Multiscale analysis of the relationship between topography and aboveground biomass in the tropical rainforests of Sulawesi, Indonesia

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Online publication date: 23 May 2011

To cite this Article Propastin, Pavel(2011) 'Multiscale analysis of the relationship between topography and aboveground biomass in the tropical rainforests of Sulawesi, Indonesia', International Journal of Geographical Information Science, 25:3, 455 — 472

To link to this Article: DOI: 10.1080/13658816.2010.518570
URL: http://dx.doi.org/10.1080/13658816.2010.518570

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Multiscale analysis of the relationship between topography and aboveground biomass in the tropical rainforests of Sulawesi, Indonesia

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(Received 30 June 2009; final version received 22 August 2010)

This article aims to explore spatial and altitudinal non-stationarity in the relationship between aboveground biomass (AGB) of tropical rainforest in Sulawesi (Indonesia) and topography. An autoregressive model through a geographically weighted regression (GWR) framework was used to study the relationship between ground-measured values of AGB and altitude above sea level at 85 sampling plots. The relationships between AGB and altitude were found to be significantly spatially variable and scale-dependent. The results also suggested high altitudinal variability in the examined relationship. Both the strength of the AGB–altitude relationship ($r$) and the altitudinal gradient ($z$) showed a high changeability in the horizontal and vertical dimensions. The complex spatio-altitudinal patterns in the GWR-based local estimates of the $r$ and $z$ parameters gave rise to both spatial and altitudinal variations in the scale effects. The approach presented in this study enables finding the most appropriate scale for data analysis within different altitudinal bands. The study found that the changes of the gradient $z$ along altitudinal transects relate to prevalent environmental conditions observed at different altitudes, whereas the optimal bandwidth was related to the terrain surface heterogeneity.

Keywords: biomass; altitudinal gradient; topography; GWR; non-stationarity; scale-dependency

1. Introduction

Terrain and its topography are paramount in ecological studies for their influence on numerous physical processes associated with the distribution of soil properties, plant growth, vegetation structure, decomposition rates and biomass accumulation (Austin et al. 1994, Coops et al. 1998). Altitude above sea level is the major factor predicting vegetation patterns in landscapes with diverse terrain conditions. Reduction in air temperature with increasing altitude reduces the energy available for plant growth and strictly affects forest vegetation (Tanner 1980, Richards 1996, Reich et al. 1997). Many studies have examined the changes in forest vegetation associated with changing altitude in a variety of forest ecosystems (Lieberman et al. 1996, Tang and Ohsawa 1997, Aiba and Kitayama 1999, Kamijo et al. 2001). Studies of the effect of altitude on forest vegetation have been commonly based on the relationships between the forest structure parameters and a set of perceived explanatory variables such as temperature, precipitation, light intensity and so on. Although strong relationships have been established between individual forest structure parameters and altitude (Takahashi et al. 2003, Miyajima and Takahashi 2007, Moser et al.

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ISSN 1365-8816 print ISSN 1362-3087 online
© 2011 Taylor & Francis
DOI: 10.1080/13658816.2010.518570
http://www.informaworld.com
2007), there are problems in determining a general model to explain small-scale geographical patterns of these relationships.

Altitudinal gradient has been typically assumed to represent a biome-specific (region-specific) constant, which is spatially stationary across the whole landscape (region) to be studied. However, recent ecological studies have shown that relationships between spatially distributed environmental variables vary across the geographical space (Brusdon et al. 2001, Wang et al. 2005). The study by Zhang et al. (2004) has shown that the tree diameter–tree height relationship in a forest sampling plot is spatially variable. Instability of the relationship between spatially distributed variables is known in the field of geography and spatial data analysis as non-stationarity and has also been investigated in several studies with remotely sensed data (Foody 2003, Propastin and Kappas 2008, Propastin, 2009). Moreover, recent ecological studies have also shown that relationships between vegetation characteristics and climatic variables appear to vary as a function of spatial scale (Foody 2004, Nelson et al. 2007, Propastin et al. 2008). These and other related studies have acknowledged the importance of spatial non-stationarity and scale effects and showed relationships and processes operating differently at different scales. With this supposition in mind, it is likely that spatial non-stationarity and scale effects should have important implications for the affect of altitude on forest vegetation. Nonetheless, implications of these issues are not thoroughly investigated yet.

This article aims to investigate the non-stationarity of the relationship between above-ground biomass (AGB) and altitude in a region of moist tropical rainforest of Sulawesi, Indonesia. The study attempted (1) to illustrate the improvement of geographically weighted regression (GWR) over the non-spatial regression with fixed parameters in modelling the biomass–altitude relationship; (2) to analyse the variability of the GWR model coefficients over space and along altitudinal transects; (3) to detect the most appropriate scale to analyse the biomass–altitude relationship; and (4) to discuss implications of environmental factors for spatial non-stationarity and scale effects in the biomass–altitude model.

2. Study area

The analysis area is located in Central Sulawesi, Indonesia (latitude 0°55′–01°54′ South, longitude 119°40′–120°29′ East), and comprises the region of the Lore-Lindu National Park with surrounding areas (Figures 1 and 2a). The study area has a very diverse relief with elevations from zero in the coastal area in the north to more than 2300 m above sea level in

![Figure 1](image-url)  
Figure 1. Location of the study area in Sulawesi, Indonesia.
The mean annual rainfall ranges from about 2000 mm in the north to more than 3000 mm in the south. The daytime temperature in lowland areas of the region is about 26°C throughout the year and falls in the mountainous areas to 15–16°C.

The natural vegetation is generally classified into three major vegetation types based on altitudinal distribution with lowland rainforest below 1000 m, pre-montane rainforest from 1000 to 1400–1500 m and mountain rainforest above 1400–1500 m (Whitten et al. 2002). These forests are dominated by wood species such as *Aglaia argentea*, *Pimelodendron amboinicum*, *Bischofia javanica*, *Cananga odorata* and *Meliosma sumatrana*. The natural forest has been subject to substantial forest conversion activities along the park boundaries. Near the national park boundaries, many previously forested areas have been transformed into perennial agro-forestry areas with cocoa and/or coffee cultivation. Some of these areas have been abandoned after short-term cultivation and reverted to secondary forest. The

![Design of the field data sampling: distribution of the sample plots inside the study area comprising the Lore-Lindu National Park with bordering areas (a), and the subplot design (random selection) within sample plots (b).](image)
secondary forests are dominated by *Acalypha catus*, *Grewia glabra*, *Homalanthus populneus*, *Macaranga hispida*, *Mallotus mollissimus* and *Pipturus argenteus*.

### 3. Data

In this study, we used ground-based biomass dataset acquired by extensive forest inventory across the Lore-Lindu National Park carried out during 2003–2008 at 85 plots. A number of plots were also located in forest areas out of the park borders. The distribution of the plots across the study area is shown in Figure 2a. The location of field survey plots was established based on a stratified random strategy using Landsat classification image (Erasmi et al. 2007) and a digital terrain model. This sampling strategy is based on the natural vegetation stratification in this region. According to the vegetation classification by Whitten et al. (2002), three forest strata were determined from combined use of the land cover image and the digital terrain model: lowland rainforest, pre-montane rainforest and montane rainforest.

All the plots had a size of $40 \times 60 \text{ m}^2$ (~0.25 ha). Geographical coordinates of the corners as well as the elevation above sea level of each plot were measured by GPS (+/−5–8 m horizontal accuracy). A nested sampling strategy organized by plot and subplot was employed to inventory test sites. Each sample plot was divided into 24 subplots with a size of $10 \times 10 \text{ m}^2$ (Figure 2b). Extensive measurements of forest stand parameters were carried out at six subplots that were selected randomly within each of the sampling plots. In each subplot, all individual trees with a diameter at breast height (DBH) greater than 10 cm were identified and measured for DBH, trunk height and total height. A thorough description of the used dataset and the treatment methods is given by Propastin (2009b). AGB of individual plots was calculated as a function of DBH, $H$, specific wood density (WD) for species of moist forest zone and stem density recorded at each sample plot (Ketterings et al. 2001, Chave et al. 2005). After that the AGB was converted to tons per hectare (t/ha).

For the total dataset, calculated AGB ranged from 12.16 to 612.30 t/ha with a mean value of 178.23 t/ha and a standard deviation of 134.75 t/ha. However, because of the altitudinal effect, the summary statistics differed significantly between the elevation strata (Figure 3). There is a general increase in AGB at the altitudes from 400 to 1000 m. Above 1000 m, the AGB of the sample plots displays a subsequent decrease as it is expected for tropical forests (Richards 1996, Whitten et al. 2002).

Meteorological data were derived from 12 climate stations situated in the study area. The dataset contains mean annual temperatures (in °C) and total global radiation (in MJ/m$^2$/year)

![Figure 3. Mean values and standard deviation of AGB (t/ha) by elevation classes for the ground-based dataset.](image-url)
for the period from 2002 to 2005. These data were used to discuss the effects of climate on AGB (see Section 6). An incorporation of temperature and global radiation data as explanatory variables into our model (described below) would be superfluous, because both variables demonstrate very strong linear relationships with altitude (Figure 7 and Discussion in Section 6). A use of them in the GWR model would not significantly improve the relationship between altitude and AGB. Moreover, incorporating these strongly related variables in the regression model would cause the effect of multicollinearity. To avoid making the paper longer, we limited the number of variables presented in our analysis only to altitude.

4. Methods

4.1. Geographically weighted regression

GWR is a local statistical technique that enables its parameter estimates to vary across space. The local estimation of the parameters with GWR is given by the equation (Fotheringham et al. 1996, 2002):

\[ y = \beta_0(\mu, \nu) + \beta_1(\mu, \nu)x + \varepsilon \]  

This regression equation orders the regression parameters to be estimated at a location for which the spatial coordinates are provided by the variables \( \mu \) and \( \nu \). In GWR, the regression and its parameters in each point of space are quantified separately and independently from other points. The size of the moving window (kernel) is less than the region size and can be varied from one point (i.e. an individual sample plot in this study) to another depending on the density of observations at certain area. Each data point is weighted by its distance from the regression point. The closer a data point is to the regression point, the more weight it reveals.

The GWR model coefficients can be estimated by solving the matrix equation:

\[ \hat{\beta}(\mu, \nu) = (X^TW(\mu, \nu)X)^{-1}X^TW(\mu, \nu)y \]  

where \( \hat{\beta} \) are intercept and slope parameters in location \((\mu, \nu)\) and \(W(\mu, \nu)\) is a weighting matrix whose diagonal elements represent the geographical weightings of observations around point \(i\):

\[ W(x_i) = \begin{pmatrix} w_{i1} & 0 & \ldots & 0 \\ 0 & w_{i2} & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \ldots & 0 & w_{in} \end{pmatrix} \]  

where \(w_{in}\) is the weight assigned to the observation at location \(n\).

Calibrating of GWR can be based on the use of either a fixed or an adaptive spatial kernel. The choice of a spatial kernel method depends on the distribution of data across the space to be studied: if the distribution is regular, then the kernel with a fixed distance is appropriate. If the distribution is not regular, then the adaptive spatial kernel method may be better (Brunsdon et al. 1996, Fotheringham et al. 2002).
4.2. Local autoregressive model using GWR

To investigate the relationship between AGB and altitude, we used the technique of conditional spatial autocorrelation. Conditional spatial autocorrelation accounts for spatial autocorrelation in an attribute that is conditioned by the distribution of another attribute. It means that while investigating the relationship between AGB and altitude we will measure autodependency in AGB, which is conditioned on altitude above sea level. To investigate spatial non-stationarity of altitude gradient, we examine conditional spatial autocorrelation in AGB through the GWR framework (Brunsdon et al. 1998, Fotheringham et al. 2002). The use of GWR framework for this task has a benefit of being able to produce local measures of conditional spatial autocorrelation in AGB. We examined the following autoregressive model with spatially varying parameters:

\[
\text{AGB}_i = k(\mu_i, \nu_i) + \rho(\mu_i, \nu_i)\text{AGB}_i^* + \alpha(\mu_i, \nu_i)\text{ALT}_i + e_i
\]  

(4)

where AGB\(_i\) represents the AGB at location \(i\); \(k\), \(\rho\) and \(\alpha\) are parameters to be estimated for location \(i\); \(e_i\) is a random error term; AGB\(_i^*\) is the average of the AGB of a defined number of nearest locations to \(i\) or within a defined radius (in this study AGB\(_i^*\) was estimated using the inverse distance weighting procedure); and ALT\(_i\) is altitude above sea level for location \(i\).

In this model, the parameter \(\alpha\) represents the rate of increase in AGB with altitude (t/ha/m). This type of model is known as a local spatial autoregressive model and \(\rho\) is a measure of the degree of spatial autocorrelation (Brunsdon et al. 1998, Fotheringham et al. 2002). In other words, the autocorrelation term represents the strength of the relationship between AGB and altitude above sea level. If such an autoregressive model is calibrated by GWR, it produces a surface of local estimates which can then be examined for the degree to which spatial dependency exists in the data.

In this study, the model in Equation (4) was used to examine the local spatial autocorrelation in AGB conditioned on altitude above sea level. The main output from GWR analysis is a set of local parameter estimates for the analysed relationship. It means that, in this study, local estimates of spatial autocorrelation (autoregressive term \(\rho\)) and altitudinal gradient \(\alpha\) could be calculated for each of the 85 sampling plots. This also has a benefit of being able to analyse spatial variability of these parameters across the study area or to examine a change of \(\rho\) and \(\alpha\) with changing altitude. All analyses were done using the software package GWR3.0 (http://ncg.nuim.ie/ncg/GWR/index.htm).

4.3. Criteria related to spatial non-stationarity, model performance and bias–precision trade-off

A number of criteria were employed in this study to assess the performance of GWR model and to test the parameter estimates. The comparison of the GWR local parameter estimates with the globally fixed estimates of the equivalent parameter is an effective means to examine the degree of non-stationarity in a relationship. In this study we used the Monte Carlo simulation that compares the observed value estimates with those obtained from randomly rearranging the data in space and forms the basis for testing individual parameter stationarity (Fotheringham et al. 2002). Akaike information criterion (AIC) was used for the evaluation of model performance and the choice of bandwidth. As a general rule, the lower the AIC, the closer is the approximation of the model to the reality. Thus, the best model is the one with the smallest values of AIC (Brunsdon et al. 1998, Fotheringham et al. 2002).
An approximate likelihood ratio test, based on the $F$-test, was used to compare the relative performance of the GWR model and ordinary least squares (OLS) model. This test is based on the assumption that the distribution of residual sum of squares (RSS) of the GWR model divided by the effective number of parameters may be approximated by a $\chi^2$ distribution with effective degrees of freedom equal to the effective number of parameters (Brunsdon et al. 1999). In this test, the resulted $F$-value represents a relative enhancement of GWR model over its OLS equivalent. More details on GWR estimation procedure and criteria related to statistical inference of GWR can be found in Fotheringham et al. (2002) and Brunsdon et al. (1998, 1999).

The relationship between expected value of the regression estimate and the precision of this estimate is a problem of statistical inference that occurs in regression modelling. In this study, the Mallows statistic ($c_p$), which was first proposed by Mallows (1973) and adapted by Brunsdon et al. (1999) for use within the concept of GWR, served as a guide for the choice of bandwidth with an optimal combination of bias and precision. The $c_p$ value was used to make a diagnosis of the bias–precision relationship and determine the bandwidth that provides an unbiased model.

5. Results

5.1. Model fitting

Because the distribution of the AGB data over the study area was not regular, the adaptive spatial kernel method was used for the calibration of the GWR model. A statistically significant relationship between AGB and altitude was established using the autoregressive model in Equation (4) through the GWR framework. We also fitted the OLS regression using the same model in Equation (4) but spatially fixed parameters. The output diagnostics for the GWR and OLS estimation are presented in Table 1. There is a significant improvement in the model fit when GWR is adopted. The value of standard error of estimation for the GWR model is considerably decreased. Note the reduction in RSS when the GWR approach is used. The coefficient of determination increased from 0.475 to 0.674 although an increase is to be expected given the difference in degrees of freedom. However, the reduction in the AIC value from the global model suggests that the local model is better even accounting for differences in degrees of freedom. The difference in AIC values between the models is more than 3 considering a statistically significant difference between the models in estimating AGB. The ANOVA tests the null hypothesis that the GWR model represents no improvement over the global model (Table 2). The result indicated a rejection of the null hypothesis ($P$-value = 0.0021 for the partial $F$-test), suggesting that the GWR framework significantly improved model fitting over the OLS model. It was evident that the relationship between the AGB and elevation was not constant across the study area.

<table>
<thead>
<tr>
<th>Diagnostic information</th>
<th>OLS model</th>
<th>GWR model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective number of parameters</td>
<td>3.00</td>
<td>7.46</td>
</tr>
<tr>
<td>Standard error</td>
<td>118.98</td>
<td>107.99</td>
</tr>
<tr>
<td>Akaike information criterion</td>
<td>898.36</td>
<td>890.16</td>
</tr>
<tr>
<td>Coefficient of determination</td>
<td>0.475</td>
<td>0.674</td>
</tr>
</tbody>
</table>
Spatial variations in the AGB–altitude relationship

Table 3 shows the descriptive statistics of the model parameters from both OLS and GWR models. These statistics are helpful to understand the degree of spatial non-stationarity in the relationship between AGB and altitude. Fotheringham et al. (2002) suggested a comparison of the range of the GWR local parameters with a confidence interval around the corresponding OLS estimate of the equivalent parameter. If the inter-quartile range of the local estimates is outside of the range of ±1 standard error of the OLS parameter, the relationship under study is suggested to be non-stationary. Table 3 indicates that for the autoregressive parameter $r$, the inter-quartile range 0.0419–0.2549 of the GWR local parameter estimates was outside the range of 0.5921–0.7555 of ±1 standard error of the OLS parameter estimate. Similarly, for the parameter $b$, the inter-quartile range −0.0882 to 0.0263 of the GWR local estimates was also outside the range 0.0211–0.1159 of ±1 standard error of the OLS parameter estimate. In other words, the GWR parameter estimates were statistically different from the corresponding OLS parameter estimates. Therefore, the model parameters of Equation (4) indeed varied from one sample plot to others within the study area. This has also been proved by Monte Carlo significance testing for each parameter in the model, which all have $P < 0.05$.

Because the spatial variation of local terrain conditions and competition were taken into account by the autoregressive GWR model, it produced better fitting for the regression relationship between AGB and altitude. The local $R^2$ of the GWR model ranged from 0.47 to 0.88 with a mean value of 0.67, which is much greater than the value of 0.47 observed by the OLS model.

Table 3. Descriptive statistics of the parameter estimates for the OLS and GWR models.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>$k$</th>
<th>$\rho$</th>
<th>$\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS model</td>
<td>1.6317</td>
<td>0.6738</td>
<td>0.0685</td>
</tr>
<tr>
<td></td>
<td>Standard error 43.1697</td>
<td>0.0817</td>
<td>0.0473</td>
</tr>
<tr>
<td></td>
<td>Lower limit of 95% CI −84.4895</td>
<td>0.4709</td>
<td>−0.0259</td>
</tr>
<tr>
<td></td>
<td>Upper limit of 95% CI 87.7529</td>
<td>0.8767</td>
<td>0.1631</td>
</tr>
<tr>
<td></td>
<td>$b$−1 SD −41.5380</td>
<td>0.5921</td>
<td>0.0211</td>
</tr>
<tr>
<td></td>
<td>$b$+1 SD 44.8014</td>
<td>0.7555</td>
<td>0.1159</td>
</tr>
<tr>
<td>GWR model</td>
<td>Minimum −141.9521</td>
<td>0.0189</td>
<td>−0.1051</td>
</tr>
<tr>
<td></td>
<td>25% quartile −103.3055</td>
<td>0.0419</td>
<td>−0.0882</td>
</tr>
<tr>
<td></td>
<td>Median −90.6817</td>
<td>0.2333</td>
<td>−0.0712</td>
</tr>
<tr>
<td></td>
<td>75% quartile −6.8062</td>
<td>0.2549</td>
<td>−0.0263</td>
</tr>
<tr>
<td></td>
<td>Maximum 44.8563</td>
<td>0.3001</td>
<td>0.0614</td>
</tr>
</tbody>
</table>
The GWR results indicate that the single estimate for each parameter derived from the
global regression technique fails to represent the AGB–altitude relationship for most of the
sampling plots and consequently has poor descriptive and predictive power. Thus, with
respect to the model estimations of the altitudinal gradient $\alpha$, the non-spatial OLS model
revealed a general increase of the AGB with increasing altitude in the study area
($\alpha = 0.068 \, \text{t/ha/m}$). This result contradicts with observations of altitudinal patterns of
biomass in tropical rainforest (Tanner 1980, Richards 1996). However, the local GWR
approach enabled us to detect high local variability of the altitudinal gradient between the
individual AGB inventory plots and proved that a large part of the AGB plots is character-
ized by a negative value of the $\alpha$ parameters indicating a decrease of AGB with increasing
elevation.

5.3. **Altitudinal variations in the AGB–elevation relationship**

The local values of the parameter estimates are very informative and have a benefit of being
able to examine both the spatial and the altitudinal variabilities of the AGB–altitude relation-
ship. To test the effects of terrain elevation on the value of the autoregressive term and
altitudinal gradient, we calculated the mean value and standard deviation of the local estimates
of $\rho$ and $\alpha$ within different altitudinal bands. For the analysis, we have tested the following
altitudinal bands: 400–600 m, 600–800 m, 800–1000 m, 1000–1200 m, 1200–1400 m,
1400–1600 m and above 1600 m.

The results of our calculations are shown in Figure 4. The scatter plots demonstrate
substantial altitudinal variations in both the autoregressive term $\rho$ and the gradient $\alpha$. Both
the mean value and standard deviation of the local estimates vary with varying altitude. The
autoregressive term $\rho$ shows a consequent increase with increasing elevation (Figure 4a).

![Figure 4](image-url)

**Figure 4.** Variations in the autoregressive term $\rho$ (a) and the altitudinal gradient $\alpha$ (b) for different
altitudinal bands.
The mean value of the $\rho$ parameter was 0.36 for the lowest altitudinal band of 400–600 m and 0.79 for the altitudinal band of >1600 m.

The local estimates of $z$ display a substantial decrease with increasing altitude (Figure 4b). The direction of the gradient $z$ varies from negative to positive values with varying altitude. The value of $z$ is strongly positive (0.009–0.052 t/ha/m for individual locations) for the altitudinal band of 400–600 m and 600–800 m indicating a general increase in AGB with increasing elevation above sea level. The AGB increase turns over to a decrease within the next altitudinal band (800–1000 m). For this band, the local estimate of the parameter $z$ shows a negative value (−0.035 t/ha/m) indicating a general decrease of AGB with increasing elevation. For the altitudinal bands above 1000 m, the value of the gradient $z$ is strongly negative. In terms of the magnitude of the altitudinal gradient, the most rapid change of AGB with increasing altitude is observed at 1200–1400 m above sea level. Here, the altitudinal gradient $z$ has a mean value of −0.11 t/ha/m.

### 5.4. Relations between the optimal bandwidth and altitude

The Mallows statistic $c_p$ was used to estimate the most appropriate scale to analyse the AGB–elevation relationship within each of the altitudinal bands from Section 5.3 above. Confidence limits of $c_p$ under the null hypothesis that GWR with a bandwidth of $k$ provides an unbiased estimator of AGB were computed and used in diagnostic plots. An example of such bias–precision trade-offs is given in Figure 5a where the calculated values of $c_p$ are plotted against the bandwidth for the altitudinal band of 800–1000 m. The vertical lines in the plots show the upper and lower 95% confidence limits of the distribution of $c_p$ with the central check showing the expected value. The black dots represent the observed values. When the dot exactly overlays the stroke we have no bias in the GWR calibration. This case would indicate the optimal bandwidth for a GWR model. When the dot lies within the confidence intervals we have a negligible bias in the GWR calibration. On the basis of this plot, the optimal bandwidth for this altitudinal class is 12,500 m.

Using the $c_p$ statistic, we obtained the most appropriate bandwidth for each altitudinal class. The results of our calculations are presented in Figure 5b. With respect to the optimal bandwidth, the results revealed that the most appropriate scale to analyse the AGB data strongly depends on the terrain altitude. The optimal bandwidth ranged from 7500 to 12,220 m for different altitudinal classes illustrating that the dependency between AGB and altitude exists over relatively short distances. The smallest optimal bandwidth (7500 m) was associated with the altitudinal class of 1200–1400 m, whereas the largest optimal bandwidth (12,220 m) was obtained for the altitudinal class of 800–1000 m.

The optimal bandwidth corresponds to the scale at which GWR provides unbiased estimation of AGB from the autoregressive model in Equation (4). But beyond the choice of the optimal bandwidth, the results also supply a range of bandwidths (for each altitudinal class) giving an estimate of the bias, which lies within prediction confidence intervals. For example, for the altitudinal class of 800–1000 m, regression estimates with a negligible bias (within 95% confidence intervals) can be provided using bandwidths from 11,000 to 13,500 m. All the bandwidths out of this scope miss the true scale of spatial variation in the relationship and provide highly biased estimations. As shown in Figure 5, there is a general decrease of prediction confidence intervals when going from a larger bandwidth to a smaller one. Obviously, the decrease of the bandwidth results in a higher accuracy of prediction at the expense of prediction confidence intervals.
5.5. Mapping the results of the autoregressive GWR model

The output from the local autoregressive GWR model was a set of localized parameter estimates and predicted AGB values. Unlike the single global values traditionally obtained in modelling, these local values can be mapped. There is a choice of mapping techniques that can be employed. Different techniques and issues concerning mapping results of GWR are discussed by Fotheringham et al. (2002) and Mennis (2006).

Shaded maps of local estimates for the three GWR parameters \( k \), \( \rho \) and \( \alpha \) and the resulted AGB values are provided in Figure 6. With respect to our application, the maps of GWR parameters and estimates of AGB values summarize the general association patterns we analysed in the sections above, especially highlighting that the measured associations between AGB and altitude do vary across the study area. The map of the intercept parameter (Figure 4a) suggests increased values of \( k \) in the south-central and south-eastern sections of the study area. The autoregressive term (Figure 6b) ranges from 0.21 to more than 0.85, instead of a constant value of 0.67 for the OLS \( \rho \) (compare Table 3). The map of the GWR-derived \( \rho \) suggests lower influence of elevation on AGB in the northern, western and south-western portions but increased influence in the central portion of the study area. Similarly, the range of the local estimates of the altitudinal gradient \( \alpha \) was from \(-0.15\) to \(0.085\) t/ha/m (Figure 6c), rather than a constant value of \(0.068\) t/ha/m in the OLS model.
(compare Table 3). The GWR-based distribution of AGB over the study area is provided in Figure 6d. The value of AGB is lower in the northern, north-western and western sections of the study area, whereas the central and south-eastern parts are characterized by higher biomass values.

Figure 6. Spatial distribution of GWR estimates for the intercept parameter (a), the autoregressive term (b), the altitudinal gradient (c) and aboveground biomass (d).
6. Discussion

Spatial and altitudinal non-stationary relationships between AGB and elevation were clearly shown in the above results. It is important to attempt to interpret the non-stationarity of the relationship in the context of ecological principles.

AGB of tropical rainforest normally shows a decreasing trend along the altitudinal transects because of the decrease of temperature and the change in other environmental factors such as precipitation and availability of solar energy indispensable for the process of photosynthesis. For tropical rainforest, the optimum temperature is about 20°C (White et al. 2000). Biomass production decreases below or above this optimum temperature. This means that a temperature decrease with increasing elevation reinforces a significant reduction of forest biomass. On the contrary, precipitation and the amount of available solar energy may increase only to a certain altitude. Beyond this level, both the amount of precipitation and the solar energy may decrease. With regard to the results of this study, the combination of the environmental factors seems to be the most appropriate at the altitude of approximately 1000 m. This altitude is characterized by optimum conditions for forest growth with a temperature value of about 20°C and the amount of global radiation of 6700–6900 MJ/m² (Figure 7). The forest inventory plots located within the altitudinal band of 1000–1100 m showed the greatest values of AGB (compare Figure 3). The AGB decreases when below and above this altitudinal band indicating poorer combinations of environmental conditions for plant growth within other altitudinal bands. As a consequence of the change in the

![Figure 7](image-url)

**Figure 7.** Relationships between environmental factors and altitude for climate stations from the study area: (a) annual temperature and (b) global radiation.
environmental conditions along altitudinal transects, we have a significant increase of AGB at the altitudes from 400 to 1000 m, and a subsequent decrease of AGB at the altitudes above 1000 m (compare Figure 3). In terms of the model estimates for the altitudinal gradient \( \alpha \), only the increase of AGB was determined through the non-spatial OLS model, whereas the GWR model was sensitive to both the increase and decrease of AGB with increasing altitude.

The results of the GWR model also showed that the combination of environmental factors in space and along altitudinal transects may be very diverse, for example, the variations in temperature, global radiation and precipitation combination between the AGB sampling plots lead to different values of \( \rho \) and \( \alpha \) parameters estimated by GWR for each location. Another factor contributing to the spatial and altitudinal variations in the GWR parameters is the composition of forest vegetation in terms of tree species and age classes. The forest vegetation in the study area is classified into four classes depending on terrain elevation and degree of anthropogenic impact: lowland forest, pre-montane forest, montane forest and secondary forest. The variations in age and tree species composition between the AGB sampling plots lead to different values of \( \kappa \) and \( \alpha \) parameters. As a consequence of the diversity of combination of the environmental factors and the dissimilarity of the forest vegetation composition between localities, patterns of the AGB–altitude relationship are very complex varying both spatially and altitudinally.

Spatial and altitudinal non-stationarity of the AGB–altitude relationship contributes to scale-dependency in the results of the GWR analysis. The relationship between AGB and altitude shows significant scale variations along altitudinal transects (Figure 5b). The complex spatial patterns of the local parameter estimates seem to be the reason for the scale effect associated with variation of elevation. Considering the size of a local sample, the effectiveness of the bandwidth used for GWR calibration demands the local homogeneity of the spatial data depending on the size of spatial units in relation to the true scale of spatial variation. For relatively homogeneous areas, the AGB–altitude relationship may be flatter. In these cases, the model fitted with a larger bandwidth provides suitable results. For areas with higher heterogeneity of terrain and vegetation composition, a steeper relationship between the AGB and altitude may result. In this case, the use of inappropriate large bandwidth distorts the underlying patterns and provides highly biased results. Therefore, the appropriate bandwidth reflects the true scale of the relationship under study that depends on heterogeneity of the spatial data.

We examined heterogeneity of surface and compared it with the optimal bandwidth. For this, we calculated the variation coefficient of the AGB sampling plots’ altitude within each of the altitudinal classes. Figure 8a displays the results of our calculation. The variability of terrain surface has a clear pattern which is reverse to the altitudinal patterns of the optimal bandwidth (compare Figures 8b and 5b). The largest optimal bandwidth (12,500 m) was found within the elevation class (800–1000 m) with the lowest heterogeneity of terrain surface (variation coefficient = 4.2). Heterogeneity of terrain surface increases downwards and upwards of this altitudinal class, whereas the optimal bandwidth decreases (Figure 8b). The terrain with the most heterogeneous surface was observed at the altitudes of above 1400 m (variation coefficient is about 9). These altitudes are characterized by the smallest optimal bandwidths (7500–8300 m).

The instability of the relationship between AGB and terrain elevation in spatial and altitudinal dimensions is indicated in the above results. The results also indicate that the scale effects observed in the AGB–altitude relationship along altitudinal transects stem from spatial non-stationarity in the relationship. Because of different heterogeneity of terrain
surface between localities, the optimal bandwidth, representing the true scale of the relationship, is a function of location. Moreover, in areas with diverse terrain conditions like the study area, the optimal bandwidth becomes a function of altitude, too. Scale variation, therefore, has a spatially and altitudinally variable effect on the relationship. All this casts doubt on modelling this relationship based on the global non-spatial regression approach and motivates us to consider geography matters and location as variables when analysing the influence of altitude on biomass in tropical rainforest.

7. Conclusions

The study investigated the influence of topography on the AGB of tropical rainforest in a region with diverse terrain conditions in Central Sulawesi, Indonesia, using autoregressive regression models based on the non-spatial global regression and the GWR. A number of issues in modelling AGB–altitude relationship were considered in this article.

An important contribution is the introduction of the local regression approach to investigate the relationship between altitude and forest biomass. The GWR framework provides greater local insight into understanding the spatio-altitudinal drifts in the relationship between the investigated variables. The results suggest that both the autoregressive term and the altitudinal gradient were highly variable in horizontal and vertical dimensions. The superiority of GWR over the non-spatial model with fixed parameter estimates is due to the consideration of the spatial variation of the biomass–altitude relationship. The non-spatial OLS regression ignores the location information and provides a false relationship. Thus, the OLS-based model obtained a positive altitudinal gradient for the AGB–altitude relationship representing a general increase of AGB with increasing terrain elevation, whereas the
GWR-based model revealed that the gradient is mostly positive at the altitudes below 1000 m and mostly negative at the altitudes above 1000 m signifying a high variability of the local estimates for the altitudinal gradient.

Another important issue addressed in this study is the application of GWR to find the most appropriate scale to analyse the terrain effects on AGB distribution. The determination of the most appropriate scale refers to the selection of the optimal bandwidth in GWR. The results have shown that the AGB–altitude relationship exists over the relatively short distances represented in the optimal bandwidth, which was found to vary with varying terrain elevation. The spatio-altitudinal variation of the optimal bandwidth was shown to be related to heterogeneity of terrain surface: higher heterogeneity enforces using the smaller bandwidth and vice versa.

And finally, an important advancement is the use of the GWR approach in exploring the implication of environmental factors on the AGB–altitude relationship. The study showed that the local spatio-altitudinal variability of the parameter estimates may be explained by the diverse patterns in the distribution of environmental factors and forest vegetation composition. Considering the environmental factors used in this study for analysis, the vertical patterns of the altitudinal gradient seem to be explained by the combination of temperature and solar radiation along altitudinal transects. Consequent improvement of vegetation growth conditions because of better combination of temperature and radiation leads to general biomass increase and is the basis for positive values of the altitudinal gradient at the altitudes of 400–1000 m, whereas ensuing deterioration of the environmental conditions at the altitudes of above 1000 m causes subsequent biomass decrease which was also reflected in negative values of the altitudinal gradient. The findings of the study demonstrated a very diverse and multifaceted character of the relationship between forest biomass and terrain at local scale and revealed the danger of generalization of this relationship through using single estimates for the altitudinal gradient or other parameters quantifying the effects of topography on vegetation.

Acknowledgements

This study is part of the German–Indonesian collaborative research project STORMA (Sonderforschungsbereich 552: ‘Stability of Rain Forest Margins in Indonesia’, subproject D6) funded by the German Research Foundation (DFG) and the financial support is gratefully acknowledged. The author gratefully thanks C. Zyschka, BSc, for her great help during the field survey in 2007. Acknowledgements are also extended to S. Erasmi, Ph.D. (Leader of subproject D6), as well as to M. Kessler, Ph.D., and J. Clough, Ph.D., who helpfully provided forest inventory data from their field surveys.

References


