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Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions

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Abstract

The full realization of the potential of remote sensing as a source of environmental information requires an ability to generalize in space and time. Here, the ability to generalize in space was investigated through an analysis of the transferability of predictive relations for the estimation of tropical forest biomass from Landsat TM data between sites in Brazil, Malaysia and Thailand. The data sets for each test site were acquired and processed in a similar fashion to facilitate the analyses. Three types of predictive relation, based on vegetation indices, multiple regression and feedforward neural networks, were developed for biomass estimation at each site. For each site, the strongest relationships between the biomass predicted and that measured from field survey was obtained with a neural network developed specifically for the site (r>0.71, significant at the 99% level of confidence). However, with each type of approach problems in transferring a relation to another site were observed. In particular, it was apparent that the accuracy of prediction, as indicated by the correlation coefficient between predicted and measured biomass, declined when a relation was transferred to a site other than that upon which it was developed. Part of this problem lies with the observed variation in the relative contribution of the different spectral wavebands to predictive relations for biomass estimation between sites. It was, for example, apparent that the spectral composition of the vegetation indices most strongly related to biomass differed greatly between the sites. Consequently, the relationship between predicted and measured biomass derived from vegetation indices differed markedly in both strength and direction between sites. Although the incorporation of test site location information into an analysis resulted in an increase in the strength of the relationship between predicted and actual biomass, considerable further research is required on the problems associated with transferring predictive relations.

Keywords: Biomass; Landsat TM data; Remote sensing

1. Introduction

Satellite remote sensing has considerable potential for the provision of information on the terrestrial environment at a range of spatial and temporal scales. Consequently, remote sensing has a major role to play in monitoring environmental change and is especially a principal focus for the collection of data over large areas (Cihlar, 2000; Franklin & Wulder, 2002). There are, however, many problems in the use of remote sensing. One major problem commonly encountered is that of generalizing or transferring knowledge and methods derived from a remotely sensed image over space and time (Cohen, Maiersperger, Spies, & Oetter, 2001; Nagendra, 2001; van Collie, Verbeke, De Wulf, & Kerckhoff, 2001; Wilkinson, 1997; Woodcock, Macomber, Pax-Lenney, & Cohen, 2001). This problem substantially limits the contribution remote sensing can make to environmental studies (Verstraete, Pinty, & Myneni, 1996).

Remote sensing has been widely used in the study of forested environments (Boyd & Danson, in press; Franklin, 2001; Sader, Hayes, Hepinstall, Coan, & Soza, 2001). Despite the long history of research focused on forests and an impressive set of exemplar studies, remote sensing has often not been able to provide the specific environmental information required by the research and user communities. For example, tropical forests play a major but uncertain role in the global carbon cycle and remote sensing has the potential to provide some of the important information required to further our understanding of the topic (Dixon et al., 1994; Royal Society, 2001). Currently,

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the greatest uncertainty in understanding the role of tropical forests in the carbon cycle is associated with the biomass of the forests (Houghton et al., 2000; Keller, Palace, & Hurtt, 2001). Although many studies have investigated the ability to estimate the biomass of forests, including tropical forests, from remotely sensed data, many problems have been encountered. These studies have also estimated biomass with varying degrees of success (e.g. Castro, Sanchez-

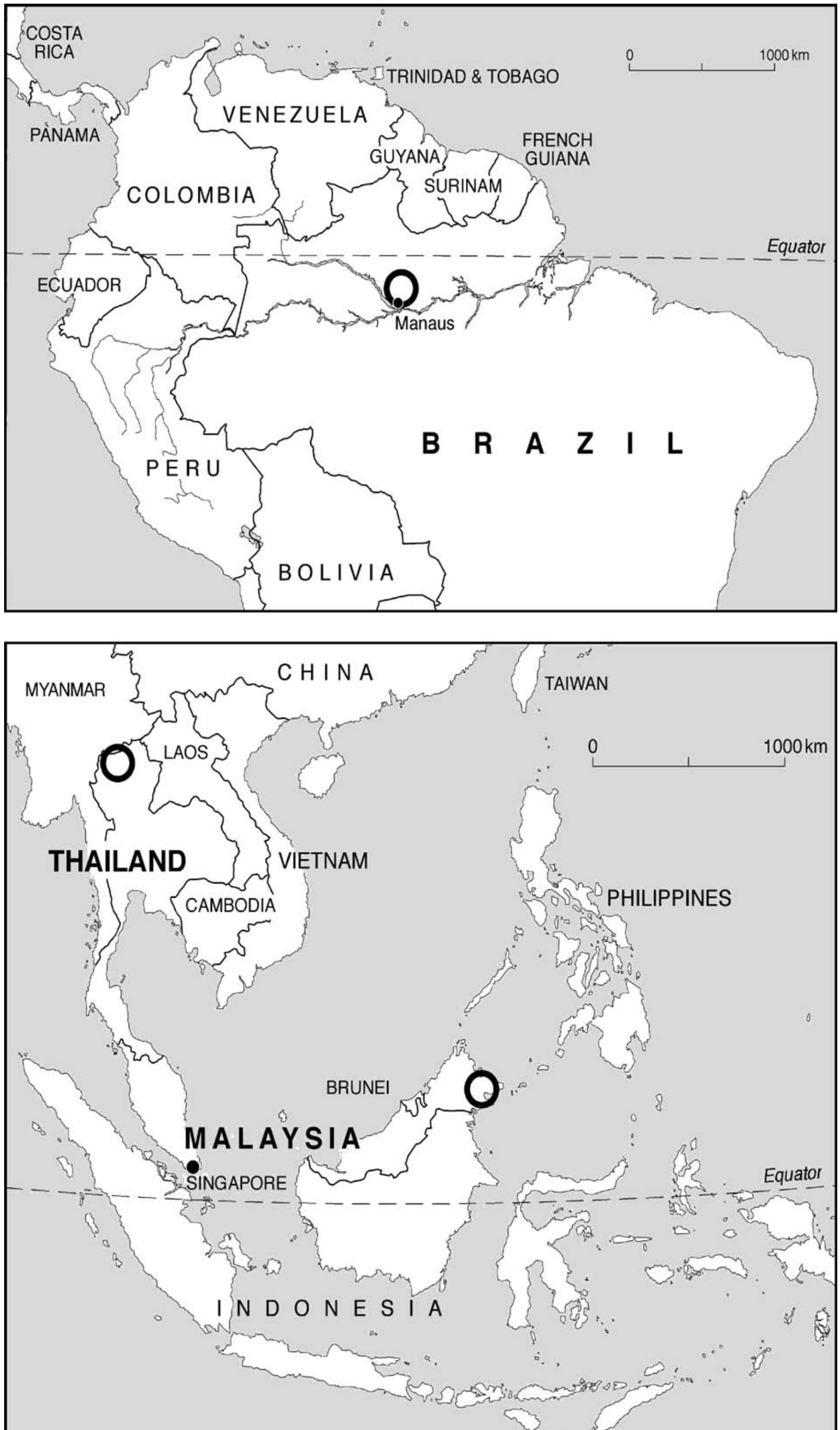

Fig. 1. Test sites. The circles highlight the location of the test sites.

Azofeifa, & Rivard, in press; Foody et al., 2001; Sader, Waide, Lawrence, & Joyce, 1989; Steininger, 2000; Tokola, Sarkeala, & Van der Linden, 2001). Of key concern here is that while there are case studies that demonstrate the accurate estimation of forest biomass from remotely sensed imagery, the methods used may not generalize accurately in space and time. That is, a relationship derived for the accurate prediction of biomass at one site or time period may not yield accurate predictions when applied to imagery of another site and/or acquired at another time.

Several forms of generalization problem can be identified (Woodcock et al., 2001). The components of this problem are typically spatial (e.g. generalization within an image or between imagery of different locations) and temporal (e.g. generalization between images of one location acquired over a period of time), and may include complications arising from issues such as variation in sensor (e.g. a time series of fine spatial resolution data may comprise SPOT HRV, Landsat MSS, TM and ETM + data, etc.), viewing conditions (e.g. due to variation in sensor view angle or solar elevation, etc.) and atmospheric properties. Irrespective of their origin, these problems limit the ability to transfer predictive relations from the situation in which they were developed, greatly limiting the value of remote sensing. In relation to studies of tropical forests, the problems of transferability may be particularly severe. The small probability of obtaining cloud-free imagery, for example, tends to necessitate the use of pragmatic rather than ideal approaches. Thus, rather than use only data from one sensor to reduce inter-sensor problems, studies may have to use whatever data sets are available.

Since it is difficult to obtain high quality remotely sensed data with appropriate corresponding ground data sets for tropical forests, it is highly desirable that any relation that is derived which yields accurate predictions of biomass is transferable. Indeed, an overall vision is for an operational method of biomass estimation to be established that may be adopted by nonspecialists, free from technical concerns linked to the particular data sets used. To reach this situation, the transferability of predictive relations must be assessed and problems encountered solved. The aim of this paper is to address an important part of this topic, namely to investigate the transferability of relations for the prediction of tropical forest biomass from Landsat TM data between distant sites, a manifestation of the across-region generalization problem discussed by Woodcock et al. (2001).

2. Test sites and data

Three test sites were used (Fig. 1). These test sites all lie within the moist zone tropical forest region and were located near Manaus (Brazil), around the Danum Valley Field Centre (Malaysia) and at a site within the Khun Khong catchment (Thailand). At each site, ground and Landsat TM data sets were acquired as close together as was practicable to facilitate meaningful comparisons (Table 1).

Table 1
Ground and remotely sensed data sets

Site	Field survey	Remotely sensed data	Number of plots total (used)	Biomass range (Mg ha^{-1})
Brazil	July/August 1993 and 1995	Landsat 4 July 1992	27 (27)	76.3–420.6
Thailand	December 1997	Landsat 5 January 1997	65 (40)	29.2–329.4
Malaysia	November and December 1997	Landsat 5 March 1997	52 (28)	64.9–639.0

Note that the plots in Brazil were located after the acquisition of the imagery and so cloud affected areas could be avoided, ensuring that the data for all plots could be used in the analysis.

2.1. Ground data

For each site, the biomass (Mg ha^{-1}) of each sample plot was taken to be the sum of the total above ground biomass of its component trees (kg) estimated using standard allometric equations. To enhance the direct comparability of the data sets, a standardized methodology was, as far as possible within the constraints of the project, used with the data acquired at each site. It was, however, impossible to use the exact same methods due to important differences in the data sets acquired at each site which are outlined below (e.g. inter-site differences in tree composition and tree size threshold used in ground data collection, etc.).

The data from Brazil relate to forests that were located to the north and northeast of Manaus. Here, data from 27 plots surveyed in the field in 1993 and 1995 were used (Lucas, Honzak, do Amaral, Curran, & Foody, 2002). Most plots were located within the INPA and Smithsonian Institute's Biological Dynamics of Forest Fragments Project (BDFFP) study area, ~ 70 km north of Manaus, with five located within the Ducke and Elger reserves (Lucas et al., 2002). Each plot was located within a large area (>1 ha) of homogeneous forest and covered a rectangular area of 100×10 m (0.1 ha), except for one plot that, due to sampling problems, was 20×15 m. The plots were located to sample a range of different types of forest which differed considerably in biomass. For every tree with a diameter at breast height (dbh, cm) >3 cm, the tree species was identified and its dbh (or diameter above any buttress, etc.) and, if practicable, height (H, m) estimated in the field. The above ground biomass of each tree in the plots was estimated using the field measurements of dbh, height and specific density of the wood (S, g cm^{-3}), when known, using the appropriate moist life zone regression equation provided by Brown, Gillespie, and Lugo (1989) (Table 2). Further details on these data may be found in Lucas et al. (2002).

The test site in Thailand was located within the Khun Khong Watershed Management Unit in the northern part of the country, located approximately 100 km northwest of Chiang Mai. The area was largely undeveloped with 75% of the 1956 ha site given over to a plantation of *Pinus kesiya*

Table 2
Equations used in the derivation of the ground data

Test site	Equation
Brazil	biomass = 38.4908 − 11.7883(dbh) + 1.1926(dbh)^2
	biomass = exp(− 3.1141 + 0.9719ln((dbh)^2H)
	biomass = exp(− 2.4090 + 0.9522ln((dbh)^2HS)
	H = exp(1.0710 + 0.5667ln(dbh))
Thailand (deciduous)	biomass = exp(− 2.134 + 2.530ln(dbh))
Thailand (coniferous)	biomass = exp(− 1.170 + 2.119ln(dbh))
Malaysia	biomass = exp(− 2.134 + 2.530ln(dbh))

Note H represents the height estimates derived from a set of family-specific height estimation curves.

(Royle ex Gordon). At this site, a range of tree age classes was present with trees planted 32, 28, 25 and 19 years prior to the sampling in 1997. The remainder of the area was covered mainly with a variety of tropical deciduous tree species. A systematic sampling scheme was used to locate 65 plots across this site. The plots and biomass-sampling scheme adopted were different from those used in Brazil. At this test site, the dbh of all trees with a dbh>10 cm within a circular plot with a radius of 12.62 m (0.05 ha) was measured (Pelz, 2000). Each plot was positioned with the aid of a GPS to help locate it within the imagery. The field data acquired at this site were separated into deciduous and coniferous species and the total above ground biomass of the each tree estimated using the appropriate moist life zone regression equation of Brown (1997) (Table 2).

The Malaysian test site comprised the forests surrounding the Danum Valley Field Centre in north eastern Borneo. This site contains forests that have been logged at differing times and intensities as well as regions of unlogged primary forest. Both the primary and logged forests were populated predominantly by dipterocarp species with the main canopy often dominated by several fast growing *Shorea* species. The canopy itself has a rough uneven appearance with some gaps and the presence of many lianas (Newbery, Campbell, Lee, Ridsdale, & Still, 1992; Newbery, Kennedy, Petol, Madani, & Ridsdale, 1999). Similar field methods to those used in Thailand were adopted at this test site (Pelz, 2000). A stratified random-sampling design was, however, used in determining the location of the plots. The strata used were contiguous tracts of forest defined by past land use, with the date of logging activity or preservation status used as discriminating attributes. In each stratum, five sample plots were located, except for one logged region in which two additional sample plots were established. In total, data were acquired for 52 sample plots during field surveys in 1997. At each sample plot, the biomass of every tree with a dbh>10 cm lying within the circular 0.05-ha plot was estimated using the same, non-conifer, equation used at the Thailand site (Table 2).

2.2. Remotely sensed data

For each test site, a Landsat TM image was acquired (Table 1). The imagery of each site was selected on the basis of temporal coincidence with the ground data and degree of cloud cover. Although the time period between image and ground data acquisition was longer than desired no major changes in the intervening periods were anticipated as the forests are not seasonal and monitored frequently, allowing the identification and removal of any areas of, for example, anthropogenically induced change. Due to their coarse spatial resolution (120 m) relative to the size of the ground data plots, the data acquired in TM band 6 were not used. Although it may be tempting to minimally process remotely sensed data (e.g. Muldavin, Neville, & Harper, 2001), pre-processing, particularly to achieve some form of radiometric standardization, is generally required in analyses based upon multiple data sets (Du, Teillet, & Cihlar, 2002; Garcia-Haro, Gilabert, & Melia, 2001; Helmer, Brown, & Cohen, 2001) and so undertaken here, using, as far as possible with the resources available, a consistent approach.

3. Pre-processing

Standard techniques were used to pre-process the Landsat TM data acquired of each test site. This pre-processing was required to bring the data to a format suitable for quantitative analysis and, in particular, to enhance direct inter-site comparability. Four main pre-processing steps involving radiometric, atmospheric, geometric and topographic correction were applied to the data acquired at each test site (except for the topographically flat site in Brazil for which a topographic correction was unnecessary). In each pre-processing step, methods commonly used in remote sensing were employed.

As an initial step, the images were radiometrically corrected. The imagery acquired of each test site depicted the relative variation in land surface remotely sensed response. Often such data are inappropriate for quantitative analysis and comparison and so some form of radiometric calibration or normalization is required (e.g. Du et al., 2002; Garcia-Haro et al., 2001). Thus, the relative data on surface reflectivity, manifest in the image digital numbers (DN), were converted into an absolute form, reflectance, on the assumption that this would aid inter-site comparison and the transferability of relations derived (Cohen et al., 2001). The first step in this process involved the calibration of the imagery using the post-launch calibration coefficients (Chavez, 1989; Price, 1987) to convert DN to top of the atmosphere radiance. This was achieved by applying

$$L_s = (\mathrm{DN} - \mathrm{offset})/\mathrm{gain}$$

where L_s represents the at-satellite spectral radiance in the specified waveband (W m^{-2} sr^{-1} μm^{-1}), and the gain and offset are the appropriate values for the sensor in the specified waveband (Mather, 1999).

An atmospheric correction was undertaken on each data set to compensate for the effects of the atmosphere on the measured remotely sensed responses. Although many of the main atmospheric problems have been effectively circumvented by using only relatively cloud-free and haze-free images of the test sites, atmospheric correction was prudent to facilitate transferability. While physically based radiation transfer modeling may be the most accurate means of correcting for atmospheric effects such methods require information on atmospheric properties that, as here, are typically unavailable. Furthermore, simple methods are often very effective for atmospheric correction of remotely sensed data (Song, Woodcock, Set, Pax-Lenney, & Macomber, 2001).

Consequently, a simple image-based atmospheric correction procedure was used. This was the modified dark object subtraction technique proposed by Chavez (1996). In this, the radiance measured from a dark object in shadow was assumed to have arisen from atmospheric scatter (path length, L_{HAZE}) and that the dark object had a minimum reflectance of 1%. L_{s} was converted to the apparent terrain surface radiance in the selected waveband, L_{T}, through

$$L_{\mathrm{T}} = (L_{\mathrm{s}} - L_{\mathrm{HAZE}})/\cos z$$

where z is the solar zenith angle.

The data for each test site were geometrically transformed and registered to a standard local map projection to facilitate linkage with the ground data. For each site, this was achieved with the aid of a set of ground control points (GCPs) to allow the definition of a mathematical transformation equation. The target was to register the image of each site to the reference projection with an estimated error of < 30 m (1 pixel). Nearest neighbor resampling was used in all of the geometrical transformations in order to minimize changes to the statistical properties of the data sets.

For the Malaysian test site, the GCPs were located mainly at road and river junctions to aid identification in the imagery and positioned with the aid of a GPS. A total of 11 GCPs were used to derive a first order polynomial transformation equation that re-projected the data with an estimated RMS error of 18 m.

For the Thailand site, ground control points were derived from 1:50 000 topographic maps. A total of 10 GCPs were used in a first order polynomial transformation that had an estimated RMS error of 28 m.

At the Brazilian test site, the image was co-registered to a Landsat TM image of the site that had previously been geometrically corrected (Lucas et al., 2002). Here, 20 GCPs were used to derive a first-order polynomial transformation equation to geometrically transform the TM data used in this study to the other image with an RMS error of 14 m.

The data for each site were, if necessary, corrected for topographic effects. This correction was required for the data acquired of the test sites in Thailand and Malaysia where, unlike the essentially flat Brazilian test site, the variation in surface topography was considerable. For the two Southeast Asian sites, the correction was required to reduce the effect of topographically induced variations in the angular geometry between the Sun, target and sensor. Due to this topographic variability, the individual facets of the landscape at the test sites were viewed under different angular geometries and consequently similar targets on different facets could have dissimilar spectral responses. A variety of approaches exist to correct for topographic effects. Here, a digital terrain model, derived for each of the Southeast Asian test sites by digitizing contours from 1:50 000 scale topographic maps, was used to correct the data. The method used was that presented by Ekstrand (1996). In this method, the amount of radiation from the Sun incident on a slope was taken to be directly proportional to the cosine of the incident angle i (the angle between the normal to the pixel and the solar beam). This was calculated from

$$\cos i = \cos e \cos z + \sin z \cos(\phi_{\mathrm{s}} - \phi_{\mathrm{n}})$$

where e is the terrain slope, ϕ_{s} the solar azimuth angle and ϕ_{n} the slope aspect. The topographic correction was achieved by

$$L_{\mathrm{H}} = L_{\mathrm{T}} \cos z / \cos i$$

where L_{H} is the radiance observed for a horizontal surface (i.e. the topographically corrected data). This approach may be refined to accommodate non-Lambertian reflectance by the integration of Minnaert constants (Meyer, Itten, Kellenberger, Sandmeier, & Sandmeier, 1993; Tokola et al., 2001) but since their calculation is problematical (Bishop & Colby, 2002; Mather, 1999) they were not used in this study.

The final pre-processing step was to convert L_{H} to reflectance (%) through

$$\text{Reflectance} = \pi d^2 L_{\mathrm{T}} / E_{\mathrm{s}} \cos z$$

where d is the Earth–Sun distance in astronomical units and E_{s} is the exoatmospheric solar irradiance for a specified waveband (W m^{-2} sr^{-1} $\mu\mathrm{m}^{-1}$).

4. Biomass prediction from the pre-processed data

At each site, the pixel containing a sample plot was identified and the reflectance in all six non-thermal Landsat TM bands extracted for the analyses. Together with the ground data on plot biomass, these spectral data were used to derive and evaluate a set of predictive relations for biomass estimation. In total, 144 plots had been surveyed in the field. Unfortunately, problems such as cloud and cloud shadow necessitated the exclusion of 49 plots, leaving 95 for the analyses.

Many approaches may be used for the prediction of biomass from remotely sensed data. Here, attention is focused on three that have been used previously to differing extents and degrees of success.

Biophysical properties have most commonly been estimated from remotely sensed data through the use of a vegetation index. A wide range of vegetation indices have been used in remote sensing for the estimation of biophysical properties (Boyd, Foody, & Ripple, 2002; Thenkabail, Smith, & De Pauw, 2002). Here, every permutation of six types of commonly used index was considered (Table 3) but only a sub-set of the results will be presented to illustrate the problem of transferability. This approach has previously yielded indices that were strongly correlated with biophysical properties of tropical forests (Foody, Boyd, & Curran, 1996). However, as it may sometimes be desirable to use the remotely sensed response more fully than in a basic vegetation index, some researchers have used regression and especially multiple regression-based analyses in extracting biophysical information from remotely sensed data (Boyd et al., 2002; Lawrence & Ripple, 1998; Steininger, 2000). Although this approach can yield accurate predictions it is sometimes difficult to satisfy the assumption underlying regression analysis. To avoid problems associated with the assumptions of standard statistical regression, a feedforward neural network may be used as an alternative to regression. Feedforward neural networks are attractive for biomass prediction as they avoid problems in using vegetation indices (e.g. index selection and incomplete use of the data's spectral information content) and multiple regression analyses (e.g. underlying assumptions) and have been used to derive accurate predictions of tropical forest biomass (Foody et al., 2001).

The 95 plots for which there was spectral and corresponding ground data were used to determine the transferability of the relations derived by each approach. The regression approach was used primarily to illustrate the relative contribution of the different spectral wavebands to biomass prediction at each site. With this approach, therefore, all of the samples acquired at one site were used to generate a multiple regression model for biomass prediction at that site. The problem of transferability was then assessed through a comparison of the equations derived at the three sites as well as through the application of the equations to the data acquired at each site.

With the vegetation indices and neural network-based approaches, the data for each test site was split into independent training and testing sets. A training set is required by a feedforward neural network in order for it to learn the underlying relationship between the spectral response and biomass. It is also required in order to select an appropriate vegetation index. For the purposes of this research, a 2:1 division of the data set into training and testing sets was used with the same sets used in the analyses based on vegetation indices and neural networks. Every possible permutation of the vegetation indices depicted in Table 3 was generated and the strength of its correlation with the biomass determined with the training data set. The 10 indices most strongly correlated with biomass, together with the widely used NDVI as a benchmark, were selected for application to the testing set. With the neural network analyses, a software package that attempted to derive an optimal multi-layer perceptron or generalized regression neural network was used. For each analysis, a constrained search was undertaken with a minimum of 1100 candidate networks evaluated. From each analysis, one network was selected on the basis of both its learning and generalization ability, as indicated by the accuracy of its predictions on the training and testing sets, respectively.

Table 3
The six types of vegetation index used ($B1$ = Landsat TM waveband 1, etc.)

Example of index formula
$B4/B3$
$(B4-B3)/(B4+B3)$
$B4/(B1+B2)$
$(B1\times B2)/B3$
$B4/(B1\times B2\times B3\times B5\times B7)$
$((B4-(B1+B2))/((B4+(B1+B2))$

As is common in remote sensing studies, predictive relations for biomass estimation were derived at each site using only the data acquired for that site. This represents the 'one place one time' approach that, while frequently adopted, is a major source of uncertainty in remote sensing (Woodcock, 2002). The approach does, however, allow the accuracy of biomass prediction to be evaluated in the normal way. Here, attention was also focused on the ability to transfer the relations between sites. That is, predictive relations were applied to sites beyond that at which they were developed. In particular, attention focused on two features of these relations. First, an evaluation of the transferability of the relations derived, as indicated by the accuracy of their predictions at a site other than that upon which they were established. If a relationship derived at one site was transferable, the expectation was that it could be used to derive predictions of biomass with a similar level of accuracy at each of the other sites. Second, the nature of the relations derived, with particular regard to the relative contribution of the different spectral wavebands, was evaluated. This was investigated as transferable relations would be expected to have other similarities in addition to the maintenance of predictive accuracy. For example, it would be expected that the vegetation indices and spectral wavebands found to be most strongly related to biomass at one site corresponded with those identified as such at the other sites. Similarly, the parameters of the regression equations would also be expected to be similar in magnitude and direction for the data from each site.

5. Results and discussion

5.1. Vegetation indices

For each test site, the 10 vegetation indices most strongly related to the biomass of the training data, together with the NDVI as the most widely used vegetation index, were used to predict the biomass of the testing data set of each test site. Tables 4–6 show the correlation coefficients derived for each scenario. Five key observations may be made from the results. First, the NDVI was never amongst the top 10

Table 4
Vegetation indices derived for the data acquired of the test site in Thailand and their correlation with biomass at each site

Index	Correlation coefficient, r (rank)			
	Training set	Testing set		
	Thailand	Thailand	Brazil	Malaysia
$(B2-(B7+B1))/(B2+(B7+B1))$	0.505 (1)	0.411 (51)	− 0.346 (12)	0.316 (13)
$(B2-(B5+B1))/(B2+(B5+B1))$	0.492 (2)	0.380 (68)	0.024 (199)	− 0.007 (221)
$B2/(B5+B1)$	0.486 (3)	0.359 (78)	0.021 (204)	0.026 (205)
$(B2\times B4)/B5$	0.483 (4)	− 0.115 (172)	− 0.043 (189)	0.099 (153)
$B7/B2$	− 0.478 (5)	− 0.323 (87)	0.186 (74)	− 0.354 (5)
$(B2-(B3+B5))/(B2+(B3+B5))$	0.469 (6)	0.335 (84)	0.120 (114)	0.017 (210)
$B2/(B3+B5)$	0.461 (7)	0.317 (92)	0.118 (116)	0.008 (219)
$(B2\times B4)/B7$	0.458 (8)	− 0.168 (152)	− 0.258 (33)	0.273 (29)
$(B2-(B3+B7))/(B2+(B3+B7))$	0.452 (9)	0.283 (109)	− 0.100 (138)	0.283 (20)
$(B5-B2)/(B5+B2)$	− 0.445 (10)	− 0.319 (89)	− 0.066 (176)	0.023 (207)
$(B4-B3)/(B4+B3)$	0.082 (193)	− 0.219 (131)	0.009 (213)	0.099 (154)

indices defined in terms of the strength of correlation with biomass observed from the analyses of the training sets. On the basis of this type of analysis, it is unlikely that the NDVI would be selected for biomass estimation, yet it remains one of the most widely used indices for this application. Second, for all indices, the correlation with biomass varied in strength between the test sites. Only for one index, that derived using the data from Thailand and ranked first from the analysis of the training data, was the magnitude of the correlation coefficient derived relatively constant across all three test sites. In all other cases, the magnitude of the correlation coefficient varied considerably, with most coefficients of insignificant value (at the 95% level of confidence). Third, the direction of the relationship between the predicted and field-based estimates of biomass commonly varied between sites. Fourth, the spectral composition of the 10 indices derived from the analysis of the training data differed considerably between sites. It was apparent, for example, that with the Thai site every index selected contained TM waveband 2 but very rarely TM waveband 4. Conversely, for the Brazilian site every index contained TM waveband 4 (and TM waveband 5) with TM waveband 2 amongst the least selected wavebands. With the Malaysian site, no spectral waveband was common to all of the selected indices, although TM waveband 3 was contained in most. Fifth, the different types of index (Table 3) were represented differently in the set selected at each site, with some absent completely. Furthermore, the type of index most strongly related to the biomass of the training set differed between sites (Tables 4–6). Together these five observations highlight problems in transferring predictive relationships between the sites. In particular, the inter-site differences in the magnitude and even direction of the correlation coefficients derived and of the relative value of the spectral wavebands for biomass prediction indicate major problems in the transference of predictive relations.

5.2. Regression analysis

The problem of inter-site transferability was also evident in the results of the multiple regression analyses. Table 7 illustrates the parameters of the multiple regression equations derived for each site. It was evident that the magnitude and often the direction of the parameters of the regression equations derived for each site differed markedly. Only one parameter, β_1, displayed a consistent direction, but this also had the greatest range in magnitude. Additionally, the amount of variation explained by the regression equations

Table 5
Vegetation indices derived for the data acquired of the test site in Brazil and their correlation with biomass at each site

Index	Correlation coefficient, r (rank)			
	Training set	Testing set		
	Brazil	Thailand	Brazil	Malaysia
$(B1\times B4)/B5$	− 0.508 (1)	− 0.436 (50)	− 0.090 (151)	0.093 (157)
$(B2\times B4)/B5$	− 0.500 (2)	− 0.115 (172)	− 0.043 (189)	0.177 (80)
$(B7\times B4)/B5$	− 0.488 (3)	− 0.229 (126)	0.079 (161)	− 0.048 (192)
$B4/B5$	− 0.480 (4)	− 0.046 (204)	− 0.092 (150)	0.156 (93)
$(B5-(B4+B3))/(B5+(B4+B3))$	0.470 (5)	− 0.070 (194)	0.094 (143)	− 0.161 (91)
$(B5-(B1+B4))/(B5+(B1+B4))$	0.469 (6)	0.004 (222)	0.075 (166)	− 0.167 (90)
$(B5-(B2+B4))/(B5+(B2+B4))$	0.468 (7)	− 0.098 (179)	0.082 (159)	− 0.174 (85)
$(B5-B4)/(B5+B4)$	0.465 (8)	− 0.036 (206)	0.085 (155)	− 0.185 (73)
$(B4-(B2+B5))/(B4+(B2+B5))$	− 0.464 (9)	− 0.107 (176)	− 0.089 (152)	0.177 (81)
$(B4-(B3+B5))/(B4+(B3+B5))$	− 0.462 (10)	− 0.026 (211)	− 0.064 (178)	0.171 (87)
$(B4-B3)/(B4+B3)$	− 0.429 (29)	− 0.219 (131)	0.009 (213)	0.099 (154)

Table 6
Vegetation indices derived for the data acquired of the test site in Malaysia and their correlation with biomass at each site

Index	Correlation coefficient, r (rank)			
	Training set	Testing set		
	Malaysia	Thailand	Brazil	Malaysia
$(B7)/(B3)$	0.524 (1)	0.155 (154)	0.256 (34)	− 0.333 (9)
$(B1 \times B3)/B7$	− 0.486 (2)	− 0.606 (13)	− 0.071 (171)	0.007 (222)
$(B1 \times B5)/B4$	− 0.479 (3)	0.258 (116)	0.151 (100)	− 0.154 (97)
$(B3-(B2+B7))/(B3+(B2+B7))$	− 0.470 (4)	− 0.084 (186)	0.202 (67)	0.137 (112)
$(B1 \times B3)/B2$	− 0.469 (5)	− 0.738 (2)	0.030 (59)	− 0.039 (198)
$(B7-B3)/(B7+B3)$	0.461 (6)	− 0.070 (195)	0.192 (71)	− 0.181 (77)
$(B4)/(B3)$	0.459 (7)	− 0.174 (148)	0.069 (173)	− 0.128 (128)
$(B2 \times B3)/B7$	− 0.451 (8)	− 0.103 (177)	0.270 (30)	− 0.008 (218)
$(B1 \times B2)/B4$	− 0.433 (9)	− 0.294 (103)	0.179 (78)	− 0.128 (126)
$(B1 \times B3)/B5$	− 0.432 (10)	− 0.373 (73)	0.038 (70)	− 0.093 (158)
$(B4-B3)/(B4+B3)$	0.405 (22)	− 0.219 (131)	0.009 (213)	0.099 (154)

was relatively small ($R^2<0.32$). Unsurprisingly, the application of a regression equation derived at one site to the data from another yielded biomass predictions that were generally weakly correlated with that measured in the field (Table 8). Again, the variation in the strength and direction of the relationships derived highlight the difficulty in transferring empirically derived relationships between sites.

5.3. Neural networks

The neural network constructed for each test site was able to predict biomass accurately, with a correlation coefficient of 0.709, 0.829 and 0.838 derived with the analysis based on the data from Thailand, Malaysia and Brazil, respectively (all significant at the 99% level of confidence; Table 9). Although this confirmed the value of neural networks for the estimation of environmental variables such as biomass from remotely sensed data, it was also apparent that the networks were generally unable to generalize, with much weaker relationships between predicted and measured biomass observed when a network was applied to a test site other than that upon which it had been trained (Table 9). In none of the six possible transferability scenarios was a statistically significant relationship between predicted and measured biomass observed. As with the vegetation indices and regression analyses, these results highlight the difficulties of transferring relations between sites.

In addition to basic inter-site problems, the difficulty of transferring a relationship was evident if the data from one site were used to predict biomass over all three combined. In terms of providing a relationship that was generalizable across all sites, each network derived from a single site was unable to predict accurately the biomass of the combined testing data. Indeed, the relationships between the predicted and measured biomass values were weak and fluctuated from $r=-0.208$ to 0.244 (insignificant at the 95% level of confidence) further highlighting the problem of transferability (Table 9).

5.4. Increasing transferability

All three approaches to biomass estimation from the remotely sensed imagery (vegetation indices, multiple regression and neural networks) appeared to be unable to generalize between sites. Since this is a major limitation to the value of remote sensing, means to reduce the problem were investigated. Here, attention focused solely on the feedforward neural network-based approach as this provided the strongest predictive relation at each site.

Since an ultimate aim is to be able to derive a predictive relation applicable to all tropical forests, an initial step to increase the accuracy of generalization was simply to use data from each site in both training and testing a network. A combined training set and combined test set, formed by amalgamating the appropriate data sets from all three sites, was used to construct and test a neural network. The biomass values predicted from this network were relatively weakly related to the measured values. Although the relationship derived was stronger than that obtained when networks trained at only one site had been applied to the combined test set (Table 9) and was statistically significant ($r=0.381$, significant at the 95% level of confidence), it explained little of the variance and would be inappropriate for operational applications.

Table 7
Parameters of the multiple regression models

Country	n	β_0		β_1		β_2		β_3		β_4		β_5		β_7	R^2
Thailand	40	168	−	9984$B1$	+	8081$B2$	+	4793$B3$	−	238$B4$	−	436$B5$	−	1338$B7$	0.300
Brazil	27	195	−	628$B1$	−	3493$B2$	−	1442$B3$	−	532$B4$	+	2487$B5$	−	1821$B7$	0.318
Malaysia	28	343	−	8160$B1$	+	7613$B2$	−	6432$B3$	+	781$B4$	−	3625$B5$	+	6226$B7$	0.251

The subscript identifies the TM waveband (β_0 is the intercept).

Table 8
Correlation coefficients observed for the relationship between the biomass predicted by a regression equation and that measured in the field

Site used in training	Site(s) regression applied to		
	Thailand	Brazil	Malaysia
Thailand	0.548	− 0.095	0.020
Brazil	− 0.341	0.564	0.032
Malaysia	0.181	− 0.443	0.501

A simple method of aiding inter-site transferability and increasing the strength of the relation between the predicted and field-based estimates of biomass values was to include information on test site location directly into the analysis. This may be achieved in a manner similar to adding a dummy variable to a regression analysis and been suggested as a means of increasing the generalization ability of neural network classifications (Wilkinson, 1997). Here, this was achieved by adding extra units to the input layer of the neural network. Each of these additional units was associated with one of the sites, with the input to a unit being 1 if the remotely sensed data were drawn from the test site otherwise the input was 0. The inclusion of test site identifiers increased the strength of the relationship between predicted and measured biomass ($r = 0.486$, significant at the 99% level of confidence) derived when the data sets from all three sites were combined. Two major outliers from the general trend were observed and their removal, although there was no particular reason for this, raised the strength of the relationship considerably ($r = 0.68$, significant at the 99% level of confidence).

5.5. Factors limiting transferability

Overall, the results highlight the problem of transferring a predictive relationship between sites, even when relatively similar techniques have been applied and standard procedures used throughout. This is a major constraint on the use of remote sensing which in turn impacts negatively on studies that aim to improve the understanding of major environmental processes and the development of operational applications using remote sensing. A variety of reasons may be put forward to help explain the difficulty in transferring a relation between sites. For example, there are uncertainties in the remotely sensed and ground data sets. Even though a highly standardized approach was followed to reduce the uncertainties that can arise from the way intermediaries and their processing systems handle data, problems are inevitable. There are, for example, many concerns about the remotely sensed data and processing techniques used. The suitability of the preprocessing methods, individually and in combination, may vary between the sites as the validity of assumptions made and coefficients used with the various standard pre-processing techniques may differ between the data sets. Problems may also be encountered at all stages of the analysis, with uncertainty occurring at each stage of the data processing chain as well as propagating along it (Dungan, 2002; Woodcock, 2002). For example, the initial step of the pre-processing, the conversion of DN to L_s, may be sub-optimal due to factors such as a temporal variation in sensor performance. These will ultimately impact upon all later processing, with uncertainties in the sensor calibration coefficients a significant source of error in the estimation of reflectance (Garcia-Haro et al., 2001).

Biomass estimation from field survey data is also far from trivial and prone to error. The methods used here, and elsewhere, were based upon relationships between biomass and basic measurements such as of tree dbh and height since direct measurement of biomass is impractical. However, there are difficulties in measuring these variables accurately and inter-species differences (e.g. wood density) should ideally be accounted for throughout. While the ground data set for the Brazilian site included tree height and wood density information, where known, this was not the case for the two Southeast Asian test sites. Furthermore, at the Brazilian test site the dbh threshold used in selecting trees for measurement was smaller than that at the two Southeast Asian test sites. In some regards, therefore, biomass may not have been expressed and represented in a consistent way. These differences could affect the detail of the results but would not be expected to change the general trends observed. Indeed, the problems discussed above are evident if only the data from Malaysia and Thailand, where similar field survey methods had been used, were considered. Further fundamental concerns are the important differences between the sites. The forests themselves, for example, differ markedly in composition and type. Consequently, the contribution of different forest attributes (e.g. LAI, structure, lianas, etc.) to the remotely sensed response may vary between sites. Different allometric equations were also required to accommodate the inter-site differences, notably the high proportion of coniferous tree species at the Thai test site. Finally, there are also additional general concerns common to most remote sensing studies. In particular, problems of linking ground and remotely sensed data abound. The timing of ground data acquisition did not correspond exactly with that for the remotely sensed data and many important constraints and problems were encountered. Given the nature of the environment, the sample design used for ground data acquisition may have been sub-optimal (Atkinson, Foody, Curran, & Boyd, 2000). Furthermore, small sample plots, of a size incompatible

Table 9
Correlation coefficients observed for the relationships between the biomass predicted by a neural network and that measured in the field

Site used in training	Site(s) network applied to			
	Thailand	Brazil	Malaysia	Combined
Thailand	0.709	− 0.132[a]	0.116	− 0.208
Brazil	− 0.203	0.838	− 0.300	0.158
Malaysia	0.209	0.588	0.829	0.244

[a] One major outlier in the relationship was deleted.

with the support (resolution) of the remotely sensed data that were difficult to locate precisely in the imagery were, as is common, used.

Having identified some of the main factors that limit the transferability of predictive relations the next step is to try to identify ways forward. The initial step of including information on test site location seemed to offer the potential to increase the transferability of predictive relations. Information on plot locations also allows the use of local rather than standard global statistical techniques that are preferable if relationships are non-stationary. This could be further refined not only to both extend the ability to transfer a relation but also to set realistic bounds on its use. These bounds may, in part, relate to forest attributes and consequently stratification of forests by key attributes may help in the selection of appropriate relations. There is also considerable scope for the refinement of the methods used. This includes issues ranging from the nature and means of data acquisition in the field (e.g. plot size, forest attributes recorded, etc.) through to its relation to the remotely sensed data (e.g. co-location of sites, regularisation of data, etc.). Increases in the accuracy of biomass prediction may also be derived through the use of additional data. Lidar data, for example, have been used previously to estimate canopy structure and biomass (Lefsky, Cohen, Acker, Parker, & Shuart, 1999; Lefsky, Cohen, Acker, Parker, Spies, et al., 1999) but fail to account for biochemical changes, indicative of productivity and hence biomass, that may be apparent in multispectral data sets. Combining lidar and multispectral data may, therefore, account for forest biochemical and biophysical properties, which could prove to be an attractive way forward for accurate biomass estimation. With this and other approaches, there are, however, many challenges to be addressed but also many opportunities to ensure the potential of remote sensing as a general tool for the prediction of biomass is realized.

6. Summary and conclusions

A key component of the argument commonly advanced for using remote sensing is that it has the potential to provide information on the environment at a range of spatial and temporal scales in a consistent manner. This is often taken to imply an ability to generalize in space and time. Thus, it should be possible to apply successfully a predictive relation beyond the site and time period at which it was developed. The results of the work reported above, however, indicate important problems in transferring predictive relations over space. The main results were:

1. The biomass of a tropical forest may be predicted accurately with a relation derived at that site. In particular, predictions derived from a neural network-based approach were strongly and significantly correlated with the biomass estimate derived from field survey at each of the three test sites ($r>0.71$, significant at the 99% level of confidence).
2. The relative contribution of different Landsat TM wavebands to predictive relations differed between sites. Wavebands that appeared to provide important information at one site were often unimportant at other sites. Thus, the composition of vegetation indices that were strongly correlated with biomass differed between sites. In addition, the magnitude and direction of regression model parameters differed between sites.
3. The accuracy of predictive relations, as indicated by the correlation with ground data, declined when they were applied to a region other than that upon which they had been developed.

These results indicate a major problem in the effective use of remote sensing. Although those familiar with the use of empirical relationships derived from remotely sensed data might have anticipated problems in transferring relationships, the issue has been rarely studied explicitly. This paper has demonstrated the nature of the problem in one major application of remote sensing, the estimation of tropical forest biomass. In particular, it has indicated the magnitude of the problem that highlights concerns associated with transferring relationships between sites. This is important as some remotely sensed variables are often used unquestioningly for the prediction of environmental properties. For example, the NDVI is commonly used in a multitude of applications, forming the basis of estimates of phenomena ranging from precipitation, through biodiversity to biomass. Although there may be many demonstrated instances in which the NDVI can be used to derive accurate estimates of the property of interest, this does not assure universal applicability. Thus, for example, the NDVI is commonly used to derive land information to drive environmental models (e.g. Guillevic et al., 2002; Los, Justice, & Tucker, 1994; Lu & Shuttleworth, 2002; Sellers et al., 1994) yet its sensitivity to variation in land surface properties varies in space and time (e.g. Castro et al., in press; Ichii, Kawabata, & Yamaguchi, 2002; Wang, Price, & Rich, 2001). In the work reported above, the direction and strength of the relationship between the biomass estimates derived from field survey and those predicted from the NDVI, in common with most of the predictive relations discussed, varied between the test sites.

The transferability problem has many components but, with regard to one, echoes the observation of Cohen et al. (2001) that absolutely calibrated imagery may not be appropriately normalized with respect to each other. The inability to transfer relations satisfactorily will greatly limit the contribution remote sensing can make in environmental studies. Although some progress in increasing the transferability of a relation through the integration of locational information into the analysis was indicated, it was apparent that further work on this topic is required if the full potential of remote sensing as a source of environmental data is to be realized. It must also be recognized that this study has focused on only one main component of a broad set of generalization problems, that of spatial generalization. The ability to generalize in time is also important, particularly in studies of environmental change. We intend to investigate the temporal transferability of the relations derived with ground and remotely sensed data scheduled for acquisition at the Malaysian test site in 2003.

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