Vehicle velocities and Congestion detection on highways from Planetscope Imagery

Master Thesis Presentation

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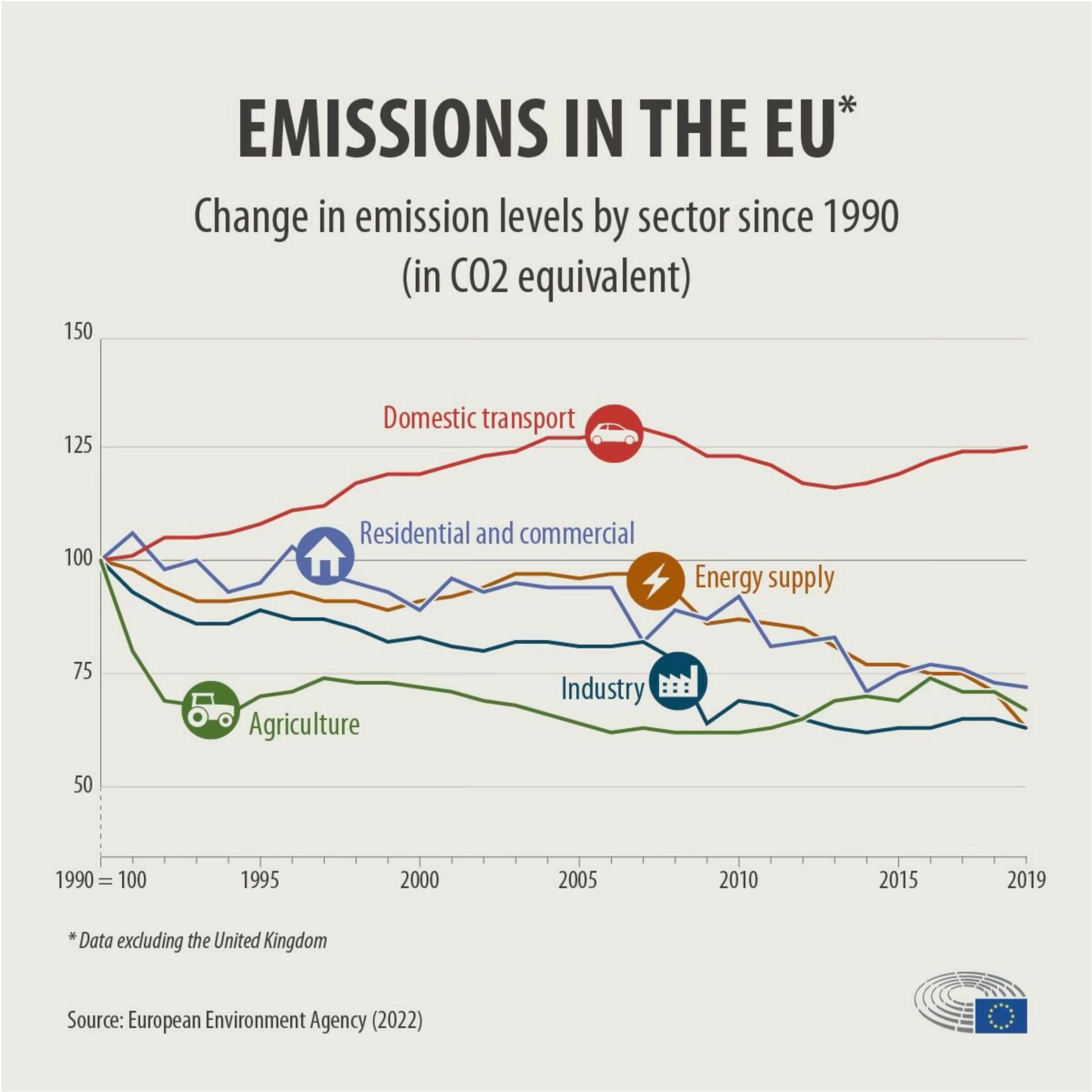
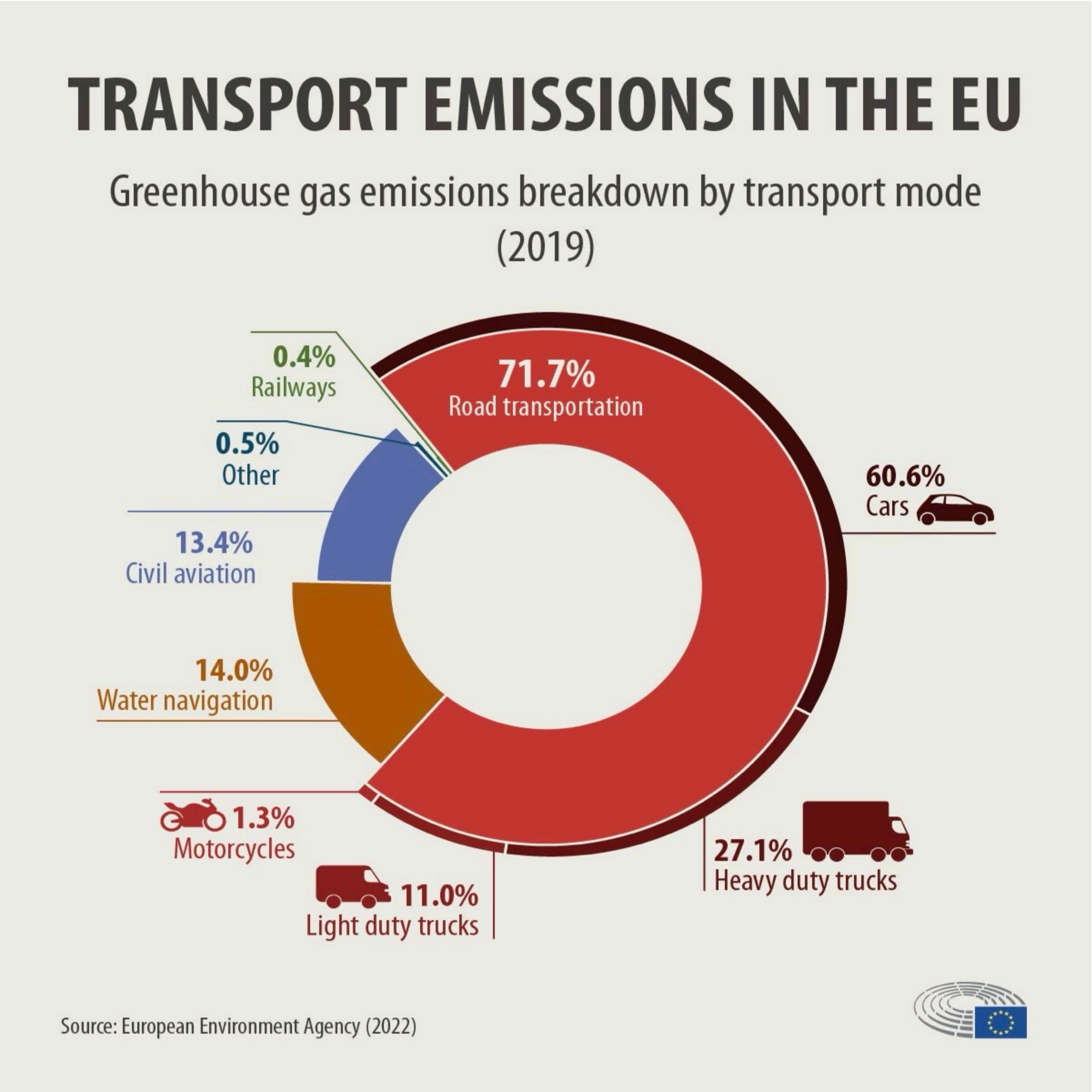
Oct 6, 2025

Motivation





28% total CO_2 emissions : Transportation

Motivation

11 %   15 %   7 %

Image source : Tom Tom

Stop and go conditions due to congestion increases emissions

Motivation

448,000 congested hours 5% ↑

859,000 km of tailbacks

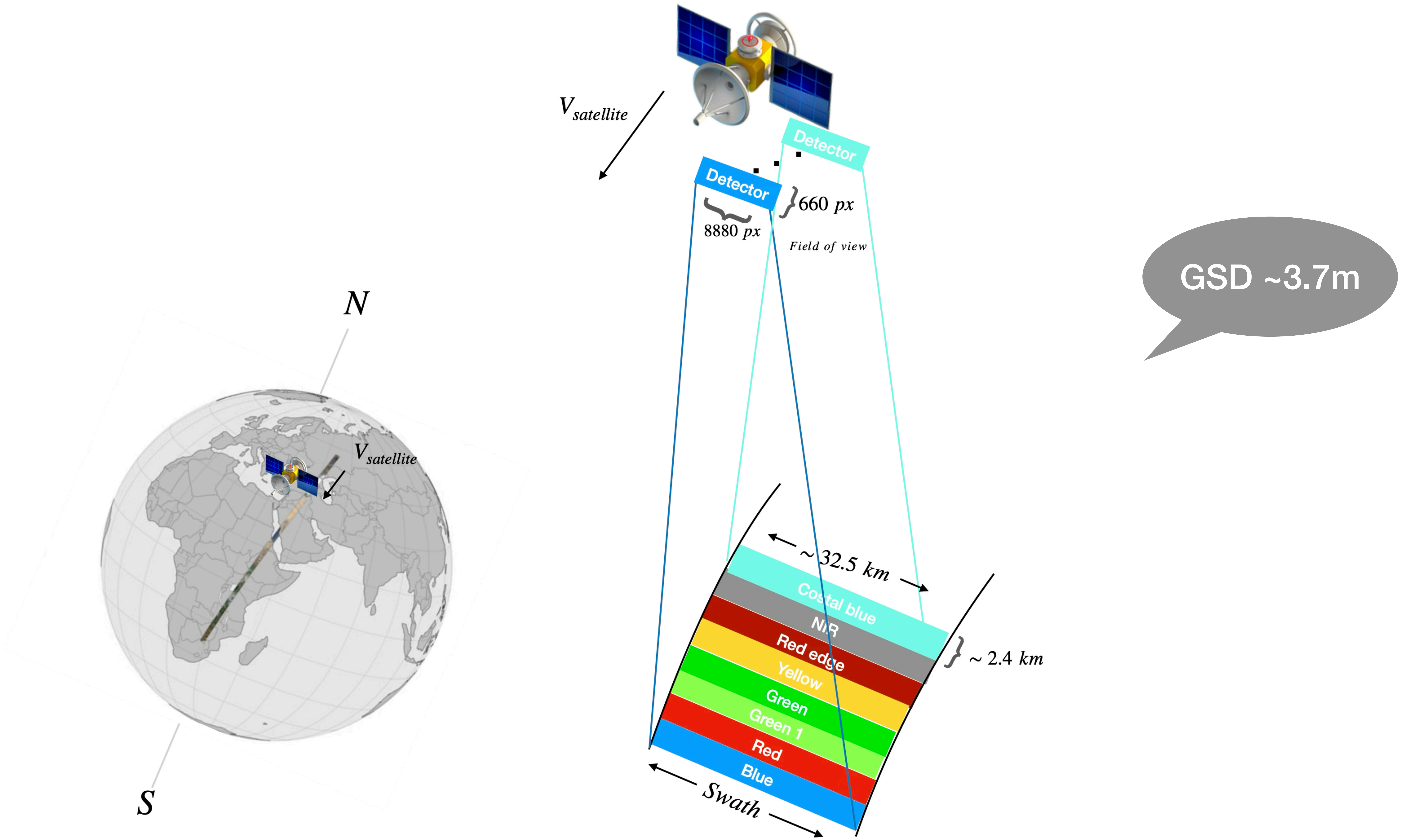
516,000 traffic jams recorded

Congestion on German Highways (2024)

Data source : ADAC

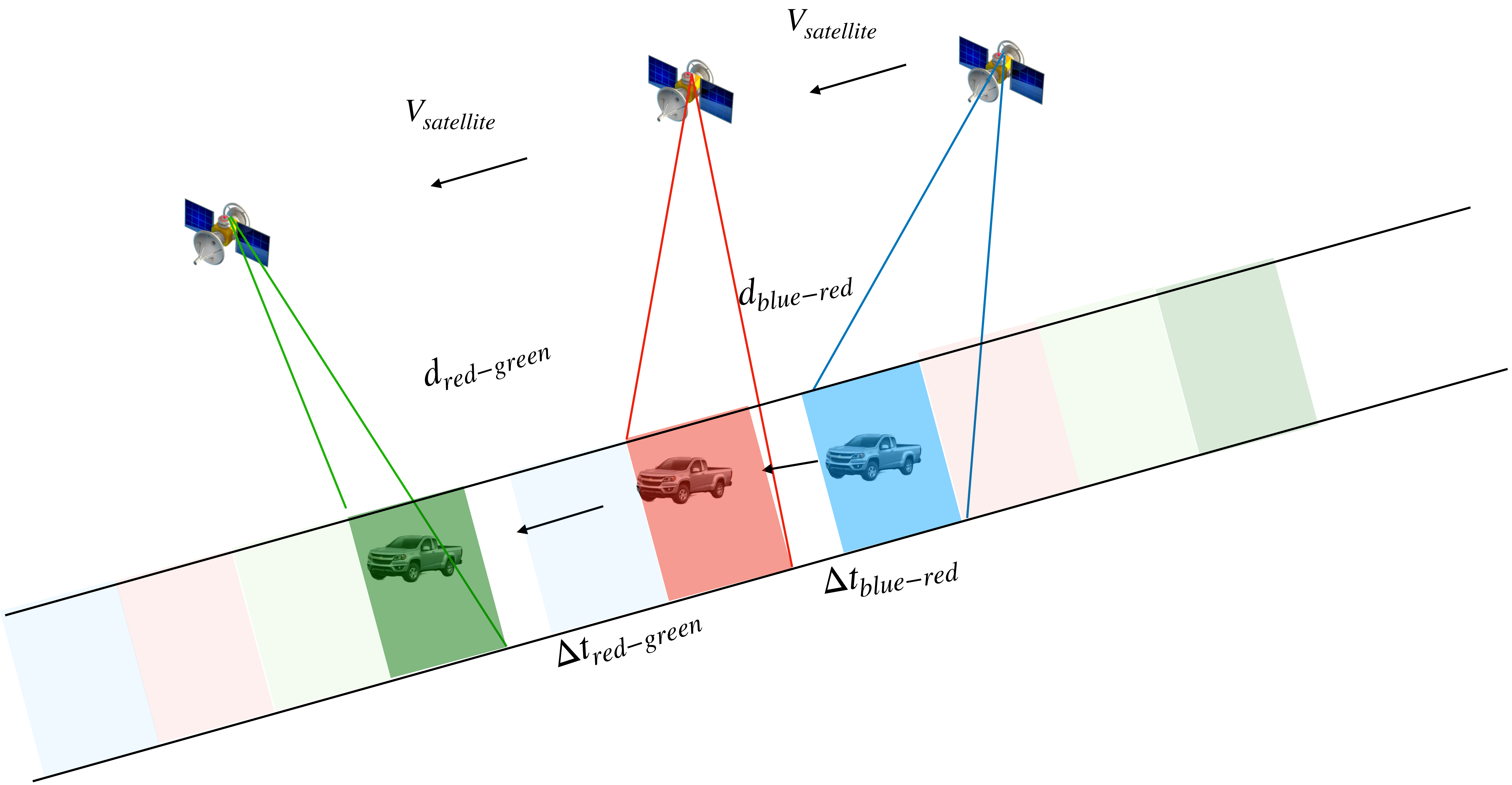
Problem Statement

Planetscope Imagery : illustration



Constellation of 120 satellites. Frequency : daily

Movement of Vehicles across bands : *illustration*



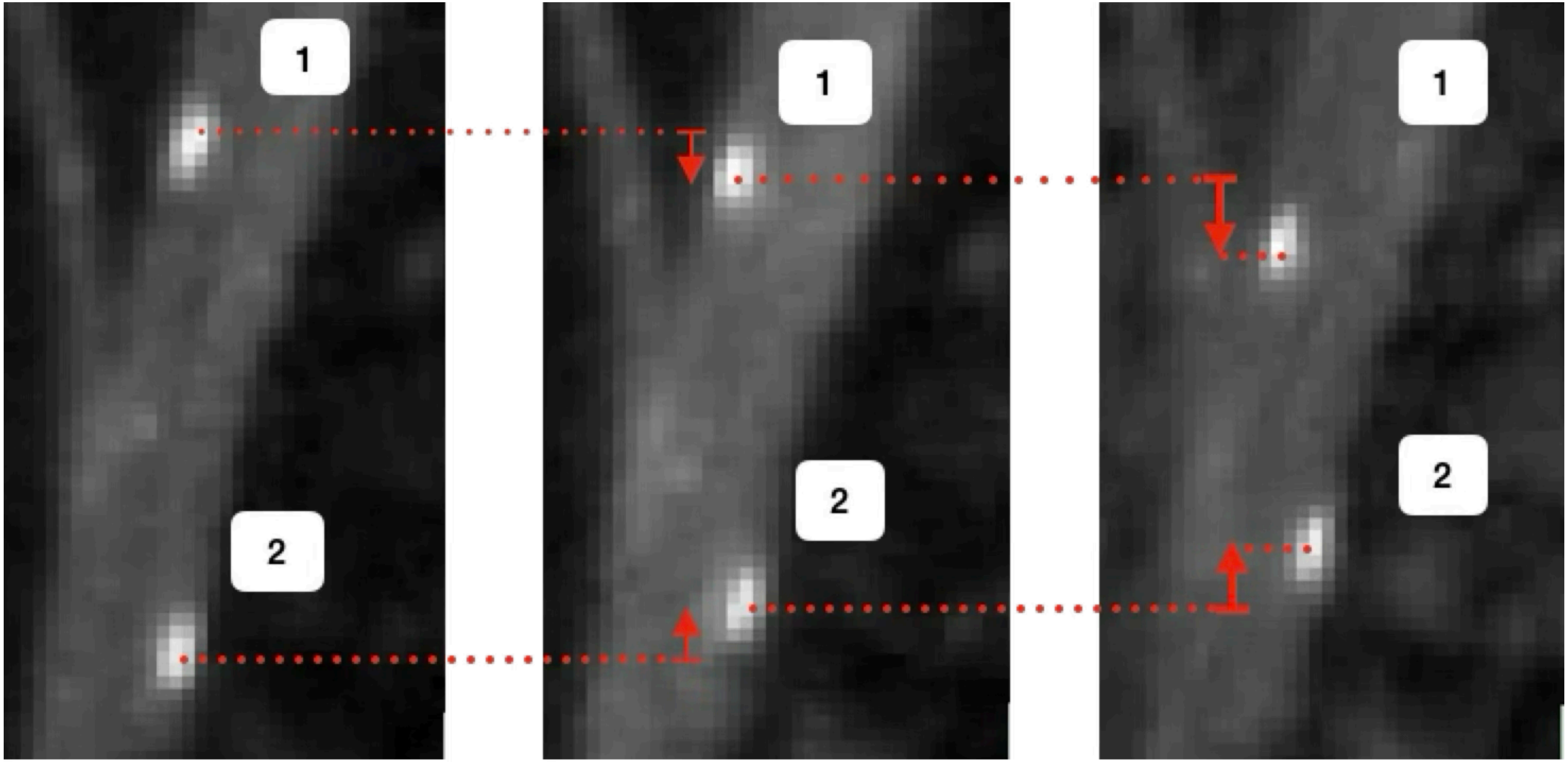
Movement of Vehicles across bands

blue band

Red band

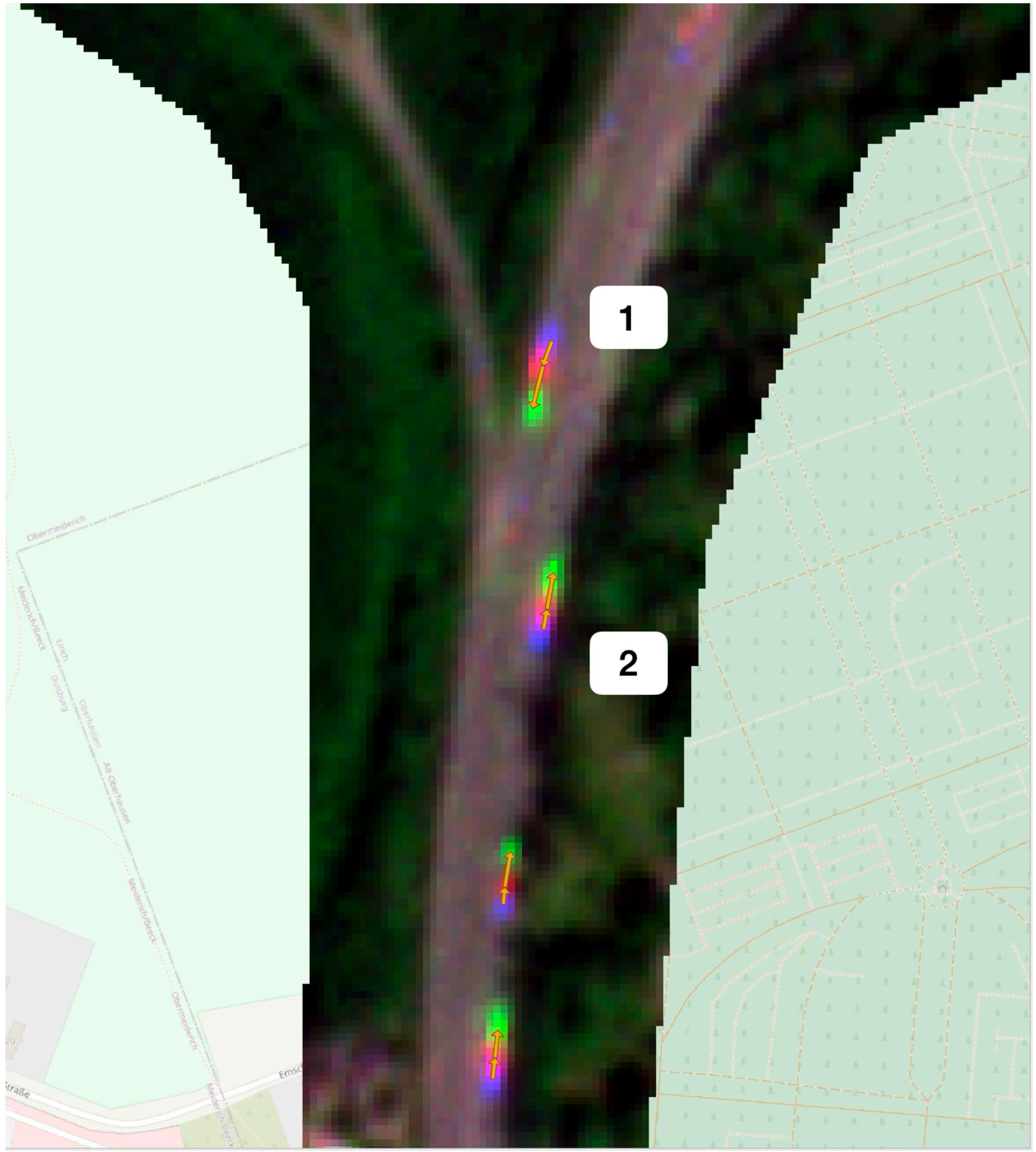
Green band

Movement of Vehicles across bands : Zoom In



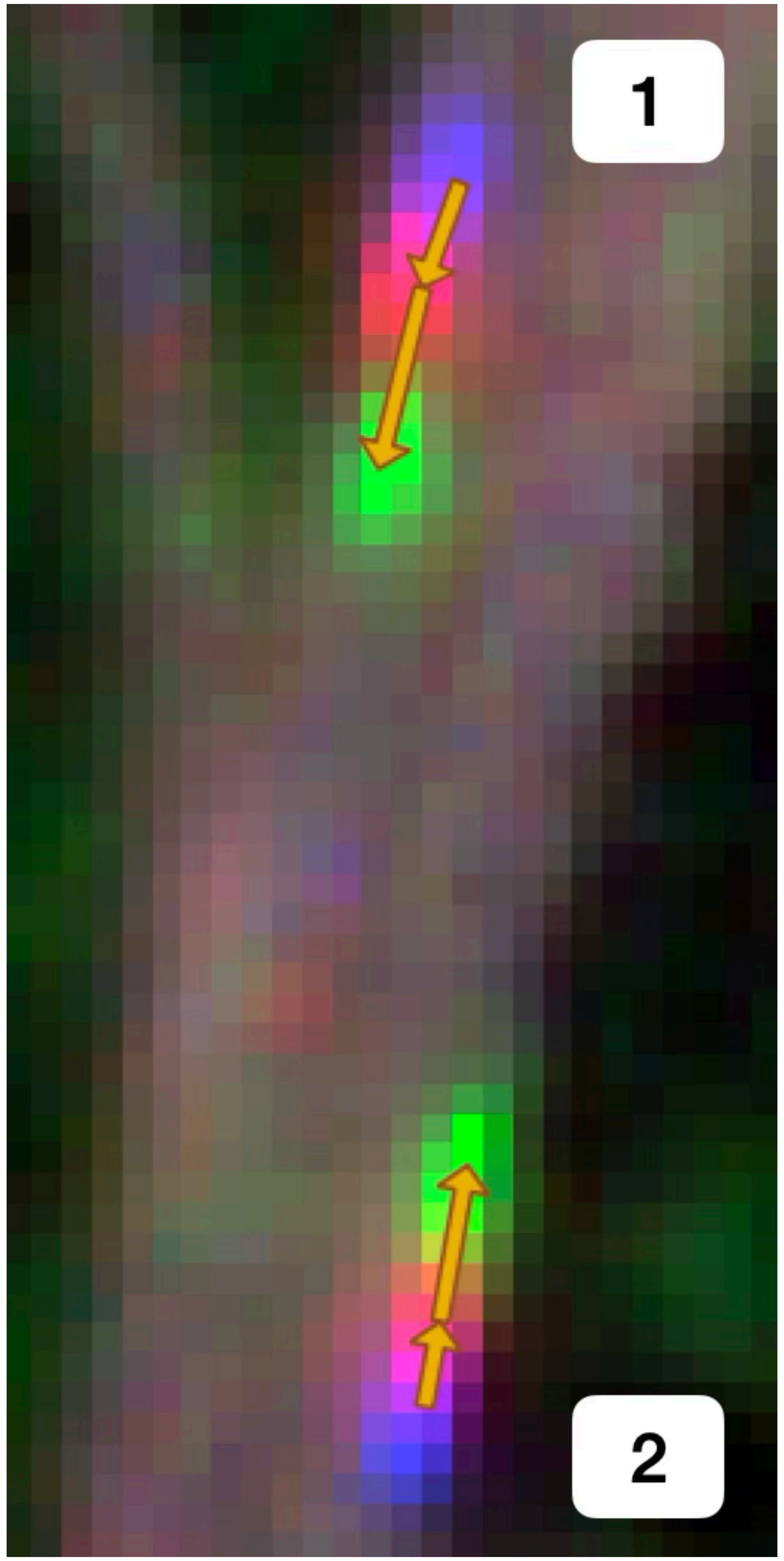
blue band Red band Green band

RGB Planetscope Imagery



Moving vehicles produce "rainbow" effect. The direction of motion is blue → red →green.

RGB Planetscope Imagery : Zoom In



RGB Planetscope Imagery

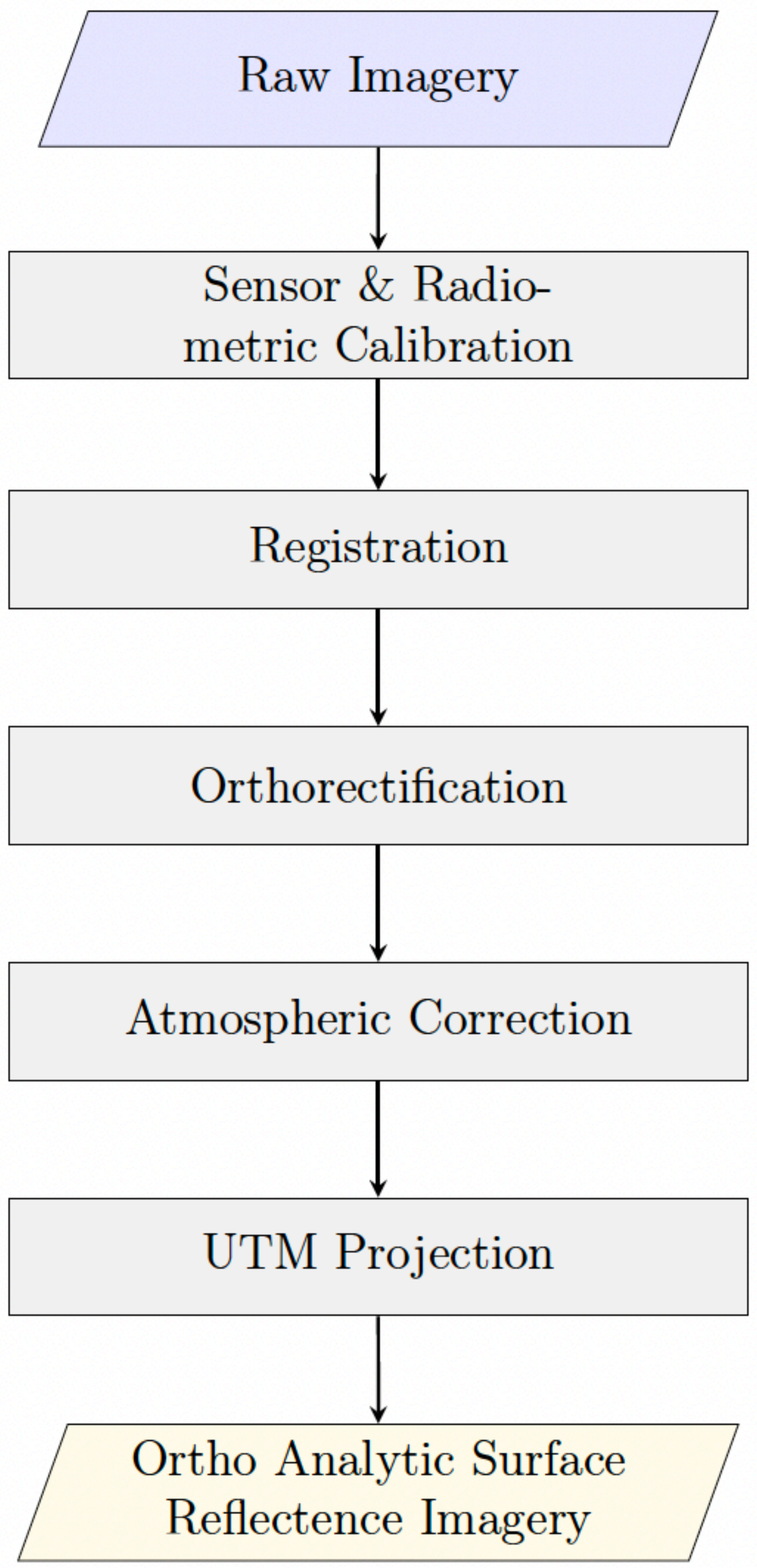
Vehicles in lane 0 are moving at low speeds compared to those in the lane 1.
As a result no "rainbow" effect in lane 0.

Goal

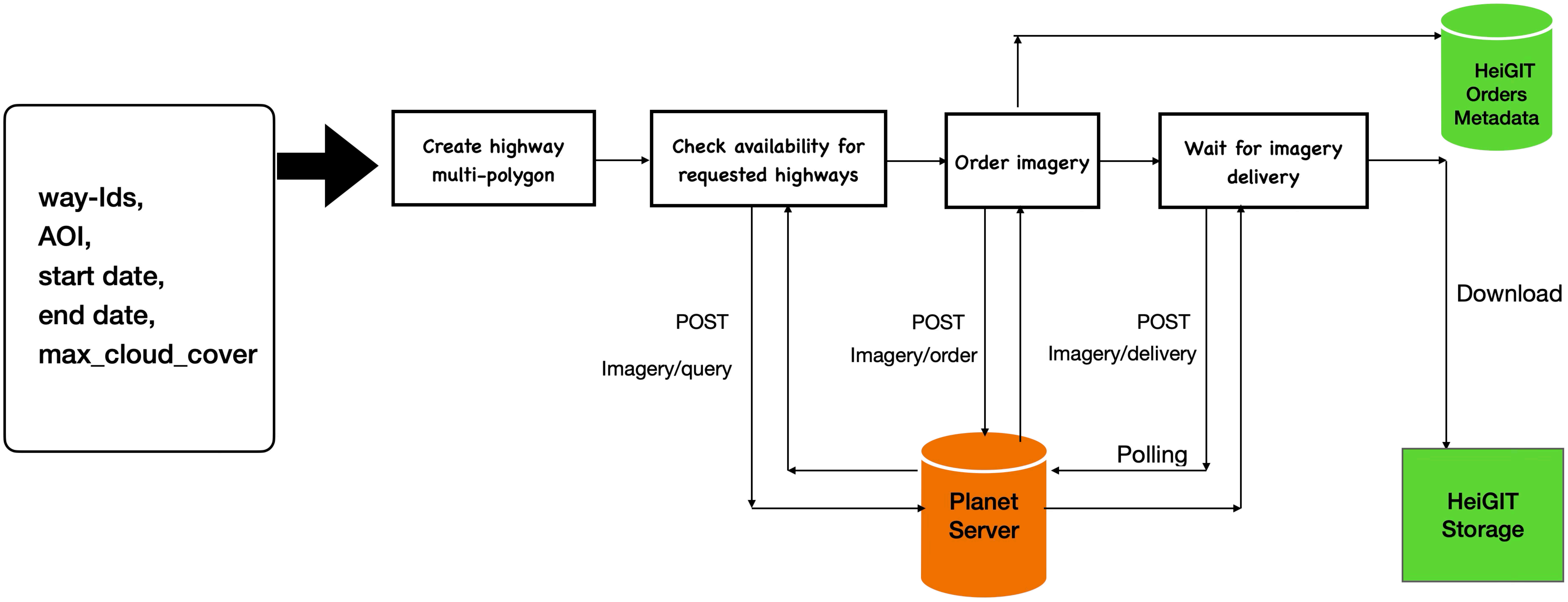
$$V^{\text{avg}}_{\text{vehicle}} = \frac{d_{blue-red} + d_{red-green}}{\Delta t_{blue-red} + \Delta t_{red-green}}$$

Data

Analysis Ready Imagery

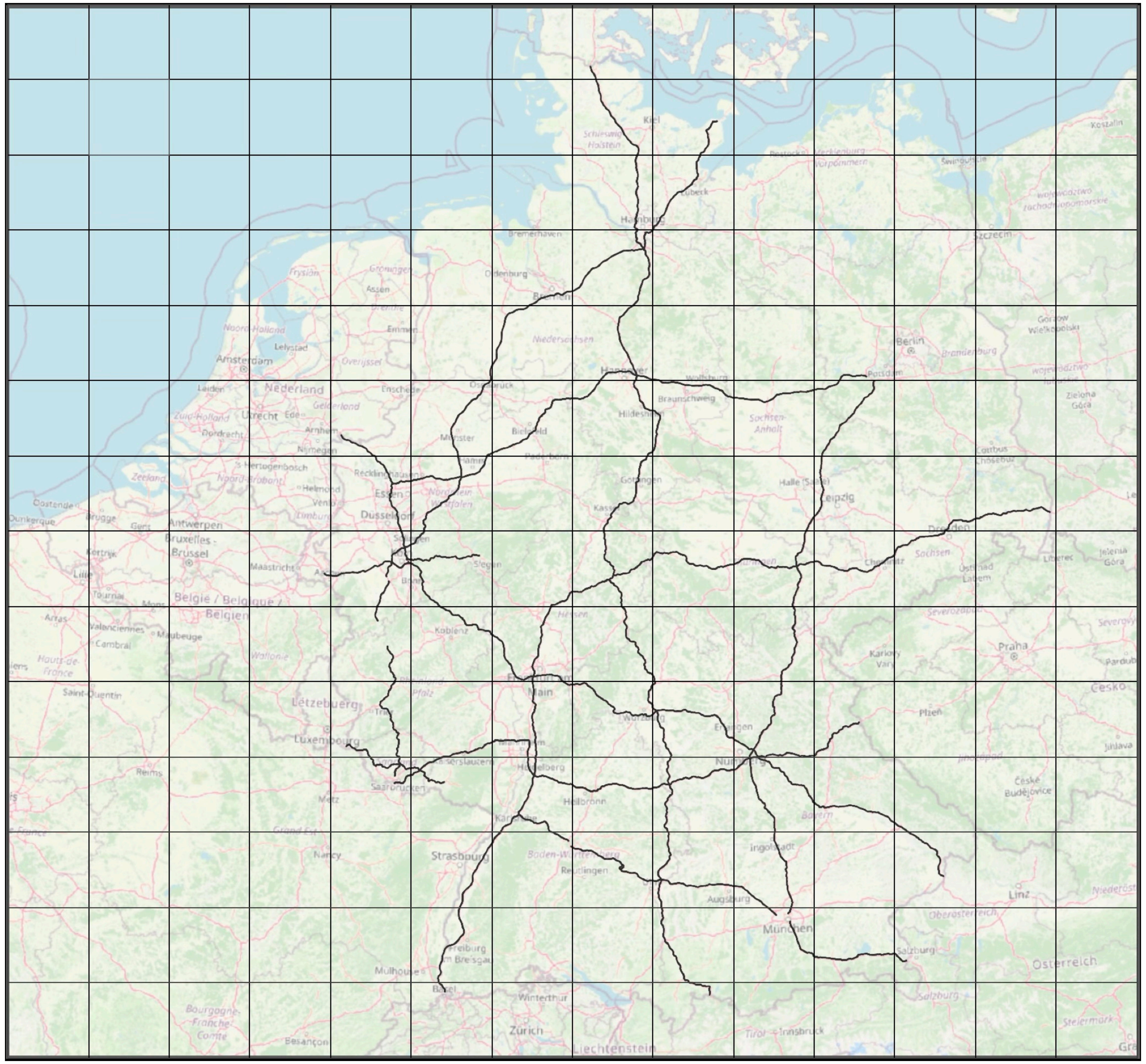


Downloading road networks at large scale



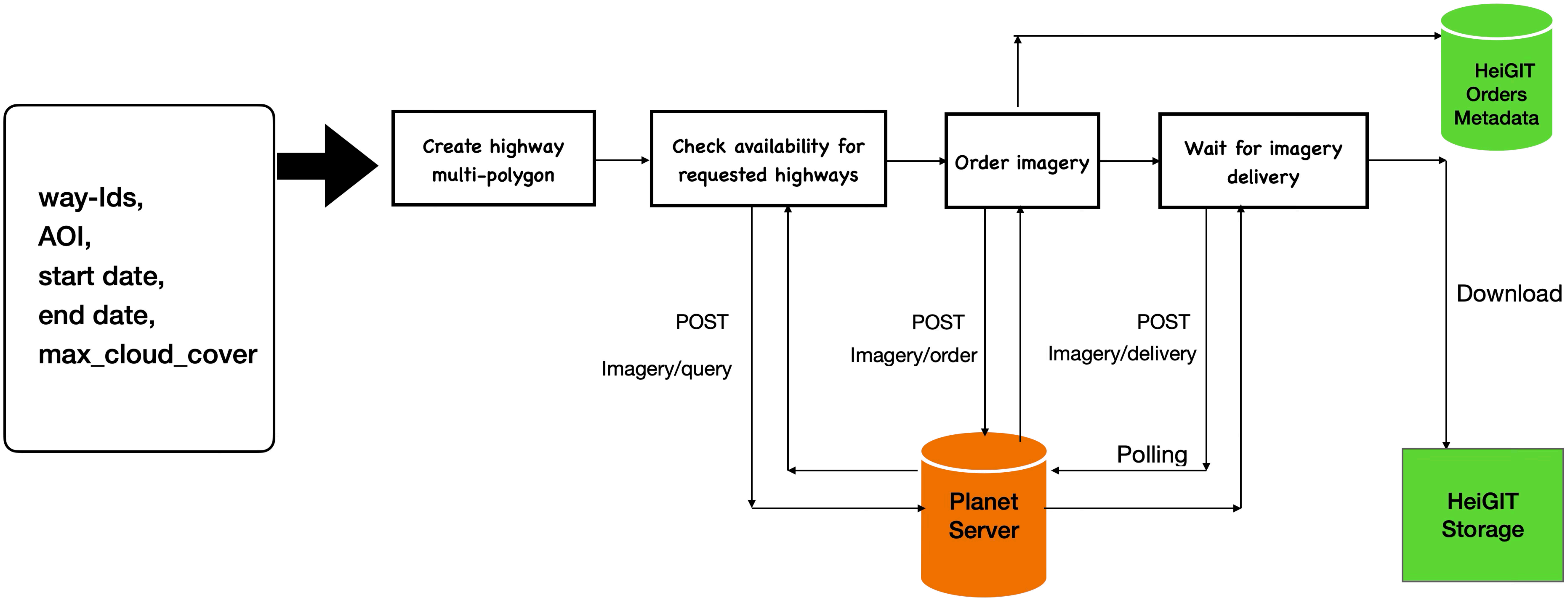
Software architecture

Downloading road networks at large scale



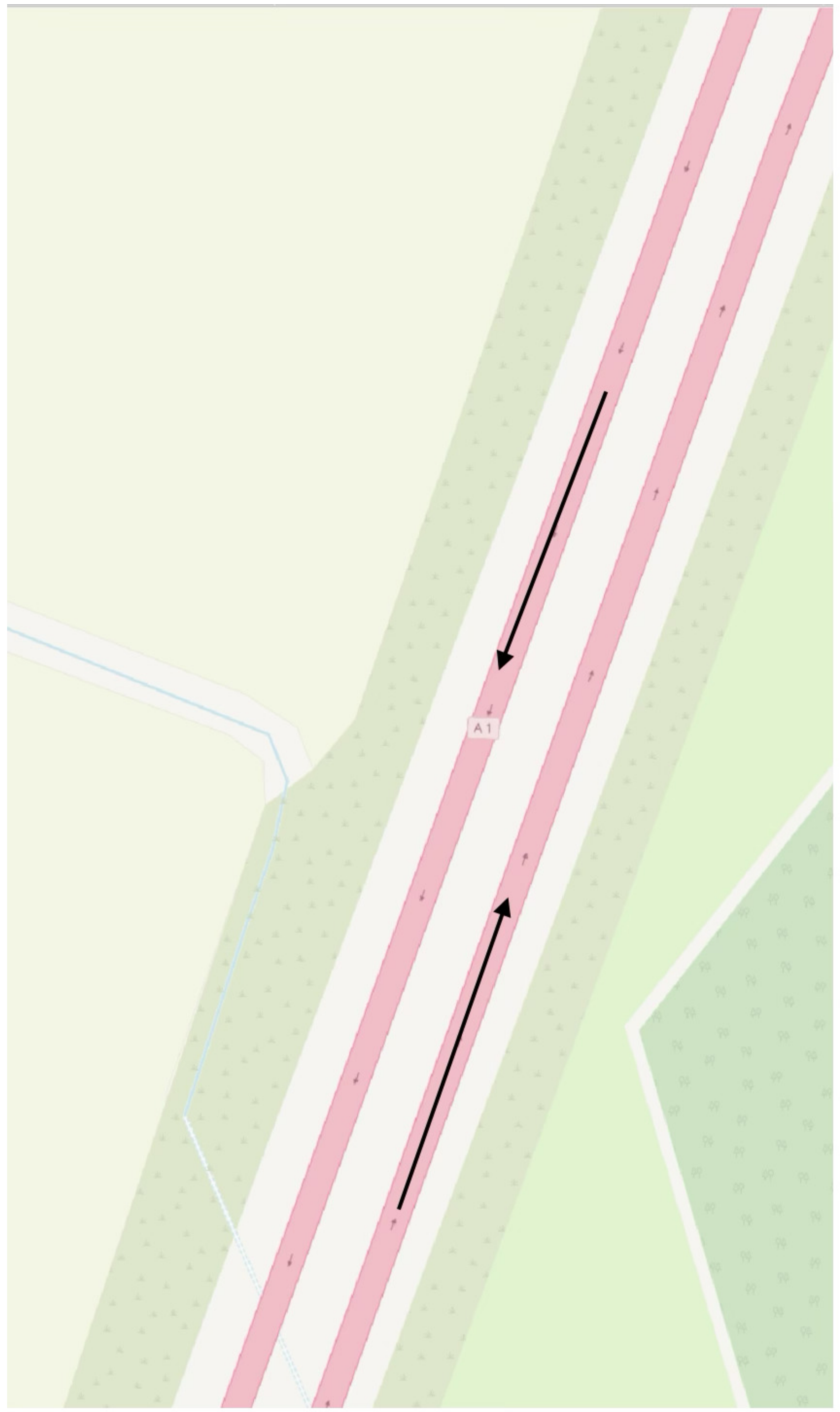
A1-A9 highways of Germany

Downloading road networks at large scale

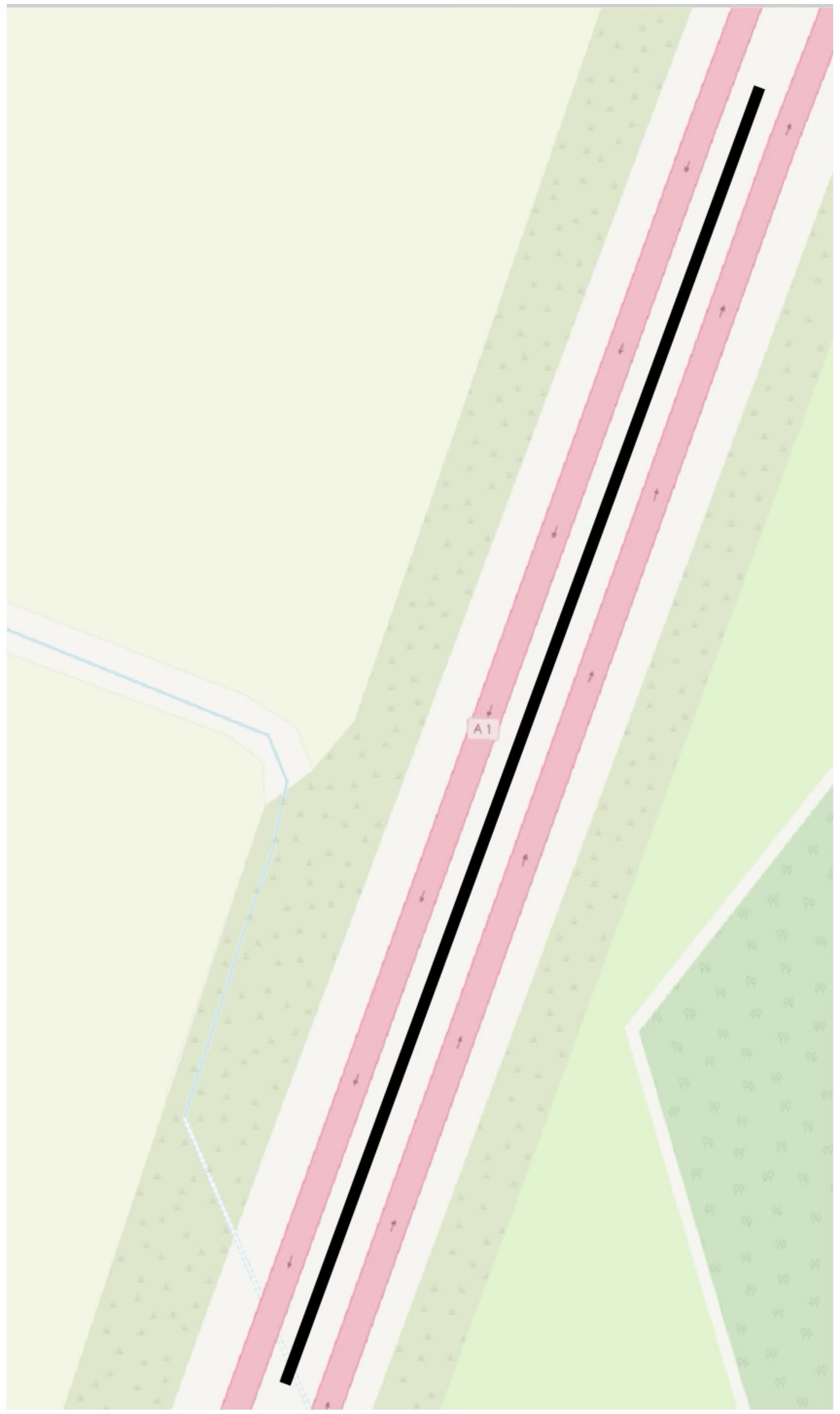


Software architecture

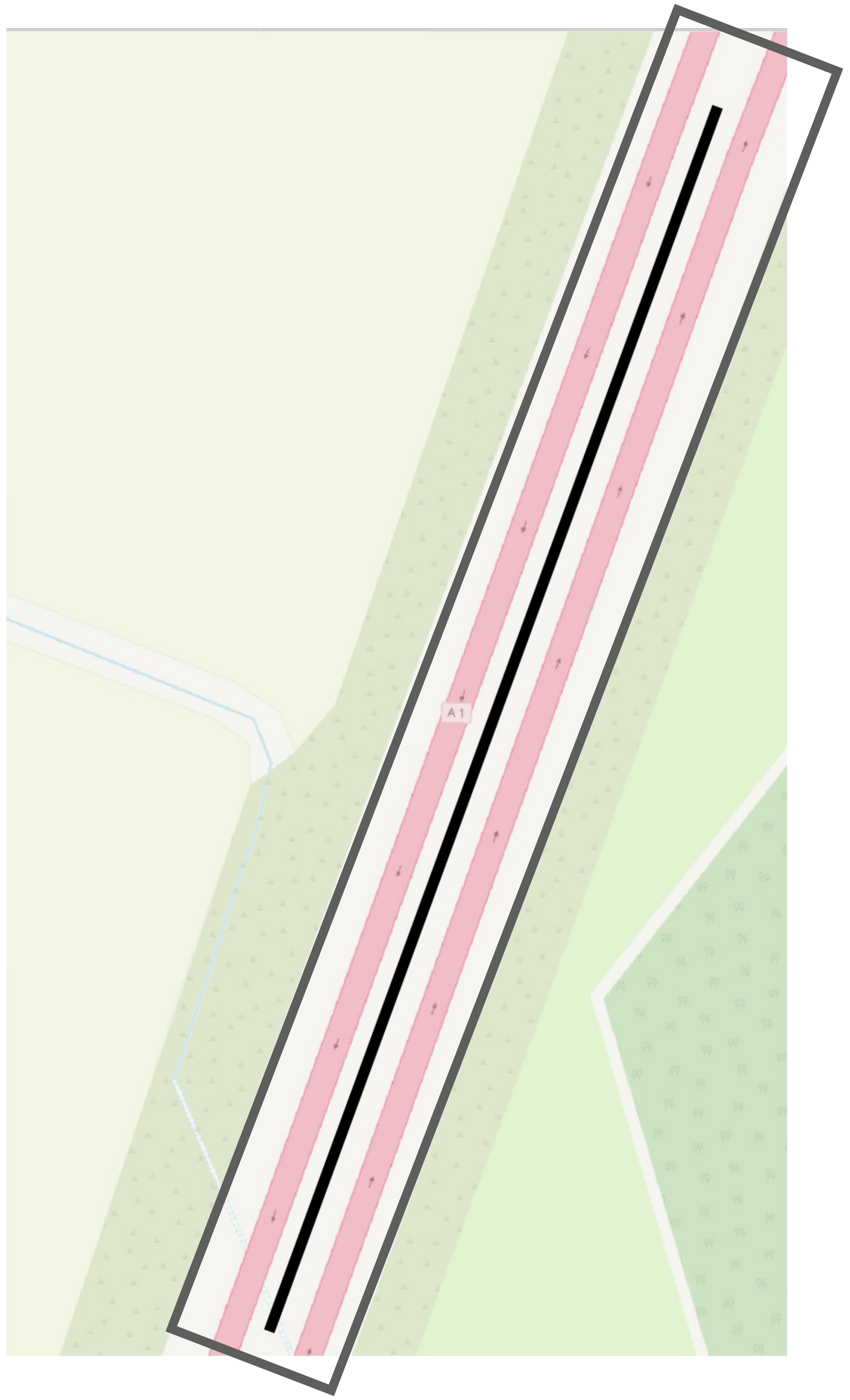
Creating Highway Polygons



Osm way

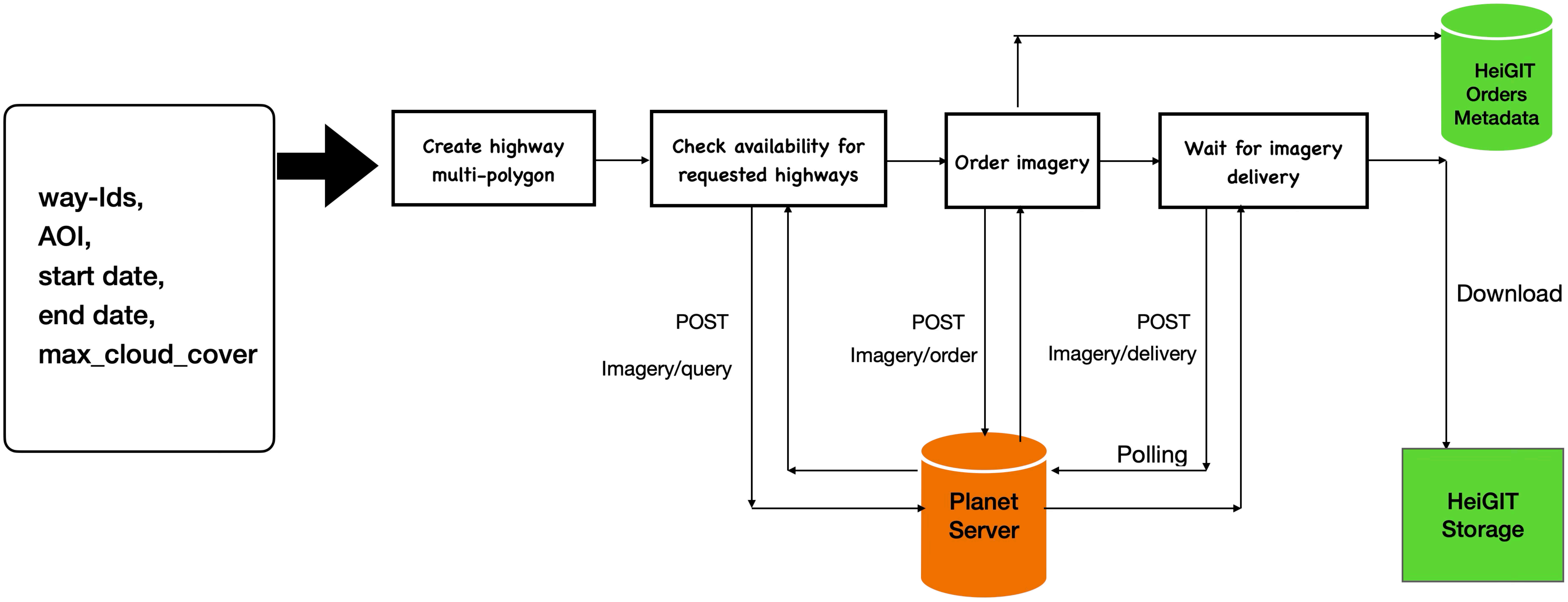


Centerline



Highway polygon

Downloading road networks at large scale



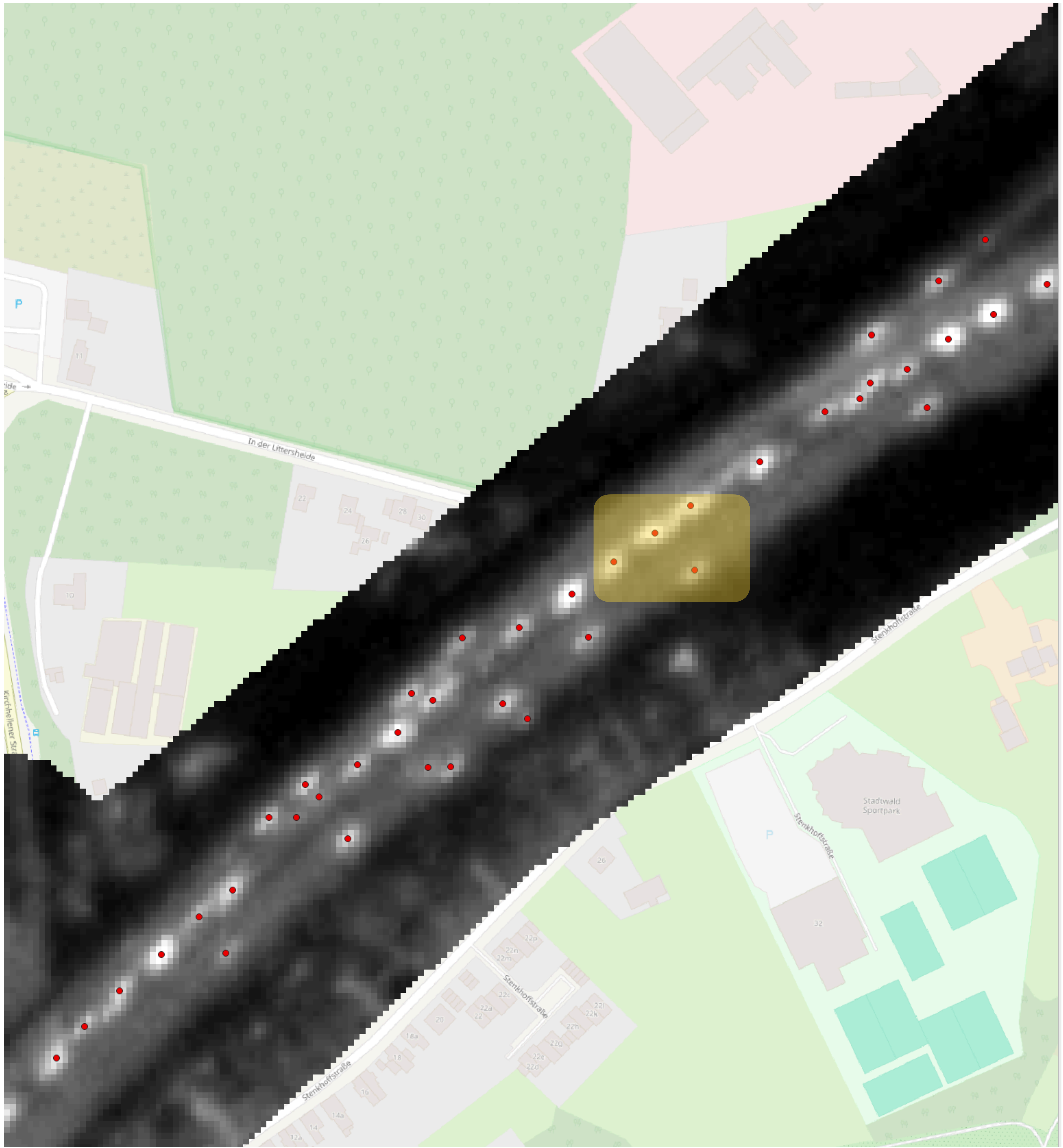
Software architecture

Preparation of highway segments for analysis

Osm way   Centerline   Highway polygon   Segments

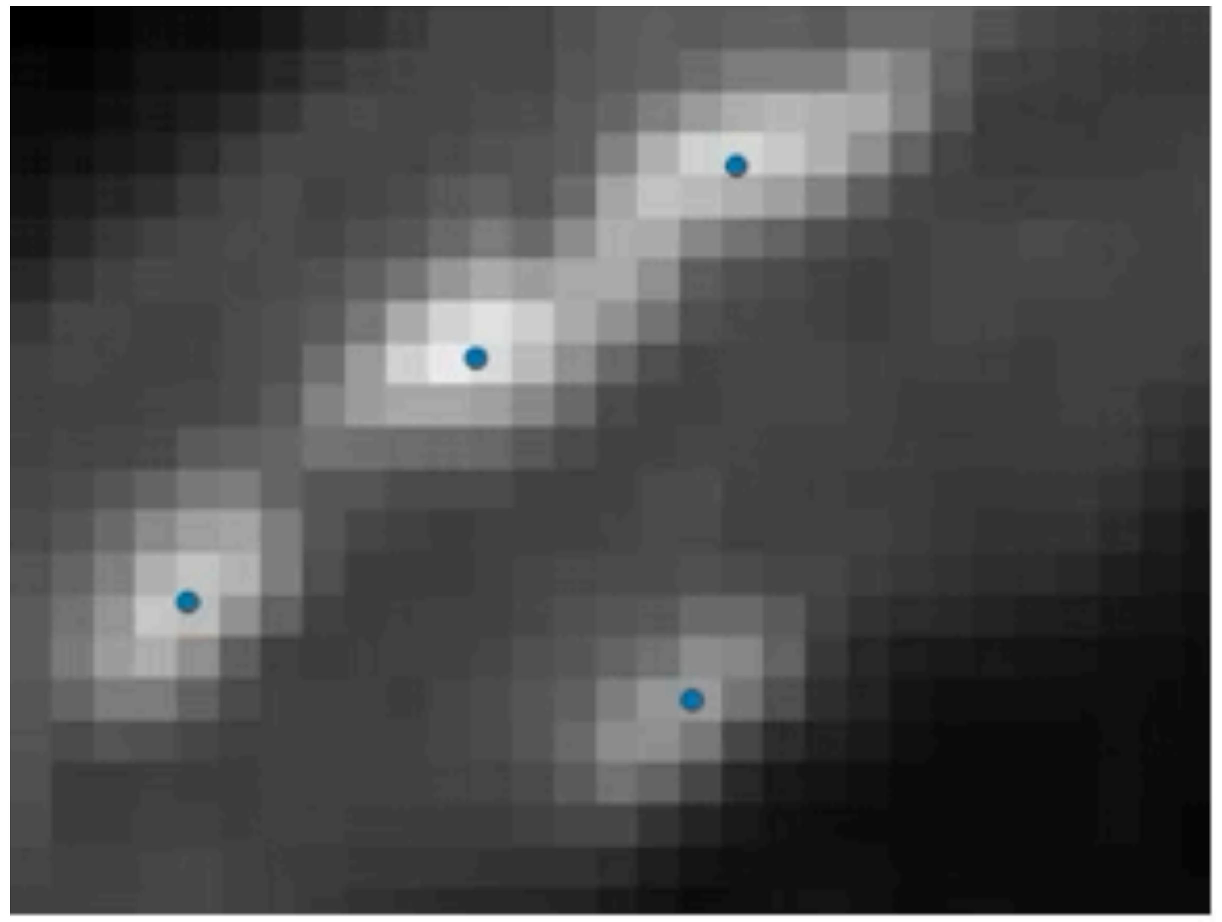
Ground Truth Labelling

Ground Truth Labelling

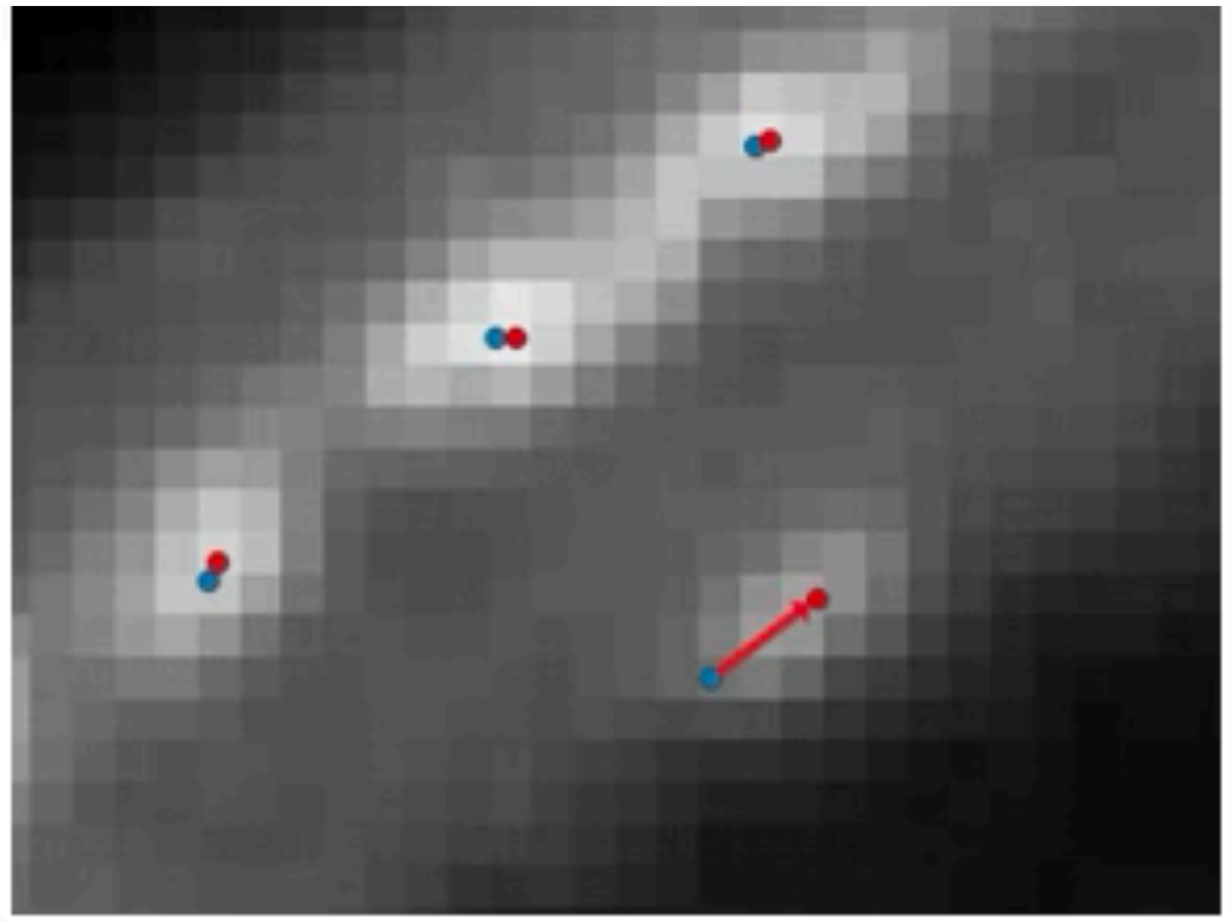


Ground Truth Labelling

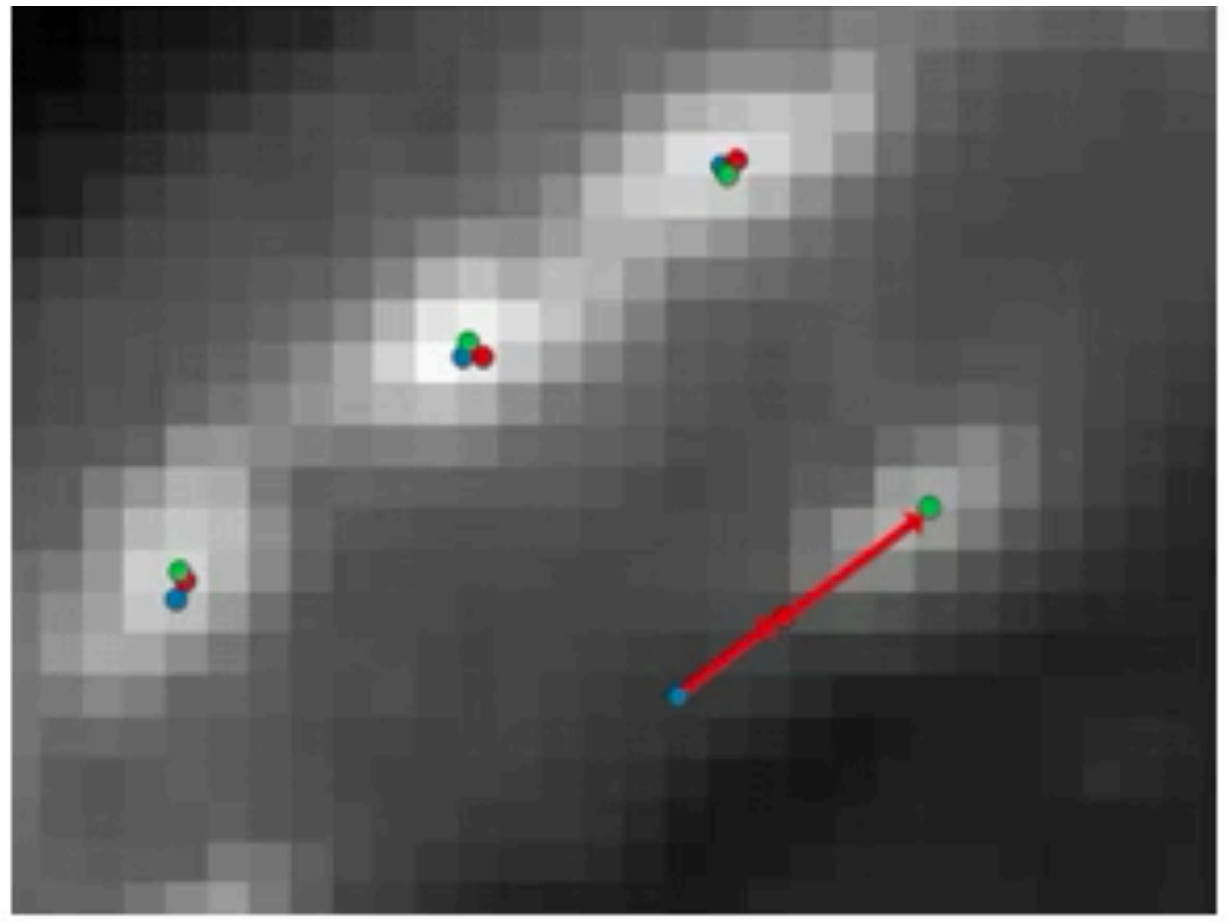
Ground Truth Labelling : Zoom In



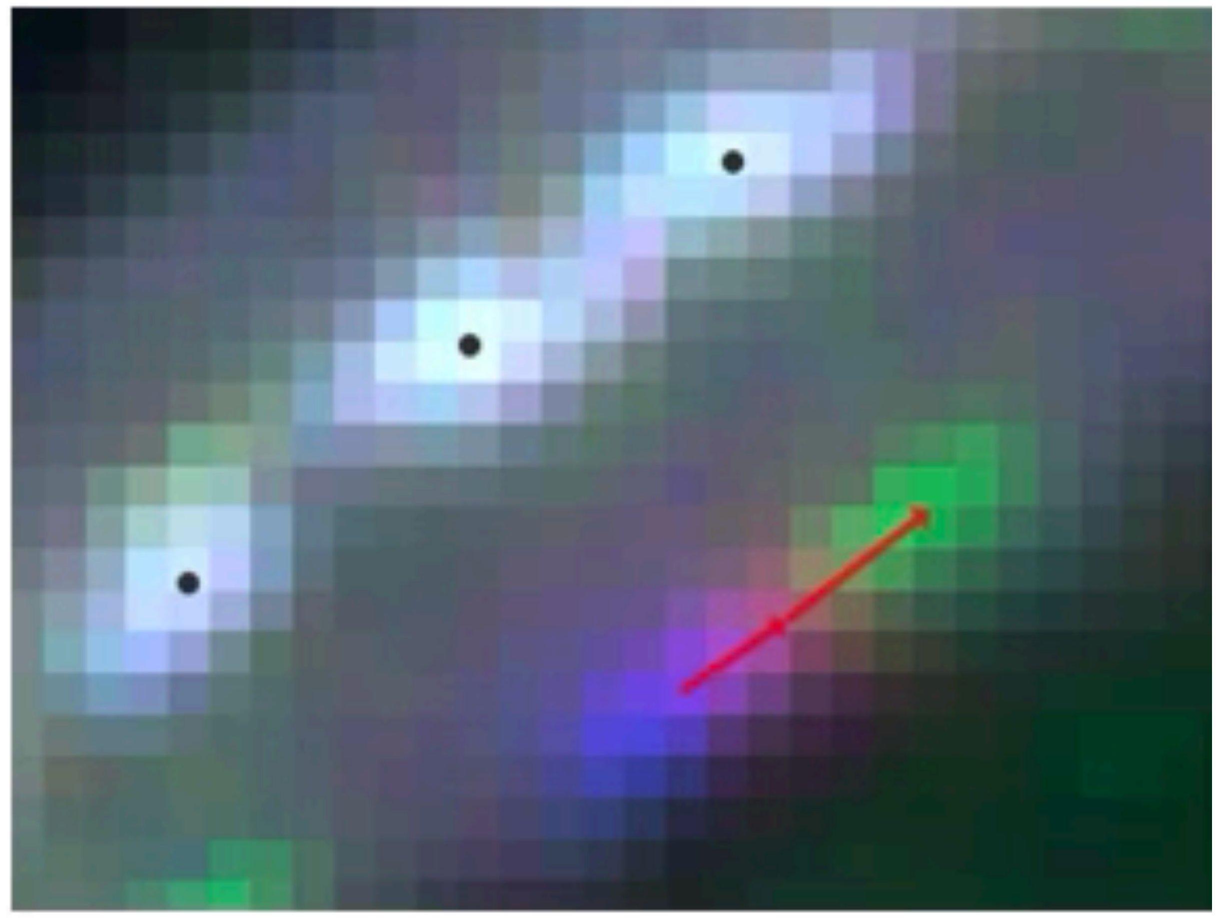
blue band



Red band

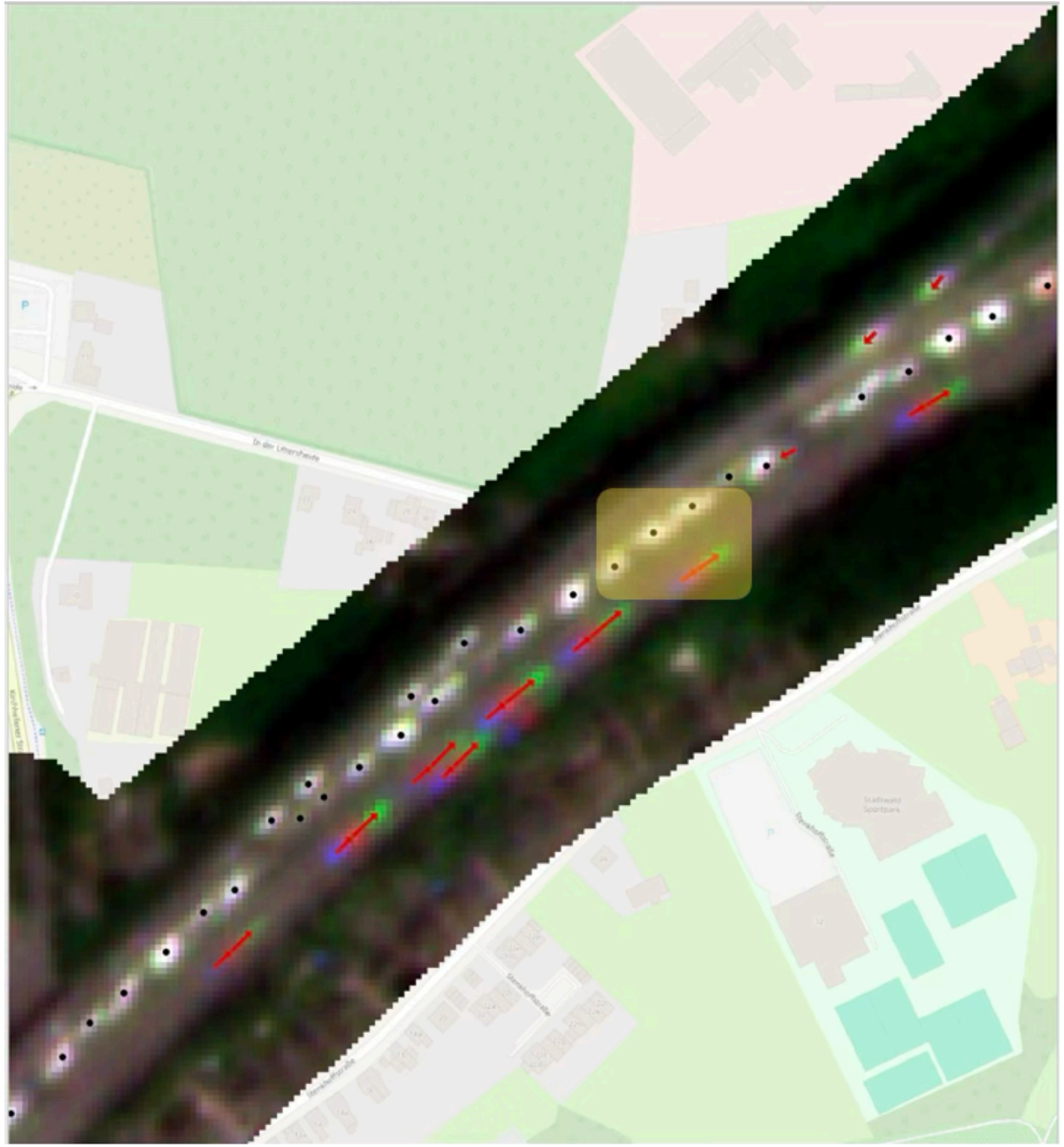


Green band



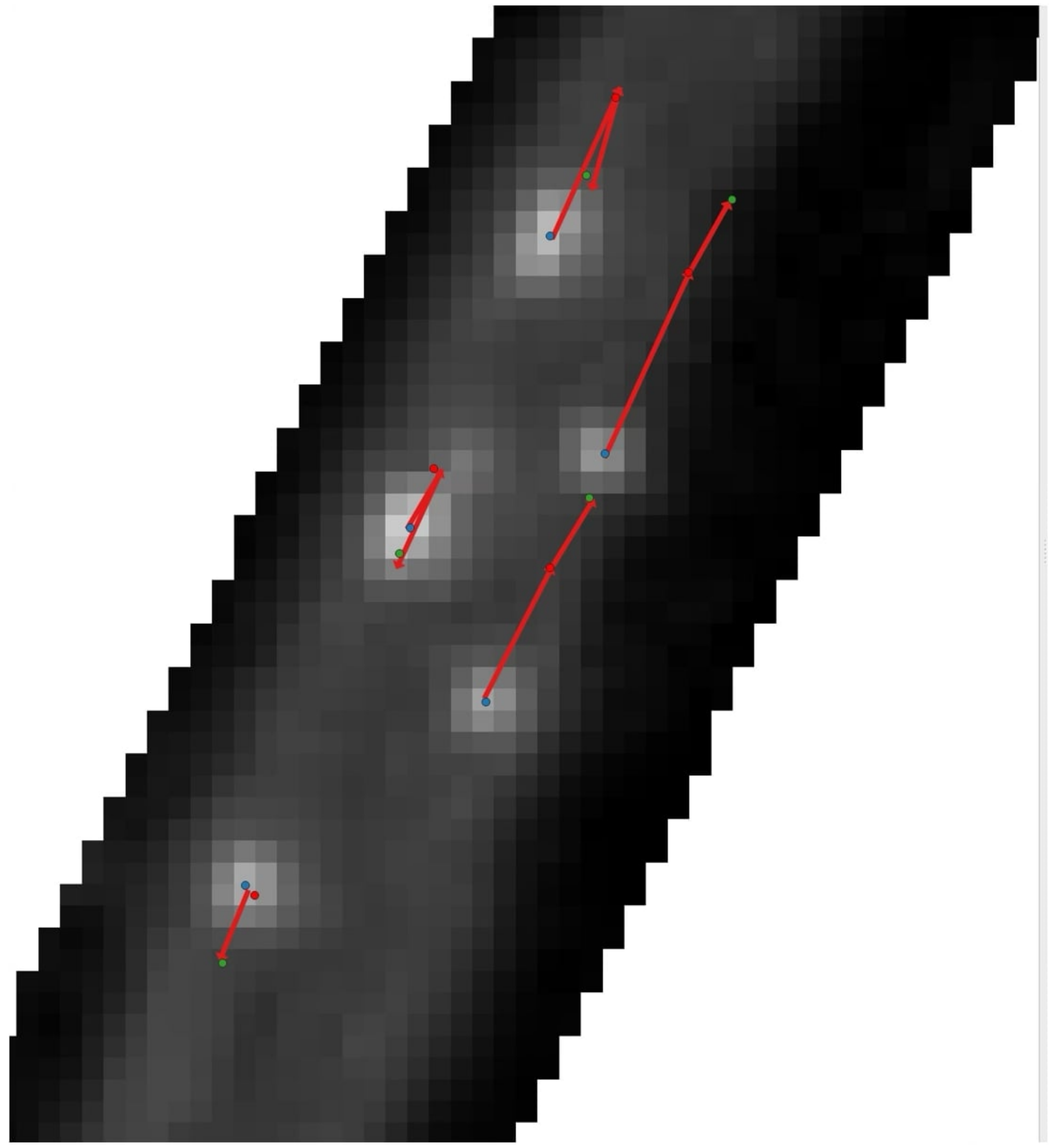
RGB band

Ground Truth Labelling

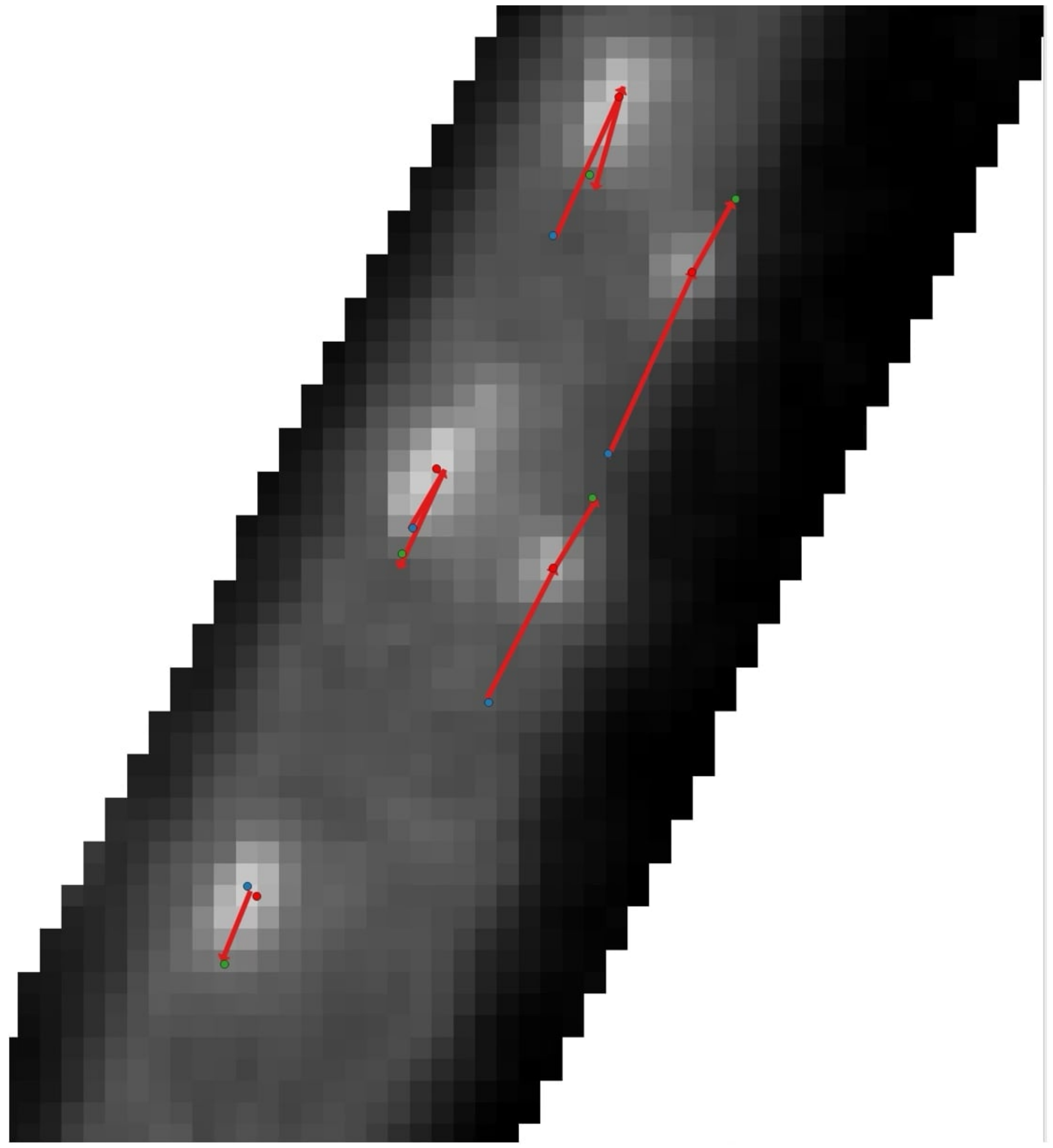


Ground Truth Analysis

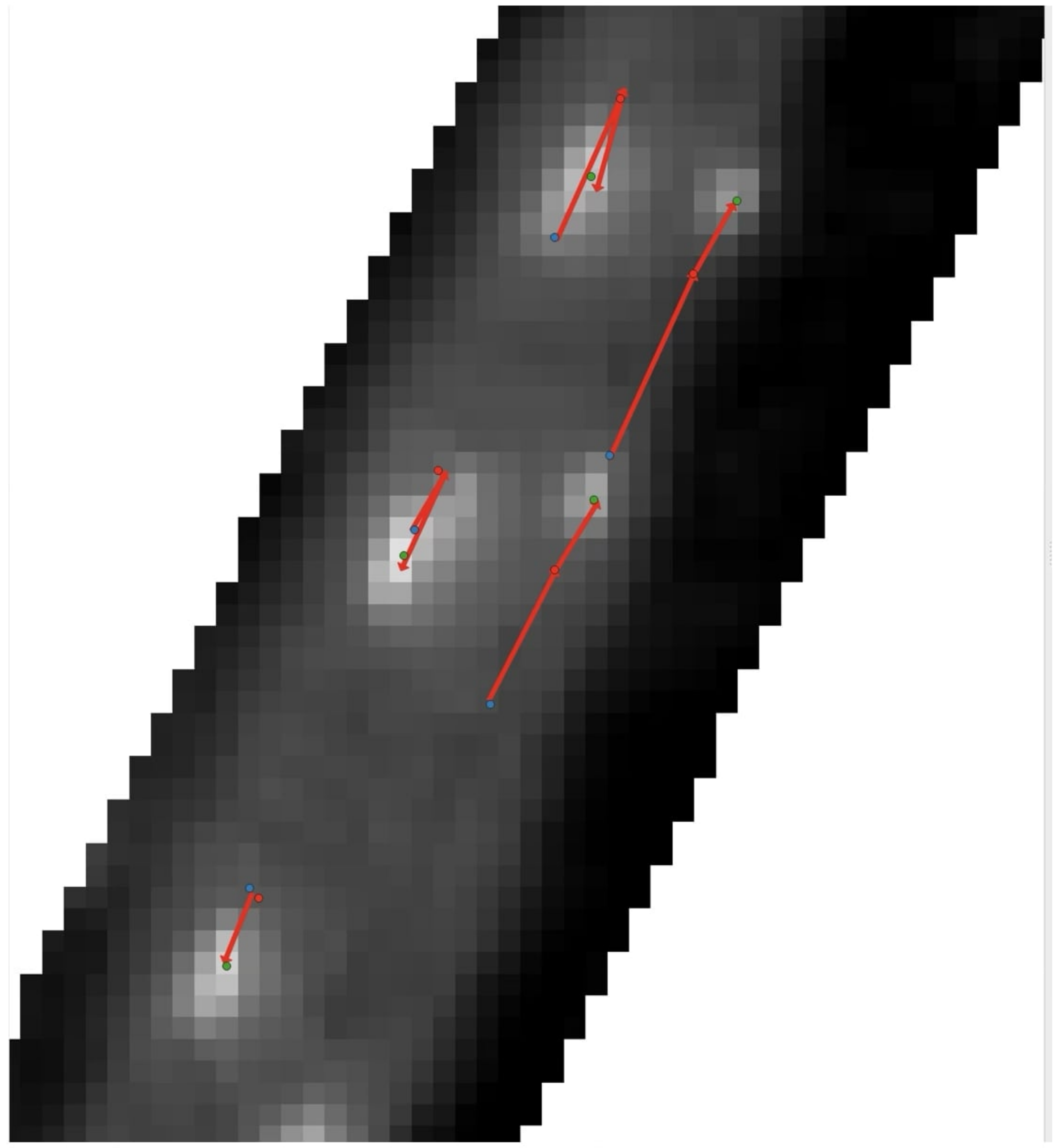
Band misalignment



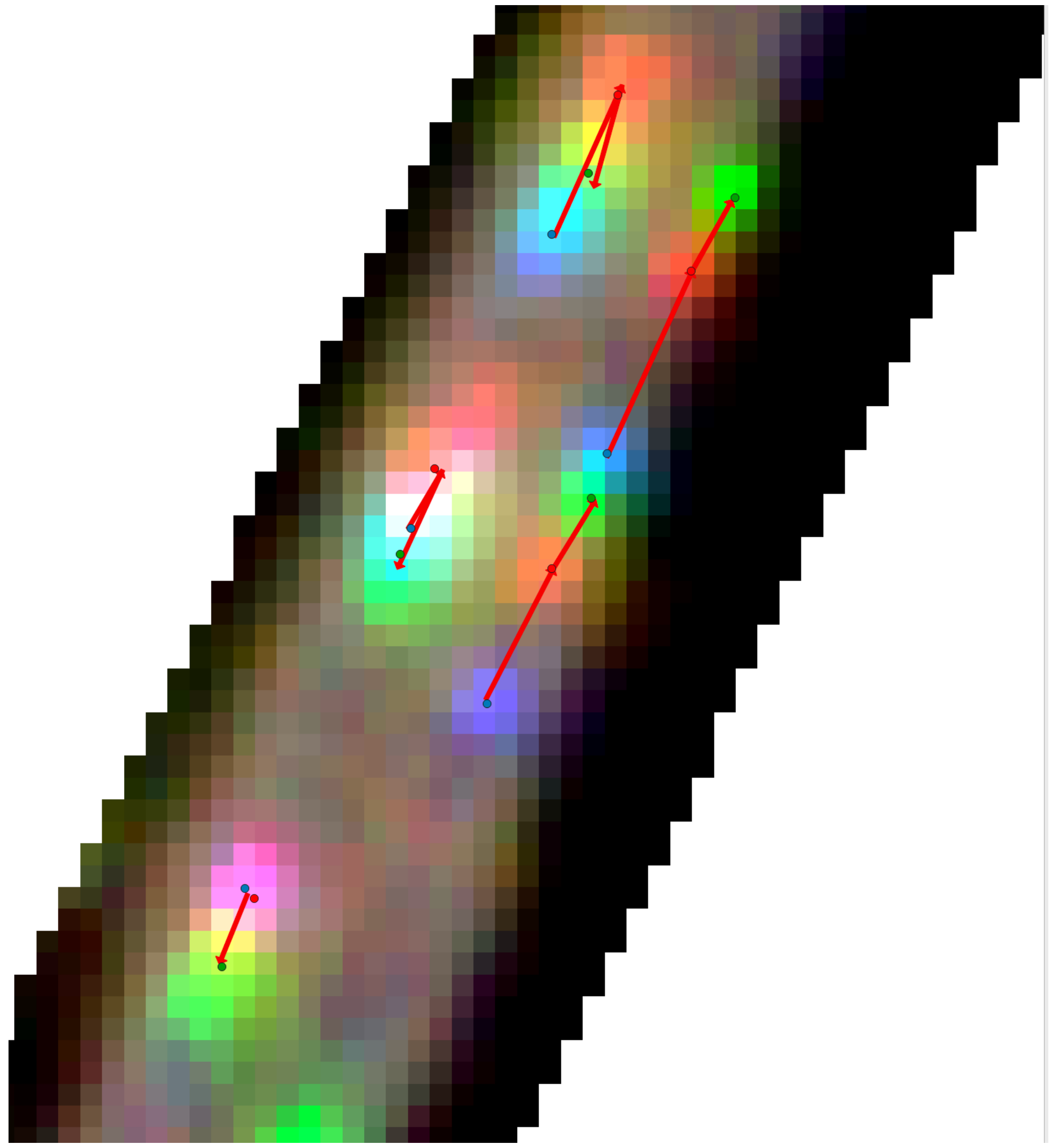
blue band



Red band

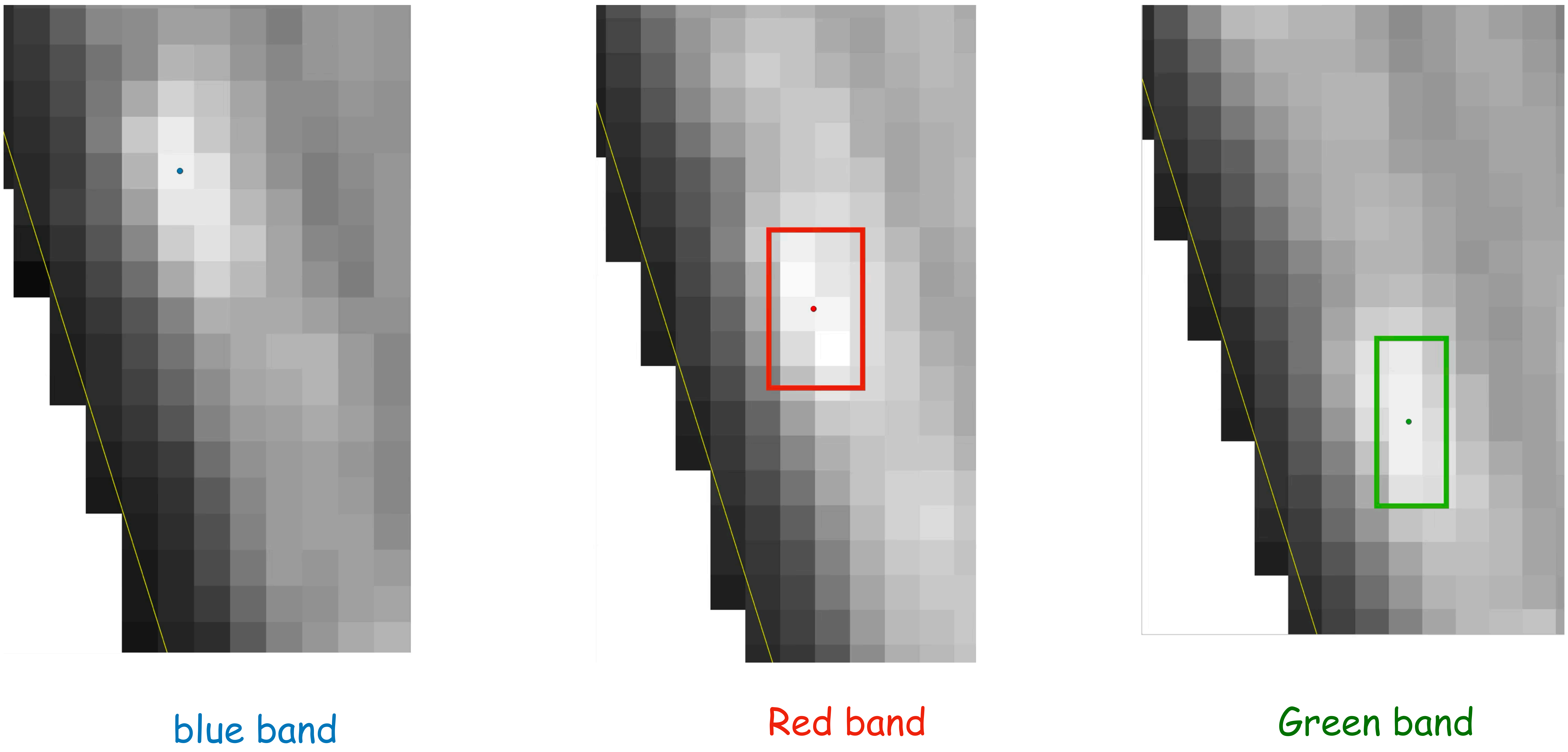


Green band



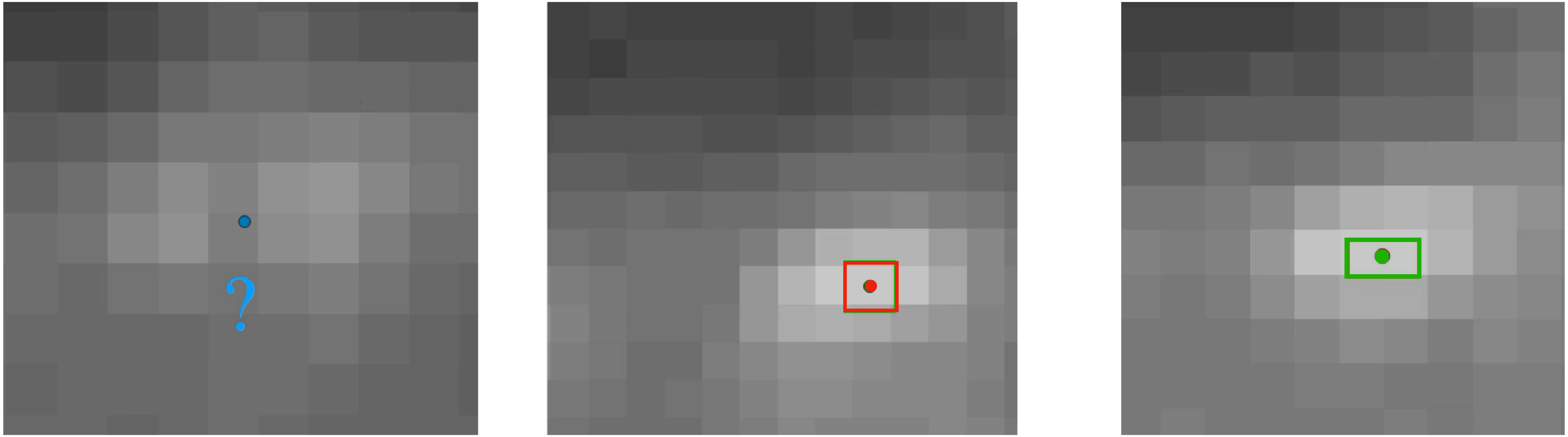
RGB band

Pixel- level ambiguity while labeling



Ambiguity in red and green channels: intensity peaks occur at multiple pixels.

Pixel- level ambiguity while labeling



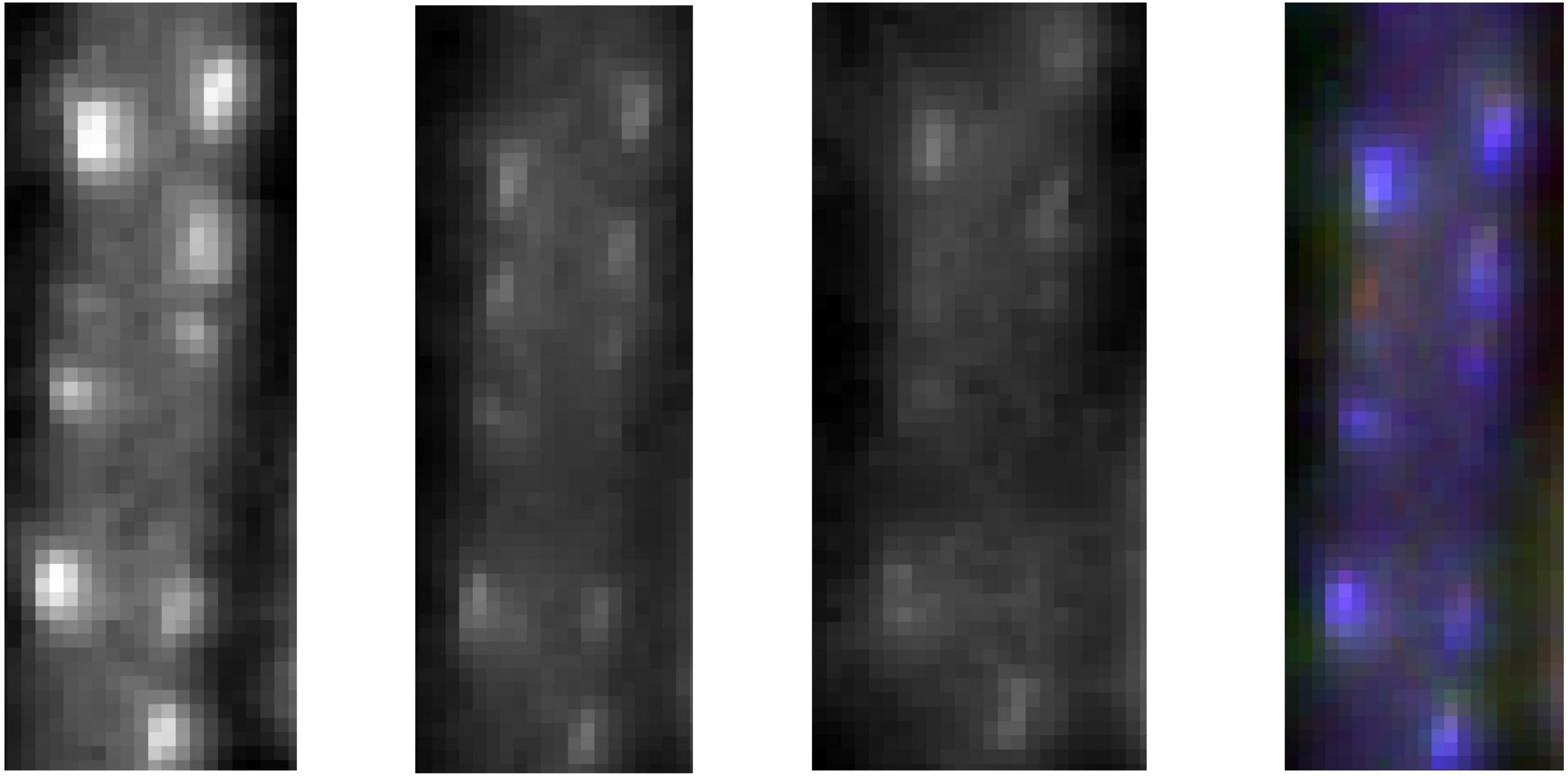
blue band

Red band

Green band

Ambiguity in the blue channel: no peak near the blob center.
Weak peaks in red and green channels.

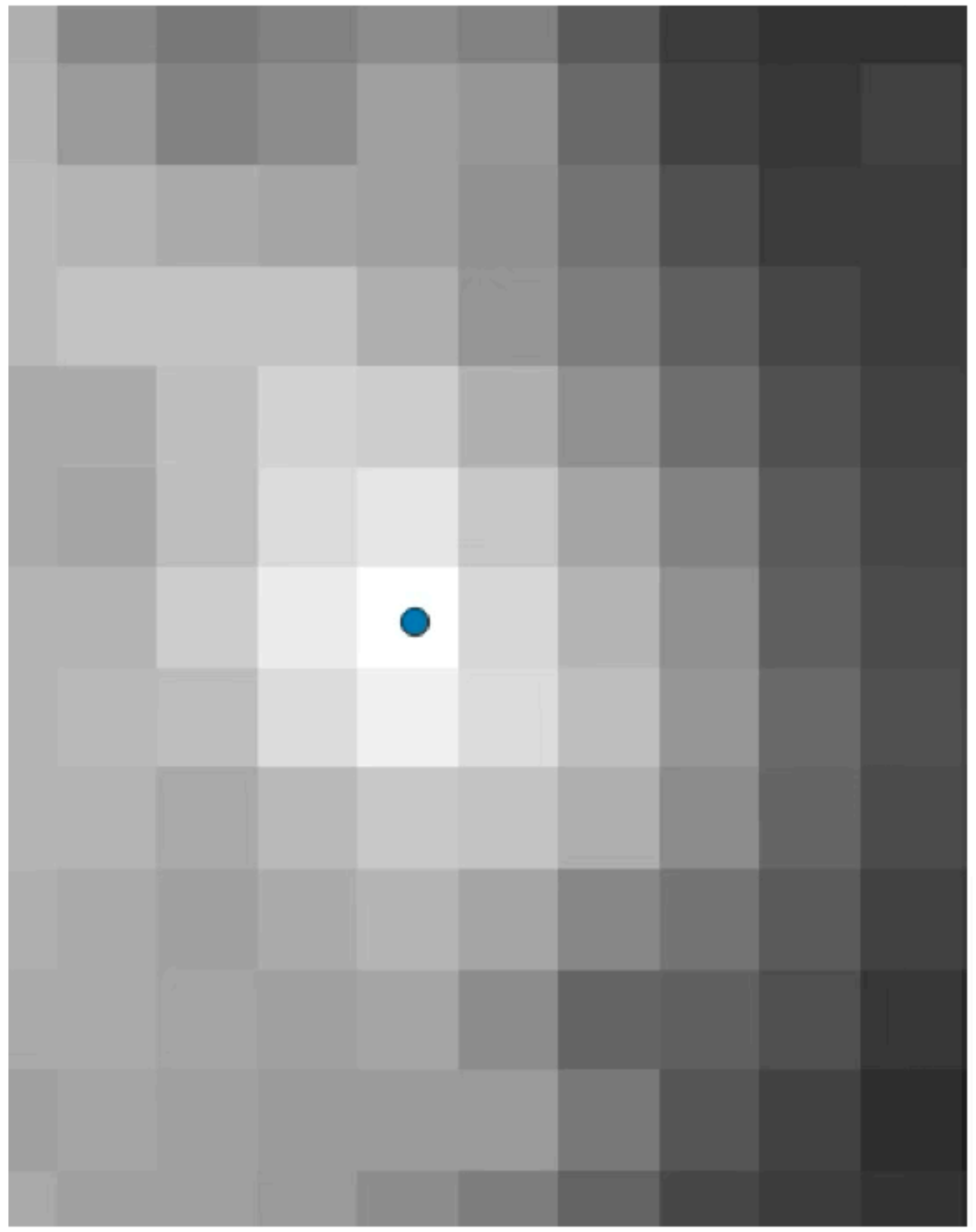
Ambiguity while labeling



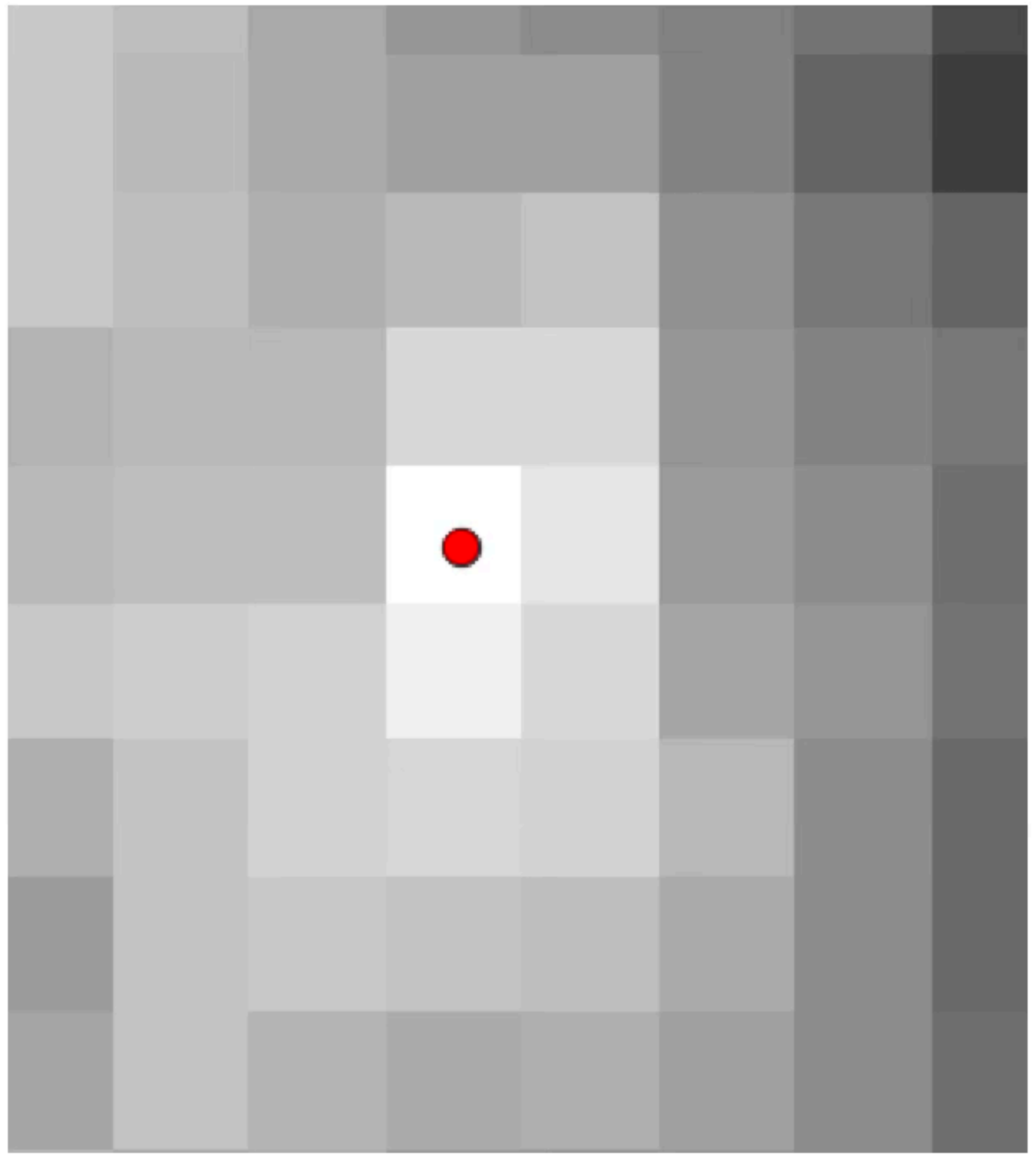
blue band   Red band   Green band   RGB band

Signal weakens progressively from blue → red → green

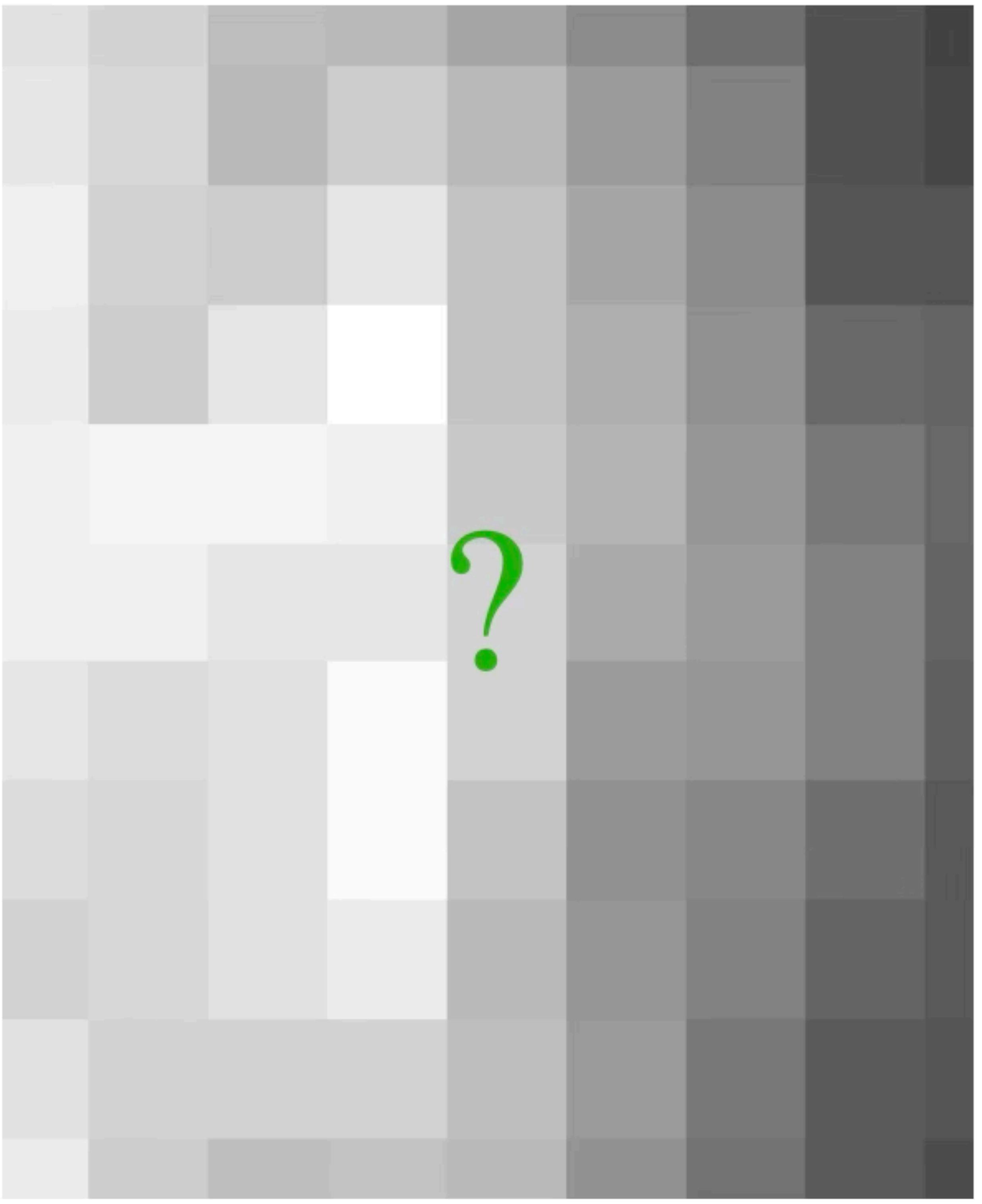
Pixel- level ambiguity while labeling



blue band



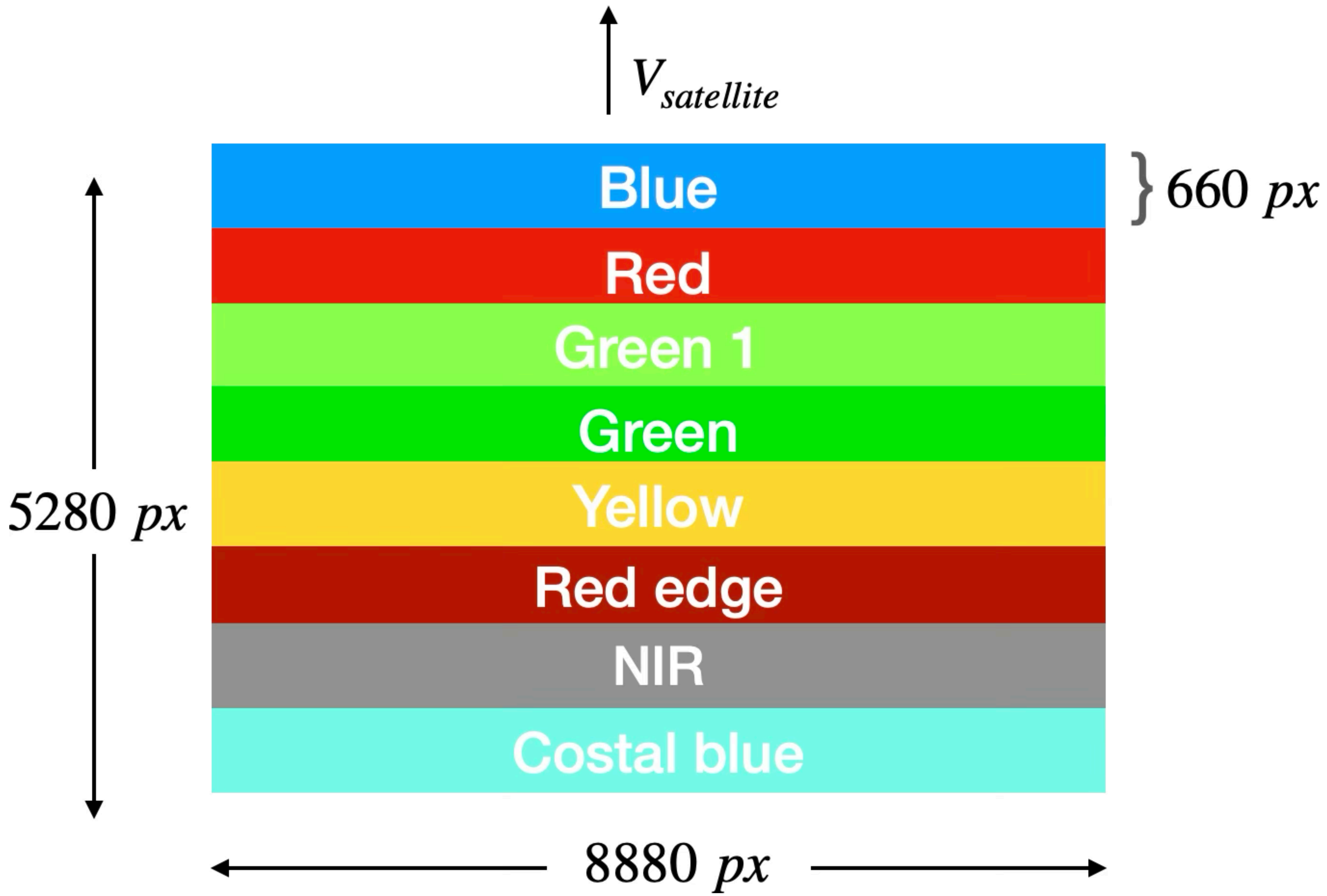
Red band



Green band

Ambiguity in the green band

Calculating inter band time delay



As the satellite moves forward, it must capture ground continuously without breaks

Calculating inter band time delay

$$\Delta t_{\mathrm{b1-b2}} = \frac{d^{\mathrm{satellite}}_{\mathrm{b1-b2}}}{V_{\mathrm{satellite}}}$$

As the satellite moves forward, it must capture ground continuously without breaks

Calculating inter band time delay

$$d_{\mathrm{b1-b2}}^{\mathrm{satellite}} = w_{\mathrm{b1-b2}}^{\mathrm{sensor-array}} \cdot \mathrm{GSD}$$

As the satellite moves forward, it must capture capture ground continuously without breaks

Calculating inter band time delay

$$\Delta t_{\text{blue-red}} = \frac{w^{\text{sensor-array}}_{\text{blue-red}} \cdot \text{GSD}}{V_{\text{satellite}}}$$

Calculating inter band time delay

$$\Delta t_{\text{red}-\text{green}} = \frac{w_{\text{red}-\text{green}}^{\text{sensor}-\text{array}} \cdot \text{GSD}}{V_{\text{satellite}}}$$

Calculating inter band time delay

GSD ~ 3.7 m

V_{sat} = 7600m/s

sensor width w = 660px

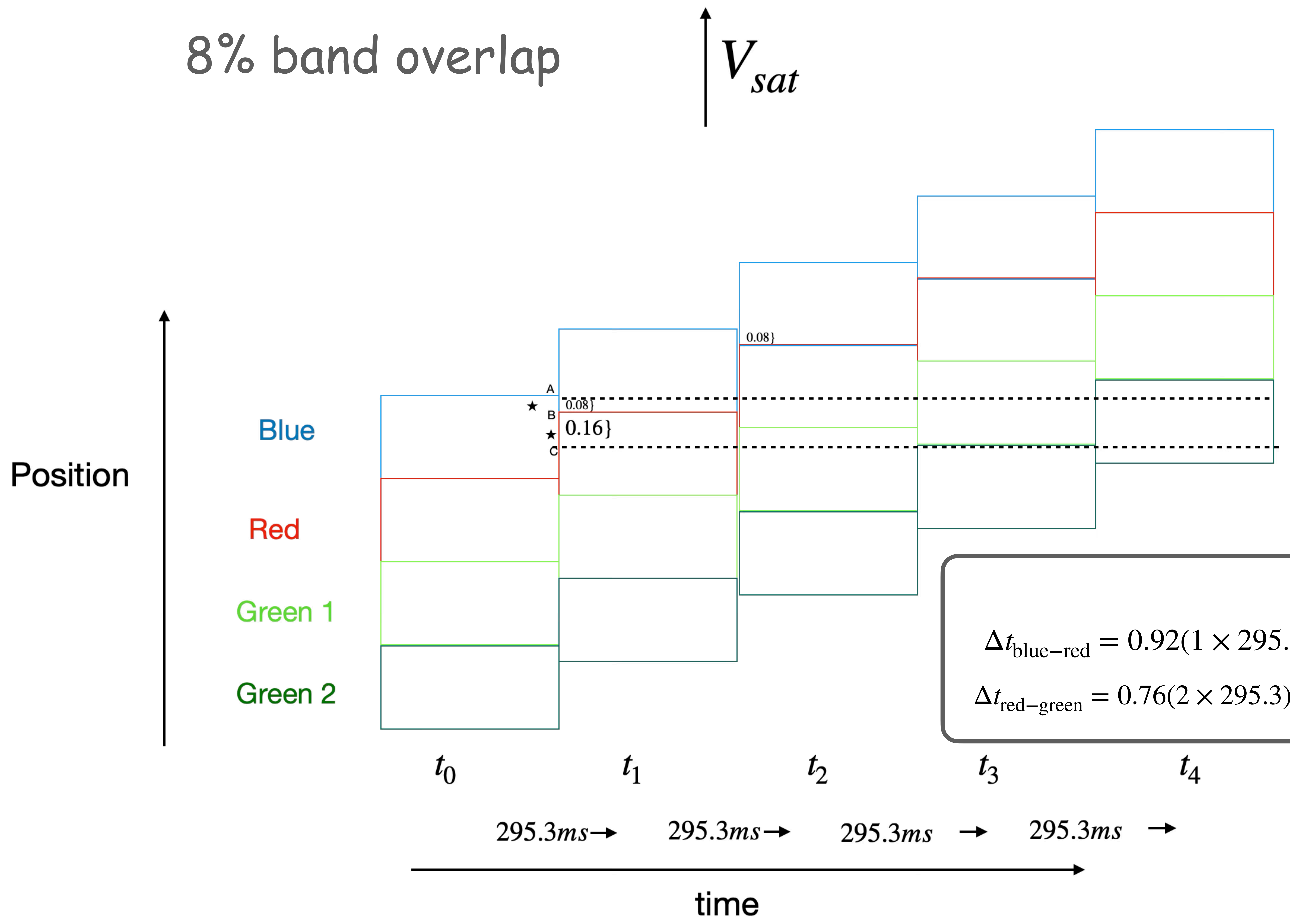
Time delay/band ~ 321ms

$\Delta t_{\text{blue}-\text{red}}$ ~ 321ms

$\Delta t_{\text{red}-\text{green}}$ ~ 642ms

Calculating inter band time delay : Overlap

8% band overlap

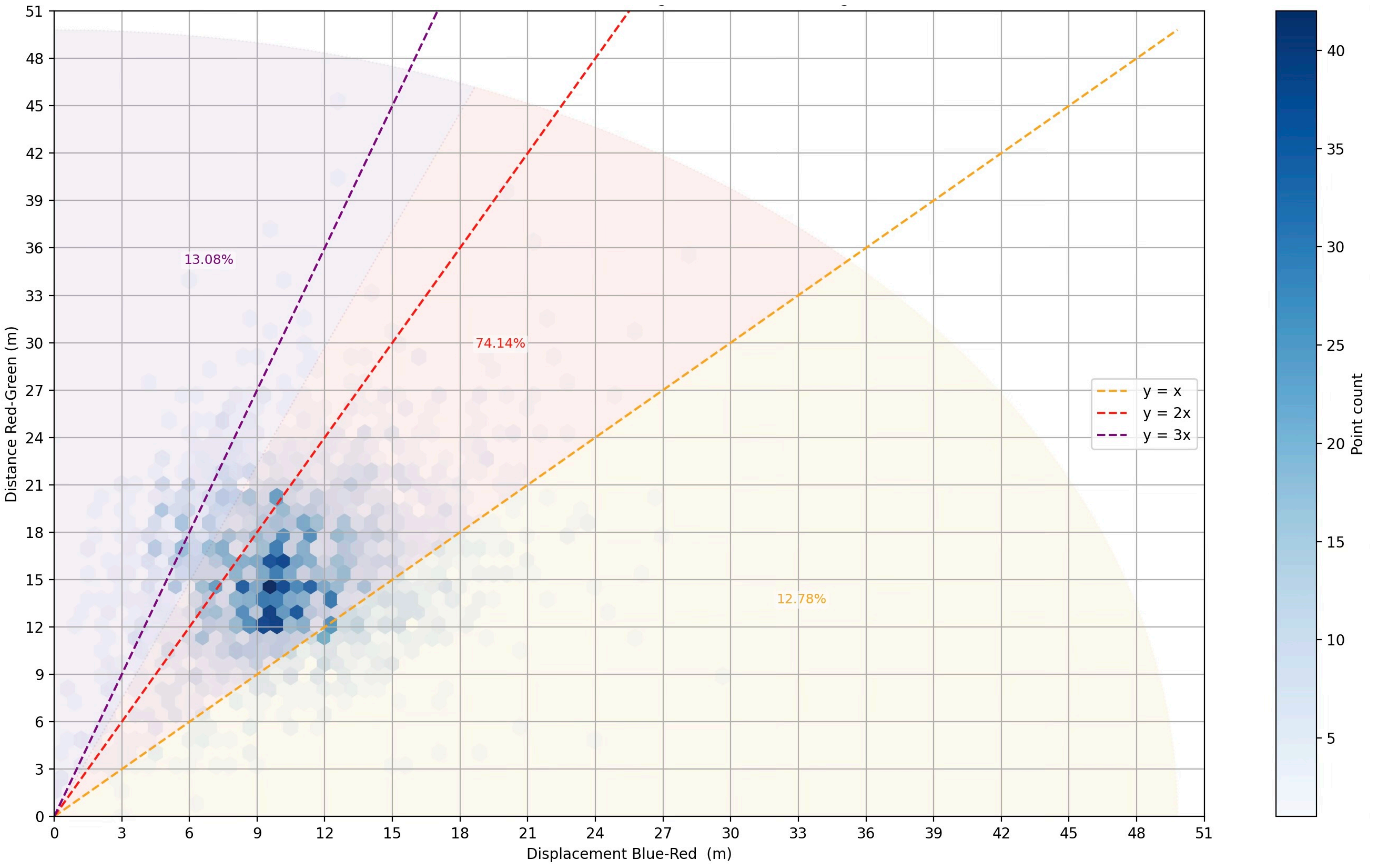


t_0, t_2, t_4	1 : 1	8 %
t_0, t_1, t_4	1 : 3	16 %
t_0, t_1, t_3	1 : 2	76 %

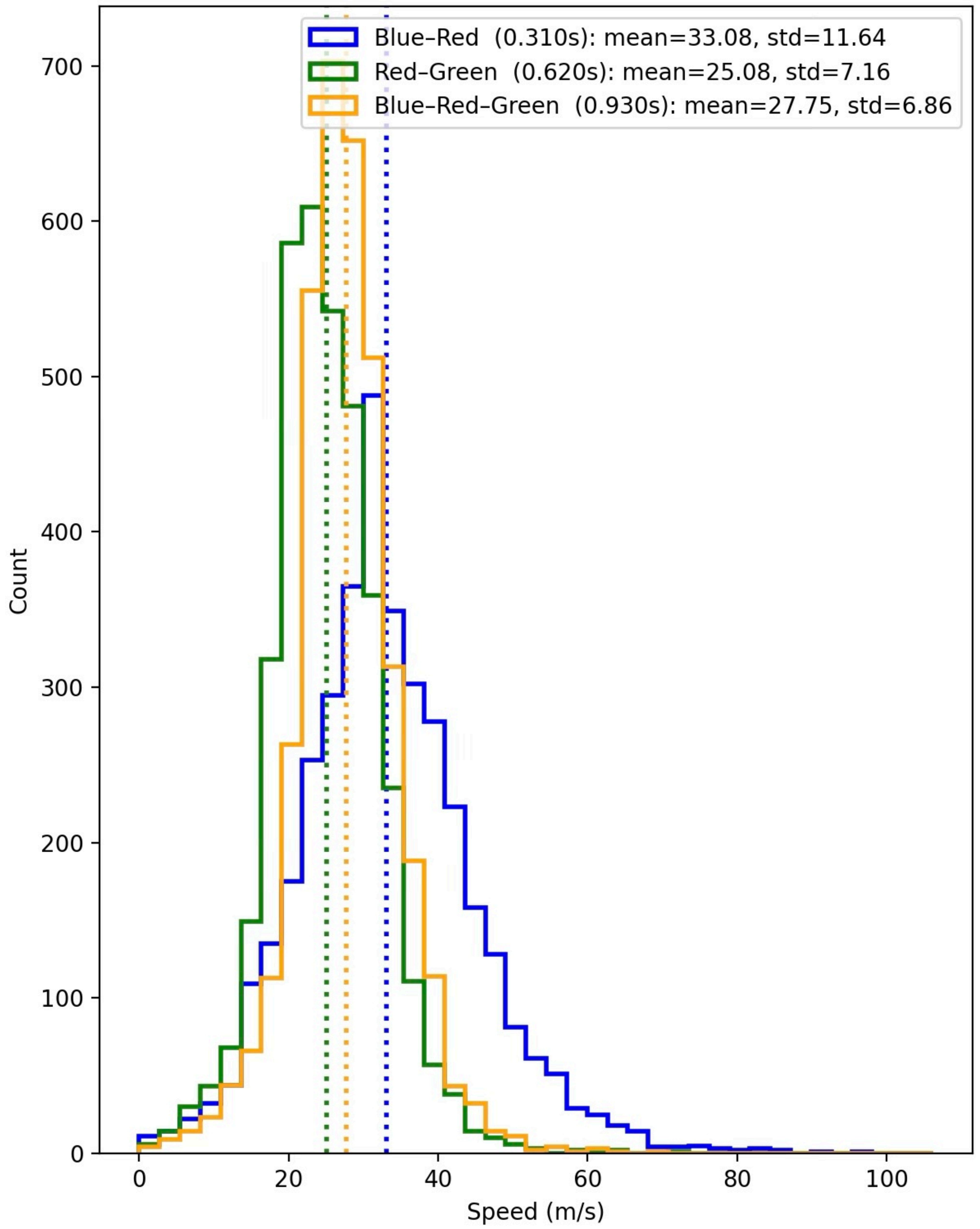
$$\Delta t_{\text{blue-red}} = 0.92(1 \times 295.3) + 0.08(2 \times 295.3) \approx 319 \text{ ms}$$

$$\Delta t_{\text{red-green}} = 0.76(2 \times 295.3) + 0.16(3 \times 295.61) + 0.08(2 \times 295.3) \approx 638 \text{ ms}$$

Ground Truth Analysis

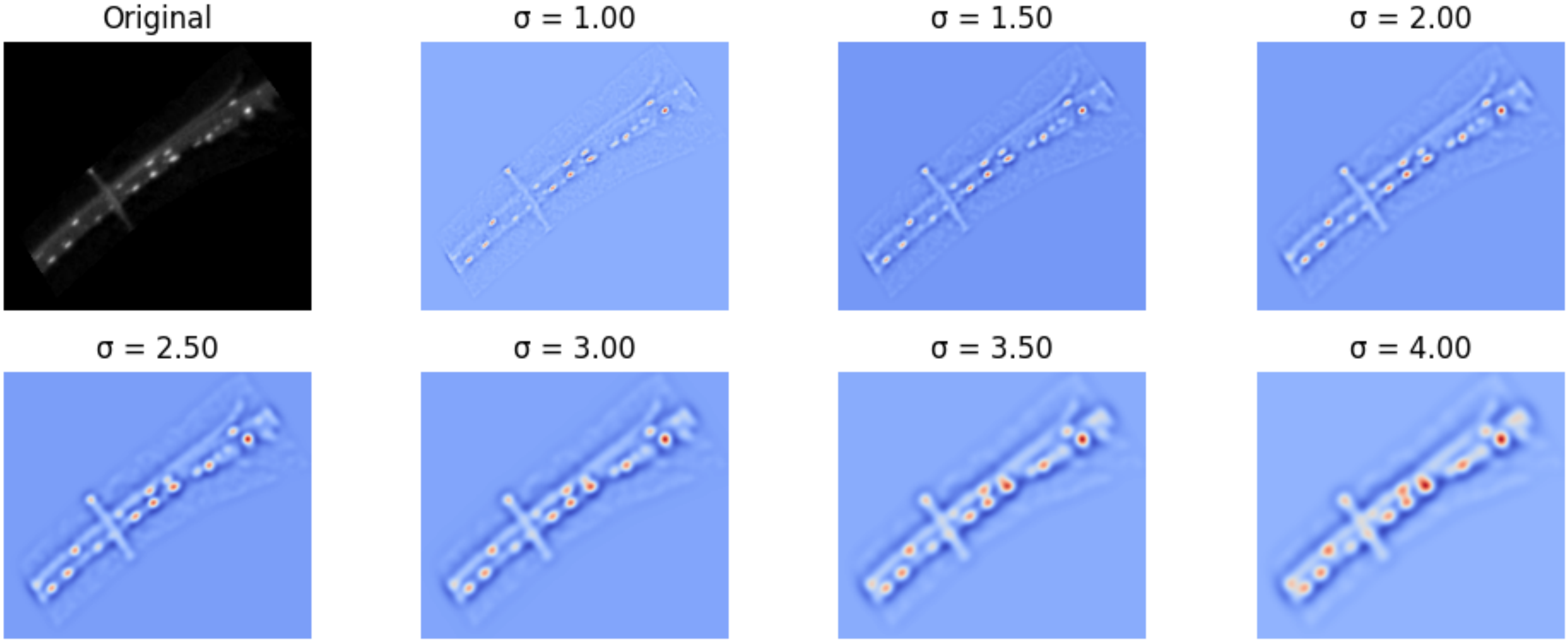


Ground Truth Analysis



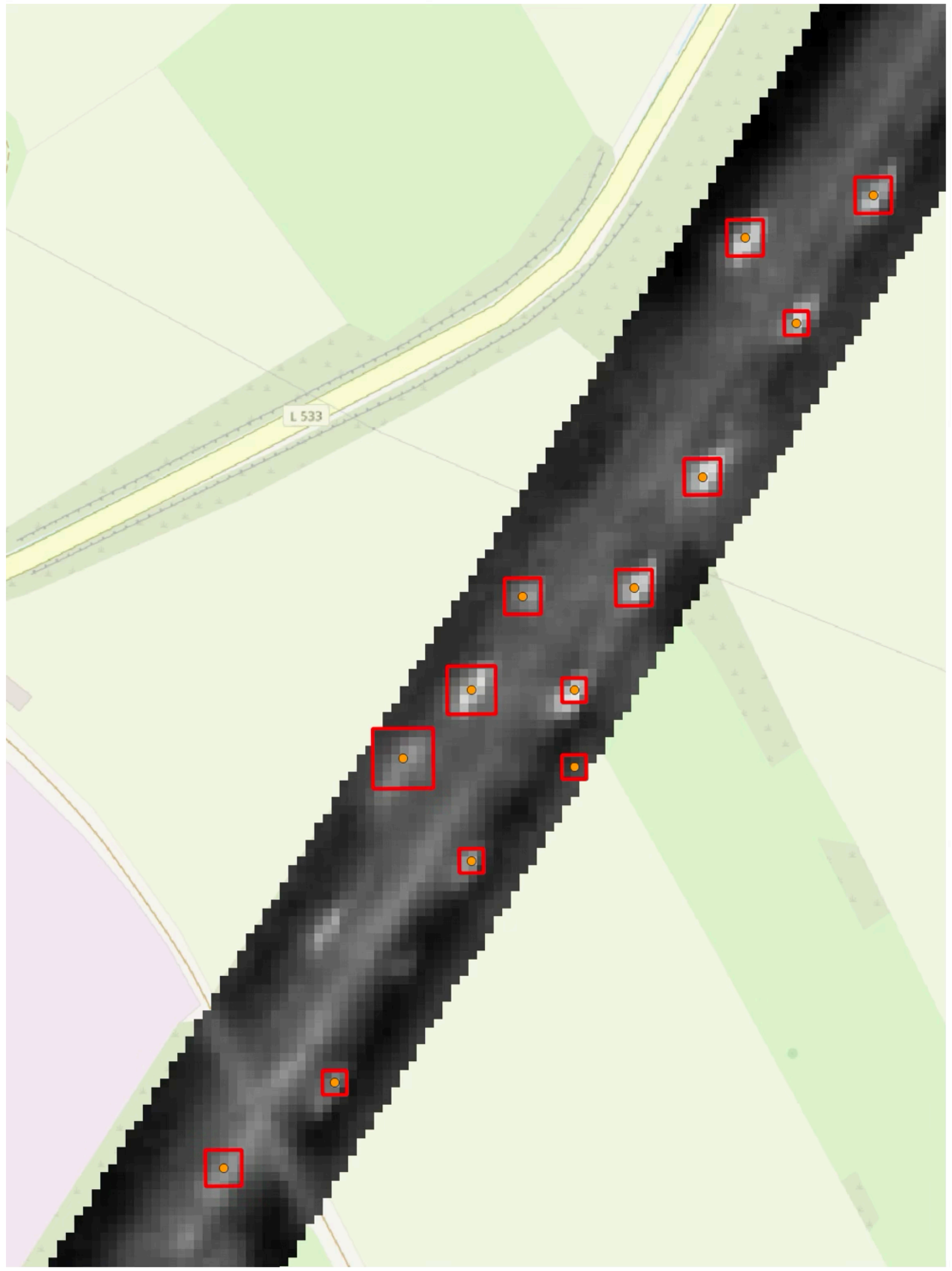
Problem Setup

Localization with Laplacian of Gaussian

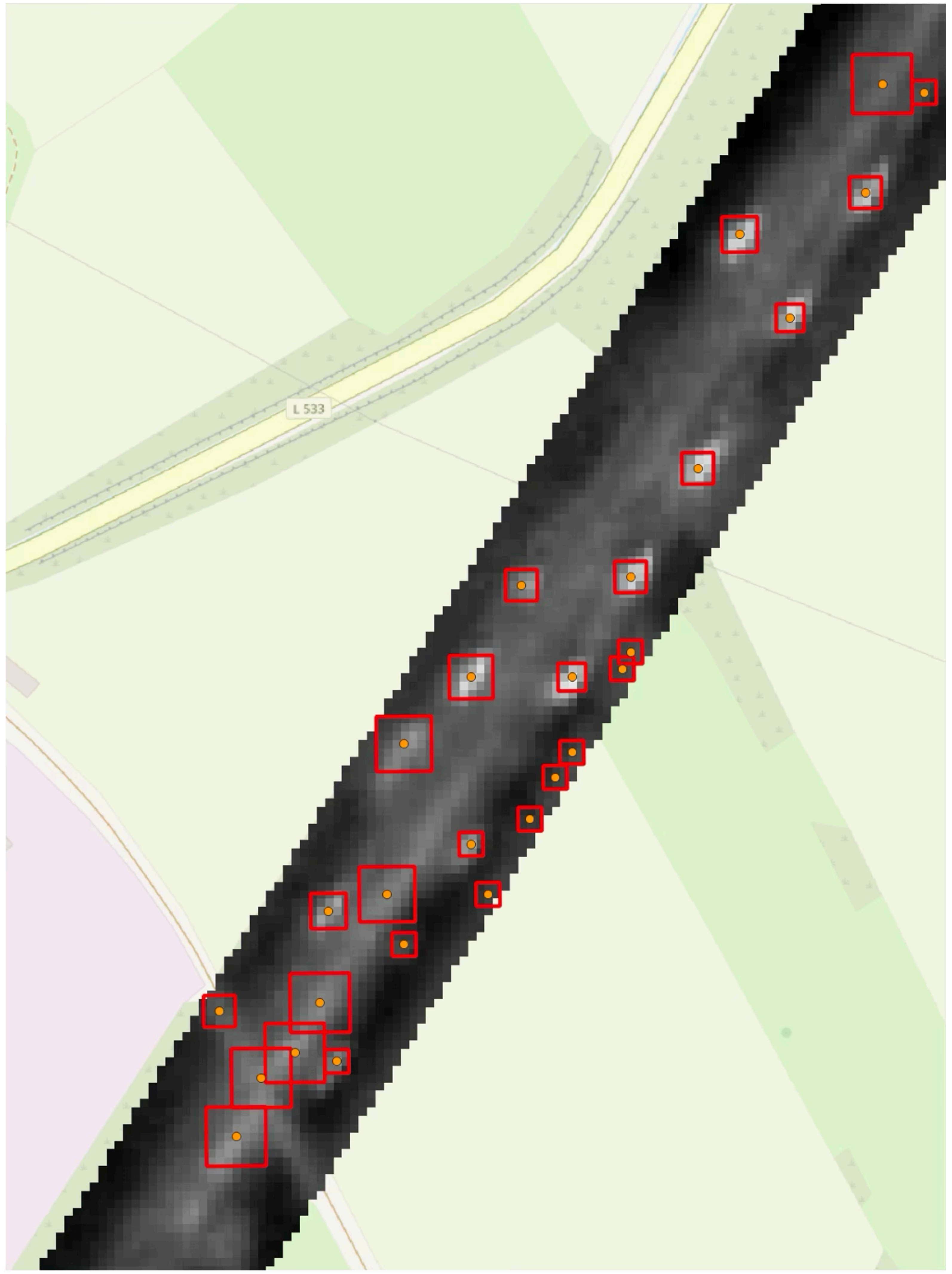


loG applied on blue channel of at varying sigmas. We choose scales upto $\sigma = 2.5$

Filtration condition for selecting maxima from loG cube

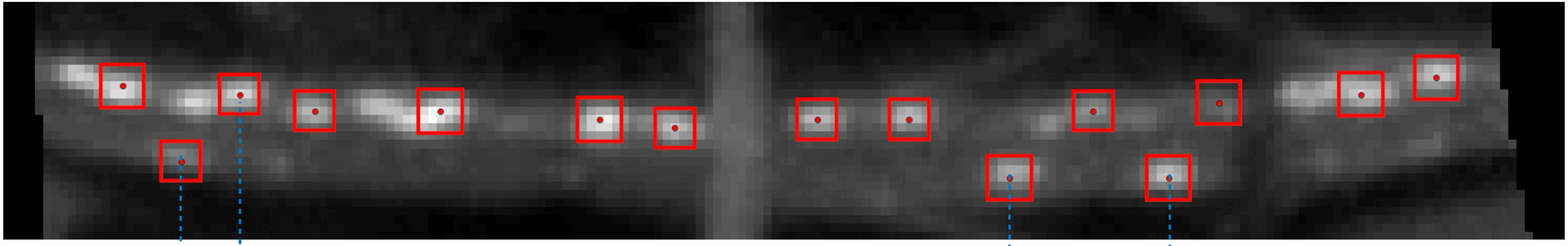


$threshold = 0.07$
&
$h\_max = 0.07$



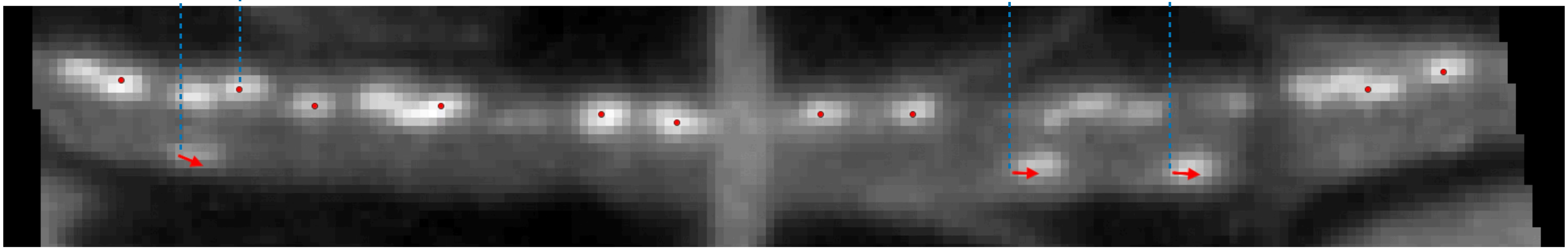
$threshold = 0.07$

Lucas Kanade method



Background - Blue

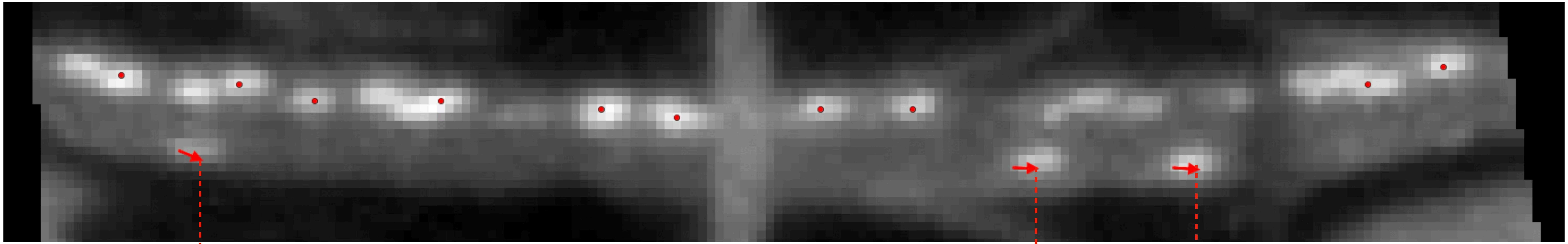
Detected vehicles using loG



Background - Red

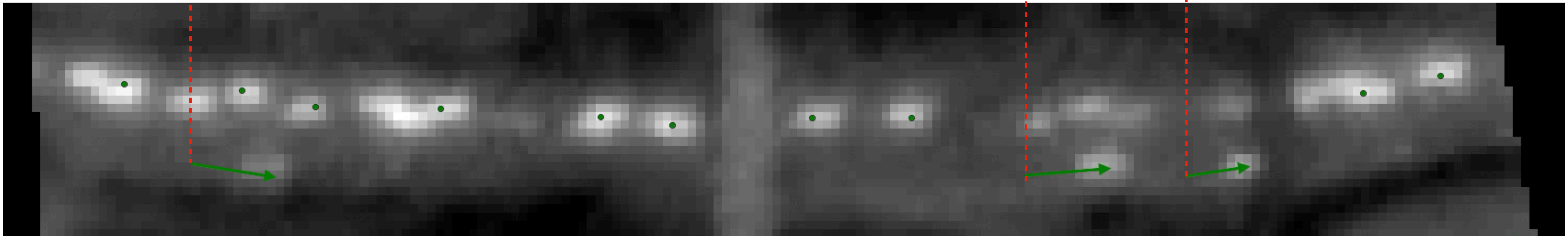
Lucas Kanade algorithm applied on B-R channels

Lucas Kanade method



Background - Red

Lucas Kanade algorithm applied on B-R channels



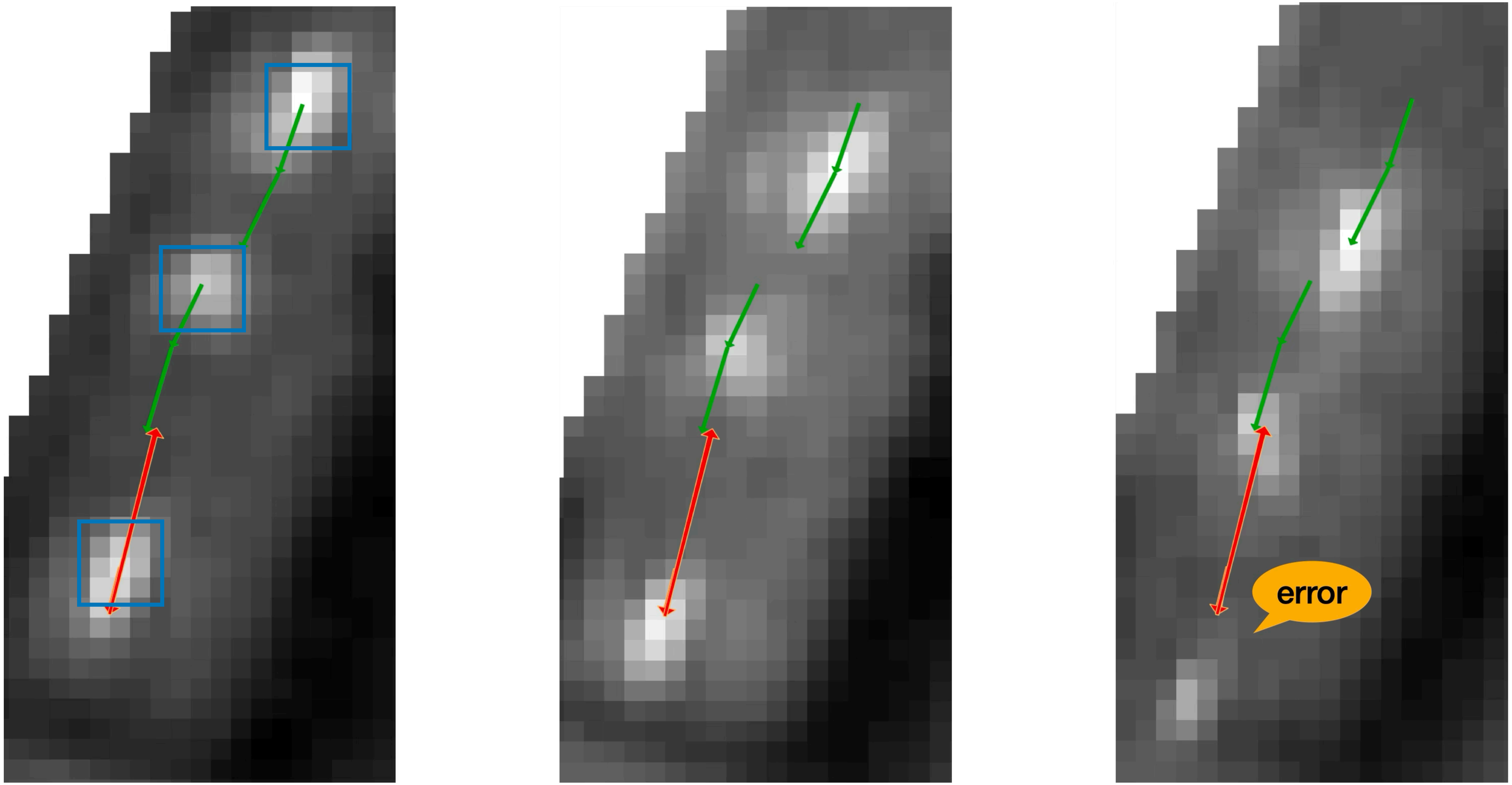
Background - Green

Lucas Kanade algorithm applied on R-G channels

Lucas Kanade method

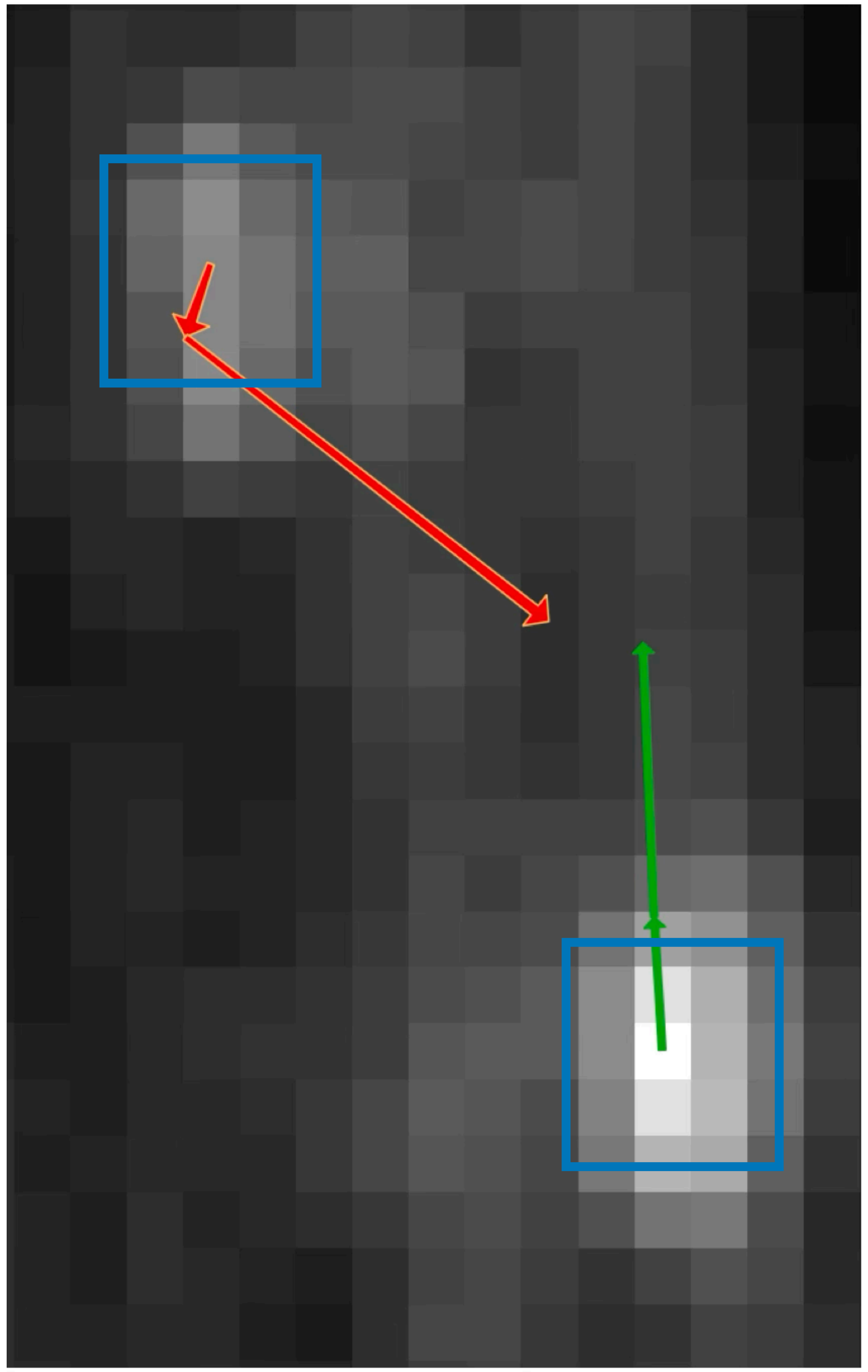
Visualization over RGB image

Nature of errors during optical flow computation

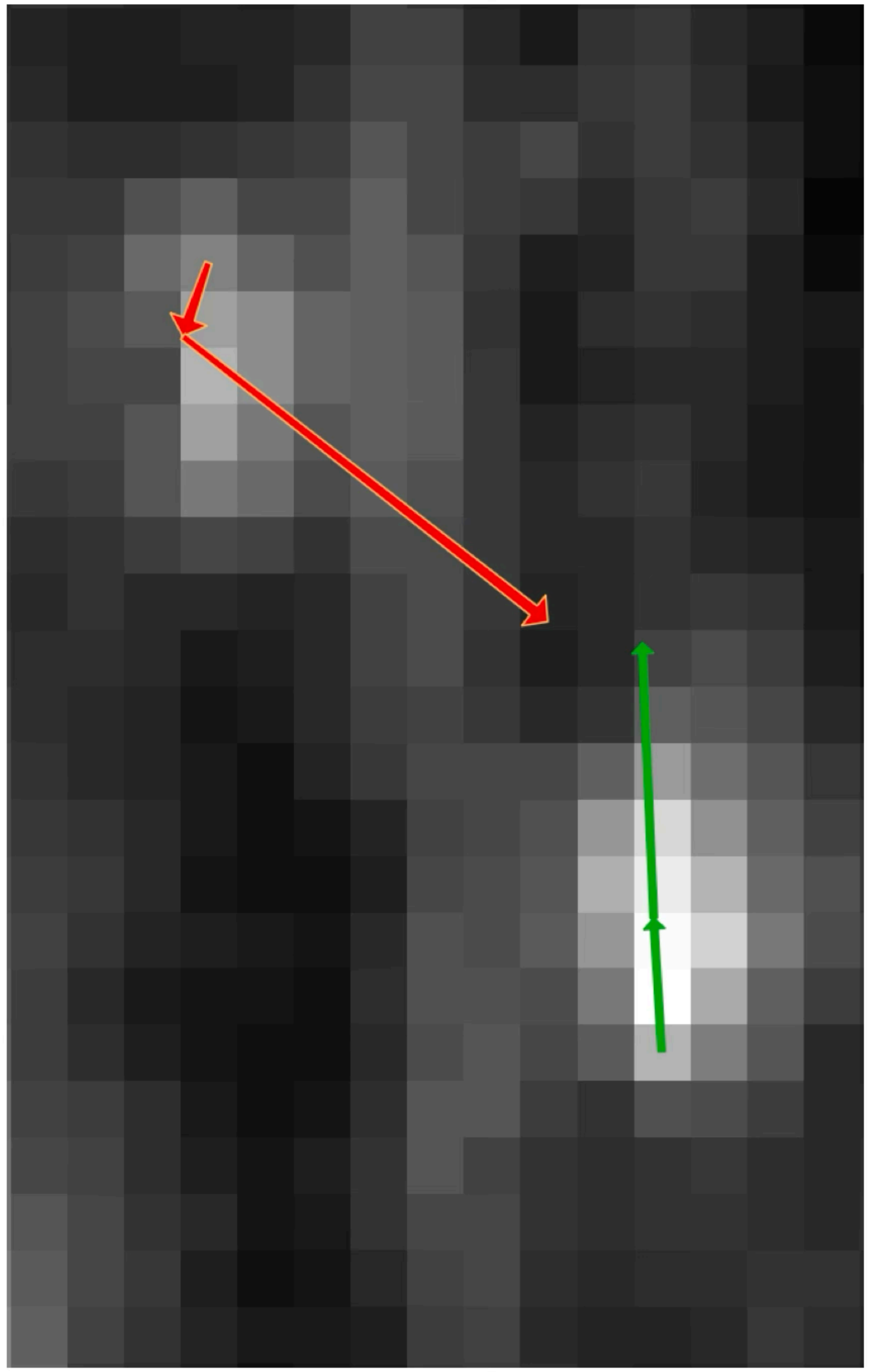


blue band   Red band   Green band

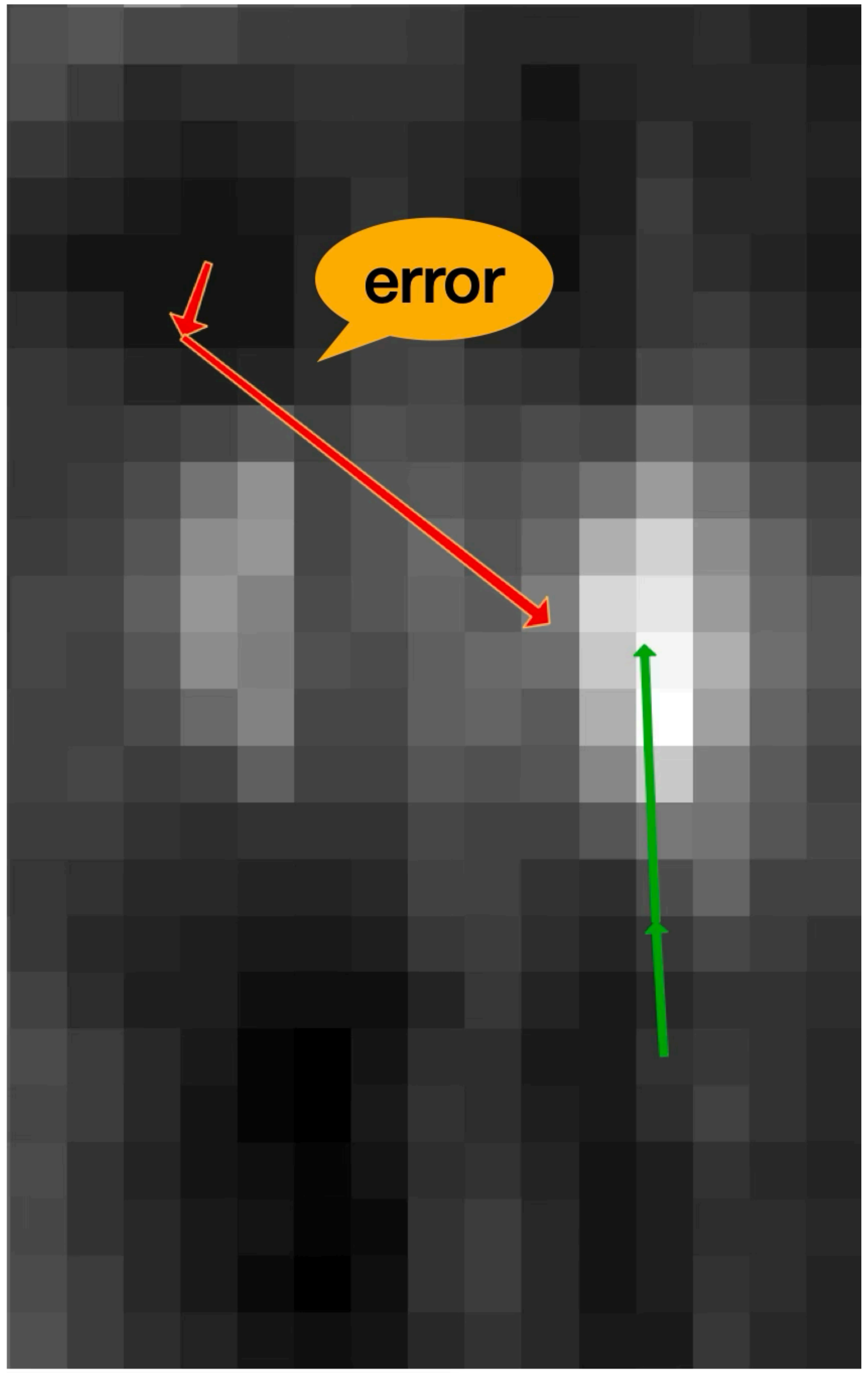
Nature of errors during optical flow computation



blue band

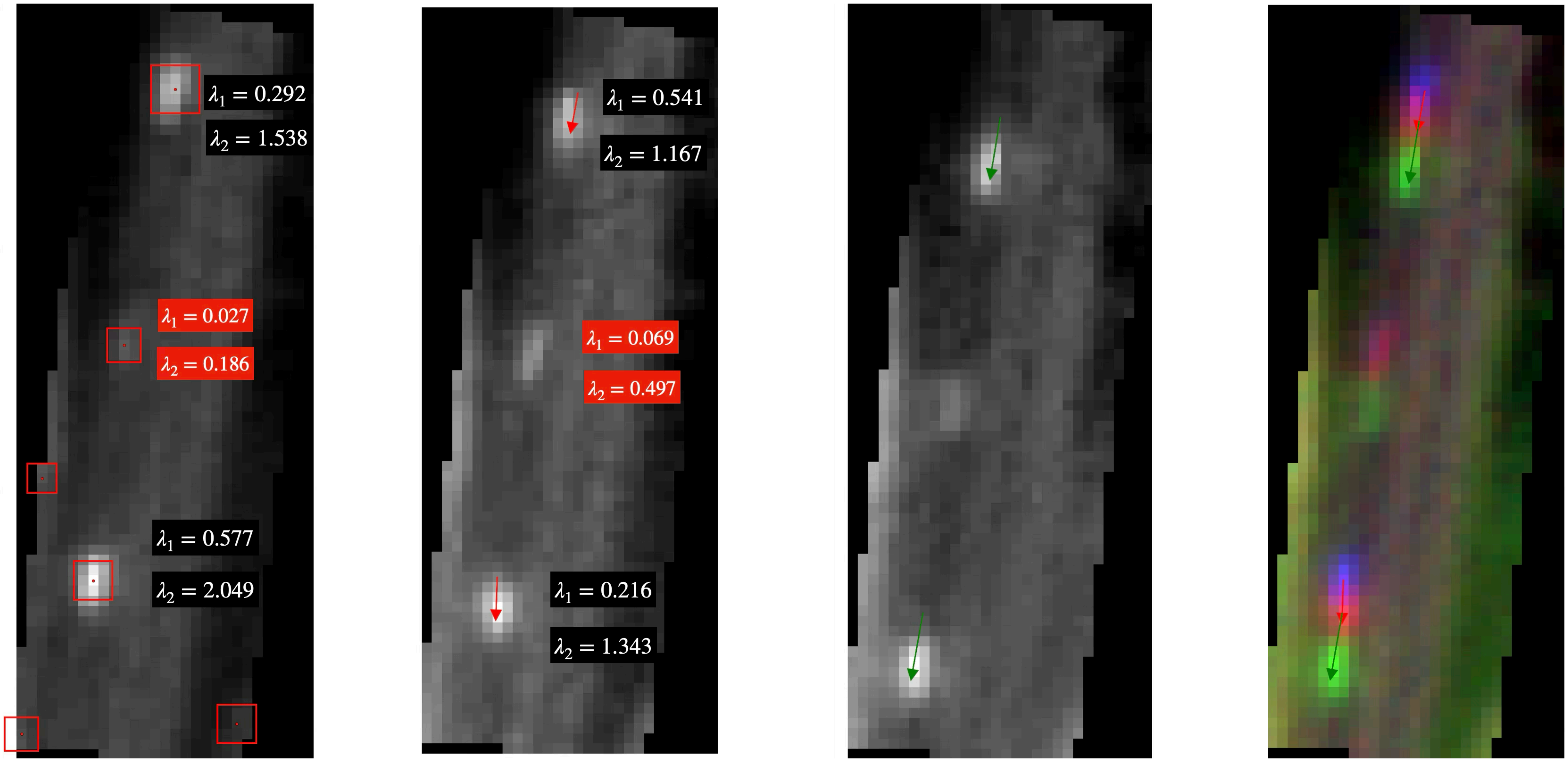


Red band



Green band

Nature of errors during optical flow computation



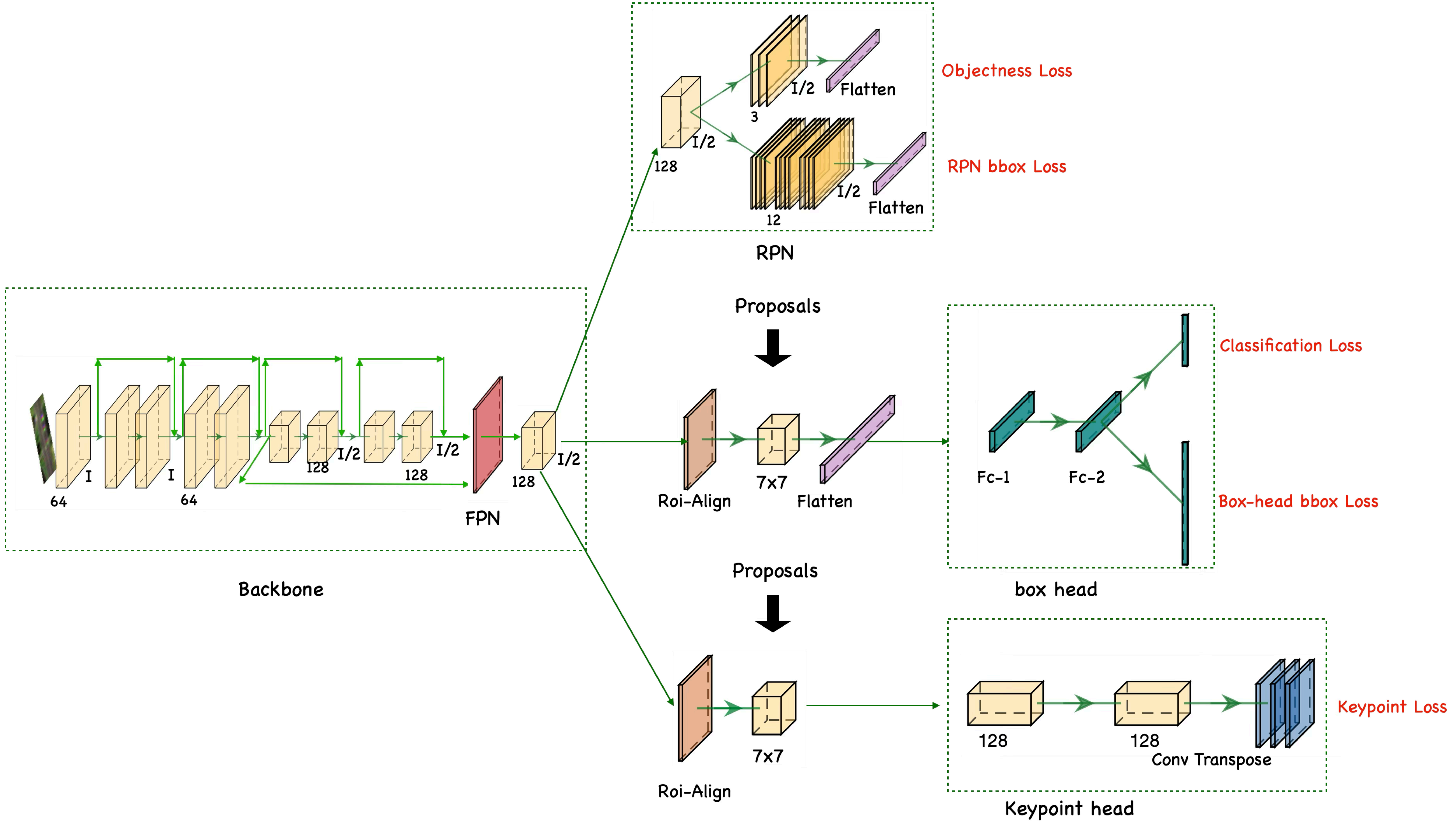
Detection with LoG

Lucas kanade algorithm on B-R channels

Lucas kanade algorithm on R-G channels

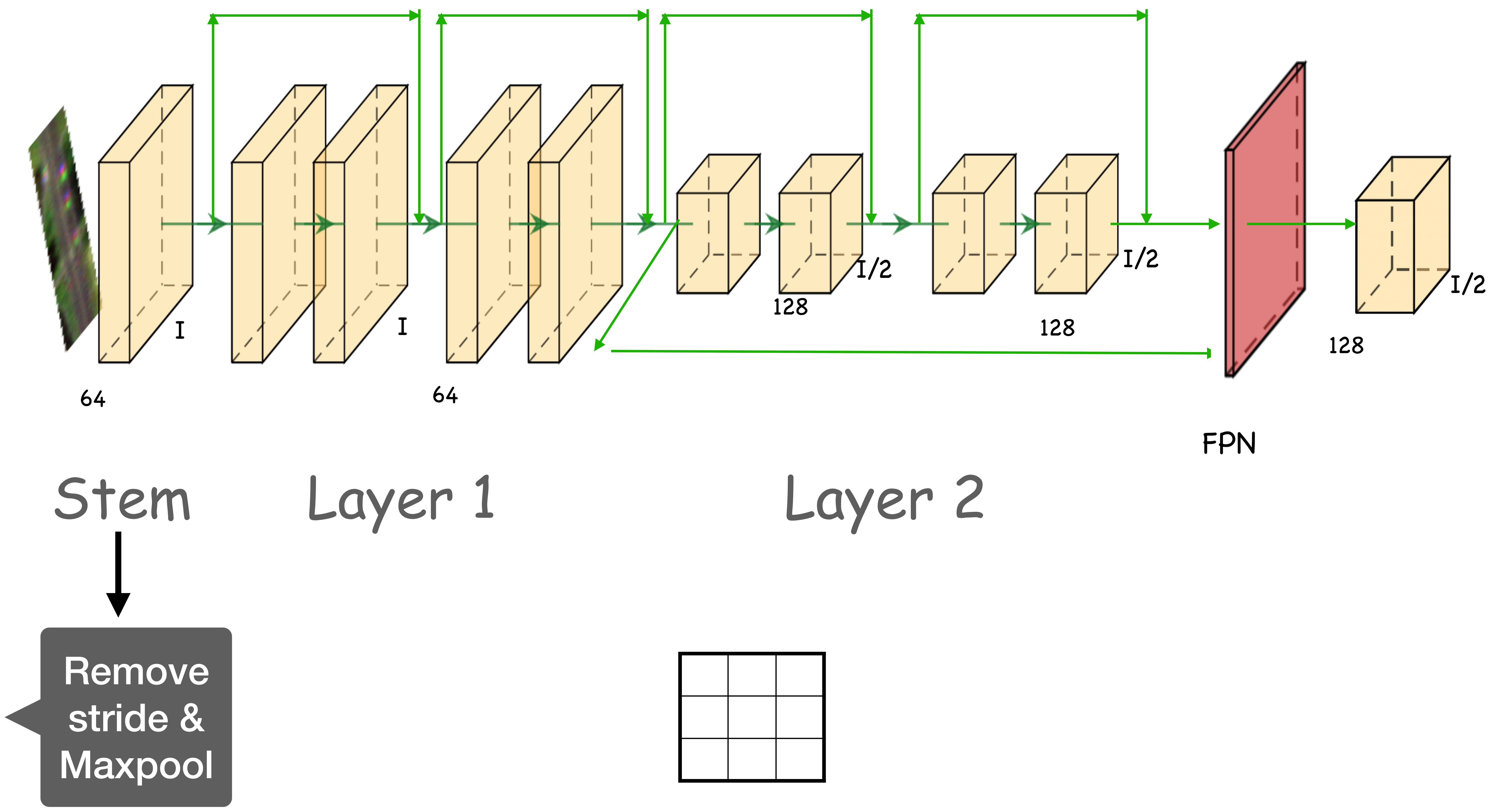
Visualization on RGB image

Keypoint Modeling



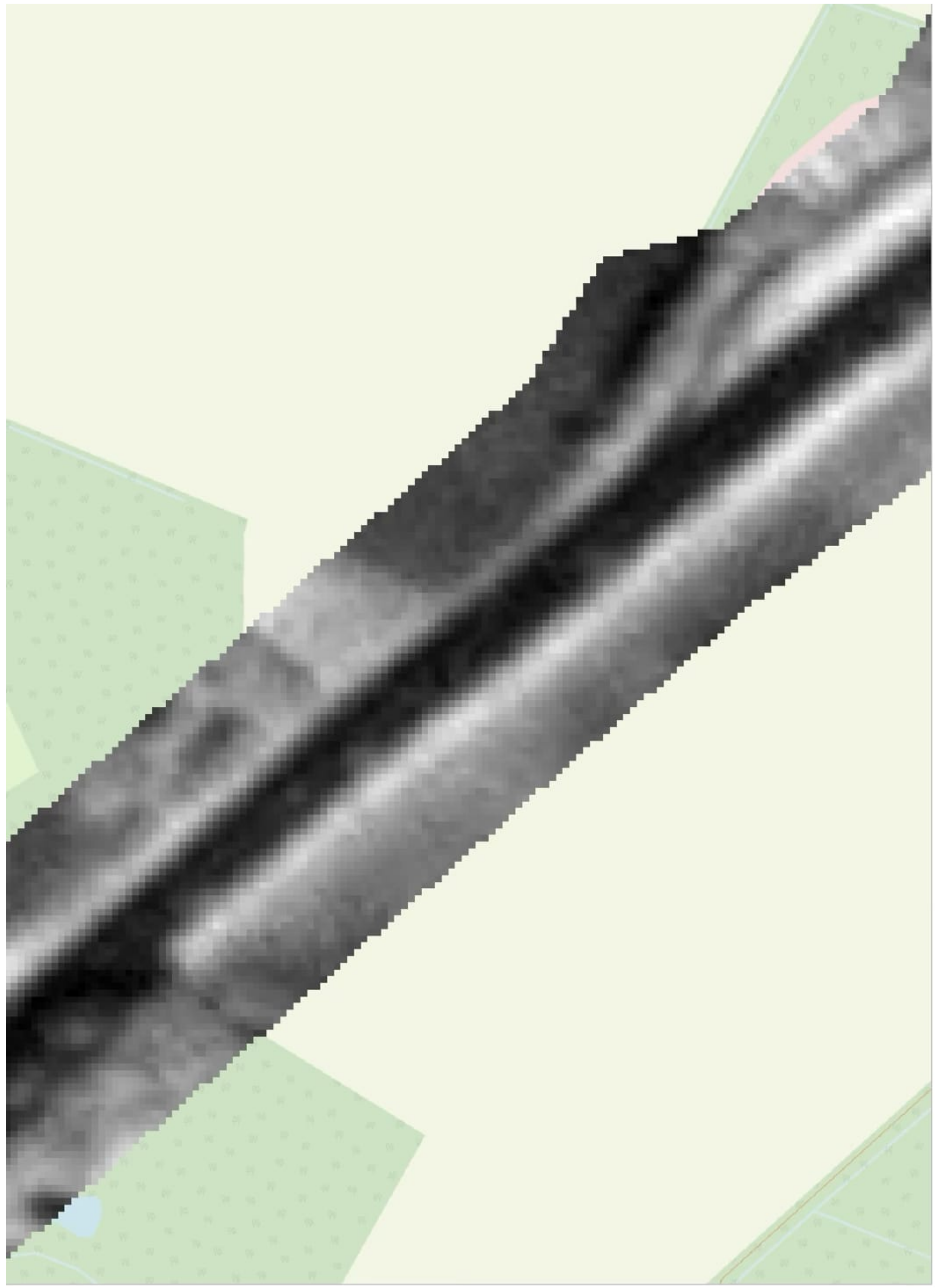
Objectness Loss
I/2
Flatten
3
I/2
128
RPN bbox Loss
I/2
Flatten
12
RPN
Proposals
Classification Loss
64
I
I
64
128
I/2
128
I/2
FPN
128
I/2
Roi-Align
7x7
Flatten
Fc-1
Fc-2
Box-head bbox Loss
Backbone
Proposals
box head
Roi-Align
7x7
128
128
Conv Transpose
Keypoint Loss
Keypoint head

Backbone

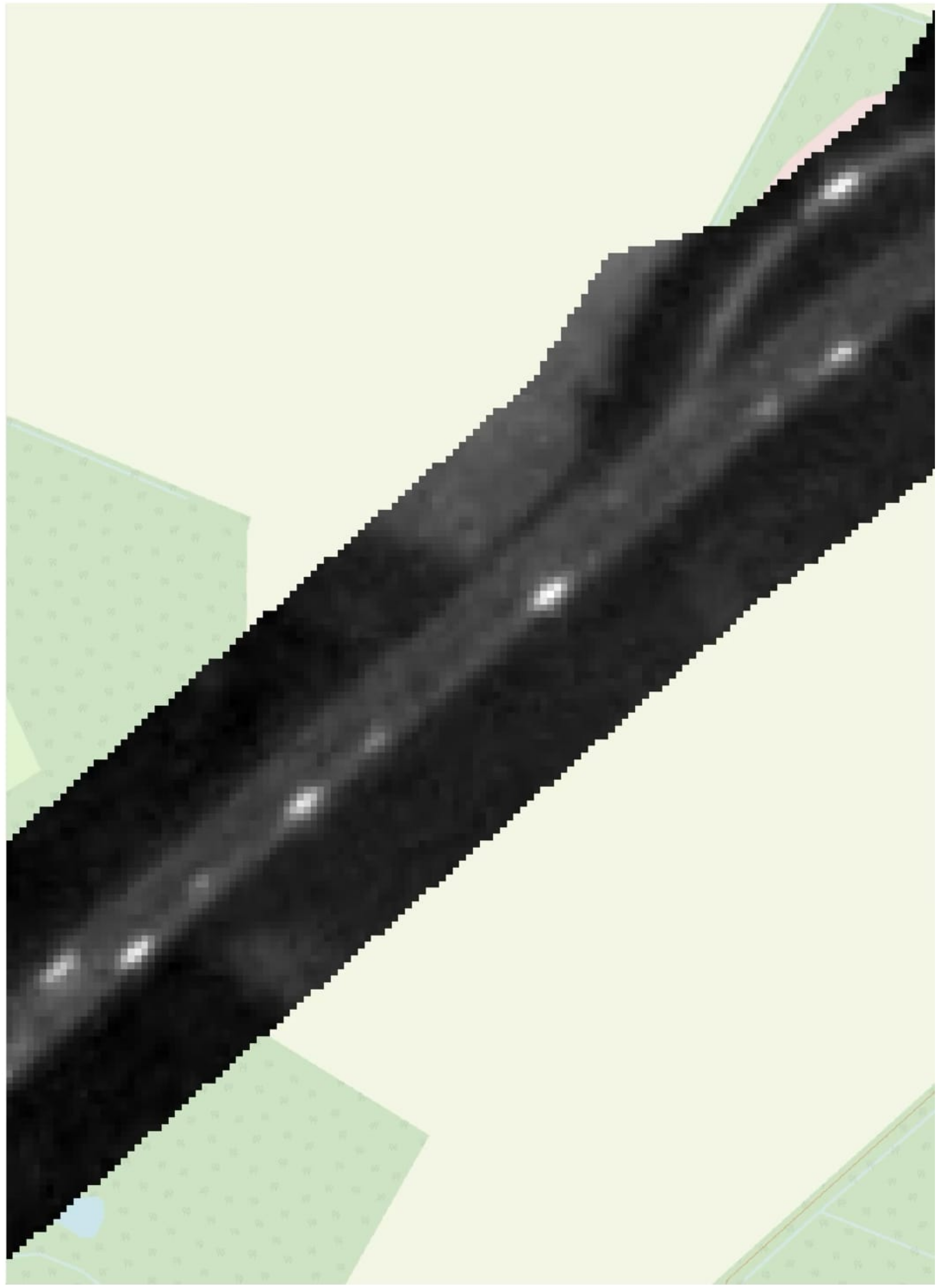


3×3 filter

Input



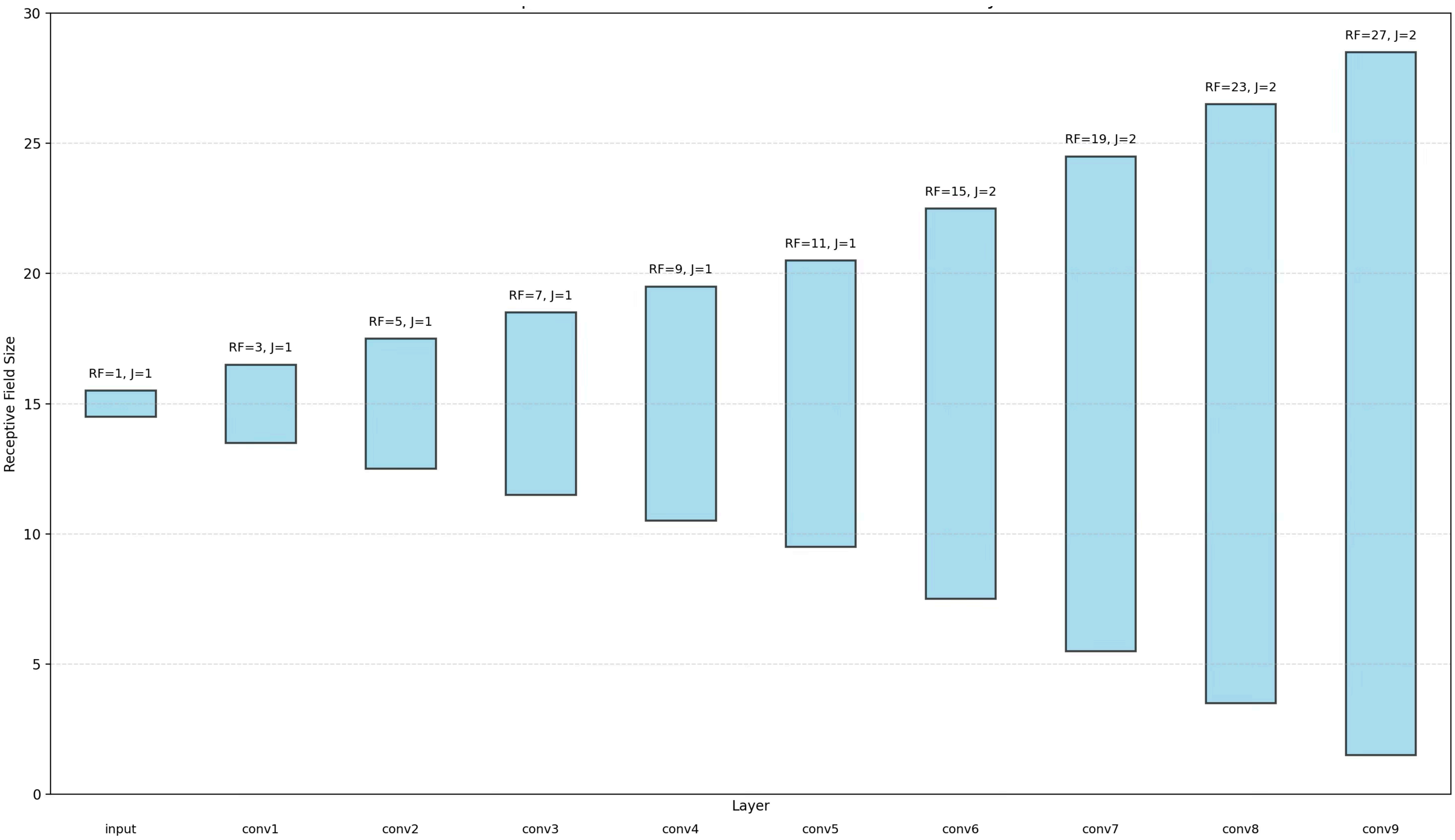
NIR channel



blue channel

NIR band is passed alongside RGB to help reduce outliers. It helps to delineate roads

Backbone : Receptive Field



Dataset Statistics

image_mean = {0.288, 0.316, 0.244, 0.427}
image_std = {0.219, 0.199, 0.191, 0.229}

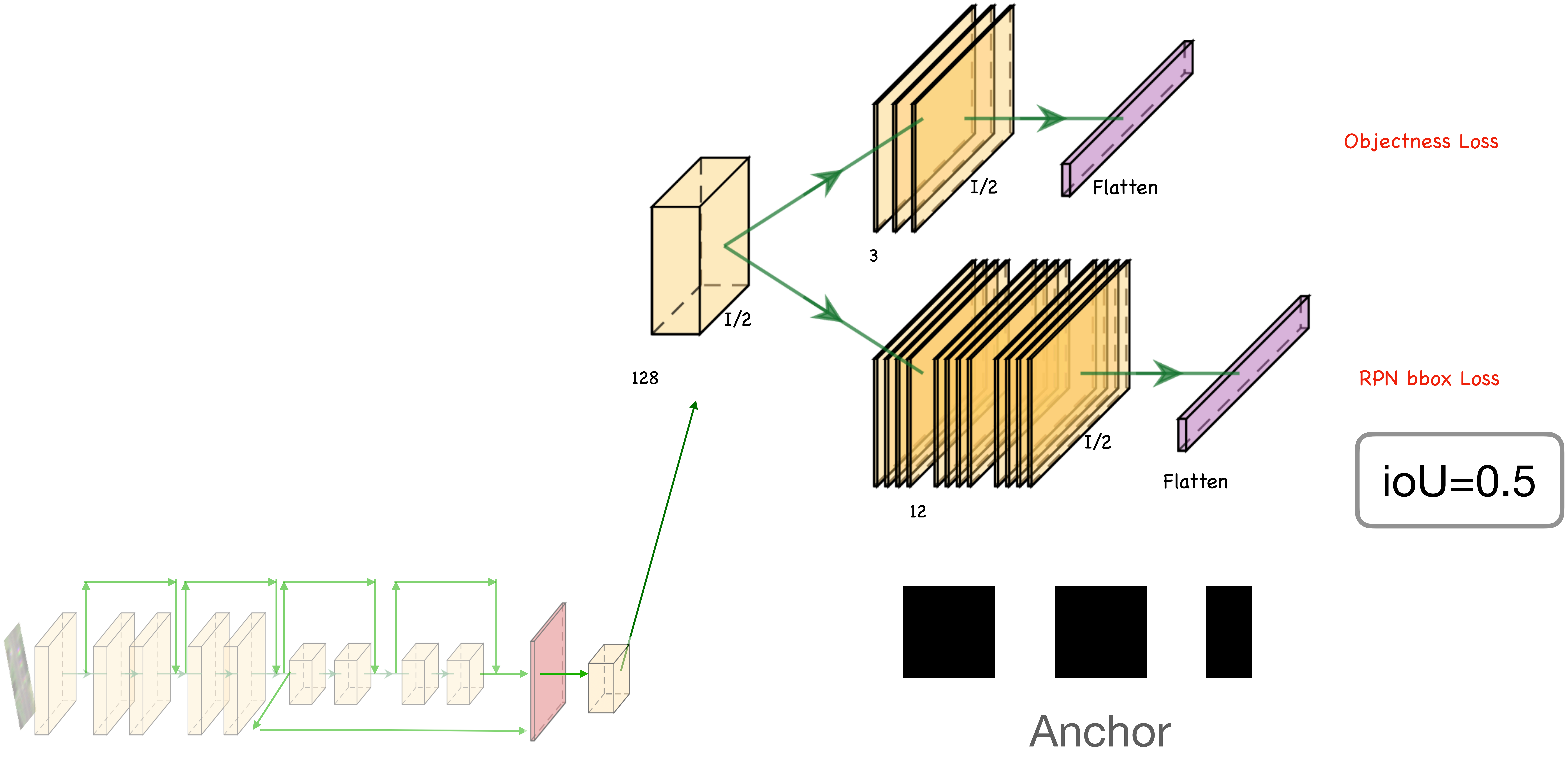
Ours

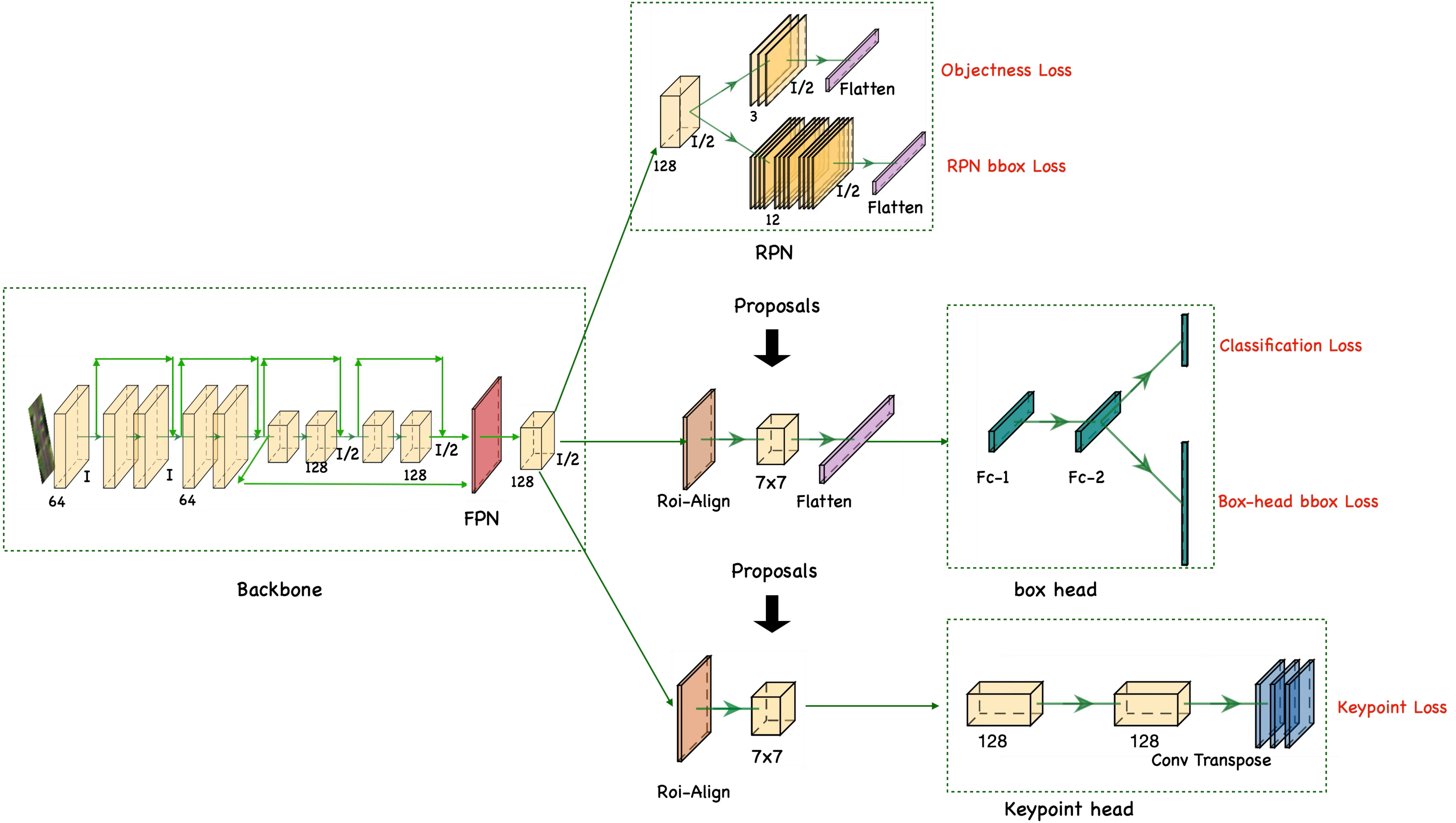
image_mean = {0.485, 0.456, 0.406}
image_std = {0.229, 0.224, 0.225}

imageNet

We normalize image with our dataset statistics

Region Proposal Network





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box head
128
128
Conv Transpose
Keypoint Loss
7x7
Roi-Align
Keypoint head

Classification & Regression Loss

$$\mathcal{L}_{\text{Focal}}(p, y) = -\alpha_t (1 - p_t)^{\gamma} \log(p_t)$$

Objectness

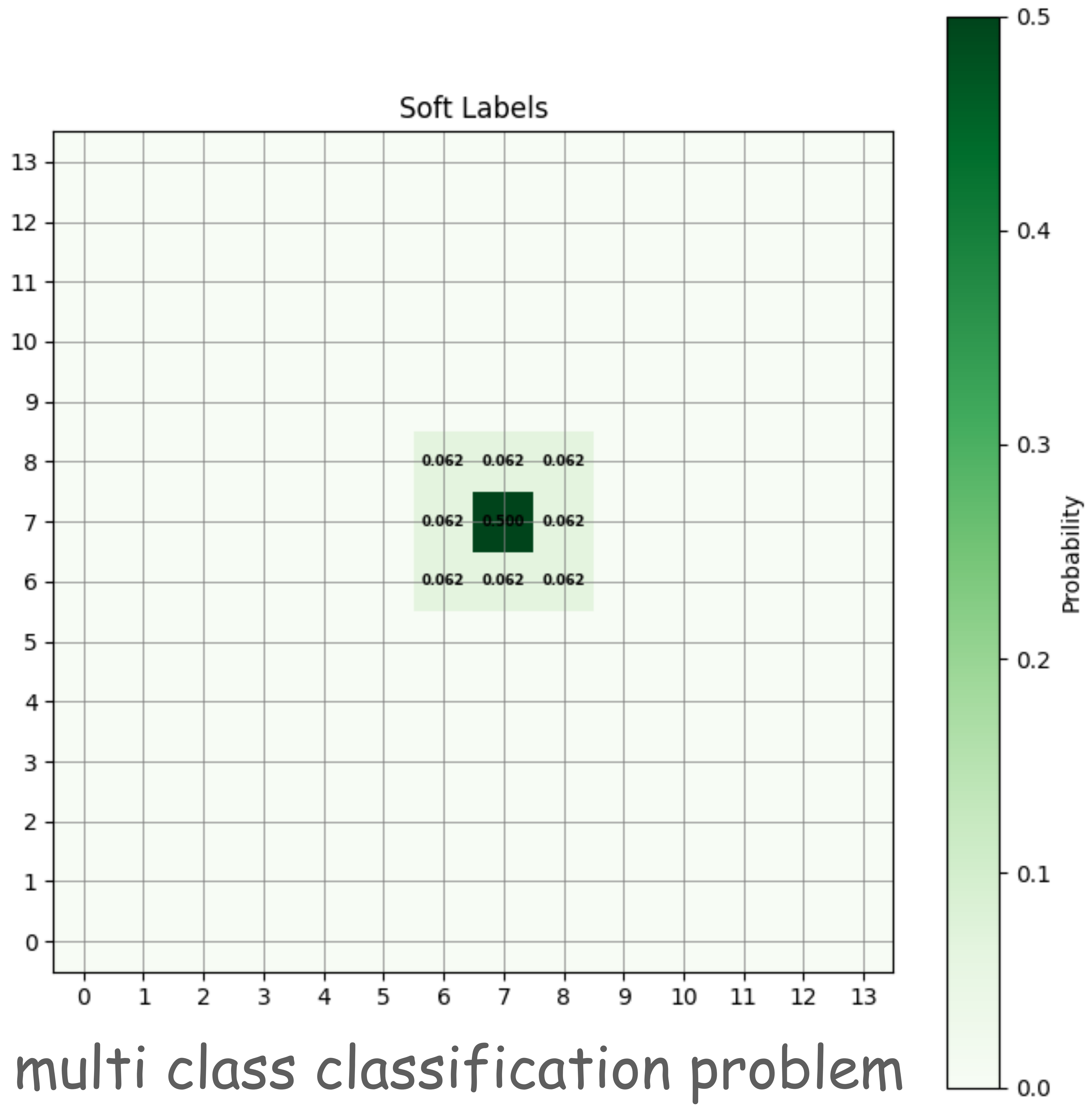
$$\mathcal{L}_{\text{Focal}} = -\sum_{c=1}^{C} \alpha_c (1 - p_c)^{\gamma} y_c \log(p_c)$$

Multi class

$$\mathcal{L}_{\text{Smooth } L_1}(x, y) = \begin{cases} 0.5(x-y)^2, & \text{if } |x-y| < 1 \\ |x-y| - 0.5, & \text{otherwise} \end{cases}$$

Regression

Keypoint Loss : Ground Truth soft labelling



multi class classification problem

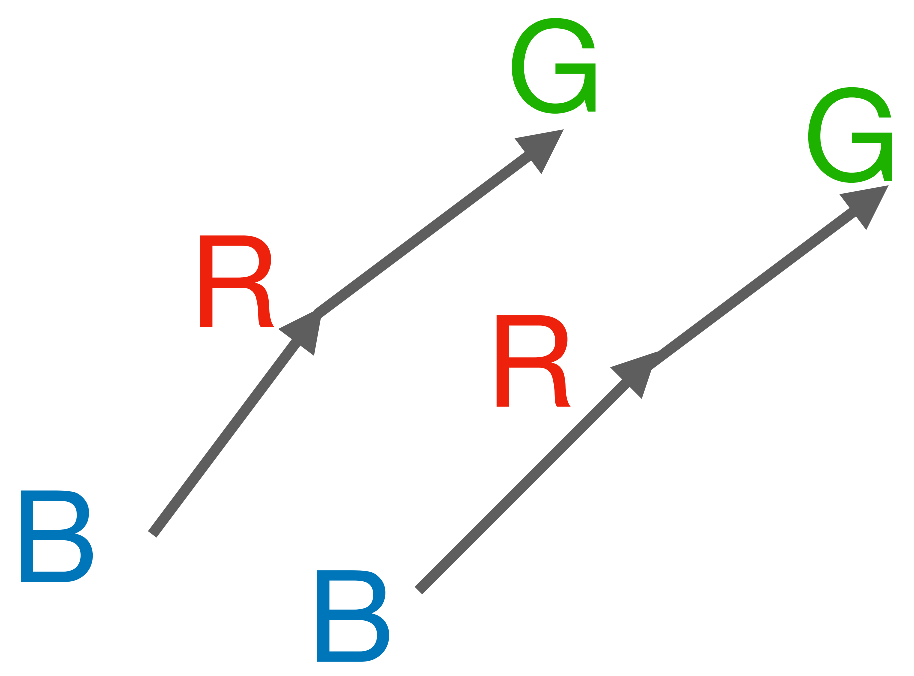
Geometric Priors : Distance Loss

$$\boxed{\mathscr{L}_{\text{dist}} = \frac{1}{|\mathscr{V}|} \sum_{(n,k)\in\mathscr{V}} H_\beta\left(\mathbf{p}_{nk} - \mathbf{g}_{nk}\right)}$$

Penalizes per keypoint deviation between prediction and ground truth

Geometric Priors : Pairwise Segment Loss

$$\mathscr{L}_{\text{seg}} = \frac{1}{|\mathcal{S}_{\text{vis}}|} \sum_{(i,j)\in\mathcal{S}_{\text{vis}}} H_\beta\Big((\mathbf{p}_j - \mathbf{p}_i) - (\mathbf{g}_j - \mathbf{g}_i) \Big)$$



Enforces consistency of the pairwise displacement vectors between keypoints

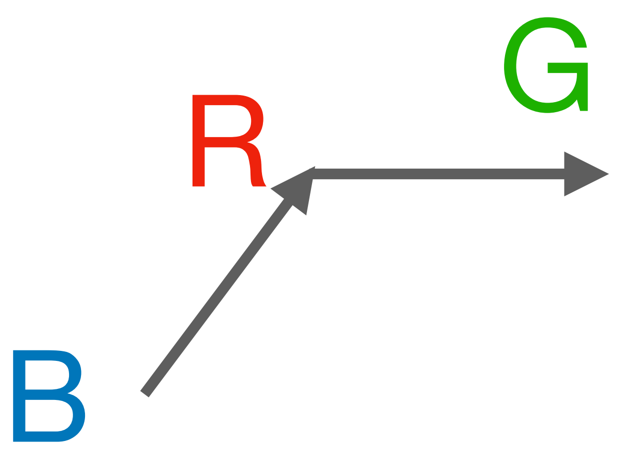
Geometric Priors : Joint angle Loss

$$\mathscr{L}_{\text{ang}} = 1 - \cos(\theta_{\text{pred}} - \theta_{\text{gt}})$$

Ensure that relative orientation of points is correct

Geometric Priors : Smoothness Loss

$$\mathscr{L}_{\text{smooth}} = \frac{1}{|\mathscr{V}|} \sum_{(n,t)\in\mathscr{V}} \left\| \mathbf{p}_{n,t+1} - 2\mathbf{p}_{n,t} + \mathbf{p}_{n,t-1} \right\|_2^2$$



$$(p_2 - p_1) - (p_1 - p_0)$$

Second finite difference

Penalizes abrupt change in velocity

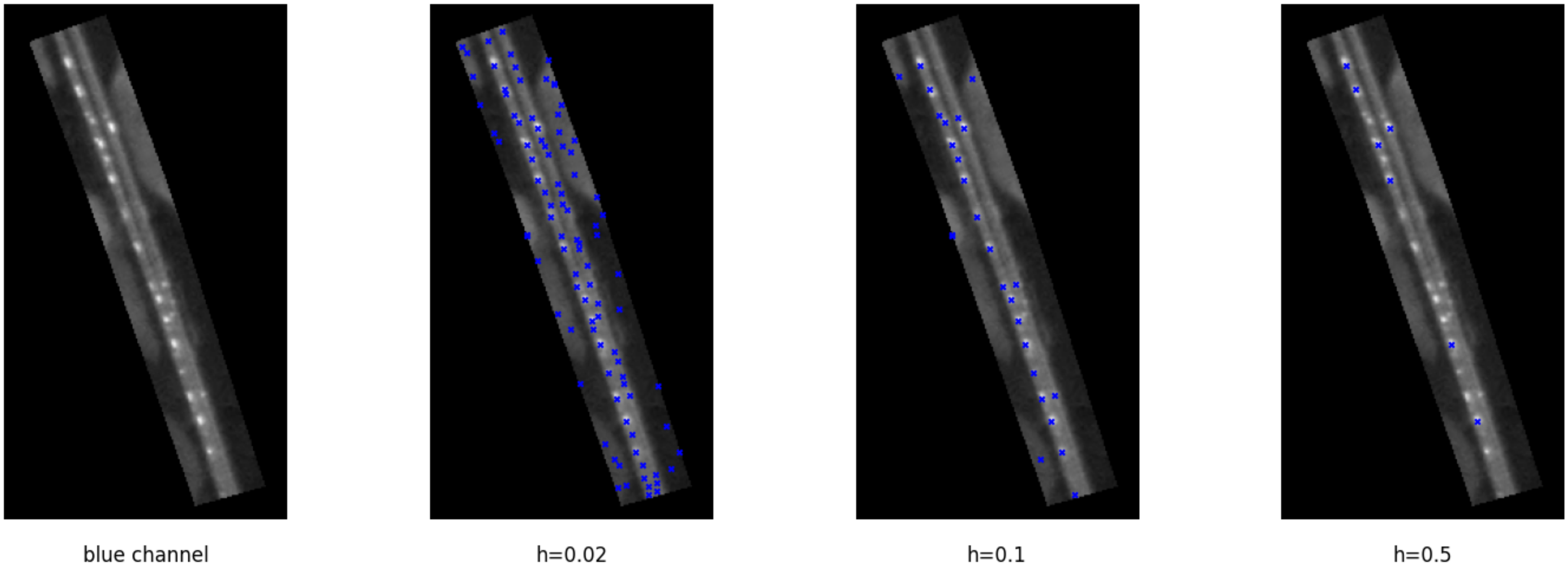
Soft argmax

$$\hat{\mathbf{x}} = \sum_i \mathbf{p}_i \cdot \frac{\exp\left(\frac{\mathbf{h}_i}{\tau}\right)}{\sum_j \exp\left(\frac{\mathbf{h}_j}{\tau}\right)}$$

To decode key points for computing geometric priors and keep it differentiable for training

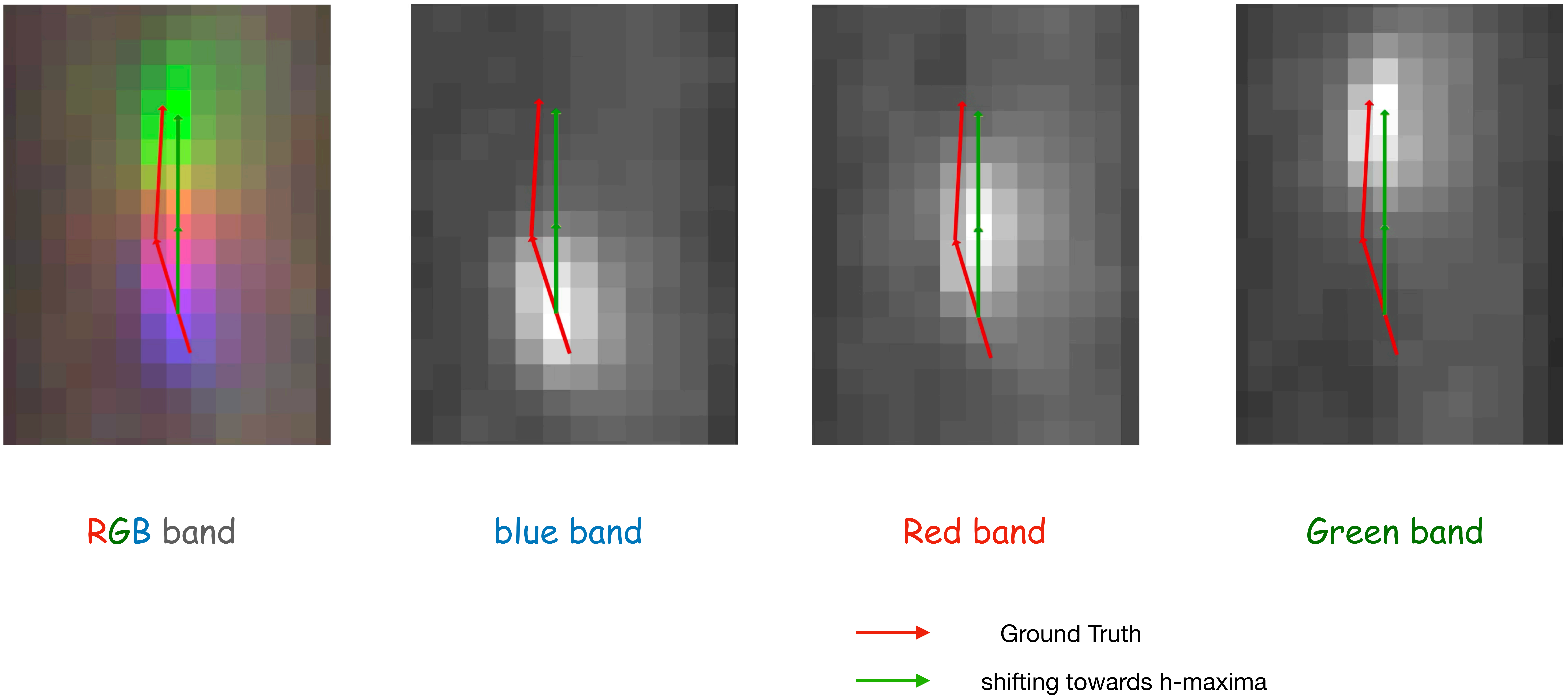
Pre & Post Processing

H-maxima

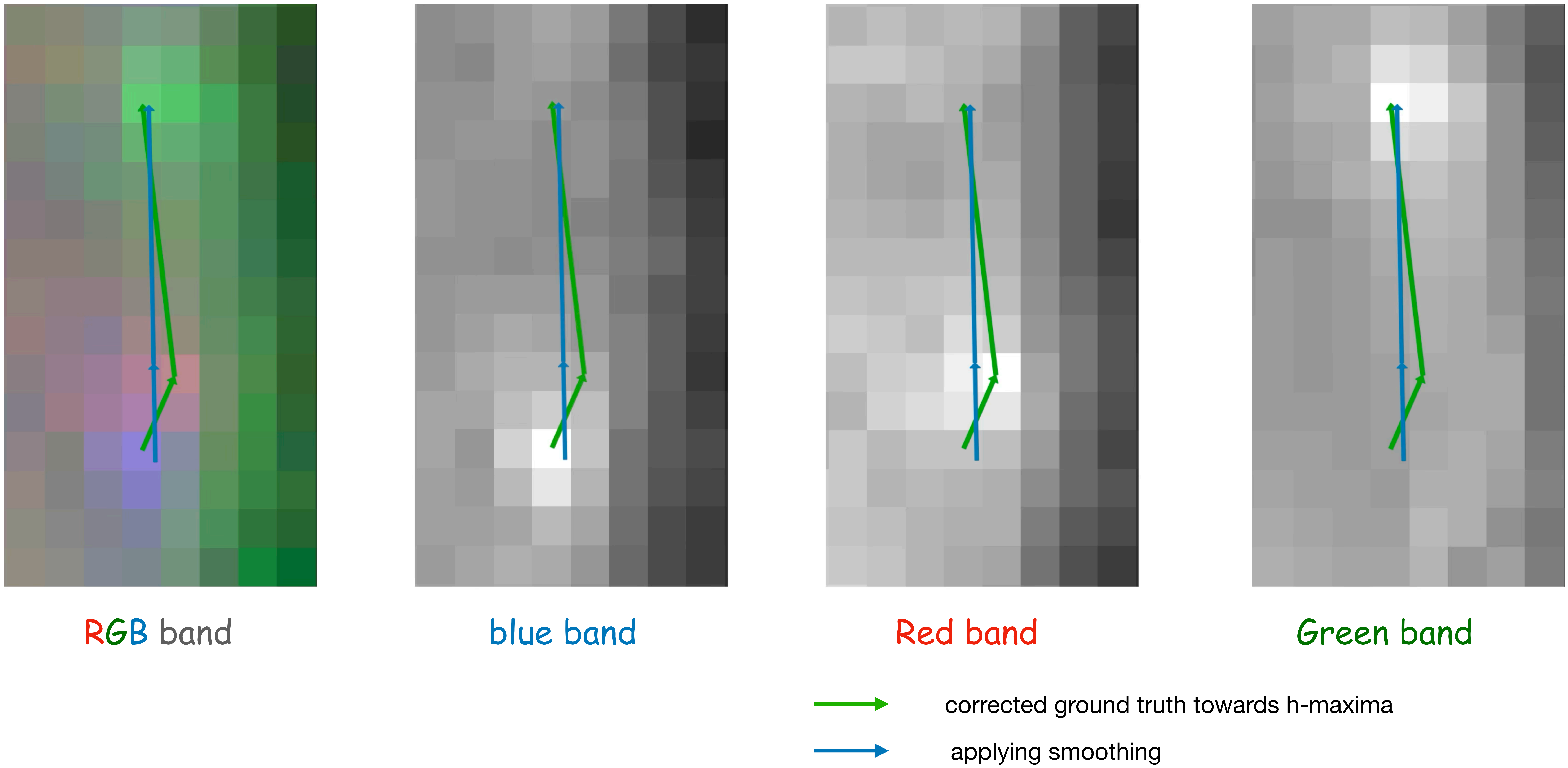


Peak detection at different h values; h=0.1 balances detection and outlier reduction.

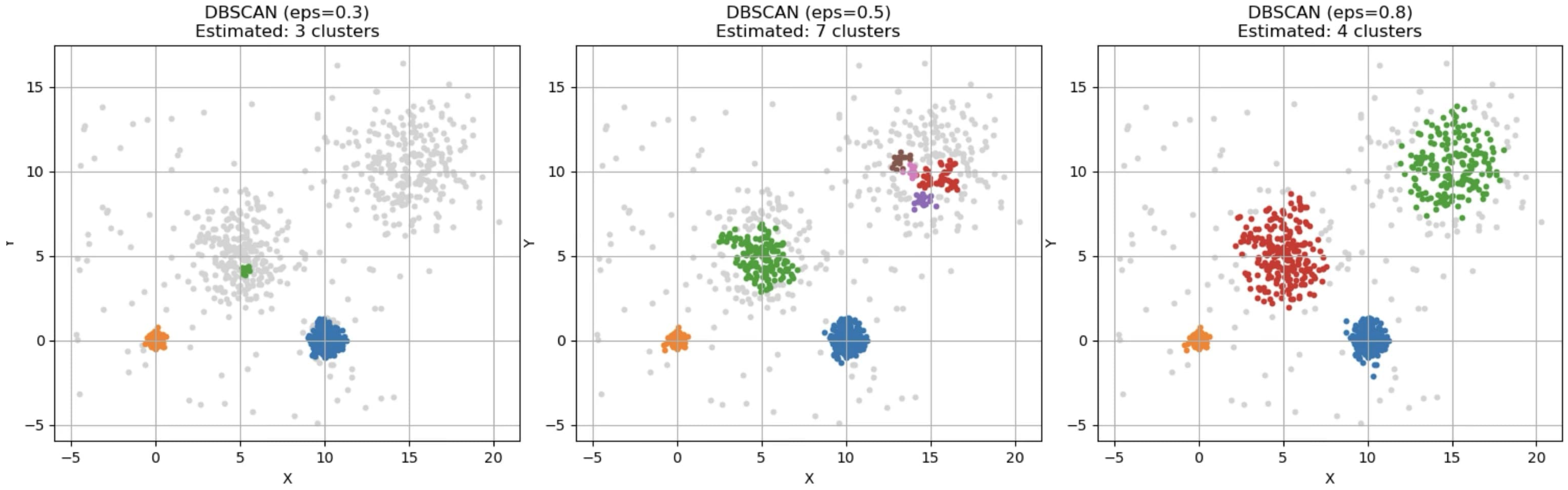
Shift towards h-maxima

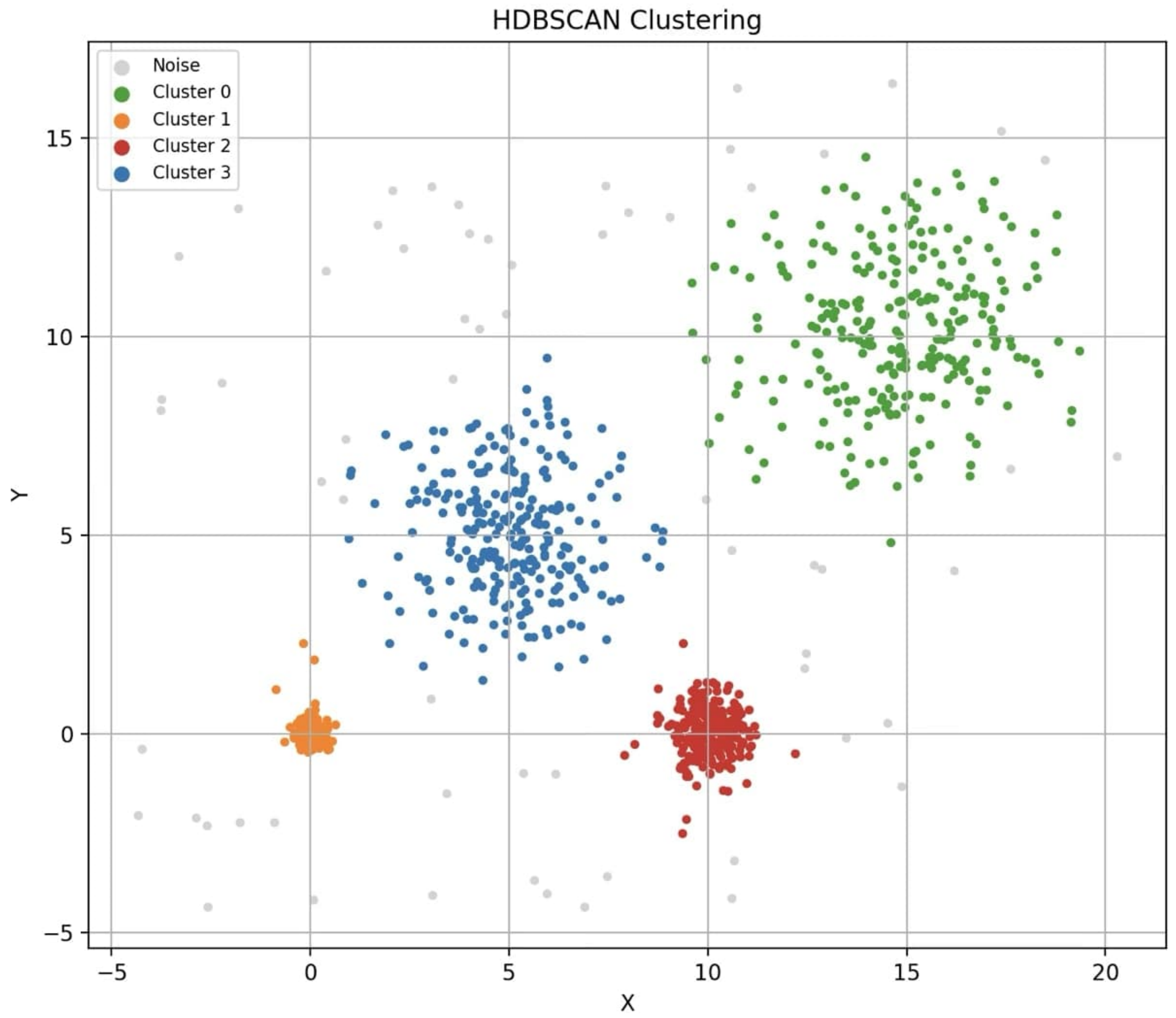


Smoothing


RGB band
blue band
Red band
Green band
corrected ground truth towards h-maxima
applying smoothing

DBSCAN vs. HDBSCAN



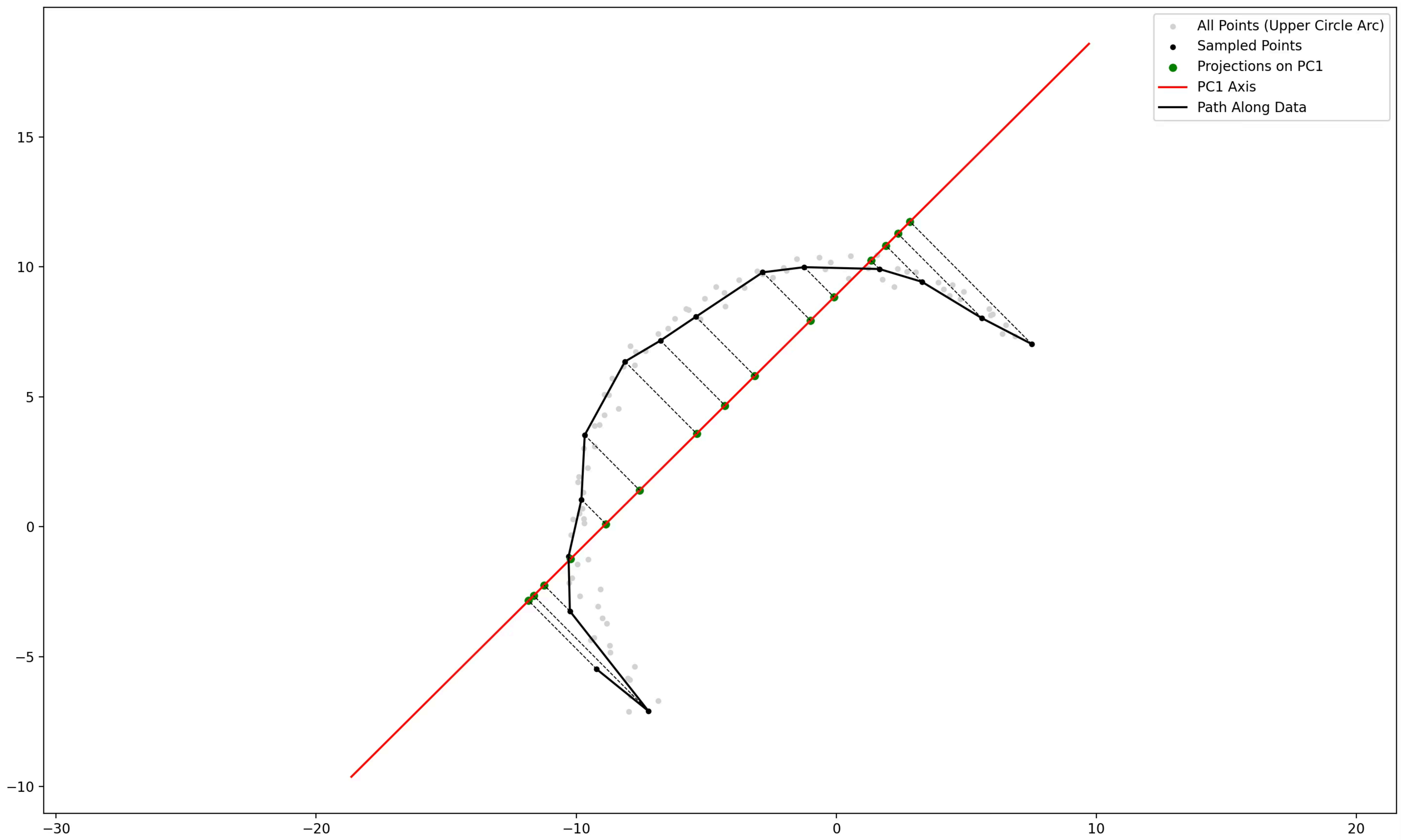


True number of clusters = 4

data with 4 clusters of varying spread

(std: 0.2, 1.5, 0.5, 2)

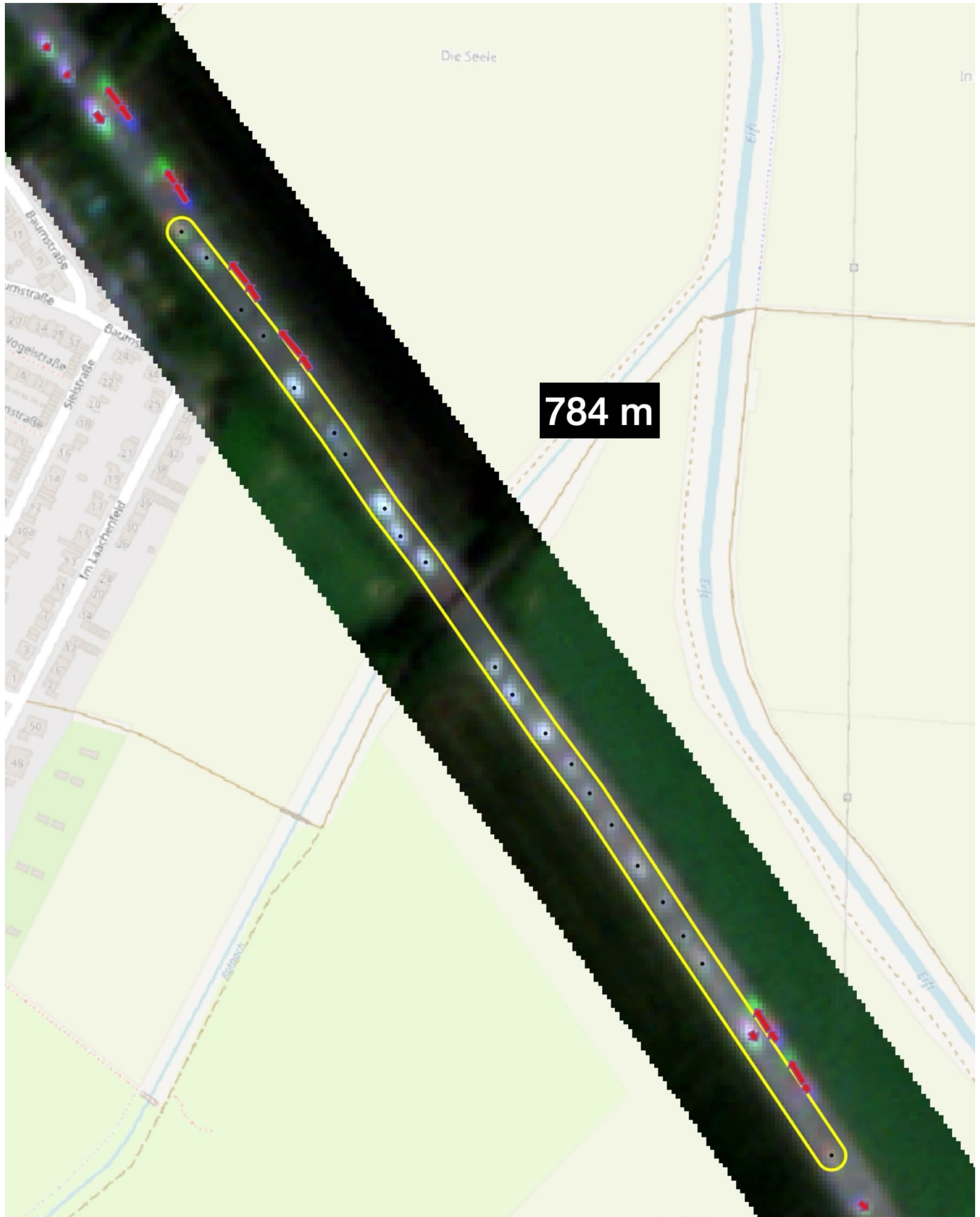
Principal Component Analysis for Length Estimation



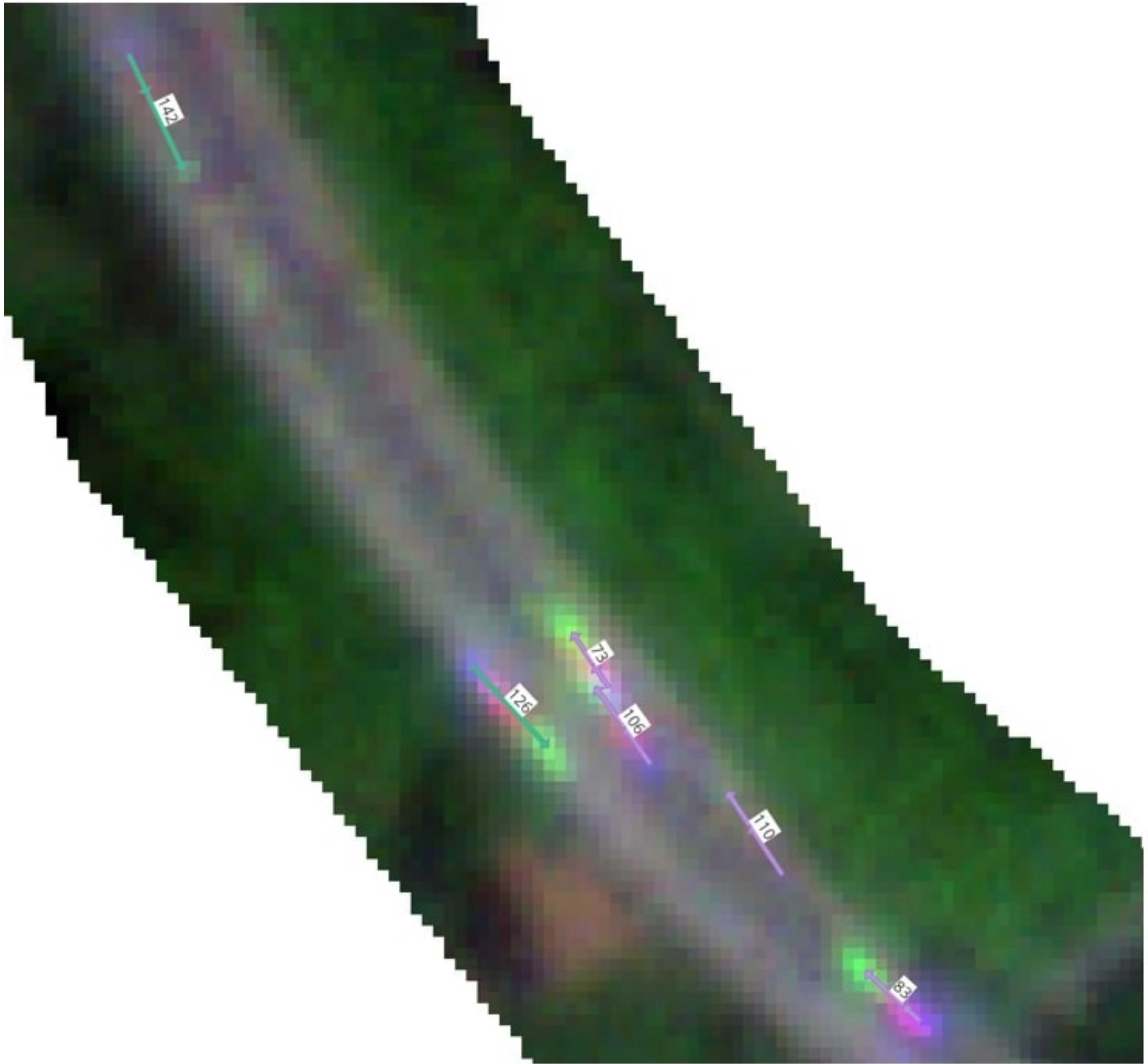
Projection of sampled points onto the first principal component axis for ordering.

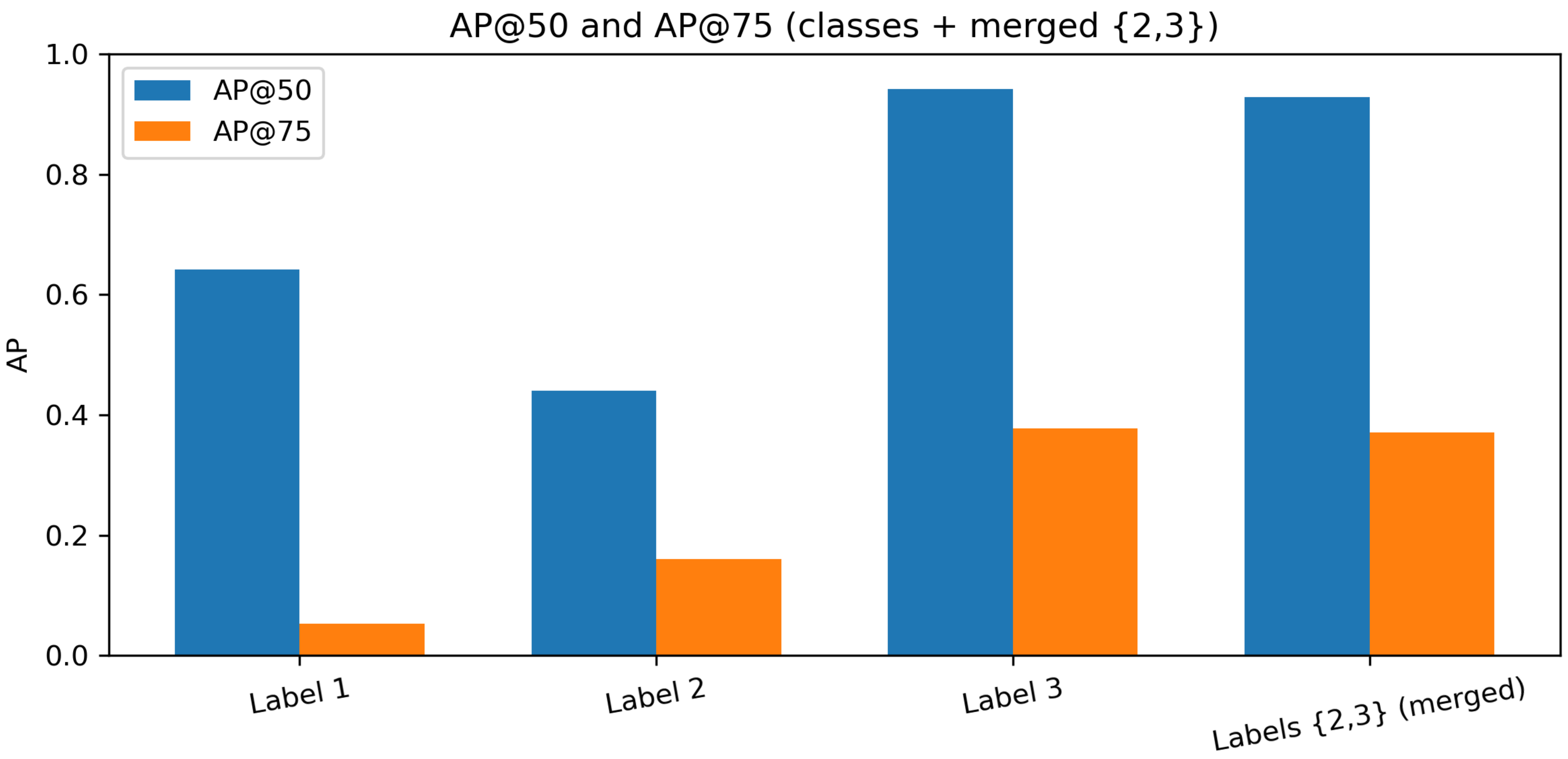
Congestion

Congestion



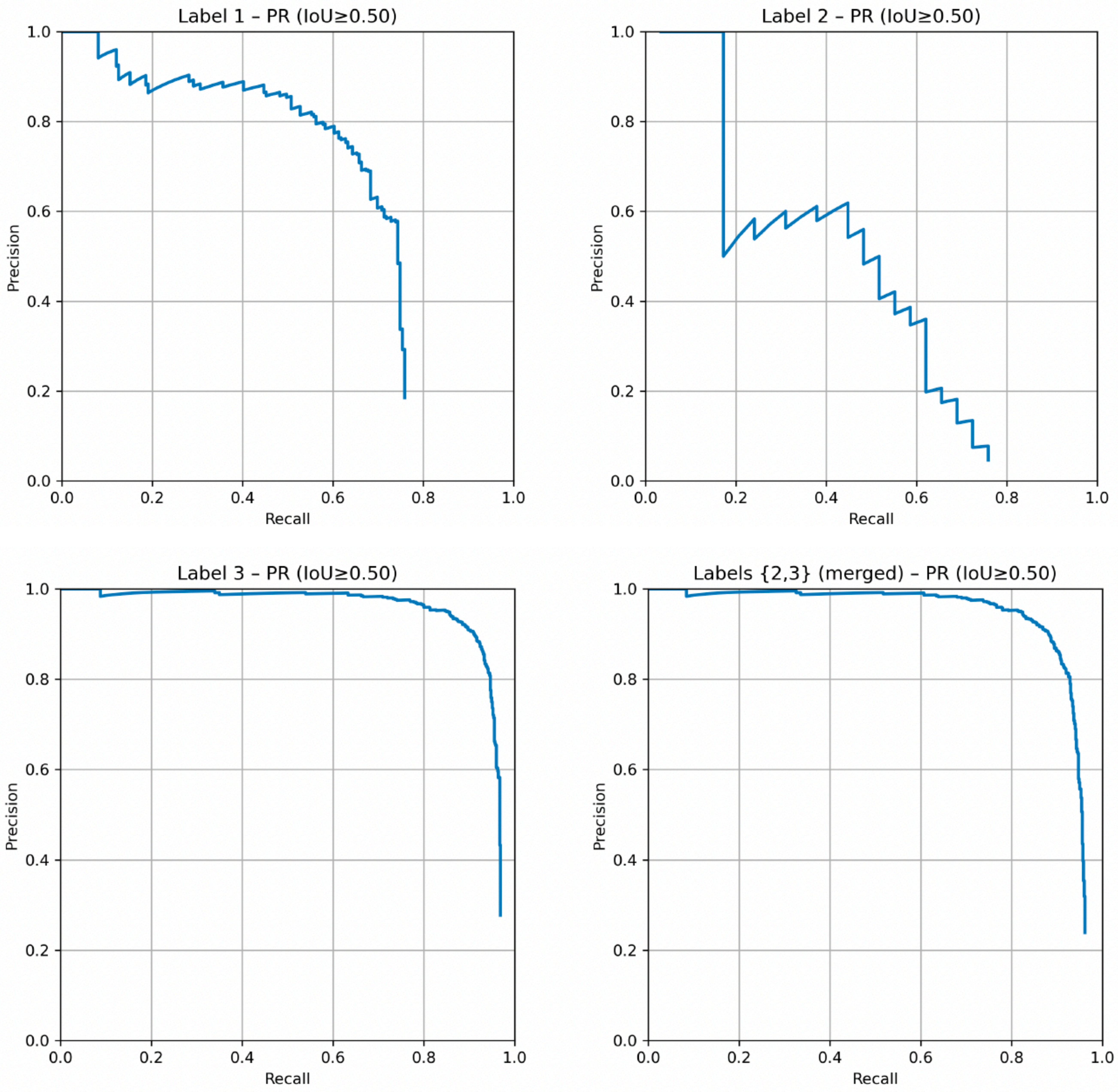
Results


142
73
126
106
110
83

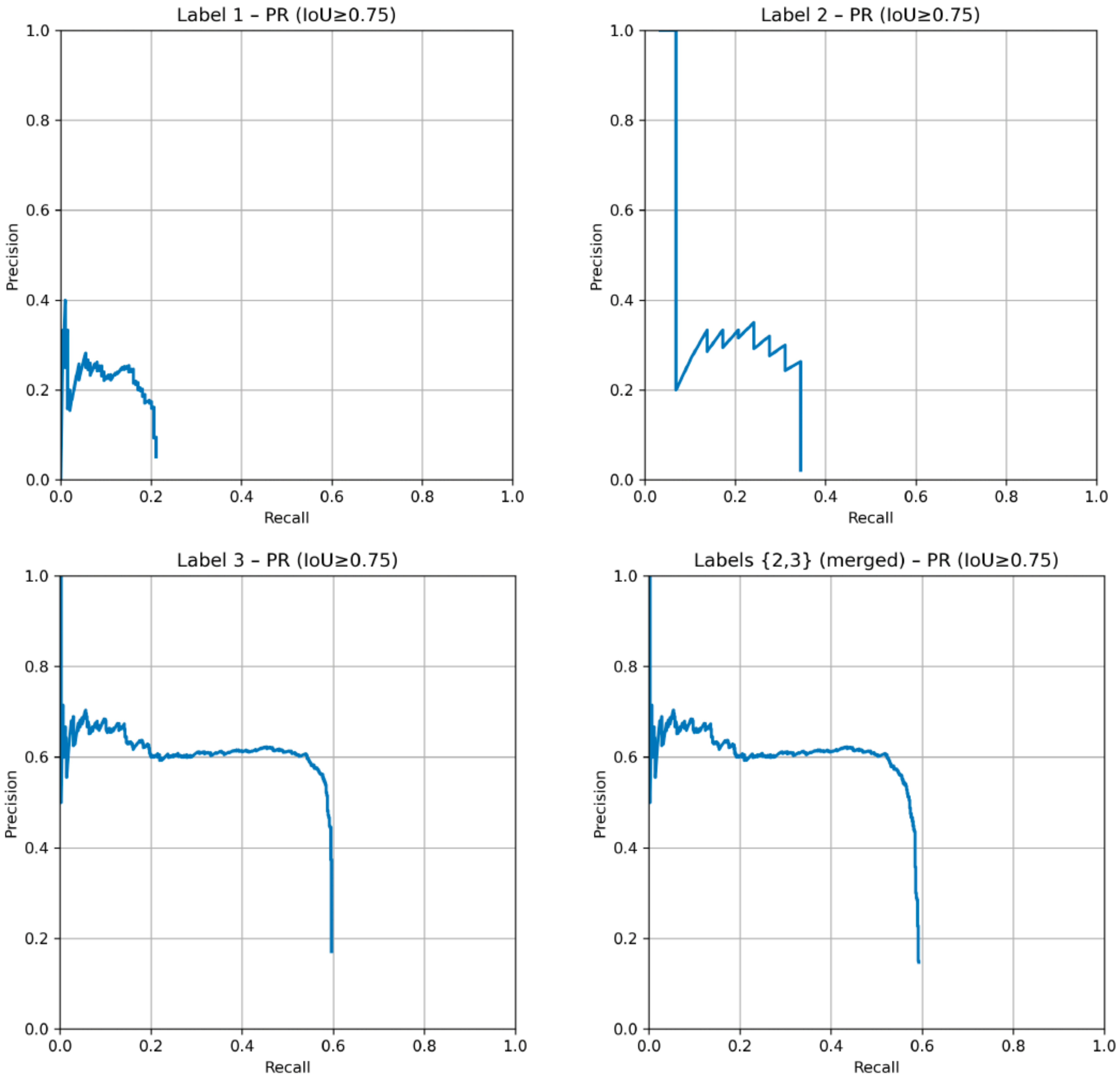

AP@50 and AP@75 (classes + merged {2,3})
AP@50
AP@75
1.0
0.8
0.6
0.4
0.2
0.0
AP
Label 1
Label 2
Label 3
Labels {2,3} (merged)

Group	$AP_{0.50}$	$AP_{0.75}$
Label 1	0.64	0.05
Label 2	0.44	0.16
Label 3	0.94	0.38
Labels {2,3} (merged)	0.93	0.37
mAP (macro over 1/2/3)	0.67	0.20

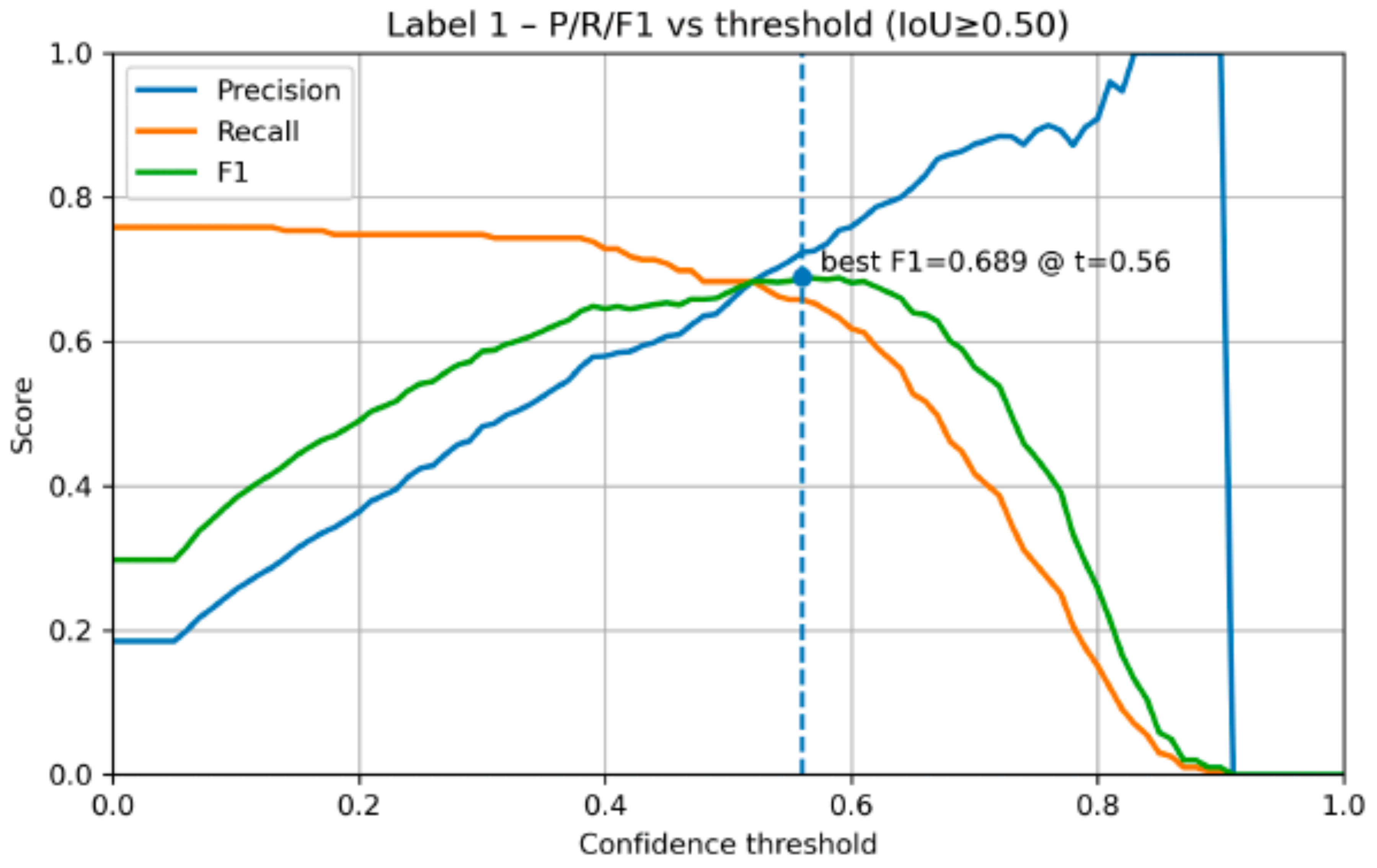
Precision- Recall Curve (IoU=0.5)

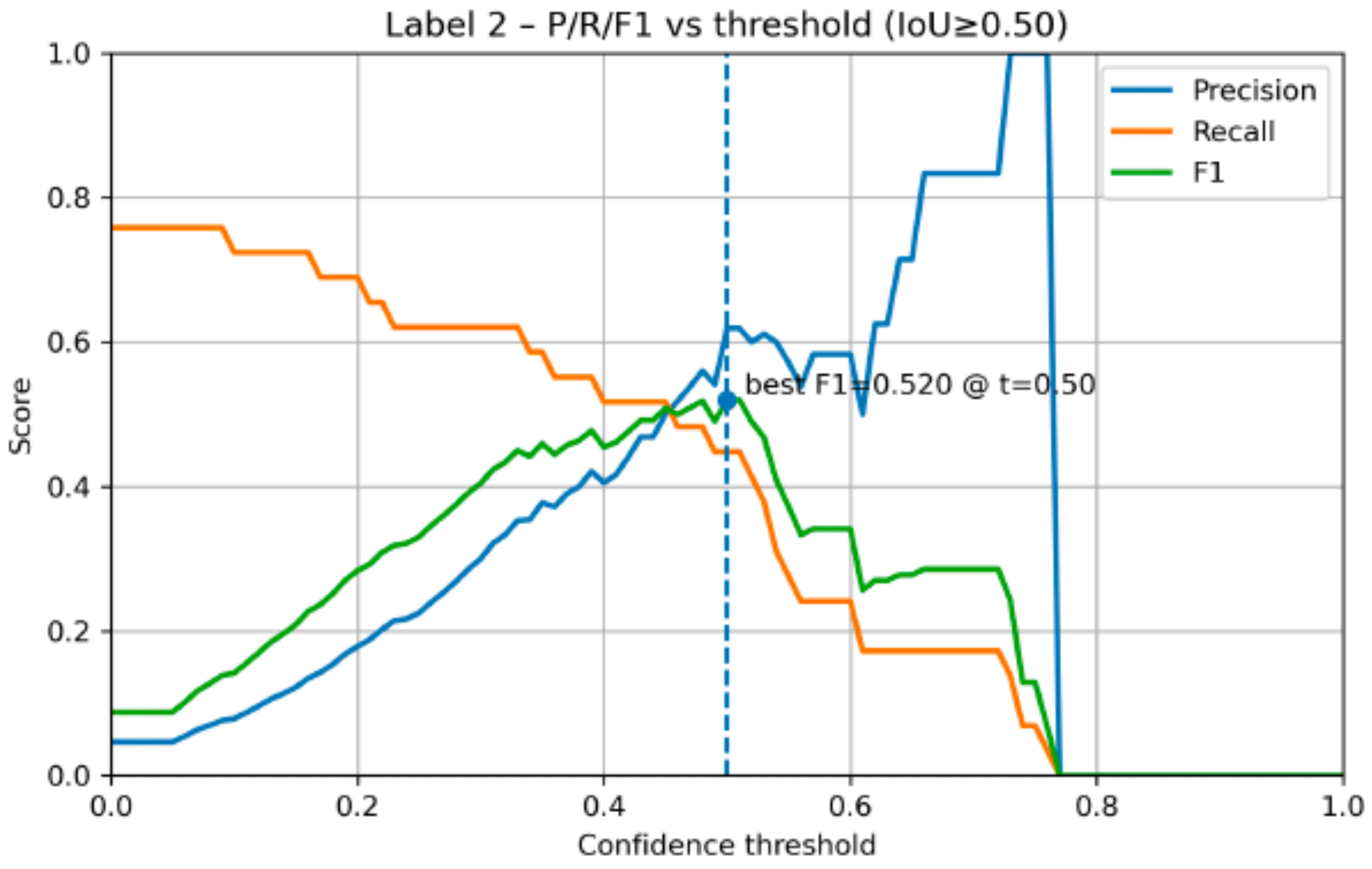


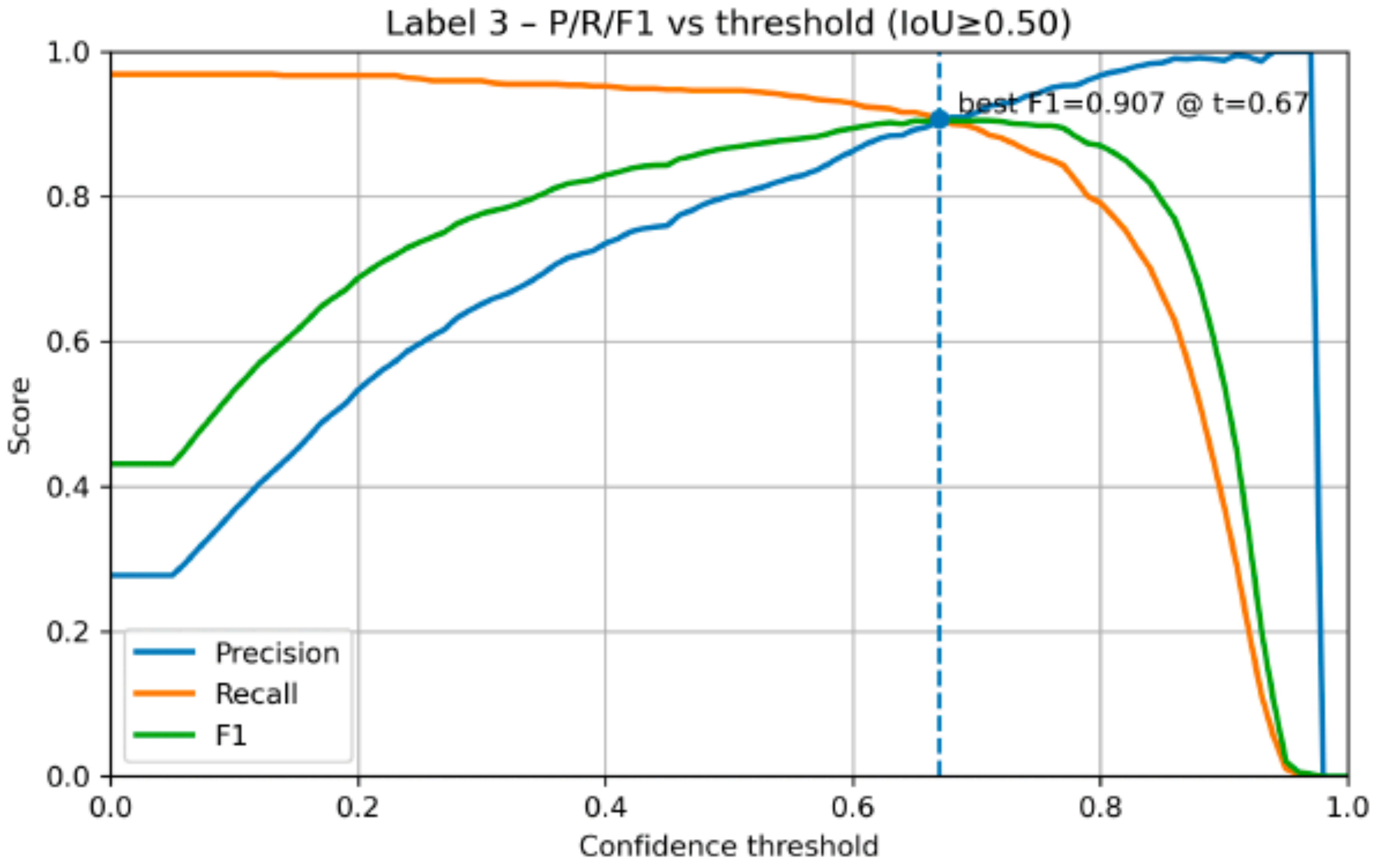
Precision- Recall Curve (IoU=0.75)

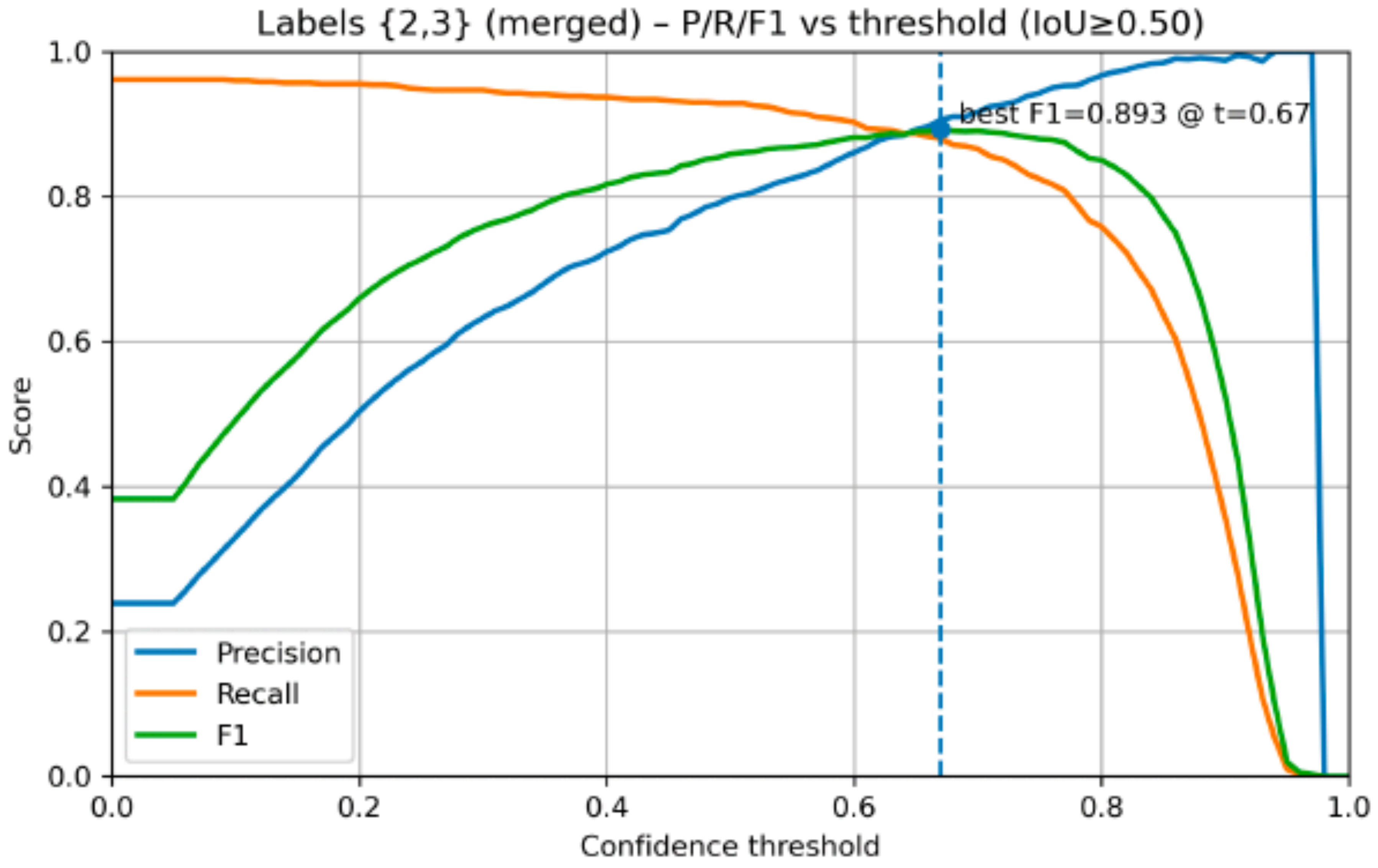


Confidence Threshold Sweep





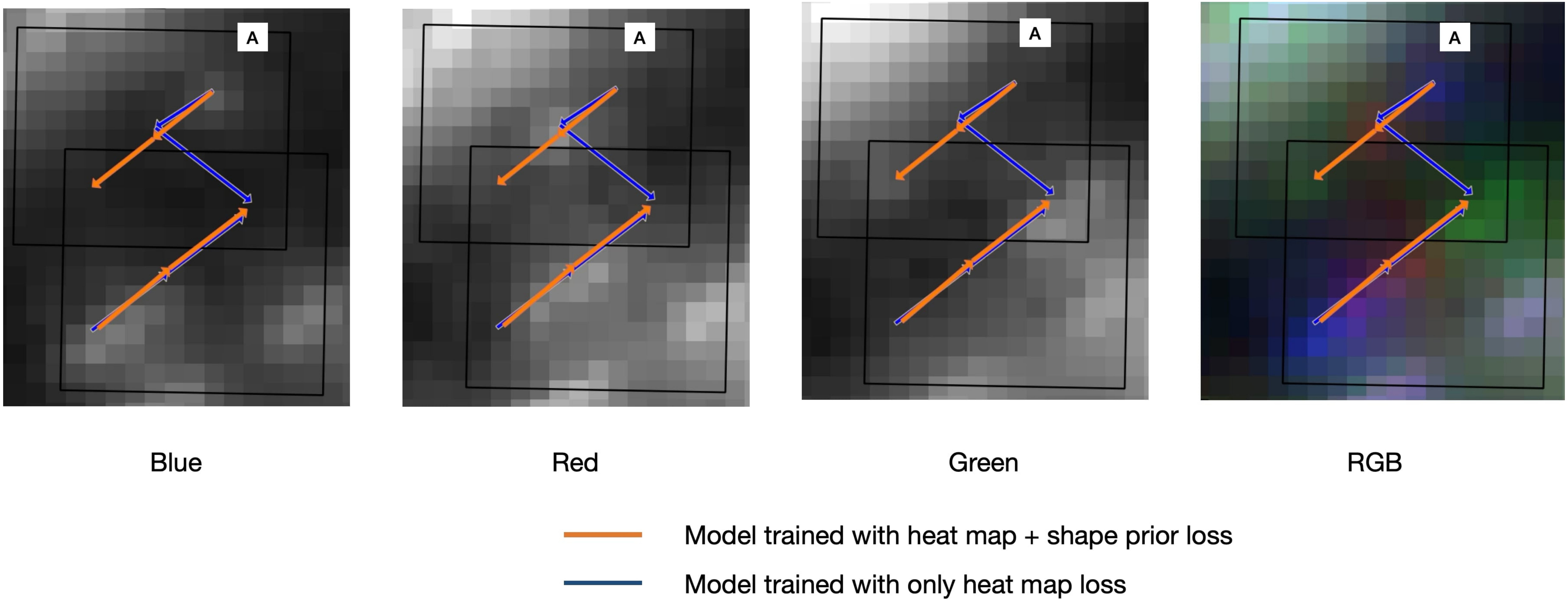




Root Mean Square Error

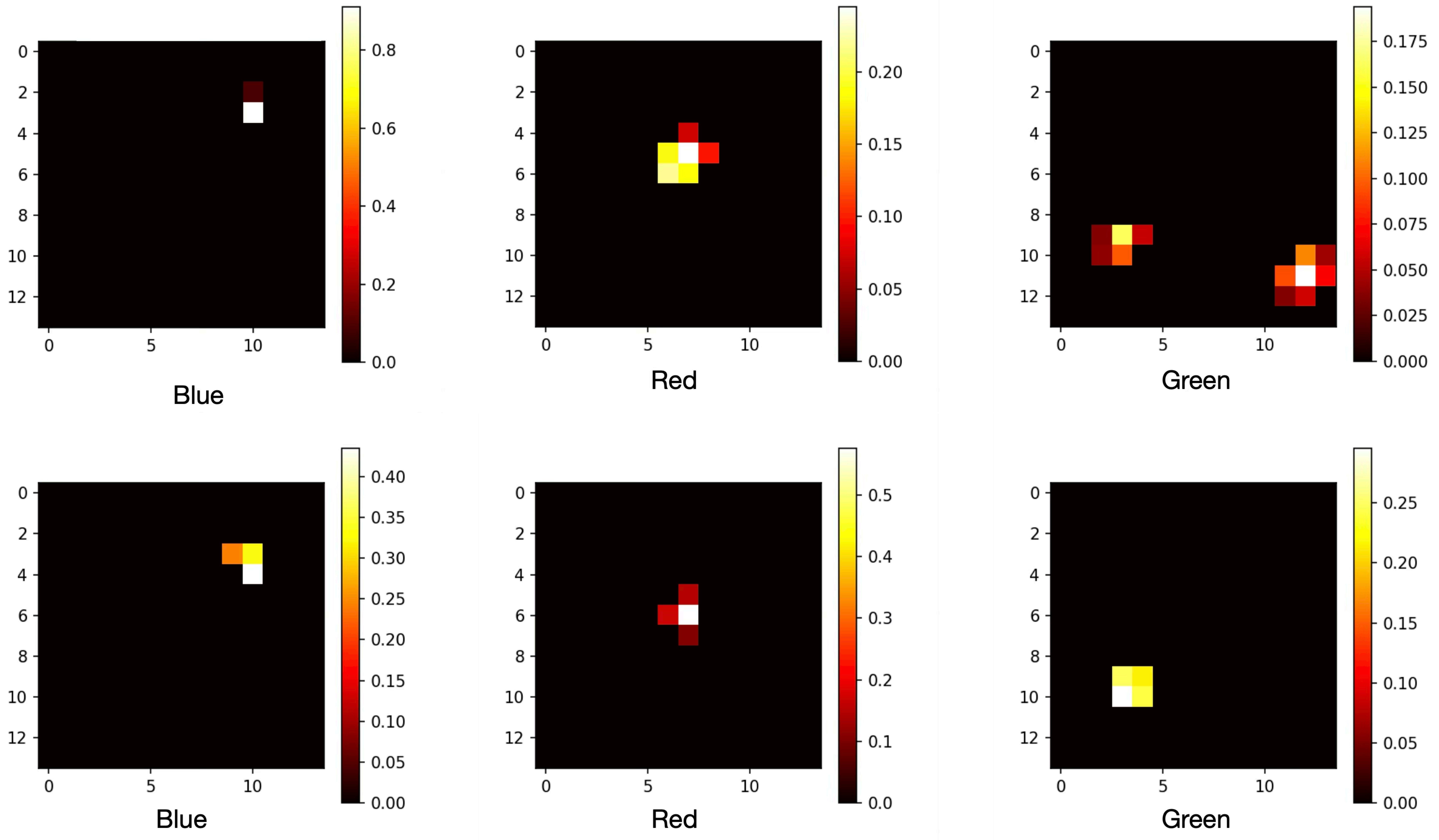
Group	RMSE (m)	RMSE (px)	n_pairs
Label 1	3.669102	1.223034	108
Label 2	6.296832	2.098944	44
Label 3	4.785135	1.595045	2142
Overall	4.772278	1.590759	2294

Ablation : Without Shape Priors



Ablation : Without Shape Priors

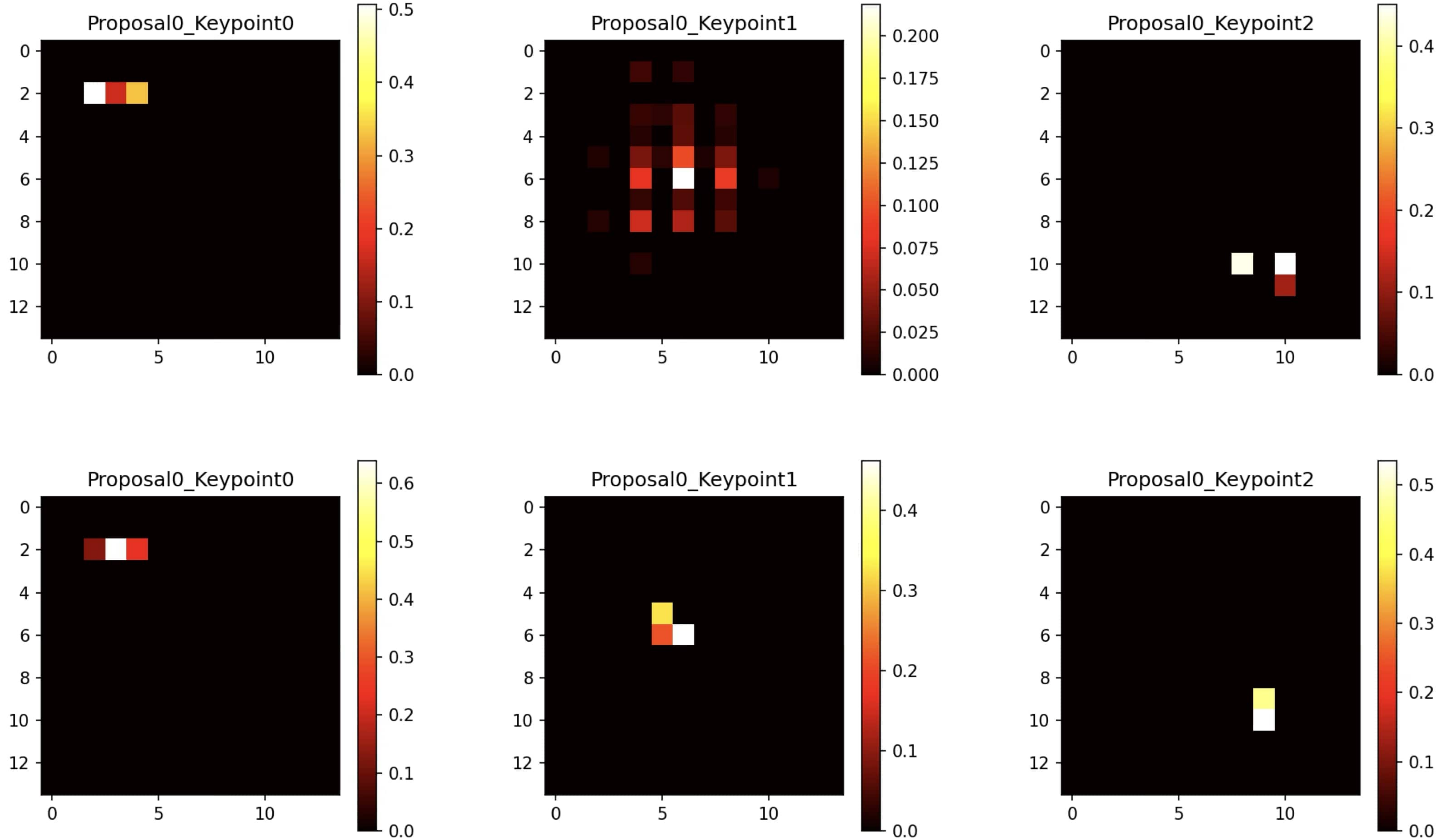
Training with just heatmap loss



Training with heatmap loss & shape prior loss

Ablation : Without Heatmap Loss

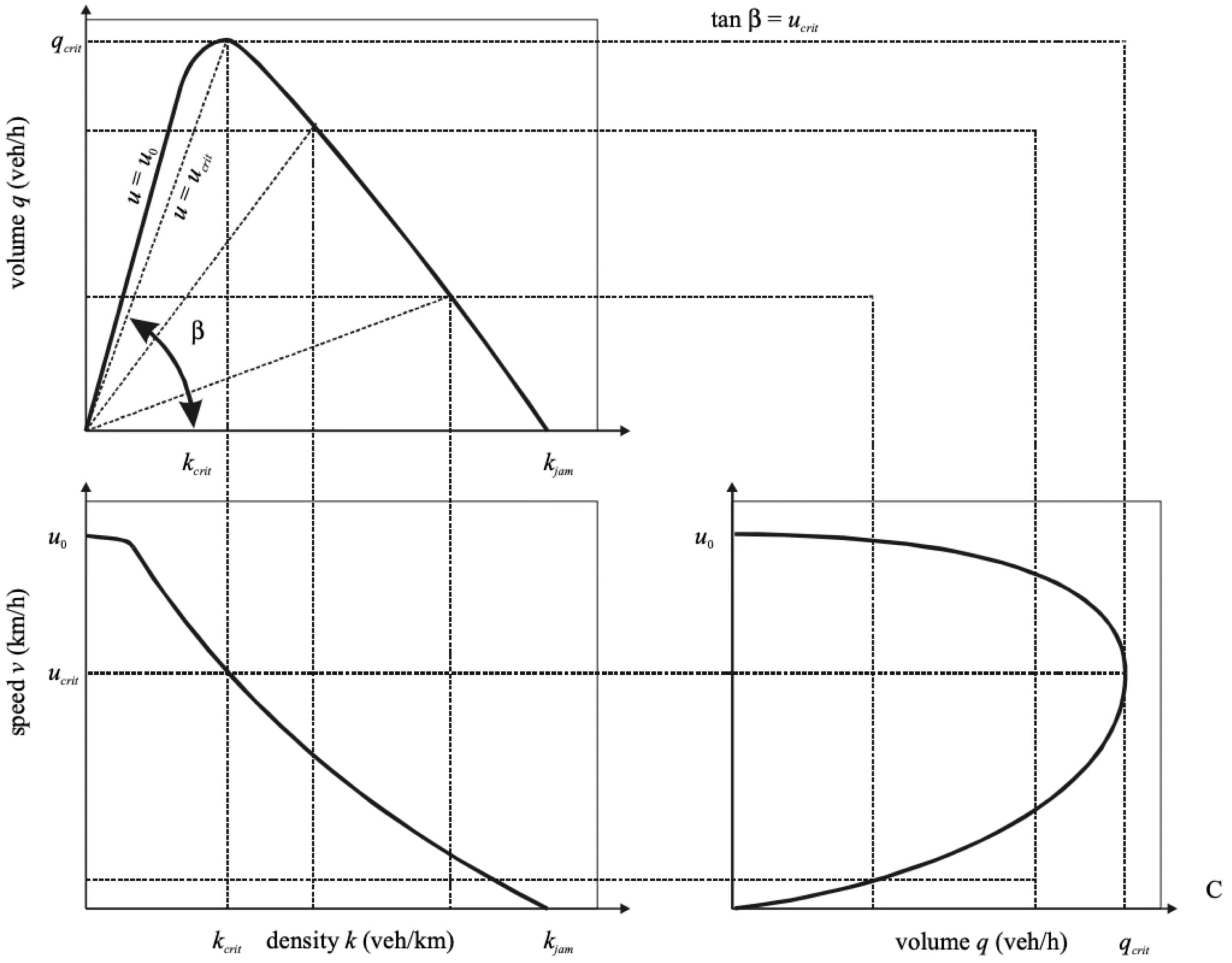
Training without heatmap loss



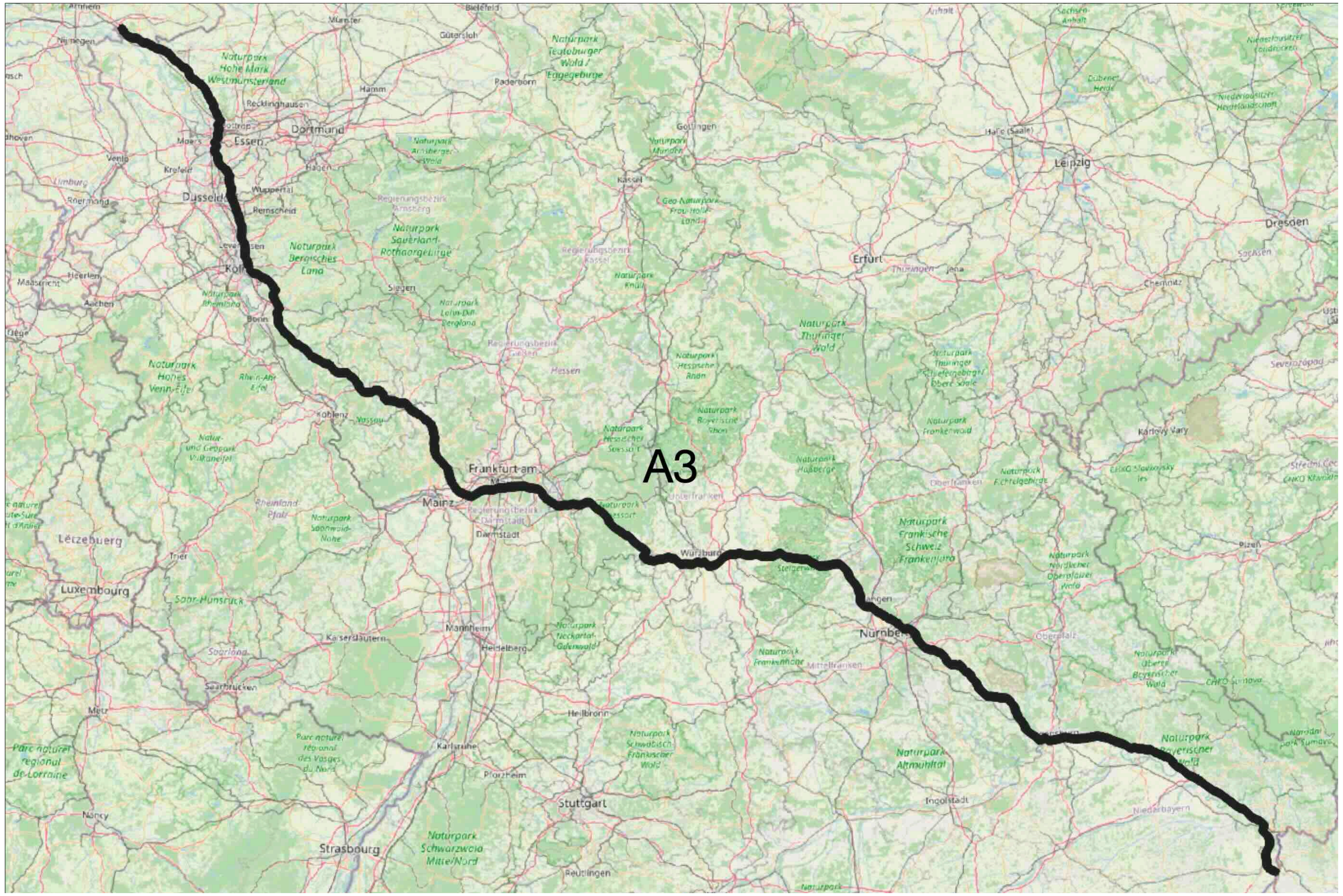
Training with heatmap loss

Validation

Fundamental diagram of traffic flow



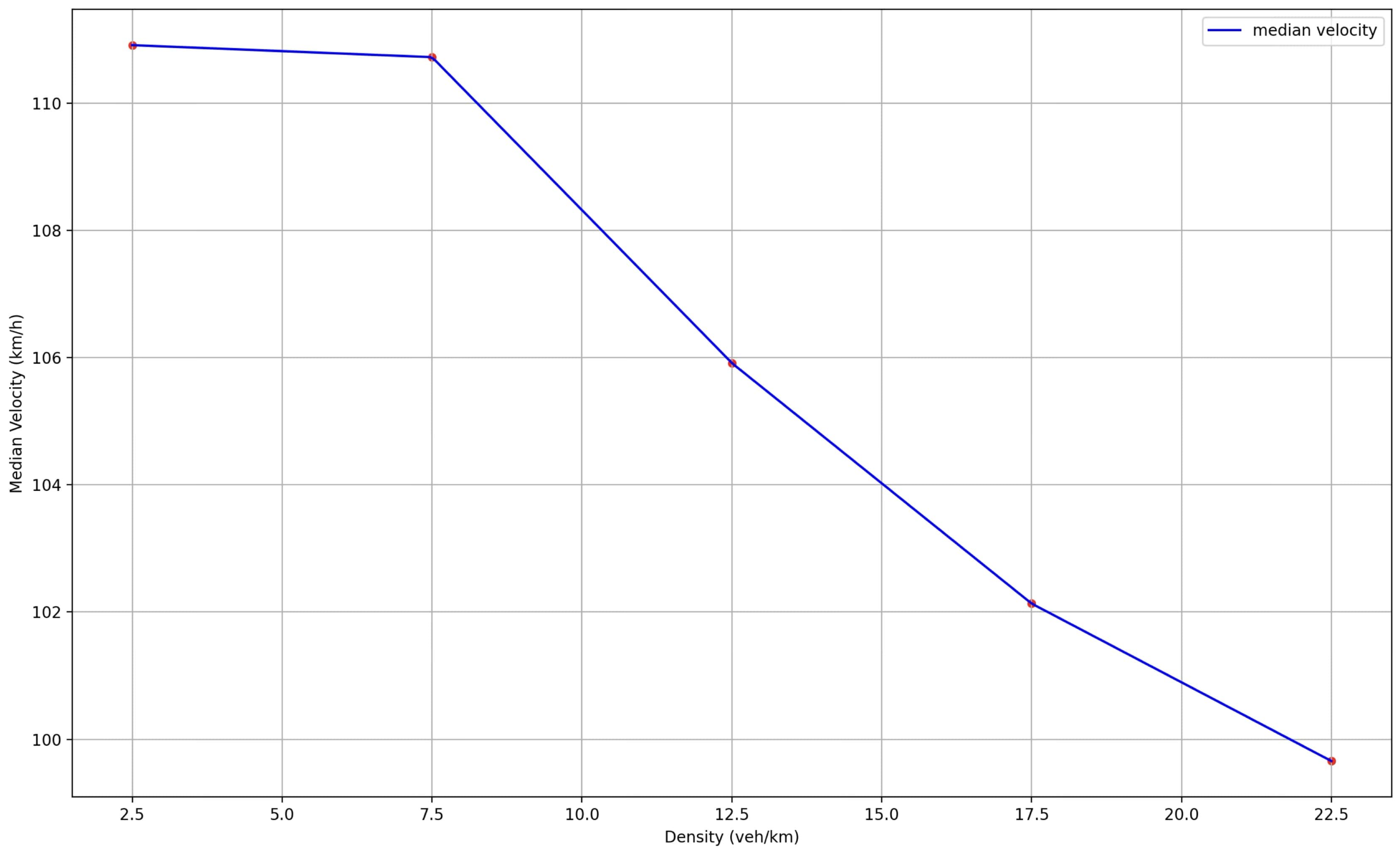
Analysis

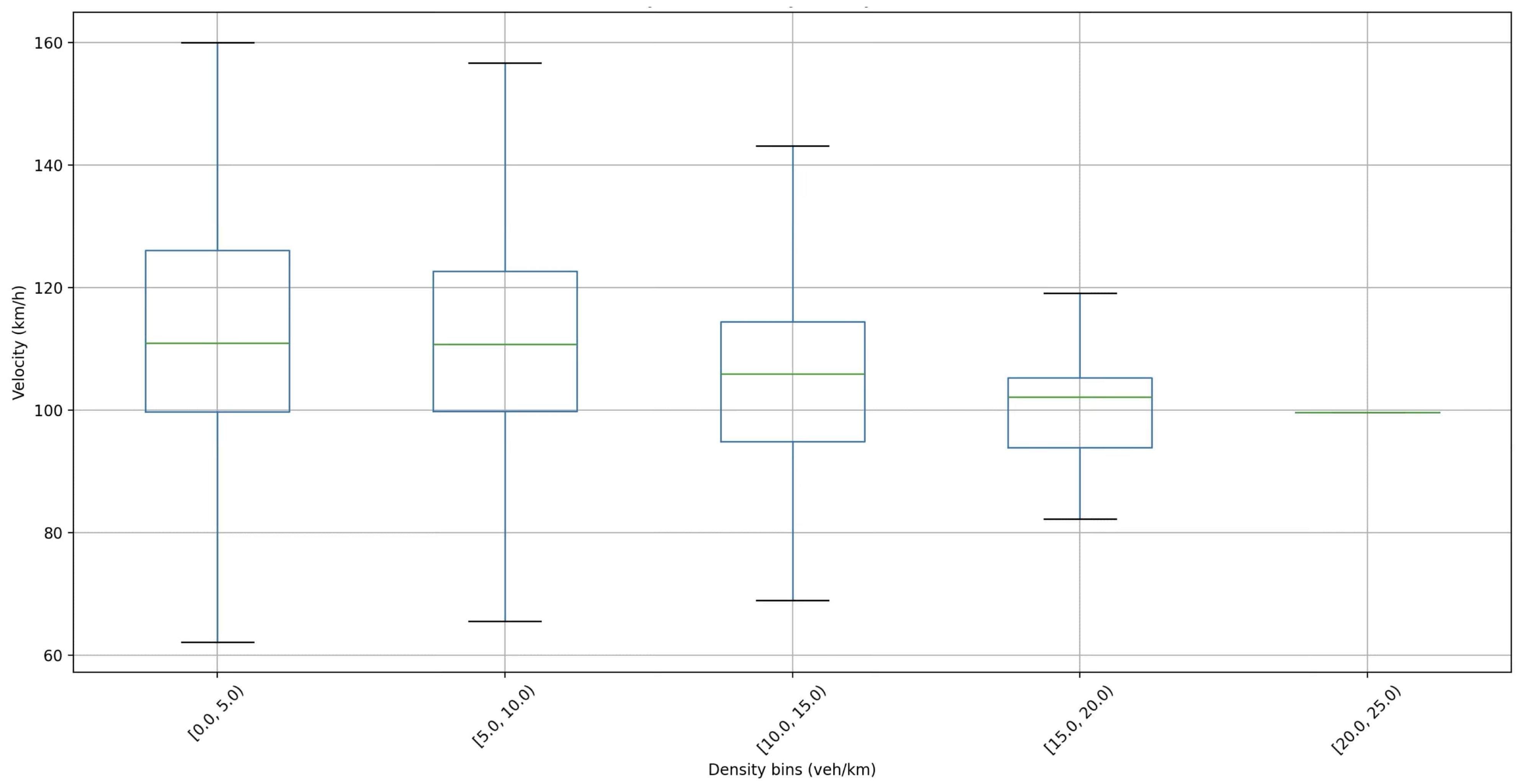


May 2, 2024

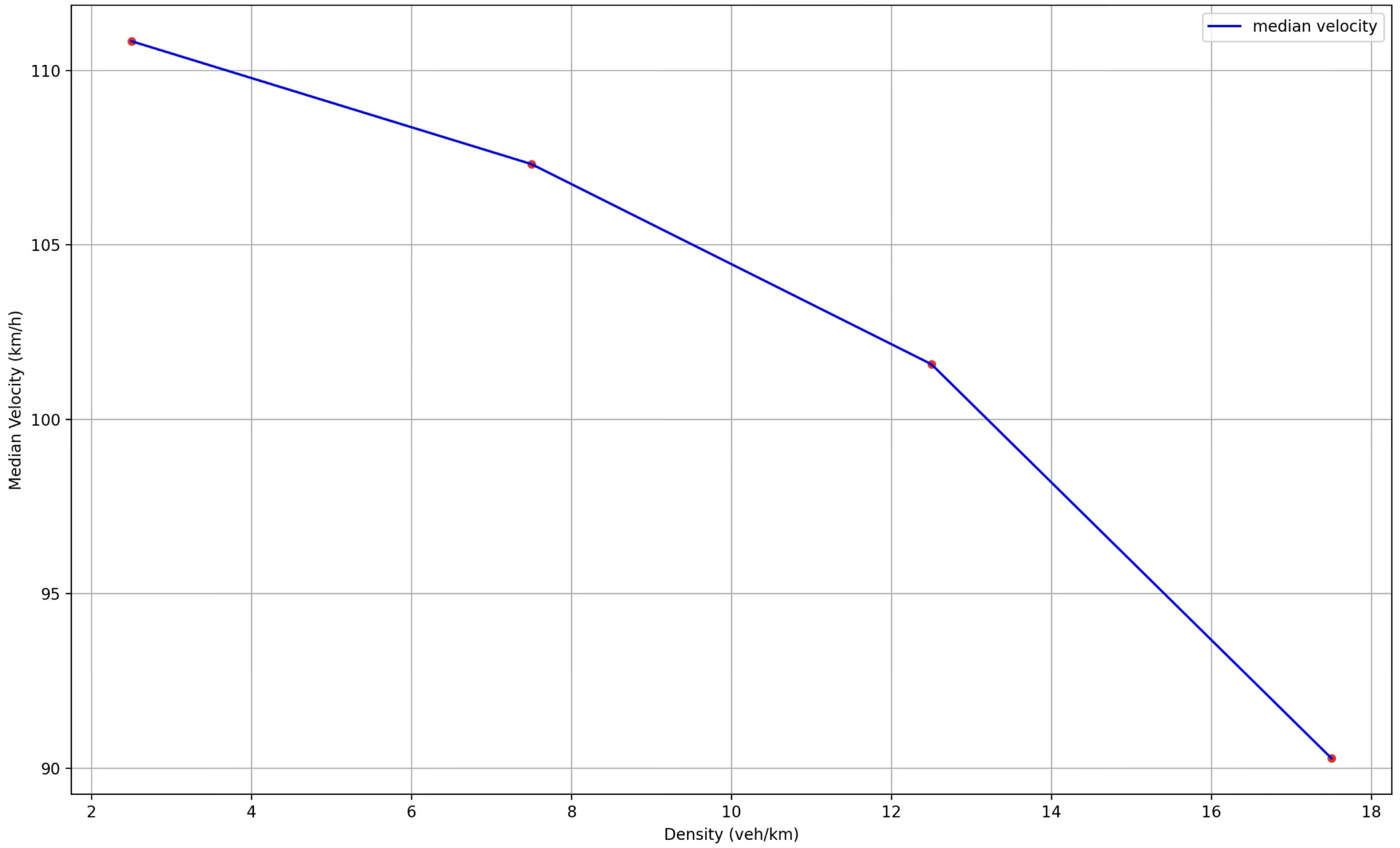
Median speeds are calculated over 300m segments

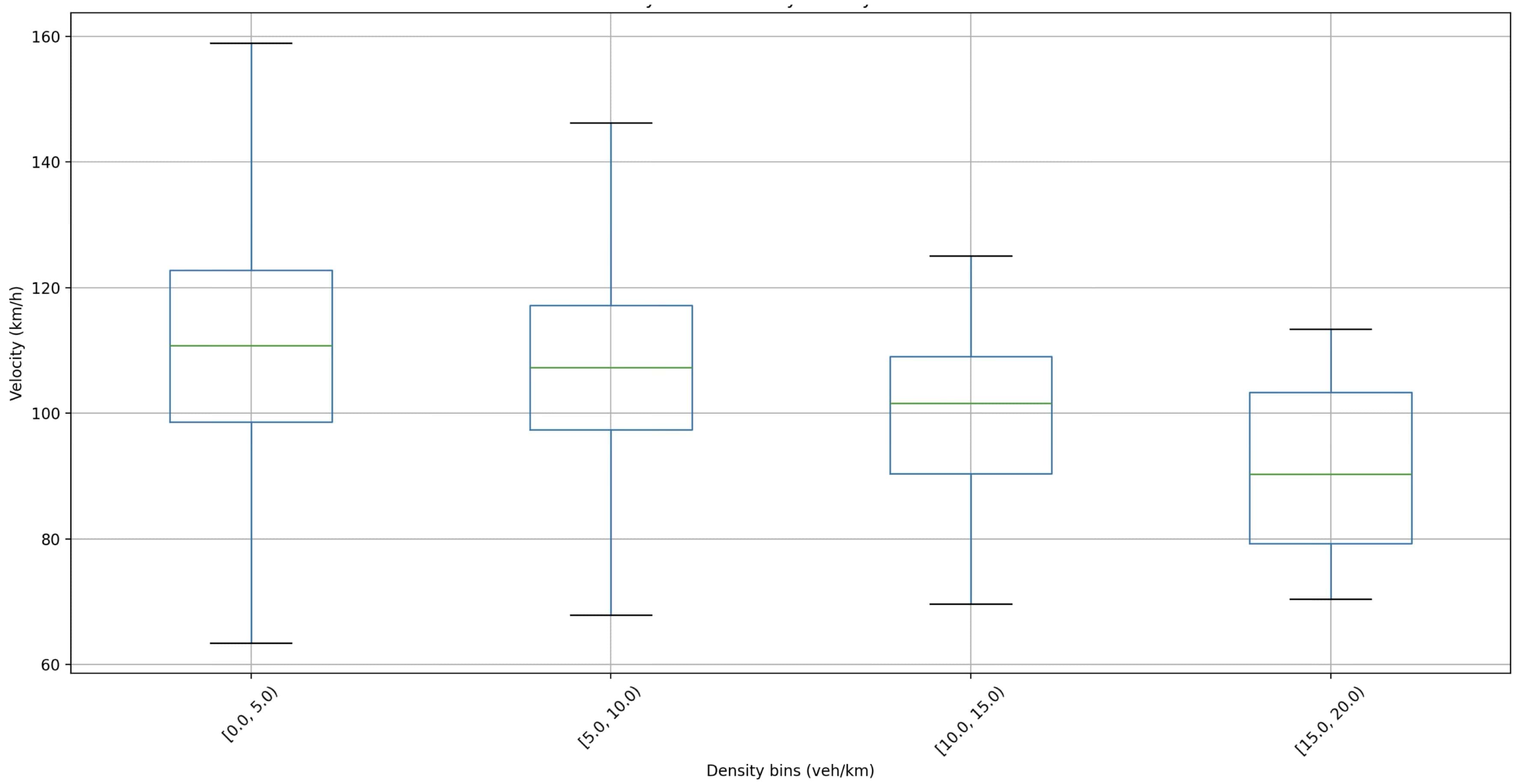
Velocity vs density





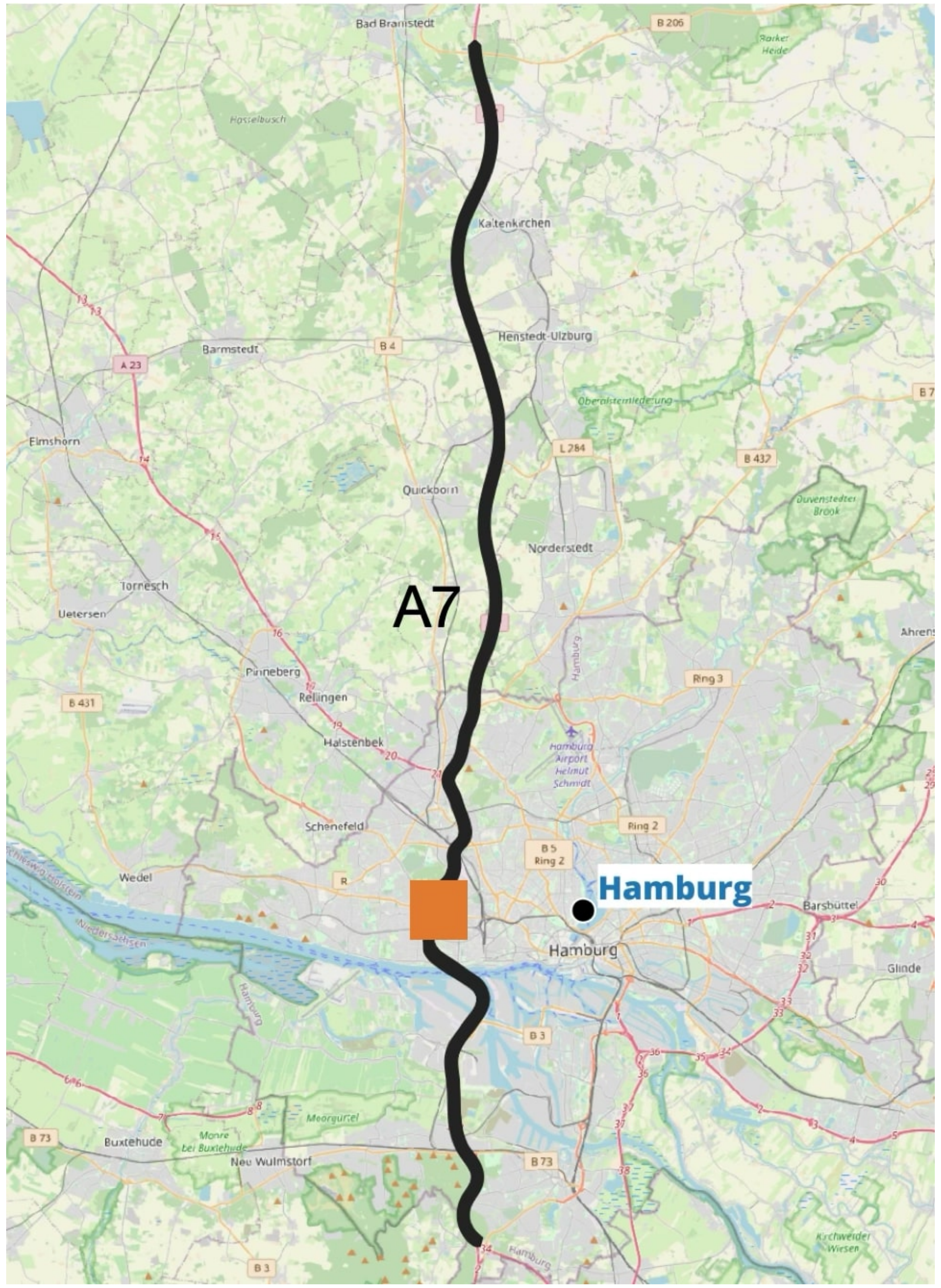
NW-SE

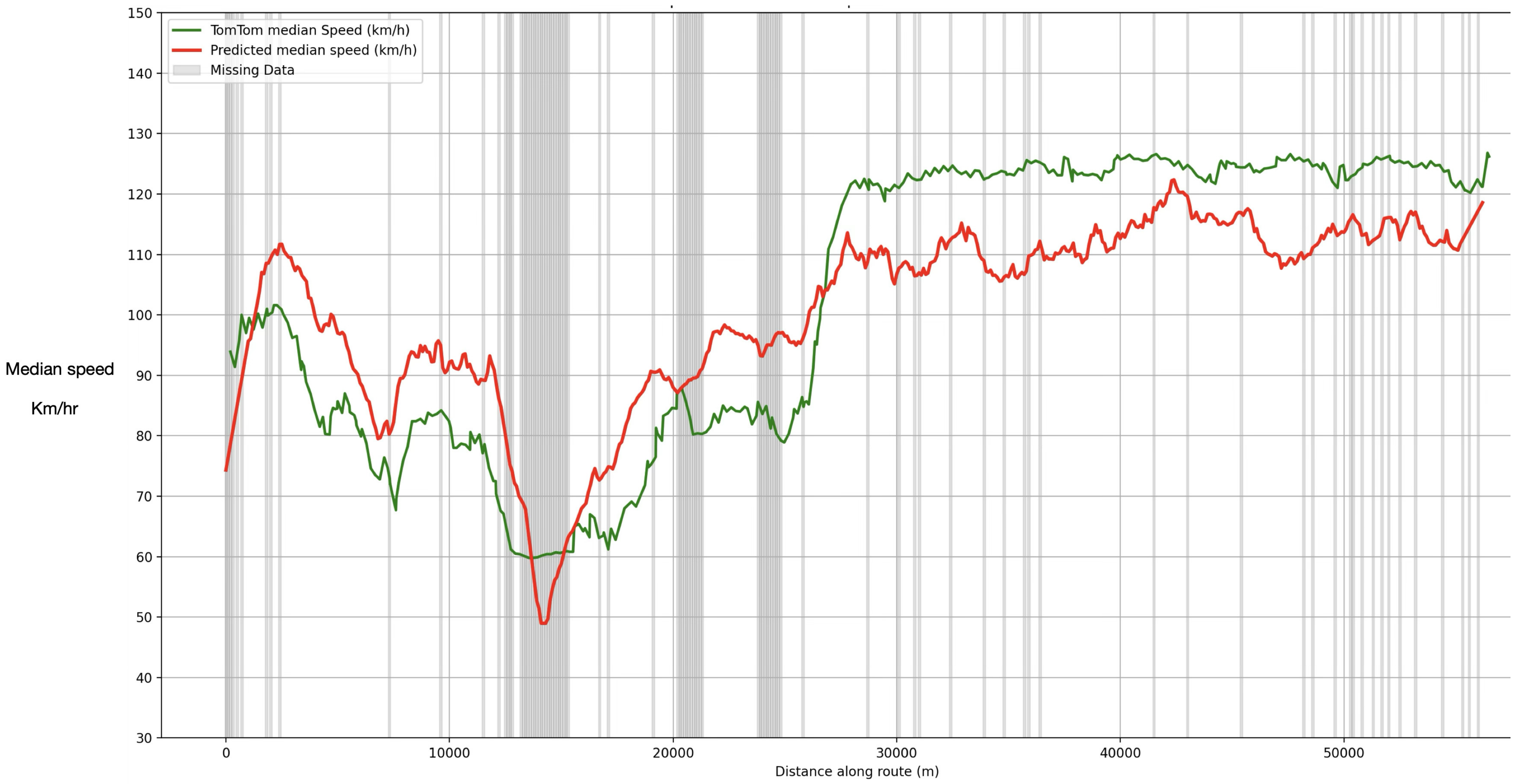




SE-NW

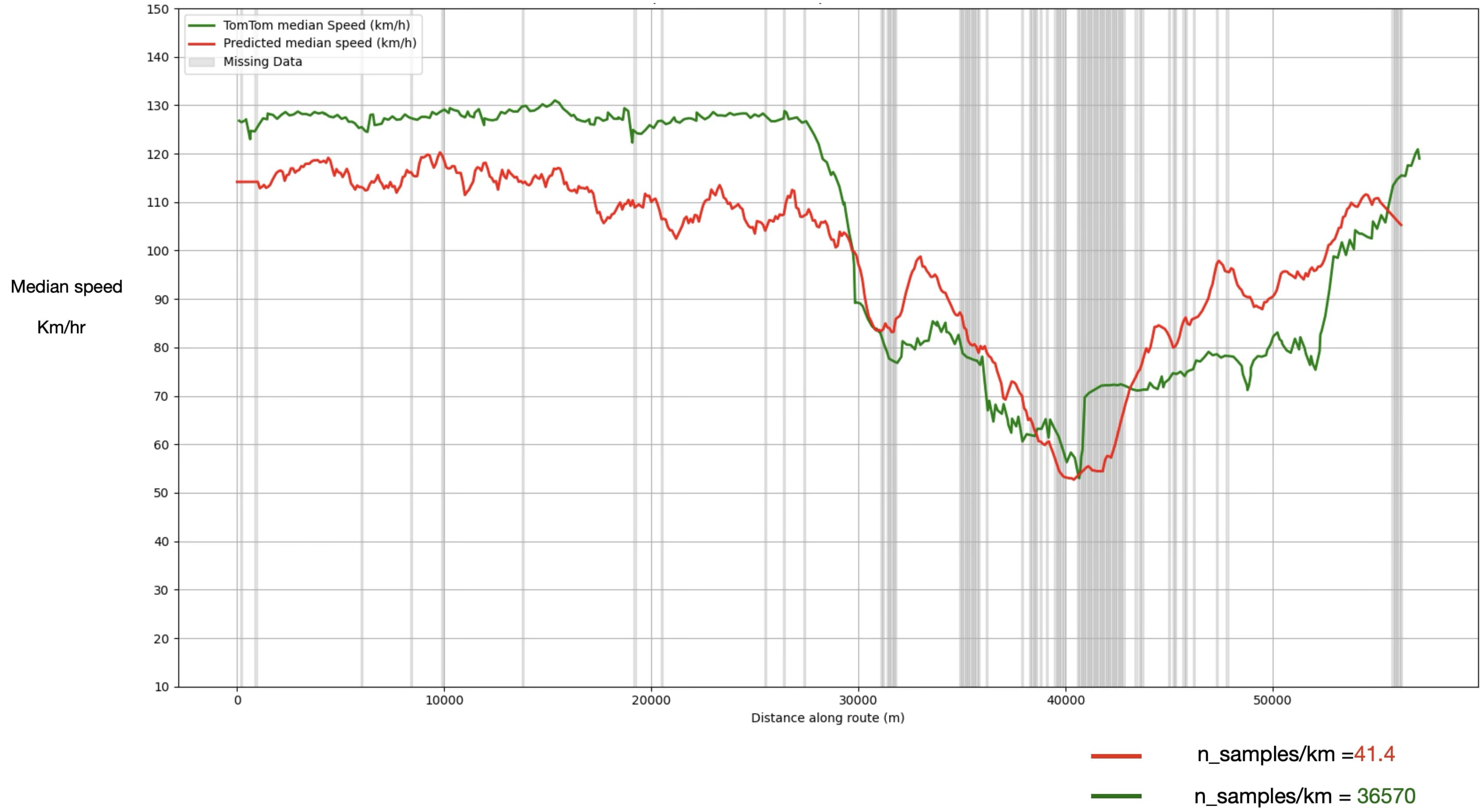
Median velocity / density bins


A7
Hamburg

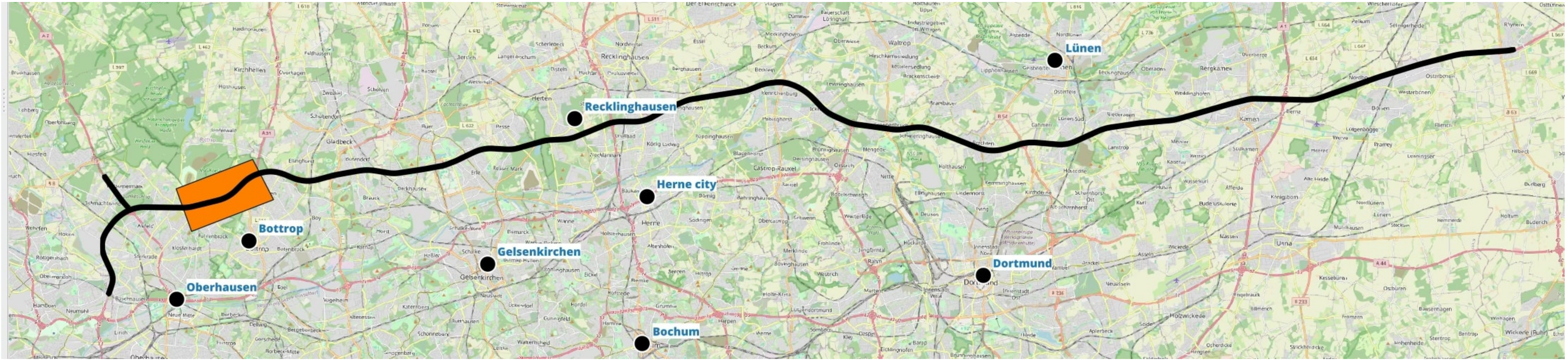


n_samples/km =29.4

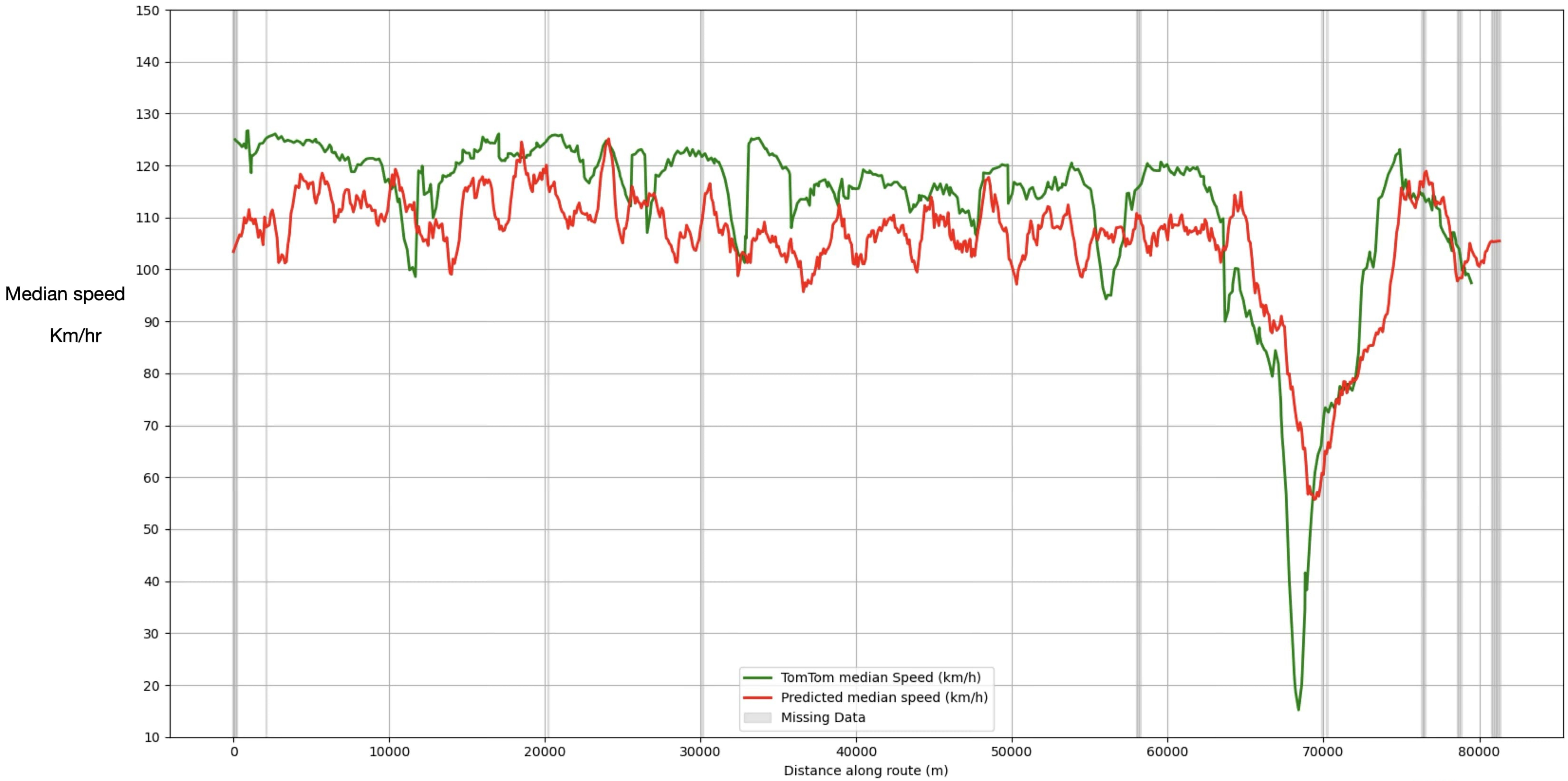
n_samples/km = 37918



TomTom median Speed (km/h)
Predicted median speed (km/h)
Missing Data
Median speed
Km/hr
150
140
130
120
110
100
90
80
70
60
50
40
30
20
10
0
10000
20000
30000
40000
50000
Distance along route (m)
n_samples/km =41.4
n_samples/km = 36570



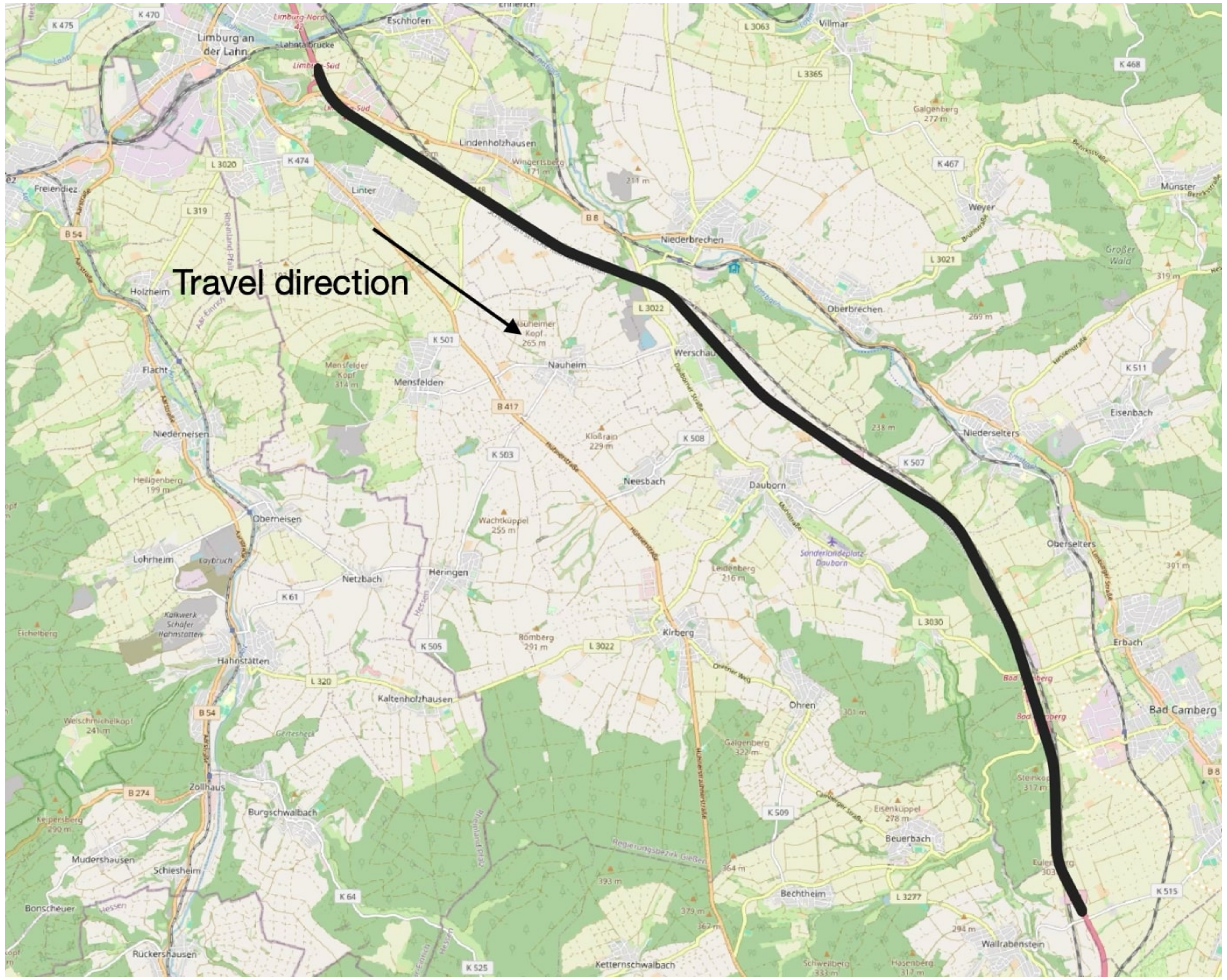
Lünen
Recklinghausen
Herne city
Bottrop
Gelsenkirchen
Dortmund
Oberhausen
Bochum



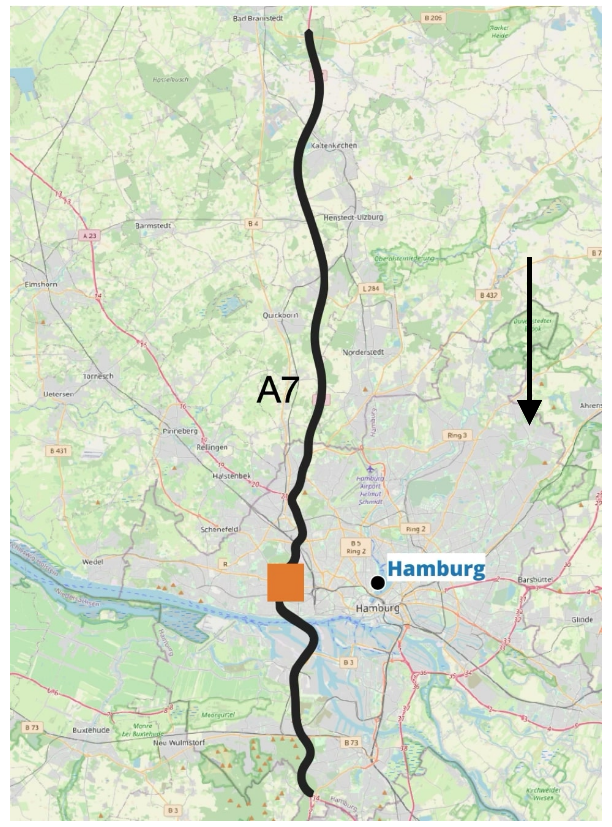
n_samples/km =75.1

n_samples/km = 40645

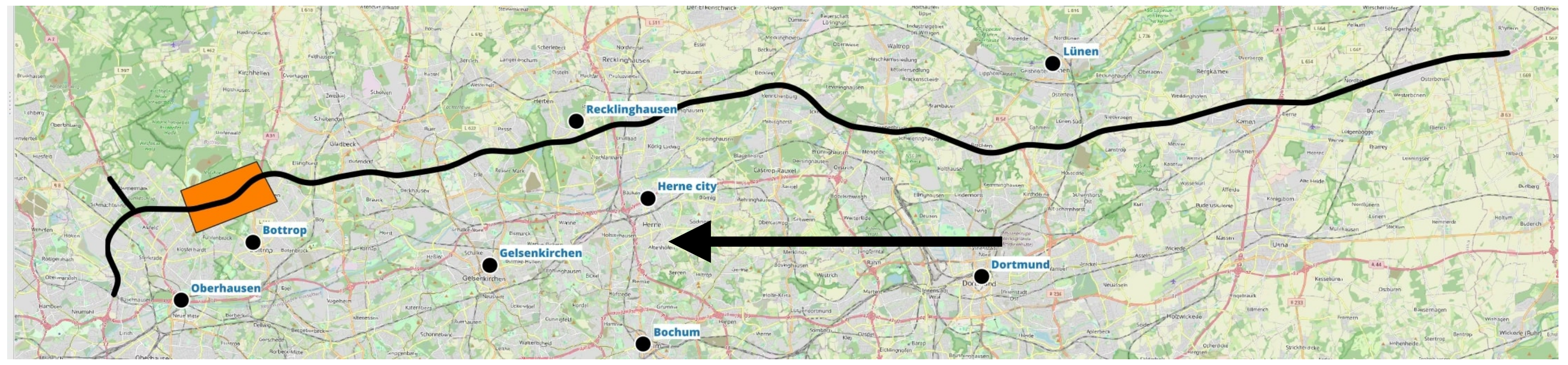
Median speed
Km/hr
150
140
130
120
110
100
90
80
70
60
50
40
30
20
10
0
10000
20000
30000
40000
50000
60000
70000
80000
Distance along route (m)
TomTom median Speed (km/h)
Predicted median speed (km/h)
Missing Data
n_samples/km =74.1
n_samples/km = 38665

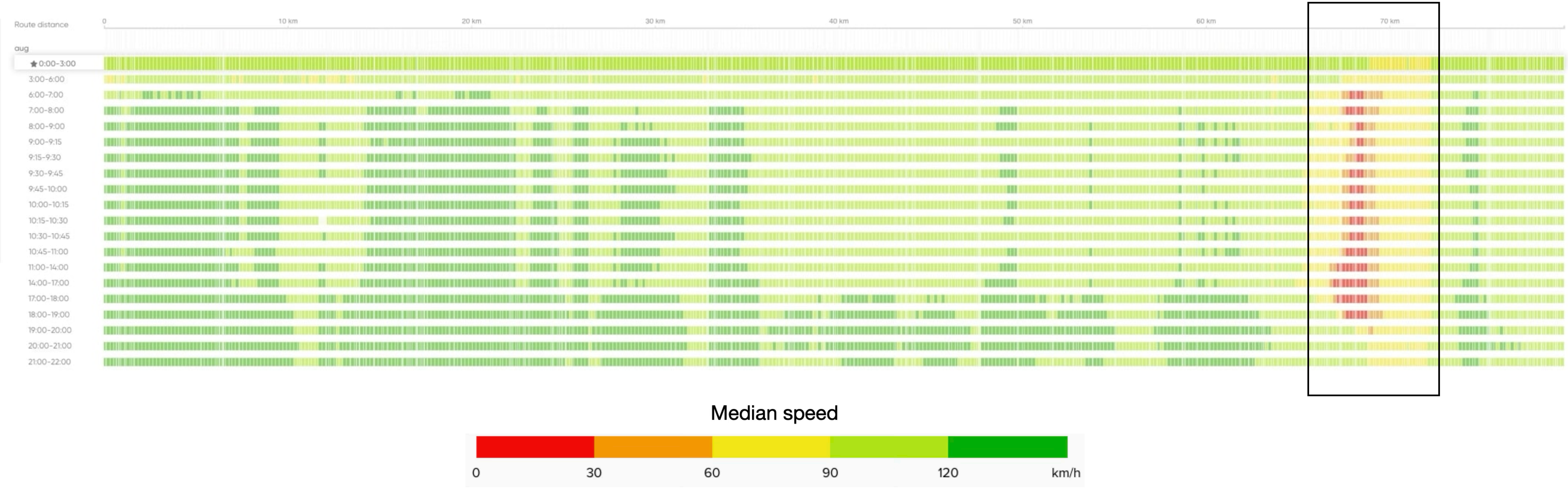

Travel direction
Limburg an der Lahn
Eschhofen
Lindenholzhausen
Linter
Niederbrechen
Oberbrechen
Villmar
Weyer
Münster
Holzheim
Flacht
Mensfelden
Nauheim
Werschau
Niederneisen
Oberneisen
Neesbach
Dauborn
Niederselters
Eisenbach
Oberselters
Lohrheim
Netzbach
Heringen
Kirberg
Hahnstätten
Kaltenholzhausen
Erbach
Bad Camberg
Ohren
Zollhaus
Burgschwalbach
Beuerbach
Mudershausen
Schiesheim
Bechtheim
Wallrabenstein
Bonscheuer
Rückershausen
Ketternschwalbach
Freiendiez

Median speed
Km/hr
150
140
130
120
110
100
90
80
70
60
50
40
30
20
10
0
2500
5000
7500
10000
12500
15000
17500
Distance along route (m)
TomTom median Speed (km/h)
Predicted median speed (km/h)
Missing Data
n_samples/km =98.6
n_samples/km = 49327

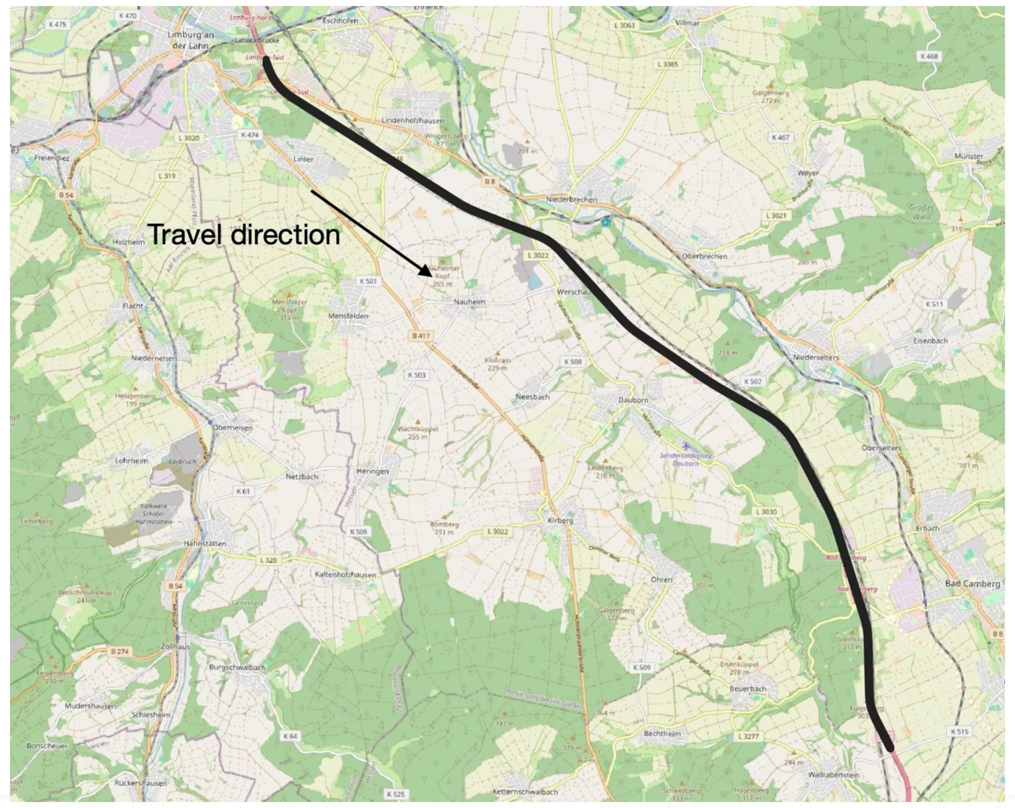


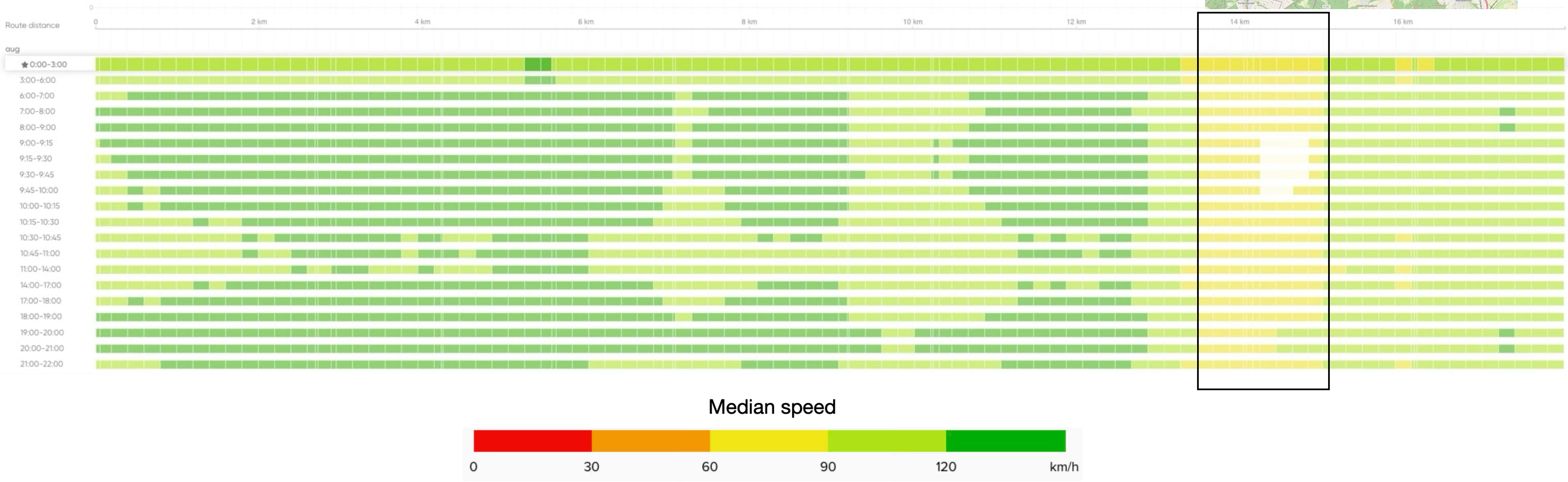
Bottleneck generally occurs at same location irrespective of the time of day





Bottleneck generally occurs at same location irrespective of the time of day

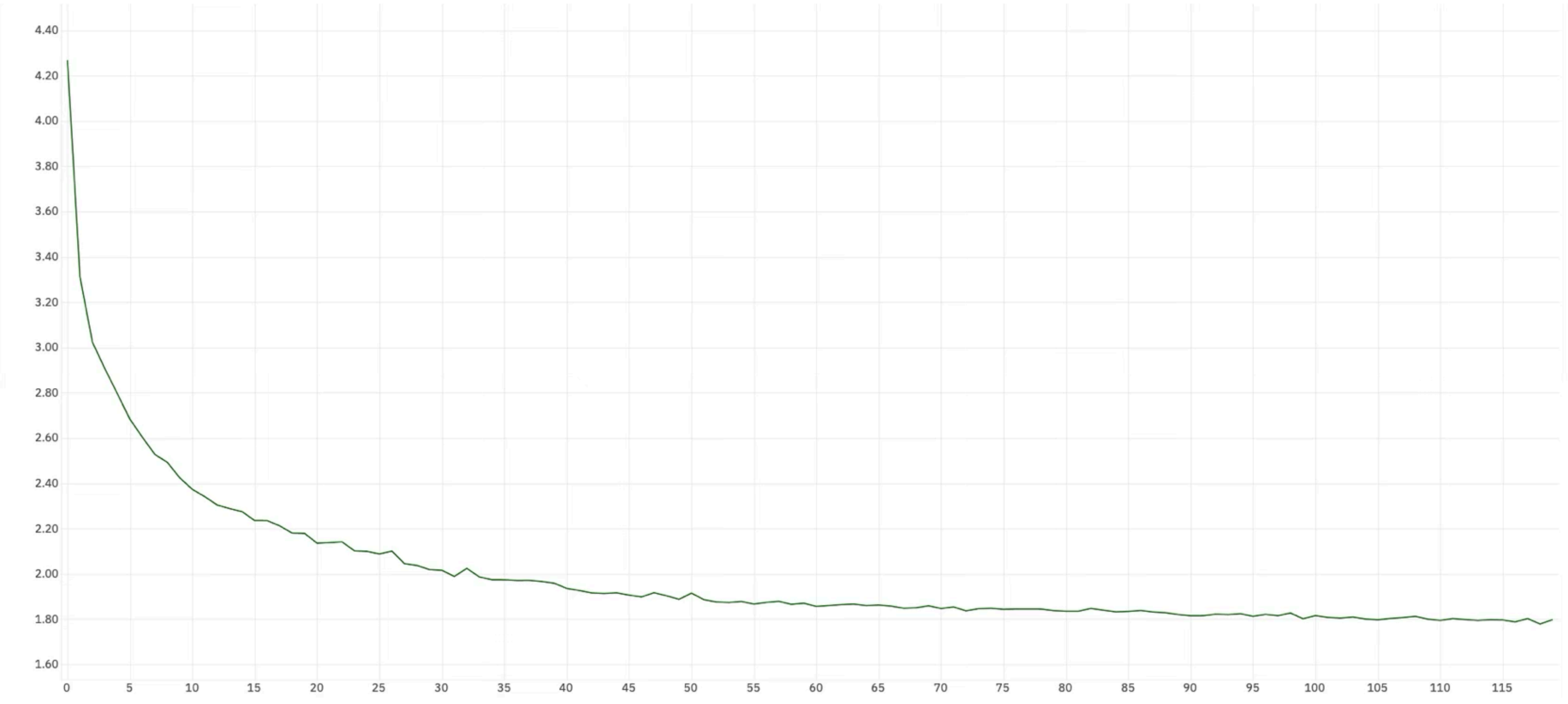




Bottleneck generally occurs at same location irrespective of the time of day

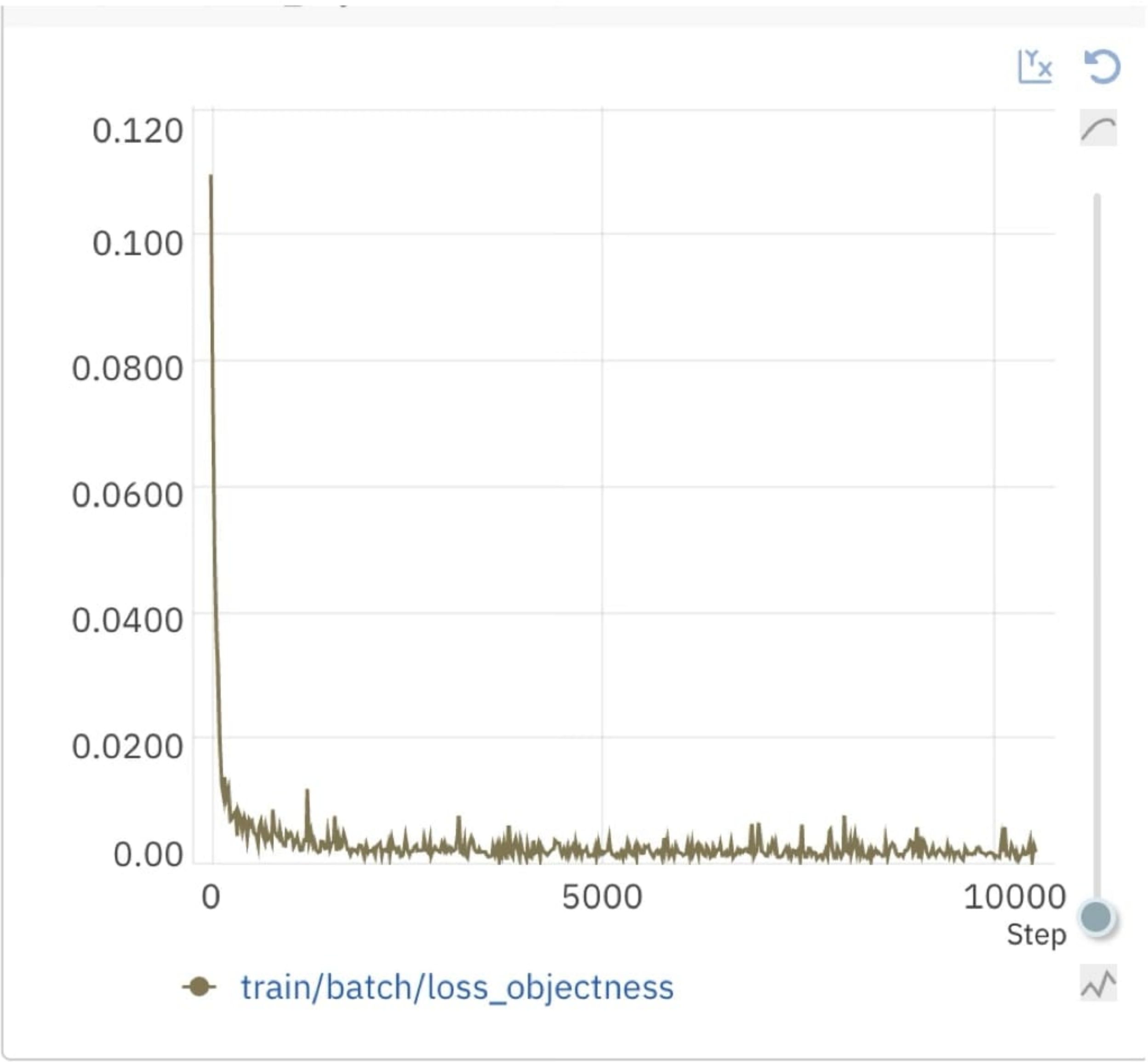
Thank You

Appendix

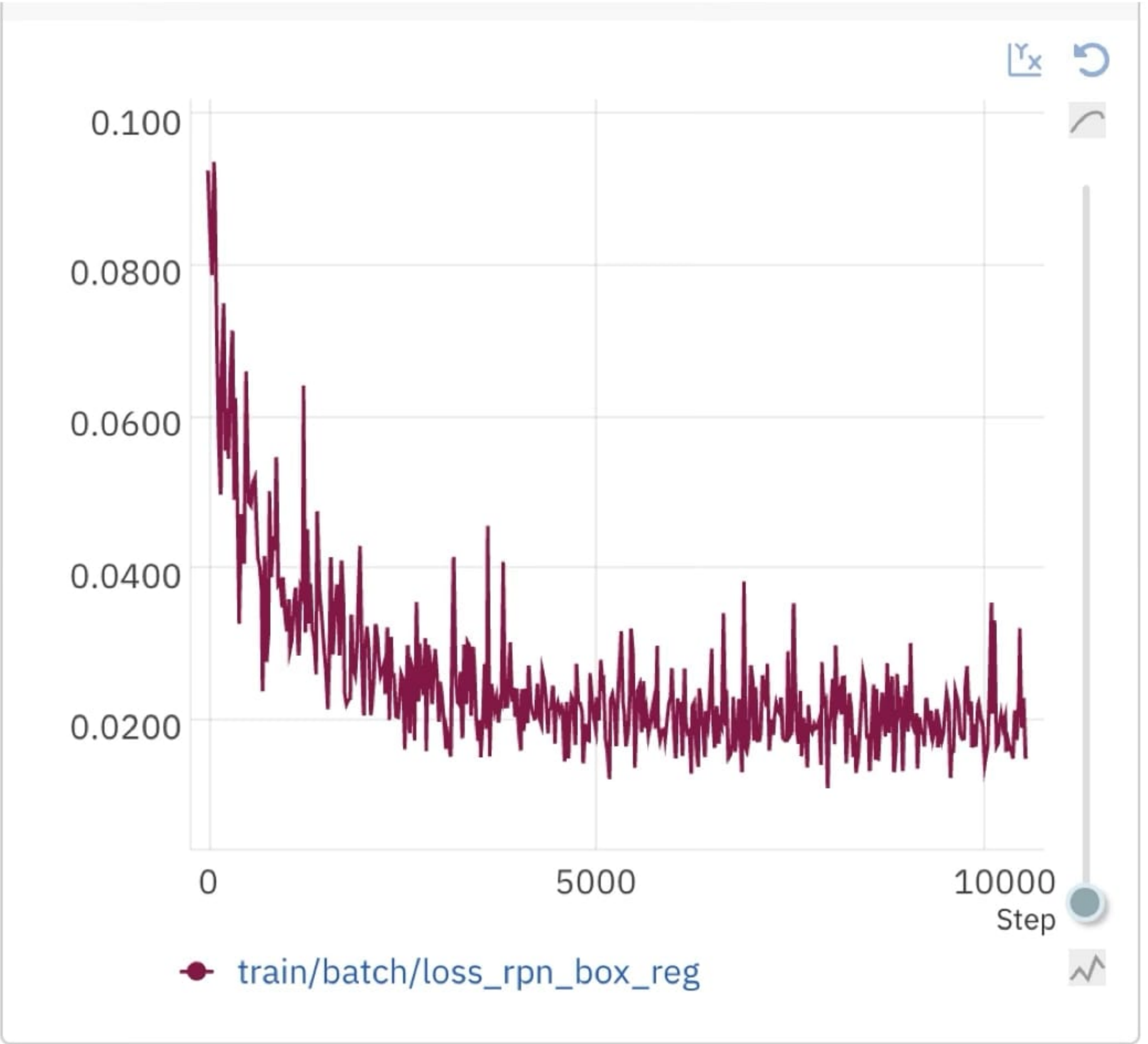


Train/epoch loss

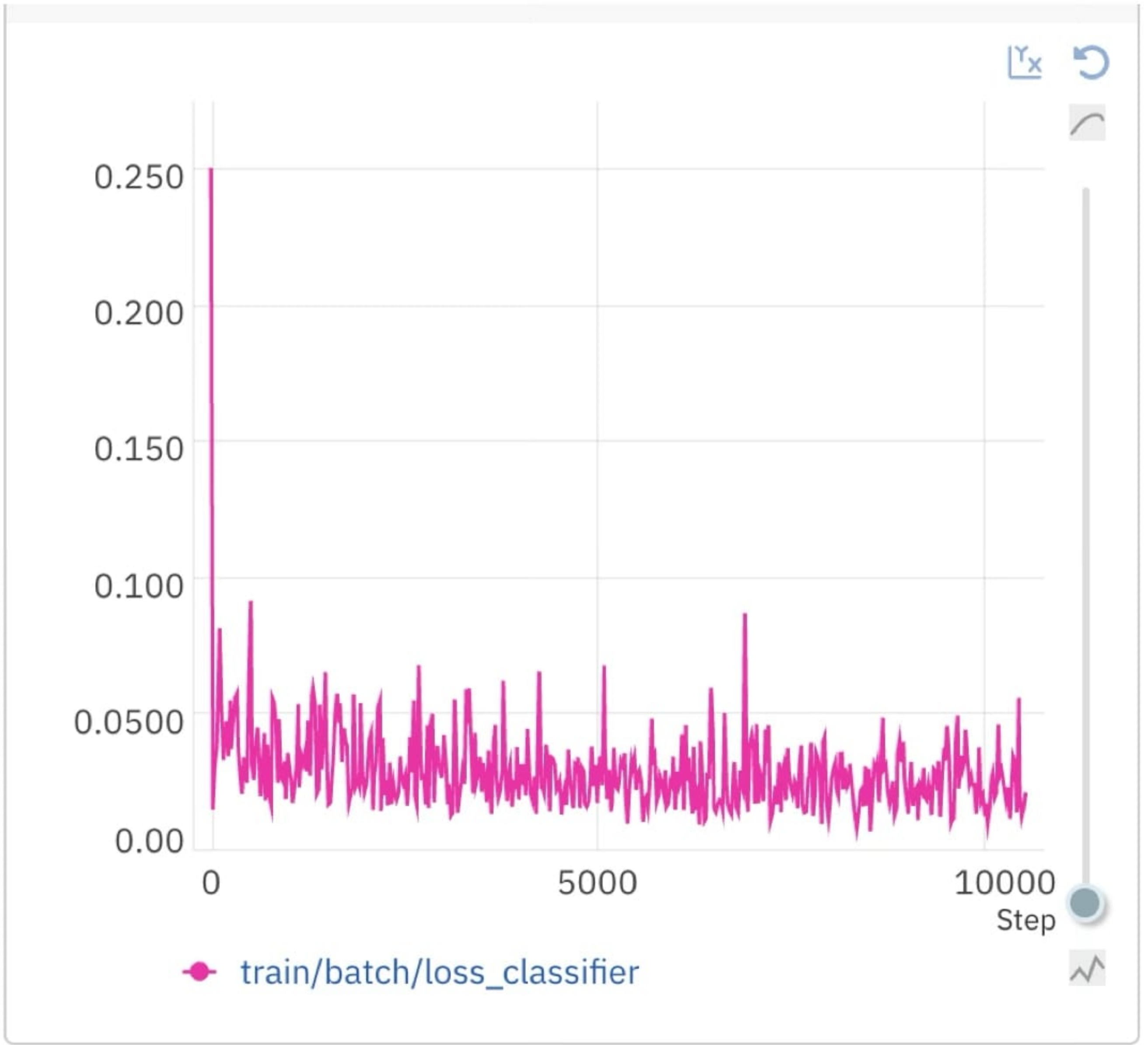
validation/epoch loss



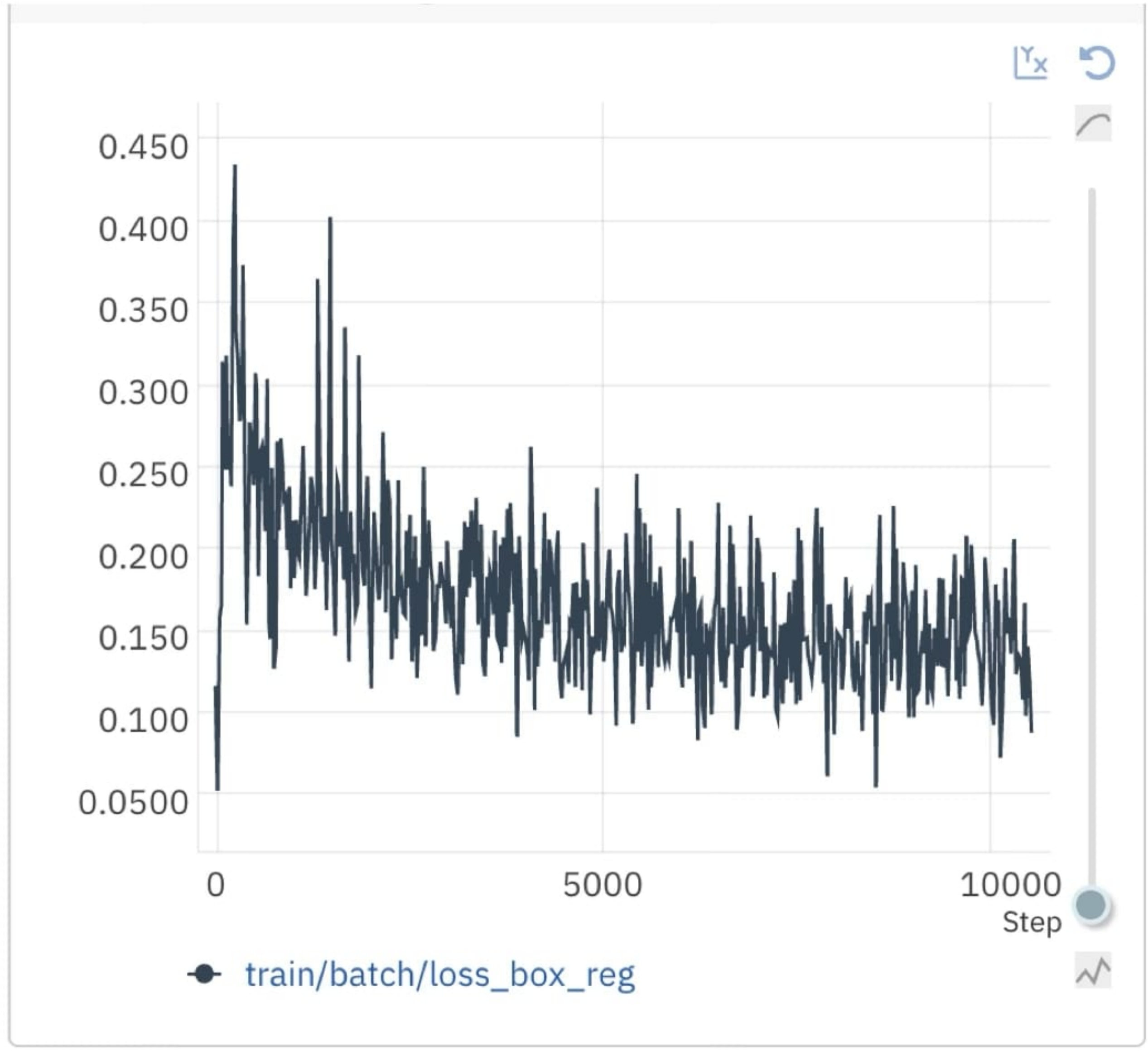
RPN objectness loss



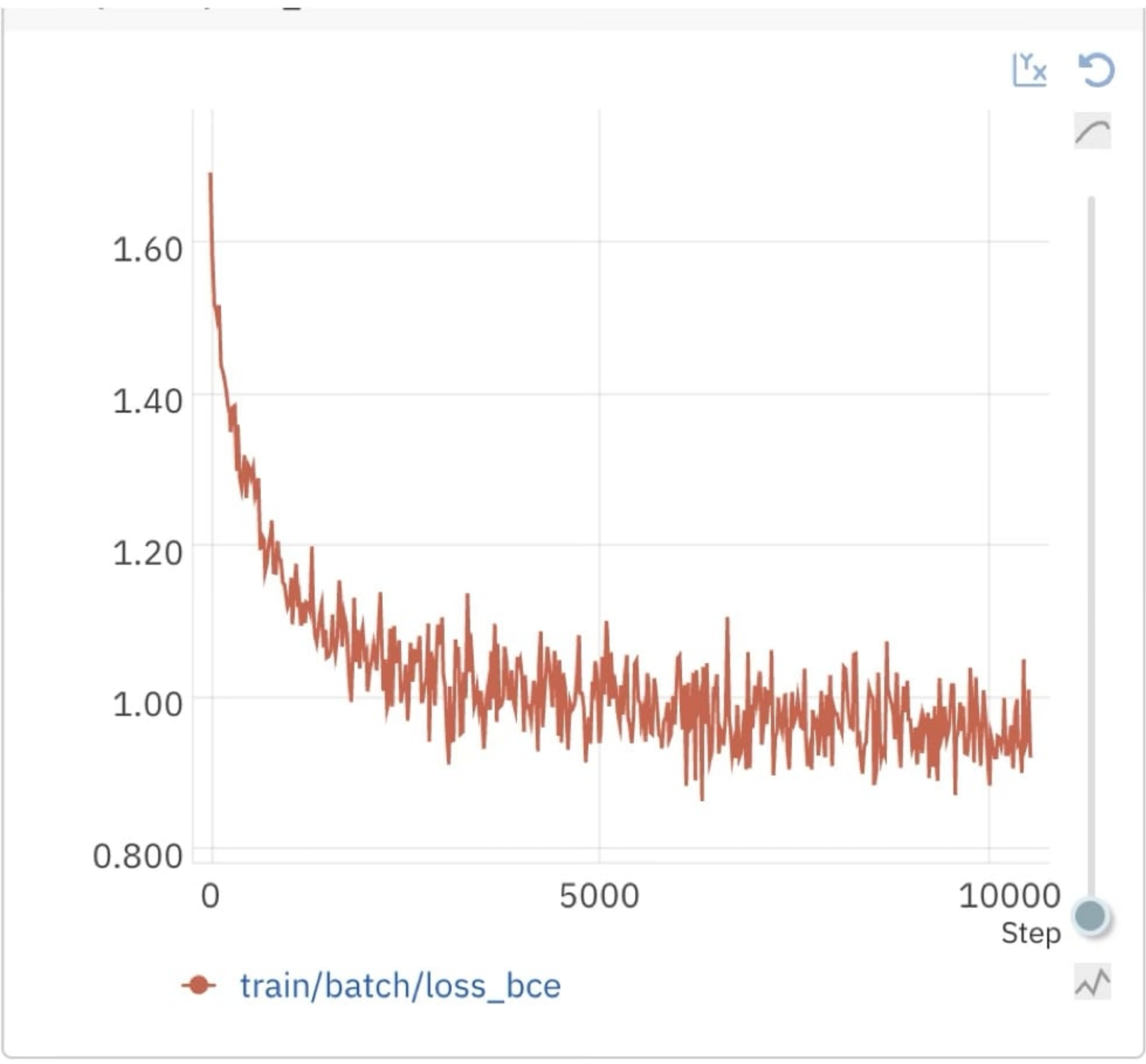
RPN proposal loss



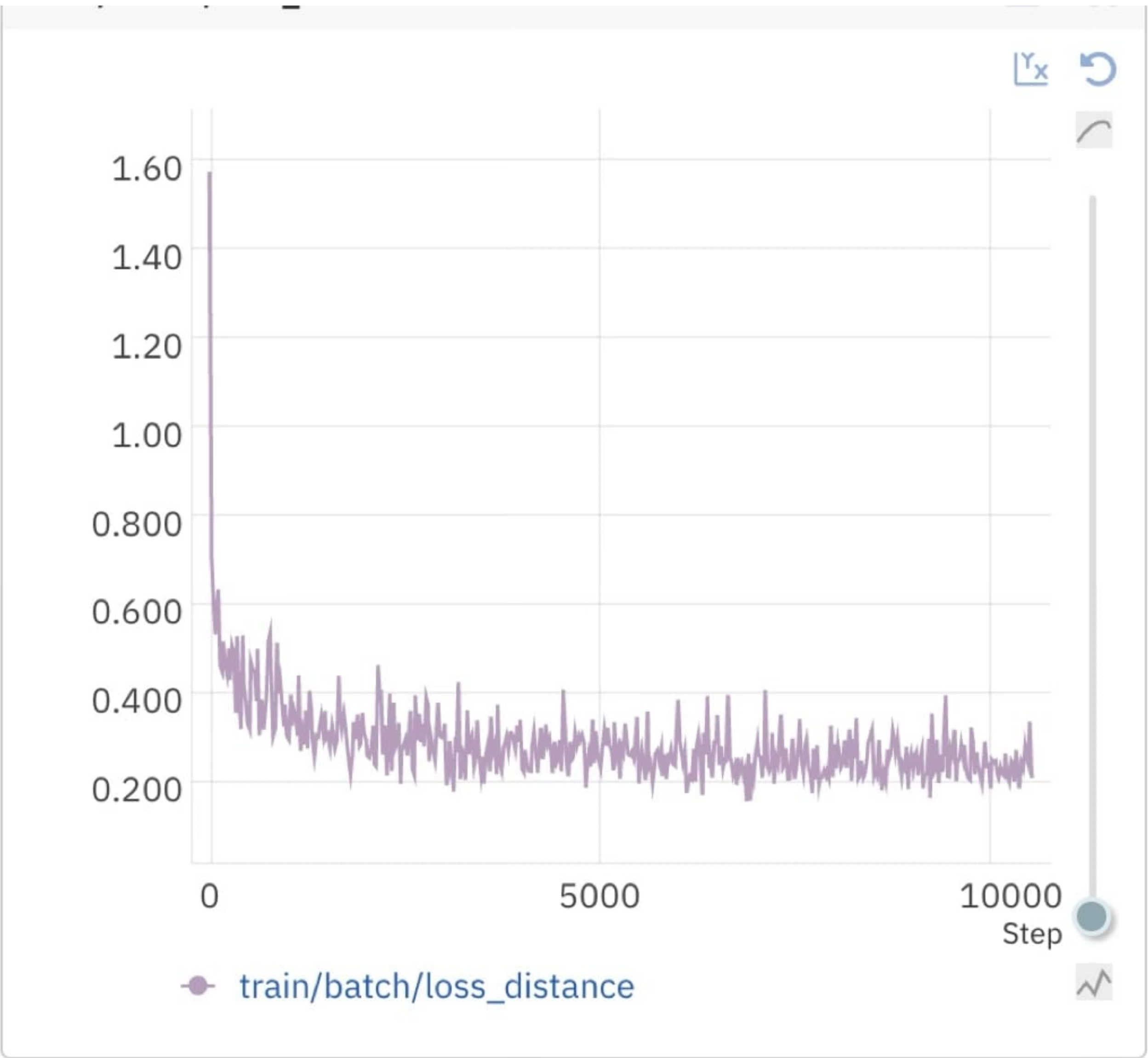
Box head classification loss



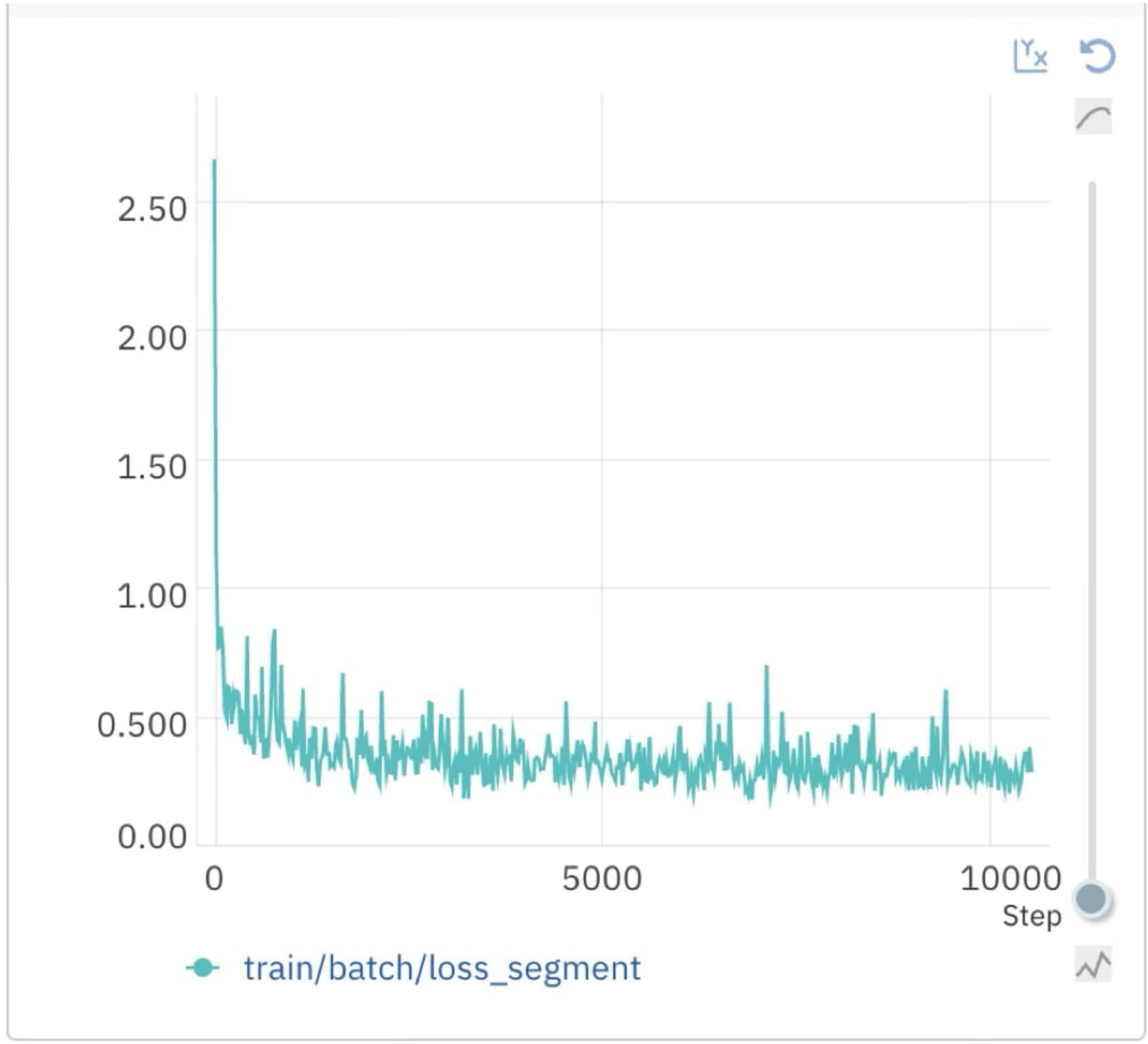
Box head proposal loss



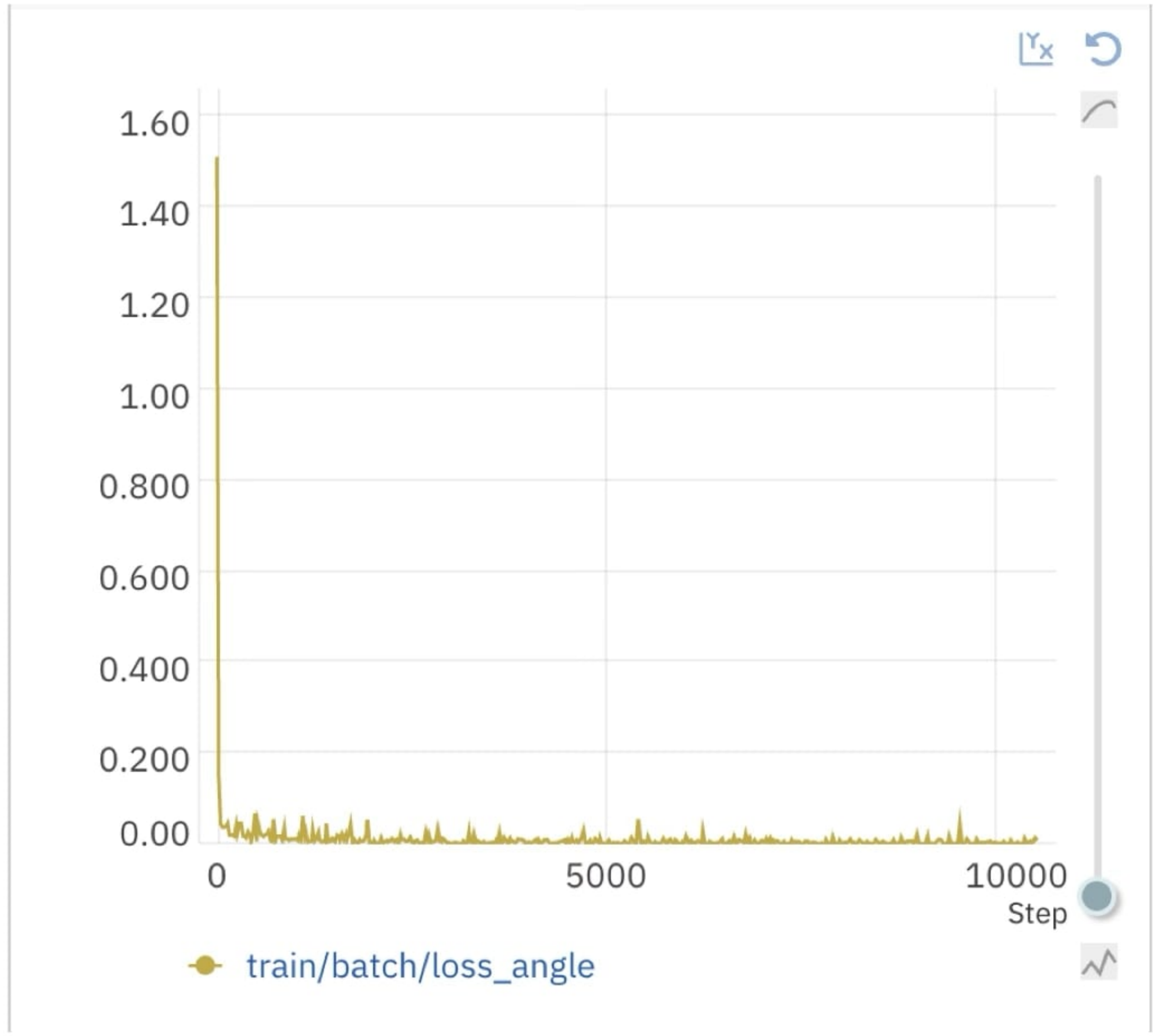
Heat map loss (focal loss)



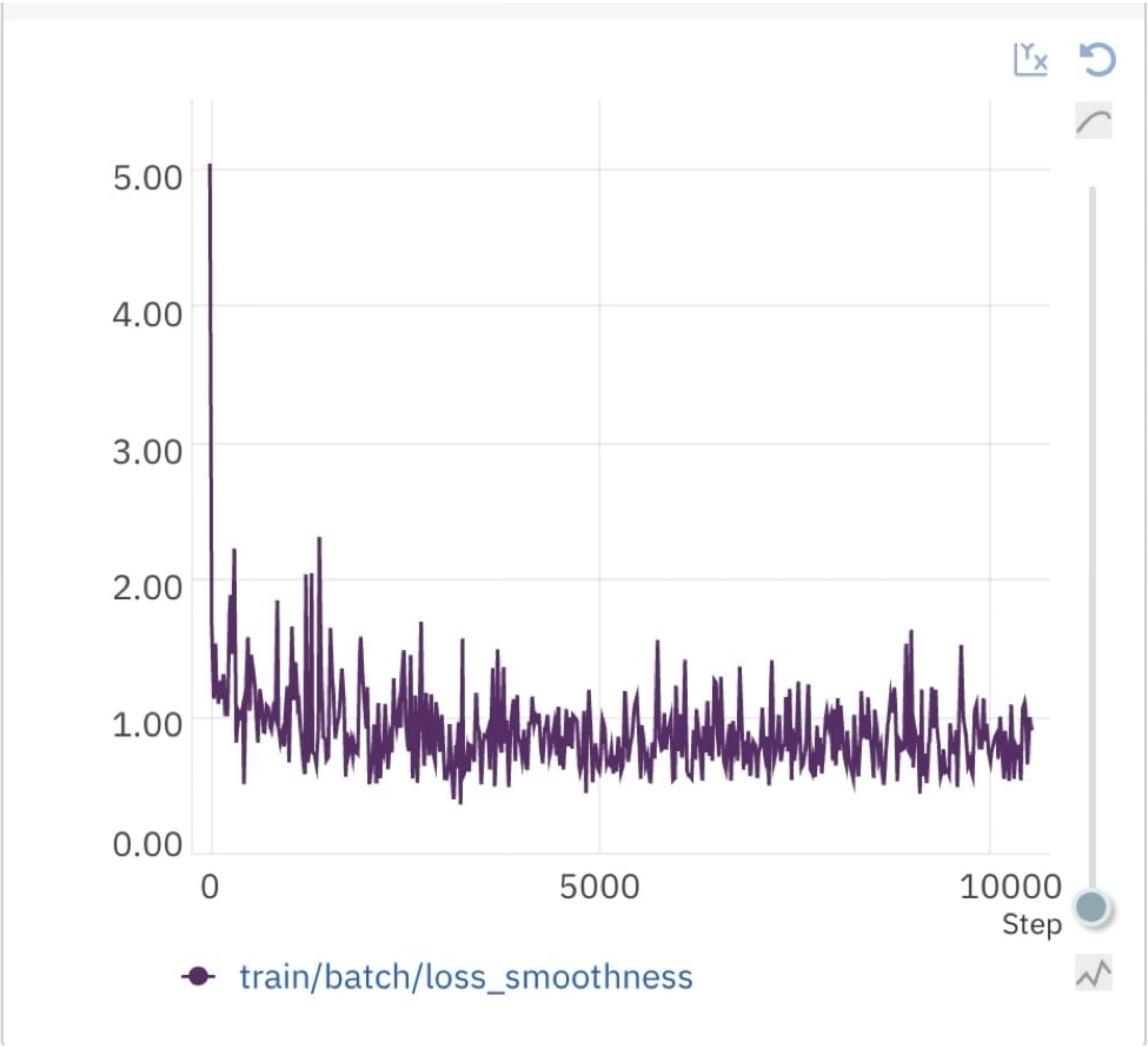
Distance loss



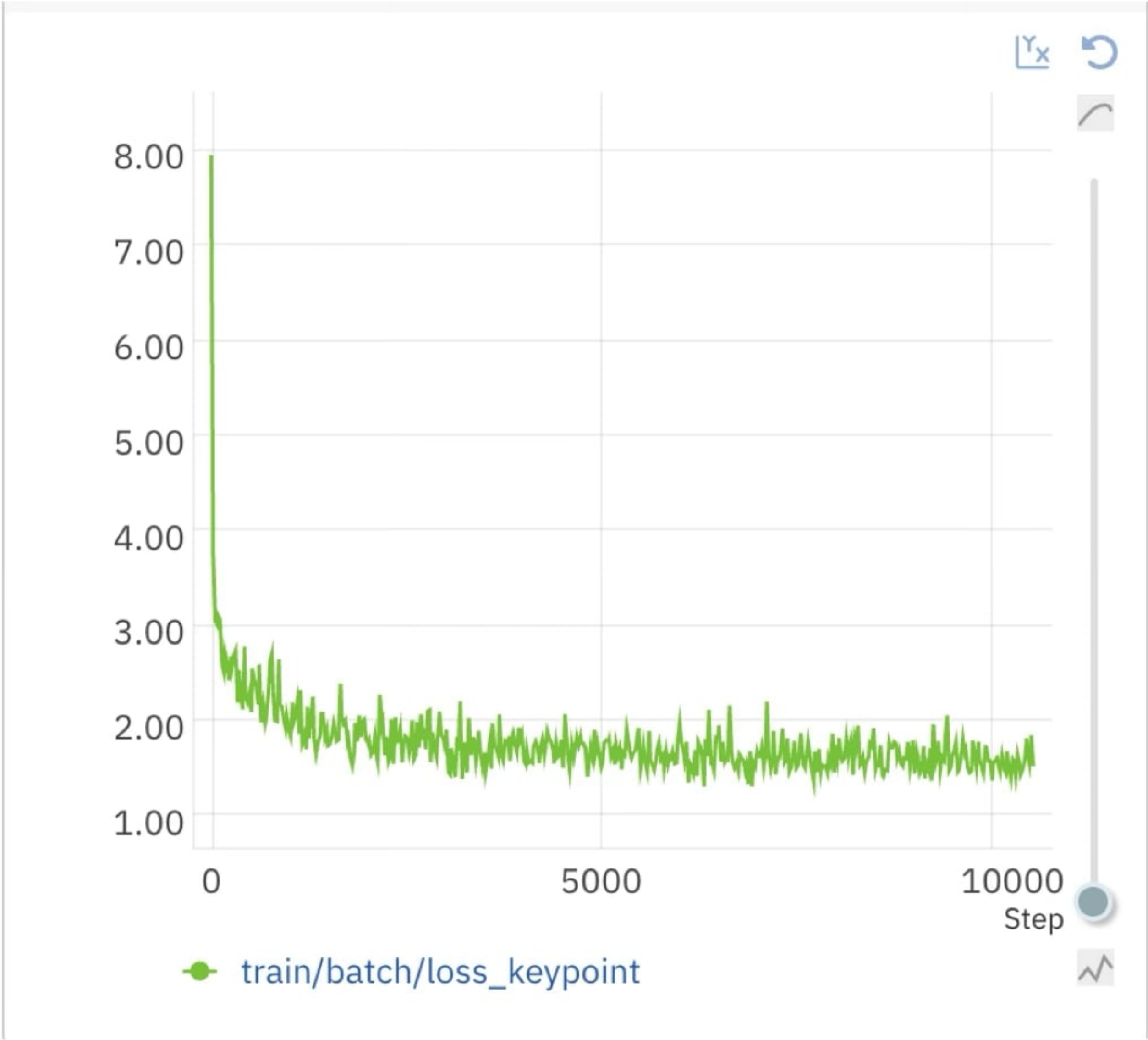
Pairwise segment loss



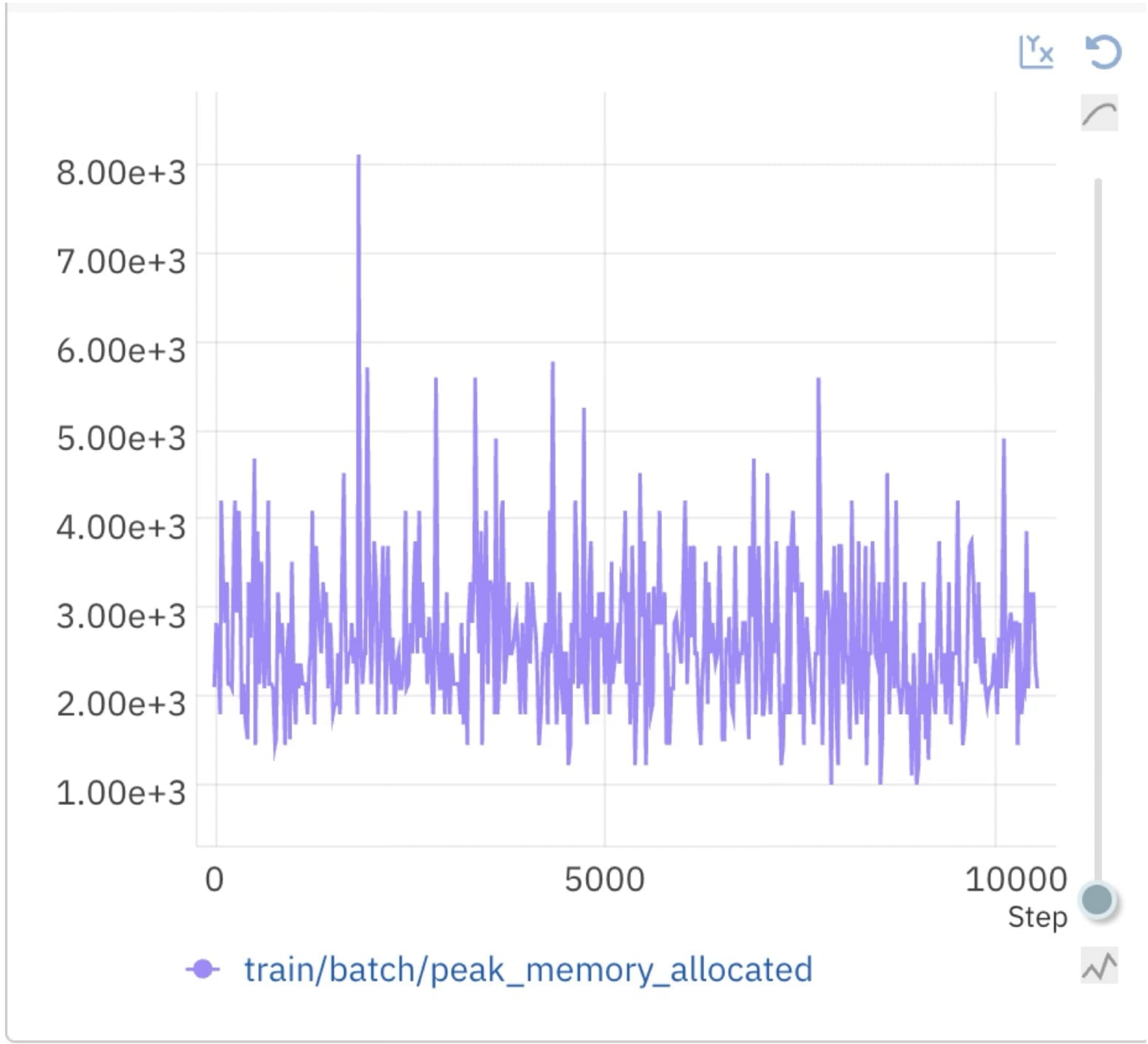
Smoothness loss



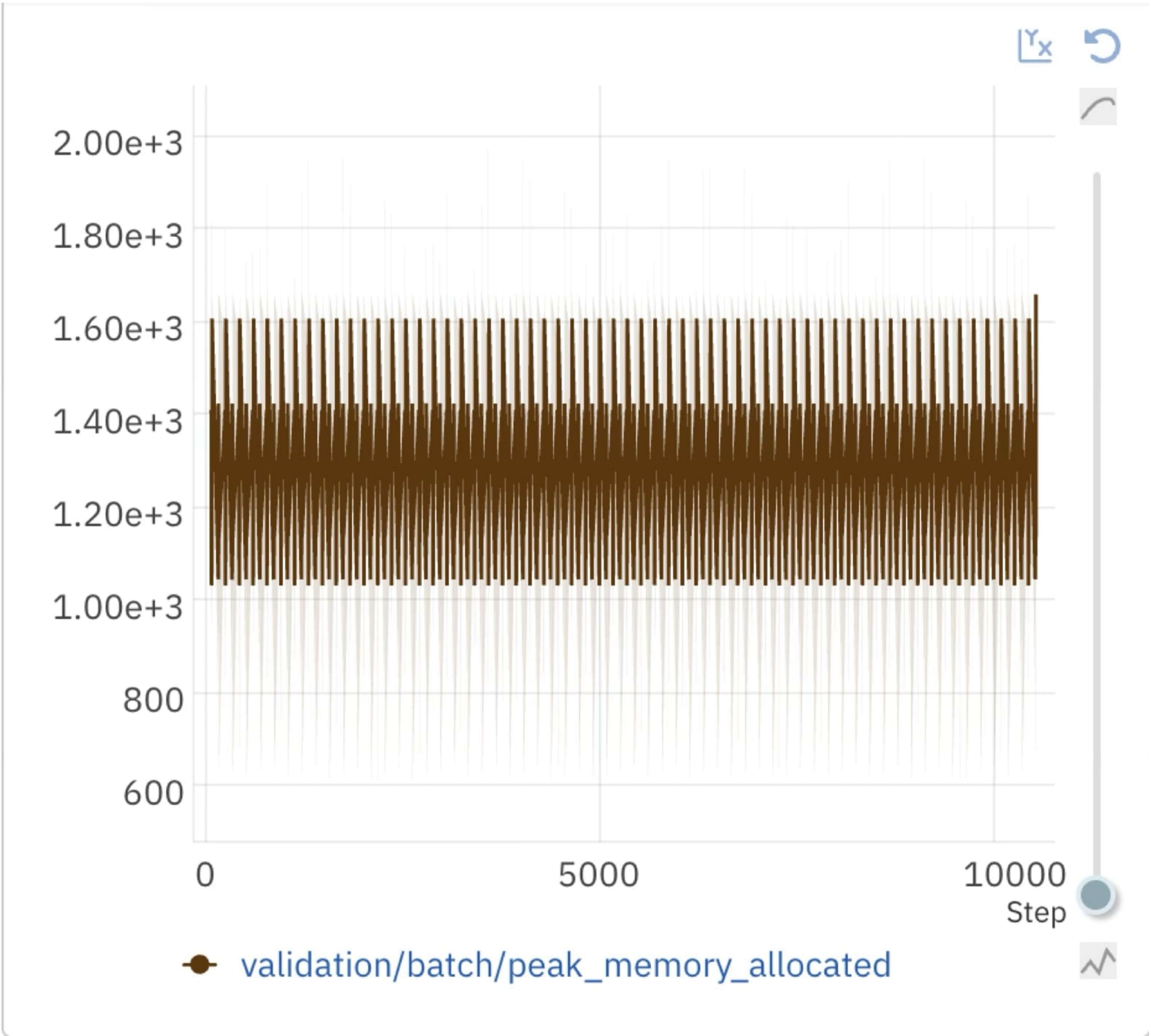
Joint angle loss



Total keypoint Loss



Peak memory allocated per batch during validation



Peak memory allocated per batch during training