Simulating long distance dispersal processes in spatially heterogeneous landscapes

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Geocomputation 2009

Alien invasion!

- New Zealand's unique flora and fauna under threat
  - direct and indirect disruption of ecosystems
- Auckland: "the weediest place on earth" (well, OK... it might be second)
  - suburban gardens
  - sprawling peri-urban development

Tradescantia fluminensis smothering understory plants

Hieracium (hawkweed) in tussock grasslands

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God knows what our backyard...

Spatial process and spatial structure

- Fragmentation is a critical aspect of the environments we are interested in
  - transport corridor edges
  - 'lifestyle' blocks in peri-urban areas
  - suburban lots
  - abandoned sites
- Relationships between dispersal and fragmentation of the most suitable habitat are likely to affect the success of invasions

New Zealand's peri-urban environments form a complex mosaic of habitats of varying susceptibility to invasion

Dispersal ecology

- Dispersal is a current research focus in ecology
  - theoretical: spatial patterns and processes
  - applied: migration in face of climate change & invasion dynamics ...

Special issue of *PNAS*, 9 December 2008, on movement ecology

Special issue of *Science*, 11 August 2006, on dispersal dynamics

Challenges of dispersal ecology

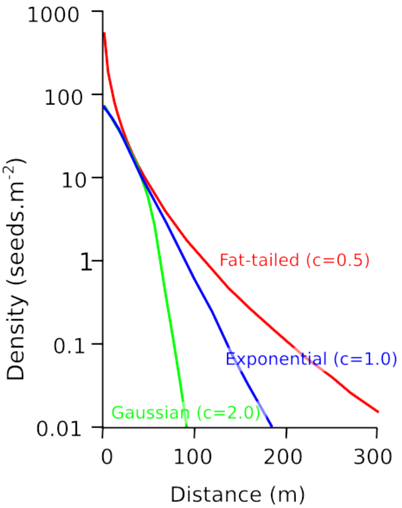
- Two components: local vs. long-distance dispersal (LDD)
  - together these define the 'dispersal kernel'
  - local dispersal events are typically strongly letptokurtic ('heavy-tailed')
  - LDD events are very rare, but are central to invasion dynamics
- Notoriously difficult to parameterise dispersal kernels in the field...

Seed dispersal in plant ecology II

From: Clark, J.S. 1998. Why trees migrate so fast: confronting theory with dispersal biology and the paleorecord. *The American Naturalist*, 152(2), 204–24.

One flexible mathematical representation of dispersal relies on a kernel function, tuneable to a number of different forms, by the parameter c:

$$f(x) = \frac{c}{2\alpha\Gamma(1/c)} \exp\left(-\left|\frac{x}{\alpha}\right|^{c}\right)$$



What kind of model?

For understanding of process

Individual-based

- Every individual is represented
- 10^6+ stems per hectare!
- Computationally demanding of memory and processing capability
- Analytically challenging—and may be aggregated to grids for analysis. . .

For management

Grid-based

- Hectare or km^2 grid cells over 10,000 km^2 or larger regions
- Only potential presence in each area matters, not individuals
- Estimate risk in each area
- Grid cells are the unit of interest, so why not model at that level?

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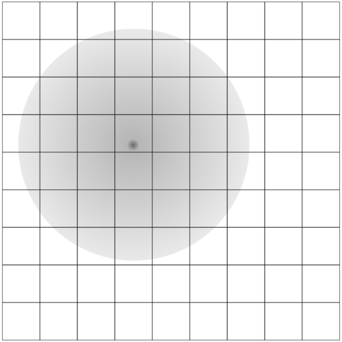
LDD makes grid-based dispersal modelling difficult

- High probability part of the kernel is small relative to grid cells
- LDD component of spread dictates a coarse grid
- Simplistic approaches overestimate rate of spread due to the local component
- Understanding how local dispersal works is key



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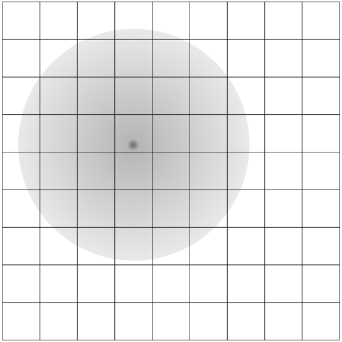

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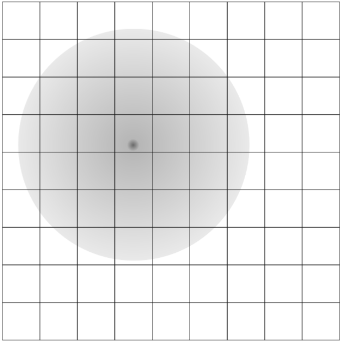

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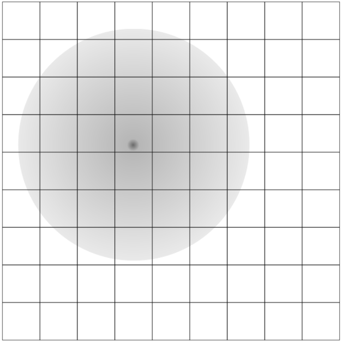

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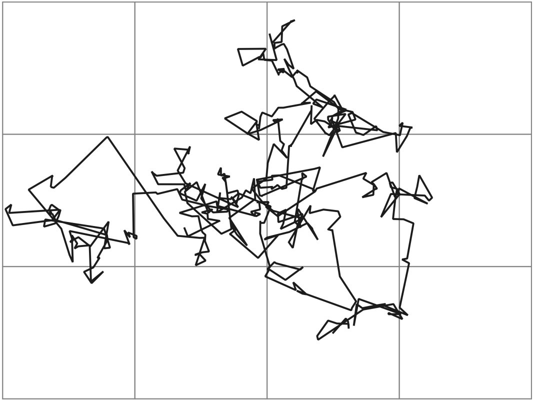

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- Real dispersal has a 'memory'
- Simple grid-based approaches don't capture this

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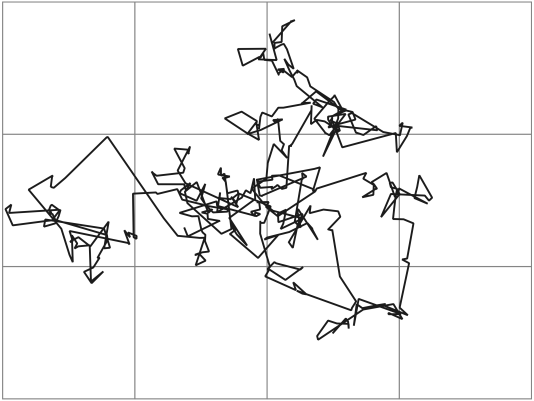

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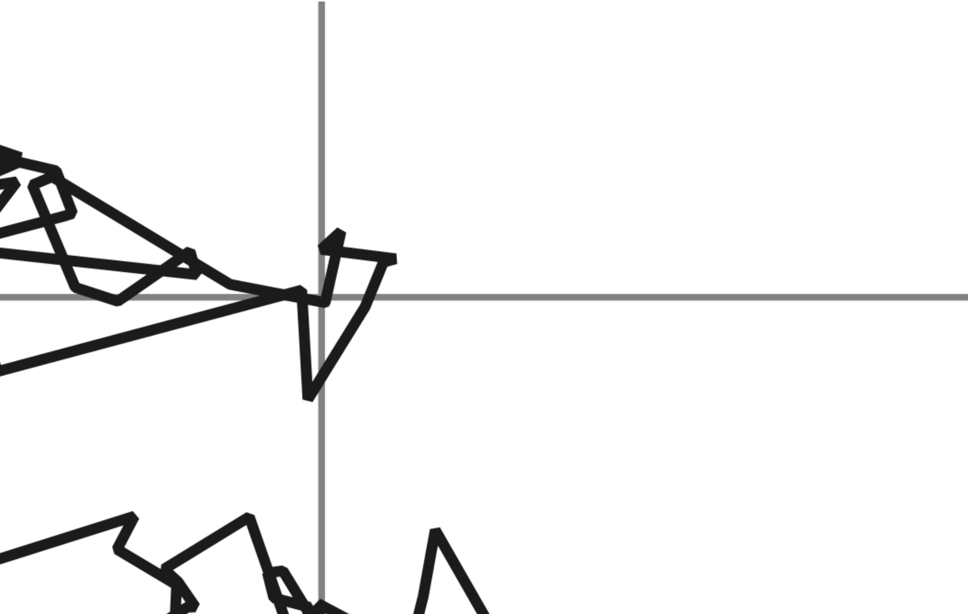

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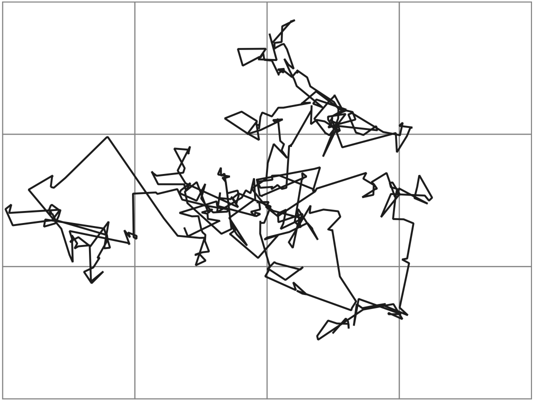

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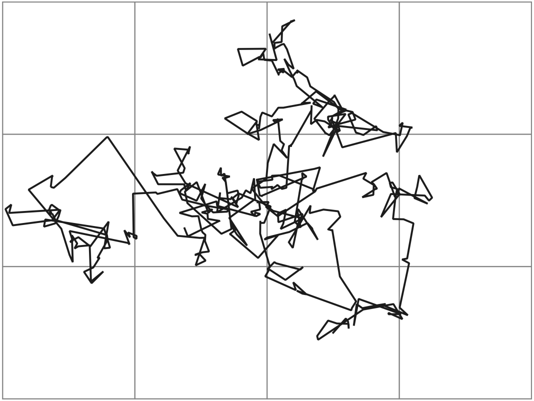

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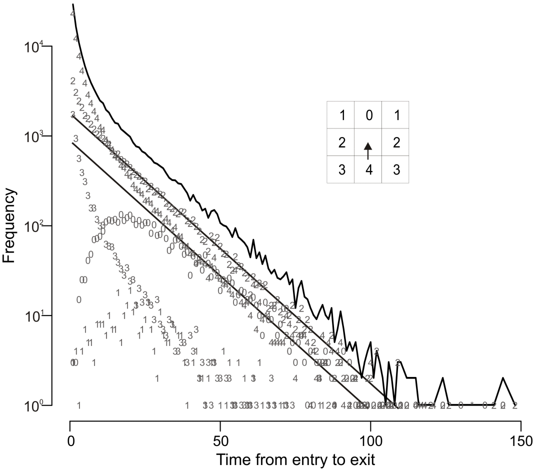

- Over short time periods moves that reverse recent moves dominate
- Over longer time frames, expected relative rates of forward-back *versus* left-right exit are seen
- An approach which replicates these features is needed

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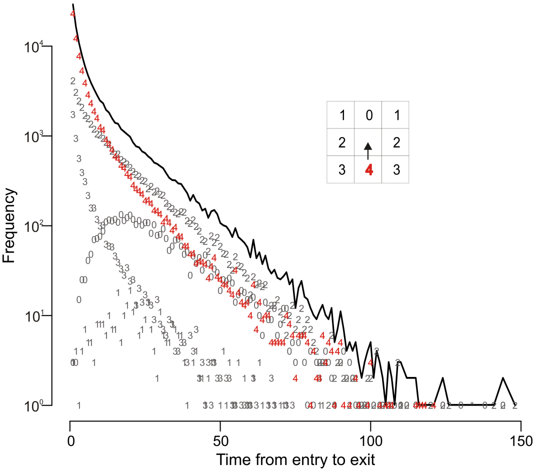

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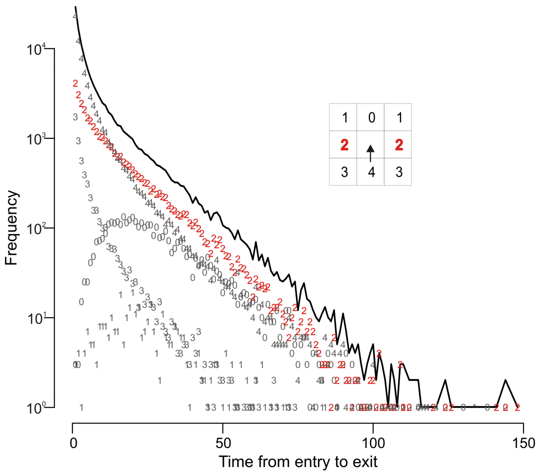

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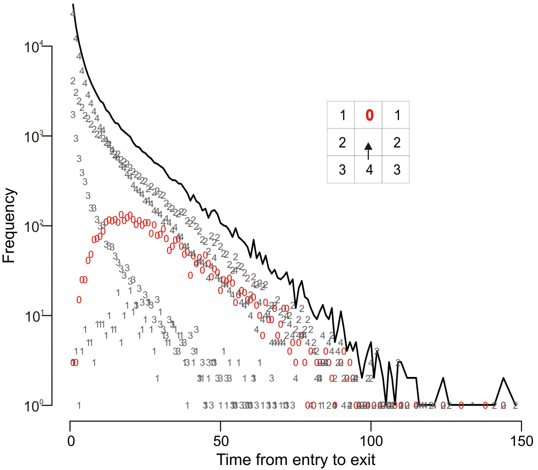

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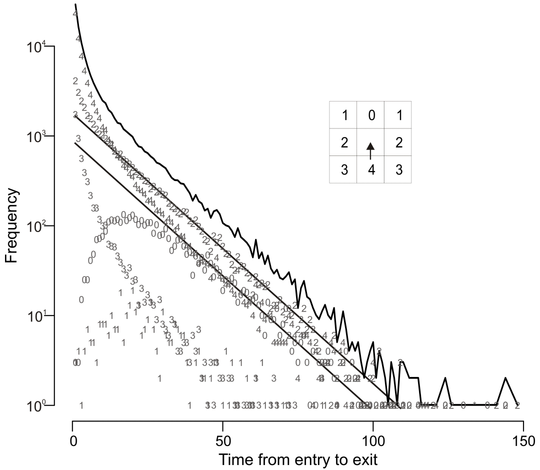

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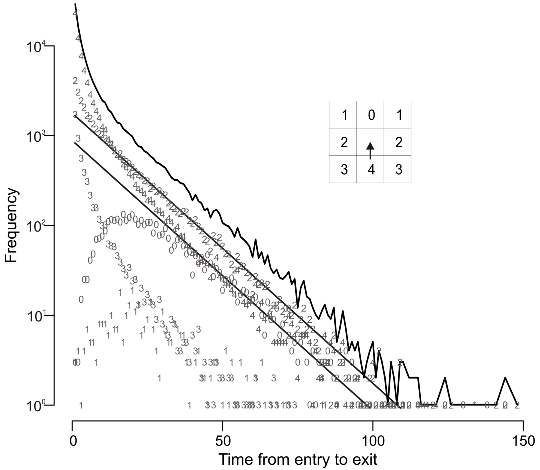

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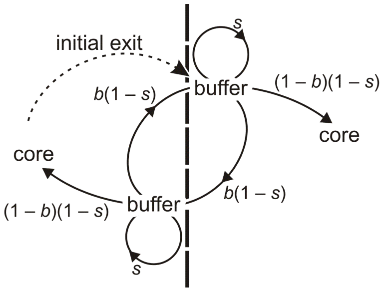
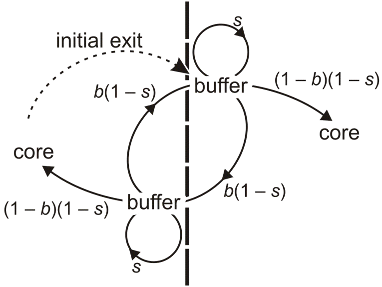
A Markov process for cell-cell transitions



- starting from the ‘core’ state in a cell, dispersal events result in exit to a neighbouring cell in a ‘buffer’ state. From there:
  - They stay in the buffer with probability s
  - They return to the original cell with probability $b(1-s)$
  - They progress into the ‘core’ state in the new cell with probability $(1-b)(1-s)$

A Markov process for cell-cell transitions



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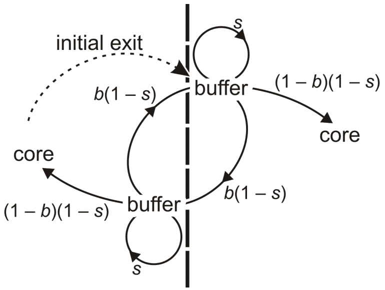

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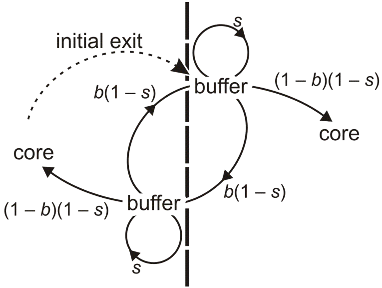

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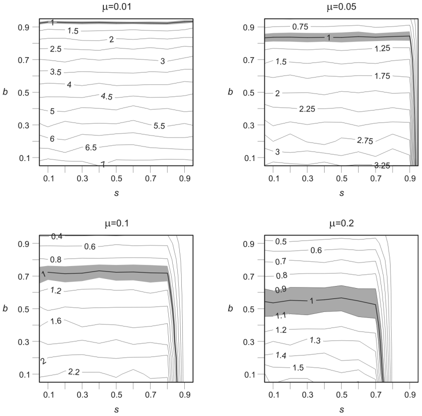
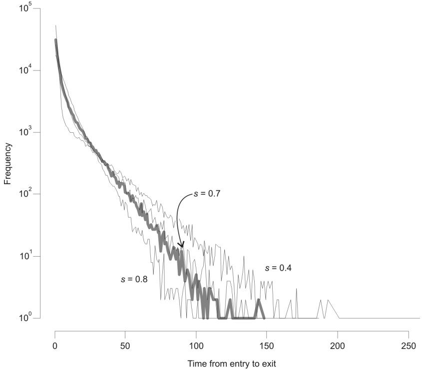
Two more-or-less independent parameters



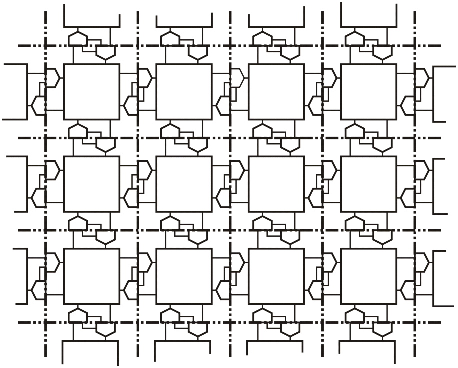
Tune b to get the right overall rate of spread



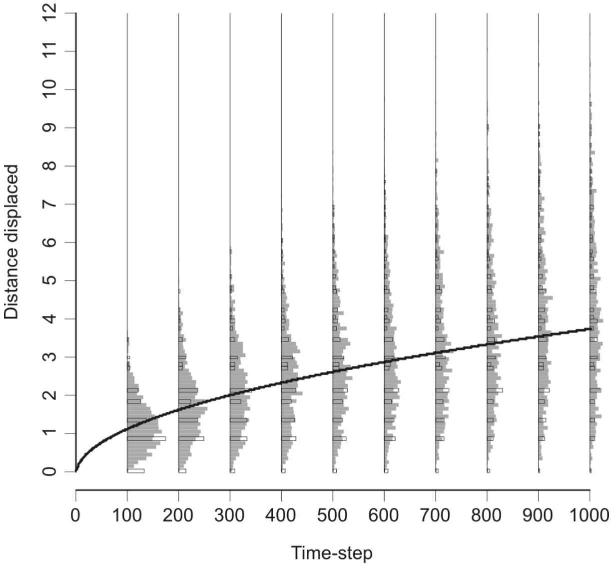
Tune s to get the right rate of oscillation immediately after entry to a new cell

Scaled up to a whole grid

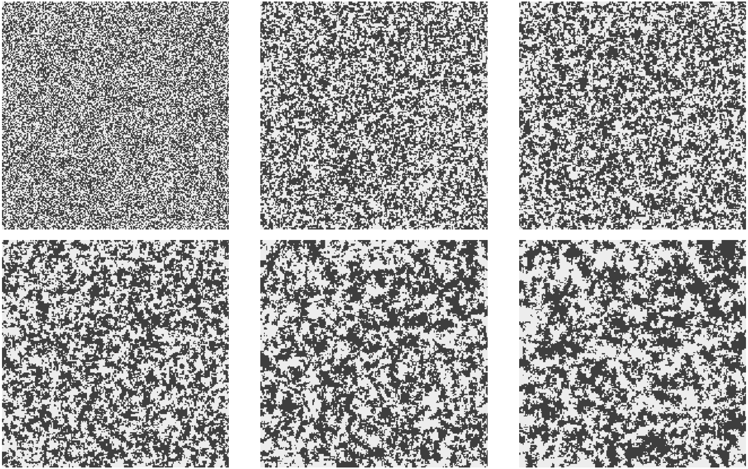
- Each cell has 5 counts at any one time, one core count, plus 4 buffer counts
- Core cases require draws from a dispersal kernel to determine exit to adjacent buffers (or LDD)
- Moves in the buffer state are probabilistic, using Poisson or binomial distributions



Good fits to simulated random walks



Voter model initialization of landscapes



All landscapes are two-phase with enforced equal areas of ‘very good’ and ‘very bad’ habitat

Kernels and replications

Four kernels

- No LDD, exponential, $\lambda = 0.05$
- LDD with $p_{LDD} = 0.001$, $\lambda = 1.0$
- LDD with $p_{LDD} = 0.001$, $\lambda = 5.0$
- LDD with $p_{LDD} = 0.001$, $\lambda = 10.0$

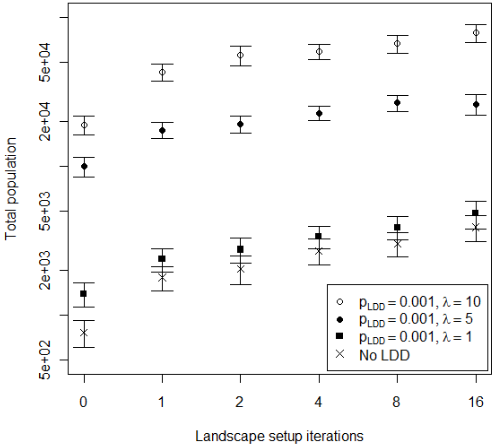
$n = 50$ landscapes

- 50 random seeds
- Same 50×6 landscapes for each kernel

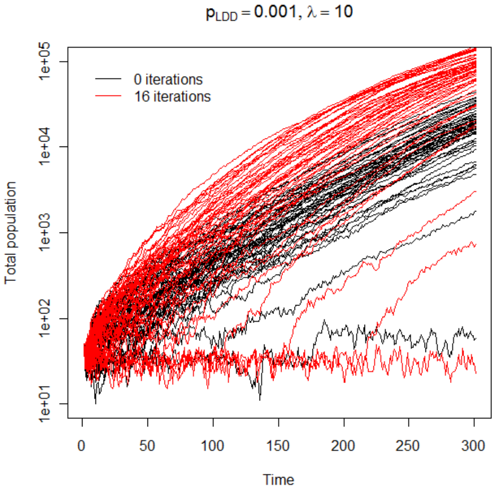
All 1200 cases run for 300 generations. Time-series and $t = 300$ total populations and extents examined

Results: overall total populations

- 95% confidence intervals for total population after 300 generations
- Long distance produces a large advantage
- Due to the ability to 'escape' from local patches and colonise new patches

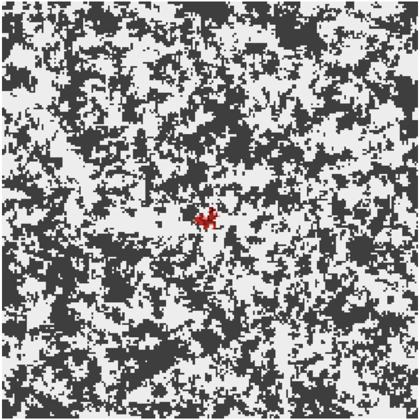


Results: importance of ‘escape’

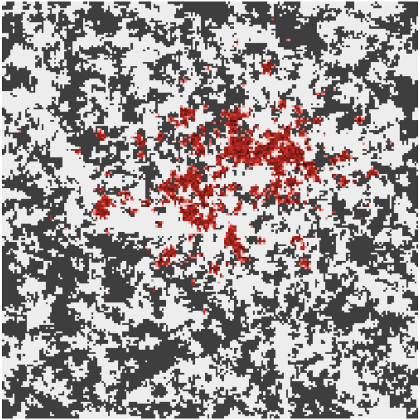


‘Escape’ from local patches of good habitat strongly controls overall outcomes

Results: contrasting patterns of spread



No LDD



$p_{LDD} = 0.001$ with $\lambda = 10$

Conclusions and further work

- Markov process representation of dispersal seems to work
- Importance of understanding what's going on, not just throwing big computers at problems, 'because we can'...
- ...clearly though, we will need grid computing to further the analysis!
- More convincing synthetic landscapes (e.g., Saura's SIMMAP)
- From the ecological perspective, we need to do more work on demographic aspects of the model

Saura, S. and J. Martinez-Millan. 2000. Landscape pattern simulation with a modified random clusters method. *Landscape Ecology*, 15, 661–77.

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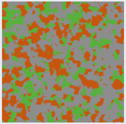
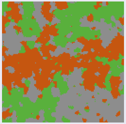

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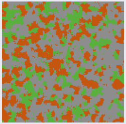

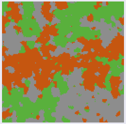

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