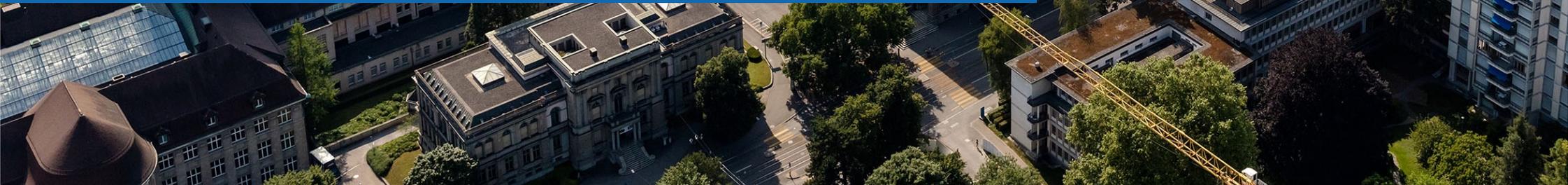




Spatial ride-pooling demand and its transferability to new cities

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Introduction

Ride-pooling systems promise to provide efficient and convenient on-demand mobility

- Multiple trips with a similar route are matched and transported with only one vehicle.
- Simulation studies have shown a **huge potential to reduce traffic, emissions and required resources.**
- Large-scale ride-pooling systems are rare and mostly operate as test services.

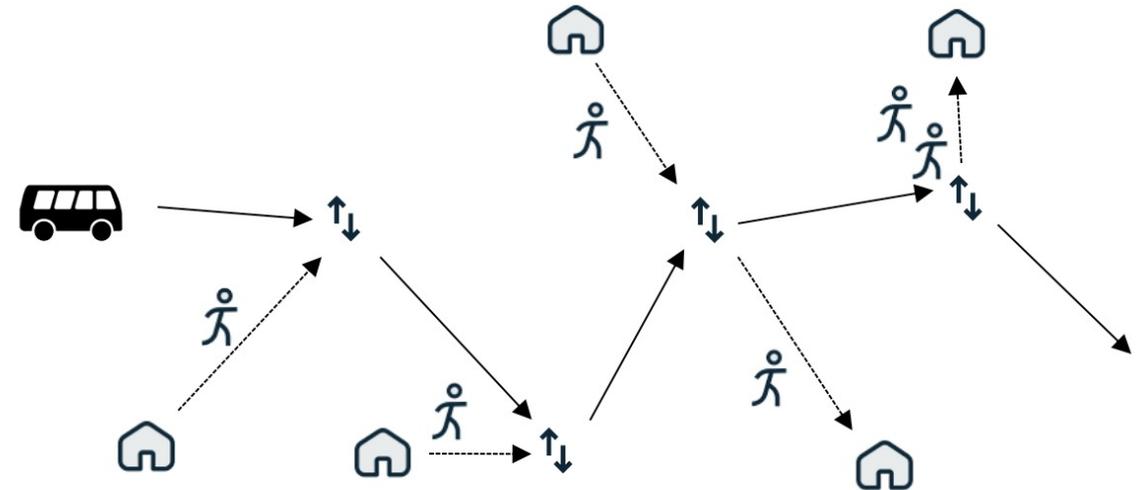


Figure 1: Exemplary ride-pooling process.

Real-world ride-pooling demand is used to estimate spatial characteristics and predict potential demand in new cities



Figure 2: MOIA ride-pooling vehicle in Hamburg.

- **MOIA** operates in Hamburg and Hanover with up to 330 vehicles.
- We analyze 1.2m and 330k MOIA trips from 2019 and 2020 in Hamburg and Hanover, respectively.
- **Spatial Regression** and **Random Forest Regression** models are estimated.

Data and methodology

Spatial demand distributions show clear demand hotspots in central areas

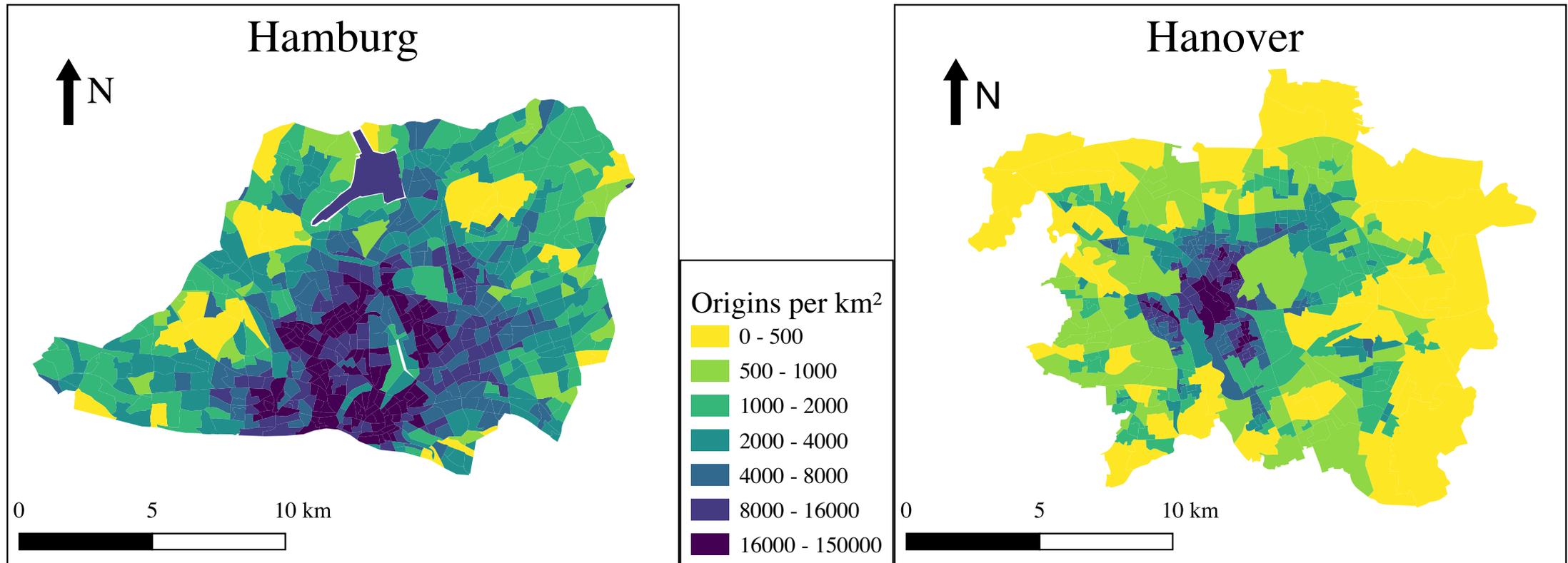


Figure 3: Spatial ride-pooling demand distribution in Hamburg and Hanover between May 2019 and February 2020.

Independent spatial variables

- Independent variables are extracted from multiple sources and matched on statistical zones.
- Previous studies find a high impact of *population*, *jobs* and *gastronomy* on demand size.
- The variables *hospitals*, *clothing shops*, *avg. age* and *car ownership* showed no significant impact.
- The airport was excluded as the Hanover airport is outside the service area.

 Population

 Jobs

OSM data

 Shops

 Gastronomy

 Culture

 Rail stops

 Distance to main train station

Methodology

1. OLS model:

$$y = X\beta + \varepsilon$$

y : Dependent variable (*ride-pooling trips*)

X : Independent variables (*spatial data*)

β : Estimated parameters

ε : Error term

2. SLX model:

$$y = X\beta + WX\theta + \varepsilon$$

W : Spatial weight matrix

θ : Estimated spillover effect

3. Random forest regression is used to estimate variable importance and partial dependencies.

We vary the models by in-/excluding the **centrality variable** *distance to main train station*.

→ **Finally, the results for Hamburg are used to predict potential demand in Hanover.**

Estimation results

OLS regression results show similar results across both cities

| | Hamburg | Hanover |
|------------------------|----------|----------|
| Population (per 1,000) | 376.6*** | 149.3 |
| Jobs (per 1,000) | 96.9*** | 104.1*** |
| Rail stops | 171.2*** | 20.1 |
| Shops | -72.2** | -43.0*** |
| Culture | 208.0*** | 130.6*** |
| Gastronomy | 104.5*** | 78.9*** |

*** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05; . p-value < 0.1

SLX regression results additionally consider the spillover effect

| | Hamburg | Hanover |
|------------------------|------------|-----------|
| Population (per 1,000) | 346.1 *** | 118.9 |
| Jobs (per 1,000) | 90.4 *** | 104.0 *** |
| Rail stops | 131.6 *** | 18.0 |
| Shops | -63.9 ** | -39.3 ** |
| Culture | 201.2 *** | 113.7 *** |
| Gastronomy | 104.1 *** | 70.6 *** |
| Lag pop. (per 1,000) | 260.4 ** | -68.7 |
| Lag jobs (per 1,000) | 91.6 * | 65.3 ** |
| Lag rail stops | -361.3 *** | -57.2 |
| Lag shops | -151.2 ** | -98.2 *** |
| Lag culture | -66.6 . | 134.5 *** |
| Lag gastronomy | 39.6 *** | 14.6 |

*** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05; . p-value < 0.1

Random forest regression shows importance of independent variables

| | Hamburg | | Hanover | |
|--------------------|-----------------------|------|-----------------------|------|
| | Incl. centrality var. | | Incl. centrality var. | |
| Gastronomy | 34.9 | 28.5 | 19.3 | 14.7 |
| Dist. Hbf | | 25.2 | | 14.4 |
| Jobs | 12.0 | 16.0 | 15.6 | 12.9 |
| Population | 11.8 | 12.8 | 3.6 | 3.3 |
| Culture | 9.5 | 8.9 | 14.2 | 13.3 |
| Rail stops | 4.4 | 3.1 | 3.9 | 4.7 |
| Shops | 0.4 | 2.9 | 3.9 | 3.5 |
| Variance explained | 62% | 66% | 63% | 67% |

Partial dependence plots show similar spatial patterns for both cities

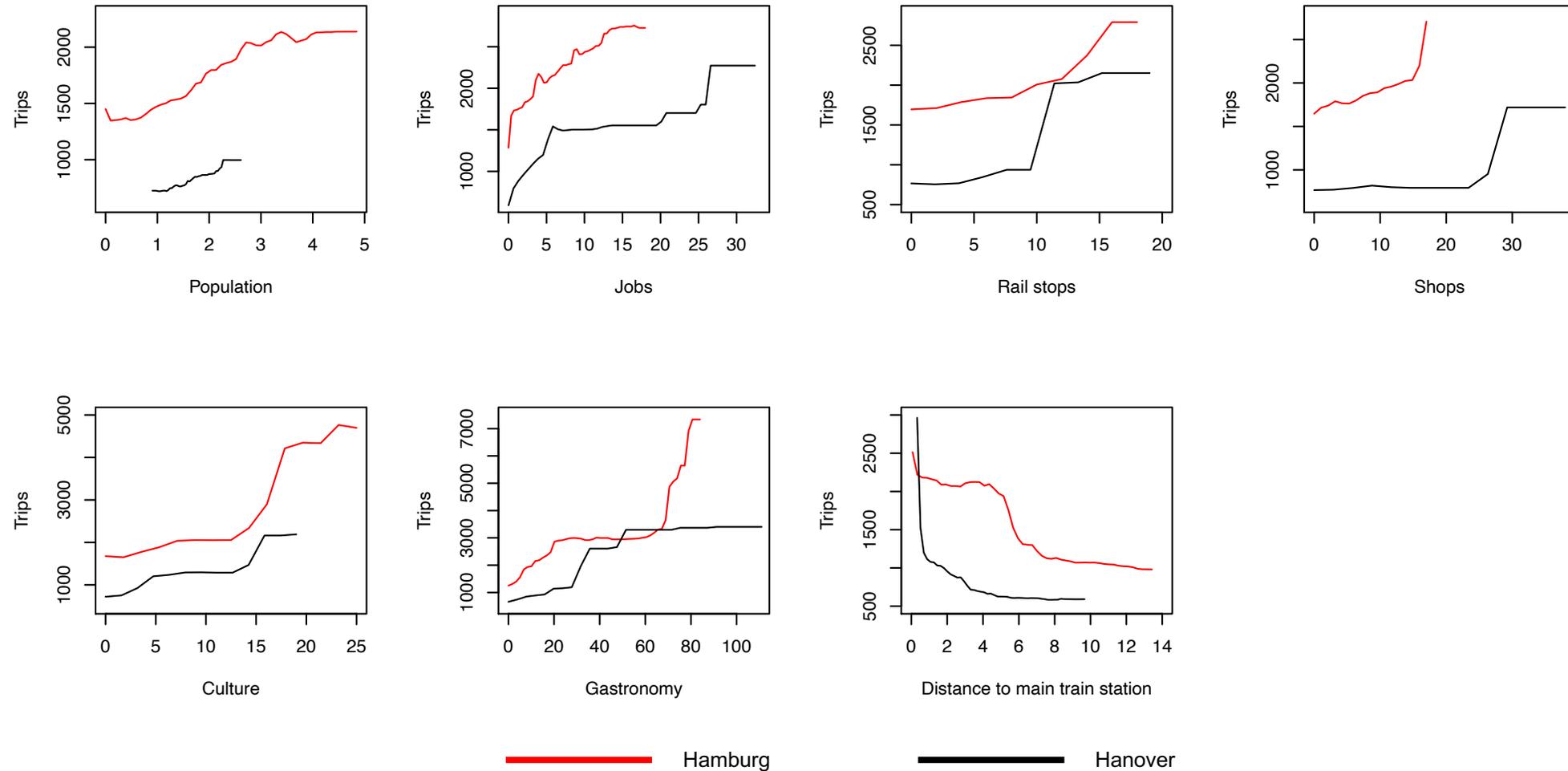


Figure 4: Partial dependence plots for Hamburg and Hanover.

Prediction results

Hanover demand is estimated based on the Hamburg regression model

| | | | | Incl. Centrality variable | | |
|---|-------|-------|-------|---------------------------|-------|-------|
| | OLS | RF | SLX | OLS | RF | SLX |
| RMSE | 3,641 | 2,941 | 2,863 | 3,963 | 3,616 | 3,262 |
| MAE | 663 | 547 | 487 | 796 | 755 | 609 |
| Overall absolute overestimation [x1000] | 230 | 166 | 57 | 299 | 270 | 137 |
| Overall relative overestimation | 76% | 55% | 19% | 99% | 89% | 46% |

→ Results show that the SLX model has the highest prediction accuracy.

The prediction error is randomly distributed across Hanover

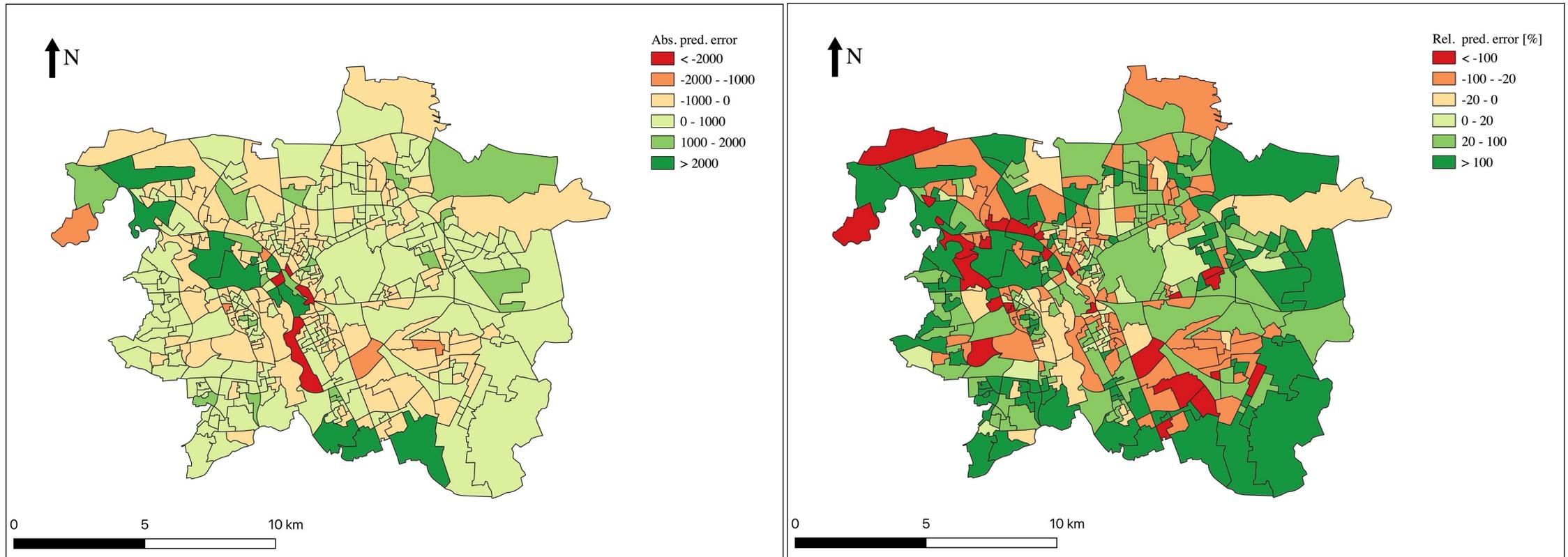


Figure 5: Absolute and relative prediction error for the demand prediction in Hanover based on the Hamburg model.

Conclusion

Conclusion

- Similar results for Hamburg and Hanover indicate a relatively stable demand pattern across cities.
- The centrality variable improves each model but is not suitable to control for the spatial pattern in both models.
- While the global trip prediction is relatively accurate, there are local deviations.
- The model provides an easily transferrable approach to estimate ride-pooling demand in new cities.
- **Multiple limitations** need to be considered:
 - Unobserved spatial impact factors
 - Supply impact
 - Competition

Thank you for the attention!

Questions?

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