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

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Abstract

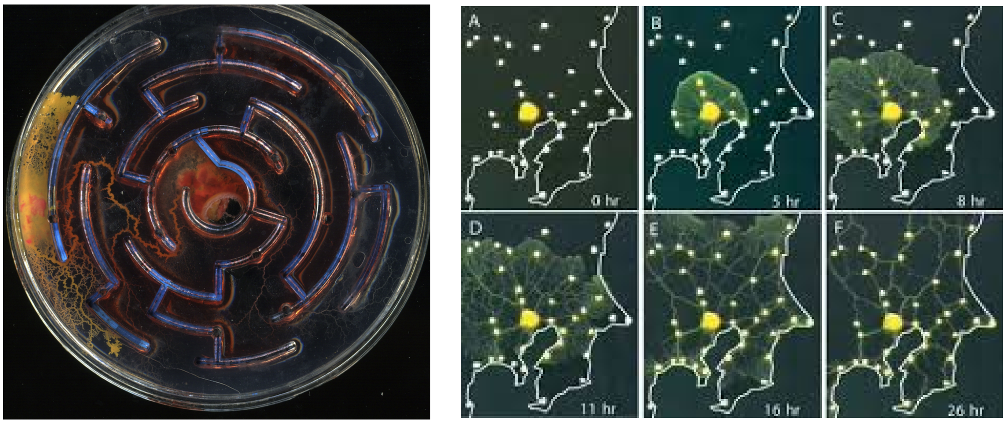
This paper will introduce an agent-based model to mimic the foraging behaviour of the slime mold species *Physarum Polycephalum* to optimise road networks in O'ahu and Hokkaido under the influence of elevation and population. Our findings are consistent across these maps and demonstrate that the addition of both factors will lead to more optimal and realistic solutions. Moreover, it was found that elevation has a significantly stronger effect on the shape of road networks than city population. Supported by biological experiments, we justify that an agent based model may substitute the use of real slime mold samples when modeling transport networks. This is relevant to the modelling of existing and future planned transport networks as well as other network related problems. We suggest that our model may be applied to archeological research or biomedicine and offer extensions for future development of our model in a 3D environment.

1 Introduction

Physarum Polyucephalum is a species of plasmodial slime mold which exhibits complex behaviour through its ability to efficiently organise itself in search for food while avoiding deterrents. Beyond applications to efficiently solving transport network problems (Tero et al., 2010), research has demonstrated slime mold can be used to design reversible logic gates (Schumann, 2017), approximate Voronoi diagrams (Jones, 2015), find the shortest path in a maze (Nakagaki et al., 2000) (Adamatzky, 2012a), and solve the travelling salesman (Zhu et al., 2018) and Steiner tree problems (Caleffi et al., 2015) in polynomial time (Zhu et al., 2018).

1.1 Physarum transport networks

Tero et al., 2010 placed oats and light on a petri dish to represent the population centres and topographical features of the Tokyo metropolitan area. After placing samples of *Physarum polycephalum* on the dish, they were able to demonstrate the slime mold grew into a network that closely mimicked Tokyo's rail network. Research into Physarum-generated transport networks has since proliferated, with some researchers demonstrating that edges generated by a Physarum network in China mirrored 90% of connections in China's traffic network Adamatzky et al., 2013.



(a) (b)

Figure 1: Examples of past Physarum experiments. Figure 1a is a demonstration of maze-solving ability of *Physarum polycephalum* (Adamatzky, 2012a) while Figure 1b is a small multiples time-lapse from the Tokyo transport network experiment conducted by (Tero et al., 2010)

1.2 Aims and motivation

There are significant limitations with the time and number of experiments required to produce results using real samples of *Physarum polycephalum*. Physarum simulations across 15 different locations by Adamatzky, 2012b required between 22 and 53 simulations per location with each simulation taking 92 hours to grow. Additionally, it is difficult to mimic variable terrain in these experiments given slime mold is capable of adapting to varying levels of salinity and light (Boussard et al., 2019).

Existing agent-based models are effective in replicating real slime mold behaviour, however, they fail to consider variations in elevation and population density; their applicability to real transport network problems is therefore limited. We propose that introducing parameters around population density and elevation will more closely model existing transport networks. Our hypothesis is:

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 proposed agent-based model will simulate the topographic and demographic features of the islands of Hokkaido in Japan and Oahu in Hawaii. If our hypothesis is proven, our model will be an alternative to physical slime mold in modelling real transport networks. This used to evaluate the effectiveness by which countries have developed their roads and railways and could inform decisions surrounding connections of population centers to key infrastructure such as power grids and telecommunications networks. Beyond this, our model could be applied to various network related problems where consideration of node weight and edge penalties is necessary. To further evaluate how well our model resembles the organism by which it was inspired, we have obtained live samples of *Physarum Polycephalum* to conduct biological experiments.

2 Implementation

2.1 Existing models

Foraging behaviour of *Physarum Polycephalum* has inspired a range of computer generated models. Tero et al., 2007 modeled the flux of protoplasm using Poiseuille flows while Gunji et al., 2008 propose a cellular automata that connects amoebic motion with network formation, both of which are capable of solving mazes and the Steiner minimum tree problem. Further equation-based approaches have been introduced with Li et al., 2020 proposing an equation-based slime mold algorithm (SMA) which uses similar heuristics to breadth-first search algorithms to find optimal growth patterns.

Jones, 2010 propose a more general ABM to what we propose in this project. In their model, agents follow the deposits of other agents to create protoplasmic flows. They include additional hyper parameters such as turn-angle, sensor angle, sensor width and sensitivity threshold. Evangelidis et al., 2017 extend this model to investigate the impact of topography on the development of Roman roads in the Balkans; but they fail to disclose details of their implementation. Moreover, the impact of elevation on their model was insignificant.

2.2 Agent based modelling approach

2.2.1 Physarum Polycephalum

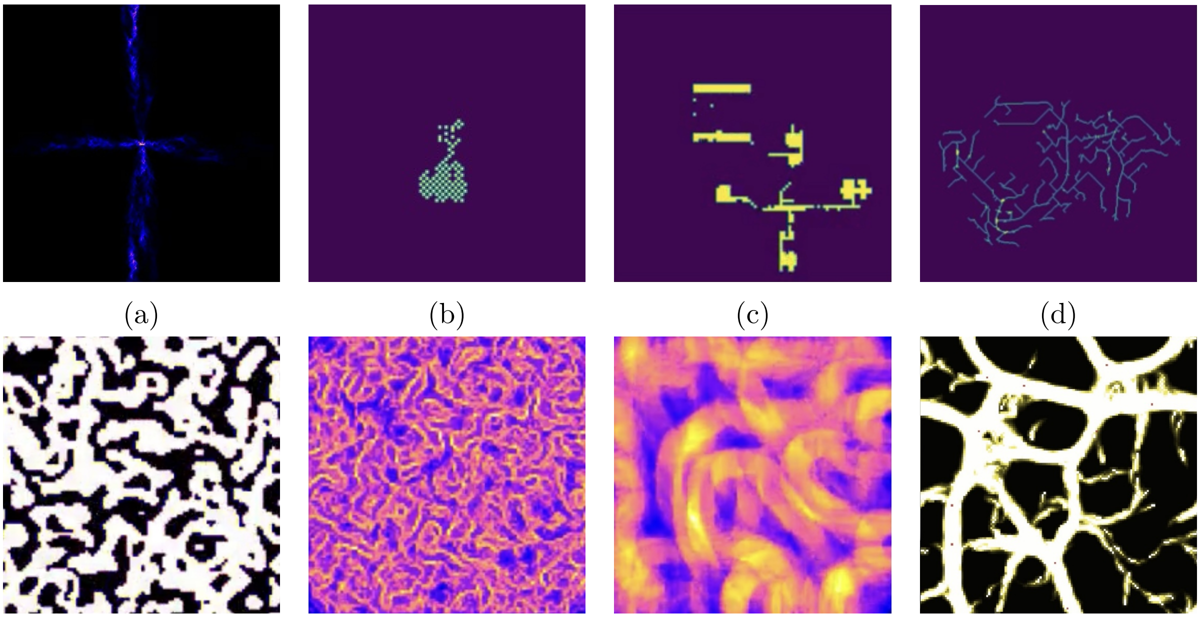
Physarum Polyucephalum is a species of plasmodial slime mold which exhibits complex behaviour through its ability to efficiently organise itself in search for food. The unicellular organism develops a reticulated network of tubes when foraging with non-centralised, molecular interactions driving protoplasmic flows in response to external stimuli (Alim et al., 2017). A feedback loop between signaling molecules at the site of external stimulus and propagating contractions through the organism gives rise to complex, intelligent patterns as it juggles between self-minimisation and growth (Boisseau et al., 2016).

2.2.2 Physarum as an ABM

Physarum Polycephalum can be represented as a large number of agents representing the protoplasmic particles. As these agents respond to stimuli, protoplasmic flows transport signalling molecules and stimulate further flows within the organism. Agents weigh the cost of movement between negative and positive stimuli to determine the direction of each movement. The interactions between these agents and their environment lead to network growth, corollary to expansion of the plasmodium.

2.3 Development process

2.3.1 Prototypes



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 2: Different preliminary prototypes and modelling approaches.

Significant effort has been devoted to prototype development. Prototypes Figure 2a to Figure 2d are cellular automata based on greedy search while prototypes 2e to Figure 2g represent the activations in spiking neural networks. Unfortunately these models proved unable to form efficient connections (with nodes and with itself) and to reach stable solutions. Figure 2h shows the first successful prototype.

The implementation of population density was straight-forward but required some parameter tuning to prevent agents from continously circling nodes. Subsequently, agents were programmed to avoid absolute elevation instead of relative elevation differences. However, it was later realised that the latter better captures the engineering constraints of actual traffic networks.

2.4 Biological slime mold experiments

To best assess how well our model resembles the organism by which it was inspired, live samples of *Physarum Polycephalum* were obtained and biological experiments conducted. Ring, 2017 led us to contact Dr.Chris Reid from the Macquarie University Department of Biological Sciences who referred us to three life sciences researchers at the University of Sydney. They were provided us with 42 Physarum samples.

In the experiments, crushed oats were used to resemble the nodes (ignoring population) while saline solution of varying concentrations was used to represent elevation quartiles and waters. Evidently, we were able to achieve a much higher level of precision and accuracy in the ABM compared to the biological experiments.

2.5 Model description

Table 1: Overview of model parameters

Property	Symbol	Owner	Exogenous	Typical values
Position	(x, y)	Agent & Patch	No	$([0, w], [0, h])$
Heading	h	Agent	No	$[0, 360\,\text{deg})$
Sensor distance	d	Agent	Yes	4
Dimension	(w, h)	Patch	Yes	(201, 201)
Terrestrial	l	Patch	Yes	True/False
Signal value	s	Patch	No	-
Elevation	z	Patch	Yes	$(0, 9.9]$
Node weight	n	Patch	Yes	$[0, 129.1]$
Agent density	p	-	Yes	1.0
Diffusion rate	δ	-	Yes	5
Evaporation multiplier	η	-	Yes	0.95
Step	t	-	No	$[0, 100]$

In the model, multiple agents move across a canvas that is partionioned into $w \times h$ patches. Properties of agents, and the environment are summarised in Table 1.

The model is initialised using a bitmap image with grey scaled pixels corresponding to the elevation, z, and RGB pixels representing the population count or node weight, n, in that area. Elevation data was obtained from the AW3D30 dataset provided by JAXA. Black pixels represent waters. Terrestrial areas are then populated (random position and heading) with an average number of p agents per patch.

In each step of the simulation, the agents determine the optimal direction of movement: either forward, 45° left, or 45° right. If there is more than one optimal patch, agents choose randomly. The optimality of a patch (x, y), relative to the agent's current position (x', y') is

$$f(x, y, x', y') = \frac{s_{(x,y)}}{1 + |z_{(x,y)} - z_{(x',y')}|} \tag{1}$$

Therefore, agents will prefer patches with large signal values and low relative height differences. Importantly, the 1 in the denominator prevents division by zero if there is no height difference. The signal value of each terrestrial patch is then incremented by their node weight (effectively providing a permanent stimulus for agents to move towards nodes), n, and the number of agents that are currently on that patch. Agents then turn towards the most optimal patch and move one step forward. Finally, the signal value is diffused by δ and reduced by $(1-\eta)$ which represents the diffusion of signalling molecules on moist surfaces or in gas so that the plasmodium can extend towards sources of food. The evaporation step prevents an unbounded accumulation of signal molecules in the simulation.

It is clear that over time agents will follow the signals deposited by other agents and nodes. This intertemporal feedback loop corresponds to the widening of tubular channels due to pressure which enables increased protoplasmic flows (Tero et al., 2007). Protoplasmic particles flowing through tubular channels is equivalent to cars, trains, planes travelling on roads, rails, or airways.

2.6 Parameter analysis

Figure 3 and Figure 4 demonstrate the impact of all seven hyperparameters summarised in Table 1. Of these, only four are independent of the map and required manual tuning to achieve stable solutions, have an adequate level of inter-connectivity, and produce precise paths. It is evident that agent density and sensor distance as well as diffusion and evaporation have insignificant interaction effects. Thus, it was deemed appropriate to tune them individually.

2.6.1 Sensor distance (d)

A greater sensor distance widens paths and promotes the traversal of small-scale topographic features. Very small sensor distances, on the other hand, adversely impacts interconnectivity as agents tend to continuously circle nodes or topographic features. A value of 5 seemed most optimal.

2.6.2 Terrestrial (l)

Clearly, agents avoid waters as they are unable to deposit signals there.

2.6.3 Elevation z

Agents are not programmed to avoid elevation, but relative elevation differences. However, since most nodes are located at mean-sea-level, a tendency of avoiding lightly shaded areas, i.e. areas of high elevation, can be observed.

2.6.4 Node weight (n)

Agents tend to approach nodes. Nevertheless, the impact of different node weights (i.e. different colored dots) is not immediately apparent from the images.

2.6.5 Agent density p

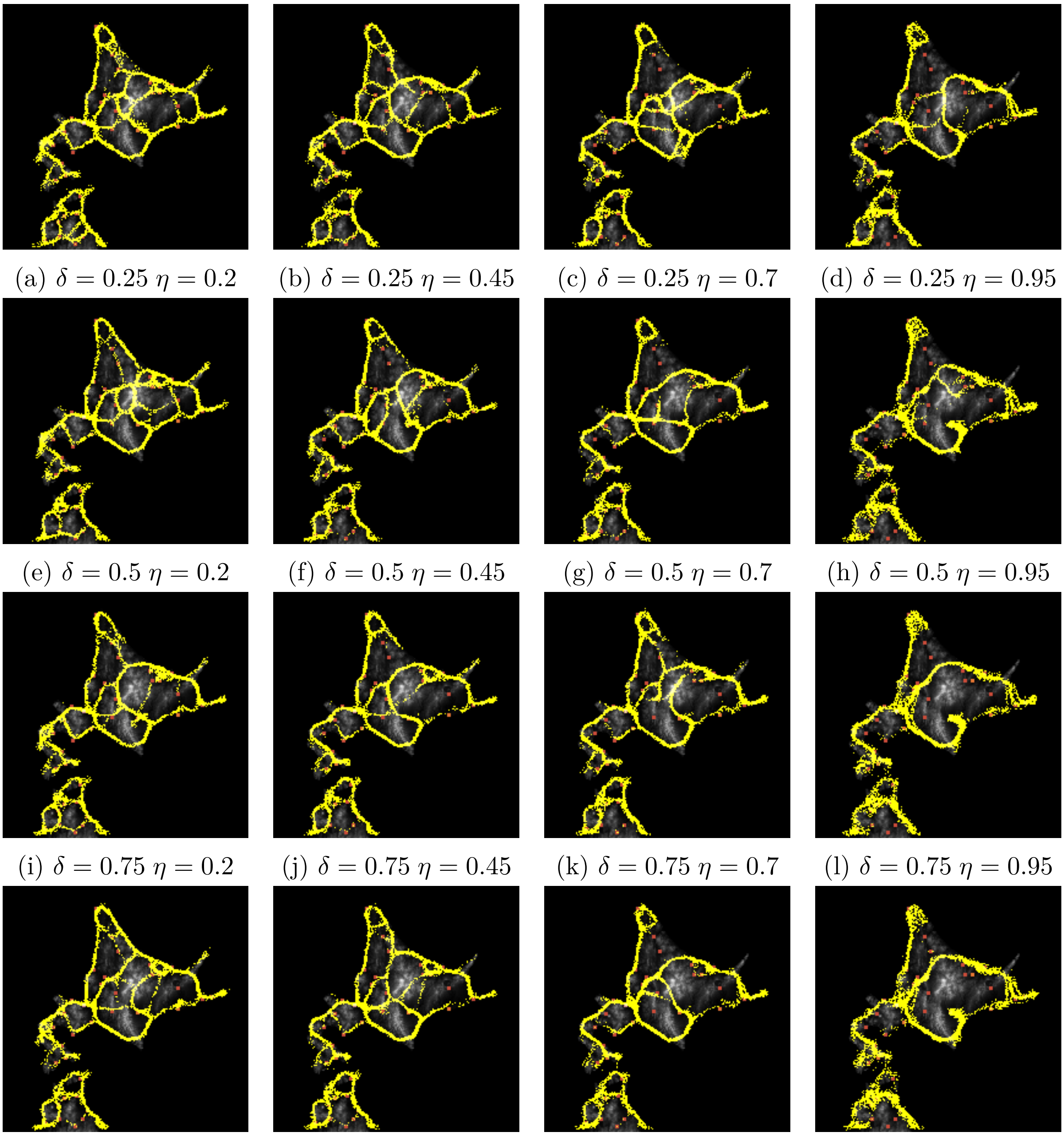
Higher levels of agent density increase the connectiveness of the agents, as expected. A level of 1.0 seemed most appropriate.

2.6.6 Aiffusion rate δ

Higher diffusion rates tend to reduce connectiveness and, thus, low value of 0.05 was chosen.

2.6.7 Evaporation multiplier η

Large evaporation multipliers adversely impact connectiveness over time. A value of 0.95 was chosen as this greatly improved the consistency of solutions -particularly in Hawaii.



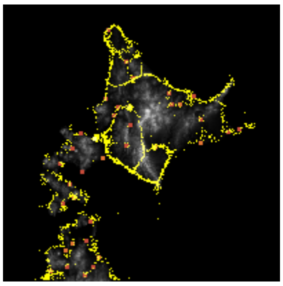
(a) $\delta = 0.25$ $\eta = 0.2$ (b) $\delta = 0.25$ $\eta = 0.45$ (c) $\delta = 0.25$ $\eta = 0.7$ (d) $\delta = 0.25$ $\eta = 0.95$

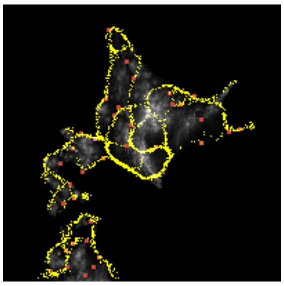
(e) $\delta = 0.5$ $\eta = 0.2$ (f) $\delta = 0.5$ $\eta = 0.45$ (g) $\delta = 0.5$ $\eta = 0.7$ (h) $\delta = 0.5$ $\eta = 0.95$

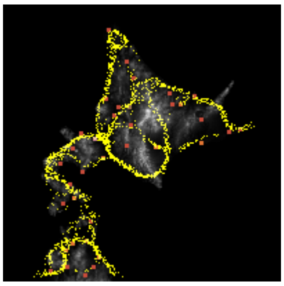
(i) $\delta = 0.75$ $\eta = 0.2$ (j) $\delta = 0.75$ $\eta = 0.45$ (k) $\delta = 0.75$ $\eta = 0.7$ (l) $\delta = 0.75$ $\eta = 0.95$

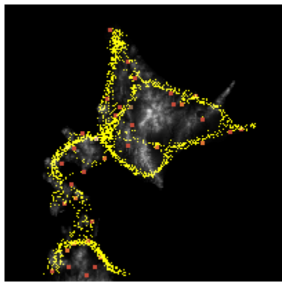
(m) $\delta = 1.0$ $\eta = 0.2$ (n) $\delta = 1.0$ $\eta = 0.45$ (o) $\delta = 1.0$ $\eta = 0.7$ (p) $\delta = 1.0$ $\eta = 0.95$

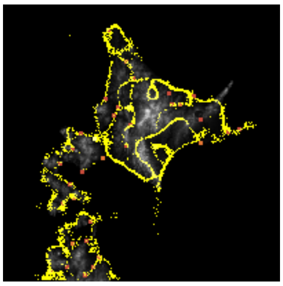
Figure 3: Generated transport network with parameters $\delta = 0.05$, $\eta = 0.95$. Rows represent changes in diffusion (δ), while columns represent changes in evaporation (η).


(a) $p = 0.25$ $d = 2.5$


(b) $p = 0.25$ $d = 5.0$


(c) $p = 0.25$ $d = 7.5$


(d) $p = 0.25$ $d = 10.0$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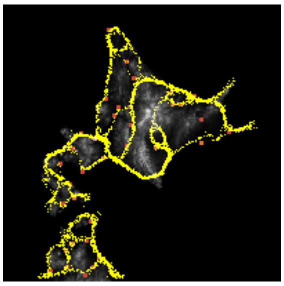
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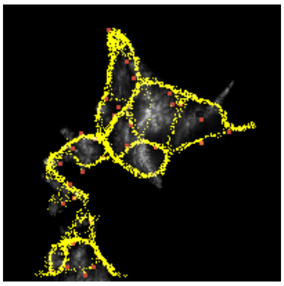
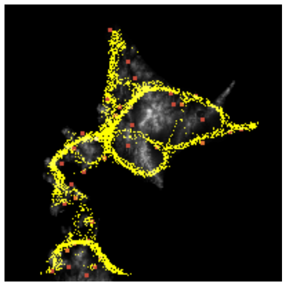
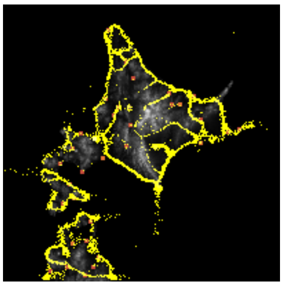
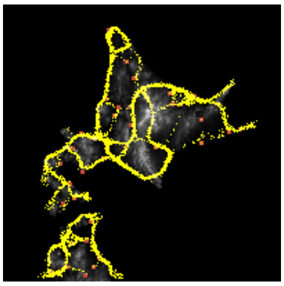
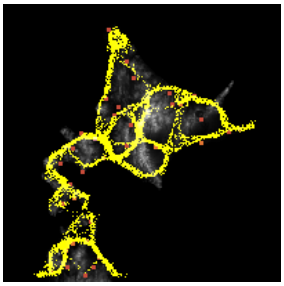
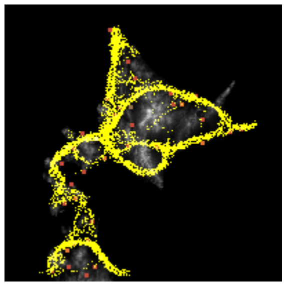

(g) $p = 0.5$ $d = 7.5$

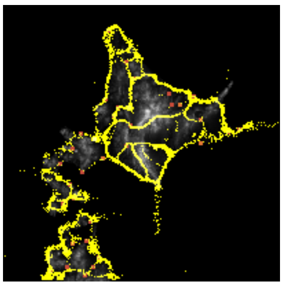

(h) $p = 0.5$ $d = 10.0$

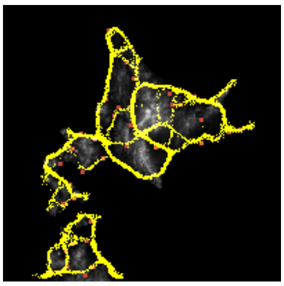

(i) $p = 0.75$ $d = 2.5$

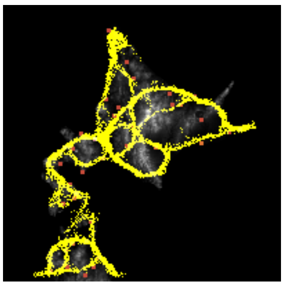

(j) $p = 0.75$ $d = 5.0$


(k) $p = 0.75$ $d = 7.5$


(l) $p = 0.75$ $d = 10.0$


(m) $p = 1.0$ $d = 2.5$


(n) $p = 1.0$ $d = 5.0$


(o) $p = 1.0$ $d = 7.5$

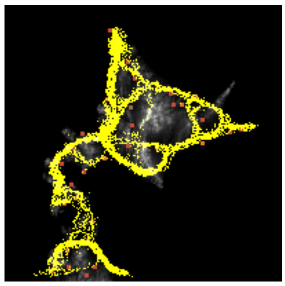

(p) $p = 1.0$ $d = 10.0$

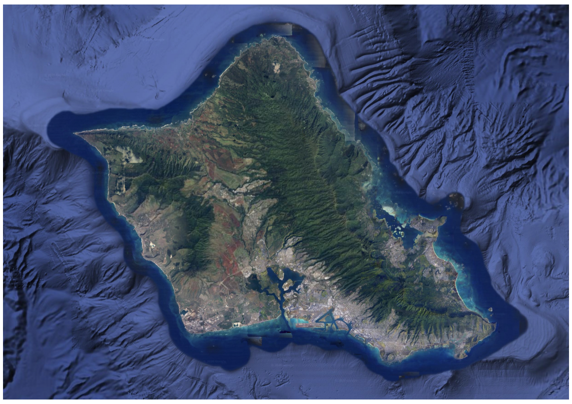
Figure 4: Generated transport network with parameters $d = 5$, $p = 1.0$. Rows represent changes in population density (p), while columns represent changes in sensor distance (d).

3 Results and analysis

3.1 Evaluation

3.1.1 Map selection

(a) Hokkaido



(b) O’ahu (Hawaii)

Figure 5: Maps used in the model. Images taken from Google Earth (Google, 2020)

The maps of Hokkaido island (Japan) and O’ahu island (Hawaii) were selected because

1. islands are self-contained areas and are less affected by factors off the map
2. the size of the area is appropriate given a limited canvas resolution and computing power
3. their population is dispersed
4. there is some variance across city population
5. the maps include mountainous regions

For Hokkaido, the 36 largest towns and cities were selected and 20 were selected for O’ahu. These cities were then assigned a node weight based on their population quantile group; 13 quantiles (corresponding to NetLogo’s color palette) were considered.

3.1.2 Evaluation metrics

Since analytic solutions to traffic network optimisation are beyond the scope of this paper, actual road networks are used as an approximation of the optimal network.

Let $S \in \mathbb{W}^{h\times w}$ denote the matrix whose elements, $S_{y,x}$ correspond to the number of agents on the patch with position (x, y). Furthermore, let $M \in \{0, 1\}^{h\times w}$ denote the matrix whose elements, $M_{y,x}$ are 1 if the actual traffic network passes through the patch with position (x, y) and 0 otherwise.

To measure network similarity, we propose the following measure

$$\rho = \frac{||S \circ M||}{||S \circ (J - M)||} \tag{2}$$

where $J \in \{1\}^{h \times w}$ denotes a matrix of ones and $\circ$ denotes the Hadamard product. The numerator can be interpreted as the overlap of the mold with the actual traffic network, while the denominator denotes the overlap of the mold with patches off the actual traffic network. Evidently, the greater ρ, the closer the simulated network is to the actual network.

The harshness of this measure can easily be adjusted by applying a Gaussian blur with a specified standard deviation, $\sigma = 1$, to M. This would reward paths for being closer to the actual network even if there is no exact overlap. Moreover, this would prevent division by zero if no agent is off the actual network. In this analysis, a value of $\sigma = 1$ was used.

To attain statistically significant results, each of the four test defined under 1.2 was repeated 100 times for each map. In each of the simulated steps, the similarity measure was calculated. The results for both maps can be seen in Figure 6.

3.2 Analysis

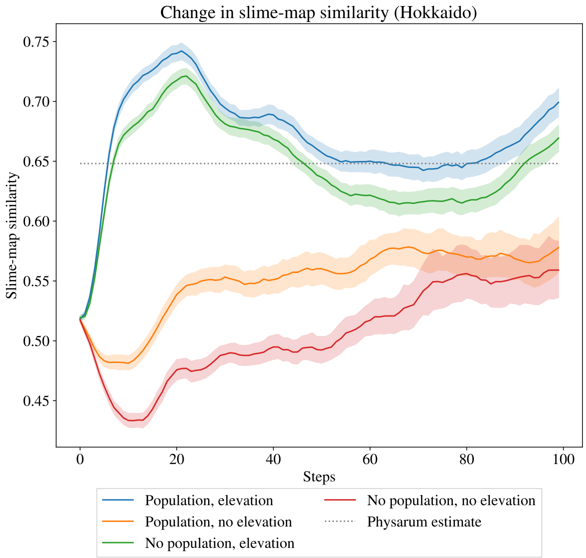
3.2.1 Slime-map similarity comparison

The shape of the curves differs across the maps which is indicative of the strong influence that topographic features and population density have on the self-organisation of agents. This also validates the implementation of both factors in our model.

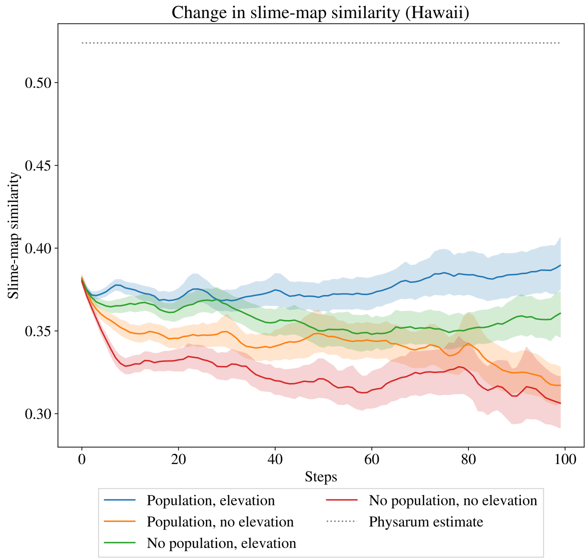
The overall slime-map similarity tends to increase in Hokkaido, while in Hawaii it tends to decrease. In Hokkaido, this trend is likely caused by the complex and narrow shape of the island which limits the directions in which agents can move. Clearly, the design of actual traffic networks is equally constrained by shore lines. With limited degrees of freedom, a slime-map overlap is more likely leading to an upwards trend in the curve.

Despite these differences, the relative relationship between the four tests is consistent across both maps: When population and elevation are considered, the simulation produced the most similar results to the actual network. On the contrary, if neither factor is considered, the slime-map similarity was lowest. Consequently, the hypothesis that considering both factors leads to more optimal transport networks cannot be rejected.

Lastly, elevation has the strongest influence on the separation of the curves which is most apparent in Hokkaido and early steps of the simulation. This implies that topographic features have a greater impact on the design of actual traffic networks than population does.



(a)



(b)

Figure 6: Change in network similarity ρ over 100 steps

3.2.2 Comparison to real *Physarum* traffic networks

In Figure 7 the various networks are juxtaposed. Comparing the first and second column it is clear that the elevation penalty discouraged agents to traverse mountainous regions, for example, the Ko'olau Range is clearly avoided in Figure 7f. Moreover, agents under the influence of both factors tend to move along the shore lines given the low elevation differences and high population density in these regions.

A comparison between the generated networks and the actual network in column 3 confirms previous findings that elevation and population positively influence network optimality. Nevertheless, the networks appear to be too dense. Figure 4 suggests, network density can be reduced by lowering population density, p. However, it was found that this also adversely impacts consistency and stability. Some experimental evidence suggests that larger canvases improve stability, ceteris paribus. The time complexity of each step is $O(whp)$, however, more steps are required to reach comparable solutions for larger canvases since distances between nodes, agents and other features are also stretched. Consequently, reducing network density without compromising stability may require considerably more computing power.

Visually, the Physarum network for Hawaii appears to be more optimal than those of our simulation. This is confirmed by the comparatively high "Physarum estimate" of over 0.524 in Figure 6). This estimate was determined by aligning photographs of the visually most optimal Physarum dishes, tracing their dominant tubular channels connecting nodes, and calculating ρ. This estimate also suggests that our model slightly outperformed actual Physarum in Hokkaido when elevation was considered but underperformed when elevation was not considered which further supports the hypothesis. However, it is important to note that the "Physarum estimate" is only based on a single sample and that manual aligning and tracing of the mold may introduce bias. Evidently, quantifying solutions of biological experiments is challenging. Adding to this, Figure 8

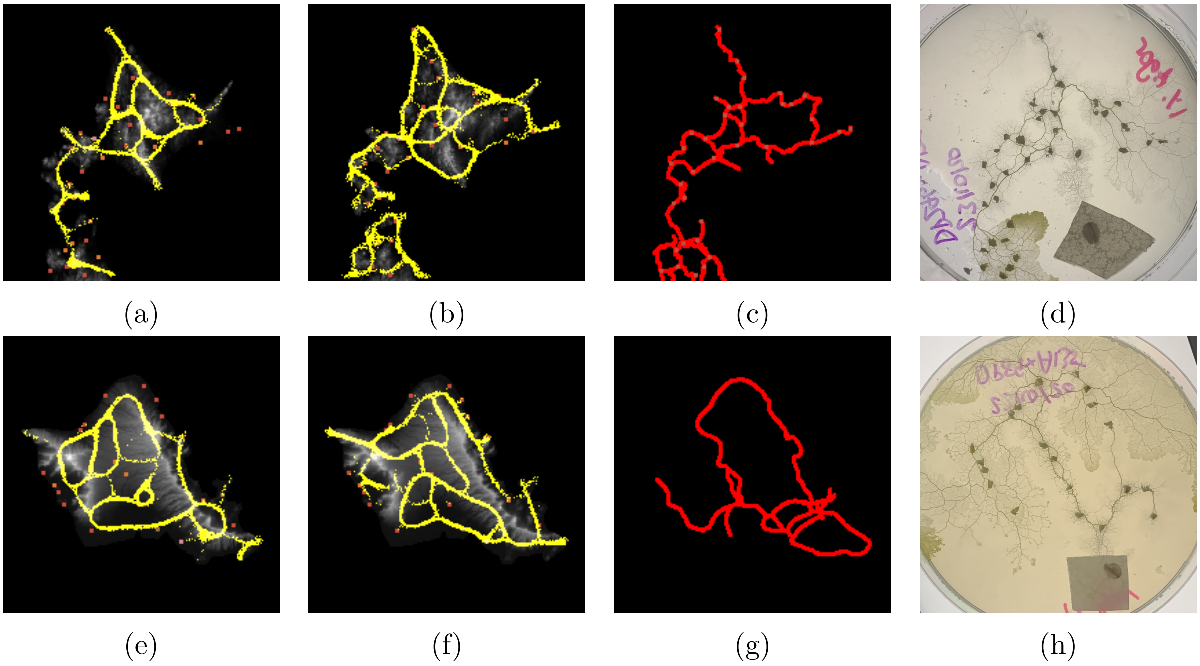
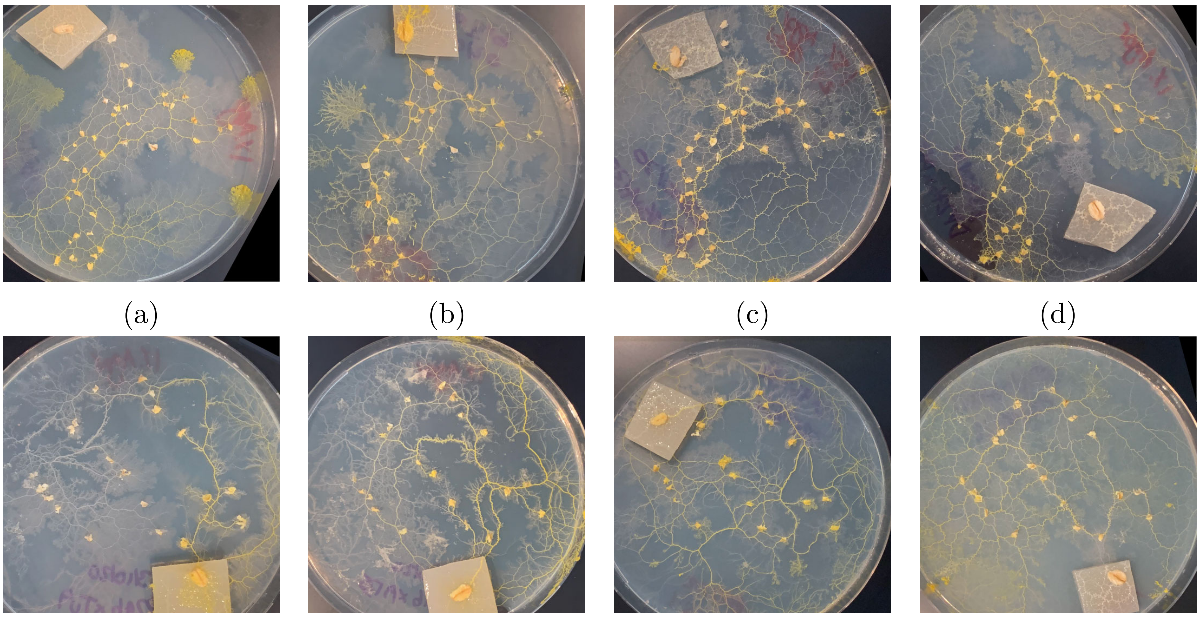


Figure 7: Generated networks for Hokkaido (top row) and Hawaii (bottom row). The columns represent: neither population and elevation, both population and elevation, the actual road network, the Physarum network

demonstrates that Physarum networks are highly inconsistent, particularly if nodes are located close to each other. Moreover, Physarum requires a tailored environment, experiments are time consuming, and it is difficult to accurately adjust the node and deterrent strength. These factors further justify the use of an agent-based model over biological Physarum to optimise transport networks.



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 8: Inconsistent Physarum networks for Hokkaido (top row) and Hawaii (bottom row)

4 Assessment and reflection

4.1 Further improvements

A weakness of the current model is that elevation and node weights are combined into a single bit map which leads to a loss of elevation data at nodes. Since the elevation of node patches is initialised to 0 and the patch optimality is based on relative height differences (see Equation 1), this may incorrectly offset the attraction of agents to nodes, particularly to nodes that are located in elevated areas, which there were few of in both maps. This can easily be fixed in future version of the model using a multi-layer approach.

Another improvement may be to consider the full range of sensor angles instead of only $-45\,\text{deg}, 0\,\text{deg}, 45\,\text{deg}$. However, this may introduce a significant computational cost.

4.2 Other applications

Beyond transport networks, our model could be applied to a range of disciplines to support network modelling. This could include the modelling of archaic road networks similar to research performed by Evangelidis et al., 2017, or further extended to model prehistoric migration patterns of ancient humans. This would allow for the estimation of road and migration networks throughout history, considering topography to link areas where human settlements have been found but roads may have decayed.

The model we propose could further be used to model circulatory systems in organisms with consideration for relative penalties (such as veins travelling between bones). The applications of this could be to investigate vascular networks to understand how organs are connected and develop which could potentially be applied to artificial organ creation. Furthermore, a backward approach, i.e. adjusting environmental factors to generate comparable networks, may be used to better understand the conditions under which vascular networks form.

4.3 Model Extensions

The model could be extended to the 3D environment. This would improve the visualisation of topography and enable the use of road gradient, α, as a more realistic penalty

$$\alpha = \arccos \frac{\langle \boldsymbol{n_s}, \boldsymbol{n_w} \rangle}{||\boldsymbol{n_s}||||\boldsymbol{n_w}||} \tag{3}$$

where $\boldsymbol{n_s}$ denotes the normal of the surface, $\boldsymbol{n_w}$ denotes the normal of the water.

Furthermore, the model could be extended by introducing competition among groups of agents, e.g. agents may reduce the other agent's signal values or adjust environmental factors in their opponent's disfavour. Such a model may provide a general solution to solving game theoretic or logic problems.

5 Conclusion

We conclude that simulated slime mold traffic networks seem to generate the most optimal solutions if both population density and topography are considered and perform worst if neither is considered. Moreover, elevation seems to have a stronger influence on network optimality than population. The proposed model outperformed actual Physarum in Hokkaido when both factors were considered. Moreover, optimising transport networks in biological experiments is much more difficult compared to an ABM approach.

5.1 Acknowledgements

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6 Appendix

6.1 NetLogo code

The following code runs on NetLogo 6.1.1. Additional bitmap images are required to run the model. These images including the model can be downloaded from: https://drive.google.com/drive/f Z4TguwPcOYy5jjgo3269k6qUxrFXBY?usp=sharing

```
patches-own [
  elevation
  signal
  node-weight
]

to load-map
  clear-all

  import-pcolors map-file

  ask patches [
    set elevation 0.0
    set node-weight 0.0
    set signal 0.0

    ifelse pcolor > 9.9 [
      ;; set node weight if pixel is colorful
      set node-weight pcolor - 9.9
    ] [
      ;; set elevation if pixel is grey
      set elevation (9.9 - pcolor)
    ]
  ]

end

to setup
  load-map
```

```

  create-turtles population * count patches [
    set color [255 255 0 255]
    set size 1.5
    setxy random-xcor random-ycor
  ]

  ask turtles [
    ;; kill turtles on the water
    if pcolor = 0 [ die ]
  ]

  ask patches [
    if pcolor = 0 [
      ;; turn waters blue
      set pcolor 104
    ]
  ]

  reset-ticks
end

to go
  ask turtles [
    ;; turn toward patch with highest signal
    ;; or turn randomly if no unique maximum
    turn-toward-signal
    fd 1

    if pcolor != 104 [
      set signal signal + 1
    ]
  ]

  diffuse signal diffusion

  ask patches
  [
    set signal signal * evaporation
    set signal signal + node-weight
  ]

  tick
end

to turn-toward-signal
  let ahead patch-ahead sniff-distance
  let to-right patch-right-and-ahead 45 sniff-distance
```

```
  let to-left patch-left-and-ahead 45 sniff-distance

  let ahead-signal -1
  let to-right-signal -1
  let to-left-signal -1

  if (ahead != nobody) [
    set ahead-signal [signal] of ahead / ( 1 + abs ([elevation] of ahead - elevation)
  ]

  if (to-right != nobody) [
    set to-right-signal [signal] of to-right / ( 1 + abs ([elevation] of to-right - e
  ]

  if (to-left != nobody) [
    set to-left-signal [signal] of to-left / ( 1 + abs ([elevation] of to-left - elev
  ]

  (ifelse to-left-signal > ahead-signal and to-left-signal > to-right-signal [
    lt 45
  ] ahead-signal > to-left-signal and ahead-signal > to-right-signal [
    ;; do not turn
  ] to-right-signal > to-left-signal and to-right-signal > ahead-signal [
    rt 45
  ] to-left-signal = ahead-signal and ahead-signal = to-right-signal [
    let r random 3

    (ifelse r = 0 [
      lt 45
    ] r = 1 [
      rt 45
    ] [
      ;; do not turn
    ])

  ] to-left-signal = ahead-signal [
    let r random 2

    ifelse r = 0 [
      lt 45
    ] [
      ;; do not turn
    ]

  ] to-left-signal = to-right-signal [
    let r random 2

    ifelse r = 0 [
```

```
      lt 45
    ] [
      rt 45
    ]
  ] [
    let r random 2

    ifelse r = 0 [
      rt 45
    ] [
      ;; do not turn
    ]
  ])
end
```