# Stochastic models for population networks

#### II: Discrete-time patch occupancy models [Exact results]

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- Individual patches may suffer local extinction.
- Recolonization can occur through dispersal of individuals from other patches.











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- In some instances there is an external source of immigration (mainland-island configuration).





















Given an appropriate model ...

- Assessing population viability:
  - What is the expected time to (total) extinction\* ?
  - What is the probability of extinction by time  $t^*$ ?
- Can we improve population viability ?
- How do we estimate the parameters of the model ?
- Can we determine the stationary/quasi-stationary distributions ?

\*Or *first* total extinction in the mainland-island setup.

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In Lecture 1 we looked at the *stochastic logistic (SL) model* of Feller\*.

\*Feller, W. (1939) Die grundlagen der volterraschen theorie des kampfes ums dasein in wahrscheinlichkeitsteoretischer behandlung. Acta Biotheoretica 5, 11–40.

## A continuous-time model

There are *J* patches. Each occupied patch becomes empty at rate *e* and colonization of empty patches occurs at rate c/J for each occupied-unoccupied pair.

The state space of the Markov chain  $(n_t, t \ge 0)$  is  $S = \{0, 1, ..., J\}$  and the transitions are:

$n \rightarrow n+1$	at rate	$\frac{c}{J}n\left(J-n\right)$
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 $n \to n-1$  at rate  $en$ 

Mainland-island version (v is the immigration rate):

$$n \rightarrow n+1$$
 at rate  $v(J-n) + \frac{c}{J}n(J-n)$   
 $n \rightarrow n-1$  at rate  $en$ 

We identified an approximating deterministic model for the *proportion*,  $X_t^{(J)} = n_t/J$ , of occupied patches at time *t*. A *functional law of large numbers* established convergence of the family  $(X_t^{(J)})$  to the unique trajectory  $(x_t)$  satisfying

$$x'_{t} = cx_{t}(1 - x_{t}) - ex_{t} = cx_{t}(1 - \rho - x_{t}),$$

namely

$$x_t = \frac{(1-\rho)x_0}{x_0 + (1-\rho - x_0) e^{-(c-e)t}},$$

being the classical Verhulst\* model.

\*Verhulst, P.F. (1838) Notice sur la loi que la population suit dans son accroisement. Corr. Math. et Phys. X, 113–121.

#### The SL model (c < e) x = 0 stable



## The SL model (c > e) x = 1 - e/c stable



**Theorem** If  $X_0^{(J)} \to x_0$  as  $J \to \infty$ , then the family of processes  $(X_t^{(J)})$  converges *uniformly in probability* on *finite time intervals* to the deterministic trajectory  $(x_t)$ : for every  $\epsilon > 0$ ,

$$\lim_{J \to \infty} \Pr\left(\sup_{s \le t} \left| X_s^{(J)} - x_s \right| > \epsilon\right) = 0.$$

#### The SL model $(c > e) \ J \rightarrow \infty$



Many species have life cycles (often annual) that consist of distinct phases, and the propensity for colonization and local extinction is different in each phase. Many species have life cycles (often annual) that consist of distinct phases, and the propensity for colonization and local extinction is different in each phase. Examples:

The Vernal pool fairy shrimp (Branchinecta lynchi) and the California linderiella (Linderiella occidentalis), both listed under the Endangered Species Act (USA)

The Jasper Ridge population of Bay checkerspot butterfly (Euphydryas editha bayensis), now extinct




## **Butterfly life cycle**

Egg  $\simeq$  4 days



Larva (caterpillar)  $\simeq$  14 days



Pupa (chrysalis)  $\simeq$  7 days







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Recall that there are *J* patches and that  $n_t$  is the number of occupied patches at time *t*. We suppose that  $(n_t, t = 0, 1, ...)$  is a discrete-time Markov chain taking values in  $S = \{0, 1, ..., J\}$  with a 1-step transition matrix  $P = (p_{ij})$  constructed as follows.

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The extinction and colonization phases are governed by their own transition matrices,  $E = (e_{ij})$  and  $C = (c_{ij})$ .

We let P = EC if the census is taken after the colonization phase or P = CE if the census is taken after the extinction phase.

#### **EC** versus **CE**



Suppose that local extinction occurs *at any given patch* with probability e (0 < e < 1), independently of other occupied patches. So, the number of extinctions when there are i patches occupied has a binomial Bin(i, e) distribution, and therefore

$$e_{i,i-k} = {i \choose k} e^k (1-e)^{i-k} \quad (k = 0, 1, \dots, i).$$

We also have  $e_{ij} = 0$  if j > i.

Suppose that colonization occurs according to the following mechanism.

If there are *i* occupied patches, then each unoccupied patch is colonized with probability  $c_i = (i/J)c$ , where  $c \in (0, 1]$  is a *fixed maximum colonization potential*, the (hypothetical) probability that a single unoccupied patch is colonized by the fully occupied network.

So, the unoccupied patches are colonized independently with the same probability, this probability being *proportional to* the number of patches with the potential to colonize.

Therefore, the number of colonizations when there are *i* patches occupied has a binomial  $Bin(J - i, c_i)$  distribution, and so

$$c_{i,i+k} = \binom{J-i}{k} c_i^k (1-c_i)^{J-i-k}, \ (k=0,1,\ldots,J-i),$$

In particular,  $c_{0j} = \delta_{0j}$ . We also have  $c_{ij} = 0$ , for j < i.

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There are other sensible choices for  $c_i$ : for example  $c_i = c(1 - (1 - c_1/c)^i)$  or  $c_i = 1 - \exp(-i\beta/J)$ .

#### **Evaluation of** *P*

We can evaluate *P* elementwise as follows.

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$$p_{ij} = \sum_{k=1}^{\min\{i,j\}} {\binom{i}{k}} (1-e)^k e^{i-k} {\binom{J-k}{j-k}} c_k^{j-k} (1-c_k)^{J-j}.$$

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If P = CE, then  $p_{0j} = \delta_{0j}$ , and, for  $i \ge 1$  and  $j \ge 0$ ,

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In particular, for  $i \ge 1$ ,  $p_{i0} = e^i (1 - c_i (1 - e))^{J-i}$ .

### **Equivalent independent phases**

For the *CE*-model,

$$\mathsf{E}(z^{n_{t+1}}|n_t=i) = (e+(1-e)z)^i (1-(1-e)c_i(1-z))^{J-i}.$$

Thus, given  $n_t = i$ ,  $n_{t+1}$  has the same distribution as  $B_1 + B_2$ , where  $B_1$  and  $B_2$  are two *independent* random variables with  $B_1 \sim Bin(i, 1 - e)$  and  $B_2 \sim Bin(J - i, (1 - e)c_i)$ .

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It is as if each of the *i* occupied patches remains occupied with probability 1 - e and each of the J - iunoccupied patches becomes occupied with probability  $(1 - e)c_i$ , all *J* patches being affected independently.

### **Equivalent independent phases**

For the *EC*-model, the best we can do is

$$\mathsf{E}(z^{n_{t+1}}|n_t = i) = \mathsf{E}\left\{z^B \left(1 - c_B(1-z)\right)^{J-B}\right\},\$$

where  $B \sim Bin(i, 1-e)$ .

However, note the large-*J* asymptotics when  $c_i = ic/J$ . Write  $p_i^{(J)}(z) = E(z^{n_{t+1}}|n_t = i)$ .

For the *CE*-model,

$$\lim_{J \to \infty} p_i^{(J)}(z) = [e + (1 - e)z \exp(-c(1 - e)(1 - z))]^i.$$

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**Branching!** 

# **Infinitely many patches**

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The number of extinctions when there are *i* patches occupied follows the Bin(i, e) law (as before), but in the colonization phase the number of colonizations when there are *i* patches occupied follows a Poisson(ic) law (previously a binomial Bin(J - i, ic/J) law).

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The effect is ...

**Theorem** Both infinite patch models are Galton-Watson branching processes.

## **Infinitely many patches - branching**

The occupied patches independently produce "offspring" according to the following distributions.

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For the *EC*-model,  $p_{10} = e$  and

$$p_{1j} = (1-e) \exp(-c) \frac{c^{j-1}}{(j-1)!} \quad (j \ge 1),$$

the interpretation being that each individual "dies" with probability e or otherwise is *joined by* a random number of new offspring that follows a Poisson(c) law.

## **Infinitely many patches - branching**

For the *CE*-model,  $p_{10} = e \exp(-c(1-e))$  and

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The individual survives with probability 1 - e or dies with probability e, and there is a random number of *new* offspring that follows a *Poisson*(c(1 - e)) law.

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We can now invoke the encylopaedic theory of branching processes.

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Recall that, given  $n_0 = i$ ,  $E(n_t) = i\mu^t$  and

$$\operatorname{Var}(n_t) = \begin{cases} i\sigma^2 t & \text{if } \mu = 1 \quad (e = c/(1+c)) \\ i\sigma^2(\mu^t - 1)\mu^{t-1}/(\mu - 1) & \text{if } \mu \neq 1 \quad (e \neq c/(1+c)). \end{cases}$$

### **Infinitely many patches - total extinction**

**Theorem** For both models extinction occurs with probability 1 if and only if  $e \ge c/(1+c)$ ; otherwise the extinction probability  $\eta$  is the unique solution to s = p(s) on the interval (0, 1), where:

*EC*-model: 
$$p(s) = e + (1 - e)s \exp(-c(1 - s))$$

*CE*-model:  $p(s) = (e + (1 - e)s) \exp(-c(1 - e)(1 - s))$ 

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And much more ...

- The expected time to extinction.
- Yaglom's theorem on limiting-conditional (quasi-stationary) distributions.

#### **Back to the J-patch models**

Recall that ...

In the extinction phase the number of extinctions when there are *i* patches occupied follows a Bin(i, e) law.

In the colonization phase the number of colonizations when there are *i* patches occupied follows a binomial  $Bin(J - i, c_i)$  law, where  $c_i = ic/J$ .
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Numerical procedures are routine.

## Simulation: P = EC



# Simulation: P = CE



## **Extinction probability: vary** *t*



## **Extinction probability: vary** *n*<sub>0</sub>



## **Expected extinction time: vary** *n*<sub>0</sub>



## Simulation: P = EC



## **Simulation:** *P* = *CE*



We can model this behaviour using a *limiting* conditional distribution (lcd)  $(m_j, j = 1, ..., J)$ ; often called a *quasi-stationary distribution* (qsd)\*.

lcd:

$$\lim_{t \to \infty} \Pr(n_t = j | n_t \neq 0) = m_j.$$

qsd:

$$\Pr(n_0 = j) = m_j \implies \Pr(n_t = j | n_t \neq 0) = m_j \quad (\forall t > 0).$$

\* In the infinite state space setting, the distinction between lcd and is both subtle and interesting.

## Simulation: P = EC



## Simulation and qsd: *P* = *EC*



## **Simulation:** *P* = *CE*



## Simulation and qsd: *P* = *CE*



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This greatly simplifies the analysis!

## **J-patch Mainland-Island models**

The behaviour of both models can be summarized in terms of a single pair of parameters (p,q):

*EC*-model: p = 1 - e(1 - c) and q = c

*CE*-model: p = 1 - e and q = (1 - e)c

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**Proposition** Given  $n_t = i$ ,  $n_{t+1}$  has the same distribution as  $B_1 + B_2$ , where  $B_1$  and  $B_2$  are two *independent* random variables with  $B_1 \sim Bin(i, p)$  and  $B_2 \sim Bin(J - i, q)$ .

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It is as if each of the *i* currently occupied patches remains occupied with probability *p* and each of the J - i currently unoccupied patches become occupied with probability *q* (all patches being affected independently). Thus the process has some of the character of an urn model. **Proposition** Given  $n_t = i$ ,  $n_{t+1}$  has the same distribution as  $B_1 + B_2$ , where  $B_1$  and  $B_2$  are two *independent* random variables with  $B_1 \sim Bin(i, p)$  and  $B_2 \sim Bin(J - i, q)$ .

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We can improve on this result ....

## J-patch Mainland-Island models

Reparameterize by setting a = p - q = (1 - e)(1 - c), being the same for both models (0 < a < 1), and  $q^* = q/(1 - a)$ . Define sequences ( $p_t$ ) and ( $q_t$ ) by

$$q_t = q^*(1 - a^t)$$
 and  $p_t = q_t + a^t$   $(t \ge 0).$ 

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**Theorem** Given  $n_0 = i$  patches occupied initially, the number  $n_t$  occupied at time t has the same distribution as  $B_1 + B_2$ , where  $B_1$  and  $B_2$  are *independent* random variables with  $B_1 \sim Bin(i, p_t)$  and  $B_2 \sim Bin(J - i, q_t)$ . The limiting distribution of  $n_t$  is  $Bin(J, q^*)$ . **Theorem** Given  $n_0 = i$  patches occupied initially, the number  $n_t$  occupied at time t has the same distribution as  $B_1 + B_2$ , where  $B_1$  and  $B_2$  are *independent* random variables with  $B_1 \sim Bin(i, p_t)$  and  $B_2 \sim Bin(J - i, q_t)$ . The limiting distribution of  $n_t$  is  $Bin(J, q^*)$ .

It is as if each of the *i* initially occupied patches remains occupied with probability  $p_t$  and each of the J - i initially unoccupied patches become occupied with probability  $q_t$  (all patches being affected independently). The limiting expected proportion occupied is  $q^*$ .

## J-patch Mainland-Island models

We have in particular that

$$\mathsf{E}(n_t | n_0 = i) = ip_t + (J - i)q_t = ia^t + Jq_t$$
$$(\to Jq^* \text{ as } t \to \infty)$$

#### and

$$Var(n_t | n_0 = i) = ip_t(1 - p_t) + (J - i)q_t(1 - q_t)$$
  
=  $ia^t(1 - a^t)(1 - 2q^*) + Jq_t(1 - q_t)$   
(  $\rightarrow Jq^*(1 - q^*)$  as  $t \rightarrow \infty$ ).

## Simulation: P = EC



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#### Simulation and sd: *P* = *EC*



## **Simulation:** *P* = *CE*



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Note that in contrast with our earlier infinite-state models, state 0 is *no longer absorbing*.

Let m = d for the *EC*-model and m = (1 - e)d for the *CE*-model.
## **Infinite-patch Mainland-Island models**

Let m = d for the *EC*-model and m = (1 - e)d for the *CE*-model.

**Proposition** Given  $n_t = i$ ,  $n_{t+1}$  has the same distribution as B + M, where B and M are two *independent* random variables with  $B \sim Bin(i, 1 - e)$  and  $M \sim Poisson(m)$ .

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It is as if each of the *i* currently occupied patches remains occupied with probability 1 - e and a Poisson distributed number of unoccupied patches become occupied, the mean number being *m* (all patches being affected independently). Indeed we observe that ...

**Proposition** The process  $(n_t)$  is a Galton-Watson process with immigration: each occupied patch has a Bernoulli Bin(1, 1 - e) distributed number of offspring and in each generation there is a Poisson(m) number of immigrants. The mean number of offspring is 1 - e (< 1) and the mean number of immigrants is m (<  $\infty$ ).

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Again we can invoke general theory.

# **Infinite-patch Mainland-Island models**

**Theorem** For the infinite-patch model with parameters e and m, given  $n_0 = i$  patches occupied initially, the number  $n_t$  occupied at time t has the same distribution as  $B_t + M_t$ , where  $B_t$  and  $M_t$  are two *independent* random variables with  $B_t \sim Bin(i, (1 - e)^t)$ and  $M_t \sim Poisson(m_t)$ , where  $m_t = (m/e)(1 - (1 - e)^t)$ . The limiting distribution of  $n_t$  is Poisson(m/e).

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## Simulation: P = EC



#### Simulation and sd: *P* = *EC*



### **Simulation:** *P* = *CE*



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A measure of persistence for the Mainland-Island models is the expected time to *first* total extinction of the *island network*. **Theorem** For the *J*-patch Mainland-Island model with parameters p and q, given  $n_0 = i$  patches occupied initially, the expected time to first enter state 0 is given by

$$\mu_{i0} = \sum_{k=1}^{J} {\binom{J}{k}} \frac{b^{k}}{1-a^{k}} - \sum_{j=0}^{i} {\binom{i}{j}} (-1)^{j} \sum_{k=0}^{J-i} {\binom{J-i}{k}} \frac{b^{k}(1-\delta_{j0}\delta_{k0})}{1-a^{j+k}}$$
$$= \sum_{n=0}^{\infty} \left[ (1+ba^{n})^{J} - (1-a^{n})^{i}(1+ba^{n})^{J-i} \right],$$

where a = p - q and b = q/(1 - p).

**Theorem** For the infinite-patch Mainland-Island model with parameters e and m, given  $n_0 = i$  patches occupied initially, the expected time to first enter state 0 is always *finite* and is given by

$$\mu_{i0} = \sum_{j=1}^{i} {\binom{i}{j}} (-1)^{j+1} \sum_{n=0}^{\infty} (1-e)^{jn} \exp\left(\frac{m}{e}(1-e)^{n}\right)$$
$$= \sum_{n=0}^{\infty} [1 - (1 - (1-e)^{n})^{i}] \exp\left(\frac{m}{e}(1-e)^{n}\right).$$