

Article

Comparative Evaluation of Hydrotreated Vegetable Oil and Conventional Diesel Using Operational Data from Heavy-Duty Trucks

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Abstract

Hydrotreated vegetable oil (HVO) is considered a promising drop-in alternative to conventional diesel fuel for reducing greenhouse gas emissions in road freight transport. However, empirical evidence on its performance under real-world operating conditions remains limited. This is particularly true for complex logistics systems such as agricultural transport. This study assesses the effect of neat HVO (HVO100) on fuel consumption using high-resolution vehicle operational data collected from three heavy-duty trucks during a full-scale sugar beet logistics campaign in Germany. Vehicle operation was recorded via a manufacturer-independent fleet management system interface and combined with satellite-based positioning data for route reconstruction. After data preprocessing and quality filtering, a total of 3353 valid transport tours were analyzed. Fuel consumption values during HVO100 operation were corrected for density-related measurement bias. The effect of fuel type was evaluated using a linear mixed-effects model. The model accounted for load status, route topography, driving speed, and their interactions. In addition, stratified pairwise comparisons were conducted across operational conditions. The results show that, in the full three-vehicle model, HVO100 was associated with a statistically significant increase in fuel consumption of 0.51 L/100 km under baseline conditions with an empty vehicle, low topographic variability, and medium driving speed, corresponding to approximately 2.3%. In a sensitivity analysis excluding the diesel-only truck, the estimated difference decreased to 0.34 L/100 km and was no longer statistically significant. Load status and topography were identified as the dominant drivers of fuel consumption with substantially larger effects than fuel choice. Overall, the findings indicate that the effect of HVO100 on fuel consumption is small relative to operational variability. Under many real-world operating conditions, operational factors outweighed the differences attributable to fuel type. These findings indicate that switching to HVO100 did not result in a substantial volumetric fuel-consumption penalty in the investigated agricultural logistics system.



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Keywords: hydrotreated vegetable oil; alternative fuels; heavy-duty trucks; fuel consumption; vehicle operational data; real-world data; agricultural logistics; route-based analysis

1. Introduction

Reducing greenhouse-gas emissions from transport is a global challenge. In 2019, direct emissions from the transport sector amounted to approximately 8.7 Gt CO₂-eq and accounted for 23% of global energy-related CO₂ emissions [1]. Within this broader

international context, Germany has introduced legally binding national targets for reducing greenhouse-gas emissions under the German Federal Climate Change Act (Bundes-Klimaschutzgesetz, KSG). According to Section 3 of the KSG, Germany aims to achieve greenhouse gas neutrality by 2045, with interim emission reduction targets of at least 65% by 2030 and 88% by 2040 compared with 1990 levels. While some sectors, such as the energy sector, have already met or even exceeded their reduction targets, the transport sector continues to fall significantly short of its goals [2–5].

Although alternative fuels and powertrains are gaining increasing market share in passenger cars [6], progress in the road freight sector remains comparatively slow. This is particularly critical given the significant contribution of heavy-duty transport to overall greenhouse gas emissions and the necessity for substantial emission reductions in this sector [7]. Several policy measures have already been introduced to accelerate this transition, such as Regulation (EU) 2023/1804 on the deployment of alternative fuels infrastructure. However, the implementation of alternative powertrains in road freight transport still faces considerable challenges.

Long-haul freight transport typically operates along major transport corridors. In contrast, agricultural logistics often take place in rural areas where infrastructure for alternative fuels and heavy-duty vehicles is limited or absent [8]. Transport demand in agricultural logistics is also characterized by strong seasonal fluctuations. Significant demand peaks may occur during harvest periods [9]. During these periods, transport capacities must be mobilized at short notice, often requiring multi-shift operation of vehicles and resulting in high vehicle utilization over a limited time frame. While agricultural logistics could benefit from alternative fuels due to daily depot returns, the aforementioned challenges are even more pronounced in this sector.

A prominent example is the transport of sugar beets, which typically takes place between mid-September and the end of January. During this period, trucks can accumulate annual mileages comparable to or even exceeding those of conventional long-haul trucks operating year-round. While a typical heavy-duty truck in Germany travels approximately 114,000 km per year [10], the vehicles analyzed in this study reached approximately 125,000 km within a single campaign period. The underlying logistics system is highly coordinated and campaign-based. It requires a continuous and tightly synchronized supply of sugar beets to the processing plant, which has only limited buffering capacity. Following harvest, the beets are temporarily stored at the field edge and loaded by specialized machinery. They are then transported to the factory and unloaded using dedicated infrastructure. To maintain stable plant operation, transport processes are organized in multi-shift systems and coordinated across geographically defined hauling groups, resulting in near-continuous vehicle utilization during the campaign. Outside of this time window, however, vehicle utilization is significantly reduced. Such strongly fluctuating utilization patterns pose additional economic and operational challenges for the adoption of alternative powertrain technologies, particularly with regard to infrastructure requirements, vehicle availability, and return on investment.

Against this background, hydrotreated vegetable oil (HVO) represents a promising and readily available drop-in alternative to conventional diesel fuel. HVO is a paraffinic diesel fuel produced by hydrotreating lipid-based feedstocks, including vegetable oils, used cooking oils, animal fats, and suitable waste and residue oils. Although HVO and fatty acid methyl ester (FAME) biodiesel can be produced from similar feedstocks, they differ fundamentally in their conversion process and chemical composition: FAME is produced by transesterification, whereas HVO is produced by hydrotreating and consists mainly of paraffinic hydrocarbons [11].

However, existing studies on HVO have often been conducted under controlled laboratory conditions, on standardized test cycles, or within limited route segments [11–13]. As a result, there is still a lack of empirical evidence on its performance under real-world operating conditions, particularly in complex and variable logistics systems such as those found in agriculture.

The present study is part of a multi-year research project investigating alternative powertrain technologies in agricultural road freight transport, with a focus on raw milk collection and sugar beet logistics. The objective of this study is to compare the fuel consumption of HVO100 and conventional diesel based on high-resolution CAN bus data obtained from real-world truck operations.

While previous studies have demonstrated the general suitability of HVO100 as a drop-in fuel for heavy-duty diesel engines, knowledge about its influence on fuel consumption under real-world operating conditions remains limited. In particular, the effects of operational factors such as vehicle load, route topography, and driving speed have rarely been investigated in long-term field operation. These operational parameters are among the dominant determinants of fuel consumption in heavy-duty transport and may substantially exceed fuel-related effects under real-world operating conditions [14,15]. Heavy-duty vehicles are particularly sensitive to road grade, with fuel consumption increasing rapidly as slope increases [16]. Furthermore, many existing studies are based on laboratory measurements or standardized driving cycles and therefore only partially reflect the variable operating conditions of agricultural freight transport.

This study analyzes a large dataset covering a wide range of real-world operating conditions. The aim is to provide further insight into HVO100-related fuel-consumption patterns and their dependence on operational conditions in agricultural logistics.

Rather than deriving universally valid absolute fuel-consumption values, the study focuses on the relative magnitude of fuel-related effects compared with dominant operational determinants. The novelty of this work lies in combining high-resolution CAN and GNSS data from a full-scale logistics campaign with a route-level mixed-effects analysis that accounts for vehicle load, route topography, and driving speed. The study therefore contributes real-world evidence on the relative importance of fuel type and operational conditions in heavy-duty agricultural logistics.

2. Materials and Methods

2.1. Vehicles and Test Area

All vehicles and tours included in this study were part of Südzucker’s sugar beet logistics operations serving the factory in Rain. During the 2024/25 sugar beet campaign, three identically equipped trucks from a single hauling group were available for data collection (Table 1).

Table 1. Technical details of the trucks used in this study.

Truck	Model	Engine	Fuel Used	Initial Odometer Reading
53	MAN TGS 18.430 4×2 BL SA	MAN D2676 LFAJ, 316 kW (430 PS)	Diesel/HVO100	104,913.5 km
49	MAN TGS 18.430 4×2 BL SA	MAN D2676 LFAJ, 316 kW (430 PS)	Diesel	188,688.2 km
57	MAN TGS 18.430 4×2 BL SA	MAN D2676 LFAJ, 316 kW (430 PS)	Diesel/HVO100	108,851.8 km

The vehicles were equipped with MAN D2676 LFAJ six-cylinder in-line diesel engines (MAN Truck & Bus SE, München, Germany) with a displacement of 12.4 L and a rated power of 316 kW. Fuel was supplied by an electronically controlled common-rail injection system with a maximum injection pressure of 1800 bar. According to the manufacturer, the engine is approved for operation with both diesel fuel complying with DIN EN 590 [17] and paraffinic diesel fuels complying with DIN EN 15940 [18], including HVO100. For conventional operation all vehicles were fueled with market standard diesel fuel (B7), which is referred to as diesel throughout this study. No modifications to the fuel system and no fuel-specific recalibration of the engine control system were performed when switching between diesel and HVO100.

The filling-station operator confirmed that the HVO100 supplied during the experimental campaign complied with DIN EN 15940, Class A. No batch-specific fuel certificate or product specification was available for the conventional B7 diesel. Therefore, Table 2 reports the relevant requirements of DIN EN 15940 Class A for HVO100 and the regulatory requirements of DIN EN 590 for B7 diesel. The lower heating values are representative literature values and were not measured for the individual fuel batches used in this study.

Table 2. Selected properties of the fuels used in the study. Values for HVO100 are based on DIN EN 15940 Class A, whereas values for B7 diesel represent the requirements of DIN EN 590. Lower heating values are representative literature values and not batch-specific measurements.

Property	Unit	B7 Diesel	HVO100
Fuel standard	–	DIN EN 590	DIN EN 15940, Class A
Cetane number	–	≥ 51	≥ 70
Density at 15 °C	kg m^{-3}	820–845	765–800
Kinematic viscosity at 40 °C	$\text{mm}^2 \text{s}^{-1}$	2.00–4.50	2.00–4.50
Sulfur content	mg kg^{-1}	≤ 10	≤ 5
Lower heating value	MJ kg^{-1}	42.0–43.58 ^a	43.6–44.11 ^a
Volumetric lower heating value	MJ L^{-1}	34.9–36.1 ^a	34.00–34.6 ^a

^a Representative literature values reported by [19]; these values do not constitute measurements of the fuel batches used in the present study.

The loading areas were located approximately 60 km from the sugar factory on average, measured as straight-line distance (Figure 1). Based on the spatial distribution of these loading sites, the transport routes can be broadly classified into two groups. A large share of the loading sites is located in the Lech Valley south of Augsburg, where routes to the factory are characterized by relatively flat terrain with a slight downhill gradient towards the north. The second group of loading sites is situated further east, in the region between Augsburg and the greater Munich area. In this area, the routes are characterized by consistently undulating terrain.

2.2. Measurement Setup

All trucks included in this study were equipped with a manufacturer-independent Fleet Management System (FMS) interface. This interface provides standardized cross-manufacturer access to selected vehicle operating parameters [20]. The FMS interface is based on the CAN bus communication standard J1939, which is widely implemented in heavy-duty vehicles [21]. Consequently, additional signals that are not part of the official FMS parameter set but are available on the J1939 network could also be accessed via this interface.

Vehicle data were recorded using a CANedge3 data logger manufactured by CSS Electronics (Aabyhoej, Denmark) [22]. In addition to the CAN interface, the logger was equipped with an integrated GNSS receiver. Position data were recorded simultaneously

with the vehicle data. An LTE modem was used for automated data transmission. To limit the resulting data volume, the loggers were configured to record each CAN message at a maximum frequency of 1 Hz. The collected data were transmitted every five minutes in MF4 format via the cellular network to an Amazon Web Services (AWS) S3 bucket, where they were made available for subsequent processing.

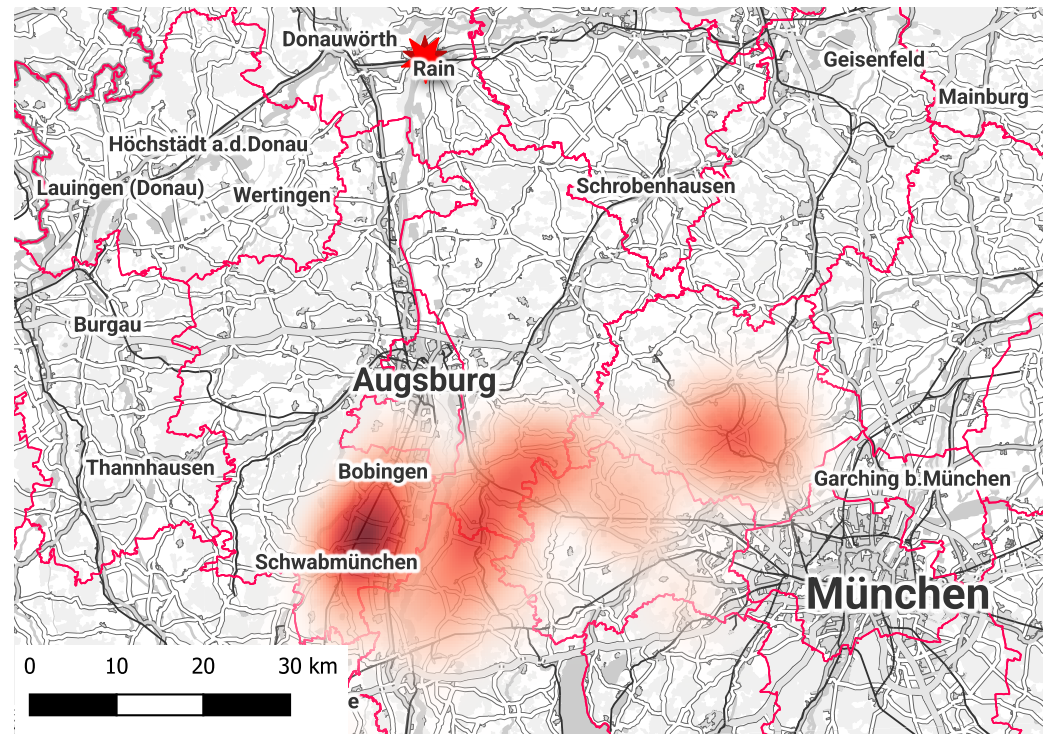


Figure 1. Distribution of the beet loading sites served by the hauling group under study, as well as the location of the sugar factory in Rain. The heatmap represents the spatial density of the beet loading sites, with more intense colors indicating a higher concentration of loading sites. The red star indicates the location of the sugar factory in Rain. Basemap: © GeoBasis-DE/BKG (2025), CC BY 4.0, <https://creativecommons.org/licenses/by/4.0/>.

2.3. Data Preprocessing and Aggregation

The MF4-to-Parquet decoder provided by CSS Electronics [23] was first used to decode the raw measurement data. Using a J1939 DBC file, the tool converts MF4 log files into decoded signals and stores them as Parquet files organized by day and PGN. To ensure reproducibility, the applied data processing workflow is described in the following.

First, a continuous time axis was generated from the first and last timestamps of the dataset and discretized into one-second intervals. All signals were aligned to this reference timeline via a timestamp-based join. Missing values were imputed depending on signal type (discrete: nearest neighbor; continuous: linear interpolation) with a limited maximum gap length of 10 consecutive samples, corresponding to 10 s at the 1 Hz temporal resolution. Position data were forward-filled only during stationary periods.

Operational state variables such as trailer coupling status, pause/engine-off periods, and loading status were derived from the measurement signals. Refueling events were detected based on significant increases in the fuel level signal. Loading events were identified using the weight signal reported by the trailer brake controller, while unloading events were detected based on weight changes and additionally validated using a geofence at the sugar factory.

To obtain detailed information about the driven routes, a map-matching procedure was applied. For this purpose, the Python 3.12 bindings of the Valhalla routing engine

were used [24]. The routing graph was generated from an OpenStreetMap (OSM) extract provided by Geofabrik GmbH (Karlsruhe, Germany) [25].

To include farm tracks and paths marked as non-drivable in the original dataset, the tool *osmfilter* [26] was used to remove the tags *access=**, *motorcar=**, *motorcycle=**, *motorvehicle=**, and *vehicle=**. Additionally, *highway=construction* was converted to *highway=unclassified*, since Valhalla does not perform routing on construction segments even during map matching.

To ensure data quality and comparability across tours, several filtering steps were applied during preprocessing. First, the route length obtained from map matching was compared with the tour length reported by the vehicle. Tours with deviations greater than 4% were excluded. This removed cases with potentially unreliable spatial reconstruction. Only one fuel station within the study area provided HVO100 during the experimental phase. Drivers therefore had to make detours to reach this station. Tours containing a refueling event were excluded to prevent these detours from affecting the route analysis.

For all remaining valid tours, operational characteristics such as average vehicle speed and fuel consumption were aggregated from the vehicle data. In addition, route-related metrics were derived from the Valhalla map-matching results, including the share of motorway driving, the number of turning maneuvers, the proportion of unpaved road segments, and the elevation profile of each tour.

2.3.1. Data Accuracy

The primary variable of interest, namely the truck's fuel consumption, is not measured directly but estimated internally based on engine parameters [27]. Consequently, the values reported via J1939 are subject to deviations and fluctuations. The magnitude of these deviations was assessed using the refueling records. For each complete refueling interval, the change in the cumulative J1939 parameter Total Fuel Used—High Resolution was compared with the corresponding fuel quantity documented on the refueling receipt. The refueling records were used solely to evaluate the accuracy of the ECU-derived values and not to determine fuel consumption at the individual-tour level. All data processing and analysis steps were carried out using Python 3.12.

2.3.2. Comparison of Operational Data for HVO100 and Diesel

Because ECU-derived fuel consumption showed a larger deviation during HVO100 operation, the HVO100 values reported for Trucks 53 and 57 were corrected by a factor of 1.065 (cf. [11]) to account for the lower fuel density. These were the only two vehicles operated with HVO100; Truck 49 was operated with diesel only and was therefore not subject to the correction. The applicability of the factor was assessed by comparing corrected and uncorrected cumulative ECU-derived fuel quantities with independent refueling records. To ensure a consistent within-vehicle comparison, this validation was likewise restricted to Trucks 53 and 57.

Based on the operational factors identified in the introduction, load status, route topography, and driving speed were selected as explanatory variables for the statistical analysis of fuel consumption. In route-based analyses, road grade is typically represented as a continuous longitudinal profile along the driven distance. However, due to its high variability, the direct use of raw grade values is not suitable for comparative analyses across routes. To address this, aggregated scalar metrics are commonly used to describe complex road profiles. For example, road roughness indices such as the International Roughness Index reduce small-scale longitudinal elevation profiles to a single representative value, enabling comparison between road segments with different geometric characteristics (cf. [28]). In

analogy to such approaches, the variability and intensity of road grade along a route were quantified using the root mean square (RMS) of the slope values.

Elevation profiles were derived from the matched route geometry using the Valhalla height service with a resampling distance of 10 m. To reduce noise in the elevation data, the height profile was smoothed using a centered rolling mean with a window size of 10 samples (corresponding to approximately 100 m). The slope between consecutive points was calculated as the elevation difference divided by the segment length and expressed as a percentage.

Since the aim of the metric is to capture the additional energy demand caused by uphill driving, negative slope values were excluded by setting them to zero. Downhill segments may reduce fuel consumption due to reduced engine load or fuel cut-off strategies, but do not contribute to additional energy demand. The RMS slope was then computed as:

$$s_i = \max\left(\frac{\Delta h_i}{\Delta d_i} \cdot 100, 0\right) \quad (1)$$

$$\text{RMS}_{\text{slope}} = \sqrt{\frac{1}{n} \sum_{i=1}^n s_i^2} \quad (2)$$

where Δh_i and Δd_i denote the elevation and distance differences of segment i , respectively, s_i is the resulting (non-negative) slope in percent, and n is the number of valid segments.

Based on the spatial and topographic characteristics of the study area described above, the tours were divided into two groups using an RMS-slope threshold of 1.5%. The threshold was selected to operationalize the distinction between the routes with lower topographic variability in the Lech Valley and the more undulating routes located further east. Tours with an RMS slope below 1.5% were classified as having lower topographic variability, whereas tours with an RMS slope of 1.5% or higher were classified as having higher topographic variability. The threshold is specific to the route conditions represented in this study and should not be interpreted as a universal engineering classification of road gradients.

Within the logistics system of sugar beet transport, partial loading does not occur; vehicles operate either fully loaded or empty. Accordingly, load status was treated as a binary variable (loaded vs. empty) in the analysis.

Vehicle speed was included as an additional explanatory variable to account for differences in driving regimes and their influence on fuel consumption. For this purpose, the average speed of each tour was calculated based on the vehicle data and categorized into three classes: low speed (<30 km/h), medium speed (30–55 km/h), and high speed (>55 km/h).

These classes reflect typical operating conditions of heavy-duty vehicles, ranging from low-speed urban driving to higher-speed operation on rural roads and motorways. However, due to the operational characteristics of the investigated logistics system, low-speed tours occurred only rarely ($n = 4$) and were therefore underrepresented in the dataset. As a result, this class was excluded from further analysis to ensure statistical robustness.

Due to temporary supply constraints of HVO100 at the filling station, continuous operation of the vehicles on HVO100 was not possible throughout the entire experimental period. During periods of limited HVO100 availability, vehicles were operated on conventional diesel fuel to maintain uninterrupted logistics operations. Fuel allocation and switching between HVO100 and diesel were therefore neither based on a predefined experimental schedule nor randomized. Because the fuel tanks were not completely drained when switching fuels, blending with residual fuel may have occurred during the transition

period after a fuel change. The exact blend ratios were not determined. The resulting temporal distribution of fuel usage across vehicles is shown in Figure 2.

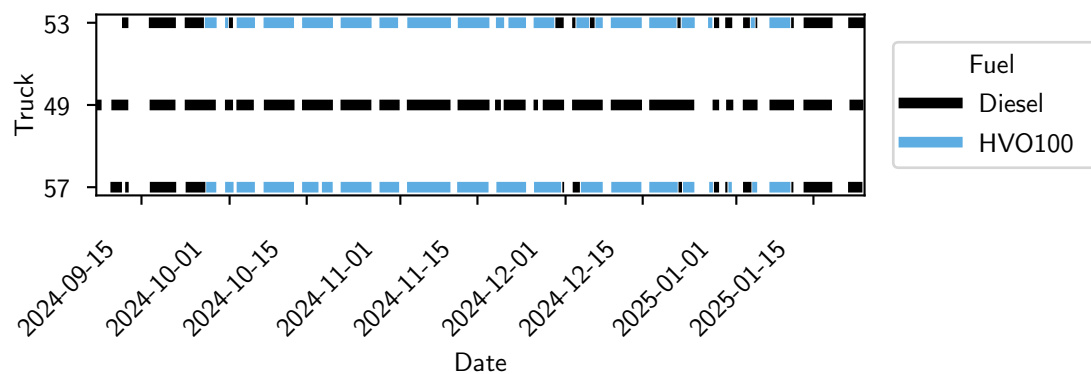


Figure 2. Type of fuel used by each truck over the course of the experimental campaign. The figure illustrates the temporal distribution of HVO100 and diesel usage across the three investigated vehicles.

2.3.3. Statistical Model

To investigate the effect of fuel type on fuel consumption, a linear mixed-effects model (LMM) was estimated using restricted maximum likelihood (REML). To account for vehicle-specific variability, a random intercept was specified for each vehicle (VIN). The model included fuel type, load status, topography, and speed as fixed effects as well as two-way interaction terms between fuel type and each operational variable. As a sensitivity analysis, the main model was repeated after excluding Truck 49, which had a higher initial mileage and was operated exclusively with diesel. Stratified pairwise comparisons (Welch's *t*-tests) were conducted for all eight combinations of load status, topography, and speed class. These tests were used as supplementary evidence only, with *p*-values adjusted using the Holm–Bonferroni method.

3. Results

A total of 4609 tours were recorded during the experimental period across the three investigated vehicles. After applying all preprocessing and filtering steps, 3353 tours remained for further analysis.

Figure 3 presents an illustrative time series from a loaded return trip from a sugar beet loading site to the factory. According to the RMS-slope classification used in this study, the selected tour belongs to the category of higher topographic variability.

3.1. Accuracy of Fuel Consumption Data

The comparison of fuel quantities obtained from refueling station records with the corresponding values from vehicle data showed an average deviation of 7.8% during the use of diesel. Owing to the density difference between diesel and HVO100 described in Section 2.3.2, as well as the measurement principle applied in the truck, the average deviation increased to 13.6% during HVO100 operation. After applying the density correction mentioned in Section 2.3.2, the mean deviation decreased to 8.1%, compared to 7.8% during diesel operation (see Figure 4).

3.2. Comparison of Fuel Consumption Between HVO100 and Diesel

Under baseline conditions (empty vehicle, lower topographic variability, medium speed), operation with HVO100 was associated with an increase in fuel consumption of 0.51 L/100 km compared to diesel ($\beta = 0.507$, $p = 0.013$).

In addition to fuel type, all operational variables showed strong and highly significant effects. Fully loaded operation increased fuel consumption by 7.33 L/100 km ($\beta = 7.332$, $p < 0.001$), while higher topographic variability increased fuel consumption by 1.90 L/100 km ($\beta = 1.901$, $p < 0.001$). In contrast, high-speed driving (>55 km/h) was associated with a reduction in fuel consumption of 1.46 L/100 km compared to medium-speed conditions ($\beta = -1.461$, $p < 0.001$).

The interaction terms show that the effect of HVO100 depended on the operational conditions. Under fully loaded operation, the difference in fuel consumption between HVO100 and diesel increased slightly ($\beta = 0.378$, $p = 0.012$), whereas the difference decreased under conditions of higher topographic variability ($\beta = -0.426$, $p = 0.004$). No significant interaction was found between fuel type and speed class ($\beta = 0.110$, $p = 0.553$), indicating that the relative fuel consumption difference was largely independent of driving speed.

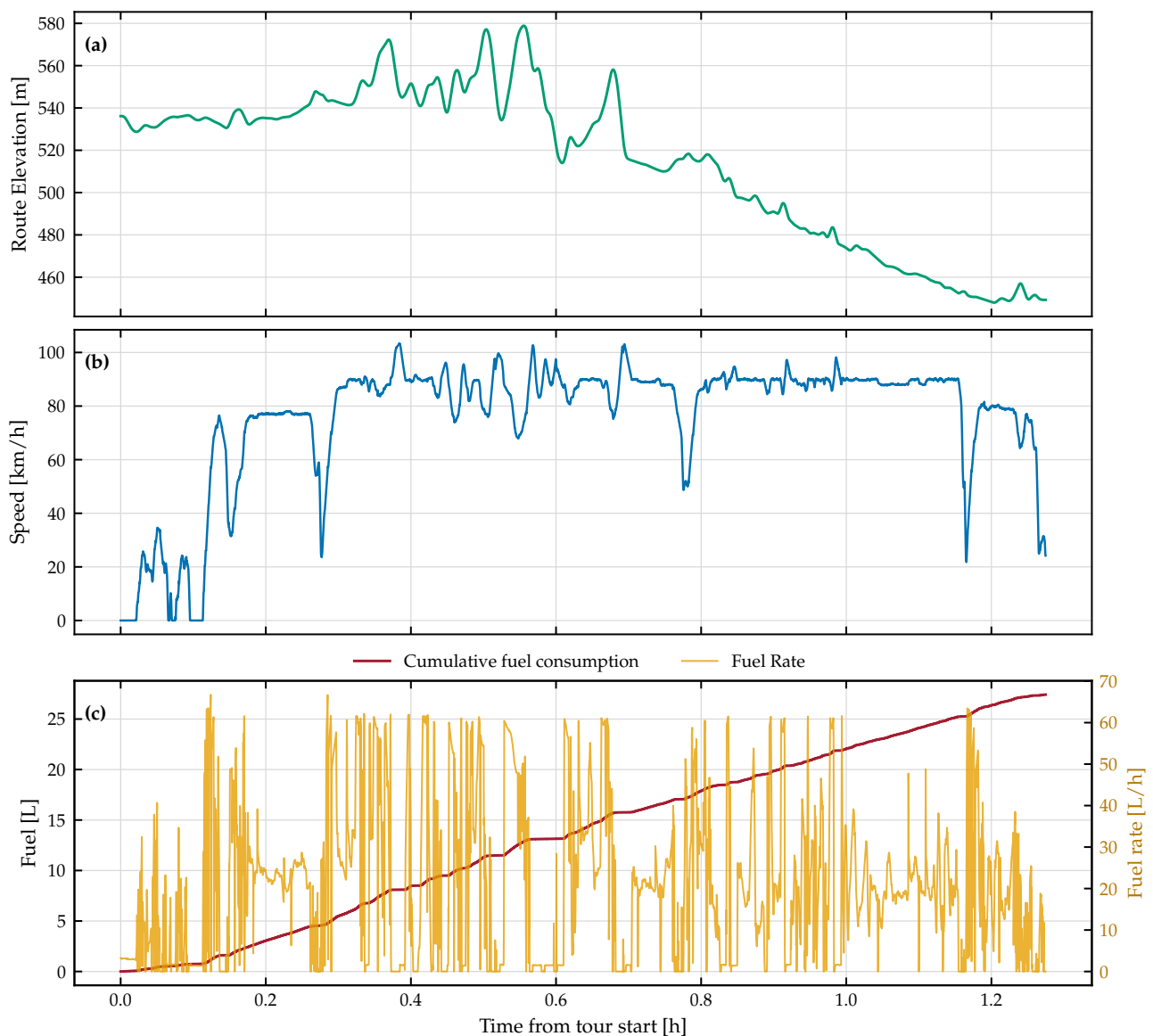


Figure 3. Illustrative time series from one analyzed loaded transport tour: (a) route elevation, (b) ECU-reported vehicle speed, and (c) instantaneous fuel rate and cumulative ECU-derived fuel consumption. The figure illustrates the temporal structure of the operational data underlying the subsequent route-level analysis.

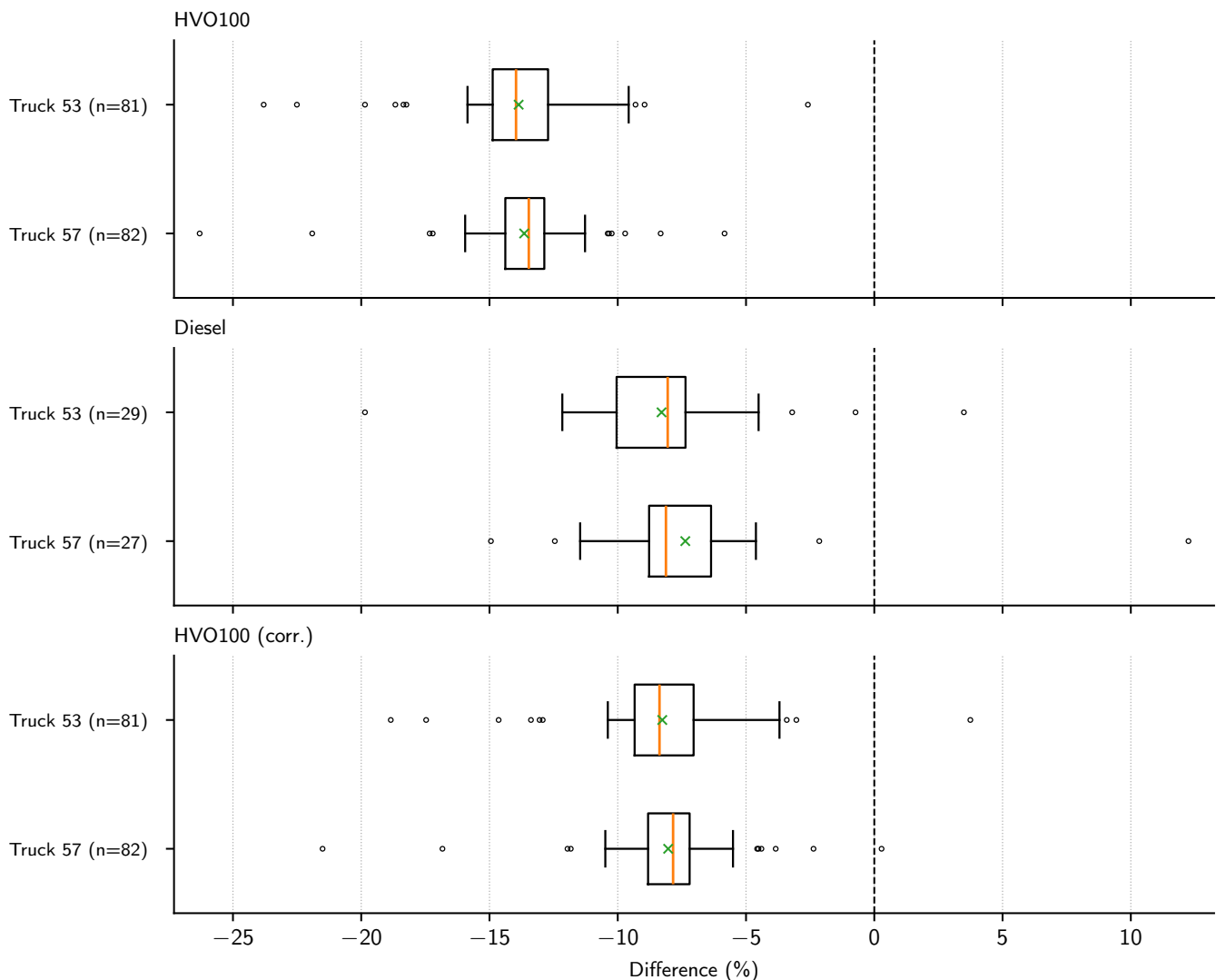


Figure 4. Vehicle-specific distributions of the relative differences between ECU-derived cumulative fuel consumption and the corresponding quantities documented in the refueling records for HVO100, diesel, and density-corrected HVO100. Only Trucks 53 and 57 are shown because these vehicles were operated with both fuels and were used to evaluate the HVO100 correction. Boxes show the interquartile range, lines the median, crosses the mean, circles outliers, and whiskers values within 1.5 times the interquartile range.

Re-estimating the interaction model without Truck 49 reduced the HVO100 coefficient from 0.507 to 0.344 L/100 km, and the effect was no longer statistically significant.

In the full three-vehicle model, the estimated HVO100 effect was statistically significant but small in magnitude, corresponding to a relative increase in fuel consumption of approximately 2–3% under the reference conditions. The absolute difference between HVO100 and diesel increased slightly under fully loaded operation, decreased under conditions of higher topographic variability, and was not significantly affected by speed class.

In the pairwise comparisons (Figure 5), significant differences between HVO100 and diesel were only found under a limited set of conditions, primarily characterized by low topographic variability and high-speed operation. Specifically, significant differences were observed for empty vehicles on terrain with low topographic variability at high speed ($p = 0.0013$) and for fully loaded vehicles under the same conditions ($p = 0.0021$). In contrast, no statistically significant differences were detected for medium-speed driving or

for any conditions involving terrain with higher topographic variability after correction for multiple testing. This applies to both empty and fully loaded operation, where adjusted p -values consistently exceeded the significance threshold.

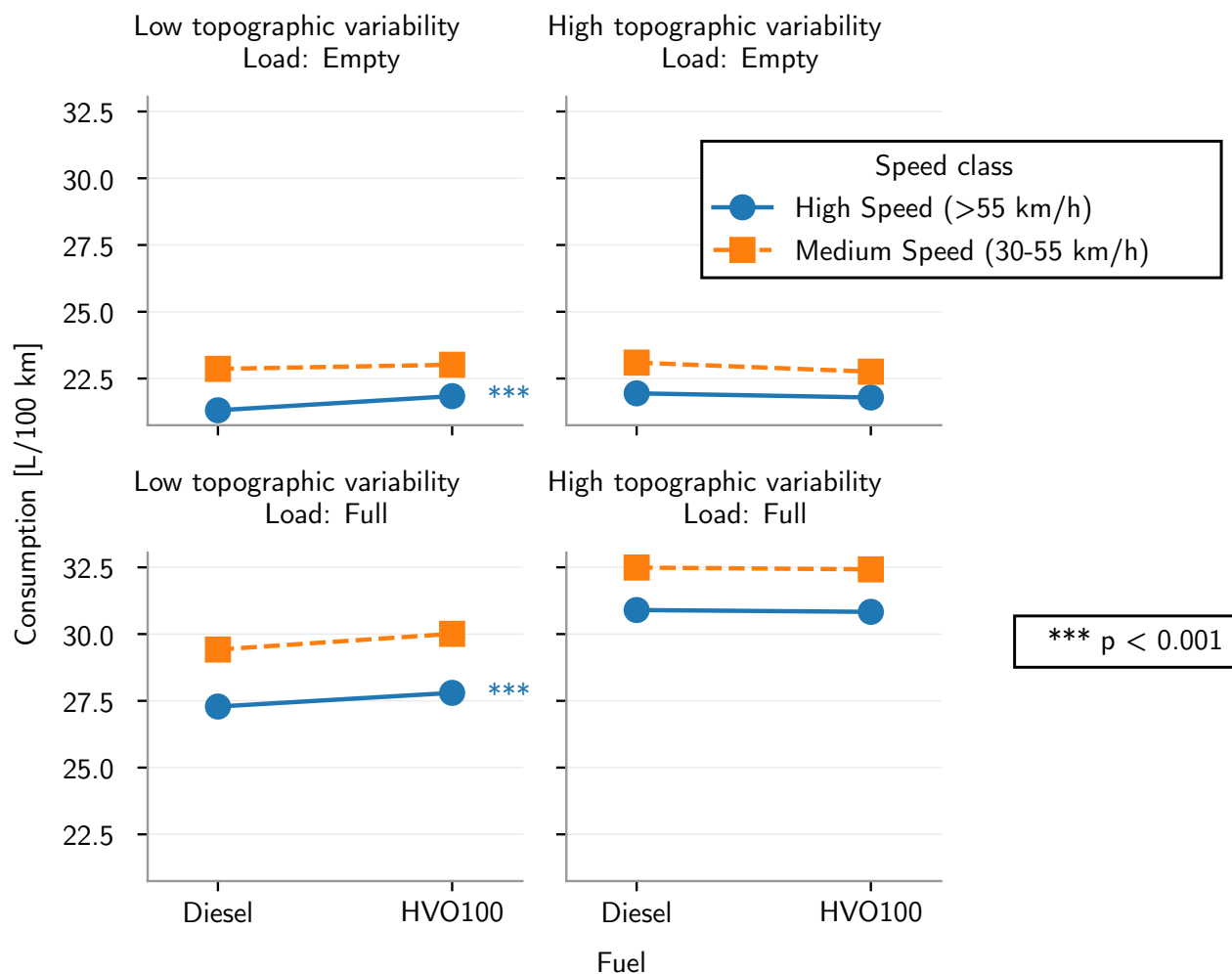


Figure 5. Fuel consumption by fuel type under different combinations of load status, topography, and speed class. Asterisks indicate statistically significant pairwise differences after Holm–Bonferroni correction.

4. Discussion

4.1. Methodological Considerations and Limitations

The present study is based on real-world operational data collected during a full-scale sugar beet logistics campaign. A key strength lies in the use of real-world operational data, which captures the combined variability and interaction of payload, route topography, traffic conditions, and driving behavior, factors that are only partially represented in standardized laboratory test cycles.

At the same time, several methodological limitations must be considered.

First, tour-level fuel consumption was derived from ECU-based estimates reported via J1939 and not from refueling records. The use of ECU-derived data was necessary because refueling records provide only aggregate fuel quantities over complete refueling intervals and do not allow fuel consumption to be assigned to individual tours. The refueling records were therefore used solely to assess the accuracy of the cumulative ECU-derived fuel-consumption values. This comparison revealed deviations for both fuels, with larger systematic differences for HVO100 prior to correction. This is consistent with previous

findings that ECU-based consumption calculations are typically calibrated for conventional diesel properties and may not directly transfer to paraffinic fuels [29]. Manufacturer-specific information on the internal fuel-consumption calculation of the MAN D2676 ECU was not available. However, applying the independently selected density correction reduced the mean deviation for HVO100 from 13.6% to 8.1%, which was comparable to the 7.8% observed for diesel. This indicates the practical applicability of the correction factor to the investigated vehicles at the vehicle-system level, although the underlying ECU calculation could not be verified directly. The applied factor represents a density-based correction only and does not account for possible viscosity- or temperature-dependent effects. Residual uncertainty therefore remains, and the reported values should primarily be interpreted as comparative indicators rather than absolute measurements.

Second, route reconstruction relied on map matching based on OpenStreetMap data. While filtering procedures improved spatial accuracy, they may have introduced selection bias by excluding tours with poor GNSS coverage or incomplete map representation.

The RMS slope provides an aggregated, direction-dependent measure of the positive gradients encountered over a complete tour but does not retain information on the sequence, duration, or spatial distribution of individual uphill sections. As illustrated by the example tour in Figure 3, a tour assigned to the category of higher topographic variability may include both undulating sections and an extended descent. Because negative gradients were set to zero while remaining part of the averaging basis, such descending sections do not contribute positively to the RMS value and can reduce the resulting value relative to an otherwise identical profile without the descent. Furthermore, a prolonged continuous climb and several shorter inclines may result in similar RMS-slope values despite producing different temporal patterns of vehicle and engine load. This limits the ability of the metric to distinguish between topographic profiles that may affect fuel consumption differently. Nevertheless, within the scope of the present study, the RMS slope provided a consistent, study-specific means of differentiating the investigated tours according to their positive-gradient characteristics.

Third, fuel assignment was not fully randomized due to temporary supply limitations of HVO100. Trucks 53 and 57 were operated with both fuels, whereas Truck 49, which had a higher initial mileage, was operated exclusively with diesel. Although vehicle-specific baseline differences were considered through a random intercept for VIN, potential differences in vehicle condition cannot be fully separated from the unbalanced fuel allocation. In addition, each truck was operated by several drivers, and the driver composition differed between vehicles. Since driver identity was not included in the model, vehicle- and driver-related influences could not be separated completely. As a sensitivity analysis, the interaction model was repeated after excluding Truck 49. Under the reference conditions, the estimated HVO100 coefficient decreased from 0.507 to 0.344 L/100 km. Although the point estimate remained positive and small, the confidence interval included zero and the effect was no longer statistically significant. These results indicate that the general direction of the estimated fuel-related difference was retained, but that its precise magnitude and dependence on operating conditions remain subject to vehicle-specific uncertainty.

Finally, the study is limited to three nearly identical vehicles from a single hauling group. While the number of tours is substantial, the small number of vehicle units restricts the generalizability of the findings to other engine types, calibrations, and duty cycles. In addition, the practical interpretation of the results is limited to fuel consumption.

4.2. Interpretation of Results in the Context of Prior Work

In the full three-vehicle model, HVO100 operation was associated with a statistically significant but small increase in fuel consumption compared with conventional diesel.

Under baseline conditions, the estimated increase is approximately 2–3%. This magnitude is consistent with previous experimental studies [11,30], which report small differences in fuel consumption between HVO and diesel depending on engine calibration and operating conditions [29]. Using the reported ranges of volumetric lower heating values (see Table 2), the estimated chemical energy input under the reference conditions ranged from approximately 762 to 788 MJ/100 km for diesel and from 759 to 773 MJ/100 km for HVO100. The ranges overlap substantially, indicating that the observed increase in volumetric HVO100 consumption does not necessarily correspond to a comparable increase in chemical energy input per distance.

At the same time, the operational parameters included in the model exhibited substantially larger effects on fuel consumption. Fully loaded operation increased fuel consumption by more than 7 L/100 km, while higher topographic variability increased fuel consumption by nearly 2 L/100 km. These findings confirm established evidence that vehicle mass and road slope dominate energy demand in heavy-duty transport [14,15]. In this context, the fuel-related effect is small relative to the inherent variability of real-world logistics operation.

The interaction analysis indicates that the fuel-related effect depends on the operating context. Differences between HVO100 and diesel were most visible on routes with lower topographic variability. Under fully loaded operation, the model estimated a slightly larger absolute difference, although this difference remained small relative to the higher total fuel consumption. Under conditions of higher topographic variability, the estimated absolute difference decreased. A plausible explanation is that increasing resistance forces dominate total energy demand under such conditions, thereby reducing the relative importance of fuel-specific effects.

From a physical perspective, a slightly higher volumetric fuel consumption for HVO100 cannot be attributed to fuel density alone. While HVO100 typically exhibits a higher lower heating value on a mass basis than conventional diesel, its substantially lower density results in a lower volumetric energy content. Consequently, a larger fuel volume is required to provide an equivalent amount of chemical energy. Beyond this direct energy-content effect, fuel-specific properties may also influence the combustion process. Compared with EN 590 diesel, HVO100 is characterized by a substantially higher cetane number and an almost complete absence of aromatic hydrocarbons [11]. Its higher cetane number generally shortens the ignition delay and can reduce the proportion of premixed combustion. Experimental investigations using a heavy-duty single-cylinder diesel engine confirmed a shorter ignition delay for HVO than for conventional diesel, while no corresponding improvement in the fuel–air mixing rate was observed [31]. Furthermore, differences in fuel density, viscosity, and chemical composition may affect injection behavior, spray formation, and combustion phasing [32]. The magnitude and direction of these effects depend on the engine operating point, injection strategy, and engine calibration.

The engines investigated in the present study retained their standard calibration for conventional diesel, and no fuel-specific recalibration of the engine-control strategy was performed. Accordingly, parameters such as injection timing, injection quantity, and exhaust gas recirculation were not specifically optimized for HVO100. Previous calibration studies have shown that the response of HVO100 can vary when such engine-control parameters are adjusted [11]. A potential mismatch between the fuel properties of HVO100 and the diesel-oriented engine calibration may therefore have contributed to the remaining consumption difference. However, since no in-cylinder pressure, injection, or heat-release data were available, the individual contributions of volumetric energy content, combustion characteristics, and engine-control behavior cannot be quantified separately.

These considerations also illustrate the difference between controlled engine experiments and real-world fleet operation. Under laboratory conditions, fuel-related effects can be isolated under well-defined boundary conditions, which may result in clearer and, depending on the experimental setup, different estimates of the effect of HVO100 on fuel consumption [33]. In real-world transport, by contrast, variations in payload, route characteristics, traffic conditions, ambient conditions, and driving behavior introduce substantial variability that can obscure comparatively small fuel-related effects. This interpretation is consistent with field-based fleet studies reporting that operational variability can exceed the differences attributable to fuel type [34]. Accordingly, the observed residual difference should not be interpreted as direct evidence of a general efficiency penalty for HVO100. Rather, the present results indicate a small increase in volumetric fuel consumption with HVO100 after accounting for the observed operational conditions, while operational factors remain the dominant source of variation.

5. Conclusions

This study evaluated the effect of HVO100 on fuel consumption using operational data from 3353 transport tours conducted by three heavy-duty trucks under real-world sugar beet logistics conditions. Under the reference conditions of an empty vehicle, lower topographic variability, and medium driving speed, HVO100 was associated with an increase in volumetric fuel consumption of 0.51 L/100 km, corresponding to approximately 2.3%. However, when the diesel-only truck was excluded in a sensitivity analysis, the estimated difference decreased to 0.34 L/100 km and was no longer statistically significant. The positive direction of the estimate was retained, but its precise magnitude therefore remains subject to vehicle-specific uncertainty.

When representative ranges of volumetric lower heating values were considered, the estimated chemical energy input per distance showed substantial overlap between the two fuels, ranging from approximately 762 to 788 MJ/100 km for diesel and from 759 to 773 MJ/100 km for HVO100. The observed increase in volumetric consumption should therefore not be interpreted as evidence of a corresponding reduction in energy efficiency.

Operational conditions had a substantially greater influence on fuel consumption than fuel type. Full loading increased consumption by 7.33 L/100 km, while higher topographic variability increased it by 1.90 L/100 km. The study therefore contributes real-world evidence that the volumetric consumption difference between HVO100 and diesel is small relative to the variability caused by operational conditions.

The findings are limited to fuel consumption and to the investigated vehicles and logistics system. Fuel consumption was derived from ECU-based data, fuel allocation was not fully randomized, and the study did not assess emissions, engine durability, maintenance requirements, or broader operational performance.

Nevertheless, the present results provide field-based evidence that the influence of HVO100 on volumetric fuel consumption is small compared with the operational variability encountered in the investigated heavy-duty agricultural transport system.

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Abbreviations

The following abbreviations are used in this manuscript:

AWS	Amazon Web Services
CAN	Controller Area Network
DBC	Database Container (CAN database file format)
ECU	Engine Control Unit
EU	European Union
FAME	Fatty Acid Methyl Ester
FMS	Fleet Management System
GNSS	Global Navigation Satellite System
HVO	Hydrotreated Vegetable Oil
HVO100	Pure hydrotreated vegetable oil fuel (100%)
J1939	SAE J1939 communication protocol for heavy-duty vehicles
KSG	German Federal Climate Change Act (Klimaschutzgesetz)
LM	Linear Mixed-Effects Model
LTE	Long-Term Evolution (cellular communication standard)
MF4	Measurement Data Format version 4
OSM	OpenStreetMap
PGN	Parameter Group Number (J1939)
REML	Restricted Maximum Likelihood
RMS	Root Mean Square
S3	Simple Storage Service (Amazon Web Services)
SAE	Society of Automotive Engineers
VIN	Vehicle Identification Number

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