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# Identifying and analyzing logistics land use: a case study of the Rhineland Metropolitan Region

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**Abstract.** In Germany, the identification of logistics land is rarely done, among other things due to the anonymization of employment and building data. The paper at hand gives an overview of data sources used for the identification of spatial patterns of logistics facilities and presents a method for identifying logistics land based on publicly available data, to present an image of the existing spatial structure of logistics land. Identified spatial hotspots are mostly located in Metropolises/Regiopolises and their suburbs, along highways in areas with flat relief, and in the vicinity of large inland terminals/inland harbors.

## 1 Introduction

Logistics activities account for a large part of land consumption. In Germany, warehouse buildings contributed about 25% of all built floor space of non-residential buildings in 2018 (Kretzschmar et al. 2021). Construction activity concentrates on a few municipalities with good transport infrastructure connections (ibid.).

Concerning the investigation of spatial patterns of logistics facilities, extensive international studies are available. Nevertheless, only Holl, Mariotti (2017) provide an overview of the methods and databases used for individual international studies, which, however, does not include German-language studies and does not focus in detail on the databases used. In Germany, there still exist only aggregated studies of logistics real estate at the NUTS 3 level (corresponding to the level of counties) or municipality level (e.g. Klauenberg, Krause Cauduro 2020, Busch 2013, Kretzschmar et al. 2021), which is also due to problems with the availability and quality of relevant data sources. In particular, small-scale studies at the level of individual logistics facilities and their respective estates have not yet been carried out.

We want to close this gap in the following article. We present a dataset that, for the first time, shows small-scale spatial patterns of logistics estates in a German study area. Based on the developed dataset, we exemplarily identify hotspots in logistics land[1].

The paper is structured as follows. Section 2 introduces the background and thereby provides inter alia an overview of data sources used for the identification and examination of spatial patterns of logistics facilities. Section 3 introduces the study area. After that, Section 4 presents the methods of identifying logistics land and further data preparation. Section 5 presents the examination of spatial autocorrelation, inter alia, the identification of hotspots of logistics land. Section 6 draws conclusions based on these examinations.

[1]The dataset can be download from https://doi.org/10.57806/dkmd9hk5

## 2 Background

In this section, we provide an overview of existing databases that are used in the study of spatial patters of logistics facilities and the specific difficulties that exist in this regard for German study areas.

### *2.1 Existing data on spatial patterns of logistics facilities*

The existing analyses of spatial patterns of logistics facilities can essentially be broken down into

- company/employment data
- data on construction activity/property trading
- survey data
- development of own databases/data fusion.

There are also special cases, such as the use of GPS tracks (see e.g. Trent, Joubert 2022). Apart from a few studies like Busch (2013), Jaller et al. (2022), Heitz et al. (2019), or Nefs et al. (2024), there is usually no consolidation of data.

#### 2.1.1 Company/employment data

Company and employment enable a view of logistic-specific companies and employment in small-scale areas such as municipalities. The classification of economic activity is generally used to identify data on logistic-specific employment and companies. For that, the Europe-wide NACE classification can be used.

Jaller et al. (2022) base their analyses in Southern California on the US Zip Code Business Patterns (ZBP), which provide information on the number of companies and employment (here NAICS 493: Warehousing and Storage; comparable to NACE 52.1) between 1998 and 2016 at the postcode district level. Holguín-Veras et al. (2022) uses the same data basis but also uses a categorization of all economic sectors into freight-intensive and service-intensive sectors from Holguín-Veras et al. (2016).

Klauenberg, Krause Cauduro (2020) and Heitz et al. (2017) base their analyses in Berlin/Brandenburg and the metropolitan regions of Paris and Randstad on aggregated company figures for NACE category 52.1 (warehousing) at the municipal level. Heitz, Beziat (2016) supplement their data from the business register for parcel services (NACE categories 52.29 and 53.20) with additional interviews with parcel service providers, as it is clear that only some of the locations of parcel service providers can be identified from the data.

The employment data is also classified in the International Standard Classification of Occupations (ISCO-08). Busch (2013) uses this classification and queries the number of employees according to various NACE aggregates (including retail (NACE G), transport and storage (NACE 49-52), CEP (NACE 53)) for the occupational group 513 'Warehousing, postal and delivery services and goods handling' for German NUTS 3 areas. Due to anonymization regulations, such surveys in Germany can only be carried out at this aggregated spatial level.

#### 2.1.2 Survey data

In their study, Sakai et al. (2015) use a freight survey in the Tokyo metropolitan region from 2003, which includes 4,109 responses (including 2,803 responses with >400 m² of floor space) from companies that use logistics facilities. The advantage here is that, in addition to data on the respective logistics facilities, logistical behavioral data can also be queried. Thus real origin-destination-relations can also be depicted. The following data on the respective companies were collected as part of the survey:

- year of construction of the logistics facility used
- tonnes transported
- truck trips generated
- goods handled
- origin and destination of the shipments.

#### 2.1.3 Data on construction activity/real estate industrial transactions

Another option, particularly for the observation of time series, is the use of transaction data in property trading or the observation of construction activity of logistics facilities.

Jaller et al. (2022) do the former: they look at transaction data for properties in Southern California between 1989 and 2018. Inter alia, these are typified by warehouse buildings and distribution buildings. Busch (2013) and Kretzschmar et al. (2021) analyze the construction activity of logistics facilities in Germany by looking at completed warehouse buildings in the statistics on construction work completed, which are part of the construction activity statistics. The main challenge here is that the identification of warehouse buildings differs depending on the relevant state statistics authority (Busch 2013). Furthermore, the reported time of building completion often does not correspond to the actual time; instead, there are often delays in reporting (Kretzschmar et al. 2021), which leads to inaccuracies.

#### 2.1.4 Development of own databases/data fusion

Heitz et al. (2019) and Nefs et al. (2024) generate their own databases by fusing datasets.

Heitz et al. (2019) implement this for the Paris metropolitan region and justify their approach by arguing, among other things, that no clear allocation to the respective logistics segment can be derived solely from the allocation to the economic activity. They use a dataset comparable to the German business register and a list of large French warehouses (Répertoire des Entrepôts) as a basis. Specific buildings are validated with aerial and street images. In addition, areas, where logistics land uses are to be expected, are searched manually, and aerial photographs and planning documents are scrutinized. The identified buildings are geocoded, and further information is added. This includes

- function of the logistics facility under consideration
- type of logistics company that operates the logistics facility under consideration
- goods processed/transhipped there (specific (beverages, food, equipment), generic (e.g., parcels, general cargo))
- destinations of the processed/transhipped goods (households, companies by sector)

Nefs et al. (2024) implement this for the Netherlands and generate a time series of logistics facilities and their respective estate for the period from 1980 to 2021. Microdata from the official Dutch business register is used for this purpose, which provides information on specific company locations, the number of employees, and the specific NACE classification of economic activity. In addition, another source on current and planned commercial estates and OpenStreetMap is used. The year of construction is also obtained from a building administration dataset. Furthermore, a visual validation is carried out, in particular, to take into account newly built, very large distribution centers, based on Google Streetview.

To extrapolate the land use of warehouse buildings at the level of NUTS 3 areas, Kretzschmar et al. (2021) use, among other things, information on the floor space of completed buildings from the construction activity statistics, and - to calculate standard values for the ratio between building footprint and total estate occupied - building footprints from an official building dataset and land lots used industrially or commercially from the Cadastre Information System ALKIS.

#### 2.1.5 Special case: GPS tracks of truck trips

One in literature discussed effect of the phenomenon of logistics sprawl is the increasing number of truck mileage. Data on real trips to/from logistics facilities can be used to empirically analyze this much-discussed effect when viewed over time. To date, there have been very few studies on this. Trent, Joubert (2022) use GPS tracks of around 16,000 vehicles used for commercial transport (1-2% of the total fleet) in South Africa between 2010 and 2014, which depict journeys in the metropolitan regions of Gauteng, Cape Town, and eThekwini.

#### 2.1.6 Additional secondary data

Further data are used when analyzing spatial patterns of logistics facilities. These essentially include:

- socio-demographic data (included in Jaller et al. 2022, e.g. population, median age, proportion of white population, median household income, median household value, public transport users)
- Data on infrastructure relevant to freight transport (locations of CT terminals in Jaller et al. 2022)
- Land use (designated commercial areas in Sakai et al. 2020)

Jaller et al. (2022) also draw on an environmental index at the level of US postcode districts, which combines indices on environmental pollution (exposure and environmental effects) and population characteristics (including socio-economic factors) at the level of ZIP code districts in California.

### *2.2 Difficulties in the study of spatial patterns of logistics in Germany*

In Germany, there are currently few studies analysing spatial patterns of logistics, e.g. Klauenberg, Krause Cauduro (2020). This is (so far) mainly due to several problems that arise from a lack of data availability:

- extensive anonymization of employment data on municipality level,
- according to Busch (2013), no clear categorization of a given building concerning the economic activity in building statistics, different from the Dutch and French dataset examined by Heitz et al. (2017),
- no georeferenced data on logistics buildings over multiple periods, such as those used e.g. by Dablanc, Rakotonarivo (2010).

## 3 Study area

The Rhineland metropolitan region is located in the West of the German state of North Rhine-Westphalia (NRW) and includes roughly the two administrative governmental districts of Cologne and Düsseldorf. It includes the metropolises of Dusseldorf and Cologne and the Western part of the Ruhr area. The metropolitan region has a share of 36% of the area of North Rhine-Westphalia and, with a population of about 9 million inhabitants, a share of 50% of the inhabitants. Relevant population growth is particularly evident in the metropolitan areas and their suburbs. Unlike many agglomerations of its size, the Rhineland metropolitan region has a polycentric spatial structure. The metropolitan cores here are Dusseldorf and Cologne.

As a central agglomeration in Central Europe, the Rhineland Metropolitan Region is the location of important transport hubs and at the same time an internationally significant business location and sales market. The metropolitan region is both a relevant source and destination for freight traffic, as well as transit traffic. Together, they contribute to a high utilization and sectional congestion of the road and rail networks and thus to a high demand for logistics space for transshipment and warehousing.

A survey among logistics stakeholders of the Rhineland Metropolitan region, as included in Leerkamp et al. (2022), has revealed the biggest weaknesses of the region in terms of logistics locations (see Figure 1). The most mentioned weakness is congestion of the road network (ibid.). Aspects that contribute to logistics sprawl, like insufficient land availability, high land prices, and lack of support from the public sector are also of high relevance. In this context, the dynamic development of e-commerce will also continue to drive the demand for locations for distribution centers as well as parcel sorting centers. Accordingly, logistics companies expect a high demand for locations on the outskirts and increasingly in the core areas of the region's major cities, too (see Figure 2).

## 4 Identifying logistics land and data preparation

The identification of logistics facilities and estates occupied by them is essentially based on the identification of estates on which logistics buildings are located. This procedure is

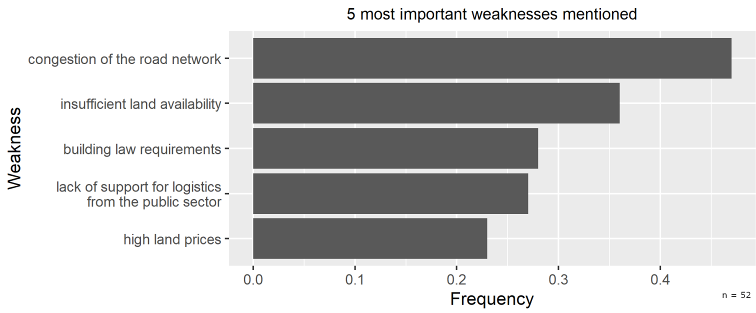


Figure 1: Most mentioned weaknesses of the Rhineland Metropolitan region as a logistics region (Leerkamp et al. 2022)

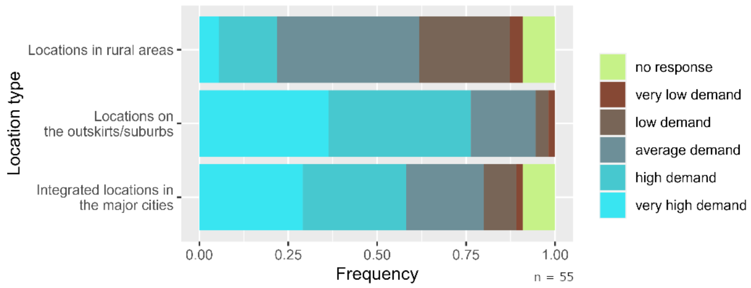


Figure 2: Demand location types for logistics facilities in the study area in the upcoming 5-10 years (Leerkamp et al. 2022)

based on Kretzschmar et al. (2021). In contrast to Kretzschmar et al. (2021), who use logistics facilities identified in exemplary NUTS 3-areas to calculate standard values for the ratio between building footprint and total estate occupied, here the individual logistics facilities identified are themselves analyzed on a small scale (1 km$^2$ grid) for an entire metropolitan region. The fact that several data sources are used with the cadastral data and OpenStreetMap means that the procedure can also be described as data fusion. In the procedure, datasets of estates are merged with datasets of logistics buildings. Figure 3 summarizes the procedure explained in the following.

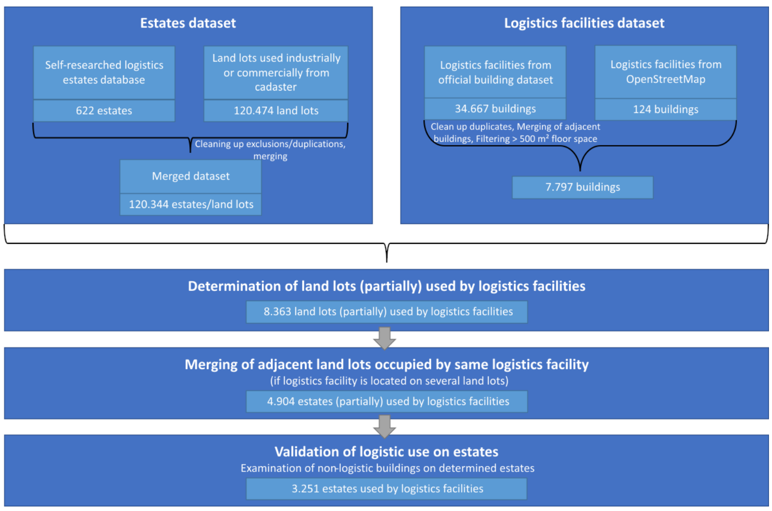


Figure 3: Identification of logistics estates

### 4.1 Used datasets and their preparation

Regarding the estates, two datasets are used. On the one hand, an already existing self-researched logistics estate database created by Leerkamp et al. (2022) and contains 622 existing logistics estates that are bigger than 2 ha. As a basis for the identification of further logistics estates, land lots used industrially or commercially are utilized from the official Cadastre Information System ALKIS (source: Geobasis NRW 2020). After merging and cleaning up the two datasets, 120,344 land lots/estates remain.

The logistics buildings are extracted from two datasets. The first one is an official building dataset (source: Geobasis NRW 2021), that is freely accessible in the state of North Rhine-Westphalia. This dataset also contains detailed information on the function of each building, so logistics buildings can be identified. However, detailed consideration shows that the categorization of the building function is not consistent throughout the region, so some logistics facilities cannot be identified by the official designation of the building function. Therefore, further logistics buildings were extracted from OpenStreetMap (source: OSM 2021).

The first dataset is edited to this effect, that duplicates are removed, adjacent buildings are merged, and very small buildings (< 500 m$^2$ floor space, proceeding according to Busch 2013) are removed. After merging the two datasets, 7,797 logistics buildings remain.

### 4.2 Identification of logistics land

The further identification of logistics land consists of three procedural steps.

The first step is the determination of land lots that are fully or partially occupied by logistics facilities (see left part of Figure 4). As a result, 8,363 land lots remain.

The second step is the generation of estates from the land lots that are (partially) occupied by logistics facilities (see top right in Figure 4). Hence, adjacent land lots, that are occupied by the same logistics facility are merged into one estate. Consequently, 4,904 estates remain, that are at least partially occupied by a logistics facility.

In the third and final step, logistics use of the estates under consideration and that have not been identified by own research is validated. For this purpose, the share of building floor space, that is used by logistics facilities is calculated for each estate (see bottom right in Figure 4). If the share is below 75%, the estate under consideration is removed. This is to ensure that only estates for which logistics is the primary function are considered.

As a result, 3,251 logistics estates are obtained and remain for further examination. Figure 5 shows the size distribution for the estates itself and the building footprints. The median of the estate size is 0.5 ha, whereas the median of the building footprint is 0.17 ha.

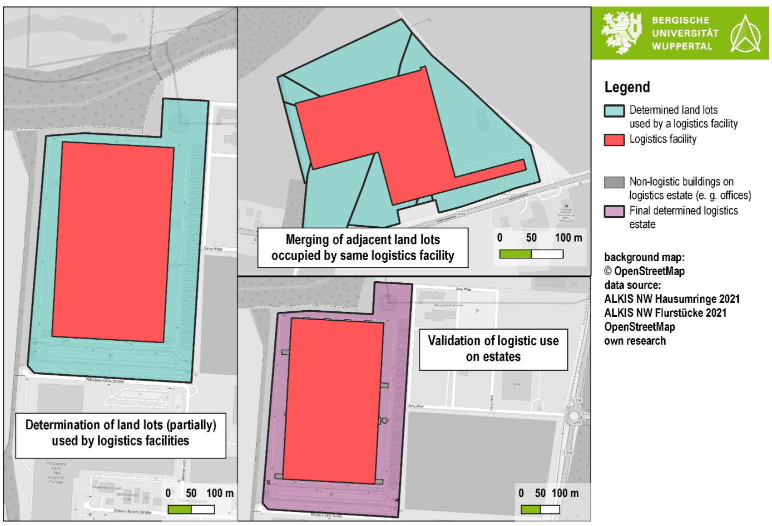


Figure 4: Procedural steps for the identification of logistics land

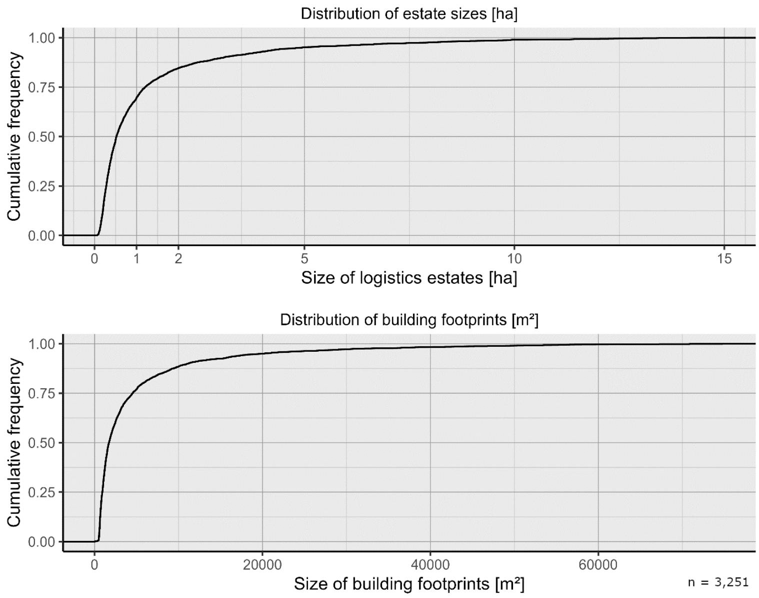


Figure 5: Size distribution of building footprints and estates of logistics land in the study area

### *4.3 Checking the dataset for completeness*

As already mentioned, the categorization of the building function in the official dataset is not uniform across the board, meaning that not all existing logistics facilities can be identified from this dataset. This is probably due to the fact that the associated survey is the responsibility of the cadastre authorities, whose focus is not on the differentiated consideration of logistics.

Through the additional use of OpenStreetMap and the development of our own database, we were able to identify additional logistics space that would not have been identified if we had only used the official building dataset. Figure 6 shows an example of a logistics estate that could only be identified as a logistics estate through the use of OpenStreetMap. A total of 455 additional logistics estates were identified in this way; this corresponds to 14% of all identified logistics estates.

As there is no knowledge of the whole population of logistics buildings, it can be assumed that the dataset does not represent a complete picture of logistics land use in the area under investigation. Nevertheless, a qualitative comparison with known logistics facilities shows that this procedure represents an approach that can be used to at least roughly determine land use by logistics for this large study area.

### *4.4 Spatial aggregation and further variables*

In the further, a 1 km² grid is used, because it also enables examinations regarding spatial autocorrelation. Therefore, further variables like the driving distance to the next inland terminals are adapted to this grid. The use of the raster also allows to consider further variables like the existing area of industrial/commercial land in each grid cell.[2] The variables used are presented in Table 1. It should be noted that employment figures were generally used at the county level due to the high level of anonymization at the municipal level.

In 1,623 of 12,773 grid cells logistics land can be determined by the method described above. Figure 7 shows the grid cells that contain identified logistics land. Evidently, they concentrate on the river Rhine, especially around the metropolises Cologne and Dusseldorf, the inland port of Duisburg, and flat suburban/exurban areas west of Dusseldorf and

[2]Standard land values for industrial/commercial land could not be determined for all grid cells with existing logistics land.

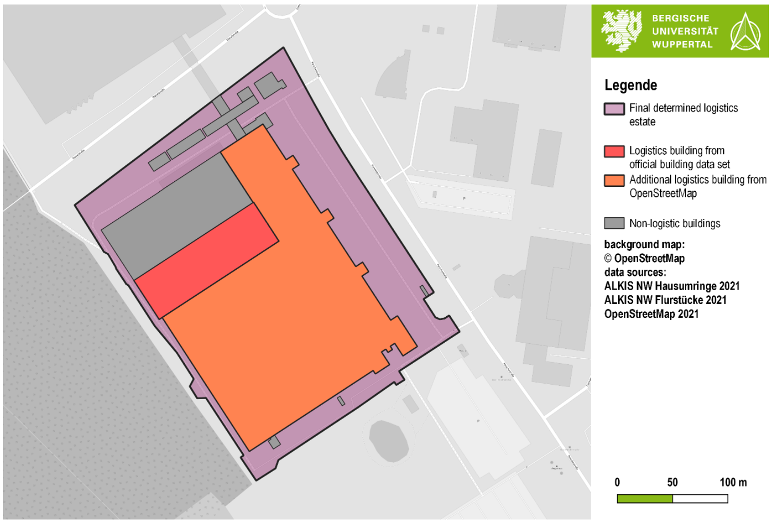


Figure 6: Example for gaps in the official building dataset

Cologne. As Figure 8 shows, these areas also account for a very large share of the total logistics land identified in the study area.

Table 1: Variables used for examination

| **Variable type** | **Variable description** | **Abbrevation** | **Aggregation of variable/ starting point** | **Data source** |
|---|---|---|---|---|
| Demographics | Population density (inh./km²) | pop_dens | Population density on municipality level | BKG (2023) |
| Accessibility | Driving distance [km] to next high-order center | dist_hoc | Centroid of grid cell | Own calculation |
| | Driving distance [km] to next inland terminal | dist_terminal | Centroid of grid cell | Own calculation |
| | Driving distance [km] to next motorway/trunk access | dist_motorway | Centroid of grid cell | Own calculation |
| Employment/ Establish-ments | Employment in NACE-category 49.4, 52, 53 on county level in 2019 | log_emp_county | County level (assignment of grid cell based on centroid) | IT.NRW (2021) |
| | Establishments in NACE-category 49.4. 52, 53 on municipal level in 2019 | log_est_mun | Municipal level (assignment of grid cell based on centroid) | IT.NRW (2021) |
| | Employees occupied in warehousing, mail and delivery, cargo handling (all NACE-categories) on county level in 2020 | wmc_emp_county | County level (assignment of grid cell based on centroid) | BA (2021) |
| Land market | Standard land value for all industrial/ commercial land in 2021 | land_value_ind | Average for indus-trial/commercial land in grid cell | Own calculation based on Bezirksregierung Köln (2021) |

Continued on next page

Table 1: Variables used for examination (continued)

| Variable type | Variable description | Abbreviation | Aggregation of variable/starting point | Data source |
|---|---|---|---|---|
| | Existing area of industrial/commercial land in 2021 | land_ind | Sum of industrial/commercial land area in grid cell | Own calculation based on Geobasis NRW (2020) |
| Logistics land | Area [ha] of logistics land identified in grid cell | log_land | Sum of grid cell | Own calculation |

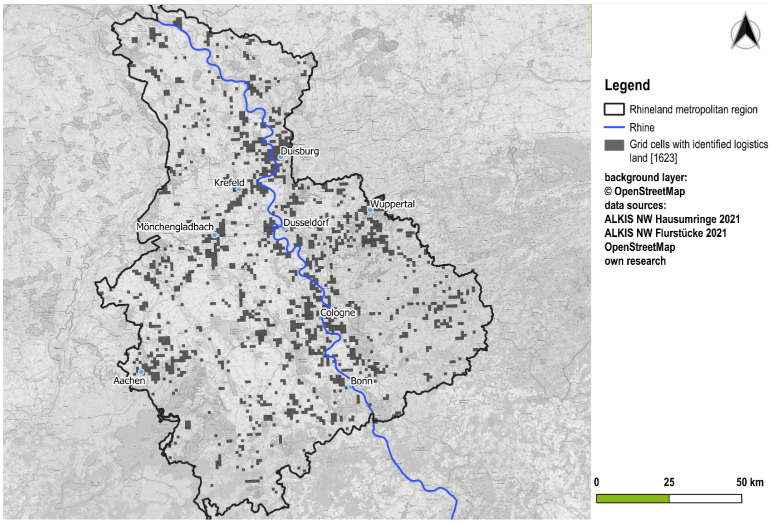


Figure 7: Grid cells with identified logistics land

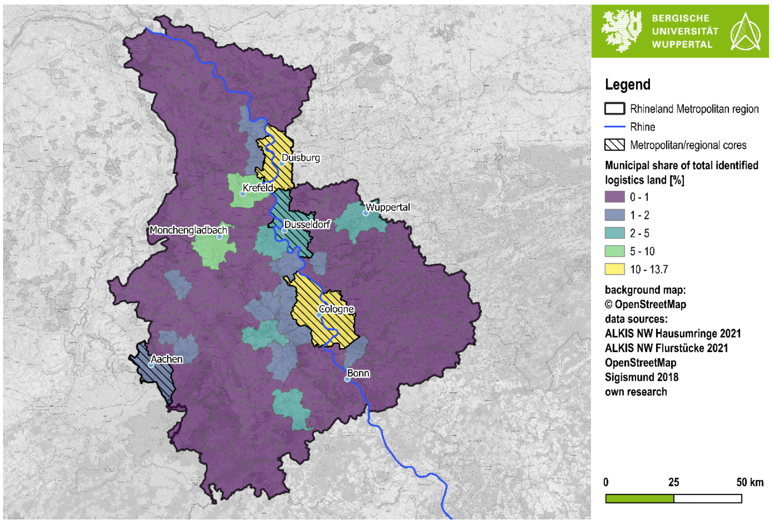


Figure 8: Municipal share of total identified logistics land

## 5 Analysis of spatial autocorrelation

As an example of the further usability of the dataset, measures of spatial autocorrelations are calculated in the following. Spatial autocorrelation is an application area of spatial statistics. According to Cliff, Ord (1970), spatial autocorrelation is defined as: "If the presence of some quantity in a county (sampling unit) makes its presence in neighboring counties (sampling units) more or less likely, we say that the phenomenon exhibits spatial autocorrelation." Here, the global and local spatial autocorrelation is calculated for the appearance of logistics land.

### *5.1 Global spatial autocorrelation*

For global spatial autocorrelation, the common Moran's I measure is used. It represents a weighted correlation, with weights increasing in spatial distance (Kirilenko 2022). It thereby measures autocorrelation over an entire area under consideration (ibid.). The Moran's I value can range from -1 to +1 (O'Sullivan, Unwin 2010, p. 206). Values greater than +0.3 indicate a strong positive spatial autocorrelation, whereas values less than -0.3 indicate a strongly negative spatial autocorrelation (ibid.).

Table 2 presents the results for the Global Moran's I-Index. With a statistically significant value of 0.235, the calculated Moran's I is close to a strong positive spatial autocorrelation (Moran's I $> 0.3$). That means the spatial pattern of logistics land in the Rhineland metropolitan region is likely to be not random.

Compared with the results of Jaller et al. (2022), who calculated the Moran I for warehouses and distribution centers they got from the Zip Code Business Pattern database for five metropolitan regions in California in 2016, the index of the Rhineland metropolitan area is similar to Southern California (0.24) that contains e.g. Los Angeles and Orange County. The only metropolitan region that has a higher index, i.e. even more concentrated logistics facilities, is San Joaquin County (0.36).

Table 2: Results for global spatial autocorrelation of the Rhineland metropolitan region

| **Indicator** | **Value** |
|---|---|
| Number of raster cells | 12,773 |
| Number of raster cells that contain logistics land | 1,623 |
| Global Moran's I-Index | 0.235 |
| Standard deviation | 52.76 |
| p-Value | $< 0.001$ |

### *5.2 Local spatial autocorrelation*

The hotspot analysis by Getis, Ord (1992) is in contrast a local measure, i.e. it is calculated for each object of investigation individually. This allows the determination of local concentrations of high or low values of an attribute (O'Sullivan, Unwin 2010). For each object $i$, the value $G_i$ is calculated, which represents the share of the sum of all attribute values (e.g. logistics employment), which is represented by the neighbors of object $i$ (located in a defined distance). Accordingly, $G_i$ will be high for objects where high values accumulate (Getis, Ord 1992). With the slightly modified $G_i^*$, the values of the object $i$ itself are also included in the consideration (ibid.). The main result is the $z$-score (corresponding to the $z$-transformation), which is the difference between the calculated $G_i$ and the expectancy-value of $G_i$ in the ratio to the standard deviation of the calculated $G_i$ (ibid.). A high $z$-score value indicates that large values of the attribute under consideration are concentrated around the location under consideration (ibid.). This must additionally be tested for statistical significance (ibid.). Busch (2013) uses this, for example, to identify hot spots in the spatial distribution of logistics employment. In this case, the $G_i^*$ is calculated contiguity-based, using the Queen's Case, i.e. for each grid all neighbors are considered, even those touched only at a single point. The respective area of logistics land in each grid cell is used as an attribute value.

As a result of the hot-spot analysis, 717 statistically significant hotspots can be identified, i.e. around these grid cells a high number of logistics land is concentrated. In some cases, grid cells with no logistics land are recognized as hot-spots, because they are adjacent to grid cells with high numbers of logistics land. These hotspots account for 65.4% of all logistics land identified in the study area. The 20 cells with the highest $z$-score, i.e. where logistics land use is highly concentrated and therefore logistics clusters exist, are located in the area of the Port of Duisburg, in a logistics park in the proximity of an inland terminal in Duisburg and a logistics park in Monchengladbach that is purely geared towards trucking.

Altogether, it can be demonstrated that the hot-spots concentrate on four regions/facilities (see Figure 9):

- Metropolises/Regiopolises and their suburbs (e.g. Aachen, Cologne)
- Along highways in sub-/exurban areas with flat relief (west of Cologne/Dusseldorf and south of Monchengladbach)
- Large inland terminals/inland harbors (above all Duisburg).

Looking only at the grid cells containing identified logistics land, the latter aspect is also recognizable in the frequency of occurrence of hotspots. Hotspots with identified logistics land are evidently located closer to inland terminals compared to the other grid cells with identified logistics land (see Figure 10). Additionally, they also contain a higher number of existing commercial/industrial land (see Figure 11). Accordingly, the trend of logistical clusterization in a polycentric area, e.g. described in van den Heuvel et al. (2013), can also be identified in the study area at hand.

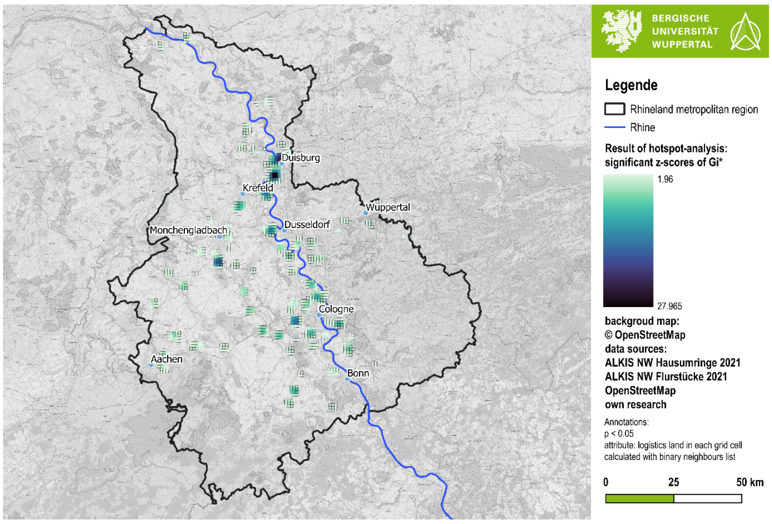


Figure 9: Identified hotspots of logistics land according to $G_i^*$-statistics by Getis, Ord (1992)

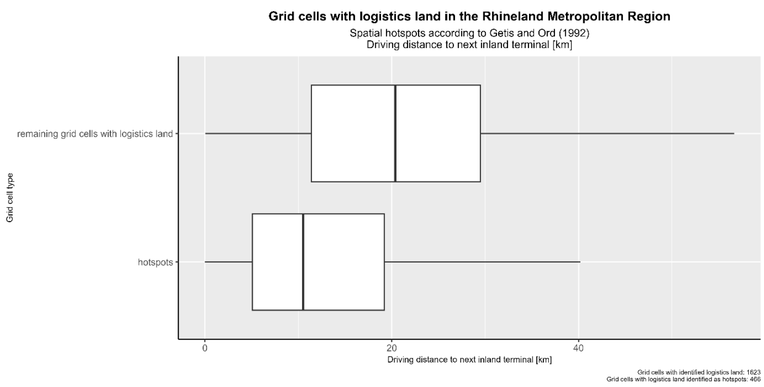


Figure 10: Boxplot for the driving distance to the next inland terminal for grid cells investigated


Figure 11: Boxplot for the existing commercial/industrial land in each grid cell

## 6 Conclusions

This paper presented a method for identifying logistics land based on publicly available data. In addition, area-wide accessibility analyses are carried out. To calculate geostatistical measures (such as Moran's I), all variables considered here were aggregated to grid cells. Accordingly, those presented here represent an image of the existing spatial structure of logistics in the Rhineland metropolitan region. A possible next step would be studies that focus on individual logistics facilities. Further, the generated dataset can also be used to identify underutilized logistics estates and thus potential for densification.

Using hotspot analysis by Getis, Ord (1992), spatial hotspots of logistics land were identified. These hotspots are mostly located in Metropolises/Regiopolises and their suburbs, along highways in areas with flat relief, and in the vicinity to large inland terminals/inland harbors. The results show that – like in other polycentric areas – logistical clusterization can also be observed in the study area at hand.

Further research is needed regarding the following aspects: First, the dataset can be used as a starting point for the observation of the development of logistics facilities over a period of time, as it is part of many other studies like Dablanc et al. (2014). Based on such observations also an evaluation of strategic municipal/regional planning regarding the presence of logistics land would be possible. Additionally, the dataset itself should be validated due to the described regionally inconsistent assignment of the building functions. Further examinations that allow also a comparability to other study areas can be done with an additional differentiation of the logistics facilities according to the typology of logistics facilities like in Heitz et al. (2019).

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