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Potential of Geospatial Technologies in Mechanized Timber Harvesting Planning

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Abstract

Mechanized timber harvesting involves various activities including road planning, and selection of harvesting systems and machineries. The emergence of geospatial technology (GSPT) i.e., geographical information system (GIS) and remote sensing in the recent decades, has been considered as the best tools to facilitate timber harvesting planning in plantation forests. GSPT provide accurate stand information enabling better decision-making and optimizing forest operations. This study was conducted at Sao hill Forest Plantation (SHFP) in Tanzania, with the objective of determining relative efficiency (RE) between geospatial approach (GSPA) and conventional approach (CA) on planning mechanized timber harvesting. 120 grapple skidders (GS) in 30 sample plots within different elevation terrain ranges were studied with time study observations in both approaches. Productivity and costs under the two approaches were estimated and modelled using generalized linear model (GLM) approach. To obtain large scale estimates of productivity and costs, Inverse Distance Weighted (IDW) interpolation approach was used. The results showed that, GSPA demonstrated higher productivity and lower unit skidding costs (i.e., 71.1 m^3/hr and 2.121 USD/m^3) compared to CA (i.e., 67.5 m^3/hr and 2.914 USD/m^3) respectively. Skidding distance and slope (p-value < 0.05) were significant predictors of the GS performance in both approaches. The pseudo R^2 ranging from 58.1% to 64.3% under CA, and from 62.9% to 60.8% under GSPA. Likewise, relative root mean square error (RMSEr) for the models under CA ranged from 49.3% to 50.4% and 33.4% to 35.2% under GSPA. Generally, the results showed that, models under GSPA have better fits and accuracy, compared to CA. Furthermore, the GSPA provided a raster representation of productivity and costs over the entire study area. Moreover, computed RE values (i.e., 1.18 and 6.17) indicated that parameter estimates for the GS productivity and costs were more precise in geospatial models (GSPM) compared to conventional models (CM). These findings highlight the potential of GSPT for an efficient large scale timber harvesting planning, by considering terrain constraints.

Keywords: Convectional, Geospatial, Grapple skidder, Productivity, Costs, Relative efficiency.

1. Introduction

Forest operation planning normally involves detailed site-specific plans for various forest activities, such as forest establishment, tending operations, road construction, and timber harvesting (Bettinger et al., 2009). It involves capturing information on environmental, economic, and social constraints as the key components for sustainable forest management (Ole-Meiludie and Skaar, 1990; Bredström et al., 2010).Timber harvesting operations, being one of the forest management objectives (Kühmaier and Stampfer, 2010), generally rely on the operational level of planning, which involves planning of the harvesting roads (skidding trails), selection of the harvesting system to be used and allocation of other resources required to accomplish the entire operations, including number of days and personnel required as well as costs of items and services (Đuka et al., 2015).

Previously, timber harvesting planning in tropical countries, including Tanzania, has been carried out using conventional methods, involving manual collection of site-specific information essential for planning (Conway, 1986; Shemwetta et al., 2007) before actual logging operation. Furthermore, through CA, other essential planning information is usually extracted from the forest management plan of the respective forest (Shemwetta, 1997), including printed topographic maps, aerial photographs, and ground survey reports (Conway, 1986; Ole-Meiludie and Skaar, 1990). However, such office-based information is frequently insufficient, re preliminary field visits to supplement missing data before commencing harvesting operations. It makes the planning activity tedious and time-consuming hence leading to operational delays (Conway, 1986).

The emergence of GSPT (i.e., Geographic Information Systems (GIS) and Remote sensing) has

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simplified planning activities by providing crucial stand information, such as terrain steepness, roughness, extraction distances, felling unit boundaries, and road networks, which are very necessary for timber harvesting planning. Through GIS technology, the analysis of topographic, ecological, and morphological characteristics of the study area can be performed (Picchio et al., 2020).

Previous studies by Perpiñá et al., (2009) and McKendry and Eastman, (1991) suggested that forest management has become interesting and successful through combining spatial and non-spatial information to facilitate decision-making particularly in the preparation of timber harvesting plans, whereby through spatial analysis, it allows optimization of forest operations based on field and machinery characteristics (Pecora et al., 2014). Additionally, the study by Suvinen (2006) and Lubello (2008) applied a GIS-based simulation model to evaluate the interaction of terrain trafficability, vehicle mobility, and terrain tractability for the harvesting machinery as among the efforts undertaken to enhance sustainable and efficient mechanized timber harvesting. Furthermore, a study conducted by Phelps et al. (2021) has proven the potential of spatial and forest road network analysis in creating thematic map information that assists in choosing proper harvesting machinery and systems that maximize productivity and profit.

Despite all the potentials shown by GSPT, most of the past logging studies, such as Banaś et al. (2021) and Okey and Visser (2020), were relied on CA as the major criterion for assessing and selecting harvesting systems and machinery to be used on logging operations (Çalişkan and Karahalil, 2017). Moreover, such an approach was based on intuitional/personal judgement, which gives less attention to the environmental constraints, particularly terrain variables, hence leading to lower machinery efficiency in terms of productivity and costs. Furthermore, CA, compared to GSPA, can cover smaller spatial areas at a time which leads to inefficient planning for large-scale timber harvesting. Therefore, this study aimed to integrate GSPT in predicting productivity and costs of mechanized skidding operations and compare its relative efficiency with the CA in order to identify the most efficient approach that minimizes costs and the negative impact on the environment while maximizing productivity and ensuring the safety of forest workers (Picchio et al., 2020). The findings from this study form a basis for the applications of GSPT in timber harvesting planning, which can be used to recommend the best timber harvesting planning under different terrain conditions in plantation forests.

2. Materials and methods

2.1 Study area description

This study was conducted at Sao Hill Forest Plantation, situated in the Southern highland of Tanzania mainland, in the Mufindi district found in Iringa region. It is located at latitudes 8^0 18′S to 8^0 33′S and longitudes 35^0 06′E to 35^0 40′E with an altitude ranging from 1,700 m to 2,000 m above the sea level (Figure 1).

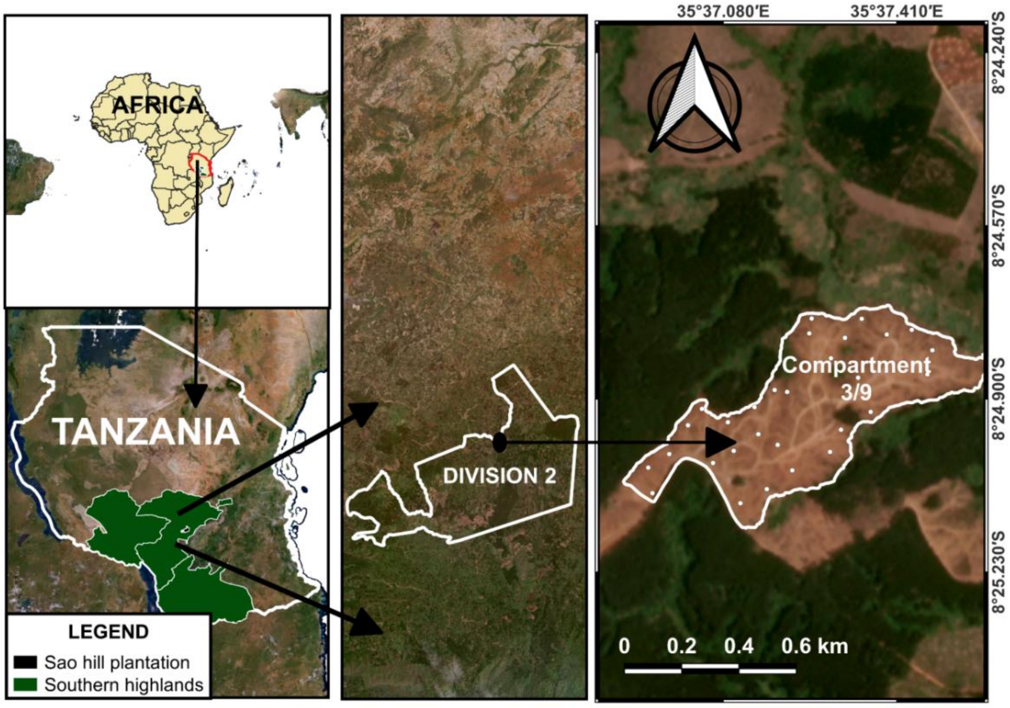

Figure 1. Map of Sao hill Forest plantation showing the compartment understudy

The plantation is estimated to cover 135,903 hectares and is administratively divided into four divisions: Irundi, Ihefu, Ihalimba and Mgololo (MNRT, 2018). The most planted tree species are exotic softwood and hardwood species, including *Pinus patula, Pinus elliottii, Pinus caribeae, Eucalyptus maidenii, Eucalyptus* *saligna, Eucalyptus camaldulensis* and *Cupressus lusitanica.* Also, it comprises some patches of grassland and indigenous tree species of *Erythrina abyssinica*, *Parinari curatellifolia*, *Apodytes dimidiata* and *Albizia petersiana*. Climate is characterized by a unimodal rainfall pattern starting from November to April and a dry season from May to late October. The mean annual rainfall is 1,300 mm. The temperatures are fairly cool, with the minimum monthly temperature range between 10°C to 18°C and the maximum range between 23°C to 28°C.

2.2 Machinery description

The machine used in this study was a CAT 525 grapple skidder owned by MPM. It is an American-manufactured caterpillar brand with the following characteristics (Table 1) as presented by RP (2007).

Table 1. GS descriptions

Machinery specifications	Description
Model	CAT 525
Configuration	Rubber-tired
Overall length	19.69 ft (6.00 m)
Overall width	10.27 ft (3.13 m)
Ground clearance	1.73 ft (0.53 m)
Wheel base	11.49 ft (3.50 m)
Engine Model	CAT 3304 DIT Diesel
Gross power	175 HP
Operating weight	15200 kg
Brakes service type	Hydraulic actuated, oil disc
Maximum Drawbar pull	19731.3 kg
Maximum forward speed	16.9 mph (27.20km/hr)
Maximum reverse speed	12 mph (19.31 km/hr)
Estimated operating weight	13558.3 kg
Grapple bunching capacity	12.5 ft^2 (1.16 m^2) (1065.9 kg)
Maximum operating distance	500 m
Maximum operating slope	30 %

CAT = Caterpillar, ft = Feet, HP = Horsepower, kg = Kilogram, m = Meter, mph = Miles per hour.

2.3 Study design

The compartment understudy was selected by considering SHFP management plan, which indicate total area harvested per annually. Data acquisition and analytical procedures for this study are described in Figure 2. To enhance total terrain variability, 30 plots of 15 m x 15 m were laid randomly throughout the compartment. Furthermore, a total of 120 GS work cycles were determined using the formula by Murphy (2005) (Equation 1), whereby; pilot time study was conducted in 10 random observations, yielding an average cycle time (i.e., mean WCT) and variance cycle time (i.e., Var WCT) of 6.873 and 0.071 minutes respectively. The desired precision (E) was 0.95.

$$n = t^2 * Var(WCT)/[E * WCT/100]^2 \qquad (1)$$

where;
n = number of work cycles to be studied
t = Student's t-value
Var $(\overline{WCT})$ = Variance of the work cycle time
E = Level of precision desired
$\overline{WCT}$ = Mean work cycle time (minutes)

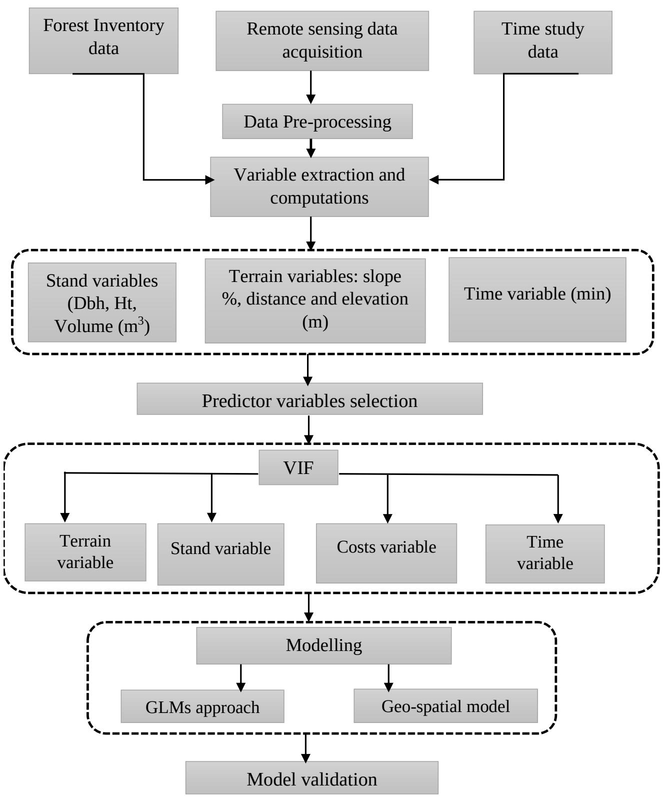

Figure 2. Methodological framework for modelling and predicting GS productivity and costs using whole tree harvesting system at SHFP

2.4 Data collection

Skidding time (minutes), tree diameter at breast height (DBH), tree height, terrain variables (elevation, distance, and slope %), and operational cost were used to predict GS productivity and costs in this study. The details of each collected variable are described below;

2.4.1 GS time variables

Skidding time was quantified using detailed time study techniques using the stopwatch. The GS time was divided into five measurable work elements, including travel empty (TE), positioning (PS), grappling (GL), travel loaded (TL), and unloading (UNL) to ensure effective quantification of the utilized time. Furthermore, necessary delays (inevitable interruption due to the nature of the work and the environment) and unnecessary delays (the wastage of time which can be eliminated by improving supervision and training to workers) (Mauya, 2022) were recorded once they occurred in operation.

2.4.2 Forest stand parameters

Before skidding operations, standing trees in all 30 plots were marked using serial numbers for easier monitoring in the subsequent operations. Then, the individual tree parameters, i.e., DBH and tree height were measured using a calliper and vertex hypsometer, respectively. Following the adopted harvesting system (i.e., Whole tree), the volume of each tree was estimated by an allometric single tree model (Equation 2) by Malimbwi et al. (2016).

$$\text{Tree volume} = \exp(-9.04925 + 1.14781 \times \ln(\text{height}) + 1.5496 \times \ln(\text{DBH})) \quad (2)$$

2.4.3 Terrain variables

Digital elevation model (DEM) for SHFP was acquired from https://earthexplorer.usgs.gov/ website with a resolution of 30m x 30m, followed by clipping into specific areas of interest (compartment understudy) using QGIS software. The input and mask layers were DEM and harvested compartment 3/9, respectively.

2.5 Data analysis

For the case of terrain analysis, elevation in the study area was classified into six categories with an interval of 26 meters above the mean sea level (Figure 3), followed by vectorization to determine the area occupied by each elevation class (Table 2).

Under GSPA, the distance from the bunching sites to the landing was determined using the least-cost path analysis on QGIS. Slope changes (%) on various spatial area of the harvested forest compartment (Figure 4) were computed indirectly by taking the difference in elevation between the landing and bunching site then dividing by the horizontal distance between two stations (Equation 3). The spatial area under each slope class is presented in Table 3, as adopted in the study by Çalişkan and Karahalil (2017).

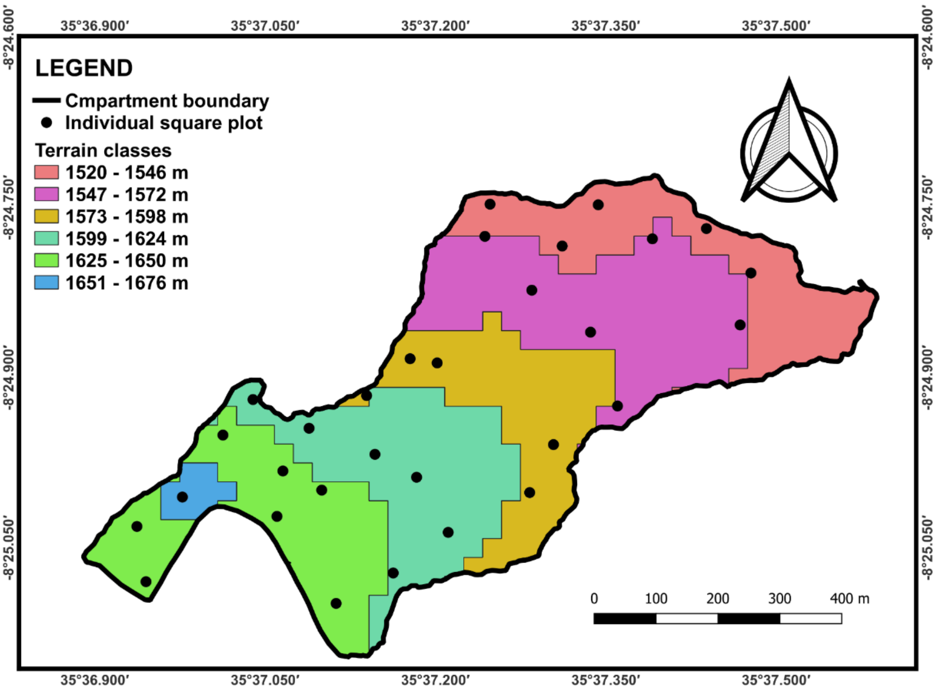

Figure 3. DEM showing terrain (elevation) classes and sample plots distributions in the study area

Table 2. Harvested area (ha) occupied by each terrain (elevation) class

S/N	Elevation classes (m)	Area occupied (ha)
1	1520 -1546	6.957
2	1546 - 1572	9.858
3	1572 - 1598	6.761
4	1598 - 1624	8.247
5	1624 - 1650	7.465
6	1650 - 1676	0.805
Total		40.1

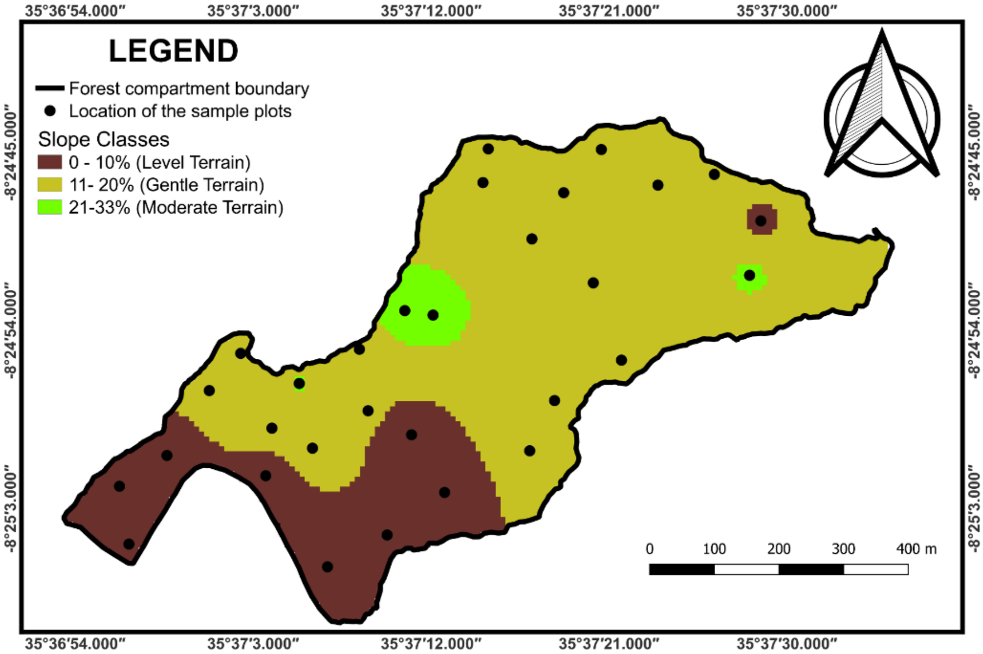

Figure 4. DEM showing slope variations on various spatial area in the harvested forest compartment under study

Table 3. Harvested area (ha) occupied by each terrain (slope) class

S/N	Slope classes (%)	Description	Spatial area (ha)
1	0 - 10	Level terrain	9.896
2	11-20	Gentle terrain	28.705
3	21-33	Moderate terrain	1.549
Total			40.1

$$Slope\ (\%) = \frac{DE}{HD} x100\% \quad (3)$$

Where; DE is the change in elevation between the landing and bunching site, HD is the horizontal distance obtained through Pythagoras theorem (Equation 4). Under CA, distance and slope were measured directly using measuring tape and vertex hypsometer.

$$Horizontal\ distance\ (HD) = \sqrt{SD^2 - DE^2} \quad (4)$$

Where; SD is the slant distance on the surface of the terrain, DE is the change in elevation between the landing and bunching site. Detailed terrain variables information is presented in Table 4.

2.5.1 GS productivity and costs estimates

Since delay time was not captured in the GSPA, in order to bring a sense of comparison with CA, GS productivity estimation (Equation 5) was performed using the formula described by Mauya (2022) and Miyajima et al. (2021).

$$P = \frac{Tvol\ (m^3)x\ (60)}{PMH} \quad (5)$$

Where; P is the GS productivity (m^3/hr), 60 is the time conversion factor from minutes to hours and PMH is the productive machine hour (i.e., delay free).

Following US dollar being a global means of exchange, unit skidding costs (Equation 6) was estimated in USD/m^3 based on Tanzania Central Bank (BOT) exchange rates of 5th April 2023, which was 1 USD to 2301.7 TSHS.

$$\text{Unit skidding costs (USD/m}^3) = \frac{\text{Hourly skidding costs (USD/hr)}}{\text{Production rate}(m^3/hr)} \quad (6)$$

Table 4. Sources and properties of the terrain variables used to develop study area DEM and slope map

S/N	Variable	Data Source	Precision Level
1	Elevation (m)	Field based data (captured using GPSMAP64csx)	± 3.0 m
2	Slope (%)	1.Field based data (i.e., Sample plot elevation captured using GPSMAP64csx)	± 3.0 m
		2.Geospatial based data (i.e., Skidding distance obtained through Least cost path on QGIS)	30 m Resolution
3	DEM	Geospatial based data (acquired from https://earthexplorer.usgs.gov/)	30 m Resolution
4	Skidding distance (m)	Geospatial based data (Obtained through Least costs path on QGIS)	30 m Resolution

2.5.2 Model development

Productivity and cost predictions were carried out using parametric and non-parametric models. Prior to parametric modelling, the normality test for selected predictor variables was performed using the Shapiro-Wilk test, followed by a multicollinearity test using variance inflation factor (VIF) analysis. Variables with a VIF value > 5 were excluded in the model (Korkmaz et al., 2014). Parametric modelling was performed based on the previous logging studies; Conrad et al. (2013), Long (2003), and Wang et al. (200 4, 2005) using the GLM approach (Equation 7) since it is flexible and can avoid data originality loss due to log and back transformations (Lindsey, 1998).

$$g(\mu i) = ni = \alpha + \beta_1 x_{i1} + \beta_2 x_{i\,2} + \beta_k x_{ik} + \varepsilon \quad (7)$$

Where; $g(\mu_i) = n_i$ is a smooth and invertible linearizing link function *g (·)*, which transforms the expectation of the response variable, $\mu i = E\ (Yi)$, to the linear predictor, α is the model intercept while "$\beta_1 x_{i1} + \beta_2 x_{i2} + \ldots \beta_k x_{ik}$" are predictor variables.

Since the data are continuous, Gaussian family and identity link was applied to ensure normal distribution of error terms.

On the other hand, geospatial (i.e., raster) models for predicting GS performance (i.e., productivity and costs) on the specific terrain were performed through Inverse Distance Weighting (IDW) interpolation techniques (Equation 8), which refers to estimation of values (i.e., productivity and costs) at unknown terrain using discrete terrain data set of specific sample plots in order to generate continuous surface.

$$Z(x) = \frac{\sum_{i=1}^{n} \frac{z_i}{d_i^p}}{\sum_{i=1}^{n} \frac{1}{d_i^p}} \quad (8)$$

where; *Z* (*x*) is the interpolated productivity and costs value at the unknown terrain. Z_i *is* the known productivity and costs at the sample plots. d $_i$ is the distance from the unknown location *x* to the sample plots. *p* is the power parameter that controls the influence of distance (normally; 1 for Euclidean distance and 2 for Manhattan distance).

2.5.3 Model validation

Model validation is usually encouraged for its accuracy (James et al., 2013; Jimmy et al., 2013). Cross validation was performed by randomly splitting 120 GS observations into ten-folds with 12 observations each. During each iteration, a subset was reserved for evaluating model performance, while the rest of subsets were utilized as a training data (James et al., 2013). The goodness of fit for the models was assessed through coefficient of determination (R^2) (Equation 9), residual, and scatter plots (Figures 8 and 9). Furthermore, model quality was assessed through relative mean square error (RMSEr) using its predicted values (Equation 11). A higher R^2 and lower RMSEr value typically signify the precise estimation of the model.

$$Pseudo\ R - squared = 1 - \left(\frac{Residual\ deviance}{Null\ deviance}\right) * 100 \quad (9)$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}} \quad (10)$$

$$RMSE_r = \frac{RMSE}{\bar{y}} x100 \quad (11)$$

Where; $\sum_{i=1}^{n}$ is the sum of all observation from i =1 to i = n, yi and $\hat{y}_i$ denote observed and predicted variables for, productivity and unit skidding costs in a given *i* observation respectively. RMSE is the root mean square error (Equation 10), $\bar{y}$ denotes observed mean productivity and costs on the entire GS observations, and n is the total number of GS observations.

Moreover, on assessing if there is a gain in precision while using GSPT on estimating GS productivity and costs, the relative efficiency (RE) of GSPM over CM, which indicates the level of accuracy for the model's parameters estimates (Equation 12) was calculated as follows:

$$Relative\ efficiency\ (RE) = \frac{Var(CM)}{Var(GSPM)} \quad (12)$$

Where; RE is the relative efficiency of GSPM over CM, Var (CM) is the variance of the CM, and Var (GSPM) is the variance of the GSPM used to estimate productivity and costs. RE value greater than 1.0 indicates higher efficiency of GSPM estimates than CM estimates on GS productivity and cost predictions.

3. Results

Harvested forest compartment exhibited a total area of 40.1 hectare (ha) with an elevation range of 1520 m to 1676 m above mean sea level (a.s.l). For both CA and GSPA, 120 skidding cycles were studied, giving an average skidding time of 4.519 minutes and 4.485 minutes, respectively. Average skidding distance and slope were observed to be 59.218 m and 13.52 % for CA, while for GSPA, it was 62.792 m and 11.02 % respectively. The harvested tree DBH ranged from 12 cm to 69 cm, averaging 32.5 cm (Figure 5).

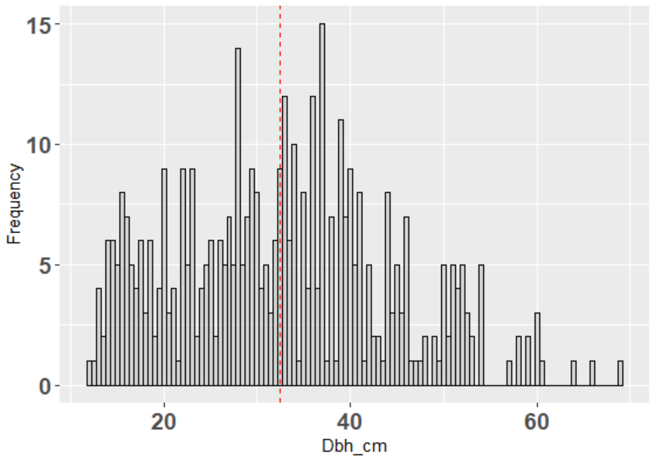

Figure 5. Tree DBH distribution throughout the compartment understudy

3.1 GS productivity and costs

For both CA and GSPA logging plans, fuel appeared to be cost fully variable which consumed 71.69 % of the total GS hourly costs, while the least costs variable was labour (L) which consumed 1.43 % of the entire operational hourly costs (Figure 6). Interest costs is zero since the machine was purchased cash without interest rate.

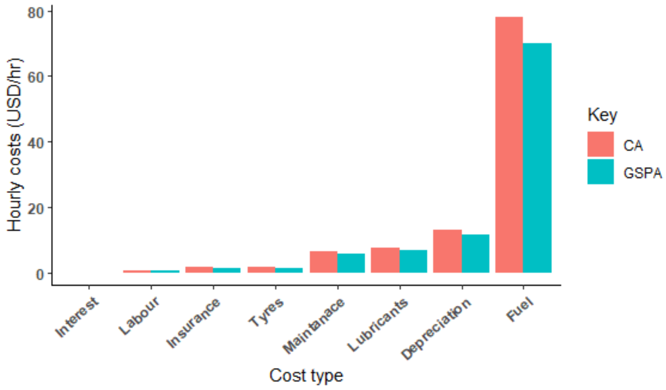

Figure 6. GS hourly costs distributions in both approaches

The average unit skidding costs in GSPA logging plan was 2.121 USD/m^3 lower than the one in CA logging plan which was 2.914 USD/m^3. On the other hand, estimated GS productivity under CA and GSP were 67.5 m^3/hr and 71.1 m^3/hr respectively. Furthermore, the performed paired t-test indicated that there is significance deference in terms of productivity and costs (p-value < 0.05) between CA and GSPA (Figure 7).

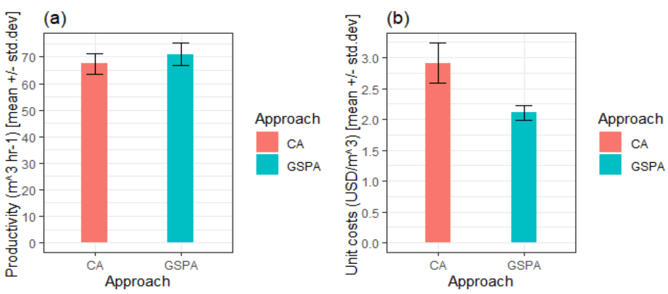

Figure 7. Error bars showing (a) average GS productivity and (b) average unit skidding costs under CA and GSPA logging plan

3.2 GS productivity and costs models

In both approaches, skidding distance (m) and slope (%) variables were good predictors for the machine productivity and costs (Table 5). Coefficient of determination (R^2) for productivity and costs models for CA logging plan was 58.1% and 64.3 % respectively, while it was 62.9% and 60.8% respectively for GSPA logging plan. Furthermore, residual and scatter plots in both approaches appeared to be normally distributed, indicating a good fit (Figure 8 and 9).

Table 5. GS productivity and costs models

Model type	Approach	Model	Pseudo R^2 (%)	$RMSE_r$ (%)
Productivity	CA	72.651 - 2.309Slope - 0.333SkD + 10.890 Av.trip volume	58.1	49.3
Unit skidding costs	CA	2.009 + 0.027Slope + 0.065 SkD – 0.422 Av.trip volume	64.3	50.4
Productivity	GSPA	59.142- 2.657Slope - 0.348SkD + 16.391 Av.trip volume	62.9	35.2
Unit skidding costs	GSPA	2.233 + 0.024Slope + 0.021 SkD – 0.425 Av.trip volume	60.8	33.4

Av. trip volume = Average tree volume per trip, CA = Conventional approach, GSPA = Geospatial approach, SkD = Skidding distance.

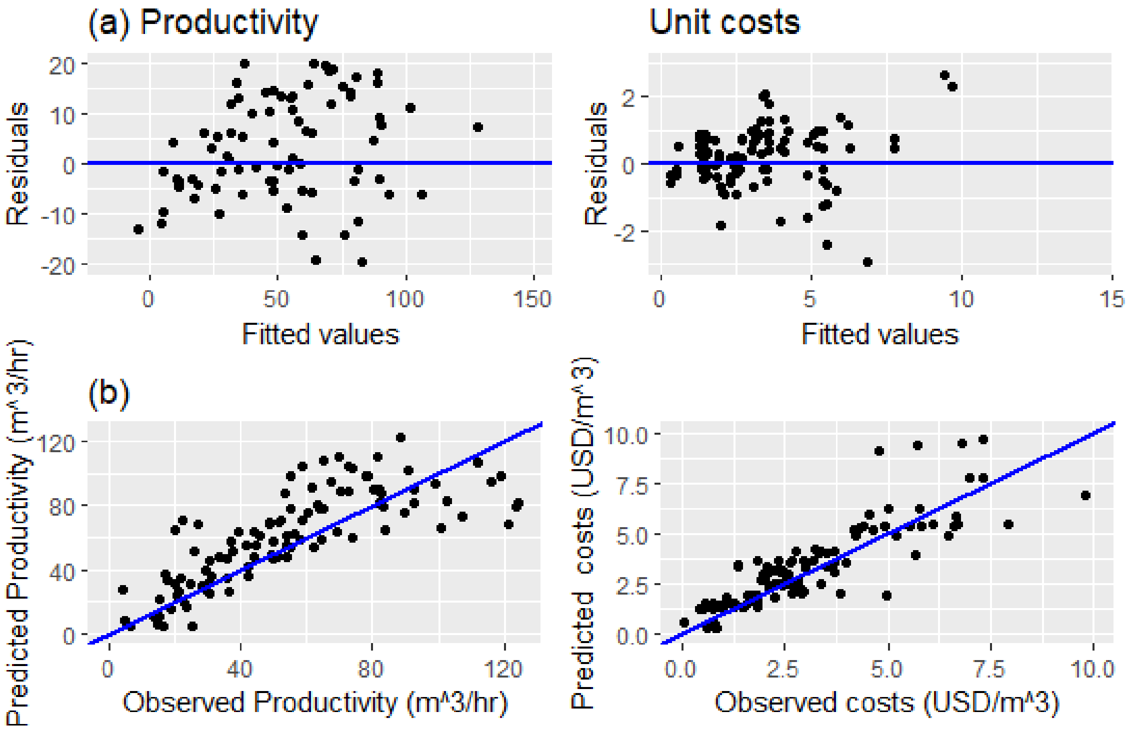

Figure 8. Residual plots (a) and scatter plots (b) for the GS productivity and costs models under CA logging planning

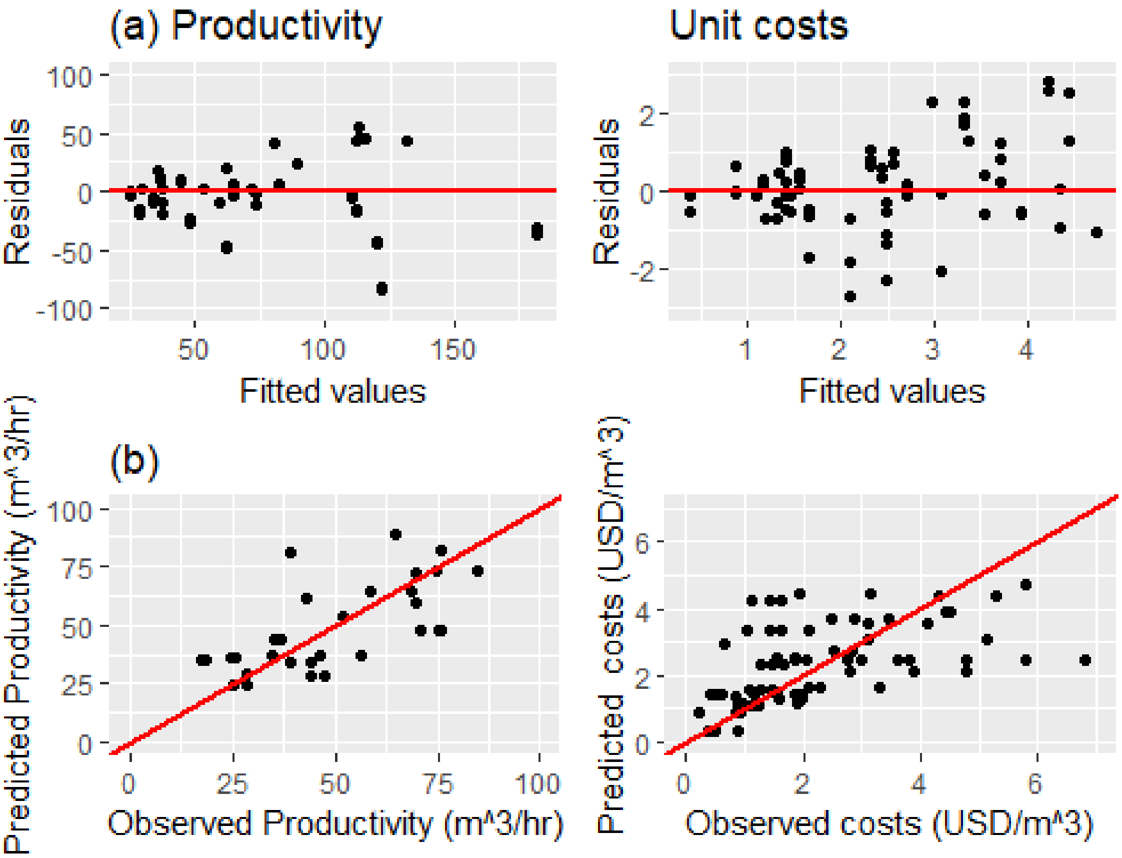

Figure 9. Residual plots (a) and scatter plots (b) for the GS productivity and costs models under GSPA logging planning

3.3 GS productivity and costs predictions

Since variable skidding distance (m) and slope (%) were observed as the main predictor of the GS performance, productivity decreased with the increase in distance and slope, while unit skidding costs increased as the terrain variables; skidding distance and slope increased in both CA and GSPA (Figure 10 and 11).

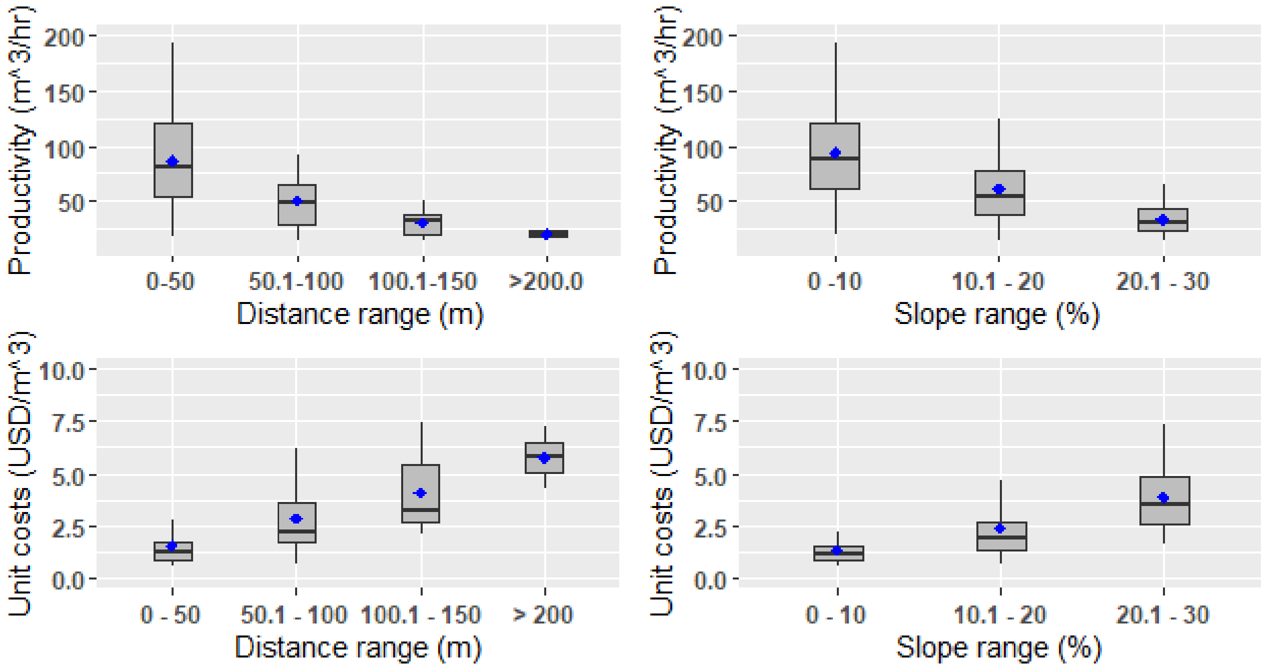

Figure 10. Boxplot showing effect of skidding distance and slope on GS productivity and costs under CA logging plan

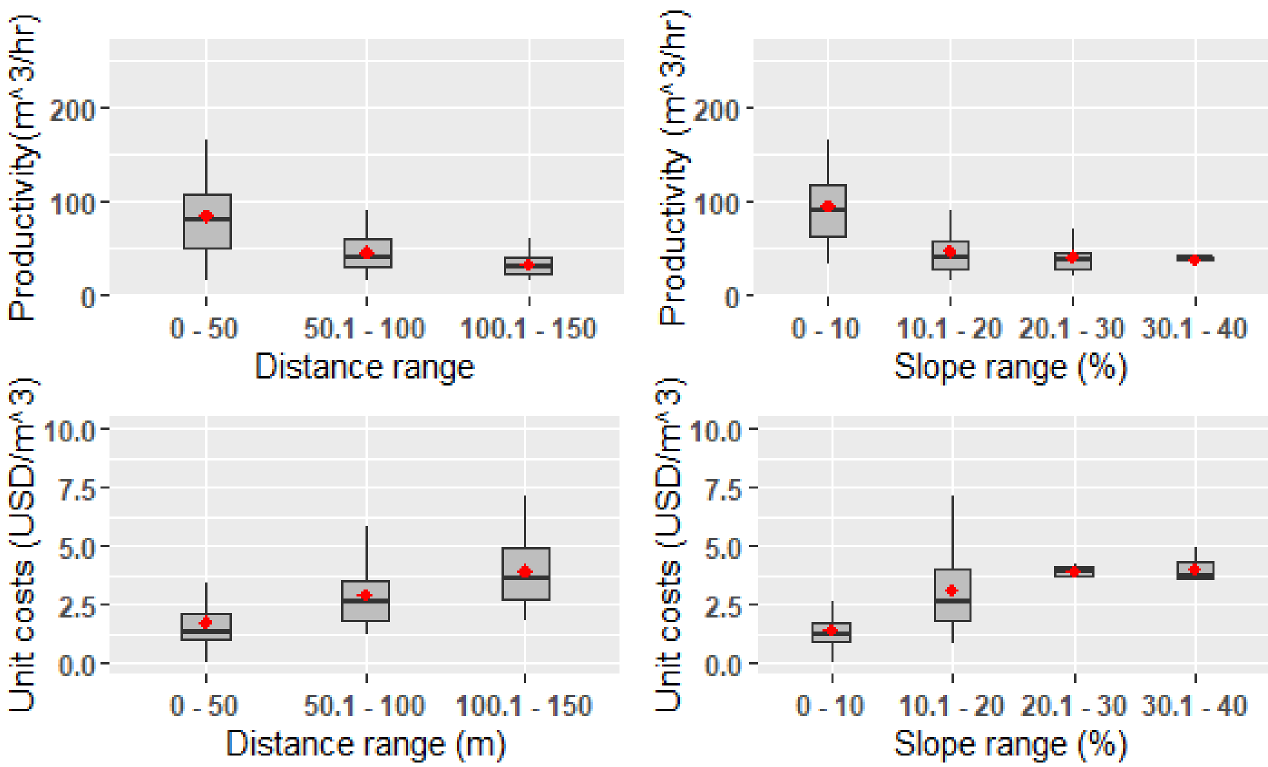

Figure 11. Boxplot showing effect of skidding distance and slope on GS productivity and costs under GSPA logging plan

For CA, the average GS productivity in all terrain classes ranged from 20.1 m^3/hr to 100 m^3/hr, while unit skidding costs ranged from 1.3 USD/m^3 to 5.8 USD/m^3. For GSPA, GS productivity ranged from 30.5 m^3/hr to 126.6 m^3/hr, while skidding costs ranged from 1.8 USD/m^3 to 4.9 USD/m^3. Furthermore, based on the developed geospatial (raster) model (Figure 12), higher GS productivity is confined to areas with lower slopes, while higher skidding costs are confined to steep terrain areas. The area occupied by each productivity and cost range are presented in Table 6.

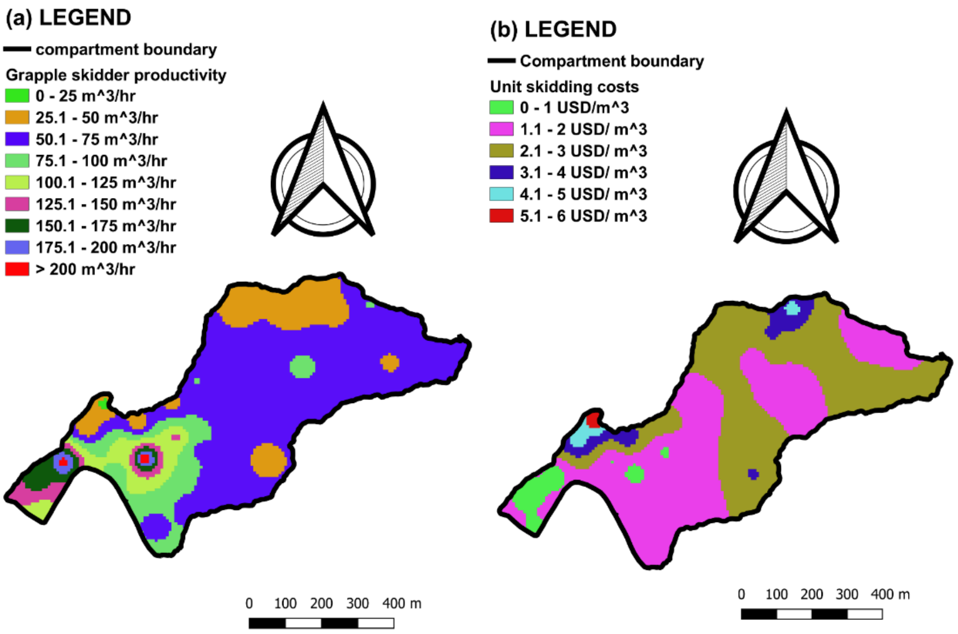

Figure 12. Raster model showing (a) GS productivity and (b) unit skidding costs on various slope ranges

Table 6. Predicted GS productivity and costs and the area associated

Productivity range (m^3/hr)	Area covered (ha)	Unit costs range (USD/m^3)	Area covered (ha)
0 - 25.0	0.1	0 - 1	1.6
25.1 - 50.0	5.9	1.1-2.0	18.5
50.1 - 75.0	24.4	2.1 - 3.0	17.3
75.1 -100.0	4.4	3.1 - 4.0	1.9
100.1 - 125.0	2.6	4.1 - 5.0	0.6
125.1 - 150.0	1.1	5.1 - 6.0	0.1
150.1 - 175.0	1.1	6.1 - 7.0	0.0
175.1 - 200.0	0.4	7.0 - 8.0	0.0
>200	0.1	>8.0	0.0
TOTAL	40.1	TOTAL	40.1

3.4 Relative efficiency between CM and GSPM on GS productivity and costs predictions

In our study, we compared the precision of productivity and cost parameter estimates between CM and GSPM. The results showed that GSPM exhibited higher precision on estimating GS productivity and costs than CM, as evidenced by its RE value of 1.18 and 6.17 for productivity and costs models, respectively. The findings were further verified by additional statistical parameters presented in Table 7.

Table 7. Statistical parameters showing relative efficiency between CM and GSPM on the GS productivity and costs predictions

Statistical Parameters	Productivity model		Costs model	
	Variables Under GSPM	Variables Under CM	Variables Under GSPM	Variables Under CM
VAR	1082.98	1277.11	1.02	6.23
SD	32.91	35.74	1.00	2.49
SE	28.31	28.40	0.82	1.88
N	120	120	120	120

VAR = Variance, SD = Standard deviation, SE = Standard error, N = Grapple skidder work cycles

4. Discussion

This study aimed to estimate and predict GS productivity and costs on various terrains using CM and GSPM at SHFP. It was mainly focused on ground skidding operations using a whole tree harvesting system. Objectively, the study intended to create baseline information on predicting mechanized skidding operations using CM and GSPM in the southern highlands of Tanzania and compare its relative efficiency to develop accurate information for future decision-making and planning. Regression analysis using the GLM approach were employed to assess the machine interaction with environmental and other stand variables in predicting GS productivity and costs.

The results revealed that the average skidding time was higher under CA, i.e., 4.519 minutes compared to 4.485 minutes in the GSPA (p-value < 0.05). Such variation might be because machinery time estimation normally varies with methodological aspects and measurement systems used (Borz et al., 2015; Orlovský et al., 2020). For instance, in this study, skidding time under GSPA was indirectly estimated using stand variables: skidding distance, slope, and average tree DBH per turn, which typically rely on predicted values, compared to CA, which measures actual time in the field using various techniques such as continuous time study technique. Moreover, skidding trails under GSPA were mainly determined using cost distance analysis, which mainly relies on the least terrain path instead of using operator intuitions (Çalişkan and Karahalil, 2017), reduce machinery traversing time.

A significant difference in GS productivity and costs (P-value < 0.05) between CA and GSPA (i.e., 67.5 m^3/hr and 71.1 m^3/hr, respectively) might be because skidding trails under CA were mainly decided through supervisor's and operator's intuitions. This might lead to poor machine performance during operations compared to GSPA, which normally relies on the least terrain (slope) variable in deciding the skidding trails. It reduced the traversing cycle time of the machine, resulting in higher productivity and lower skidding costs. Therefore, these findings signify the potential of integrating GSPT (i.e., DEM) into a mechanized timber harvesting plan since it provides basis for analyzing GS efficiency (Đuka et al., 2015). For instance, through cost distance analysis, we can easily determine the shortest and easiest route for the machine (i.e., Grapple skidder) mobility and trafficability, which will help to increase machinery efficiency (Phelps et al., 2021).

GS productivity and cost predictor variables (distance, slope, and average volume per turn) were significant (p-value < 0.05) in both CM and GSPM. Geospatial-based productivity and cost models showed better performance with lower RMSEr values of 35.2% and 33.4%, respectively, compared to CM with RMSEr values of 49.3% and 50.4%, respectively. It implies that extracted terrain variables (slope and skidding distance) from resampled DEM with 15m x 15m resolution bring more accurate terrain information for predictions than the variables measured though CA. Similarly, studies by Agüera-Vega et al. (2020) and Kienzle (2004) reported that the accuracy of the DEMs is highly correlated with spatial resolution. For instance, we can use grid cells of 5m x 5m to capture precise terrain information (i.e., altitude and slope) (Kienzle, 2004). Furthermore, all predictor variables in CM and GSPM show goodness of fit. Unit skidding cost variables of CM showed higher goodness of fit by having a higher R^2 value of 64.3%, followed by productivity model in GSPA with R^2 value of 62.9%. The lowest R^2 value (58.1%) was observed in the productivity model under CA. The accuracy level for the model depends much on the closeness between observed and predicted variables, which are highly influenced by DEMs spatial resolution and data acquisition and processing efficiency (Agüera-Vega et al., 2020; Liu and Zhang, 2008). The closer values between observed and predicted values, the more accurate model (Figures 8 and 9).

Variables: skidding distance, slope, and skidded volume per turn were significant predictor variables for GS productivity and costs in both CM and GSPM. For both approaches, GS productivity decreased when the terrain variables, such as skidding distance and slope, increased. Conversely, unit skidding costs were positive correlated with distance and slope (Figure 10 and 11). The potential of GSPM (i.e., DEM) in predicting GS productivity and costs were further revealed through a raster model (Figure 12) developed on QGIS software. Whereby 60.8% of the forest compartment area exhibited a predicted productivity range of 50 – 75 m^3/hr (Table 6) with an average of 71.1 m^3/hr, which is much closer to the predicted value obtained through parametric regression models using the GLM approach.

Furthermore, productivity and cost models under GSPA demonstrated higher precision for the GS parameter estimates, by having RE value > 1. Similarly, the SE estimates for GSPM were relatively much smaller than CM. To achieve similar level of precision in CM, number of GS observations should be increased by a factor equivalent to the RE value (Mauya et al., 2015) (i.e., 18% and 17%) for productivity and cost estimates, which are equivalent to 142 and 140 observations respectively.

Variations in efficiency between approaches (i.e., models) might be due to multiple factors, including sample size (Kachamba et al., 2017), the accuracy and consistency of the measuring instrument/procedures, the operating environment, the diversity of collected field variables, and the computational approach used to derive predictor variables. These factors align with the findings of Okey and Visser (2020), who investigated the influence of extraction method and processing location on forest harvesting efficiency in individual forest harvesting operations in New Zealand between 2009 and 2018.

5. Conclusion

Effective planning for sustainable and environmentally friendly timber harvesting operations is essential for the long-term management of forest resources in order to ensure benefits for present and future generations. The accuracy of planning techniques employed in various geographical locations varies depending on the measurements and quantification methods used. Among the different models used to predict GS productivity and costs, CM and GSPM have demonstrated superior performance, although with variations in accuracy levels.

In large-scale timber harvesting scenarios, GSPM holds greater potential than the CM. It enables rapid coverage of extensive areas, providing parameter estimates with higher accuracy for predictions. By obtaining highly precise stand and terrain information, managers can make informed decisions regarding selecting and allocating appropriate harvesting systems and resources. This optimization can maximize productivity while minimizing overall operation costs and mitigating associated environmental impacts.

Although GSPM utilizing Digital Elevation Models (DEM) derived from SRTM offer sufficiently accurate information for predicting GS productivity and costs, their efficiency, as shown in Table 7, may be influenced by the spatial resolution of the utilized imagery when extracting terrain variables (i.e., distance and slope). For future research, it is recommended to explore other remote sensing techniques such as Radial Basic Functions (RBF), Multi-log Function interpolation (MLF), ordinary kriging (KR), or spline-based interpolation and other platforms with higher resolution imagery for more accurate predictions of productivity and costs.

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