

Original Research Article

Modified Linear Models for Diameter, Height and Volume for *Pinus caribaea* Using R - Programme in Kifu Forest

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Abstract: Understanding the relationship between diameter breast height (dbh), tree height and volume helps in optimizing log selection for different purposes based on required timber volume. The purpose of the study was to create a modified model for diameter breast height, tree height and volume for *Pinus caribaea* to adequately fit all relevant variations in the data using R programme. Dbh is better predictor variable compared to tree height when volume is considered as a response variable. But this alone could not meet the assumptions of linear regression model. This therefore prompted the use of all data collected where by the tree height was considered as random effect. This was useful in the fitting of all data of the collected variables to a more useful relation in estimation of their linear regression relationship. The accuracy of this model was improved by addition of log function. Data of *Pinus caribaea* tree volume, dbh and height was collected. One hundred (100) trees were sampled in 1 hectare of pinus plantation with a range of corresponding tree dbh and height across the plantation in to a data set known as “mypinedata”. We wanted to know how dbh and height of *Pinus caribaea* as predictor variables affected its volume as a response variable. Comparison of dbh and height for best predictor variable for volume as a response in the linear regression model showed dbh as a preferred variable. However to meet the assumptions the linear relationship of volume, dbh and height was modified to fit all relevant data to improve on the model. The modified model for dbh- volume linear relationship was consequently created to cater for the adequate fit of the data or relevant variations using height as a random effect. Therefore modified model proved better fit for volume, dbh and height relationship in *Pinus caribaea* stand as deduced from its data summary and the assumptions when the log function was added. The assumptions for the modified model were met for the plot of residuals and qqplot and the data summary showed the multiple R-square of one (1) and AIC equals -6774.94. This confirmed the functions’ high accuracy compared to volume-dbh linear regression model with multiple R-square of 0.9029 and AIC of -228.4545. Consequently in volume, dbh and height *Pinus caribaea* relationship, dbh can be taken as a standard predictor variable and height as random effect, and log function as a base function for the modified model, so confirming the functions’ high accuracy.

Keywords: Diameter breast height (dbh), volume and height relationship, linear regression model, modified model, *Pinus caribaea*, R.

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INTRODUCTION

A modified model for diameter, height and volume relationship was derived from the linear regression model by first determining suitable predictors for the model for *Pinus caribaea* tree stand (Tanovski *et al.*, (2023)). The existing parameters were modified to improve its fit to the data using R

programme (R Development Core Team (2005)). The modified model for predictor variable and response variable would probably require adjustments to the existing models to better fit the variables being studied. This involves using different functional forms or incorporating additional predictor variables (Muhammad *et al.*, (2025)). The purpose of the study was to create a modified model for diameter breast

height (dbh), height and volume for *Pinus caribaea* data to adequately fit all relevant variations in the data (Di Cosmo *et al.*, (2020)). The variables' data relationships can be an effective tool for estimating volume, biomass and other forest parameters (Ng'andwe *et al.*, (2019)), including predicting growth and yield (Cysneiros *et al.*, (2020)) for *Pinus caribaea* species (Chenge, (2021)). Though this general relationship exists it is not one to one correspondence, for instance multiple height measurements are associated with the same value of dbh across different trees. This variations can be due to genetic differences within the species or localized environmental factors (Baral, (2017), Bauwens (2016)). The need for the modified model was therefore to accurately capture the relationships due to the variations in growth patterns, site conditions and other factors. For example in *Pinus caribaea* stand, the same dbh value captured one or more height values in different trees and the same volume calculated was reflected in different dbh values. Generally larger dbh hold more volume compared to smaller dbh demonstrating the linear nature of volume calculation based on the dbh and yet the accuracy of volume estimation is to be improved by modification of these existing variable in the linear relationship. The modifications are targeted at improving the model's accuracy, reduce bias and provide better volume estimations for *Pinus caribaea* plantations. Understanding the relationship between dbh and volume helps in optimizing log selection for different purposes based on required timber volume. For example it allows accurate estimation of timber yields and matching trees with specific product requirements (Fortin *et al.*, (2019)). This is essential for managing forest resources, and making informed decisions about harvesting and processing logs. We decided to get the relationship between diameter, height and volume of *Pinus caribaea* by collecting data on these respective parameters. The explanatory variables were standardized before proceeding with the analysis so that they have a mean of equal to zero and standard deviation of one, therefore ensuring that the estimated

coefficients are all on the same scale making it easier to compare effect sizes. The R function, `scale()`, (R Development Core Team (2005)) was used to center the data (the column mean is subtracted from the values in the column) and then scales it (the centered column values are divided by the column's standard deviation). This ensured that they had a mean of zero ("centering") and standard deviation of one ("scaling"). Therefore the estimated coefficients are all on the same scale, making it easier to compare effect sizes. The data was fitted to linear regression model with volume as the response and, dbh and height compared independently as the predictors using R and were visualized using `ggplot2`. The dbh on the x-axis represented the dbh of a specific tree and the volume on the y-axis represented the total cubic volume of the tree calculated using formula that incorporated both dbh and height. The plot of log volume against log dbh displayed linear and positive relationship meaning as the dbh of a tree stem increases its volume also increases at a progressive rate. For a given dbh, longer trees have higher volume, potentially shifting the plot upwards. This makes dbh a key input for estimating tree volume using various models (Friday *et al.*, 2023).

METHODOLOGY

The purpose of this method was to incorporate all measured predictor variables to improve model accuracy in volume, diameter and height relationship for *Pinus caribaea* tree species.

1. We collected data on *Pinus caribaea* tree volume and sampled 100 trees in 1 hectre of pinus plantation with a range of corresponding tree dbh and height across the plantation in to a data set known as "*mypinedata*". We wanted to know how predictor variables (dbh and height) affected its volume as a response variable. We first looked at the distribution of its volume in the data using the distribution histogram from R command.

```
Input function:
> (hist(mypinedata$volume)
```

2. Predictor variables were standardized using R function; `scale()`.

```
Input function:
> mypinedata$predictorvariable <- scale(mypinedata$predictorvariable).
```

3. The data was fitted to linear regression model with volume as the response and dbh and height compared for the best choice of predictor using R and was visualized using `ggplot2`.

4. After the choice of predictor variable,

```
Input function:
> basic.lm, which = 1
```

linear regression model modification was needed to better fit relevant data by addition of random effect.

5. Assumption were checked for compliance for linear regression model (basic.lm) and modified models:

i. *the plot of the residuals:*

ii. QQplot:

Input function:
> *basic.lm, which = 2*

RESULTS AND DISCUSSIONS

A. Distribution of the response variable (volume)

We wanted to know how predictor variables of the *Pinus caribaea* affect the tree volume. This was by first having a look at the distribution of the response variable (volume), **figure 1**.

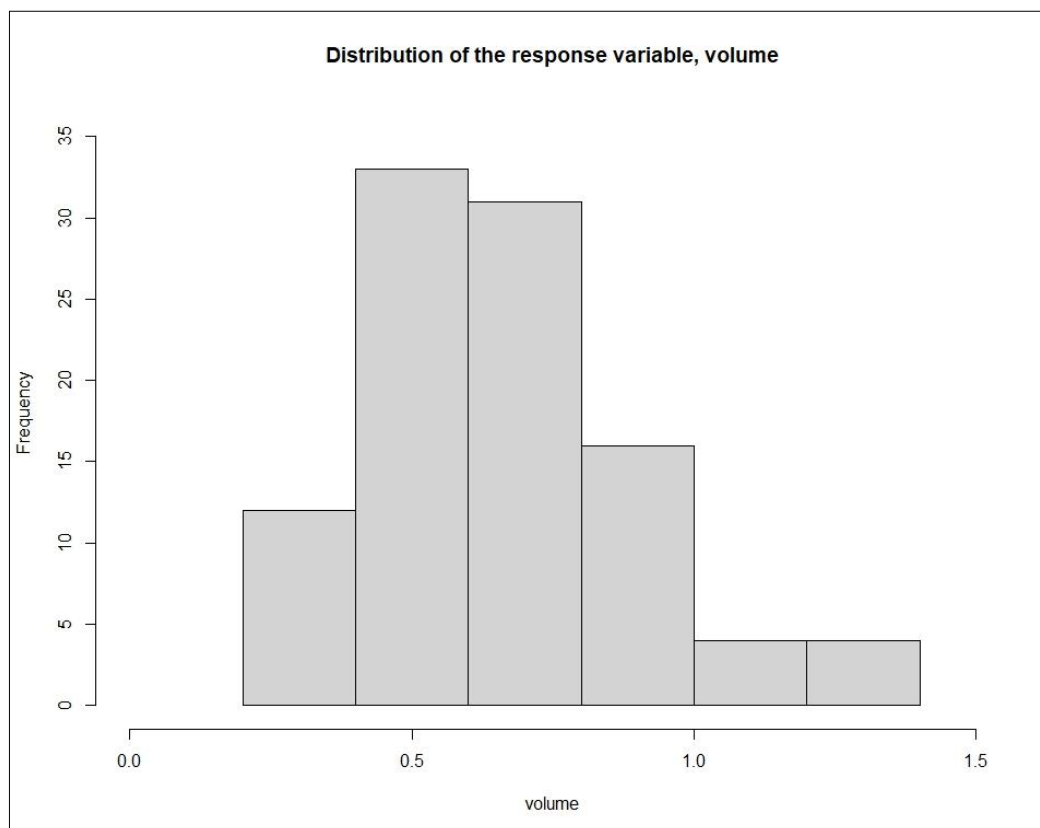


Figure 1: How predictor variables of the *Pinus caribaea* affects the tree volume

B. Selection of predictor variable for better data fit

The effect of the compared predictor variables, dbh and height was done by fitting all data in one analysis using linear regression model with volume as the response. The standardized diameter breast height (dbh2) and height (height 2) were the compared predictors.

a) Dbh-volume relationship

The plot of log volume against log dbh displayed linear and positive relationship meaning as the dbh of a tree stem increases its volume also increases at a progressive rate. Larger dbh hold more volume compared to smaller dbh demonstrating the linear nature of volume calculation based on the dbh. For a given dbh, longer trees had a higher volume, potentially shifting the plot upwards, **figure 2**. Therefore this linear relationship can be modified to fit all relevant data to improve on the volume estimation making dbh a consistent measure of tree volume.

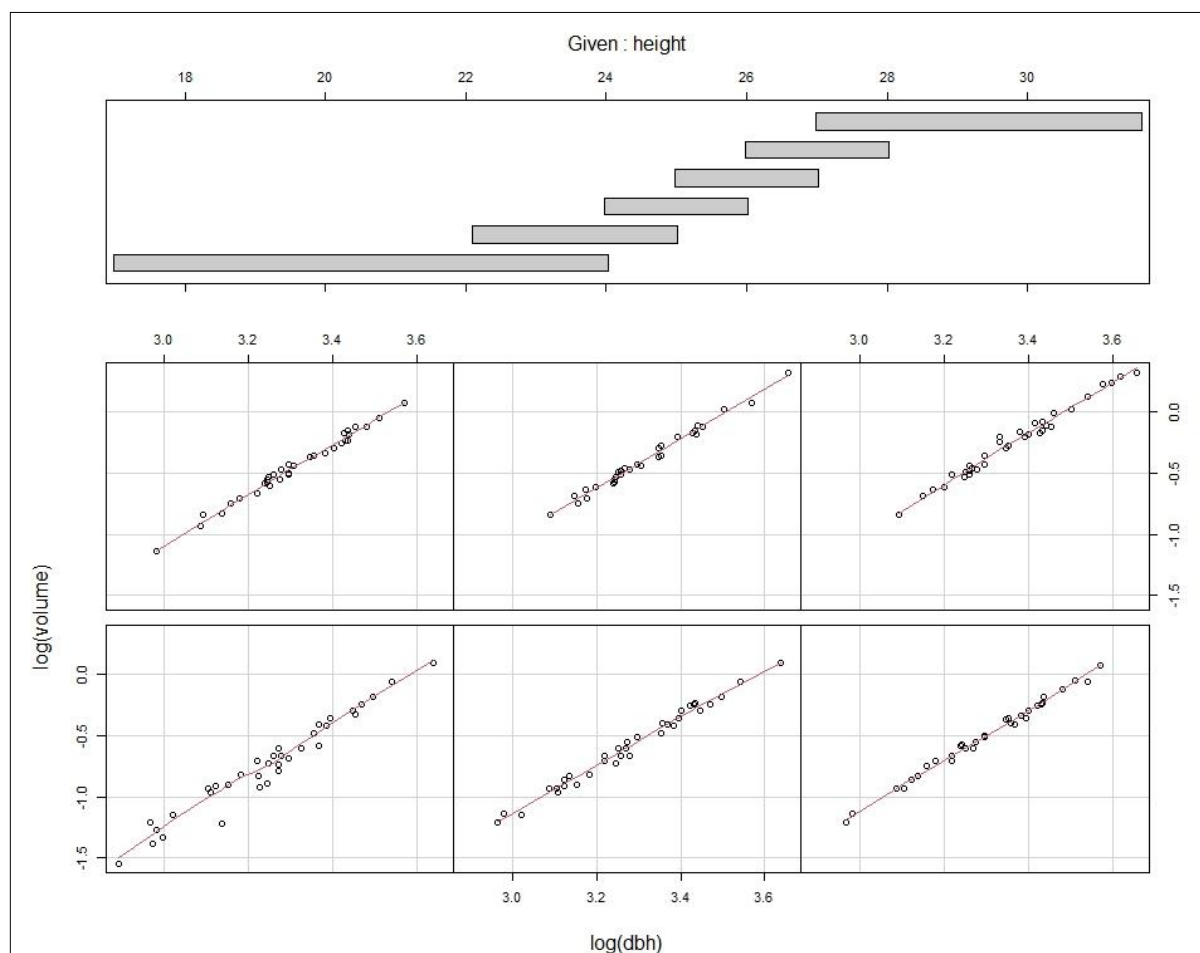


Figure 2: Displayed dbh- volume linear and positive relationship

The output of dbh as predictor variable and volume as response in fitted linear regression model

(*basic.lm*) is shown in the summary 1, below and the plot was viewed with ggplot2 in **figure 3**.

Input function:
`>basic.lm <- lm(volume ~ dbh2, data = mypine2data)`
`>summary(basic.lm)`

Summery 1: The output of dbh as predictor variable in volume estimation

Call:
`lm(formula = volume ~ dbh2, data = mypine2data)`

Residuals:
 Min 1Q Median 3Q Max
 -0.17429 -0.04542 0.01059 0.04647 0.17369

Coefficients:
 Estimate Std. Error t value Pr(>|t|)
 (Intercept) 0.652870 0.007569 86.26 <2e-16 ***
 dbh2 0.229625 0.007607 30.19 <2e-16 ***

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 Residual standard error: 0.07569 on 98 degrees of freedom
 Multiple R-squared: 0.9029, Adjusted R-squared: 0.9019
 F-statistic: 911.2 on 1 and 98 DF, p-value: < 2.2e-16

b) Height -volume relationship

Summary 2, shows the output of volume as the response and standardised height (height2) as the predictor in fitted linear regression model (*basic.lm2*)

```
Input function:
> basic.lm2 <- lm(volume ~ height2, data = mypine2data)
> summary(basic.lm2)
```

Summery 2: The output of height as predictor variable in volume estimation

```
Call:
lm(formula = volume ~ height2, data = mypine2data)
Residuals:
    Min     1Q   Median     3Q      Max
-0.32259 -0.14776 -0.02498  0.10854  0.59218
Coefficients:
(Intercept) 0.65287 0.01953 33.427 < 2e-16 ***
height2 0.14366 0.01963 7.319 6.99e-11 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1953 on 98 degrees of freedom
Multiple R-squared: 0.3534,    Adjusted R-squared: 0.3468
F-statistic: 53.56 on 1 and 98 DF, p-value: 6.992e-11
```

Comparison of dbh2 and height2 for best fit predictor variables and volume as response variable is plotted by ggplot2 (**figure 3** and **figure 4**).

```
Input function:
> library(ggplot2)
> (prelim_plot <- ggplot(mypine2data, aes(x = predictor variable, y = volume)) +
  geom_point() +
  geom_smooth(method = "lm"))
```

Plotted comparison of response - predictor linear regression model fitting from summery 1 and 2 above.

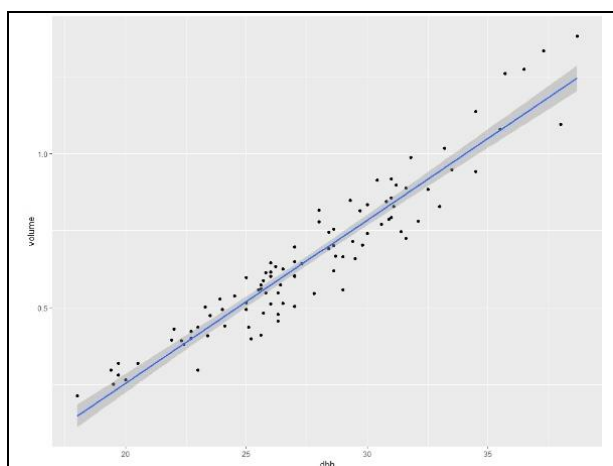


Figure 3: Model fitted with volume as the response and standardized dbh as predictor

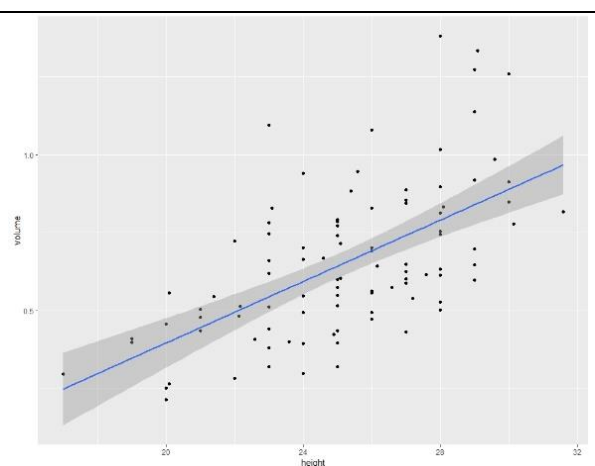


Figure 4: Model fitted with volume as the response and standardized height as a predictor

From the summery plot and the linear model, dbh does better as predictor variable in our volume test as a response variable assuming the assumptions are

met. Summery of the coefficients of the compared predictor variables in **figure 3** and **figure 4** are shown in **table 1** below.

```
Input function:
> print(AIC(basic.lm))
> print(BIC(basic.lm))
> print(AIC(basic.lm2))
> print(BIC(basic.lm2))
```

Table 1: Summary of the coefficients of the compared predictor variables

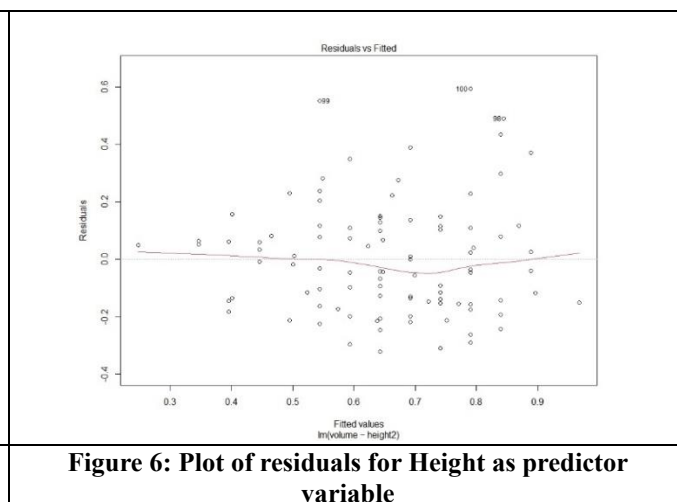
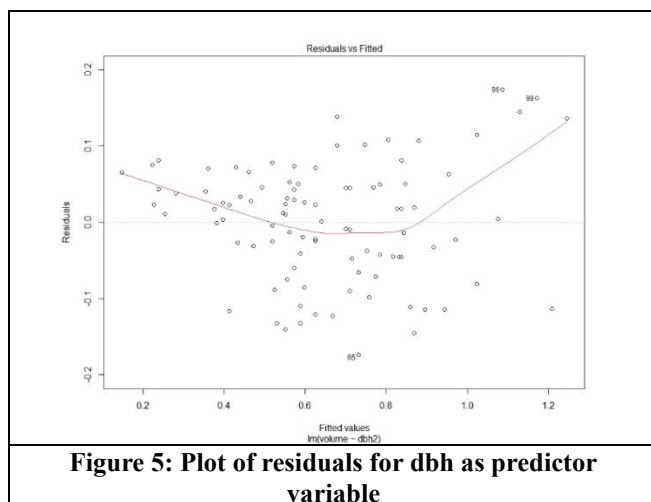
Predictor	Multiple R-squared:	AIC	BIC	p-value
dbh	0.9029	-228.4545	-220.639	2.2e-16
height	0.3534	-38.86599	-31.05048	6.992e-11

Residual plots how predictor variables met linear regression model assumptions

```
Input function:
> plot(basic.lm, which = 1; # Plot of the residuals for dbh as predictor and
> plot(basic.lm2, which = 1; # Plot of the residuals for height as predictor
```

The plot of the residuals was not perfect for dbh because the red line of the plot which is expected to be horizontal at residuals zero was not even near to the flat

line as compared to the height as shown in **figure 5** and **figure 6** respectively.

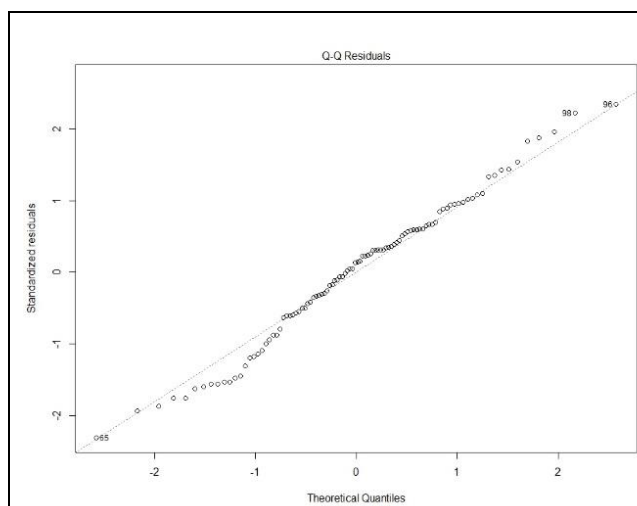
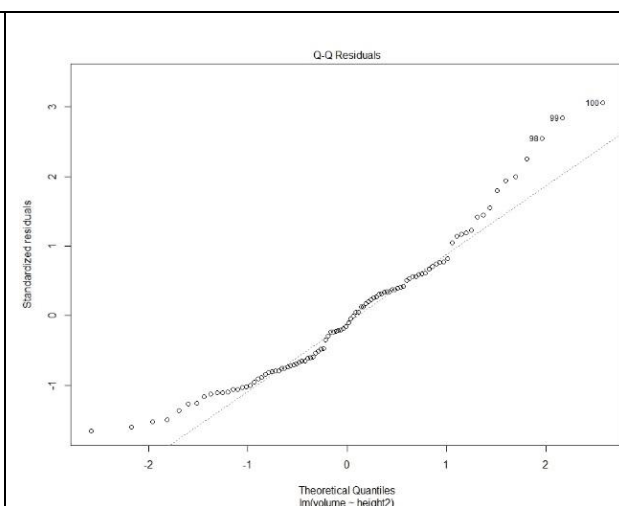


The qqplot for dbh showed more perfect with points ideally falling onto the diagonal dashed line with a bit off at the both extreme sides. While height as predictor variable showed points more off the diagonal

dashed line at both extreme sides (**figure 7** and **figure 8** respectively).

Comparison of normal Q-Q plot for predictor variables and volume as a response:

```
Input function:
> plot(basic.lm, which = 2; # QQplot for dbh as predictor and
> plot(basic.lm2, which = 2; # QQplot for height as predictor
```


Figure 7: qqplot for dbh as a predictor variable

Figure 8: qqplot for height as a predictor variable

C. Modification of the current linear regression model

Though the data summary, the plot and the linear model, showed dbh as a better predictor variable than height for volume estimation, it was not perfect for all the assumptions tested (figure 5). Therefore model modification was needed to better relevant data fit.

The random effects in the study were drawn from the stand population and the interest was in the variance of these effects across the *Pinus caribaea* stand population. The random effects compared for better fit included diameter classes and tree height.

Modified model for dbh - volume linear relationship was consequently created to cater for the adequate fit of the data or relevant variations.

The random effect was added to the linear regression model (*basic.lm*). The modifications involved adding a random effect to account for the variation of volume within the same and different diameters at breast height. This variations were derived from **figure 10** that a single tree dbh may have different

volumes within the stand and yet generally a lower dbh has a lower volume and consistently a higher dbh has a higher volume. Also in **figure 2**, multiple height measurements are associated with the same value of dbh across different trees and yet generally longer trees had a higher volumes.

1. Add diameter class as a random effect to our linear model (*basic.lm*)

We want to use all the data, but account for the data coming from different diameter (dbh) classes. Diameter classes were also used to verify data for independence. It was found out that data within each diameter class was more similar to each other than the data from the other diameter class. The diameter classes classified dbh above 25cm that was more convertible to timber and that below 25cm which was less convertible to timber in *Pinus caribaea*. This decision was based on the final use of the stand for timber to help the farmer make appropriate decisions on harvesting. Data verification based on diameter classes is visualized in **figure 9** and this plot was substantiated by the plot of the multiple analyses by diameter class, **figure 10**.

Input function:

```
> boxplot(volume ~ diameter_class, data = mypine2data, xlab="Diameter class", ylab="Volume", main="Data observation independence")
```

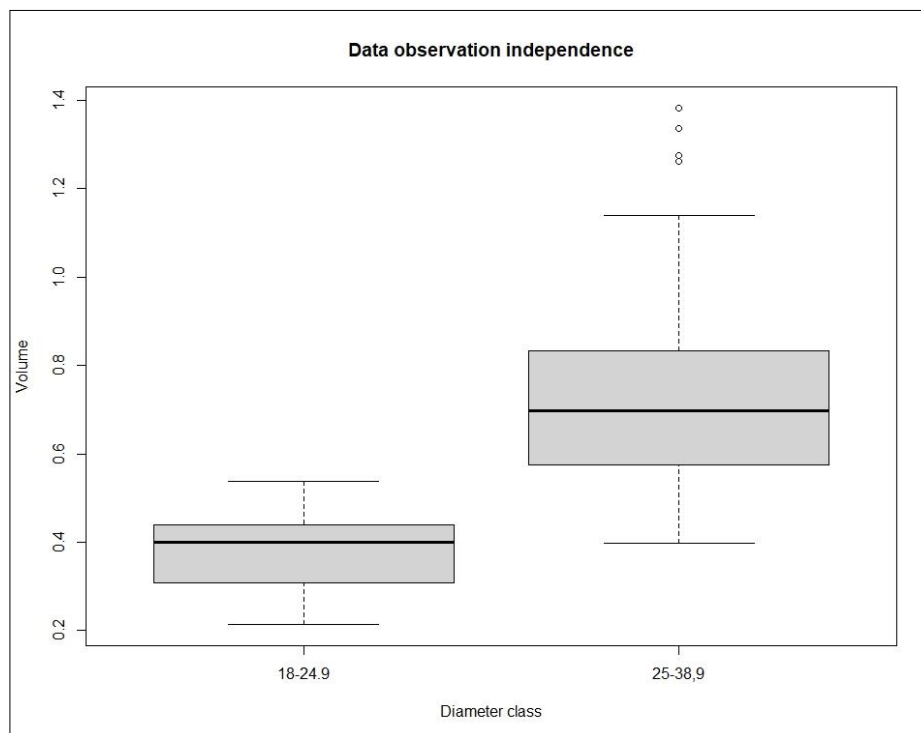


Figure 9: Data verification based on diameter classes for independence

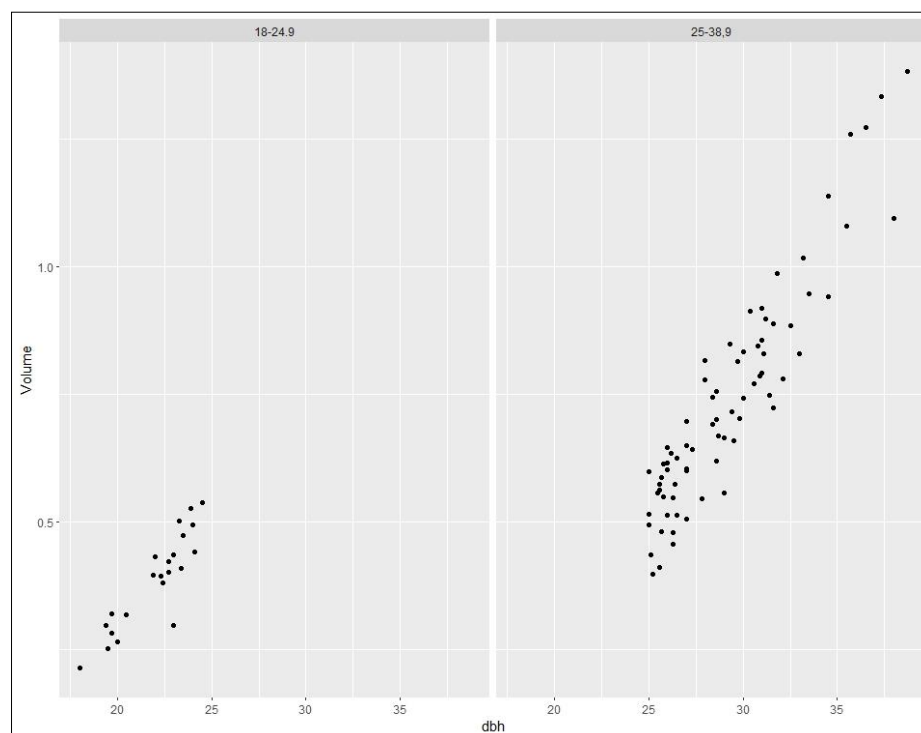


Figure 10: Data verification plot for independence by diameter classes

Considering the **figures 9 and 10** above, therefore the dbh classes vary both in the dbh and in their volume. This confirms that our observations from within each of the classes aren't independent.

Summary of adding diameter class as a random effect to our linear model (summary 3).

Input function:

```
> diameter_class.lm <- lm(volume ~ dbh2 + diameter_class.lm, data = mypine2data)
> summary(diameter_class.lm)
```

Summery 3: adding diameter class as a random effect to our linear model

```

Call:
lm(formula = volume ~ dbh2 + diameter_class, data = mypine2data)

Residuals:
    Min       1Q   Median       3Q      Max
-0.165710 -0.045560  0.001451  0.051744  0.151919

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.70411    0.02008  35.060 <2e-16 ***
dbh2           0.24924    0.01027  24.268 <2e-16 ***
diameter_class25-38,9 -0.06655    0.02428  -2.741  0.0073 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07329 on 97 degrees of freedom
Multiple R-squared:  0.9099,    Adjusted R-squared:  0.908
F-statistic: 489.6 on 2 and 97 DF, p-value: < 2.2e-16

```

2. Add height as a random effect to our linear model (*basic.lm*)

Summery of modified model (*basic.lm3*) by adding height as a random effect to our linear model (*basic.lm*) is shown in (summery 4).

```

Input function:
> basic.lm3 <- lm(volume ~ dbh2 + height, data = mypine2data)
> summary(basic.lm2)

```

Summery 4: Adding height as a random effect to our linear model

```

Call:
lm(formula = volume ~ dbh2 + height, data = mypine2data)

Residuals:
    Min       1Q   Median       3Q      Max
-0.045072 -0.022205 -0.013975  0.003129  0.135402

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.053416  0.036864  1.449  0.151
dbh2         0.204417  0.004235  48.268 <2e-16 ***
height       0.023778  0.001454  16.354 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03925 on 97 degrees of freedom
Multiple R-squared:  0.9742,    Adjusted R-squared:  0.9736
F-statistic: 1828 on 2 and 97 DF, p-value: < 2.2e-16

```

Adding height as a random effect to the linear regression model offers a better data fit compared to

diameter class in the volume estimation as summarized by the coefficients in the table 2 below:

Table 2: Summery of the coefficients of the modified models for volume estimation

Random effect added	Multiple R-squared	AIC	BIC	p-value
Diameter class	0.9099,	-233.9125	-223.4918	< 2.2e-16
height	0.9742	-358.8264	-348.4057	< 2.2e-16

From table 2, the modified model with height as the random effect looks better than that of the diameter class. But height added as a random effect in

the modified model does not meet the assumption for linear regression as shown in plot of the residuals in **figure 12** and the qqplot in **figure 13**.

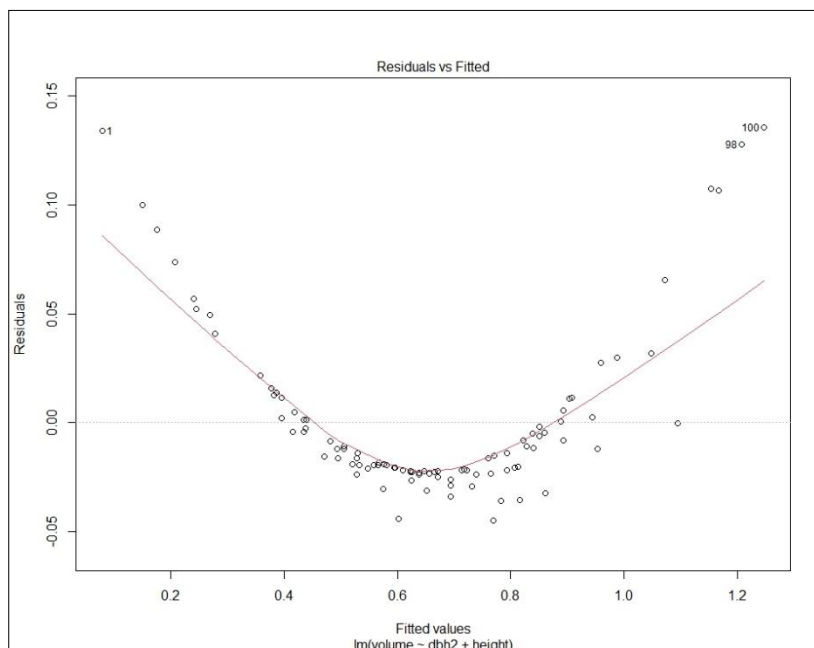


Figure 11: Plot of residuals using height as random effect

QQplot for volume estimation using height as random effect

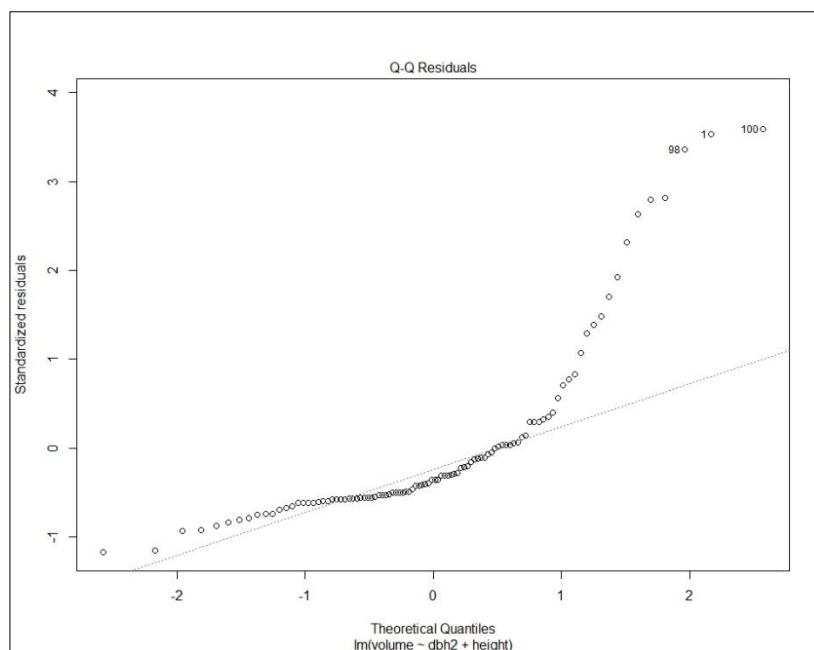


Figure 12: QQplot using height as random effect

We would therefore prefer to modify “basic.lm3” by adding a base function (log) to improve on the model fit.

3. Linear model modification by adding log function to our basic.lm3

The modified model (fm2) in this case was derived from dbh - volume linear relationship (basic.lm)

```
Input function:
> fm1 <- lm(log(volume) ~ log(dbh), data = mypine2data)
> summary(fm1)
```

by incorporating the addition of height as a random effect (basic.lm3) and a “log” base function to improve its fit to the data, as shown in summary 5 and 6:

- a) Summary fm1, (see summary 5) of modified model by addition of the log function to dbh - volume linear relationship (basic.lm).

Summery 5: Adding log function to dbh - volume linear relationship (basic.lm)

```
Call:
lm(formula = log(volume) ~ log(dbh), data = mypine2data)
Residuals:
Min 1Q Median 3Q Max
-0.34011 -0.06061 0.01331 0.08041 0.22439

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) -8.03041 0.23358 -34.38 <2e-16 ***
log(dbh) 2.28188 0.07065 32.30 <2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1115 on 98 degrees of freedom
Multiple R-squared: 0.9141, Adjusted R-squared: 0.9133
F-statistic: 1043 on 1 and 98 DF, p-value: < 2.2e-16
```

b) Summary fm2, of the addition of the log function to “basic.lm3” as an update of fm1 for better data fit.

```
Input function:
> fm2 <- update(fm1, ~. + log(height), data = mypine2data)
> summary(fm2)
```

Summery 6: Adding log function to “basic.lm3”

```
Call:
lm(formula = log(volume) ~ log(dbh) + log(height), data = mypine2data)

Residuals:
Min 1Q Median 3Q Max
-1.776e-14 -2.015e-16 9.450e-17 4.094e-16
1.975e-15

Coefficients:
Estimate Std. Error t value
(Intercept) -1.032e+01 5.644e-15 -1.829e+15
log(dbh) 2.000e+00 1.308e-15 1.529e+15
log(height) 1.000e+00 1.734e-15 5.766e+14
Pr(>|t|)
(Intercept) <2e-16 ***
log(dbh) <2e-16 ***
log(height) <2e-16 ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.914e-15 on 97 degrees of freedom
Multiple R-squared: 1, Adjusted R-squared: 1
F-statistic: 1.936e+30 on 2 and 97 DF, p-value: < 2.2e-16

> step(fm2) Start: AIC=-6774.94
log(volume) ~ log(dbh) + log(height)

Df Sum of Sq RSS AIC
<none> 0.0000 -6774.9
- log(height) 1 1.2181 1.2181 -436.8
- log(dbh) 1 8.5695 8.5695 -241.7
```

Call:
lm(formula = log(volume) ~ log(dbh) + log(height), data = mypine2data)

Coefficients:
(Intercept) log(dbh) log(height)
-10.32 2.00 1.00

The model (fm2) assumptions were met as shown in summary 6, plot of residuals and qqplot in **figure 13** and **figure 14** respectively with multiple R-square of one (1) and AIC equals -6774.94 .

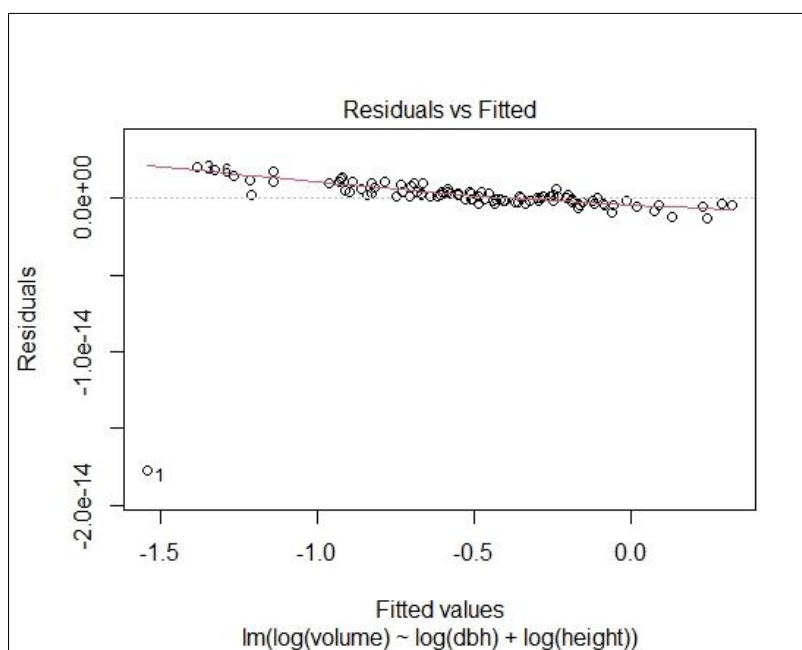


Figure 13: Residual plot for “fm2” model

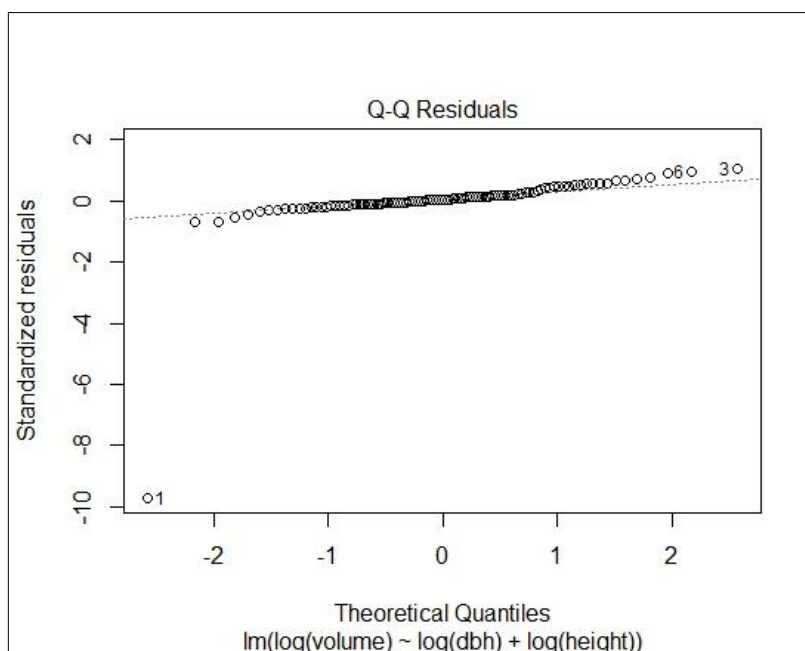


Figure 14: QQplot for “fm2” model

Therefore modified (fm2) offered a better fit for volume estimation in *Pinus caribaea* stand as

deduced from its summary and the assumptions, **figure 13** and **figure 14**.

CONCLUSION AND DISCUSSION

The relationship between volume, dbh and height was important in the establishment of linear regression model which was modified to fit all the relevant data. The linear regression model based on volume as response variable and dbh as predictor variable. (*basic.lm*). According to the analysis dbh made a better predictor variable compared to height. Even if so, height was considered as a better random effect compared to diameter class in the development of a modified model (*basic.lm3*). However this too was short in meeting the linear regression assumptions therefore a log function was added to the modified model “*basic.lm3*” to better the data fitting. The results showed a more preferred data fitting with multiple R-squared of one (1) and AIC equal to -6774.94. This was much better compared to “*basic.lm3*” with multiple R square of 0.9742 and AIC of -358.8264 and “*basic.lm*” with multiple R square of 0.9029 and AIC of -228.4545. Consequently the modified model (fm2) can be used for the estimation of the volume of *Pinus caribaea* in the plantation stand. Therefore in modeling modified *Pinus caribaea* standing tree volume dbh can be taken as a standard predictor variable, height as random effect and log function as a base function so confirming the functions’ high accuracy.

REFERENCES

- Bauwens, S.; Bartholomeus, H.; Calders, K.; Lejeune, (2016), P. Forest Inventory with Terrestrial LiDAR: A Comparison of Static and Hand-Held Mobile Laser Scanning. *Forests* 2016, 7, 127, doi:10.3390/f7060127.
- Baral S., ((2017)), Modeling height-diameter relationship and volume of teak (*Tectona grandis* L. F.) in central lowlands of Nepal. *J. Trop. For. Environ.*, 07 (2017), pp. 28-42, 10.31357/jtfe.v7i1.3020
- Chenge I.B. (2021), Height–diameter relationship of trees in Omo strict nature forest reserve, Nigeria, *Trees For. People*, 3 (2021), Article 100051, 10.1016/j.tfp.2020.100051
- Cysneiros, A.L. Pelissari, T.D. Gaui, L.D. Fiorenti, D.C. deCarvalho, T. Borges, S. Filho, S.d.A. Machado (2020), Modeling of tree height–diameter relationships in the atlantic forest: effect of forest type on tree allometry, *Can. J. For. Res.*, 50 (2020), pp. 1289-1298, 10.1139/cjfr-2020-0060
- Di Cosmo, L., & Gasparini, P. (2020). Predicting diameter at breast height from stump measurements of removed trees to estimate cuttings, illegal loggings and natural disturbances. *South-east European forestry: SEEFOR*, 11(1), 41-49.
- Friday N. Ogana, Emma Holmström, Ram P. Sharma, Ola Langvall, Urban Nilsson, Optimizing height measurement for the long-term forest experiments in Sweden, *Forest Ecology and Management*, Volume 532, 2023, 120843, ISSN 0378-1127. <https://doi.org/10.1016/j.foreco.2023.120843>. (<https://www.sciencedirect.com/science/article/pii/S0378112723000762>)
- Fortin M., Van Couwenberghe R., Perez V., Piedallu C. (2019), Evidence of climate effects on the height-diameter relationships of tree species, *Ann. For. Sci.*, 76 (2019), 10.1007/S13595-018-0784-9
- Muhammad Junaid Ismail, Tika Ram Poudel, Akber Ali, Lingbo Dong (2025), Incorporating stand parameters in nonlinear height-model for uneven-aged *Larix gmelinii* forests,,diameter mixed-effects Published in *Frontiers in Forests and Global Change*, January 2025, DOI 10.3389/ffgc.2024.1491648.
- Ng’andwe P., Chungu D., Yambayamba A. M., Chilambwe A., Modeling the height-diameter relationship of planted *Pinus kesiya* in Zambia. *For. Ecol. Manag.*, 447 (2019), pp. 1-11, 10.1016/j.foreco.2019.05.051
- R Development Core Team (2005). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL: <http://www.R-project.org>.
- Tanovski, Vladimir & Matović, Bratislav & Risteski, Mihajlo & Trajkov, Pande. (2023). Modelling the tree height-diameter relationship of Macedonian pine (*Pinus peuce* Gris.) forests in North Macedonia. *Journal of Forest Science*. 69. 497-513. 10.17221/68/2023-JFS. URL: <https://doi.org/10.17221/68/2023-JFS>

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