A Shadow Detection Method for Remote Sensing Images using VHR Hyperspectral and LIDAR Data

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Outline

- Introduction
- Dataset
  - Lidar data
  - HS images
- Proposed methodology
- Results
- Conclusions and discussion

Introduction

- Overarching purpose of this work
  - Facilitate automatic (re-)recognition and detection of targets in deep shadows
- Research aspects
  - Combine 3D and spectral data for shadow detection
  - Can a supervised classifier learn to distinguish between the spectra of shadow and non-shadow pixels, respectively?
- Combined lidar and spectral data increasingly available
  - Sweden (and other countries) is currently being laser scanned during a few years, in order to make a new national elevation model

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Introduction

- With an ideal 3D model, shadows could be predicted through line-of-sight analysis
  - However, remotely sensed 3D data is not ideal
    - Resolution
    - Lidar gives points rather than surfaces
    - Representation (here: 2D raster)
    - Data registration errors between lidar and HS data
- We should still be able to use 3D data to support detection of shadows in hyperspectral images

Dataset

- Test area
  - City of Norrköping, Sweden
  - 10 km^2 in total, of which 1 km^2 was used in this work
- Simultaneous acquisition of lidar data and HS images
  - Aircraft, 750 m altitude
- Lidar
  - Optech ALTM Gemeni
  - 3D points -> raster DSM (25 cm pixels)
- Hyperspectral
  - Itres CASI 1500, line scanner
  - 24 bands (equal size), center wavelenghts 381.9 nm – 1040.4 nm
    - Trade-off between spatial and spectral resolution
  - Pixel size about 40 cm (native)
  - Orthorectification -> 50 cm pixels

Dataset

- Orthorectification and registration errors (as expected)
  - < about 2 m, varying across the image
- Movement of objects
  - Mosaicking performed without explicitly minimizing inconsistencies between data sets

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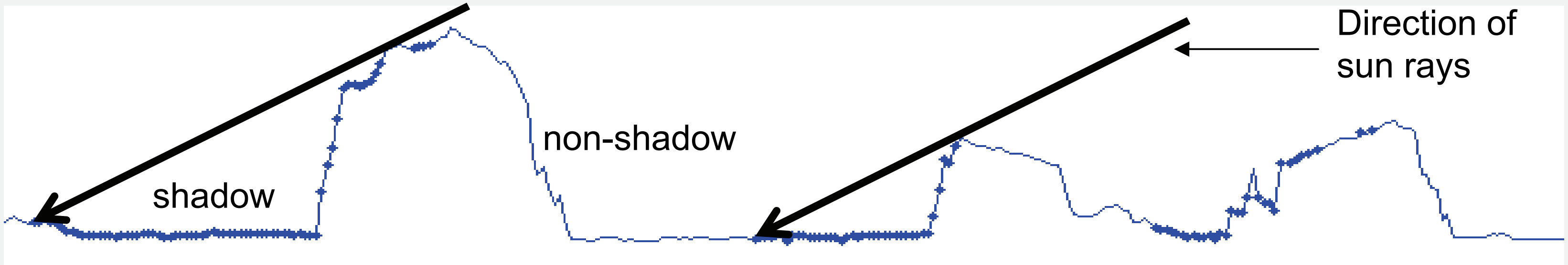
Methodology

1. *Create a rough shadow image through line-of-sight analysis of Digital Surface Model (DSM)*

- Use approximate sun position at the time of HS image acquisition
- Mark pixel *p* as non-shadow if there are no pixels with higher elevation above the straight line connecting *p* and the sun



- In practice, disregard pixels close to *p, to* decrease the influence of the noise
- This rough shadow image contains errors due to
  - Limited resolution, rasterization, misregistration wrt hyperspectral image

Methodology

2. *In the rough shadow image, detect the interior of large shadow and non-shadow regions, respectively*

- Apply distance transform and threshold
  - The choice of threshold determines the minimum region size
  - Depends on registration errors, here: 2 m
- Idea: the remaining pixels correspond to shadow/non-shadow pixels in the HS image

Methodology

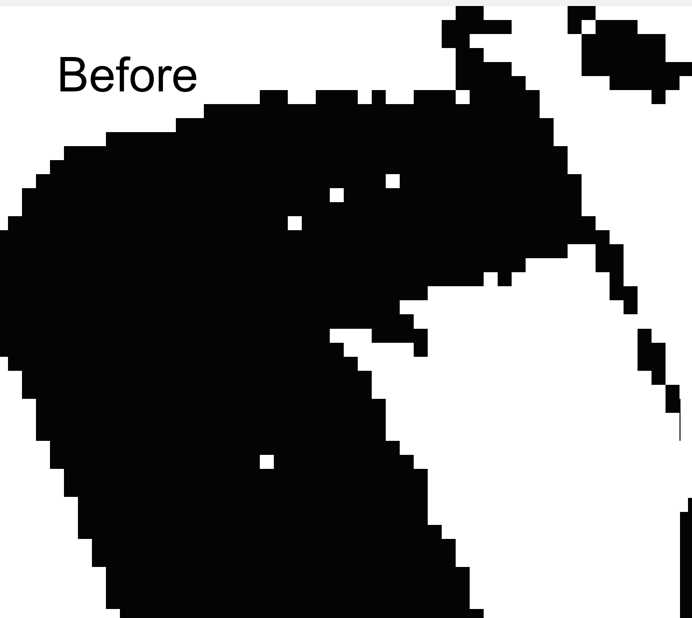
3. *Use the large shadow/non-shadow regions for training a supervised classifier operating on the spectral data*

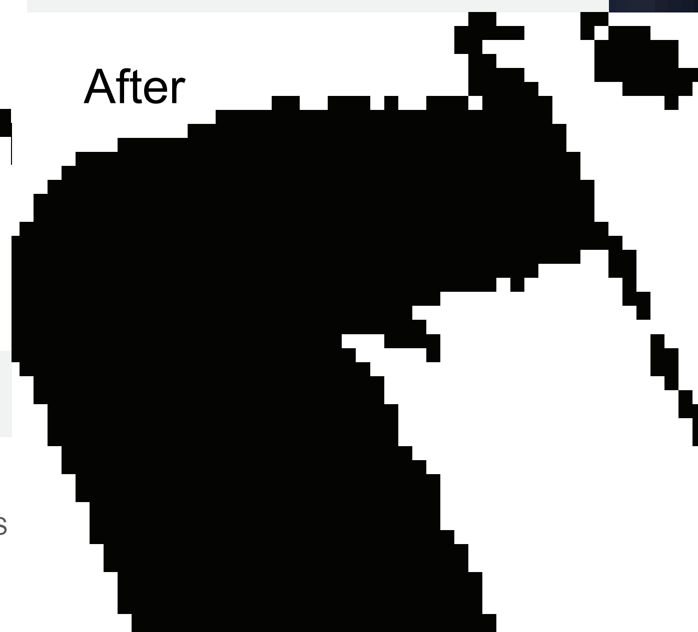
- Two-class problem: shadow and non-shadow
- Teach the classifier what the spectra of shadows/non-shadows pixels look like in the particular region
- Tough classification task!
- Here: Support Vector Machine

Methodology

4. Post-processing of the result

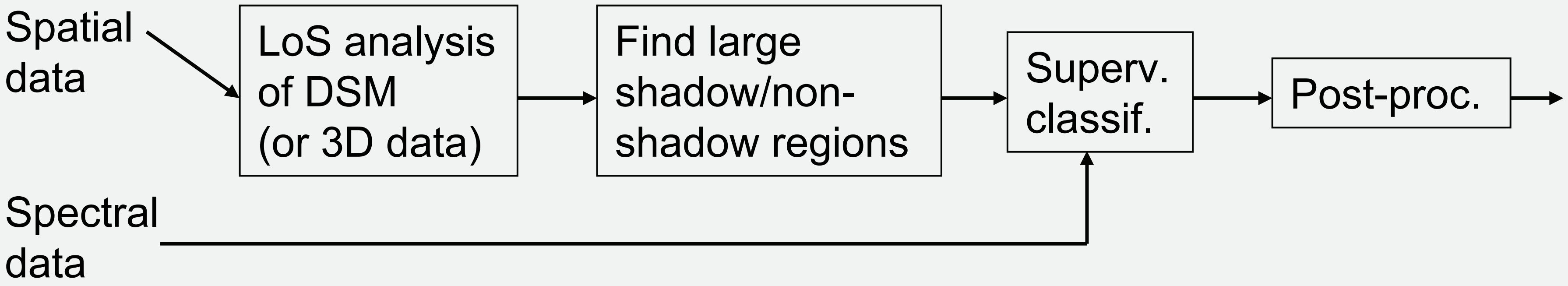
- Here: fill holes through standard image morphology





Methodology

- Block diagram:



- Required a priori information:
  - Approx. time of image acquisition -> sun position -> LoS
  - Approx. mismatch between images -> size of training regions

Results

Shadows from DSM

Interior shadow/non-shadow regions (for training)

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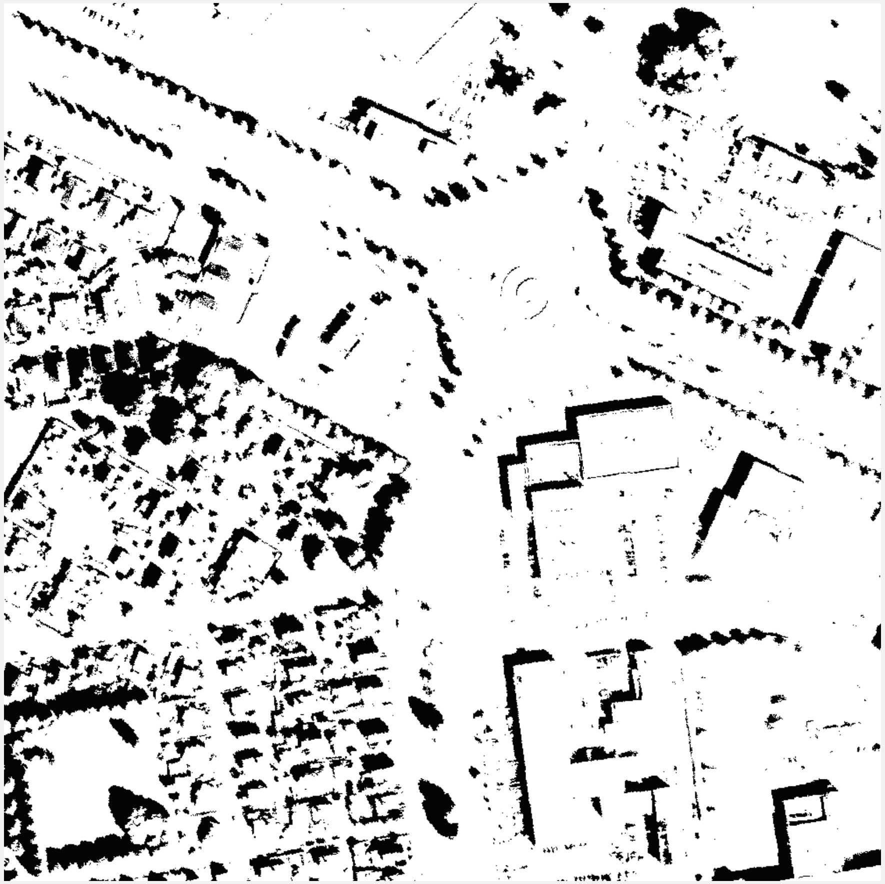
Results



Final shadows

Three bands (RGB)
from HS image

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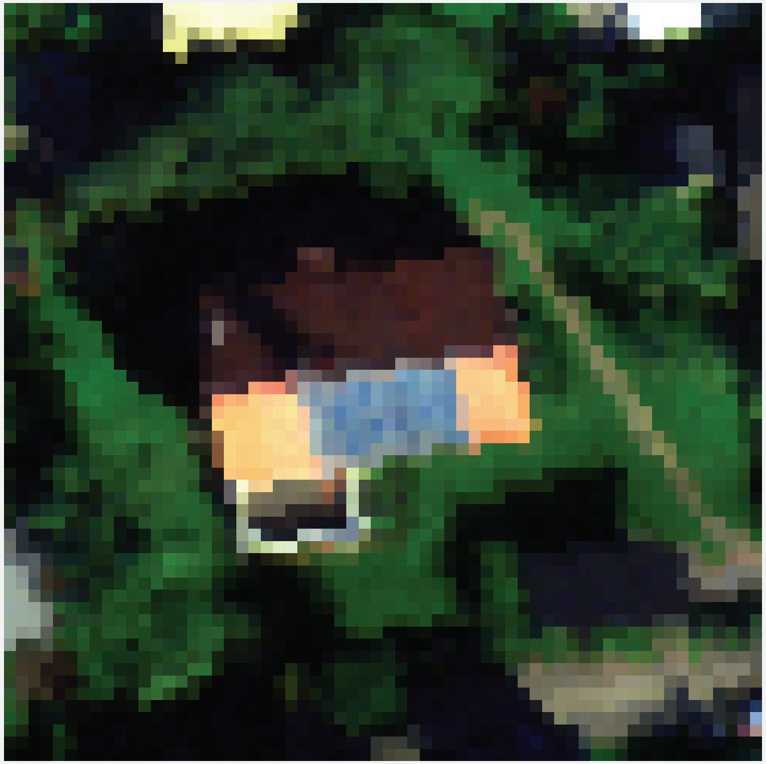
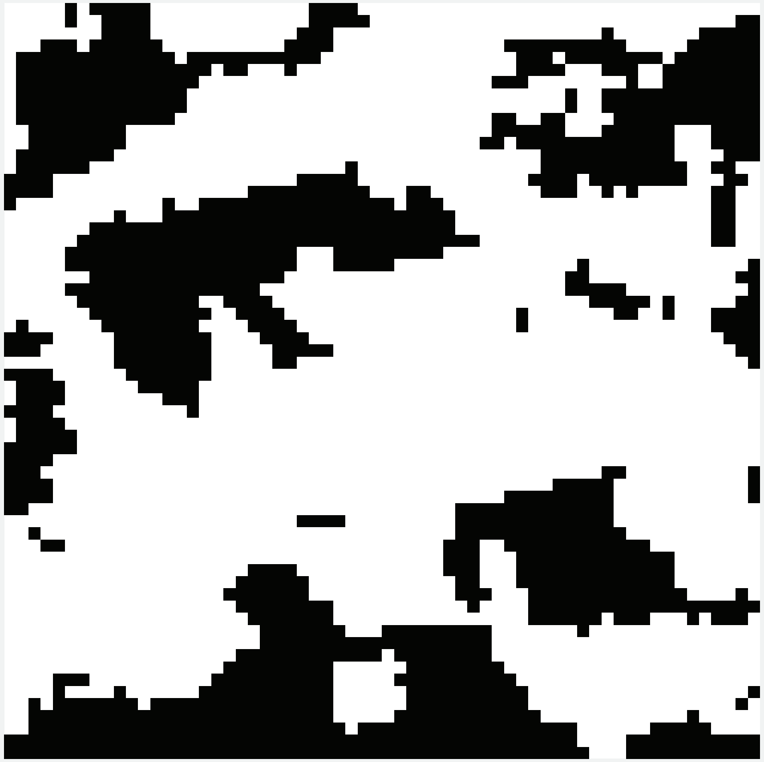
Results

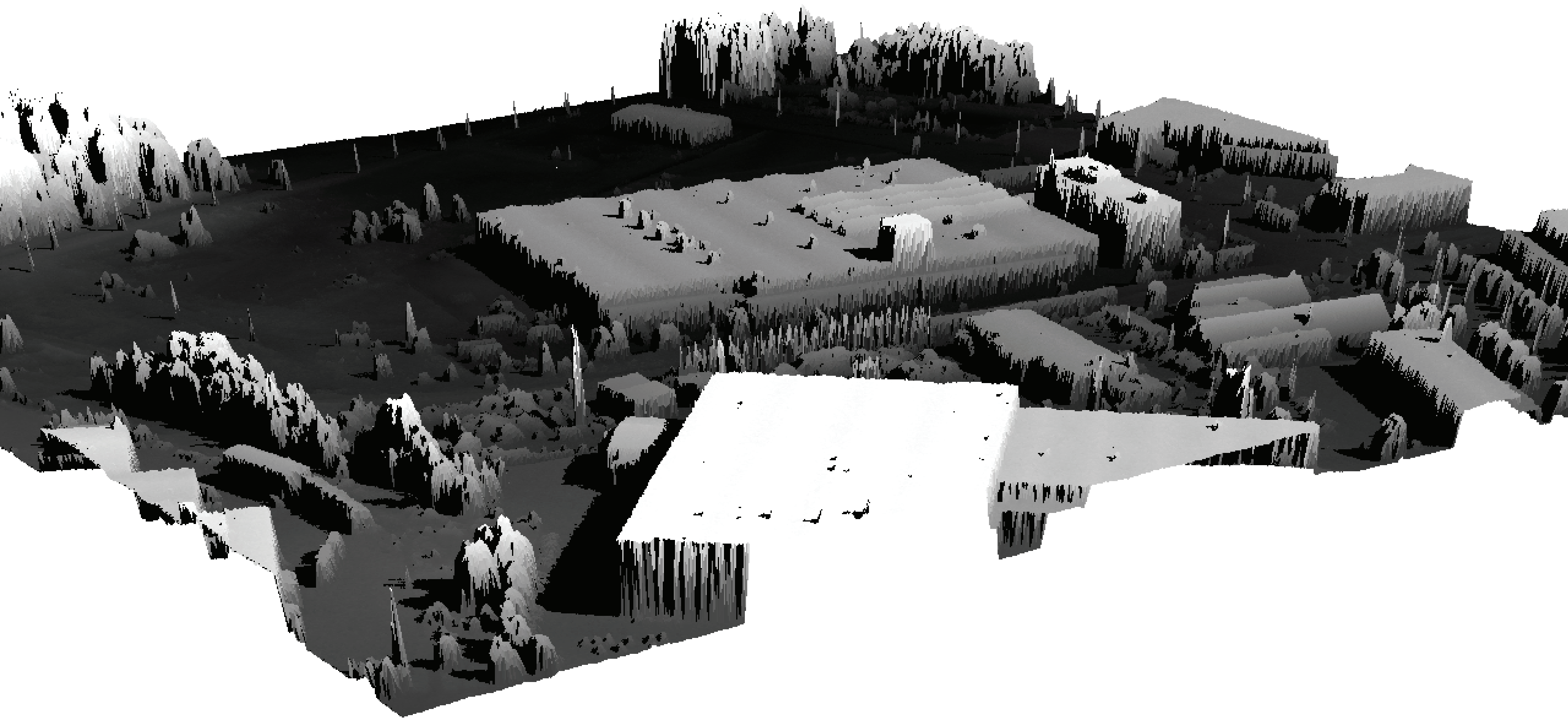




Close-up

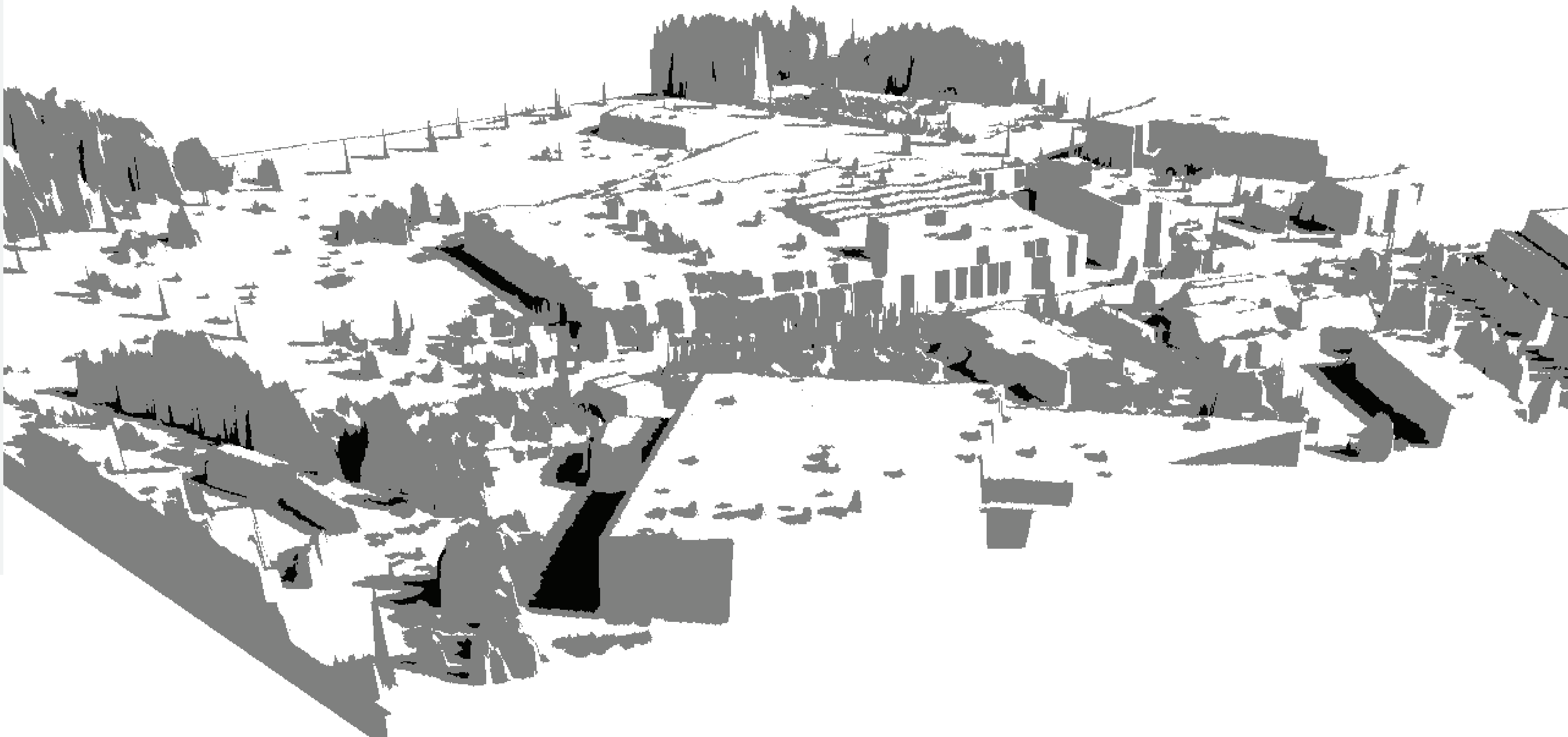
Results

Shadows from DSM



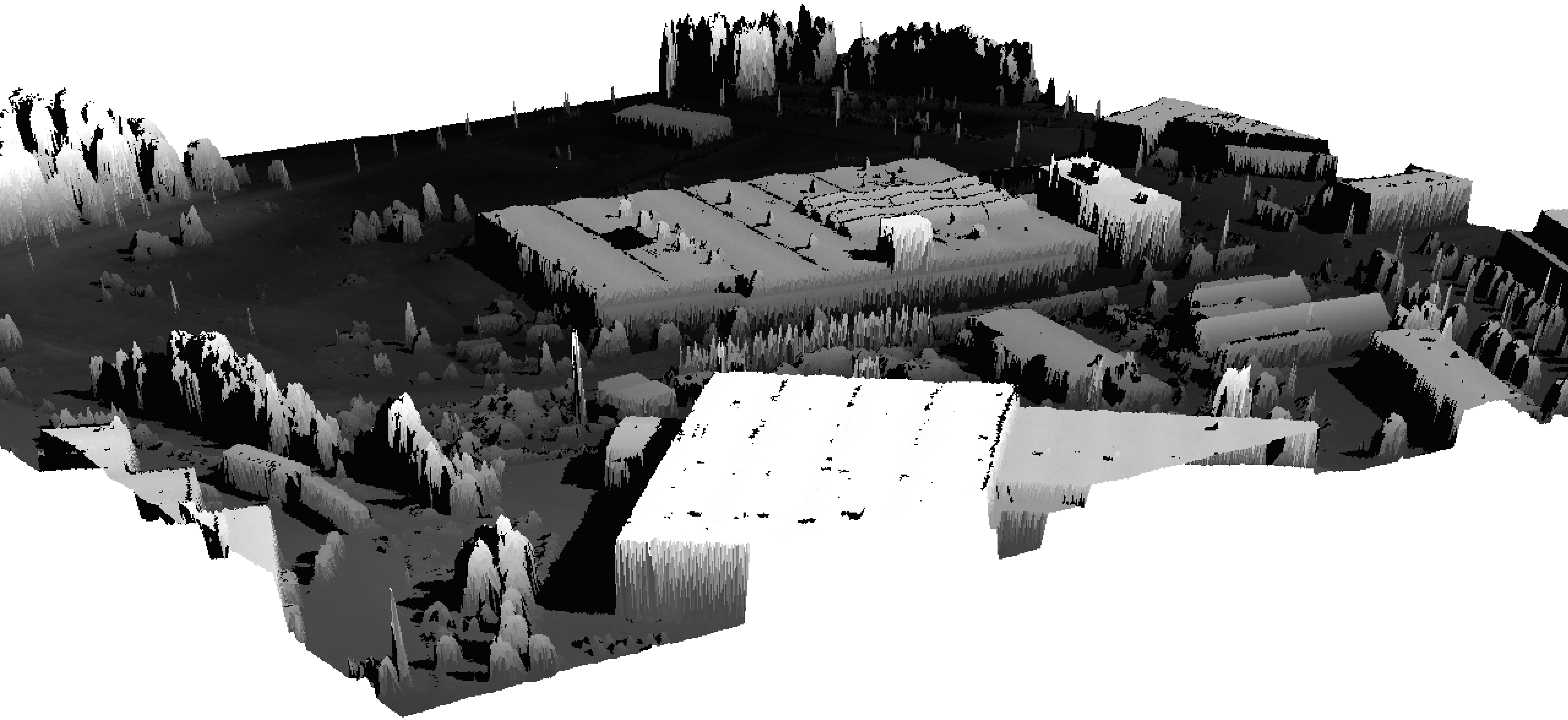
Results

Interior of large shadow (black) and non-shadow (white) regions



Results

Final shadows



Results

RGB draped onto DSM

Conclusions and discussion

- A shadow detection method based on line-of-sight analysis and subsequent supervised classification of HS images was presented
- Quite simple method
- Surprisingly good results
  - Though, no quantitative assessment done (yet)
  - Pixels classified individually using spectra
  - Handles non-uniform, moderate mismatches between DSM and images
- Partial shadows (e.g of small, thin objects) sometimes missed
  - Less relevant for us: cannot hide a target there anyway…

Conclusions and discussion

- Many aspects to be further explored
  - Performance assessment
  - Include local, spatial analysis
  - Band selection
  - How much data is needed for training classifier?
    - How large mis-registration errors still give enough training data?
  - Try with low-res DSM
  - Capturing gradual transitions between shadow and non-shadow pixels (i.e. produce a non-binary shadow image)
    - Use classification certainty measure?

Thank for your attention!
Questions? Comments?

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