Investigating the performance of genetic algorithms selection method in estimating stand-level structural and biophysical variables of lowland dipterocarp forest from LiDAR data

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Abstract. Genetic Algorithms (GAs) methods are rarely been used as a selection method in developing the model for estimating forest’s variables as compared to stepwise regression method. This study aims to investigate the performance of GAs as a selection method in finding the best predictor variables. Five models were developed to test the performance of GAs methods in estimating stand-level structural and biophysical variables of the forest, namely as mean height (Hm), stand density (S), basal area (G) square mean diameter (Dg), and biomass (B). The results have shown GAs methods produce better model for Hm and Dg as compared to stepwise regression method in term of adjusted R² and RMSE values. However, models for S, G and B based on stepwise regression method outperformed the GAs methods. This study has shown the capability of GAs in finding the best airborne lidar scanning (ALS) metrics for the development of best model in estimating stand-level structural and biophysical variables of lowland dipterocarp forest.

1. Introduction
The use of Light Detection and Ranging (LiDAR) in forestry sector has become more prominent in past recent years. This data has the capability in providing information on forest structure either visually or statistically which can not be provided by any optical image. The use of terrestrial LiDAR system (TLS) provides detail information on the environment of the forest while airborne LiDAR system (ALS) can covers wider coverage than the TLS system. Many studies have been done with the use of LiDAR data in forestry [1]. Such studies are tree identification, forest structure and composition, modelling, mapping and others. The estimation of forest structure, like stand density, basal area, mean height and quadratic mean diameter, using LiDAR data have received much attention by the researchers [1-7]. Most of the estimation of these variables gave accurate results as compared to same studies done using others data. Same also goes with biomass estimation. Lots of studies have shown promising results when LiDAR data were used [8-10].

Several techniques can be use in estimating forest structure and biophysical variables. Such techniques are linear and nonlinear approaches, classification and regression trees (CART) and also random forest [11-15]. Multivariate linear regression is a common technique used in developing the model for the estimation of structure and biophysical variables of forest when involving more than one predictor variables [16,17]. Lidar metrics derived from LiDAR data usually been used in modelling those variables [18-20]. This method combines two or more metrics in order to produce better model
based on optimize criteria such as Aikake Information Criterion (AIC), Bayesian Information Criterion (BIC), Mallow’s Cp, Adjusted $R^2$ or root mean square error (RMSE).

Machine learning techniques such as genetic algorithms (GAs) introduced a new paradigm into data mining process and can be used to select subsets of predictor variables that optimize criteria such as AIC, BIC, RMSE and others [21]. Based on biological genetics and evolution, this technique tries to find the most optimal value from a population of $k$ subsets and $n$ generations. Each subset consists of a random combination of predictor variables. The subsets that returns the most optimal value is selected as the most suitable subset for predictor variables. Only few studies on the use of GAs as selection method for developing models for forest variables were carried out until now although this technique are well established and used in other applications [22-27].

Thus, the objective of the study was to investigate the performance of GAs as a selection method in selecting the predictor variables to developed the models for estimation of stand-level structural and biophysical variables of lowland dipterocarp forest using ALS dataset. Models were developed using multivariate regression method with the use of AIC as optimize criteria. The developed models of each forest variables were compared with the models developed using stepwise regression method.

2. Methodology

2.1. The Study Area

The study area is located at Sungai Menyala Forest Reserve, Port Dickson, Negeri Sembilan, Malaysia. This forest reserve was gazetted in 1917 with a total area of 1,305 ha and managed by Forestry Department of Negeri Sembilan State. It is one of the lowland dipterocarp forest in the west coast of Peninsular Malaysia with just only 5 to 6 kilometers from the coastline. This forest reserve is also one of the area designated as eco-edutourism park in Peninsular Malaysia by the Forestry Department.

![Figure 1. The location of study area](image_url)
2.2. Field Plot Data
A total of 40 forest inventory plots were established for development and verification of the models generated from the ALS metrics. The selection of plot locations is based on ground elevation, canopy height and tree cover information extracted from the ALS data. The sampling activities are also cover disturbed area due to natural or human activities. A circular plot with a radius of 20 m was established on each plot [28]. The location of each plot was located in the field using Trimble GPS. Tree information such as diameter at breast height (DBH), bole height, total height and species were measured and recorded during the inventory.

Four structural variables, namely as total mean height (Hm), stand density (S), basal area (G) and square mean diameter (Dg), and one biophysical variable, which is biomass (B), were derived from field inventory data. Details calculation on Hm, S, G and Dg can be referred to studied done by Montealegre et al.[29]. Total biomass on each plot were calculated based on allometric function established by Chave et al. [30]. The summary statistics of Hm, S, G, Dg and B of all plots are listed in Table 1. The performance of GAs was evaluated based on the capability of this algorithm in selecting the best parameters for the estimation of those variables.

| Forest variables | Min. | Max. | Range | Mean | SD |
|------------------|------|------|-------|------|----|
| Hm (m)           | 5.3  | 24.8 | 19.23 | 18.0 | 3.8|
| S (stem ha⁻¹)    | 30.1 | 1113.2 | 1083.0 | 396.0 | 199.0|
| G (m² ha⁻¹)      | 3.2  | 49.8 | 46.6  | 25.4 | 10.5|
| Dg (cm)          | 12.2 | 48.6 | 36.4  | 30.3 | 8.4|
| B (Mg ha⁻¹)      | 35.6 | 762.4 | 726.8 | 319.6 | 157.2|

2.3. LiDAR Processing
LiDAR data was acquired in April 2015 using RIEGL LMS-Q560 sensor with an average flying height of 450 m. The acquisition of LiDAR data was only covers part of the forest reserve. The resulting ALS point density for all return, last return and ground return only 12.39, 7.31 and 1.04 points m² respectively. The final product was delivered in 1 x 1 km tiles containing point’s coordinates and classes and projected with a projection of West Malaysia Rectified Skew Orthomorphic (Kertau RSO). ALS metrics on each plot were derived using FUSION v3.6 open source software [31]. A normalized LiDAR data was used as a data input for the derivation of the ALS metrics. A total of 34 ALS metrics, consisting of information on canopy height’s, canopy height percentile’s, canopy height variability’s and canopy density’s metrics, were produced. These metrics were then used to developed the best models in estimating forest structural and biophysical variables with GAs as a methods to find and select the best ALS metrics on each model.

2.4. Genetic Algorithms Selection Method
GAs are adaptive heuristic search method based on the evolutionary idea of natural selection and genetics. This method is great for finding solutions to complex search problems such as finding the best combination for the best solution. A randomly generated population from few to thousand individuals were created at the beginning of the process. Each individual was evaluated and calculated their ‘fitness’ values. Only several best individuals, which have the highest fitness values, were kept for next generation. New individuals were created during crossover process in the next generation. The best individuals from previous generation were combined and mutate with individuals from new generation. Better individual with better fitness value may produced in that generation. The best individuals are kept for next generation. This process is repeated until either this algorithms have found the solution or reach the maximum generation. A total of 1000 individuals consisting of 34 random binary sequences were generated at the initial process. Code 1 represents the ALS metric is selected in model’s development while code 0 represent otherwise. Each individual was modelled using multivariate regression analysis, and evaluated its fitness based on AIC value. The maximum generation was set to 100.
2.5. Stepwise Regression Selection Method

Stepwise regression is a common method in multivariate regression analysis where the choice of predictive parameter is carried out by an automatic procedure. Adjusted $R^2$, AIC, BIC and Mallow’s Cp are some of the standards in determining the best model for this method. Three approaches, which are forward selection, backward elimination and bidirectional elimination, can be used in developing the model. Stepwise regression method was also applied to the data. AIC value and bidirectional elimination approach were selected to find the best models of each variable using this method.

2.6. Evaluation on Genetic Algorithm Selection Method

The performance of GAs as a selection method in developing the best models on each variable was assessed by comparing the best models from GAs and stepwise regression methods. Comparison on adjusted adjusted-$R^2$ and RMSE on each model were also made in this study. All established models were validated using leave-one-out cross validation (LOOCV) technique. Analysis of Variance (ANOVA) was performed to compare models developed using stepwise and GAs methods. The test was done at 95% confidence level. Analysis from data preparation, model development until model validation were performed using R statistical environment [32].

3. Results and Discussion

A summary of the structural and biophysical variables estimated using field data is shown in Table 1. There are significant variations in all of the parameter assessed based on the range values from the table. Thus, a minimum of 40 field plots is adequate to develop the model. The plot size used during field inventory is also appropriate and represent on the ground especially G and B. The estimation of forest variables derived from ground data may be improve by extending the plot size and intensify the sampling. A full census by measuring all trees in the plot would gave better estimation of those variables. However, these approaches will require more manpower, time and effort to accomplish it.

The structure and composition of disturbed and old growth forests are varies from one and another. Old growth forest usually have higher Hm than disturbed forest. Larger trees were also dominated in that area making it higher in term of G, Dg and B when compared to disturbed forest. Old growth forest tends to have lower S than disturbed forest since larger trees were dominated in that area. These variations can be seen visually and statistically as shown in Figure 2. ALS metrics generated by Fusion’s software provides details information on forest structure at plot basis. Prediction on forest variables such as Hm, S, G, Dg and B using the ALS metrics is possible.

Overall, all ALS metrics, except elevation minimum, were used more than once in developing the models as shown in Table 2. ALS metrics of P60 and elevation SD were the most used metrics in predicting forest variables either using stepwise regression or GAs methods. The number of ALS metrics which have been selected in developing the models using GAs are varies from stepwise regression method despite both methods used AIC as a criteria. Less ALS metrics were observed when using GAs methods for developing the models. Hm was best estimates using 5 ALS metrics when GAs methods was employed. Ten ALS metrics were selected to acquire the best model for Dg. S, G and B were best estimates using 13 ALS metrics but only differ in combination of ALS metrics used in the models. As for stepwise regression method, Hm, S, G, Dg and B were best estimates using 19, 17, 21, 29 and 27 ALS metrics respectively.

A slight improvements was observed for Hm when GAs methods were used. The adjusted $R^2$ value for Hm model using GAs methods is 0.491 with RMSE of 2.47m while the adjusted $R^2$ and RMSE values for Hm model using stepwise regression method are 0.448 and 2.79m as shown in Table 3. Although the differences is minimal, both models did not performs on par with previous studies done by other researchers [8,13,18,20,33,34]. Dg model based on GAs method shown modest improvement than stepwise regression method. The adjusted $R^2$ and RMSE values were improved from 0.191 to 0.446 and 7.33cm to 5.17cm. However, both models perform under par when compared to other studies [16-19]. Unlike Hm and Dg, models for G and B were performed well in estimating these variables and models developed using stepwise regression perform better than GAs methods. Adjusted $R^2$ values for models prediction for G and B using stepwise regression methods are 0.862 and 0.851.
while models prediction for G and B using GAs methods are 0.717 and 0.791 respectively. GAs methods perform poorly when predicting S with an adjusted R^2 and RMSE of 0.054 and 136.95 stem ha\(^{-1}\). Model for S developed using stepwise regression method perform better with an adjusted R^2 and RMSE of 0.224 and 80.83 stem ha\(^{-1}\). Despite that, both model’s precision were lower when comparing with past studies [16,18-20,35]. Only G models have shown a significant difference at 95% confidence level when ANOVA was performed. It shown that the method of selections in selecting the best ALS metrics need to be considered when it involving the prediction of this variables. Either method of selections can be used when developing models for Hm, S, Dg and B. The performance of GAs methods were comparable with the stepwise regression method in term of adjusted R^2 and RMSE values. Models may be improve with the use of others criteria as fitness value instead of AIC. Other settings in GAs methods like number of population, mutation and crossover value need to be explore and optimize in order to get the best setting in developing the models of forest variables. The addition of sampling points is also can help in developing better models. The ground survey need to be done if more sampling points are needed. Noise in the data may occur and need to be remove prior to the process of developing the models since both selection methods don’t have the capability in identifying the noise/outliers in the data. Thus, the presence of noise/outliers in the data may affect on the accuracy of the models. In addition, time is also may need to be consider when performing GAs as this method may require a lot of time as compared to stepwise regression method. Stepwise regression method just require less than a minute to find the best model while GAs methods need around 2 hours to accomplish. The use of higher end computers with parallel processing may reduce the time to less than an hour.

![Figure 2. Metrics associated with vertical distribution of LiDAR returns in selected field plots: (a) disturbed forest and (b) old growth forest.](image)

| Canopy Height Percentile Metrics | Value | ALS Metrics | Value |
|---------------------------------|-------|-------------|-------|
|                                |       | F01         | 0.02  |
| 0.18                           |       | F05         | 1.88  |
| 0.85                           |       | F10         | 9.23  |
| 5.94                           |       | F20         | 20.80 |
| 6.73                           |       | F30         | 25.50 |
| 7.37                           |       | F40         | 32.00 |
| 8.30                           |       | F50         | 35.90 |
| 9.66                           |       | F60         | 39.00 |
| 10.49                          |       | F70         | 41.70 |
| 11.03                          |       | F75         | 42.42 |
| 11.71                          |       | F80         | 43.06 |
| 13.53                          |       | F90         | 44.63 |
| 14.58                          |       | F95         | 45.67 |
| 17.10                          |       | F99         | 46.65 |
| **Canopy Height & Variability Metrics** |       | **Elev. Mean** | 31.78 |
| **Elev. Mean** | 0.03 | Elev. SD | 13.24 |
| **Elev. Variance** | 10.17 | Elev. CV | 0.42 |
| **Elev. IQ** | 4.28 | Elev. Kurtosis | 3.00 |
| **Elev. Kurtosis** | 3.06 | Elev. Mode | 41.98 |
Overall, GAs methods can be used as one of the selection methods to find the best predictor variables in estimating stand-level structural and biophysical variables of forest. Other forest types such as hill, upper hill, montane, peat swamp and mangrove forests can use this approach and not only applicable to lowland dipterocarp forest.

Table 2. Summary of best models on each variables based on GAs and stepwise regression methods.

| Selection Method | Genetic Algorithms (GAs) | Stepwise Regression |
|------------------|--------------------------|---------------------|
| **Forest Variables / ALS Metrics** | | |
| Hm (m) | S (stem ha$^{-1}$) | G (m$^2$ ha$^{-1}$) | Dg (cm) | B (Mg ha$^{-1}$) | Hm (m) | S (stem ha$^{-1}$) | G (m$^2$ ha$^{-1}$) | Dg (cm) | B (Mg ha$^{-1}$) |
| Intercept | -1.58 | -4968 | 15.44 | 230.2 | 83.85 | -39.9 | 2943 | 190.2 | -62.2 | 3688 |
| **Canopy Height Percentile Metrics (m)** | | |
| P01 | -3.52 | 292.1 | 18.26 | 164 |
| P05 | 0.69 | -0.77 | 79.28 | -6.08 | 48.5 |
| P10 | -39.1 | 0.80 | -0.87 | 3.80 | 48.5 |
| P20 | -20.7 | -1.52 | -12.2 | 7.68 |
| P25 | 4.35 | 15.88 |
| P30 | 113.3 | -4.62 | -11.7 | 36.1 |
| P40 | -0.95 | -9.62 | -137 |
| P50 | -212 | 6.38 | -288 | 7.56 | 302 |
| P60 | -46.3 | -2.15 | 0.12 | -19.4 | 12 | 3.12 | 107.6 |
| P70 | -654 | -1.05 | 61.0 | 22.22 | 1.68 | -1.05 | 1432 |
| P75 | -165 | -1.23 | -11.0 | 485 | 19.25 | 270.9 |
| P80 | -163 | 8.10 | -10.8 | 4.5 | -175 |
| P90 | -0.01 | -131 | -3.37 | -49.1 | 2.19 | -18.7 | 262 |
| P95 | -159 | -11.4 | 4.95 | -141 |
| P99 | 1.07 | -57.8 | -1.58 | 2.27 | -21.6 | -4.88 | 63.9 |
| **Canopy Height & Variability Metrics (m)** | | |
| Elev. Minimum | -0.79 | 0.72 | 10.2 | -1.05 |
| Elev. Mean | 863.3 | 11.14 | -17.7 | 141.7 | 1432 |
| Elev. Mode | -0.59 | -6.37 | -1.02 | 22.22 | 1.68 | -1.22 | 14.4 |
| Elev. SD | 244.4 | 5.32 | -4.56 | 61.0 | -11.3 | 1224 | 94.64 | -35.2 | 1073 |
| Elev. Variance | -15.2 | -1.10 | 20.44 | 1.17 | -1 | 9.58 |
| Elev. CV | 19.28 | 96.45 | -5873 | -256 | 176.6 | -2220 |
| Elev. IQ | 136.9 | -2.83 |
| Elev. Skewness | -4.08 | 6.23 | 201.9 | 16.46 | 656.1 | 97.45 | 1176 |
| Elev. Kurtosis | 6.42 | -29 | -480 |
| **Canopy Density Metrics (%)** | | |
| % first returns above 1.00 | 62.92 | -2.54 |
| % all returns above 1.00 | -1.98 | -38.9 | -6.1 | -109 |
| % first returns above mean | 20.44 | 1.17 | -1 | 9.58 |
| % first returns above mode | -0.14 | -1.25 | 0.45 | -16.5 | -1.01 | 0.92 | -11.7 |
\begin{table}
\centering
\begin{tabular}{|l|c|c|c|c|c|}
\hline
Forest Variables & Stepwise Regression & Genetic Algorithms & ANOVA Test & \\
 & $\text{Adj-R}^2$ & RMSE & (GAs) & ($p$-value) & \\
\hline
Hm (m) & 0.448 & 2.79 & 0.491 & 2.47 & 0.6128 (not significant) \\
S (stem $\text{ha}^{-1}$) & 0.224 & 80.83 & 0.054 & 136.95 & 0.8337 (not significant) \\
G ($\text{m}^2 \text{ha}^{-1}$) & 0.862 & 4.20 & 0.717 & 4.86 & 0.0004 (significant) \\
Dg (cm) & 0.191 & 7.33 & 0.446 & 5.17 & 0.9367 (not significant) \\
B (Mg $\text{ha}^{-1}$) & 0.851 & 65.55 & 0.791 & 62.70 & 0.0571 (not significant) \\
\hline
\end{tabular}
\caption{Validation results for the estimated variables}
\end{table}

4. Conclusion
This study has shown the performance of GAs as a selection methods in selecting the best ALS metrics for the estimation on stand-level structural and biophysical variables of lowland dipterocarp forest. The final models based on this method have shown mixed results with models developed using stepwise regression method. GAs methods perform better in developing models for Hm and Dg while stepwise regression method were better in developing models for S, G and B. Future studies need to be done in maximizing the setting for GAs especially on fitness criteria for the improvement of the models with better prediction of forest variables.

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