



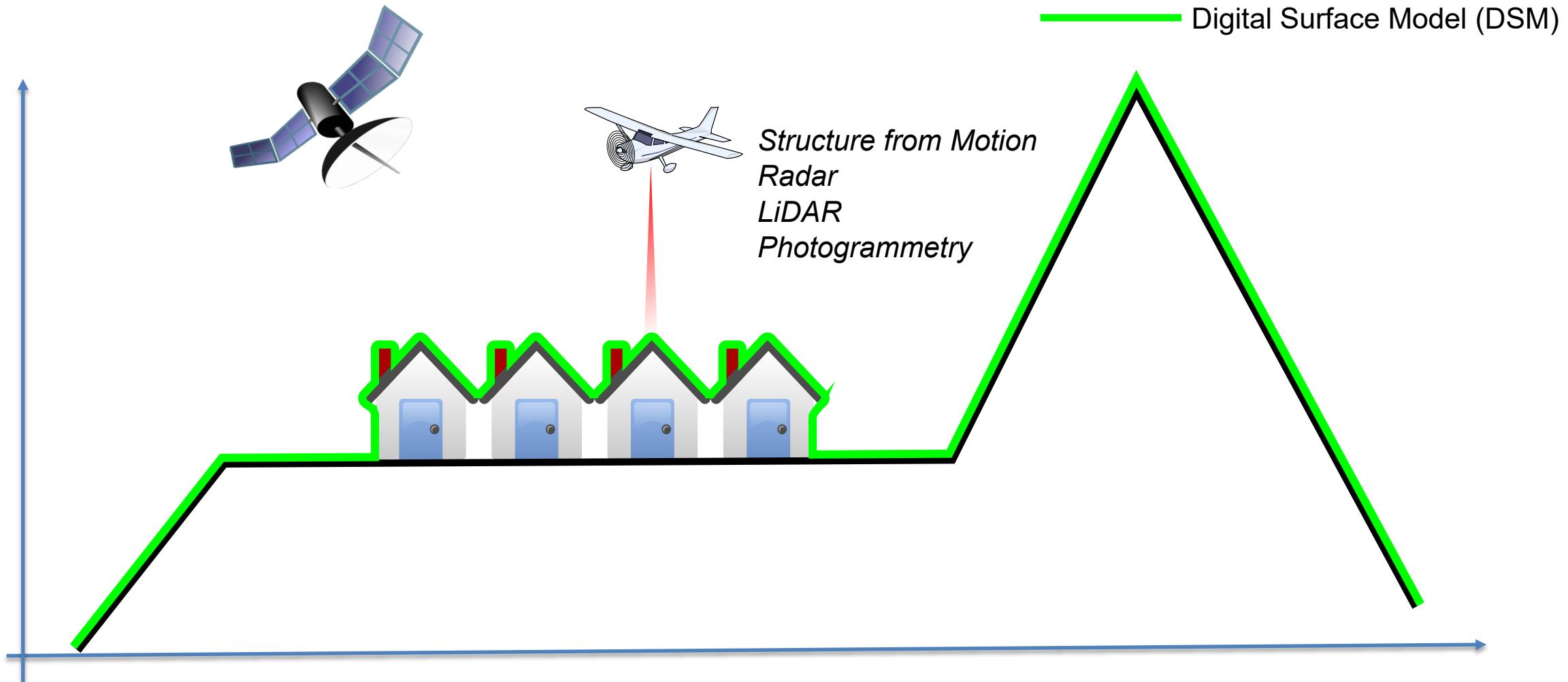
THE OHIO STATE UNIVERSITY
COLLEGE OF ENGINEERING

Large-scale DSM Registration via Motion Averaging

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May 16, 2024

Digital Surface Model (DSM)



Orthophoto | City Models | Digital Terrain Models | Vectorized Building footprints ...

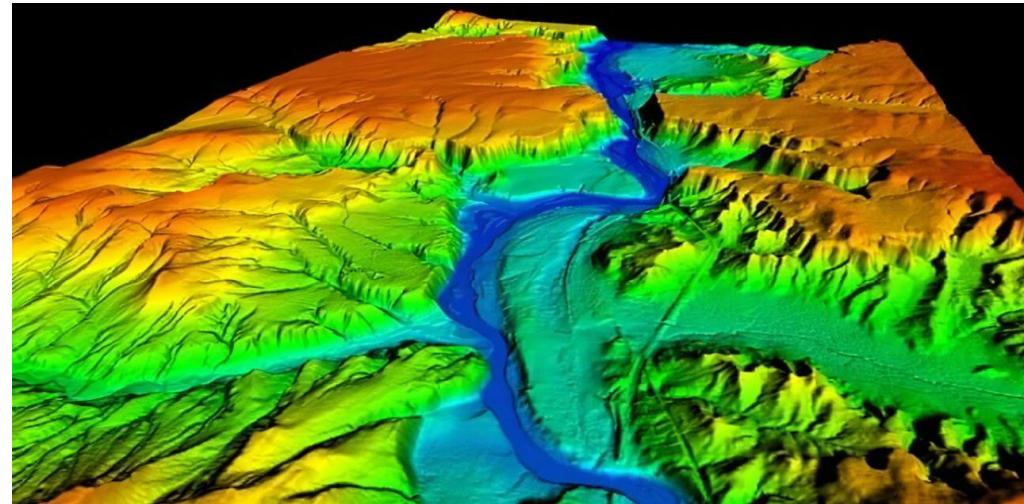
Global-scale mapping

SRTM DEM

ASTER DEM

NASA DEM

ALOS 3D



~ 30 m spatial resolution

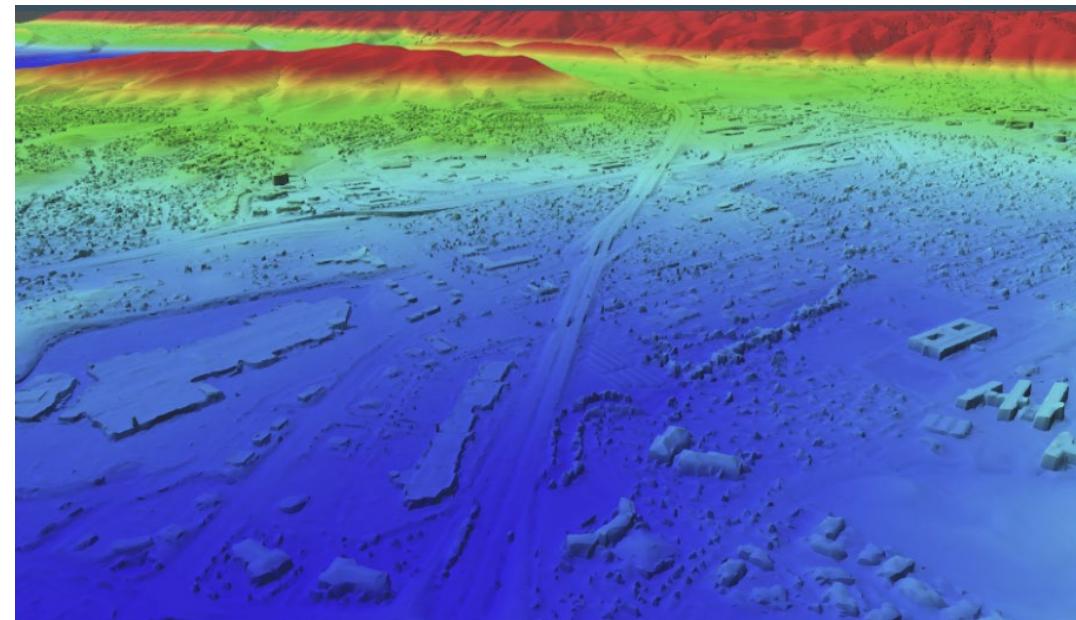
+/- 90 m vertical accuracy

Maxar 3D Foundation

Airbus WorldDEM

ZY-3, GF etc.

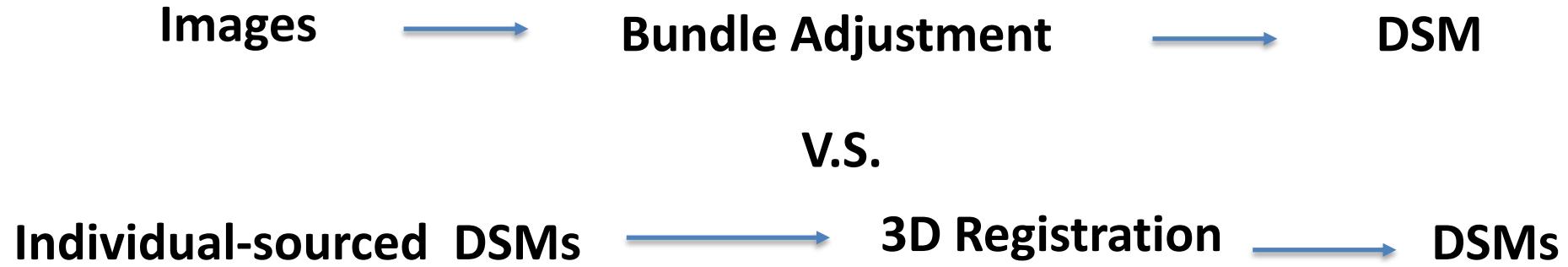
....



~ 5-0.5 m spatial resolution

+/- 3-10 m vertical accuracy

Single-source V.S Multi-source



- More sources mean better data availability
- Ability to incorporate sources beyond images
- Potentially more cost-effective.

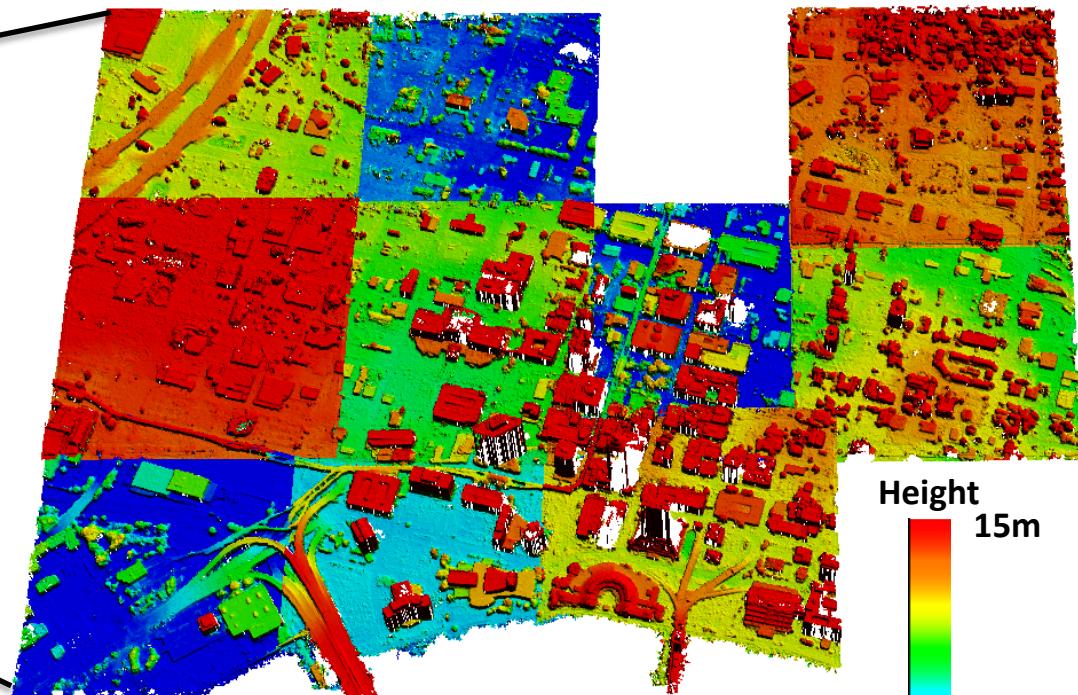
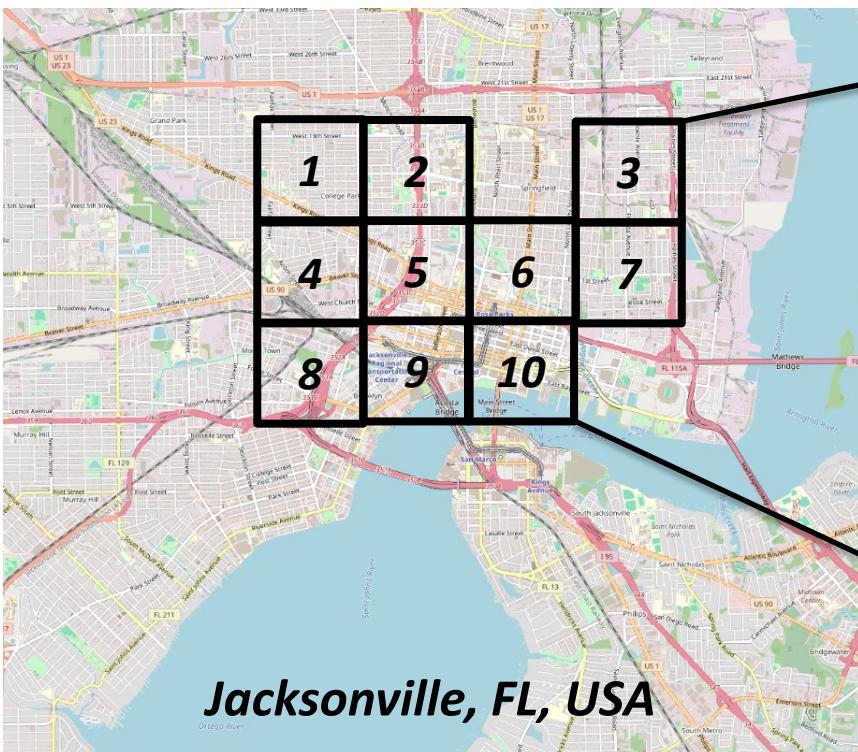
Problem

Biases exist on individually generated DSMs

Dataset: DFC 2019

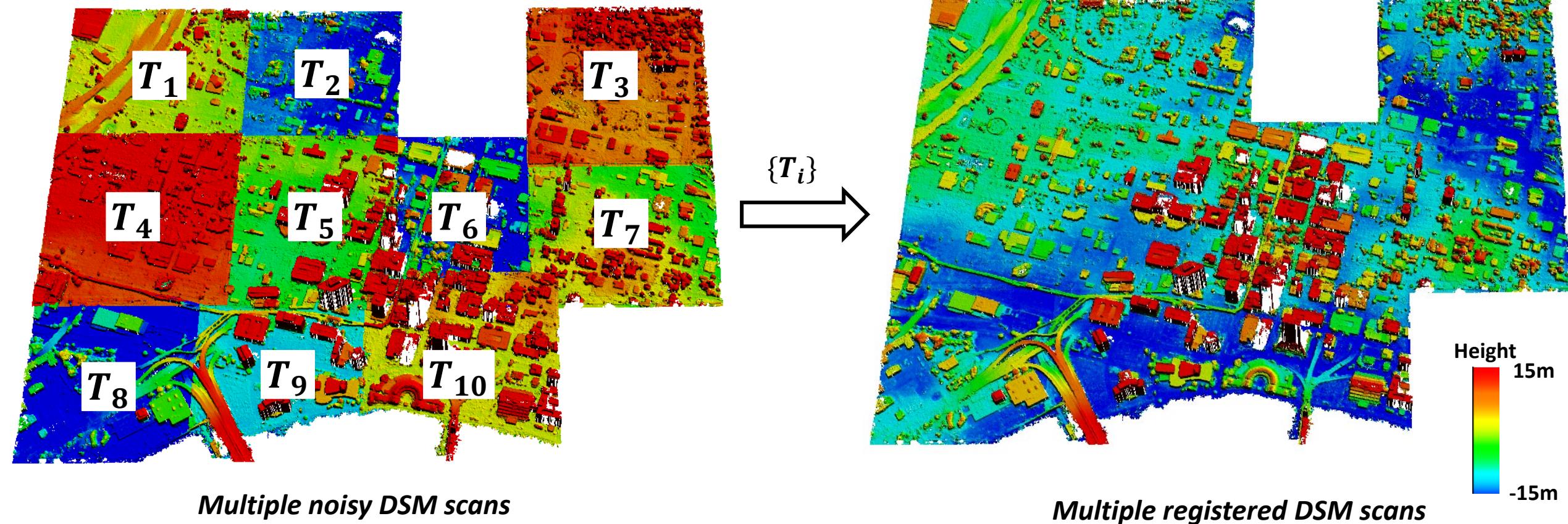
Sensor: 26 WorldView2/3 images, LiDAR

Time span: Apr,2016 - Aug,2017



Core of this work

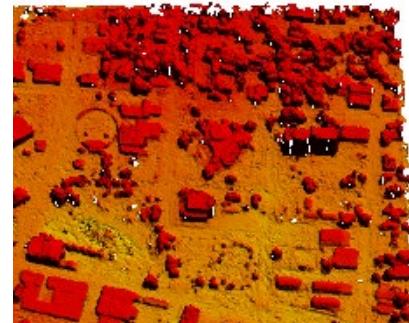
Estimate the global transformation $\{T_i\}$ to remove the systematic errors of given DSMs



Challenges

1. Large computation & memory consumption

height: ~10,000 px



#points: ~ 100 million

width: ~10,000 px

2. Some area are flat and featureless

Featureless area leads to ill-posed problem.



Satellite texture

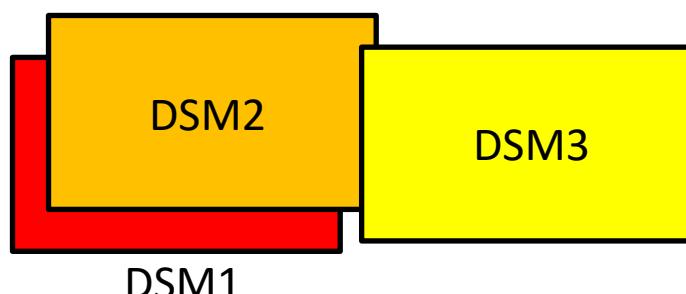


DSM

Height
15m
-15m

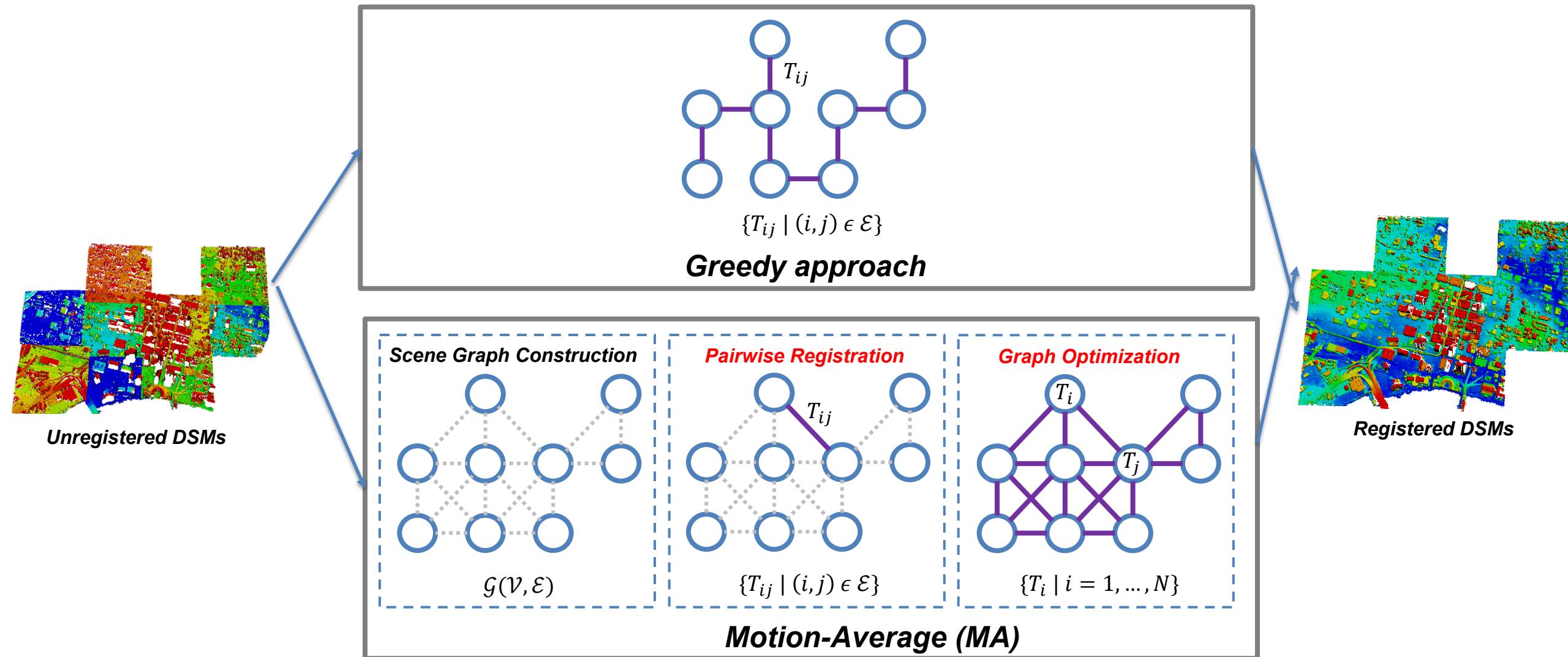
3. Varying degree of overlaps

Partial overlapping affects the registration accuracy, which need to be handled respectively



Registration of DSM 1&2 **Easy**
 Registration of DSM 2&3 **Hard**

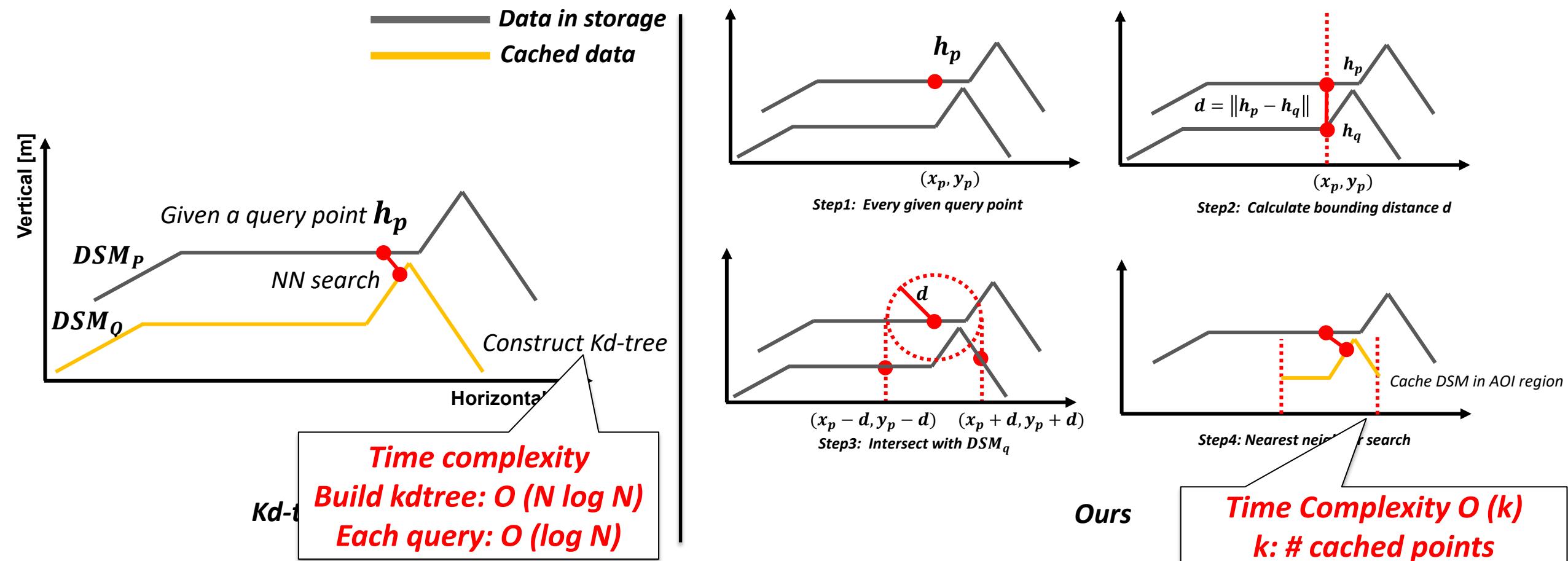
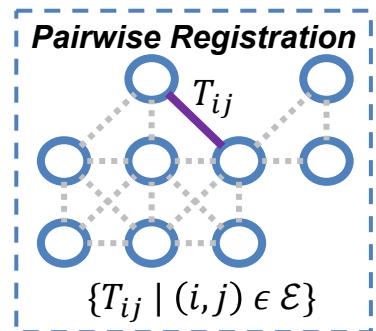
Methodology



Methodology

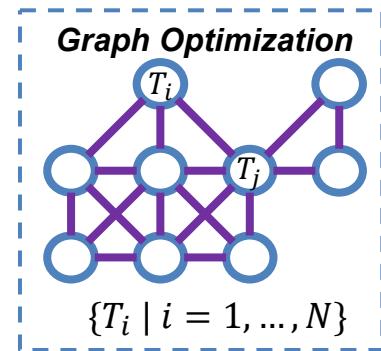
1. Pairwise DSM registration : DSM-ICP

Most resource consuming part is correspondence search. We proposed a fast and exact nearest neighboring search method using the grid structure of DSM.



Methodology

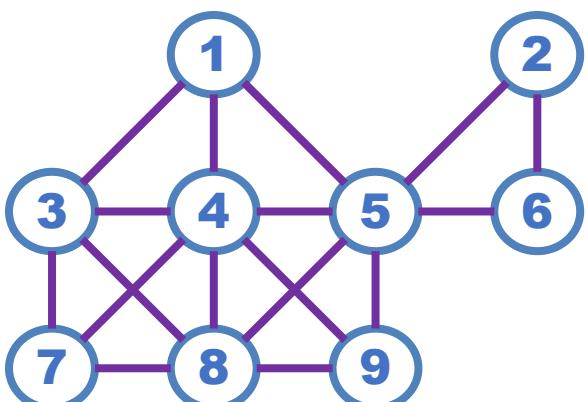
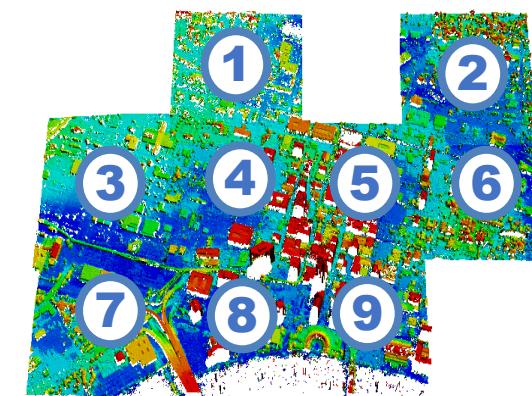
2. Multiview registration: Motion average



Errors are distributed across the graph

Observation: pairwise transformation $\{T_{ij}\}$

Optimizable variable: global transformation $\{T_i\}$



Ours

$$\min_{\{T_i\}} \sum w_{ij} \|T_{ij} - T_i^{-1} \cdot T_j\|_F^2$$

$$w_{ij} = s_{ij} * r_{ij}$$

Overlap ratio

Pairwise registration quality

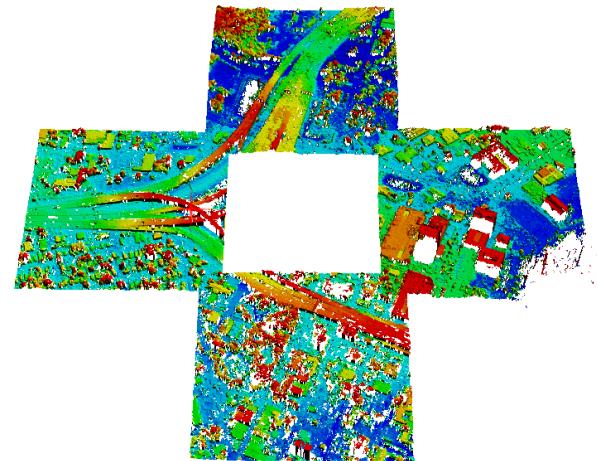
$$r_{ij} = \frac{e^{-err_{ij}}}{\sum_{(i,j)} e^{-err_{ij}}}, err_{ij} \text{ is pairwise registration error}$$

Experiment

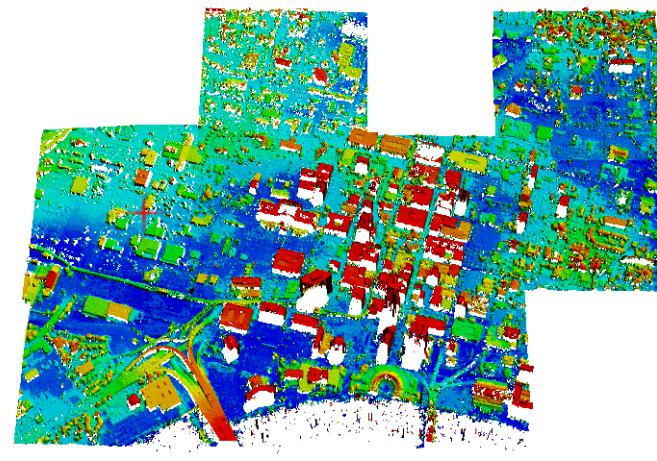
Dataset: DFC 2019 [1]

Ground truth: airborne
LiDAR

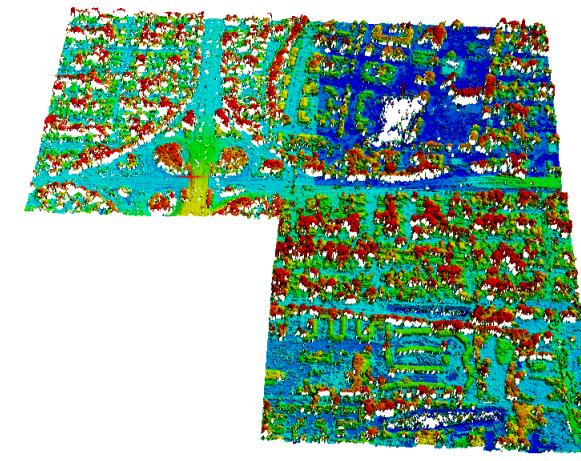
Metric: RMSE



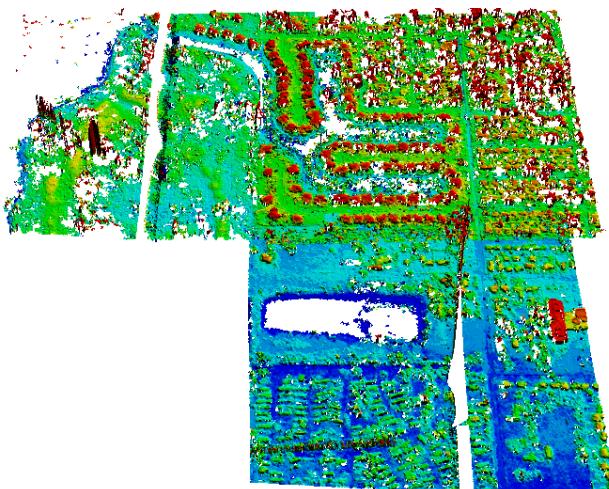
Jacksonville Area1 (4 DSMs, 4.5 KM²)



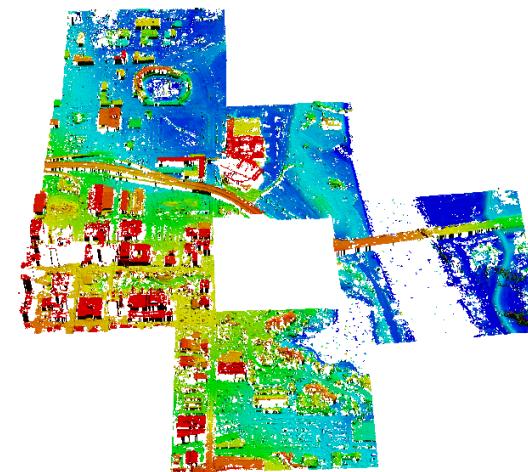
Jacksonville Area2 (9 DSMs, , 6 KM²)



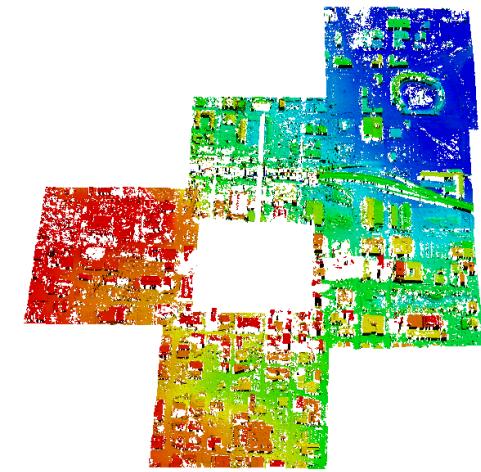
Jacksonville Area3 (3 DSMs, 2 KM²)



Omaha Area1 (3 DSMs, 2 KM²)



Omaha Area2 (6 DSMs, 6 KM²)



Omaha Area3 (6 DSMs, 6 KM²)

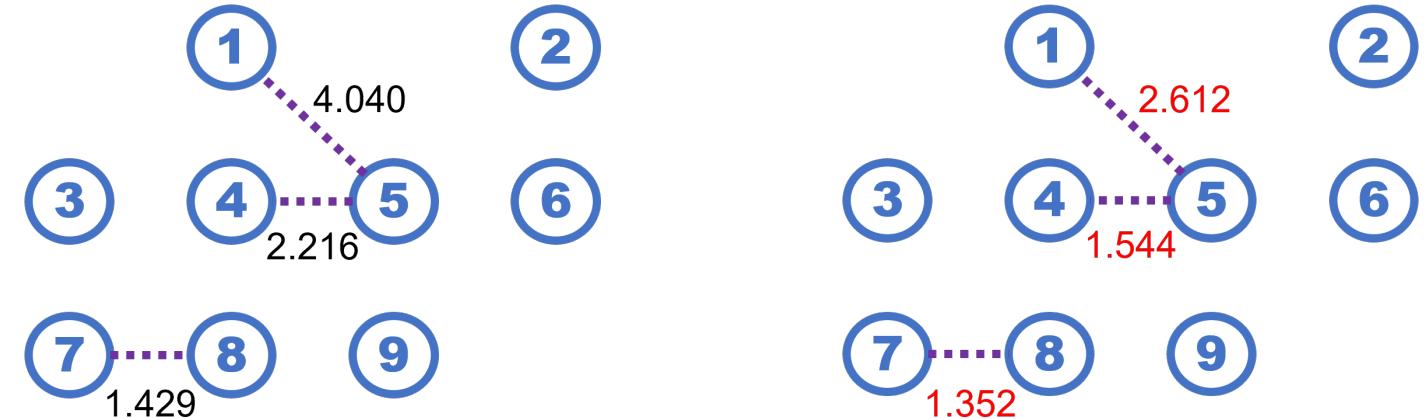
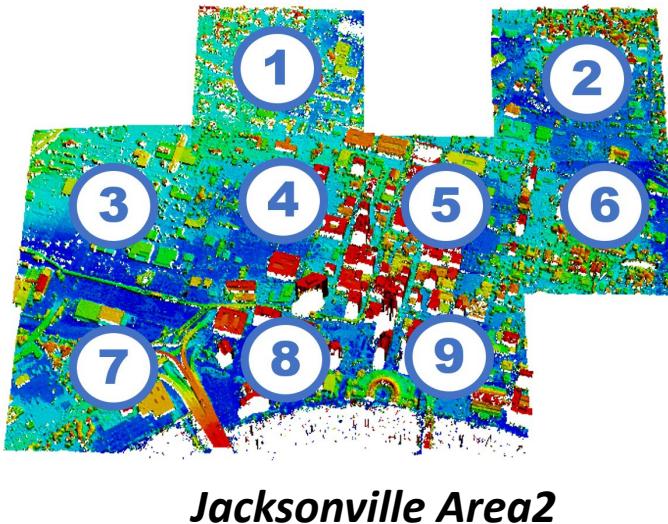
Experiment

Accuracy of multiple registration

<i>Method</i>	<i>RMSE [m]</i>					
	<i>JAX1</i>	<i>JAX2</i>	<i>JAX3</i>	<i>OMA1</i>	<i>OMA2</i>	<i>OMA3</i>
<i>Greedy</i>	2.305	2.166	2.756	2.065	1.461	1.667
<i>M-A</i>	2.302	2.129	2.756	2.065	1.451	1.539

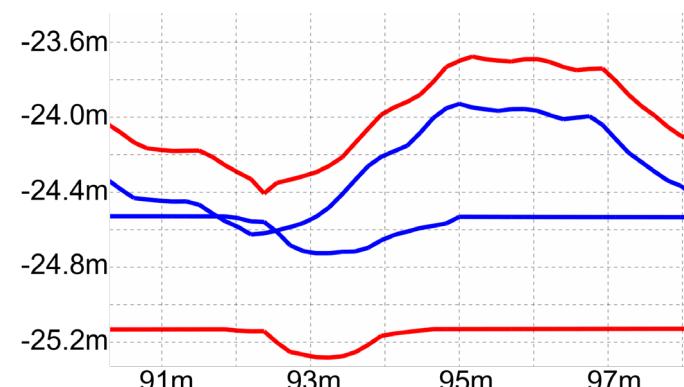
Experiment

Accuracy of multiple registration

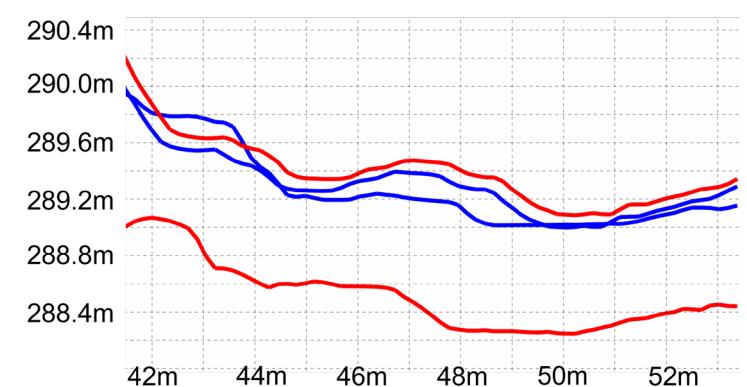


Pairwise accuracy (RMSE [m]) of greedy's results

Our result
 — Ours
 — Greedy method

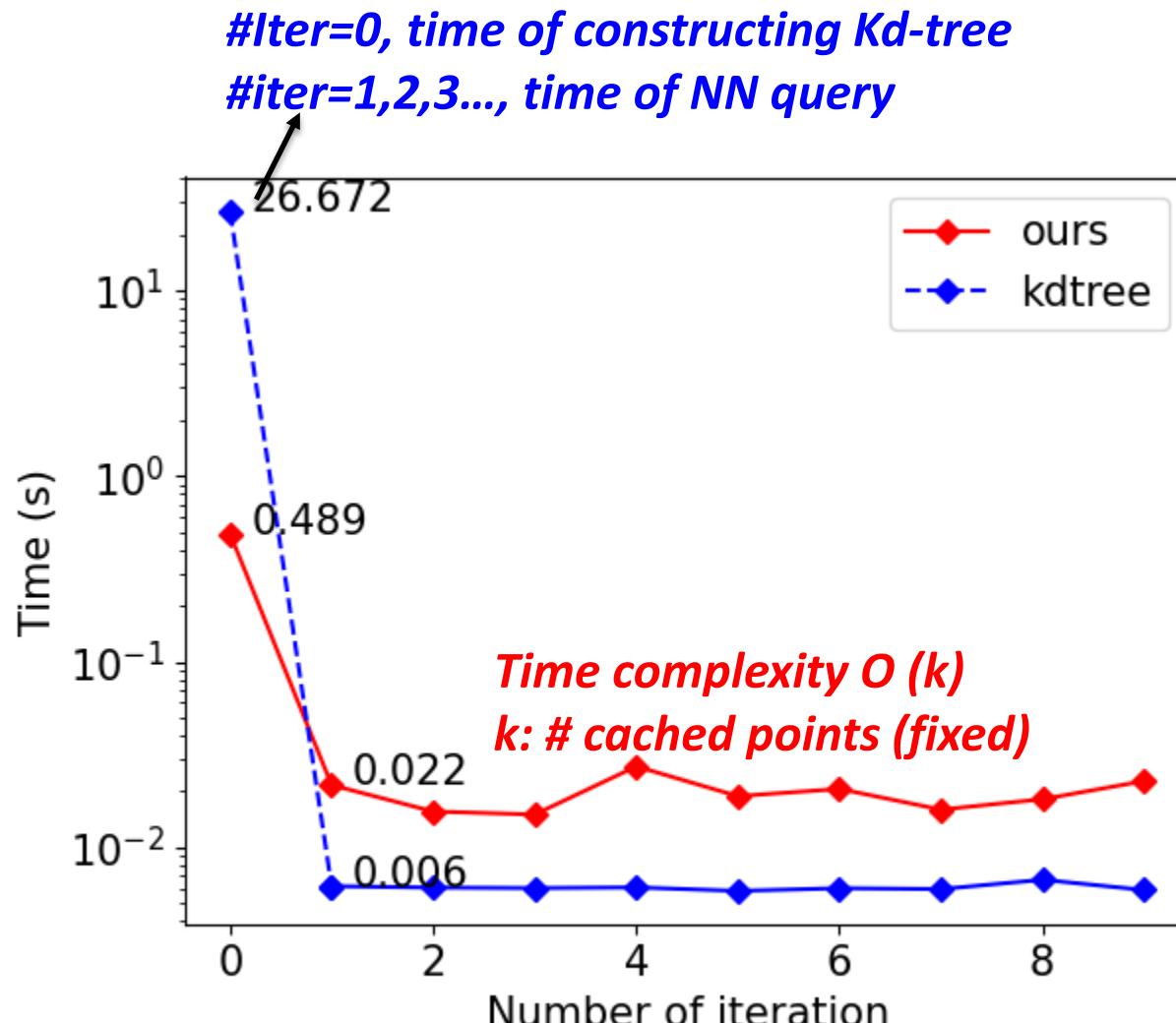


Profile in Jacksonville area2

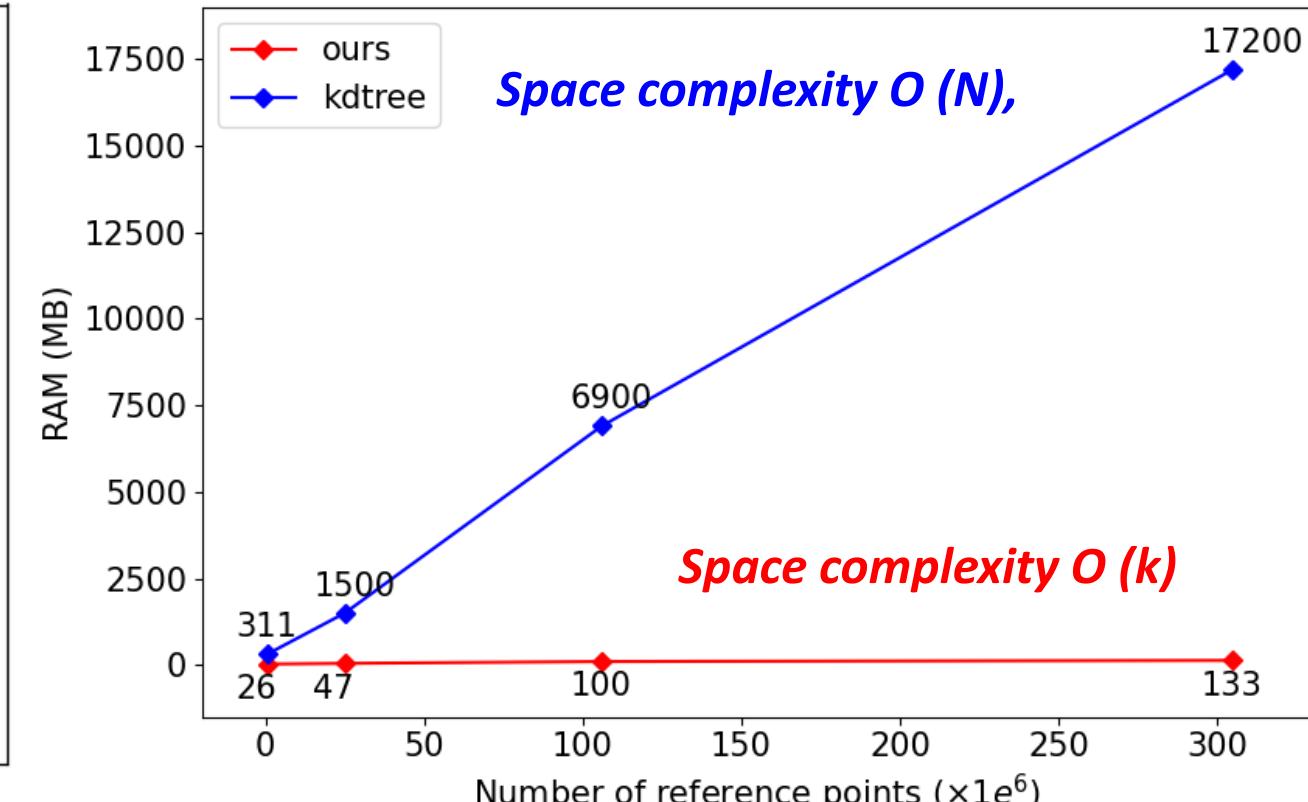


Experiment

Time consumption of pairwise registration



Memory consumption of pairwise registration



106 million points

Experiment

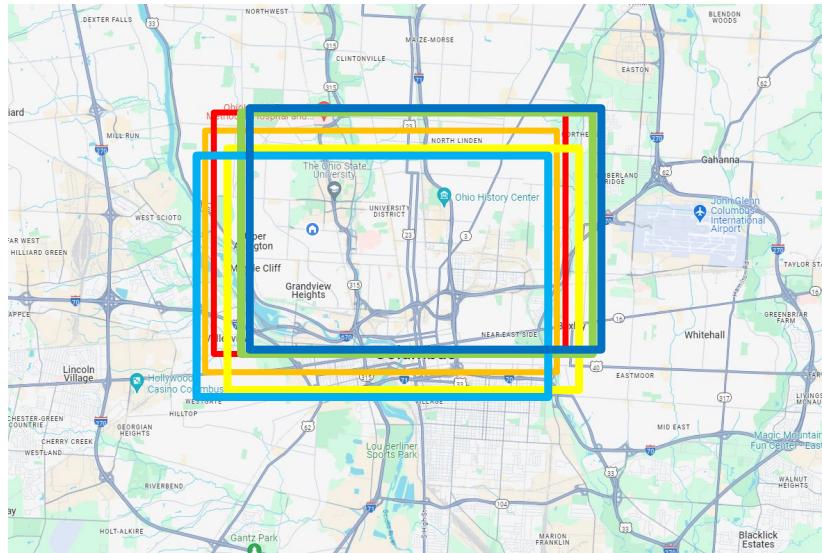
Wide area DSM (132 individual DSMs)



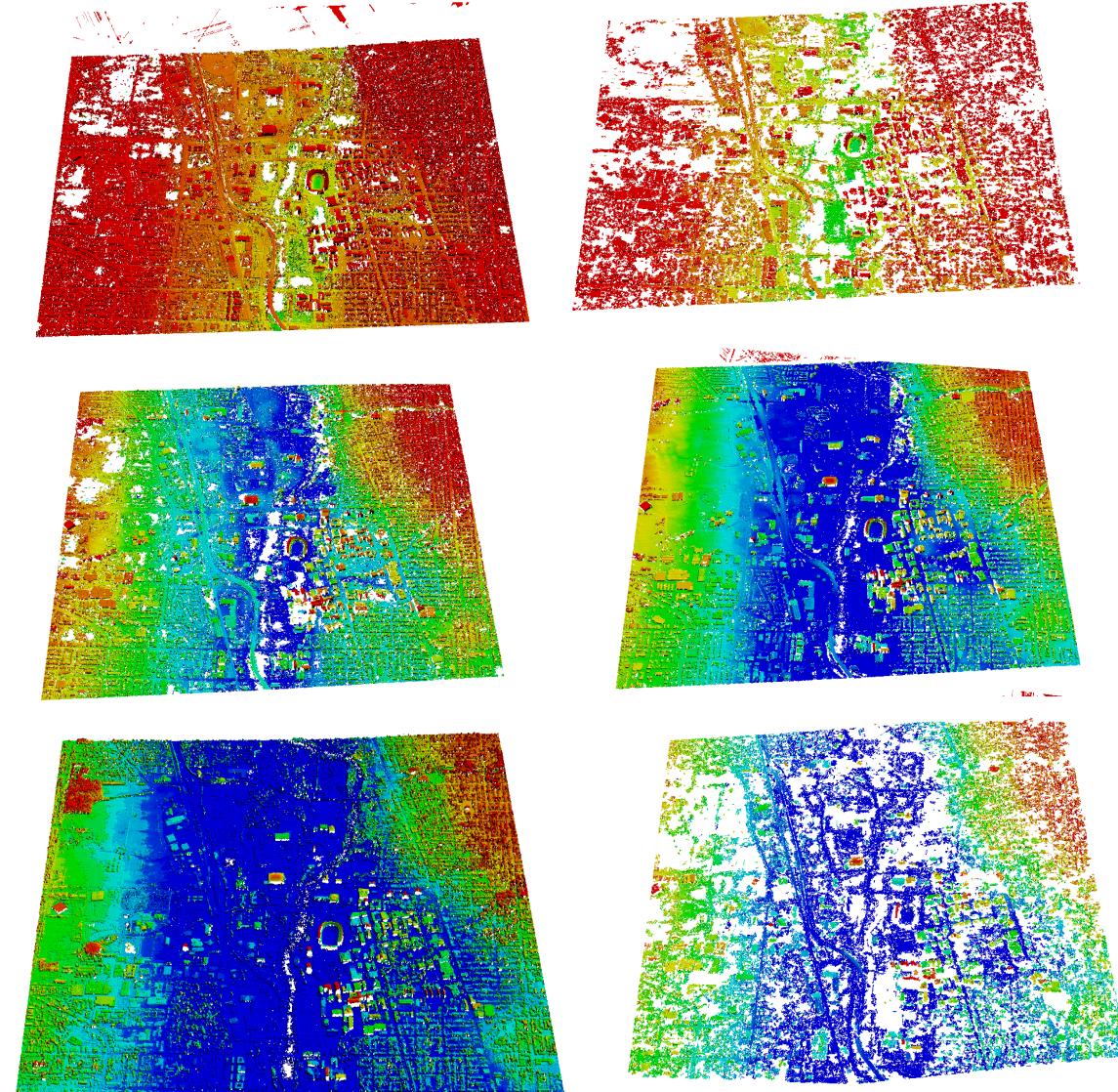
Santa Cruz, Argentina, 4974 KM²

Experiment

Wide area DSM (66 individual DSMs, including LiDAR DSM and Drone DSMs)



15 KM²
Columbus, OH, USA

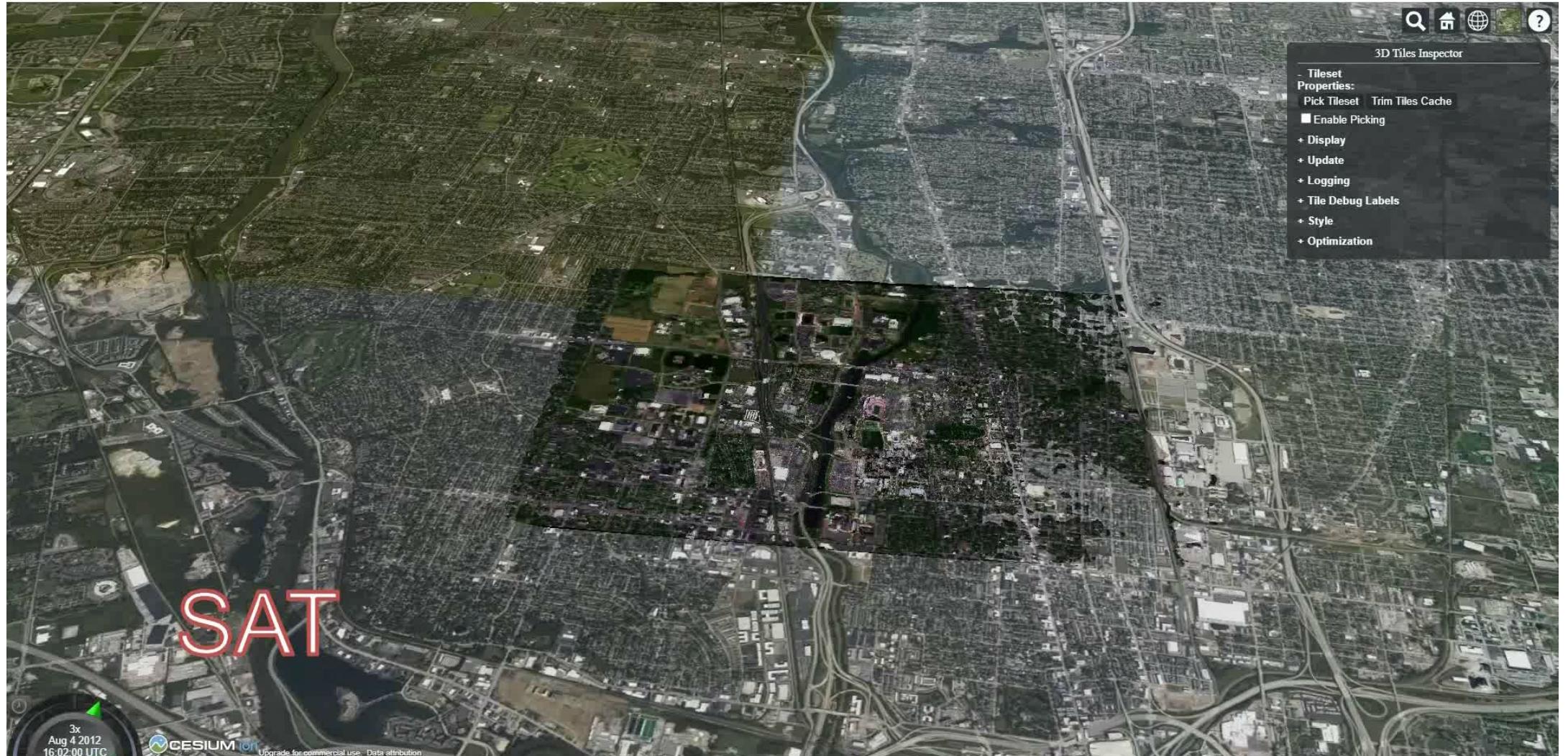


240m
 190m
 16

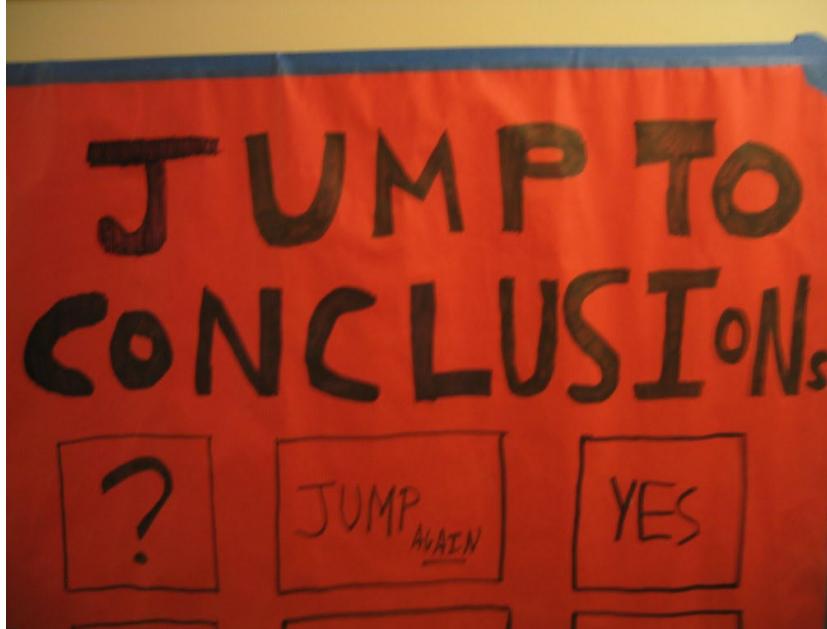


Experiment

Multi-source DSM



Columbus, OH, USA



- The use of the grid-structure is in good favor of large-scale DSM registration
- The motion average method is extremely effective in reducing systematic biases over multiple DSMs.