ST-SimNet: STGCN for Urban Freight Forecasting

Rafal Marek Tarczynski

TU Delft TNO

TU Delft

01

Setup

02

Challenges

& Methodology

03

Outcomes

& Future Work

01

Setup

Core Problem

Context

Innovation

81%

OF TOTAL CO_2 EMISSIONS

FROM FREIGHT

Road
Freight Transportation

TU Delft TNO

Context

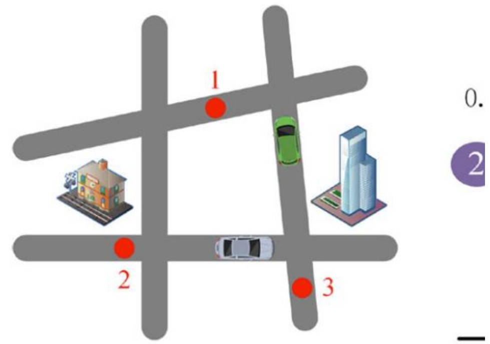
- Road Freight Delivers to cities and must deal with many regulations
- There is a similarity in traffic behaviour across similar contexts and conditions
- We have access to detailed data about Roads and Built Environment

Research Question:
To what extent can insights into urban morphology, modeled with Spatio-Temporal Graph Neural Networks, enhance the accuracy and adaptability of freight transportation predictions in the Netherlands?

Related Work

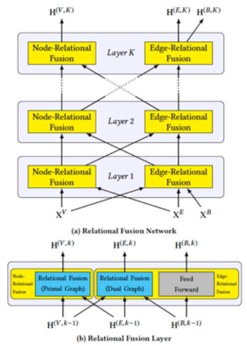
Literature

Tool



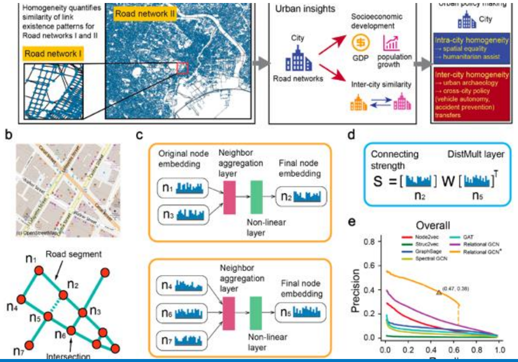
Spatio-Temporal GNNs for Traffic Prediction

Xiong et al. (2024)



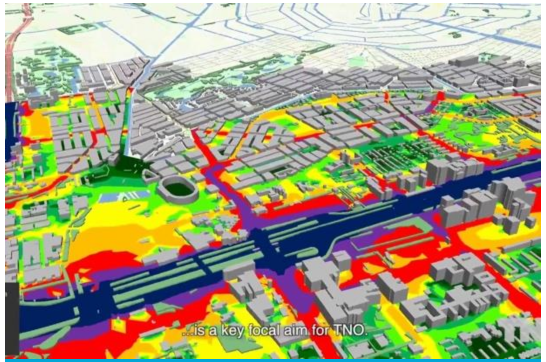
Graph Neural Networks for Road Networks

Jepsen et al. (2019)



Urban Morphology in Graph based Urban Analysis

Xue et al. (2021)

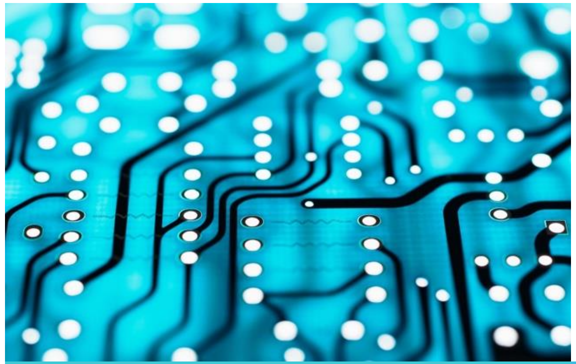


Digital Twin Frameworks

TNO (2023)

TU Delft TNO

Timeline



Idea

Geomatics
& Architecture

Roads
& Urban Morphology

Data

Model

ST-SimNet

Node Regression

Results

02

Challenges & Methodology

Glossary

- **Feature:** A characteristic or property used by the model to make predictions,
  e.g. road width, building density, or traffic flow at a location.
- **Node:** A point in the network — intersection of road segments.
- **Edge:** A connection between two nodes, representing a road.
- **Urban Morphology:** The form and structure of urban spaces
  e.g. building shapes, land use, street layout.
- **Training:** The process of teaching a machine learning model using historical data.

Challenges

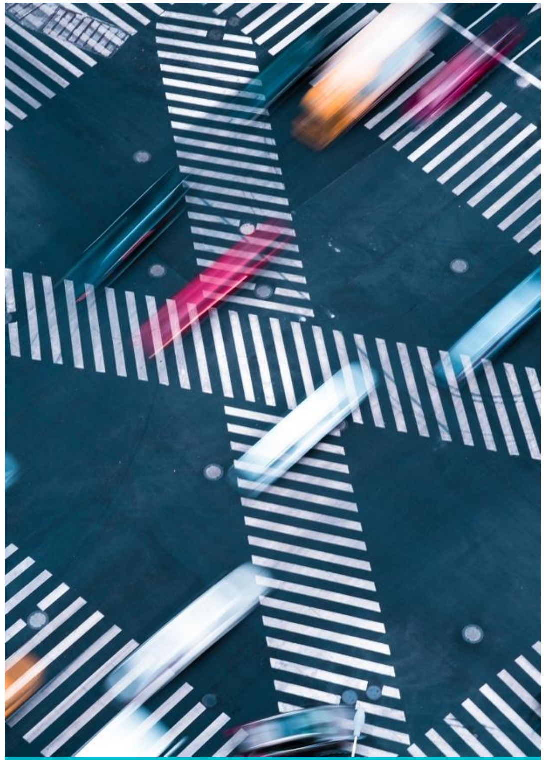
& Idea

Detailed and precise vectorised ***Road Networks***

World-class data in ***Built Environment***

Lack of data ***Connection***

Data



Roads >

PC6 >

Buildings >

Roads

Directed road network from MASS-GT & TNO’s Digital Twin

Opportunity: Detailed network enables graph-based traffic prediction

Challenge:
Requires adjacency matrix construction and graph generation

Postcode 6

Dutch postcode zones with socio-demographic statistics

Opportunity: Captures invisible context behind freight flow patterns

Challenge: Sparse or privacy-restricted data in some zones

Buildings

Detailed building data with physical, modal, and contextual features

Opportunity: Enhances traffic predictions with high-resolution morphology

Challenge: Aggregation and accurate linkage to network nodes is complex

Some Available Models

Recurrent GNNs	Convolutional GNNs	Spatio-Temporal GNNs
Adversarial GNNs	Graph Attention Networks	Graph Reinforcement Learning

Limitation of Existing Approaches

Only model dynamic or static structure

Lack of contextual understanding

Limited generalisability to new cities

Take either dynamic or static data

Pipeline

Step 1	Step 2	Step 3	Step 4	Step 5
Collect Inputs Dynamic flows & static urban data	**Build Graph** Spatial network with node features	**Learn Patterns** Temporal and spatial convolutions	**Fuse Features** Merge static & dynamic info	**Predict Flows** Forecast node-level freight activity

Pipeline

Step 1	Step 2	Step 3	Step 4	Step 5
Collect Inputs Dynamic flows & static urban data	Build Graph Spatial network with node features	Learn Patterns Temporal and spatial convolutions	Fuse Features Merge static & dynamic info	Predict Flows Forecast node-level freight activity

Data

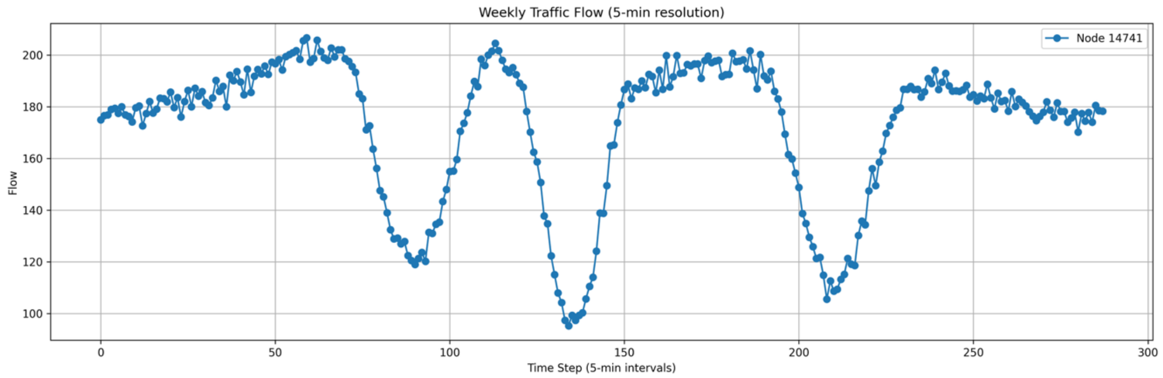
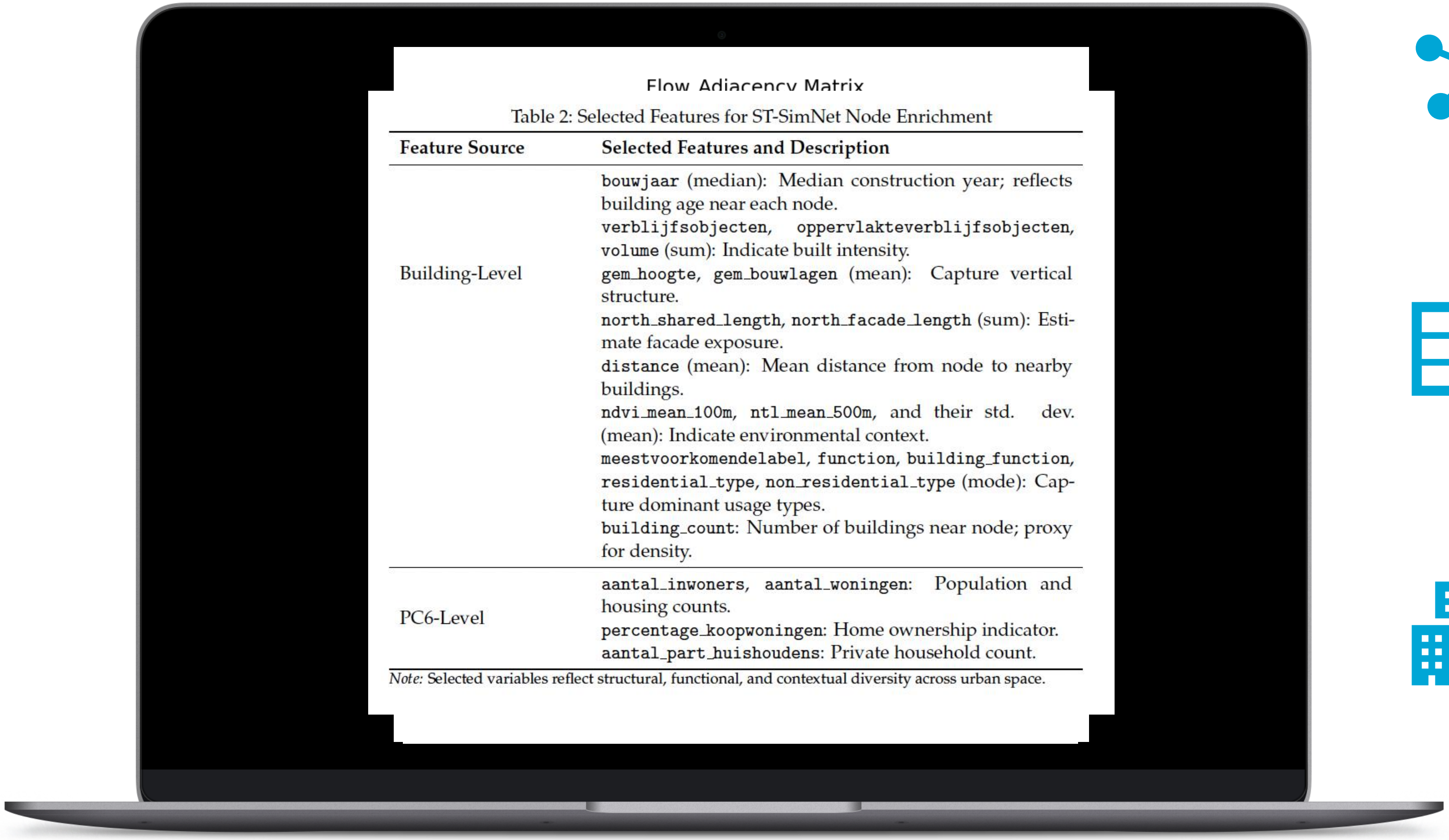


Table 2: Selected Features for ST-SimNet Node Enrichment

Feature Source	Selected Features and Description
Building-Level	`bouwjaar` (median): Median construction year; reflects building age near each node. `verblijfsobjecten`, `oppervlakteverblijfsobjecten`, `volume` (sum): Indicate built intensity. `gem_hoogte`, `gem_bouwlagen` (mean): Capture vertical structure. `north_shared_length`, `north_facade_length` (sum): Estimate facade exposure. `distance` (mean): Mean distance from node to nearby buildings. `ndvi_mean_100m`, `ntl_mean_500m`, and their std. dev. (mean): Indicate environmental context. `meestvoorkomendelabel`, `function`, `building_function`, `residential_type`, `non_residential_type` (mode): Capture dominant usage types. `building_count`: Number of buildings near node; proxy for density.
PC6-Level	`aantal_inwoners`, `aantal_woningen`: Population and housing counts. `percentage_koopwoningen`: Home ownership indicator. `aantal_part_huishoudens`: Private household count.

Note: Selected variables reflect structural, functional, and contextual diversity across urban space.

Loading Data and Graph Generation



Flow Adjacency Matrix

Table 2: Selected Features for ST-SimNet Node Enrichment

Feature Source	Selected Features and Description
Building-Level	`bouwjaar` (median): Median construction year; reflects building age near each node. `verblijfsobjecten`, `oppervlakteverblijfsobjecten`, `volume` (sum): Indicate built intensity. `gem_hoogte`, `gem_bouwlagen` (mean): Capture vertical structure. `north_shared_length`, `north_facade_length` (sum): Estimate facade exposure. `distance` (mean): Mean distance from node to nearby buildings. `ndvi_mean_100m`, `ntl_mean_500m`, and their std. dev. (mean): Indicate environmental context. `meestvoorkomendelabel`, `function`, `building_function`, `residential_type`, `non_residential_type` (mode): Capture dominant usage types. `building_count`: Number of buildings near node; proxy for density.
PC6-Level	`aantal_inwoners`, `aantal_woningen`: Population and housing counts. `percentage_koopwoningen`: Home ownership indicator. `aantal_part_huishoudens`: Private household count.

Note: Selected variables reflect structural, functional, and contextual diversity across urban space.

Graph
Create a directional graph linking the nodes.

Adjacency Matrix
Create an adjacency matrix and save it as a sparse matrix.

Urban Morphology Descriptors
Select and assign UMD to nodes.

UMD Assignment

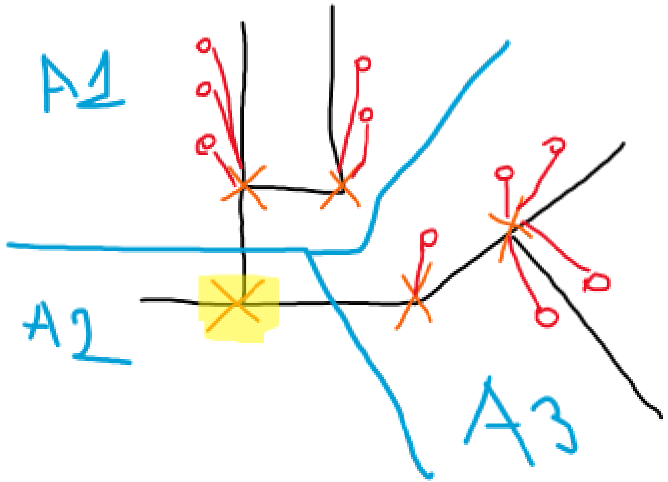
Algorithm 3.3: Assign building data to nearest graph nodes and compute aggregated morphological descriptors

---

Input: Graph nodes (`GeoDataFrame`), buildings dataset with morphological attributes (CSV)
Output: Node-level urban morphology profiles

Load the building data and convert it into a `GeoDataFrame` with CRS EPSG:28992;
Load the graph node data from shapefile with the same CRS;
For each building, find the nearest graph node using spatial join;
Assign the building and its attributes to that node;
Group buildings by their assigned node;
foreach *node* **do**
  Aggregate building attributes:
  - Use `median` for temporal features (e.g. construction year)
  - Use `sum` for quantities (e.g. volume, units)
  - Use `mode` for categorical fields (e.g. function type)

Attach the aggregated attributes to the corresponding nodes in the graph;
foreach *node without buildings* **do**
  Assign a zero vector as morphological input;



Pipeline

Step 1
Collect Inputs
Dynamic flows & static urban data

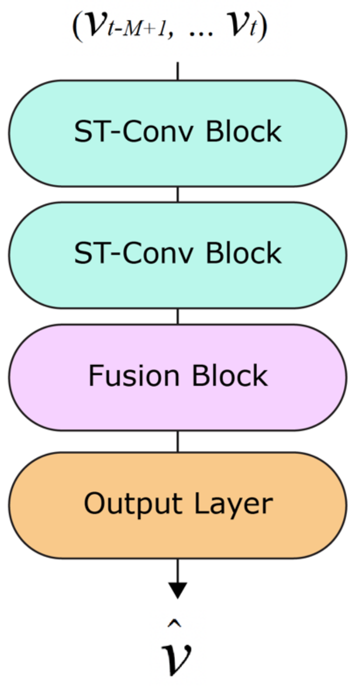
Step 2
Build Graph
Spatial network with node features

Step 3
Learn Patterns
Temporal and spatial convolutions

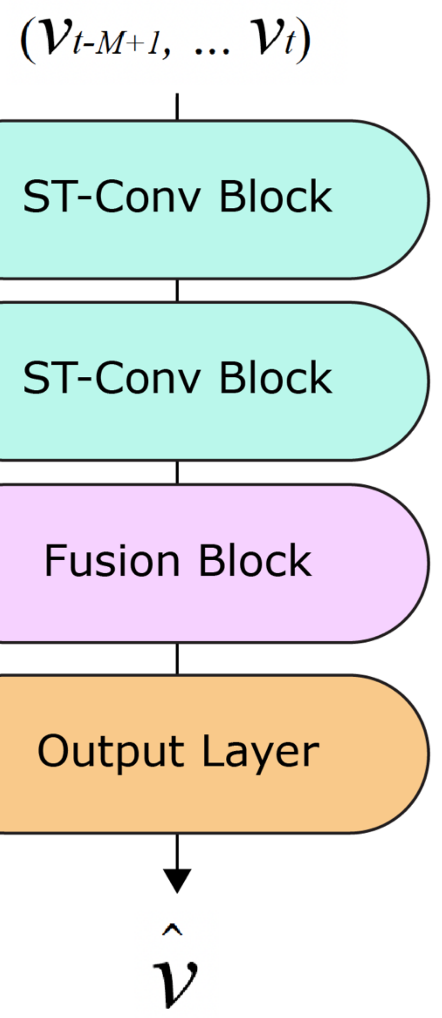
Step 4
Fuse Features
Merge static & dynamic info

Step 5
Predict Flows
Forecast node-level freight activity

ST-SimNet's Architecture



ST-SimNet's Architecture



Fusion Block – Convex Fusion

$$\mathbf{z}_i = (1 - \sigma(\alpha)) \cdot \mathbf{h}_i + \sigma(\alpha) \cdot \mathrm{MLP}_{\mathrm{umd}}(\mathbf{s}_i).$$

Where:

- $\mathbf{h}_i$ – dynamic spatio-temporal embedding of node i
- $\mathbf{s}_i$ – static urban morphology features of node i
- $\mathrm{MLP}_{\mathrm{umd}}$ – two-layer Multi-Layer Perceptron projecting $\mathbf{s}_i$ into the latent space of $\mathbf{h}_i$
- α – trainable scalar controlling the fusion balance
- $\sigma(\cdot)$ – sigmoid function ensuring output in $[0, 1]$
- $\mathbf{z}_i$ – fused node representation used for prediction

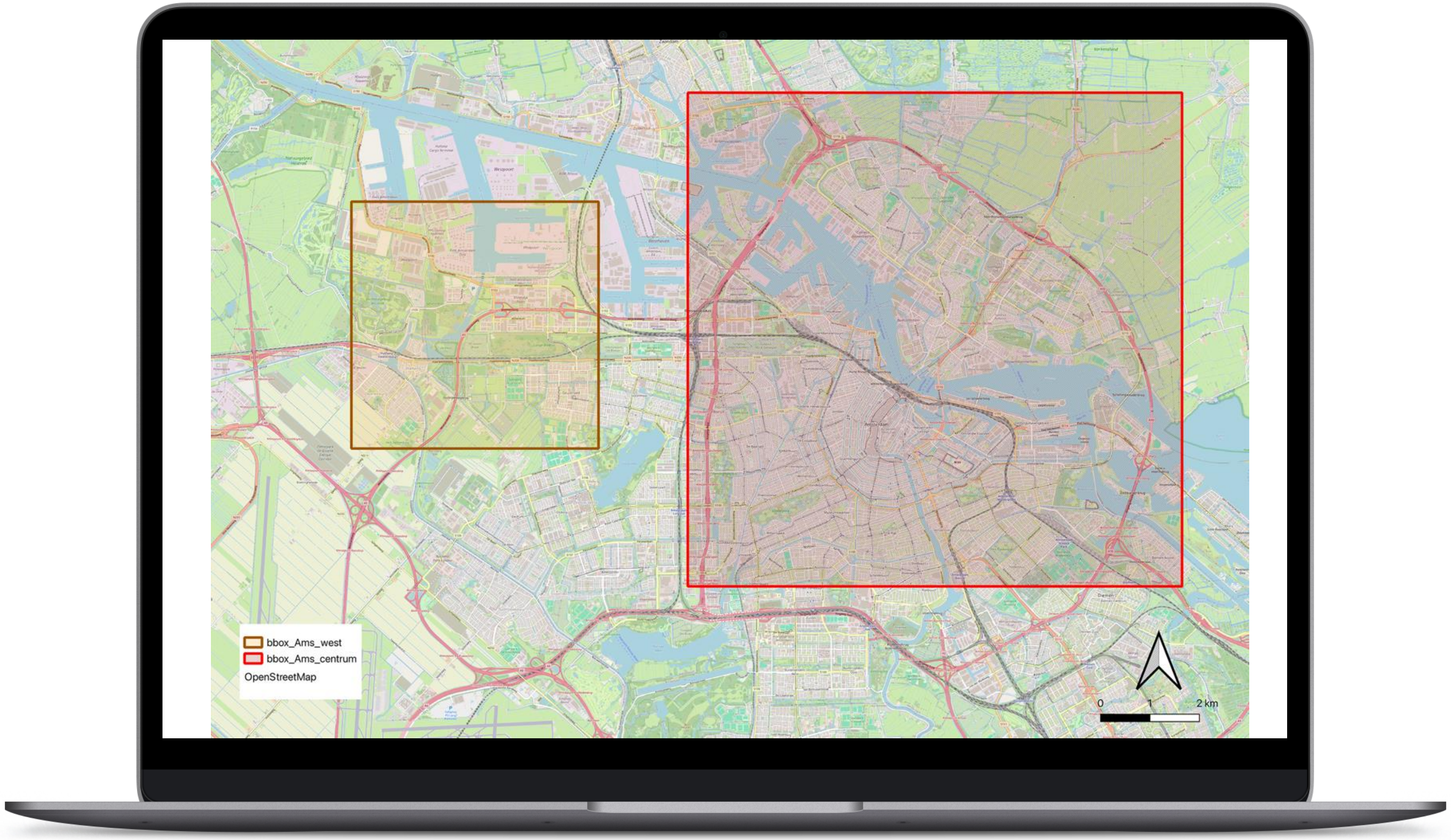
Let it sink

03

Outcomes & Future Work

ST-SimNet Results

Areas of Interest



Experiment Design

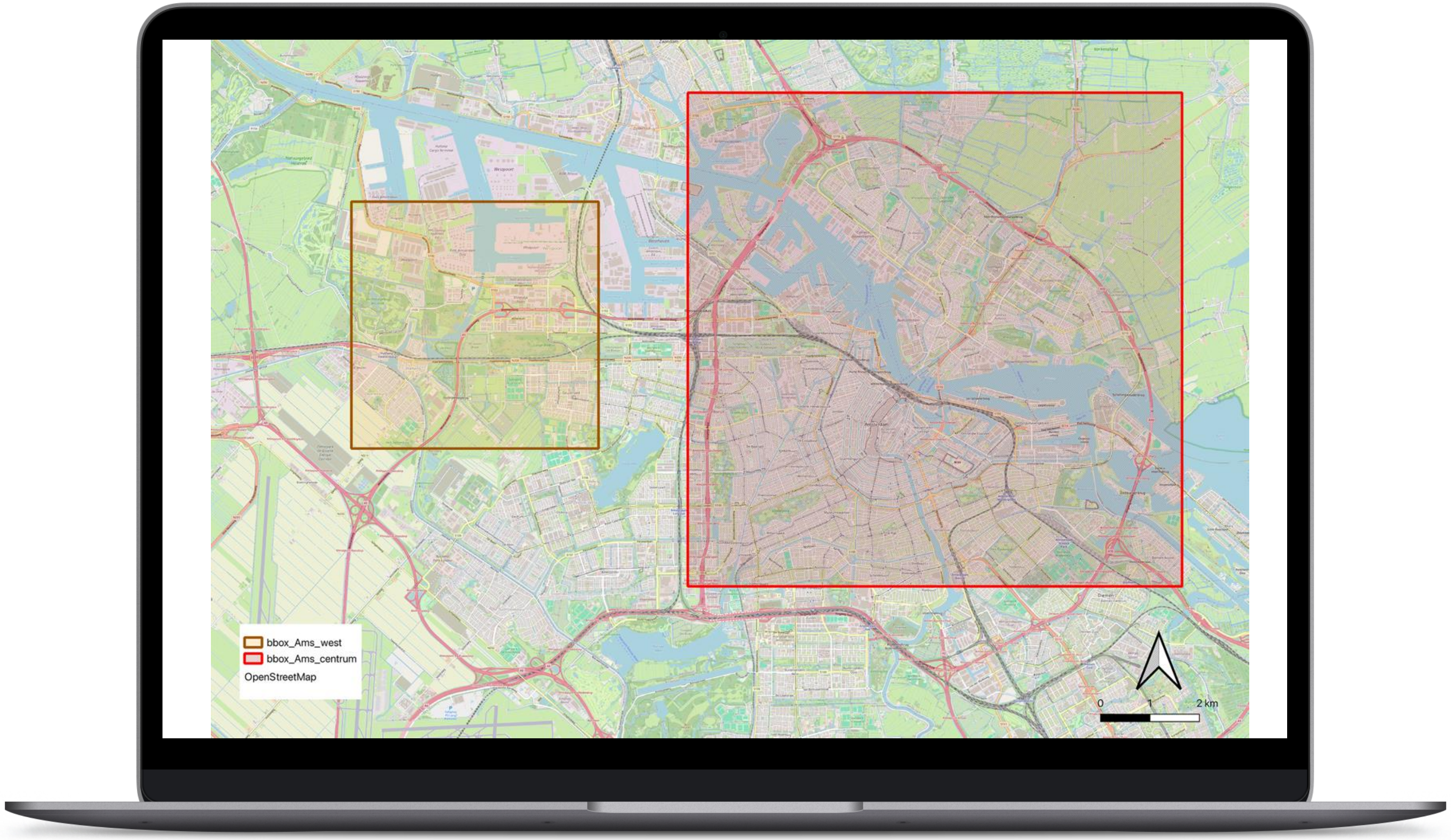
STGCN vs. ST-SimNet
Baseline STGCN (only static) vs. enhanced with dynamic data

Training time
50 epochs – West

100 epochs – Centre

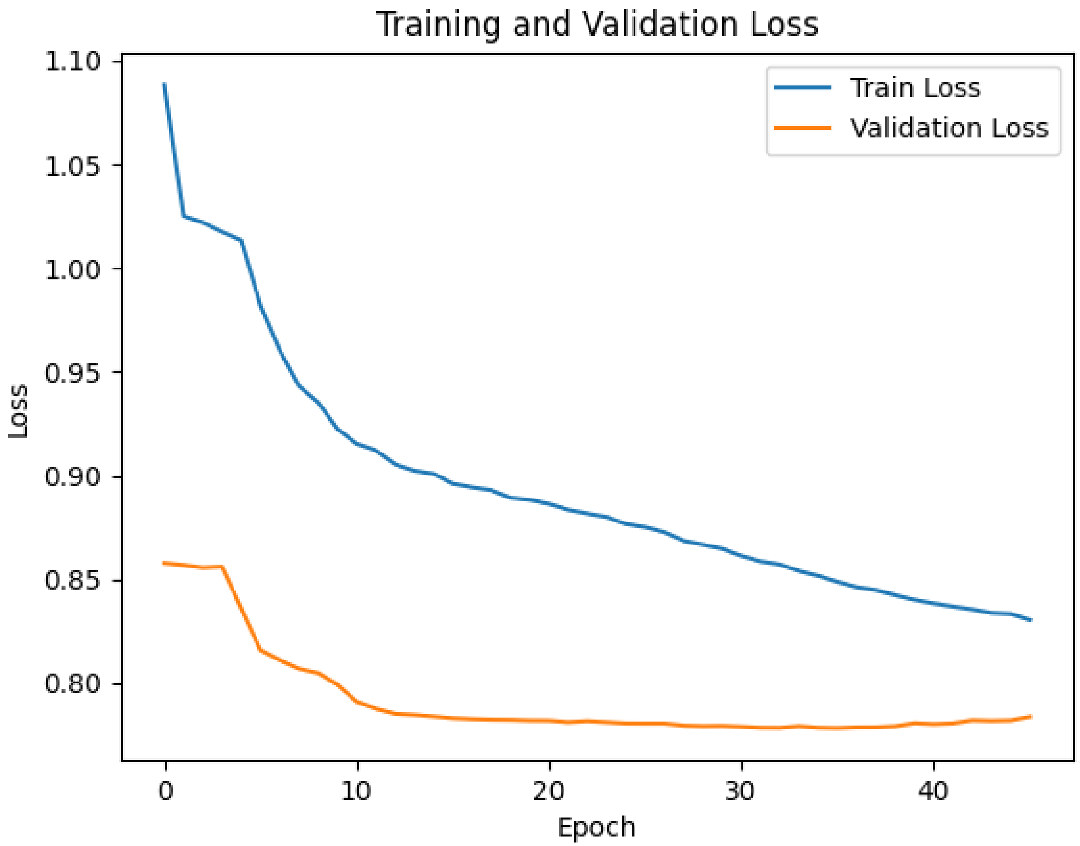
Numeric and Visual Validation
Metrics check and visual inspection in QGIS

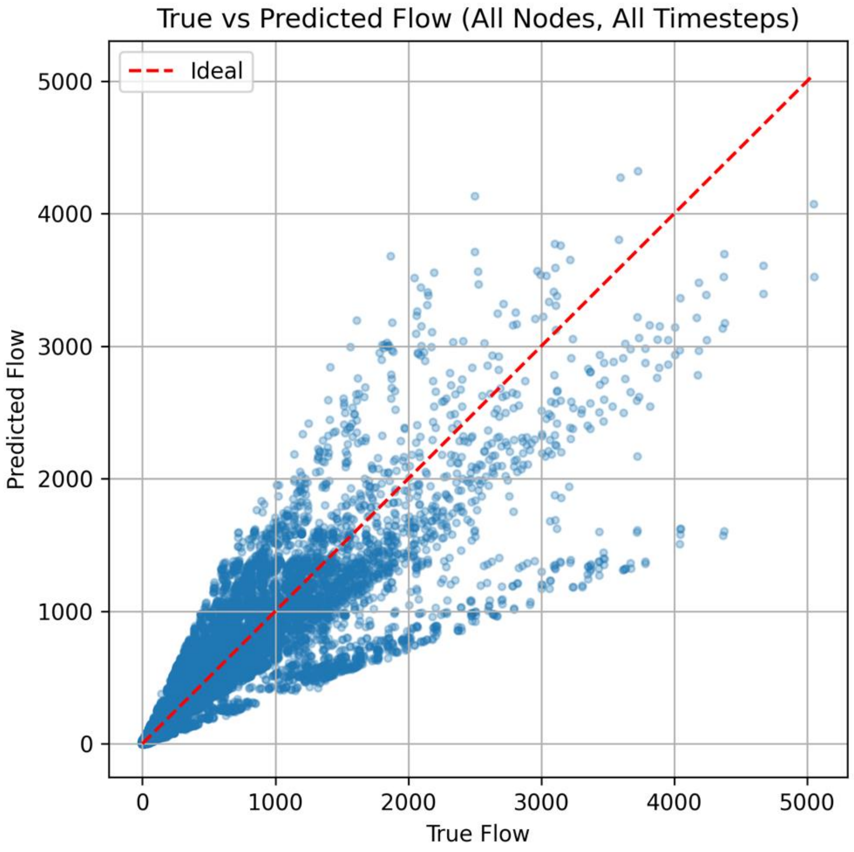
Areas of Interest



Amsterdam West – Dynamic (no UMD)

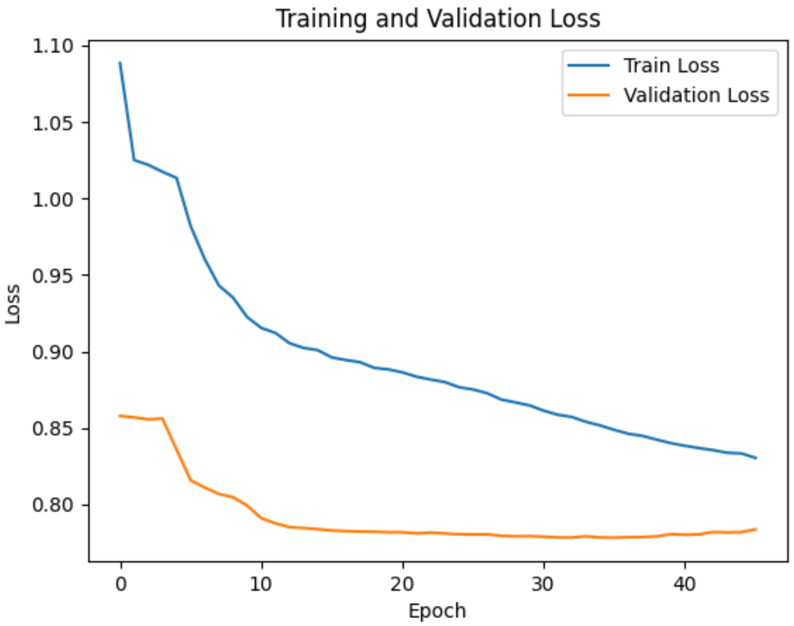
50 epochs

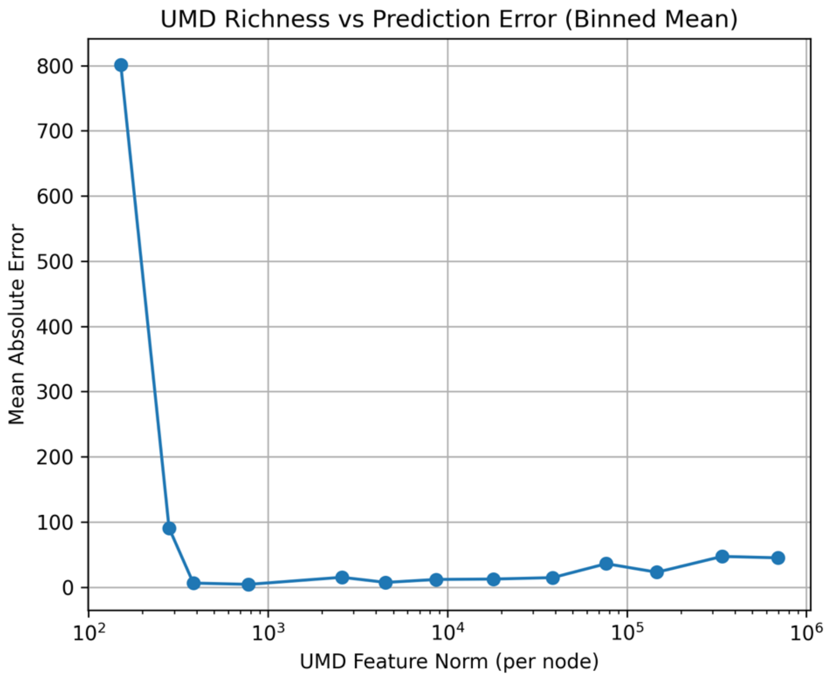


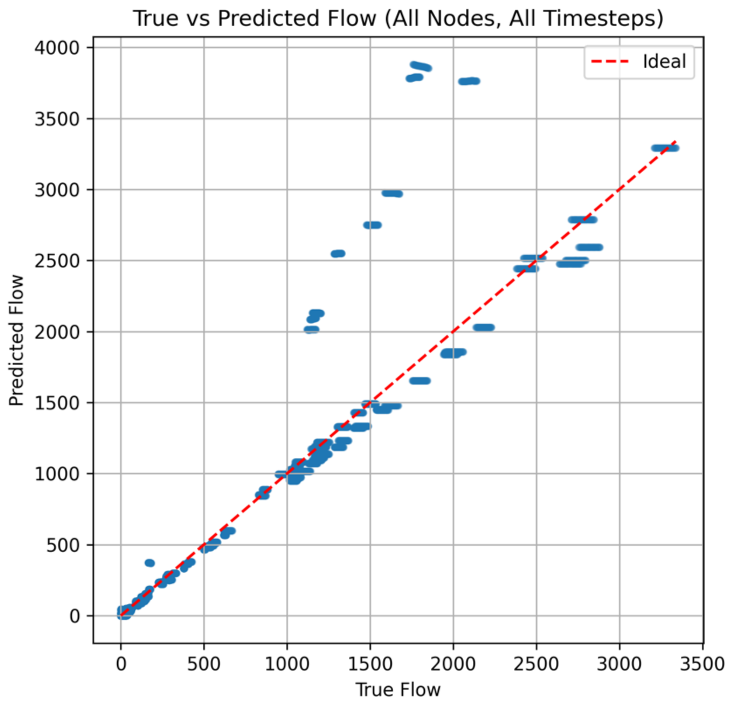


Amsterdam West – Dynamic + Static

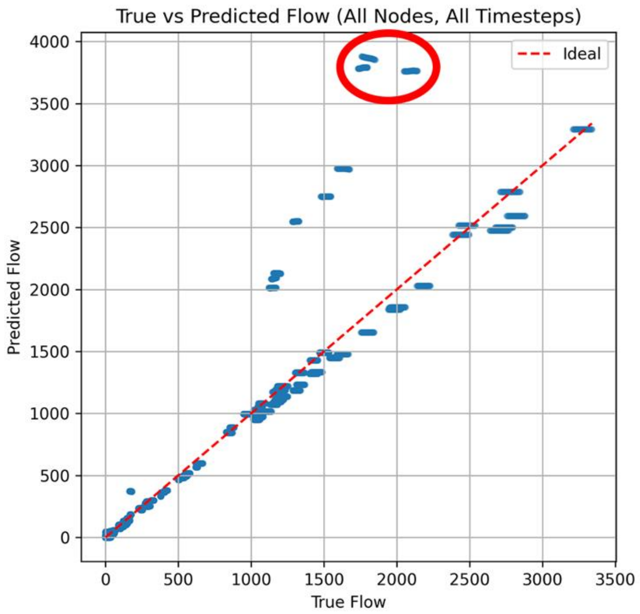
50 epochs



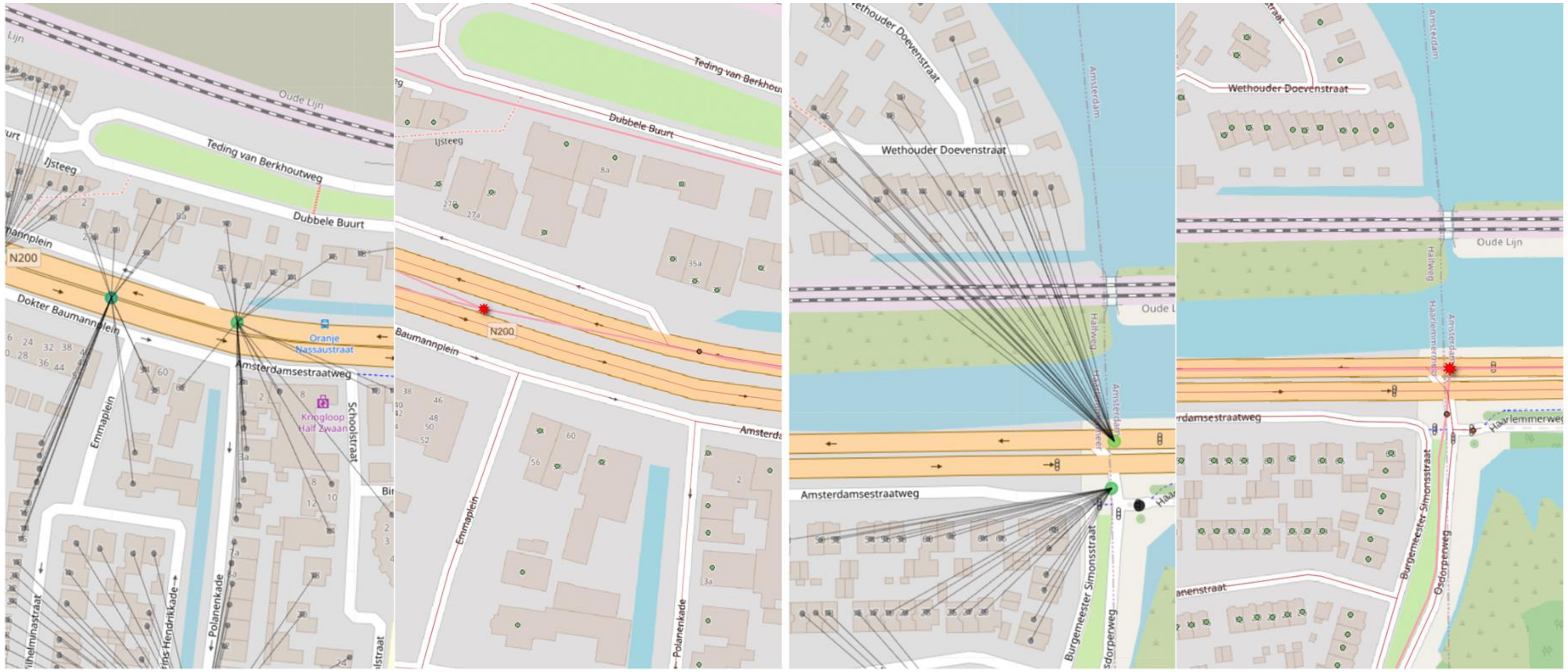


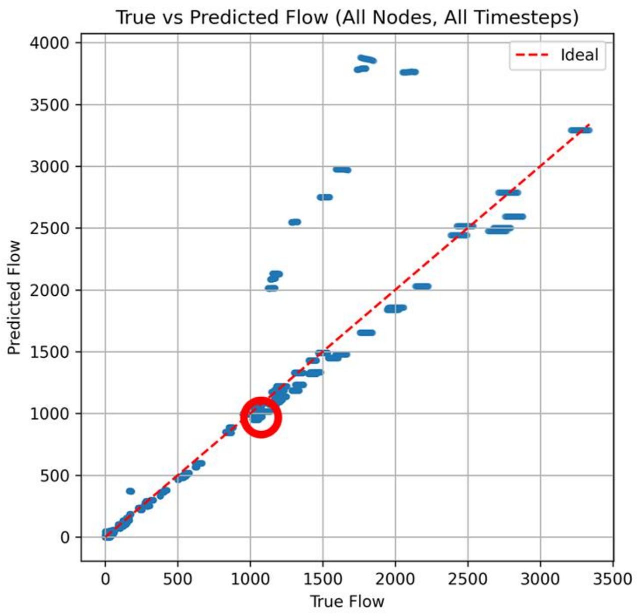


Visual Inspection

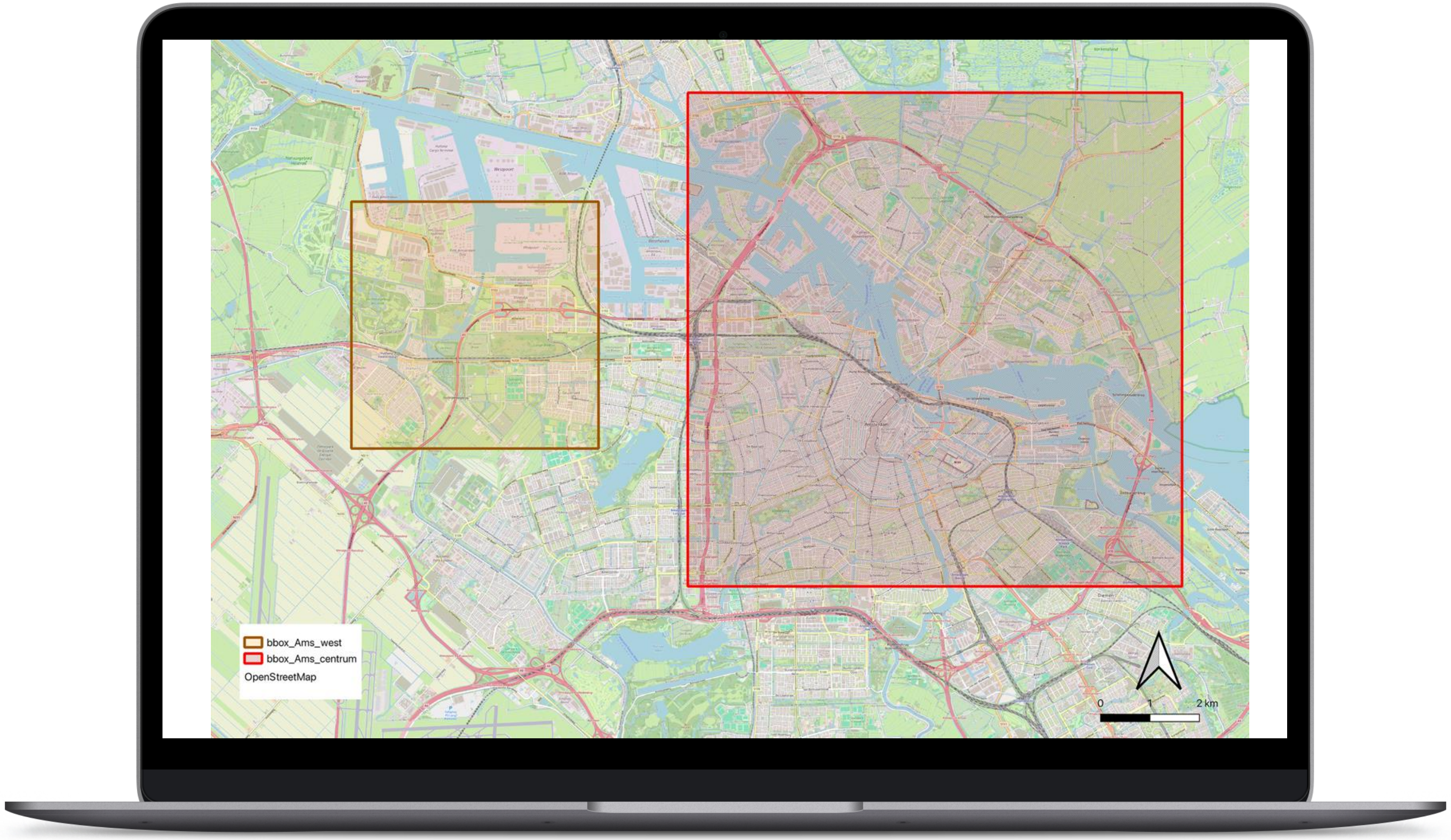


Visual Inspection



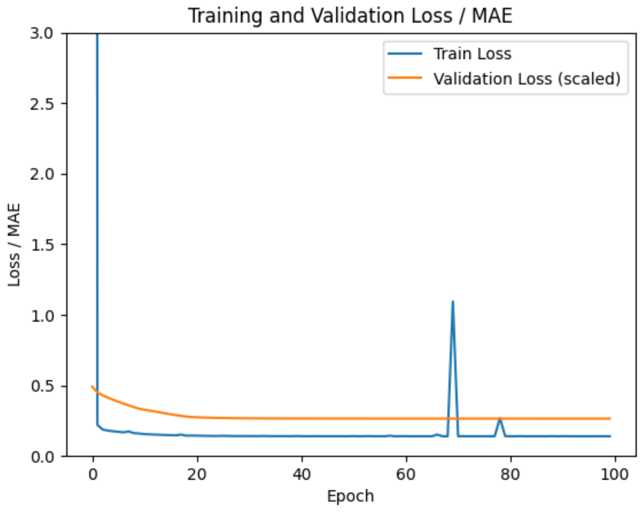


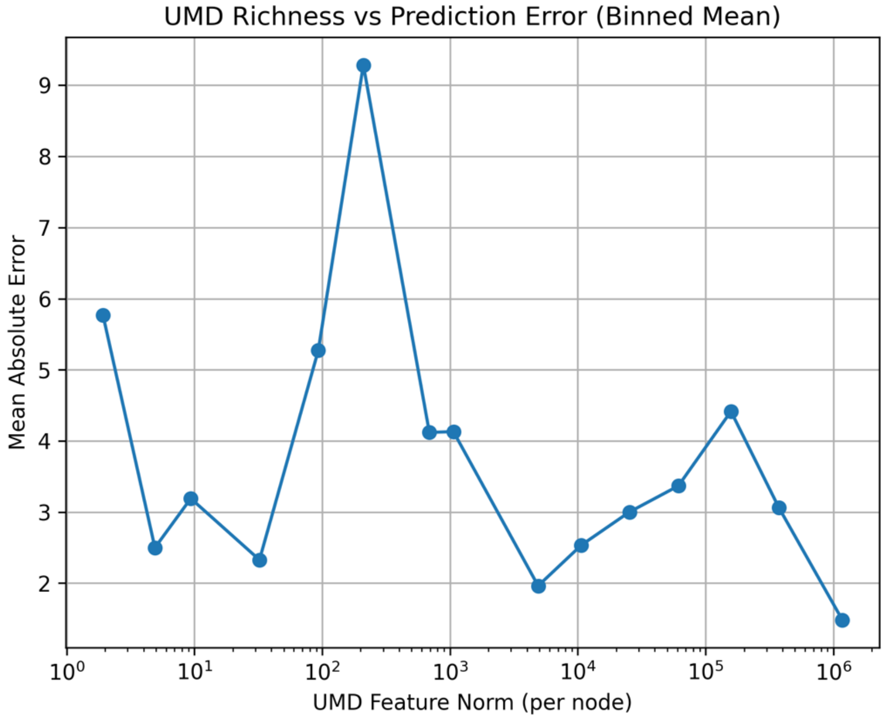
Areas of Interest

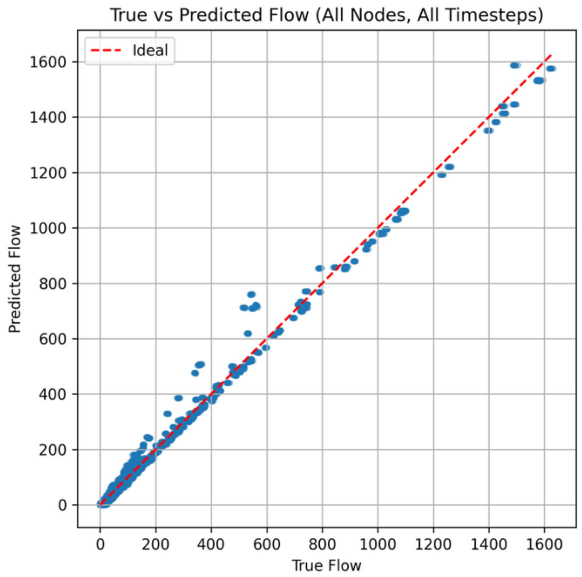


Amsterdam Centrum – Dynamic + Static

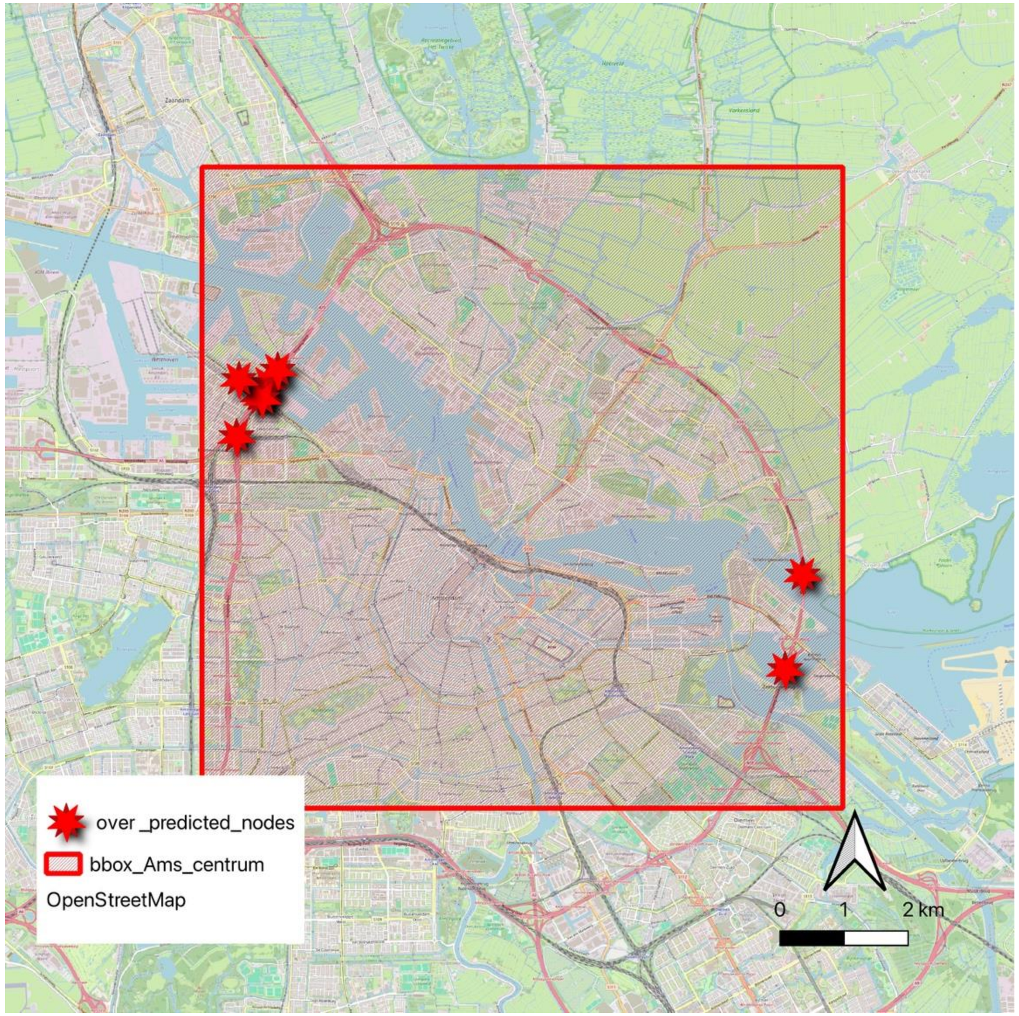
100 epochs

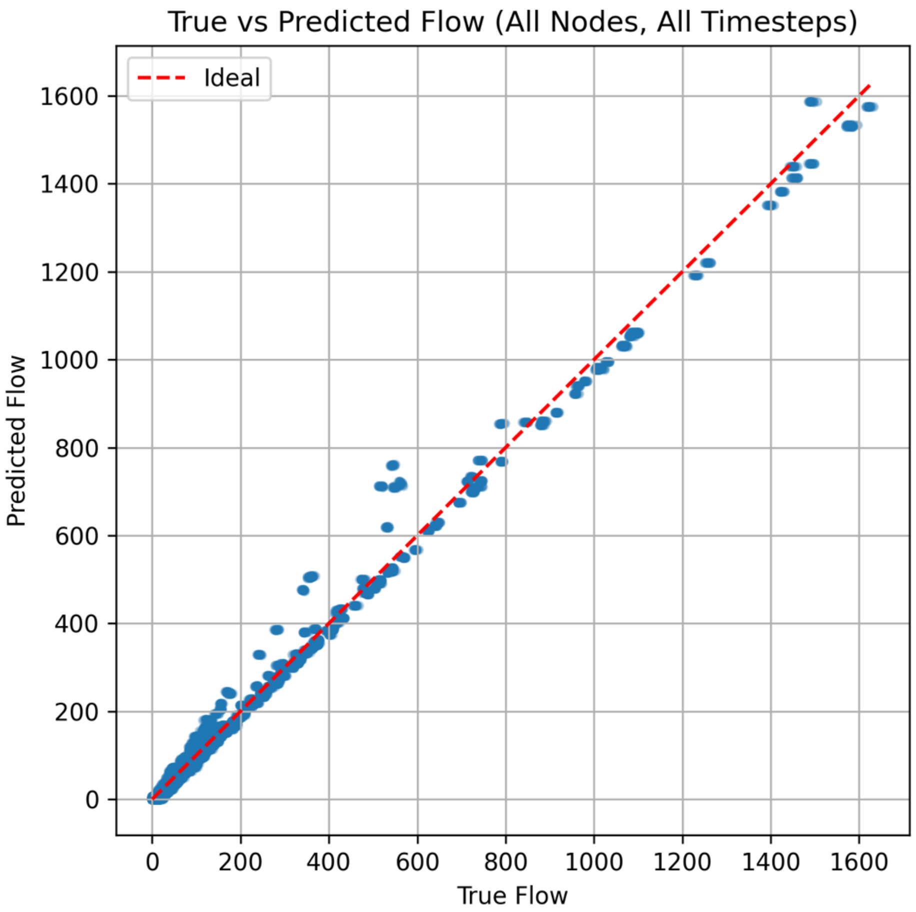






Visual Inspection





8.16

MAE

36.13

RMSE

0.53

WMAPE

0.57

UMD Weight

0.25

Test Loss

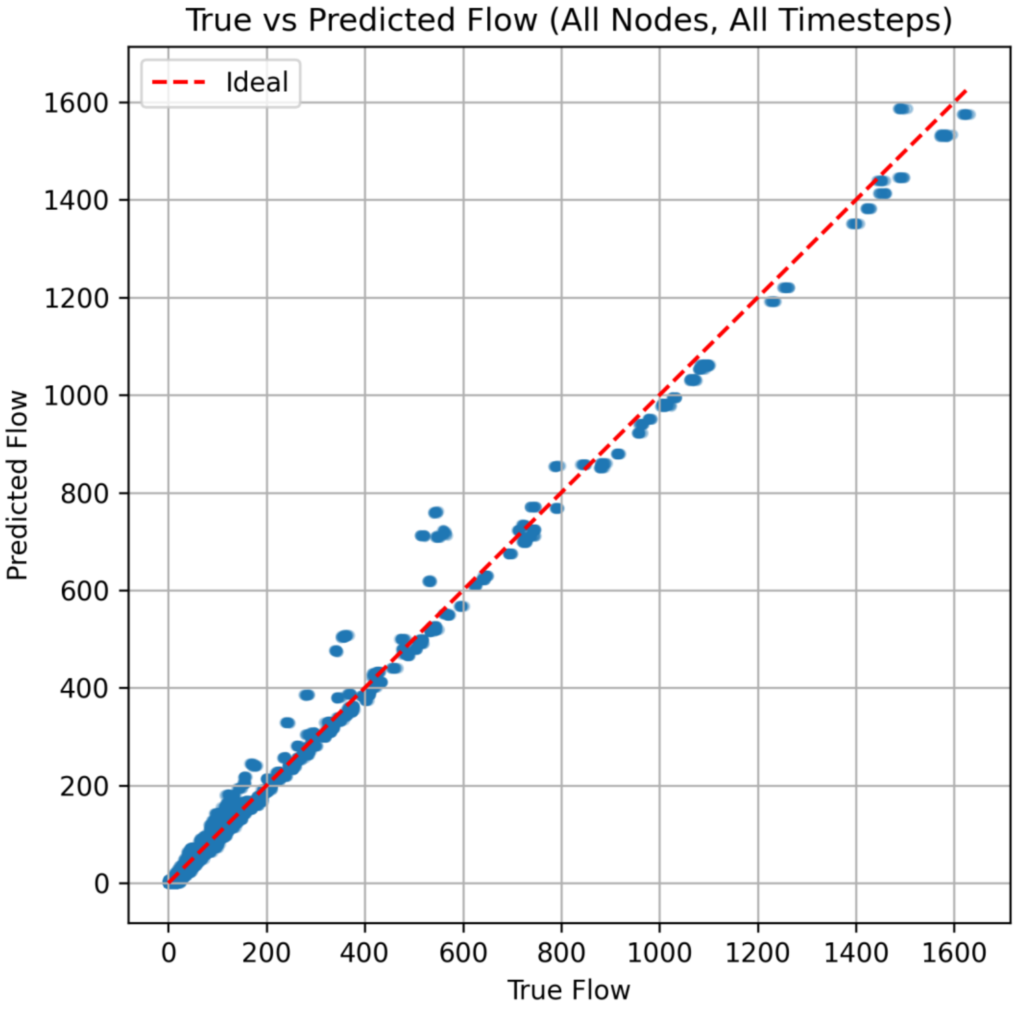
0.27

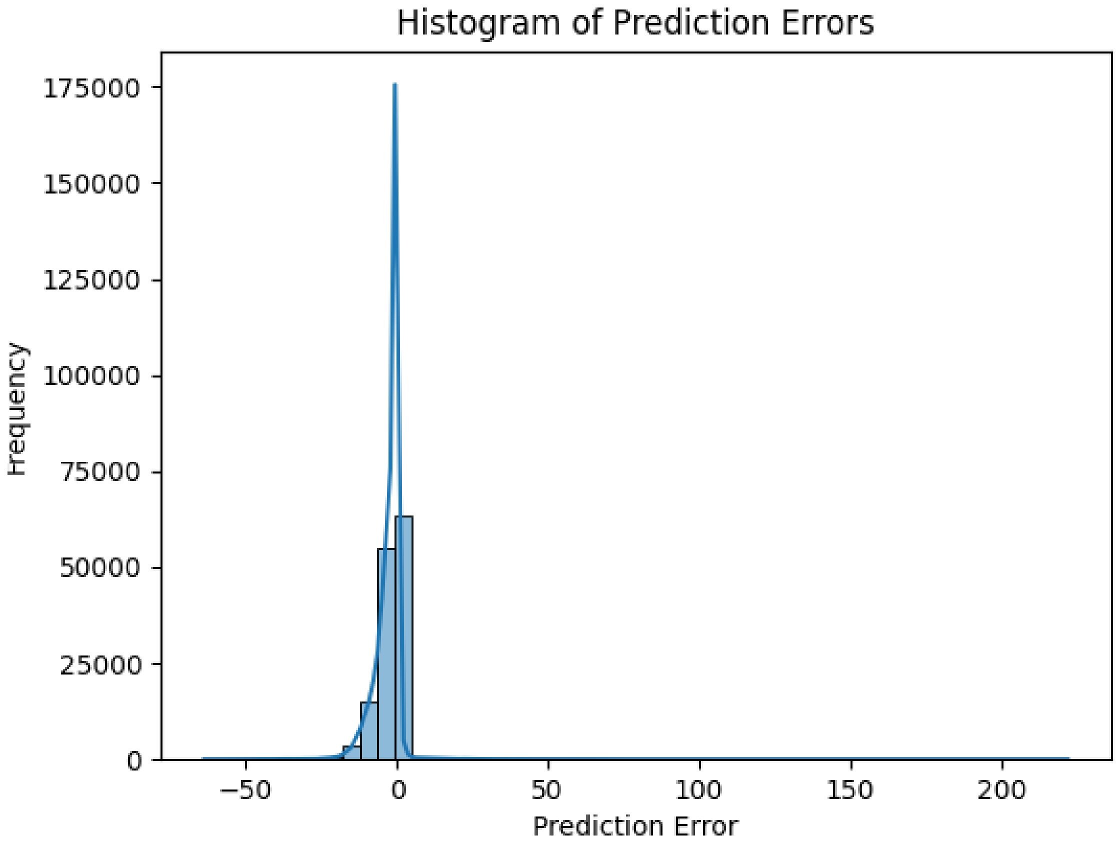
Validation Loss

Research Question:

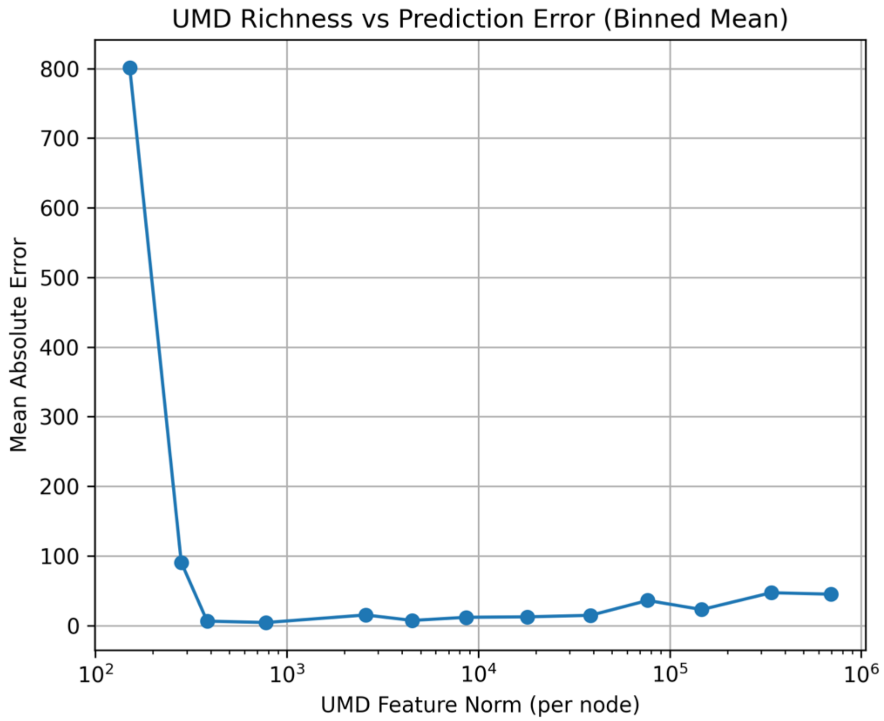
To what extent can insights into urban morphology, modeled with Spatio-Temporal Graph Neural Networks, enhance the accuracy and adaptability of freight transportation predictions in the Netherlands?

Visual Inspection

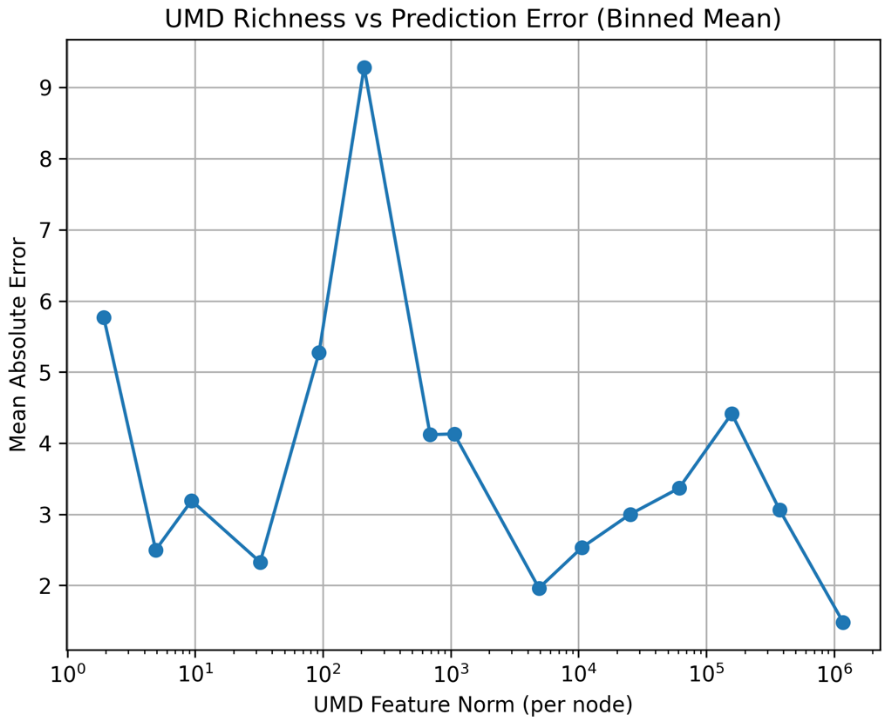




UMD vs. MAE



50 epochs, Ams West



100 epochs, Ams Centre

Tool for TNO

(MASS-GT+VMA)+ST-SimNet

Once trained, ST-SimNet can extend freight flow predictions to regions without dynamic traffic data, offering a scalable, morphology-informed solution for national-level logistics modelling.

Future Work

01

Application-specific integration

02

Topographic augmentation

03

Improved fusion mechanisms

04

Generalisation and transfer learning

05

Probabilistic and multi-modal forecasting

Want to know more?

Please refer to a written version of my Master Thesis

Thank you for your support!

Finn
Winkelmann

Martijn
Meijers

Azarakhsh
Rafiee

Amin
Jalilzadeh

Saeed
Rahmani

Herman
de Wolff

Thank you for your attention

Rafal Marek Tarczynski