## Metapopulations in evolving landscapes

#### Phil. Pollett

The University of Queensland

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# Metapopulations



Glanville fritillary butterfly (Melitaea cinxia) in the Åland Islands in Autumn 2005.



Phil. Pollett (The University of Queensland)

#### Collaborators



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Hodgkinson, L., McVinish, R. and Pollett, P.K. Approximations and limit theorems for a class of discrete-time occupancy processes. Submitted.

A stochastic patch occupancy model (SPOM)



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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 at time *t*.



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Assume that colonization and extinction happen in distinct, successive phases.

For many species the propensity for colonization and local extinction is markedly different in different phases of their life cycle. 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





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



$$ar{X}_{i,t}^{(n)} = rac{1}{n} \sum_{j=1}^n X_{j,t}^{(n)} D(z_i, z_j) a_j$$
 ("connectivity").

 $D(z, \tilde{z}) \ge 0$  measures ease of movement between patches located at z and at  $\tilde{z}$ ,  $a_j$  is a weight related to the size of the patch j and  $c : [0, \infty) \to [0, 1]$  (colonisation function).



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**Examples**:  $D(z, \tilde{z}) = \exp(-\beta ||z - \tilde{z}||)$  and  $c(x) = 1 - \exp(-\alpha x)$ , where  $\alpha, \beta > 0$ .



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#### Assumptions:

- (A)  $a_i \in (0, A]$  for some  $A < \infty$ .
- (B)  $z_i \in \Omega$  where  $\Omega$  is a compact subset of  $\mathbb{R}^d$ .
- (C)  $D(z, \tilde{z})$  is positive, uniformly bounded, and equicontinuous: for every  $\epsilon > 0$  there exists a  $\delta > 0$  such that if  $||z_1 z_2|| < \delta$ , then  $\sup_{z \in \Omega} |D(z_1, z) D(z_2, z)| < \epsilon$ .
- (D) c is increasing and Lipschitz continuous, with c(0) = 0 and c'(0) > 0.



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Then, given the current state  $X_t^{(n)}$  and survival probabilities  $S_t^{(n)} = (s_{i,t}, i = 1, ..., n)$ , the  $X_{i,t+1}^{(n)}$  (i = 1, ..., n) are independent with transitions

$$\Pr\left(X_{i,t+1}^{(n)}=1 \mid X_t^{(n)}, S_t^{(n)}\right) = s_{i,t}X_{i,t}^{(n)} + s_{i,t} c(\bar{X}_{i,t}^{(n)}) \left(1-X_{i,t}^{(n)}\right).$$



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(E) We will assume that  $(s_{i,t})_{t=0}^{\infty}$ , i = 1, ..., n, are independent Markov chains taking values in [0, 1] with common (Feller) transition kernel P(s, dr).



# Examples of the survival probability model $(s_t)_{t=0}^{\infty}$

**Example 1** Patches are classified as being suitable or unsuitable for occupancy:

$$s_{t+1} = egin{cases} s^* & ext{with probability } p(s_t) \ 0 & ext{with probability } 1-p(s_t), \end{cases}$$

where  $p:[0,1]\mapsto [0,1]$  is a continuous function, so that

$$P(s,dr) = p(s)\delta_{s^*}(dr) + (1-p(s))\delta_0(dr).$$



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**Example 2** Following McKinlay and Borovkov<sup>†</sup>, suppose that

$$s_{t+1} = egin{cases} s_t - D_{t+1}s_t & ext{with probability } p(s_t) \ s_t + U_{t+1}(1-s_t) & ext{with probability } 1-p(s_t), \end{cases}$$

where  $p : [0,1] \mapsto [0,1]$  is continuous, and  $(D_t)$  and  $(U_t)$  are sequences of independent and identically distributed random variables on [0,1] with distributions  $F_D$  and  $F_U$ .

<sup>†</sup> McKinlay, S. and Borovkov, K. (2016) On explicit form of the stationary distributions for a class of bounded Markov chains. *Journal of Applied Probability* 53, 231–243.



## Climax community species





In the homogeneous case, where  $D \equiv 1$ ,  $a \equiv 1$ , and  $s_i = s$  is the same for each *i*, the number  $N_t^{(n)}$  of occupied patches at time *t* is Markovian, and, letting the initial number  $N_0^{(n)}$  of occupied patches grow at the same rate as *n* we arrive at:

**Proposition 1** If  $N_0^{(n)}/n \xrightarrow{p} x_0$  (a constant), then

$$N_t^{\scriptscriptstyle(n)}\,/\,n \stackrel{
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with  $(x_t)$  determined by  $x_{t+1} = f(x_t)$ , where

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



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# CE Model - Quasi stationarity



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ACEM∫

Return now to the general case, where patch survival probabilities evolve in time, and we keep track of which patches are occupied ...

$$\Pr\left(X_{i,t+1}^{(n)}=1 \mid \boldsymbol{X}_{t}^{(n)}, \boldsymbol{S}_{t}^{(n)}\right) = s_{i,t}X_{i,t}^{(n)} + s_{i,t} c\left(\frac{1}{n}\sum_{j=1}^{n}X_{j,t}^{(n)}D(z_{i}, z_{j})a_{j}\right)\left(1-X_{i,t}^{(n)}\right).$$



Define sequences  $(\sigma_{n,t})$  and  $(\mu_{n,t})$  of random measures by

$$\sigma_{n,t}(B) = \frac{1}{n} \sum_{i=1}^{n} a_i \mathbb{1}_{\{(s_{i,t}, z_i) \in B\}}, \qquad B \in \mathcal{B}([0,1] \times \Omega),$$
$$\mu_{n,t}(B) = \frac{1}{n} \sum_{i=1}^{n} a_i X_{i,t}^{(n)} \mathbb{1}_{\{(s_{i,t}, z_i) \in B\}}, \qquad B \in \mathcal{B}([0,1] \times \Omega).$$



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Equivalently, define  $(\sigma_{n,t})$  and  $(\mu_{n,t})$  by

$$\int h(s,z)\sigma_{n,t}(ds,dz) = \frac{1}{n}\sum_{i=1}^n a_i h(s_{i,t},z_i), \qquad h \in C^+([0,1] \times \Omega),$$

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where  $C^+(\mathcal{D})$  is the space of continuous functions  $h: \mathcal{D} \mapsto [0, \infty)$ .



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where  $C^+(\mathcal{D})$  is the space of continuous functions  $h: \mathcal{D} \mapsto [0, \infty)$ .

For example  $(h \equiv 1)$ ,  $\int \mu_{n,t}(ds, dz) = \frac{1}{n} \sum_{i=1}^{n} a_i X_{i,t}^{(n)}$ , the proportion of occupied patches at time t weighted according to patch size.



The landscape  $(s_{i,t}^{(n)}, a_i, z_i; i = 1, ..., n)$  at time *t* is summarized by  $\sigma_{n,t}$ . The metapopulation (occupancy process) is summarized by  $\mu_{n,t}$ .



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Large metapopulation. First we let *n* get large.

If (time t = 0)  $\sigma_{n,0} \stackrel{d}{\rightarrow} \sigma_0$ , then  $\sigma_{n,t} \stackrel{d}{\rightarrow} \sigma_t$  for all t, and  $\sigma_{t+1} = \mathcal{G}(\sigma_t)$ .

Similarly if  $\mu_{n,0} \stackrel{d}{\rightarrow} \mu_0$ , then  $\mu_{n,t} \stackrel{d}{\rightarrow} \mu_t$  for all t, and  $\mu_{t+1} = \mathcal{H}(\mu_t, \sigma_t)$ .



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Landscape in equilibrium. Next we see that if the survival probability model  $(\mathbf{S}_t^{(n)})$  is stationary, then  $\sigma_t \to \sigma$  as  $t \to \infty$ . We find that  $\mu_t$  is absolutely continuous with respect to  $\sigma$ , and the corresponding Radon-Nikodym derivative  $\phi_t := \partial \mu_t / \partial \sigma$  satisfies a simplified recursion  $\phi_{t+1} = \mathcal{R}(\phi_t)$ . We learn that if a given patch with survival probability s is located at z, then  $\phi_t(s, z)$  is the large-metapopulation probability that it is occupied.



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**Metapopulation in equilibrium**. Finally, we find the fixed points  $\phi_{\infty} := \partial \mu_{\infty} / \partial \sigma$  of  $\mathcal{R}$ , and distinguish between the (complementary) cases (i) where there is only the trivial fixed point  $\partial \mu_{\infty} / \partial \sigma \equiv 0$ , being globally stable (*evanescence*), and (ii) where there is a unique non-zero fixed point and all non-zero trajectories converge to it (*persistence*).


(F) Assume that  $\sigma_{n,0} \stackrel{d}{\rightarrow} \sigma_0$  for some non-random measure  $\sigma_0$ .

This will be satisfied, for example, if the random vectors  $(a_i, s_{i,0}, z_i)$ , i = 1, 2, ..., are iid.



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**Lemma 1**  $\sigma_{n,t} \stackrel{d}{\rightarrow} \sigma_t$  for all  $t = 1, 2, \ldots$ , where  $\sigma_t$  is defined by the recursion  $\mathcal{G}$ :

$$\int h(s,z)\sigma_{t+1}(ds,dz) = \int h(s,z)\int P(r,ds)\sigma_t(dr,dz), \quad h\in C^+([0,1]\times\Omega).$$

[Recall that P(s, dr) is the common transition kernel of the  $(s_{i,t})_{t=0}^{\infty}$ , i = 1, ..., n.]



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For a large population (n large),  $\sigma_t(ds, dz)$  describes the landscape at time t.



#### Limiting behaviour of the metapopulation (n large)

**Theorem 1** Suppose that  $\mu_{n,0} \xrightarrow{d} \mu_0$  for some non-random measure  $\mu_0$ . Then,  $\mu_{n,t} \xrightarrow{d} \mu_t$  for all t = 1, 2, ..., where  $\mu_t$  is defined by the recursion  $\mathcal{H}$ : for  $h \in C^+([0,1] \times \Omega)$ ,

$$\begin{aligned} \int h(s,z)\mu_{t+1}(ds,dz) &= \int s\mathcal{P}h(s,z)(1-c(\psi_t(z)))\mu_t(ds,dz) \\ &+ \int s\mathcal{P}h(s,z)c(\psi_t(z))\sigma_t(ds,dz), \end{aligned}$$

where

$$\mathcal{P}h(s,z) = \int h(r,z)P(s,dr)$$
 and  $\psi_t(z) = \int D(z,\tilde{z})\mu_t(d\tilde{s},d\tilde{z}).$ 

[Recall that  $c(\cdot)$  is the colonization function.]



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 and  $\psi_t(z) = \int D(z,\tilde{z})\mu_t(d\tilde{s},d\tilde{z}).$ 

[Recall that  $c(\cdot)$  is the colonization function.]

Think of  $\psi_t(z)$  as being the large-metapopulation  $(n \to \infty)$  connectivity at time t for a patch located at z, and  $c(\psi_t(z))$  as being the corresponding potential of the metapopulation to colonize that patch.



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$$\begin{split} \int h(s,z)\mu_{t+1}(ds,dz) &= \int s\mathcal{P}h(s,z)(1-c(\psi_t(z)))\mu_t(ds,dz) \\ &+ \int s\mathcal{P}h(s,z)c(\psi_t(z))\sigma_t(ds,dz), \end{split}$$

where

$$\mathcal{P}h(s,z) = \int h(r,z)P(s,dr) \text{ and } \psi_t(z) = \int D(z,\tilde{z})\mu_t(d\tilde{s},d\tilde{z}).$$

[Recall that  $c(\cdot)$  is the colonization function.]

Think of  $\psi_t(z)$  as being the large-metapopulation  $(n \to \infty)$  connectivity at time t for a patch located at z, and  $c(\psi_t(z))$  as being the corresponding potential of the metapopulation to colonize that patch.

(G) Assume that the survival probability model is stationary, aperiodic, and Harris positive recurrent with invariant measure  $\nu$ :  $\nu(dr) = \int_0^1 \nu(ds)P(s, dr)$ .



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**Lemma 2** As  $t \to \infty$ ,  $\sigma_t$  converges to a product measure  $\sigma = \nu \times \bar{\sigma}_0$ , where  $\bar{\sigma}_0(A) = \sigma_0([0, 1] \times A)$ , for measurable  $A \subset \Omega$ .



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Let  $P^*$  be the *dual* (or *time-reverse*) transition kernel:

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**Theorem 2** The limiting measure  $\mu_t$  is absolutely continuous with respect to  $\sigma$  and the corresponding Radon-Nikodym derivative  $\phi_t := \partial \mu_t / \partial \sigma$  satisfies the recursion  $\mathcal{R}$ :

$$\phi_{t+1}(s,z) = \int_0^1 r \,\phi_t(r,z) P^*(s,dr) + c(\psi_t(z)) \int_0^1 r \,(1-\phi_t(r,z)) \,P^*(s,dr),$$

where (now we may write)  $\psi_t(z) = \int D(z, \tilde{z}) \int \phi_t(\tilde{s}, \tilde{z}) \nu(d\tilde{s}) \bar{\sigma}_0(d\tilde{z})$ .

In addition to providing a simplified recursion

$$\phi_{t+1}(s,z) = \int_0^1 r \,\phi_t(r,z) P^*(s,dr) + c(\psi_t(z)) \int_0^1 r \,(1-\phi_t(r,z)) \,P^*(s,dr).$$

to describe large-metapopulation behaviour, the Radon-Nikodym derivative has a nice interpretation as the probability that a given patch is occupied when the number of patches is large:

**Corollary** The limiting occupancy of a single patch follows a Markov chain  $(X_{i,t}, s_{i,t})_{t=0}^{\infty}$ with time dependent transition probabilities: For fixed  $i, X_{i,0}^{(n)} \xrightarrow{p} X_{i,0}$  implies that  $X_{i,t}^{(n)} \xrightarrow{p} X_{i,t}$  for all t = 1, 2, ..., where

$$\Pr(X_{i,t+1} = 1 \mid X_{i,t}, s_{i,t}) = s_{i,t}X_{i,t} + s_{i,t}c(\psi_t(z_i))(1 - X_{i,t}),$$

and, if

$$\Pr(X_{i,0} = 1 \mid s_{i,0} = s, z_i = z) = \phi_0(s, z),$$

then

$$\Pr(X_{i,t} = 1 \mid s_{i,t} = s, z_i = z) = \phi_t(s, z)$$







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#### USA light polution - proxy for patch weight





#### Potential patch positions $(z_i)$





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#### Patch weights (n = 540)





# Evolution of $\phi_t(s, z)$ (t = 0)





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# Evolution of $\phi_t(s, z)$ (t = 1)





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# Evolution of $\phi_t(s, z)$ (t = 2)





# Evolution of $\phi_t(s, z)$ (t = 3)





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# Evolution of $\phi_t(s, z)$ (t = 4)





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# Evolution of $\phi_t(s, z)$ (t = 5)





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# Evolution of $\phi_t(s, z)$ (t = 6)





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# Evolution of $\phi_t(s, z)$ (t = 7)





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# Evolution of $\phi_t(s, z)$ (t = 8)





# Evolution of $\phi_t(s, z)$ (t = 9)





## Evolution of $\phi_t(s, z)$ (t = 10)





# Evolution of $\phi_t(s, z)$ (t = 11)





# Evolution of $\phi_t(s, z)$ (t = 12)





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# Evolution of $\phi_t(s, z)$ (t = 13)





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### Evolution of $\phi_t(s, z)$ (t = 14)





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# Evolution of $\phi_t(s, z)$ (t = 15)





## Evolution of $\phi_t(s, z)$ (t = 16)





# Evolution of $\phi_t(s, z)$ (t = 17)





# Evolution of $\phi_t(s, z)$ (t = 18)





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## Evolution of $\phi_t(s, z)$ (t = 19)





## Evolution of $\phi_t(s, z)$ (t = 20)




## Evolution of $\phi_t(s, z)$ (t = 21)





## Evolution of $\phi_t(s, z)$ (t = 22)





## Evolution of $\phi_t(s, z)$ (t = 23)





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## Evolution of $\phi_t(s, z)$ (t = 24)





## Evolution of $\phi_t(s, z)$ (t = 25)





## Evolution of $\phi_t(s, z)$ (t = 26)





## Evolution of $\phi_t(s, z)$ $(t = \infty)$





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#### When the landscape is in equilibrium





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# Simulation (t = 0) - initial occupancy $oldsymbol{X}_0^{(n)}$





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## Simulation (t=0) - initial occupancy probability $\phi_0(s,z)$





## Simulation (t = 0)





#### Simulation (t = 1)





#### Simulation (t = 2)





#### Simulation (t = 3)





#### Simulation (t = 4)





## Simulation (t = 5)





## Simulation (t = 6)





#### Simulation (t = 7)





## Simulation (t = 8)





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#### Simulation (t = 9)





#### Simulation (t = 10)





#### Simulation (t = 11)





#### Simulation (t = 12)





#### Simulation (t = 13)





## Simulation (t = 14)





## Simulation (t = 15)





#### Simulation (t = 16)





#### Simulation (t = 17)





#### Simulation (t = 18)





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## Simulation (t = 19)





#### Simulation (t = 20)





#### Simulation (t = 21)





#### Simulation (t = 22)





#### Simulation (t = 23)





#### Simulation (t = 24)





#### Simulation (t = 25)




# Simulation (t = 26)





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# Simulation (t large)





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## The limiting metapopulation in equilibrium

The fixed points  $\phi_\infty:=\partial\mu_\infty/\partial\sigma$  of the simplified recursion satisfy

$$\phi_{\infty}(s,z) = c\left(\psi(z)\right) \int r P^{*}(s,dr) + \left(1 - c\left(\psi(z)\right)\right) \int r \phi_{\infty}(r,z) P^{*}(s,dr),$$

where  $\psi(z) = \int D(z, \tilde{z}) \mu_{\infty}(d\tilde{s}, d\tilde{z}) = \int D(z, \tilde{z}) \phi_{\infty}(\tilde{s}, \tilde{z}) \sigma(d\tilde{s}, d\tilde{z}).$ 



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Think of  $\psi(z)$  as being the equilibrium large-metapopulation connectivity for a patch located at z, and  $c(\psi(z))$  as being the corresponding equilibrium potential of the population to colonize that patch.



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Based on the spectral radius of a certain bounded linear operator, we are able to distinguish between the (complementary) cases (i) where the simplified recursion has only the trivial fixed point  $\partial \mu_{\infty} / \partial \sigma \equiv 0$ , this fixed point being globally stable (*evanescence*), and (ii) where it has a unique non-zero fixed point and all non-zero trajectories converge to this fixed point (*persistence*).

