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Opportunity to integrate machine management data, soil, terrain and climatic variables to estimate tree harvester and forwarder performance

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Abstract The Cut-to-Length (CTL) harvesting system is nowadays predominant in the field of mechanized forest operations, consisting mainly in harvesters and forwarders forestry machines. These machines are equipped with an On-Board Computer (OBC) that collects a large amount of information concerning machine parameters such as harvested timber, travelled distance or fuel consumption. Stream machine data are sent to the machine fleet management system (FMS) on cloud, stored and automatically summarized on hourly, daily, weekly, or monthly basis. Understanding the benefits of data mining techniques - in finding trends and patterns - exploiting FMS database in relation to topographic and climatic condition is still an ongoing open research question. The present work aims at verifying if and how machine´s performance indicators (e.g. fuel consumption) recorded and summarized on a hourly basis by the FMS are influenced by site specific parameters, such as terrain morphology, soil type, wet soil condition, and weather conditions, derived from open source portal. A specific methodology in machine data acquisition and datasets implementation has been set in this study. The dataset results in a combination of three sub-datasets, consequently merged, filtered and analyzed. A first sub-dataset is made up of "machine data", a second is made up of "environmental data", and a third set of data is made of "climatic data". The obtained results revealed that the combination of different data sources' provides significant insight into understanding machine performance. Moreover, the integration of terrain morphology and climatic data have direct impact on the machine fuel consumption, harvester machine in particular. However, in order to address specific interactions among variables with greater robustness, further investigations into this project will consider the whole set of variables on a smaller scale (e.g., case study) with higher data resolution.

Keywords: precision forestry, industry 4.0, Cut-to-Length, full-mechanized, long-term monitoring, logging.

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Introduction

The sustainability of active forest management requires a continuous improvement of the eco-efficiency of wood harvesting operations including the reduction of Green House Gasses (GHG) emissions per unit of wood volume harvested, that can be achieved by gathering more accurate knowledge on the behavior of the machines, such as understanding the effect of the terrain morphology or the configuration of the traction system (Marchi et al. 2018, Schweier et al. 2019).

Machine fuel consumption is one of the most critical parameter in any mechanized forest operation as it is required for proper economic and environmental evaluations (Holzleitner et al. 2011, Prinz et al. 2023). In fact, concerning the carbon footprint of forest operations, the fuel consumption and related CO_2 emissions plays a crucial role on the Life Cycle Assessment and on the CO_2 balance or GHG emission of the wood products (Picchi et al. 2022).

The Cut-to-Length (CTL) harvesting system is widely applied worldwide in forestry (Nurminen et al. 2006) in the field of mechanized forest operations, consisting mainly in harvesters and forwarders machines (Ackerman et al. 2017, Mologni et al. 2018, Cadei et al. 2020, Hartsch et al. 2022). These machines are generally equipped with an On-Board Computer (OBC) that collects a large amount of information concerning either machine parameters and harvested timber (Eriksson & Lindroos 2014, Kemmerer & Labelle 2021, Hartsch et al. 2021). Stream machine data is saved through the machine Fleet Management System (FMS) on a cloud service, stored in servers and automatically summarized in specific indicators on hourly, daily, weekly or monthly basis (Bacescu et al. 2022, Polowy & Molińska-Glura 2023), making it possible to monitor the whole fleet of machines and gather detailed information even from remote locations (Polowy & Molińska-Glura 2023). Moreover, the use of Controller Area Network data loggers (CAN-bus) and cloud-based services have greatly expanded the potential for constructing more efficient models to retrieve information on secondary variables, such as fuel consumption (Cadei et al. 2020 a, Kemmerer & Labelle 2021, Kärhä et al. 2023, Prinz et al. 2023).

Previous studies in the literature have shown that a variety of factors can influence the harvester and forwarder efficiency, and relative fuel consumption, such as rolling distance and tree or load size (Spinelli et al. 2004, Tiernan et al. 2004, Ghaffariyan et al. 2012, Walsh & Strandgard 2014), operator experience and qualifications (Tervo et al. 2010, Strubergs et al. 2022), log size and assortment type (Väätäinen et al. 2006, Plamondon & Pitt 2013, Spinelli & Magagnotti 2013), as well as loading angle and distance (Hartsch et al. 2022). Moreover, terrain-related factors such as physical soil properties (Horn et al. 2007), terrain slope (Strandgard et al. 2015, Berendt et al. 2020), driving intensity and machine traction configuration (Prinz et al. 2023) have proved to have a strong influence on the efficiency. Machine performance is also affected by soil trafficability, defined as the ability of a terrain to support and provide traction for vehicle operations (Shoop 1993), and it is mainly determined by soil type, soil moisture, micro- and macro-topography of the terrain (Suvinen et al. 2009, Hoffmann et al. 2022, Prinz et al. 2023). This means that soils with high water saturation levels and low bearing capacity have a direct impact on operational machine efficiency, thus fuel consumption (Saarilahti 2002, Salmivaara et al. 2020).

The retrieval of information needed to address terrain trafficability and soil conservation have been widely researched, such as the development of Depth-To-Water (DTW) maps for soil moisture and sensible terrain identification (Ågren et al. 2015, Schönauer et al. 2021, Latterini et al. 2022, Hoffmann et al. 2022), or weather-climatic index (Murphy et al. 2009, Dilmi et al. 2020). On the other hand, few studies have analyzed the use of data mining techniques in finding trends and patterns exploiting FMS database for both tree harvester and forwarders in setting significant similar predictors (e.g., machine management, terrain, and soil variables) (Polowy & Molińska-Glura 2023). In order to provide support to the optimization of harvesting strategies, an in-depth study on the effect of combined ground conditions and working intensity is particularly relevant when forest operations are observed over a long-time span.

The aim of this study is to investigate the influence of site-specific parameters, such as terrain morphology, soil type, wet soil conditions, and weather conditions, on the performance indicators of wheeled Cut-to-Length (CTL) harvesters and forwarders, particularly focusing on fuel consumption, over one year. This research utilizes automatic machine data collection via the Fleet Management System (FMS) and integrates environmental and climatic data to detect trends and patterns that impact machine efficiency.

Materials and Methods

Monitored areas

The harvesting operations considered in the study period are located in Germany between the districts of Soest and Hochsauerlandkreis, North Rhine-Westphalia (Figure 1) and the time period covered was the whole year 2022 (from 01/01/2022 until 31/12/2022). The study focuses on a fully-mechanized CTL system based on the combination of a harvester and a forwarder, which represent the most common harvesting system in the study area.

The forest targeted by the harvesting operations consisted mainly in Norway spruce stands (Picea abies Karst.) and semi-natural mixed stands with beech (*Fagus sylvatica* L.), silver fir (*Abies alba* Mill.), larch (*Larix decidua* Mill.), Scots pine (*Pinus sylvestris* L.), as well as birch (*Betula pendula* Roth) pedunculate oak (*Quercus robur* L.) and sessile oak (*Quercus petraea* Matt.). The main information related to the study sites are summarized in Table 1.

The study areas report a history of high intensity harvesting activities in the last decades following the large damages due the storms Kyrill and Friederike, that struck Central Europe in 2007 and 2018 respectively. Therefore, most of the treatments included in the study referred to clear-cuts of damaged trees as well as dry-dead trees from bark beetle outbreak pests (Figure 2).

Table 1 Main characteristics of the study area.

Variable	Unit	
Country		Germany
Region		Sauerland, North-Rhine-Westphalia
Coordinates EPSG: 4326	(long/lat)	8.017874 / 51.477830
Elevation	m	220-400
Mean Temp. (yearly)	°C	8.9
Mean precipitation (yearly)	mm	790
Main productive tree species		beech, Norway spruce

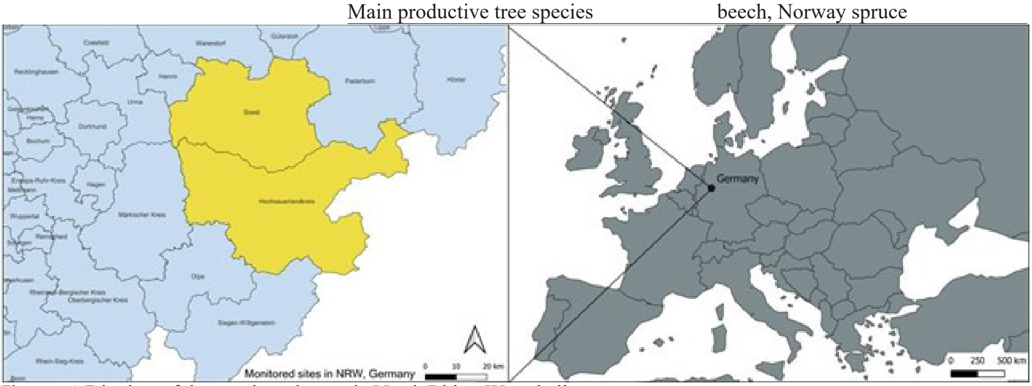

Figure 1 Districts of the monitored areas in North Rhine-Westphalia.

Figure 2 Representatives stands of the monitored areas characterized by damaged trees as well dry-dead trees from bark beetle.

Data acquisition

The final dataset creation was acquired through a series of steps comprising datasets merging, filtering and synchronization, after the information was automatically recorded by the forest machines OBCs during working activity. The steps related to data acquisition and following elaborations are summarized in Figure 3.

The flowchart shows the input of three main data sources, which have been consequently merged, filtered and analyzed. The first data source is made up of the machine data directly downloaded from the FMS system of the machines. The second is made up of terrain data, derived from the Geological Service NRW and subsequent elaborations on QGIS environment, and a third data source is made of meteorological data, downloaded from the German Weather Service online portal.

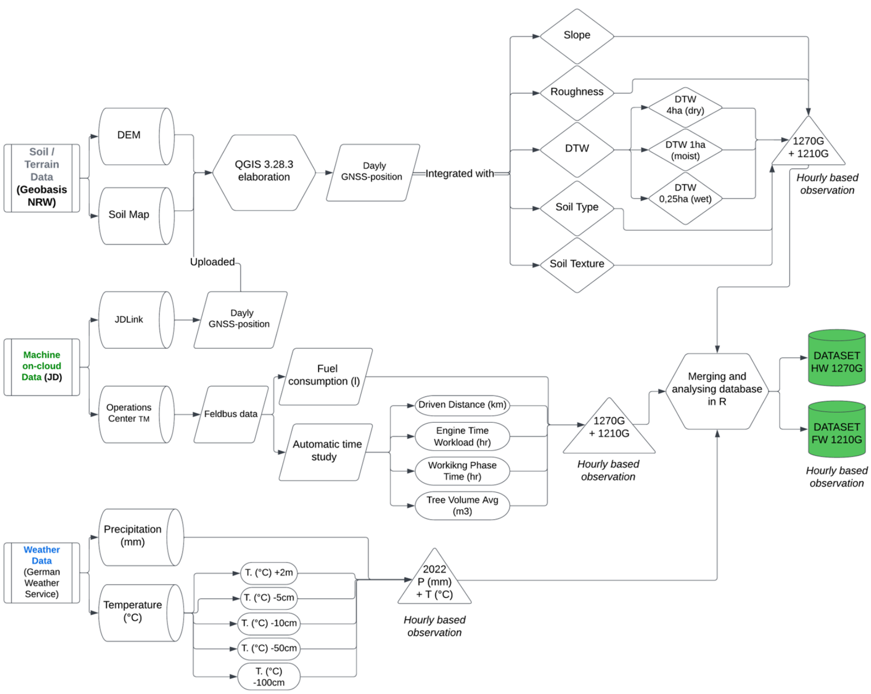

Figure 3. Flowchart summarizing the design of data collection for the present study.

Machine data collection

The data was obtained from a harvester and a forwarder owned by State Enterprise for Forestry and Timber of North Rhine-Westphalia. The harvester (HW1270G) was a 200 kW John Deere 8-wheeled 1270G model with rotating and self-leveling cabin and equipped with the H425 harvesting head (Table 2). The forwarder (FW1210G) was a 156 kW John Deere 8-wheeled 1210G model with rotating and self-leveling cabin (Table 2). Both machines were provided with Windows-based TimberMatic™ (John Deere, Moline, IL, USA) as a control system.

Considering John Deer being the manufacturer of both machines, the data registered by the FMS was collected through JDLinkTM and Operations CenterTM (John Deere, Moline, IL, USA). From the JDLink system portal it was possible to acquire the position of the machines over time (i.e., latitude and longitude), recorded using the Global Navigation Satellite System (GNSS) system of the forest machine and with variable frequencies: GNSS raw data ranges from 1 records hour-1 when machine is in idle or parked (e.g., night-time) up to 130 records hour-1 when machine is driving or working. From the Operations Center portal, data related to the machine parameters (including productivity) was acquired on an hourly basis report and organized as table. Each report provides a series of standardized information regarding harvester´s production (specifically about tree count number, average tree volume and tree production rate) and forwarder´s grapple activity, as well as driven distance and fuel consumption.

The chosen data frequency (hourly-based) does not guarantee a high spatial data resolution; however, it represents the maximum detail achievable using the manufacturer's proprietary system. The overview of all the collected machine data variables is contained in Table 3.

Table 2 Harvester´s and forwarder´s specifications.

	Unit	HW 1270G	FW 1210G
Model	-	John Deere 1270G	John Deere 1210G
Engine	-	John Deere PowerTech™ Plus 6090	John Deere PowerTech™ Plus 6068
Emission standards		EPA IT4/EU Stage III B	EPA IT4/EU Stage III B
Power	kW	200	156
Transmission	-	Hydrostatic-mechanical, 2-speed gearbox	Hydrostatic-mechanical, 2-speed gearbox
Wheel number	n◦	8	8
Tire size	-	710/45-26.5	710/45-26.5
Weight with harvester head	t	22.2	
Weight empty	t		18.1
Payload	t		13
Year of manufacture		2021	2019
Machine work hours		1042.2	2721.4

Table 3. Machine data: Different elements considered in the study.

Machine data			
Unit	**FW 1210G**	**HW 1270G**	**Description**
km	DistHighGear	DistHighGear	Distance traveled in high gears in the hour
km	DistLowGear	DistLowGear	Distance traveled in low gears in the hour
km	DistTOT	DistTOT	Sum of DistHighGear and DistLowGear
h		TimehOther	Machine hours distribution Other time
h		TimehPrep	Machine hours distribution Preparation time for the next grappling
h		TimehProcess	Machine hours distribution Processing time
-		TreeCountStandard	Stem Count Information Standard tree count
m3		TreeVolAvg_m3	Average standard tree volume
m3/h		ProdVol_m3h	Tree production rate
-	GrappleLoading		Gripper Count Loading
-	GrappleUnloading		Gripper Count Unloading
h	TimeCrane		Machine usage by machine status: grappling
h	TimeDrive		Machine usage by machine status: driving
h	TimeDriveCrane		Machine usage by machine status drive and grapple
h	TimeEngineStop		Machine use for machine status Engine stopped
l/h	FlowFuel	FlowFuel	Average fuel flow rate

Terrain data

Soil type and texture information was derived from the soil map of North Rhine-Westphalia provided by the Geological Service NRW (Geologischen Dienstes NRW - GEOportal. NRW) at a scale of 1:50.000 and available in shape file format (.shp) (Schrey 2014). The soil map published in 2014 describes the soil structure down to a maximum depth of 2 m or up to the solid rock, with the soil units listed according to the German pedological system (Mückenhausen 1962). The terrestrial section includes the groundwater-free soils or soils only influenced by groundwater in the deeper subsoil (e.g., Ranker, Rendzina, brown earths, parabrown earths, podzols and pseudo-gley). Both the Digital Elevation Model (DEM) of the forest sites and the DTW maps were provided in raster format (.tif) by the governmental authority of the Bezirksregierung Köln region, derived from a LiDAR flight performed in 2019. The cell size resolution for all the raster data was of 1 m derived from a point density ranging from 4-10 points m^{-2} and an accuracy of ±0.2 m.

The DTW is provided as index showing the least elevation difference between surface flow channels and nearby landscape areas (Schönauer et al. 2021), i.e., DTW values are zero in the areas consisting of surface flow channels. Moving upwards from flow channels, DTW values increase, indicating a decreased soil moisture away from surface waters. The DTW scale is metric and can be interpreted as a relative measure of soil drainage condition, which approximates the tendency of a point in the landscape to be saturated. Therefore, areas with lower values show a higher tendency to retain water on the surface or layers of soil saturated with water (Murphy et al. 2009). This map was reclassified assigning values ranging from “0”, areas with surface channels, to a maximum value “100”, where the higher the value the drier the soil (Schönauer et al. 2019, Latterini et al. 2022). For this study, the DTW metrics adopted considered the wet conditions at the highest resolution possible, therefore the initial map with flow initiation area (FIA) of 0.25 ha was adopted following the procedure of Schönauer & Maack (2021) to deliver the best performance (Schönauer et al. 2021). A categorization of DTW values was then performed, with the creation of 5 categories with thresholds based on soil drainage condition, ranging from DTW Cat. 1 (“very poor”), DTW Cat. 2 (“poor”), DTW Cat. 3 (“imperfect”), DTW Cat. 4 (“moderate”) to DTW Cat. 5 (“well/excessive”).

Weather data collection

The weather data consisted in annual air/soil temperature and rainfall yearly series, derived and reconstructed in hourly aggregated information. The weather data on the investigated areas for the period considered was obtained as daily station observations (.txt) referred to the weather station Arnsberg-Neheim - located at 159 m a.s.l., number 7330 (https://cdc.dwd.de/portal/) - from the German Weather Service - DWD (Deutscher Wetterdienst) online portal.

Dataset implementation

Dataset implementation and all numerical elaborations were conducted using RStudio (Team 2009), while QGIS 3.28.3 (QGIS 2015) was used mainly to analyze GNSS machine position in relation to soil and terrain spatially data. Preliminarily to the dataset creation, data from sensors of HW1270G and FW1210G was organized following the procedure and methodology proposed by Polowy and Molińska-Glura 2023 and Bacescu et al. 2022: the GNSS machine positions were acquired from JDLink using the daily report created every day from 00:00:00 to 23:59:59. Consequently, data report from Operations Center and the related fieldbus information was acquired from January 2022 to December 2022 with hourly-based level. Moreover, in QGIS environment, the DEM was used to derive the “slope” and “roughness”. The DTW map values, as well as information of soil type and texture, were adjusted over the selected sites, implementing the spectrum of information coupled to each GPS machine position. For both machines (FW1270G and HW1210G) were performed the same following operations.

1. First, in Rstudio, the GNSS positions and the fieldbus report were synchronized to match the time step and chosen time unit (1 h). Then, the data was filtered to exclude from

the analysis the hours when the machine is not actually neither working nor traveling, taking as reference the effective "working time", given by the Operations CenterTM report. Finally, a position file for each machine was created.

2. The position files were loaded in QGIS and matched with DEM-derived information and soil map attributes. To extract this information, "sample raster value" function was used for of slope, roughness and DTW map values. For soil type and texture, on the other hand, a "join attributes by location" function was performed, due to the original scale and format (.shp) of the soil map provided.

3. After merging the information in a single file, the terrain slope was divided in classes following the National Terrain Classification NTC (Erasmus 1994). Terrain slope classification range is divided into 7 classes, evenly subdivided. Class 1 (Level – up to 11%), Class 2 (Gentle – 11-20%), Class 3 (Moderate – 20-30%), Class 4 (Steep 1 – 30-35%), Class 5 (Steep 2 – 35-40%), Class 6 (Steep 3 – 40-50%), and Class 7 (Very Steep – more than 50%).

4. Following the structure of the "Soil map of the Geological Service NRW" (Schrey 2014) and with the intent of summarizing more information, soils with similar genesis or comparable characteristics and properties were categorized into three main classes composed of ground units belonging to the same soil subtype and variety. In order to improve the clarity of the results, soils affected by groundwater and temporarily waterlogged due to seepage water stagnation were classified under the category "GS." These gley soils typically have a loamy to clayey texture, low permeability, and tend to develop mottling due to alternating periods of saturation and drying. Nonetheless, pseudo-gley soils, characterized by a loamy to clay-loam texture, also experience periodic waterlogging due to inadequate drainage. On the other hand, the macro-category of brown earth soils "B" includes new clay minerals, brown-colored, and loamy soils. These soils generally retain good structure and water retention capacity. Brown earths and para-brown earths have a loamy to clay-loam texture, are well-drained, and fertile, eventually suitable for agriculture.

5. Climate data on investigated geographic area was provided as well. The data was obtained using DWD data. In fact, for each observation time unit (1 h) – made up of machine performance parameters and other previous mentioned topographic data – also hourly average temperature (air and soil) and hourly precipitation values were coupled in the dataset.

6. Finally, a table file containing the hourly positions and sampled information (slope, roughness, soil type, soil texture, DTW values and meteorological data) was created for each of the two machines.

Finally, Machine data, Environmental data and Climatic data was coupled and synchronized based on the data and hour field (format: 20YY-MM-DD, HH:00).

Harvester (HW1270G) and Forwarder (FW1210G) dataset´ variables slightly differs in the "Machine data" section, as listed in Table 3, while for "Environmental data" (Table 4) and "Climatic data" (Table 5) the same variables occur.

Table 4. Environmental data: Different elements considered in the study.

Environmental data			
Unit	**FW 1210G**	**HW 1270G**	**Description**
%	Slope		Terrain surface inclination
m	Roughness		Irregularity in elevation (highs and lows) within a terrain unit
cm	DTW value		Relative measure of soil drainage condition
-	Soil Type		Types of soil based on the dominating size of the particles within a soil

Table 5. Climatic data: Different elements considered in the study.

Climatic data			
Unit	**FW 1210G**	**HW 1270G**	**Description**
mm/h	Precipitation		Precipitation in millimeters in height collected in an hour
°C	Temperature at +2 m above ground		Surface soil temperature
°C	Temperature at -5 cm below ground		Measurement of the ground's inherent warmth. Measurement of warmth/coldness in the top 5 cm of the ground.
°C	Temperature at -100 cm below ground		Measurement of the ground's inherent warmth.

Dataset analysis

According to our current state of knowledge, the assessment of fully-mechanized harvesting system through the use of FMS developed by Bacescu et al. (2022) is the least demanding approach for collecting and investigating data related to forest machines for an extended period of time, hereby, support decisions in the optimization of harvesting strategies in terms of technological and environmental efficiency (Bacescu et al. 2022). To achieve the objective of this study, two levels of analysis were performed. First, descriptive statistics tests were computed on both HW1270G and FW1210G to assess the reliability of the datasets creation workflow and methodology. Then, the relation between machine performance parameters (e.g., travelled distance and related fuel consumption) and terrain data (soil types, slope and DTW classes) was analyzed applying statistical tests, among which Shapiro-Wilk test, Mann-Whitney U-test and the non-parametrical test of Kruskal-Wallis. Finally, the fuel consumption information was retrieved through a stepwise multiple regression analysis. All the analysis were performed using RStudio (Team 2009).

Descriptive statistics

Machine data

Before performing any statistics on the machine data, logical filters have been applied on the dataset to eliminate outliers, zero values of false-observations following a procedure suggested by Zuur et al (2010). First, effective machine working time (e.g., engine time) for both machines has been filtered to a minimum of 0.5 hour (half-hour) to a maximum of 1 hour. Since harvesting sites´ logistic required often travelling time up to half-hour, this threshold was defined as the least portion of productive work time used to change work object with regard to activity or position within the definition of the work task (e.g., felling, delimbing, bucking, skidding, loading) following the terminology suggested by the Proceedings IUFRO 1995, XX World Congress (Björheden & Thompson 2000). After that, travelled distance was set to be greater than zero kilometers to exclude from analysis "service time" (e.g., repair, maintenance or refuel times) during which the machine could possibly not have travelled (Björheden & Thompson 2000).

Further conditions of exclusion from the dataset are the proportions of zero working time, hence zero productivity (Eriksson & Lindroos 2014): specifically for HW1270G, observations related to processed trees per hour lower than six (6) were removed. A similar filter was applied to the FW1210G dataset, observations of grappled log per hour equal to zero (0) were filtered and excluded as well. Originally, HW1270G dataset counted 204 working days, while 197 working days were registered for FW1210G dataset. The resulting total working hours counted in 892 time-related observations (entire hourly recorded) for harvester HW1270G, while 794 time-related observations for forwarder FW1210G. However, the Operations CenterTM automatically creates an hourly report, even when effective working time is actually lower than 60 minutes. To overcome the issue, the effective engine time (i.e., real time of running engine) was taken into consideration (Bacescu et al. 2022). After the conversion, the outcome produced 789.20 working hours (reduction of ca. 12%) for harvester HW1270G and 733.3 working hours (reduction of ca. 8%) for forwarder FW1210G.

However, to seek clarity on further statistics of the study, the entire hourly recorded values was adopted: 892 observations for harvester HW1270G and 794 time-related observations for forwarder FW1210G.

Terrain data

First, to better analyze the results, a Shapiro-Wilk test was applied to assess the data normality for both machine datasets and for each one of the terrain variables, resulting in a non-normal distribution.

Thus, descriptive statistics (minimum, maximum, mean, median and standard deviation) were computed for each terrain variable (Slope, Roughness, DTW and Soil type). In the case of Soil type, the classes (i.e., B and GS) have been converted into numerical values, B=1 and GS=2. After that, the mean value of each variable was compared using a two-tailed Mann-Whitney U-test (α=0.05) and considering the two datasets HW1270G and FW1210G as two independent sample groups.

Climatic data

Similarly to the Terrain data, the Climatic data variables distribution was checked for normality using the Shapiro-Wilk test, with the result of a non-normal distribution.

Following the normality assessment, descriptive statistics were calculated for the four meteorological variables (Precipitation, Temperature +2 m above ground, Temperature -5 cm below ground, Temperature -100 cm below ground). In this case, no variable conversion was needed. After that, a two-tailed Mann-Whitney U-test (α=0.05) was performed on the two machine datasets.

Machine performance analysis

General performance of a CTL system depends on several factors (Proto et al. 2018), with ground conditions and slope terrain having a major impact on the overall machine performance (Stampfer 1999, Spinelli et al. 2002). For this reason, the terrain variables were investigated to assess their influence on the overall machine performance variables: total travel distance, travel distance in high gear, travel distance in low gear, and fuel rate for both machines; number of trees, tree average volume in the hour and production volume uniquely for the harvester, whereas grapple loading and grapple unloading were considered for the forwarder.

Considering the different number of levels for each variable (soil type=2; slope=6; DTW=5), different statistical tests have been adopted. For each machine, the soil type was tested using a two-tailed Mann–Whitney U test (α=0.05), whereas for Slope and DTW it was used the non-parametrical test of Kruskal-Wallis (α=0.05). The hypothesis tested if the mean value of the same set of common machine variables changes accordingly to different soil types, slope classes and DTW classes. If the test results indicated p values larger than 0.05, the null hypotheses were rejected and the differences in machine variables mean values‘ were assumed to be from random variation.

Regression analysis models for fuel consumption

The regression analysis was adopted for modelling each machine's fuel consumption, as a proxy variable for performance, explained by the independent variables of HW1270G (i.e., driven distance, number of trees, tree´s average volume, production rate volume, soil type, slope, roughness, DTW, precipitation and temperature) and of FW1210G (i.e., driven distance, number of grappled logs, soil type, slope, roughness, DTW, precipitation and temperature). The chosen method used was a stepwise multiple regression, a procedure used to build a regression model from a set of predictor variables by entering and removing predictors in a stepwise manner into the model until there is no statistically valid reason to enter or remove any more. In this case, a bi-directional model was selected, in which the variable that meets given inclusion and exclusion criteria, therefore explaining most of the variation, is entered first into the model (Eriksson and Lindroos 2014). Then, other qualified variables are entered and excluded stepwise according to their contribution to the level of explained variation. The procedure stops when there is no model change available that meets the inclusion or exclusion criteria of variables. Inclusion and exclusion criteria were both set to α=0.05, which means that a variable was entered if its p-value resulted lower than 0.05 and removed from a given model when greater than 0.05.

Results

Descriptive statistics

Machine variables - Harvester (HW1270G)

Initially, the annual dataset for the harvester (HW1270G) comprised 204 working days, corresponding to a total of 1505 hourly observations. However, after applying a data reduction algorithm, a 14% decrease in the number of working days and a 41% reduction in the initial hourly observations were observed. Consequently, all subsequent analyses were conducted on a recalibrated dataset, consisting of 176 monitored working days, equivalent to 892 hourly observations.

During the analyzed study period, 33% of the time was spent on process operations such as tree cutting, felling, delimbing, and bucking to length. More than 49% of the remaining time was dedicated to preparation, specifically moving to the next tree. Approximately 18% of the total time was also considered non-productive, including other non-directly productive activities. By applying these percentages to the total time, 297 hours were spent on process operations, 436 hours on preparation, and 159 hours on non-productive time, respectively.

Within this time, the harvester bucked 40617 logs with a total volume of about 21188.4 m^3, equal to a total fuel consumption of 14350.3 liters.

An overview of the descriptive statistics of the HW1270G variables is presented in Table 6. The total travel distance in high gear accounts for 10.1% of the total travelled distance, while remaining 89.9% of the total travel distance was driven in low gear. Concerning the maximum total travelled distance of 7.63 km, it corresponds to 7.43 km - equivalent to the maximum total travelled distance in high gear - and the remaining 0.19 km distance low gear. Within this observational unit hour a number of 13 trees was processed, tree average volume was 0.47 m^3 with an average production rate of 7.9 m^3/h and a fuel consumption of 22.0 l/h. Concerning the maximum travelled distance in low gear is equal to 3.47 km. Within this observational unit hour, a number of 16 trees was processed, tree average volume was equal to 0.43 m^3 with an average production rate of 6.2 m^3/h and a fuel consumption of 23.0 l/h.

Machine variables - Forwarder (FW1210G)

Initially, the annual dataset for the forwarder (FW1210G) consisted of 197 working days, corresponding to a total of 1557 hourly observations. However, after applying a data reduction algorithm, an 18% decrease in the number of working days and a 49% reduction in the initial hourly observations were observed. Consequently, all subsequent analyses were conducted on a recalibrated dataset, consisting of 162 monitored working days, equivalent to 794 hourly observations. Approximately 50% of the time was spent on loading logs during the analyzed study period. Another 24% of the remaining time was dedicated to unloading operations, while 14% was spent driving the forwarder unloaded and 10% driving the forwarder loaded. Moreover, an additional 2% of the time was recorded for road travel between sites.

Applying these percentages to the total time, it can be stated that out of the 794 analyzed

Table 6. A summary of the variable recorded at the harvester HW1270G study site.

Variables	Min	Mean	Max	Median	SD	TOT
Total travel distance in the hour (km)	0.03	0.57	7.63	0.40	0.59	511.10
Travel distance high gear in the hour (km)	0	0.06	7.43	0	0.41	51.69
Travel distance low gear in the hour (km)	0.03	0.51	3.47	0.39	0.40	459.41
Number of tree (n°/h)	7.00	45.53	136.00	39.00	26.88	40617
Tree average volume in the hour (m3)	0.07	0.67	2.49	0.56	0.43	599.86
Production volume (m3/h)	1.24	26.26	72.09	24.85	12.08	23428.37
Fuel rate (l/h)	7.45	18.11	27.67	18.37	2.71	16158.48

hours, 394 were allocated to loading, 191 to unloading, 109 to driving the forwarder unloaded, and 82 to driving the forwarder loaded. Additionally, 18 hours were spent on road travel. Within this time, the forwarder (FW1210G) grappled logs for a total of 50962 times, for a total fuel consumption of 8873.9 liters.

From the descriptive statistics (Table 7), an overview of data regarding total travelled distance, travelled distance in low and high gear, number of logs grappled and fuel consumption is presented. It can be seen that the total travel distance in high gear accounts for 9.4% of the total travelled distance, while remaining 90.6% of the total travel distance was driven in low gear. Concerning the maximum total travelled distance equal to 8.93 km, corresponds to 8.89 km - equal to maximum total travelled distance in high gear - and the remaining 0.034 km distance low gear. Within this observational unit hour, a number of 10 logs were grappled while loading and other 7 logs were grappled while unloading, with a fuel consumption of 19.4 l/h. Concerning the maximum travelled distance in low gear is equal to 3.32 km. Within this observational unit hour, a number of 29 logs were grappled while loading and other 13 logs were grappled while unloading, with a fuel consumption of 21.8 l/h.

Terrain variables

In general, both machines have worked in similar terrain conditions covering an almost identical range of slope and roughness values. Nevertheless, some significant differences can be identified and are reported by the statistical analysis, with both p-Value below the established threshold (0.05). More pronounced differences are present in the DTW values distribution, highlighted by both SD and p-Value. The parametrization of the Soil type and following statistics described that both machines worked more in GS soils (GS=2) rather than B soils (B=1), with significant differences, nevertheless (Table 8).

Despite the proposed approach is limited to only statistical terrain parameters differences, to gain a better understanding of these differences it was necessary further investigation: according to current practices, in well managed forests, soil disturbance is confined onto a few selected areas where forest machines drive, i.e. skid trails (Cambi et al. 2015). However, in this case, an additional in-depth QGIS analysis

Table 7. A summary of the variable recorded at the forwarder FW1210G study site.

Variables	Min	Mean	Max	Median	SD	TOT
Total travel distance in the hour (km)	0.11	1.05	8.93	0.92	0.68	838.02
Travel distance high gear in the hour (km)	0	0.09	8.89	0	0.54	78.55
Travel distance low gear in the hour (km)	0.001	0.95	3.32	0.88	0.50	759.46
Grapple loading (n°/h)	7.00	45.26	131.00	45.00	19.55	35944.00
Grapple unloading (n°/h)	7.00	18.91	96.00	17.5	8.63	15018.00
Fuel rate (l/h)	5.09	12.17	22.28	11.91	2.10	9669.67

Table 8. A summary of the Environmental variables recorded at the study site for both HW1270G and FW1210G..

Variables	Machine	Min	Mean	Max	Median	SD	p-Value
Slope (%)	HW1270G	3.26	15.09	45.97	14.01	6.25	0.003099*
	FW1210G	3.72	14.20	47.28	13.25	5.47	
Roughness (m)	HW1270G	0.12	0.40	1.24	0.37	0.16	0.01053*
	FW1210G	0.11	0.38	1.23	0.35	0.14	
DTW (0.25ha)	HW1270G	18.26	82.12	100.09	86.89	19.28	1.541e-11*
	FW1210G	21.91	78.72	100.09	80.40	15.39	
Soil type (-)	HW1270G	1.00	1.59	2.00	2.00	0.49	0.03923*
	FW1210G	1.00	1.64	2.00	2.00	0.48	

Notes: ´*` highlights the significant level of confidence at α=0.05.

discovered that either harvester and forwarder did not always operated simultaneously in the same logging site. Therefore, over the whole year 2022, the machines worked in some harvesting areas in different days, even weeks, and conditions, especially DTW conditions.

Climatic variables

Based on the descriptive statistics (Table 9), the machines have worked, over the year period of observations, in similar conditions of precipitations, considering the range of values. Although significant differences are present also for Precipitation, they are more pronounced for the temperature variables, with major differences obtained for the Temperature -5cm below ground at the significance level considered (α=0.05).

The results obtained from the descriptive statistics for the climatic variables underlined what obtained from the terrain variables, highlighting how the two machines worked independently throughout 2022. Working the same harvesting area not always simultaneously is described by the presence of different meteorological conditions.

Machine performance analysis

The overall machine's performance analysis is divided considering the three variables used (Soil type, Slope class and DTW class) and summarized in Table 10. Moreover, the complete results are displayed in Table A1 in the Annex.

Regarding soil types, the total number of observations in the HW1270G dataset is 892, while the FW1210G dataset has 794 records. Within the HW1270G dataset, there are 892 observations, with 527 in brown soils and 365 in gley and pseudogley soils. In the FW1210G dataset, there are 794 observations, with 508 in brown soils and 286 in gley and pseudogley soils. The Mann-Whitney test showed that, in the case of the harvester and for the significance level considered (α = 0.05), the soil type greatly

Table 9. A summary of the Environmental variables recorded at the study site for both HW1270G and FW1210G.

Variables	Machine	Min	Mean	Max	Median	SD	p-Value
Precipitation (mm/h)	HW1270G	0	0.086	4.8	0	0.42	0.02913*
	FW1210G	0	0.065	4.8	0	0.37	
Temperature +2m above ground (°C)	HW1270G	-9.4	13.5	35.5	13.6	8.54	1.023e-10*
	FW1210G	-8.8	16.1	37.8	15.8	8.18	
Temperature -5cm below ground (°C)	HW1270G	-3.5	14.3	36.6	13.25	9.81	3.287e-11*
	FW1210G	-3.5	17.4	38.5	17.5	9.49	
Temperature -100cm below ground (°C)	HW1270G	5.2	11.9	19.3	12.9	4.74	7.98e-08*
	FW1210G	5.2	13.2	19.3	13.3	4.46	

Notes: ´*` highlights the significant level of confidence at α=0.05.

Table 10. A summary of p-values calculated with the Mann-Whitney test (soil types) and the Kruskal-Wallis test (Slope classes and DTW classes) for each variable of the two machines harvester (HW1270G) and forwarder (FW1210G).

Variables	Soil types		Slope classes		DTW classes	
	HW1270G	FW1210G	HW1270G	FW1210G	HW1270G	FW1210G
Total travel distance (km)	0.01992*	0.2242	5.28E-07*	2.87E-04*	< 2.2e-16*	2.13E-13*
Travel distance high gear (km)	0.01951*	0.2122	0.1383	0.03606*	0.000581*	0.5824
Travel distance low gear (km)	0.00589*	0.03661*	1.23E-06*	1.31E-03*	< 2.2e-16*	1.69E-12*
Number of tree (n°/h)	0.009669*	-	0.5794	-	< 2.2e-16*	-
Tree average volume in the hour (m^3)	0.1	-	0.4612	-	4.76E-08*	-
Production volume (m^3/h)	1.70E-06*	-	2.13E-04*	-	0.04034*	-
Fuel rate (l/h)	0.07962	0.1924	7.41E-04*	4.85E-07*	0.01445*	2.56E-06*
Grapple loading (n°/h)	-	0.123	-	0.07193	-	0.4207
Grapple unloading (n°/h)	-	0.2768	-	0.002571*	-	0.39

Notes: ´*` highlights the significant level of confidence.

influenced the overall machine performance for 5 machine parameters. Overall, statistically significant differences are not emerging overall for the "Fuel rate" and for the "Tree average volume in the hour".

When it comes to the forwarder, the statistical test showed that the soil type produced differences in the "Travel distance low gear" but not for the other considered machine parameters.

Considering the Slope, for the HW1270G set, only 3% of the observations are counted within class 4 and 6, with the remaining 97% of the observations within lower slope class 1 to 3 (Figure 4). This uneven distribution of observations among the slope classes is mainly due to operational reasons: forest machines' operativity and productivity - without winch assistance - is generally limited by slope greater than 35-40% (class 4) (Hittenbeck 2006, 2010). To assess the presence of significant differences, the Kruskal-Wallis test was applied, choosing a threshold of α=0.05. In this case, the different slope classes produced significant differences with respect to "Total travel distance", "Travel distance low gear", "Production volume" and "Fuel rate".

Similarly, the distribution of values for FW1210G showed that the machine worked in almost identical slope conditions for almost the entire period considered: with only 1% of the records counted within class 4 and 6, and the remaining 99% within lower slope class 1 to 3. The variables that emerged from the Kruskal-Wallis test as significantly influenced by the slope class are the same as HW1270G, with the presence of "Grapple unloading" instead of the volume of production.

The DTW frequency classes distribution is shown in Figure 5. Both machines worked for the majority of the time (in average, more than 92%) in areas with good or excellent drainage conditions (within class 4 and 5). This uneven distribution of observations among the DTW

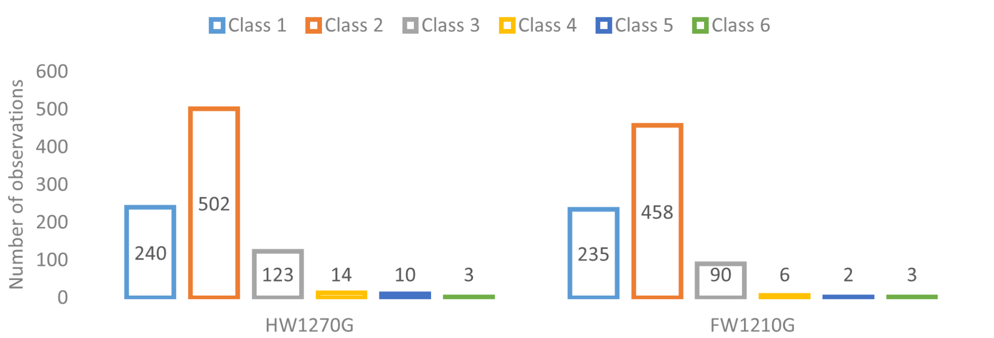

Figure 4. Number of observations and division according to the slope variable classes

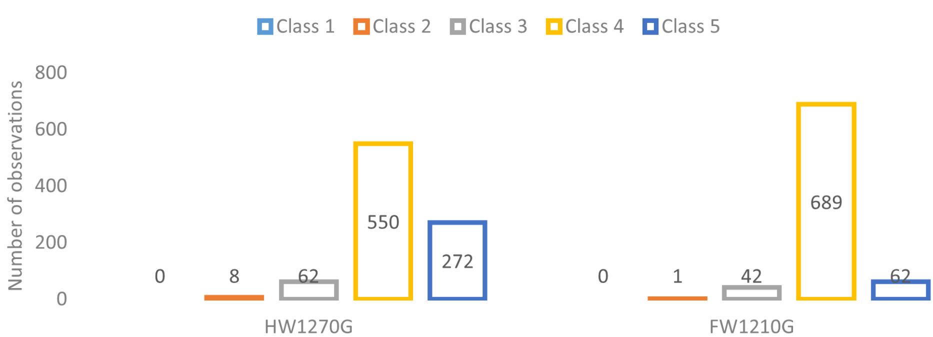

Figure 5. Number of observations and division according to the DTW variable classes.

classes is mainly due to operational reasons: machine operativity highly depends on vehicle weight, ground contact surface and soil moisture (Cambi et al. 2015). In order to avoid rut depth and soil disruption, high water-saturated soil areas are avoided. Also in this case, the Kruskal-Wallis test was performed for each machine dataset. In the case of HW1270G, the test detected significant differences for all the machine parameters considered, with respect to the levels of DTW. For FW1210G, on the other hand, the influence of DTW classes is less pronounced being responsible for significant differences only for three out of six parameters ("Total travel distance", "Travel distance low gear", and "Fuel rate".

Regression analysis models for fuel consumption

The main assumption when using a stepwise multiple regression model is the inclusion of a variable in the model with the condition that it has to produce statistically significant effects on the Residual Mean Squares Error (RMSE) of the model. At each step, a different linear regression models was evaluated in using and selecting the independent variables by stepwise regression to predict fuel consumption (Proto et al. 2018). The number of valid observations collected during the tests was large enough to develop a solid model for predicting which variables among machine, environmental and climatic data have a stronger relation and impact on fuel consumption from both machines (Kärhä et al. 2023). The conducted analysis confirmed the importance of the combined collected machine, terrain and meteorological information. In Table 11 and Table 12 the main findings in the stepwise regression are shown for harvester (HW1270G) and forwarder (FW1210G), respectively.

The general tendency for harvester fuel consumption is to be directly linked with machine activities, in particular the ones involved with the use of the processing head, i.e. the number of trees processed (Step=1) and

Table 11. Harvester (HW1270G) result of the stepwise multiple regression model for fuel consumption.

Step	Variable	R-Square	Adj. R-Square	C(p)	AIC	RMSE
1	Number of tree (n°/h)	0.304	0.304	1301.743	4501.676	3.0107
2	Travel distance low gear (km)	0.504	0.502	676.952	4202.887	2.5450
3	Production volume (m^3/h)	0.636	0.635	260.704	3927.091	2.1793
4	Slope (%)	0.663	0.661	179.799	3862.029	2.1000
5	Travel distance high gear (km)	0.693	0.691	86.355	3780.013	2.0046
6	Temperature -5cm below ground (°C)	0.703	0.701	55.538	3751.195	1.9714
7	Tree average volume in the hour (m^3)	0.711	0.708	35.392	3731.779	1.9489
8	DTW (0.25ha)	0.716	0.713	20.842	3717.433	1.9322
9	Soil type (-)	0.719	0.716	13.743	3710.315	1.9235
10	Precipitation (mm/h)	0.720	0.716	12.572	3709.116	1.9211

Note: ($F = 225.6$; $p < 0.05$; $R^2 = 0.72$)

Table 12. Forwarder (FW1210G) result of the stepwise multiple regression model for fuel consumption.

Step	Variable	R-Square	Adj. R-Square	C(p)	AIC	RMSE
1	Travel distance low gear (km)	0.544	0.543	158.356	3058.733	1.6565
2	Total travel distance (km)	0.584	0.583	77.315	2987.974	1.5833
3	Grapple unloading (n°/h)	0.606	0.604	32.750	2946.054	1.5411
4	DTW (0.25ha)	0.615	0.613	15.853	2929.514	1.5242
5	Roughness (m)	0.619	0.616	10.039	2923.719	1.5177
6	Grapple loading (n°/h)	0.621	0.618	6.882	2920.532	1.5137

Note: ($F = 215.2$; $p < 0.05$; R2 = 0.62) production volume (Step=3) and the travelled distance (Step=2) (Table 11). While the model is significant for the data directly downloaded from the FMS, such as travelled distance and volume production data (i.e., number of processed trees, average production volume and average tree volume), five additional components are positively influencing the fuel consumptions as Slope, Soil temperature, DTW, soil type and precipitation.

The same analysis was repeated on the forwarder FW1210G (Table 12). The general tendency follows the harvester´s, with fuel consumption being directly influenced by the machine activity with distance travelled (Step=1; Step=2) and grappled logs (Step=3) rather than terrain and climate variables. Similarly to the HW1270G set, two additional components that are overall influencing the fuel consumption to some extents are the DTW and Roughness. However, no other terrain (i.e., slope) nor climate variables (i.e., precipitation) were detected in affecting the forwarder performance in increasing fuel consumption.

Discussion

This study represents the first attempt in integrating machine management data from On-Board Computer (OBC), soil, terrain and climatic variables, when assessing tree harvester and forwarder performance. Following the methodology of past study (Holzleitner et al. 2013, Cadei et al. 2020 b; Bacescu et al. 2022, Polowy & Molińska-Glura 2023) aimed at exploiting FMS and semi-automated method to monitor forest processes and assessing related forest fuels, we aimed at providing a more comprehensive information framework. Forestry operations take place in natural, uneven, rough or soft ground and it is therefore important to address how off-road vehicles move (Cambi et al. 2015, Marchi et al. 2018, Tavankar et al. 2021, Latterini et al. 2022).

The results of this study highlighted that fuel consumption (and associated productivity) is significantly influenced by the primary activities of the machines, such as the use of the processing head for the harvester and the grapple for the forwarder, as well as the traveling distance. These results agree with more recent findings from Eriksson and Lindroos (2014), where comparing different productivity models for forwarder machines, they found that productivity its greatly influenced by load capacities as well as extraction distances, in both felling and thinning sites. Proto et al (2018) confirmed these findings for forwarding operations, directly comparing different machine models and stand treatments (i.e., large clear cut and selective cut).

The relationship between productivity and travelling distances is also affected by different soil types (particularly for HW1270G), slope classes, and the Depth to Water (DTW) classes. Higher slope classes were confirmed to reduce travel speed, and therefore decrease productivity (Strandgard et al. 2015). However, regarding soil water content, where soil moisture exceeds the 20% of terrain saturation, logging operations should be avoided to reduce the emissions of pollutants, the impacts on soil and to be more cost-effective (Tavankar et al. 2021). Furthermore, this problem can be avoided in the planning phase of operations with the use of DTW maps, excluding areas with a higher probability of soil saturation. Although, this information is not yet coupled with possible areas susceptible to soil compaction (Latterini et al. 2022).

Weather and climate variables have a strong influence on harvesting operations during working hours, and intense weather conditions - which have a direct influence on the trafficability of the terrain and/or the ability of off-road vehicles to transmit traction (Hittenbeck 2013, Berendt et al. 2020, Hoffmann et al. 2022) - can interrupt harvesting activities altogether, also following forest regulations on the trafficability of forest soils (Kuratourium für Waldarbeit und Forsttechnik

(KWF), Bundesinformationszentrum Landwirtschaft in der Bundesanstalt für Landwirtschaft und Ernährung 2021).

From this study results some remarks emerged to be addressed.

i. Retrieval of data. The methodology for data collection proved to be a practical alternative to field campaigns, particularly over long observation periods, as confirmed by previous research (Bacescu et al. 2022, Polowy & Molińska-Glura 2023, Mologni et al. 2024). Moreover, fuel consumption and machine parameters were automatically recorded by the machine's Fleet Management System (FMS) and stored in the cloud system (JDLink). However, the hourly-based observation approach offered an approximation of actual working time, with differences in the number of working days being approximately 14% for the harvester and 18% for the forwarder. On the other hand, high-resolution soil mapping and weather data helped overcome the drawbacks of partial inaccuracy and the time-consuming nature of field campaigns (Schönauer et al. 2021, Latterini et al. 2022).

ii. Data handling. The handling and synchronization of the machine data, together with terrain and climate information, proved to be challenging (Melander et al. 2020). Indeed, the statistical testing for the terrain and climatic variables for both HW1270G and FW1210G turned to be significant for all of them. An additional in-depth GIS analysis found that these outcomes could have been possibly related to some unsynchronized activities of the machines (Melander et al. 2020). In fact, when the harvester was operating in a specific location, the forwarder never worked in that same area during the observed period, as expected, resulting in a statistical discrepancy in terms of harvested area and meteorological conditions apparently for the whole monitored period. For this reason, this methodology needs to be further improved and validated.

iii. Machine operability. Following the machine fleet for one entire year highlighted that immediate program changes and operational flexibility on behalf of the operators is to be expected, in particular due to adverse meteorological conditions. The mean hourly precipitation for the observed dataset was 0.0825 (mm/h) for HW1270G and 0.0692 (mm/h) for FW1210G, indicating that during heavy or consistent rainfall phenomena the machines were not operating in the forest. In fact, regional prescription does not allow to enter and operate in the forest during consistent and continuous rainfall with consequent high risk of rutting and soil disruption (Kuratourium für Waldarbeit und Forsttechnik (KWF), Bundesinformationszentrum Landwirtschaft in der Bundesanstalt für Landwirtschaft und Ernährung 2021). Indeed, the precipitation was among the variables having a significant effect on the fuel consumption when included in the model only for the harvester, resulting in reduced soil strength (Mederski et al. 2021). On the other hand, the same did not occur when considering the forwarder operativity (Prinz et al. 2023), which is even more influenced by heavy rainfall events, especially in spring and autumn when it comes to conduct low-impact operations (Hoffmann et al. 2022).

iv. Feasibility of the model. The regression models for fuel consumption granted significant and informative results, but they should be used carefully for predicting fuel consumption. It is not yet clear to what extent the model is influenced by site-specific factors. In fact, the model requires a comprehensive set of training examples from different forest conditions before producing reliable predictions, which depends on the availability of fieldbus data, also experienced by Melander et al. (2020). While machine data is utilized at different levels during investigations, the full potential of combining FMS data and GIS analysis is often not realized (Kemmerer & Labelle 2021). No single factor fully explains fuel consumption in forest operations, reflecting the complex relationships between variables and fuel consumption (Prinz et al. 2023). This aligns with ongoing research towards a more complete concept of precision forestry and Forestry 4.0 (Kovacsova & Antalova 2010, Müller et al. 2019, Reitz et al. 2019).

Conclusions

The purpose of this study was to assess the possibility of analysing machine performance indicators, specifically the fuel consumption of individual wheeled CTL harvesters and forwarders, over a one-year period using automated machine data collection through FMS, terrain parameters, and meteorological conditions.

The analysis of machine performance and forest attributes, as well as their combination, is a continuously evolving research area, moving towards a comprehensive concept of precision forestry and Forestry 4.0. The findings of this study contribute to this research direction, aligning with previous research on ground-based forestry machines. Understanding the interaction between ground conditions and working intensity is particularly important over long observation periods. Integrating FMS data with environmental and weather data enhances the understanding of machine performance, such as fuel consumption, over medium to long periods, enabling more rational analysis in terms of data collection and process analysis.

A promising research direction involves characterizing specific case studies with higher frequency machine data sampling and detailed environmental and climatic data. This can ensure robust assumptions and a deeper understanding of working dynamics, even with low-resolution data. Future investigations should focus on exploiting OBC machine data from FMS, considering the complete set of variables on a smaller scale with higher frequency to address specific interactions among variables more robustly.

Statistically, machine fuel consumption for both harvesters and forwarders is not influenced by environmental and climatic conditions but by factors closely related to machine activity. Based on this study outcomes, further investigations should address closer stand characterization, as well the possible effects of running gear configuration on machine performance and soil impact.

Compliance with ethical standards

Conflict of interest

Authors declare there is no conflict of interest.

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Supporting information

Table S1 Harvester (HW1270G) and forwarder (FW1210G) performance analysis in different soil type (Mann-Whitney test). **Table S2** Harvester (HW1270G) and forwarder (FW1210G) performance analysis in different slope classes (Kruskal-Wallis test). **Table S3** Harvester (HW1270G) and forwarder (FW1210G) performance analysis in different DWT classes (Kruskal-Wallis test).

References

Ackerman P., Williams C., Ackerman S., Nati C., 2017. Diesel consumption and Carbon Balance in South African pine clear-felling CTL operations: A preliminary case study. Croatian Journal of Forest Engineering 38(1): 65–72.

Ågren A. M., Lidberg W., Ring E., 2015. Mapping Temporal dynamics in a forest stream network—Implications for riparian forest management. Forests *6*(9): 9. https://doi.org/10.3390/f6092982

Bacescu N. M., Cadei A., Moskalik T., Wiśniewski M., Talbot B., Grigolato S., 2022. Efficiency assessment of fully mechanized harvesting system through the use of fleet management system. Sustainability 14(24): 24. https://doi.org/10.3390/su142416751

Berendt F., Tolosana E., Hoffmann S., Alonso P., Schweier J., 2020. Harvester productivity in inclined terrain with extended machine operating trail intervals: A German case study comparison of standing and bunched trees. Sustainability (Switzerland) 12(21): 1–10. https://doi.org/10.3390/su12219168

Björheden R., Thompson M.A., 2000. An international nomenclature for forest work study. In: Proceeings, IUFRO 1995 S3 : 04 Subject Area : 20th World Congress, Caring for the Forest: Research in a Changing World. 1995 August 6-12; Tampere, Finland. Miscellaneous Report 422. Orono, ME: University of Maine: 190-215. https://www.fs.usda.gov/research/treesearch/12276

Cadei A., Marchi L., Mologni O., Cavalli R., Grigolato S., 2020. Evaluation of wood chipping efficiency through long-term monitoring. Environmental Sciences Proceedings 3(1): 17. https://doi.org/10.3390/IECF2020-08078

Cadei A., Mologni O., Röser D., Cavalli R., Grigolato S., 2020. Forwarder productivity in salvage logging operations in difficult terrain. Forests, 11(3): 341. https://doi.org/10.3390/F11030341

Cambi M., Certini G., Neri F., Marchi E., 2015. The impact of heavy traffic on forest soils: A review. Forest Ecology and Management 338: 124–138. https://doi.org/10.1016/j.foreco.2014.11.022

Dilmi M.D., Barthès L., Mallet C., Chazottes A., 2020. Iterative multiscale dynamic time warping (IMs-DTW): A tool for rainfall time series comparison. International Journal of Data Science and Analytics 10(1): 65–79. https://doi.org/10.1007/s41060-019-00193-1

Erasmus D., 1994. National terrain classification system for forestry. ICFR Bull Ser 11(94):12.

Eriksson M., Lindroos O., 2014. Productivity of harvesters and forwarders in CTL operations in northern Sweden based on large follow-up datasets. International Journal of Forest Engineering 25(3): 179–200. https://doi.org/10.1080/14942119.2014.974309

Ghaffariyan M., Sessions J., Brown M., 2012. Machine productivity and residual harvesting residues associated with a cut-to-length harvest system in southern Tasmania. Southern Forests: A Journal of Forest Science 74(4): 229–235. https://doi.org/10.2989/20702620.2012.741770

Hartsch F., Kemmerer J., Labelle E. R., Jaeger D., Wagner T., 2021. Integration of harvester production data in German wood supply chains: Legal, social and economic requirements. Forests 12(4): 460. https://doi.org/10.3390/f12040460

Hartsch F., Schönauer M., Breinig L., Jaeger D., 2022. Influence of loading distance, loading angle and log orientation on time consumption of forwarder loading cycles: A pilot case study. Forests 13(3): 384. https://doi.org/10.3390/f13030384

Hittenbeck J., 2006. Tractive forces, slip and slopes. ISTRO (Hg.). Proceedings of Istro 17: 16–26.

Hittenbeck J., 2010. Inclination limits for high mechanized harvesting. FORMEC 2010.

Hittenbeck J., 2013. Estimation of trafficable grades from traction performance of a forwarder. Croatian Journal of Forest Engineering: Journal for Theory and Application of Forestry Engineering 34(1): 71–81.

Hoffmann S., Schönauer M., Heppelmann J., Asikainen A., Cacot E., Eberhard B., Hasenauer H., Ivanovs J., Jaeger D., Lazdins A., Mohtashami S., Moskalik T., Nordfjell T., Stereńczak K., Talbot B., Uusitalo J., Vuillermoz M., Astrup R., 2022. Trafficability prediction using depth-to-water maps: The status of application in northern and central European forestry. Current Forestry Reports 8(1): 55–71. https://doi.org/10.1007/s40725-021-00153-8

Holzleitner F., Kanzian C., Stampfer K. 2011. Analyzing time and fuel consumption in road transport of round wood with an onboard fleet manager. European Journal of Forest Research 130(2): 293–301. https://doi.org/10.1007/s10342-010-0431-y

Holzleitner F., Kanzian C., Höller N. 2013. Monitoring the chipping and transportation of wood fuels with a fleet management system. Silva Fennica 47(1): 899.

Horn R., Vossbrink J., Peth S., Becker S., 2007. Impact of modern forest vehicles on soil physical properties. Forest Ecology and Management 248(1–2): 56–63. https://doi.org/10.1016/j.foreco.2007.02.037

Kärhä K., Haavikko H., Kääriäinen H., Palander T., Eliasson L., Roininen K., 2023. Fossil-fuel consumption and CO_2eq emissions of cut-to-length industrial roundwood logging operations in Finland. European Journal of Forest Research. https://doi.org/10.1007/s10342-023-01541-4

Kemmerer J., Labelle E.R., 2021. Using harvester data from on-board computers: A review of key findings, opportunities and challenges. European Journal of Forest Research 140(1): 1–17. https://doi.org/10.1007/s10342-020-01313-4

Kovacsova P., Antalova M., 2010. Precision forestry-definition and technologies. Sumarski List 134: 603–611.

KWF 2021. Kuratourium für Waldarbeit und Forsttechnik (KWF), Bundesinformationszentrum Landwirtschaft in der Bundesanstalt für Landwirtschaft und Ernährung, 2021. Bodenschutz im Wald: 92.

Latterini F., Venanzi R., Tocci D., Picchio R., 2022. Depth-to-water maps to identify soil areas that are potentially sensitive to logging disturbance: Initial evaluations in the mediterranean forest context. Land 11(5): 709. https://doi.org/10.3390/land11050709

Marchi E., Chung W., Visser R., Abbas D., Nordfjell T., Mederski P.S., McEwan A., Brink M., Laschi A., 2018. Sustainable Forest Operations (SFO): A new paradigm in a changing world and climate. Science of the Total Environment 634: 1385–1397. https://doi.org/10.1016/j.scitotenv.2018.04.084

Mederski P.S., Borz S.A., Đuka A., Lazdiņš A. 2021. Challenges in forestry and forest engineering: case studies from four countries in East Europe. Croatian Journal of Forest Engineering 42(1): 117–134. https://doi.org/10.5552/crojfe.2021.838

Melander L., Einola K., Ritala R. 2020. Fusion of open forest data and machine fieldbus data for performance analysis of forest machines. European Journal of Forest Research 139(2):213–27. doi: 10.1007/s10342-019-01237-8.

Mologni O., Dyson P., Amishev D., Proto A.R., Zimbalatti G., Cavalli R., Grigolato, S., 2018. Tensile force monitoring on large winch-assist forwarders operating in British Columbia. Croatian Journal of Forest Engineering 39(2): 193–204.

Mologni O., Lahrsen S., Roeser D. 2024. Automated Production time analysis using fpdat ii onboard computers: A Validation study based on whole-tree ground-based harvesting operations. Computers and Electronics in Agriculture 222: 109047. https://doi.org/10.1016/j.compag.2024.109047

Mückenhausen E., 1962. Entstehung, Eigenschaften und Systematik der Böden der Bundesrepublik Deutschland. DLG Verlags.

Müller F., Jaeger D., Hanewinkel M., 2019. Digitization in wood supply – A review on how Industry 4.0 will change the forest value chain. Computers and Electronics in Agriculture 162: 206–218. https://doi.org/10.1016/J.COMPAG.2019.04.002

Murphy P.N.C., Ogilvie J., Arp P., 2009. Topographic modelling of soil moisture conditions: A comparison and verification of two models. European Journal of Soil Science 60(1): 94–109. https://doi.org/10.1111/j.1365-2389.2008.01094.x

Nurminen T., Korpunen H., Uusitalo J., 2006. Time consumption analysis of the mechanized cut-to-length harvesting system. Silva Fennica 40(2). https://www.silvafennica.fi/article/346

Picchi G., Sandak J., Grigolato S., Panzacchi P., Tognetti R., 2022. Smart harvest operations and timber processing for improved forest management. Climate-Smart Forestry in Mountain Regions, 317-359.

Plamondon J., Pitt D. G., 2013. Effects of precommercial thinning on the forest value chain in northwestern New Brunswick: Part 2 – Efficiency gains in cut-to-length harvesting. The Forestry Chronicle 89(04): 458–463. https://doi.org/10.5558/tfc2013-087

Polowy K., Molińska-Glura M., 2023. Data mining in the analysis of tree harvester performance based on automatically collected data. Forests 14(1): 165. https://doi.org/10.3390/f14010165

Prinz R., Mola-Yudego B., Ala-Ilomäki J., Väätäinen K., Lindeman H., Talbot B., Routa J., 2023. Soil, driving speed and driving intensity affect fuel consumption of forwarders. Croatian Journal of Forest Engineering 44(1): 31–43. https://doi.org/10.5552/crojfe.2023.1725

Proto A.R., Macrì G., Visser R., Harrill H., Russo D., Zimbalatti G., 2018. Factors affecting forwarder productivity. European Journal of Forest Research 137(2): 143–151. https://doi.org/10.1007/s10342-017-1088-6

QGIS A., 2015. Free and open source geographic information system. Open Source Geospatial Foundation Project.

Reitz J., Schluse M., Roßmann J., 2019. Industry 4.0 beyond the Factory: An application to forestry. Tagungsband Des 4. Kongresses Montage Handhabung Industrieroboter: 107–116. https://doi.org/10.1007/978-3-662-59317-2_11

Saarilahti M., 2002. Soil interaction model [ECOWOOD project deliverable D2.].

Salmivaara A., Launiainen S., Perttunen J., Nevalainen P., Pohjankukka J., Ala-Ilomäki J., Sirén M., Laurén A., Tuominen S., Uusitalo J., Pahikkala T., Heikkonen J., Finér L., 2020. Towards dynamic forest trafficability prediction using open spatial data, hydrological modelling and sensor technology. Forestry: An International Journal of Forest Research Forestry, 93: 662–674. https://doi.org/10.1093/forestry/cpaa010

Schönauer M., Maack, J., 2021. R-code for calculating depth-to-water (DTW) maps using GRASS GIS. Zenodo. https://doi.org/10.5281/zenodo.5718133

Schönauer M., Talbot B., Jaeger D., 2019. Terrain accessibility maps for 4 case study areas. https://doi.org/10.13140/RG.2.2.20707.17444

Schönauer M., Väätäinen K., Prinz R., Lindeman H., Pszenny D., Jansen M., Maack J., Talbot B., Astrup R., Jaeger D., 2021. Spatio-temporal prediction of soil moisture and soil strength by depth-to-water maps. International Journal of Applied Earth Observation and Geoinformation 105: 102614. https://doi.org/10.1016/j.jag.2021.102614

Schrey H. P., 2014. Bodenkarte von Nordrhein-Westfalen 1:50.000: BK 50 [Inhalt, Aufbau, Auswertung]. Geologischer Dienst Nordrhein-Westfalen.

Schweier J., Magagnotti N., Labelle E.R., Athanassiadis D., 2019. Sustainability impact assessment of forest operations: a review. Current Forestry Reports 5(3): 101–113. https://doi.org/10.1007/S40725-019-00091-6/TABLES/1

Shoop S.A., 1993. Terrain characterization for trafficability. Cold Regions Research and Engineering Lab Hanover NH.

Spinelli R., Magagnotti N., 2013. The effect of harvest tree distribution on harvesting productivity in selection cuts. Scandinavian Journal of Forest Research 28(7): 701–709. https://doi.org/10.1080/02827581.2013.821517

Spinelli R., Owende P. M., Ward S. M., 2002. Productivity and cost of CTL harvesting of Eucalyptus globulus stands using excavator-based harvesters. Forest Products Journal *52*(1): 67.

Spinelli R., Owende P., Ward S., Tornero M., 2004. Comparison of short-wood forwarding systems used in Iberia. Silva Fennica 38(1). https://doi.org/10.14214/sf.437

Stampfer K., 1999. Influence of terrain conditions and thinning regimes on the productivity of a track-based steep-slope harvester. Proc Int Mountain Logging and 10th Pacific Northwest Skyline Symp, Corvallis, OR, USA, 28 March-1 April 1999.

Strandgard M., Mitchell R., Acuna M., 2015. Impact of slope on forwarder load size and productivity. Proceedings of the 48th FORMEC Symposium 2015, Oct 4-8, 2015, Linz, Austria, 101-105.

Strubergs A., Lazdins A., Sisenis L. 2022. Use of ctl harvester .hpr and .mom files to analyze impact of operator training on productivity. 21st International Scientific Conference Engineering for Rural Development, 432-437. https://doi.org/10.22616/ERDev.2022.21.TF148

Suvinen A., Tokola T., Saarilahti M., 2009. Terrain trafficability prediction with GIS analysis. Forest Science 55(5): 433–442. https://doi.org/10.1093/forestscience/55.5.433

Team R.D.C., 2009. A language and environment for statistical computing. Http://Www. R-Project. Org.

Tavankar F., Nikooy M., Latterini F., Venanzi R., Bianchini L., Picchio R. 2021. The effects of soil moisture on harvesting operations in *Populus* spp. plantations: Specific focus on costs, energy balance and GHG emissions. Sustainability 13(9): 4863. https://doi.org/10.3390/su13094863

Tervo K., Palmroth L., Koivo H., 2010. Skill evaluation of human operators in partly automated mobile working machines. IEEE Transactions on Automation Science and Engineering 7(1): 133–142. https://doi.org/10.1109/TASE.2009.2025364

Tiernan D., Zeleke G., Owende P.M.O., Kanali C.L., Lyons J., Ward S.M., 2004. Effect of working conditions on forwarder productivity in cut-to-length timber harvesting on sensitive forest sites in Ireland. Biosystems Engineering 87(2): 167–177. https://doi.org/10.1016/j.biosystemseng.2003.11.009

Väätäinen K., Ala-Fossi A., Nuutinen Y., Röser D., 2006. The effect of single grip harvester's log bunching on forwarder efficiency. Baltic Forestry 12: 64–69.

Walsh D., Strandgard M., 2014. Productivity and cost of harvesting a stemwood biomass product from integrated cut-to-length harvest operations in Australian *Pinus radiata* plantations. Biomass and Bioenergy 66: 93–102. https://doi.org/10.1016/j.biombioe.2014.01.017

Zuur A. F., Ieno E. N., Elphick C. S., 2010. A protocol for data exploration to avoid common statistical problems. Methods in Ecology and Evolution 1(1): 3–14. https://doi.org/10.1111/j.2041-210X.2009.00001.x