# Fitting a spatial coalescent model 

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## Phylogenetic problem:

Given sequence data $D$, want to infer genealogy $g$ and any parameters $\theta$ controlling mutation or populations processes.

$$
P(g, \theta \mid D) \propto P(D \mid g, \theta) P(g \mid \theta) P(\theta)
$$

Most common model for genealogy, $P(g \mid \theta)$, is Kingman's coalescent.

Phylogeographic problem:

As well as $D$ have $L$, location of each sequence. Now want to infer $g, \theta$ and $\mu$, parameters controlling spatial movement.

$$
P(g, \theta, \mu \mid D, L) \propto P(D \mid g, \theta) P(g, L \mid \theta, \mu) P(\theta, \mu)
$$

## Existing models

1. Structured coalescent, fixed number of panmictic demes

$$
\begin{gathered}
P(g, \theta \mid D, L) \propto P(D \mid g, \theta) P(g, L \mid \theta, \mu) P(\theta, \mu) \\
=P(D \mid g, \theta) \int_{L_{\text {ancestral }}} P\left(g, L, L_{\text {ancestral }} \mid \theta, \mu\right) d L_{\text {ancestral }} P(\theta, \mu)
\end{gathered}
$$

2. Finite demes but genealogy process does not a prior depend on location process

$$
P(g, \theta \mid D, L) \propto P(D, L \mid g, \theta, \mu) P(g \mid \theta) P(\theta, \mu)
$$

3. Continuous space with Brownian motion down lineages, separate from genealogy process. Based on Wright-Malecot forward model where position of off-spring is normally distributed with centre at parent.

## Problems with existing models

- Deme structure often not natural or known
- Even when known, number of demes must be small for structured coalescent (3-4 max?)
- A priori assumption of neutrality of location process unsatisfactory
- Wright-Malecot model does not produce uniform distribution across space

Clumping in Wright-Malecot model


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## Continuous landscape coalescent - forward process

Variation of the spatial $\Lambda$-Fleming-Viot process of Etheridge, Barton, Véber et al.

- reproduction/death/migration events no longer centred on individuals
- Start with individuals spread uniformly across landscape
- Reproduction and extinction events (REXs) occur at exponential intervals with rate $\lambda$
- at a REX, a centre $c$ is chosen uniformly across landscape
- each individual at I dies with some probability according to its distance from the centre, $u(I, c)=\mu K(I, c, \theta)$
- new individuals are born at location $I^{\prime}$ are rate according to distance from centre, so at rate $\propto u\left(I^{\prime}, c\right) d l^{\prime}$
- All newly born individuals are the off-spring of a single individual at $k$ who was alive before event and is chosen according to distance from centre $v(k, c) \propto K(I, c, \theta)$


## Continuous landscape coalescent

The reverse process follows the ancestry of a sample of lineages. Suppose a single lineage is at location $/$.

- REX events still occur at rate $\lambda$
- Lineage at location / hit by REX with centre $c$ with probability $u(I, c)$, jumps to new location $I^{\prime}$ according to pdf $v\left(I^{\prime}, c\right)$
- Lineages coalesce when both hit by same REX event, move to same new location.



## Inference

Want the posterior $P(\lambda, \mu, \theta, g \mid D, L)$
To calculate, need to augment the space to include full history:

$$
P(\lambda, \mu, \theta, g \mid D, L)=\int_{L_{a n c}, M} P\left(\lambda, \mu, \theta, L_{a n c}, M \mid D, L\right) d L_{a n c} d M
$$

Approximate this integral using Bayes theorem and Markov chain Monte Carlo sampling.

## Choose a more interpretable parametrisation

Hard to interpret $\lambda, \mu, \theta$ except in terms of model. Instead, use parameters common from Wright-Malecot model: neighbourhood size

$$
\mathcal{N}=\frac{2}{\mu}
$$

diffusion rate

$$
\sigma^{2}=4 \theta^{4} \lambda \pi \mu
$$

and $\theta$.

Derivation is based on relationship between coalescent rate and effective population size $N_{e}$.

## Simulations

- Landscape is $10 \times 10$
- $N_{e} \sim U([100,5000])$
- $\mathcal{N} \mid N_{e} \sim U\left(\left[N_{e} \times 10^{-3}, N_{e} \times 10^{-2}\right]\right)$.
- $\theta \sim U([1.5,4])$.
- 50 samples taken uniformly from 10 triangular regions comprising an average $17 \%$ of landscape
- Sequences of length 500bp simulated under Kimura model over tree.
- 500 repetitions

Median and $95 \%$ credible interval estimates for $\mathcal{N}$


Comparison of Bayesian estimation of $\mathcal{N}$ with fixation index based estimation method


Median and 95\% credible interval estimates for $\sigma$


## Median estimates for $\sigma$



## Summary

- It may be a feasible alternative to structured coalescent or other approximate models when doing inference
- But will need to generalise: to allow changing landscapes and non-constant populations
- Paper and software will be available soon

