DETERMINING ABOVEGROUND BIOMASS OF A FOREST RESERVE IN MALAYSIAN BORNEO USING K-NEAREST NEIGHBOUR METHOD

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SEO HS, PHUA MH, ONG R, CHOI B & LEE JS. 2014. Determining aboveground biomass of a forest reserve in Malaysian Borneo using k-nearest neighbour method. This study examined the use of the k-nearest neighbour (k-NN) method to estimate aboveground biomass of a logged-over tropical forest in Sabah, Malaysia. To estimate aboveground biomass, field data as well as digital number and normalised difference vegetation index (NDVI) values from Landsat TM-5 data were used to determine the optimum horizontal reference area and the number of reference sample plots (k). An accuracy assessment showed that enhancing the digital number value was superior to enhancing the NDVI value. Root mean square errors of no filtering and 3 × 3 filtering were minimum when k = 4 and k = 5 respectively, when a horizontal reference area of 17 km was applied. The bias was underestimated by 2.01 and 1.62 tonnes ha^{-1} for k = 4 and k = 5 respectively. Total aboveground biomass of the forest management unit estimated by enhancing the digital number value was 6,873,299 tonnes and average biomass density was 248.8 tonnes ha^{-1}. The results suggest that the k-NN method is an alternative way to estimate and map aboveground biomass of a forest management unit.

Keywords: Geographic information system (GIS), REDD+

SEO HS, PHUA MH, ONG R, CHOI B & LEE JS. 2014. Menentukan biojisim atas tanah hutan simpan di Malaysia Borneo menggunakan kaedah titik terdekat k (k-NN). Kajian ini menggunakan kaedah titik terdekat (k-NN) untuk menganggar biojisim atas tanah hutan tropika sudah kerja di Sabah, Malaysia. Bagi menganggar biojisim atas tanah, data lapangan serta nilai nombor digital dan indeks tumbuhan beza ternormal (NDVI) daripada data Landsat TM-5 diguna untuk menentukan kawasan rujukan mengufuk optimum dan jumlah plot sampel rujukan (k). Penilaian ketepatan menunjukkan bahawa keputusan lebih baik jika nombor digital ditingkatkan berbanding NDVI. Apabila kawasan rujukan mengufuk 17 km digunakan, nilai ralat punca min kuasa dua tanpa penurasan serta dengan penurasan 3 × 3 adalah minimum apabila nilai k masing-masing ialah 4 dan 5. Bias dikurang anggar masing-masing sebanyak 2.01 tan ha^{-1} and 1.62 tan ha^{-1} apabila k = 4 dan k = 5. Jumlah biojisim atas tanah unit pengurusan hutan yang dianggarkan dengan meningkatkan nilai nombor digital ialah 6,873,299 tan dan purata ketumpatan biojisim ialah 248.8 tan ha^{-1}. Keputusan mencadangkan bahawa kaedah k-NN dapat digunakan sebagai kaedah alternatif untuk menganggar serta memeta biojisim atas tanah unit pengurusan hutan.

INTRODUCTION

Forests contain 85% of the global aboveground carbon (Tan et al. 2007). Tropical forests are important as carbon sink and source of global carbon cycling. Tropical deforestation and degradation contribute 15–25% of global greenhouse emissions per year due to unprecedented changes in land cover and landuse (Malhi & Grace 2000, Houghton 2005). Recently, the REDD (reducing emissions from deforestation and forest degradation) programme, which evolved into REDD+ (reducing emissions from deforestation and forest degradation and carbon stock enhancement), has included forest-management activities which are considered important global mechanisms to reduce if not stop carbon emissions from deforestation and forest degradation in the tropics (Stern 2007). Although progress was made during negotiations at the United Nations Framework Convention on Climate Change (UNFCCC) Conference of the Parties, major efforts are still needed from the scientific community to develop effective and rigorous systems to monitor and predict changes in global forest carbon stocks and evaluate the consequences of different management strategies. Information on the amount

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and location of forest carbon at tier 3 necessitates the use of remote-sensing technology. The tier represents a level of methodological complexity for representing landuse areas. Tier 1 is the basic method, tier 2 intermediate and tier 3, most demanding in terms of complexity and data requirements. Tier 3 extends tier 2 by allowing landuse changes to be tracked on a spatial basis (IPCC 2006).

Field surveys undoubtedly produce the most accurate biomass information but are also the most labour intensive and time consuming. Moreover, it is difficult to conduct such surveys in inaccessible terrain and the resulting data are difficult to interpolate over spatially large areas (Phua & Saito 2003). Remote sensing with ground inventory data is a reliable approach for estimating forest biomass. Many forest biomass estimation studies have been carried out using medium-resolution satellite data such as Landsat, ALOS-PALSAR and Landsat ETM+ (Phua & Saito 2003, Alexandra et al. 2012). Previous remote-sensing studies of forest biomass estimated forest stock, leaf area index and stand age using regression analysis (Powell et al. 2010). Regression models for estimating aboveground biomass of tropical forests have resulted from original spectral bands or transformed vegetation indices from medium-resolution satellite data. However, such approaches tend to underestimate biomass content in tropical forests due to dense canopy structure (Gibbs et al. 2007).

Recent studies have utilised field surveys and remotely-sensed data to estimate forest biomass of unsurveyed areas or to increase statistical accuracy (Holmgren et al. 2000, Tokola 2000, Lee et al. 2004). In particular, the k-nearest neighbour (k-NN) method and the national forest inventory have been applied to estimate forest biomass and construct biomass thematics (Katila & Tomppo 2001, Makela & Pekkarinen 2004, Yim et al. 2007, Jung et al. 2010). High- and mid-resolution satellite images have been used to create carbon maps based on k-NN and linear regression analyses in a catchment of the Siberian forest tundra (Fuchs et al. 2009). The k-NN method has been used with satellite spectral bands and vegetation indices to estimate volume of forest stands and carbon storage (Franco-Lopez et al. 2001, Thessler et al. 2008, Yoo et al. 2011). Despite its potential, application of the k-NN method to estimate aboveground biomass of a tropical forest has been insufficient. In this study, we examined the use of k-NN method with geographic information system (GIS) and satellite data to estimate aboveground forest biomass of a production forest reserve in Sabah, Malaysia. The k-NN estimation results of the spectral bands and vegetation index were compared with GIS data.

MATERIALS AND METHODS

Study area

The study area, Tangkulap Forest Reserve (FR), is situated almost in the middle of Sabah, Malaysian Borneo (Figure 1). Tangkulap FR is a class II commercial forest reserve under the classification of the Sabah Forestry Department. Climate of this interior part of Sabah is characterised by frequent rainfall and high temperatures throughout the year. Tangkulap FR has an undulating to hilly topography and is dominated by lowland mixed dipterocarp forest with varying degrees of degradation.

The forest management unit of Tangkulap FR (27,550 ha) was licensed for conventional intensive logging in 1970 and was divided into 57 compartments. Forests in the Tangkulap FR were repeatedly logged until 2002 when the Sabah Forestry Department decided to pursue low-impact logging. Only one parcel of land is under conservation (293 ha). Since 2002, no harvesting has been conducted in Tangkulap FR. This management decision was encouraged by the success of Deramakot FR, located next to Tangkulap FR, in obtaining a sustainable forest management certification by the Forest Stewardship Council in 1997 (Lagan et al. 2007).

Field data

Figure 2 shows the methodology used in this study. Field data from 32 circular permanent sample plots, each with a radius of 20 m, were derived by stratified random selection. Within these plots, diameter at breast height (dbh) > 10 cm was measured for all trees in 2008. The dbh measurements were converted to aboveground biomass (AGB, dry weight in kg) for each individual tree using the allometric equation for tropical rain forests as follows (Brown 1997):

$$AGB = e^{-2.134 + 2.53 \times \ln(dbh)} \quad (1)$$

The data also included longitudinal and latitudinal positions for the centre of sample plots using global positioning system (GPS) devices. Field-measured biomass data were imported into ArcGIS 10.0 to combine with GIS data using coordinates (Table 1).

GIS and satellite data

GIS data that were used in this study included forest compartment and subcompartment maps,

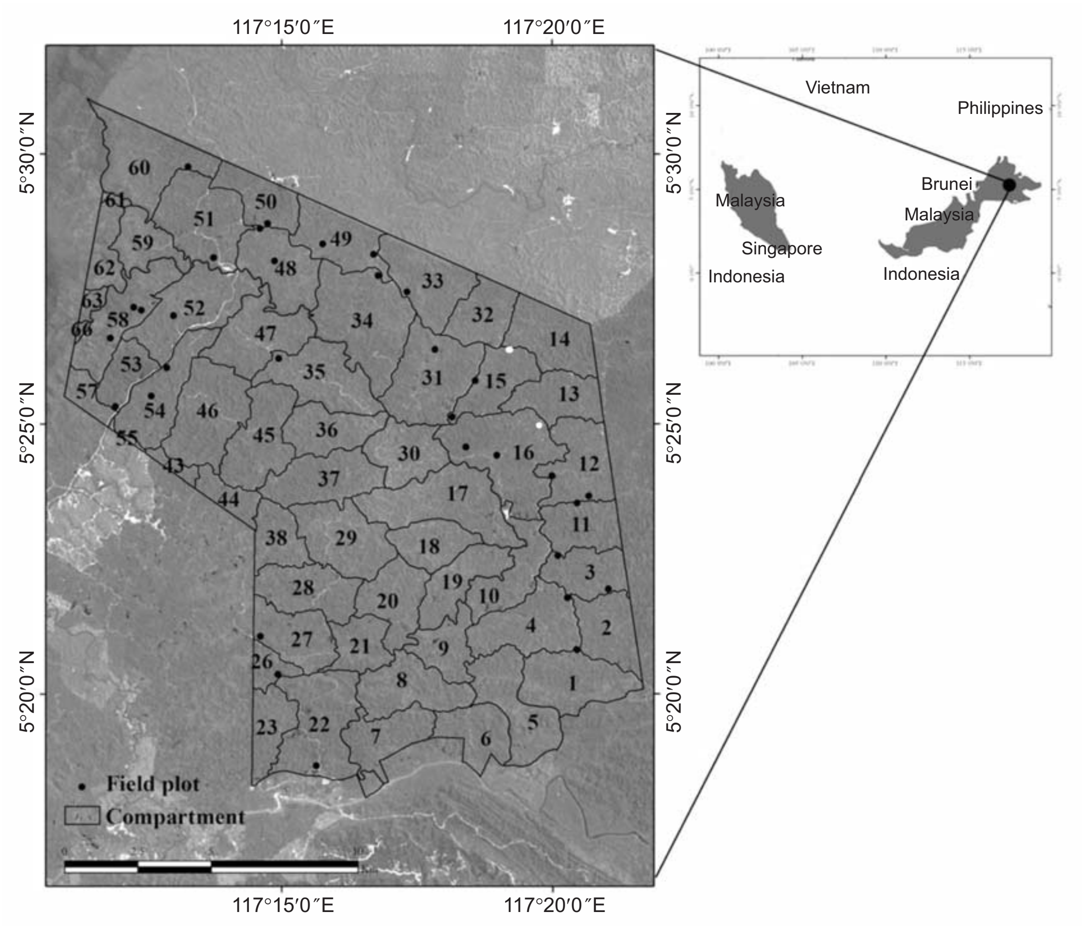

Figure 1 The Tangkalup Forest Reserve of Sabah in Malaysia

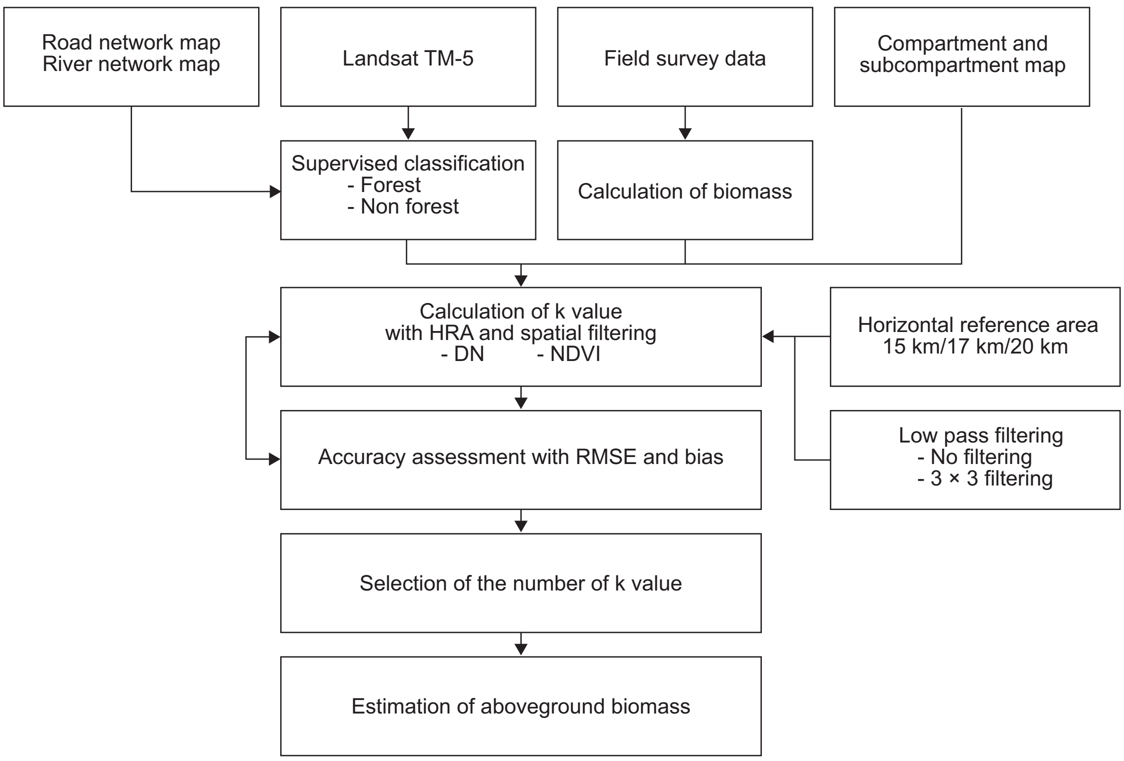

Figure 2 Schematic methodology for estimating aboveground biomass using k-NN algorithm; DN = digital number, NDVI = normalised difference vegetation index, RMSE = root mean square error

Table 1 Field sample plot numbers by aboveground biomass

Aboveground biomass (tonnes ha^{-1})	n
≤ 200	11
201–300	13
301–400	5
≥ 401	3
Total	32

road network maps and river network maps with a scale of 1:50,000. A Landsat 5 Thematic Mapper (TM) satellite image, acquired on 11 October 2009 (path/row = 117/56), was used to provide forest spectral information. TM sensor had a swath width of 185 km and temporal resolution of 16 days. The image consisted of seven bands and this study used the digital number values of six bands with a spatial resolution of 30 m. Band 6 (thermal infrared), which had 120 m spatial resolution, was excluded from our analysis.

Forest biomass estimation using the k-NN method

The k-NN method is a non-parametric estimation method and is well-known for classifying data from target sample plots (unobserved areas) to the most analogous data values of researched reference plots by utilising additional information such as satellite images (Tomppo 1990). An advantage of using k-NN method for forestry applications is that a precise estimate can be used instead of a regression model estimation because the method estimates target sample plots by referring to field survey plot data (Tomppo 1990, Yim et al. 2007).

Establishment of the reference sample plot

Estimating forest information in a target sample that is not surveyed using k-NN method requires selecting a reference sample (Tokola & Heikkilä 1997, Katila & Tomppo 2001). Reference sample plots was established based on degree of similarity between digital number values of each satellite image band for a target sample plot and a reference sample plot (Yim et al. 2009). This study employed the Euclidian distance equation to determine the degree of similarity (equation 2):

$$d_{t,r} = \sqrt{\sum_{i=1}^{m} (x_{i,t} - x_{i,r})^2} \qquad (2)$$

where $d_{t,r}$ = distance between target sample plots (t) and reference sample plots (r); $x_{i,t}$ and $x_{i,r}$ = digital number values of each band of t and r on a spectral band i; and m = number of satellite bands. Weight (w) was calculated based on $d_{t,r}$ as follows:

$$w_{t,r} = \frac{\frac{1}{d_{t,r}}}{\sum_{r=1}^{m} \frac{1}{d_{t,r}}} \qquad (3)$$

Unobserved area estimation ($\hat{y}_t$) was computed by the k-NN method using experimental value (y_r) and weighted value of each reference sample plot ($w_{t,r}$) (equation 4):

$$\hat{y}_t = \sum_{r=1}^{k} w_{t,r} \times y_r \qquad (4)$$

Many estimation studies have used image-transformation model such as vegetation index to estimate stock or forest biomass (Franco Lopez et al. 2001, Yim et al. 2009, Yoo et al. 2011). We applied Landsat TM digital number values and the normalised difference vegetation index (NDVI) to compare accuracy and estimate aboveground biomass. The NDVI is one of the most widely used parameters for estimating forest biomass production. The NDVI is calculated by near infrared band (NIR) and red bands (R) of Landsat TM images and is defined as:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \qquad (5)$$

Classification of horizontal reference area

In general, accuracy of estimated values using k-NN method is affected by the size of target area and the number of reference sample plots and their spatial distribution (Tokola & Heikkilä 1997, Tokola 2000, Yim et al. 2009, Jung et al. 2010). For this purpose, horizontal reference area was divided into three divisions (20, 17 and 15 km).

Spatial filtering

Spectral digital number values are affected by atmosphere, image sensor error, data transmission and reception noise problems, particularly if the forest is located in a mountainous area (Tokola & Heikkilä 1997). Spatial filtering is required to reduce influence of these factors. Spatial filtering refers to the mathematically defined kernels of variation during rapid increase or decrease of spatially consecutive pixels. Normal kernels have odd numbers such as 3 × 3 or 5 × 5. The kernel moves from pixel to pixel in an image and the central pixel value is computed from values of the member pixels. We applied a statistical verification process using the 3 × 3 filtering method to remove mixed-cell effects from digital number values.

Statistical verification

Cross-validation was employed to verify the estimates furnished by k-NN method. Optimum reference sample plot numbers (k) (Katila & Tomppo 2001, Yim et al. 2009) and overall accuracy were computed with a fifth matrix root mean square error (RMSE) and the bias for estimating capacity evaluation was computed using equations 6 and 7 (Franco Lopez et al. 2001, Yim et al. 2007):

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \qquad (6)$$

$$\text{Bias} = \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n} \qquad (7)$$

where y_i = forest biomass field data measurement, $\hat{y}_i$ = forest biomass estimates using k-NN method and n = number of reference sample plots.

Measurements and estimations of reference sample plots were separated into four classes and overall accuracies were computed and compared to evaluate biomass measurements estimated from the k-NN method.

RESULTS AND DISCUSSION

Optimum horizontal reference area and number of reference sample plots without filtering

Comparison of accuracy during changes in horizontal reference area

The average RMSE value of aboveground biomass using digital number values was lowest when horizontal reference distance was 17 km (100.8 tonnes ha^{-1}) followed by 20 km (101.7 tonnes ha^{-1}) and 15 km (103.8 tonnes ha^{-1}) (Figure 3a). In contrast, the RMSE of aboveground biomass using NDVI values was lowest when horizontal reference distance was 15 km (101.5 tonnes ha^{-1}) followed by 20 km (105.1 tonnes ha^{-1}) and 17 km (105.3 tonnes ha^{-1}) (Figure 4a). Previous studies have reported that RMSE tends to become smaller as horizontal reference area increases (Katila & Tomppo 2001). However, we found no significant difference in accuracy of RMSE when the horizontal reference area changed. Horizontal reference area of the minimum RMSE results in variations in forest structure, geographical conditions and sample plot plans (Katila & Tomppo 2001). Previous studies have been conducted at the national, city or county level whereas the present study used a small regional area as the analysis level. It seemed that using horizontal distance had little influence on the study results.

Selection of number of reference sample plots

Minimum RMSE of forest biomass based on the number of reference plots (k) decreased rapidly when k = 1–4 at 17 km horizontal reference area in the case of digital number. In contrast, RMSE increased when k was > 4. Thus, k = 4 was selected for the optimum reference plot where RMSE was 96.5 tonnes ha^{-1}. RMSE of NDVI at 15 km horizontal reference area decreased rapidly until k reached 1–3 and RMSE increased gradually when k was > 3. Thus, k = 3 was selected as the optimum reference plot where RMSE was 99.4 tonnes ha^{-1}. Reference plot k values were distributed broadly in previous studies based on target area size, but they mostly fell in the range 5–10 (Franco-Lopez et al. 2001, Katila & Tomppo 2001, Makela & Pekkarinen 2004, Fuchs et al. 2009, Jung et al. 2010). RMSE tended to decrease with increasing number of reference sample plots regardless of spatial filtering. This result was similar to those of Franco-Lopez et al. (2001) and Katila and Tomppo (2001). Bias for digital number values was underestimated in all sectors except for k = 1, indicating that bias was -2.0 tonnes ha^{-1} when k = 4. Bias for NDVI values showed similar tendency compared with that of digital number and the bias was -3.7 tonnes ha^{-1} when k = 3.

Optimum horizontal reference area and number of reference sample plots with filtering

Comparison of the accuracy during changes in horizontal reference area

The RMSE of aboveground biomass per ha using digital number values showed similar results

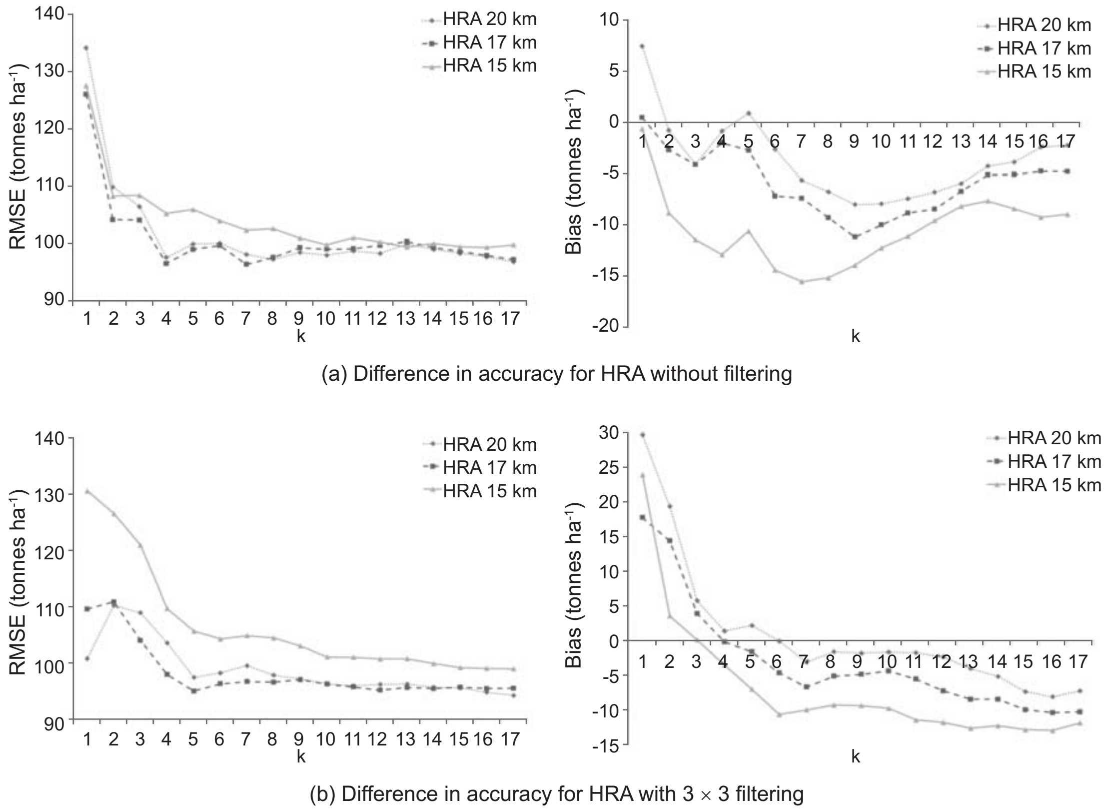

Figure 3 Root mean square error (RMSE) and bias for different horizontal reference area (HRA) divisions and neighbour plot numbers by original image (left: RMSE, right: bias)

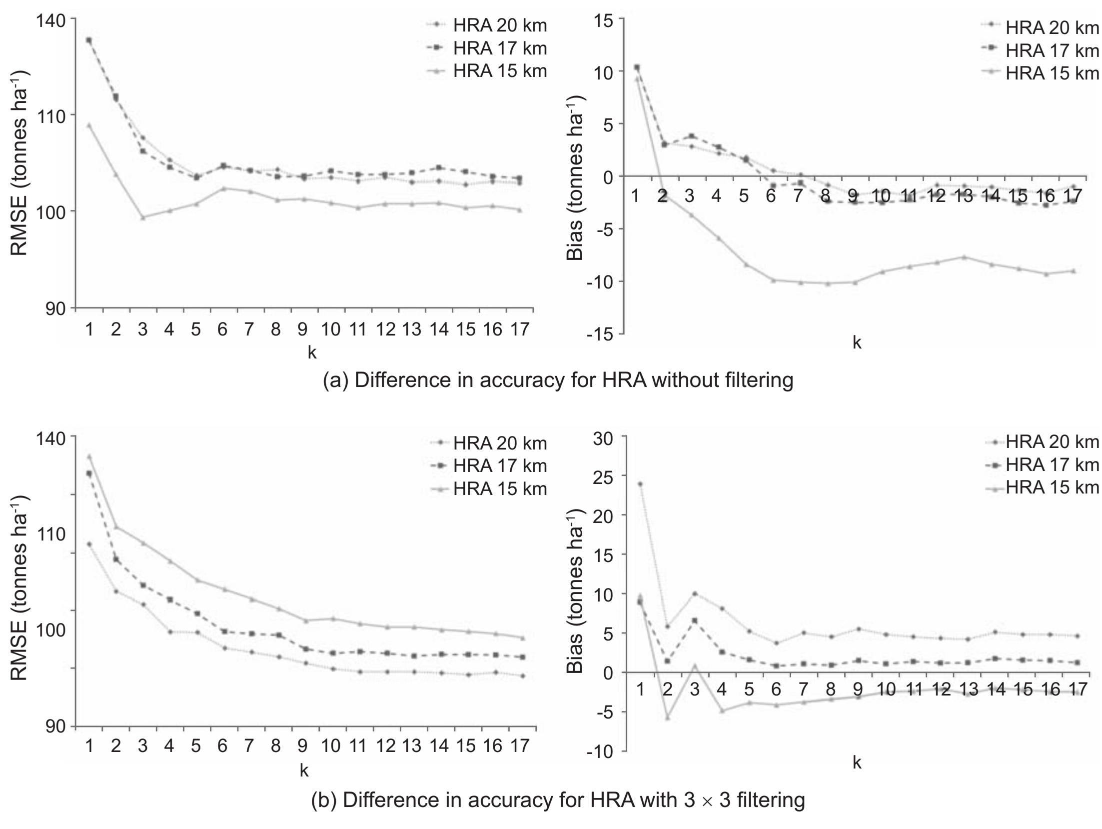

Figure 4 The root mean square error (RMSE) and bias for different horizontal reference area (HRA) divisions and neighbour plot numbers by normalised difference vegetation index (left: RMSE, right: bias)

compared with that of digital number without filtering. Average RMSE was better in the order 17, 20 and 15 km and the average RMSE values were 98.2, 98.8 and 106.5 tonnes ha^{-1} respectively (Figure 3b). Accuracy of RMSE improved by approximately 2.6 tonnes ha^{-1} after filtering. In contrast, RMSE of aboveground biomass per ha using NDVI was also similar to that of NDVI without filtering. Average RMSE was better in the order 20, 17 and 15 km, and the average RMSE values were 103.6, 107.5 and 112.6 tonnes ha^{-1} respectively (Figure 4b). RMSE increased by approximately 1.4 tonnes ha^{-1} after filtering.

Selection of the number of reference sample plots

Minimum RMSE of forest biomass based on reference plots decreased rapidly when k = 2–5 at horizontal reference area 17 km in the case of digital number (3 × 3 filtering). In contrast, RMSE increased when k > 5. Thus, k = 5 was selected for the optimum reference plot where RMSE was 95.1 tonnes ha^{-1}. RMSE improved by 1.4 tonnes ha^{-1} after 3 × 3 filtering. However, RMSE of NDVI (20 km horizontal reference area) decreased gradually until k = 11. Therefore, we selected k = 11 as the optimum reference plot where RMSE was 99.4 tonnes ha^{-1}.

Digital number bias tended to be underestimated with k > 4. The digital number bias was -1.6 tonnes ha^{-1} when k = 5. Bias accuracy improved by approximately 0.4 tonnes ha^{-1} after filtering whereas NDVI bias was overestimated in all sectors. NDVI bias was 4.6 tonnes ha^{-1} when k = 11.

Estimated aboveground biomass of the tropical forest

Total biomass estimated by k-NN method was 7,144,032 tonnes for digital number (no filtering) and 7,467,254 tonnes for NDVI (no filtering). Average forest biomass per ha was 258.6 and 270.3 tonnes ha^{-1} respectively. Compared with estimates conducted with reference plots, total biomass was overestimated by approximately 100,000–400,000 tonnes and average forest biomass per ha was overestimated by approximately 3–15 tonnes ha^{-1}. Biomass estimates were applied with spatial filtering. Biomass estimated for digital number was 6,873,299 tonnes (3 × 3 filtering) and for NDVI, the value was 7,091,543 tonnes (3 × 3 filtering). Average forest biomass per ha was 248.8 and 256.7 tonnes ha^{-1} for digital number and NDVI respectively (Figure 5, Table 2). Compared with estimates conducted with reference plots, the digital number estimate (3 × 3 filtering) was underestimated by approximately 200,000 tonnes and average forest biomass per ha was underestimated by approximately 6.3 tonnes ha^{-1}.

Forest biomass per ha in the forest management unit was 259.1 tonnes ha^{-1} for digital number (no filtering) and 263.4 tonnes ha^{-1} for NDVI (no filtering) (Figure 6). Biomass per ha in the forest management unit was 248.1 tonnes ha^{-1} for digital number (3 × 3 filtering) and 257.3 tonnes ha^{-1} for NDVI (3 × 3 filtering). Biomass decreased 11.0 and 6.1 tonnes ha^{-1} after 3 × 3 filtering.

Overall accuracy of the biomass estimated using k-NN method was 31–59%, which was comparable with the 41% result by Franco-Lopez et al. (2001). The producer's accuracy values for NDVI (no filtering = 38%, 3 × 3 filtering = 77%) and digital number (no filtering = 92%, 3 × 3 filtering = 100%) were highest at 201–300 tonnes ha^{-1} range (Table 3). According to the index transformation comparison, digital number (no filtering) with a basic band value was higher than NDVI by 25% (no filtering) in the overall accuracy. Additionally, overall accuracy of digital number value was 9% higher than that of NDVI when 3 × 3 filtering was

Table 2 Comparison of aboveground biomass (AGB) estimated from field survey and k-nearest neighbour (k-NN) method

Method		AGB (tonnes ha^{-1})				AGB (tonnes)
		Mean	Minimum	Maximum	Standard deviation	
Field survey (n = 32)		255.1	127.4	505.9	91.8	7,047,342
k-NN						
DN	No filtering	258.6	127.5	505.9	37.7	7,144,032
	3 × 3 filtering	248.8	127.4	505.9	37.3	6,873,299
NDVI	No filtering	270.3	127.4	505.9	80.5	7,467,254
	3 × 3 filtering	256.7	127.4	505.8	41.3	7,091,543

DN = digital number, NDVI = normalised difference vegetation index

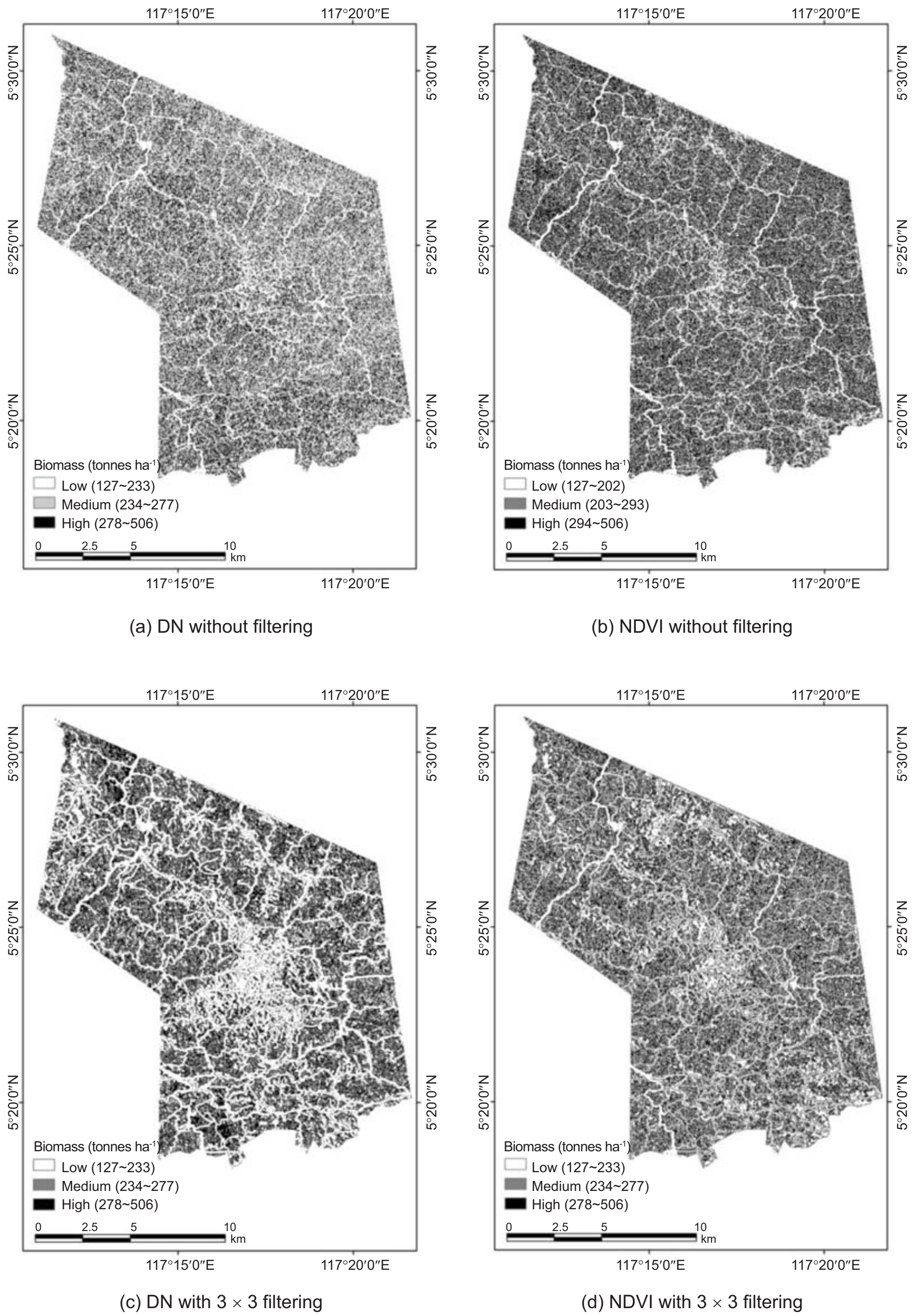

Figure 5 The distribution of aboveground biomass by image enhancement: low, medium and high values in biomass represent white, grey and black colour respectively; DN = digital number, NDVI = normalised difference vegetation index

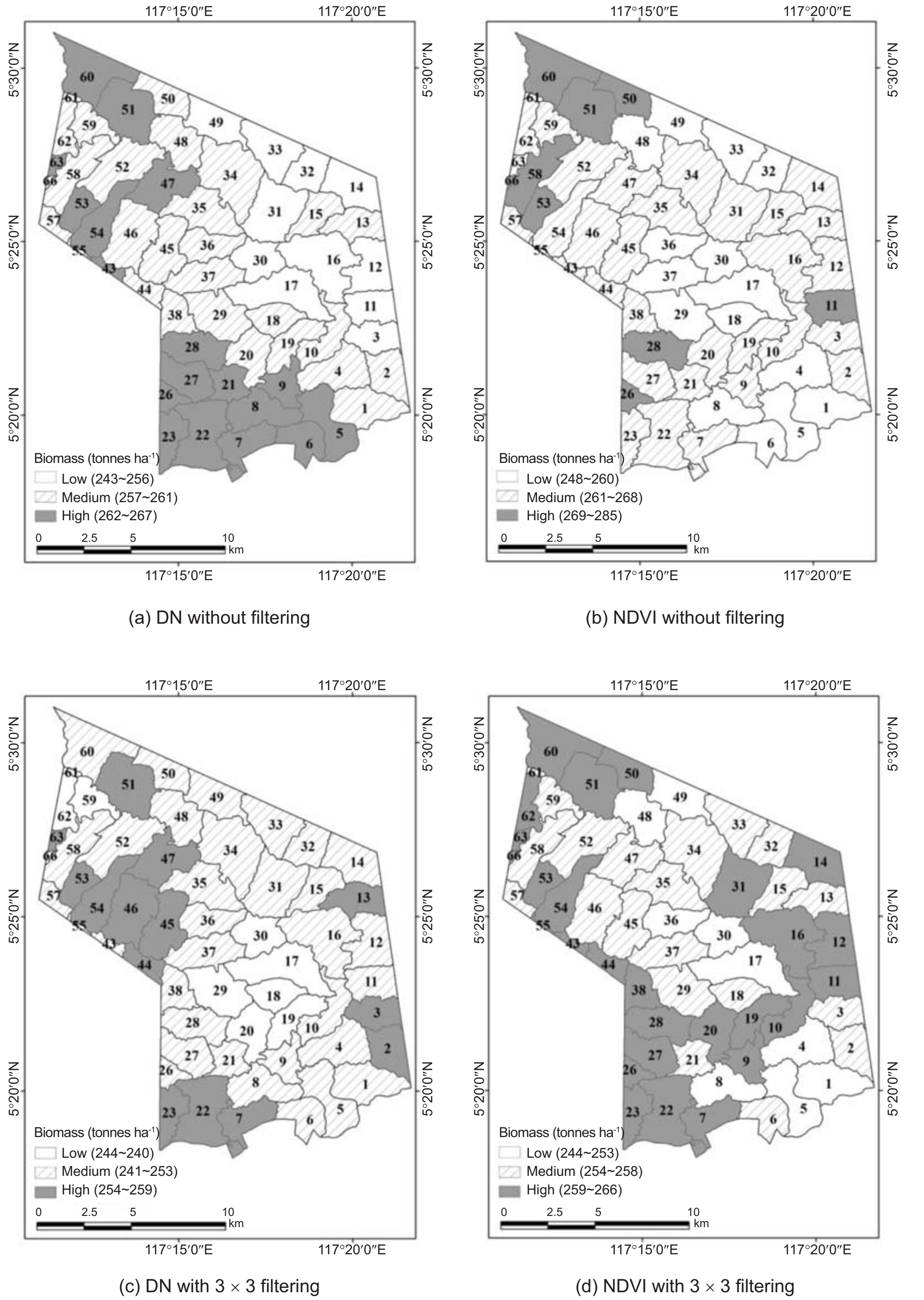

Figure 6 The distribution of aboveground biomass for each forest management unit after various image enhancement; DN = digital number, NDVI = normalised difference vegetation index

Table 3 Accuracy assessment of aboveground biomass (AGB) estimated from k-nearest neighbour (k-NN) method

Estimated AGB (tonnes ha $^{-1}$)			Reference AGB (tonnes ha $^{-1}$)					
			≤ 200	201–300	301–400	≥ 401	Total	Producer's accuracy
DN	No filtering	≤ 200	4	-	-	-	4	1.00
		201–300	7	12	4	2	25	0.48
		301–400	-	1	1	-	2	0.50
		> 401	-	-	-	1	1	1.00
		Total	11	13	5	3	32	
		User's accuracy	0.36	0.92	0.20	0.33		0.56
	3 × 3 filtering	< 200	4	-	-	-	4	1.00
		201–300	7	13	4	2	26	0.50
		301–400	-	-	1	-	1	1.00
		> 401	-	-	-	1	1	1.00
		Total	11	13	5	3	32	
		User's accuracy	0.36	1.00	0.20	0.33		0.59
NDVI	No filtering	≤ 200	4	2	-	-	6	0.67
		201–300	3	5	3	1	12	0.42
		301–400	3	6	-	1	10	0.00
		> 401	1	-	2	1	4	0.25
		Total	11	13	5	3	32	
		User's accuracy	0.36	0.38	0.00	0.33		0.31
	3 × 3 filtering	< 200	4	-	-	1	5	0.80
		201–300	6	10	4	1	21	0.48
		301–400	1	3	1	-	5	0.20
		> 401	-	-	-	1	1	1.00
		Total	11	13	5	3	32	
		User's accuracy	0.36	0.77	0.20	0.33		0.50

applied. This result was similar to that of Yoo et al. (2011) while Franklin (1986) reported no correlation between spectrum values and stands with closed crowns which resulted in an estimation error.

CONCLUSIONS

We estimated the aboveground biomass and distribution of tropical forest in a production forest reserve using k-NN method in combination with field survey data, Landsat TM-5 image spectral bands and GIS data. The k-NN method determined the number of reference plots based on RMSE and bias to select an optimum k value according to the horizontal reference area settings and filtering. NDVI (3 × 3 filtering) had smaller RMSE values as the horizontal reference area range decreased, whereas digital number (3 × 3 filtering) value showed the opposite tendency. RMSE had a tendency to decrease as k value increased and the effect of filtering was significant. Furthermore, RMSE and bias analyses showed that applying spectral band using k-NN method was more effective than applying NDVI. Therefore, we need to further examine how these changes (e.g. sample number and location) affect the accuracy of results obtained using k-NN method with different sample plot numbers and locations. Remotely-sensed data such as Aster and Spot that have similar resolution with Landsat TM-5 should also be considered in developing alternative methods for biomass estimation. Nevertheless, k-NN method with the existing field survey data is useful to estimate aboveground biomass of unobserved areas for mapping forest management or regional units. Therefore, applying this approach in a multitemporal context can be an effective tool that allows measurements of carbon emissions and verification of the reduction in emissions.

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REFERENCES

Alexandra CM, Joshua BF & Yadvinder M. 2012. Evaluating the potential to monitor aboveground biomass in forest and oil palm in Sabah, Malaysia, for 2000–2008 with Landsat ETM+ and ALOS-PALSAR. *International Journal of Remote Sensing* 33: 3614–3639.

Brown S. 1997. *Estimating Biomass and Biomass Change of Tropical Forests: A Primer*. FAO Forestry Paper 134. Food and Agriculture Organization of the United Nations, Rome.

Franco-Lopez H, Ek AR & Bauer ME. 2001. Estimation and mapping of forest stand density, volume and cover type using the k-nearest neighbors method. *Remote Sensing of Environment* 77: 251–274.

Franklin J. 1986. Thematic mapper analysis of coniferous structure and composition. *International Journal of Remote Sensing* 7: 1287–1301.

Fuchs H, Magdon P, Kleinn C & Flessa H. 2009. Estimating aboveground carbon in a catchment of the Siberian forest tundra: combining satellite imagery and field inventory. *Remote Sensing of Environment* 113: 518–531.

Gibbs HK, Brown S, Niles JO & Foley JA. 2007. Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environmental Research Letters* 2. Doi:10.1088/1748-9326/2/4/045023.

Holmgren J, Joyce S , Nilsson M & Olsson H. 2000. Estimating stem volume and basal area in forest compartments by combining satellite image data with field data. *Scandinavian Journal of Forest Research* 15: 103–111.

Houghton RA. 2005. Tropical deforestation as a source of greenhouse gas emissions. Pp 13–21 in Moutinho P & Schwartzman S (eds) *Tropical Deforestation and Climate Change*. Instituto de Pesquisa Ambiental Amazônia, Belém.

IPCC (Intergovernmental Panel on Climate Change). 2006. *006 IPCC Guidelines for National Greenhouse Gas Inventories*. Institute for Global Environmental Strategies, Hayama.

Jung JH, Heo J, Hong YS, Kim KM & Lee JB. 2010. Estimation of aboveground biomass carbon stock in Danyang area using k-NN algorithm and Landsat TM seasonal satellite images. *Journal of the Korean Society for Geospatial Information System* 18: 119–129.

Katila M & Tomppo E. 2001. Selecting estimation attributes for the Finnish multi source national forest inventory. *Remote Sensing of Environment* 76: 16–32.

Lagan P, Mannan S & Matsubayashi H. 2007. Sustainable use of tropical forests by reduced-impact logging in Deramakot Forest Reserve, Sabah, Malaysia. *Ecological Research* 22: 414–421.

Lee JY, Yang DY, Kim JY & Chung GS. 2004. Application of Landsat ETM+ image indices to classify the wildfire area of Gangneung, Gangwon Province, Korea. *Journal of Korean Earth Science Society* 25: 754–763.

Makela H. & Pekkarinen A. 2004. Estimation of forest stand volumes by Landsat TM imagery and stand-level field-inventory data. *Forest Ecology and Management* 196: 245–255.

Malhi Y & Grace J. 2000. Tropical forests and atmospheric carbon dioxide. *Trends in Ecology and Evolution* 15: 332–337.

Phua MH & Saito H. 2003. Estimation of biomass of a mountainous tropical forest using Landsat TM data. *Canadian Journal of Remote Sensing* 29: 429–440.

Powell SL, Cohen WB, Healey SP, Kennedy RE, Moisen GG, Pierce KB & Ohmann JL. 2010. Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: a comparison of empirical modeling approaches. *Remote Sensing of Environment* 114: 1053–1068.

Stern N. 2007. *The Economics of Climate Change: The Stern Review*. Cambridge University Press, Cambridge.

Tan KT, Lee KT, Mohamed AR & Bhatia S. 2007. Palm oil: addressing issues and towards sustainable development. *Renewable and Sustainable Energy Reviews* 13: 420–427.

Thessler S, Sesnie S, Ramos Bendana ZS, Roukolainen K, Tomppo E & Finegan B. 2008. Using k-NN and discriminant analyses to classify rain forest types in a Landsat TM image over northern Costa Rica. *Remote Sensing of Environment* 112: 2485–2494.

Tokola T. 2000. The influence of field sample data location on growing stock volume estimation in Landsat TM based forest inventory in eastern Finland. *Remote Sensing of Environment* 74: 422–431.

Tokola T & Heikkilä J. 1997. Improving satellite image based forest inventory by using a priori site quality information. *Silva Fennica* 31: 67–78.

Tomppo E. 1990. Satellite image-based national forest inventory of Finland. *International Archives of Photogrammetry and Remote Sensing* 28: 419–424.

Yim JS, Kong GS, Kim SH & Shin MY. 2007. Forest thematic maps and forest statistics using the k-Nearest Neighbor technique for Pyeongchang-Gun, Gangwon-do. *Journal of Korean Forest Society* 96: 259–268.

Yim JS, Han WS, Hwang JH, Chung SY, Cho HK & Shin MY. 2009. Estimation of forest biomass based upon satellite data and national forest inventory data. *Korean Journal of Remote Sensing* 25: 311–320.

Yoo SH, Heo J, Jung JH, Han SH & Kim KM. 2011. Estimation of aboveground biomass carbon stock using Landsat TM and ratio images: k-NN algorithm and regression model priority. *Journal of the Korean Society for Geospatial Information System* 19: 39–48.