Evaluating low-carbon urban planning strategies across urban typologies using causal machine learning

Florian Nachtigall, Felix Wagner, Felix Creutzig

Motivation

Informing low-carbon urban planning globally

Problem

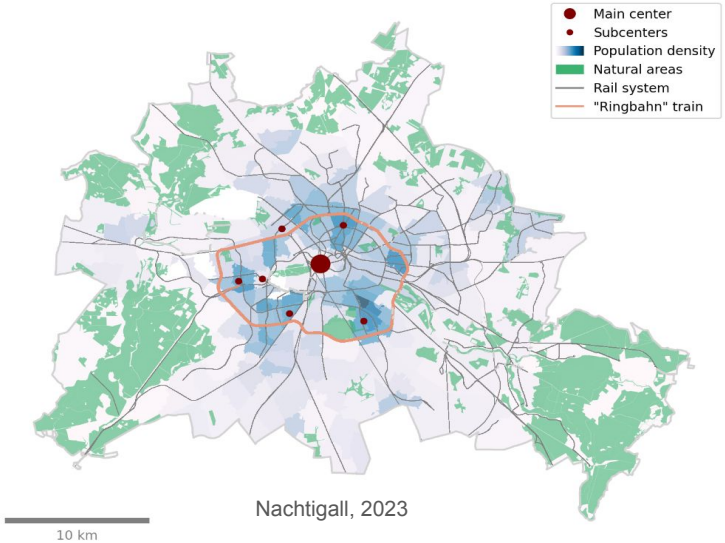
- General planning concepts such as compact or transit-oriented development are recommended by the IPCC
- A place-specific understanding of how this translates to the local context is lacking

Goal

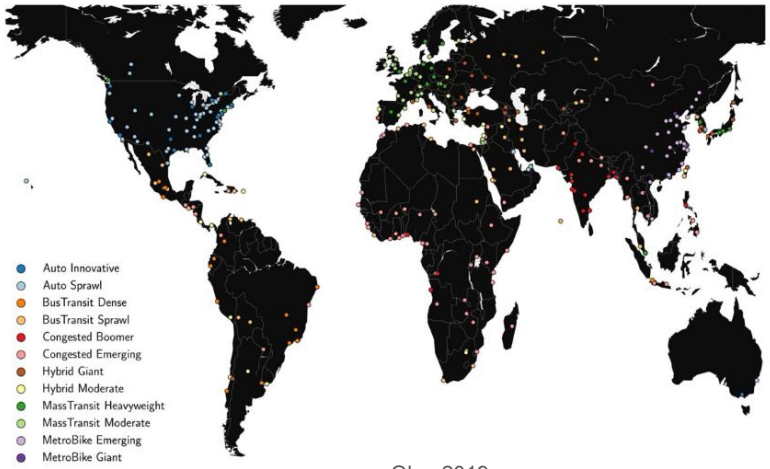
- Develop a methodology that identifies optimal locations for low-carbon housing development while accounting for the local context
- Evaluate which urban planning strategy works best in which context

Research questions

Low-carbon urban planning



Nachtigall, 2023



Oke, 2019

(1) Where to locate new housing to minimize travel-related CO_2 emissions of future residents?

(2a) How do cities differ in this regard?

(2b) Can an urban typology help guide cities on where to locate new housing?

Methods

I. Data & preprocessing II. Feature engineering III. Causal inference

From travel surveys to a typology for low-carbon urban planning

1. **Inventorying induced CO_2 emissions:** For each neighborhood, determine influence of the built environment on travel-related CO_2 emissions of residents
2. **Scenario analysis:** Which residential planning strategy minimizes CO_2 emissions?
3. **City comparison:** How do optimal strategies and spatial patterns of induced CO_2 emissions differ?

current status

4. **Urban typology:** Identify clusters of cities with common decarbonization pathways

Methods

How to determine travel-related CO_2 emissions of future residents?

1. Inventorying induced CO_2 emissions

1.1. **Surveyed travel behavior**

Calculate household travel-related CO_2 emissions
from travel diaries based on mode-specific emission factors

1.2. **Household** travel-related CO_2 emissions

Relate travel behavior to built environment characteristics of the neighborhood
and determine how it facilitates travel-related CO_2 emissions on average

1.3. **Neighborhood average** of travel-related CO_2 emissions

Control for residential self-selection
via socio-demographics & travel-related attitudes

1.4. **Debiased neighborhood average** of travel-related CO_2 emissions

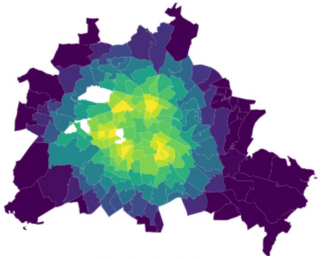
Methods

How to determine travel-related CO_2 emissions of future residents?

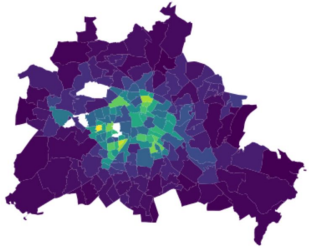
SrV travel survey

Mode	Trip_Purpose	Trip_Duration	Trip_Distance	emissions
Transit	Home-Work	20	729.0	47.385
Transit	Work-Home	30	729.0	47.385
Foot	Home-Leisure	30	7000.0	0.000
Foot	Leisure-Home	10	254.0	0.000
Foot	Leisure-Home	30	7000.0	0.000
...	...	...	...	...
Car	Home-Work	60	28110.0	4553.820
Car	Work-Home	60	26952.0	4366.224
Transit	Home-Work	70	22268.0	1447.420
Car	Home-Shopping	10	2581.0	418.122
Car	Shopping-Home	10	2581.0	418.122

Distance [m] to nearest subcenter



POI density index



Learning the relationship between BE, RSS & TB

DML model

Estimating the debiased effect

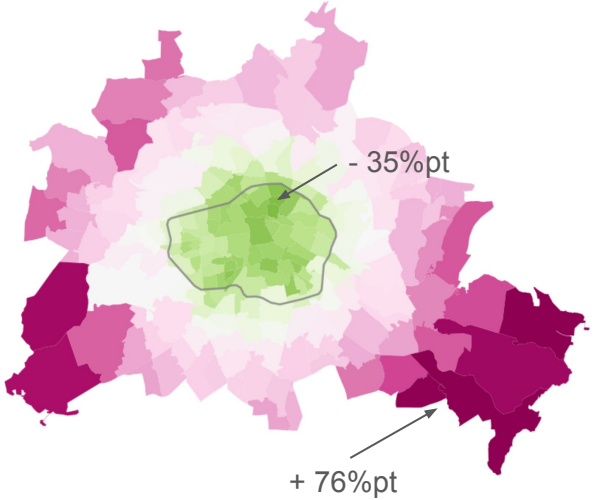


Figure 1. Average effect of built environment on travel-related CO_2 emissions for each neighborhood in Berlin

Results

I. Berlin case study II. Scaling across Europe III. Identifying patterns across cities

Berlin case study: Evaluating planned housing projects

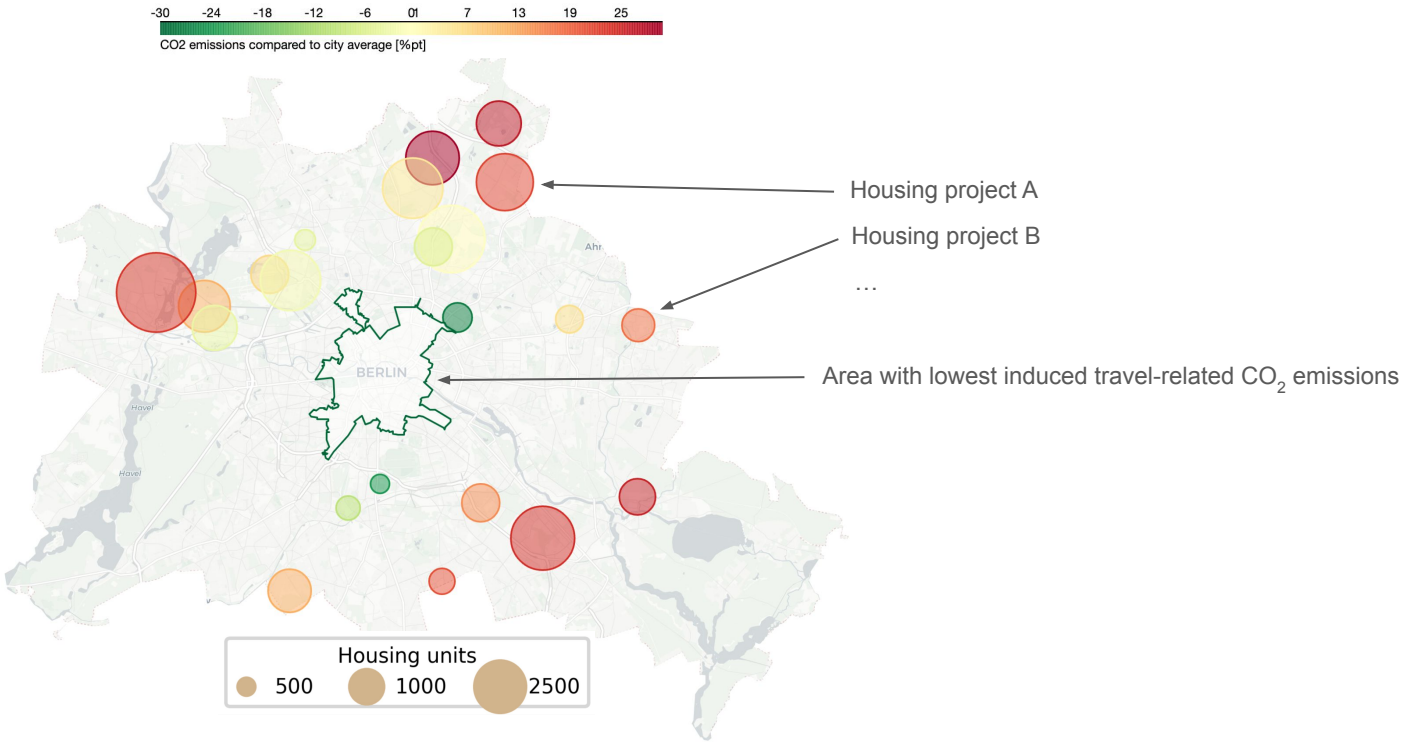
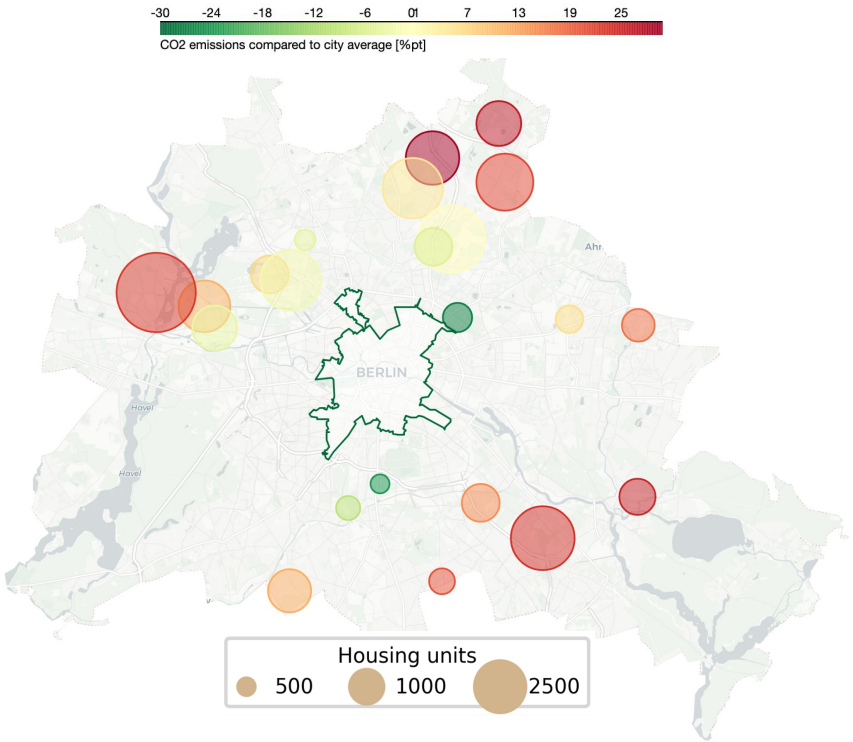


Figure 2. Induced travel-related CO_2 emissions from planned residential projects compared to the urban average.

Berlin case study: Evaluating planned housing projects



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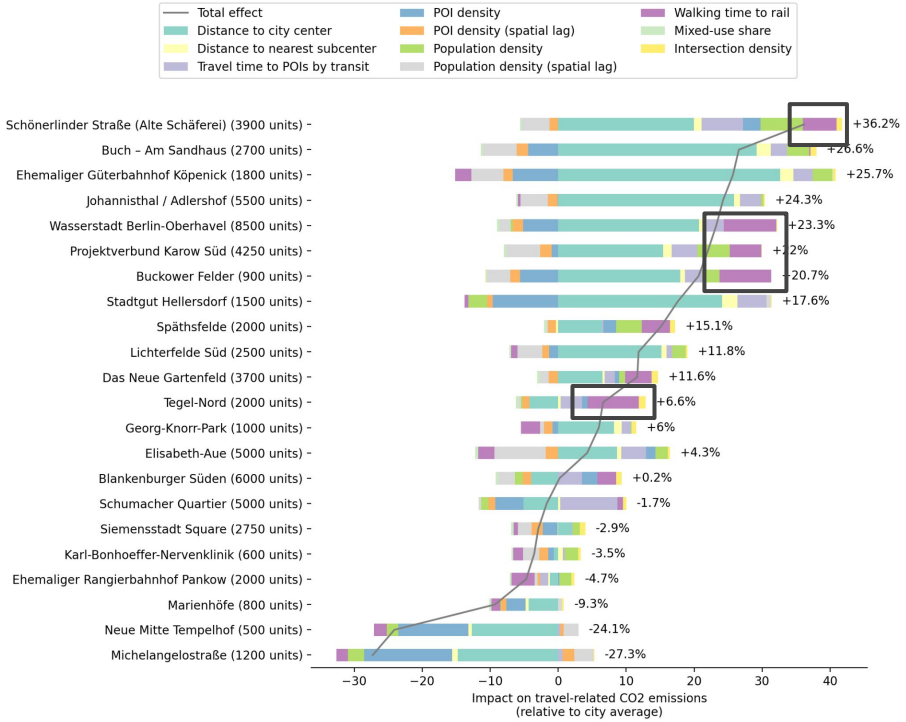
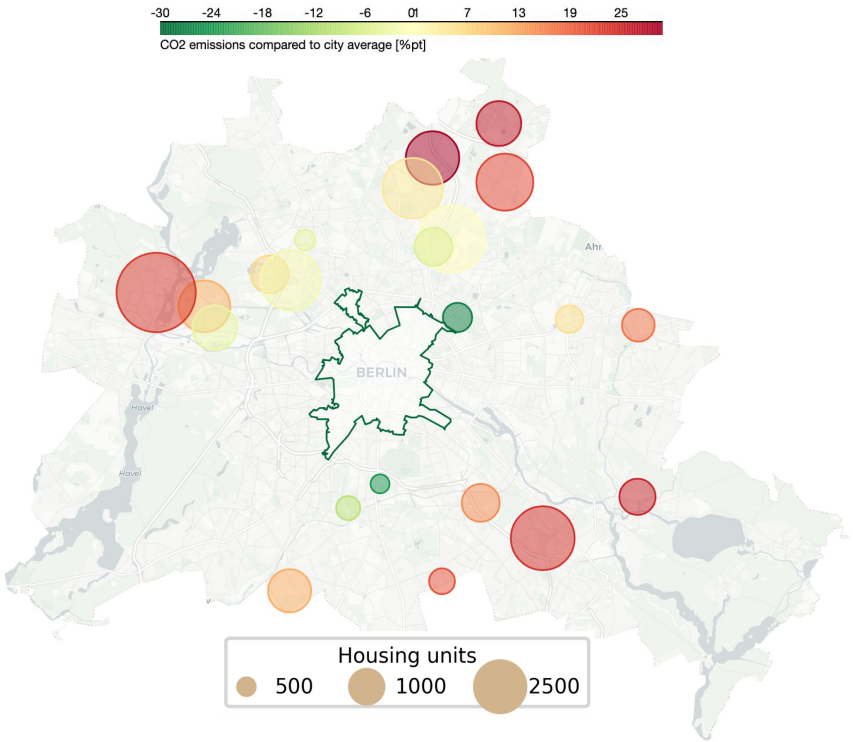


Figure 3: Decomposition of the built environment effect for each planned settlement

Berlin case study: Evaluating alternative planning strategies



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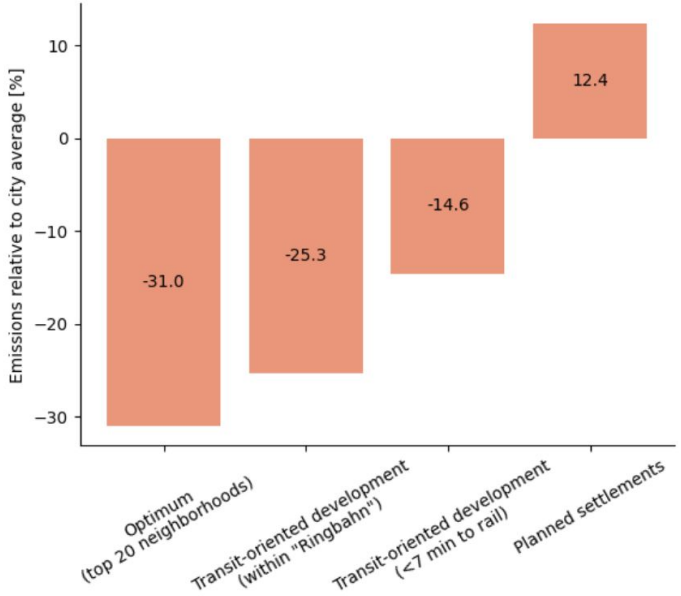


Figure 4: Comparison of different residential planning strategies.

Scaling to other European cities

- Analyzing 19 European cities from Berrill et al., 2024

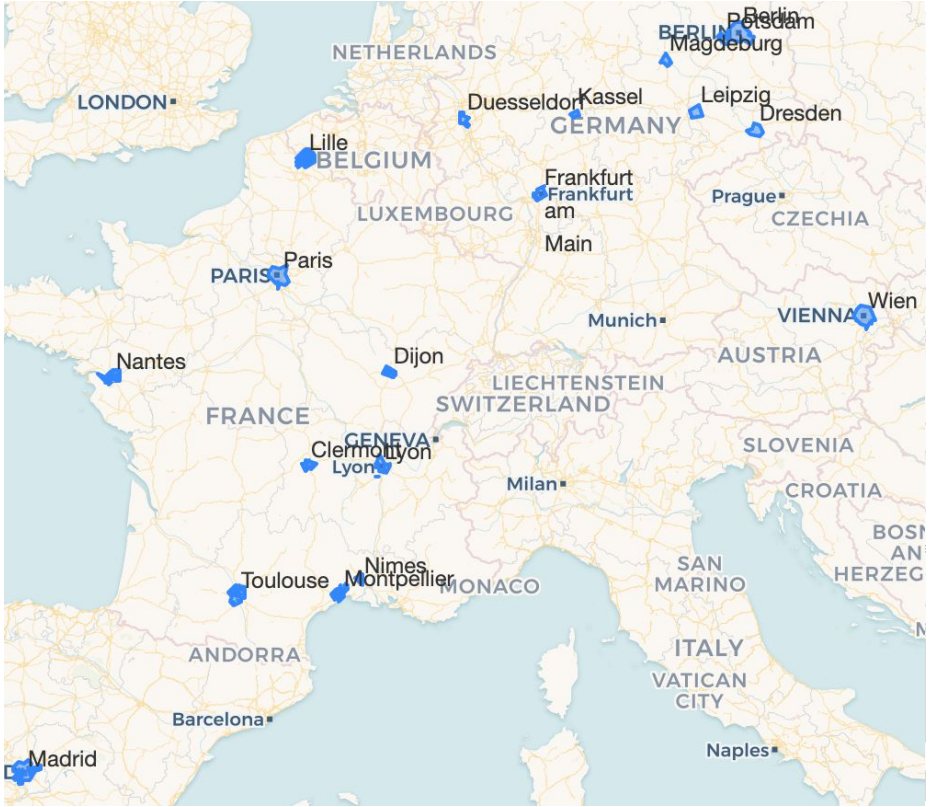


Figure 6. Overview of analyzed cities.

How do cities differ in how their built environments affect travel?

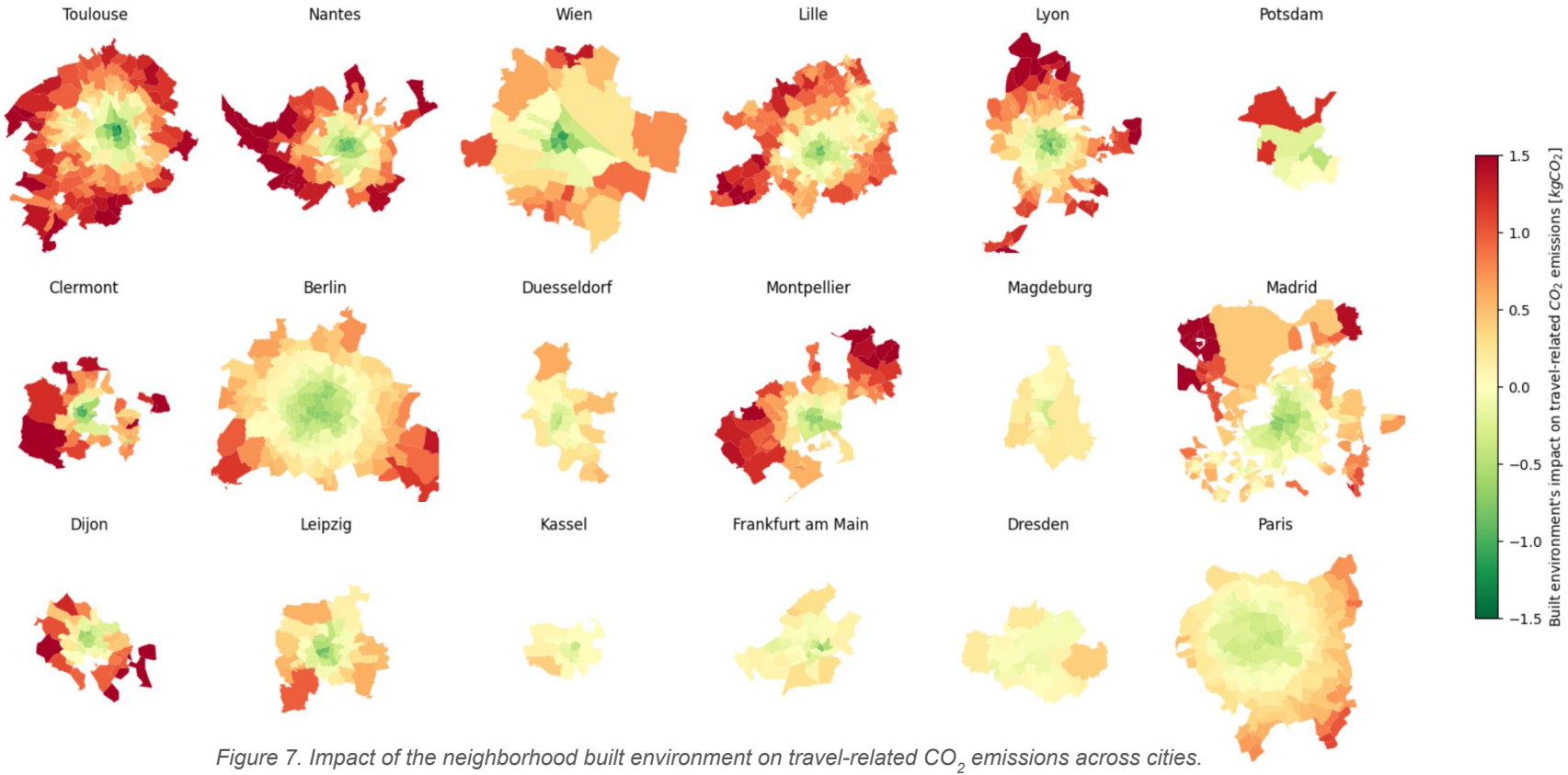


Figure 7. Impact of the neighborhood built environment on travel-related CO_2 emissions across cities.

Emissions savings from compact development

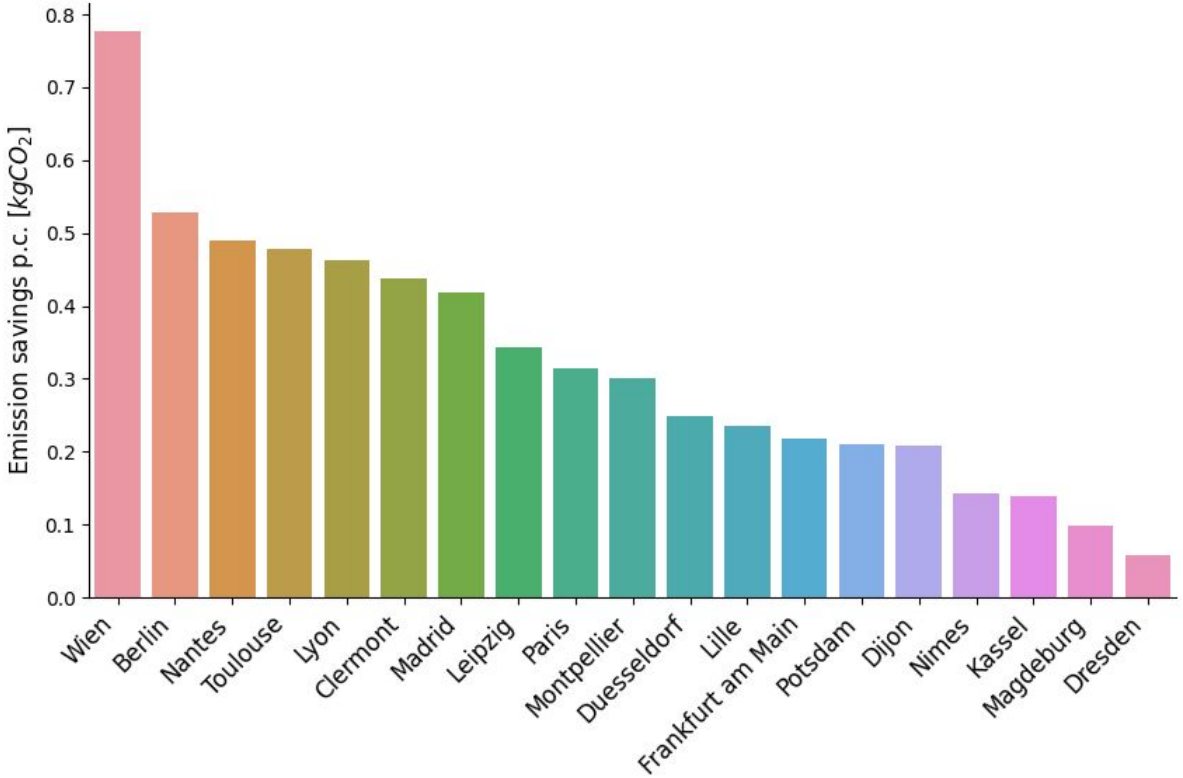


Figure 9: CO_2 savings from compact development within 5 km radius of most sustainable neighborhood.

Spatially differentiated compact development

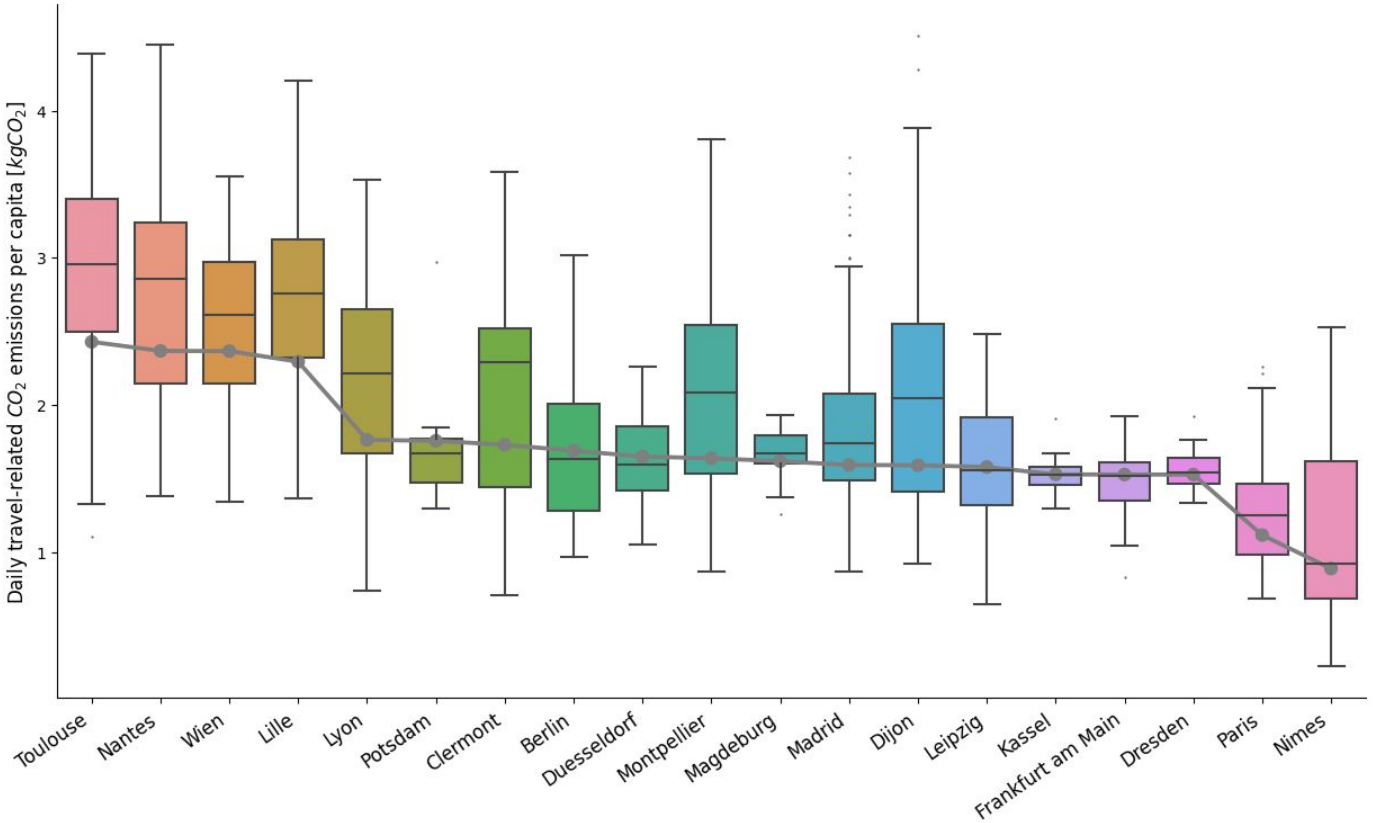


Figure 10. Boxplot of variance in neighborhood travel-related CO_2 emissions due to the built environment. The gray line indicates the average household emissions in the city.

Spatially differentiated compact development

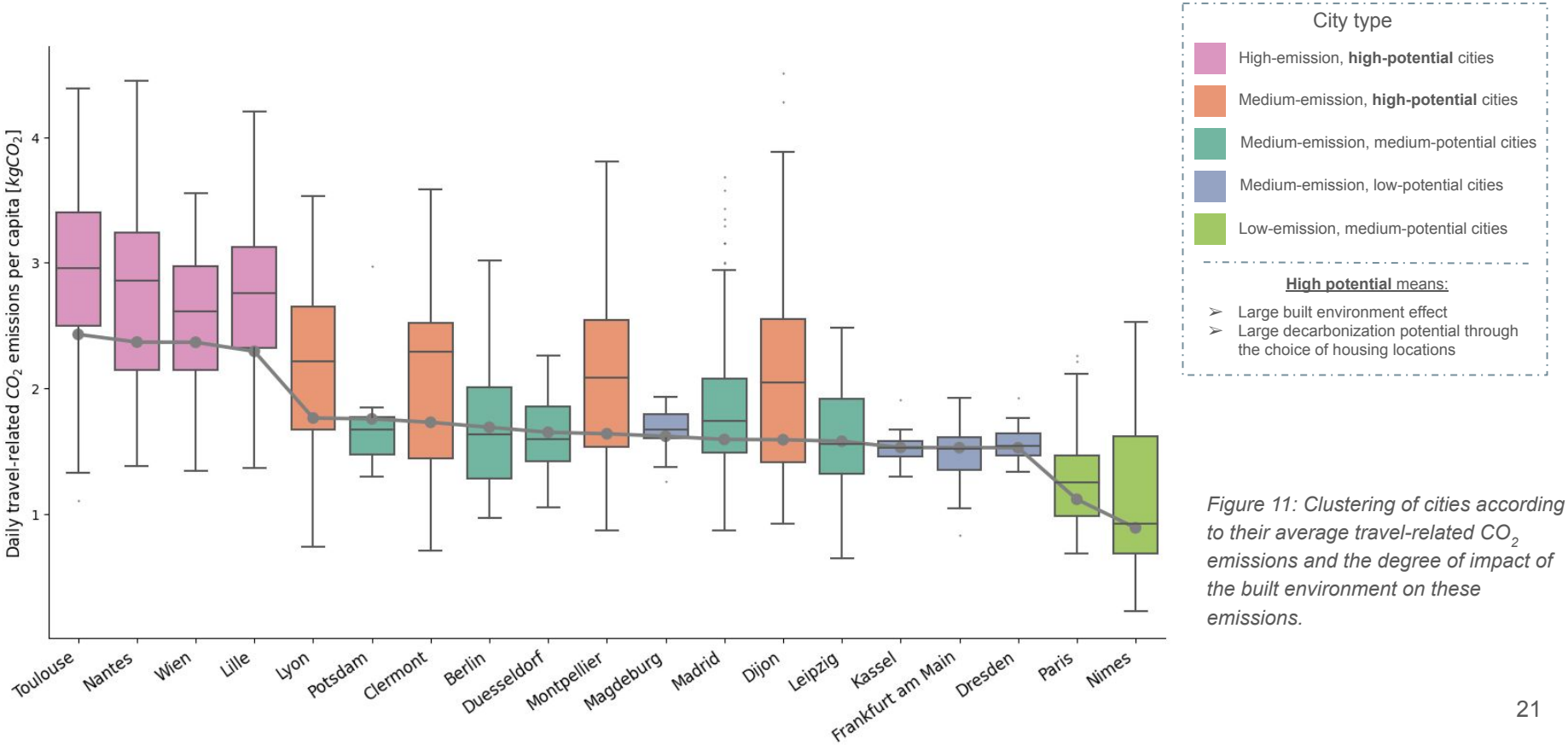


Figure 11: Clustering of cities according to their average travel-related CO_2 emissions and the degree of impact of the built environment on these emissions.

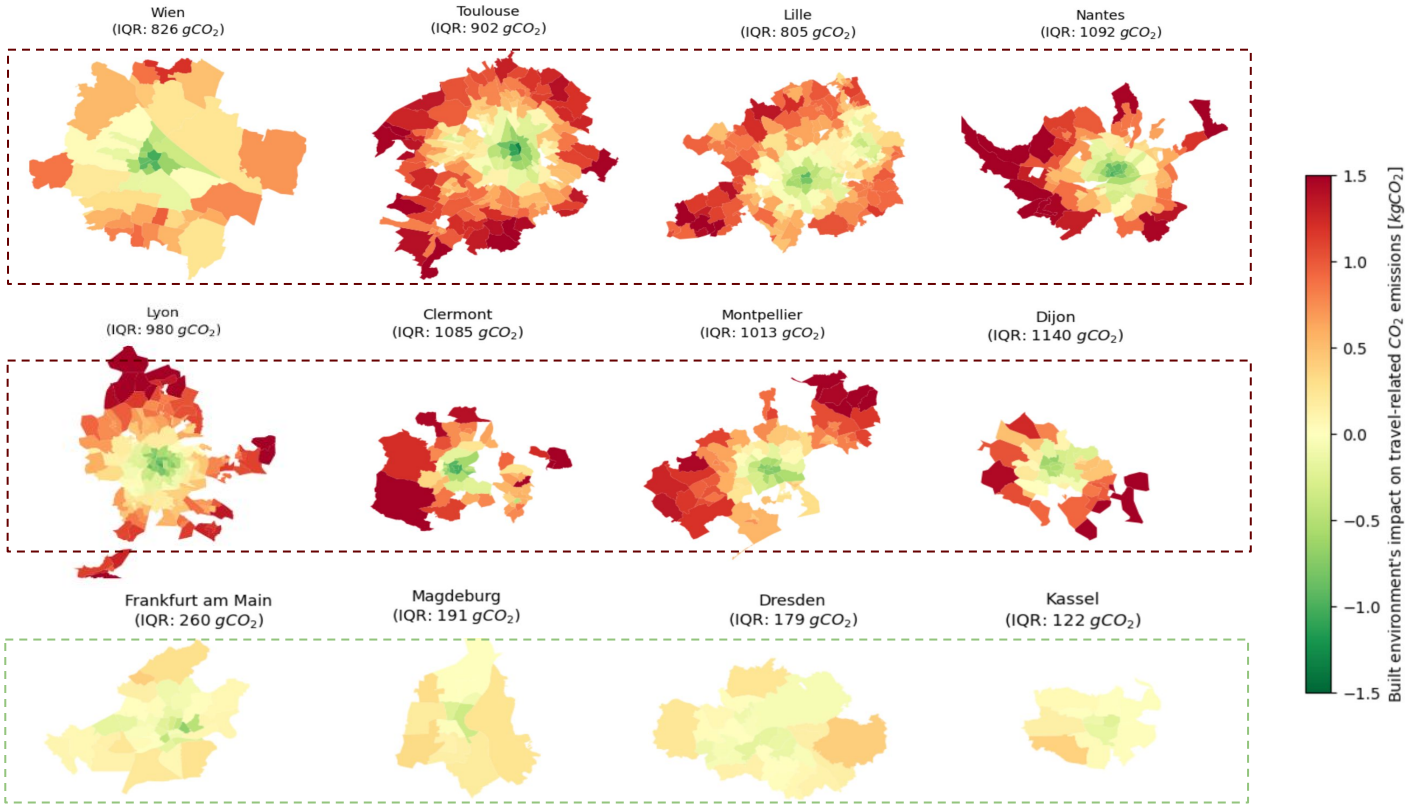
Discussion

Low-carbon urban planning for:

High-emission, **high-potential** cities

Medium-emission, **high-potential** cities

Medium-emission, **low-potential** cities



Take-aways

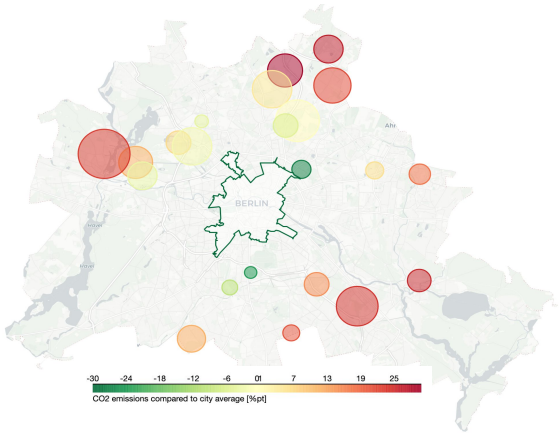
Using travel surveys, each neighborhood's impact on travel-related CO_2 emissions can be determined, enabling:

1. Evaluation of locations for housing projects & spatially differentiated compact development

Applying the approach across multiple cities allows for:

2. Identifying cities with urgent need and large urban planning leverage to decarbonize transport
3. Identifying shared spatial patterns, deriving an urban typology for low-carbon residential planning [outlook]

1



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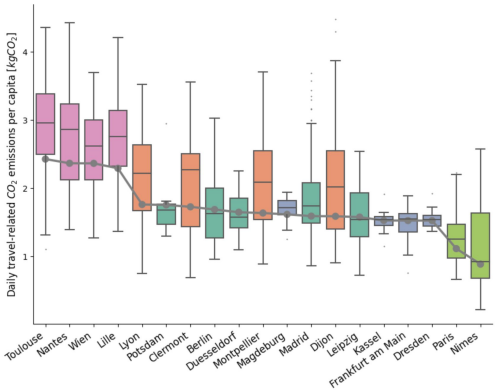

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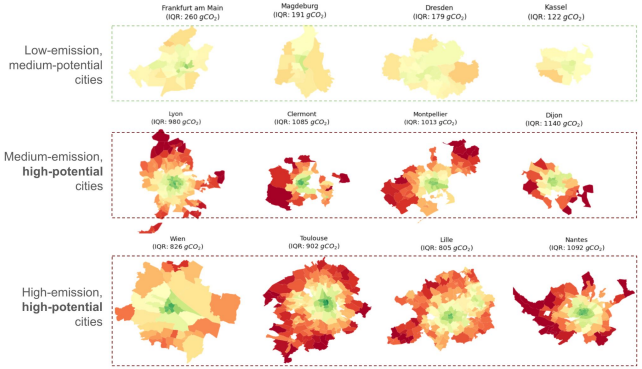

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Feature engineering: Built environment & travel preferences

5D's of compact development	Feature name	Description
Destination accessibility	Distance to center	Distance to neighborhood with highest POI density
	Distance to subcenter	Least distance to any of the 10 neighborhoods with highest POI density
	POI density index	Local POI density for offices, schools, kindergarten, and universities
Density	Population density	Population density of the built-up area
Diversity	Land use	Share of mix-use areas
Design	Car-friendliness index	Provision of expressway kilometers per capita
	Walkability index	Intersection density in the built-up area
Distance to transit	Transit accessibility index	Gravity model-based index describing the average spatio-temporal transit accessibility of a neighborhood

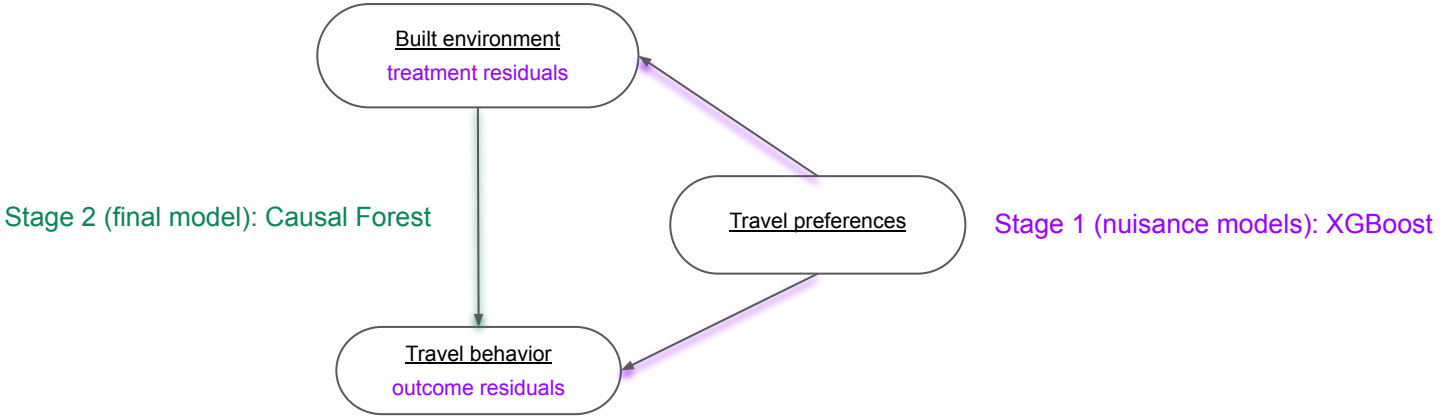
Table 2: ***Built environment characteristics.*** *Overview of all built environment characteristics considered in*

Category	Variable name	Description
Socio-demographics	Income	Average household income
	Household size	Average number of persons living in a household
	Age	Average age of adult (>18 years) residents
	Higher education	Share of people older than 25 with university degree
Proxies for travel-related attitudes	Car ownership	Average number of private & company cars per household
	Bike ownership	Average number of bicycles owned per person
	Driving license	Average share of adults (>18 years) with driving license
	Transit subscription	Average share of people with monthly transit subscription (incl. children and people with disabilities with free ride tickets)
	Political preferences	Electoral share of the Green party in constituencies intersecting the neighborhood in the last regional elections

Table 1: ***Travel preferences.*** *Overview of all socio-demographic traits and proxies for travel-related attitudes*

Controlling for residential self-selection using Double Machine Learning

Identify treatment level	Define treatment as the difference to the average built environment
Stage 1: Debiasing / estimation of nuisance parameters ■ Predicting outcome from controls -> *outcome residuals* ■ Predicting treatment from controls -> *treatment residuals*	Stage 1: Debiasing / estimation of nuisance parameters ■ Predict CO_2 emissions from travel preferences ■ Predict built environment (choice) from travel preferences
Stage 2: Estimation of heterogeneous treatment effect ■ Predicting *outcome residuals* from *treatment residuals* and controls	Stage 2: Estimation of heterogeneous treatment effect ■ Predict residual CO_2 emissions from built environment residual



Berlin case study: Evaluating planned housing projects

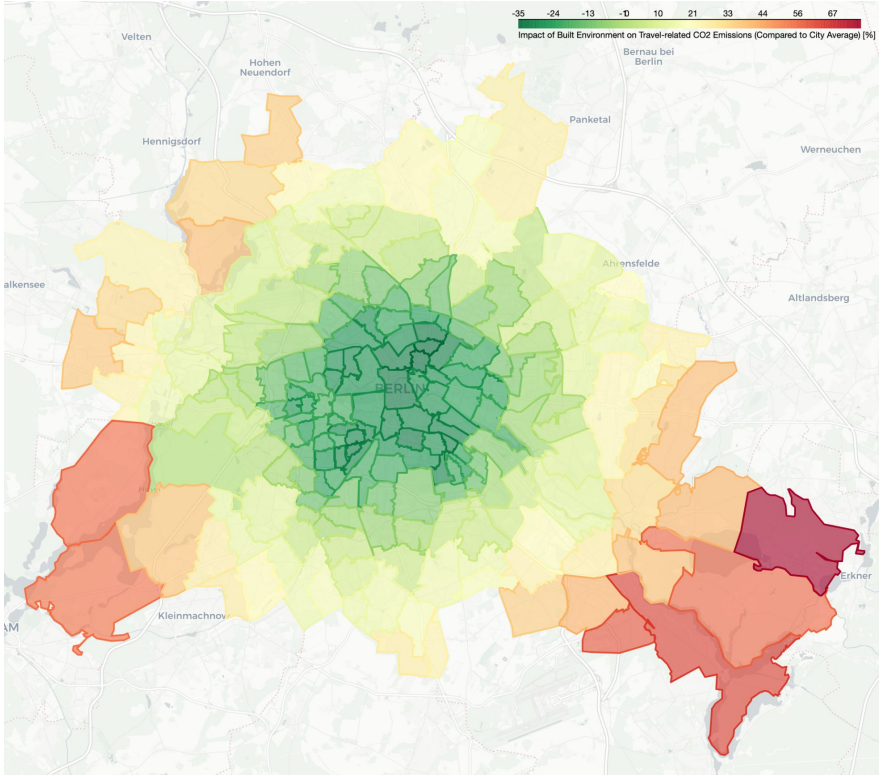
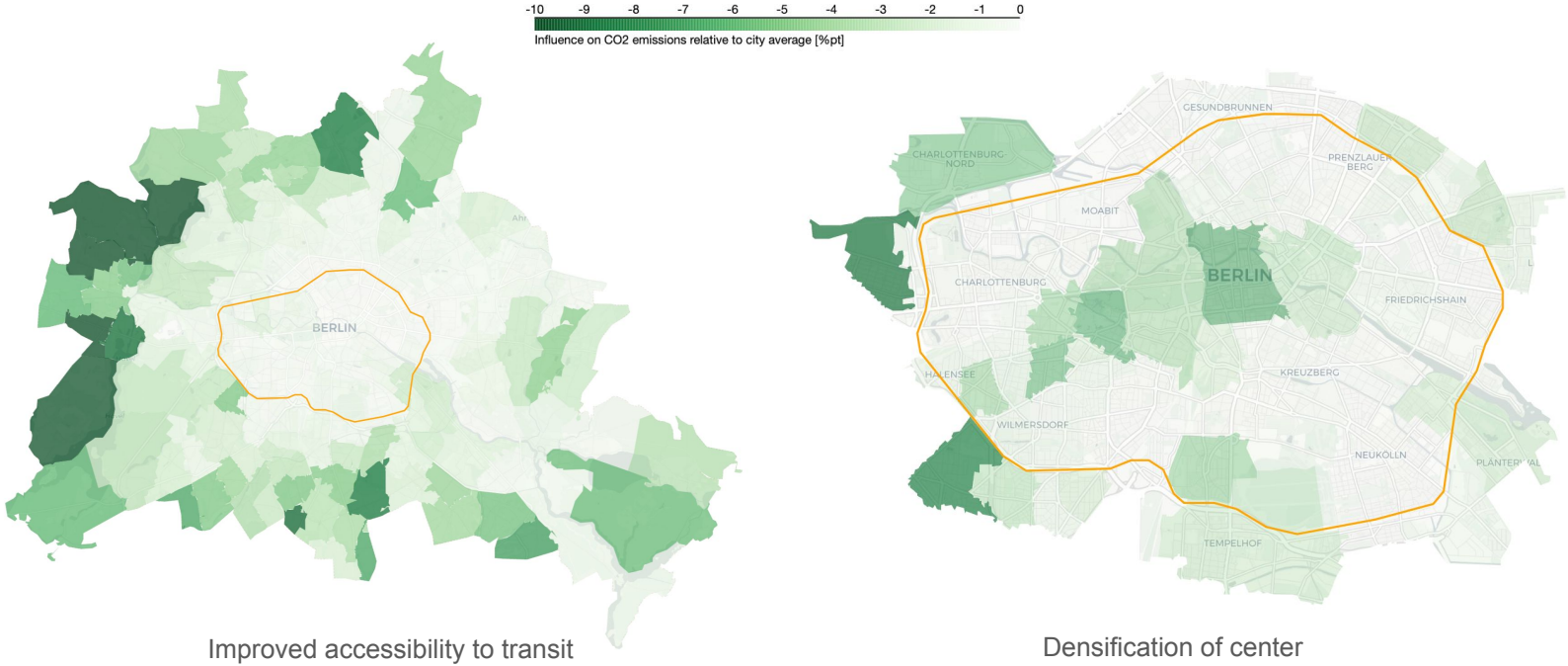


Figure 2. Induced travel-related CO_2 emissions compared to the urban average.

Berlin case study: Modeling of increased density & transit accessibility



Improved accessibility to transit

Densification of center

Figure 5: Prospective modeling of urban planning scenarios in terms of their impact on travel-related CO_2 emissions.

Low- and high-emission neighborhoods

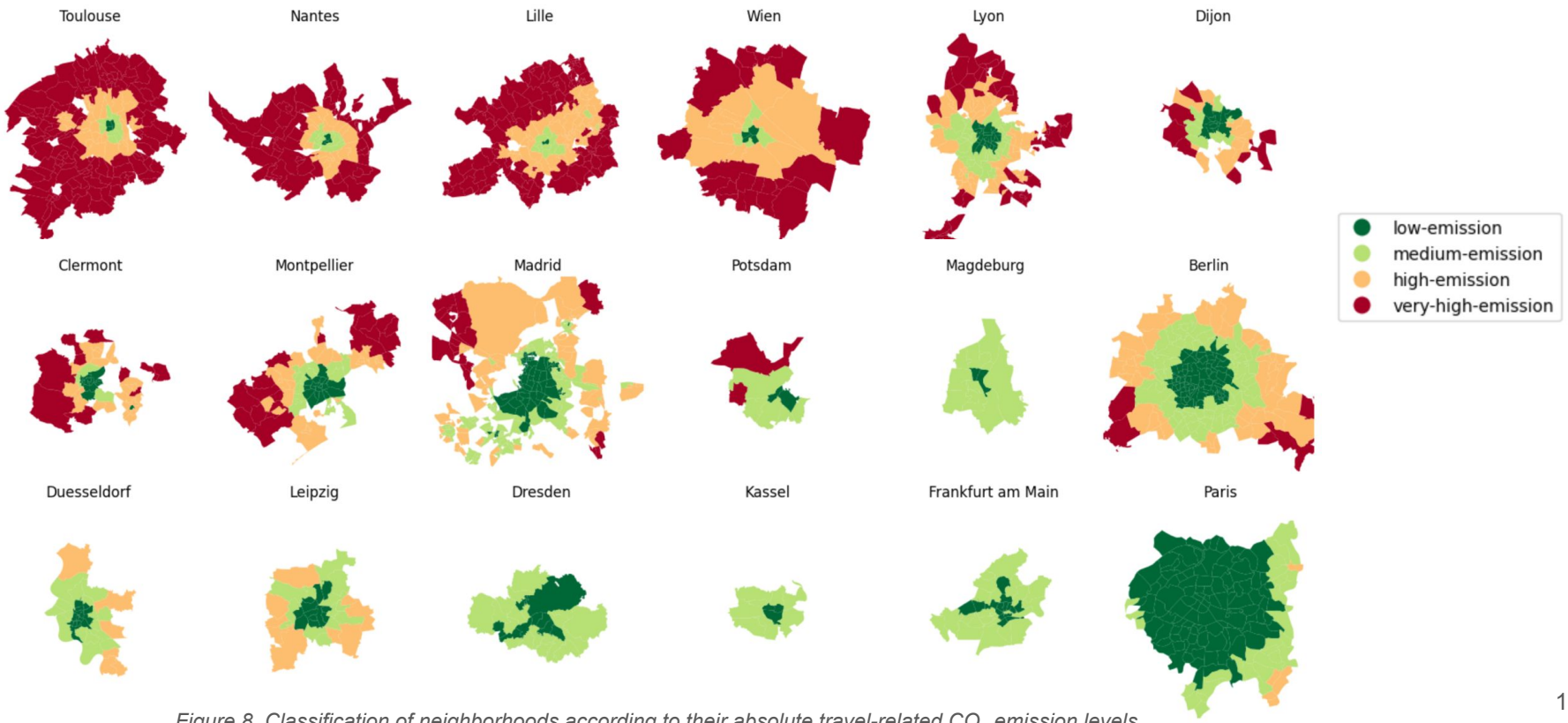


Figure 8. Classification of neighborhoods according to their absolute travel-related CO_2 emission levels.

Spatially differentiated compact development

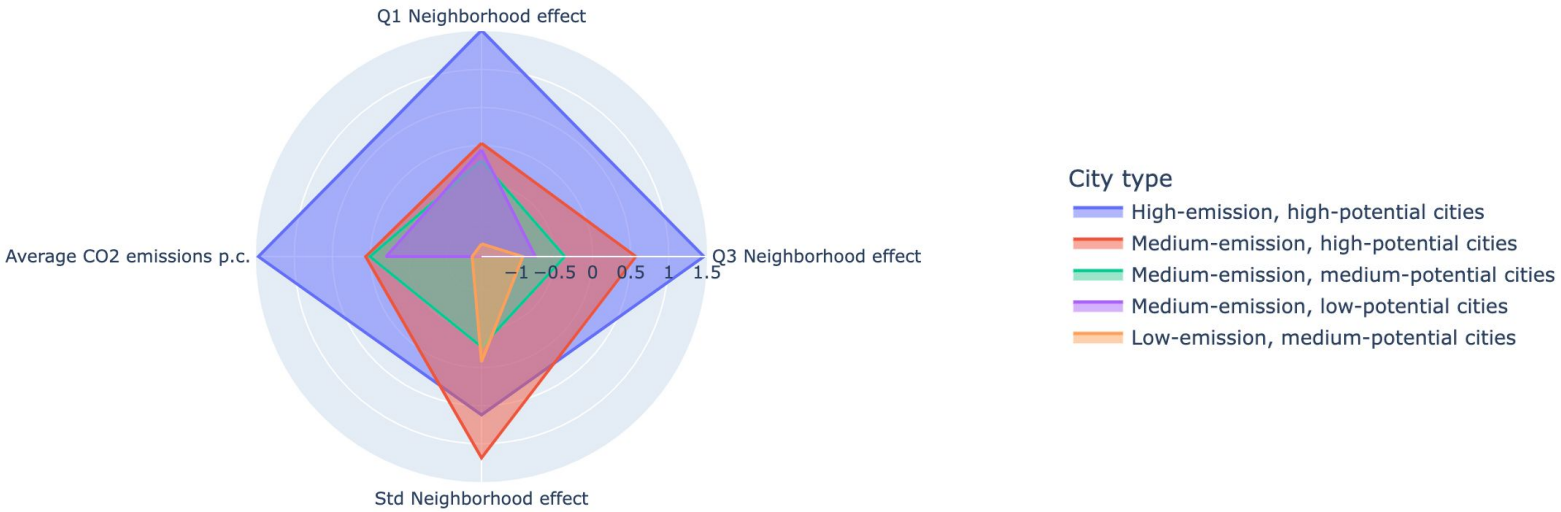
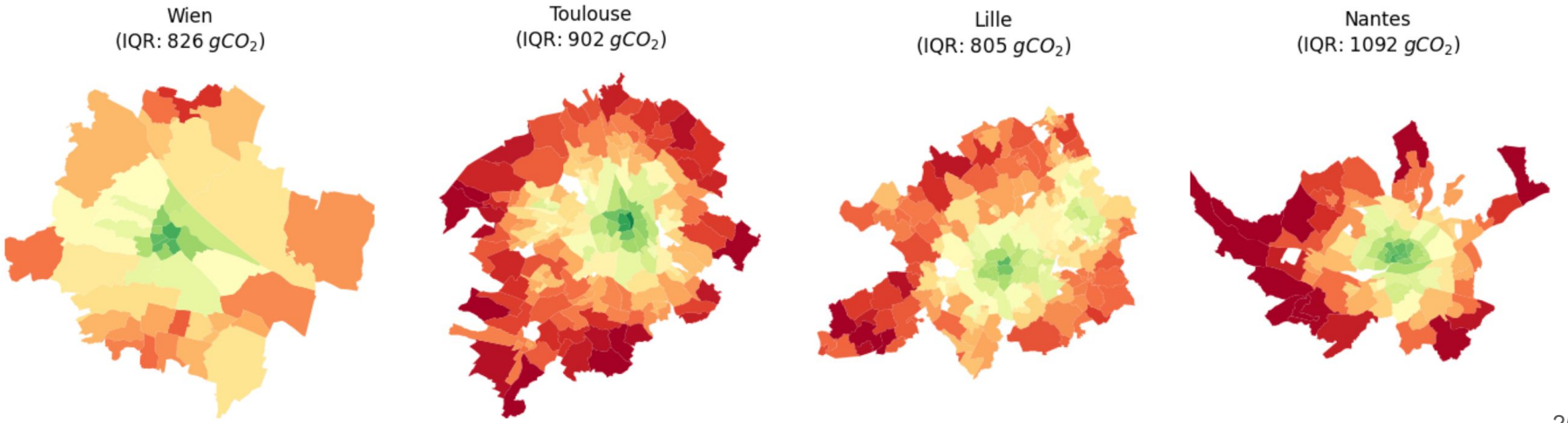


Figure 12: Difference between city clusters in terms of their average travel-related CO2 emissions and the 25th percentile, 75th percentile, and standard deviation (std) of the neighborhood built environment effect on emissions.

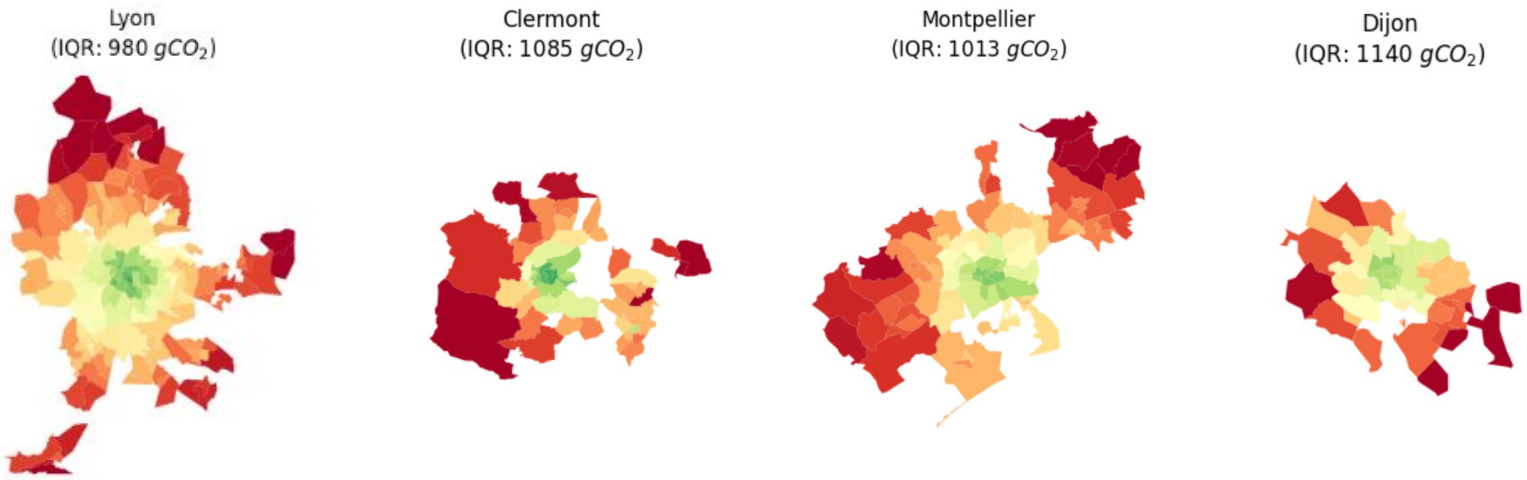
Low-carbon urban planning for: High-emission, high-potential cities

- High per capita travel-related CO_2 emissions
  - ➢ Urgent need for decarbonization of urban transport
- Large impact of built environment on travel-related CO_2 emissions
  - ➢ High potential for targeted compact development



Low-carbon urban planning for: Medium-emission, high-potential cities

- Large impact of built environment on travel-related CO_2 emissions
  - ➢ High potential for targeted compact development



Low-carbon urban planning for: Medium-emission, low-potential cities

- Impact of the built environment on travel-related CO_2 emissions differs only marginally within the city
  - ➢ Absolute emissions are similar between neighborhoods
  - ➢ Lower mitigation potential through targeted residential planning