# The limiting behaviour of a patch occupancy model

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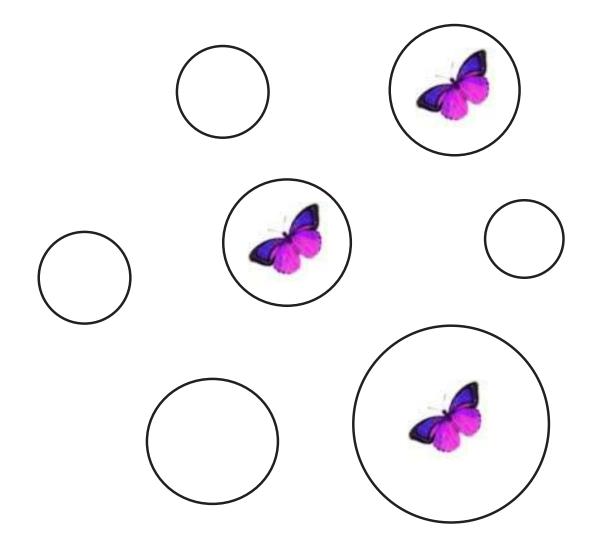
McVinish, R. and Pollett, P.K. (2010) Limits of large metapopulations with patch dependent extinction probabilities. Adv. Appl. Probab. 42, 1172-1186.

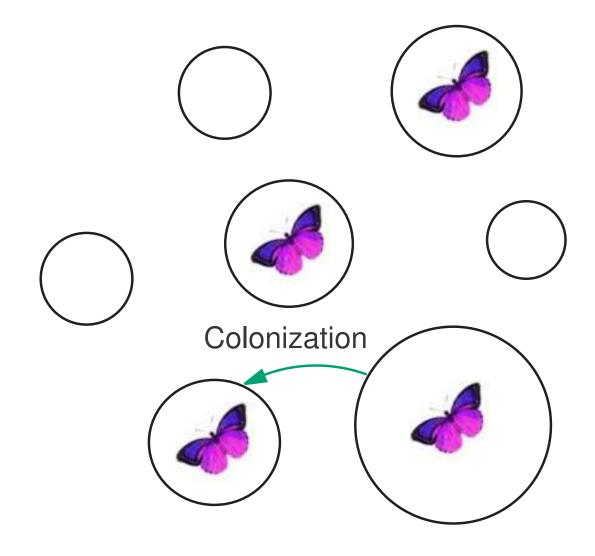
McVinish, R. and Pollett, P.K. (2011) The limiting behaviour of a mainland-island metapopulation. J. Math. Biol. To appear.

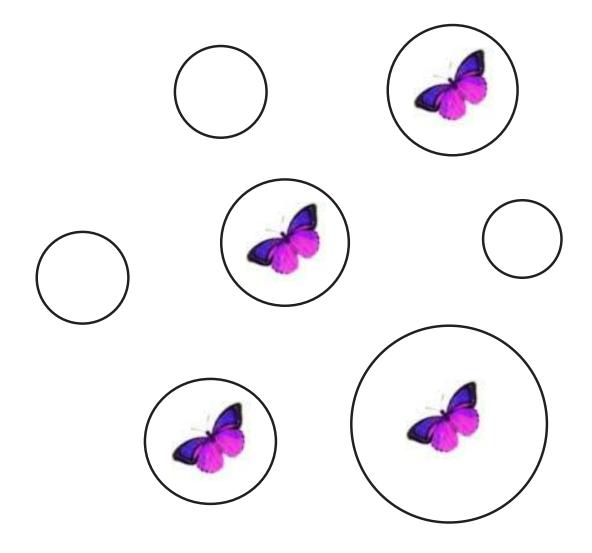
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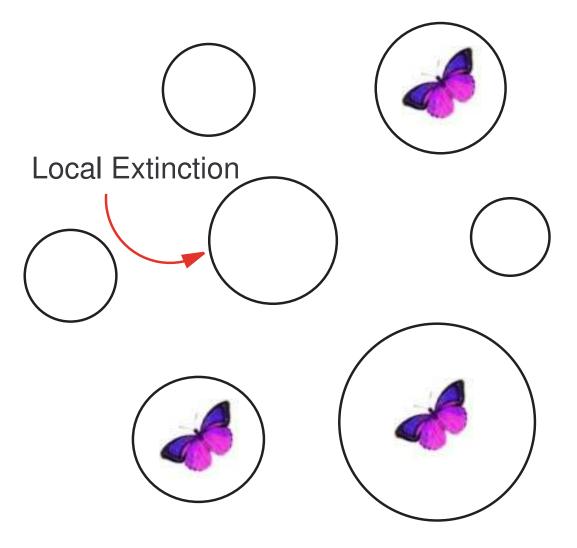
McVinish, R. and Pollett, P.K. (2013) The limiting behaviour of a stochastic patch occupancy model. J. Math. Biol. Under revision.

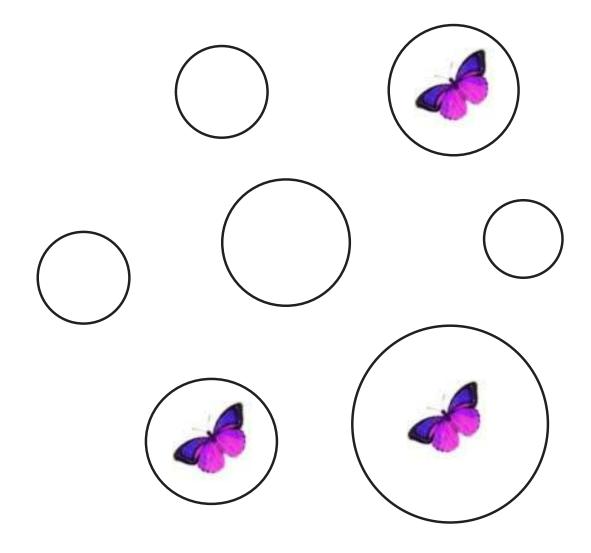
McVinish, R. and Pollett, P.K. The limiting behaviour of Hanski's incidence function metapopulation model. Submitted.

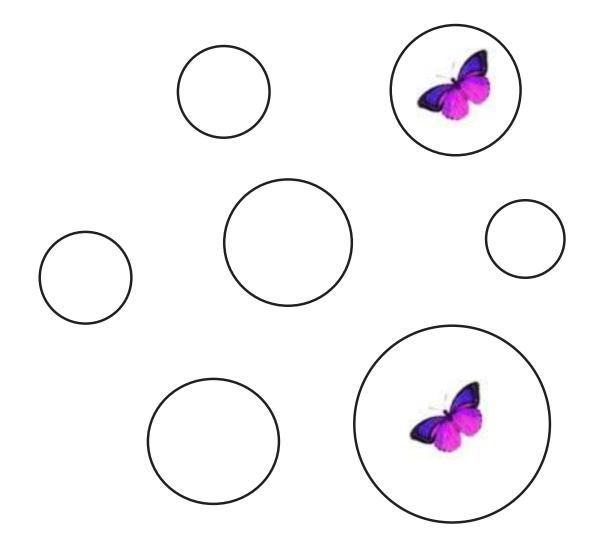


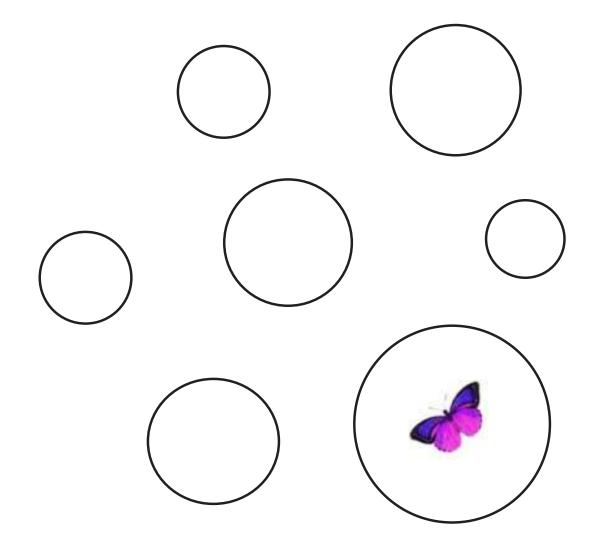


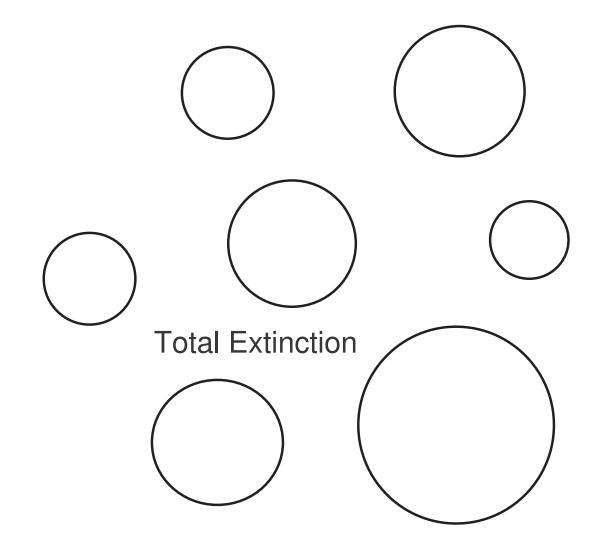


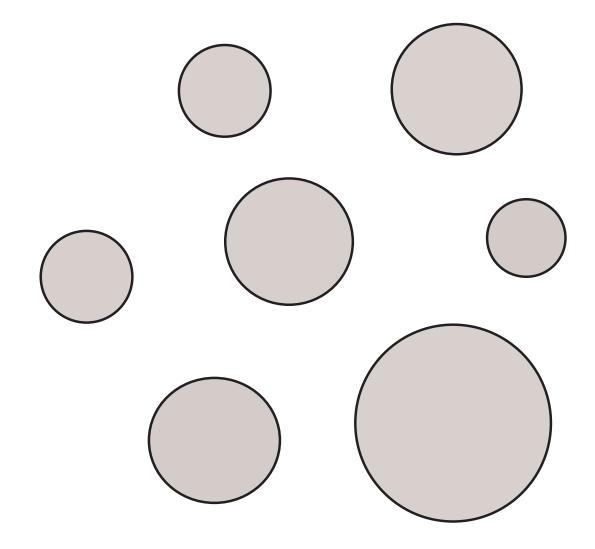


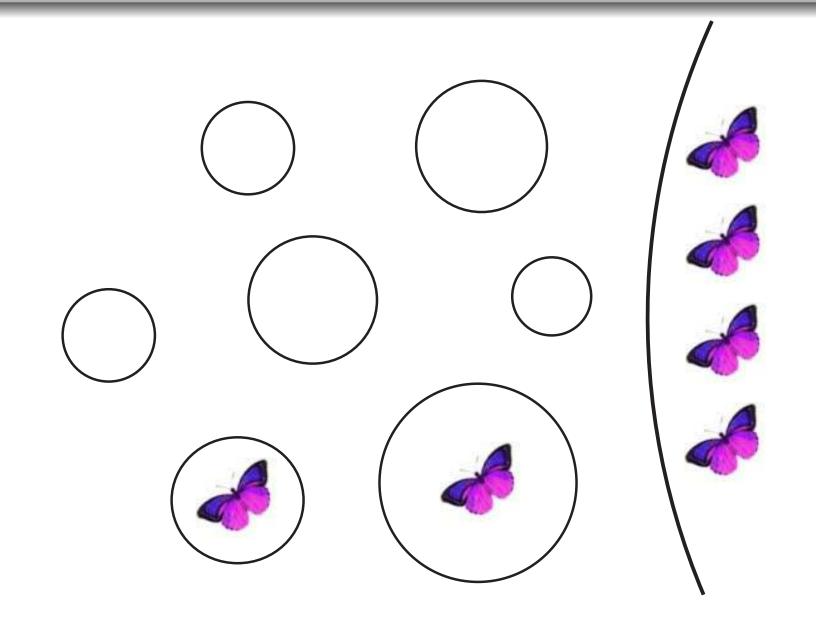


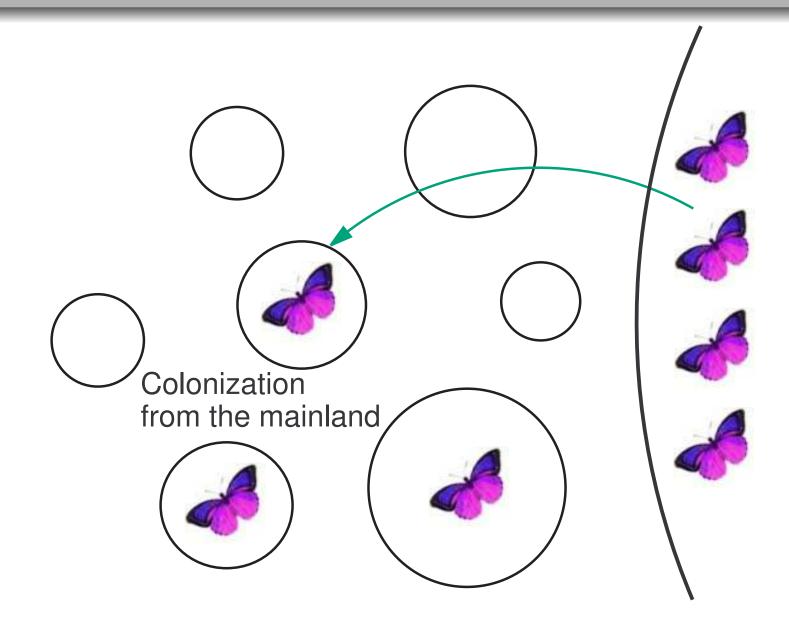


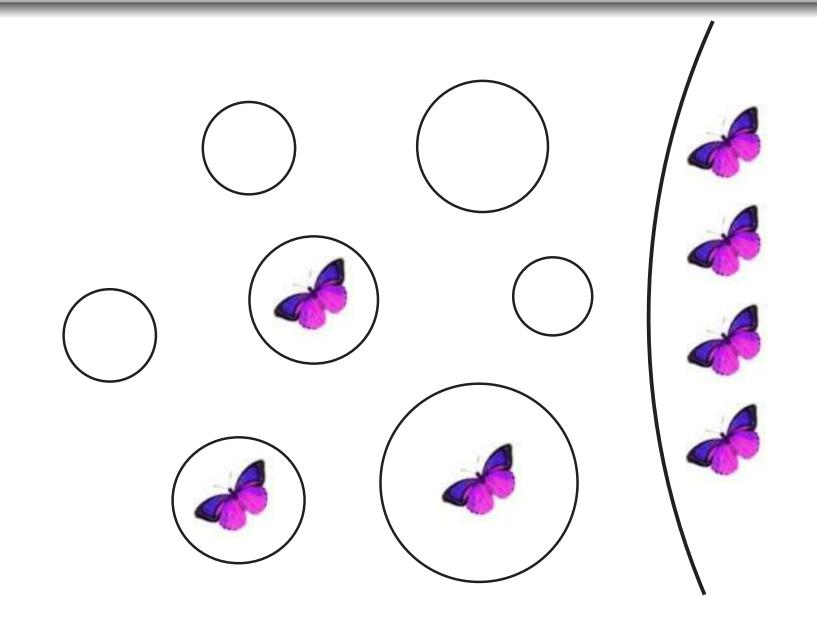


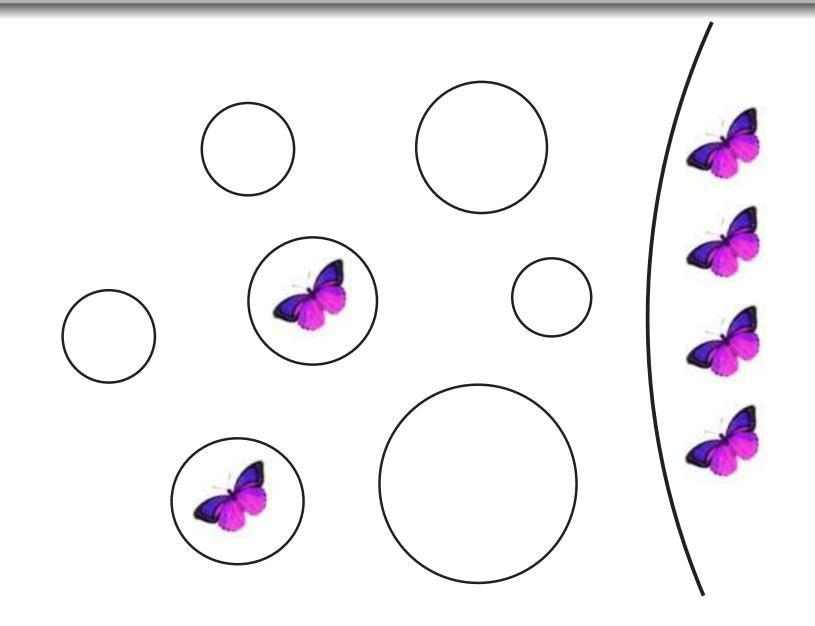


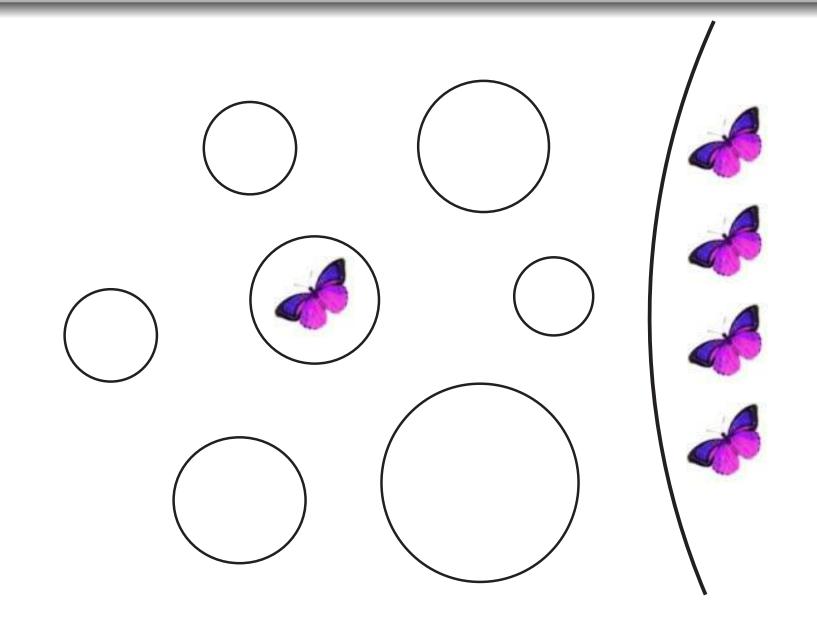


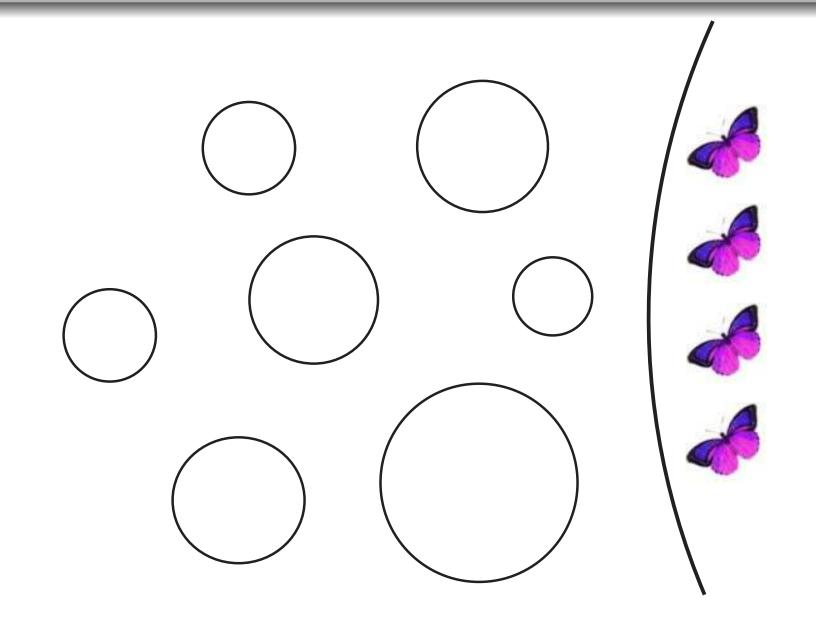


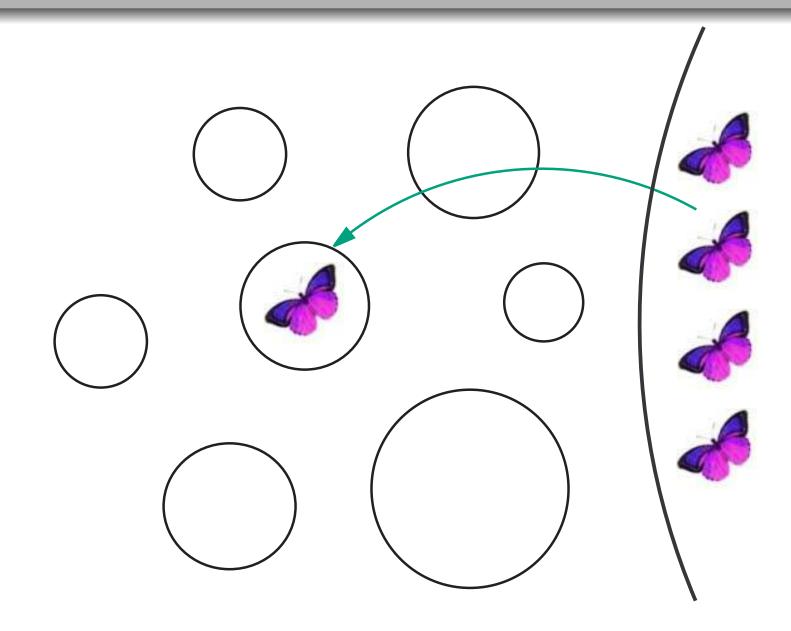


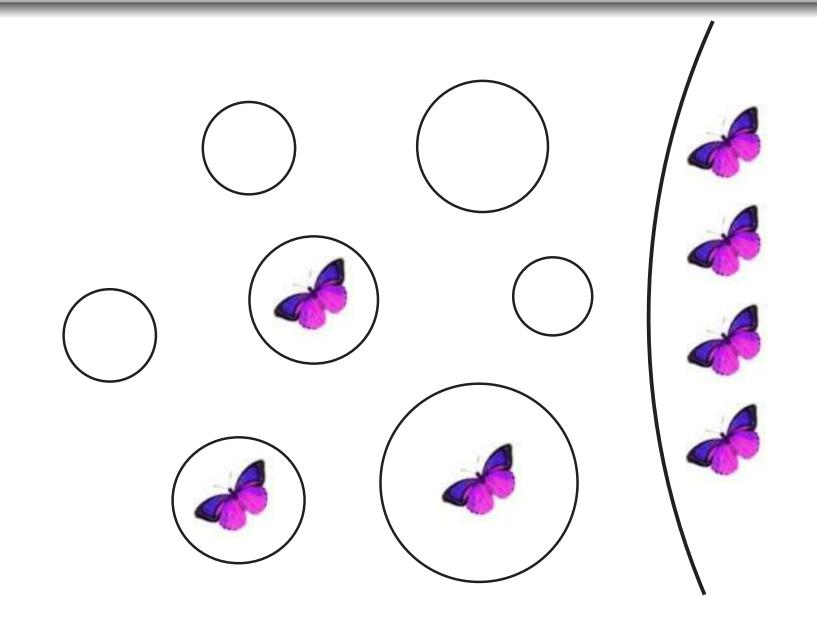














Suppose that there are n patches.

Let  $X_t^{(n)} = (X_{1,t}^{(n)}, \dots, X_{n,t}^{(n)})$ , where  $X_{i,t}^{(n)}$  is a binary variable indicating whether or not patch *i* is occupied.

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For each n,  $(X_t^{(n)}, t = 0, 1, ...)$  is assumed to be a Markov chain.

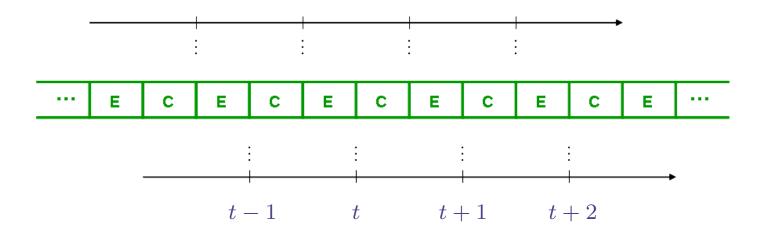
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We will we assume that the population is *observed after successive extinction phases* (CE Model).

Colonization: unoccupied patches become occupied independently with probability  $c(n^{-1}\sum_{i=1}^{n} X_{i,t}^{(n)})$ , where  $c: [0,1] \rightarrow [0,1]$  is continuous, non-decreasing and concave.

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[In our most recent work, we allow the patch colonization probability  $c(\cdot)$  to depend on the *positions* of all patches and their *areas*.]

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$$X_{i,t+1}^{(n)} \stackrel{d}{=} Bin\left(X_{i,t}^{(n)} + Bin\left(1 - X_{i,t}^{(n)}, c\left(\frac{1}{n}\sum_{j=1}^{n} X_{j,t}^{(n)}\right)\right), s_i\right)$$

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n = 30,  $s_i \sim \text{Beta}(25.2, 19.8)$  ( $\mathbb{E}s_i = 0.56$ ) and c(x) = 0.7x

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[Survival probabilities listed for occupied patches only]

 $c(x) = c(\frac{10}{30}) = 0.7 \times 0.\dot{3} = 0.2\dot{3}$ 

## **SPOM**

Thus, we have a *Chain Bernoulli* structure:

$$X_{i,t+1}^{(n)} \stackrel{d}{=} Bin\left(X_{i,t}^{(n)} + Bin\left(1 - X_{i,t}^{(n)}, c\left(\frac{1}{n}\sum_{j=1}^{n} X_{j,t}^{(n)}\right)\right), s_i\right)$$

In the *homogeneous case*, where  $s_i = s$  (non-random) is the same for each *i*, the *number*  $N_t^{(n)}$  of occupied patches at time *t* is Markovian.

It has the following *Chain Binomial* structure:

$$N_{t+1}^{(n)} \stackrel{d}{=} Bin\left(N_t^{(n)} + Bin\left(n - N_t^{(n)}, c\left(\frac{1}{n}N_t^{(n)}\right)\right), s\right)$$

Letting the initial number  $N_0^{(n)}$  of occupied patches grow at the same rate as  $n \dots$ 

**Theorem** [BP] If  $N_0^{(n)}/n \xrightarrow{p} x_0$  (a constant), then

 $N_t^{(n)}/n \xrightarrow{p} x_t$ , for all  $t \ge 1$ ,

with  $(x_t)$  determined by  $x_{t+1} = f(x_t)$ , where

$$f(x) = s(x + (1 - x)c(x)).$$

[BP] Buckley, F.M. and Pollett, P.K. (2010) Limit theorems for discrete-time metapopulation models. Probability Surveys 7, 53-83.

 $x_{t+1} = f(x_t)$ , where f(x) = s(x + (1 - x)c(x)).

Stationarity: c(0) > 0. There is a unique fixed point  $x^* \in [0,1]$ . It satisfies  $x^* \in (0,1)$  and is stable.

*Evanescence*: c(0) = 0 and  $1 + c'(0) \le 1/s$ . Now 0 is the unique fixed point in [0, 1]. It is stable.

Quasi stationarity: c(0) = 0 and 1 + c'(0) > 1/s. There are two fixed points in [0, 1]: 0 (unstable) and  $x^* \in (0, 1)$  (stable).

[Notice that c(0) = 0 implies that c'(0) > 0.]

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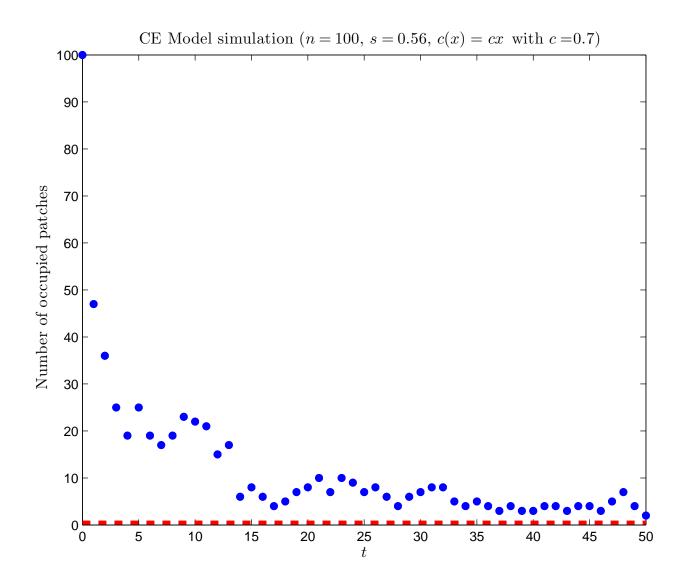
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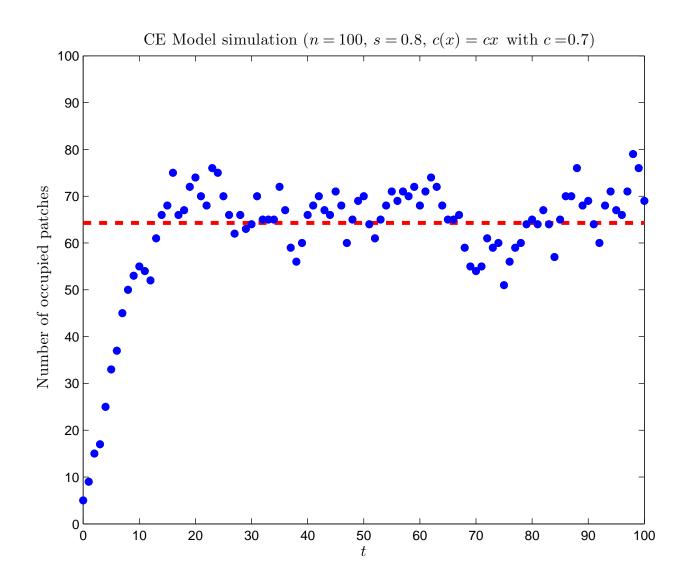
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#### **CE Model - Evanescence**



## **CE Model - Quasi stationarity**



Returning to the general case, where patch survival probabilities  $(s_i)$  are *random* and *patch dependent*, and we keep track of which patches are occupied ...

$$X_{i,t+1}^{(n)} \stackrel{d}{=} Bin\left(X_{i,t}^{(n)} + Bin\left(1 - X_{i,t}^{(n)}, c\left(\frac{1}{n}\sum_{j=1}^{n}X_{j,t}^{(n)}\right)\right), s_i\right).$$

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Notice that

$$X_{i,t+1}^{(n)} \stackrel{d}{=} Bin(X_{i,t}^{(n)}, s_i) + Bin(1 - X_{i,t}^{(n)}, s_i c(\frac{1}{n} \sum_{j=1}^n X_{j,t}^{(n)})).$$

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 $\sigma_n(B) = \#\{s_i \in B\}/n, \qquad B \in \mathcal{B}([0,1]),$ 

 $\mu_{n,t}(B) = \#\{s_i \in B : X_{i,t}^{(n)} = 1\}/n, \qquad B \in \mathcal{B}([0,1]).$ 

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Equivalently, we may define  $(\sigma_n)$  and  $(\mu_{n,t})$  by

$$\int h(s)\sigma_n(ds) = \frac{1}{n}\sum_{i=1}^n h(s_i)$$
$$\int h(s)\mu_{n,t}(ds) = \frac{1}{n}\sum_{i=1}^n X_{i,t}^{(n)} h(s_i),$$

for *h* in  $C^+([0,1])$ , the class of continuous functions that map [0,1] to  $[0,\infty)$ .

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for *h* in  $C^+([0,1])$ , the class of continuous functions that map [0,1] to  $[0,\infty)$ . For example  $(h \equiv 1)$ ,

$$\int \mu_{n,t}(ds) = \frac{1}{n} \sum_{i=1}^{n} X_{i,t}^{(n)} \quad (\mathbf{I})$$

(proportion occupied).

# A measure-valued difference equation

**Theorem** Suppose that  $\sigma_n \stackrel{d}{\rightarrow} \sigma$  and  $\mu_{n,0} \stackrel{d}{\rightarrow} \mu_0$  for some non-random measures  $\sigma$  and  $\mu_0$ . Then,  $\mu_{n,t} \stackrel{d}{\rightarrow} \mu_t$  for all  $t = 1, 2, \ldots$ , where  $\mu_t$  is defined by the following recursion: for  $h \in C^+([0,1])$ ,

$$\int h(s)\mu_{t+1}(ds) = (1 - c_t) \int sh(s)\mu_t(ds) + c_t \int sh(s)\sigma(ds),$$

where  $c_t = c(\mu_t([0, 1])) = c(\int \mu_t(ds))$ .

#### Moments

Set  $h(s) = s^k$ . Then, our recursion is

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where  $c_t = c (\mu_t([0,1])) = c (\int \mu_t(ds))$ . So, with moments defined by  $\bar{\sigma}^{(k)} := \int s^k \sigma(ds)$  and  $\bar{\mu}_t^{(k)} := \int s^k \mu_t(ds)$ ,

$$\bar{\mu}_{t+1}^{(k)} = (1 - \bar{\mu}_t^{(0)})\bar{\mu}_t^{(k+1)} + \bar{\mu}_t^{(0)}\bar{\sigma}^{(k+1)},$$

and the theorem allows to conclude that

$$\frac{1}{n} \sum_{i=1}^{n} s_i^k X_{i,t}^{(n)} \ \left( = \int s^k \mu_{n,t}(ds) \right) \ \to \bar{\mu}_t^{(k)},$$

for example,  $\frac{1}{n} \sum_{i=1}^{n} X_{i,t}^{(n)} \rightarrow \overline{\mu}_{t}^{(0)}$ .

# **Equilibria**?

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Let  $\mathcal{M}$  be the set of measures that are absolutely continuous with respect to  $\sigma$  and whose Radon-Nikodym derivative is bounded by 1,  $\sigma$  – a.e.

We shall be interested in the behaviour of solutions to our recursion starting with  $\mu_0 \in \mathcal{M}$ .

# **Equilibria**?

"Differentiating" with respect to  $\sigma$ , we see that our recursion can be written

$$\frac{\partial \mu_{t+1}}{\partial \sigma} = s \frac{\partial \mu_t}{\partial \sigma} + sc_t \left( 1 - \frac{\partial \mu_t}{\partial \sigma} \right).$$

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Furthermore, a measure  $\mu_{\infty} \in \mathcal{M}$  will be an equilibrium point of our recursion if it satisfies

$$\frac{\partial \mu_{\infty}}{\partial \sigma} = s \frac{\partial \mu_{\infty}}{\partial \sigma} + sc_{\infty} \left( 1 - \frac{\partial \mu_{\infty}}{\partial \sigma} \right),$$

where  $c_{\infty} = c (\mu_{\infty}([0, 1])).$ 

# **Equilibria**?

**Theorem** Suppose that c(0) = 0 and  $c'(0) < \infty$ . Let  $\psi^*$  be a solution to the equation

$$\psi = R_{\sigma}(\psi) := \int \frac{sc(\psi)}{1 - s + sc(\psi)} \sigma(ds).$$
(1)

The fixed points of our recursion are given by

$$\mu_{\infty}(ds) = \frac{sc(\psi^*)}{1 - s + sc(\psi^*)}\sigma(ds).$$

Equation (1) has the unique solution  $\psi^* = 0$  if and only if

$$c'(0) \int \frac{s}{1-s} \sigma(ds) \le 1.$$

Otherwise, there are two solutions, one of which is  $\psi^* = 0$ .

# **Recovery of a near-extinct population**

Return to our patch occupancy model ....

$$X_{i,t+1}^{(n)} \stackrel{d}{=} Bin(X_{i,t}^{(n)}, s_i) + Bin(1 - X_{i,t}^{(n)}, s_i c(\frac{1}{n} \sum_{j=1}^n X_{j,t}^{(n)})).$$

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First notice that if c has a continuous second derivative near 0, then, for fixed m,  $Bin(n - m, c(m/n)) \xrightarrow{d} Poi(\lambda m)$  as  $n \to \infty$ , where  $\lambda = c'(0)$ . So, if every patch had the same survival probability, then we might expect the number of occupied patches  $(N_t^{(n)}, t = 0, 1, ...)$  to converge to a Galton-Watson process (see [BP] for details).

As before, treat the collection of patch survival probabilities of occupied patches at time *t* as a point process on [0, 1], but now define  $(S_t^{(n)}, t \ge 0)$  by  $S_t^{(n)} = \{s_i : X_{i,t}^{(n)} = 1\}$ .

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Extinction of the metapopulation by time t corresponds to the event that  $S_t^{(n)}$  is the empty set.

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The aim is to show that there is a point process  $S_t$  such that  $S_t^{(n)} \Rightarrow S_t$  as  $n \to \infty$  and then to evaluate  $\lim_{t\to\infty} \Pr(S_t = \emptyset)$ .

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Extinction of the metapopulation by time t corresponds to the event that  $S_t^{(n)}$  is the empty set.

The aim is to show that there is a point process  $S_t$  such that  $S_t^{(n)} \Rightarrow S_t$  as  $n \to \infty$  and then to evaluate  $\lim_{t\to\infty} \Pr(S_t = \emptyset)$ .

We now work with the sequence  $(\mu_{n,t})$  of random measures defined by  $\mu_{n,t}(B) = \#\{s_i \in B : X_{i,t}^{(n)} = 1\}, B \in \mathcal{B}([0,1]).$ 

**Tools**\*

Define the *probability generating functional* (p.g.fl) of a point process *S* by

$$G_{S}[\xi] = \mathbb{E}\left(\prod_{s \in S} \xi(s)\right),$$

where  $\xi : [0,1] \rightarrow [0,1]$  is some Borel function. It determines the point process uniquely. Convergence of  $G_{S_t^{(n)}}$  to  $G_{S_t}$ establishes that  $S_t^{(n)} \Rightarrow S_t$ . Furthermore,

$$\Pr\left(S_t = \varnothing\right) = \lim_{b \downarrow 0} G_{S_t}[1_b(x)].$$

\*Daley, D. J. and Vere-Jones, D. (2008) An Introduction to the Theory of Point Processes. Volume II: General Theory and Structure, 2nd Edn., Springer, New York. **Theorem** Suppose that  $S_0^{(n)}$  converges weakly to a point process  $S_0$  as  $n \to \infty$  (its p.g.fl being  $G_{S_0}$ )\*.

Then,  $S_t^{(n)}$  converges weakly to a point process  $S_t$  whose p.g.fl satisfies the recursion  $G_{S_{t+1}}[\xi] = G_{S_t}[h[\xi]]$   $(t \ge 0)$ , where  $h[\xi]$  is given by

$$h[\xi](s) = (1 - s(1 - \xi(s))) \exp\left(-c'(0) \int y(1 - \xi(y)) \,\sigma(dy)\right).$$

\*More general than (as earlier) fixing the initial configuration and letting  $n \to \infty$ .

The limit point process  $(S_t, t = 0, 1, ...)$  is a *multiplicative population chain*\*, where each member of the population at time *t* produces offpring independently of the other members of the population. The offspring from the member of the population "located" at *s* is generated according to an inhomogeneous Poisson process with intensity measure  $c'(0)s\sigma(\cdot)$ , and the original member of the population survives to the next generation with probability *s*.

\*Moyal, J.E. (1962). Multiplicative population chains. Proc. R. Soc. Lond. A, 266, 518-526.

**Theorem**  $S_t$  eventually becomes empty with probability 1  $(S_t = \emptyset$  for some t > 0) if

$$c'(0)\int \frac{s}{1-s}\sigma(ds) \le 1.$$

Otherwise, it eventually becomes empty with probability  $G_{s_0}[g]$ , where  $g(s) = \psi(1-s)/(1-\psi s)$ , with  $\psi$  (< 1) being the unique solution to

$$\psi = \exp\left(-c'(0)\int \frac{(1-\psi)s}{1-\psi s}\,\sigma(ds)\right),$$

that is, with probability

$$\mathbb{E}\left(\prod_{s\in S_0}\frac{\psi(1-s)}{1-\psi s}\right).$$

Suppose that  $(s_i)$  are chosen *independently* according to  $\sigma$  and patches are initially occupied independently with probability  $p_n$ , where  $np_n \rightarrow \lambda$  (> 0).

Suppose that  $(s_i)$  are chosen *independently* according to  $\sigma$  and patches are initially occupied independently with probability  $p_n$ , where  $np_n \rightarrow \lambda$  (> 0). Then,

$$G_{S_0^{(n)}}[\xi] = \mathbb{E}\left(\prod_{s \in S_0^{(n)}} \xi(s)\right) = \mathbb{E}\left(\mathbb{E}\left(\prod_{i=1}^n \xi(s_i) \middle| X_0^{(n)}\right)\right)$$
$$= \mathbb{E}\left(\prod_{i=1}^n (X_{i,0}^{(n)}\xi(s_i) + 1 - X_{i,0}^{(n)})\right) = \left(p_n \int \xi(s)\sigma(ds) + 1 - p_n\right)^n$$

Suppose that  $(s_i)$  are chosen *independently* according to  $\sigma$  and patches are initially occupied independently with probability  $p_n$ , where  $np_n \rightarrow \lambda$  (> 0). Then,

$$\begin{split} G_{s_0^{(n)}}\left[\xi\right] &= \mathbb{E}\left(\prod_{s\in S_0^{(n)}}\xi(s)\right) = \mathbb{E}\left(\mathbb{E}\left(\prod_{i=1}^n \left|\xi(s_i)\right| X_0^{(n)}\right)\right) \\ &= \mathbb{E}\left(\prod_{i=1}^n (X_{i,0}^{(n)}\xi(s_i) + 1 - X_{i,0}^{(n)})\right) = \left(p_n \int \xi(s)\sigma(ds) + 1 - p_n\right)^n \\ &\sim \left(1 - \frac{\lambda}{n} \left(1 - \int \xi(s)\sigma(ds)\right)\right)^n \to G_{s_0}[\xi], \quad \text{as } n \to \infty, \end{split}$$

where

$$G_{s_0}[\xi] = \exp\left(-\lambda\left(\int 1 - \xi(s)\,\sigma(ds)\right)\right).$$

So,  $S_0^{(n)} \Rightarrow S_0$ , where  $S_0$  contains a *Poi*( $\lambda$ ) number of points distributed on [0, 1] independently according to  $\sigma$ .

So,  $S_0^{(n)} \Rightarrow S_0$ , where  $S_0$  contains a *Poi*( $\lambda$ ) number of points distributed on [0, 1] independently according to  $\sigma$ .

That is, in the limiting initial patch configuration, there is a  $Poi(\lambda)$  number of occupied patches, and the survival probabilities are distributed independently according to  $\sigma$ .

#### **Example - probability of total extinction**

In the example, where the limiting (*n* large) initial patch configuration had a *Poi*( $\lambda$ ) number of occupied patches, and survival probabilities were distributed independently according to  $\sigma$ , the "limiting metapopulation" will eventually go extinct with probability 1 if

$$c'(0)\int \frac{s}{1-s}\sigma(ds) \le 1.$$

Otherwise, it will go extinct with probability

$$\exp\left(-\lambda\int \frac{1-s}{1-\psi s}\,\sigma(ds)\right).$$

#### **Example - probability of total extinction**

In the case where  $\sigma$  is the beta distribution with parameters  $\alpha$  and  $\beta$  (both > 0), that is

$$\sigma(ds) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{\alpha - 1} (1 - s)^{\beta - 1} ds, \qquad s \in [0, 1],$$

we have that

$$\int \frac{s}{1-s} \sigma(ds) = \begin{cases} \frac{\alpha}{\beta-1} & \text{if } \beta > 1\\ \infty & \text{if } \beta \le 1. \end{cases}$$

#### **Example - probability of total extinction**

So, the "limiting metapopulation" (*n* large) will eventually go extinct with probability 1 if  $\beta \ge 1 + \alpha c'(0)$ . Otherwise, it will go extinct with probability

$$\exp\left(-\lambda\int \frac{1-s}{1-\psi s}\,\sigma(ds)\right),$$

where  $\psi$  solves (uniquely)

$$\psi = \exp\left(-c'(0)\int \frac{(1-\psi)s}{1-\psi s}\,\sigma(ds)\right).$$