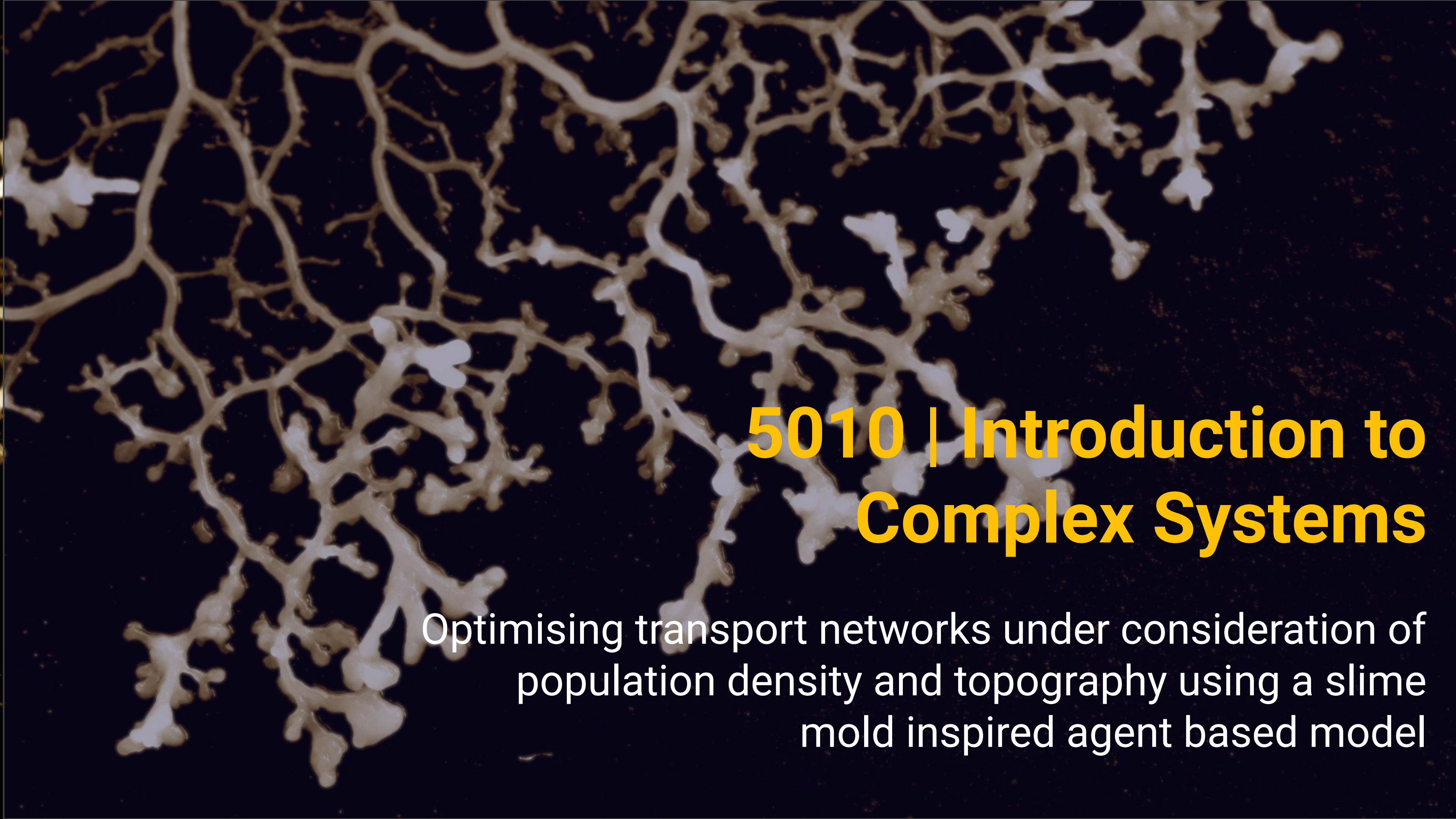
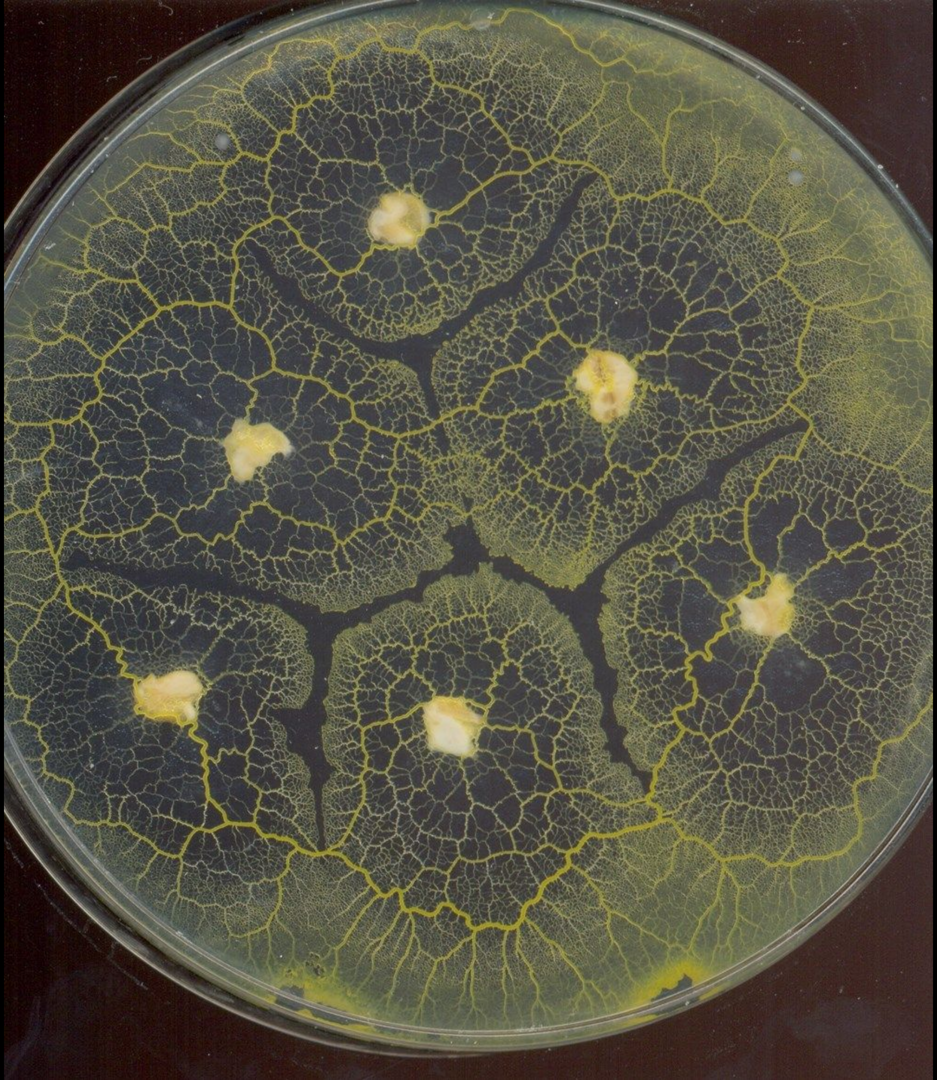


5010 | Introduction to Complex Systems

Optimising transport networks under consideration of population density and topography using a slime mold inspired agent based model

Adamatzky, A. (2012)



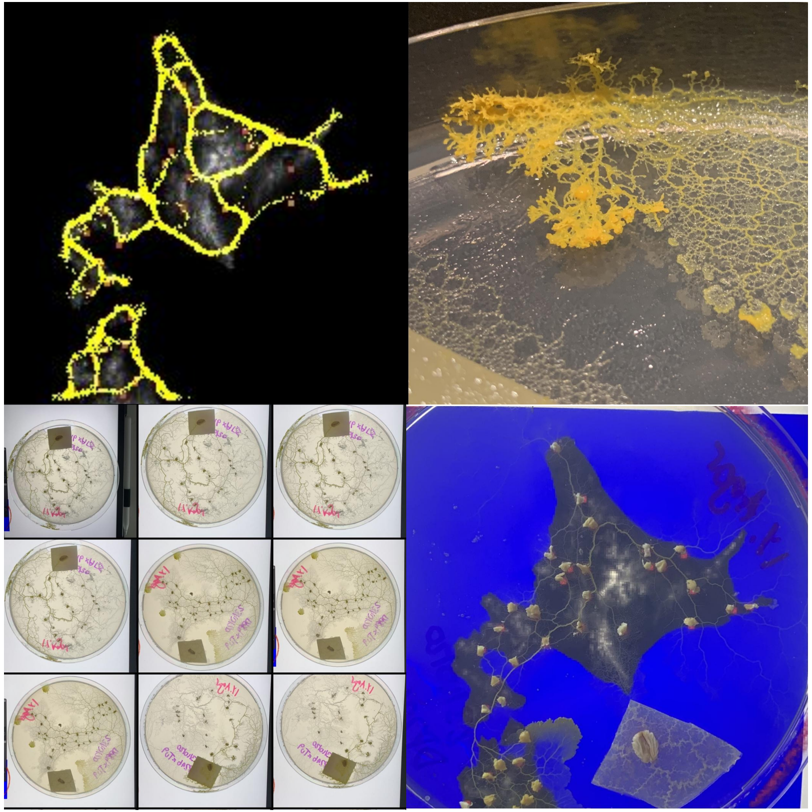
Bland, E. (2009)

Efficient transport networks

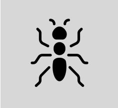
- Mold detects food at a distance
- Mold projects itself in a fanlike configuration
- Food is connected in the most efficient way possible
- Mold avoids areas it’s already explored

Aims

- Develop a mold inspired ABM to optimise transport real-world networks
- Compare the generated network to an actual traffic network and physarum
- The ABM should adapt to population density and topography



Previous research: dynamic foraging algorithms

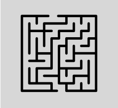


Algorithms emerge based on the foraging behaviour of ants, applied to NP-hard problems

1990s

2000

Slime mold species, *physarum polycephalum* was found capable of finding the shortest path in a maze

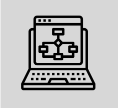


Slime mold applied to transport network problems - connecting populations based on food placement in a dish

2010

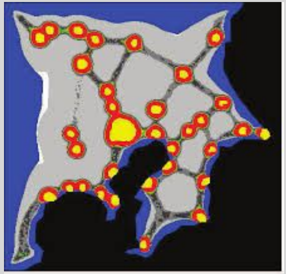
2010 onwards

Proliferation of agent based models, inspired by slime mold seek to solve various network related problems



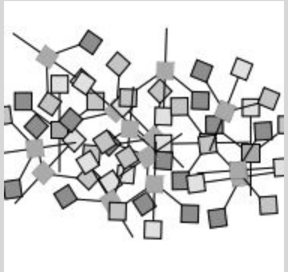
Dorigo, M., & Gambardella, L.(1997).
Nakagaki, T., Yamada, H., & Tóth, Á.(2000)
Tero, A., Takagi, S., Saigusa, T., Ito, K., Bebber, D., & Fricker, M. et al. (2010).

Existing Slime Mold ABMs & Applications



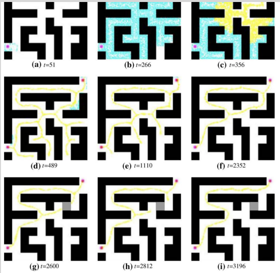
Houbraken et al. (2012)

Development of fault-tolerant networks to connect population centres



Jones (2010)

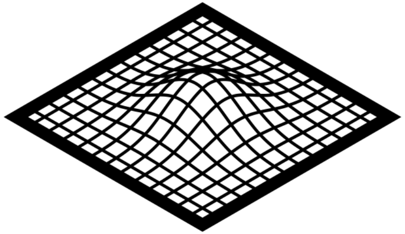
Studies of pattern formation and approximations of transport networks



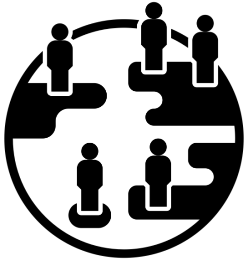
Liu et al. (2015)

Path finding and maze solving using a multi-agent system

Limitations of existing models



Limitation: The topographical features of geographies are ignored.
Outcome: Mold generated networks fail to penalise growth in highly elevated areas



Limitation: Distribution of population and city sizes are ignored
Outcome: Network attention isn't varied to support major cities and will favour clusters of towns

Our Hypothesis

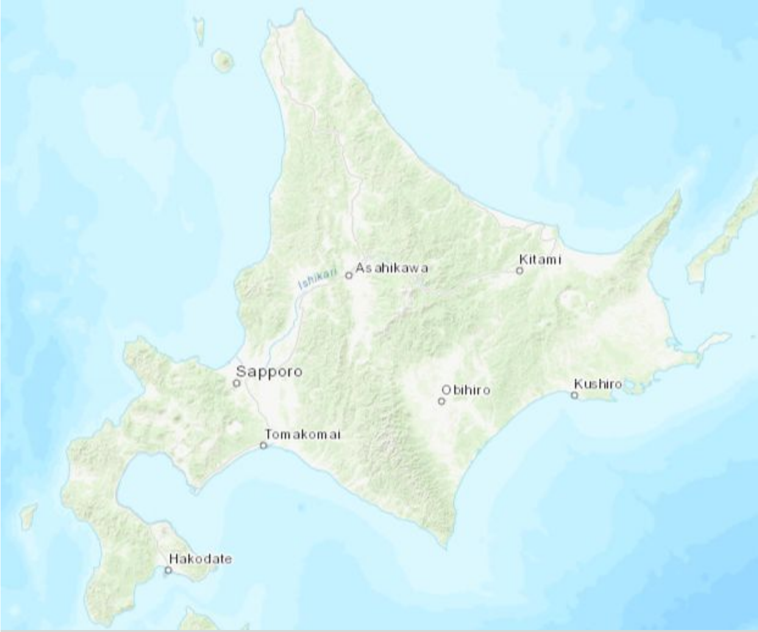
"Simulated slime mold traffic networks generate more optimal solutions if population density and topography are considered than networks that are generated without considerations for population density and topography."

Our Tests

1. *Include variation in population density and topography*
2. *Include variation in population density and <u>not</u> topography*
3. *Include variation in topography and <u>not</u> population density*
4. *<u>Neither</u> variation in population density <u>nor</u> topography are included*

Model Candidates

Island of Hokkaido (Japan)



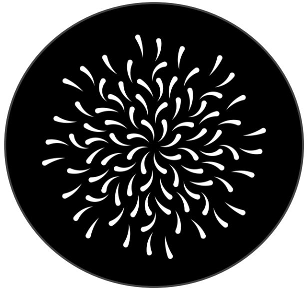
Island of O'ahu (Hawaii)

Model Candidate Justification

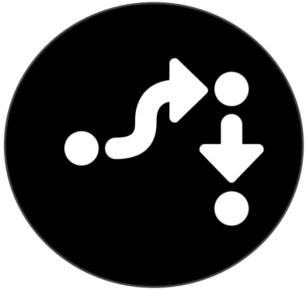
1. Self contained areas
2. Size of the area not too large given a limited canvas resolution
3. Numerous population centers
4. Variance in the population numbers
5. High variance in elevation

Slime Mold as an ABM

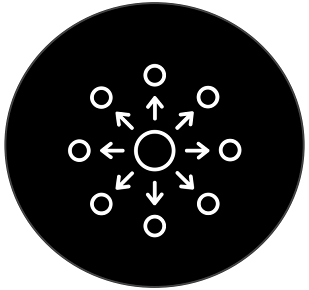
Micro Level



A *large number of agents* representing protoplasmic particles

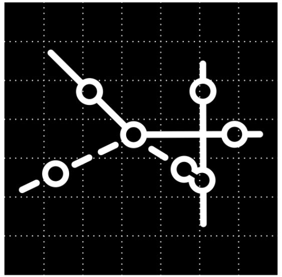


Protoplasmic flows transport signalling molecules which *stimulate further flows*



Tubular pressure leads to *expansion of plasmodium*, i.e. network growth

Macro Level

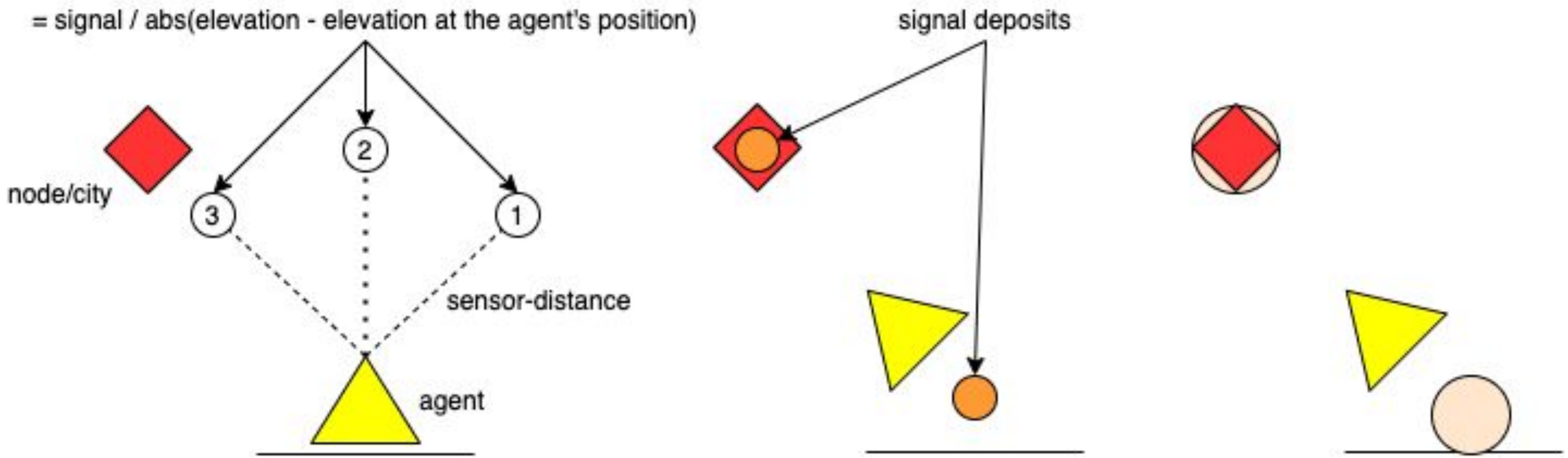


Connected network of agents following dominant paths to connect to nodes

Properties of our slime mold inspired ABM

	Agent Properties			Patch Properties				Additional Hyperparameters		
	Position	Heading	Sensor Distance	Position	Signal Value	Elevation	Node Weight	Agent density	Diffus. Rate	Evap. Multiplier
Symbol	(x,y)	h	d	(x,y)	s	$s\Delta$	n	p	δ	η
Hyperparam.	*no*	no	yes	no	no	no	yes	yes	yes	yes
Typical values	-	-	5	-	-	-	[0, 129.1]	100%	5%	95%

Model dynamics



1. Agent compares the quality of the patches a sensor-distance to the left, ahead, and to the right

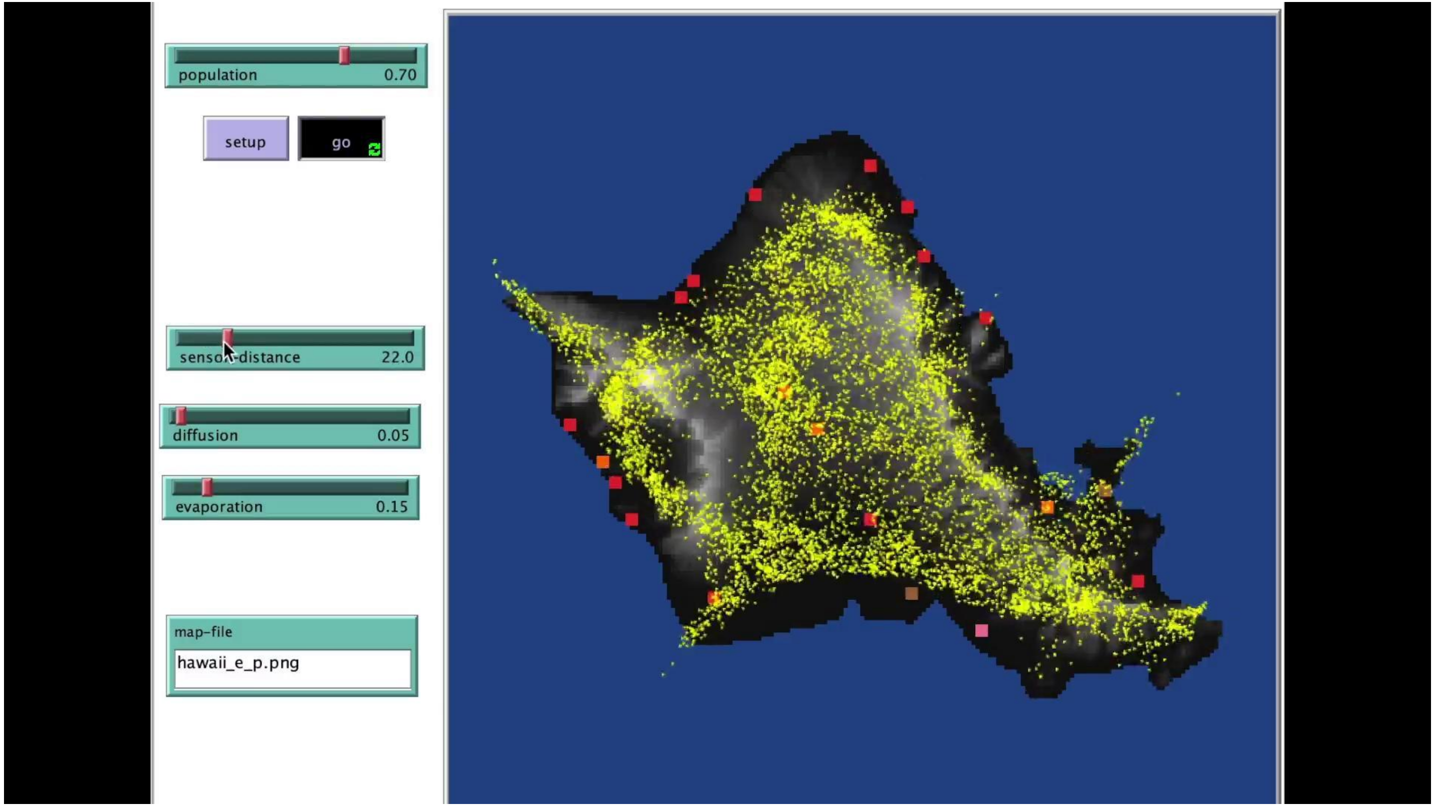
2. The agent and nodes increment the signal value at their current patch

3. Agent turns towards the patch with the highest signal value and moves one step forward

4. The signal values are diffused and reduced according to the evaporation rate

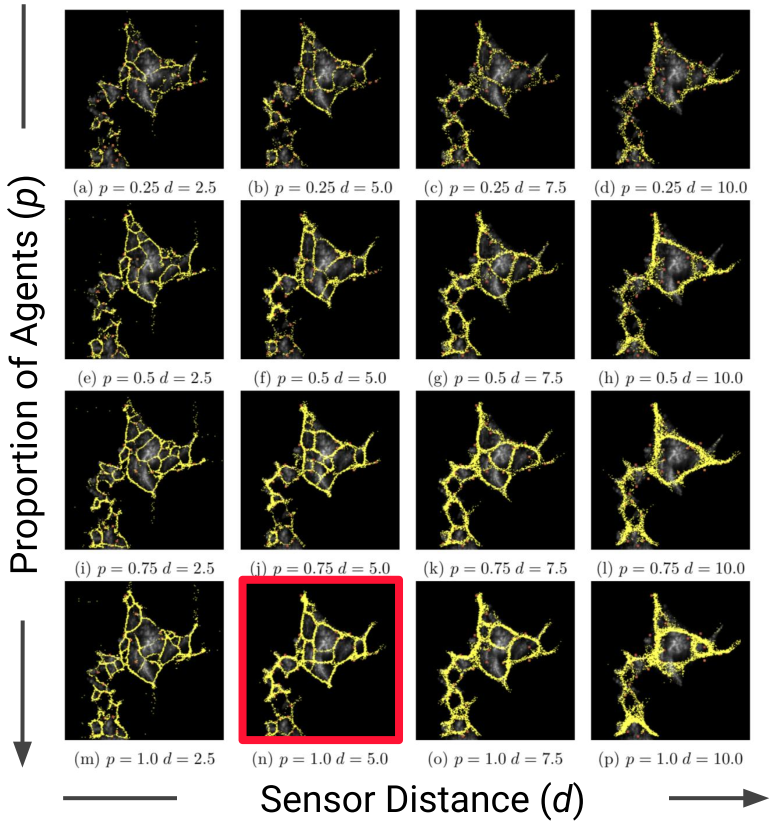
5. Repeat from step 1.

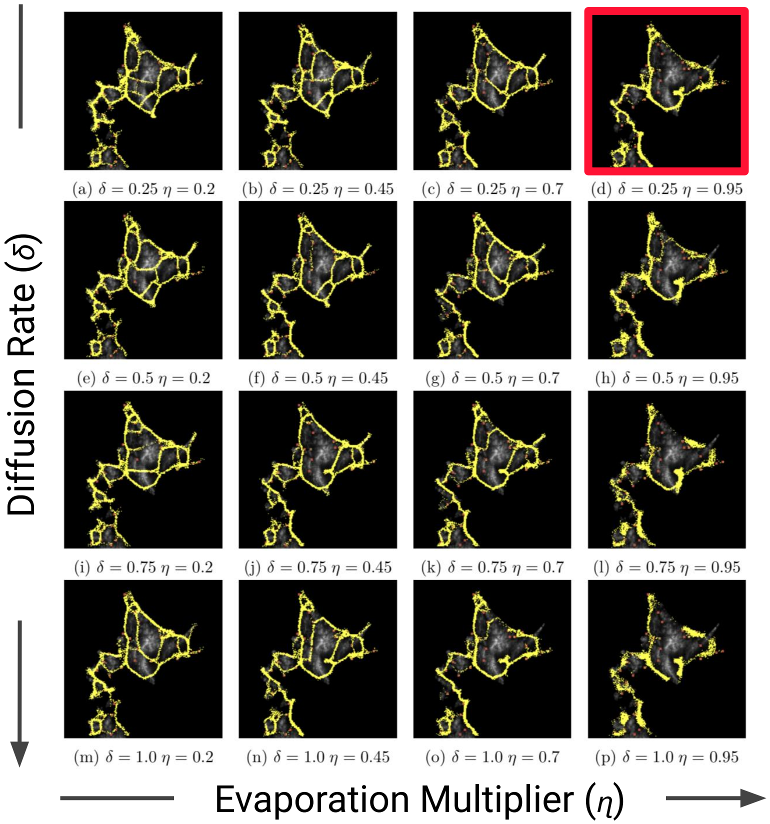
Model Demonstration in NetLogo



Parameter Selection

Selected Parameters





Map (no population, no elevation)

O‘ahu (Hawaii)

Hokkaido

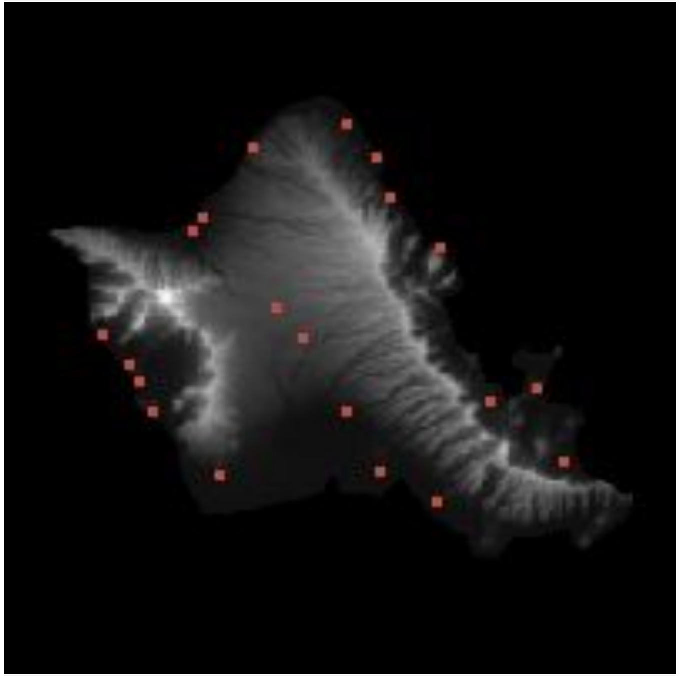
Map (population, no elevation)

O‘ahu (Hawaii)

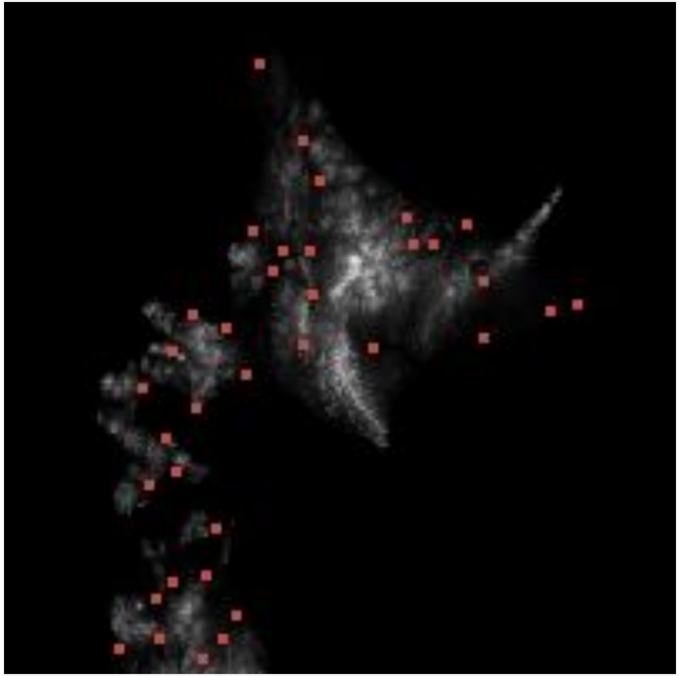
Hokkaido

Map (elevation, no population)

O‘ahu (Hawaii)

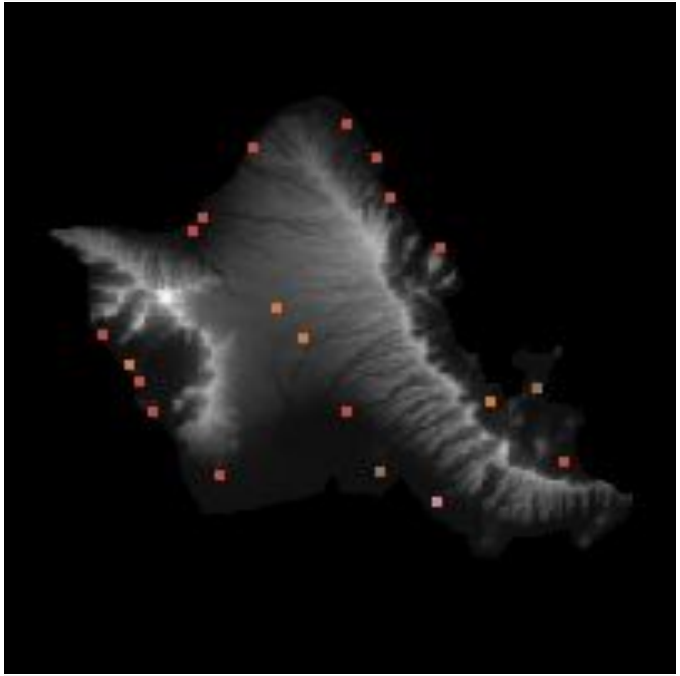


Hokkaido

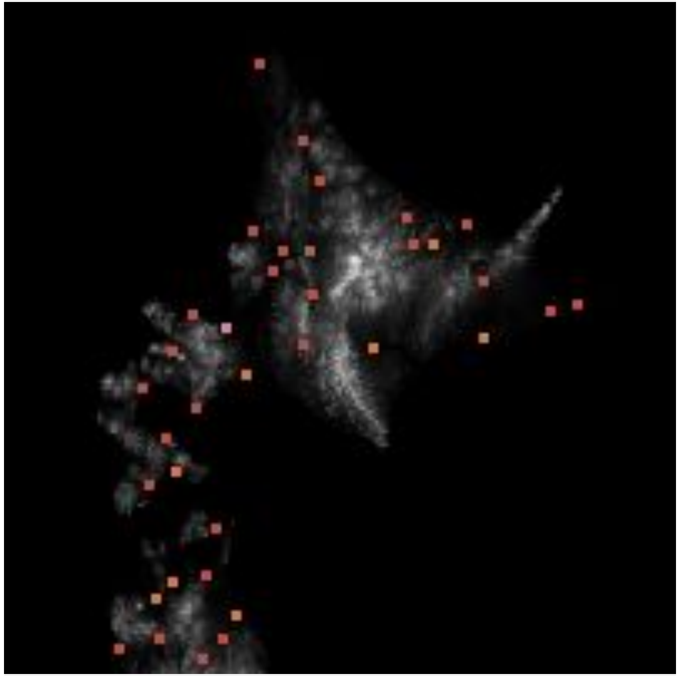


Map (population and elevation)

O‘ahu (Hawaii)

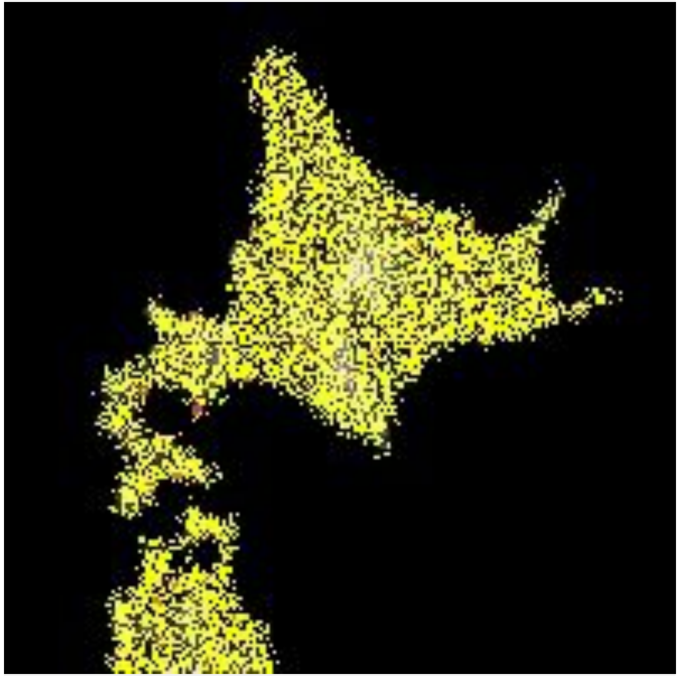


Hokkaido

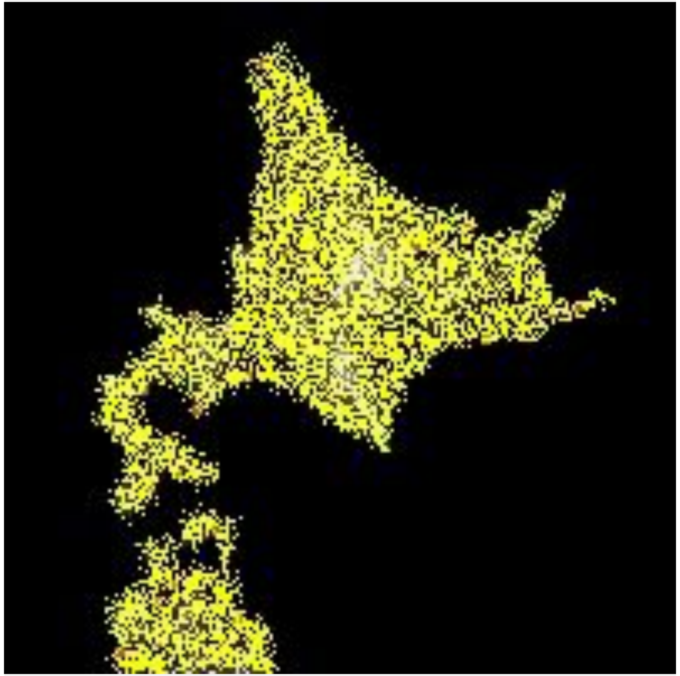


Generated networks (Hokkaido)

No population/elevation

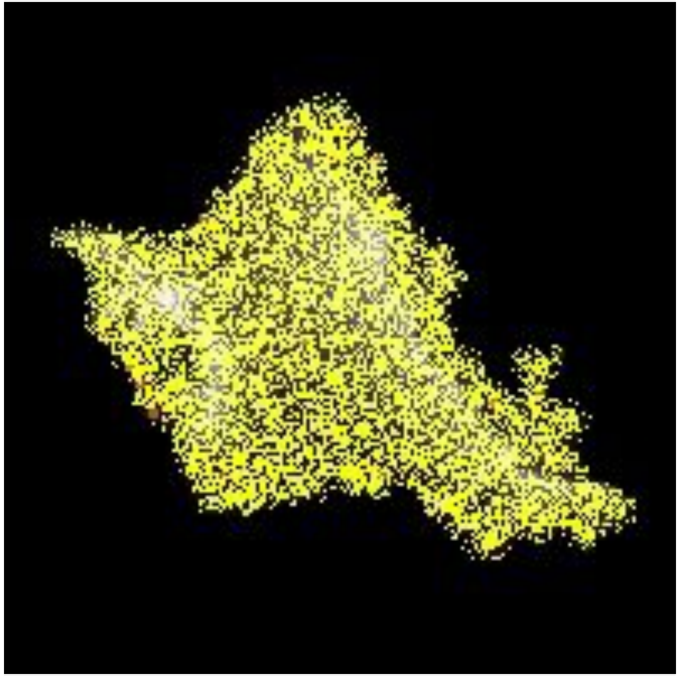


Population elevation

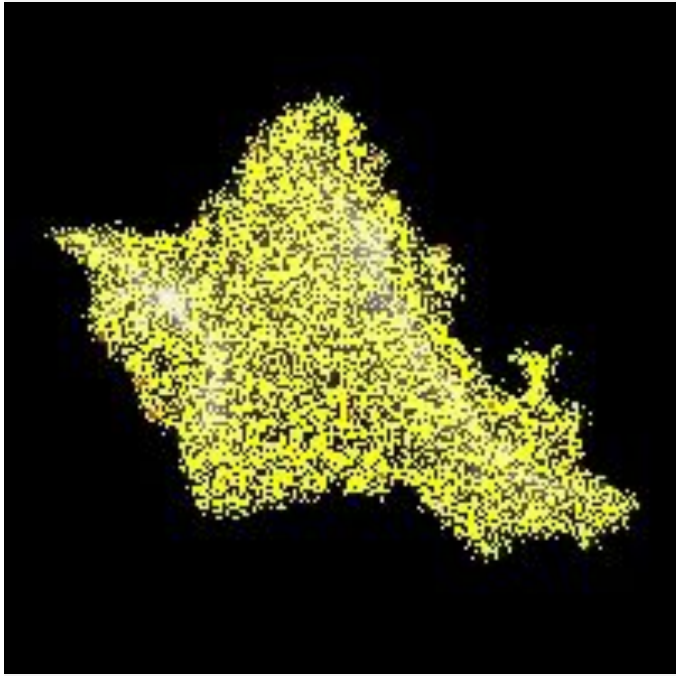


Generated networks (O’ahu/Hawaii)

No population/elevation



Population elevation

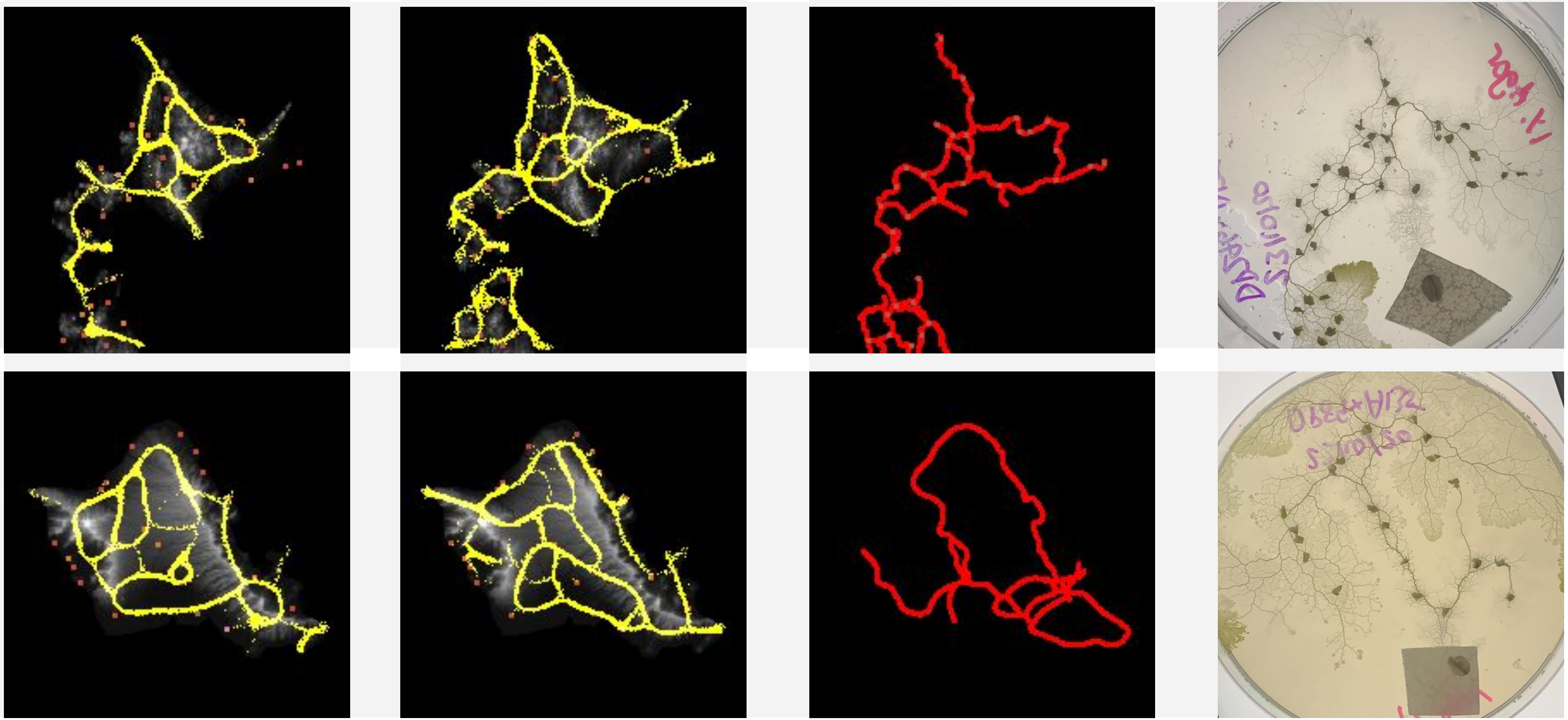


Network comparison

Model (no P/E) | Model (P/E) | Map | Mold

Hokkaido

O‘ahu (Hawaii)



Model evaluation

Slime-map similarity measure:

$$\gamma = \frac{|S \circ M|}{|S \circ (J - M)|}$$

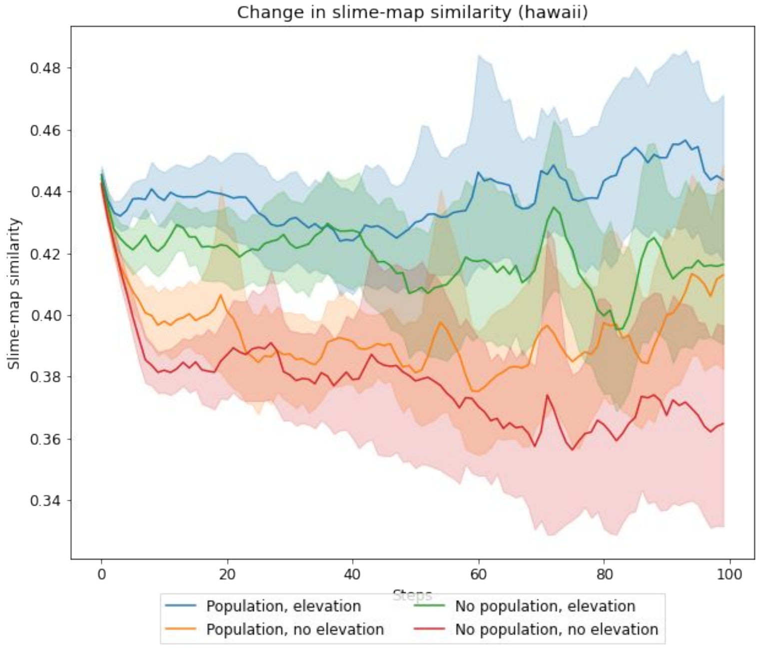
- *J* denotes the matrix of ones
- M denotes the actual map of the traffic network
- S denotes the generated map

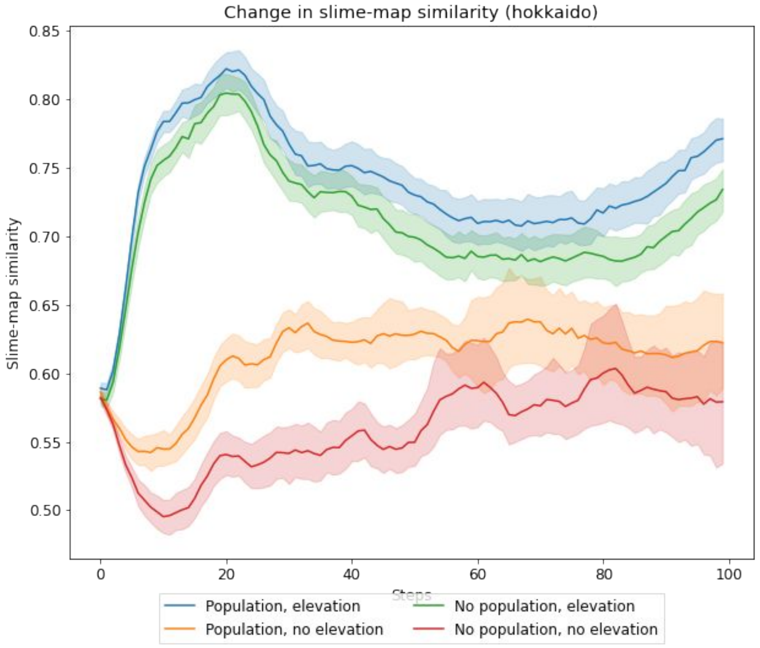
$$S = \begin{bmatrix} 0 & 0 & 12 & 0 \\ 0 & 4 & 0 & 0 \\ 15 & 0 & 7 & 0 \\ 0 & 0 & 0 & 9 \end{bmatrix} \qquad M = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$S \circ M = \begin{bmatrix} 0 & 0 & 12 & 0 \\ 0 & 0 & 0 & 0 \\ 15 & 0 & 7 & 0 \\ 0 & 0 & 0 & 9 \end{bmatrix} \qquad S \circ (J\text{-}M) = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Preliminary results (slime-map similarity)

- The model performed best under the influence of both elevation and population density
- It performed worst when neither factor was considered
- Elevation reduces the variance slightly





Hypothesis test

Slime-map similarity (highest to lowest) for both maps:

1. Elevation and population are considered
2. Elevation is considered but population is not
3. Elevation is not considered but population is
4. Elevation and population are not considered

The hypothesis cannot be rejected

- ➔ The model may generate more optimal solutions if elevation and population are considered
- ➔ Elevation may appears to have a greater impact on network optimality than population density

Model evaluation

How does Shannon entropy ("randomness") of the network change over time?

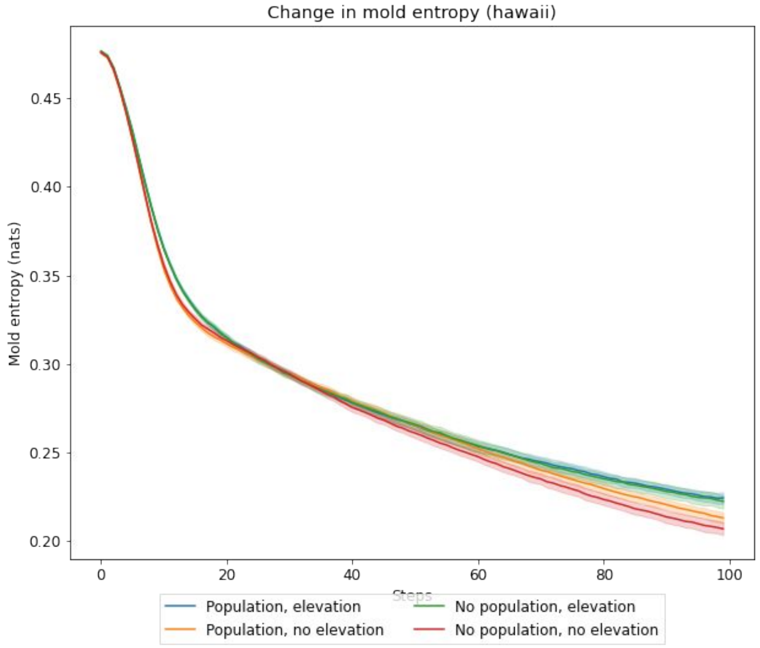
$$H(X) = -\sum_{\mathcal{S}_X} p_X(x) \log p_X(x)$$

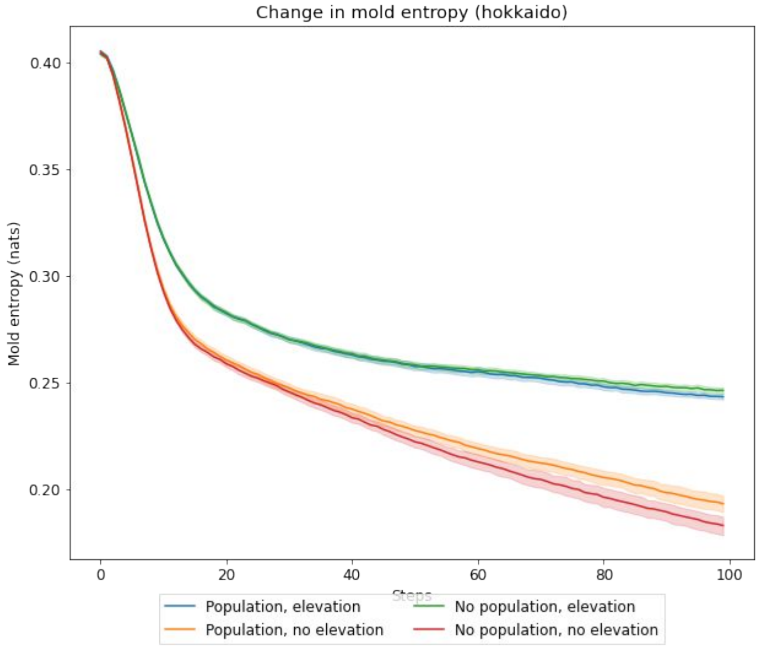
How does the mutual information (model-free correlation between mold and actual map, mold and elevation, mold and population) change over time?

$$I(X;Y) = \sum_{\mathcal{S}_Y} \sum_{\mathcal{S}_X} p_{(X,Y)}(x,y) \log \left(\frac{p_{(X,Y)}(x,y)}{p_X(x)\, p_Y(y)} \right)$$

Preliminary results (entropy)

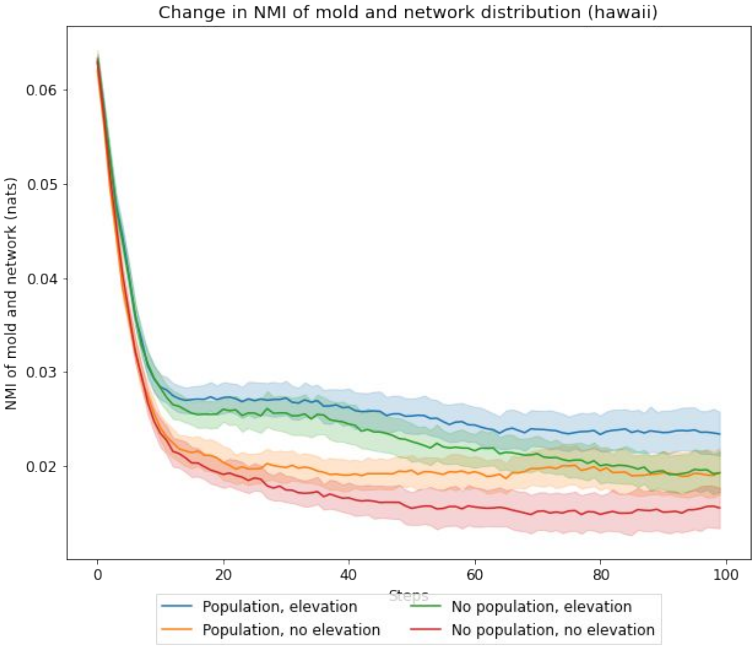
- Randomness of the network decreases over time
- Under the influence of elevation, the network appears more random

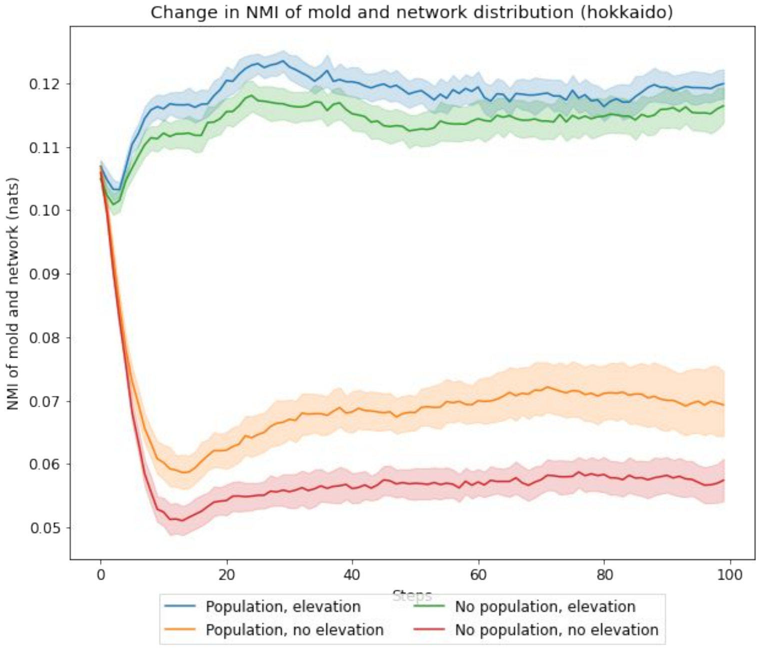




Preliminary results (I[Slime, Map])

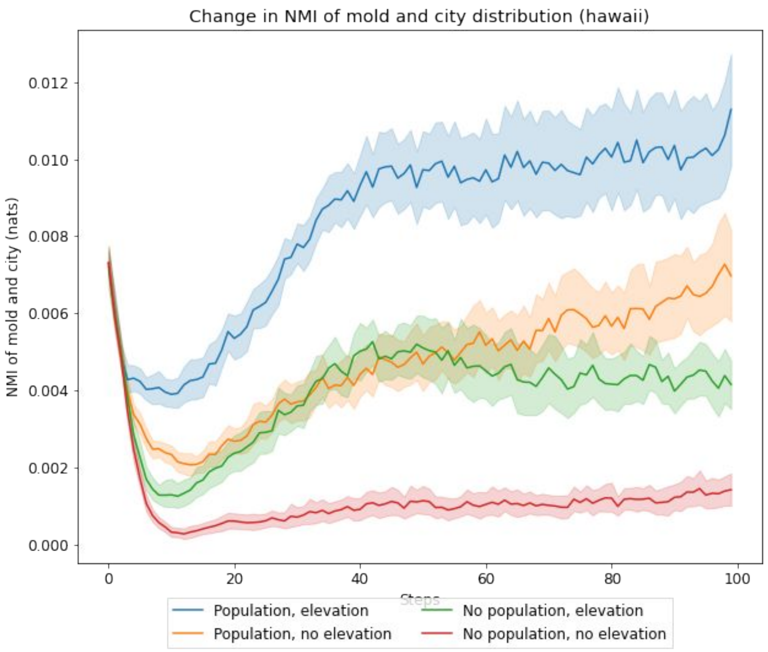
- I(Slime, Map) is highest if elevation and population is considered and lowest if not
- Mutual information decreases in Hawaii and increases in Hokkaido

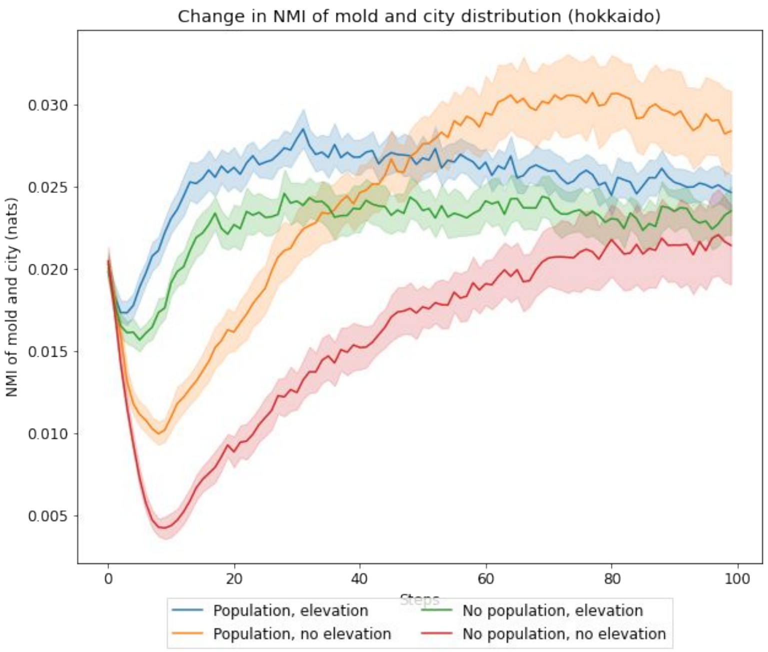




Preliminary results (I[Slime, Cities])

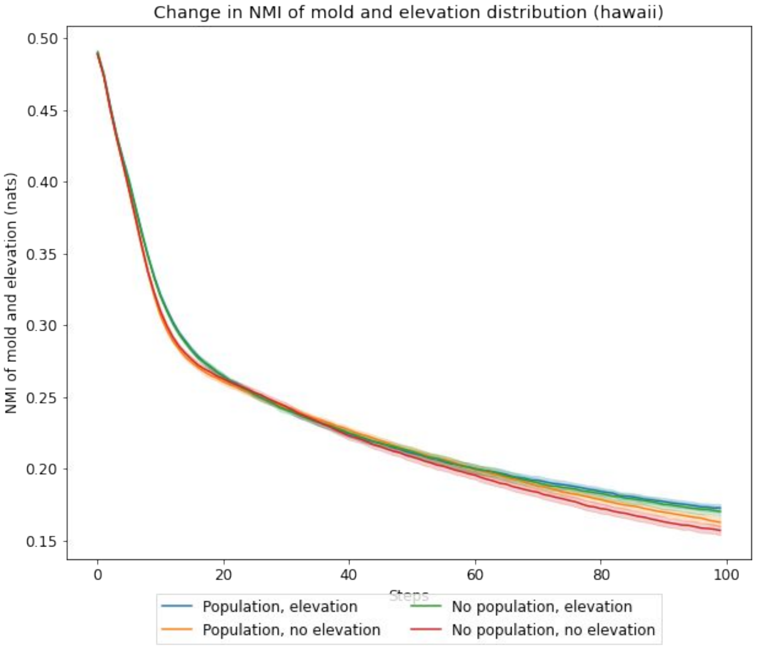
- Lowest correlation between slime and cities if population and elevation are not considered

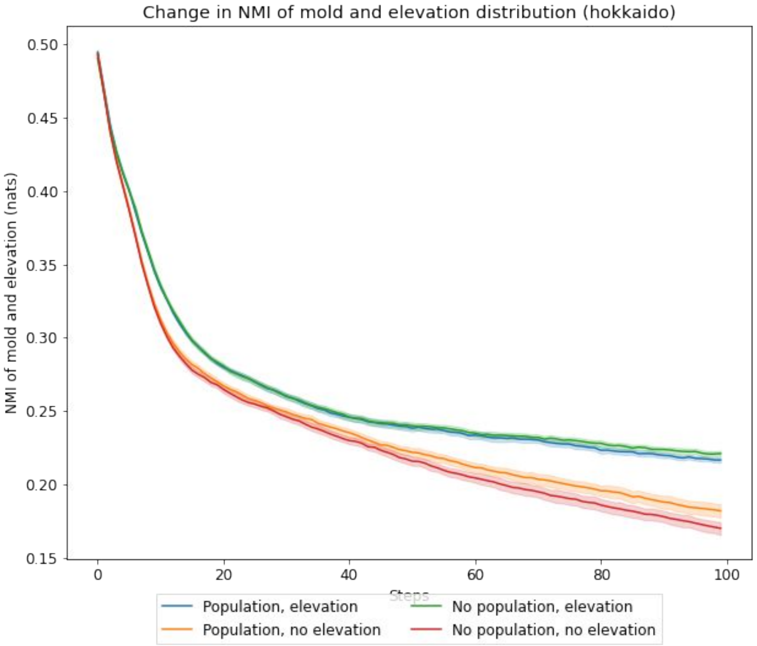


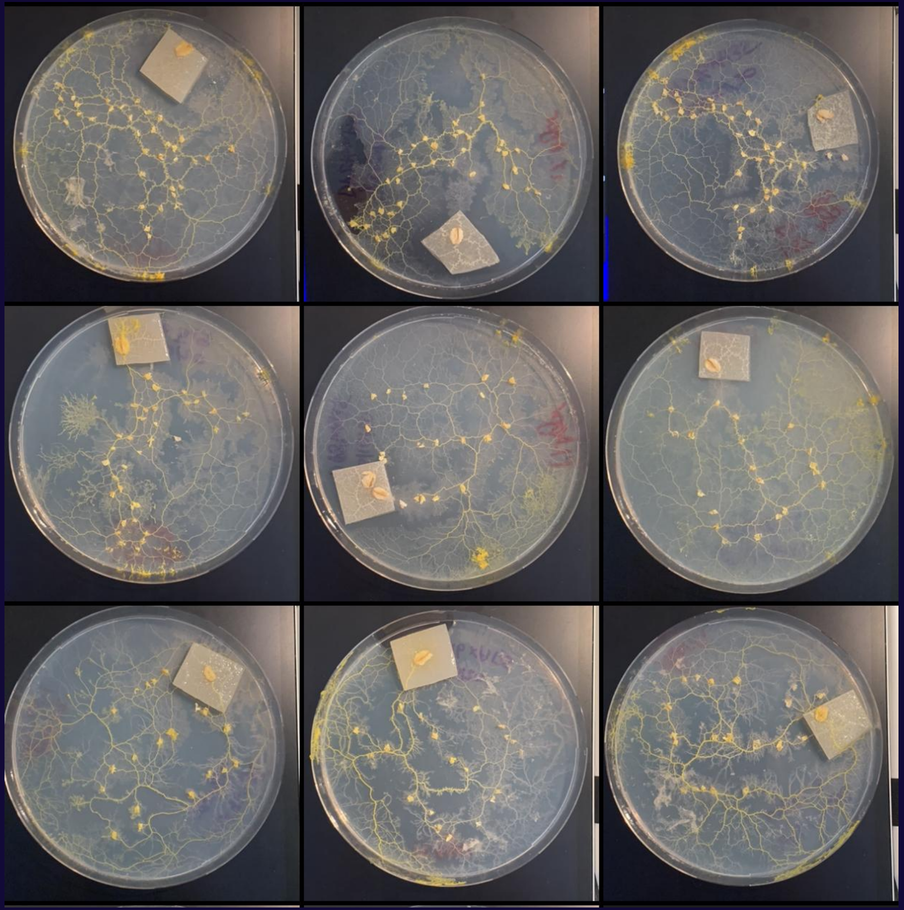


Preliminary results (I[Slime, Elevation])

- Higher correlation between slime and elevation if elevation is considered







Challenges in using actual slime mold compared to ABM

- ➔ Requires tailored environment
- ➔ Inconsistent network formation
- ➔ Time consuming to grow and conduct experiments
- ➔ Difficult to adjust node and deterrent strength
- ➔ Difficult to quantify solution

Results Summary

01 Using elevation and population produced the most similar results to actual traffic networks

02 Elevation had the strongest influence on network optimality

03 Compared to real smile mold networks, our model is a much faster, adjustable and consistent solution

04 Our solution has practical applications for real-life traffic network modelling

Further Model Developments

Introduce memory for agents to allow the model to ‘remember’ where it has travelled already and improve efficiency at which a solution is discovered

Improve model tuning using evolutionary algorithms to select optimal parameters

Implement controls to reduce the influence that large cities have on the behaviour of agents

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