Master Thesis - Defense
26/06/2019

Learning Traversability for a Legged Robot

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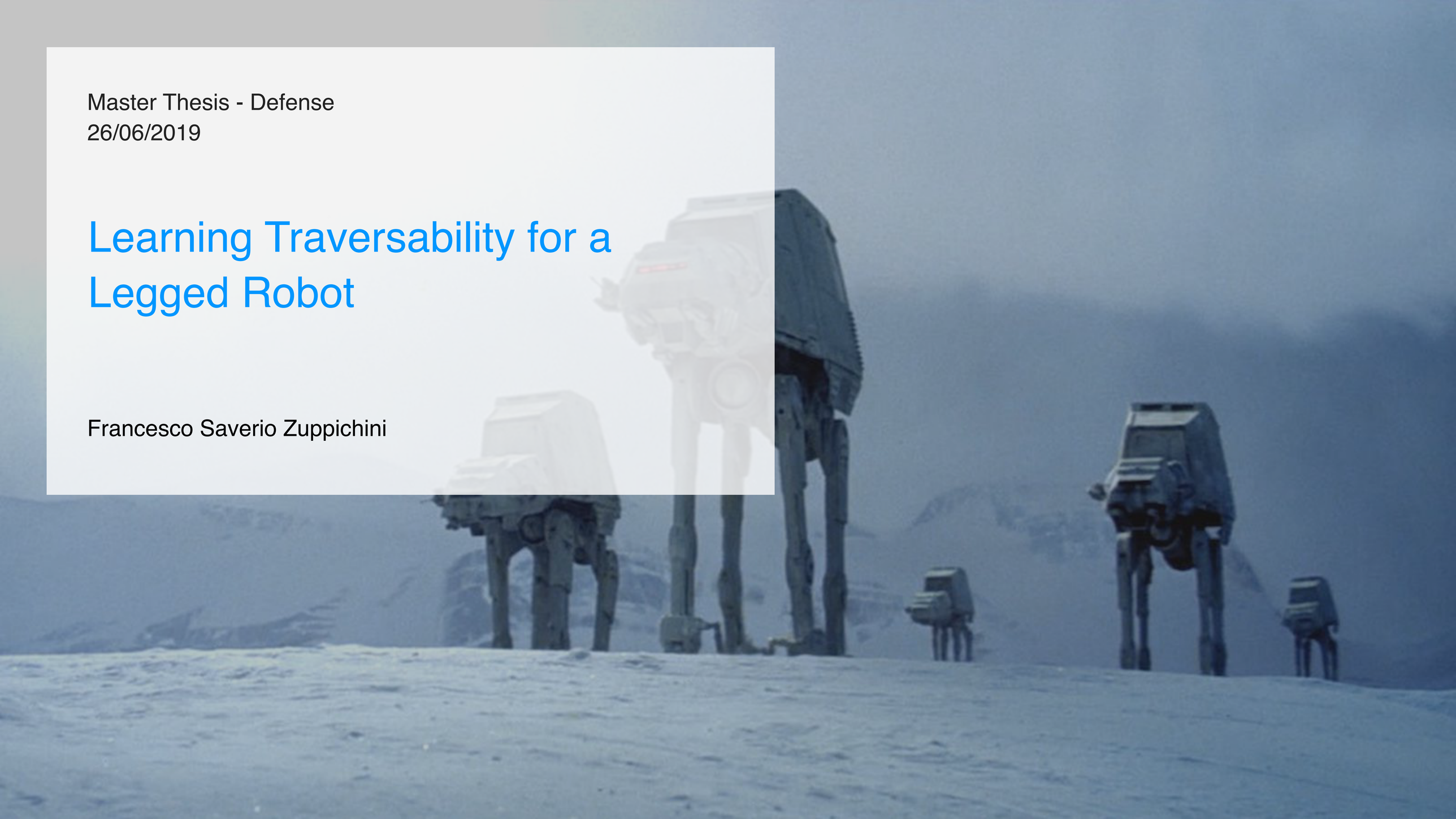
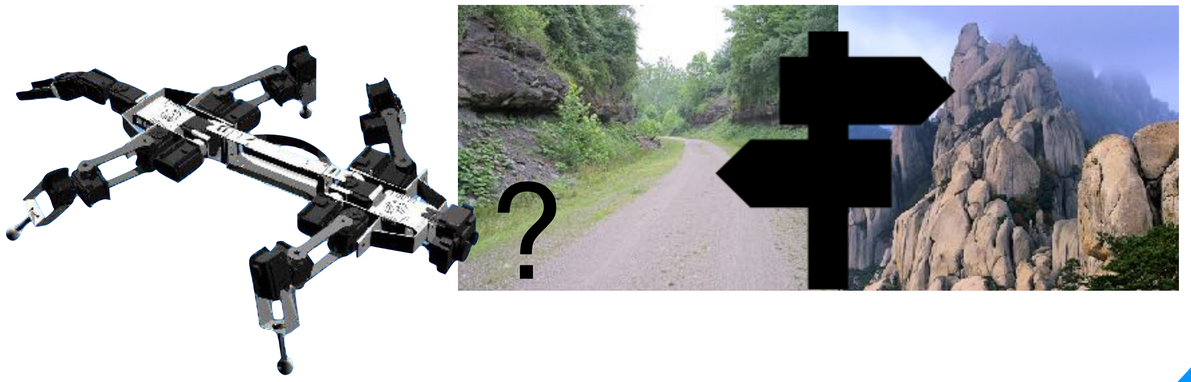


1.
Problem

1. Problem

Definition

Traversability estimation is the task to understand which part of the terrain can be travelled



1. Problem

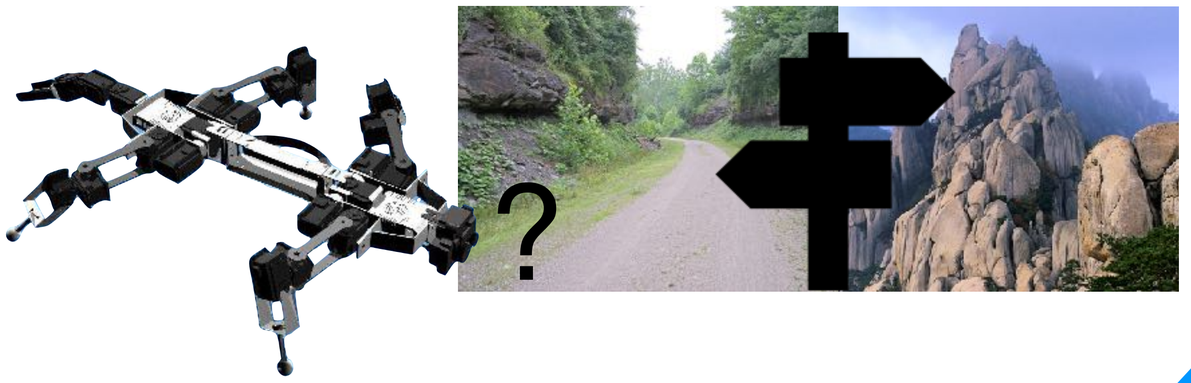
Why it is hard?

add different terrains

Depends on terrains geometric and material

Specific on the robot

We want to generalise



2.
Solution

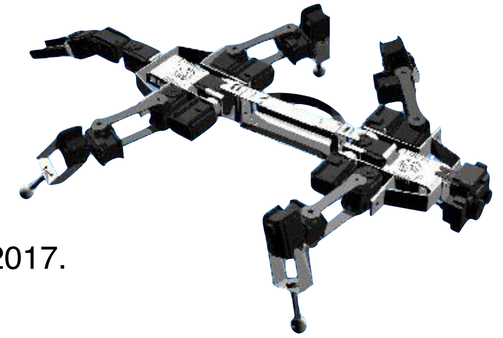
2. Solution

Based on an on going research at IDSIA [1]

Developed a framework to estimate traversability for any robots

Uses entirely simulation data

Tested on a legged robot



[1] R. O. Chavez-Garcia, J. Guzzi, L. M. Gambardella, and A. Giusti. Learning ground traversability from simulations. 2017.

2. Solution

Robot

> Krock
>
> Developed at EPFL
>
> Able to traverse difficult terrains

Better introduce the robot after this slide

Real

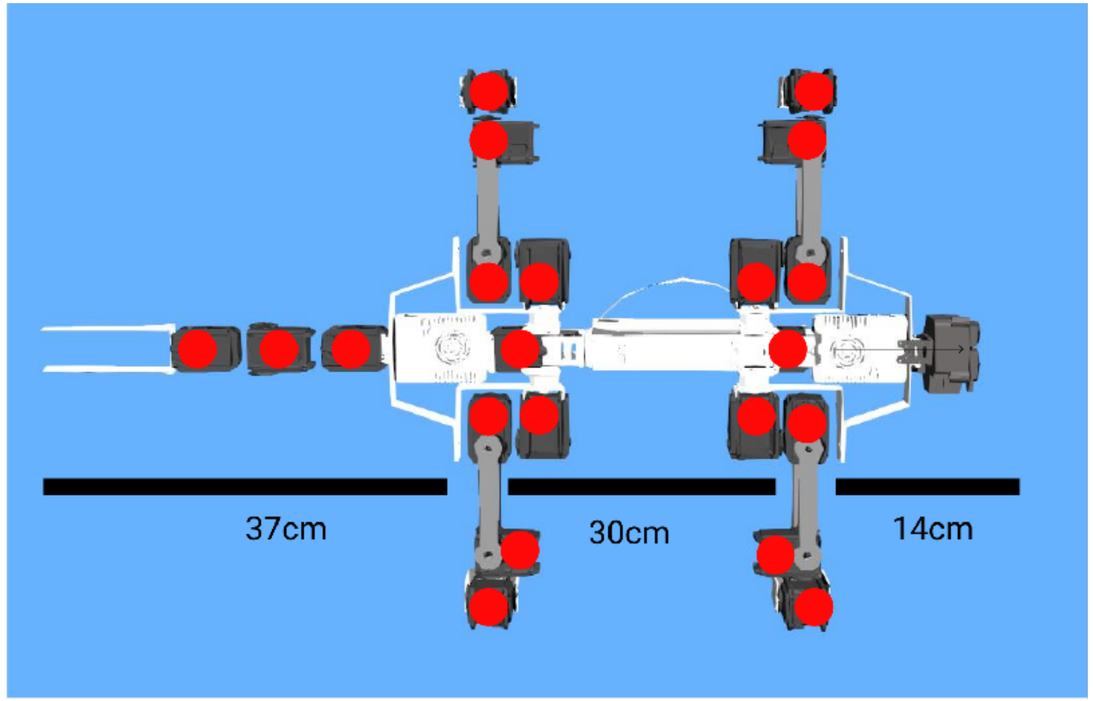
Simulated

2. Solution

Robot

21 motors (210/299 CHF each)

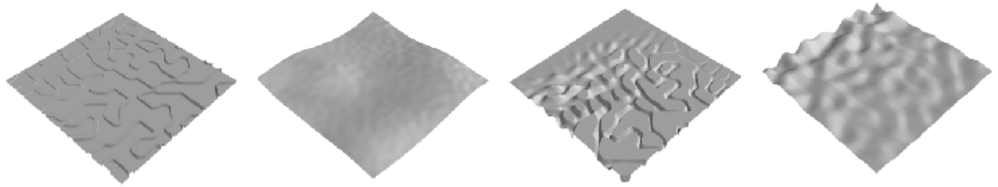
85cm

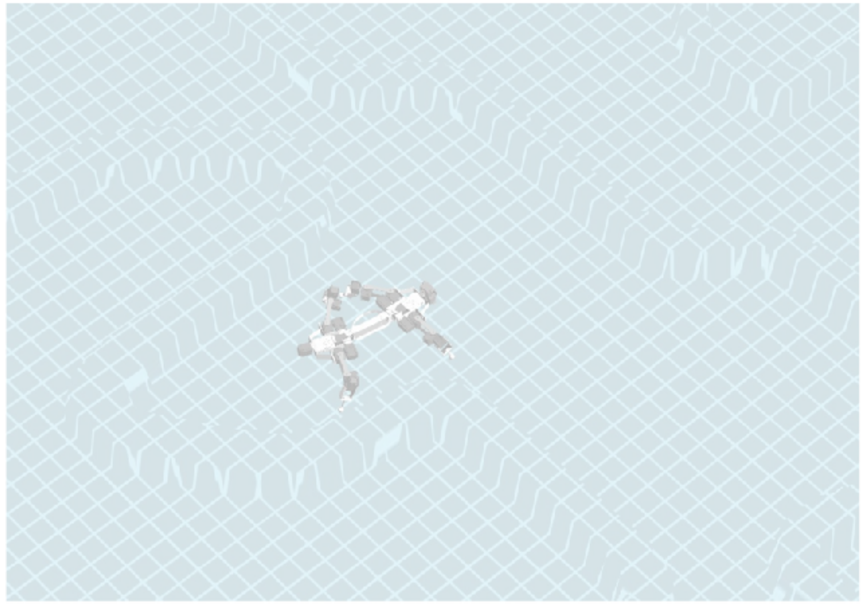


Robot top view. Motors highlighted with red circle

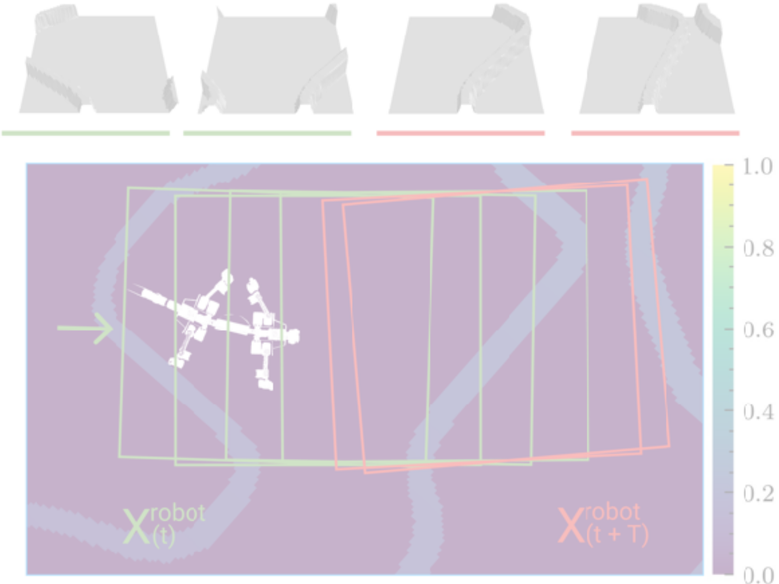
2. Solution

1. Ground generation

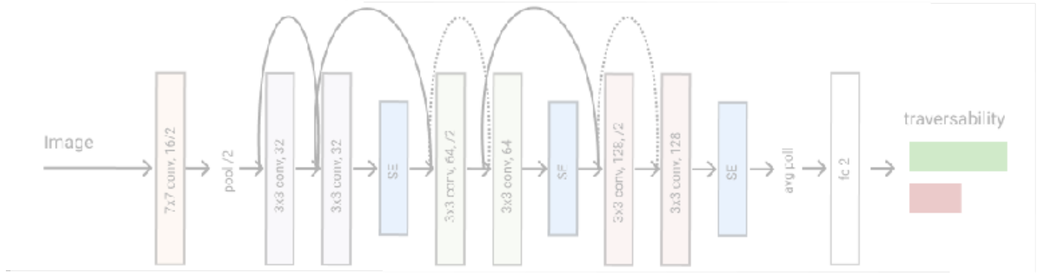




2. Simulation



3. Dataset generation

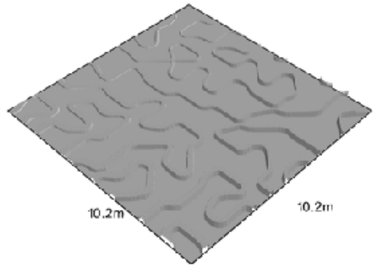


4. Estimation

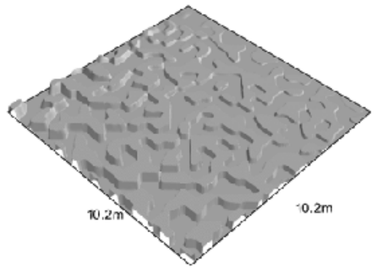
2. Solution

Ground generation

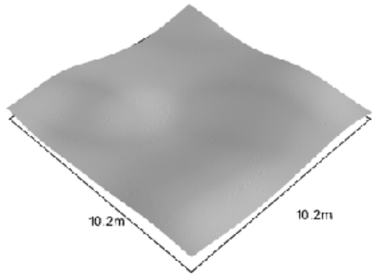
- Perlin noise
- Thirty maps
- Unique features (bumps/holes…)
- Store as images



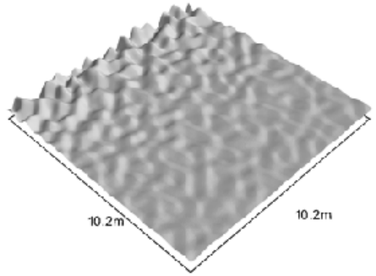
Bars



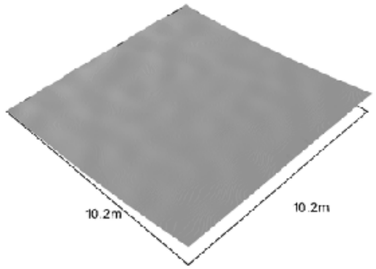
Steps



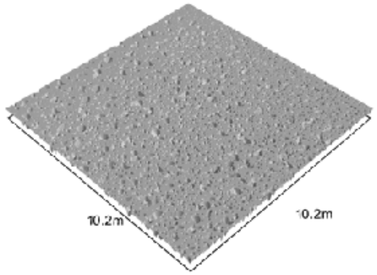
Bumps



Bumps



Ramp



Holes

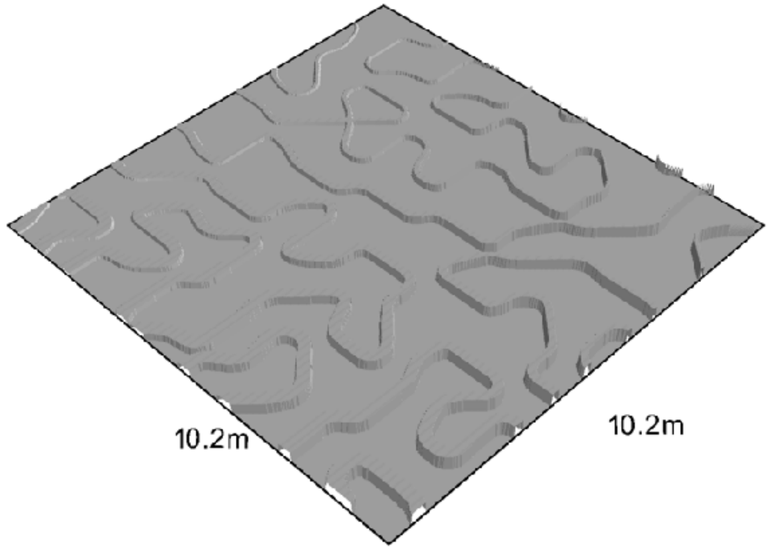
2. Solution

Images

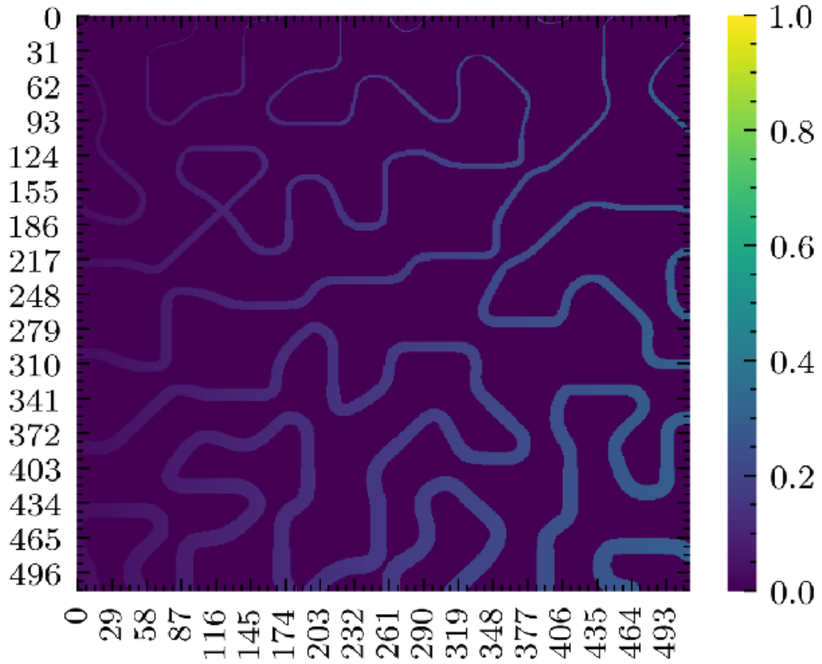
Encode elevation data

Pixel value represents height

Resolution of 2cm/px



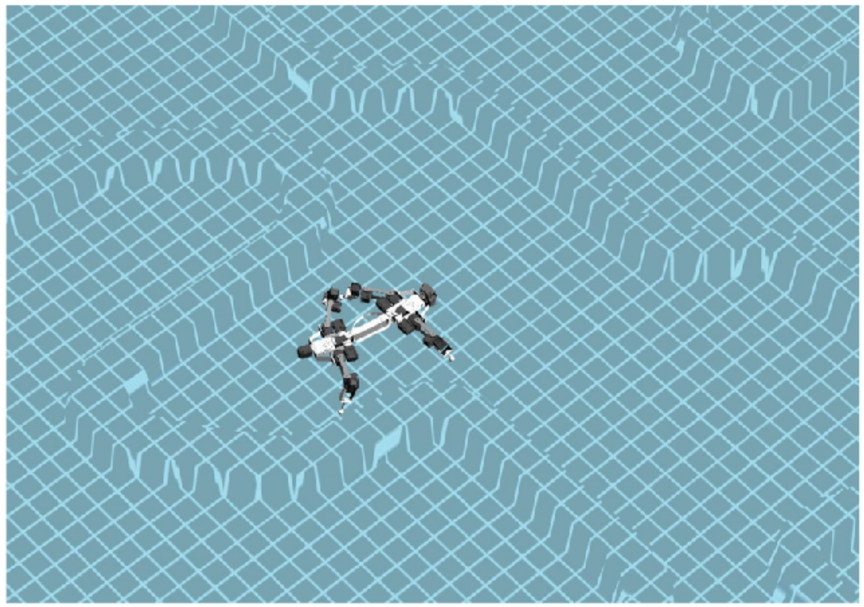
Bars



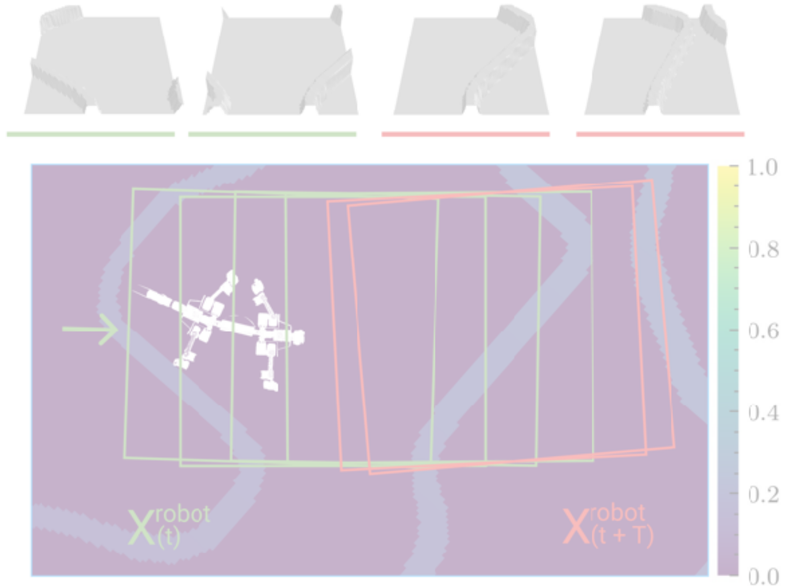
Corresponding image

2. Solution

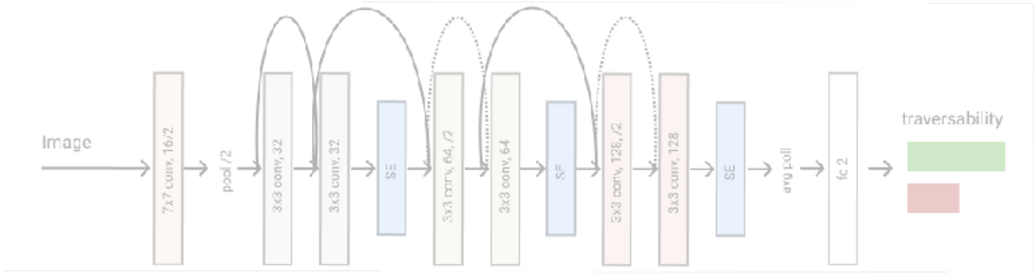
1. Ground generation



2. Simulation



3. Dataset generation

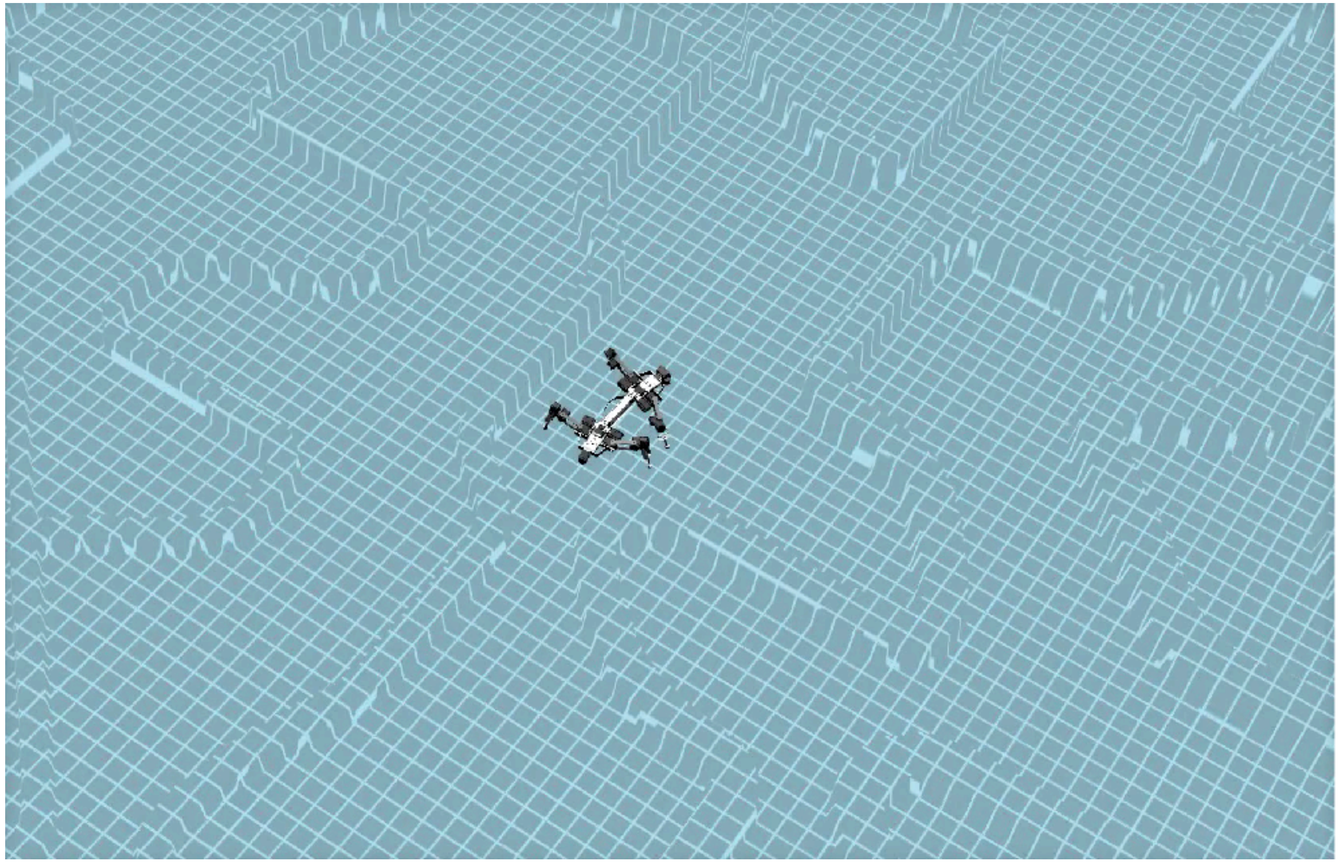


4. Estimation

2. Solution

Simulation

- Load map
- Spawn robot
- Walk forward (fixed controller)
- Store its pose

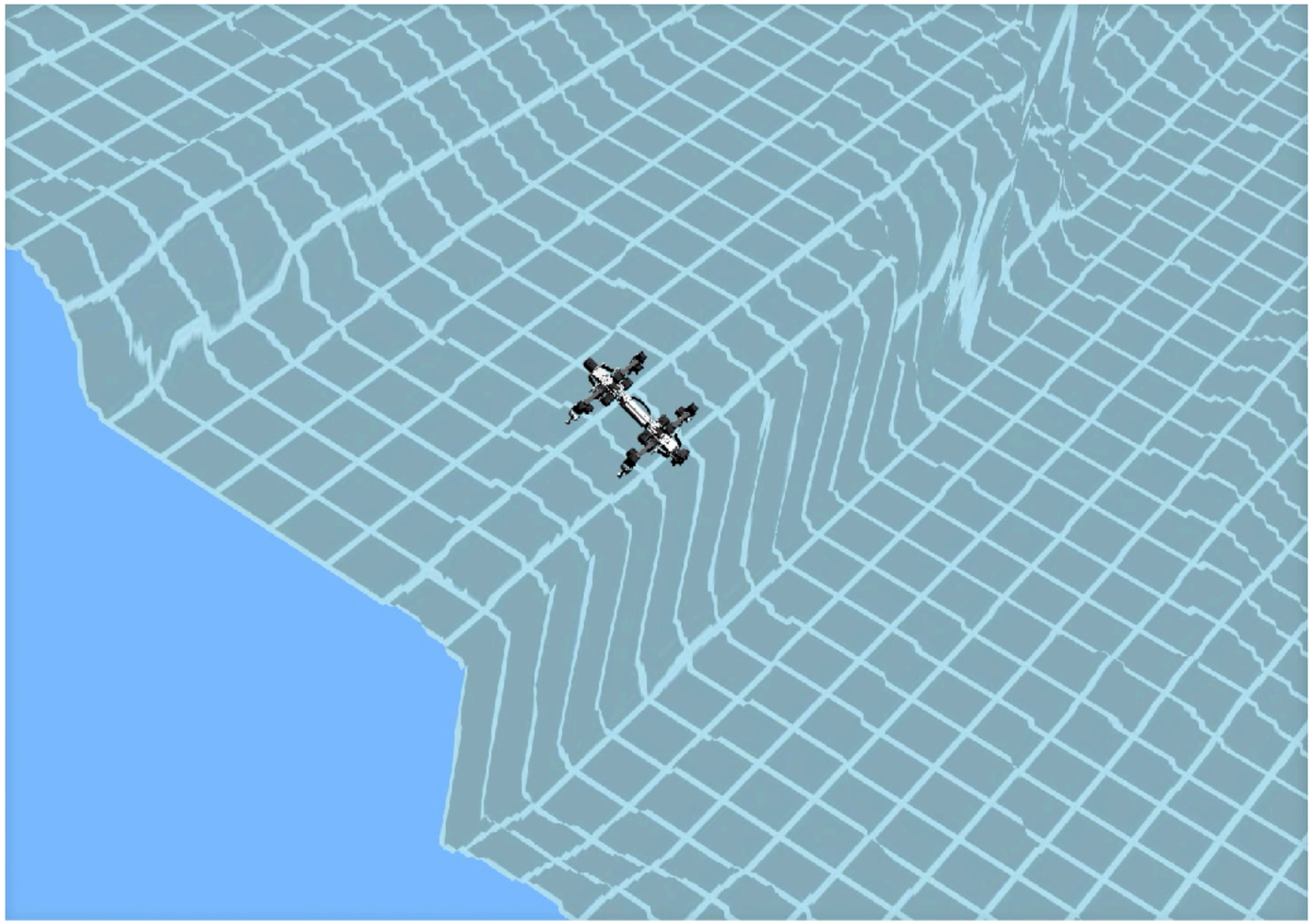


Robot inside the simulation

2. Solution

Simulation

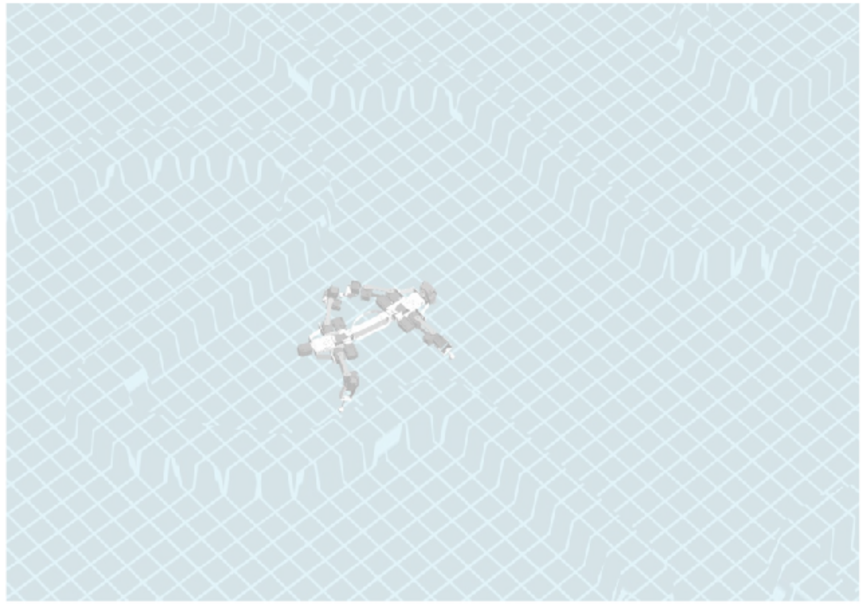
- Cheap
- Fast (parallelization)
- No need for real hardware
- No worries about damages



Robot falling down

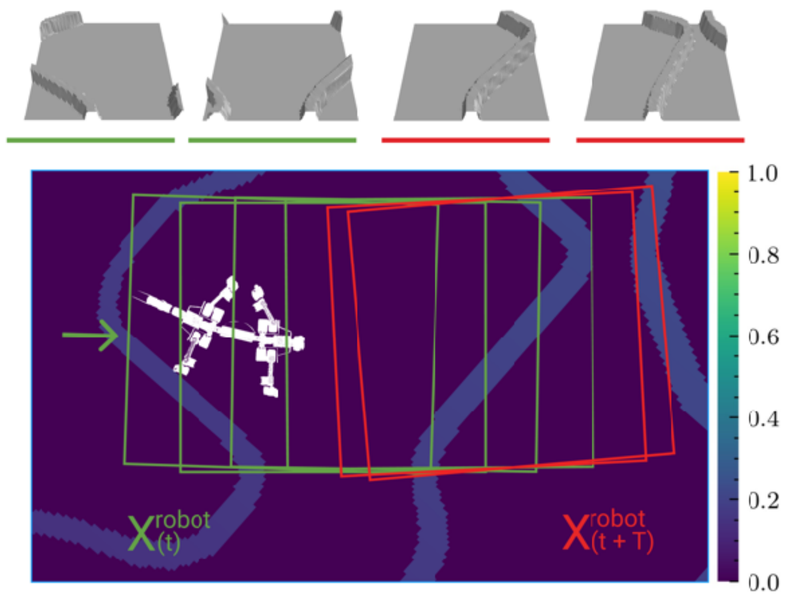
2. Solution

1. Ground generation

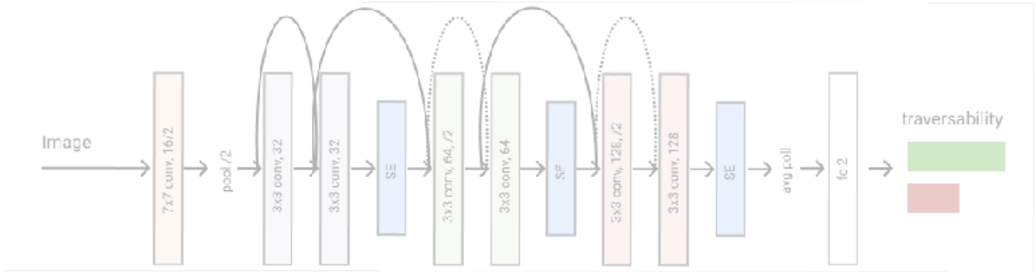


2. Simulation

3. Dataset generation

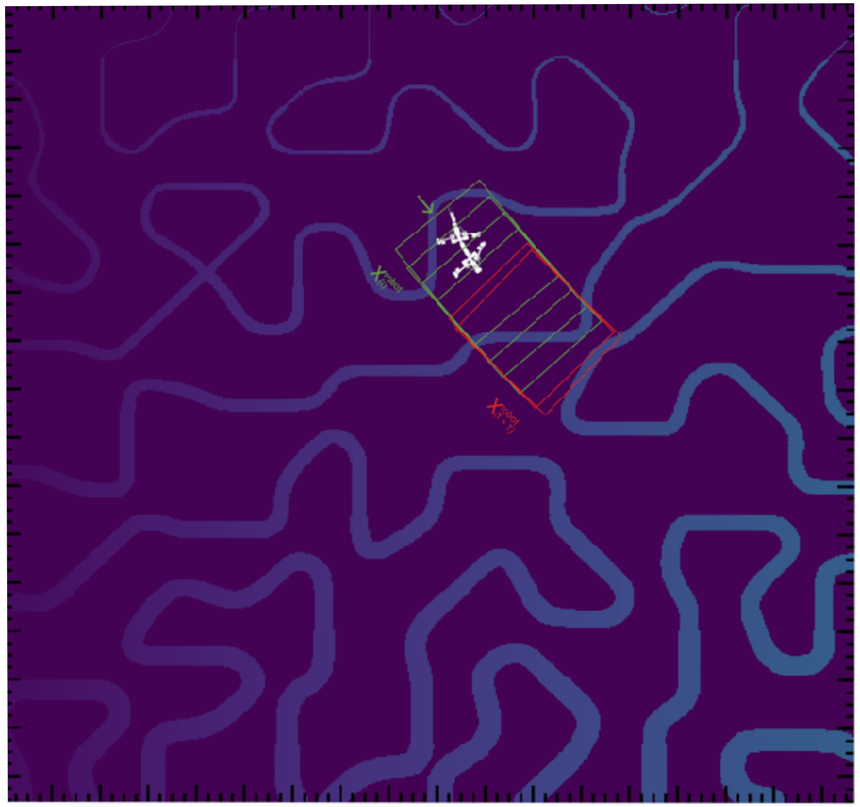


4. Estimation

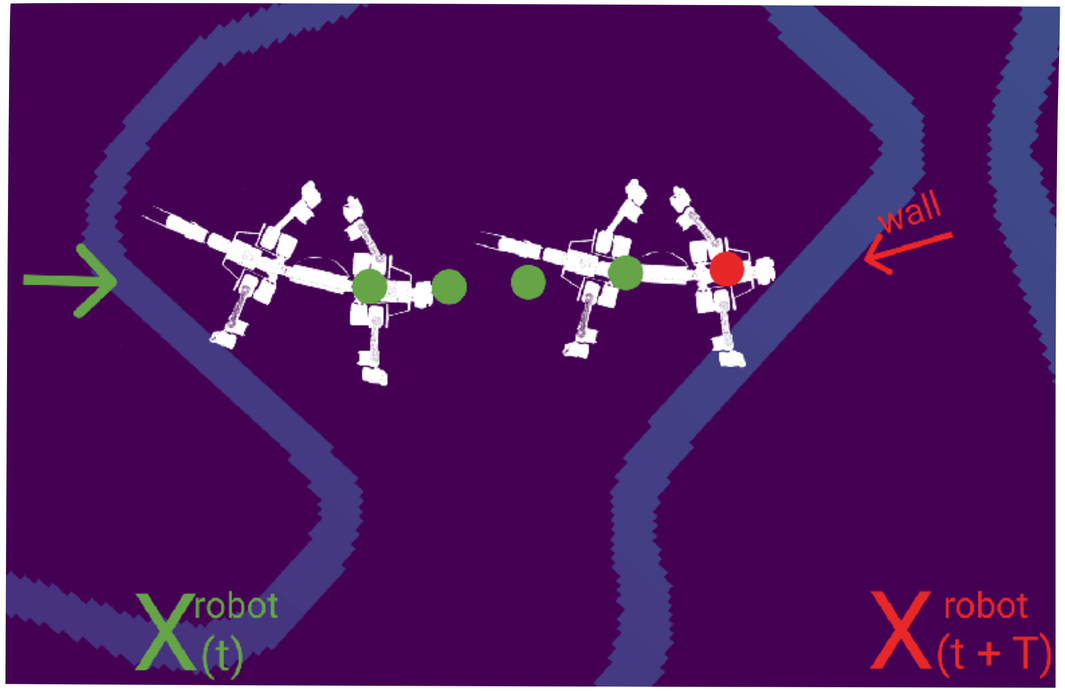


2. Solution

Dataset generation



Trajectory in bars

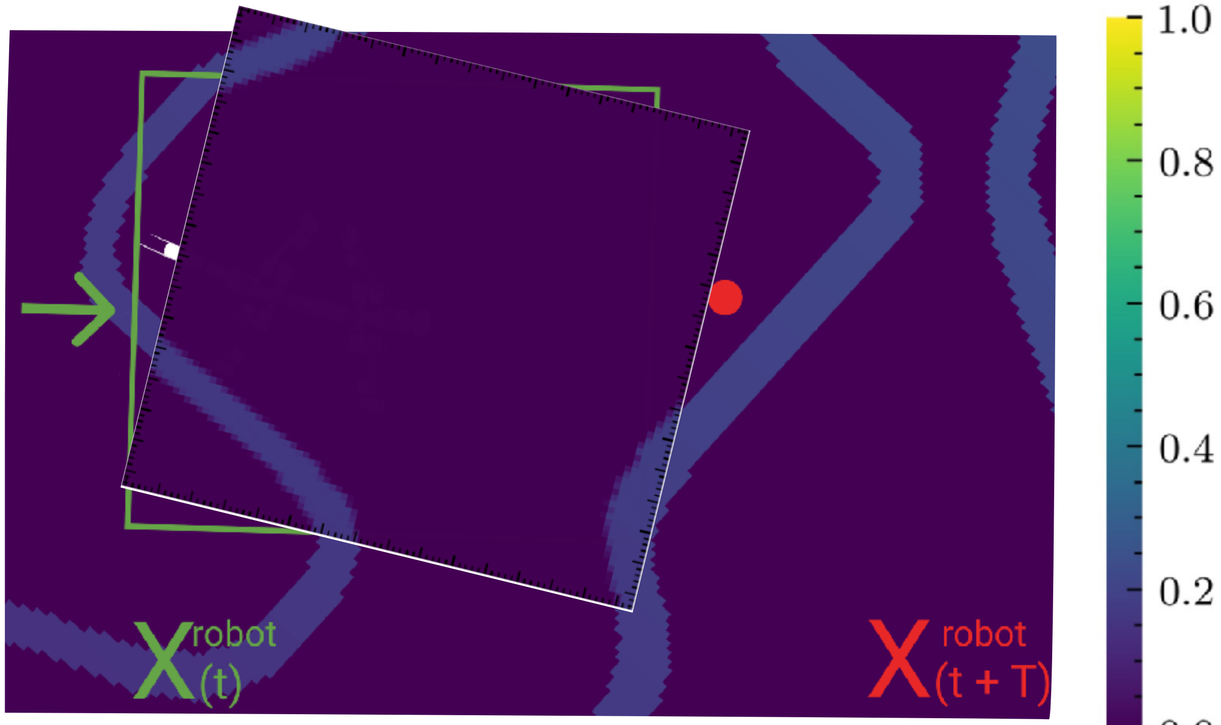


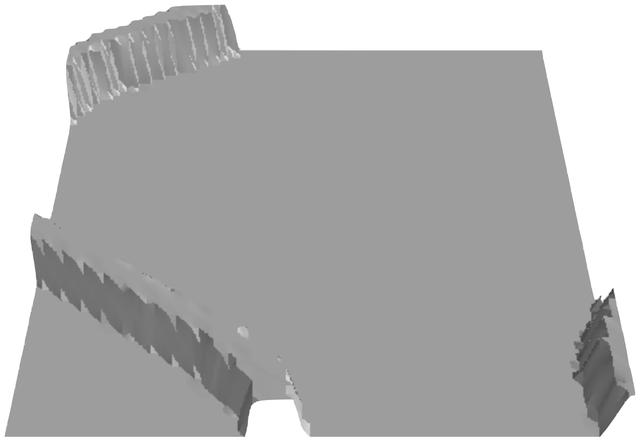
Zoom

2. Solution

Threshold = 20cm

Time window (T) = 2s



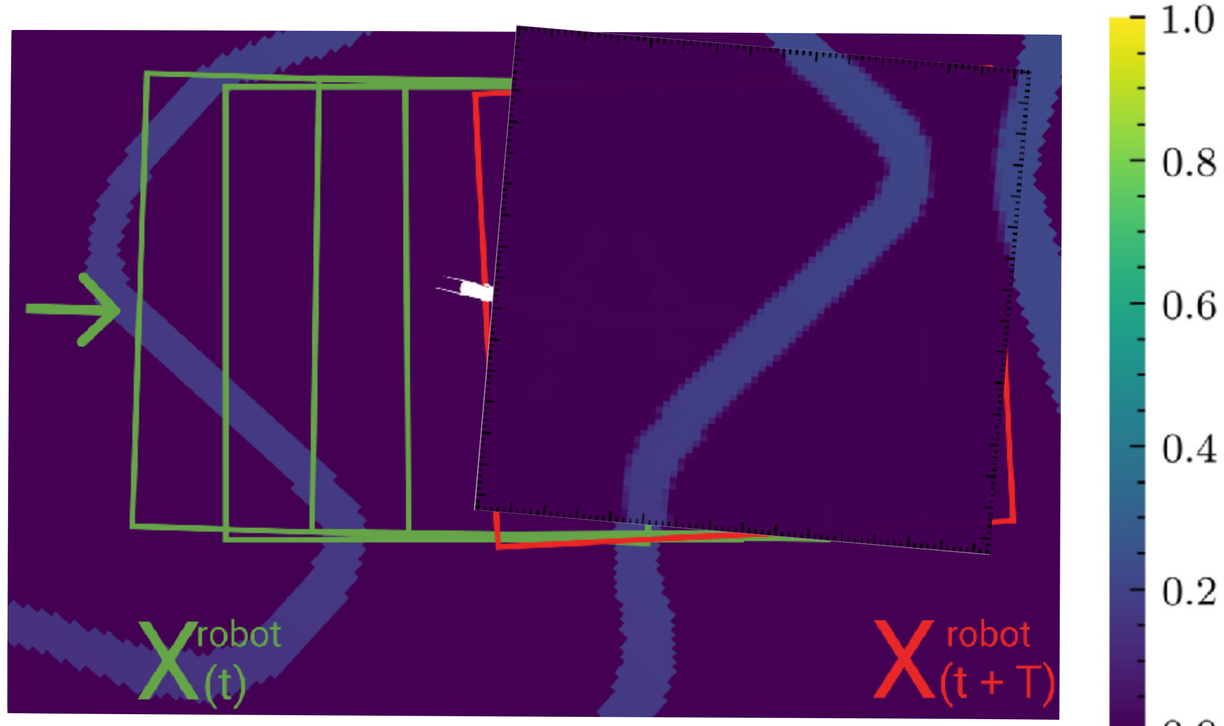


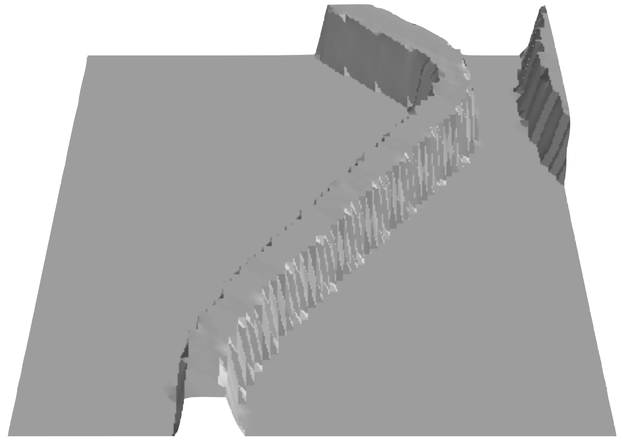
Advancement = 67cm

2. Solution

Threshold = 20cm

Time window (T) = 2s

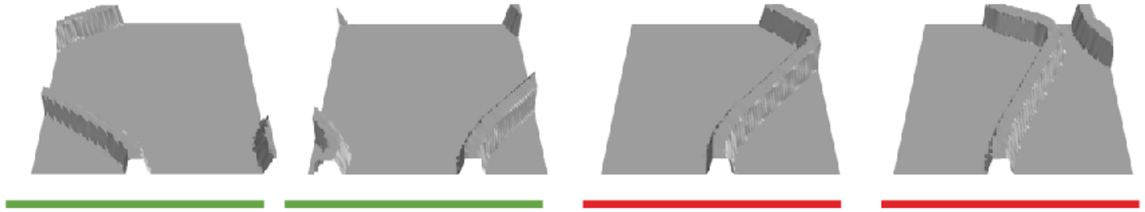


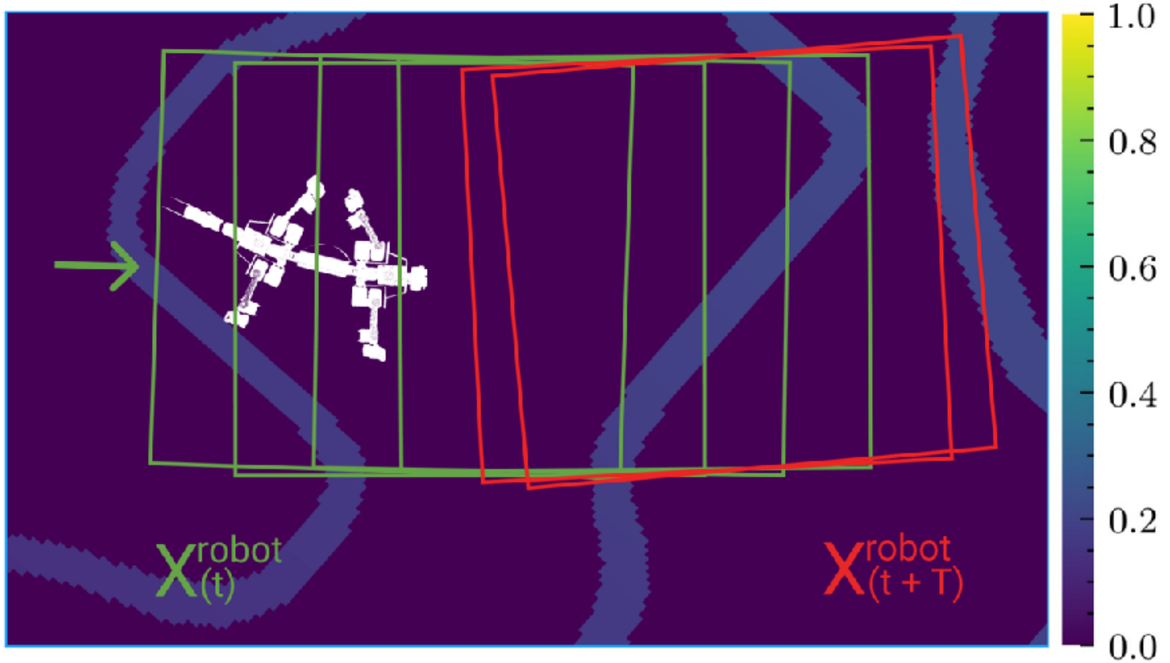


Advancement = 0.02cm

2. Solution

Dataset generation





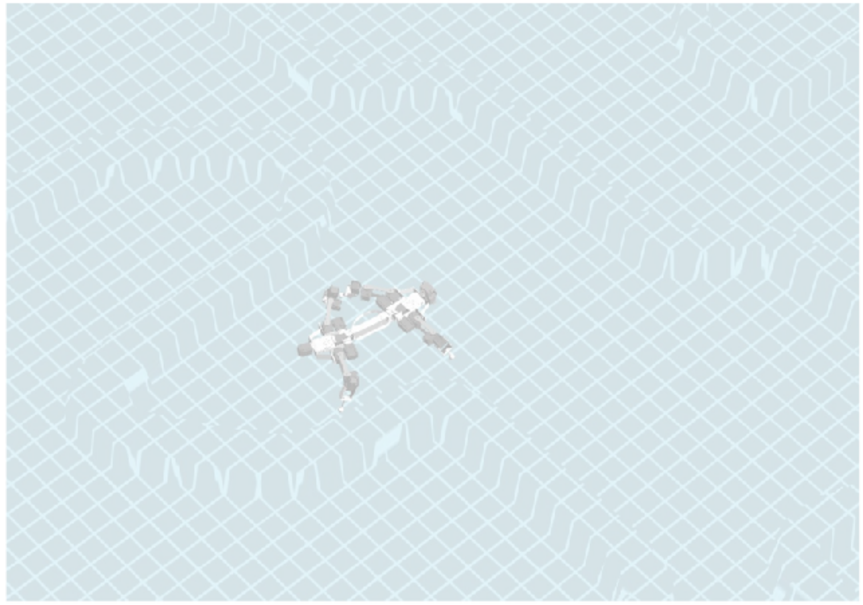
1660 simulations

5 hours of simulation

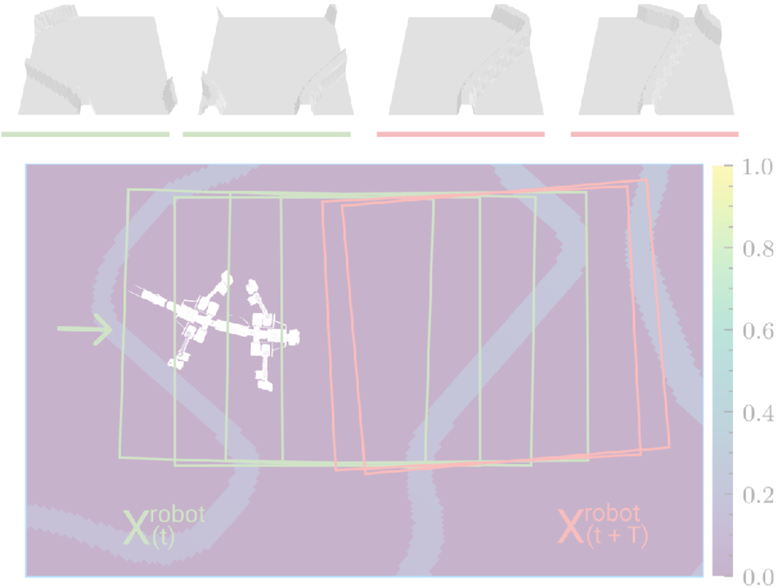
470k patches

2. Solution

1. Ground generation

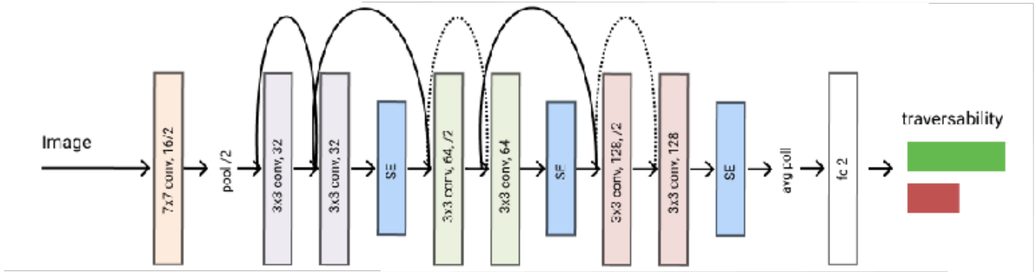


2. Simulation



3. Dataset generation

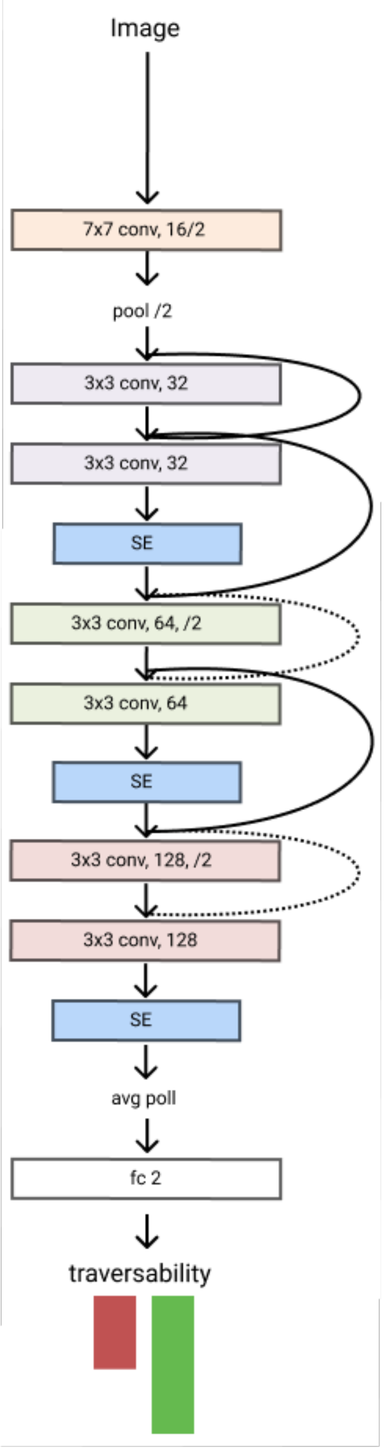
4. Estimation



2. Solution

Convolutional neural network (CNN)

- Ground patches as inputs
- Learn directly on raw data
- Outputs traversability probabilities



2. Solution

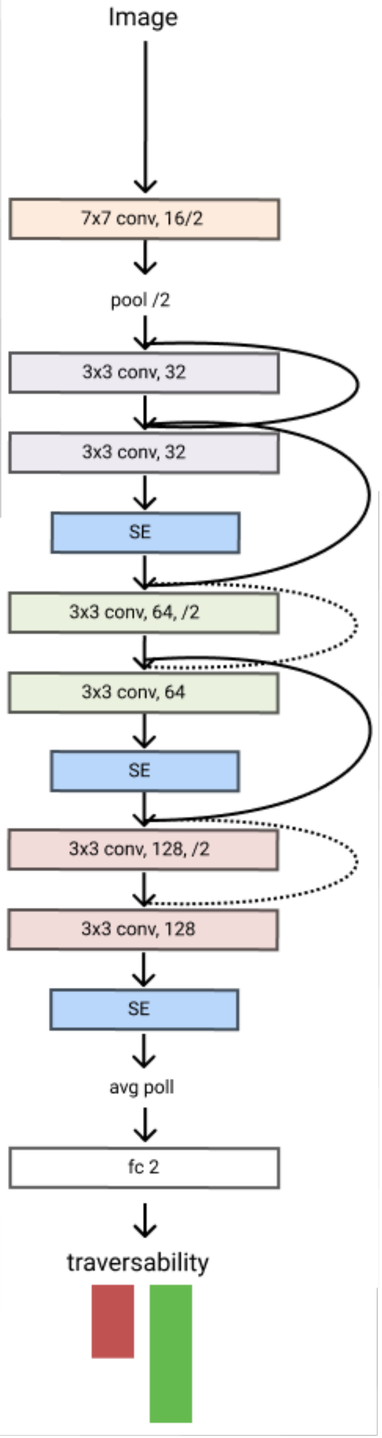
Convolutional neural network (CNN)

Novel architecture

Based on recent researches on residual networks [2],[3],[4],[5]

1/3 smaller than the original CNN

Trained in 10m on GPU



[2] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition, 2015.

[3] K. He, X. Zhang, S. Ren, and J. Sun. Identity mappings in deep residual networks, 2016.

[4] S.Ioffeand and C.Szegedy Batchnormalization 2015.

[5] J. Hu, L. Shen, S. Albanie, G. Sun, and E. Wu. Squeeze-and-excitation networks, 2017.

3.
Results

2.1 Results

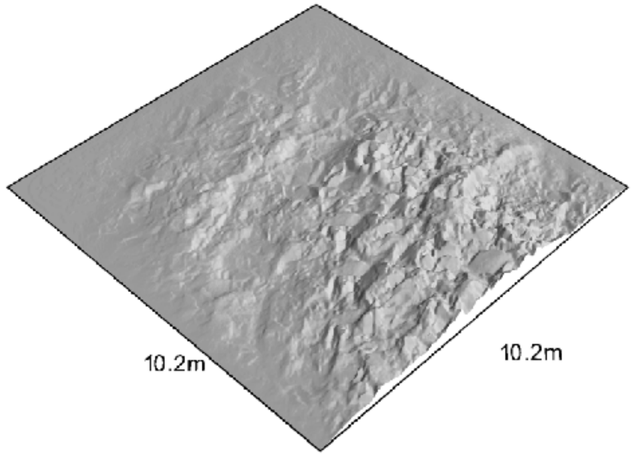
Quantitative evaluation

Good performance

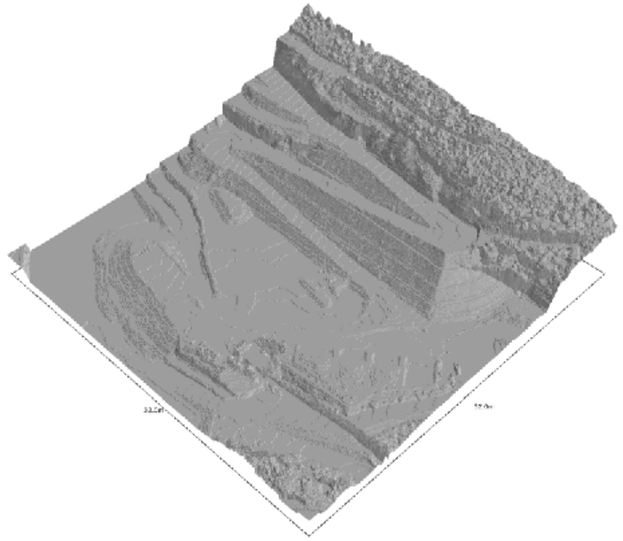
Numbers are hard to understand

Dataset			MicroResNet7x7-SE		Size(m)	Resolution(cm/px)
Type	Name	Samples	ACC	AUC		
Synthetic	Training	429312	-	-	10×10	2
	Validation	44032	95.2 %	0.961	10×10	2
	Arc Rocks	37273	85.5 %	0.888	10×10	2
Real evaluation	Quarry	36224	88.2 %	0.896	32×32	2

Table 5.2. Classification results of MicroResNet7x7-SE on different datasets.



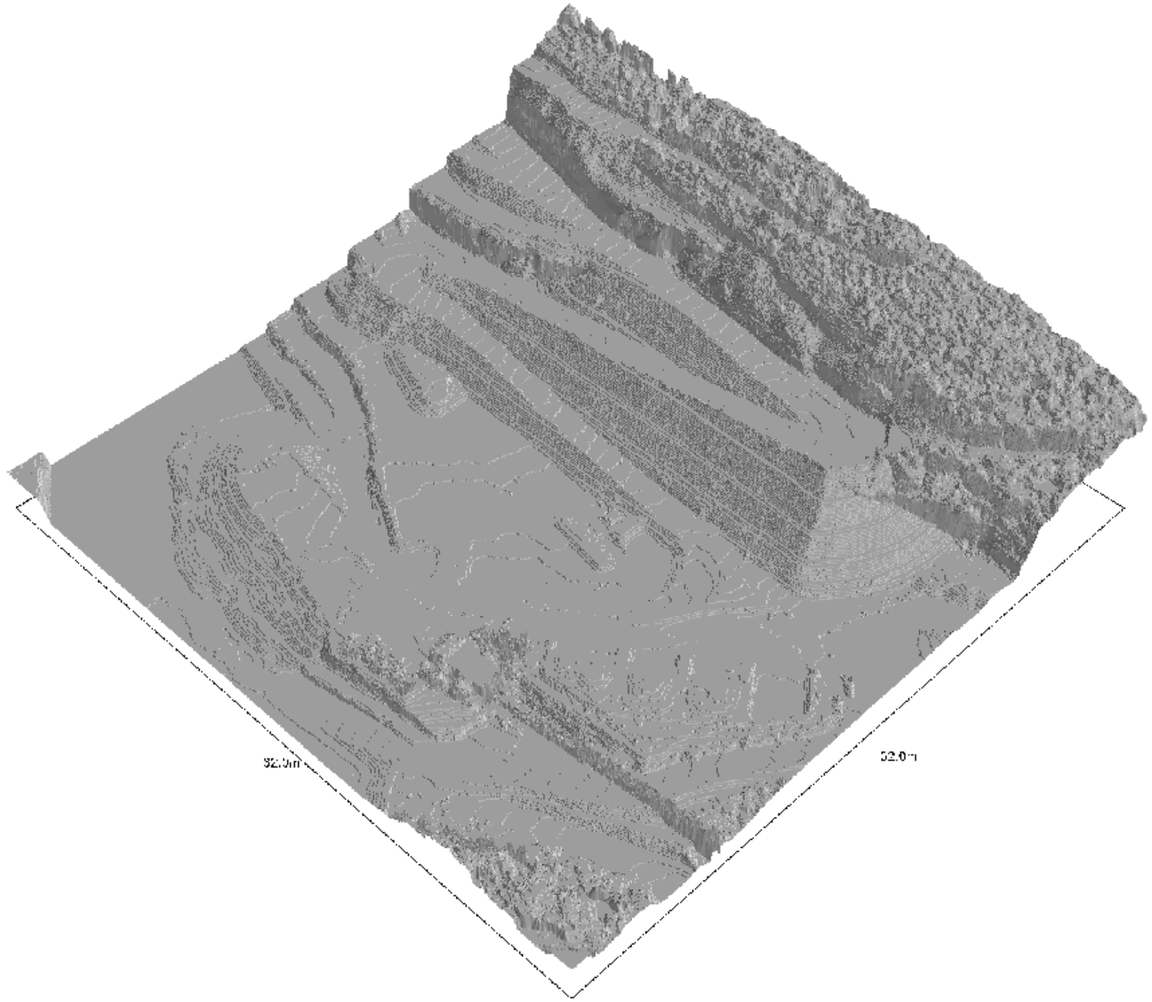
arc rocks



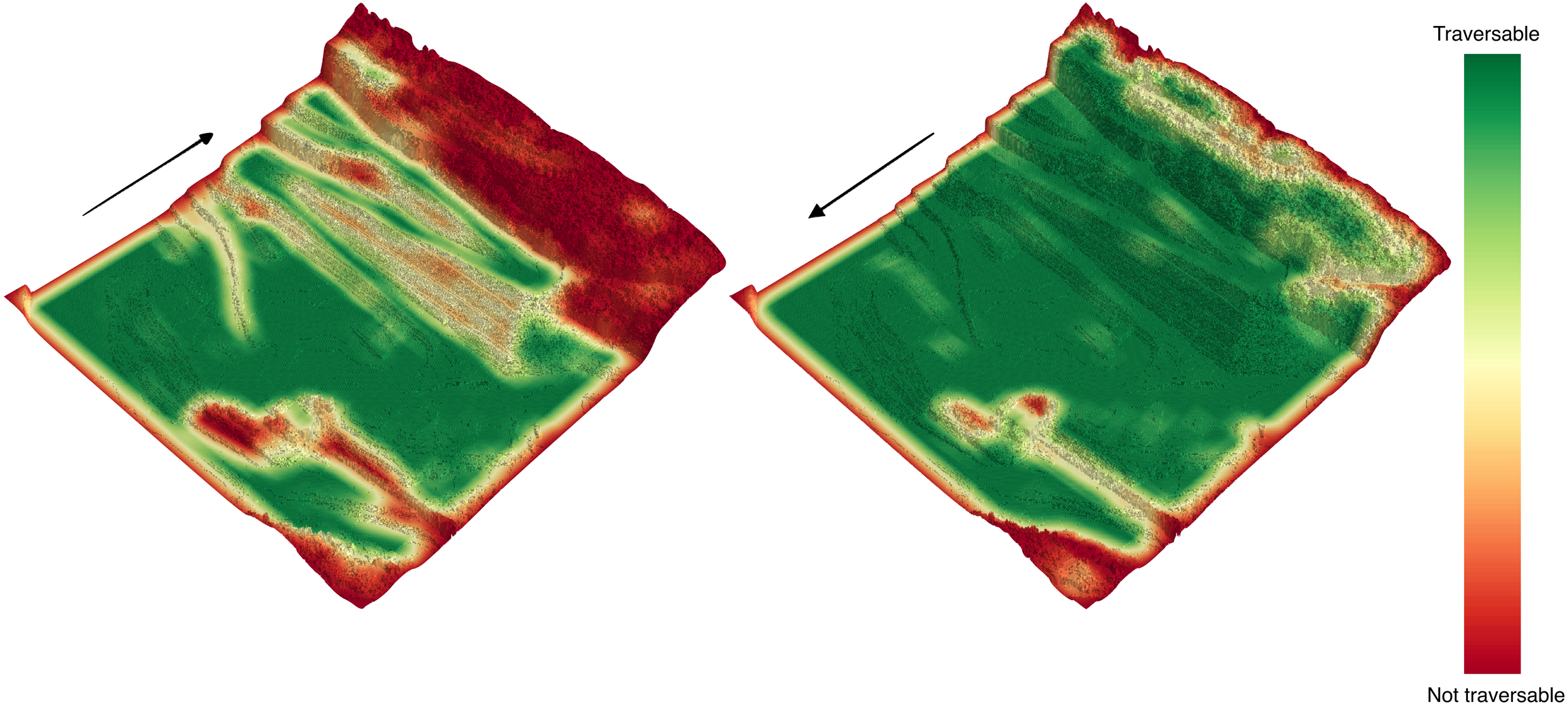
quarry

2.1 Results

Qualitative evaluation

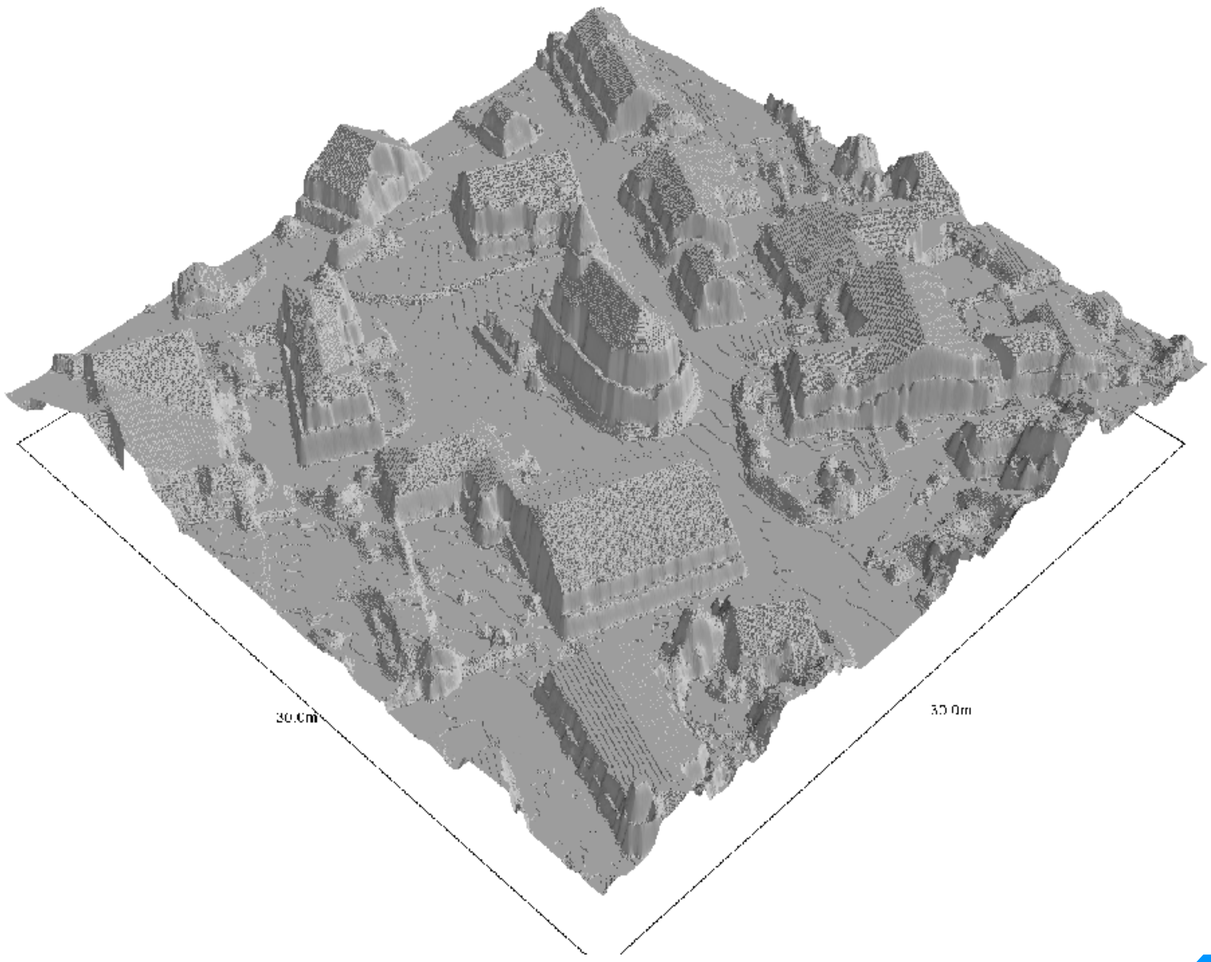


2.1 Results

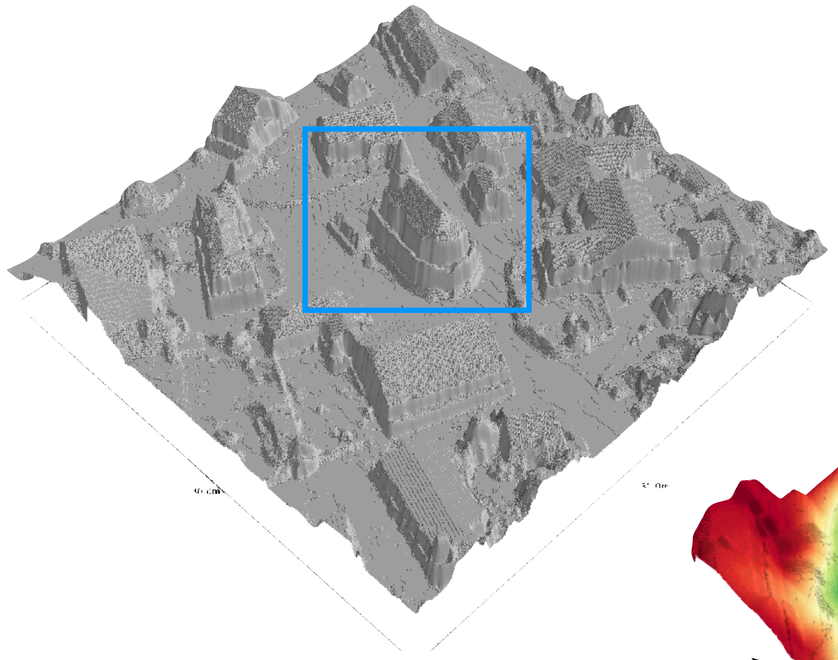


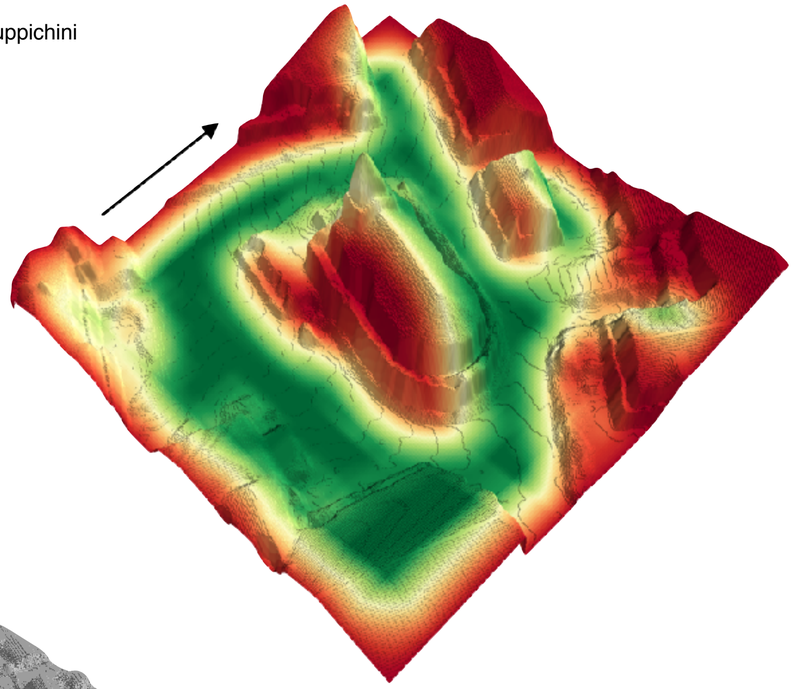
2.1 Results

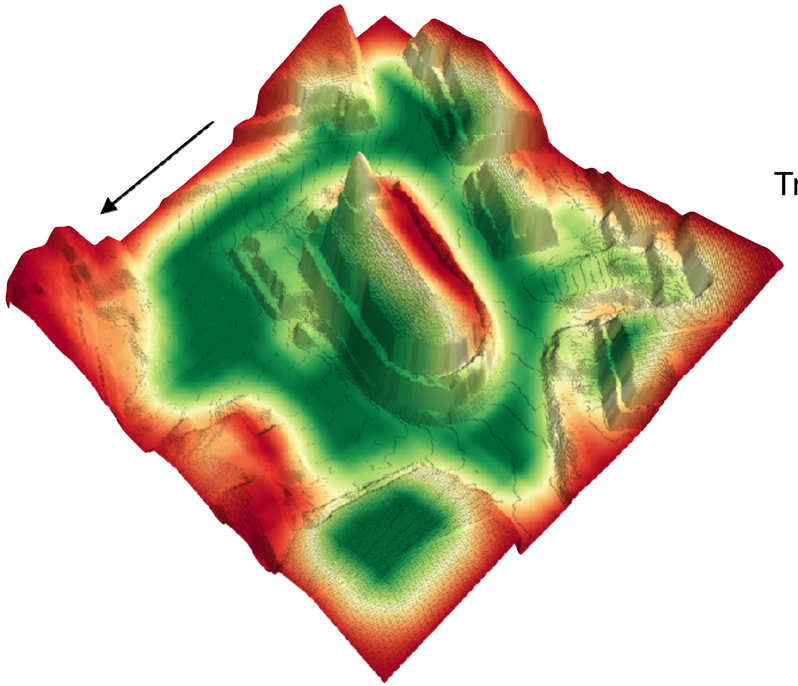
A small village

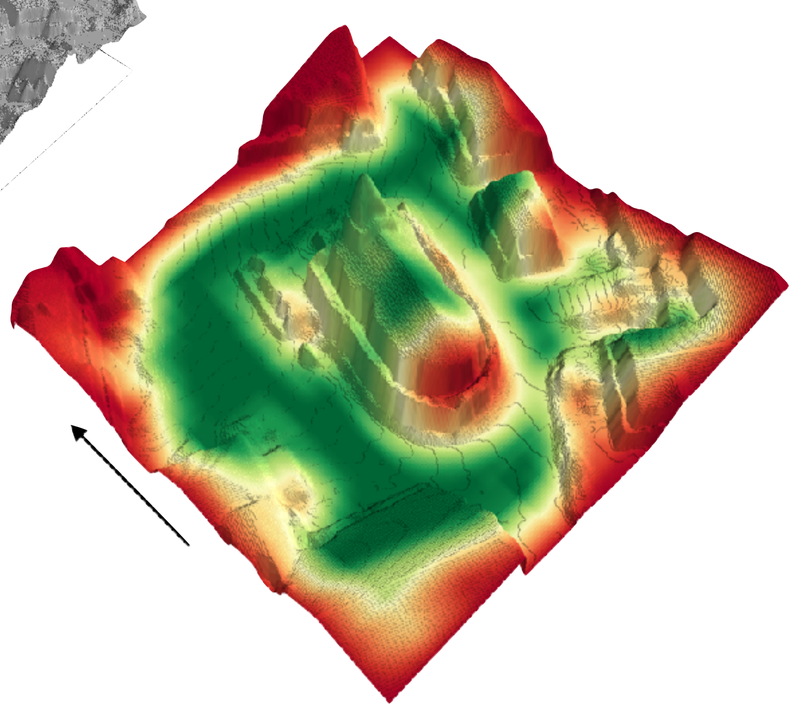


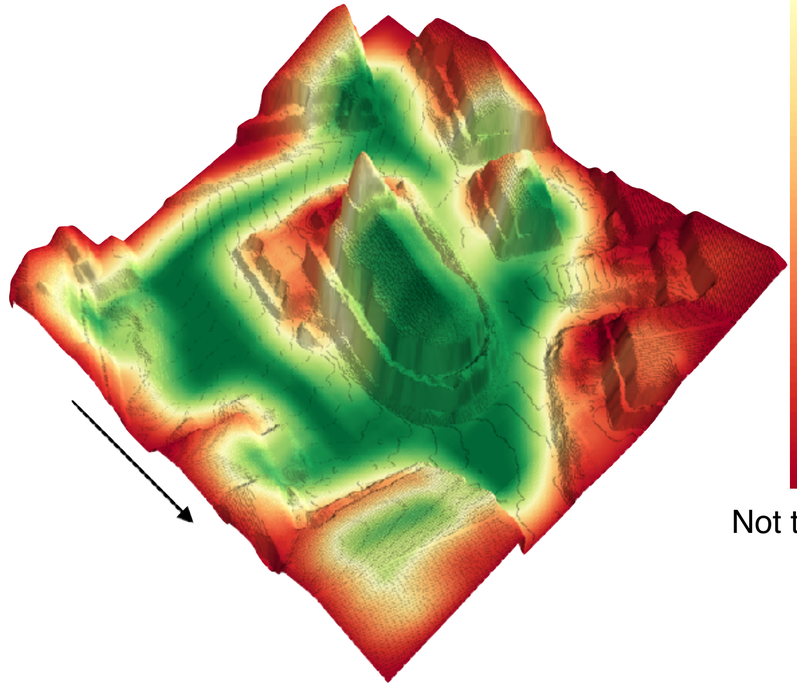
2.1 Results











4.
Understand the results

2. Solution

Interpretability

How can we understand what the estimator learned?

What is the most traversable ground?

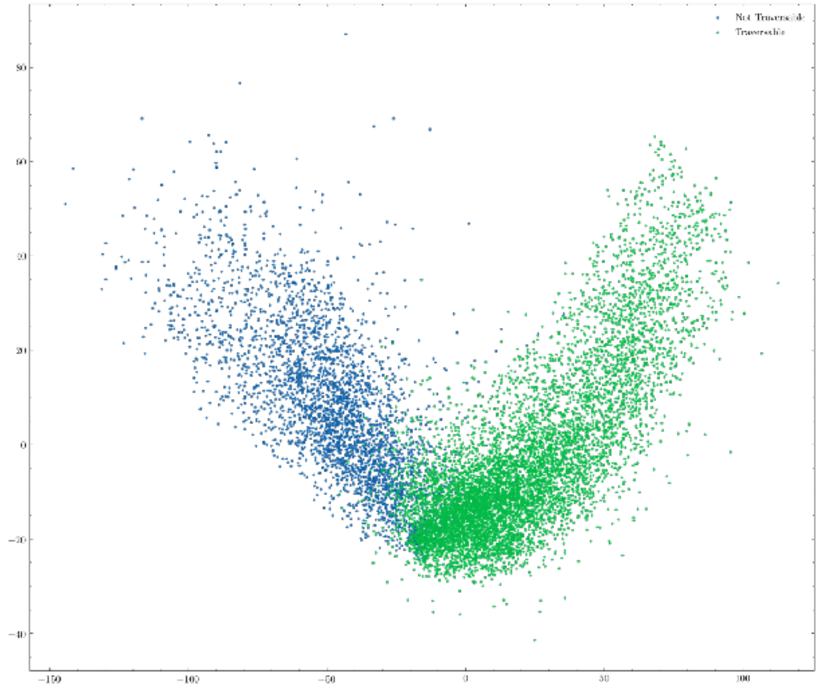
Where is the model looking?

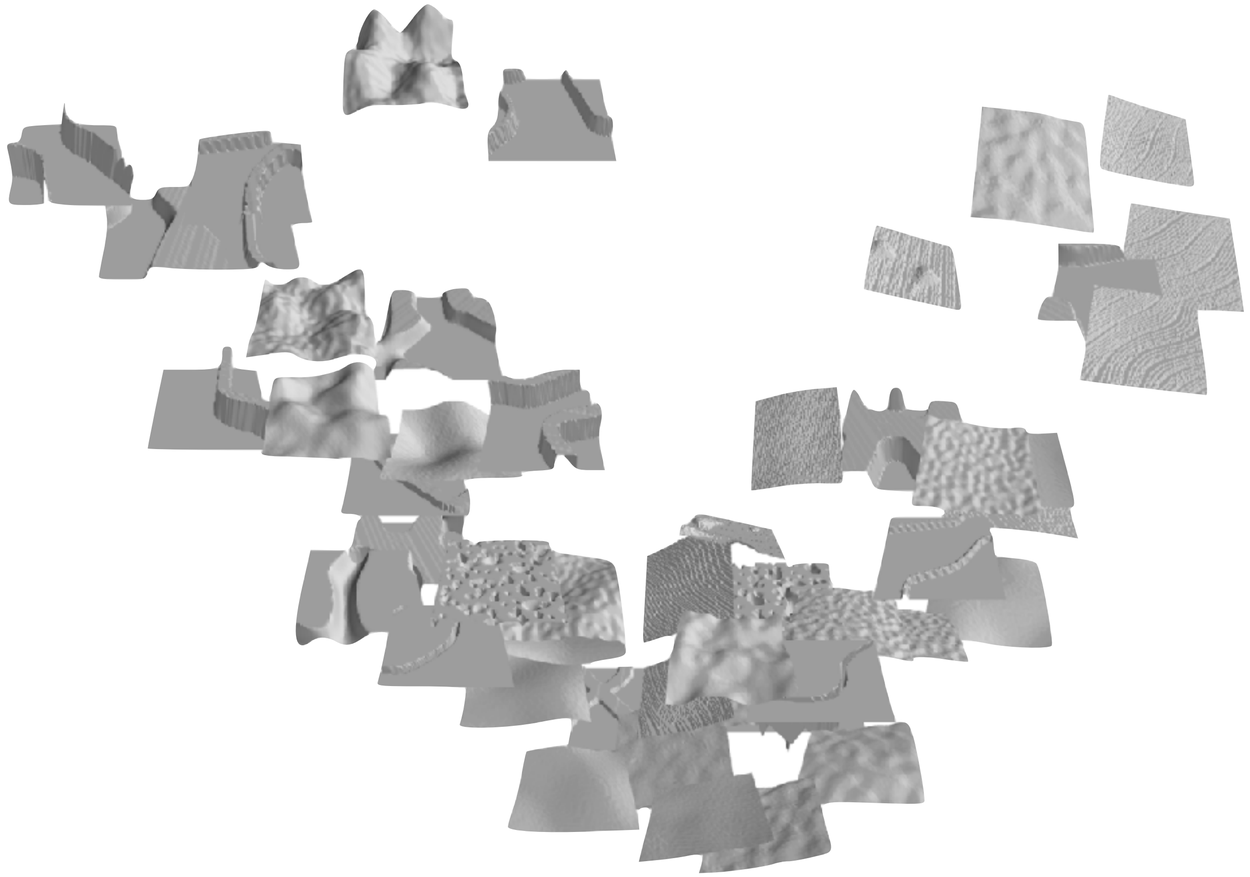
Are there any terrains that fool the model?

Are the outputs consistent?

2.1 Understand the results

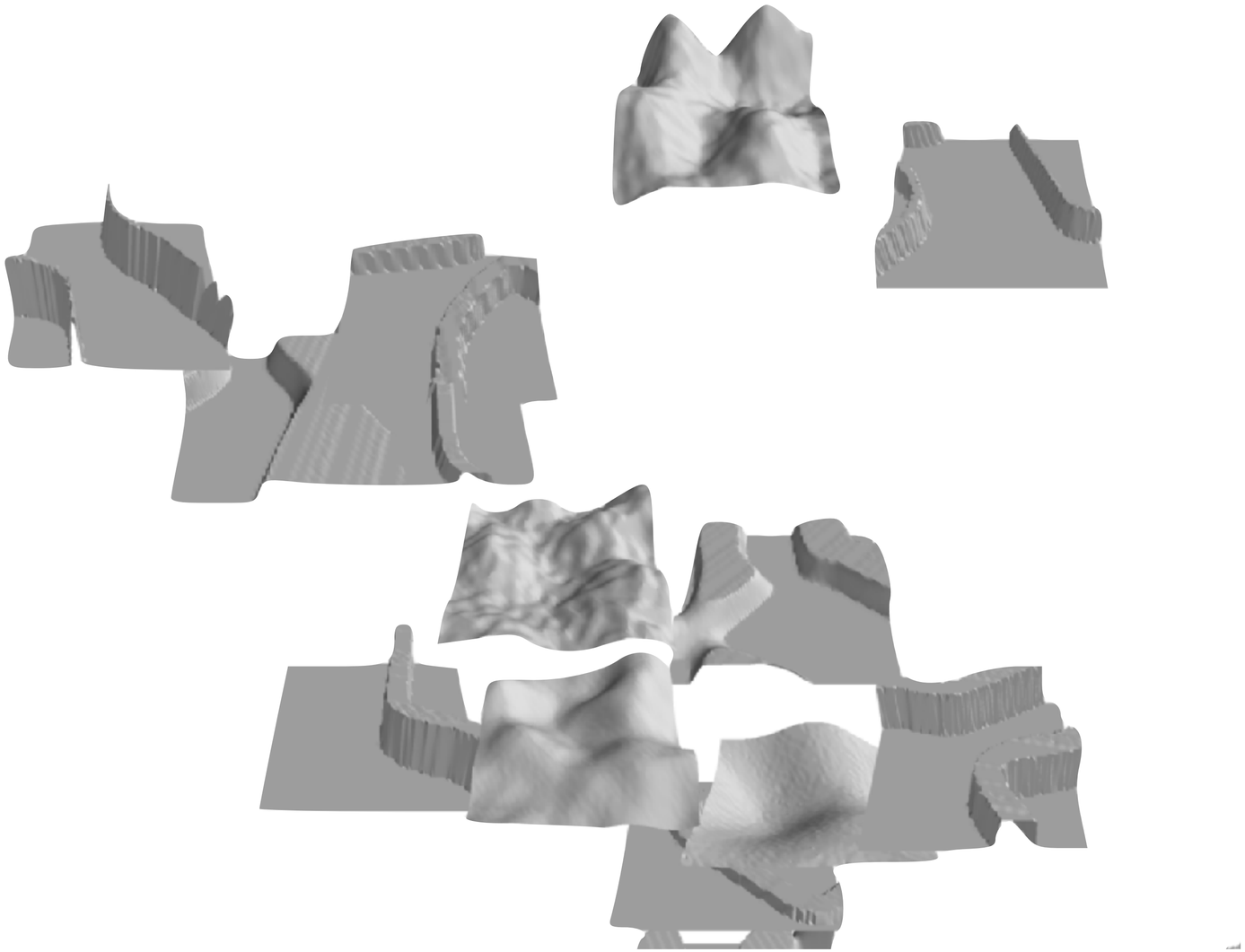
Separability





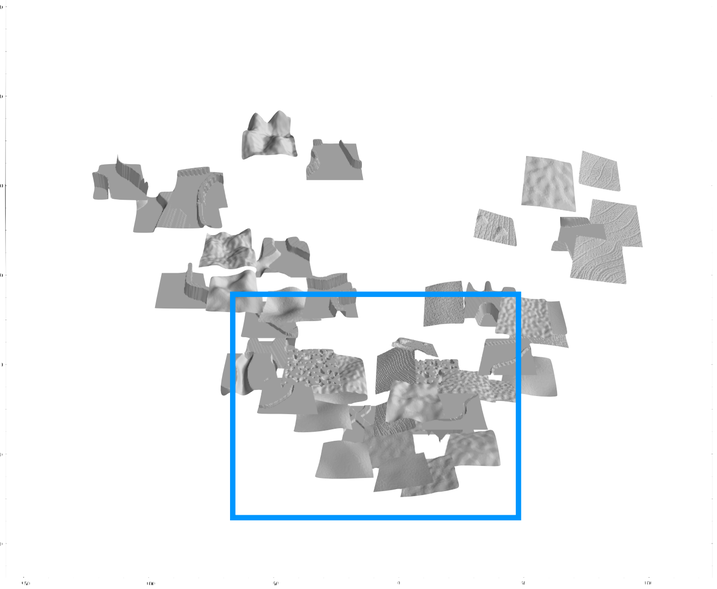
2.1 Understand the results

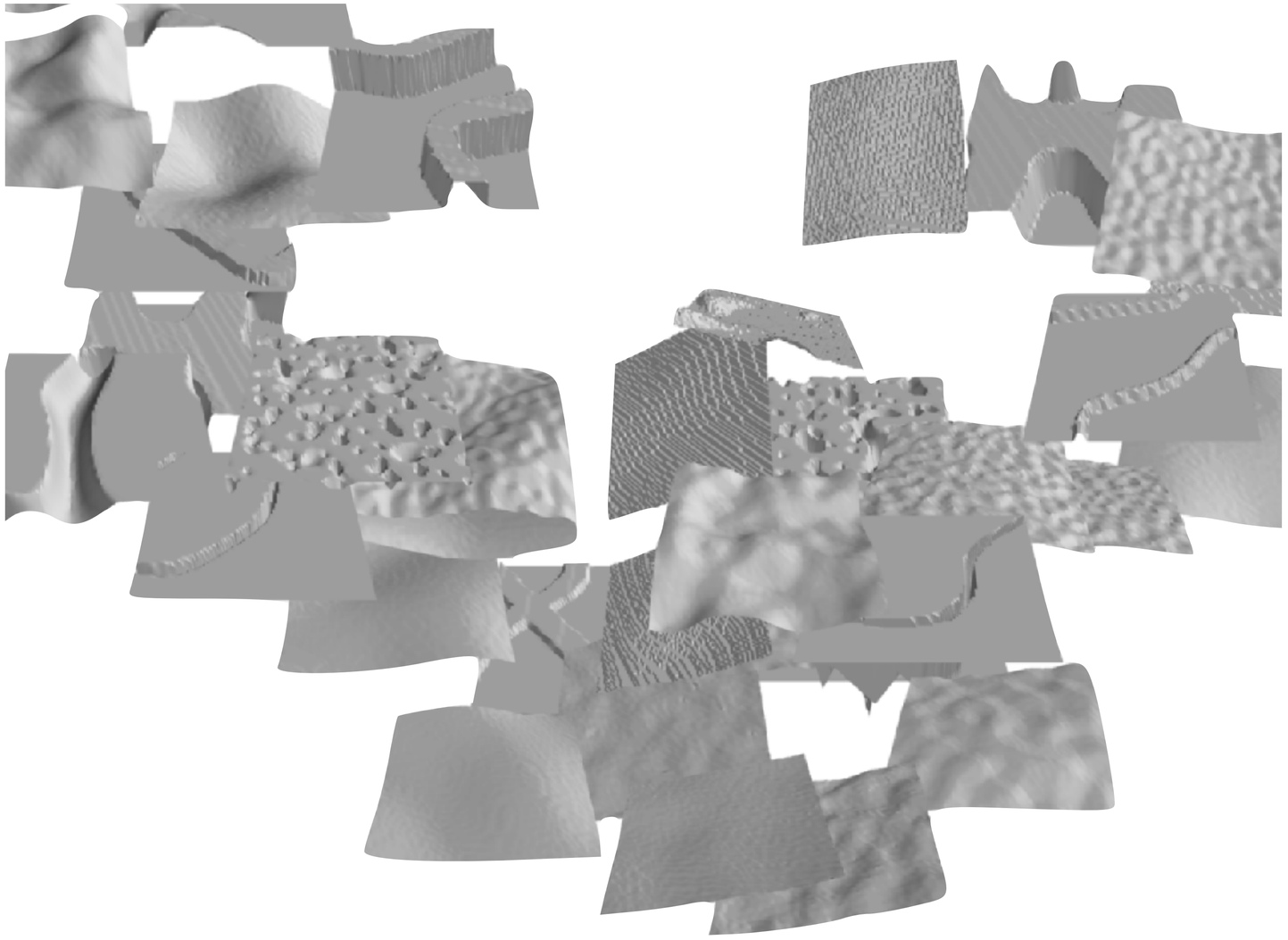
Separability



2.1 Understand the results

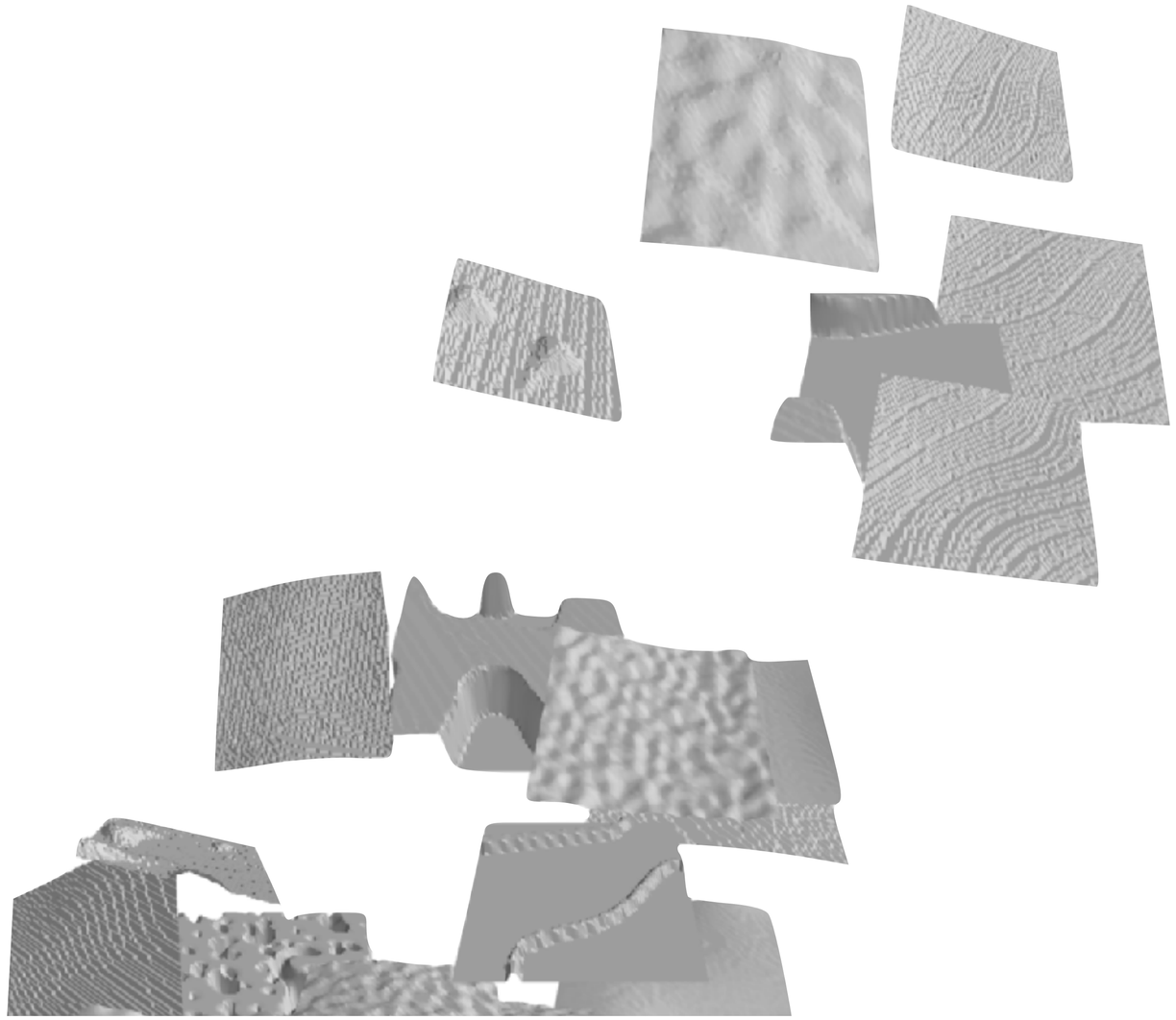
Separability





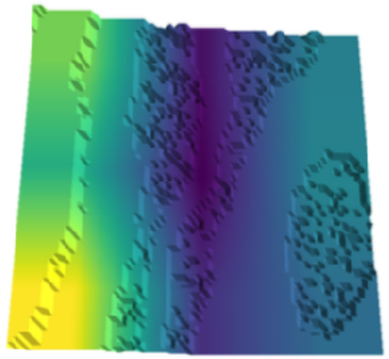
2.1 Understand the results

Separability

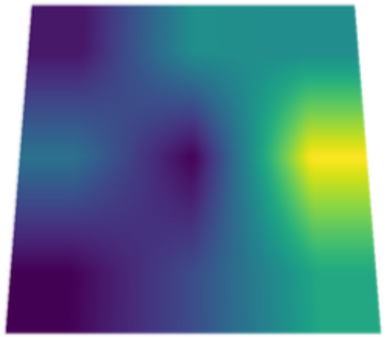


2.1 Understand the results

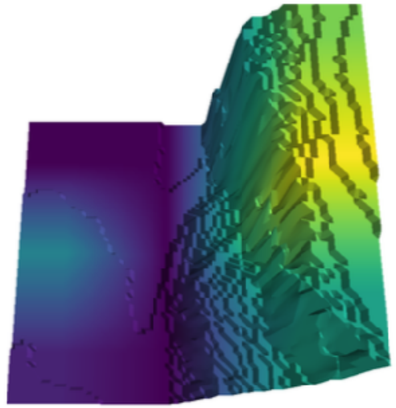
Is the model looking in the right spot?



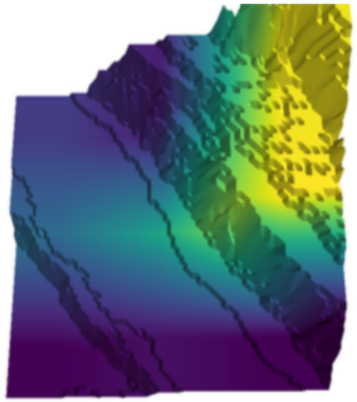
(r) 0.67cm



(h) 0.47cm



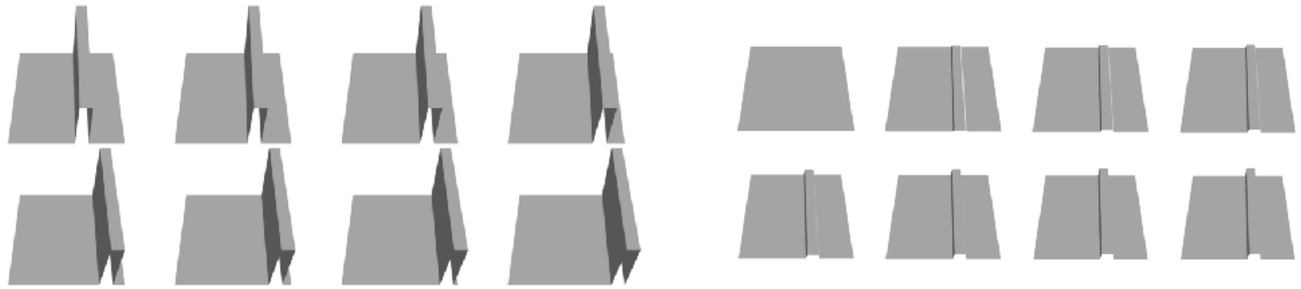
(c) -0.05cm



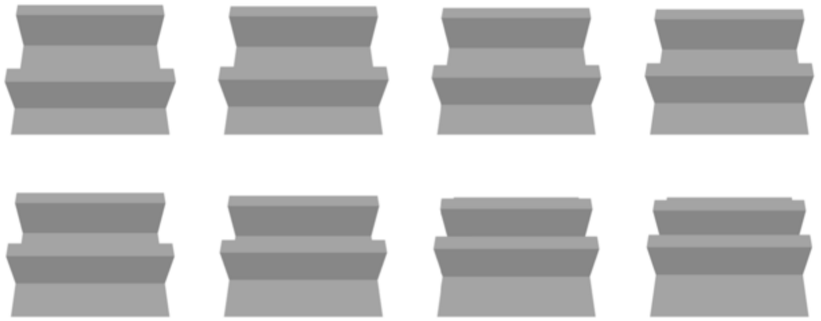
(s) 0.46cm

2.1 Understand the results

Robustness

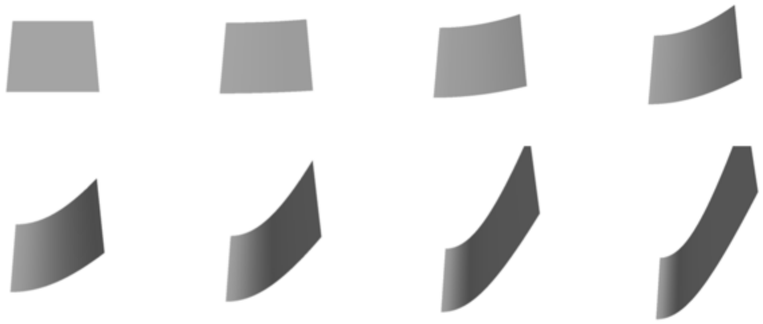


Tested on walls, corridors and ramps



The models is confused by corridors

- Lack of examples in the training set
- Easily fixable by generating new ground with corridors



5.
Conclusion

2. Solution

Contributions

Novel implementation of the framework

New architecture

Deep interpretation of the results

We understood the model capabilities and the limitations

2. Solution

What I have learned?

Data is everything

Organize experiments

Deep interpretation of the results

2. Solution

Limitations

Current approach relies only on geometric informations

Performance depends on the quality of the data

We did not use all the robots informations

2. Solution

Future work

Additional inputs to the model, material and legs position

Thank you for your attention

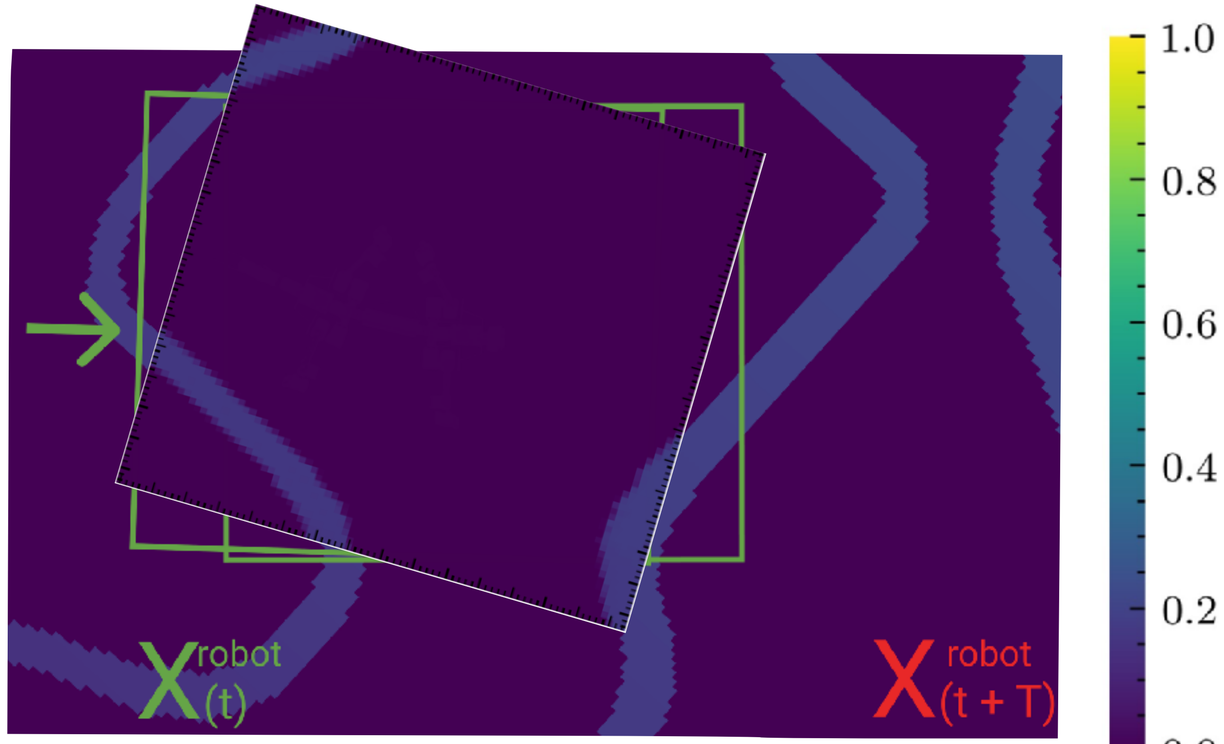
Thank to Professor Giusti and Omar.
To all the USI and Decanato staff.
To Dario, Mirko, Umberto and Alessia.
To my beloved parents.
To all my friends from Italy, Federico, Paolo, Giuseppe, Nicola.
Amazing open source community.

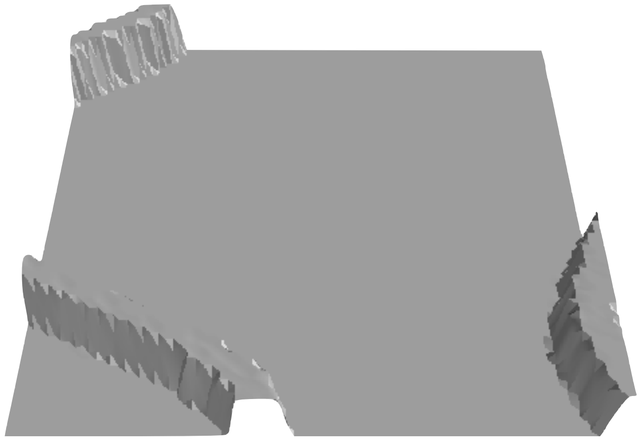
Francesco Saverio Zuppichini

2. Solution

Threshold = 20cm

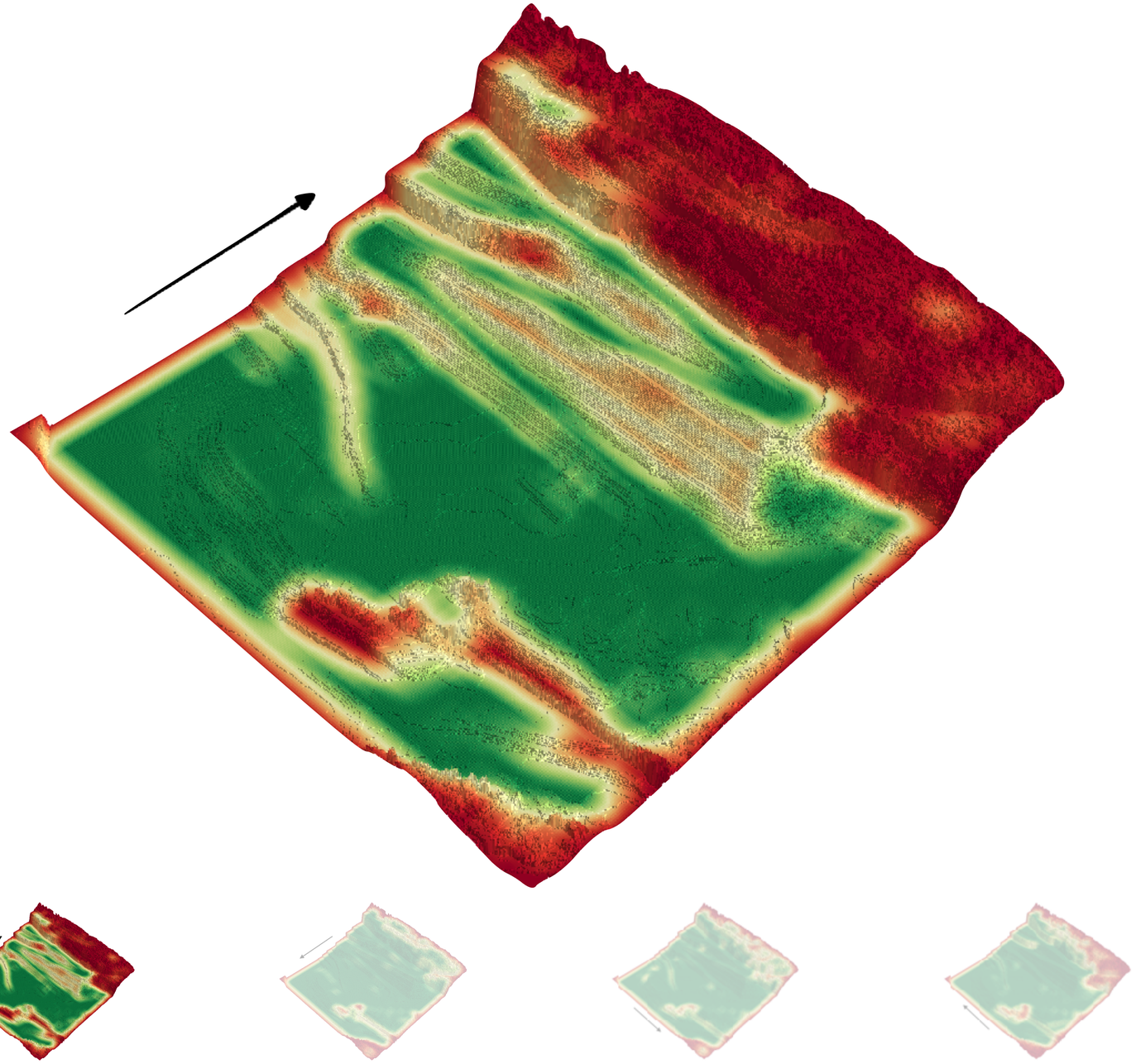
Time window = 2s



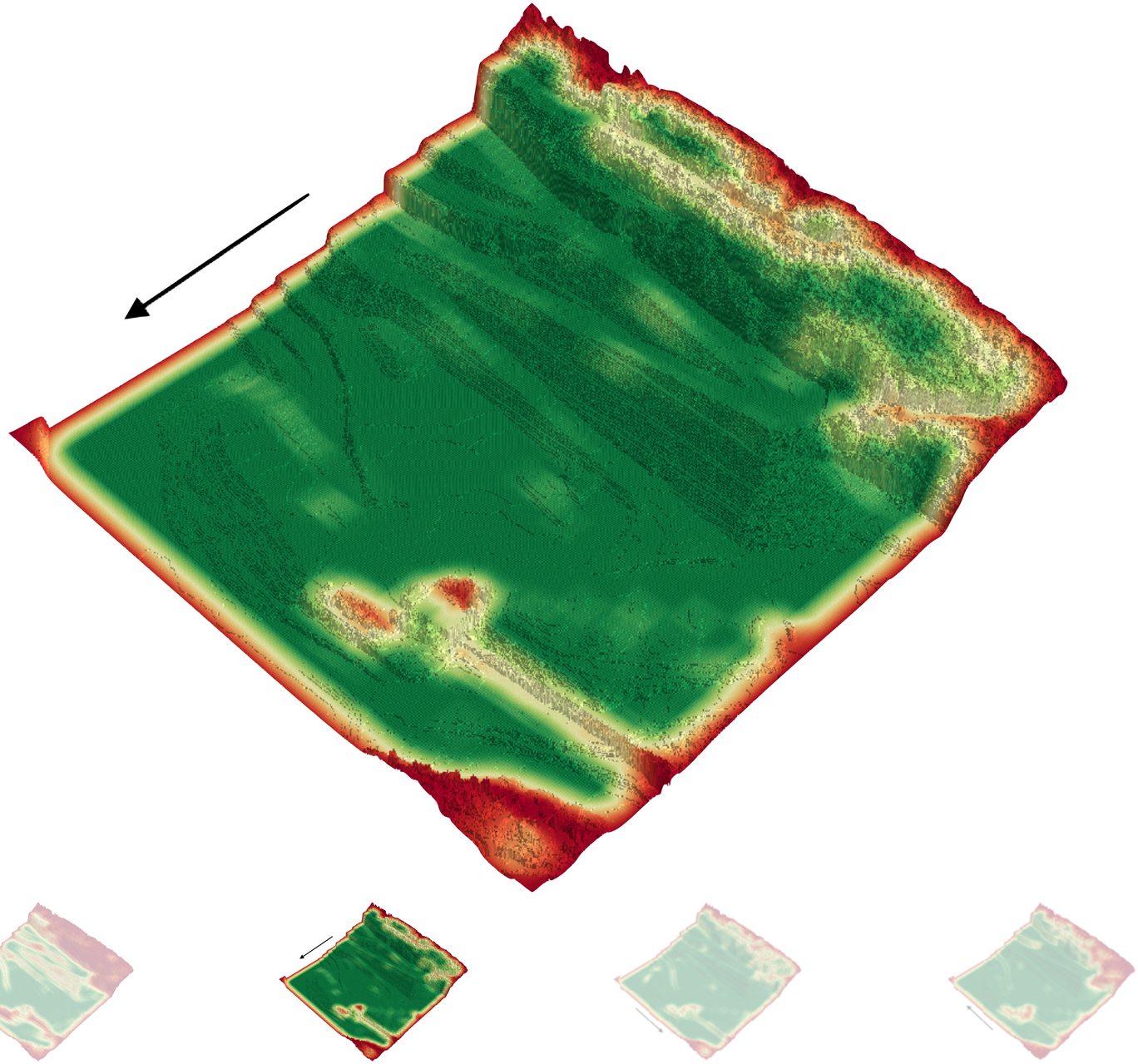


Advancement = 68cm

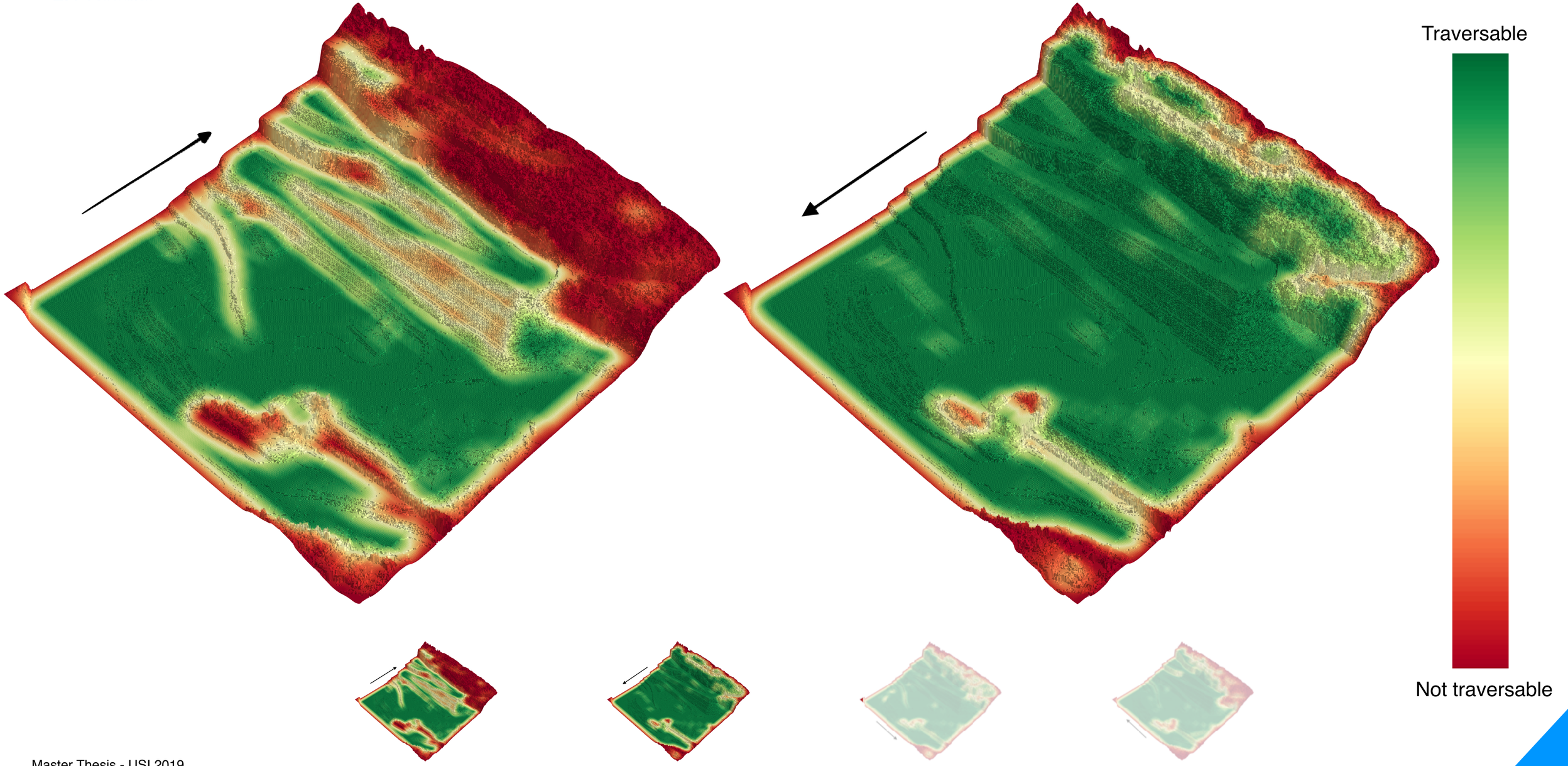
2.1 Results



2.1 Results



2.1 Results



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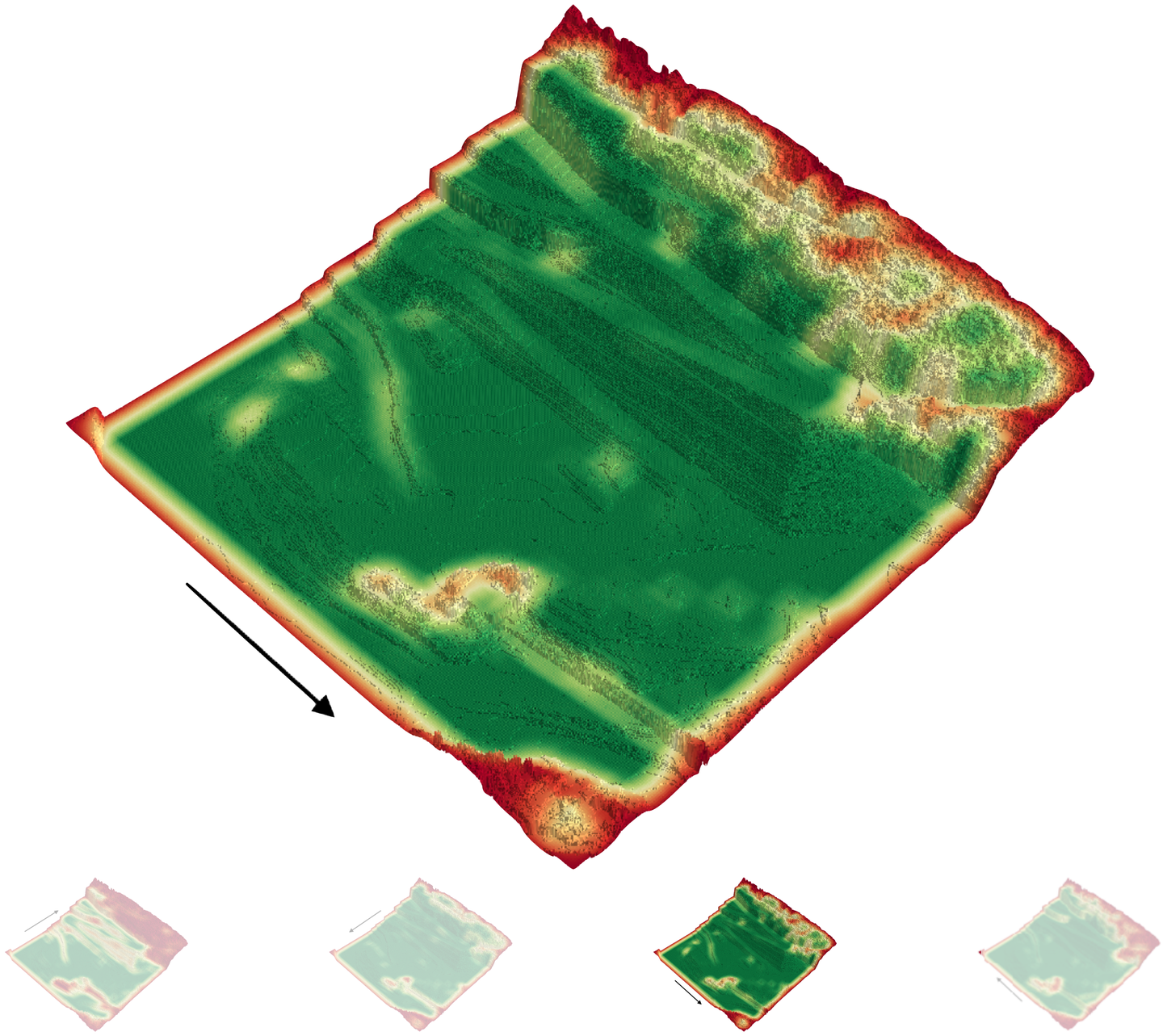
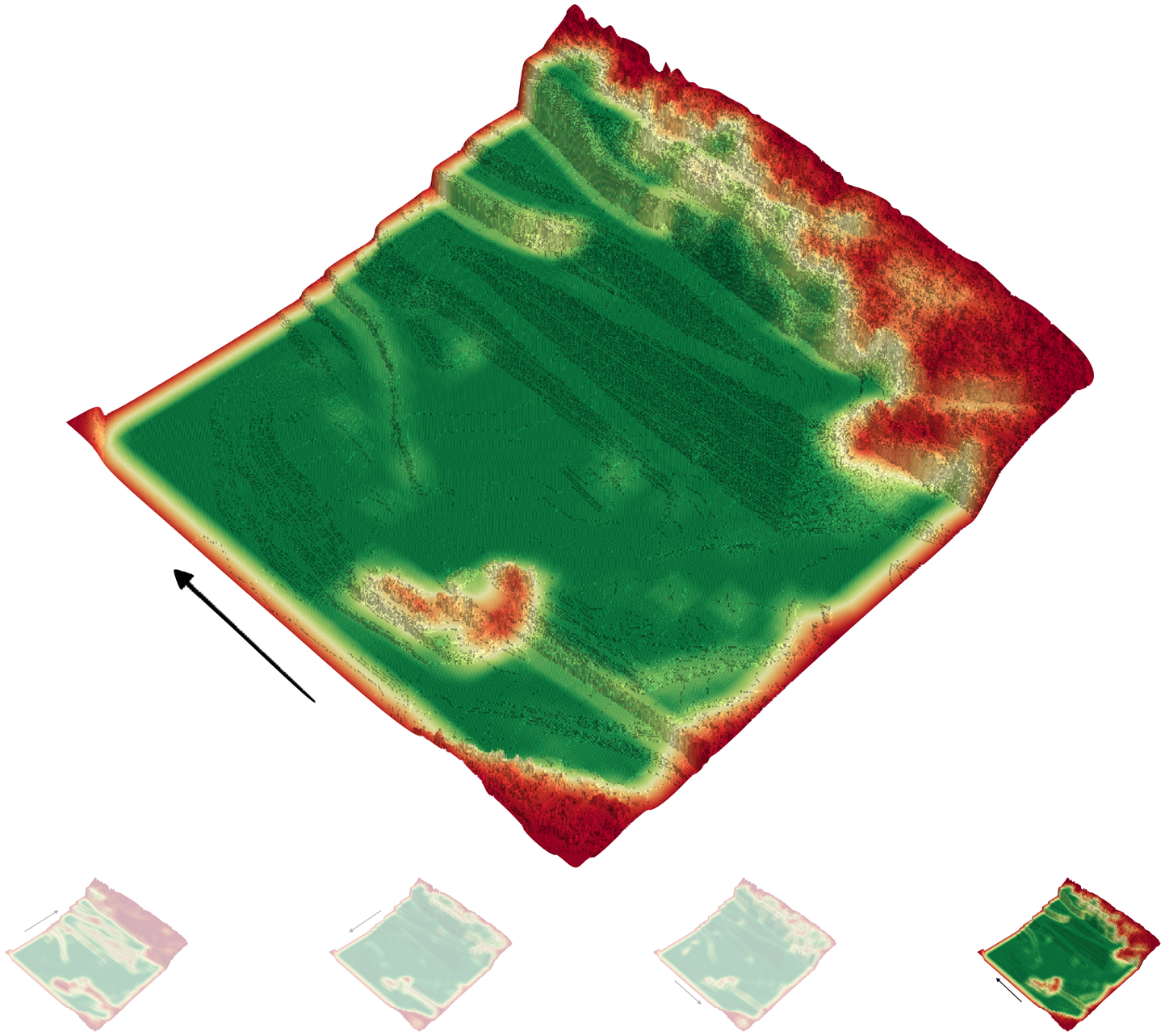
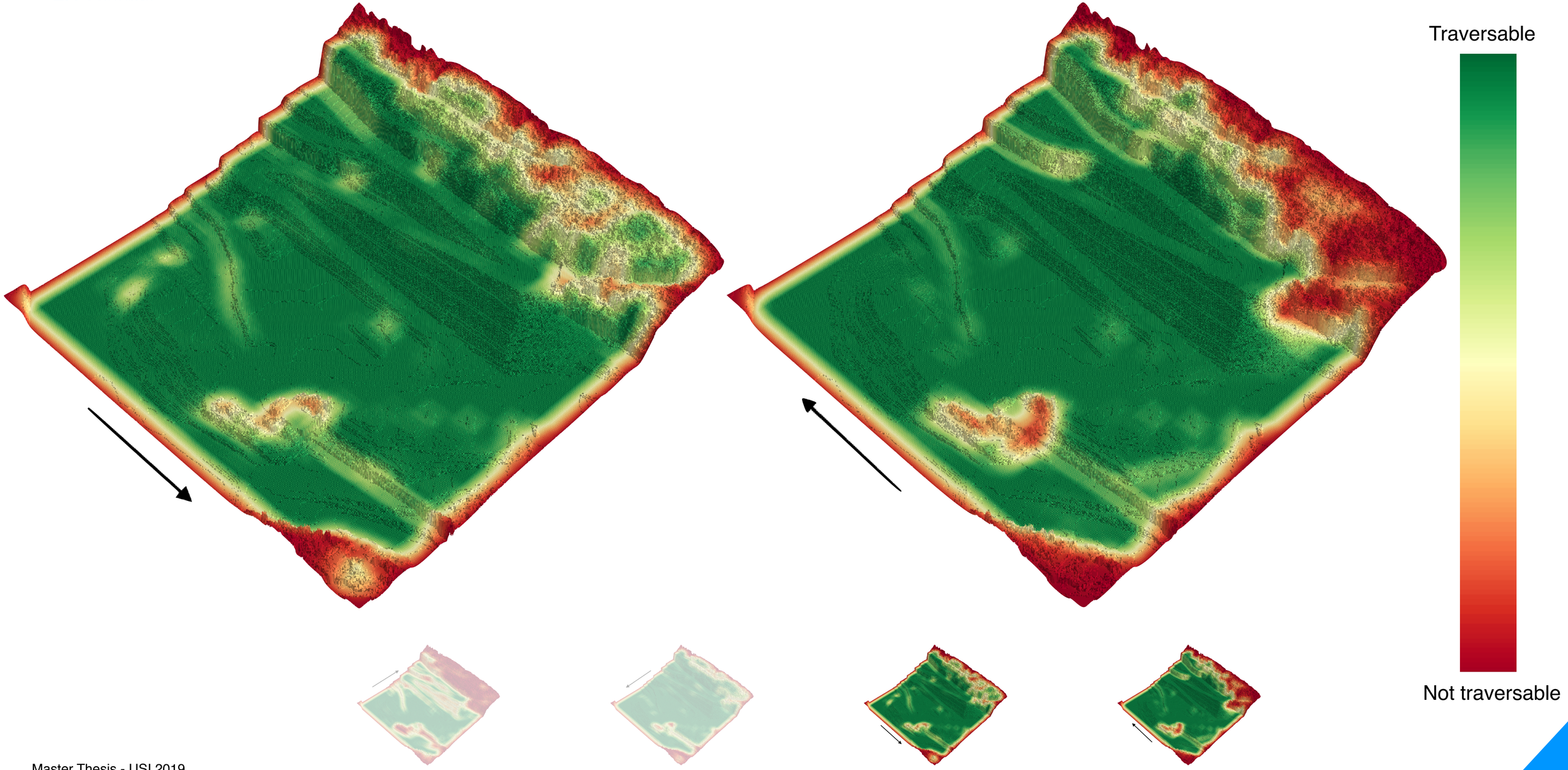


2.1 Results



2.1 Results



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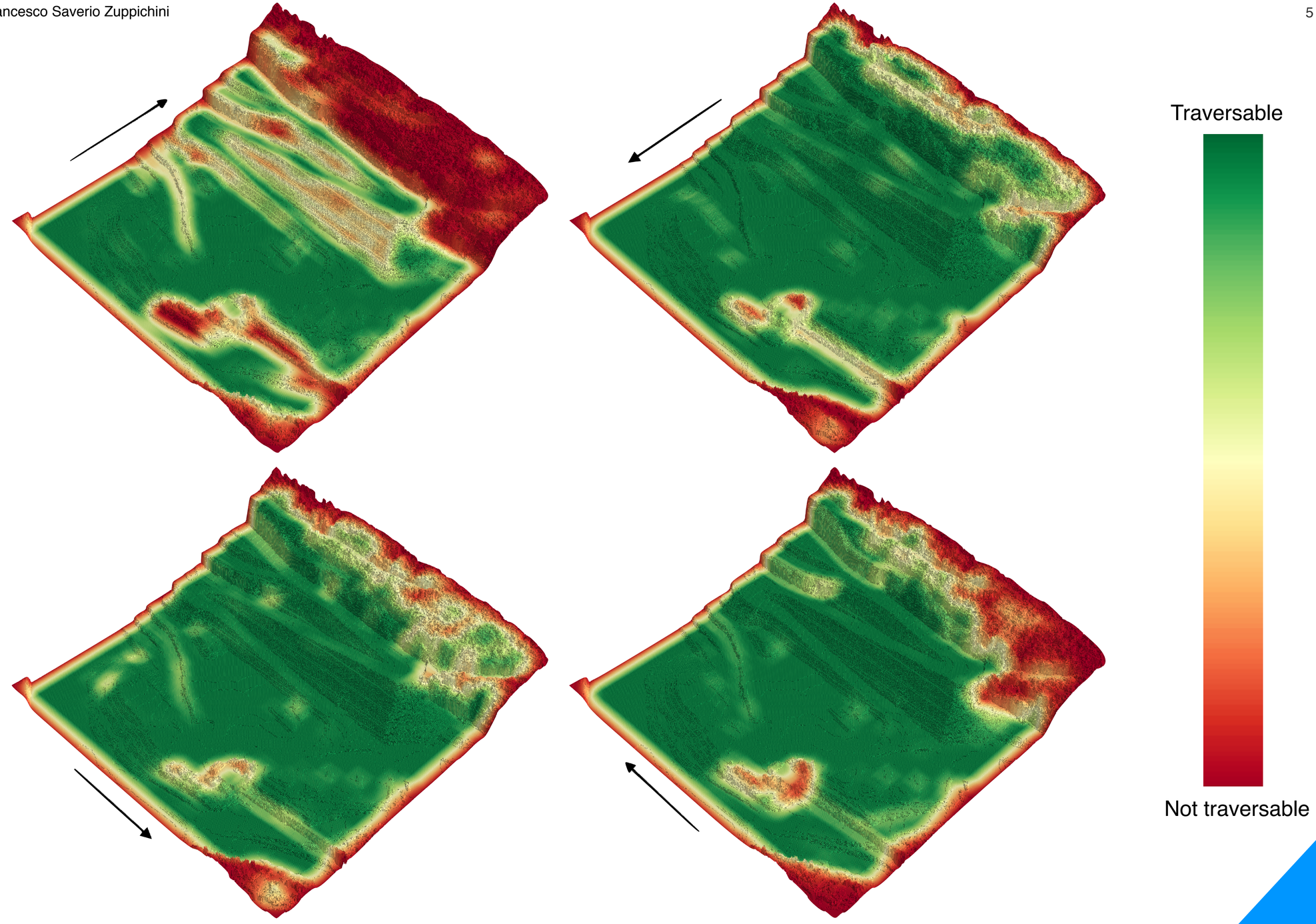
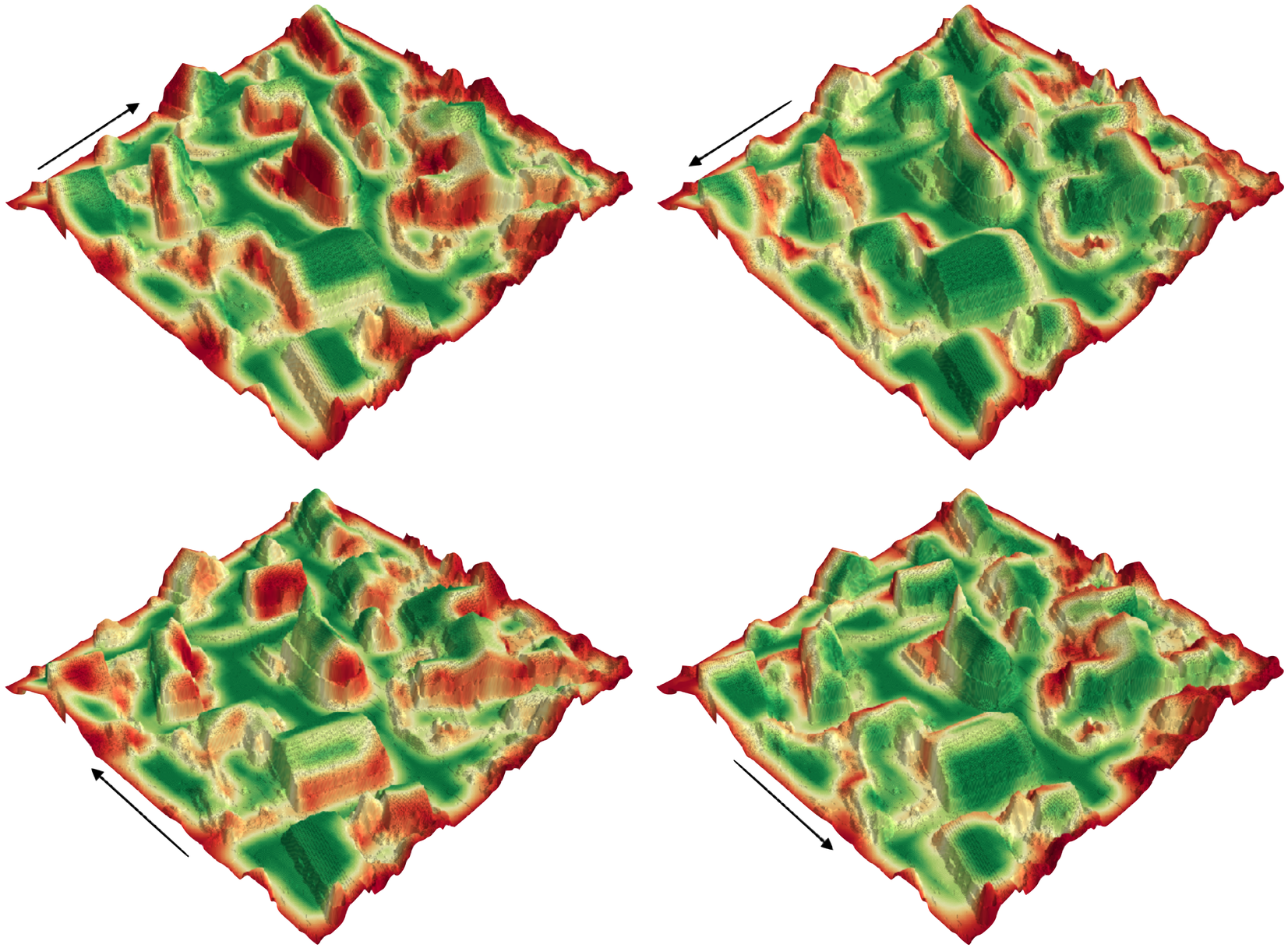
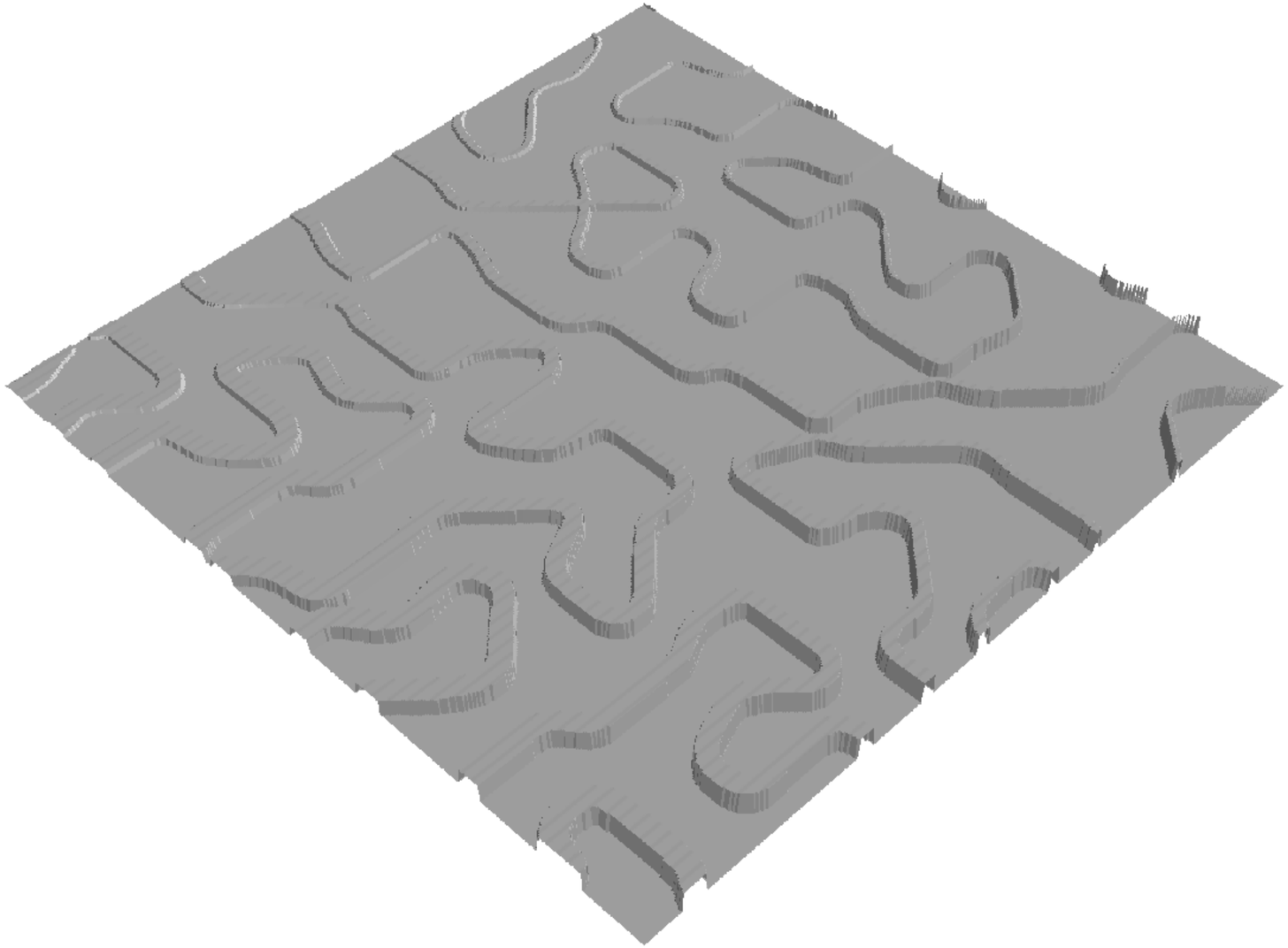


2.1 Results

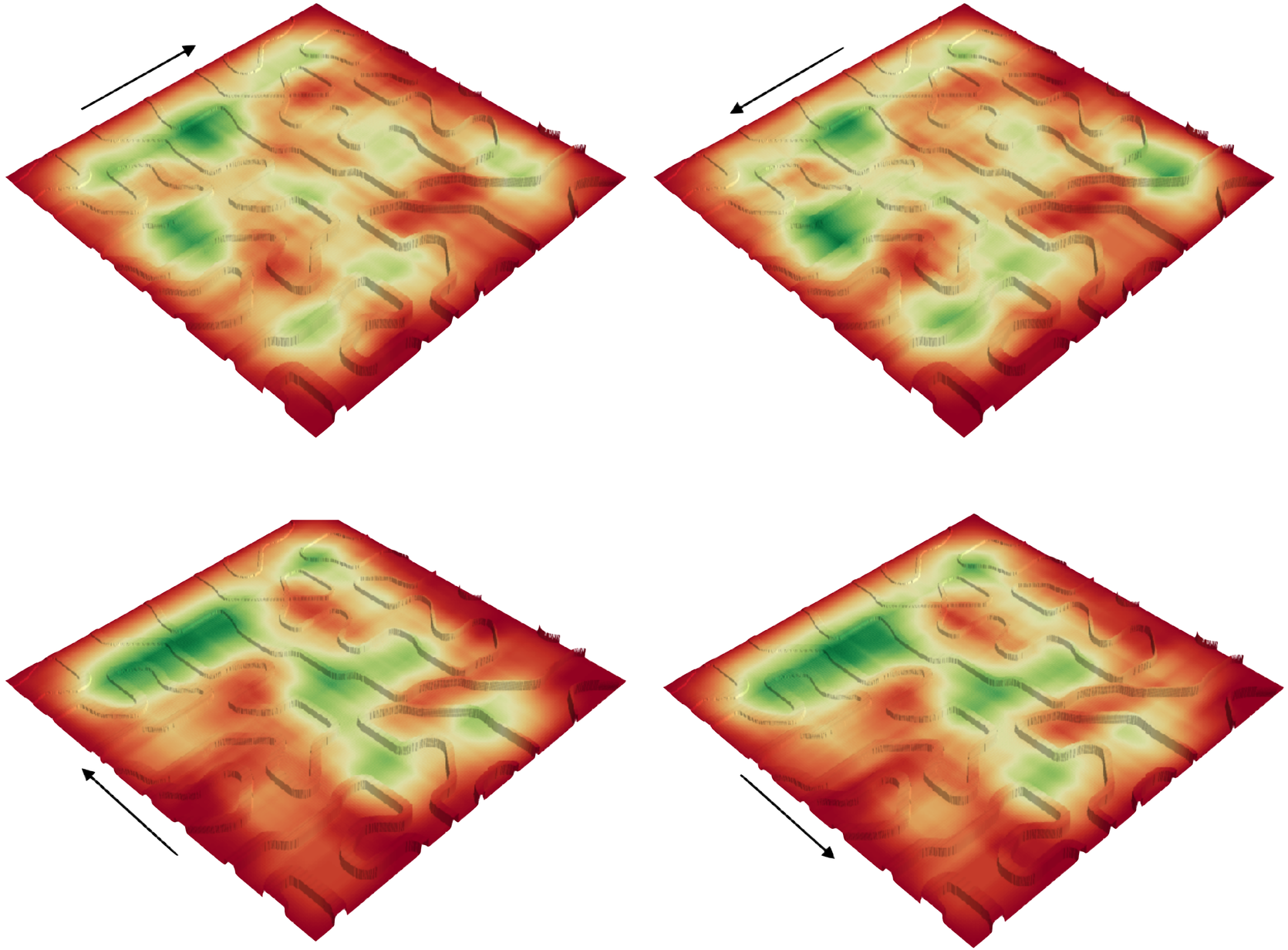


2.1 Results

Bars



2.1 Results



2.1 Results