CLASSIFICATION AND FOREST PARAMETER EXTRACTION OF PATAGONIAN LENGA FORESTS WITH ASTER AND LANDSAT ETM+ DATA

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ABSTRACT

The goal of this project was to improve the mapping and monitoring system of the Directorate of Forest and Parks of the Province of Chubut, Patagonia. In providing updated quantitative and qualitative knowledge of Patagonian vegetation, mainly native forests, sustainable forest resource management shall be improved. In this paper object-oriented classification using eCognition software is presented as well as the feasibility of modeling measured forest parameters of Lenga *(Nothofagus pumilio)* stands by relating them to vegetation indices derived from ASTER and Landsat ETM+ data.

Forest parameters such as leaf area index (LAI), diameter at breast height (DBH), basal area, volume among others were measured and related to the satellite data by using simple and multiple linear as well as non-linear regression analysis. The findings of forest parameter determination showed that LAI can be estimated with ASTER data at a relative root mean square error (RRMSE) around 12%. The best determination results were achieved for the forest parameters DBH and basal area with relative RMSE around 26% and 30% respectively. Volume was estimated with lower accuracy. a relative RMSE of 45% was achieved.

INTRODUCTION

The subantarctic native forests of Patagonia are on the verge of extinction due to the lack of awareness of the essential role they play in the fragile ecosystem. The pressure on these forests is constantly growing and the conservation is threatened by not only natural induced fires but also by increasing intentional forest fires, illegal or uncontrolled timber and wood extraction, domestic animal overgrazing, human encroaching activities, and the replacement of native trees by fast-growing exotic species. The economic crisis in Argentina that started in 2001, deteriorated the situation even further.

Patagonia requires a forest measuring and monitoring system that responds to the forest department authorities to report on sustainable forest development and to ensure a sustainable development in national parks. The creation of products for forest inventories, monitoring sustainable forest management, landscape management and forest carbon accounting has to be established. Despite growing interest in, and general concern for sustainable forest management, many interested parties are ill-equipped to judge if the current management practices are sustainable. Accordingly, first quantitative and qualitative information must be gathered, managed and updated. Due to physical remoteness, lack of funds and personnel, spatially referenced datasets for the forested areas of Patagonia are either nonexistent or out of date and thus unreliable. Satellite remote sensing can be an efficient and cost-effective way to acquire up-to-date and accurate land cover and topographic information. In respect of limited funding, it was decided that the remote sensing datasets would consist of the low-cost scientific sensor ASTER, and Landsat ETM+ data which were provided free of charge by the Argentine Space Agency.

The problem with tree type maps based on medium resolution satellite data of especially mountainous terrain, derived with traditional per-pixel classification methods, is that the accuracy is fairly low due to large variability in reflectance within forest stands and spectral confusion of species (Frank, 1988, Itten and Meyer, 1993, Meyer et al., 1993). A division of pixels into meaningful objects of homogeneous areas by segmenting an image can help in such cases to solve the problem. The generated segments act as image objects whose physical and contextual characteristics can be described by means of fuzzy logic. As such much improvements concerning accuracy and interpretability can be reached when working with medium and high resolution remote sensing data. In this work eCognition was applied with emphasis on tree type discrimination and accounting for the difficult mapping of mixed forest vegetation in the transition zones of the Patagonian forest ecosystem towards the steppe ecotone. The software eCognition is the first commercially available product for object-oriented and multi-scale image analysis.

Structural attributes of forest stands that are of interest as part of a general forest inventory might include tree density, DBH, basal area, volume, biomass, and stage of development. Some of these attributes can be considered as forest conditions to be estimated at some level of precision. Applications of remote sensing aimed at these continuous aspects of the forest inventory have been driven largely by empirical or semi-empirical model estimation (Jakubauskas, 1996), (Puhr, et al. 2000), (Ardö, 1992), (Trotter, et al. 1997), (Ekstrand, 1994), (Eklund, et al. 2001). Empirical models might be constructed using the understanding derived from physically based models coupled with laboratory, field, and actual or simulated remote sensing data. Unfortunately, purely empirical models can have the disadvantage of being highly site specific. But the most important advantage of empirical modeling is the simplicity to establish the model. Finding the resources to complete the simple normative design that is required to establish a purely empirical relationship between spectral response and a forest parameter is easy (Franklin, 2001), even in highly inaccessible areas. Besides the above mentioned attributes of forest stands LAI is another important structural attribute of forest ecosystems because of its potential to be a measure of energy, gas and water exchanges (Franklin, 1991). Physiological processes such as photosynthesis, transpiration and evapotranspiration are functions of LAI (Pierce, et al. 1988). Vegetation indices can be used to capture the way in which red and near-infrared reflectance differ in a single measure. The common approach to LAI estimation is again empirical or semi-empirical modeling, involving correlation of spectral indices with field estimates and the extension of such estimates over larger areas with regression (Eklund, et al. 2001), (Chen, et al. 1996), (Brown, et al. 2000).

RESEARCH AREA

The study area is situated in the west of the Argentine Province of Chubut (70° 45’ - 71° 35’ W, 40° 58’ - 43° 32’ S) in Patagonia. Topographically the study area is dominated by the eastern trailing edge of the Andes in the west and the Patagonian Plains in the east. It includes parts of Los Alerces National Park, that protects a small part of the natural forest belt along the eastern flanks of the Andes as well as the great grassland plains to the east. The area encompasses approximately 14 400 km^2.

The Andes of southern Chile and southwestern Argentina are a major determinant of climate and vegetation patterns in southern South America. Patagonian forests in Argentina are growing along the eastern trailing edge of the Andes from Río Colorado at 38° S until Beagle Channel at 54° 53’ S. The deciduous, temperate forest ecotone in the north of Patagonia is dominated at high-elevation and/or xeric sites by deciduous Lenga (*Nothofagus pumilio)*. At 42° S the deciduous Lenga forests are mainly growing at heights between 900 and 1600 m asl. At these elevations Ñire *(Nothofagus antarctica)* is also present. It covers poor soils and grows often as bush. On better soils Ñire can reach heights of 5-10 m. At mid-elevation sites the evergreen Coihue *(Nothofagus dombeyi)*, which can occur as rich, pure stands, appears at rather humid sites near lakes and rivers. Dryer, rocky areas in-between are covered by Ciprés de la Cordillera *(Austrocedrus chilensis)*. Ciprés can form pure stands in dry, rocky areas or appear together with Radal *(Lomatia Hirsuta)* and Maitén *(Maytenus Boaria)* (Schmalz, 1992), (Veblen, et al. 1996). The evergreen Coihues often advance towards Ciprés and Lenga *(Nothofagus pumilio)* stands. The understories of Coihue forests are typically dominated by Caña Colihue *(Chusquea culeou)*, a bamboo specie. The eastern part of the research area belongs to the Andean-Patagonian steppe. The Patagonian steppe is dominated by shrubs and grass species. Intensive grassland, locally called *mallines,* exists near rivers.

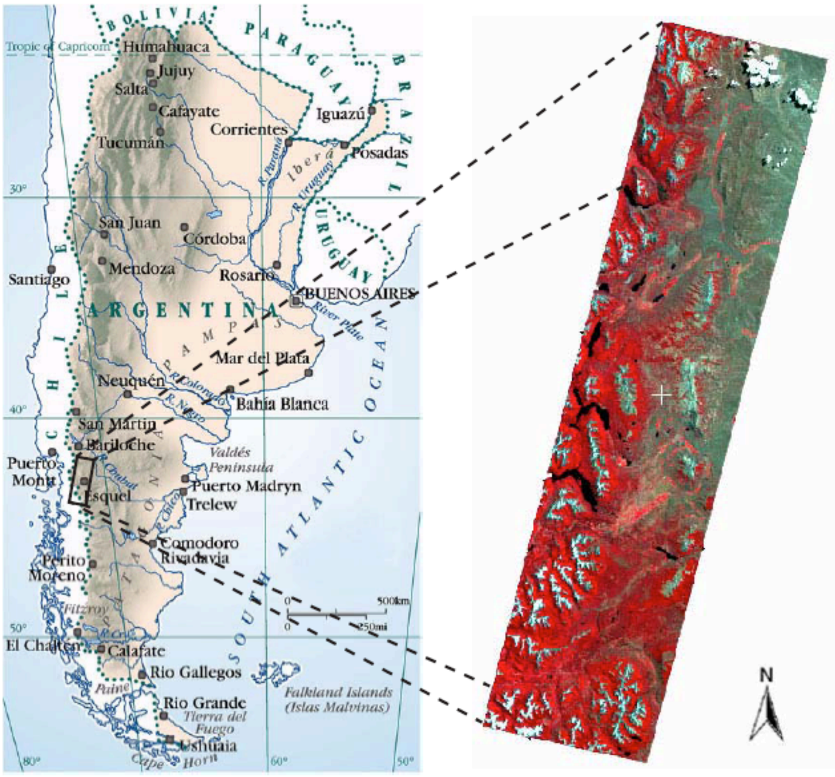

Figure 1. Topographical map of Argentina including an outline of the study area. The study area is represented by a mosaic of four ASTER scenes.

DATA

In total six datasets were processed i.e. four ASTER Level 1A scenes acquired on 18 January 2002 and two Landsat ETM+ Level 1G scenes taken on 21 February 2000. After an intense field campaign collecting differentially corrected ground control points a digital elevation model (DEM) was derived from the ASTER datasets and then an accurately orthorectified, mosaicked and radiometrically corrected remote sensing database was established. Additionally, LAI measurements based on hemispherical canopy photography (upwards and downwards directed) were made for Lenga forest as well as forest parameters collected, i.e. tree density, diameter at breast height and tree height. Basal area, volume and biomass were calculated from allometric equations, previously developed in the research area.

OBJECT-ORIENTED CLASSIFICATION APPROACH

eCognition[*] software is the first commercially available product for object-oriented and multi-scale image analysis. As opposed to most other pattern recognition algorithms which operate on a pixel-by-pixel basis, eCognition segments a multispectral image into homogeneous objects, or regions, based on neighboring pixels and spectral and spatial properties. The segmentation algorithm does not only rely on the single pixel value, but also on pixel spatial continuity (texture, topology). The resulting formatted objects carry the value and statistic information of the pixels that they consist of as well as texture, form (spatial features) and topology information in a common attribute table. The user interacts with the procedure and, based on statistics, texture, form and mutual relations among objects, defines training areas. Image segmentation can be performed at different levels of resolution, or

[*] Definiens Imaging GmbH, Trappentreustrasse 1, 80339 Munich, Germany

granularity. It is controlled by a user-defined threshold called scale parameter. A higher scale parameter will allow more merging and consequently bigger objects, and vice versa. The homogeneity criterion is a combination of color respectively spectral values and shape properties (shape splits up in smoothness and compactness). By applying different scale parameters and color/shape combinations, the user is able to create a hierarchical network of image objects. For the classification of the segments, two types of nearest neighbor expressions can be used in eCognition: the nearest neighbor (NN) and the standard nearest neighbor (Std. NN) expression. The NN expression and its feature space can be individually adjusted to classes, membership functions introduced and fuzzy rule applied, whereas the Std. NN expression works with a defined feature space for selected classes. Classification can be performed at different levels of the classification hierarchy. Multi-level segmentation, context classification and hierarchy rules are also available (Baaz, et al. 2003).

FOREST PARAMETER ESTIMATION

A selection of 19 vegetation indices (VI's) were computed from the atmospherically corrected ASTER and Landsat ETM+ data. The best performing VI's are presented in Table 1. Additionally, the tasseled cap coefficients brightness, greenness and wetness were derived from the Landsat ETM+ data. The relations between single band reflectances, vegetation indices and LAI, DBH, basal area, volume among others were analyzed. The division of the forest stand attributes into distinct classes was also tested, but discarded since no estimation improvements were obtained. Preliminary bivariate correlation analysis was performed to select promising spectral bands and vegetation indices for the statistical analysis.

Table 1. Definition of the presented vegetation indices. The letters A and E stand for ASTER and ETM+ respectively.

Vegetation Index	Formula**	Reference
MVI A – Mid-infrared VI	$\frac{nir}{mir_1}$	Fassnacht et al., 1997
mNDVI(A3, A4) – modified normalized difference VI	$\frac{nir - mir_1}{nir + mir_1}$	Jürgens, 1997

Linear and non-linear curve-fitting as well as multiple regression analysis was performed by applying the selected reflectances and vegetation indices as independent variables. The models were evaluated by cross-validation. The training and validation datasets were randomly selected. Two-thirds of the totally 38 measurement plots were used as training set (n = 23) and the remaining one-third (n = 15) of the measurement plots as validation set. The recorded descriptive parameters cultivation, regeneration, vitality, stand structure and understory were investigated qualitatively, but won't be discussed in this paper.

RESULTS

Object-oriented classification

The choice of the appropriate scale parameters on each segmentation level is the most crucial task in an eCognition project. Scale is mainly defined by the geometric resolution of the geodatabase and the physical entities that have to be classified. In this project two levels of image objects were segmented representing different scales (Figure 2). The scaling parameter used for level 2 was 60, which should create segments of forest stands, urban areas and mallines. Level 1 was scaled with a factor of 9 creating segments of groups of trees and bushes, grass patches and single buildings. The homogeneity criterion parameters were set as follows: color: 0.8, shape: 0.2, smoothness: 0.9 and compactness: 0.1. The ASTER bands 1 to 3 were given a weighting factor of 2, the NDVI derived from ASTER was given a weight of 1. The remaining channels were not considered for segmentation. The weighed bands were selected visually based on high spectral contrasts in-between tree stands.

** nir = near-infrared; mir_1 = 1.5μm – 1.7μm; mir_2 = 2.1 – 2.4 μm.

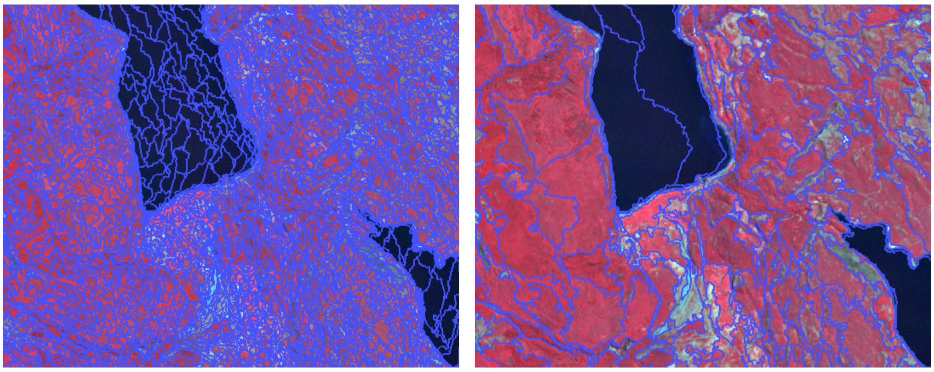

Figure 2. Segmentation level 1 (left) and segmentation level 2 (right).

Thirty features of each object, used in this analysis, were calculated from the 24 spectral and ancillary bands, including two shape features compactness and the length/width ratio and four neighborship relation features. Classification was performed on one segmentation level only. After segmentation, training objects were identified for each class and a combination of std. NN and fuzzy membership classification rule was developed.

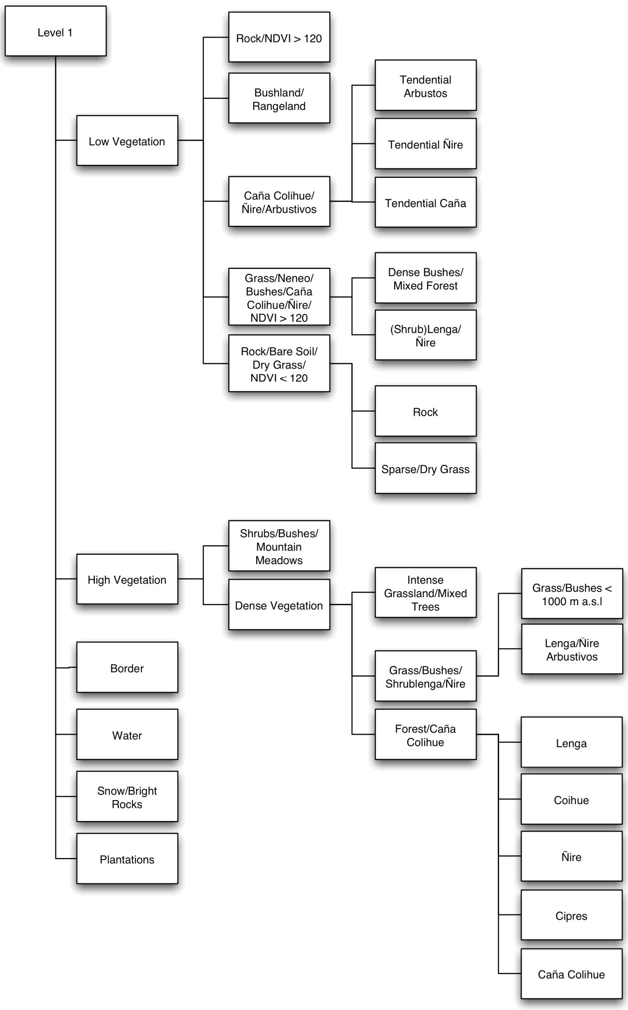

Figure 3. Developed class hierarchy.

First six overall classes, covering large areas, were separated. They were easily classified by either Std. NN or membership function. The main focus was directed to the subclassification of the class high vegetation; it includes the forested areas as well as high vegetative grasslands and thick shrubs or bushes. The subclassification of the class low vegetation, was of less interest. Nevertheless, the class includes some dumose representatives of Lenga and Ñire growing in harsh conditions (Figure 3).

As can be seen in Table 2 the accuracy assessment achieved an overall accuracy of 82.04% and a kappa coefficient 0.8002. After weighting the misallocated errors according to their importance, a weighted kappa of 0.8185 was calculated. The tree type classes were concentrated on, followed by the Intense Grassland/Mixed Forest and the Shrublenga/Ñire classes whilst the classification rule was developed. The classes with less importance in accuracy were the low vegetation classes such as Bushland/Rangeland, Dry/Sparse Grass or Tendential Bush class.

Looking at the producer and user accuracies of the tree type classes, it can be stated that they all reached an accuracy of at least 70% except for the coniferous tree type Ciprés. Ciprés was mostly misclassified as Coihue or Bushes/Mountain Meadow. The reasons for these misallocations are apparent. Ciprés is growing in inhomogenous, small stands mostly together with Coihue, preferring dry and rocky habitats. Ciprés has moreover a low spectral reflectance in the near-infrared (nir) comparable to shrubs or bushes. The producer accuracy of the classified bamboo specie Caña Colihue reached an acceptable result, whereas the user accuracy is with 56.3% too low. Caña Colihue groundtruth area was often misclassified as other tree types such as Lenga, Coihue, Mixed Forest or Ñire. This is mainly due to the fact that Caña Colihue is growing in the forest understory when the habitat is moist enough. Caña Colihue is also the first plant to grow after forest fires, so too Ñire. The misallocations of the other tree species with accuracies higher than 70% were mostly among each other or with the class Intense Grassland/Mixed Forest. The classes Intense Grassland/Mixed Forest, Bushes/Mountain Meadow, Shrublenga/Ñire and Tendential Arbustos were rather difficult to classify and assess, since they are all a mixture of several plant species. Even so, it can be of high importance to the future users as these mixed classes, depending on the habitat, location and elevation, can give them a good idea of what kind of vegetation is most probably growing in a specific location. Always reminded that as to date no such vegetation information is available for the area. Intense Grassland/Mixed Forest was mostly misclassified as other forest classes or Caña Colihue. The classes representing different bush vegetation were mainly misclassified among each other. While establishing the groundtruth database not many patches of these bush vegetation classes were mapped, which resulted in few groundtruth area, that influenced the accuracies. The remaining classes Dry/Sparse Grass, Plantations, Rock and Water reached rather high accuracies due to specific spectral characteristics of the classes. The class Plantation was classified with the help of an imported plantation map into the classification database. The user and producer accuracies of these four classes reached at least 90%.

Table 2. Accuracy statistics containing user- and producer accuracy for each class as well as overall accuracy, kappa coefficient and weighted kappa.

Class	User	Producer
Caña Colihue	0.563	0.8378
Ciprés	0.3961	0.6488
Ñire	0.7321	0.7157
Coihue	0.9168	0.709
Lenga	0.9592	0.8656
Intense Grassland/Mixed Forest	0.3847	0.8133
Bushes/Mountain Meadow	0.288	0.4776
Dry/Sparse Grass	0.9908	0.9505
Shrublenga/Ñire	0.3521	0.2342
Plantations	0.9542	0.9871
Bushland/Rangeland	0.9183	0.9477
Tendential Arbustos	0.7744	0.122
Rock	0.9839	0.9428
Water	0.9997	0.9987
Kappa Coefficient	0.8002	
Weighted Kappa Coefficient	0.8185	
Overall Accuracy	0.8204	

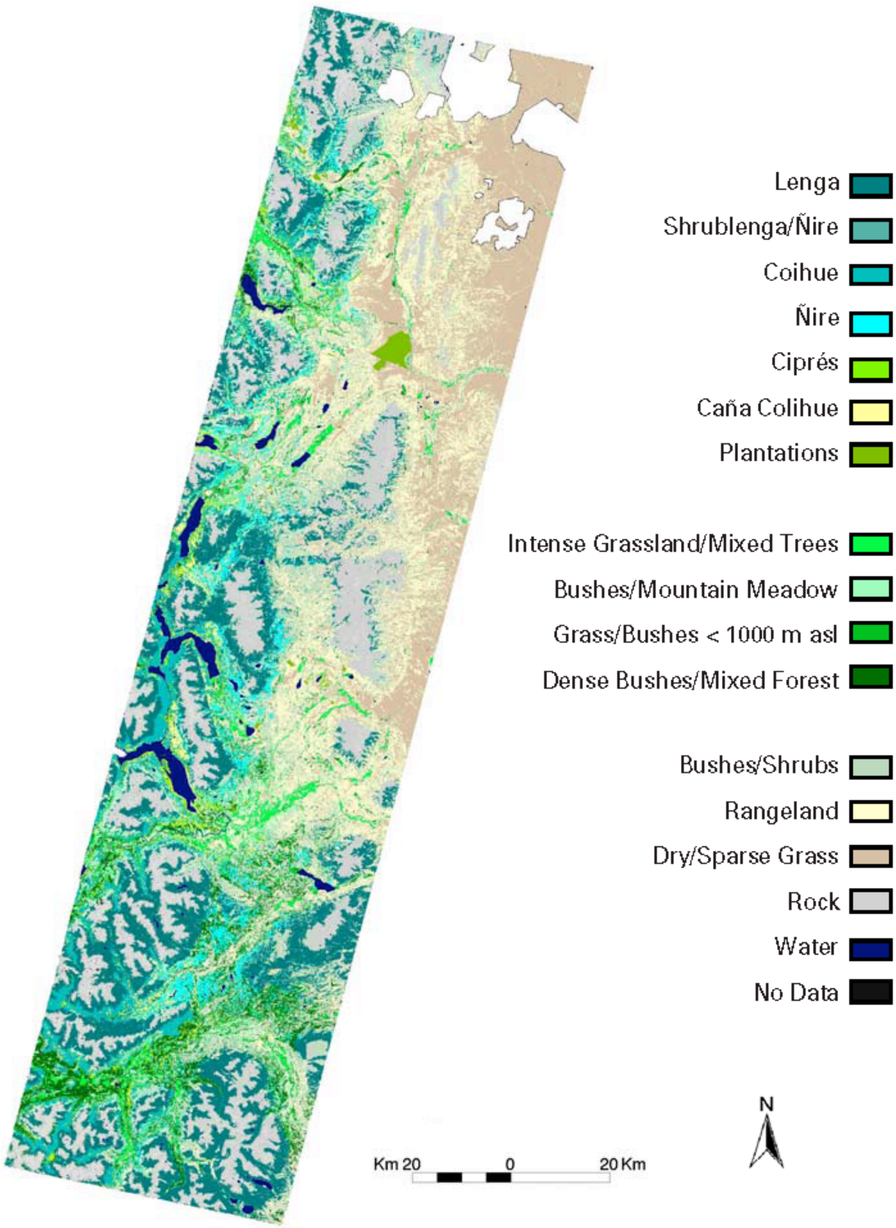

Figure 4. Object-oriented land use classification.

Forest parameter estimation

Overall correlation, selecting all measurement plots, was performed first to identify potentially suitable vegetation indices to predict LAI and the other forest parameters. Statistically significant ($p = 0.01$ or $p = 0.05$) correlating spectral bands and vegetation indices were selected and regression analysis, based on cross-validation, performed. Simple and multiple linear regression analysis as well as non-linear regression analysis was performed for the ASTER and Landsat ETM+ derivatives and the parameters. For every model shrinkage, the difference between the validation dataset R^2 and the training set R^2, and R^2 were calculated. Additionally, relative RMSE was calculated. A summary of the parameter estimates is listed in Table 3.

LAI. Vegetation indices containing information from middle-infrared bands ranging between 1.5 μm-1.8 μm (mir_1), MVI A (mid-infrared vegetation index), based on ASTER bands and mNDVI (A3,A4) (modified normalized difference vegetation index) performed best. They achieved an an R^2 of 0.707 and 0.704 respectively. The mir_1 band in combination with the nir band seems to contain more information relevant to the characterization of LAI than the combination of red and nir bands.

Table 3. Parameter estimates for linear and logarithmic regression models and respective shrinkage. Validation of models (n=15): Coefficient of determination (R^2) and relative RMSE (RRMSE). R^2 in bold signify statistically significant correlation coefficients (p = 0.01 (2-tailed)) else (p = 0.05 (2-tailed)).

Estimated Parameter	Band/VI	a	b	Shrinkage	R2	RRMSE [%]
LAI	MVI A	-0.896501	0.96922	-0.304	**0.707**	11.281
LAI	mNDVI(A3,A4)	-1.866269	7.805989	-0.279	**0.704**	12.082
DBH	Greenness	366.468593	-1.872857	-0.127	0.365	25.414
DBH	ETM4	102.029356	-0.908809	-0.092	0.299	25.934
Basal area	ASTER6	174.037130	-5.713072	-0.425	**0.619**	28.765
Basal area	mNDVI(A3,A4)	-13.028741	121.469501	-0.391	**0.445**	31.263
Volume	LAI	177.837909	161.138929	-0.115	0.223	37.619
Volume	LAI uw+dw lin.	-74.1367	192.42176	-0.056	0.348	35.481

DBH. Highest R^2 was achieved by two single bands, the tasseled cap derivative greenness, and ETM+ band 4. The best estimations of DBH were obtained with Landsat ETM+ derived bands or indices. It can be seen that small DBH were rather underestimated while large DBH values were well modeled or only slightly underestimated (Figure 4). It was observed that the higher DBH, the older are the trees and the more complex the stand structure. With complex stand structures shadow influences increase and consequently nir reflectance decreases, a negative relationship between DBH and nir region is the consequence. Due to its high sensitivity to vegetation density, greenness behaves similar to the nir band.

Basal Area. Basal area correlated strongly with several spectral bands and vegetation indices as well as the LAI. The ASTER mir_2 bands (ranging between 2.1 μm and 2.4 μm) achieved the best estimations of basal area ASTER band 6 performed best with an R^2 of 0.619. The best performing vegetation indices were mNDVI (A3,A4) and mNDVI (A3,A5) with an R^2 of 0.445.

Most of these best performing estimators are based on ASTER mir_2 reflectances. The strong negative correlations of the mir_2 bands with basal area can be explained by higher shadow influences and less atmospheric scattering in complexly structured forest stands containing trees with high basal area (Puhr, 2000). The nir bands relation to basal area is inverse. The stronger the inverse, the better the relation to basal area and consequently the prediction (Ekstrand, 1994). In this research the ASTER nir band correlated moderately with basal area whereas ETM+ band 4 hardly correlated with basal area. The higher basal area, the more mir_2 reflectances are controlled by understory and the mir - basal area relationship flattens off (Puhr, 2000). This could explain the slight underestimation of high basal area values in this study (Figure 4).

Volume. Volume correlated mostly with the ASTER reflectances, still correlations were low and only ASTER band 8 and ASTER band 9 correlated significantly at the 0.01- level. The modeled volume results, derived from ASTER band8 and ASTER band9, achieved very low R^2, 0.158 and 0.174 respectively. Solely LAI uw+dw (including upward and downward measurements) and LAI (consisting of the upward measurements only) yielded acceptable volume estimations; LAI uw+dw with a simple linear model and a logarithmic model attained the best R^2 and relative RMSE. For denser stands and canopy cover of 100%, basal area and biomass may continue to increase, while the signal recorded is not altered anymore, making a log transformation of the data or a logarithmic regression analysis necessary (Franklin, 1986). However, in this study, initial testing indicated slightly lower results for a logarithmic curve estimation because in natural Lenga forests, canopy cover seldom reaches 100% and therefore a linear relationship is more appropriate.

The highest R^2 was 0.348 and is significant at the 0.05- level of confidence, as well as the second best model result with an R^2 of 0.309. Relative RMSE are between 35.48% and 37.62%. If LAI uw+dw and LAI are modeled with their best estimator, the relative RMSE changes reasonably. Relative RMSE for the modeled volume via the modeled LAI amounts to 38.48% with an $R^2 = 0.176$ (p = 0.119); and the modeled volume based on the linearly modeled LAI uw+dw amounts to 39.55% where $R^2 = 0.144$ (p = 0.163).

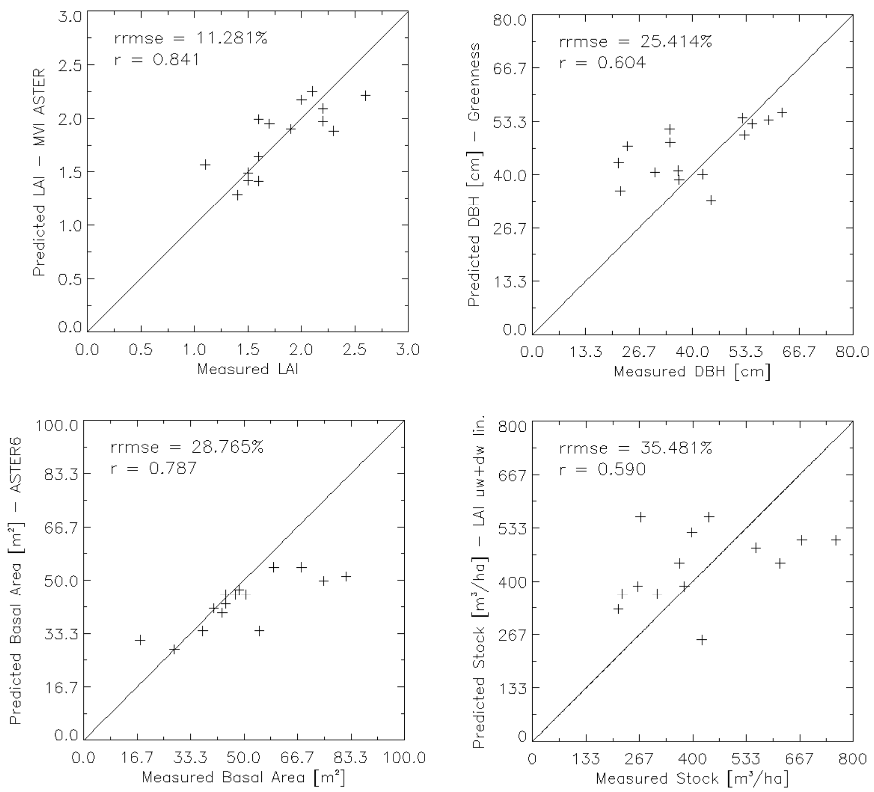

Figure 4. Measured vs. modeled forest parameters. Best performing VI, band or parameters were plotted. Each cross corresponds to a measurement plot. The diagonal line represents the 1:1 relationship.

CONCLUSIONS

Conclusion on object-oriented classification

Segmentation evaluation showed that the choice of the appropriate scale parameter, criterion and band are a crucial task in an object-oriented classification. The successful creation of meaningful objects will decide on successful discrimination of the defined vegetation classes, e.g. tree types.

With the current class hierarchy and the selected features a stable rule base was developed. Application of the rule base on other datasets will most probably need minor adjustments. Some of the tree types were successfully classified for the first time, such as Ñire and Caña Colihue. Additionally the class Lenga was divided in qualitatively varying subclasses. At high elevation and windy locations Lenga grows in a shrubby form called Shrublenga which was to date hard to distinguish from Ñire.

The accuracy assessment was performed by using the weighted kappa to account for the error severity of some classes. With this method an overall accuracy of 82.04% and a weighted kappa coefficient of 0.8185 was achieved. For all tree type classes accuracies of at least 70% were achieved, except for the coniferous Ciprés which was mostly misclassified with Coihue. User accuracy reached 39.61% and producer accuracy 64.88%. The bamboo specie Caña Colihue achieved an user accuracy of 56.30% and a producer accuracy of 83.78%. The quantitative accuracies of the remaining vegetation classes have to be interpreted with care due to two reasons: a) for the class Shrublenga/ Ñire only little groundtruth was available and b) some of the transition zone vegetation classes are radiometrically similar, but are too distinct considering their habitat to be merged. During the development of the rule base intermediate classification results were discussed with the local authorities and thus adjusted and improved.

Conclusions on Forest Parameter Determination

LAI measurements of Lenga stands tend to be rather low, LAI values between 1.00 and 2.60 were measured. The number of South Andean stands for which LAI has been measured is very small. Comparable values were measured for Lenga in Tierra del Fuego with values between 1.70 and 2.80. In this study all calculations were actually performed with the plant area index, instead of the effective LAI, since the used LAI calculation software did not yet account for foliage clumping and non-photosynthetic material. Thus future research should investigate the influences of foliage and non-photosynthetic material on LAI determination of Lenga stands.

Determination of LAI performed best with a vegetation index based on mir_1 and nir reflectances such as MVI A and mNDVI (A3,A4). LAI was estimated with ASTER data at relative RMSE around 12% for Lenga forest stands. Working with Landsat ETM+ data lead to slightly higher RMSE due to different radiometric configuration and lower geometric resolution. Vegetation indices that account for canopy or soil background or atmospheric influences did not improve the RMSE.

DBH was best estimated by a model based on the tasseled cap derivative greenness. Relative RMSE for DBH estimation of Lenga stands were around 26%. The highest R^2 was low, the model explained only 29.8% of the behavior of the dependent variable, DBH. Even so, when looking at the small RMSE, the results are promising.

Determination of basal area worked best with ASTER band 6, a mir_2 band. Basal area was estimated with ASTER data at relative RMSE around 30% for Lenga stands if vegetation indices included information from mir and nir reflectances. Working with data from comparable sensors lead to higher RMSE. The established model was strong, it explained 61.9% of the behavior of basal area. Compared to results from other studies, the determination of basal area for Lenga stands can be considered as successful.

The use of vegetation indices and spectral bands from ASTER and Landsat ETM+ was not successful in determining volume of Lenga forests. No significant correlation existed. LAI was the most suitable parameter, indirectly definable from remote sensing data, to estimate volume. Relative RMSE of volume determination were around 40%, if LAI was modeled with MVI derived from ASTER data. The R^2 was low, the model explained only 17.6% of the behavior of the dependent variable, volume. The results show that a logarithmic model can yield slightly better results than a linear model for Lenga forests. Compared to other studies of volume estimation, the achieved relative RMSE is good. However, the model based on modeled LAI was weak and the application of more promising methods such as the k-nearest neighbor estimation method should be considered.

One of the objectives of this study was to generate forest parameter maps for the Lenga forests, the main commercial woods in South Argentina and Chile. Remotely sensed data was linked to biophysical characteristics to be able to accurately extract biophysical forest parameters on a large scale without the need for elaborate fieldwork. The best regression models found for each of the estimated forest parameters were applied to the respective remote sensing dataset. Only image pixels classified as Lenga stands in the object-oriented classification map were considered. The generated forest parameter maps are a valuable, non-replaceable resource. They were integrated into the GIS of the CIEFAP (Centro de Investigacion y Extension Forestal Andino Patagonico) and the Directorate of Forest and Parks. The generated maps will serve as input to future planning of Lenga forest management so as to guarantee sustainable forest management.

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