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Living on the highway? Addressing highway infrastructure potential through object detection

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ABSTRACT

The rapid increasing demand for freight transport has precipitated a critical need for expanded highway infrastructure, including Heavy Goods Vehicle (HGV) parking spaces. Utilizing state-of-the-art object detection techniques in satellite imagery, we conduct a comprehensive analysis to assess the current availability of HGV parking facilities along German highways. We relate our results to HGV traffic volume data. Our findings reveal local disparities in infrastructure supply and demand. In a next step, we conduct location analysis to determine regions impacted the most by identified undersupply. Our results deliver valuable insights to both, specialized real estate developers and policymakers likewise.

1. Introduction

Advancing globalization and the rise of e-commerce have significantly increased international cargo traffic, thus intensifying Heavy Goods Vehicle (HGV) traffic on European highways. While the number HGVs can rapidly grow, the necessary infrastructure, particularly HGV parking facilities, lags behind (Krasniuk et al., 2024). This results in a more heavily used infrastructure, accentuated by the scarcity of HGV parking facilities. This scarcity forces drivers into untenable situations such as parking illegally in unsafe locations (Nevland et al., 2020). This often literally ends with drivers living on the highway. Fatigue due to insufficient rest also diminishes driver reaction times, heightening the risk of collisions in emergency situations (National Academies of SciencesEngineeringand Medicine, 2016). With road freight accounting for an impressive 72.2 % of Germany's total freight volume (DHL Freight, 2023) and a market size of USD 63.88 billion, the strategic importance of HGVs becomes unmistakably clear (Schenker, 2024). These figures not only highlight the sector's substantial contribution to the national economy but also draw attention to the urgent need to address infrastructural deficiencies, specifically the lack of truck parking facilities, that threaten to undermine this crucial economic pillar while at the same time offering a rare investment opportunity for specialized real estate developers. Moreover, the lack of necessary infrastructure prevents the settlement of companies that decide on their location based on prevailing infrastructure (Champagne and Dubé, 2023)

The existing literature extensively discusses the challenges of heavy goods vehicle parking shortages, often highlighting safety risks, economic impacts, and regional disparities. Most prior research has been limited in geographic scope or reliant on traditional methods – for example, localized corridor case studies and driver surveys – which fail to capture the full complexity of supply–demand mismatches at a broader network level. Recent data-driven efforts have begun to emerge (e.g. clustering of GPS trajectories or time-series forecasting of occupancy), yet advanced geospatial machine learning techniques remain underexplored in this domain. Notably, the use of high-resolution satellite or aerial imagery with object-detection algorithms to systematically map HGV parking infrastructure is rare. A recent study by Hellekes et al. (2023) demonstrates the potential of deep learning on aerial images for general parking inventory, but such an approach has not been applied to large-scale HGV parking facilities. This leaves an evident gap in the literature regarding granular, up-to-date mapping of truck parking supply using geospatial machine learning, especially when aiming to assess entire highway networks rather than single sites. To overcome these limitations, our study employs satellite imagery obtained from Google Maps API and polygon coordinate date from OpenStreetMap. We utilize advanced machine learning techniques, specifically the YOLOv8 object detection algorithm, to systematically quantify the availability and distribution of HGV parking spaces along German highways.

Unlike conventional studies, our methodology provides up-to-date, granular insights into parking supply while integrating demand-side traffic volume data from automated traffic count data (Bundesanstalt für Straßenwesen, 2024) for a holistic assessment. Our traffic-driven

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demand model accounts for factors such as regulatory driving constraints, freight volume growth, driver behavior, and infrastructural capacity. By correlating the supply data with detailed demand-side traffic volume information, we establish local supply-demand equilibria highlighting regional disparities and identifying areas with the most significant undersupply. We also show actionable opportunities for specialized real estate developers and policymakers, offering a strategic framework to address the pressing shortage. This approach not only advances the field of transport infrastructure analysis but also lays the groundwork for scalable, technology-driven solutions across other regions and countries.

The critical nature of HGV parking availability and its implications for specialized real estate developers necessitate a comprehensive data set for systematic analysis, which has been lacking. Without accurate data, estimates of the HGV parking supply may be significantly distorted, hindering developers and investors from making informed decisions. Our novel data-driven approach aims to map HGV parking lots and relate them to their demand, thereby enhancing the understanding of the overall parking situation for long-haul trips and enables identifying location potential for infrastructure real estate developers. To the best of our knowledge, such a study has not been conducted for Germany or any other European country to date.

To understand the investment case this paper seeks to determine, it is essential to grasp how truck and rest stops as part of the highway service infrastructure generate revenue. Their business model is based on a variety of income streams that together can create a stable and profitable financial structure. Many infrastructure facilities earn revenue from the rental of parking spaces, especially for HGV drivers who are required to take their legally mandated rest periods. However, a substantial part of the monetization of these truck parking spaces comes not from the rental itself but from the presence of on-site real estate such as restaurants, shops, or sanitary facilities. These additional offerings make the infrastructure facilities an attractive destination for drivers and significantly contribute to overall value creation. Consequently, many truck stops operate restaurants, cafés, or fast-food chains. Another important revenue driver is the sale of fuel and automotive accessories. Additional income is also generated through the sale of products such as motor oil, windshield wipers, and other accessories.[1] That this can be lucrative is illustrated by the figures from Germany's largest service station provider, Tank & Rast, which had a revenue of 537 million euros in 2021 (Piller, 2023).

Section 2 commences with a review of the literature. Section 3 presents our methodological framework, while Section 4 is dedicated to our results. Both aspects are integrated in Section 5, where we show regional differences and locational investment opportunities for specialized real-estate developers. We conclude our findings in Section 6.

2. Literature review

The significant role of trucks in local and long-haul commerce is well-documented, particularly given their crucial function in connecting production hubs with consumers across vast geographies (Sadek et al., 2020). However, the challenge of providing adequate parking infrastructure for HGVs remains pressing. In the U.S., Garber et al. (2002) identified severe shortages along I-81, while a broader state-level audit by Parametrix (2005) confirmed systematic overcapacity across Washington's interstates. Similar issues have been reported in Europe. Chatterjee and Wegmann (2000) showed that a significant share of HGV drivers park illegally due to the lack of legal alternatives, a finding echoed by Boris and Brewster (2016), who found that over 80 % of U.S. drivers parked illegally at least once a week. A comparable situation was documented for Germany (Niederrheinische IHK, 2024).

Illegal parking is not only a regulatory failure but also a safety issue. Boggs et al. (2019) demonstrated a direct link between full parking facilities and increased ramp crashes, while Nourinejad and Roorda (2017) outlined the broader societal costs of such behavior. Anderson et al. (2018) and Horn (2015) further illuminated the regulatory dilemma: drivers often park on ramps to avoid exceeding legal driving limits, while enforcement agencies are reluctant to intervene. The lack of suitable amenities at existing stops exacerbates this behavior, as shown by Krasniuk et al. (2024), who emphasized that HGV drivers often bypass facilities that lack appropriate services.

Despite increasing demand and evident safety concerns, the evaluation and planning of HGV infrastructure remain fragmented. Most studies focus on small-scale observations, regional case studies, or behavior-based surveys. For example, Mahmud et al. (2020) use clustering methods to explore how facility amenities influence parking duration, and Nevland et al. (2020) develop a typology of formal and informal truck parking based on GPS tracking—but neither study attempts to assess supply-demand balances at a network level. Patel et al. (2022) and Wu et al. (2024) utilize passive GPS and geofencing techniques, respectively, to identify parking behaviors and demand clusters, yet they do not quantify infrastructure supply or evaluate its adequacy. Likewise, Sadek et al. (2020) and Seya et al. (2020) focus on modeling parking occupancy or driver decision-making but offer no scalable methods to inventory parking infrastructure itself.

Building upon a year of extensive truck parking data collection, Sadek et al. developed a dynamic forecasting model capable of predicting truck parking occupancy at any given time within the current day (Sadek et al., 2020). The model's effectiveness is assessed using the Root Mean Square Error (RMSE), offering a quantitative measure of its accuracy. In their model, Irzik include the capacity of truck parking facilities along a freeway section, the average daily traffic volume of heavy goods vehicles in the section, and the section's length (Irzik, 2019). This approach is encapsulated within a multiple regression analysis framework.

In parallel, real estate literature has explored location analysis for traditional asset classes, often through regression or GIS-based methods. Champagne and Dubé (2023) demonstrate that transportation infrastructure heavily influences industrial location decisions. Yet, site selection for infrastructure-specific assets like truck stops has received little empirical attention. Rabianski et al. (2001) and Fryrear et al. (2001) propose frameworks for community-specific or GIS-based site assessment, while Rymarzak and Siemińska (2012) highlight that specialized real estate is frequently constrained by immobile physical resources. However, all these approaches are either too general or reliant on highly localized datasets. As Kabir et al. (2020) point out, incomplete or missing data further complicates infrastructure site assessment, often requiring manual data collection to fill gaps.

Recent developments in computer vision and deep learning offer new pathways to overcome these limitations. Redmon et al. (2015) introduced the YOLO framework, revolutionizing object detection by enabling real-time processing of image data. Yu et al. (2022) and Jenkins and Burton (2008) have shown the accuracy and efficiency of deep learning applications across a range of domains. However, to date, very few studies have applied these methods to HGV infrastructure. A notable exception is Hellekes et al. (2023), who used a CNN to detect general parking capacity in urban areas using aerial imagery. Yet even this effort did not address highway-specific or truck-specific parking supply.

A broader strand of research in remote sensing demonstrates how object detection techniques can be applied to high-resolution satellite imagery for infrastructure-related tasks. Comprehensive reviews by Ma et al. (2019) and Zhu et al. (2017) highlight the growing sophistication of convolutional neural networks (CNNs) and real-time detection architectures like YOLO, with successful applications in domains such as building footprint extraction, road detection, and traffic surveillance. Empirical studies have illustrated the technical viability of these

[1] Some infrastructure facilities also offer additional services such as car washes, workshops, or shops for drivers 'supplies, further enhancing their revenue streams.

methods: for example, Yang et al. (2019) propose R3Det, a refined single-stage detector capable of accurately identifying rotated objects in aerial imagery, which is crucial for non-axis-aligned targets like parked trucks.

Despite advances in deep learning for satellite imagery, key limitations remain for logistics-focused infrastructure mapping. First, relying on axis-aligned bounding boxes (AABBs) compromises detection accuracy when objects - like trucks in rest areas - are rotated or angled. Orientation-aware detectors, such as R3Det (Yang et al., 2019), address this by refining bounding boxes to better fit rotated instances. Second, domain generalization remains problematic: models trained on urban datasets often underperform in highway or rural contexts due to differences in vehicle scale, background textures, and scene composition (Zhao et al., 2019). Finally, the field often lacks practical validation: while many studies report performance metrics like mAP or IoU, few benchmark their results against real-world infrastructure inventories or spatial planning requirements, limiting applicability for logistics decision-making.

Our study addresses these gaps by training a YOLOv8 model using orientation-aware bounding boxes (OBBs), tailored specifically to HGV parking layouts visible in high-resolution satellite imagery. This adjustment improves detection performance in rotated and spatially dispersed configurations and supports a more precise inventory of truck parking infrastructure. In doing so, we advance the application of geospatial deep learning beyond general object recognition and toward actionable infrastructure analysis.

Table 1
Overview of key literature on HGV parking and infrastructure site selection.

Publication	Methodology	Focus Area	Supply-Demand Gap Modeled?	Real-time Detection?	YOLO/Deep Learning Used?	HGV-specific?	Data Type/Source
Anderson et al. (2018)	Survey	Driver ramp parking decisions	×	×	×	✓	Oregon highway observations
Boggs et al. (2019)	Correlation study	Crash rates vs. parking overcapacity	✓	×	×	✓	Crash & parking capacity data
Boris and Brewster (2016)	Survey	Illegal parking frequency	×	×	×	✓	U.S. truck driver diaries
Champagne and Dubé (2023)	Meta-analysis	Infrastructure & industrial site selection	×	×	×	×	Systematic literature review
Chatterjee and Wegmann (2000)	Survey	Legal vs. illegal parking split	×	×	×	✓	Driver-reported data
Fryrear et al. (2001)	Survey	GIS in real estate (not parking-specific)	×	×	×	×	U.S. commercial real estate data
Garber et al. (2002)	Case study	Corridor capacity shortfalls (I-81)	✓	×	×	✓	Survey and observational data
Hellekes et al. (2023)	CNN-based object detection	Urban curbside parking detection	×	✓	✓	×	Aerial imagery, GIS
Horn (2015)	Field interviews	Enforcement reluctance for ramp parking	×	×	×	✓	Local enforcement input
Jenkins and Burton (2008)	Deep learning demo	General model performance (not parking-related)	×	✓	✓	×	Visual recognition data
Kabir et al. (2020)	Data imputation	Missing infrastructure data	×	×	×	×	Infrastructure databases
Krasniuk et al. (2024)	Scoping review	Amenities & parking mismatch	✓	×	×	✓	Literature synthesis
Liermann et al. (2019)	Industry overview	AI in finance and infrastructure	×	×	✓	×	Industry use cases
Mahmud et al. (2020)	Cluster analysis	Amenities vs. parking duration	×	×	×	✓	GPS + facility inventory
Nevland et al. (2020)	Classification	Legal vs. illegal truck parking	×	✓	×	✓	GPS data (Canada)
Niederrheinische IHK (2024)	Industry survey	Illegal parking prevalence (Germany)	×	×	×	✓	Survey analysis
Nourinejad and Roorda (2017)	Simulation	Policy impact on parking demand	×	×	×	✓	Urban truck parking data
Parametrix (2005)	Descriptive audit	State-wide capacity utilization	✓	×	×	✓	Facility observations (Washington)
Patel et al. (2022)	Clustering & classification	Stop purpose classification	×	×	×	✓	Passive GPS traces
Rabianski et al. (2001)	Theoretical framework	Corporate real estate location analysis	×	×	×	×	Literature
Redmon et al. (2015)	Model development	YOLO introduction	×	✓	✓	×	Image datasets
Rymarzak and Siemińska (2012)	Empirical	Real estate placement constraints	×	×	×	×	Polish land-use data
Sadek et al. (2020)	Time-series forecasting	Truck parking occupancy	×	✓	×	✓	California truck parking data
Seya et al. (2020)	Tobit & choice modeling	Truck parking behavior (micro-level)	×	×	×	✓	Digital tachograph data (Japan)
Stang et al. (2023)	Explainable AI	Commercial property valuation	×	×	✓	×	Location & transaction data
Wu et al. (2024)	Spatio-temporal clustering	Stop clustering (demand identification)	×	×	×	✓	GPS trajectories (Shanghai)
Yu et al. (2022)	Computer vision	General object detection methods	×	✓	✓	×	Image data
[Our Work]	Deep learning (YOLOv8) + GIS analysis	Real-time HGV parking detection & supply-demand modeling	✓	✓	✓	✓	Aerial imagery + road network + geo-data

Note: This table gives an overview of reviewed literature. A publication is marked with a check mark if it contains the stated methodologies or topics and with a cross if it does not.

As the literature reveals, although the problem of truck parking scarcity is well recognized, there remains a significant methodological and empirical gap: no existing study systematically quantifies the spatial distribution of HGV parking infrastructure at a national scale using scalable, real-time methods. Most research either analyzes driver behavior, focuses on urban delivery logistics, or employs static survey data without integrating dynamic traffic or supply-side geospatial data. Moreover, while object detection and machine learning are increasingly used in real estate valuation (Stang et al., 2023) and parking analysis (Hellekes et al., 2023), their application to truck-specific highway infrastructure is virtually nonexistent.

Our study fills this gap by combining high-resolution satellite imagery with YOLOv8 object detection to assess the current supply of HGV parking infrastructure along Germany's entire highway network. We further integrate traffic flow data to estimate localized demand and evaluate regional supply-demand mismatches. This approach offers a scalable, technology-driven framework that advances beyond both survey-based and GPS clustering methods, enabling systematic infrastructure assessment across spatial scales. As such, it provides actionable insights for both policymakers and real estate developers in a domain where data limitations have long hampered planning and investment.

We have compiled overview Table 1 to include all relevant academic studies based on their methodological approach, data type, and relevance to HGV parking infrastructure. This structured summary highlights where prior work stops short, thereby clarifying the novelty of our paper's geospatial machine learning approach.

3. Determining the HGV parking situation

Our study addresses the outlined research gap by introducing a novel, data-driven approach that leverages state-of-the-art object detection models and comprehensive satellite imagery to evaluate HGV parking availability along German highways. Fig. 1 shows why Germany is of particular relevance when considering transport infrastructure. The German highway network includes key logistics axes and connects the European north with the south and the east with the west. The transport infrastructure is therefore used by large numbers of Europeans likewise. However, it is certainly feasible to replicate this approach on similar transportation networks, for example in the US or China.

The institutional setting in Europe differs between three categories of highway infrastructure facilities offering parking spaces. While service stations and truck stops are considered managed facilities, rest areas are usually unmanaged. Focusing on the situation in Germany, according to the German General Administrative Regulation on the Road Traffic Regulations (VwV-StVO), service stations are designated rest stops located directly along Germanys federal highway system. These service areas typically include amenities such as fuel stations, restaurants, restrooms, and parking spaces. Service stations are accessible directly from the highway without the need to exit.

Truck stops offer similar amenities as service areas but are usually located near highway exits, rather than directly on the highway itself (§15 of the German Federal Trunk Road Law (FStrG)). They offer a broader range of services, often including larger parking areas, more diverse dining options, repair services, and overnight accommodations. Truck stops cater particularly to long-haul truck drivers. To access a truck stop, drivers need to leave the highway and then re-enter it again after their stop. These are comparable to Pilot Flying or TA Petro in the US.

Rest areas are, just as service stations, located directly along the highway. However, they usually offer less amenities limited to parking spaces and washrooms. While a recent study by Mahmud et al. identified differences in usage of infrastructure facilities depending on HGV drivers' origin and break duration (Mahmud et al., 2020), all three mentioned categories offer HGV parking spaces and are therefore included in the following analysis.

3.1. Overview

Fig. 2 gives an overview of our methodological approach addressing the infrastructure adequacy and potential of HGV parking facilities. We gain traffic and infrastructure data from two major sources and combine them once we isolated supply and demand estimates for HGV parking. First, we gather polygon coordinates for all HGV parking facilities along German highways from OpenStreetMap (2024). In a second step, we use Google Maps API to collect satellite imagery for all extracted polygon coordinates from the first step. After that, we manually create bounding boxes for 10,000 single HGV parking spots to train and validate a YOLO v8 object detection algorithm. Once the algorithm is sufficiently trained, we apply it for an out of sample prediction to assess all satellite images gained in the second step. This results in a holistic supply data set of HGV parking spots at each location identified in the previous steps. Parallel to the supply data processing, we collect traffic data from the automated traffic count (Bundesanstalt für Straßenwesen, 2024). This data is cleaned up for long haul HGV traffic and updated with the 2024 growth rate for heavy goods traffic. In a next step, the traffic data counters are matched with highway kilometers to receive a local mapping of traffic flows. Further, we apply a simple economic model to estimate local HGV parking supply.

However, the adequacy of infrastructure can only be assessed when supply and demand are matched on a local level. We therefore combine the demand data estimated by simple economic modelling and the supply data gained from the object detection approach to set up local equilibriums. Based on deviations from the equilibria, we draw conclusions comparing local juxtapositions of HGV parking supply and demand. Our results may support the expansion of local HGV parking infrastructure by creating an independent database for authorities and real estate developers. The subsequent sections present our detailed procedure stepwise.

3.2. Supply side

To determine the number of HGV parking spaces in Germany, we first acquired bounding boxes coordinates for truck stops, service stations and unmanaged rest areas along Germany's highways from OpenStreetMap. We retrieved both managed and unmanaged parking areas. Using the retrieved coordinates, we extracted recent (year 2024) satellite imagery from Google Maps API. To avoid potential overlapping and double counting, we implemented a custom algorithm that dynamically adjusted the queried coordinates while maintaining a constant zoom level of 19 across our satellite imagery, ensuring data accuracy in our analysis.[2] A total of 11,398 images were retrieved, split into 931 images for truck stops, 6802 for (unmanaged) rest areas and 3665 for service stations.

To estimate the number and spatial distribution of available parking spaces, we employed the YOLOv8 algorithm, leveraging the Oriented Bounding Box (OBB) technique. This model, pre-trained on satellite images, is adept at accurately delineating the angular orientation and shape of parking spaces. The YOLO model series is recognized as state-of-the-art and is constantly updated and improved. Although YOLOv8-OBB in its original version was not specifically trained on HGV parking lots (as can be seen in Fig. 3, only large and small vehicles are recognized on the example satellite image), its capabilities can be enhanced through training and validation with an annotated dataset to address the unique characteristics of HGV parking spaces, which are often angled, as illustrated in Fig. 4. The refined model should therefore be able to make out-of-sample predictions on unseen images regarding

[2] Google's satellite images can be retrieved at different zoom levels. Level 0 is the most zoomed out, and level 22 is the most zoomed in. After manual testing, we found that zoom level 19 provides the best combination of high-quality images and detailed information across the country.

Fig. 1. Germany's Position in the European Highway Network
Note: This figure visualizes European highway networks in blue color, while the federal borders of Germany are marked in red color. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

the availability and spatial distribution of HGV parking spaces. Alternative pretrained object detection models beyond YOLO are of limited use in our research because our methodology requires orientation aligned with OBBs. At the time of deployment and testing, only a few models had been pretrained on the necessary type of data, primarily satellite imagery. Consequently, we did not conduct a comparative performance evaluation with other models. Other relevant models aside from YOLO include those from the MMDetection toolbox and Seodore.

For the creation of a structured training and validation dataset from satellite images, we manually had to annotate visible HGV parking spots. A total of 519 images were annotated, resulting in 10,483 parking spaces being identified. Each parking space within the images was annotated with an oriented bounding box mask to delineate its perimeter. This resulted in a dataset with one single class for the truck parking. The size for each image was fixed at 640x640 pixels. For the training and validation process, we utilized a pre-trained YOLOv8x-OBB model, running for 300 epochs on a Tesla T4 GPU with a batch size of 16. As the speed of the model was not an important factor in our research, the YOLOv8x-OBB model is the extra-large ('x') version of YOLOv8. We used the Adam optimizer with a learning rate of 0.002, a momentum of 0.9 and default settings for augmentation. An "epoch" refers to one complete pass through the entire dataset in both forward and backward propagation through the neural network. While more epochs can lead to better accuracy, there is also a risk of overfitting the data, whereby the model becomes too focused on the given data and is unable to generalize outside of the training or validation data. The hyperparameters were selected in accordance with the recommended settings provided by the model's developers. As we did not encounter any significant issues (e.g. overfitting or low accuracy) when running the model with these settings, and as the object detection task that we trained the model on aligns with standard satellite object detection tasks, we did not adjust the hyperparameters ourselves. Furthermore, we adopted a 70–15–15 randomized split for annotated images to train, validate, and test the model. Specifically, 70 % of the annotated images were used to train the model to detect HGV parking spots, 15 % were used to validate the model's performance, and the remaining 15 % were reserved for out-of-sample testing to evaluate the model's generalization capabilities. This split seemed appropriate since the number of annotations, and thus ground truth data, was limited. A split with more training data (e.g. 80–10–10) would have potentially resulted in lower reliability of the validation and test dataset outputs.

3.3. Demand side

To determine HGV traffic demand for infrastructure facilities, our approach uses data from the German Federal Roads Office (Bundesanstalt für Straßenwesen, 2024) highway traffic meters from 2021. This includes 1227 traffic meters on federal highways. First, we match highway meters with highway kilometers applying interpolation.[3] Next, we generate driving distance polygons for 15-km travel distances to determine the number of reachable parking spaces in each highway section. We thereby base our approach on the average driving distance drivers spend to find eligible parking spaces for a break (Niederrheinische IHK, 2024). This enables us to compare demand and supply for each highway kilometer. In a last step, we identify zones with varying levels of demand coverage.

The parking requirements of HGVs vary significantly between short-term and long-term needs. Short-term parking, which includes curbside spaces for urban and residential deliveries, is distinct from long-term parking that accommodates rest stops and overnight parking. This

[3] We applied linear interpolation to fill in missing data gaps between traffic counters in line with Loder et al. (2019).

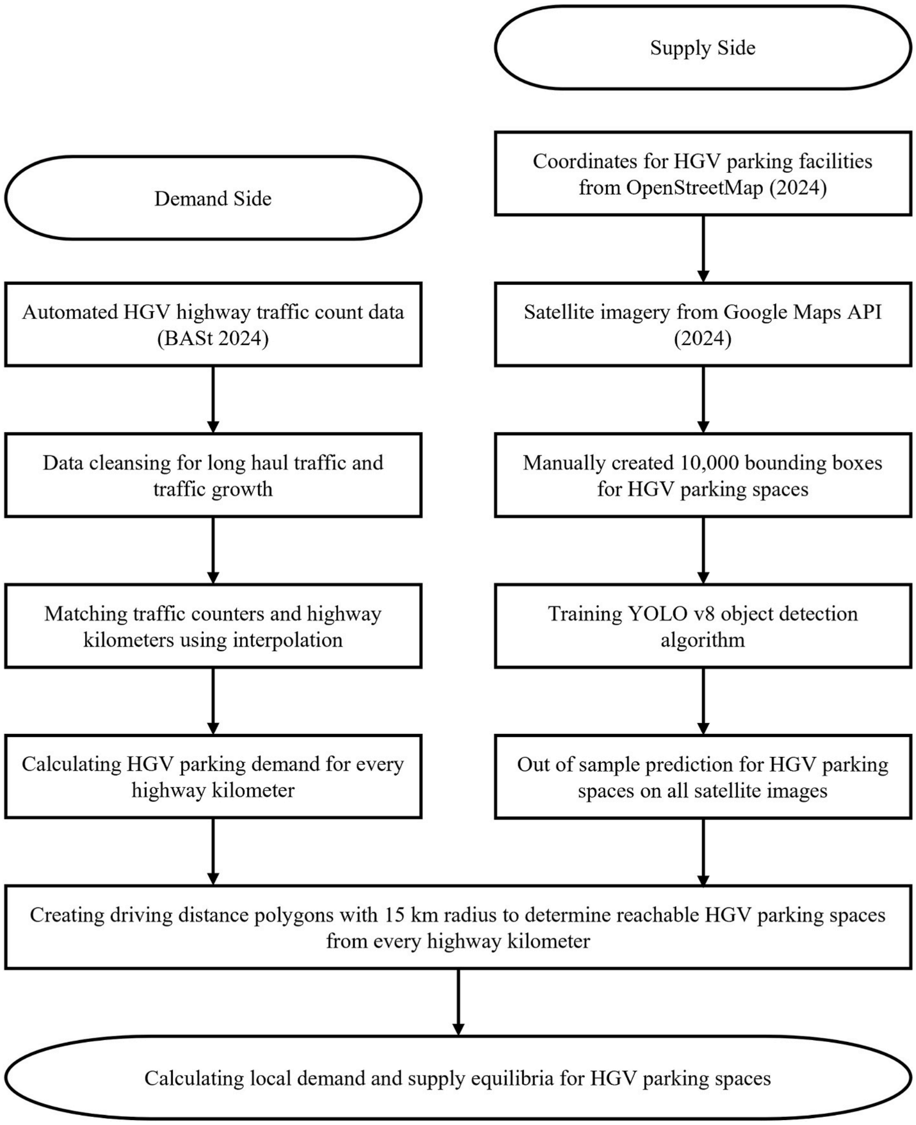

Fig. 2. Methodological Framework
Note: This figure illustrates the stepwise methodological framework applied to determine supply and demand for HGV parking spaces along German highways resulting in the calculation of local equilibriums.

differentiation is crucial for accurate demand estimation (Amer and Chow, 2017; Chen et al., 2017; Mitman et al., 2018; Schmid et al., 2018). Long-haul trips, often classified by distances exceeding 400 km (Pècheux et al., 2002) or 500 km (Ortúzar S. & Willumsen, 2011), necessitate longer stops due to the need for driver rest, with trips over 900 km requiring significantly more time (Gingerich et al., 2016).

Pècheux et al. (2002) first developed a simple demand model for HGV parking being dependent on traffic volume, driving times and seasonal peaks. Based on the evidence of Vital and Ioannou (2021), Wu et al. (2024) and Seya et al. (2020) on HGV drivers scheduling their breaks anticyclical to avoid overcrowding and traffic congestion, we enrich the baseline approach of Pècheux et al. (2002) by allowing for multiple daily usage of a single parking spot. Aligning with Patel et al. (2022), we further include the effect of temporary closures and construction into the demand estimation. Lastly, regulatory driving time constraints are added since the European Union imposes precise requirements regarding working conditions (European Union, 2024). Considering the above-mentioned studies and the described extensions, we apply the baseline equation (2) to estimate the average effective demand $D_{i,t}$ on HGV parking spaces based on the data obtained from the automated traffic count (Bundesanstalt für Straßenwesen, 2024):

$$D_{i,t} = s_{LH} * \Delta_{t,t-1} N_{i,t} * p_{i,t} \quad (2)$$

$$s_{LH} = 1 - s_{SH} \quad (3)$$

where i indexes highway sections and t indexes time. $N_{i,t}$ refers to the average daily HGV volume, whereas $\Delta_{t,t-1}$ determines the aggregated growth rate for HGV volume applied on 2021 data to enable later comparison with 2024 supply data. s_{LH} and s_{SH} denote the average share of long and short haul traffic, respectively. Following the approach of Pècheux et al. (2002), we assume only long haul traffic to demand resting facilities. Therefore, the total traffic volume is reduced by the share of short haul traffic s_{SH} as shown in equation (3). The probability of an HGV seeking a parking space exactly on a considered highway kilometer (rest probability) i is denoted by p and estimated applying equation (4).

$$p_{i,t} = \frac{n_t}{d_t O_{i,t}} * (1 + P_{i,t}) * (1 + v_{i,t}) \quad (4)$$

$$d_t = T_t * V_t \quad (5)$$

Fig. 3. Pre-trained Model Output on Sample Image
Note: This figure illustrates a sample satellite image of HGV parking infrastructure along a German highway. The pre-trained model applies an object detection algorithm that classifies identified objects into previously known categories. Geospatial data was acquired from Google API and OpenStreetMap.

Fig. 4. Manual Annotation of Parking Spaces
Note: This figure illustrates a sample satellite image of HGV parking infrastructure along a German highway. Bounding boxes in red color were created manually to mark HGV parking spaces. Geospatial data was acquired from Google API and OpenStreetMap. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Thereby, d_t denotes the average driving distance that drivers can cover without a break. That value is expressed in equation (5) by the product of the average HGV speed on highways (V_t) and the allowed maximum driving time until a break is required by law (T_t). The number of breaks per day required by law and the occupancy factor of supplied parking spaces are denoted by n_t and $O_{i,t}$, respectively. A peaking factor $P_{i,t}$ is assumed to allow for seasonal peaks. Further, a structural vacancy rate $v_{i,t}$ is applied to control for illegal parking and temporary closures. To estimate the demand for highway infrastructure facilities offering parking spaces for each observed highway kilometer, we use the data and necessary assumptions summarized in Table 2. We thereby rather underestimate than overestimate the actual demand. However, we cannot prevent including HGV traffic in the demand estimation which only arises due to the search for available infrastructure and would not occur if supply and demand were distributed locally equal.

We use the average share of long-haul traffic s_{LH} to correct the average HGV volume $N_{i,t}$ derived from BASt (Bundesanstalt für Straßenwesen, 2024) for long haul traffic drivers in need for rest areas on their freight routes. The remaining volume of long-haul traffic vehicles is then adjusted for the growth in freight volume between 2021 and 2024, since the retrieved most recent data covers only the 2021 vol

To calculate the rest probability, we primarily rely on EU regulation governing the working conditions of truck drivers on the road network in the European Union. Therein, the minimum number of breaks per day n_t and the maximum driving time allowed without a break T_t are defined. Further, the occupancy factor of parking spots $O_{i,t}$ can be derived applying the mandatory rest periods (European Union, 2024). The average speed of HGVs on German highways is derived from §18 of the German traffic law. To further control for seasonal peaks $P_{i,t}$ we adopt the assumption of Pècheux et al. (2002) since peaks in freight volume appear similar comparing the US and Germany. The structural vacancy of parking spaces $v_{i,t}$ is derived applying the scheduled highway construction per year (Deutscher Bundestag, 2024).

Table 2
Overview of assumptions.

Notation	Description	Assumption	Source
s_{LH}	Average share of trucks that are long-haul	0.33	Bundesamt für Logistik und Mobilität (2024)
$\Delta_{t,t-1}$	Average aggregate growth rate for HGV volume on German highways	3.5 % per annum	Bundesministerium für Digitales und Verkehr (2023)
n_t	Number of breaks per day for HGV drivers	2.0	European Union (2024)
T_t	Maximum allowed driving time without break	4.5 h	European Union (2024)
V_t	Average speed of HGV on German highways	80 km/h	§ 18 of the German traffic law[a]
$O_{i,t}$	Occupancy factor of parking spots	2.67	European Union (2024)
$P_{i,t}$	Seasonal peaking factor	0.15[b]	Pècheux et al. (2002)
$v_{i,t}$	Structural vacancy of parking spaces	0.012	Deutscher Bundestag (2024)

Note: This table lists the applied values for the demand estimation applying the afore mentioned equations (2)–(5). The assumptions were gathered with respect to the German highway and German regulation regarding HGV drivers. When applying equations (2)–(5) on data other than Germany, assumptions may differ.

[a] A recent study by Trabert et al. (2018) on HGV accidents on German highways reveals an average speed of 89.7 km/h supporting our conservative approach of assuming an average HGV speed corresponding to the maximum allowance.

[b] No reason to assume that seasonal peaks differ between US and Germany.

4. Results

4.1. Identified HGV parking supply

The objection detection approach outlined in section 3.2 results in the following supply of HGV parking spots summarized in Table 3. We identified approximately 71,300 parking spots in three different categories. While service stations and unmanaged rest areas offer roughly the same number of parking spaces, truck stops provide a smaller part of the infrastructure.

The German Ministry of Transport conducted a nationwide survey on the truck parking situation in April 2018. They recorded 2200 locations. Based on the survey, the number of HGV parking spaces was estimated about 70,800 (Bundesministerium für Digitales und Verkehr, 2020). Our data suggests an increase of parking spaces of about 500 since the survey was conducted.

Fig. 5 illustrates the spatial distribution of HGV parking spots aggregated on a NUTS-2[4] level in Germany using a color-coded map. The regions are shaded from dark purple, indicating fewer than 1000 parking spots, to light yellow, indicating over 4000 parking spots. Regions in the eastern and southeastern part of Germany, which are shaded in dark purple, have the lowest supply of parking facilities. In contrast, central regions, depicted in light yellow, have the highest number of parking spots, exceeding 4,000, indicating infrastructure capable of accommodating higher volumes of freight traffic. Fig. 5 reveals notable regional disparities in the availability of HGV parking infrastructure.

4.2. Model performance

The resulting metrics indicate a robust performance in both the training and validation processes. After 300 epochs, the model exhibits low loss levels, with precision at 0.89, recall at 0.85, and a mean average precision @ 50 of 0.92, all suggesting a high degree of model accuracy. Overfitting does not appear to be a significant issue up to Epoch 300, although there is a gradual increase in the disparity between training and validation losses.

The results from our test dataset containing 71 unseen images, follow the initial results from training and validation dataset metrics and indicate a high level of performance (see Table 4). The precision, measured at 88.7 %, indicates a high rate of correct positive predictions for parking space detection. The model also achieved a recall rate of 85.4 %, demonstrating its ability to reliably identify the vast majority of relevant instances within the dataset. The mean Average Precision scores provide an overarching indication of the model's accuracy across different Intersection over Union (IoU) thresholds: 91.8 % at an IoU of 0.50. The metrics collectively attest to the model's robust performance, rendering it a highly reliable tool for estimating the supply of HGV parking spaces. We refrain from describing the results in terms of F1 scores, precision-recall curve, and confusion matrix since we are only predicting one class.

Table 3
Total number of HGV parking spots.

Category	Identified HGV Parking Spots
Service stations	29,194
Truck stops	13,927
Unmanaged rest areas	28,222
Total	71,343

Note. This table presents the adjusted results of the application of a trained YOLOv8 algorithm on satellite imagery containing HGV parking facilities. The algorithm assessed 4596 images detecting 71,343 HGV parking spaces in total. The definitions for mentioned categories are in subsection 3.

The utilized methodology to identify the supply of parking spaces through satellite imagery delivers granular up-to-date data and is designed to be universally applicable across different geographical regions, underscoring its potential for widespread implementation. In our case, we use the model to predict all parking spaces visible on our 11,398 images. While object detection offers high efficiency and scalability, it also involves uncertainties related to transparency and accuracy. Object detection mechanisms may be at a disadvantage in these respects compared to manual counts. The degree of explainability in object detection remains limited, and this—along with the underlying data sources—can introduce biases into the models. These biases may lead to errors in out-of-sample predictions, potentially resulting in the over- or underestimation of available truck parking spaces. Larger and more accurate training and validation datasets are essential in order to mitigate such biases. Manual counts, by contrast, are normally less prone to such errors and do not require extensive data preparation. Another challenge in our specific use case is that satellite imagery may obscure some parking spaces with obstacles such as trees or equipment, which limits visibility and detection accuracy.

As shown in subsection 3.2, our approach demonstrates a high degree of accuracy. Since there are still missing parking spaces that are not correctly detected, we calculate a correction factor C for approach i as the difference between predicted parking spaces and actual parking spaces from the test dataset using the following equation (1):

$$C_i = \frac{Actual\ Labels}{Predicted\ Labels} \tag{1}$$

The resulting coefficient C for the approach i (see Table 3 for results) equals 1.068, with which we adjust our model results.

4.3. Estimated HGV parking demand

Based on equations (2)–(5) applying the previously described data and the assumptions listed in Table 2, Fig. 6 illustrates the aggregated absolute parking demand for HGVs in NUTS-2 regions in Germany using a color gradient from light beige to dark grey. The regions shaded in dark grey represent those with the highest demand. Notably, eastern regions fall into this category, indicating high freight parking demand. Conversely, regions shaded in light beige have the lowest demand, with fewer than 1000 parking spots needed. These areas, particularly distributed in the southwest of Germany, experience less HGV parking demand along German highways.

4.4. Local equilibrium

Matching supply and demand enable us to identify local equilibriums as well as over- and undersupplied areas. Referring to a quotation of Glaeser and Joshi-Ghani stating that "the infrastructure need in enormous, but so is the possibility of building the wrong infrastructure" (Glaeser and Joshi-Ghani, 2014), it is essential to prioritize local over global comparisons. Inefficiencies arise as soon as supply and demand are spatially distant from each other. Therefore, we distinguish between micro view evaluation at the level of highway kilometers and the macro view evaluation at the aggregated level of NUTS-2 regions. We thereby allow micro level insights relevant for specialized developers and macro level insights with special interest for regional planning authorities and policymakers.

4.4.1. Micro view

Equation (6) expresses the equilibrium $E_{i,t}$ for HGV parking spaces on a given kilometer i at time t. Whenever supply and demand are balanced, their quotient $Q_{i,t}$ equals 1 and a local equilibrium sets in.

$$E_{i,t} \equiv 1 \equiv Q_{i,t} \tag{6}$$

[4] NUTS stands for Nomenclature of Territorial Units for Statistics in the European Union.

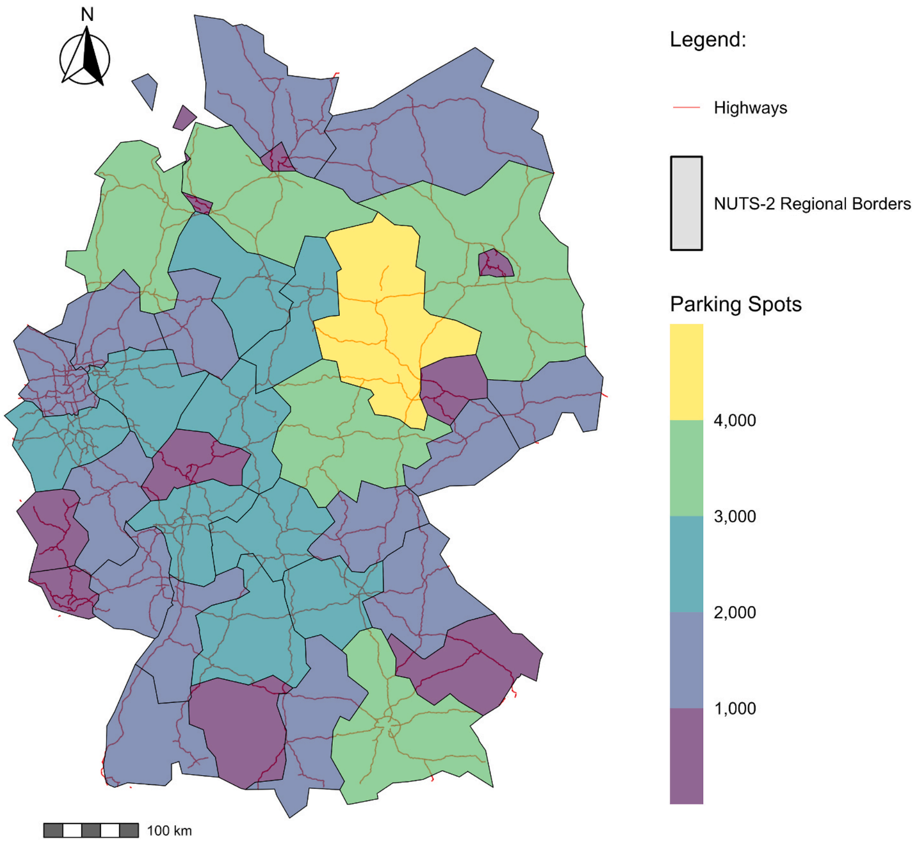

Fig. 5. Parking Supply along German Highways
Note. Geospatial data acquired from Google API and OpenStreetMap. The applied R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy (2024).

Table 4
YOLOv8-OBB model performance metrics on test data.

Metric	Value
Total Images Processed	71
Total Instances Detected	1523
Precision Box	0.887
Recall (R)	0.854
mAP at IoU = 0.50 (mAP50)	0.918
mAP at IoU = 0.50–0.95 (mAP50-95)	0.647

Note: This table summarizes results of the application of a trained YOLOv8 algorithm on unseen satellite imagery containing HGV parking spaces. The algorithm assessed 71 images detecting 1523 parking spaces with bounding boxes.

$$Q_{i,t} = \frac{S_{i,t}}{n(D_{i,t})} \; with \; n \in [1, \ldots, 13180] \tag{7}$$

Equation (7) highlights, how supply and demand are compared in their quotient $Q_{i,t}$. $D_{i,t}$ represents the demand for HGV parking spaces on kilometer i, and $S_{i,t}$ represents the supply of HGV parking spaces on kilometer i. $n(D_{i,t})$ represents the number of polygons (or kilometers) from which the supply $S_{i,t}$ can be reached.[5] We thereby assume a uniform distribution of supply on demanders.

Fig. 7 illustrates an example of reachable parking spaces from a given kilometer i within a 15 km polygon in green color.

[5] The number of polygons from where supply can be reached is limited by the total number of analyzed highway kilometers.

4.4.2. *Macro view*

Equation (6) assumes that an equilibrium ($E_{i,t} \equiv 1$) is achieved when the supply perfectly matches the demand. In other words, each region's parking supply is ideally distributed among the drivers from all regions that can access it. If $E_{i,t} > 1$, it suggests that there is an oversupply in region i, meaning the available parking spaces exceed the demand. Conversely, if $E_{i,t} < 1$, it indicates a shortage, where the demand for parking spaces outstrips the available supply and the need for additional parking facilities.

Fig. 8 illustrates the average ratio of HGV parking supply to demand aggregated on NUTS-2 regions in Germany, using a color gradient from dark blue to yellow. Regions shaded in **grey** indicate an undersupply (i.e. $E_{i,t} < 1$), with the parking infrastructure failing to meet the average demand, though not as severely as in regions shaded in dark blue.

Fig. 9 offers a clear depiction of the median supply versus demand ratio for HGV parking aggregated on the level of NUTS-2 regions in Germany, using a color gradient from dark purple (indicating severe undersupply or $E_{i,t} < 1$) to yellow (indicating an exact balance between supply and median demand or $E_{i,t} \equiv 1$). The map reveals that the vast majority of regions are experiencing an undersupply of parking facilities, with many areas shaded in blue to dark purple, indicating ratios as low as 0.2.

The comparison between the results from average versus median aggregation of supply versus demand ratios demonstrates that, in both scenarios, there is a significant and widespread undersupply of HGV parking across Germany's NUTS-2 regions. Regardless of whether median or average aggregation is applied, the maps consistently show that most regions are shaded in colors indicating undersupply, such as grey, blue, or dark blue.

However, the severity of these shortfalls varies. Bremen, North Rhine, Berlin, and Lower Bavaria show the largest gaps, while other

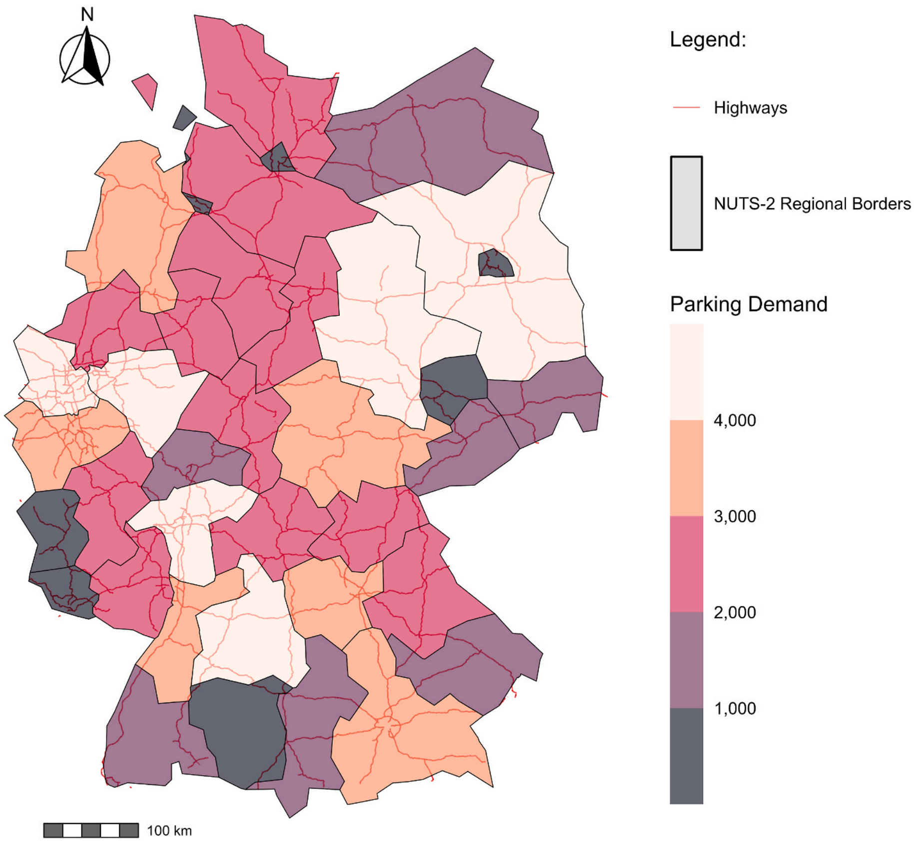

Fig. 6. Parking Demand along German Highways
Note. Geospatial data acquired from Google API and OpenStreetMap. The R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy, 2024.

regions - such as parts of Brandenburg and Lower Saxony - appear closer to balance.

We distinguish between three spatially grounded explanatory mechanisms that emerge from visual patterns in the data. The first mechanism, which we refer to as freight corridor concentration, suggests that the most acute mismatches occur along Germany's primary freight routes. In particular, regions such as Lower Bavaria (southeast), North Rhine (west), and Bremen (north) appear to suffer from infrastructure stress not solely due to local traffic volumes, but as a result of cumulative demand from long-distance transit freight. The second mechanism relates to rest cycle timing effects. Some regions, notably Lower Bavaria (southeast) and Hesse (middle west), may experience heightened parking demand due to their position within typical long-haul driving schedules—specifically, locations that fall within 4.5 or 9-h intervals on common east–west or north–south routes. These points in the journey correspond to mandatory rest breaks, concentrating demand independently of total throughput. The third explanatory mechanism pertains to urban freight bottlenecks. Highly urbanized regions such as Bremen, Dusseldorf (North Rhine), and the Frankfurt Rhein-Main area (Hesse) exhibit persistent undersupply that can plausibly be attributed to spatial constraints, dense last-mile delivery activity, and logistical complexity.

4.4.3. Location analysis for potential investments

In infrastructure or real estate investments, supply and demand are typically among the key determinants in location analysis. Our methodology operates on a meta-level, making it applicable across a wide range of investment scenarios. For example, in infrastructure analysis—such as ports or passenger vehicle parking—satellite imagery and demand data can be effectively utilized. There is also significant potential for real estate developers, particularly in the logistics sector. Our methodology for measuring truck parking demand is both scalable and applicable beyond the German market. Satellite data is generally available for the entire built environment, though resolution varies by continent and country. In order to meaningfully combine supply and demand data, reliable truck traffic frequency counts are required — data that is typically only available in industrialized countries. Within Europe, the applied methodology offers a cost-effective and scalable approach to identifying potential undersupply in truck parking infrastructure.

The identified undersupply has significant implications for both specialized real estate developers and policymakers. For developers, the regions experiencing the most severe undersupply represent key opportunities for investment. By leveraging our data, we can precisely identify the polygons—specific areas within these regions—that are most in need of additional HGV parking infrastructure. This targeted approach allows developers to focus their efforts on areas where demand is highest, ensuring that new facilities will meet an urgent need and likely see high utilization.

For policymakers, Fig. 9 highlights the urgent need to address the infrastructure shortfalls that are widespread across the country. By using the data to pinpoint exactly where the undersupply is highest, policymakers can prioritize regions for funding and development, ensuring that resources are allocated to the areas with the greatest need. This strategic investment could help alleviate parking shortages, reduce illegal parking, and enhance road safety for HGV drivers, ultimately leading to more efficient freight transport and economic benefits across Germany. While Figs. 8 and 9 indicate a general trend of undersupply, the ability to pinpoint specific areas of greatest need provides a powerful tool for targeted action and investment. Overall, we show that there is a strong investment case for specialized developers.

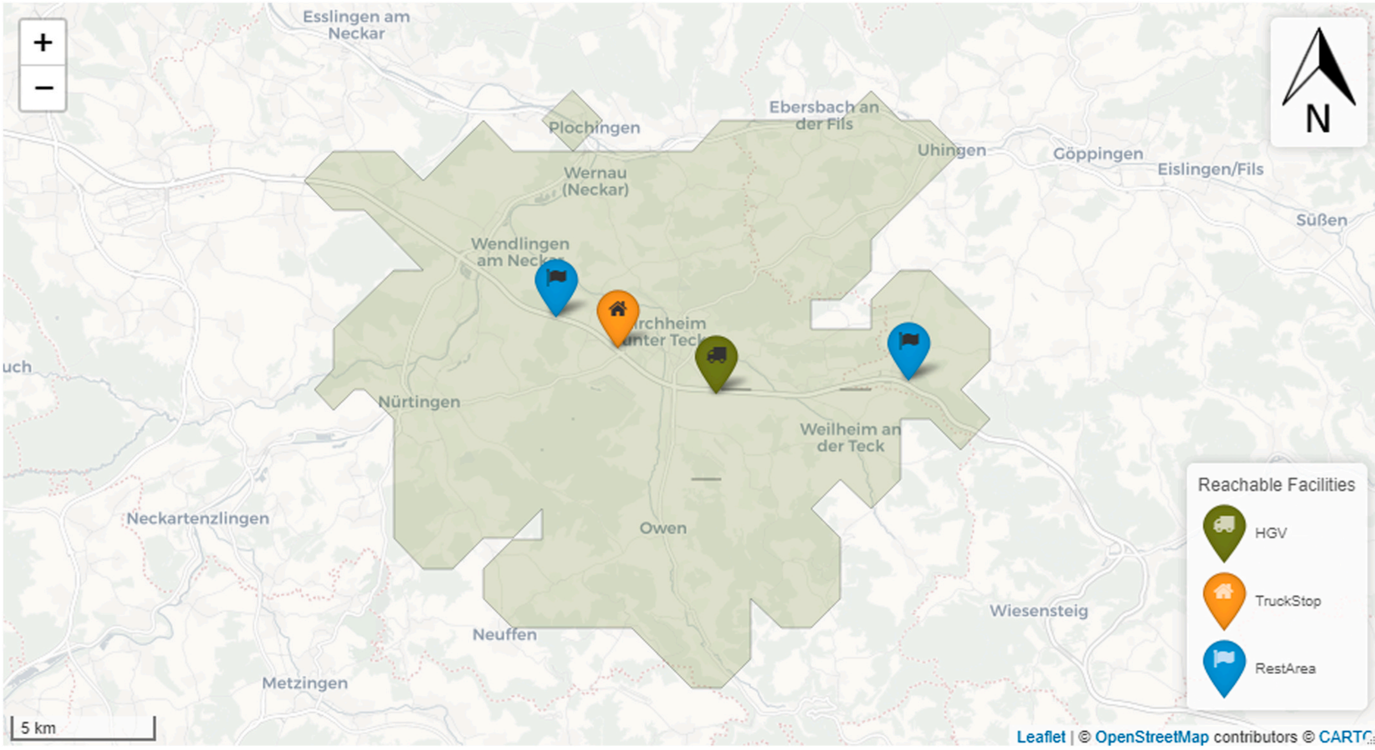

Fig. 7. Driving Distance Polygon (Reachable HGV Parking Spots within 15 km Radius)
Note. This figure illustrates an example polygon in green color and highway infrastructure facilities assigned with markers in orange and blue color on a German highway. Geospatial data acquired from Google API and OpenStreetMap. The R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy, 2024. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

5. Policy debate

Our analysis of HGV parking infrastructure along German highways reveals a critical imbalance between available supply and escalating demand, presenting both challenges and opportunities for specialized real estate developers. Despite the Ministry of Transport's five-point plan, which includes initiatives like creating new truck parking options, enhancing telematic parking procedures, and optimizing existing space utilization, the gap between current provision and the needs of HGV operators remains significant (Bundesministerium für Digitales und Verkehr, 2020). These governmental measures, while forward-thinking, have not fully addressed the complexity of the issue, particularly when considering the potential role of private sector investment in bridging this gap.

A central factor inhibiting private investment in HGV parking is the current market structure, particularly the dominant position of Tank & Rast.[6] As the quasi-monopolistic operator of service station on the Autobahn network, Tank & Rast offers free parking subsidized through ancillary services such as fuel and food sales. This model effectively crowds out competition: private developers must operate on non-federal land and charge for parking to achieve cost recovery, placing them at a structural disadvantage. The absence of price signals in the free parking segment—combined with exclusive access rights granted to Tank & Rast—prevents market-driven capacity expansion in high-demand areas. The German Monopolies Commission and other regulatory bodies have raised concerns that these long-term concession agreements restrict competition and innovation, even in adjacent sectors such as electric vehicle charging (German Council of Economic Experts, 2024). The result is a systemic under-provision of HGV parking, exacerbated by high entry barriers—both institutional and economic—for new market participants. Developers face substantial upfront costs, uncertain demand, and inferior locations relative to the Autobahn network.

Importantly, the economic viability of developing new paid parking infrastructure is also limited by HGV drivers' behavioral preferences. Drivers consistently prioritize free parking until it is fully occupied. Only then do they consider alternatives—either paid facilities or, increasingly, informal and often illegal parking. This behavior aligns with discrete choice models under capacity constraints (Ben-Akiva and Lerman, 1985), in which individuals select the highest-utility option given costs, accessibility, and availability. Paid parking typically involves both monetary costs and detours off the highway, reducing its relative utility. When enforcement against illegal parking is weak, and the perceived safety risk is low, informal parking becomes a rational, if undesirable, alternative for drivers operating under strict legal rest time constraints.

This behavioral dynamic reflects a deeper market failure (see model in Appendix): the absence of enforceable and differentiated pricing mechanisms results in inefficient allocation. Paid infrastructure may remain underused, while free and illegal parking options are chronically oversubscribed. Urban parking economics has demonstrated similar effects, where rigid pricing and insufficient enforcement lead to demand spilling over into unregulated or unauthorized spaces (Arnott and Inci, 2006; Verhoef et al., 1995). In the context of HGV infrastructure, this implies that expanding paid options alone—without corresponding adjustments in pricing, accessibility, or enforcement—is unlikely to resolve the imbalance.

The problem of parking scarcity is not unique to HGVs; urban areas face similar challenges with passenger vehicle parking, driven by legal requirements and the escalating cost of maintaining these spaces (Lehner and Peer, 2019; Yan et al., 2019). However, the

[6] Tank & Rast GmbH has a 93 percent market share and is owned by an investor consortium consisting of Allianz, Munchner Ruck, Canada's pension fund OMERS, and the China Investment Corporation (Piller, 2023).

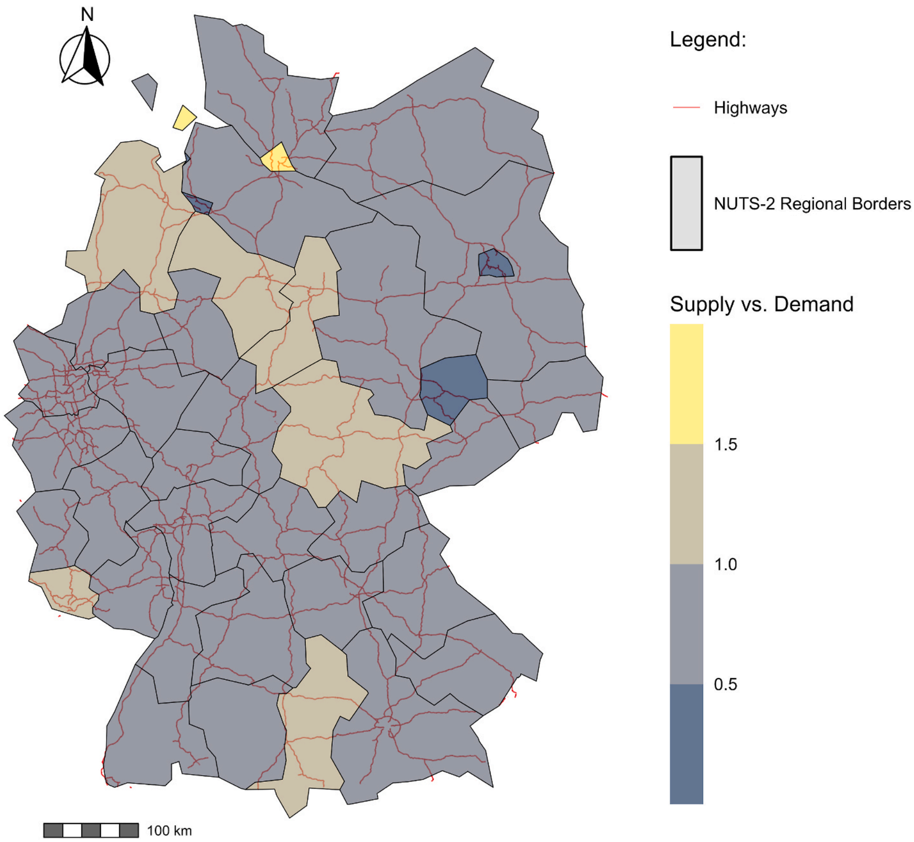

Fig. 8. Average Aggregation of Supply and Demand along German Highways
Note. Geospatial data acquired from Google API and OpenStreetMap. The R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy, 2024.

afore-mentioned absence of parking fees for HGVs and the specific demand for exclusive HGV parking spaces (Malik et al., 2017; Pècheux et al., 2002) further complicate the issue. Technology, particularly real-time information applications on HGV parking availability, has been identified as a potential solution to alleviate some of these challenges (Boris and Johnson, 2015; Martin and Shaheen, 2013; Trépanier, 2010). Nonetheless, land use policies significantly limit the development of new parking facilities, with jurisdictions often imposing restrictions on HGV parking on roadsides or other spaces (Giuliano et al., 2018; Perry et al., 2017). These high entry barriers compound the challenges pertaining to HGV parking provision.

Urban areas, where land is particularly scarce and expensive, face the most significant challenges. Zoning policies and urban densification targets frequently prohibit the construction of adequate HGV parking lots, presenting a substantial barrier to resolving the parking shortage (Giuliano et al., 2018; Meyer, 1999). Innovative solutions, such as adapting vacant or underutilized urban properties for HGV parking during off-peak hours, have been suggested as viable alternatives (Perry et al., 2017). Tax incentives and the implementation of nominal overnight parking fees could offer financial viability for these initiatives (Fleger et al., 2002).

6. Conclusion

The findings of this paper provide a comprehensive analysis of the current state of HGV parking infrastructure in Germany, with a specific focus on the implications for specialized real estate developers. First. we utilize machine learning methods to determine the actual supply of HGV parking spaces along German highways. This approach allows for an accurate and current number that can be updated regularly. We then matched our supply-side results with demand determined from traffic volume. The analysis reveals a critical and widespread undersupply of HGV parking spaces, with neither median nor average demand being adequately met across most regions.

The inability to meet demand on both the median and average levels highlight the potential for high returns on investment in the HGV parking sector. This situation presents a unique opportunity for developers to enter a market with minimal competition and significant unmet needs, ensuring that new developments are quickly absorbed by the market and generate stable revenue streams.

The long-term growth potential of the HGV parking sector is another consideration for specialized real estate developers. As Germany remains a central hub in European and global logistics, the demand for HGV parking is expected to grow alongside the expansion of freight transport activities. Developers who can strategically target these underserved areas stand to benefit from an immediate and sustained demand for parking infrastructure. Moreover, the development of infrastructure facilities improves working conditions for HGV drivers so that they no longer must live on the highway.

Lastly, the paper emphasizes the importance of adopting innovative solutions to effectively address the infrastructure and in particular the parking shortfall. Traditional real estate development strategies may fall short in this complex and regulated market. Developers who can leverage technology—such as real-time parking availability systems—or explore creative land use strategies, particularly in constrained urban environments, will be better equipped to meet the challenges of the market. Accordingly, further research potential lies in the collection and analysis of locally detailed data on infrastructure demand. Moreover, economic studies on subsidies and regulation are needed to evaluate targeted policy measures addressing the imbalance between highway infrastructure demand and supply.

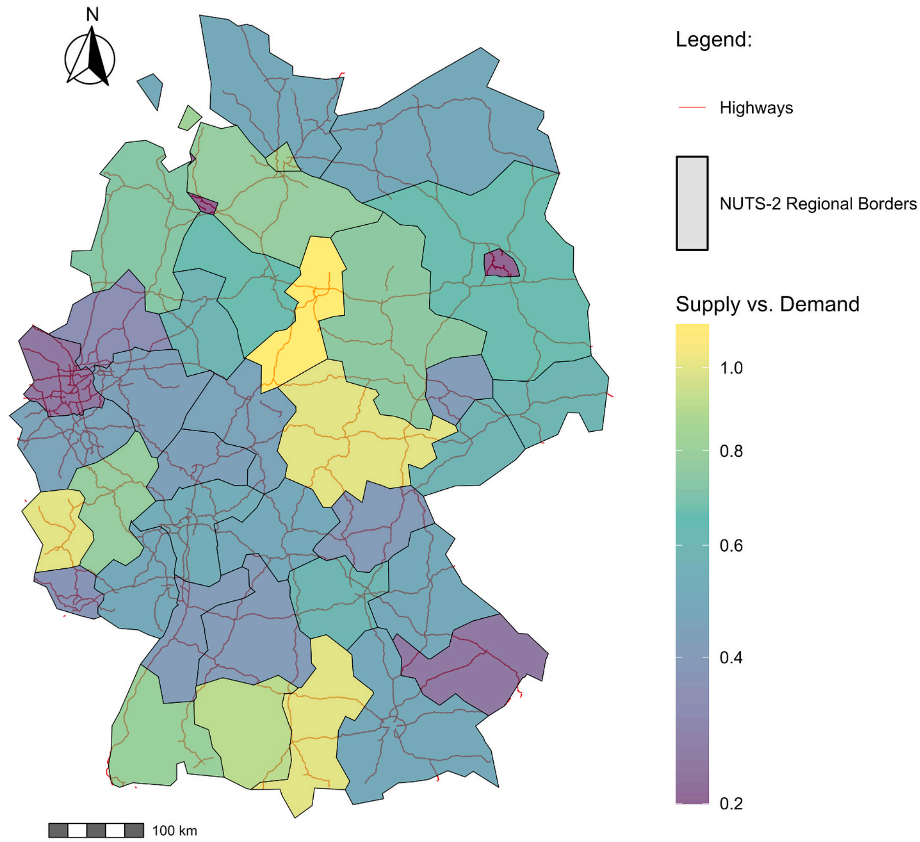

Fig. 9. Median Aggregation of Supply and Demand along German Highways
Note. Geospatial data acquired from Google API and OpenStreetMap. The R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy, 2024.

CRediT authorship contribution statement

Albert Grafe: Writing – review & editing, Writing – original draft, Resources, Investigation, Formal analysis, Conceptualization. **Julius Range:** Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Benedikt Gloria:** Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of interest statement

The authors report there are no competing interests to declare.

Appendix. 9

We model the parking decision of HGV drivers as a discrete utility-maximizing choice between three options: (A1) free public parking (typically at rest areas directly along the Autobahn), (A2) paid private parking (usually off-network), and (A3) illegal parking (e.g., on ramps or industrial roadsides). This extended framework accounts for the empirical observation that many drivers opt for unauthorized parking even when paid options exist, particularly when free facilities are fully occupied, and enforcement is weak.

Let drivers derive utility U from each option as follows:

Utility U_f from free parking:

$$U_f = \theta u_f + (1-\theta)u_p \tag{A1}$$

where θ is the probability of finding an available free spot, and u_f is the utility derived from it. If no free spot is found, the fallback utility u_p reflects a switch to paid parking.

Utility U_p from paid parking:

$$U_p = -C_p - T + \varepsilon_p \tag{A2}$$

where C_p denotes the monetary cost, T captures the time and fuel penalty for diverting off the highway, and ε_p is an idiosyncratic error term capturing preference heterogeneity.

Utility U_i from illegal parking:

$$U_i = -R - S + \varepsilon_i \tag{A3}$$

where R represents the expected financial penalty from enforcement (if applicable), S is the perceived safety risk (e.g., collisions or theft), and ε_i is an individual-specific shock.

Drivers are expected to choose the option with the highest expected utility. In this framework, illegal parking can dominate paid parking in cases where monetary and detour costs $(C_p + T)$ outweigh enforcement risks and perceived safety penalties $(R + S)$. This helps explain the widespread persistence of unauthorized truck parking along European freight corridors despite the existence of fee-based alternatives.

The structure aligns with capacity-constrained discrete choice models (Ben-Akiva and Lerman, 1985) and insights from urban parking economics (Arnott and Inci, 2006; Verhoef et al., 1995). Empirical extensions could estimate choice probabilities using a multinomial or mixed logit model and simulate scenarios under varying levels of enforcement, pricing, or capacity expansion. Such a model also supports policy insights: for example, increasing the perceived risk of enforcement R or lowering the cost of paid parking C_p could reduce illegal parking incidence.

Data availability

The authors do not have permission to share data.

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