | :---: | :---: | ---: |
| 77 | 1 | 92 | 138 | 107 | 188 |
| 78 | 0 | 93 | 168 | 108 | 120 |
| 79 | 0 | 94 | 194 | 109 | 90 |
| 80 | 1 | 95 | 213 | 110 | 64 |
| 81 | 2 | 96 | 270 | 111 | 54 |
| 82 | 5 | 97 | 285 | 112 | 25 |
| 83 | 3 | 98 | 310 | 113 | 17 |
| 84 | 4 | 99 | 329 | 114 | 14 |
| 85 | 9 | 100 | 350 | 115 | 6 |
| 86 | 20 | 101 | 361 | 116 | 0 |
| 87 | 33 | 102 | 357 | 117 | 0 |
| 88 | 35 | 103 | 339 | 118 |  |
| 89 | 51 | 104 | 318 |  |  |
| 90 | 67 | 105 | 261 |  | Total |
| 91 | 97 | 106 | 177 |  | 4975 |

As an illustration, we give in Table 4 the observed frequency distribution for model II $a$, corresponding to the continuous-time model for which the exact distribution is given in § 6.

The main difference between this observed distribution and the exact form for the equivalent continuous-time model is in the scale of the variance $\sigma^{2}$ (one notes in passing that in both cases $\mu_{3} \sim-\sigma^{2}$ ). It is, however, always possible to make the variances of the two types of model more in agreement by adopting a smaller unit of time in the discretetime model, as is illustrated in the cases of $\mathrm{I} a$ and $\mathrm{I} b$ in the above table.

It may also be of interest to consider the recurrence times which were observed in this set of realizations for model II $a$. Regarding the occurrence of a particular integer as a specified state $S$ being occupied, the mean life-time spent in the state $S, T_{1}=1 /\{1-P(S \mid S)\}$,
could be determined from the typed lists of results, and hence the mean recurrence time for the state $S$,

$$
\Theta_{1}=T_{1} \frac{1-P(S)}{P(S)}
$$

The observed values of $T_{1}$ and $\Theta_{1}$, neglecting the tails of the distribution where the observed frequencies became small, are given in Table 5.

Table 5

| State $S$ | Observed |  | Normal approximation $\Theta_{1}$ | State $S$ | Observed |  | Normal approxi |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\overbrace{T_{1}}$ |  |  |  | $\overparen{T_{1}}$ | $\Theta_{1}$ | $\begin{gathered} \text { mation } \\ \Theta_{1} \end{gathered}$ |
| 85 | 1-1250 | $623 \cdot 0$ | $551 \cdot 7$ | 100 | 1.0870 | 14.3 | 13.8 |
| 86 | 1.0000 | $247 \cdot 7$ | $343 \cdot 2$ | 101 | 1.0841 | $13 \cdot 9$ | $14 \cdot 1$ |
| 87 | 1.0312 | 154.5 | $220 \cdot 5$ | 102 | $1 \cdot 0593$ | $13 \cdot 7$ | $14 \cdot 8$ |
| 88 | 1.0294 | 145.2 | 146.4 | 103 | 1-1042 | $15 \cdot 1$ | 16.1 |
| 89 | 1.0851 | 104.7 | 100.5 | 104 | 1-1042 | $16 \cdot 1$ | 18.0 |
| 90 | 1.0835 | $78 \cdot 0$ | 71.2 | 105 | $1 \cdot 0830$ | $19 \cdot 6$ | $20 \cdot 9$ |
| 91 | 1.0211 | 51.4 | $52 \cdot 2$ | 106 | 1.0727 | 29.1 | $25 \cdot 0$ |
| 92 | 1.0455 | $38 \cdot 7$ | 39.5 | 107 | 1-1124 | 28.4 | $30 \cdot 9$ |
| 93 | 1.0573 | $30 \cdot 7$ | $30 \cdot 9$ | 108 | $1 \cdot 0526$ | $42 \cdot 6$ | $39 \cdot 5$ |
| 94 | 1.0838 | 28.7 | $25 \cdot 0$ | 109 | 1.0465 | 56.8 | $52 \cdot 2$ |
| 95 | 1-1036 | $24 \cdot 7$ | $20 \cdot 9$ | 110 | 1.0159 | $77 \cdot 9$ | 71.2 |
| 96 | 1.0887 | $18 \cdot 9$ | 18.0 | 111 | $1 \cdot 0000$ | $91 \cdot 1$ | $100 \cdot 5$ |
| 97 | 1.0634 | 17.5 | $18 \cdot 1$ | 112 | 1.0870 | $215 \cdot 2$ | 146.4 |
| 98 | 1.0954 | $18 \cdot 4$ | 14.8 | 113 | $1 \cdot 0625$ | 309.8 | $220 \cdot 5$ |
| 99 | $1 \cdot 0717$ | $15 \cdot 1$ | $14 \cdot 1$ | 114 | $1 \cdot 0000$ | $354 \cdot 8$ | $343 \cdot 2$ |

If the conditional probability of $S$, given $S$ at the preceding instant, $P(S \mid S) \sim P(S)$, as appears very roughly to be the case in this example (e.g. for the ten states disposed symmetrically about the mean, the average $P(S \mid S)=0.0785$ and the average $P(S)=0.0630$ ), then

$$
\Theta_{1} \sim 1 / P(S) .
$$

Taking the first approximations to the moments of the discrete-time distribution, when the death-rate remains constant, viz.

$$
\begin{aligned}
\text { mean } & =(\lambda-1) / \alpha=m, \\
\sigma^{2} & =2 d m /\left\{1-(1 / \lambda)^{2}\right\}, \\
\mu_{3} & =0,
\end{aligned}
$$

then the normal approximation is

$$
\Theta_{1} \sim \sqrt{ }(2 \pi) \sigma \exp \left[\frac{(N-m)^{2}}{2 \sigma^{2}}\right] .
$$

These figures are given in the third column of the above table, and it will be seen that although the departures from normality of the actual distribution are appreciable, yet on the whole the approximation indicates the order of magnitude of the observed recurrence times, more particularly for the states which are less than the mean value. By extrapolation

$$
1 / P(1) \sim 7.0 \times 10^{70}
$$

and it is evident, without proceeding any further, and without taking the approximate value too literally, that the probability of random extinction for this system is negligible, even in the case of the discrete-time model with its larger variance.

## 8. Comparison of approximate moments with empirical RESULTS FOR A TWO-SPECIES SYSTEM

Two bivariate distributions were computed for a system of two competing species fluctuating in the region of the stable stationary state. It was assumed in both cases that the death-rate ( $d$ ) of each species remained constant, and in the set of deterministic equations defining the expectations for this type of system (Leslie \& Gower, 1958),

$$
\begin{align*}
& E\left\{N_{1}(t+1) \mid N_{1}(t), N_{2}(t)\right\}=\frac{\lambda_{1} N_{1}(t)}{1+\alpha_{1} N_{1}(t)+\beta_{1} N_{2}(t)},  \tag{30}\\
& E\left\{N_{2}(t+1) \mid N_{1}(t), N_{2}(t)\right\}=\frac{\lambda_{2} N_{2}(t)}{1+\alpha_{2} N_{2}(t)+\beta_{2} N_{1}(t)}, \tag{31}
\end{align*}
$$

the following parameters were adopted in System A,

$$
\begin{aligned}
& \lambda_{1}=2.5, \quad d_{1}=0.1145, \quad \alpha_{1}=0.008, \quad \beta_{1}=0.003, \\
& \lambda_{2}=2.0, \quad d_{2}=0.3151, \quad \alpha_{2}=0.00625, \quad \beta_{2}=0.0025 .
\end{aligned}
$$

In the second case, System B, the same set of parameters was used, except that the value of $\alpha_{1}$, was changed to $\alpha_{1}=0.005$. The computed distributions were based on 1000 observations for A, and on 995 for B.

The first approximations to the moments are (assuming that both $N_{1}$ and $N_{2}$ are distributed normally about the stationary state)

$$
\begin{align*}
& \operatorname{mean}\left(N_{1}\right)=\frac{\alpha_{2}\left(\lambda_{1}-1\right)-\beta_{1}\left(\lambda_{2}-1\right)}{\alpha_{1} \alpha_{2}-\beta_{1} \beta_{2}},  \tag{32}\\
& \operatorname{mean}\left(N_{2}\right)=\frac{\alpha_{1}\left(\lambda_{2}-1\right)-\beta_{2}\left(\lambda_{1}-1\right)}{\alpha_{1} \alpha_{2}-\beta_{1} \beta_{2}}, \tag{33}
\end{align*}
$$

and for the marginal distributions,

$$
\begin{equation*}
\mu_{3}\left(N_{1}\right)=\mu_{3}\left(N_{2}\right)=0 ; \tag{34}
\end{equation*}
$$

while the variances and covariances may be obtained from the solution of the equations which have already been given for the discrete-time model (Leslie \& Gower, 1958, §5). The results are shown in Table 6.

Table 6

|  | System A |  | System B |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Approximation | Observed | Approximation | Observed |
| Mean ( $N_{1}$ ) | 150.0 | $150 \cdot 82$ | 268.4 | $270 \cdot 16$ |
| Mean ( $N_{2}$ ) | $100 \cdot 0$ | 99.19 | 52.6 | 50.75 |
| $\sigma\left(N_{1}\right)$ | 7.84 | 7.85 | 11.06 | 11.37 |
| $\sigma\left(\mathrm{V}_{8}\right)$ | 11.49 | 12.03 | 11.68 | 12.42 |
| $\rho\left(N_{1}, N_{3}\right)$ | -0.384 | -0.446 | -0.529 | -0.602 |
| $\gamma_{1}\left(N_{1}\right)$ | 0 | +0.001 | 0 | -0.005 |
| $\gamma_{1}\left(N_{2}\right)$ | 0 | +0.074 | 0 | -0.022 |

The agreement between the approximations and the observed means, standard deviations and correlation coefficients seems very satisfactory in both cases; while the magnitude of the skewness coefficients suggest that both distributions could be regarded as approximately bivariate normal in form.

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