

**Erdsicht - Einblicke in geographische
und geoinformationstechnische Arbeitsweisen**

Schriftenreihe des geographischen Instituts der Universität Göttingen,
Abteilung Kartographie, GIS und Fernerkundung

Herausgegeben von Prof. Dr. Martin Kappas



Anke Gleitsmann

Exploiting the Spatial Information in High Resolution Satellite Data and Utilising Multi-Source Data for Tropical Mountain Forest and Land Cover Mapping



ibidem

Anke Gleitsmann

**Exploiting the Spatial Information
in High Resolution Satellite Data
and Utilising Multi-Source Data for
Tropical Mountain Forest and Land Cover Mapping**

ERDSICHT - EINBLICKE IN GEOGRAPHISCHE UND GEOINFORMATIONSTECHNISCHE ARBEITSWEISEN

Schriftenreihe des Geographischen Instituts der Universität Göttingen,
Abteilung Kartographie, GIS und Fernerkundung

Herausgegeben von Prof. Dr. Martin Kappas

ISSN 1614-4716

- 7 *Jobst Augustin*
Das Seegangsklima der Ostsee zwischen 1958 und 2002 auf Grundlage numerischer
Daten
ISBN 3-89821-572-5
- 8 *Martin Kappas*
Naturraumpotential und Landnutzung im Oudalan – eine Fallstudie aus dem Sahel
Burkina Fasos zur Anwendbarkeit von Fernerkundungsmethoden im regionalen
Maßstab
ISBN 3-89821-664-0
- 9 *Ortwin Kessels*
Qualitätsanalyse verschiedener digitaler Geländemodelle und deren Eignung für die
Prozessierung von Satellitenbilddaten in den Tropen
ISBN 3-89821-603-9
- 10 *Christian Knieper*
Remote Sensing Based Analysis of Land Cover and Land Cover Change in Central
Sulawesi, Indonesia
ISBN 3-89821-646-2
- 11 *Mareike Lehrling*
Klimaentwicklung in Alaska - eine GIS-gestützte Erfassung und Analyse der raum-
zeitlichen Entwicklung von Temperatur und Niederschlag
ISBN 3-89821-670-5
- 12 *Daniel Karthe*
Trinkwasser in Calcutta
Versorgungsproblematik einer indischen Megastadt
ISBN 3-89821-661-6
- 13 *Enrico Kalb*
Landnutzungsinterpretation und Erosionsmodellierung der Küstenregion von Nordost
Bali, Indonesien
ISBN 3-89821-666-7

Anke Gleitsmann

**EXPLOITING THE SPATIAL INFORMATION
IN HIGH RESOLUTION SATELLITE DATA AND
UTILISING MULTI-SOURCE DATA FOR
TROPICAL MOUNTAIN FOREST AND LAND COVER MAPPING**

ibidem-Verlag
Stuttgart

Bibliografische Information Der Deutschen Bibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über <<http://dnb.ddb.de>> abrufbar.

∞

ISBN-13: 978-3-8382-5727-3

© *ibidem*-Verlag

Stuttgart 2006

Alle Rechte vorbehalten

Das Werk einschließlich aller seiner Teile ist urheberrechtlich geschützt. Jede Verwertung außerhalb der engen Grenzen des Urheberrechtsgesetzes ist ohne Zustimmung des Verlages unzulässig und strafbar. Dies gilt insbesondere für Vervielfältigungen, Übersetzungen, Mikroverfilmungen und elektronische Speicherformen sowie die Einspeicherung und Verarbeitung in elektronischen Systemen.

Vorwort des Herausgebers

Die Reihe „Erdsicht – Einblicke in Geographische und Geoinformationstechnische Arbeitsweisen“ soll Forschungsergebnisse und Arbeiten im Bereich der Erdsystemforschung vorstellen. Die Betrachtung der Erde als System ist als Inhalt heutiger und zukünftiger Geowissenschaftlicher Gemeinschaftsforschung dringend gefordert. Die Herausforderungen liegen zum einen in der Erforschung der vielfältigen Interaktionen zwischen den verschiedenen Teilbereichen des Systems Erde. Hierzu zählen Wechselwirkungen zwischen fester Erde und Atmosphäre, zwischen der Landoberfläche und der Hydrosphäre oder zwischen Biosphäre, Hydrosphäre und Atmosphäre. Der Mensch steht dabei mit seinen zentralen Nutzungsansprüchen (Ernährung – landwirtschaftliche Nutzung – Ressourcennutzung) im Mittelpunkt eines vielfach vernetzten Erdsystems. Der Mensch verändert Landschaften und Atmosphäre und greift somit in alle Skalenbereiche des Erdsystems ein. Insofern müssen diese Veränderungen beobachtet und bewertet werden, damit Konzepte für ein nachhaltiges Erdsystemmanagement auf den unterschiedlichen Raum- und Zeitskalen entwickelt werden können. Die neuen Geoinformationstechniken (Geostatistik; Geographische Informationssysteme – GIS; luft- und Satellitengestützte Fernerkundungssysteme – Remote Sensing) helfen dabei das System Erde zu beobachten und zu begreifen. Ohne diese Techniken ist eine ganzheitliche Betrachtung der Erde und eine flächenhafte Bereitstellung von Informationen über das Erdsystem nicht möglich.

Die vorliegende Dissertation beschäftigt sich mit den Möglichkeiten des Informationsgewinns aus räumlich hochaufgelösten Satellitendaten, wie sie beispielsweise mit den IKONOS-Daten seit 1999 verfügbar sind. Das Untersuchungsgebiet ist ein Gebirgsbereich in der Dominikanischen Republik, wo tropische Bergwälder und landwirtschaftliche Nutzung aufeinandertreffen. Genaue räumliche Informationen sind hier wichtig, um Ressourcenschutz und Ressourcennutzung sinnvoll miteinander kombinieren zu können.

Martin Kappas

Abstract: Exploiting the Spatial Information in High Resolution Satellite Data and Utilising Multi-Source Data for Tropical Mountain Forest and Land Cover Mapping

The heterogeneous, fragmented land cover pattern of the upper catchment area of the Río Yaque del Norte, in the Cordillera Central of the Dominican Republic, is typical for many tropical mountain areas. Parts of the catchment area have been colonised in the course of the 20th century, in spite of their marginality for agricultural land use purposes. At the same time, there are still several types of primary mountain forests remaining in this mountain range, among them fragmented cloud forest areas with threatened endemic species. Deforestation and unsustainable land use methods on the steep slopes of the study area have led to erosion and land degradation. There are efforts to foster more sustainable land use practices, to reforest some areas and to protect the threatened ecosystems. Detailed spatial land cover information would be important for improving the basis of the necessary land management decisions.

The study area is challenging for forest and land cover mapping. The usefulness of medium resolution (e.g. Landsat) satellite data for mapping its vegetation types is limited, because the small-scale mix of land cover types leads to a large proportion of mixed pixels in such data. The introduction of a new generation of commercial high spatial resolution satellites like IKONOS has led to new possibilities for more detailed classifications of special interest areas, but the high resolution data also pose new challenges for automated land cover mapping. Single pixels in these data fail to integrate the elements of the target classes (e.g. forest types) and the increased amount of spatial information contained in the data cannot be fully extracted by using the per-pixel multispectral classification approaches which are common for medium resolution satellite data. To make use of the high resolution spatial information contained in the IKONOS panchromatic channel in automated classifications, customised texture parameters were created and used as additional channels in the classification. At the same time, several methods for the spatial integration of the multispectral data were tested and compared, in

order to make the spectral signals of the image primitives more representative of the target classes. Both the spatial integration of the multispectral data (especially low pass filtering) and the introduction of texture parameters led to significantly increased classification accuracies. The integration of multi-source data as input for the classifiers (combining additional Landsat multispectral channels or DEM-derived topographic models with the IKONOS data sets) did not lead to significantly improved results, compared to the results which were achieved with IKONOS data alone. However, the elevation data did show some potential to increase the separability of some classes. They could probably have been more useful if a higher resolution DEM had been available. The Maximum-Likelihood-Classifier produced better results than the tested non-parametric classifiers. With the optimised methods, a detailed land cover classification (13 classes, six of which represented forest types) was possible using information derived from the IKONOS data. There were some inherently problematic classes like open pine forest and agro-forestry, but for most forest classes, good classification accuracies could be achieved, particularly for the ecologically important cloud forest class.

Acknowledgements

This study was conducted in the Cartography, GIS and Remote Sensing Department at the Geographical Institute of the University of Göttingen. My supervisor was Professor Dr. Martin Kappas, who also introduced me to the Dominican Republic. I would like to thank him for suggestions, support and being always open for discussions. I am also grateful to my other colleagues at the department, particularly Dr. Stefan Erasmi for discussions, suggestions and occasional technical support and Glenda Rodriguez for having been such a friendly room (office) mate. In the Dominican Republic, I was kindly assisted by Ramón Elias Castillo (PROGRESSIO) and Dr. Thomas May with their local botanical knowledge, and by staff members of the PROCARYN-Project, particularly Thomas Heindrichs, Pablo Ovalles, Humberto Checo, Henning Peter and the 'Extensionistas' (field workers), among others. I'd also like to thank the PROCARYN freelancers Pai Spehs and Wieland Künzel, and Wieland and his wife Shoko for their hospitality in Santo Domingo. During the first field work campaign, the PROCARYN interns Anja and Randy (University of Göttingen) und Vivien und Dassa (Students of the agricultural and forestry college ISA in Santiago) helped me to collect field data. During a part of the second field work campaign, I could share field work resources and some of the generated photos with Nicole Erler. I'm grateful that my husband Lars accompanied me during the second field work campaign. He contributed his back-country driving skills, some of the ground photographs and particularly the oblique aerial photographs. His support and suggestions were very important for me during my work for this study. I'd also like to give special thanks to my parents, whom I could always rely on while exploring the world, and whose support enabled me to study an interesting subject. Wiebke Dietrich, my parents, Stefan Erasmi and Lars helped me with the proof-reading of the thesis script.

This work was financed for the most part by a graduate grant of the state of Lower Saxony (Graduiertenförderung), together with financial travel support by the DAAD (German Academic Exchange Service) and the DFG (German Science Commission).

Contents

Vorwort des Herausgebers	v
Abstract	vi
Acknowledgements	viii
Contents	ix
List of Figures	xiii
List of Tables	xv
List of Plates	xvi
List of Abbreviations	ixx
Copyright Notice	xxi
1 Introduction	1
1.1 Aims and Objectives	4
1.2 Central Hypothesis	5
1.3 Outline	5
2 Methodical Background	7
2.1 Use of Remote Sensing in Forest Mapping	7
2.2 The Role of Spatial Resolution in Satellite Remote Sensing, with Particular Regard to Forest Mapping	13
2.3 Texture and its Role in Land Cover and Forest Classification	23
2.4 Image Segmentation	33
2.5 Multi-Source Data Integration and GIS in Vegetation Mapping	37
2.6 Classification Issues	43
2.7 Considerations for the Assessment of Classification Accuracy	57
3 Forest Resources and Land Cover in the Dominican Republic, with Special Regard to the Upper Catchment Area of the Río Yaque del Norte	63
3.1 The Environment	63
3.1.1 Geology and Relief	65
3.1.2 Climate	69
3.1.3 Hydrology	74
3.1.4 Morphology	75
3.1.5 Soils	76
3.1.6 Natural Vegetation	76

3.2 Human Influence on Forest and Land Cover	88
3.2.1 History of Deforestation and Forest Degradation in the Dominican Republic ..	88
3.2.2 Consequences of Deforestation	94
3.2.3 Forest Laws and Forest Policy	97
3.2.4 Reforestation Efforts and Commercial Forestry	100
3.2.5 National Parks and Scientific Reserves	101
3.2.6 Environmental Projects	105
3.2.7 Agricultural Land Use in the Study Area	106
3.2.8 Agroforestry	108
3.2.9 Degraded and Secondary (Semi-Natural) Vegetation in the Study Area	109
3.3 Information for Forest and Land Use Management in the Dominican Republic ...	111
3.3.1 Forest Mapping and Inventories since 1950	111
3.3.2 Information Needs	115
4 Data and Tools	117
4.1 Satellite Data	117
4.1.1 Landsat-7	117
4.1.2 IKONOS-2	118
4.2 Aerial Photographs	121
4.3 Digital Elevation Model	123
4.4 Maps	123
4.5 Tools	124
5 Field Work	125
6 Data Pre-Processing	129
6.1 Landsat ETM+ Pre-Processing	129
6.2 IKONOS Pre-Processing	131
6.3 Digital Elevation Model	135
7 Landsat ETM+ Classification of the Upper Catchment Area of the Río Yaque del Norte	137
7.1 Initial Scheme of Informational Classes	137
7.2 Classification of Landsat-7 ETM+ Data	137
7.3 Post-Classification Processing	139
7.4 Accuracy Assessment	140

7.5 Results and Discussion	141
8 Methods for an Optimised Information Extraction from IKONOS Data for Forest and Land Cover Mapping	147
8.1 Classification Scheme for the Eastern Test Area	147
8.2 Spatial Exploration of IKONOS Data Using Variograms	150
8.3 Extraction of Texture Parameters from High Resolution Data	151
8.3.1 GLCM Texture	151
8.3.2 Local Variance	154
8.4 Spatial Integration of IKONOS Data	155
8.4.1 Spatial Aggregation in Square Windows	155
8.4.2 Low Pass Filtering	157
8.4.3 Image Segmentation	157
8.5 Data Integration	160
8.5.1 IKONOS Spectral-Textural Data Integration	160
8.5.2 Multi-Source Data Integration	161
8.6 Training Areas	166
8.7 Feature Selection and Signature Separability	168
8.7.1 Reduction of Texture Channels after Correlation Analysis	168
8.7.2 Feature Selection	170
8.7.3 Signature Separability	171
8.8 Classifications of the Eastern Test Area	172
8.8.1 Maximum Likelihood Classification	176
8.8.2 K-Nearest-Neighbour Classification	179
8.8.3 Neural Networks Classification	179
8.8.4 Object-Oriented Nearest-Neighbour Classification of Segmented Data	181
8.9 Post-Classification Processing	182
8.10 Accuracy Assessment	183
9 Results and Discussion of Processing Methods and Classifications Involving IKONOS Data	189
9.1 Interpretation of Experimental Variograms	189
9.2 Results of Spatial Integration of Multispectral Data	192
9.2.1 Effects of Spatial Integration on Within-Class Spectral Variability	192

9.2.2 Effects of Spatial Integration on Classification Accuracy	196
9.3 Effects of Integrating Texture Features	204
9.3.1 Class Separability with and without Texture Channels	204
9.3.2 Classification Accuracy with Spectral and Textural Features	208
9.4 Combining Landsat ETM+ and IKONOS Data	215
9.5 Use of Non-Parametric Classification Methods and Integration of Ancillary Data	218
9.5.1 Using Non-Parametric Classifiers to Classify Spectral-Textural Data Sets ...	218
9.5.2 Integration of Ancillary (DEM-Derived) Data as Additional Channels in MLC	219
9.5.3 Non-Parametric Classification of Data Sets Including DEM-Derived Data	224
9.5.4 Use of DEM-Derived Data in Post-Classification Sorting	228
9.6 Discussion of the Classification Results and Accuracy Assessment Methods	229
9.6.1 Validity of the Calculated Accuracy Measures	229
9.6.2 Success and Limitations in Mapping Detailed Forest and Land Cover Classes with IKONOS Data, Considering Land Cover Fuzziness	230
9.6.3 <i>A Posteriori</i> Probabilities and the Spatial Distribution of Errors	237
9.6.4 Elimination of Reference Points Close to Land Cover Class Boundaries from the Accuracy Assessment	239
9.6.5 Fuzzy Accuracy Assessment	241
9.6.6 Class Aggregation	241
10 Conclusions and Perspectives	243
11 Zusammenfassung	251
References	265
Appendix 1: Plates – Land Cover Types of the Study Area	A1
Appendix 2: Plates – Land Cover Maps and Legends	A13
Appendix 3: Satellite Metadata and Scripts	A17

List of Figures

Figure 1: Variogram	19
Figure 2: A 5×5 image window and the corresponding Grey-Level Co-Occurrence Matrix	25
Figure 3: Proportion of within-class texture pixels to total pixels	31
Figure 4: The Dominican Republic	63
Figure 5: The study area “Upper Catchment Area of the Río Yaque del Norte” (UCRYN)	64
Figure 6: Geological map of the study area	68
Figure 7: Climate chart for Jarabacoa	72
Figure 8: Landsat-7 ETM+ image subset of the upper catchment area of the Río Yaque del Norte	119
Figure 9: IKONOS multispectral sub-image of the eastern test area	122
Figure 10: IKONOS multispectral data, 4 m resolution, RGB 432 (left) and panchromatic data, 1m resolution (right)	122
Figure 11: Field work	128
Figure 12: Scan-misalignment in the Landsat-7 ETM+ Level 0R data (left) and the area after correction (right)	129
Figure 13: Distribution of GCPs in the western sub-image during orthorectification	135
Figure 14: Spectral class signatures (channel means) from Landsat data	138
Figure 15: Sequence of processing operations for the classification of data sets involving IKONOS data	147
Figure 16: 1 m resolution panchromatic image subsets used for the calculation of experimental semivariograms	150
Figure 17: 100×100 pixels subset of a cloud forest area in the panchromatic IKONOS image with nine vertical and nine horizontal transects	151
Figure 18: Texture colour composite	154
Figure 19: A detail of the 4 m resolution multispectral IKONOS image and the same area after averaging in square windows to 8 m resolution and 12 m resolution	156
Figure 20: The IKONOS sub-image after low pass filtering (3×3 average filter)	158
Figure 21: Multiresolution image segmentation with scale parameter 16 (above) and 20 (below)	158
Figure 22: Spectral-textural colour composite (RGB: NIR, red, GLCM Contrast) at 4 m resolution	161
Figure 23: Elevation (above), slope (left) and ‘incidence60’(right) images generated from the DEM	164
Figure 24: The training areas in the eastern test area	168

Figure 25: The reference points used for the accuracy assessment in the eastern test area	185
Figure 26: Experimental variograms of forest transects, from 1 m resolution panchromatic (450-900 nm) data	190
Figure 27: Experimental variograms of grassland transects, from 1 m resolution panchromatic (450-900 nm) data	191
Figure 28: Within-class standard deviation at different spatial resolutions after block averaging and at 4 m resolution after mean filtering	194-195
Figure 29: Classification of the 4 m multispectral data without any spatial integration ...	196
Figure 30: Product of user's accuracy (UA) and producer's accuracy (PA) for selected classes for IKONOS 4 channel 14 class classification (5×5 mode filtered)	199
Figure 31: Diagrams of overall accuracies for 4 channel multispectral classification (14 classes) with different spatial resolutions, pre-classification mean filters and post-classification mode filters used	201
Figure 32: Classification of the 3×3 mean filtered multispectral data set, results are 7×7 mode filtered	203
Figure 33: Maximum likelihood classification of segmented multispectral data (scale parameter 20)	203
Figure 34: Classification based on texture data only (data set 22), results are 3×3 mode filtered	210
Figure 35: Classification of the spectral-textural data set 18 (3×3 mean filtered multispectral data and three texture channels), results are 7×7 mode filtered	210
Figure 36: Class-specific accuracy measure (product of user's accuracy and producer's accuracy) for three spatial resolution/integration cases with and without the inclusion of texture features in the classification	214
Figure 37: Landsat ETM+ classification of the eastern test area, 3×3 mode filtered	216
Figure 38: MLC result for the spectral-topographic data set 27, 8 m resolution, no mode filter	221
Figure 39: Sketch of probability density functions of two classes, shown for a one-dimensional feature space	221
Figure 40: ANN classification result of data set 32 (IKONOS ms channels 1-4, GLCM Texture <i>ENT</i> , <i>SD</i> , <i>CONT</i> , elevation), demonstrating how this classifier confines classes like pine forest, palm dominated forest, cloud forest, secondary forest and agroforestry to certain ranges of elevations which they then dominate to an unrealistic extent	227
Figure 41: Diagram of causes of ambiguities between class pairs (beyond mixed boundary pixels) in the eastern test area	234
Figure 42: Schematic representation of pines (omitting shadows) on a grass background with a 4 m raster, illustrating the boundary uncertainty between grassland and the open pine forest class	235
Figure 43: <i>A posteriori</i> probabilities for the class assigned in a maximum likelihood classification of data set 18	238

Figure 44: Unfiltered MLC result of data set 18 with classes depicted only if PP1 > 0.66, and white areas where PP1 is lower	238
------------------------------------------------------------------------------------------------------------------------------------	-----

List of Tables

Table 1: Comparison of three classifications of forest and woodland types of the Dominican Republic	79
Table 2: ETM+ characteristics	118
Table 3: IKONOS-2 instrument characteristics	120
Table 4: IKONOS-2 orbital information	120
Table 5: Acquisition parameters of IKONOS images used in this study	121
Table 6: Decision rules applied during post-classification sorting	139
Table 7: Land cover classes in the UCRYN Landsat classification	140
Table 8: Confusion matrix for the Landsat classification	142
Table 9: Reduction of classification detail through class aggregation	144
Table 10: Land cover classes in the eastern test area	148
Table 11: Scale parameters and sizes of resulting image object primitives in the segmentation of the eastern test area	160
Table 12: Training pixels per class at 4 m resolution	167
Table 13: Correlation coefficients for texture channels (scaled to 8 bit), eastern test area	169
Table 14: Classifications conducted for the eastern test area	173-175
Table 15: Normal distribution of channel DN's in the class training areas	176
Table 16: IKONOS ms channels 1-4, eastern test area, 14 class classification, overall accuracy [%], (overall Kappa index of agreement in brackets)	197
Table 17: Overall accuracies [%] for 14 class classification of low pass filtered Ikonos ms channels 1-4, eastern test area (Kappa index of agreement in brackets)	200
Table 18: Overall accuracies [%] for four segmentation levels achieved with object-based nearest neighbour classifications, and in one case MLC	201
Table 19: Signature separability (Bhattacharyya distance), using the four IKONOS multispectral bands at 8 m resolution	206
Table 20: Signature separability (Bhattacharyya distance), using the four IKONOS multispectral bands at 8 m resolution and GLCM <i>standard deviation</i> , <i>contrast</i> and <i>entropy</i>	207
Table 21: Signature separability (Bhattacharyya distance), using the four IKONOS multispectral bands at 8 m resolution and GLCM <i>standard deviation</i> , <i>contrast</i> and <i>entropy</i> for 13 classes (after merging the class signatures of Sfo and SFd) ...	208
Table 22: Comparison of overall accuracy [%] and Kappa index of agreement (in brackets) for the IKONOS multispectral data with and without the inclusion of texture features in the classification (13 classes)	211

Table 23: Comparison of overall accuracy [%] and Kappa index of agreement (in brackets) for the IKONOS multispectral data with and without the inclusion of texture features in the classification and with post-classification mode-filtering (13 classes)	212
Table 24: Classification accuracy (13 classes) for multispectral data sets at 8 m resolution consisting of IKONOS data or IKONOS data combined with Landsat data	217
Table 25: Overall accuracy [%] and Kappa index of agreement (in brackets) for classifications of data set 14 with different classifiers (13 classes)	219
Table 26: Results of maximum likelihood classifications for 8 m resolution data sets with different combinations of spectral, textural and topographic channels	222
Table 27: Overall accuracy [%] and Kappa index of agreement (in brackets) for classifications of data set 27 (Ikonos ms channels 1-4, DEM-based elevation, slope and incidence60, at 8 m resolution) with different classifiers (13 classes)	225
Table 28: Overall accuracy [%] and Kappa index of agreement (in brackets) for non-parametric classifications of spectral-textural-topographic data sets	226
Table 29: Confusion matrix for the IKONOS classification, MLC of data set 18, 7×7 mode filtered, 13 classes	231
Table 30: Improvement (in %) of the overall accuracy values when using the testing sample without points close to boundaries, compared to the values achieved with the complete testing sample	240
Table 31: Class aggregation and corresponding overall accuracies, based on the 7×7 mode filtered MLC result for data set 18	242

List of Plates

Plate 1: Natural open pine forest at 2700 m elevation in the Cordillera Central, 28 February 2002	A1
Plate 2: Natural pine forest at 2300 m elevation, with fire scars on the right side, 28 February 2002	A1
Plate 3: Remainder of native <i>Pinus occidentalis</i> in an agricultural area at 900 m a.s.l. (eastern test area), March 2002	A1
Plate 4: Mixed pine and humid broadleaved forest at 900 m elevation, above the Río Jimenoa, 27 March 2003	A1
Plate 5: <i>Didymopanax tremulus</i> - <i>Magnolia pallescens</i> cloud forest, Reserva Científica Ebano Verde, 1400-1500 m a.s.l., 10 March 2003	A2
Plate 6: Cloud forest, Reserva Científica Ebano Verde, 1400 m a.s.l., 19 March 2002 ...	A2
Plate 7: Cloud forest with <i>Dicranopteris pectinata</i> ground cover, Reserva Científica Ebano Verde, approximately 1300 m a.s.l., 19 March 2002	A2
Plate 8: <i>Magnolia pallescens</i> (Ebano verde), Reserva Científica Ebano Verde, 10 March 2003	A3

Plate 9: Calimetal (<i>Dicranopteris pectinata</i>), Reserva Científica Ebano Verde, 1150 m a.s.l., 10 March 2003	A3
Plate 10: Aerial view of palm dominated forest (light green areas are fern / <i>calimetal</i> , large crowns are broadleaved and pine trees), 23 March 2003	A4
Plate 11: Broadleaved riparian forest with <i>Prestoea montana</i> as a subdominant species, eastern test area, Scientific Reserve Ebano Verde, 10 March 2003	A4
Plate 12: Humid evergreen broadleaved forest (Salto de Jimenoa, 650 m a.s.l.), March 2003	A5
Plate 13: Humid evergreen broadleaved forest in the National Park Armando Bermúdez, 1200 m a.s.l., 2 March 2002	A5
Plate 14: Riparian forest in forest surroundings, Scientific Reserve Ebano Verde, 1200 m a.s.l., 19 March 2002	A5
Plate 15: Riparian forest bordered by pasture area, 1100 m a.s.l., March 2003	A5
Plate 16: Aerial view of broadleaved riparian forest in between grassland (pasture) areas just outside of the Scientific Reserve Ebano Verde, eastern test area, 23 March 2003	A6
Plate 17: Degraded remains of broadleaved semi-deciduous forest in the area of the Tavera reservoir, March 2003	A6
Plate 18: Aerial view of the Presa de Tavera, 23 March 2003	A6
Plate 19: A slope with young pine trees after a probably deliberate fire, western UCRYN, March 2003	A7
Plate 20: Young pine plantation with older pine stands in the background, western UCRYN, 1000 m a.s.l., March 2003	A7
Plate 21: <i>Pinus caribaea</i> plantation, Scientific Reserve Ebano Verde, eastern test area, March 2003	A7
Plate 22: <i>Acacia mangium</i> plantation, southern UCRYN, March 2003	A7
Plate 23: Grassland, eastern test area, March 2003	A8
Plate 24: Grassland (pasture) with trees and in the northern UCRYN, March 2003	A8
Plate 25: Intensive agriculture including Chayote fields in the alluvial plain of La Ciénaga, March 2003	A8
Plate 26: Chayote field, western UCRYN, 22 March 2002	A8
Plate 27: Bean field, March 2002	A8
Plate 28: Bean fields, March 2003	A8
Plate 30: Coffee without shade, low ground coverage, western UCRYN, 1300 m a.s.l., March 2002	A9
Plate 31: Coffee with high ground coverage and some trees, western UCRYN, 1300 m a.s.l., March 2002	A9
Plate 32: Agroforestry: medium-sized coffee plantation with <i>Inga vera</i> and banana plants, southern UCRYN, March 2002	A9
Plate. 33: Small area of mixed agroforestry, eastern test area, March 2003	A9

Plate 34: Agroforestry: coffee under pine trees, 31 March 2003	A9
Plate 35: Two views of open (degraded) lower montane pine forest, with bracken dominating the herbaceous layer, southern UCRYN, between 1200 and 1300 m a.s.l., March 2002	A10
Plate 36: Eastern test area (buffer zone of Reserva Científica Ebano Verde), around 900 m a.s.l. Land cover mix of crops and grassland, <i>matorral</i> , broadleaved riparian forest along the river, pines in the form of small closed stands, single pines and groups of pines / open pine forest with a transition to grassland, some landslide scars, March 2003	A10
Plate 37: Secondary forest, Scientific Reserve Ebano Verde (agricultural use before 1989, photographed 19 March 2002)	A11
Plate 38: Secondary forest with pines. Eastern test area, March 2003	A11
Plate 39: Secondary forest in the Scientific Reserve Ebano Verde, eastern test area, March 2003	A11
Plate 40: Hurricane damaged pine plantation, regeneration mostly broadleaved. Eastern test area, 1200 m a.s.l., March 2003	A12
Plate 41: <i>Matorral</i> . Eastern test area, March 2003	A12
Plate 42: Transition rough grassland – <i>matorral</i> . Eastern test area, March 2003	A12
Plate 43: Landsat ETM+ classification of the upper catchment area of the Río Yaque del Norte	A13
Plate 44: Legend for classifications of the eastern test area	A14

List of Abbreviations

ANN: Artificial Neural Network

a.s.l.: above sea level

ASM: Angular Second Moment (GLCM texture feature)

AVHRR: Advanced Very High Resolution Radiometer

BD: Bhattacharyya Distance

C: Celsius

CONT: Contrast (GLCM texture feature)

CORR: Correlation (GLCM texture feature)

CRIES: Comprehensive Resource Inventory and Evaluation System

D: Divergence

DED: Deutscher Entwicklungsdienst (German Development Service)

DEM: Digital Elevation Model

DTM: Digital Terrain Model

DGF: Dirección General de Foresta

DIRENA: Departamento de Inventario de los Recursos Naturales (Department for the Inventory of Natural Resources)

D/SS: Dissimilarity (GLCM texture feature)

DN: Digital Number

DNP: Dirección Nacional de Parques

e.g.: for example

ENT: Entropy (GLCM texture feature)

ETM+: Enhanced Thematic Mapper Plus

FAO: Food and Agriculture Organisation of the United Nations

FRA 2000: Global Forest Resources Assessment 2000

GCP: Ground Control Point

GIS: Geographical Information System

GLCM: Grey-Level Co-occurrence Matrix

GLCV: Grey-Level Co-occurrence Vector

GMT: Greenwich Mean Time

GPS: Global Positioning System

GSD: Ground Sample Distance

GTZ: Deutsche Gesellschaft für Technische Zusammenarbeit GmbH

ha: hectare

HOM: Homogeneity (GLCM texture feature)

ICEC: International Classification of Ecological Communities

ICM: Instituto Cartográfico Militar

i.e.: that is

Ifov: Instantaneous Field Of View

IHS: Intensity, Hue, Saturation

INDHRI: Instituto Nacional de Recursos Hidráulicos (National Institute for Water Resources)

IRS: Indian Remote Sensing

ISA: Instituto Superior de Agricultura (in Santiago de los Caballeros, Dominican Republic)

KfW: Kreditanstalt für Wiederaufbau

KIA: Kappa index of agreement

km: kilometre

k-NN: k-Nearest-Neighbour

LAI: Leaf Area Index

m: metre

MLC: Maximum Likelihood Classification

MODIS: Moderate Resolution Imaging Spectroradiometer

ms: multispectral

MSS: Multispectral Scanner

NOAA: National Oceanic and Atmospheric Administration

NGO: Non-Governmental Organisation

NIR: Near Infra-Red

NNC: Neural Network Classification

No.: Number

NP: National Park

OA: Overall Accuracy

OEA (OAS): Organización de los Estados Americanos (Organization of American States)

PROCARYN: Proyecto Maneja y Conservación de la Cuenca Alta Río Yaque del Norte (Project for the Management and Conservation of the Upper Catchment of the Río Yaque del Norte)

RGB: Red, Green, Blue (display colour channels)

RMSE: Root Mean Square Error

SAR: Synthetic Aperture Radar

SD: Standard Deviation (GLCM texture feature)

SEA: Secretaría de Estado de Agricultura (Ministry of Agriculture)

s: second

SEMARENA: Secretaría de Estado de Medio Ambiente y Recursos Naturales (Ministry for Environment)

SPOT HRV XS: SPOT High Resolution Visible Multispectral

SR: Scientific Reserve

StNN: Standard Nearest Neighbour Classification

TD: Transformed Divergence

Tex: Texture

TM: Thematic Mapper

TMCF: Tropical Mountain Cloud Forest

UCRYN: Upper Catchment Area of the Río Yaque del Norte

UNESCO: United Nations Educational, Scientific and Cultural Organization

USAID: United States Agency for International Development

USGS: United States Geological Survey

UTM: Universal Transverse Mercator

VAR: Variance

Abbreviations of Land Cover Class Names

AF: Agroforestry

BG: Bare ground

brn: Burnt areas

BRF: Broadleaved riparian forest

bu: Built-up areas

Cal: *Calimetal* / fern

CF: Cloud forest

Cof: Coffee without shade

Cr: Other crops

GL: Grassland

Mat: Matorral

MF: Mixed forest

PFd: Dense pine forest

PFo: Open pine forest

PmF: Palm dominated forest

SF: Secondary forest

SFd: Dense secondary forest

SFo: Open secondary forest

W: Water

Copyright Notice

Includes material (c) Space Imaging LLC.

1 Introduction

Tropical ecosystems are changing rapidly as a result of human activity. Land cover changes in the tropics include deforestation and landscape fragmentation, often in connection with the colonisation of marginal areas. Achard et al. (2002) state that between 1990 and 1997, 5.8 ± 1.4 million ha of humid tropical forest were lost per year and 2.3 ± 0.7 million ha were visibly degraded. The world-wide loss and degradation of tropical forests has far-ranging ecological and climatic consequences. Tropical mountain forests in particular play a central role in many aspects of sustainable development. They can be linked with soil conservation and the prevention of land degradation, water supply and climate change, biodiversity, and tourism development, apart from providing timber and other forest products (Price & Butt 2000).

The Caribbean islands are a region where the population density is much higher than in many continental tropical countries and the proportion of forests which have survived on these islands is accordingly low (Lugo 1995). The Dominican Republic has seen the destruction of most of its forests in the course of the 20th century, but due to its mountainous relief and historically relatively low population density, some considerable parts of its rich and varied natural vegetation are still remaining – in contrast to its disastrously degraded neighbouring country Haiti.

The problems of deforestation, especially in the mountain areas, are recognized in the Dominican Republic and there are efforts to protect selected areas of natural forests and to reforest mountain areas which are degraded or in danger of further degradation. However, as in many developing countries, there is a lack of information on forest resources. More information would be needed for forest management planning and for monitoring the sustainable development of forests in agreement with Agenda 21 of the Rio Earth Summit 1992 (Lund 1996). According to Saket (2002), most developing countries were unable to provide detailed information to the Global Forest Resources Assessment 2000 (FRA 2000), and only 10 % could

provide information on changes in area. None of the countries in Latin America and the Caribbean reported information based on country-wide field sampling, but most could provide area estimates based on remote sensing. The "*Inventario de Cobertura Forestal*" (inventory of forest coverage) published by the Dominican ministry of the environment in 2001 (SEMARENA 2001a) is based mostly on the classification of several Landsat scenes from the 1990s.

Remote sensing is a necessary data source for mapping, spatial analysis and geo-referenced information (Kleinn 2002). Even if remote sensing technologies cannot provide the same information that would be the result of a complete forest inventory based on extensive field sampling as conducted in many developed countries, they can provide information about some core attributes like forest area and area by forest type, among other things. Only remote sensing can provide full-cover, spatially explicit information on the location of forest types, changes of forest cover and forest fragmentation. The resulting land cover maps can serve as one basis for forest management and protection. They could also help to choose an optimized sample, reducing the necessary intensity of field sampling if further forest inventory efforts were to follow. Land cover maps are also needed as an input for the analysis and modelling of interrelationships of landscape processes.

Classifications based on Landsat or similar medium-resolution satellite data can give a first overview over the spatial distribution of the major vegetation units, but they are often inadequate when dealing with the heterogeneous land cover patterns that are characteristic for many tropical mountain areas due to topographic, climatic, geologic and edaphic variations and land use patterns including subsistence agriculture and shifting cultivation.

The recent introduction of commercially available high spatial resolution satellite imagery has brought about new possibilities and new challenges for the field of satellite remote sensing of the environment. Before the launch of IKONOS-2 in 1999 imagery of a comparable spatial resolution was only available from airborne sensors. Changing the spatial resolution of the

measurement changes the information content and statistical properties of image data (Marceau et al. 1994a), and digital image analysis methods used with medium resolution satellite images are not always applicable. Increasing the spatial resolution of an image reduces the integrating effect of larger pixels and thus the homogeneity within land cover classes. High (and very high) spatial resolution imagery such as aerial photographs is traditionally interpreted by manually delineating vegetation boundaries (Coulter et al. 2000). In these cases, the human interpreter does not only use the information of grey levels or colours, but also attributes like texture, patterns, location, form, and size. Correspondingly, automated digital analysis of high spatial resolution images should include methods which use not only the per-pixel spectral information but also the spatial information present in these images.

One way to utilise the spatial information from high resolution imagery is to extract texture parameters which can then be included in the classification process. Texture in digital image analysis is the variability or the spatial relationship of grey levels in a pixel neighbourhood or window. Image texture parameters can be derived from a variety of first- and second-order statistics. Texture is related to the size and distribution of objects in the scene and to the spatial resolution of the imagery. In high resolution cases, where the pixels are smaller than the size of the objects in the image (which is the case for IKONOS images of forest), texture information can be expected to be especially valuable for class discrimination.

The spatial resolution of high resolution imagery may be too high for optimal per-pixel classification results of heterogeneous land cover classes like forest, because the different elements of a class (e.g. illuminated crowns, shaded crown parts and understorey vegetation) are not integrated in the single pixels. It may thus be necessary to perform some kind of spatial integration before classification, e.g. by reducing the spatial resolution of the imagery or using a low pass filter. Another way to incorporate the spatial context is image segmentation, followed by object oriented image analysis. Image

segmentation divides an image into separated, spatially continuous regions which are homogeneous with respect to some characteristic or characteristics. The resulting image objects are more meaningful than single pixels and allow for object-oriented or per-parcel image classification.

Given the influence of elevation and other terrain variables on vegetation, valuable ancillary information for forest classifications in mountainous areas can be derived from digital elevation models (DEM). Appropriate data integration methods are needed to be able to use multi-source data (satellite and DEM-derived), data of different spatial resolutions, as well as spectral and textural data in the classification process. The established maximum likelihood classification method has some limitations as to the types of data it is appropriate for and it is not adapted for using data of different scales. Therefore, other (non-parametric) classification methods or ways to incorporate ancillary data in pre- or post-classification processes have to be considered.

Geographical entities such as forests are not only scale-dependent in their definition, but they are also inherently fuzzy, with indeterminate boundaries (Cheng 2002). Detailed classifications of natural and semi-natural vegetation in particular entail fuzziness in the class definitions and the spatial delineation of class areas. In addition, the occurrence of mixed pixels on class borders can never be completely avoided even in high resolution imagery. Therefore, the concept of fuzziness is important when addressing the unavoidable uncertainties in class definition, classification and the resulting maps.

1.1 Aims and Objectives

This study aims at finding, testing and comparing methods for forest and land cover mapping in tropical mountainous terrain using automated classifications of recent optical satellite data, comparing the usefulness of medium and high resolution satellite data and combining multi-source data in order to improve classification results.

The main objectives are

- to produce a regional land cover base map using Landsat ETM+ data;
- to evaluate high resolution satellite data (IKONOS) for mountain forest and land cover mapping;
- to test the usefulness of spatial information (texture) for improving the discrimination of forest and other land cover classes;
- to test the usefulness of different kinds of spatial integration of high resolution data, including segmentation;
- to produce an integrated data set as a basis for an optimised classification;
- to test and compare suitable classification methods;
- to generate optimised land cover maps of the study area, discriminating forest formations and other physiognomic vegetation units.

1.2 Central Hypothesis

Digital image classification of high spatial resolution satellite data can contribute to improved results in (localised) tropical mountain forest mapping compared to medium resolution satellite data. The successful use of high resolution data for automated land cover classifications requires that the spatial characteristics of these data are taken into consideration and that the spatial information contained in the high resolution data is extracted and used in the classification process as well as the spectral information.

1.3 Outline

In the following chapters, I will present the theoretical framework of this study and then describe the land cover (especially the forests) and the land use in the study area, including the physical and historical basis for the current situation. The next chapter describes the data that were available to me for

this study. The first methodological chapters describe the field work and the pre-processing methods used. Chapter 7 explores the possibilities and limitations of a land cover classification without high resolution data. After that, the methods used to extract additional information from high-resolution data are described and, subsequently, the results of the analysed issues (questions of spatial resolution and spatial integration, use of texture, multi-source data integration, classification methods, assessment of results) are described and discussed. The tenth chapter presents the conclusions of this study. It is followed by a summary in German.

2 Methodical Background

2.1 Use of Remote Sensing in Forest Mapping

In many countries outside the tropics, remote sensing is an established tool used in forest mapping and, in combination with ground sampling, in forest inventory (Tomppo 1996, Sutter 1990, Magnussen 1997, Tickle et al. 1998) as well as in forest damage surveys (Thomas 1990). Most of these practical applications involve the use of high spatial resolution remote sensing data, and aerial photographs are still the most common data source used, even though digital air-borne data have gained in importance in recent years (Kayitakire et al. 2002). The analysis of these high resolution images is dominated by manual, non-automated methods (Magnussen 1997, Biggs 1996, Sutter 1990), although this is time-consuming and can lead to inconsistent results (Green 2000). The automatic analysis of aerial imagery is mostly still in the experimental rather than the operational stage (Pouliot et al. 2002, Kadmon & Harari-Kremer 1999, Atzberger & Schlerf 2002).

Until 1999, only airborne sensors and cameras provided high resolution data for forestry applications, while multispectral high resolution satellite data with a repetitive coverage were not commercially available. Since then, a number of high resolution satellites have been put into orbit. Satellites like IKONOS-2 and QuickBird represent a new generation of remote sensing satellites, delivering multispectral imagery with spatial resolutions of 4 m and less. The advent of high resolution satellite data since 1999 provides new incentives to develop automated analysis methods for digital high resolution remote sensing data. Automated methods for forest classification and the mapping of biophysical stand parameters with digital airborne data have been tested for example in North America (Quackenbush et al. 2000, St-Onge & Cavayas 1995, Franklin et al. 2001a, Cosmopoulos & King 2004, Leckie et al. 2003, Kellndorfer et al. 2003) and Europe (Baulies & Pons 1995). IKONOS high resolution satellite data were used by Goetz et al. (2003) to map tree cover

and by Hirata et al. (2002) and Franklin et al. (2001b) to test techniques for the extraction of information about coniferous forest stands.

Medium resolution satellite data like Landsat are used in some large area forest inventories for example in Finland (Tomppo 1996), but are not deemed to be suitable information sources for practical forest management purposes by Holmgren & Thuresson (1998) and Pitt et al. (1997). Remote sensing cannot deliver information about all the variables which field sampling produces for a forest inventory, but on the other hand, field sampling cannot produce geo-referenced information with complete coverage for a whole region. Spatially explicit information about the area and distribution of forest and land cover types can only be gained with the help of remotely sensed data (Kleinn 2002). Consequently, Landsat TM (Thematic Mapper) and similar optical satellite data are much used in regional forest type and land cover mapping (e.g. Franklin 1992, Koch et al. 2002). There are also efforts to estimate parameters like forest age and crown closure from Landsat TM data (Jakubauskas & Price 2000, Franklin et al. 2003, Xu et al. 2003). There are many more studies using satellite data for forest mapping, but an exhaustive review of the use of medium to low resolution optical data (e.g. Latifovic et al. 2004) and synthetic aperture radar (SAR) data (e.g. Dobson et al. 1996, Kelldorfer et al. 1998) for regional to global forest and land cover mapping would go beyond the scope of this overview.

Besides high spatial resolution satellite data, other new data sources for detailed forest information are airborne lidar (light detection and ranging), which can be used to provide measurements of the vertical canopy structure (Means et al. 2000, Hudak et al. 2002, Dubaya & Drake 2000), and airborne and satellite hyperspectral data (Ustin & Trabucco 2000, Martin et al. 1998). Specialized techniques like these, aiming to provide detailed information for forest managers, are usually developed in non-tropical countries like Canada and Finland, but the aims and conditions of boreal and temperate forest mapping and management are in many respects quite different from the situation in the tropics.

Remote sensing of tropical forests

In many tropical developing countries, there is a lack of even very basic forest information which would be needed for effective forest protection and management. For the Global Forest Resources Assessment 2000 (FAO 2001), none of the Latin American and Caribbean countries could provide forest information based on country-wide field sampling, while about half of these countries had mapped their forest resources using aerial photographs or satellite imagery, providing area estimates for more or less detailed or broad forest types (Saket 2002). Terrestrial surveys of tropical forests are usually difficult and expensive due to poor accessibility and the heterogeneous forest structure (Köhl 1996).

Many tropical forest studies using remote sensing are focused on deforestation. Tropical deforestation is typically studied over large areas using medium and low resolution satellite data, most commonly of the Landsat sensors MSS, TM and ETM+ (Skole & Tucker 1993, Sanchez-Azofeifa et al. 2002, Ichii et al. 2003). Deforestation studies are usually multitemporal studies where for a single date, often just the classes 'forest' and 'non-forest' are separated (Millington et al. 2003, Peralta & Mather 2000, Alves et al. 1999). Wang et al. (2003) refine these simple forest/non-forest classifications by trying to estimate the forest canopy cover fraction within Landsat pixels, Herrera et al. (2004) differentiate between forest, non-forest and trees outside forest, and Asner et al. (2003) differentiate between several land cover types in deforested areas, but they all treat the remaining forest as a single class. This is the case in many deforestation and tropical land cover classification studies, despite the large variety of tropical forest types.

Several authors have classified different successional stages of tropical forest regeneration (Thenkabail et al. 2004a, Kimes et al. 1999, Foody et al. 1996). Efforts to differentiate between different mature forest types are rare in comparison to forest/non-forest classifications. Tuomisto et al. (1994) and Paradella et al. (1994) used mainly visual interpretation of Landsat images to distinguish several tropical vegetation types. The statistical spectral separa-

bility of ecological forest types was studied by Singh (1987) using Landsat MSS data and by Hill & Foody (1994) and Foody & Hill (1996) using Landsat TM data. They came to the conclusion that between three and four groups of forest types were spectrally separable based on these multispectral data, but not all land cover classes which were identified in the field could be separated. Hill (1999) managed to classify six Amazonian forest types using segmented Landsat data. Riaza et al. (1998), García & Alvarez (1994) and Behera et al. (2001) also classified several tropical forest types on three different continents using medium resolution multispectral satellite data. Country-wide forest type and land cover mappings were conducted for Puerto Rico by Helmer et al. (2002) and for the Dominican Republic by Tolentino & Peña (1998) using Landsat TM and ancillary data, and for Mexico by Mas et al. (2002) using visual interpretations of Landsat ETM+ data. Low spatial resolution data (AVHRR) are used by Ferreira & Huete (2004) to monitor woodland, shrubland and grassland vegetation types in the Brazilian Cerrado.

Medium and low resolution optical satellite data are also used in the estimation of tropical forest biophysical characteristics like leaf area index (LAI) or biomass (Foody et al. 2003, Kalácska et al. 2004, Thenkabail et al. 2004a, Atkinson et al. 2000). Another application for these data is the mapping of burned areas resulting from tropical forest fires (Stibig et al. 2001, Fuller & Fulk 2001).

Newly available hyperspectral satellite data have not yet been used much in tropical forest applications (Thenkabail et al. 2004a), while there are a few examples for the application of the new high spatial resolution satellite data. IKONOS data have been used for the validation of products derived from lower resolution data (Wang et al. 2003, Morissette et al. 2003). They have also been tested for forest land use and land cover classifications as well as for the estimation of forest biomass and the detection of selective logging (Clark et al. 2004, Thenkabail et al. 2004a, Hurtt et al. 2003). High resolution remote sensing data is also needed to resolve the narrow mangrove fringes along tropical coastlines. Wang et al. (2004b) compare IKONOS and Quickbird images for mangrove mapping and achieve slightly better

classification results with the IKONOS data. Davis & Jensen (1998) study the correlation between mangrove biophysical variables and airborne high resolution data. There are also examples of traditional aerial photograph interpretation for the mapping of tropical forests (e.g. Hudson 1991).

SAR data is often seen as a solution to the problem of frequent cloud cover in tropical areas which renders much of the optical satellite data unusable. However, the information about moisture and vegetation structure that is contained in radar data (Dobson et al. 1995) is not necessarily suitable for the separation of ecological forest types. Costa (2004) and Simard et al. (2000), using JERS-1 and Radarsat data, were successful mainly in separating different types of floodplain forest and aquatic vegetation in tropical river basins but did not map more than a single dense upland forest class. In addition, the classification of Simard et al. (2000) worked well only in the low topography region, while the terrain induced geometric and radiometric distortions in the radar data hampered the classification in a more mountainous area.

One of the challenges of tropical forest and land cover mapping is the discrimination of agroforestry (Hurt et al. 2003). Agroforestry (main land use agriculture) is usually not included in the definition of forest (e.g. FAO 2001), but can look very similar from a remote sensing view point, with a more or less dense tree canopy and sometimes crops in the form of shrubs (e.g. coffee) below. Helmer et al. (2000) could not separate coffee cultivation from moist forest in Puerto Rico using Landsat TM data and ended up with a mixed class. Langford & Bell (1997) also find that their 'coffee' and 'woodland' classes are often confused. Hill (1999) managed to separate six different tropical forest types in segmented Landsat TM data but could not separate agricultural land containing trees from other open-canopied forest classes.

When forest is mapped it needs to be defined first. For the FAO's global forest resources assessment (FRA 2000), forest is defined as "lands of more than 0.5 hectares, with trees able to reach a minimum height of 5 meters maturity *in situ* and with a canopy cover of more than 10 percent, which are not primarily under agricultural or urban land use" while other wooded land