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AUSTRIAN INSTITUTE OF TECHNOLOGY
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Towards Better Urban Travel Time Estimates Using Street Network Centrality

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Problem Statement

We want to:

1. Predict travel time / speed on a certain road at a certain time
2. Where we don't have measurements
3. Using only street network data – NO travel demand data

Travel Time Prediction

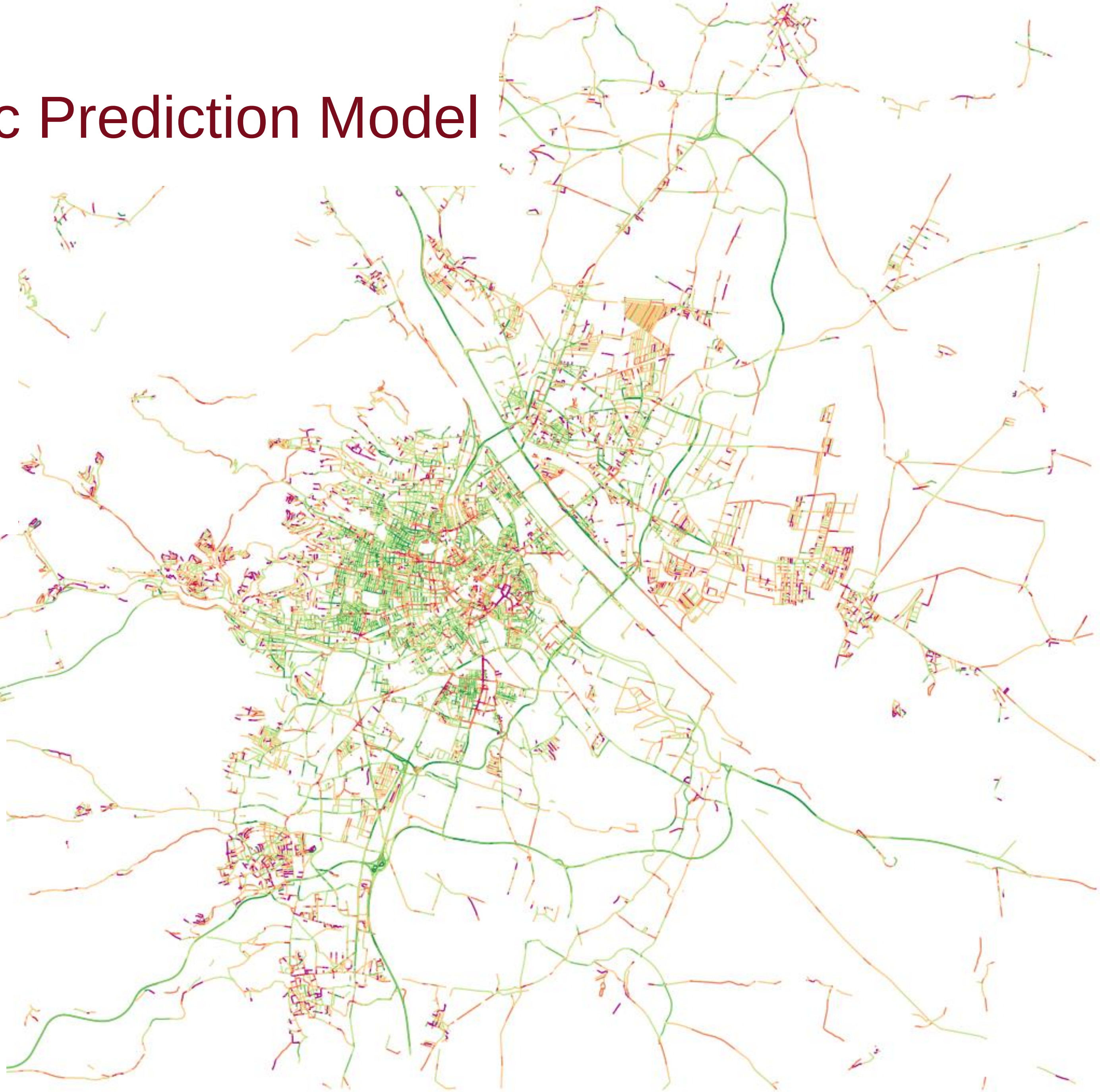
Usual approaches:

- Sensor measurements
- Traffic model
- Fallback: Speed limit $\times$ correction factor

Our Basic Prediction Model

Explanatory Variables:

- Time of day
- Road class
- Speed limit



MAPE

- 0 to 5
- 5 to 10
- 10 to 20
- 20 to 30
- 30 to 50
- 50 to 60
- > 60

Centrality

1. **Closeness**: “Central” ←→ “Peripheral”

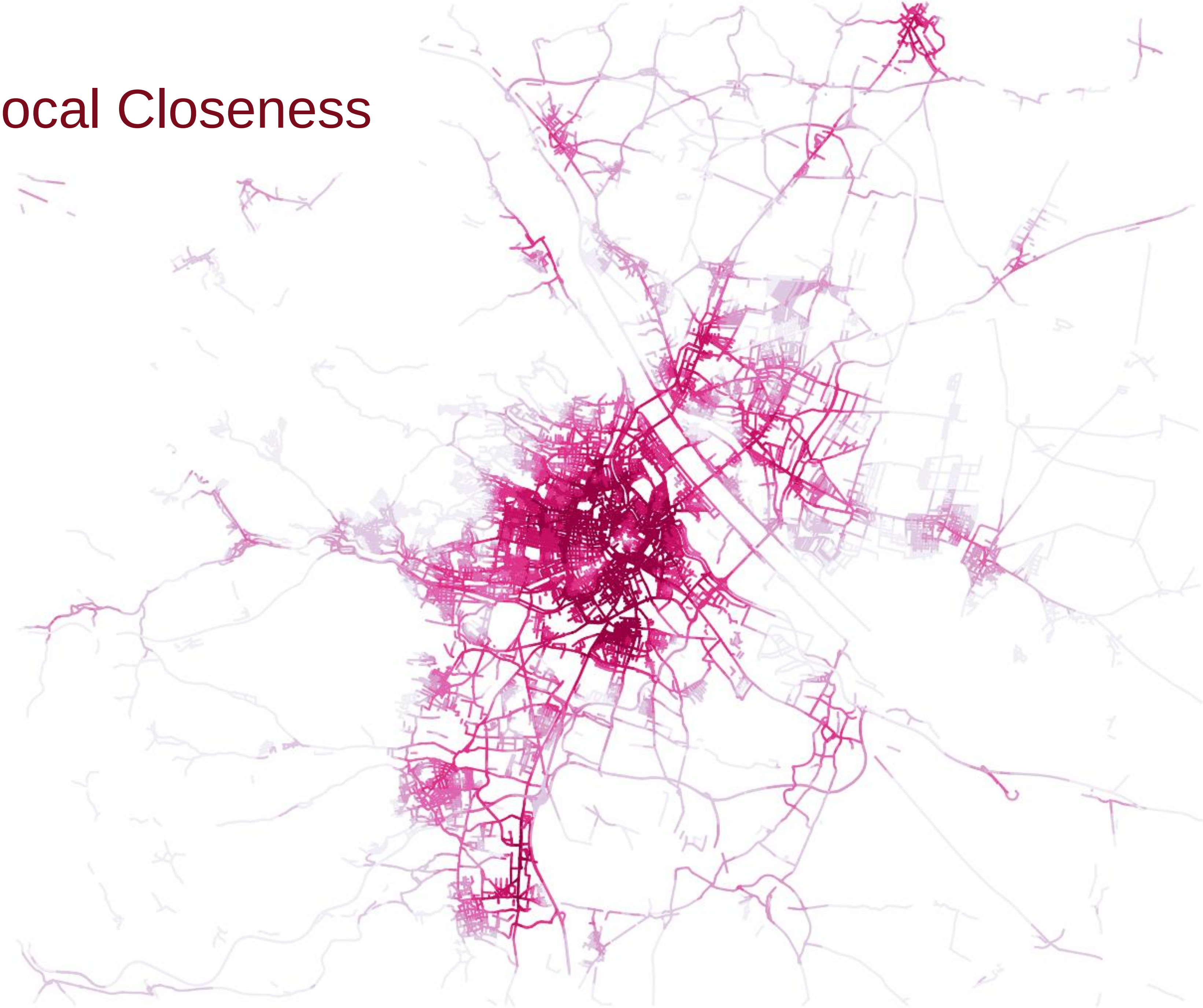
   How far is it to all other network nodes?

2. **Betweenness**: “Important” ←→ “Unimportant”

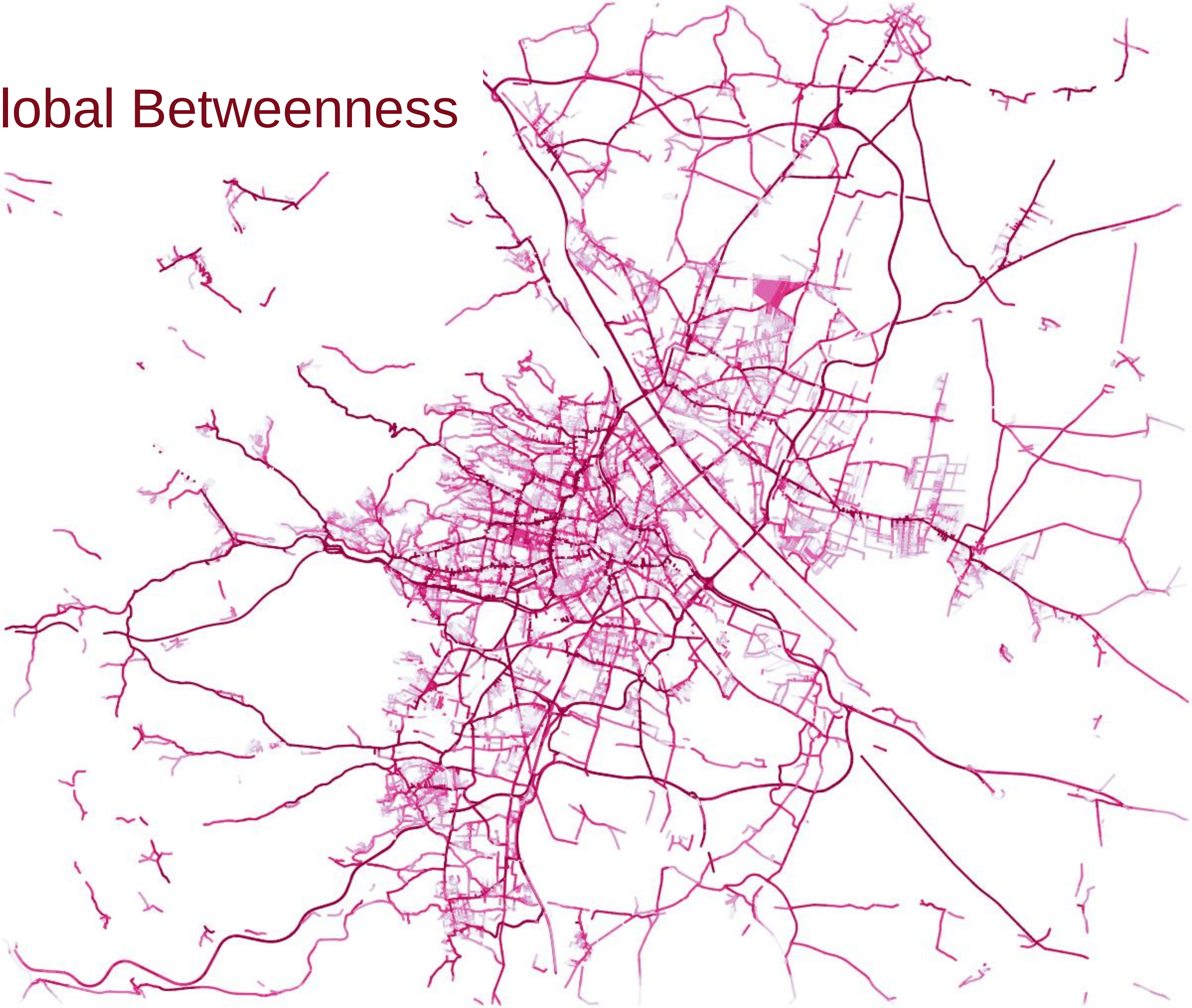
   How often is this location on the shortest paths between network nodes?

Global Closeness

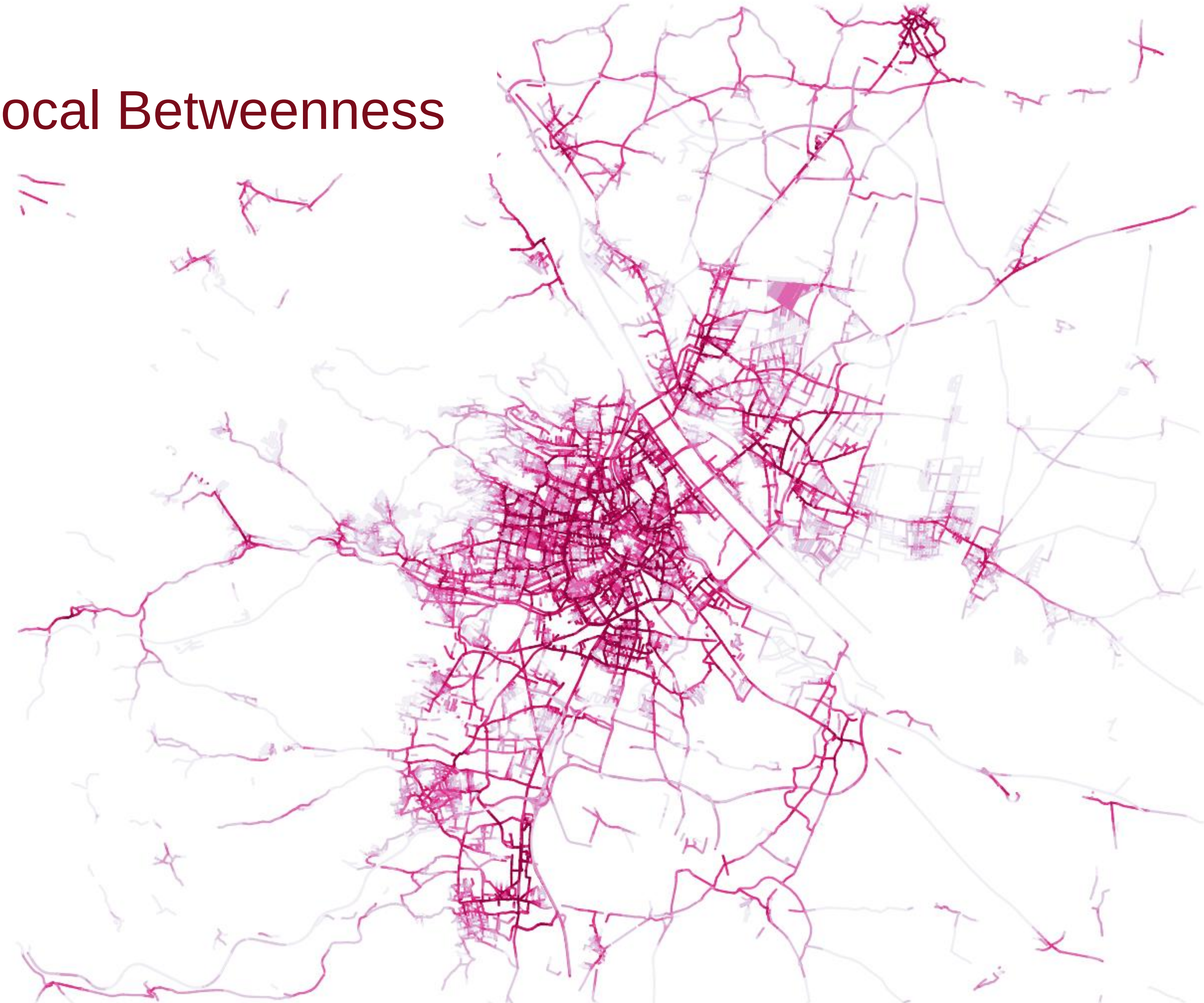
Local Closeness



Global Betweenness



Local Betweenness



Linear Regression Model

Standard linear ordinary least square (OLS) regression model

$$Y = X\beta + \varepsilon$$

where

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

Estimators:

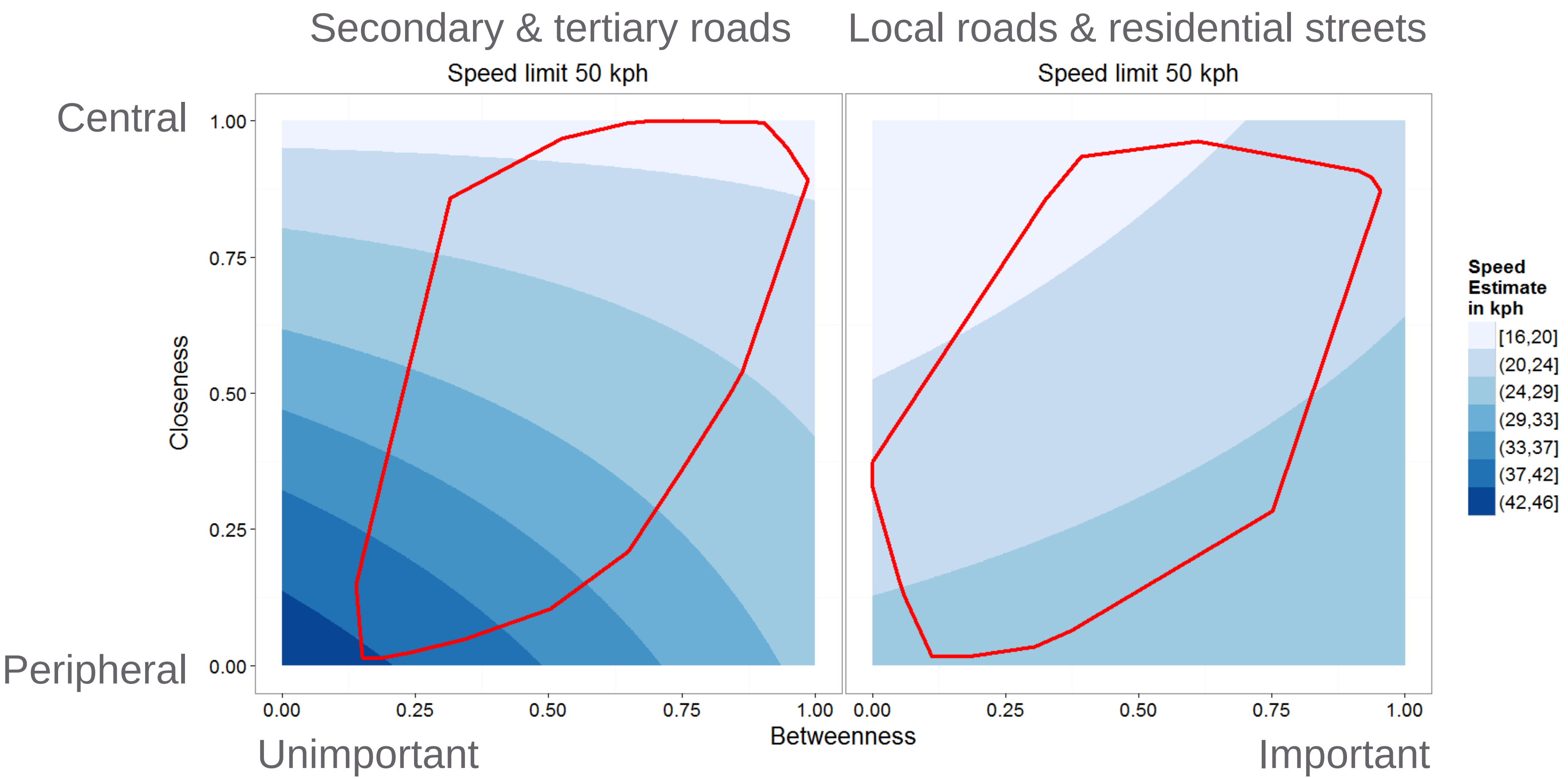
$$\widehat{\boldsymbol{y_{t,f}}} = \boldsymbol{\beta_t} + \boldsymbol{\beta_{f,s}} \cdot \boldsymbol{s} + \boldsymbol{\beta_{f,b}} \cdot \boldsymbol{b} + \boldsymbol{\beta_{f,c}} \cdot \boldsymbol{c} + \boldsymbol{\beta_{f,bc}} \cdot \boldsymbol{b} \cdot \boldsymbol{c}$$

Where

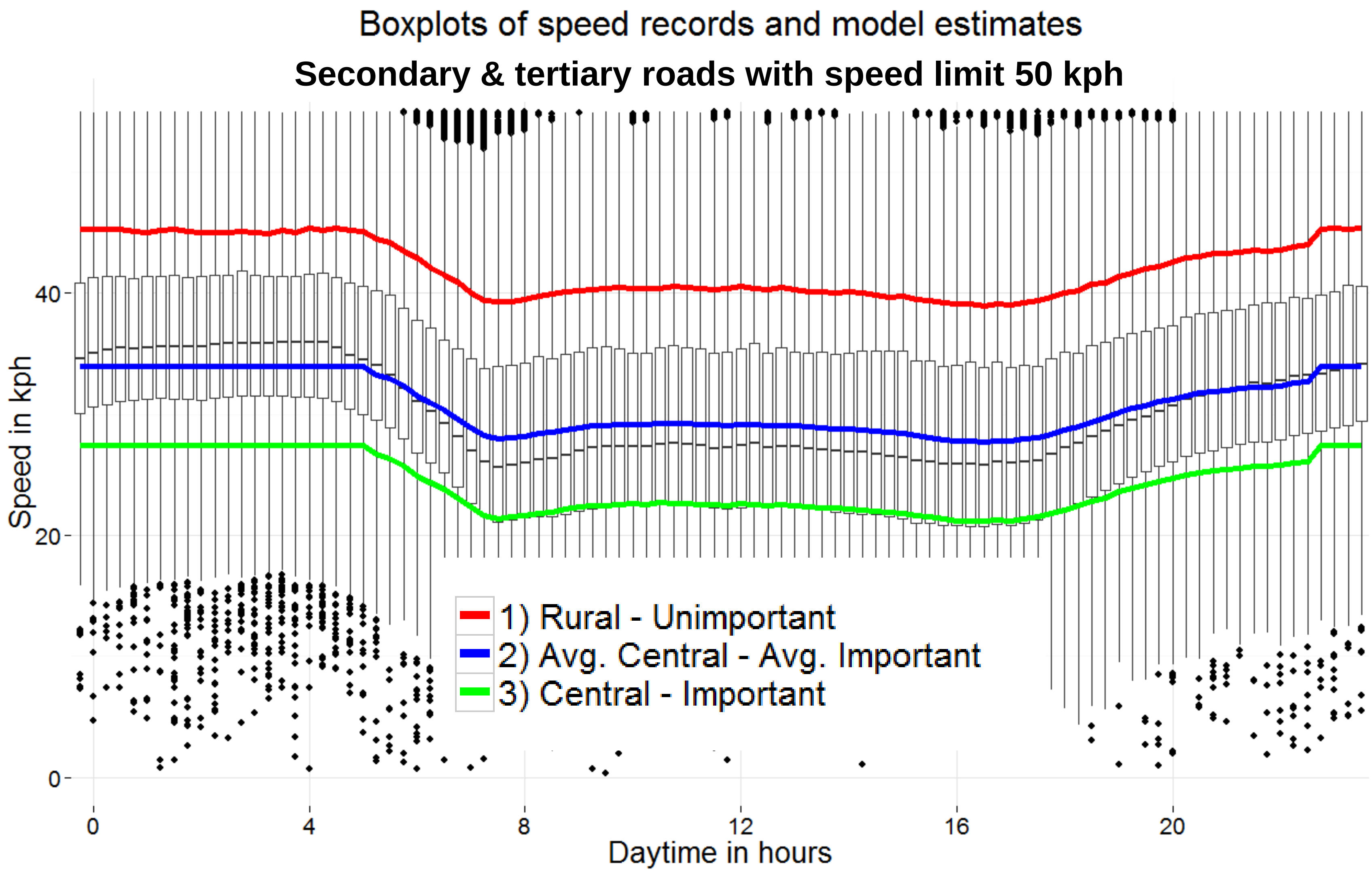
- Y … Speed records
- X … Model matrix (daytime t, frc f, betweenness b, closeness c, speed limit s)
- $\hat{\beta}$ … stacked vector of
  OLS estimates β_t, $\beta_{f,s}$, …
- *b … betweenness*
- *c … closeness*
- *s … speed limit*
- ε … Residual

Centrality Model Parameters

$$\widehat{y_{t,f}} = \beta_t + \beta_{f,s} \cdot s + \beta_{f,b} \cdot b + \beta_{f,c} \cdot c + \beta_{f,bc} \cdot b \cdot c$$



Result1: Improved Coverage of Estimators

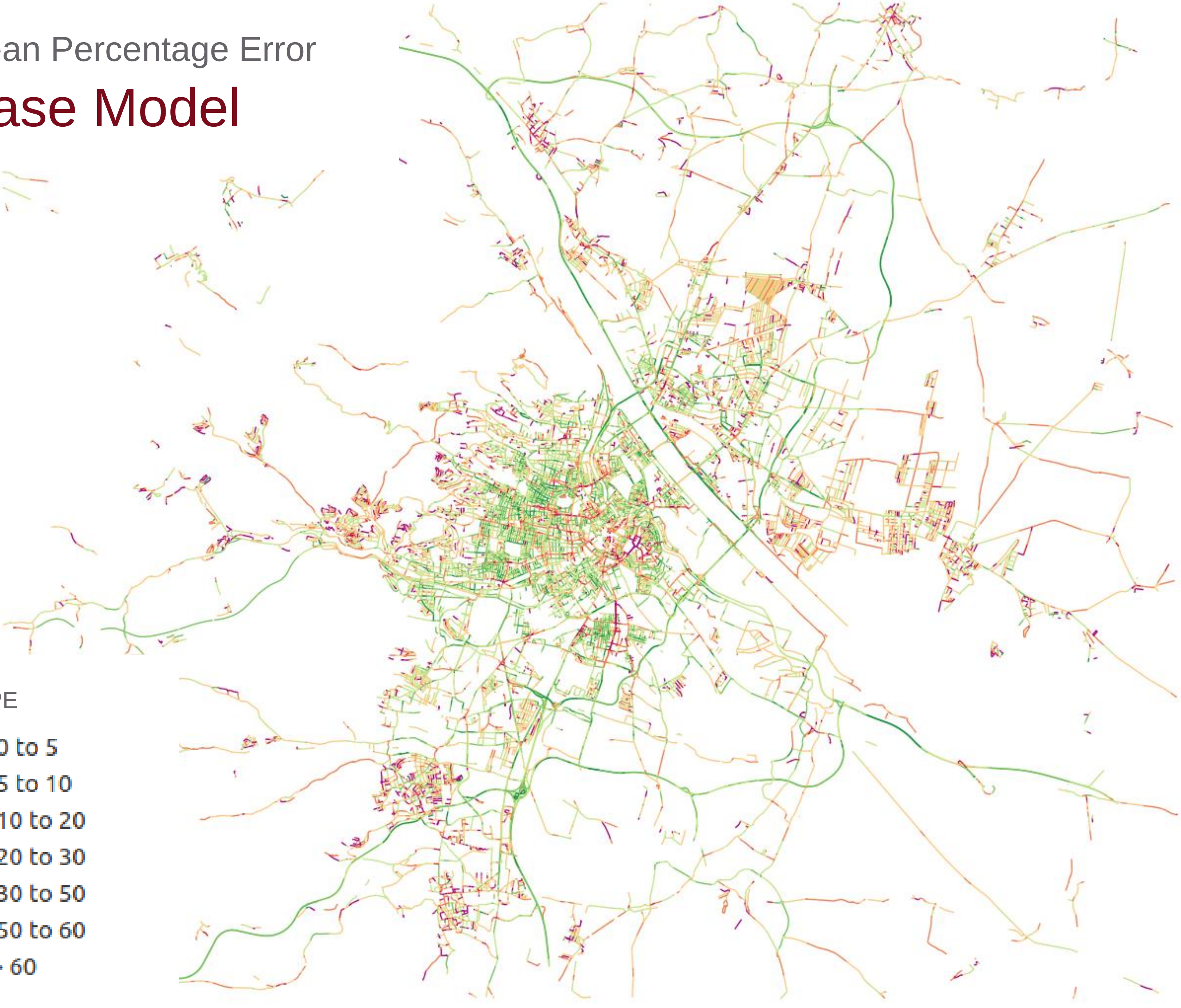


Interpretation of Results

1. **Base model**
2. 1st extension using **global centrality**
3. 2nd extension using **local centrality**

Mean Percentage Error

Base Model



MAPE

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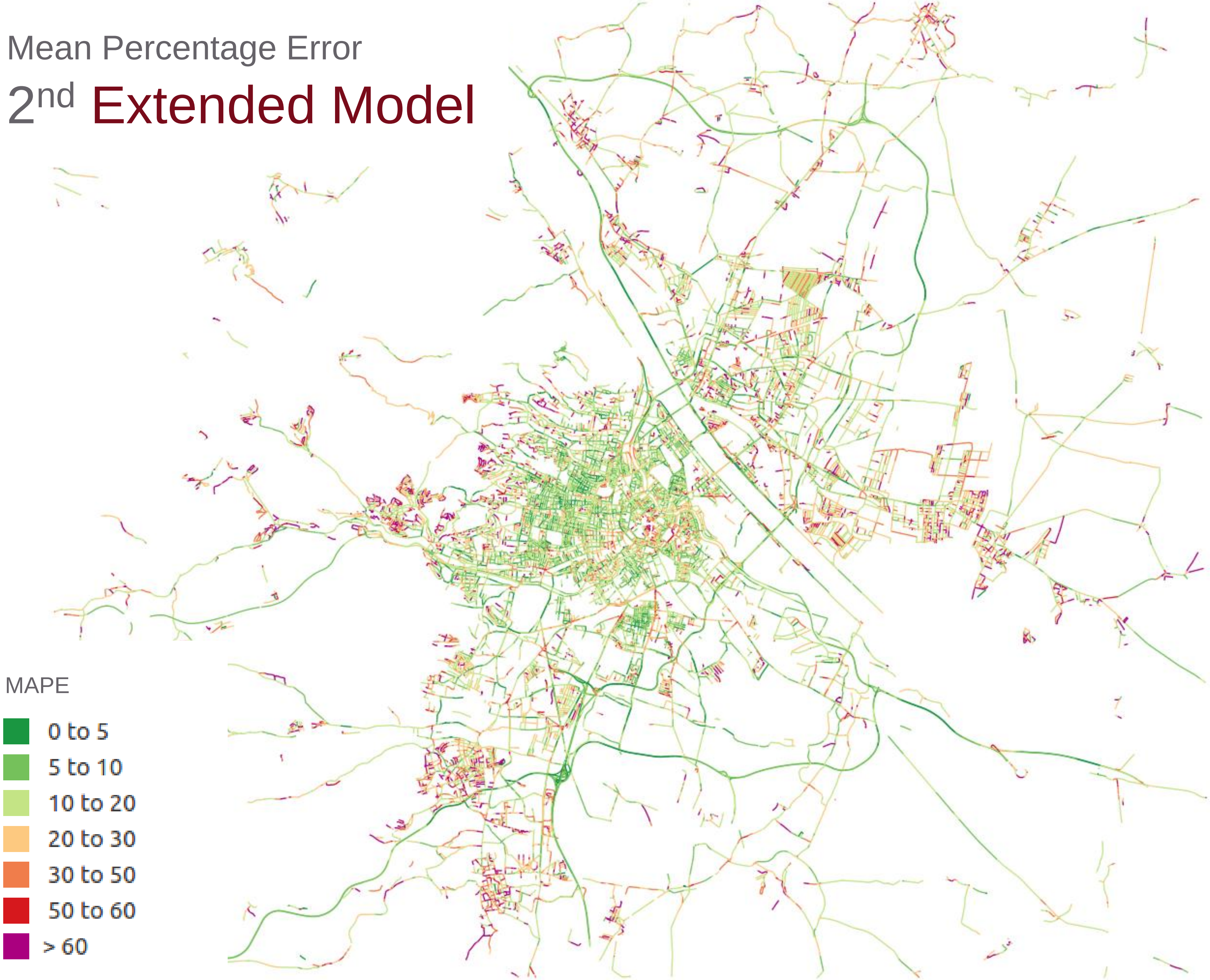
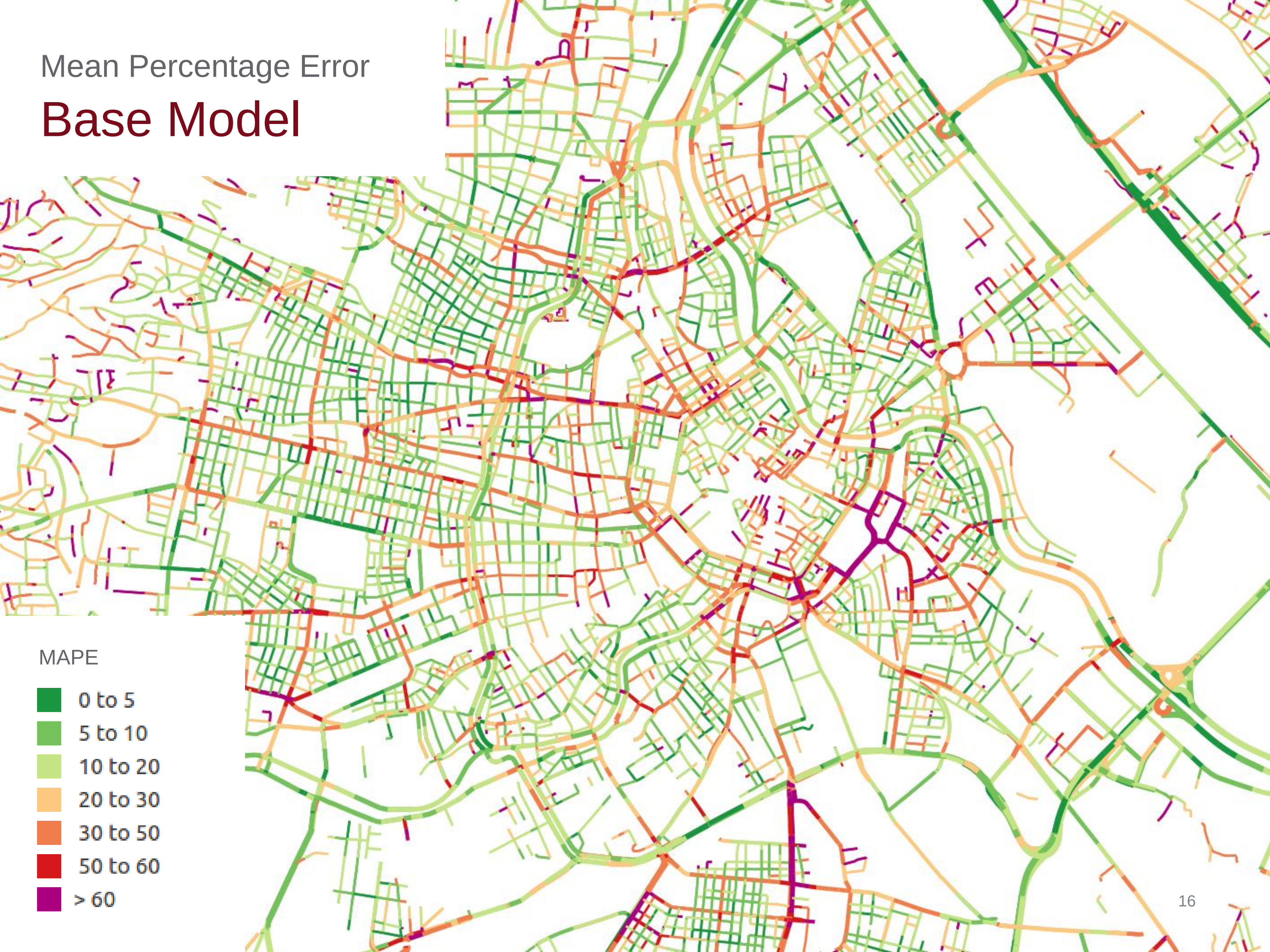
Mean Percentage Error

2nd Extended Model



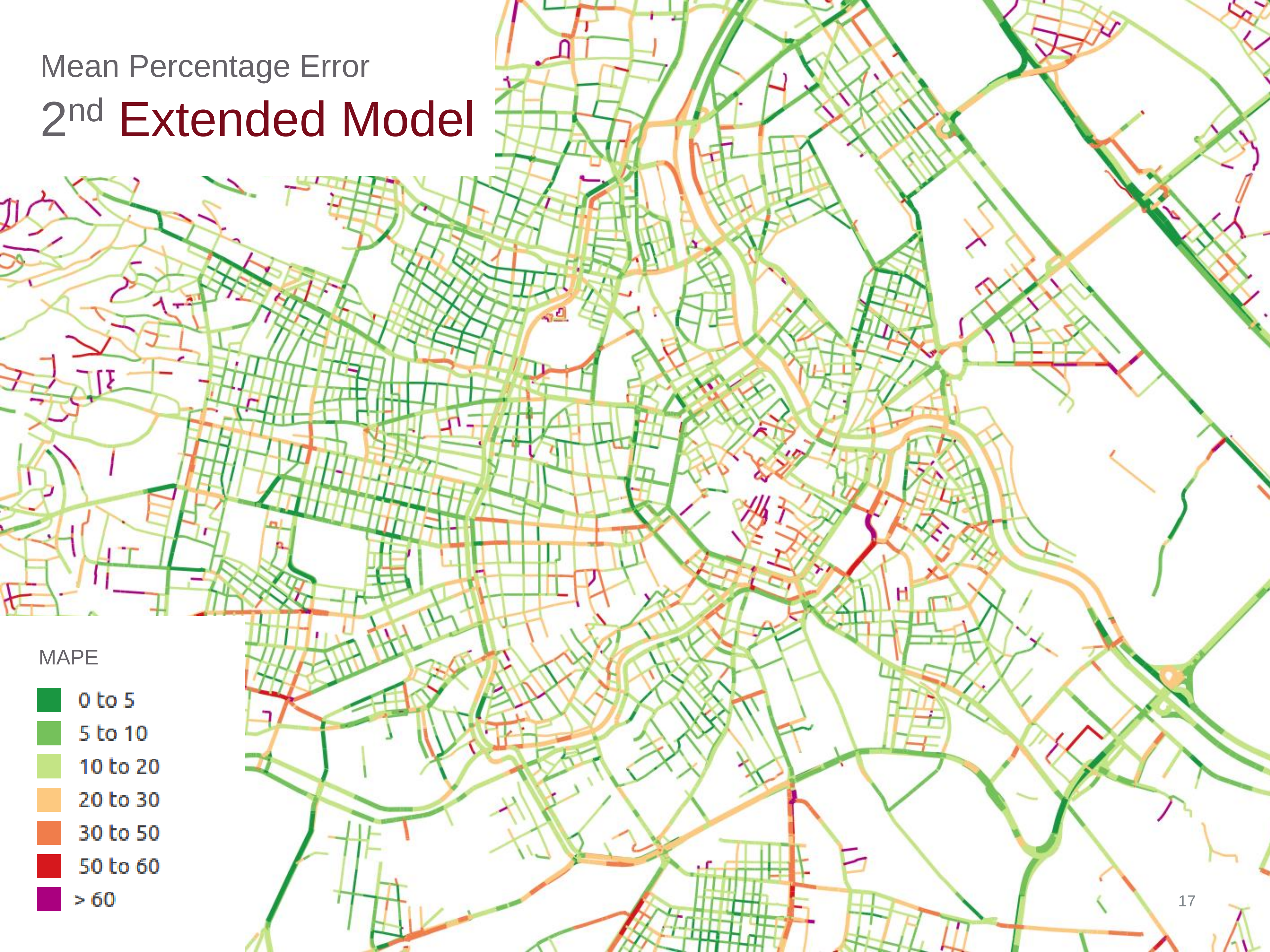
Mean Percentage Error

Base Model



Mean Percentage Error

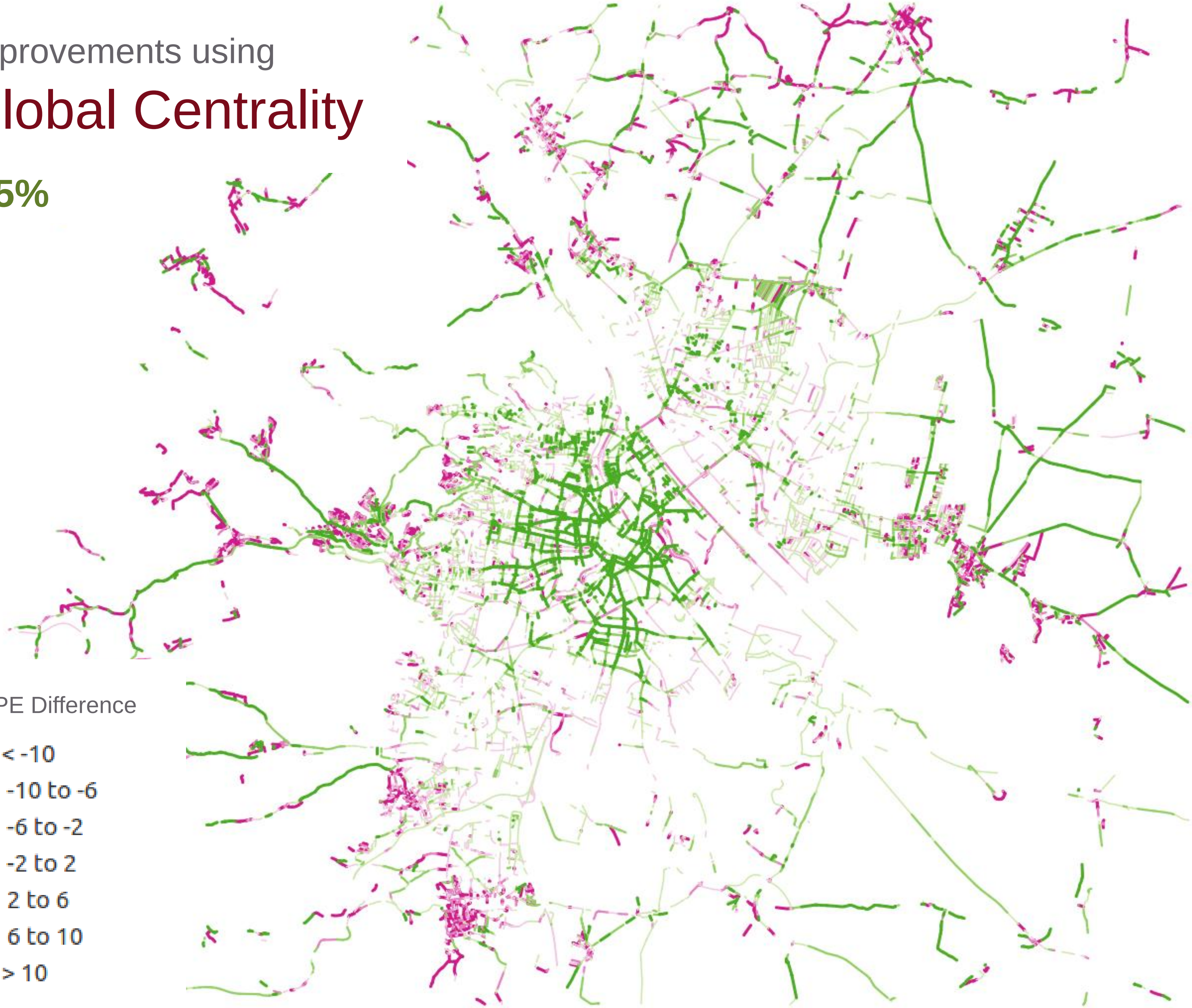
2^{nd} Extended Model



Improvements using

Global Centrality

8.5%



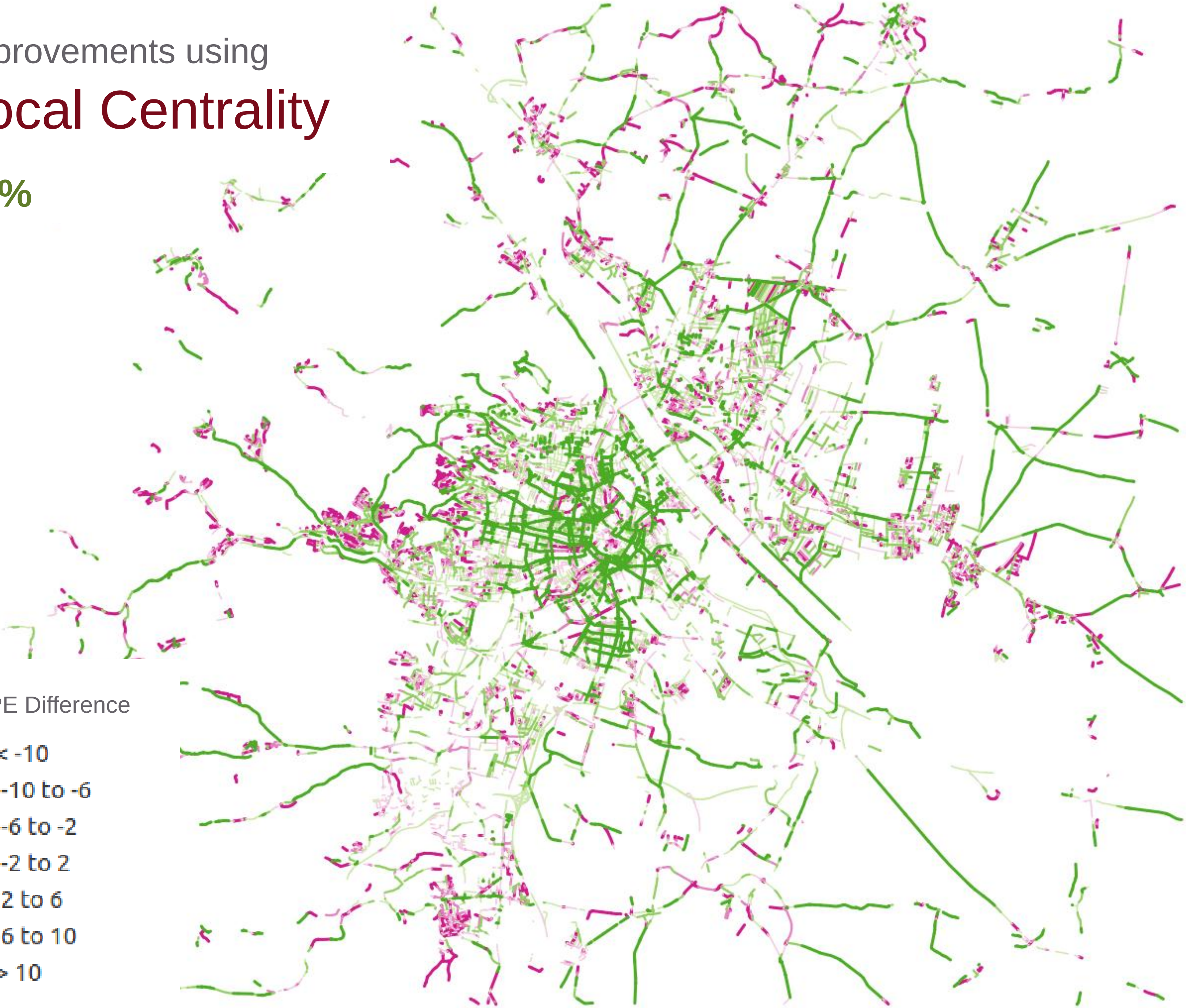
MAPE Difference

	< -10
	-10 to -6
	-6 to -2
	-2 to 2
	2 to 6
	6 to 10
	> 10

Improvements using

Local Centrality

14%



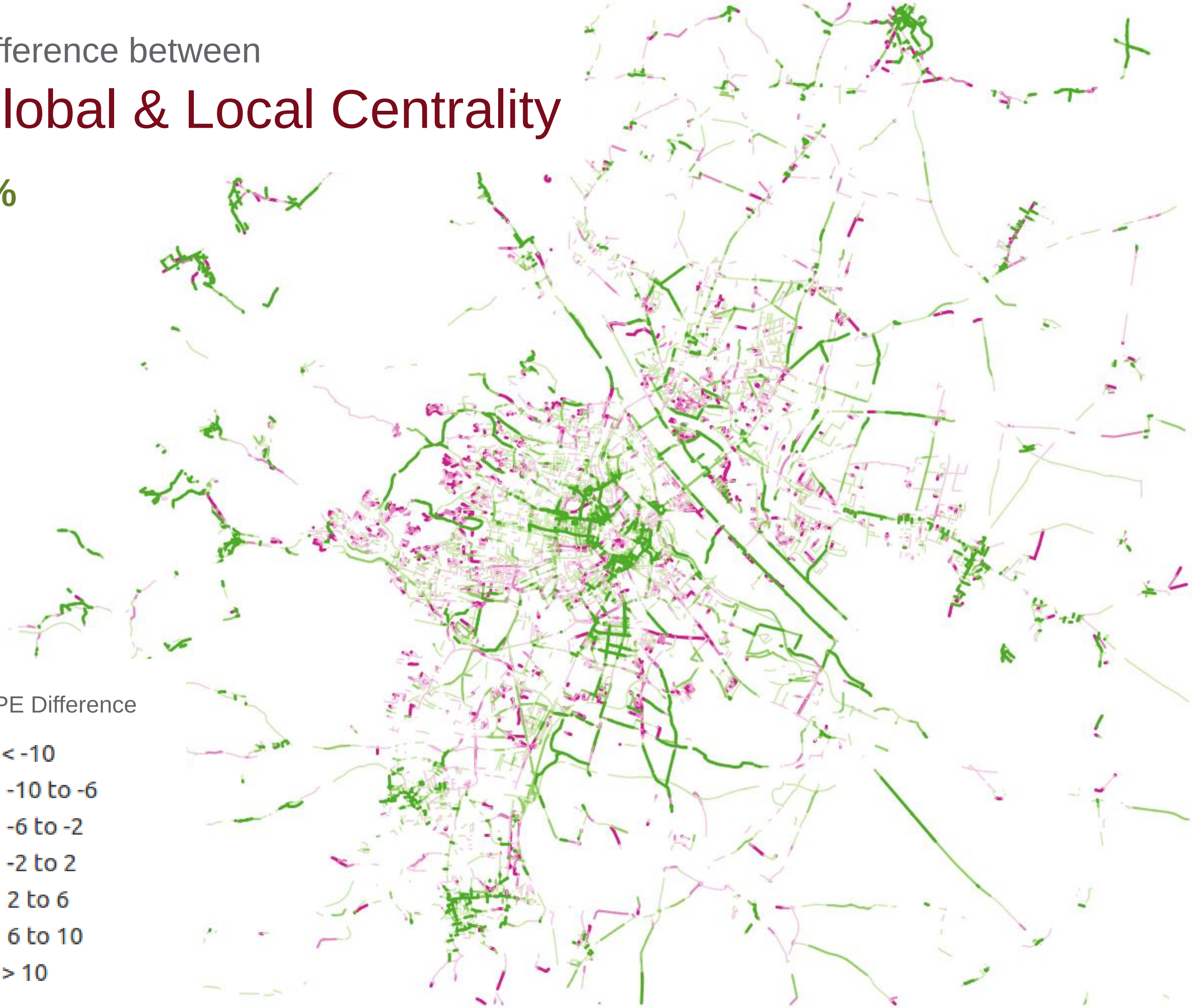
MAPE Difference

- < -10
- -10 to -6
- -6 to -2
- -2 to 2
- 2 to 6
- 6 to 10
- > 10

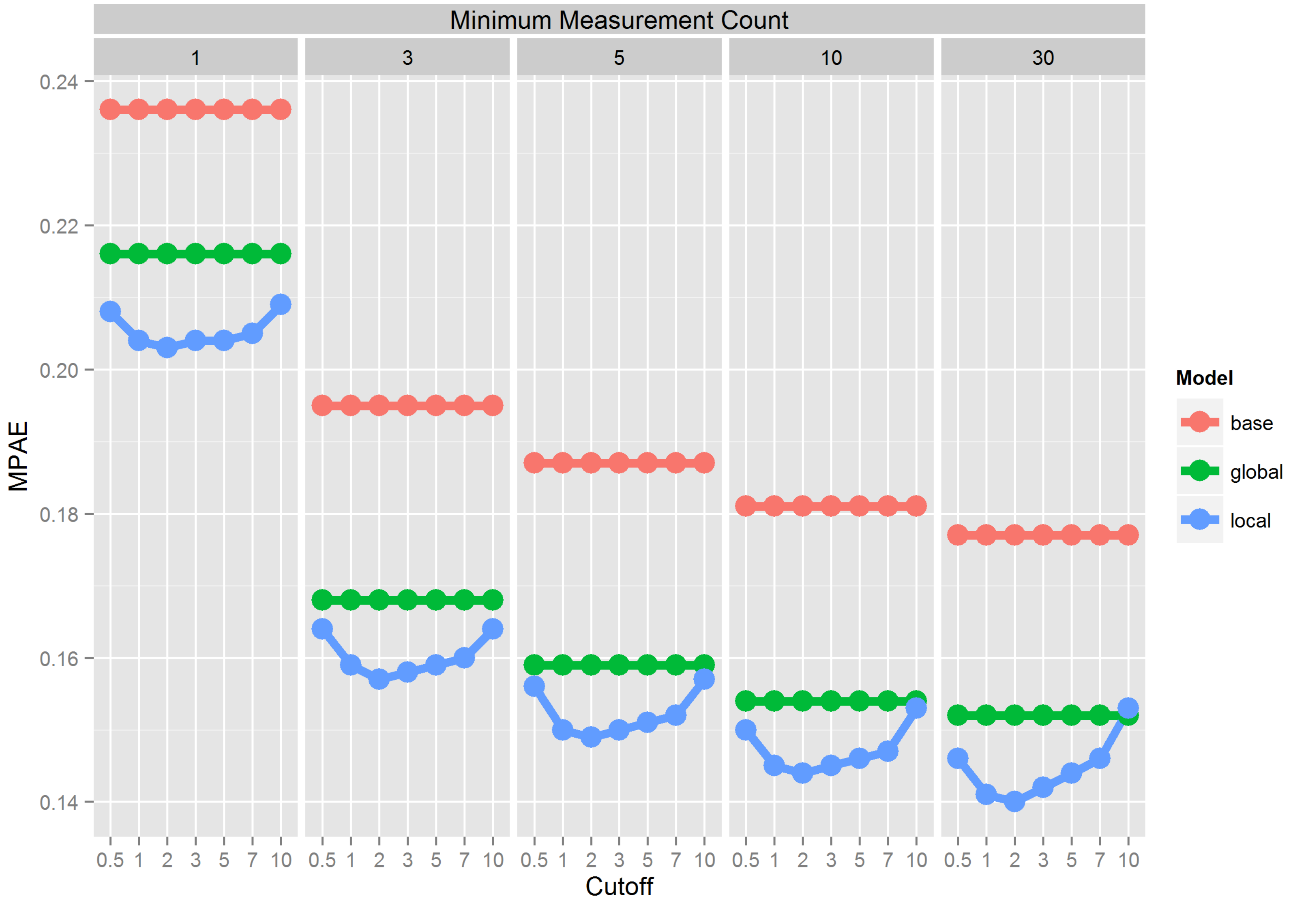
Difference between

Global & Local Centrality

6%



Model Performance Summary



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