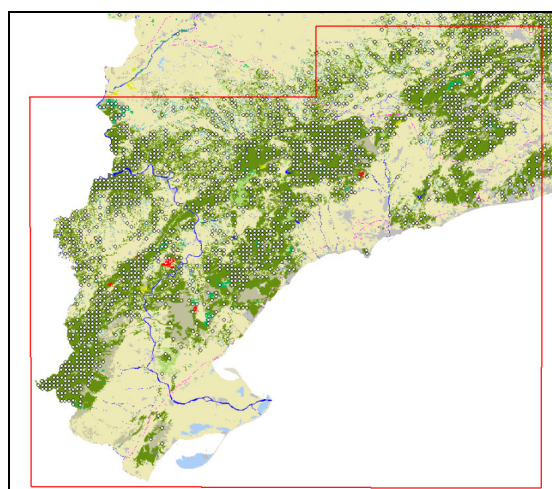
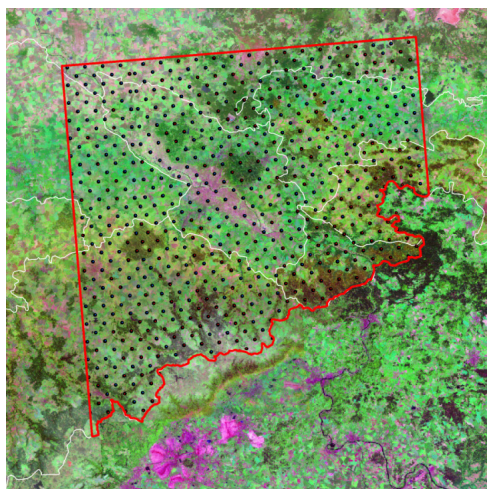
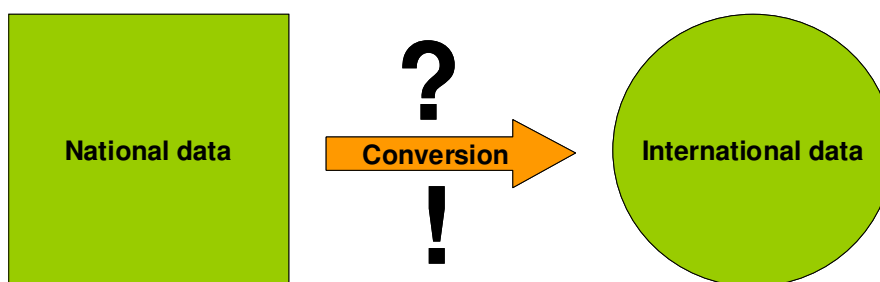


Pilot study on harmonising National Forest Inventories in Europe

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“Pilot study on harmonising National Forest Inventories in Europe”

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Preface

The present study was developed in the context of Regulation (EC) 2152/2003 on the monitoring of forest and environmental interactions, the so-called "Forest Focus" Regulation.

The Forest Focus regulation centered specifically on the monitoring of the effects of atmospheric pollution and fires on European forests, previously addressed by Council Regulation (EEC) No 3528/86 of 17 November 1986 on the protection of the Community's forests against atmospheric pollution and Council Regulation (EEC) No 2158/92 of 23 July 1992 on protection of the Community's forests against fire. Furthermore, "Forest Focus" aimed at encouraging the exchange of information on the condition of and harmful influences on forests in the Community and enabling the evaluation of ongoing measures to promote conservation and protection of forests, with particular emphasis on actions taken to reduce impacts negatively affecting forests.

In order to promote a comprehensive understanding of the relationship between forests and the environment, the scheme also included the financing of studies and pilot projects aiming at the development of monitoring schemes for other important factors such as biodiversity, carbon sequestration, climate change, soils and the protective function of forests. The EC launched and financed a series of seven studies dealing with the following topics:

1. *Climate change impact and carbon sequestration in European forests*
2. *Development of a simple and efficient method field assessment of forest fire severity*
3. *Use of National Forest Inventories to downscale European forest diversity spatial information in five test areas, covering different geo-physical and geo-botanical conditions*
4. *Harmonizing National Forest Inventories in Europe*
5. *Development of harmonised Indicators and estimation procedures for forests with protective functions against natural hazards in the alpine space*
6. *Linking and harmonizing the forests spatial pattern analyses at European, National and Regional scales for a better characterization of the forests vulnerability and resilience*
7. *Evaluation of the set-up of the Level I and Level II forest monitoring under Forest Focus.*

This study is dealing with topic 4 in the above list. Its specific objective were demonstrating and implementing in real cases the harmonization of forest information using National Forest Inventory (NFI) data. The pilot study is thus a first attempt in Europe to provide harmonized NFI information at the supra-national level.

Different technical approaches to harmonise selected NFI variables have been tested and evaluated. Four proposed approaches have been tested with real data for selected test sites in three different countries, namely Germany, Spain and Italy. For each of the three countries two test sites were selected, which represent different forest ecosystems but also most typical forests landscapes of the countries.

This pilot project constitutes a first operational attempt to harmonize national datasets in order to derive a unique Forest Information database at European level that should allow the compilation and analysis of European forest datasets.

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Executive Summary

The ‘Pilot study on harmonising National Forest Inventories in Europe’ is a contract study of the Joint Research Centre (JRC) of the European Commission. The two years study was financed by the EC Forest Focus scheme and started in December 2006 and ended in December 2008. The study was coordinated and conducted by the Institute for World Forestry (University of Hamburg, UHH) in cooperation with the following three partners: Dipartimento di Scienze e Tecnologie Ambientali Forestali (DISTAF), Centre de Recerca Ecològica i Aplicacions Forestals (CREAF) and the European Forest Institute (EFI).

The objective of the “Pilot study on harmonising National Forest Inventories in Europe” was to test and evaluate different technical approaches to harmonise the National Forest Inventory (NFI) variables *forest area*, *forest types* and *diameter distribution*. **Four proposed approaches** were tested with real data for selected test sites in three different countries, namely Germany, Spain and Italy. For each of the three countries two test sites were selected, which represent different forest ecosystems but also most typical forests landscapes of the countries.

Within **Approach 1** Landsat data are used in combination with terrestrial NFI data to produce “coarse” forest area maps. In a next step the main attributes used in defining forest area (*minimum with*, *minimum area* and *minimum crown coverage*) are evaluated on sub-plots using high resolution DOP data. Based on the resulting high resolution sub-samples, the forest area is re-calculated from the new classified data sets (forest/non-forest). Regression models are built between forest area from the low resolution data and the forest area from the high resolution data. The whole forest area estimated from the low resolution data is finally calibrated with the resulting regression coefficient. Based on different selected national definition thresholds and the international definition of FAO, harmonised forest cover data are produced for two selected test areas, namely Germany Saxony and Spain Pyrenees. The results of the two test sites clearly demonstrate that the proposed methodology effectively harmonises the NFI variable ‘forest area’ according to international reference standards such as of the FAO. The results show that differences between national definitions and/or international reference standards (see FAO) lead to differences in forest area estimation between 1-3%.

Linking NFIs with EC Forest Focus/ ICP Forests assessments is another option to harmonise NFI data according to international reference definitions. The objective of **Approach 2** is to calibrate NFI forest type information to an international standard by using EC Forest Focus/ ICP Forests Level I data as an additional reference value. Forest type in this study is classified as *predominantly broadleaved*, *predominantly coniferous* and *mixed forests*. The concept of the method is based on the classification of Landsat data by applying *tree species* data from NFI and Level I respectively. Data are used as training data to produce forest type maps for two different standards: national standard (based on NFI) and international standard (using Level I as a sub-sampling of NFI). The pilot study shows that at test site level different factors were limiting the feasibility of this approach. The main obstacles, which hindered a successful implementation of the approach, were a) the low number of Level I plots per test site, b) the kNN classification inaccuracies and c) the usage of categorical classes instead of metrical data. Most critical for the applicability of the harmonisation Approach 2 is the low number of Level I plots at test site level.

The primary objective of **Approach 3** is to develop and test two different technical approaches to harmonise NFI data on forest types by a) using CLC2000 definitions as a reference standard or b) using CLC2000 as an already harmonised data input for NFI based forest type mapping. The CLC project was chosen as it represents an important harmonised already available European reference data set and methodology for land use/land cover analysis. Like in Approach 2, forest type is classified as *predominantly broadleaved*, *predominantly coniferous* and *mixed forests*. In Approach 3A obtained figures on forest types are provided in tabular format only. Data are basically obtained by re-classifying NFI plot data according to CLC reference standards and the applied threshold of 75 % for discriminating forest types. In Approach 3B instead, NFI data are re-classified according to the CLC definition like in Approach 3A, but are also used to produce forest

type maps by remote-sensing image classification. Especially the map-based approach offers new opportunities to detect forest types status and changes by combining NFI field data with CLC standards and data. The approach seems especially applicable for large scale assessments.

Forests can be characterised also by their DBH distributions, which is a core variable to assess other core variables like growing stock and carbon stock. As most NFIs in Europe apply different thresholds for DBH assessment, it is crucial to have harmonised and reliable estimates of the number and size of trees below a certain applied threshold. This counts especially for the reporting on the UNFCCC Kyoto Protocol. The primary objective of **Approach 4** is to derive diameter distribution models for main tree species for each test site, taking into account specific DBH thresholds as they could theoretically be defined by international standards. In addition to these DBH distribution models, differences in percentage are calculated comparing the estimated diameter distribution with observed diameter distribution. The Weibull and the Negative Exponential function provided highest goodness-of fit for DBH data. In addition to the distribution modelling, the contribution of DBH classes below the defined threshold to the estimates on total growing stock and total carbon stock are evaluated. Results show that the contribution of lower DBH classes (0-11 cm) affects only 2-5 % of the total growing stock or carbon stock. The results show also that the approach can be applied relative easily to any NFI data set, thus allowing harmonising DBH data to any DBH threshold across Europe.

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List of Acronyms

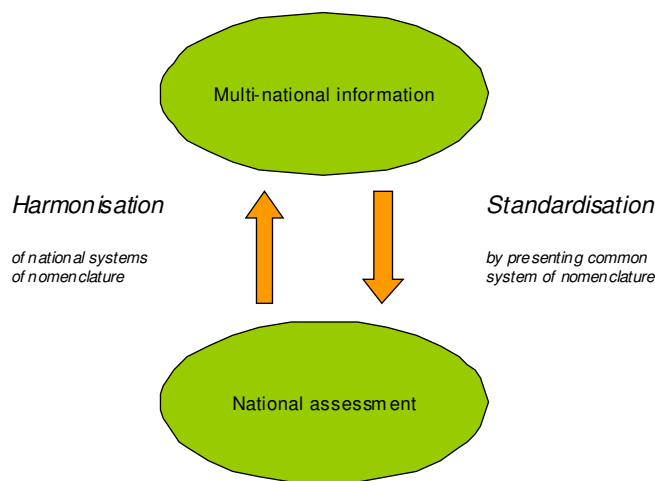
a.s.l	above sea level
ADD	Average Diameter Distribution
Brd	Broadleaved
BSI	Bare Soil Index
CBD	United Nations Convention on Biological Diversity
CLC	Corine Landcover Classification
Con	Coniferous
COST	European Cooperation in the field of Scientific and Technical Research
CREAF	Centre de Recerca Ecològica i Aplicacions Forestals
DBH	Diameter at Breast Height
DDVI	Difference Difference Vegetation Index
DISTAF	Dipartimento di Scienze e Tecnologie Ambientali Forestali
DOP	Digital Orthophotos
EEA	European Environmental Agency
EFI	European Forest Institute
EFICS	European Forest Communication and Information System
ENFIN	European National Forest Inventory Network
ETM	Enhanced Thematic Mapper
FAO	Food and Agriculture Organisation of the United Nations
FRA	Forest Resources Assessment
ICP	International Co-operative Programme
IPVI	Infrared Percentage Vegetation Index
IW	Interpretation Window
JRC	Joint Research Centre
kNN	k-Nearest Neighbour
MCPFE	Ministerial Conference on the Protection of Forests in Europe
MIR	Middle Infrared
Mix	Mixed
NDVI	Normalised Difference Vegetation Index (NDVI)
NFIs	National Forest Inventories
NIR	Near Infrared
PCC	Programme Coordinating Centre
RMSE	Root Mean Square Error
SAVI	Soil Adjusted Vegetation Index
TBFRA	Temperate and Boreal Forest Resources Assessment
UHH	University of Hamburg
UK	United Kingdom
UNFCCC	United Nations Framework Convention on Climate Change
LB	Lower Bound
UB	Upper Bound

1. Introduction

Harmonised and reliable forest information at the European level is a key issue for forest and environmental policy. Although a considerable amount of valuable information on forests is already available in all member states, there are still significant differences between country assessments, mapping and monitoring methods which makes information comparability often difficult.

Problems of comparability of national data and the reliability of aggregated results arise mainly because of differences in a) the national systems of nomenclature, i.e. measurement rules and definitions, b) inventory concepts and c) the reference periods. Those differences can be made compatible in two different ways: a) by harmonisation and by b) standardisation.

Fig. 1.1: Harmonisation and Standardisation (Köhl et al., 2000).



There are distinct differences between the concepts underlying harmonisation and standardisation (see Köhl et al., 2000). **Harmonisation** is based on existing national assessment regimes. Harmonisation utilises available national data and transfers them to meet an internationally agreed system of nomenclature. It can be seen as a ‘bottom up approach’ starting from an existing divergence and ending in a state of comparability by simultaneously maintaining the reliability of information.

Standardisation is a different concept; it focuses on a common standard and can be seen as a top-down approach that forces national systems to adopt the standard. The implications of standardisation are critical. On the one hand it requires that an international standard can be found and agreed upon. On the other hand it forces countries to a) either give up their national systems of nomenclature and adopt the common standard – a decision that will result in the loss of national time series – or b) implement two parallel systems of nomenclature (i.e. their national system and the international standard), which would result in increasing costs and inconsistencies.

It is widely accepted that standardisation avoids inconsistencies but can show substantial differences to individual and national approaches. Standardisation is thus rather operational in the context of newly arising information needs and corresponding attributes, or when it aims at finding the smallest common denominator between national systems of nomenclature (i.e. the maximum threshold for diameter at breast height found in national systems).

Harmonisation approaches should not result in new standards. Harmonisation should be defined as a bottom-up approach, which takes existing standards and developments effectively into account and finds best available synergies and harmonisation options to make different national

data and assessments comparable. A fundamental goal is to provide harmonisation solutions, which allow national authorities to continue their data assessment in a way that meets up their explicit interests and capacities. Harmonisation approaches should define widely applicable solutions, which allow national authorities to continue national data assessments without changing or integrating new standards of data assessment and measurements rapidly. At least necessary adoptions and new implementations should be kept on a minimum by using efficiently, synergies between national and international but also between previous and newly applied approaches of monitoring, assessment and reporting. Especially as data of changes are of high interest in monitoring environmental conditions, it should be granted that existing time series, like National Forest Inventories (NFIs) can also be continued in future. That does not mean that new developments in techniques and policy should not be considered and implemented in existing national data assessments as much as possible. In general, minimum costs but high efficiency should be the objectives of performing and implementing harmonised data assessments.

The objectives of the proposed harmonisation approaches are:

- demonstrate different harmonisation approaches for selected forest variables and for different forest ecosystems;
- perform and test harmonisation approaches with real data;
- apply approaches for different selected test areas within three different countries;
- compare approaches between a) similar and b) different forest ecosystems;
- consider international data as EC Forest Focus/ ICP Forests Level I, CLC 2000 and JRC forest/non-forest mask as possible reference standards;
- consider standards and definitions accepted on international level as reference standards (like from UNECE/FAO TBFRA 2000, MCPFE C&I, FAO FRA, UNFCCC and CBD);
- consider activities and available outcomes of the ENFIN COST E43.

For the pilot study on harmonising National Forest Inventories in Europe four different approaches for three most relevant variables, namely *forest area*, *forest types* and *diameter distribution*, are proposed and tested and evaluated considering their use and applicability. The four proposed harmonisation approaches are:

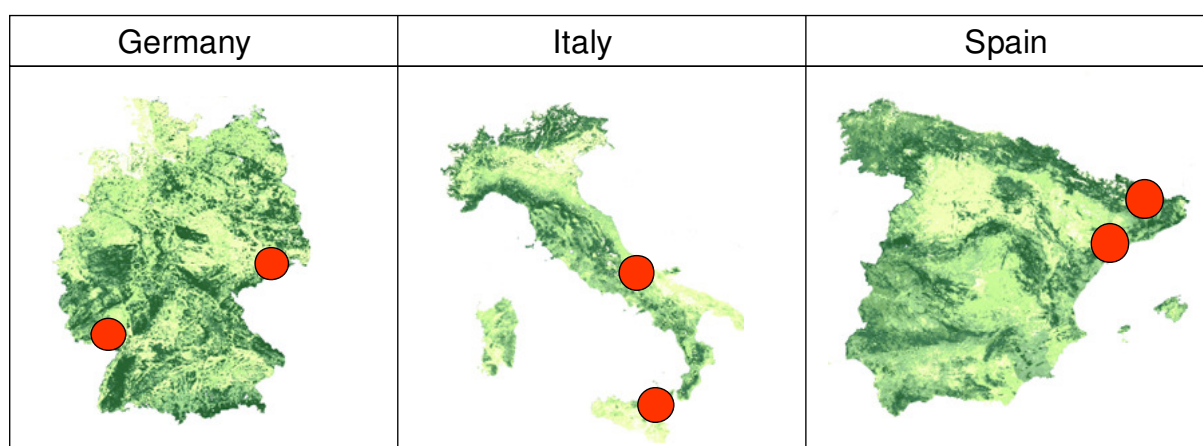
- Approach 1: Sub-Sampling of High Resolution Remote Sensing Data**
 -> Variable: Forest area
- Approach 2: Sub-Sampling Approach using EC Forest Focus/ ICP Forests Level I data**
 -> Variable: Forest types (*broadleaved, coniferous, mixed*)
- Approach 3: Combining NFI data with CLC2000**
 -> Variable: Forest types (*broadleaved, coniferous, mixed*)
- Approach 4: Extrapolating stand typical parameter functions**
 -> Variable: Diameter distribution, (Growing stock, Carbon stock)

2. Test Sites and Data

The pilot study aims to demonstrate various harmonisation approaches under real environmental conditions. Therefore original data from three different countries are used to test proposed harmonisation approaches, namely from **Germany**, **Spain** and **Italy**. For each of the three countries **two test sites** were selected, which preferably represent two different forest ecosystems but also most typical forests landscapes of the countries.

The following test sites are selected to demonstrate proposed harmonisation approaches (see Fig. 2.1 and Annex I):

Fig. 2.1: Selected test area (see also Annex I).



Germany – Saxony

Represents a test site of about 510 000 ha located in south-east Germany with a forest coverage of about 30% represented by 622 NFI clusters (NFI grid 2.83x2.83 km). The forest is located in the continental forest zone in the low mountain range (100 – 900 m). The spatial patterns of forests are rather heterogeneous and fragmented. About 70% are coniferous forests with spruce being the most dominant tree species. The test site includes: a) the National Park Saxony Switzerland with different forest protection zones b) different landscape protection areas, like the eastern part of the Ore Mountains and c) large scale forest damage caused by storms, snow, ice and the depositions of air pollution.

Germany – Rhineland-Palatinate

Represents a test site of 360 000 ha located in the south-west of Germany with a forest coverage of about 50%. The selected test area contains 900 NFI clusters¹ (NFI grid 2x2 km) with 3 600 NFI sampling plots in total of which 1 969 are located in the forest. The low mountain range is dominated by a highly aggregated forest patch. The most abundant tree species is beech (*Fagus sylvatica*) mixed by Pine, Spruce, Douglas Fir, Oak and Maple.

¹ In the German NFI one NFI cluster consist of four concentric sampling plots (www.bundeswaldinventur.de).

Italy – Sicily

Represents a test site of about 2 570 900 ha located in southern Italy and corresponds to the Sicily administrative region. The test site is located in the Mediterranean biogeographical region. In Sicily altitudes range from the sea level to 3 300 m a.s.l. Forest coverage is about 7%. The study area contains 25 709 NFI plots located on the basis of a non-aligned systematic sampling based on a grid of 1x1 km. 3 749 plots are forest. The selected test area is characterised by Mediterranean broadleaved forests, especially *Quercus pubescens*, *Quercus ilex*, *Quercus suber*. Mediterranean pine stand forests are also represented.

Italy – Molise

Represents a test site area of about 70 900 ha located in the south-central Italy in the administrative region of Molise. Altitudes range from 200 to 1 700 m a.s.l. Forest coverage is about 48%. The forests are dominated by broadleaved stands. *Quercus cerris*, *Quercus pubescens* and *Fagus sylvatica* are the prevalent species. Coniferous forests are mainly of artificial origin. A local forest inventory is available for two administrative areas of “Comunità montana Alto Molise” and “Comunità Montana Trigno Medio Biferno”. Plots are located on the basis of a non-aligned systematic sampling based on a grid of 1x1 km. The test area contains 709 plots with 349 plots located in forest.

Spain – Pyrenees

Represents a test site area of about 790 000 ha where about 25% are forest with 1 600 NFI plots (located only in forest area). The area is located in the eastern part of Spain with altitudes from sea level to 1 000 m a.s.l. The forest is dominated mainly by young *Pinus halepensis* and other typical Mediterranean tree species like *Quercus ilex*. The forest is strongly affected by forest fires, which affected changes in tree species, stand structure and stand age and regeneration dynamics. The forest landscape is fragmented in small patches surrounded by agriculture. There are not many management practices applied due to the low productivity of Mediterranean forests.

Spain – South Catalonia

Represents a test site area of about 440 000 ha where 44% are forest with 1 900 NFI plots (located only in forest area). The Pyrenees area is located in the north-eastern part of Spain with an altitudinal range of 1 000 to 3 000 m a.s.l. affected by alpine climate. The forests are dominated by different semi-natural coniferous forests (*Pinus sylvestris* and *Pinus uncinata* and *Abies alba*) and some patches of broadleaved forests (*Fagus sylvatica* and different oak species). The intensity of management practices is low because the main part of this forest is publicly owned and located in protected areas.

For each test site the following data were prepared and provided by the partners UHH, DISTAF and CREAM as well as by the JRC (see also Annex II):

- NFI data (original plot data at tree level for selected test variables)
- Digital-Orthophotos (DOP)
- EC Forest Focus/ ICP Forests data (Level I)
- CLC2000 data
- BioSoil data

For each of the selected test sites original NFI data (plot data at tree level) were compiled and provided. NFI data are the primary object of the proposed harmonisation approaches. The parameters provided are: xy-coordinates, forest/non-forest, tree species, forest types and diameter distributions.

In addition to NFI data, remote sensing data like Landsat 7 ETM and high resolution data like Digital-Orthophotos (DOP) (0,2-2 m resolution) were prepared and provided for selected test areas. Based on NFI data and using Landsat 7 ETM, forest cover masks according to the explicit national forest definition of the selected test sites were produced.

The provision of remote sensing data is important as some of the proposed harmonisation approaches include remote sensing techniques as promising solutions to enhance NFIs for harmonised data assessment. Remote sensing can be seen as a neutral data source, which enables data evaluations according to various international definitions and standards independently from individual national data assessments and data collection systems (see Approach 1).

Another important objective of the proposal for harmonisation is to integrate and combine NFI data with international data sets as EC Forest Focus/ ICP Forests Level I data (see Approach 2) or with Corine Land Cover CLC2000 data (see Approach 3). Within different approaches it was tested whether already existing international data as EC Forest Focus/ ICP Forests Level I data, CLC2000 data and JRC forest mask can be used as international reference data for harmonising NFI variables, like forest area, forest types or diameter distribution.

3. Approach 1: Sub-sampling of high resolution remote sensing data – Variable: Forest area

Main Authors: Aljoscha Requardt, Rene Siwe, Thomas Riedel

Introduction

The most important variable in forest information is ‘forest area’. It defines the population from which samples are taken. In addition, many other variables presented in units per area (e.g. volume in m³/ha) or as an area proportion (e.g. proportion of privately owned forests) utilise a ratio including total forest area as denominator. Forest area is one of the key variables in international forest policy processes and related reporting requirements. Therefore, the variable forest area is strongly discussed in the context of international systems of nomenclature and harmonisation. Major results of the EU funded EFICS Study 1994-1997 on defining forest area for example, were utilised to support negotiations in the scope of the UNECE/FAO TBFRA 2000, the FAO FRA and its Kotka Conferences and the MCPFE C&I process. In ongoing harmonisation initiatives like the ‘FAO Expert Meetings on Harmonising Forest related Definitions for Use by Various Stakeholders’ and the COST Action E43 on the ‘Harmonisation of National Forest Inventories in Europe’, the nomenclature used for forest area is still of major concern.

According to the EFICS study (1997) and the latest results of the COST Action E43 (2004-2008), forest area definitions applied in Europe show a high diversity. Although defined differently, most definitions applied in Europe and especially within international forest policy processes have a similar structure, which includes a set of measurable quantitative parameters together with threshold values and various qualitative (descriptive) parameters. Qualitative parameters for defining forest consider other land use and land cover variables and are often explained by additional explanatory notes. The main quantitative parameters used by most European countries and international conventions to define forest area are: *minimum width*, *minimum area*, *minimum crown coverage*, *minimum production* and *tree height* (see Table 3.1 and 3.2). Differences between applied definitions mainly arise from the threshold values established for quantitative parameters, and from the land use categories to be referred to as ‘forest’ (see EC EFICS, 1997; Päivinen and Köhl, 2005; Vidal et al., 2008).

Table 3.1: National forest area definitions and applied parameter thresholds (after EFICS, 1997).

Country	min width [m]	min crown coverage [%]	min area [ha]	min production [m ³ /ha/year]
Denmark	20	30	0.5	
Germany	10	-	0.1	-
Finland	-	-	0.25	1
France	15	10	0.05	-
Greece	30	10	0.5	-
Ireland	40	20	0.5	4
Italy	20	10	0.5	-
Netherlands	30	20	0.5	-
Austria	10	30	0.05	-
Portugal	15	10	0.2	-
Sweden	-	-	0.25	1
Switzerland	25 – 50	20	-	-
Spain	25	5	2.5	-
UK	50	20	2	

Table 3.2: International forest area definitions and applied parameter thresholds (after FAO 2002).

	min width [m]	min crown coverage [%]	min area [ha]	min tree height [m]	min production [m ³ /ha/year]
FAO/UNECE	20	10	0.5	5	-
Worldbank	-	10	1	2	-
UNFCCC, Kyoto	-	10-30	0.05-1	2-5	-
EFICS	10 40	10 30	0.05 0.5	- -	- -
UNEP/CBD/ SBSTTA 2001	-	10	0.5	5	-

In this harmonisation approach a sub-sampling of high resolution remote sensing data (like Digital Orthophotos (DOP)) is used to calibrate and assess the variable 'forest area' estimated by terrestrial National Forest Inventories (NFIs) according to different selected national or international forest area definitions.

This approach is a combined inventory process to estimate 'forest area' according to different definitions. Combined forest inventories generally use two data sources: a field assessment and remote sensing data (aerial photographs and satellite images). A wide variety of applications exist for combined forest inventories (Bowden et al., 1997; Johnston, 1982; Köhl and Sutter, 1991). However, only a limited number of operational applications can be found. This is due to the fact that remote sensing products are a) not readily available due to temporal restrictions, b) too expensive, c) do not provide the necessary amount of auxiliary information or d) do not meet the desired spatial and/or thematic accuracy. Nevertheless, remote sensing applications provide a cost effective way to analyse various forest related parameters as opposed to terrestrial sampling. The remote sensing phase can be utilised in two different ways:

- full coverage of the inventory area or
- randomly or systematically chosen parts of the inventory area (area frames).

National forest masks are produced either on the basis of moderate resolution data like Landsat ETM in combination with terrestrial NFI data or on the basis of high resolution data like DOPs. Within this approach forest area for representative test sites in different bio-geographical regions are estimated by a double sampling approach, analysing sub-samples of high resolution remote sensing data (like DOPs) according to different national and international definitions. The forest area previously assessed from a wall-to-wall analysis of moderate resolution remote sensing image based on NFI data of the entire bio-geographical region is used to calibrate (correct) the forest area estimated from the sub-samples. A flexible and cost effective tool is designed that will facilitate the interpretation of forest area based on NFI data to any required standard.

The methodology developed within Approach 1 was tested in three different bio-geographical regions across Europe: Saxony (Germany), Pyrenees (Spain) and Sicily (Italy).

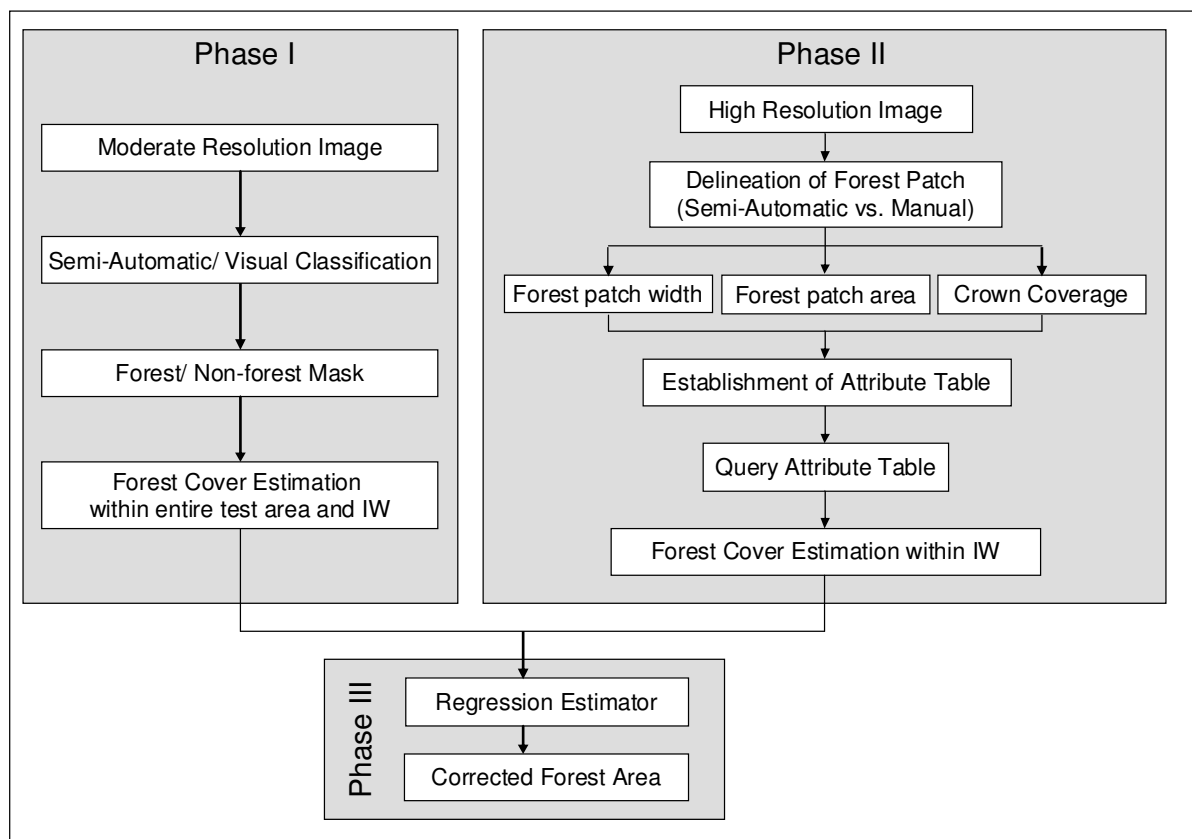
Methodology

Methodology – Overview

The methodology can be viewed in **three phases**: first, forest area for the respective test sites is derived from national forest masks²; next, forest area is estimated from analysing sub-samples of high resolution images according to the thresholds applied in different national and international definitions; and last, a regression model is built between the national reported forest area and the forest area derived from the high resolution sample frames. The regression estimator is used to calibrate the estimated forest area according to the applied reference definition. Fig. 3.1 summarises the details of the applied methodology.

² The forest masks were not produced within the frame of this project. They are national forest masks produced locally based on NFI and made available by project partners.

Fig. 3.1: General workflow of Approach 1, showing the different steps.



In the first Phase ‘forest area’ is determined for the three bio-geographical regions from the respective forest masks. In the second Phase, the three most common parameters for defining ‘forest area’ *minimum width*, *minimum area* and *crown coverage* (see EC EFICS 1997; Päivinen and Köhl, 2005; Vidal et al., 2008), are assessed within sample frames (herein after referred as ‘Interpretation Windows (IW)’) of high resolution data.³ In Phase III, the forest areas according to different definition thresholds are determined by building a regression between Phases I and II.

Table 3.3 summarises the national and international definitions and parameter thresholds that were taken into consideration in this approach. The FAO definition was taken into account as it represents one of the most applied international definitions in many pan-European or global forest related reporting obligations (like forest data assessments of FAO, UNECE, MCPFE, Eurostat, EEA). To test the applicability of the approach and to show that the approach is flexible to any definition, national definitions and their parameter thresholds were also taken into account. In addition to the test country definitions, namely Germany, Spain and Italy, the definition of the UK and Austria were also considered as they represent the maximum and minimum forest definition parameter thresholds that are applied. UK has the highest parameter threshold for *minimum width* and Austria has the lowest threshold for all three considered parameters. Basically, a GIS attribute table is established using the three definition parameters such that it could be queried based on the different parameter thresholds in the respective definition (see Table 3.3).

³ The attributes *minimum tree height* and *minimum production* are more complex to evaluate with remote sensing techniques. Moreover, they are not considered in many national definitions and as a result were not taken into account.

Table 3.3: Selected forest area definitions and applied parameter thresholds as reference standards and selection criteria for assessing forest area per selected test site.

	Minimum Width (m)	Min Crown Coverage (%)	Minimum Area (ha)
FAO	20	10	0.5
Germany	10	-	0.1
Spain	25	5	2.5
Italy	20	10	0.5
Austria	10	30	0.05
UK	50	20	2

An analysis of these three parameters on full coverage of high resolution data for entire forest areas within a country or region is an arduous task. Consequently, only a sub-sampling of high resolution data is feasible. The sub-samples are either randomly or systematically distributed in the selected forest region (see Phase II).

Phase I: Determination of Forest Area from Moderate Resolution Imagery

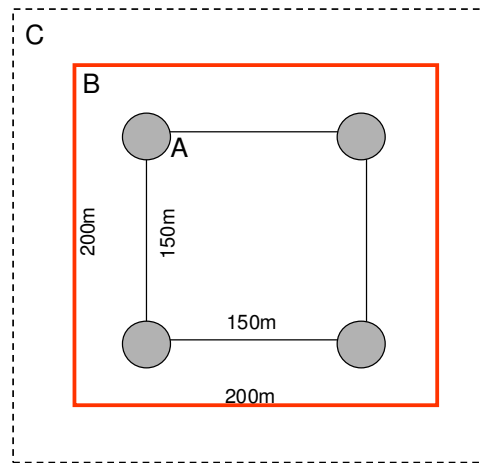
Forests/non-forest masks for the three test sites, partly produced nationally⁴, were implemented in this phase. The methods used in establishing the forest masks are briefly explained in the respective test area sections of this approach. The forest area for the entire test site is derived from the national forest mask calibrated according to NFI data as well as the forest area within the corresponding Interpretation Window (IW) areas (Fig 3.2). The mean and standard deviation for the forest area estimate in the Interpretation Window (IW) areas from the national forest mask is also calculated. The variance and confidence intervals given a probability $p=95\%$ is estimated to calculate the regression coefficient (see Phase III).

Phase II: Determination of Forest Area from High Resolution Sample Frames (Interpretation Windows)

In the second phase, a systematic or random remote sensing sub-sampling is performed on the high resolution imagery within the selected test area. Interpretation Windows within this study were established within the respective test areas. The Interpretation Windows are 200x200 metre rectangles with a corresponding buffer zone (see Fig. 3.2). The buffer zone was designed to ensure that the entire extent of the forest patches outside the interpretation windows is taken into consideration during delineation (see Fig 3.2, Zone C).

⁴ The Spanish, Italian forest masks of selected test sites were produced by national authorities and are used as a national reference for forest area estimation. The forest mask of the German test site Saxony instead is the outcome of a research project conducted by the University of Hamburg in 2007 (Oehmichen et al, 2007). Within the German NFI forest masks are not produced or used for discriminating forest/non-forest.

Fig. 3.2: Interpretation Window (IW) overlaid on an NFI cluster (Saxony, Germany). The NFI cluster is represented by rectangle A; B is the actual interpretation window and C is the buffer zone around the cluster.

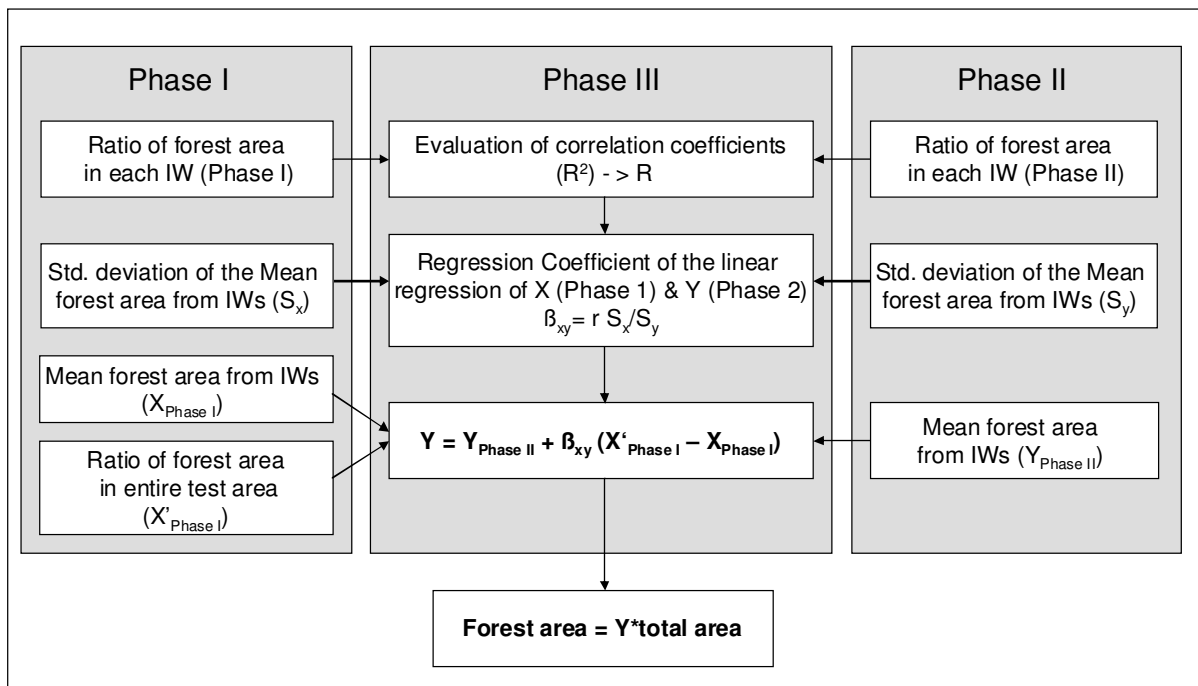


Basically, two approaches can be adopted in delineating forest areas from remote sensing data: **semi-automatic** or **manual on-screen digitisation**. Both approaches were tested and their efficacy in effectively delineating forest patches analysed. Workload and time consumption were also taken into consideration during the comparison.

Phase III: Calculating Regression Coefficients and Forest Area Estimation

As aforementioned, a regression model was built between the forest areas derived from the interpretation of high resolution data (Phase II) according to the corresponding national and international definitions and the forest area acquired from the national forest mask (Phase I). Fig. 3.3 below illustrates the incorporation of the forest area estimates from Phases 1 and 2 in the regression model (Phase III).

Fig. 3.3: Regression model for forest area estimates from steps I and II.



Coefficients of determination (R^2) were calculated to evaluate the strength and direction of the linear relationship between Phase I and Phase II.⁵ Outliers are assessed to evaluate extreme differences between Phase I and Phase II forest area estimates. The statistical significance of the correlation equation parameters was evaluated at 5% level for each definition applied.

The regression estimator (equation 3.1) was used to calculate the total forest area for each test site according to each applied definition (see Fig. 3.3). The regression estimator used is adapted after Köhl, 1994. Köhl proposed the regression estimator in a double-sampling approach to estimate the timber volume from aerial photographs (Phase I) and terrestrial sampling (Phase II).

$$Y = Y_{\text{Phase II}} + \beta_{xy} (X'_{\text{Phase I}} - X_{\text{Phase I}}) \quad (3.1)$$

where,

- $X'_{\text{Phase I}}$ = Mean forest area of the entire test site derived from Phase I (national forest mask).
- $X_{\text{Phase I}}$ = Mean forest area in IWs obtained from Phase I (national forest mask).
- $Y_{\text{Phase II}}$ = Mean forest area in IWs obtained from high resolution image with respective national/ international definition (Phase II).
- β_{xy} is the regression coefficient of the linear regression of X and Y which is calculated thus.

$$\beta_{xy} = rS_x/S_y \quad (3.2)$$

where,

- S_x is the standard deviation of Phase I;
- S_y is the standard deviation of Phase II.

The 'forest area' in the entire test site according to each definition is determined by multiplying the corrected mean (Y) for each definition with the total area of the test site.

$$\text{Forest Area} = Y * \text{Total Area} \quad (3.3)$$

⁵ The coefficient of determination (R^2) is a descriptive measure between 0 and 1, indicating a) how good one term is at predicting another and b) how well the regression line approximates real data.

Forest Patch Delineation Process (Phase II in detail)

Semi-Automatic Segmentation of Forest Cover Patches

The semi-automatic approach was the multiresolution segmentation approach provided by Definiens Imaging eCognition® software package. The objective of the segmentation was to delineate homogenous forest stands. Generation of image objects was achieved through an image segmentation procedure in eCognition® termed *multiresolution segmentation*. Multiresolution segmentation partitions an image into homogeneous multi-pixel regions based on several interpreter-defined parameters. The interpreter influences the output of the segmentation process through specification and weighting of input data and definition of parameters affecting the size, spectral homogeneity, spatial homogeneity, and shape of the resulting image objects.

The multiresolution segmentation technique was implemented on the digital orthophotos (DOP) for the Saxony and Pyrenees test sites. DOP image subsets corresponding to the interpretation windows were created for the test site. Normalised Difference Vegetation Index (NDVI) was then calculated as in equation 3.4 and loaded alongside the original bands (Red and NIR) in the eCognition® software package. The NDVI was included due to its ability to discriminate green vegetation.

$$\text{Red} + \text{NIR} / \text{Red} - \text{NIR} \quad (3.4)$$

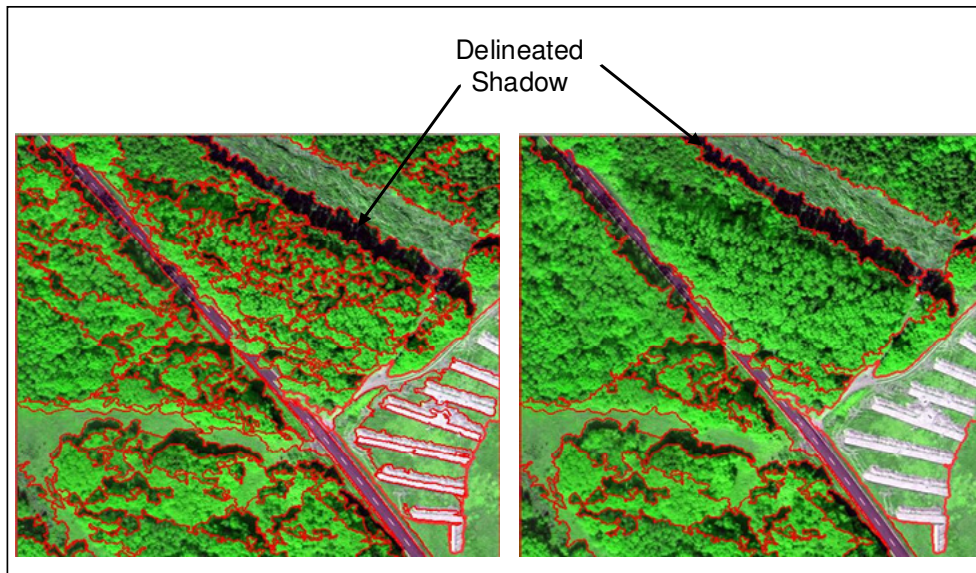
The DOP subset images were partitioned into image objects using the eCognition® software. Decisions regarding selection and weighting of inputs to the segmentation process were made based on spectral and spatial characteristics of original DOP bands, derived NDVI and experimentation. With respect to the general spectral characteristics, near-infrared reflectance and NDVI are most often associated with the ability to discriminate changes in vegetation, (Hildebrandt, 1996). In terms of spatial characteristics, the DOP bands, with a spatial resolution of 0.2 m captures substantial detail. Moreover, layers of varying spatial resolutions can be simultaneously used in eCognition® as the software automatically re-samples to the spatial resolution of the highest resolution input layer.

There is a high degree of correlation among the three bands representing the visible portion of the spectrum, but much lower correlation between the near-infrared band and the visible bands. In response to the above considerations and observations, the weightings of the multispectral bands were arranged such that the visible bands were assigned equal weights, and the NIR and NDVI bands were assigned three times the weight of a visible band.

The segmentation input/weighting scenario described above was tested against several other input/weighting combinations, including assigning equal weights to all bands, and omitting individual bands. The resultant patches (segments) were evaluated visually (Fig. 3.5).

The input scenario described above produced the most satisfactory segmentation results. Settings for the remaining eCognition® segmentation parameters (scale, colour, shape, smoothness, and compactness) were determined through a similar experimental process. It should be noted that it was necessary to experiment the segmentation parameters for each interpretation window as no pre-defined settings could effectively be applied for the segmentation in all the windows. Furthermore, it was necessary to perform post processing (merging and splitting of objects) to actually obtain the desired objects (forest patches).

Fig. 3.4: Automatic delineation of forest patches (a) scale 200 and (b) scale 300.



Manual On-Screen Digitisation of Forest Cover Patches

Forest patches within the interpretation windows were delineated manually using ArcGIS 9® software. The digitisation of the forest patches took into consideration the minimum and maximum forest area and forest patch width as defined in the different national and international forest definitions. Forest patches which fall below the minimum thresholds for minimum area and minimum width according to the selected definitions were not evaluated further.

In all test sites, each manually delineated forest patch was given an attribute. Five thematic categories were discerned:

- (i) Wooded land area (coppice and forest)
- (ii) Wooded land area (garden, parks, cemeteries, trees outside forest)
- (iii) Wooded linear areas along linear objects like roads, rivers, rails etc.
- (iv) Non wooded land in forest (e.g.: clear-cuts, fields, gravel roads > 5 m)
- (v) Other land-cover classes

In addition to the thematic forest patch categories a set of criteria and guidelines were outlined to ensure an effective and consistent delineation of the forest patches and to guide interpreters in the *forest/non-forest* decision:

- Potential forest areas are spatially homogenous areas, stocked with trees, which can be distinguished from the neighbouring landscape through conspicuous structural differences. Conspicuous structural differences refer mainly to differences in crown coverage.

- Forest patch: This is a closed traverse formed by linking tree crown apexes (centres). As a result, single lines of trees in the landscape are not considered as potential forest areas.

- Forest boundary: The following objects are considered as forest patch boundaries: tarred roads; rivers, streams with a width greater than 5 m; power transmission lines and rails;. Bridges with trees underneath are not considered as patch boundaries.

- Gravel forest roads greater than 5 m, forest aisles greater than 5 m, protective stripes greater than 5 m, meadows in forest, non-wooded areas in forest should be delineated and given a corresponding attribute. They general fall under 'non-wooded areas in forest' (category iv).

- Wooded areas within settlements should be delineated as potential forest areas.

- A 10 m buffer zone around the interpretation window is taken into consideration during forest patch delineation to avoid leaving out large forest patches when only a small portion of it appears within the window (see Fig 3.5).

Comparing the Effectiveness of Semi-Automatic Segmentation and On-Screen Digitisation

To optimise the approach it was of interest to evaluate the efficacy of both, the semi-automatic and the manual approach for delineating forest patches within each IW.⁶ Generally, the spatial orientation of artificial objects, such as roads, rails etc. is more easily identified visually than automatically. Linear objects with a width greater than 5 metre, which constituted forest patch boundaries, were difficult to delineate automatically. This was especially the case when tree crowns from forest patches on both sides of the object overlap. In such instances, the automatically derived object needs to be separated manually into distinct patches. Such patches are easier to delineate manually than automatically.

Shadows of individual trees make a distinct segmentation of forest patch edges difficult. They are often segmented as separate objects (see Fig. 3.4 above) or as part of the forest patch. The semi-automatic approach required immense interpreter input – like segment merging and/or segment splitting. Furthermore, different scales had to be tested for the parameters smoothness/compactness and colour/shape ratios for each Interpretation Window (IW) to determine the scales, which will most effectively delineate the forest patches. As a result, each Interpretation Window (IW) had to be analysed individually. This led to a substantial increase in workload.

Edges of the semi-automatic delineated patches appear more of natural character, while those of the manual approach are often straight lines. Another disadvantage of the manual approach is the subjectivity of interpretation implying that different interpreters will definitely delineate patches differently, whereas in the semi-automatic approach, the patches will be delineated in the same way irrespective of the interpreter, on condition that the segmentation parameter thresholds are the same.

Due to the necessary post processing (merging and splitting of segments), which was necessary for the automatically derived segments, the manual on-screen digitisation approach was favoured and adopted for the subsequent analysis. This decision was further supported by the fact that each Interpretation Window (IW) required an experimental process to define its ideal segmentation parameter scales. Thus, all forest patches for all Interpretation Windows of the selected test sites Saxony, Pyrenees and Sicily were delineated manually and definition parameters *minimum area*, *minimum width* and *minimum crown coverage* determined.

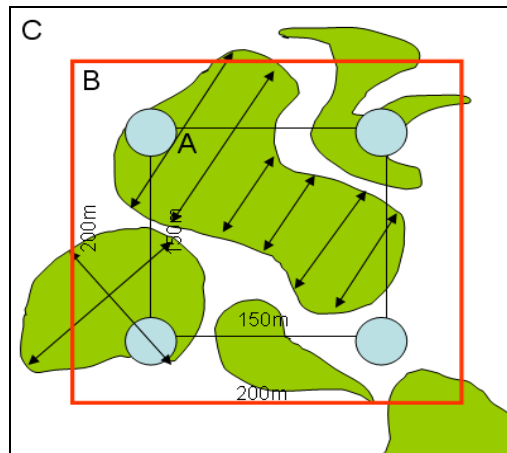
Interpretation Windows (IW) of the three test sites were delineated by one experienced interpreter, to keep the interpreter bias consistent. Examples of delineated forest patches within the IWs were cross-checked by another interpreter with local experience and knowledge about forest area characteristics and pattern distribution. By this a good Quality Assurance was achieved.

⁶ For the evaluation of efficacy of the automatic vs. the manual approach most homogenous stands in the test site Saxony were selected to minimise the effect of bias caused by non-homogenous forest patches.

Determination of Forest Patch Width and Crown Coverage

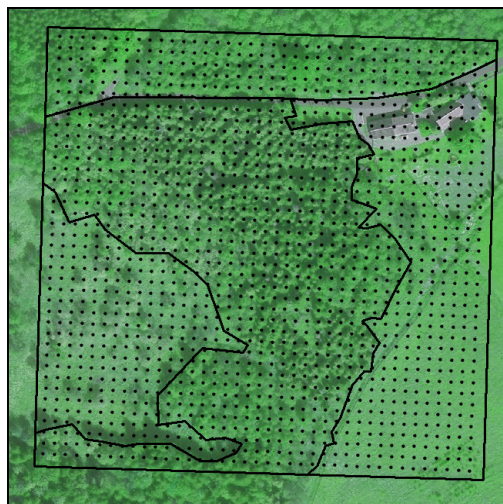
For *oblong* forest patches, the average minimum width was determined by drawing seven parallel lines across each patch (see Fig. 3.5) and calculating the mean value. For the assessment of forest patch width of *round* forest patches, two lines were drawn across each other (Fig. 3.5) and the average value determined. Generally, the minimum width was determined only for patches with a width less than 50 m (see maximum threshold of UK definition).

Fig. 3.5: Determination of mean forest patch width.



The crown coverage for each patch was determined by overlaying a point grid matrix of 5x5 meter on each Interpretation Window (see Fig. 3.6). The percentage of crown coverage for each patch was then assessed by calculating the ratio between a) the number of points that fall on tree crowns and b) the total number of points within an entire patch. To consider the effects of different crown coverage, different patches with different crown coverage were delineated and distinguished also within large compact forest area patches.

Fig. 3.6: 5x5 meter grid points for assessing crown coverage for each forest patch and each IW.



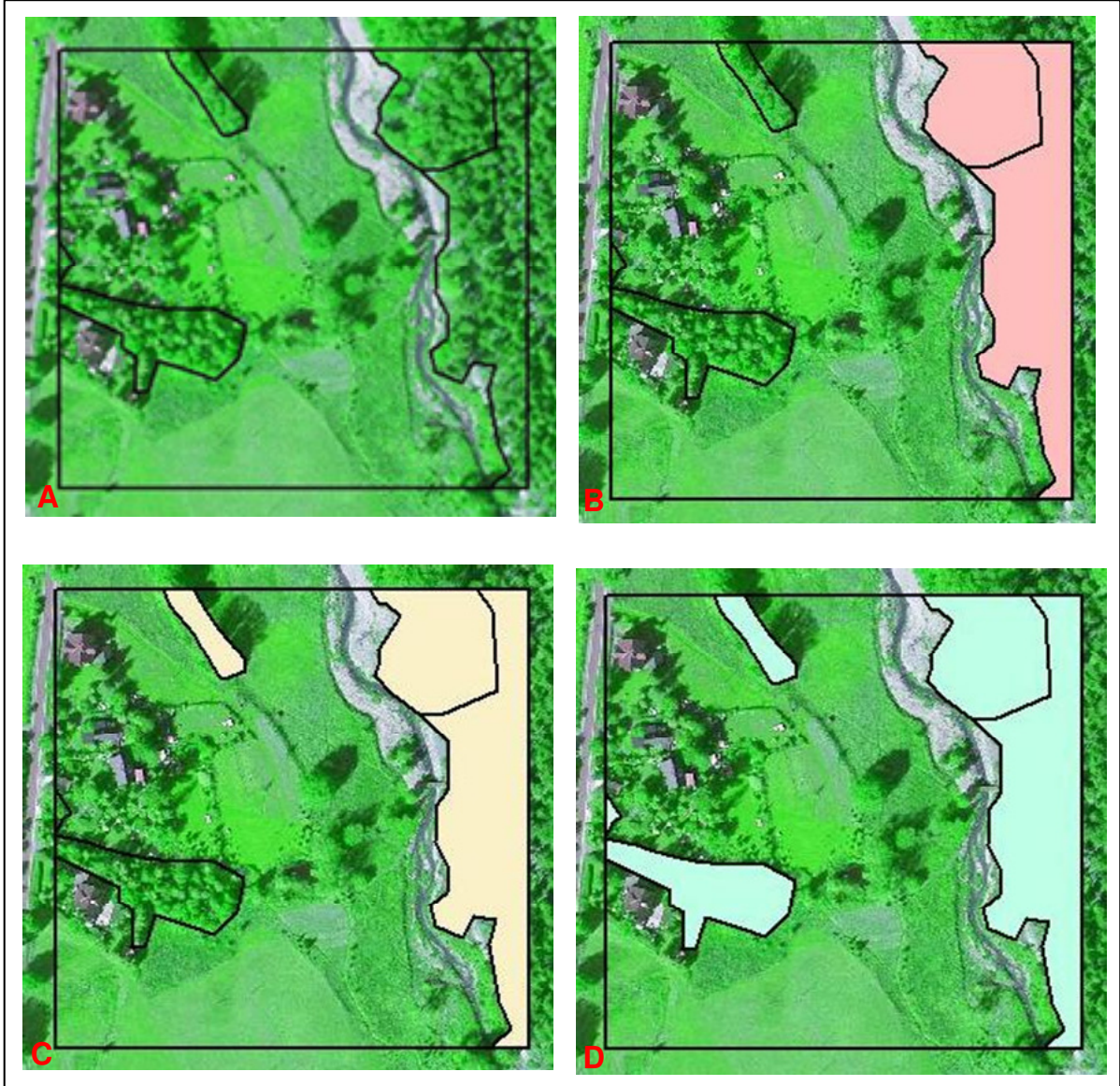
Establishing an Attribute Table and Estimating Forest Area in Sample Frames (Interpretation Windows)

An attribute table containing the *area*, *width* and *crown coverage* of each delineated patch as well as the “ID” of the respective interpretation window was established. The attribute table was

then queried based on thresholds of the FAO definition (international standard) and the five national definitions (Germany, Spain, Italy, UK and Austria) and the forest area within each sample frame determined for the respective definitions (see Table 3.3, Chapter 3.2.1).

An example of the effect of applying the different selected definitions on a sample frame is illustrated in Fig. 3.7 below. Depending on the definition applied, patches, which attain (or fail to attain) the thresholds for the corresponding definition, are (or are not) considered as forest.

Fig. 3.7: (A) Digitised Interpretation Window (IW) with delineated forest patches; (B) forest patches, which fulfil the criteria of UK and Spanish definitions; (C) patches, which fulfil the criteria for FAO and Italian definitions; (D) patches, which fulfil the criteria for Austrian and German definitions.



For each of the IWs the percentage of forest cover is assessed and descriptive statistical parameters mean and standard deviation calculated for each definition applied. The variance and confidence intervals at $p=95\%$ were calculated for each definition.

Results – Saxony

Phase I: Determination of forest area using Landsat ETM image

The forest mask for the test site Saxony was used as national reference data. Based on NFI II data the forest mask was produced from Landsat ETM by applying the threshold classification approach (Oehmichen, 2007). Thresholds were applied on the individual Landsat bands to separate forest from non-forest. Lower and upper boundaries were established based on the spectral signatures of the forest for each channel. Depending on whether a pixel value in a specific channel falls within the defined boundary it was categorised as forest or non-forest. The total forest area in the test site Saxony as evaluated from the Landsat ETM (Phase I) is estimated at 145 215 ha, corresponding to 28.8% of the total test site (502 010 ha). The overall classification accuracy is 95.4 %.

Phase II: Evaluating forest area based on national/international definitions

In the test site Saxony, 622 Interpretation Windows (IW) were systematically overlaid on NFI clusters – including *forest* and *non-forest* cluster. Forest patches within the IW were manually delineated on a DOP with a spatial resolution of 0.2 m. *Minimum width*, *minimum area* and *percentage crown coverage* were evaluated for each forest patch and an attribute table was established with the short listed parameters. The table was queried based on the parameter thresholds of the applied national and international definitions to obtain the forest area according to the respective definitions. The mean and standard deviation as well as the variance and confidence intervals at p=95% were calculated for each definition to finally compute the regression coefficient for forest area estimation.

Phase III: Regression Coefficients

Correlations were built between the forest area estimated within the Interpretation Window (IW) of the national forest mask (Phase I) and the forest area estimated from the analysis of DOP according to each applied definition (Phase II). The results are depicted in scatter plots (Fig. 3.8 to Fig. 3.13) with the respective correlation equations and coefficients of determination (R^2). All the equation parameters were determined to be statistical significant at 95 %. The coefficients of determination were above 0.89, indicating a strong linear correlation between Phase I and Phase II.

Fig. 3.8: Test site Saxony: Scatter plot showing the relationship between Phase I (forest estimates from Landsat) and Phase II (forest cover estimate according to the German definition).

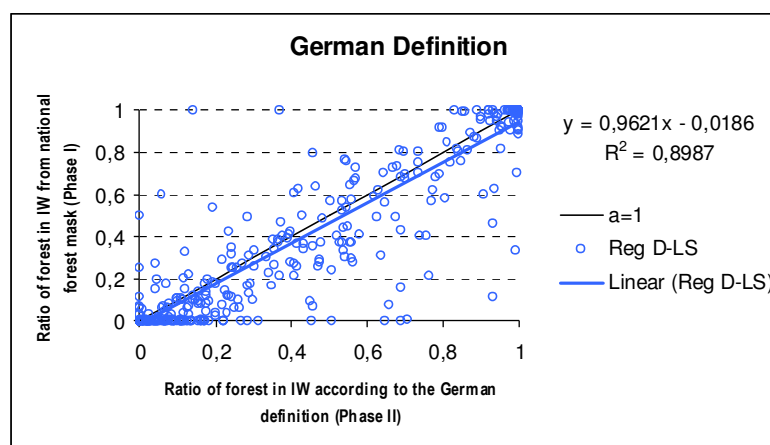


Fig. 3.9: Test site Saxony: Scatter plot showing the relationship between Phase I (forest estimates from Landsat) and Phase II (forest cover estimate according to the Spanish definition).

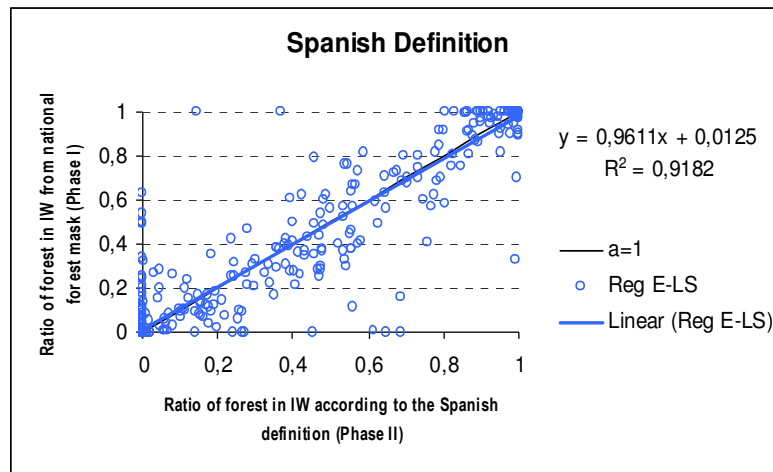


Fig. 3.10: Test site Saxony: Scatter plot showing the relationship between Phase I (forest estimates from Landsat) and Phase II (forest cover estimate according to the Italian definition).

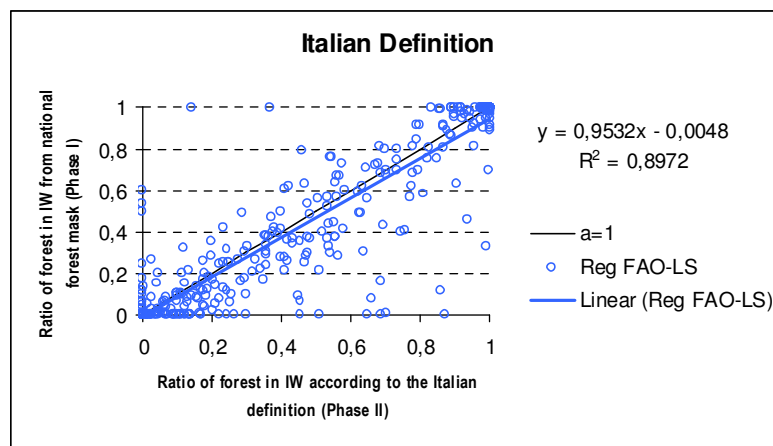


Fig. 3.11: Test site Saxony: Scatter plot showing the relationship between Phase I (forest estimates from Landsat) and Phase II (forest cover estimate according to the Austrian definition).

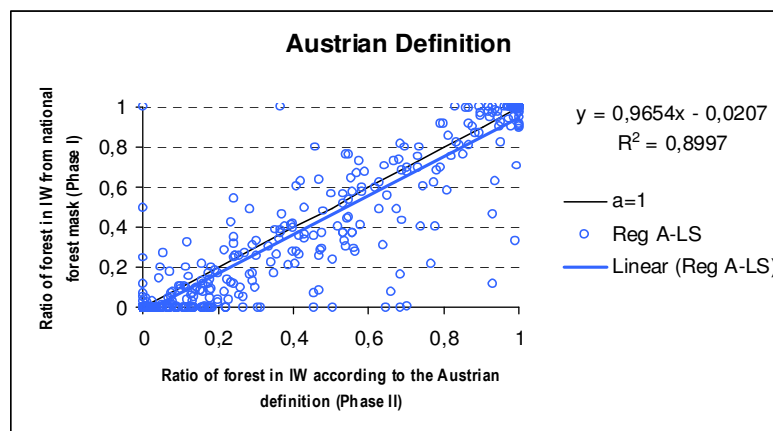


Fig. 3.12: Test site Saxony: Scatter plot showing the relationship between Phase I (forest estimates from Landsat) and Phase II (forest cover estimate according to the UK definition).

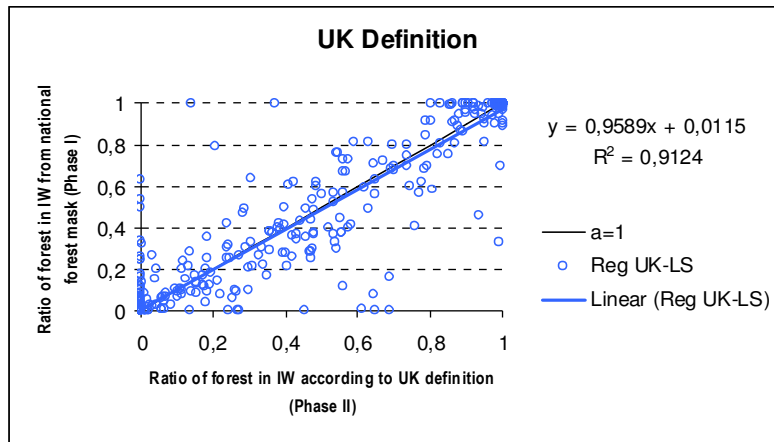
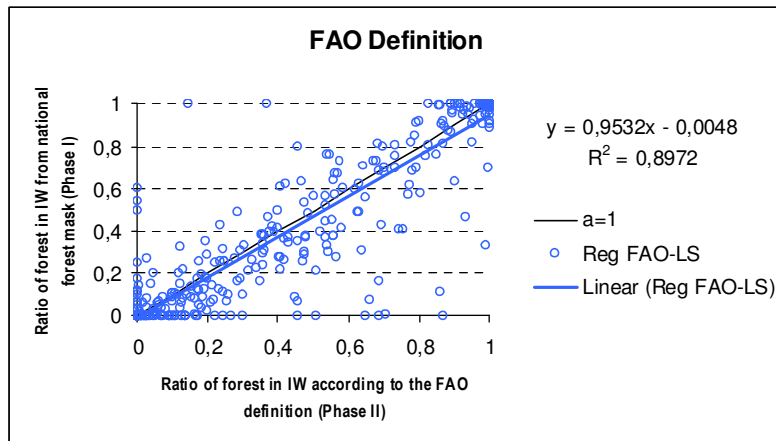


Fig. 3.13: Test site Saxony: Scatter plot showing the relationship between Phase I (forest estimates from Landsat) and Phase II (forest cover estimate according to the FAO definition).



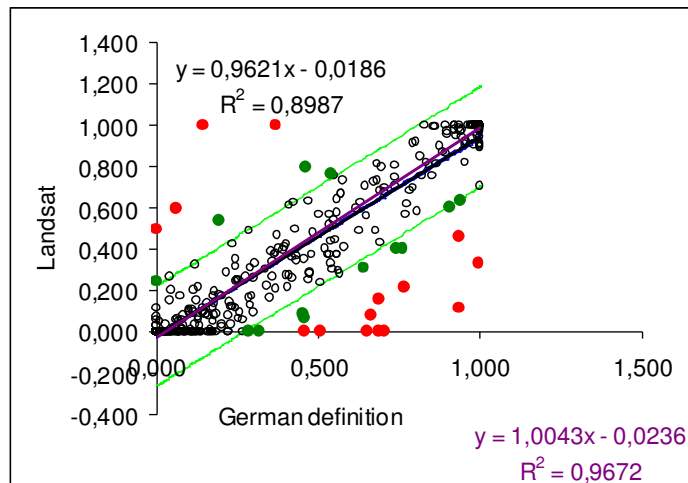
A large percentage of the variation in the data (between 89.7% and 91.8%) from the applied national and international definitions could be explained by the regression equation. The highest R^2 was obtained from Spanish definition whereas the lowest R^2 was obtained from the FAO and Italian definitions.

Selected examples of outliers were analysed to assess the differences in the Phase I and Phase II methodologies. The following reasons account for some of the differences:

- Methodological errors in Phase I interpretation: For example in one IW “water” was classified as “forest” in the Phase I forest mask.
- Thresholds applied in Phase II Interpretation: Certain small forest patches with attributes below applied thresholds are considered as *non-forest* in the Phase II but are considered as *forest* in Phase I.

As expected a substantial increase was noticeable in R^2 , when outliers were excluded from the analysis. Considering the German definition for example, R^2 increased from 0.89 to 0.96 when the outliers were excluded. Similar trends were recognised for the other definitions. Fig. 3.14 below illustrates the effect of excluding the outliers from the analysis. 95.6 % of the points fall within the range of 2 standard deviations of the mean.

Fig. 3.14: Exclusion of outliers (red dots = outliers with >3 times standard deviation; green dots = outliers with >2 but <3 times standard deviation).



The confidence intervals (p=95%) of forest area estimates (Phase II only) vary from +/-488 ha for Austrian definition to +/-495 ha for the UK and Spanish definition (see Table 3.4).

Table 3.4: Confidence interval at 95 % of forest area estimates, Phase II only (test site Saxony).

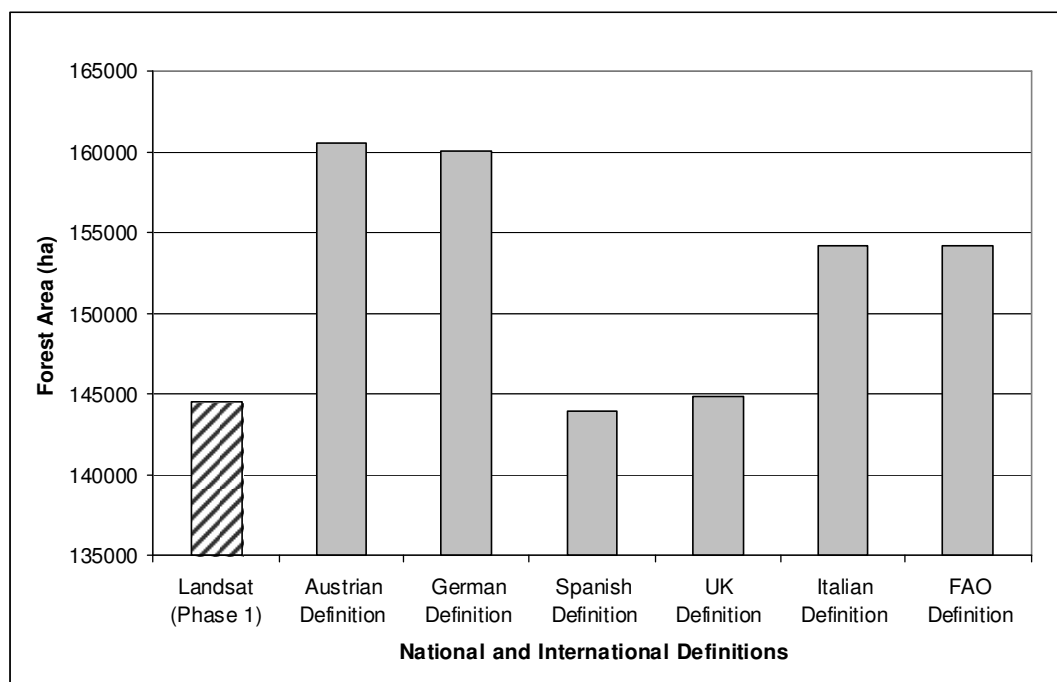
	Y Phase II mean	st. dev.	R^2	confidence interval	forest area [ha]	confidence interval [ha]
Austrian Def.	0,321	0,387	0,949	+/- 0,001	161188	+/- 488
German Def.	0,320	0,388	0,948	+/- 0,001	160672	+/- 490
Spanish Def.	0,288	0,392	0,958	+/- 0,001	144538	+/- 495
UK Def.	0,290	0,392	0,955	+/- 0,001	145417	+/- 495
Italian Def.	0,308	0,391	0,947	+/- 0,001	154861	+/- 494
FAO Def.	0,308	0,391	0,947	+/- 0,001	154861	+/- 494
Landsat IW	0,289				145215	

Table 3.5 summarises the statistical parameters for the regression estimator, which were used to correct the forest area estimate for each applied definition. The final forest cover estimates are illustrated in Fig. 3.15. The lowest forest area for the test site Saxony was obtained from the Spanish definition since it has the highest threshold value for *minimum area* (2.5 ha) while the highest forest area was obtained from the Austrian definition because it has the lowest threshold values for the attributes *minimum area* and *minimum width* (0.01 ha and 10 m respectively). For the test site Saxony, mainly the *minimum area* and the *minimum width* parameters were decisive in the forest area estimation. Almost all the forest cover patches had a *minimum crown coverage* greater than 30 % (see highest threshold from Austrian definition).

Table 3.5: Summary of statistical parameters, evaluated for the regression estimation (test site Saxony).

	Y Phase II mean	se %	reg-coeff. β_{xy}	X ⁺ Phase I (LS)	X Phase I (LS-IW)	Y mean_corr.	forest area corr. [ha]
Austrian Def.	0,321	1,550	0,965	0,288	0,289	0,320	160539
German Def.	0,320	1,555	0,962	0,288	0,289	0,319	160025
Spanish Def.	0,288	1,573	0,961	0,288	0,289	0,287	143892
UK Def.	0,290	1,572	0,959	0,288	0,289	0,288	144772
Italian Def.	0,308	1,568	0,953	0,288	0,289	0,307	154220
FAO Def.	0,308	1,568	0,953	0,288	0,289	0,307	154220
Landsat Phase I (total area)				0,288			144542

Fig. 3.15: Forest area estimates of the test site Saxony according to selected national/international definitions (Phase III).



Results – Pyrenees

Phase I: Determination of forest area using Aerial photographs

Unlike for the test site Saxony, the available forest mask for the Pyrenees test site was based on high resolution aerial photographs. The forest mask was established from a visual interpretation of aerial photographs. The total forest area is 232 309 ha accounting for 53 % of the total area of the test site. The forest areas within the 500 IW areas for the Pyrenees test site were determined from the national forest mask and the mean and standard deviation calculated.

Phase II: Evaluating forest area based on national/international definitions

The Spanish National Forest Inventory plots cover only forest area therefore the IWs could not be overlaid on inventory plots as was the case in test site Saxony. Instead 500 Interpretation Windows were established randomly over the whole test area. Similar to the test site Saxony, the forest patches within the IWs and its buffer zones were manually delineated and *minimum width*, *minimum area* and *crown coverage* determined. An attribute table was created and queried according to the different definition thresholds and the forest area for each IW determined according to each selected definition. Statistical parameters; mean, standard deviation, variance and confidence intervals at 95% were calculated for each applied definition.

Phase III: Regression Coefficients

Like for the test site Saxony, correlations were established between the forest area determined from the respective definitions (Phase II) and the forest area estimated in Phase I (national forest mask). The correlation equations and the coefficients of determination R^2 are depicted in the scatter plots on Fig. 3.16 to Fig. 3.21. All the equation parameters were statistically significant at 5% level. The coefficients of determination obtained for the test site Pyrenees were approximately 0.71.

Fig. 3.16: Test site Pyrenees: Scatter plot showing the relationship between the Phase I and Phase II (forest cover estimate according to the Italian definition).

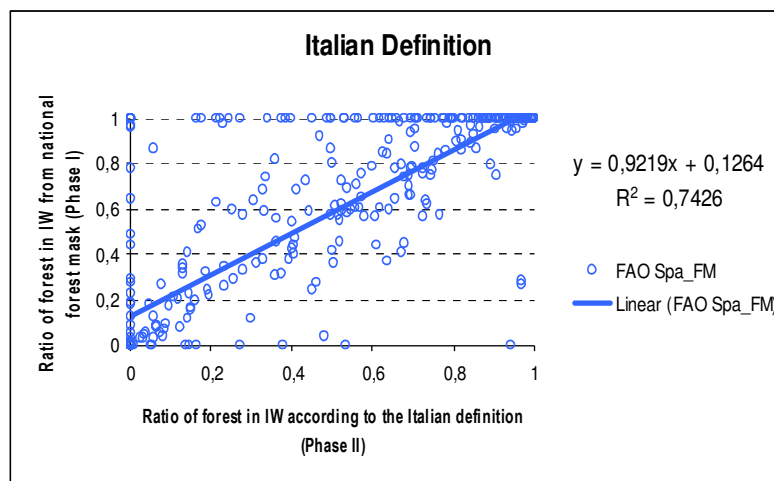


Fig. 3.17: Test site Pyrenees: Scatter plot showing the relationship between the Phase I and Phase II (forest cover estimate according to the Austrian definition).

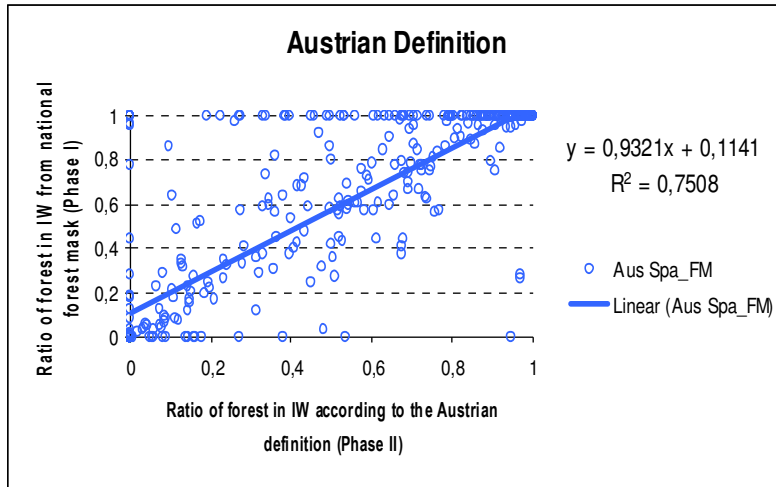


Fig. 3.18: Test site Pyrenees: Scatter plot showing the relationship between the Phase I and Phase II (forest cover estimate according to the German definition).

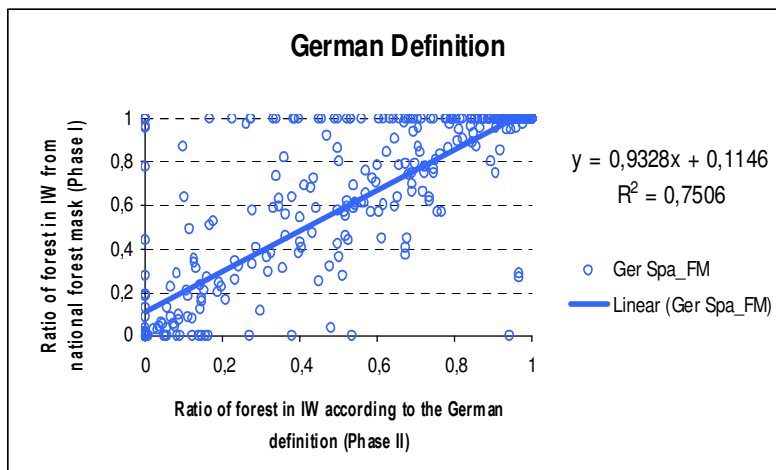


Fig. 3.19: Test site Pyrenees: Scatter plot showing the relationship between the Phase I and Phase II (forest cover estimate according to the Spanish definition).

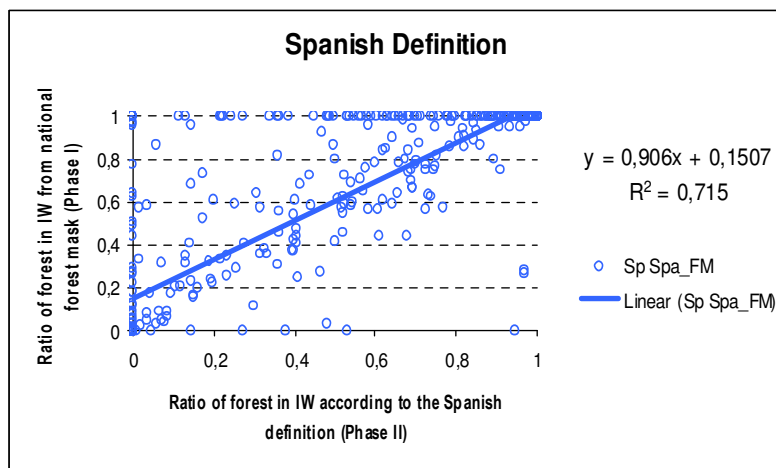


Fig. 3.20: Test site Pyrenees: Scatter plot showing the relationship between the Phase I (forest estimates from Landsat) and Phase II (forest cover estimate according to the UK definition).

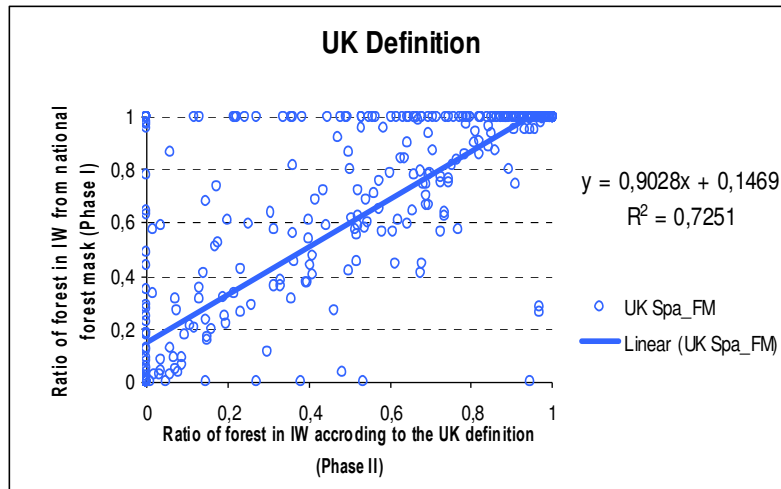
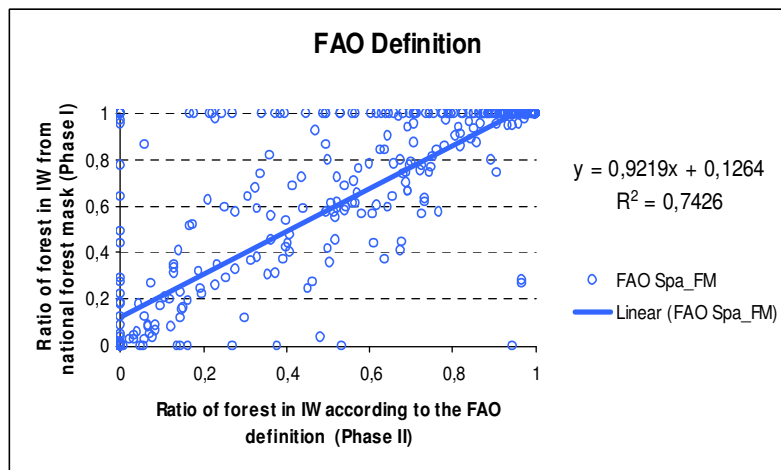


Fig. 3.21: Test site Pyrenees: Scatter plot showing the relationship between the Phase I and Phase II (forest cover estimate according to the FAO definition).

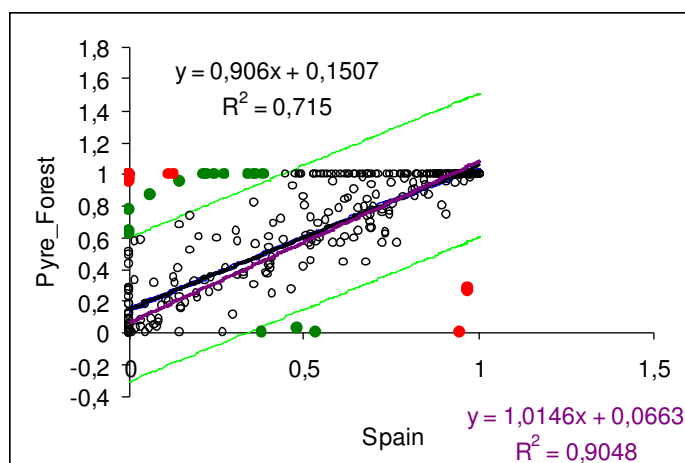


The highest R^2 was obtained from the Austrian definition (0.75), which indicates that 75 % of the variance within the data can be explained by the regression. The German definition had the second highest R^2 (0.75) followed by the Italian and FAO definitions (0.74), UK definition (0.72) and Spanish definition (0.71).

Like in the test site Saxony, outliers were examined to explain the differences between Phase I and Phase II. It can be concluded that the occurrence of different vegetation forms (shrub land, sparse and compact forest, macchia etc.) in the Pyrenees landscape makes it difficult for an interpreter to distinguish forest from the other vegetation forms. There was often confusion between forest and shrub land and most often trees were classified as shrubs and vice versa.

Outliers were excluded to analyse the effects on R^2 . Approximately 93.6% of the points fall within 2 standard deviations from the mean. As expected there was a significant increase in the R^2 when outliers were excluded. For the Spanish definition R^2 increased from 0.71 to 0.9 (Fig. 3.22). Similar trends were observed for all the other definitions.

Fig. 3.22: Exclusion of outliers (red dots = outliers with >3 times standard deviation; green dots = outliers with >2 but <3 times standard deviation).



The confidence intervals (p=95 %) of forest area estimates (Phase II only) vary from +/-451 ha for German definition to +/-458 ha for the UK definition (see Table 3.6).

Table 3.6: Confidence interval at 95 % of forest area estimate, Phase II only (test site Pyrenees).

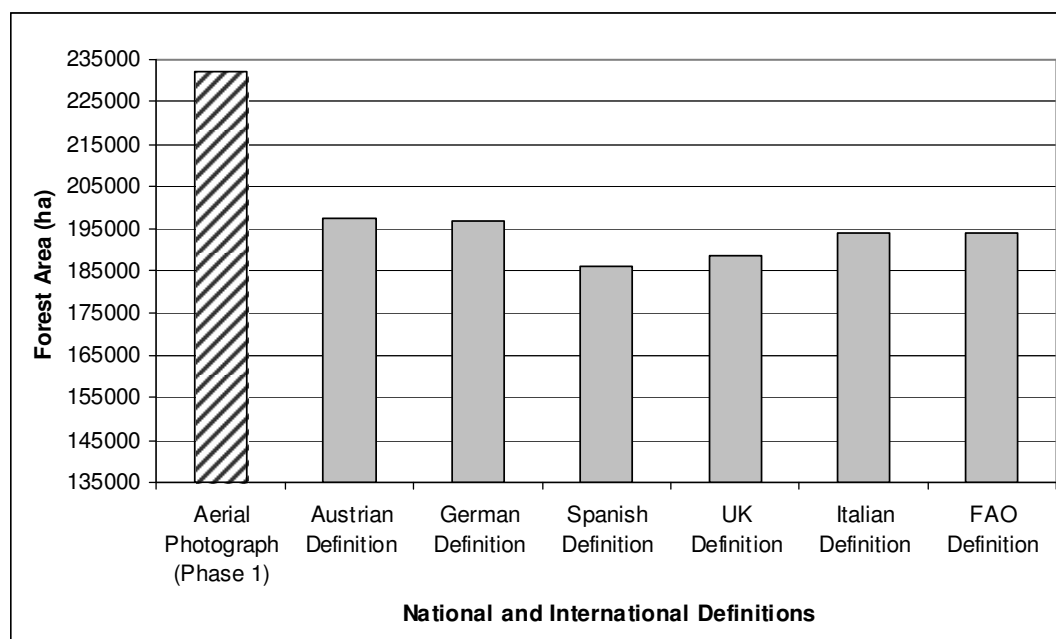
	Y Phase II mean	st. dev.	R ²	confidence interval	forest area [ha]	confidence interval [ha]
Austrian Def.	0,477	0,410	0,866	+/- 0,001	208902	+/- 452
German Def.	0,477	0,410	0,866	+/- 0,001	208531	+/- 451
Spanish Def.	0,451	0,412	0,846	+/- 0,001	197279	+/- 453
UK Def.	0,457	0,416	0,852	+/- 0,001	199764	+/- 458
Italian Def.	0,469	0,412	0,862	+/- 0,001	205351	+/- 454
FAO Def.	0,469	0,412	0,862	+/- 0,001	205351	+/- 454
Aerial-Photogr. IW	0,559				244639	

The regression estimator was used to evaluate the forest area in the test site according to the different definitions by building a regression between Phase I and Phase II statistical parameters (see equation 3.1, 3.2 and 3.3). The statistical parameters and final 'corrected' forest area estimates according to each definition are shown in Table 3.7 and illustrated in Fig. 3.23. The lowest forest area for the test site Pyrenees was obtained from the Spanish definition since it has the highest threshold value for *minimum area* (2.5 ha), while the highest forest area was obtained from the Austrian definition due to its lowest threshold values for the attributes *minimum area* and *minimum width* (0.01 ha and 10 m respectively).

Table 3.7: Summary of statistical parameters, evaluated for the regression estimation (test site Pyrenees).

	Y Phase II mean	se %	reg-coeff. β_{xy}	X' Phase I (Mask)	X Phase I (Mask-IW)	Y mean_corr.	forest area corr. [ha]
Austrian Def.	0,477	3,474	0,931	0,531	0,559	0,451	197421
German Def.	0,477	3,474	0,933	0,531	0,559	0,450	197032
Spanish Def.	0,451	3,390	0,906	0,531	0,559	0,425	186110
UK Def.	0,457	3,414	0,903	0,531	0,559	0,431	188633
Italian Def.	0,469	3,455	0,922	0,531	0,559	0,443	193984
FAO Def.	0,469	3,455	0,922	0,531	0,559	0,443	193984
Aerial-Photogr. Phase I (total area)				0,531			232309

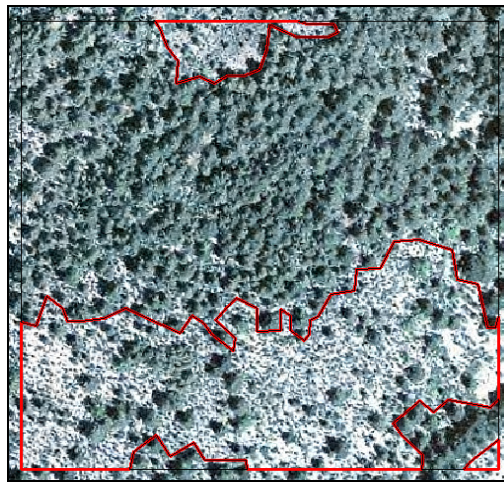
Fig. 3.23: Forest area estimate of the test site Pyrenees according to selected national/international definitions (Phase III).



The differences between Phase I and Phase II estimates are significantly large. The reason for this differences is presumably the confusion between shrub land, sparse and compact forest, leading often to different interpreter views on “what is forest and what is not forest” specifically in Mediterranean forests. Fig 3.24 below depicts an Interpretation Window showing two typical patches classified as ‘non-wooded areas in forest’ (see category iv). Therefore, the influence of delineated and classified ‘non wooded land in forest’ patches had to be re-assessed.

To evaluate the effects of ‘sparse forest’ or ‘no-forest’ patches on the assessment of total forest area per test site, the crown coverage of these “non-wooded land in forest” patches (previously considered as non-forest) was further analysed and re-considered in the forest area assessment.

Fig. 3.24: Interpretation Window with patches classified as ‘non-wooded areas in forest’ (see category iv).



When assessing the effects of different definition thresholds (see Table 3.3) on the non-wooded land in forest, it can be observed that non of the category (iv) patches considered in the analysis fulfilled the thresholds of the Spanish and UK definition. There was a slight increase in the forest cover according to the FAO and Austrian definitions (1899 ha and 1131 ha respectively). The forest cover according to the German definition had a significant increase of about 6 600 ha because the German definition does not have any threshold value for *crown coverage*.

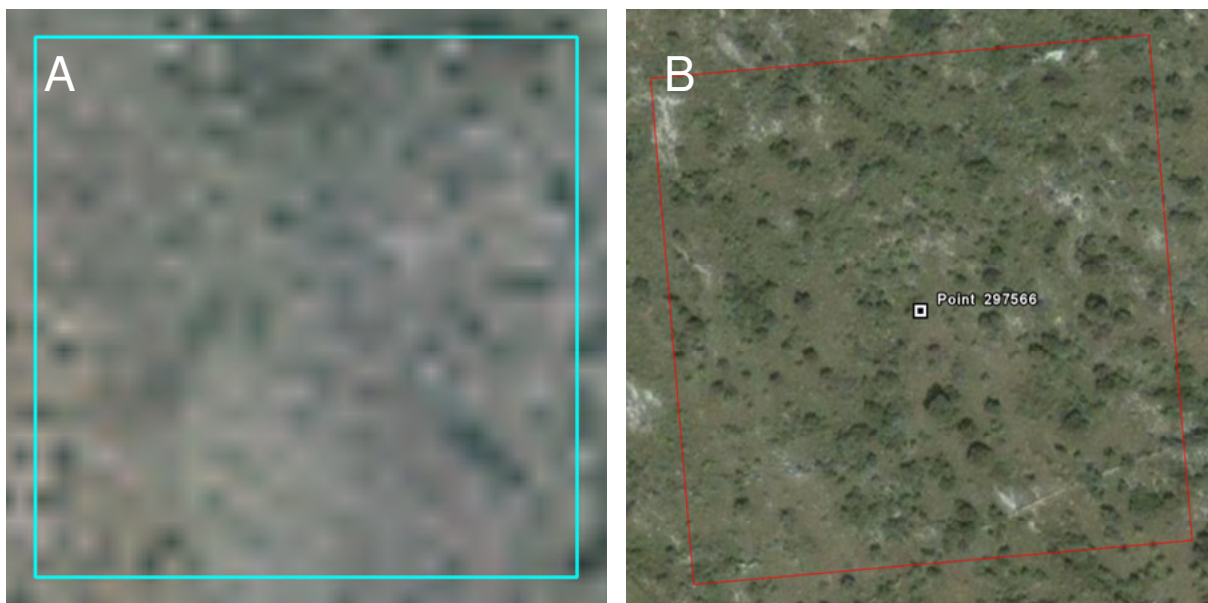
Most forest area mapping and assessments based on remote sensing data implement a minimum mapping unit of 25 ha (CORINE) and seldom use the parameter *minimum width* for interpreting or classifying the imagery. Based on this, the extra patches were further analysed based solely on the parameter crown coverage in order to understand the large difference between the forest area estimated from the forest mask of Spain and the forest area estimated according to the Spanish definition. Analysing the patches based on crown coverage alone led to an increase of 6 600 ha of forest according to the Spanish definition.

Results – Sicily

Due to the poor quality of the remote sensing imagery for Sicily, this approach could not be successfully implemented in the test site. The following reasons explain the inapplicability of the approach in the test site Sicily:

- Low resolution image.
- Poor data quality (fuzzy/skewed image), which caused following further problems:
- Fine details in forest cover were difficult to discern.
- Delineated forest patches are quite extensive.
- Impossible to calculate crown coverage.
- Almost all patches fulfil the minimum area and minimum width thresholds.
- No difference in forest total, based on the different definition thresholds.

Fig. 3.25: Difference in resolution between available remote sensing data (A) and remote sensing data of the same interpretation window from Google Earth (B).



JRC forest masks as reference data for Phase I

There are several efforts of mapping forests at different scales and different extents. The regional or national efforts, as it is shown by the case studies Saxony and Pyrenees vary also in level of detail, sources of information and forest definition. Their use for international comparison and for various international policy and reporting purposes is rather limited due to methodological inconsistencies. To eschew the effects of these inconsistencies in the presented harmonisation approach a pan-European forest mask is of utmost importance. Standardised pan-European forest masks are provided for example by the Joint Research Centre (JRC) of the European Commission. Forest/non-forest masks are available for the reference years 1990, 2000 and 2006. For producing the masks, a fully automatic image processing methodology was applied using Landsat ETM+ and CLC2000 and the SRTM Digital Elevation Model as ancillary data.

The possibility of using the JRC pan-European forest mask to substitute the national forest masks in Phase I was tested. Therefore correlations were built between the forest area in the Interpretation Window areas of the JRC forest mask and the Phase II estimates (according to the applied definitions) for the Saxony and Pyrenees test sites. Fig. 3.26 and 3.27 illustrate scatter plots for correlations between the JRC forest mask and the forest area according to the FAO definition for Saxony and Pyrenees test sites respectively.

Fig. 3.26: Scatter plot showing the relationship between the Phase I (forest estimates from JRC) and Phase II (forest cover estimate according to the FAO) for test site Saxony.

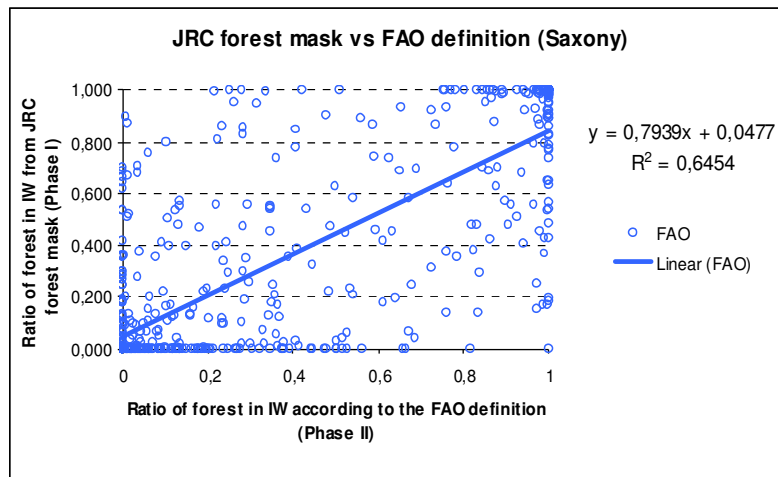
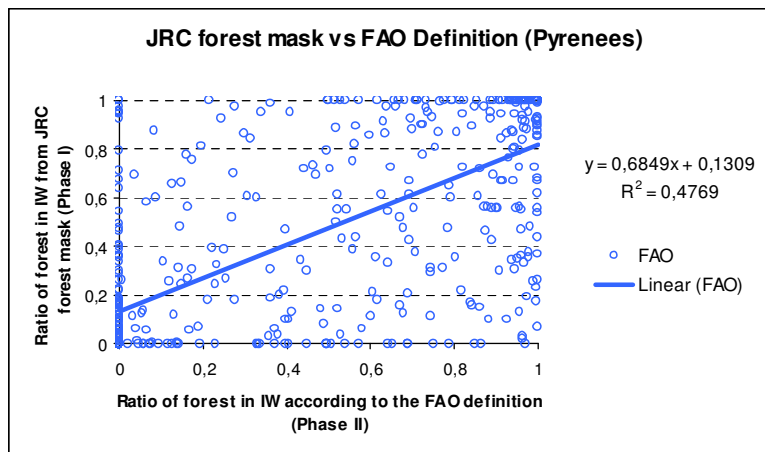


Fig. 3.27: Scatter plot showing the relationship between the Phase I (forest estimates from JRC) and Phase II (forest cover estimate according to the FAO) for test site Pyrenees.



The coefficients of determination obtained, indicate a poor correlation (approximately 0.47) between Phase II and the JRC masks (Phase I) for the Pyrenees test site. For the Saxony test site the correlation coefficients were approximately 0.64.

Correlations were also built between the JRC forest mask and the corresponding national forest masks for the Saxony and Pyrenees test sites (Fig 3.28 and 3.29). The correlation for the Saxony test site was 0.64 while that for the Pyrenees test site was 0.39.

Fig. 3.28: Scatter plot showing the relationship between the Phase I (forest estimates from German forest mask) and Phase II (forest cover estimate from JRC mask).

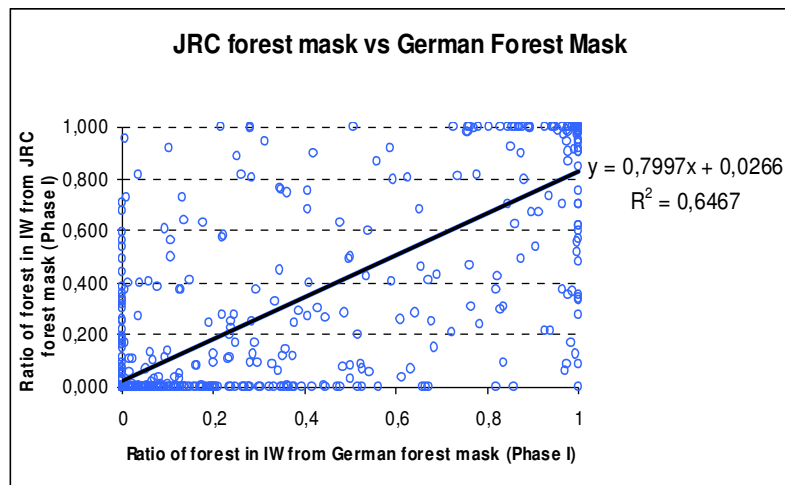
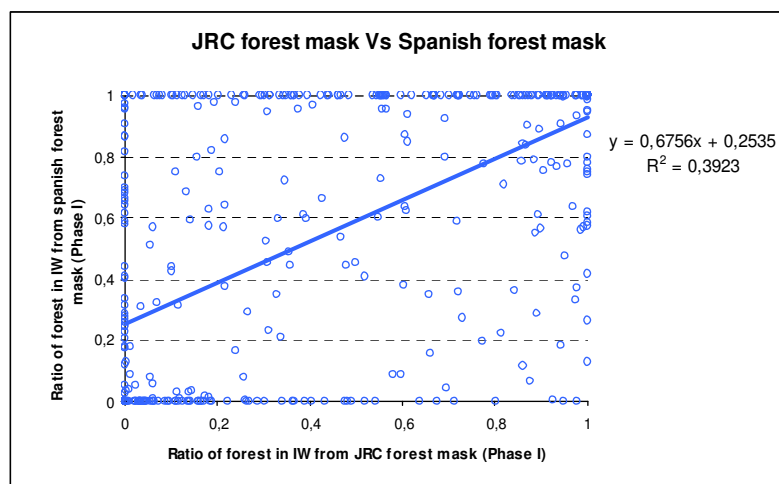


Fig. 3.29: Scatter plot showing the relationship between the Phase I (forest estimates from Spanish forest mask) and Phase II (forest cover estimate from JRC mask).



The differences between the Spanish forest mask and that of JRC can be due to one or a combination of the following reasons:

- Aerial photographs constituted the basic data set for the Spanish forest mask while the JRC mask is based on Landsat data.
- The Spanish mask is based on a visual analysis while the JRC forest mask is based on a semi-automatic approach. Furthermore, the semi-automatic approach will definitely require the use of training data, which in the Pyrenees will definitely be complex considering the confusion in identifying the different vegetation forms.
- Differences in acquisition date, geolocation and image quality.
- Occurrence of forest fires causing large scale changes in forest pattern.

Discussion

The primary objective of the approach was to develop an effective and flexible tool that facilitates the assessment of the variable 'forest area' according to any reference definition. The results obtained, demonstrate that the proposed methodology effectively harmonises forest area information on the basis of NFIs according to international reference standards such as the FAO. By integrating a remote sensing double-sampling approach, using high-resolution data, forest area definition parameters, like *minimum area*, *minimum width* and *minimum crown coverage*, can easily be interpreted and evaluated to any reference definition and parameter thresholds. This is demonstrated by evaluating 'forest area' according to the thresholds of five different national definitions. The results indicate that differences in forest area estimates are mainly due to one or a combination of the following reasons:

- a) differences due to methodology – see differences between Phase I and Phase II;
- b) differences due to input data – see the use of high or moderate resolution data;
- c) differences due to interpreter views on what is forest and what not – see confusion between sparse forest, shrub land and forest, especially in the Mediterranean region;
- d) differences due to forest area definitions and parameter thresholds.

The proposed approach is a technical approach which outcome depends very much on a) the quality and resolution of sub-sampling imagery and b) the effective delineation of forest patches within each of the high resolution samplings. The importance of high quality data is evident in the test site Sicily where the Approach was inapplicable due to skewed, low quality imagery. In this case, it is difficult to identify forest area and separate them from other vegetative forms. Forest patches are impossible to identify for an interpreter, likewise the forest patch boundaries. The results of the Pyrenees instead show the necessity of having a good knowledge of the spatial structure and characteristics of the forests in each assessed region when interpreting high resolution imagery. The example of the Pyrenees clearly demonstrates the extent to which the confusion between *sparse forest*, *shrub land* and *forest*, especially in the Mediterranean region, affects the results of forest patch delineation and therefore total forest area assessment.

Basically forest patch delineation for the test site Saxony was much easier to conduct than for the Pyrenees. The major reason was that forest patch boundaries and edges between different land use categories are much better to discern in central or northern European landscapes than in Mediterranean regions, as represented by the Pyrenees test site (see also discussion below). Therefore results of forest area estimates and the effects of different definitions applied needs to be discussed from different points of view and for each test site separately.

For the test site Saxony, the difference between the highest forest area estimate (according to Austrian definition) and lowest forest area estimate (according to Spanish definition) is 16600 ha, meaning a difference of about 3.31%. This difference is explained mainly by the respective thresholds of *minimum width* and *minimum area*, which are lowest in the Austrian definition and highest in the Spanish definition. Generally it is evident that Phase III estimates (see Chapter 3.3, Fig 3.15) are higher than the Phase I estimate, except for the Spanish definition. The difference between Phase I (forest mask based on Landsat) and Phase III (German definition) is about 3%. As the same definition is applied in both cases, it is obvious that differences in forest area estimates of Phase I and Phase III, result rather from differences in methodological approaches than from differences between definitions and parameter thresholds applied.

Table 3.8: Test site Saxony: Forest area assessment according to different definitions and resulting differences between in ha.

	Phase I - Landsat	Austrian Def.	German Def.	Spanish Def.	UK Def.	Italian Def.	FAO Def.
ha	144 542	160 539	160 025	143 892	144 772	154 220	154 220
Phase I - Landsat	144 542	0	15 997	15 483	650	230	9 678
Austrian Def.	160 539		0	514	16 647	15 767	6 319
German Def.	160 025			0	16 133	15 253	5 805
Spanish Def.	143 892				0	880	10 328
UK Def.	144 772					0	9 448
Italian Def.	154 220						0
FAO Def.	154 220						0

Table 3.9: Test site Saxony: Forest area assessment according to different definitions and resulting differences between in percent [%].

	Phase I - Landsat	Austrian Def.	German Def.	Spanish Def.	UK Def.	Italian Def.	FAO Def.
%	28,79	31,97	31,87	28,66	28,83	30,72	30,72
Phase I - Landsat	28,79	0,00	3,18	3,08	0,13	0,04	1,93
Austrian Def.	31,97		0,00	0,10	3,31	3,14	1,25
German Def.	31,87			0,00	3,21	3,04	1,15
Spanish Def.	28,66				0,00	0,17	2,06
UK Def.	28,83					0,00	1,89
Italian Def.	30,72						0,00
FAO Def.	30,72						0,00

The estimate of Phase III according to the German definition can be taken as the national assessment and report on forest area, whereas Phase III according to FAO is the harmonised estimate, which fulfils international information requirements. Looking at the results from the international reporting point of view, it can be recognised that differences between ‘German definition’ and ‘FAO definition’ estimates are relatively low, with 1.15%. The maximum difference between national definition estimates and the one according to FAO is about 2% (see difference between Spanish and FAO definition).

For the Pyrenees test site, the highest forest area value is the estimate of the Phase I (national forest mask based on Aerial Photographs) with 232 309 ha. All Phase III estimates (according to different national definitions and the FAO definition) instead are much lower, varying between 186 109 and 197 420 ha. The difference between Phase I and Phase III according to the Spanish definition is approximately 46 200 ha, representing a difference of more than 10%. This enormous difference becomes more interesting considering the fact that both, Phase I and Phase III estimates, were on the basis of a) the same source of information (Aerial Photographs) and b) the same image interpretation technique (visual interpretation). This means the differences are not due to different input data sets (like for Saxony), but mainly due to differences in forest patch delineation and interpreters’ views on what is forest and what not.

Looking at the Spanish national forest reporting, like to the FAO FRA 2005 or MCPFE/UNECE 2007, forest coverage is reported with 57%, of which 36% are regarded as ‘forest’ and 21% are classified as ‘other wooded land’. Considering the 5% threshold for *minimum crown coverage* applied in the Spanish forest definition, a clear distinction between ‘forest’ and ‘other wooded land’ seems difficult. In this respect, it is assumed that in Phase I, the Spanish national forest mask, no differences are made between ‘forest’ and ‘other wooded land’ and that parameter thresholds of the national definition, like *minimum crown coverage*, were applied only to a limited extent. This probably explains the enormous differences between Phase I and Phase III estimates for the Pyrenees test site.

Table 3.10 Test site Pyrenees: Forest area assessment according to different definitions and resulting differences between in ha.

	Phase I - Aerial Phot.	Austrian Def.	German Def.	Spanish Def.	UK Def.	Italian Def.	FAO Def.
ha	232 309	197 420	197 031	186 109	188 632	193 984	193 984
Phase I – Aerial Phot.	232 309	0	34 889	35 278	46 200	43 677	38 325
Austrian Def.	197 420		0	389	11 311	8 788	3 436
German Def.	197 031			0	10 922	8 399	3 047
Spanish Def.	186 109				0	2 523	7 875
UK Def.	188 632					0	5 352
Italian Def.	193 984						0
FAO Def.	193 984						

Table 3.11: Test site Pyrenees: Forest area assessment according to different definitions and resulting differences between in percent [%]

	Phase I - Aerial Phot.	Austrian Def.	German Def.	Spanish Def.	UK Def.	Italian Def.	FAO Def.
%	53,09	45,12	45,03	42,53	43,11	44,33	44,33
Phase I – Aerial Phot.	53,09	0,00	7,97	8,06	10,56	9,98	8,76
Austrian Def.	45,12		0,00	0,09	2,59	2,01	0,79
German Def.	45,03			0,00	2,50	1,92	0,70
Spanish Def.	42,53				0,00	0,58	1,80
UK Def.	43,11					0,00	1,22
Italian Def.	44,33						0,00
FAO Def.	44,33						

Comparing Phase III estimates, it can be recognised that differences between the definitions itself instead are much lower, varying between 0.09 and 2.6%.

Similar to the results of the test site Saxony, the highest forest area estimate of Phase III was obtained from the Austrian definition while the lowest was from the Spanish definition. Also here, the difference of about 2.6% can be accounted by the high thresholds for *minimum width* and *minimum area* in each respective definition. The lowest difference between Phase III estimates results between the application of Austrian and German definition, with about 0.09%. Differences between international standard (FAO) and national reference standards vary between 0.7 and 1.8%.

Looking at the results of forest area estimates for both test sites, Saxony and the Pyrenees, it can be concluded that high differences result mainly from differences in the methodological approach than from differences in definition parameters. Differences between Phase I and Phase III, but applying the same definition, vary between 3% (see Saxony) and 10.5% (see Pyrenees). From the view point of definitions and parameter thresholds instead, differences are lower, varying between minimum of 0.09 and maximum of 3.31%.

Differences in forest area estimation are specifically relevant when it comes to the national data reporting and fulfilment of international reporting obligations, like the MCPFE/UNECE C&I reporting, the FAO Forest Resources Assessment (FRA) and in particular the UNFCCC Kyoto Protocol (Article 3.3 and 3.4). The effect of differences in forest area estimation is explained by taking the results from the test site Saxony as an example and projecting these on the German national scale.

Taking for example the difference between German definition and FAO definition of 1.15% and projecting these on the 11 076 Mill. ha forest in Germany, the estimate on total forest area would be about 127 000 ha less, when applying the FAO definition. Applying instead the Spanish or the Austrian definition, would result in a difference of +/- 366 000 ha (see differences of 3.31%).

From the perspective of Kyoto Protocol reporting, differences between 1.15 and 3.31% in forest area estimates have considerable implications on the accounting of carbon and the green house gas emissions reporting from forests under LULUCF. Taking again the German forest as an example, the mean value of forest carbon stock per ha is estimated with 115 t C/ha (see Köhl et al., 2006). A difference of 3.31% in forest area estimation, equal to +/- 366 000 ha, would mean a

difference in forest carbon stock of +/- 42.5 Mill. t C. Particularly relevant are the implications on the national estimates of emissions/ carbon stock changes. The annual amount of carbon sequestration in woody biomass in German forests is estimated at 1.5 t C/ha (see Häussler et al., 2006), which is equivalent to about 5.5 t CO₂. With respect to a difference of +/- 366 000 ha in forest area, the difference in calculating annual net changes would be about 550 000 tons of carbon or 2 Mill. t CO₂. Taking instead the difference between German and FAO definition of only 1.15%, the difference in carbon sequestration per ha and year would be about 191 000 t C/ha equal to 697 000 t CO₂/ha.

Coming back to the technical aspects of the proposed approach, and comparing the two situations of Saxony and Pyrenees, it can be recognised that in the test site Saxony, Phase III forest area estimates are higher than Phase I while in the Pyrenees test site Phase III forest area estimates are lower than the Phase I estimate. The main explanation for this is that in Saxony, forest boundaries and patches are clearly distinguishable from other land use categories and can consequently be easily delineated. On the contrary, in Pyrenees, there is a high uncertainty in identifying forest areas due to a) confusion with other land cover categories, b) patch boundaries are difficult to discern and c) sparse forest areas are often considered as non-forest areas (see below).

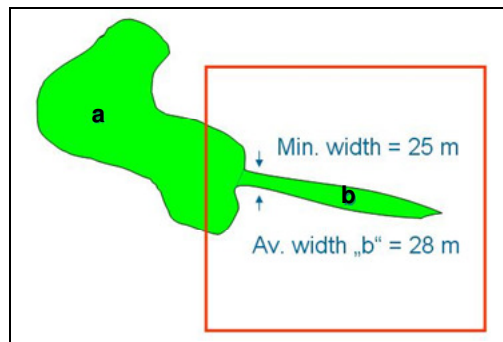
The effect of the three forest defining parameters in the forest/non-forest decision was similar in both test sites. It can be concluded that mainly the parameters *minimum area* and *minimum width* were decisive in deciding whether a patch is considered as 'forest' or not. These two definition parameters played therefore a significant role in total forest area estimation. For the test site Saxony, the attribute *crown coverage* was indecisive while for the Pyrenees test site the attribute was of little significance. Almost all of the patches (see patch category: i, ii, and iii)⁷ had a crown coverage estimated above 30 % (see Austrian definition), since most of the so-called 'sparse forest areas' were classified under category iv 'non-wooded areas in forest'.

Due to the moderate correlation between Phase I and II estimates in the Pyrenees test site, the category iv patches (non wooded areas in forest) were re-assessed on the premise that they are potential forest areas. The aim was to test the effect of the parameter *crown coverage* on these patches especially with respect to the Spanish threshold of 5%. The results indicate that the inclusion of these patches in the analysis led to slight changes only (approximately 1000 ha) in the forest area estimates according to the Austrian, FAO and Italian definitions. There was an increase of about 6000 ha according to the German definition as the attribute *crown coverage* is not included in the German definition. And there was no change in the forest cover estimates according to the UK and Spanish definition as all the category iv patches (non-wooded land in forest) failed to fulfil the other two parameters *minimum width* and *minimum area*. This again approves the significant role of these two definition parameters.

The methodology proposed, requires evaluating the three forest defining parameters for each forest patch. While the determination of *patch area* and *crown coverage* is straight forward, the determination of *patch width* is slightly complex especially when dealing with patches with complex structures that for example extend outside the Interpretation Window. Fig. 3.30 is an arbitrary example to illustrate the problem.

⁷ **i:** wooded land area in forest; **ii:** wooded land in gardens, parks, cemeteries; **iii:** linear wooded areas along linear objects

Fig. 3.30: Example of forest patch where determining forest patch width is difficult.



The total area of the patch is for example 2.3 ha, that is 'a' + 'b'. It is also possible to view the patch as two separate patches 'a' and 'b' in which case their sizes are 2.1 and 0.2 ha respectively. Taking the UK definition for example: minimum width 50 m and minimum area 2 ha the following conclusions can be made:

- Average width of 'a' (without 'b') = 55 m implies Area **is** forest (UK)
- Average width of 'b' (without 'a') = 28 m implies Area **is not** forest (UK)
- Average width of total area ('a' and 'b') = 40 m implies Area **is not** forest (UK)

The patch was treated as one patch ('a' + 'b') in cases where there are no structural differences between 'a' and 'b'. It should be noted that this situation is unique and does not necessarily occur frequently.

Furthermore, the specific characteristics of South European forest (occurrence of compact and sparse forests, other wooded land, like macchia or shrub land) make the application of the methodology in this area quite challenging. Within this study, the forest patches for the Pyrenees test site were delineated by a German expert and this consequently affected the correlations (moderate R^2 compared to the high R^2 values obtained in Saxony). Examples of delineated patches were sent to the Spanish project partners for cross-checking and evaluation. In general, the majority of discrepancies in the forest patches delineation in Pyrenees can be summarised as follows:

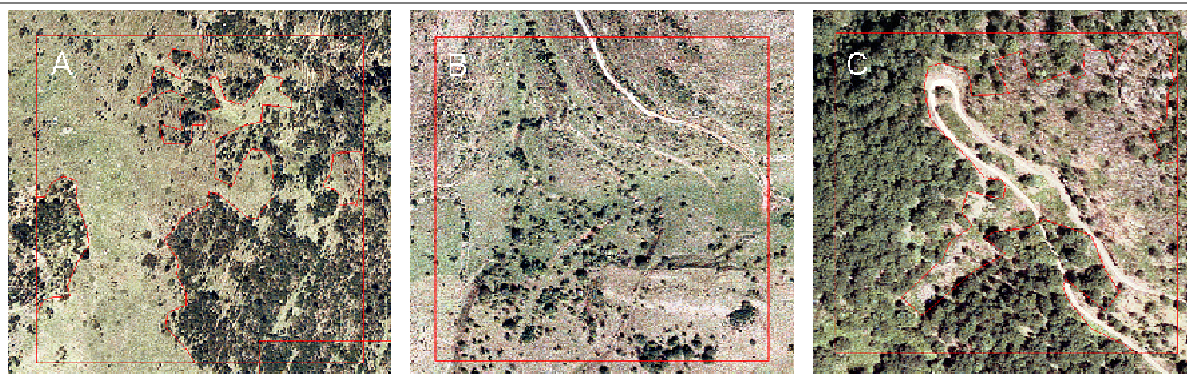
A) Confusion between trees and shrubs: The habitus of tree species in the region is rather small. Even some tree species which have a potential to grow tall remain rather small and of low vigour, mainly because of specific site and climatic conditions, especially in high altitude regions. Such trees can easily be considered as shrubs, especially if the interpreter is not familiar with the area and local forest characteristics. Fig. 3.31-A gives an indication of a shrub area that was considered as forest.

B) Sparse forest: Most of the sparse forest areas were classified as 'non wooded areas in forest' (category iv) and consequently not considered as forest, as patch boundaries were difficult to discern. As mentioned above, the Spanish NFI considers any forest with a crown coverage above 5 % as forest. Fig. 3.31-B illustrates an example of sparse forests that was not considered as forest.

C) Roads and paths: Another challenge in the Mediterranean region was to distinguish gravel from tarred roads, which is defined as a decisive parameter in patch boundary delineation (see delineation criteria, Chapter 3.2.5.2). In the conception of the Spanish NFI, paths or gravel roads with small widths are not considered as patch boundaries. Fig. 3.31-C shows forest patches separated by a gravel road as interpreted by the German interpreter. Patches like these would most likely not be separated by a Spanish interpreter.

D) Forest boundaries: Smaller trees or sparse forest areas closed to compact forests were most left out or re-grouped in a non-forest category. See examples in Fig 3.31-B and C.

Fig. 3.31: Examples of forest/non-forest patches in the Pyrenees test site: A) confusion between trees and shrubs; B) sparse forests; C) roads and path.



For the test area Saxony, the primary sample (Phase I) constituted forest mask established from Landsat ETM. The forest masks for the other test sites Pyrenees (Spain) and Sicily (Italy) were produced using different data sets (DOP for the case of Spain) with different technical specifications (definition of forest, scale, image processing technique etc). Imagery classification to produce national regional forest masks were done by different interpreters. To minimise the effect of different data sets but also of different interpreters' views, a harmonised European forest mask would be necessary, which again could be taken as harmonised data set for Phase I. The JRC forest mask for Europe (2000) was taken as a harmonised data set and its suitability for Phase I tested in this study. Correlations between the Phase II data and the JRC forest mask were established for the Pyrenees and Saxony test site. The results clearly show that the correlations between JRC masks and national mask are better in the Saxony test site than in the Pyrenees, meaning the pan-European harmonised mask is of higher accuracy in the northern and central parts of Europe than in the southern Mediterranean region. This again ascertains the enormous challenges in classifying south-European forests with its specific characteristics – especially by an automatic or semi-automatic classification process such as conducted by JRC.

Within the proposed approach, definition parameters like *minimum production* and *minimum tree height* were not taken into consideration, because a) they are complex to assess with remote sensing data and b) most national definitions do not consider these two additional parameters. That notwithstanding, it would be surely of interest to evaluate the effect of these parameters on forest area estimates, especially considering the effect of tree height as for example defined by FAO with a threshold of 5 meter. With respect to the delineation experiences made in this study, the parameter *minimum height* can be regarded as a decisive parameter for distinguishing shrub land and forest, especially in the Mediterranean region. Tree height was partly taken into account by considering shadow effects as an additional indicator to distinguish shrubs from trees when interpreting high resolution images.

In this context, it should be recalled that national and international definitions also take into account additional descriptive 'qualitative' parameters, like different land use forms and the spatial relation of forest patches with respect to other land use forms in the forest area. To incorporate these qualitative parameters in the analysis, it is necessary to provide additional distinctive attributes to each delineated forest patch (like type of land-use, neighbourhood information etc.). Presently, it seems difficult to incorporate qualitative parameters in forest area assessments as proposed in this approach, as there are lots of inconsistencies in the definitions. For example, in the German definition a Christmas tree plantation is considered a forest only, if it is located in a forest. It is not considered a forest if situated close to urban areas/houses (see BMELV, 2001). Such particular situation for example is not taken up in the Spanish or Italian definition.

To minimise this complexity in the framework of this pilot study, all wooded areas were considered as potential forest irrespective of their location while non-wooded areas were considered as non-forest. The effect of qualitative parameters was analysed for a few samples taking the German definition into consideration. Attributes of neighbourhood patches (like nearness

to parks, cemeteries, urban areas etc.) were added to the delineated patches and used as additional parameters in the forest/non-forest decision. It is important to note that stocked areas within urban areas, cemeteries and parks are not considered as forest according to the German definition. Consequently, a significant reduction in the amount of forest area was recognised when these qualitative parameters were included.

Within the frame of this approach, two procedures for patch delineation were tested, namely the semi-automatic segmentation and the manual on-screen digitisation. Due to substantial increase in workload and time consumption per Interpretation Window (splitting and merging of segments and determining thresholds for segmentation parameters), the on-screen digitisation was favoured and implemented in this project. Nevertheless it needs to be revealed that the on-screen digitisation in itself is a subjective and slow procedure.

An automatic segmentation of the forest patches would surely save time and avoid inconsistencies and therefore support an implementation of the approach at a wider scale, like at national or European level. Unfortunately current available automatic segmentation procedures, as provided by *Definiens eCognitionTM*, fail to meet up with the demands of this particular approach. Considering the fact that the delineation is done only within samples (Interpretation Windows) and not as full coverage assessment, the manual digitisation is feasible also at national or even European scale. The challenge will be to determine the appropriate number and sizes of sample frames (Interpretation Windows) representative of forest regions.

Discussing the options of a wide scale implementation of the proposed approach, it needs to be revealed that a) high resolution imagery (which are often costly) and b) interpreter experience and knowledge about local forest structures and characteristics, are two fundamental requirements for assuring high efficacy of the approach. A wide scale implementation will require clear standards defining a forest patch and its boundary lines. A set of forest patch delineation criteria such as developed and tested in this study (see Chapter 3.2.5.2) could be taken as a first basis for European implementation. Generally, to reduce the impact of interpreter subjectivity on the patch delineation within different forest regions, it is important to establish clear manuals to guide interpreters during the delineation process. The CLC classification of 1990 and 2000 is a good example, showing that an implementation of a standardised approach at a European scale is feasible, when a central coordination and technical support is assured.

Conclusions

The results of the two test sites Saxony and Pyrenees clearly demonstrate that the proposed methodology effectively harmonises the NFI variable ‘forest area’ according to international reference standards such as of the FAO. The proposed remote sensing double-sampling approach, using high-resolution data, facilitates that forest area definition parameters, like *minimum area*, *minimum width* and *minimum crown coverage*, can easily be assessed and evaluated to any reference definition and parameter thresholds. The study shows that the implications of differences in forest area estimates are considerable when it comes to the reporting on international obligations, like on MCPFE C&I, FAO, FRA and UNFCCC Kyoto Protocol. Particularly relevant are the implications to the forest emissions reporting under the Kyoto Protocol and LULUCF. Differences between national definitions and/or international reference standards such as of the FAO lead to differences in forest area estimation between 1-3%. Projecting these on the national scale, the amount of total forest carbon stock and changes, which could be taken into account or not, is considerable.

With respect to the proposed approach, the study shows that the most decisive quantitative parameters for forest patch delineation are *minimum area* and *minimum width*. *Crown coverage* is of particular relevance in the Mediterranean region, to discriminate sparse forest from compact forest patches. These three quantitative parameters are not taken up in all national forest definitions, see for example German, Finish or Swiss definition. To achieve a harmonisation of

forest area definitions and assessments, it requires that most decisive parameters in the *forest/non-forest* definition are taken up in all definitions. The study shows that the interpreter view and experience on what is forest and not, is highly relevant for an effective forest patch delineation and total forest area assessment. Therefore, in addition to the quantitative parameters, qualitative parameters should also be taken into account in forest definitions and clear standards developed. With respect to the proposed approach of manual forest patch delineation, most relevant are a clear definition of forest borderlines and a set of standardised classification criteria to distinguish forest patches to other land use classes and their relation to next neighbourhood patches. Highly relevant is also the use of a harmonised reliable data set for Phase I. The JRC forest masks are definitely of high importance and a first milestone for harmonising forest area assessments in Europe. Taking a pan-European harmonised forest mask as Phase I in combination with the proposed approach, applying an additional high resolution sub-sampling approach as Phase II, an objective and reliable assessment of the variable 'forest area' according to any reference definition is absolutely feasible for most regions of Europe.

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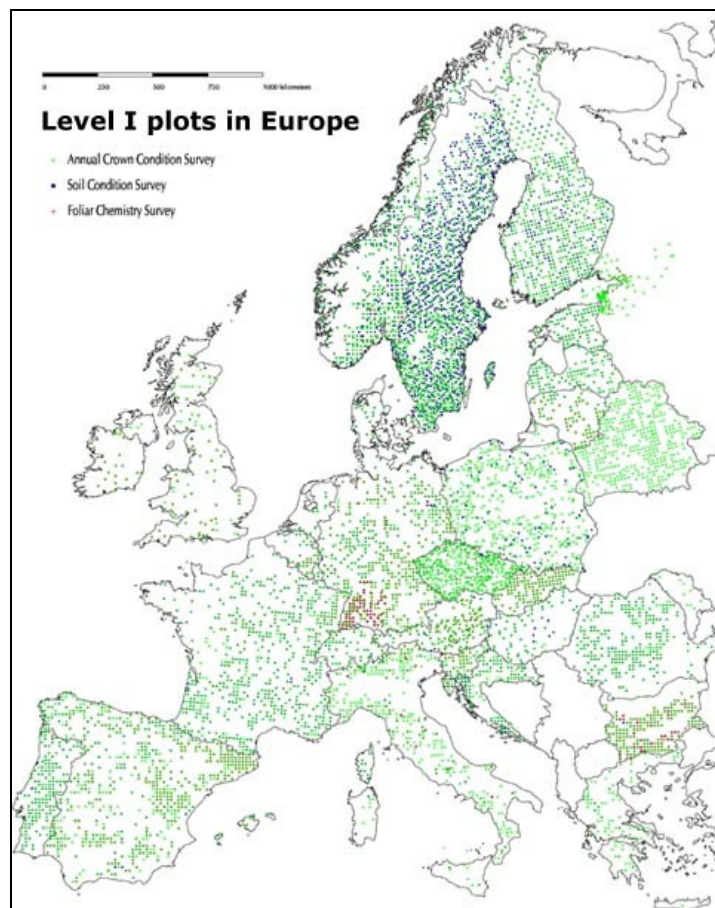
4. Approach 2: Sub-sampling approach using EC Forest Focus/ ICP Forests Level I – Variable: Forest types

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Introduction

EC Forest Focus/ ICP Forests data can be regarded as one of the best available internationally standardised data within Europe and even worldwide. The data assessment of EC Forest Focus/ ICP Forests is equally performed in all member states according to the EC Forest Focus/ ICP Forests manual. For monitoring of forest condition and its spatial and temporal changes on large scale, the so-called Level I network has been established. The Level I system covers the main forests in Europe adequately. The Level I network consists of approximately 6000 monitoring plots, which are systematically arranged in a nominal 16x16 km grid throughout Europe (see Fig. 4.1)

Fig. 4.1: EC Forest Focus/ ICP Forests Level I.



Linking NFIs with EC Forest Focus/ ICP Forests assessments is one option to harmonise NFI data according to international reference definitions. The idea of linking both systems and using synergies between is widely accepted and supported by various experts in the domain of forest monitoring (see ongoing discussions about future monitoring activities in the EU). Within the three case study countries, Germany, Italy and Spain, different approaches of linking NFIs with Level I

are under discussion or even already implemented at regional level (see PCC ICP Forests Meeting, Hamburg 2006).

At the moment, “tree species” is the only common variable of both monitoring systems. The information “tree species” is the key-information for deriving the three classic forest types, namely: *predominantly broadleaved*, *predominantly coniferous* and *mixed forests*.

The objective of Approach 2 is to calibrate NFI forest type information to an international standard by using Level I data as an additional reference value. The concept of the method is based on the classification of remote sensing data by applying tree species data from National Forest Inventory (NFI) and Level I respectively as training data to produce forest type maps for two different standards: national standard (based on NFI) and international standard (using Level I as a sub-sampling of NFI). Using spatial information such as Landsat-ETM different forest type maps for the selected test area can be produced showing forest type area according to the two standards. In addition different relation factors can be calculated, which express the ratio between the area of NFI forest type area and the area of forest types adjusted/harmonised by using Level I. Such relation factors allow the harmonisation of national forest type data to international standard and can be applied to make a link between Level I and NFI assessments.

Methodology

Input data

The sub-sampling approach with Level I data is based on the following input data sets that were delivered by the project partners for all six test areas:

- Level I plots (international standard) – tree species information;
- NFI plots with attached categorical forest type information based on national standard for all test sites (categories: broadleaved, coniferous, mixed);
- NFI plots with attached metrical forest type information based on national standard for test sites Saxony and Sicily (percentage of coniferous and broadleaved forest in each plot);
- Landsat-ETM data (7 multispectral bands, 30 m resolution);
- National forest masks (forest / non-forest) derived from classification of Landsat data, based on national forest definitions.

NFI plot data

For each test site the NFI plot data were delivered with categorical forest type information attached. At the time the work for this harmonisation approach was carried out (April - December 2007) the 2nd NFI in Italy was not yet finished. Therefore data of a local inventory based on the same scheme as the NFI were provided for Molise test area. Table 4.1 gives an overview of NFI plots used in the project for the different test areas. The plot data are classified into the three forest types based on different thresholds depending on the national definitions for mixed forest. In Italy a minimum of 75 % of conifers or broadleaved trees per forest area is applied to discriminate coniferous and broadleaved forest respectively while forest with smaller area proportions of both forest types is classified as mixed forest. For Spain the threshold is 70 %. For Germany there exists no definition for mixed forest. The German NFI data were provided with information of 5 forest types: *Pure coniferous forest*, *pure broadleaved forest*, *coniferous forest with small share of broadleaved trees*, *broadleaved forest with small share of conifers*, and *mixed forest with equal shares of coniferous and broadleaved trees*. Within the frame of this project the latter three classes were assigned to *mixed forest* while pure coniferous and pure broadleaved forest were classified to *coniferous* and *broadleaved forest* respectively. The differences between the national forest type

definitions (thresholds) and the internationally accepted threshold of 75 % as applied by CLC or as accepted by the MCPFE (MCPFE 2003) are important to consider when harmonising national data to an international standard.

In addition, NFI plots with metrical forest type information were provided for the two test sites Saxony and Sicily. The plots show the percentage of coniferous and mixed forest based on the area proportion of the tree species for each plot. These data were used to test if classification accuracies and correlation analyses can be improved by applying metrical instead of categorical forest type information.

EC Forest Focus/ ICP Forests Level I data

Percentages for the three forest types were derived for every ICP plot based on the amount of sample trees per tree species. This approach is different from the forest type information of the NFI plots which is based on canopy cover (forest area) and thus has to be considered as a limiting factor for the comparability of both data sets. To classify coniferous, broadleaved and mixed forest a minimum threshold of $\geq 75\%$ proportion of coniferous or broadleaved trees was applied to discriminate predominantly coniferous and broadleaved plots. All other plots were classified as mixed forest. This threshold is equivalent to the CLC classification of forest types and represents an international standard such as adopted by MCPFE. As the Level I data are based on a 16x16 km grid the amount of ICP plots per test site is rather low in comparison to the amount of available NFI plots as can be seen from Table 4.1 and Fig. 4.2.

Table 4.1: Number of NFI and Level I plots per test area by forest type.

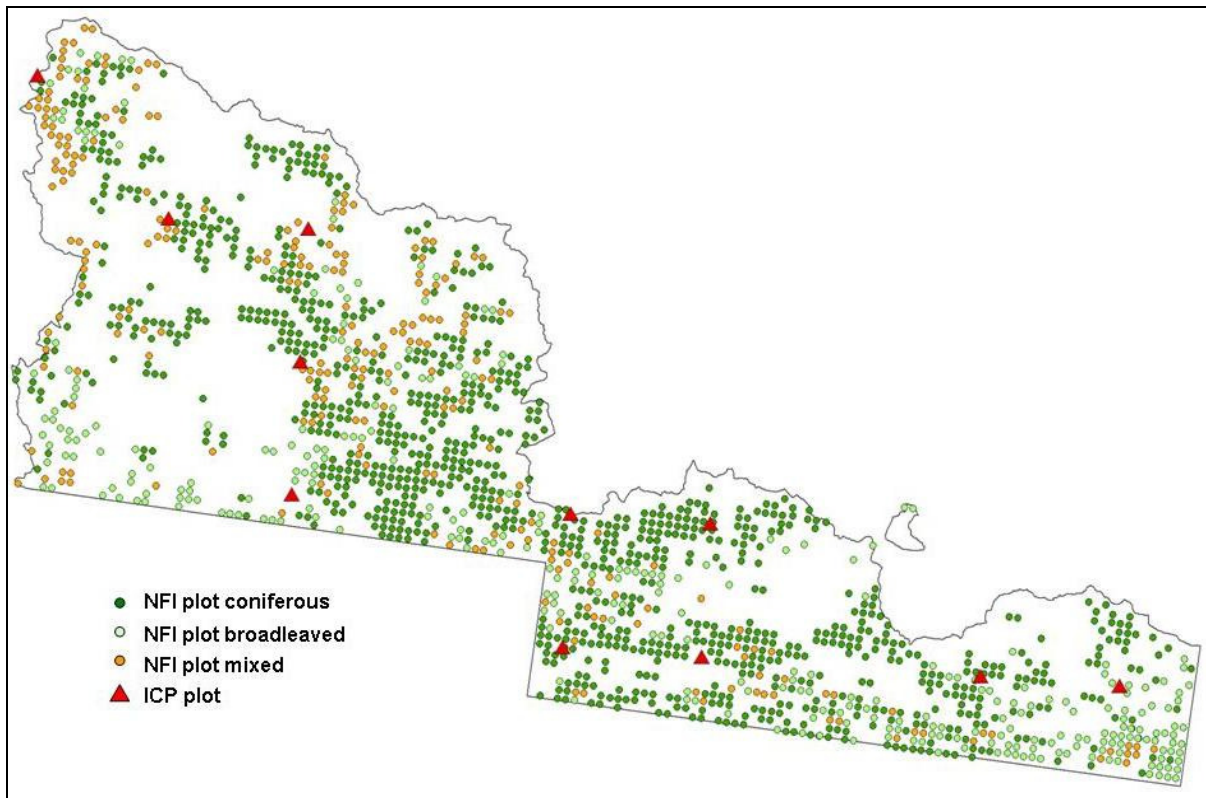
Test sites	NFI plots ⁸				ICP plots (16x16 km)			
	total	con	brd	mi x	total	con	brd	mi x
Saxony	679⁹/622¹⁰	226 ⁹	83 ⁹	388 ⁹	6	5	1	0
Rhineland-Palatinate	1837⁹/900¹⁰	215 ⁹	329 ⁹	1293 ⁹	9	3	3	3
Molise	257	8	231	18	2	-	2	-
Sicily	626	109	455	62	5	2	2	1
Pyrenees	1612	1037	326	249	11	7	3	1
South Catalonia	1829	1304	150	375	17	12	2	3

⁸ NFI sampling density for the different countries / test sites: Italy 1x1 km (Phase I, non-aligned systematic sampling method), Spain 1x1 km, Saxony (Germany) 2.83x2.83 km (NFI cluster density), Rhineland-Palatinate (Germany) 2x2 km (NFI cluster density).

⁹ Number of applied sampling plots.

¹⁰ Number of NFI clusters (clusters of a maximum of 4 sampling plots).

Fig. 4.2: NFI and Level I plots within the Pyrenees test area.



Landsat-ETM data

Based on the Landsat bands different vegetation indices were calculated. Depending on the test site, the following indices were applied in the forest type classification (see also Table 4.2): Normalized Difference Vegetation Index (NDVI), Infrared Percentage Vegetation Index (IPVI), Difference Difference Vegetation Index (DDVI), Soil Adjusted Vegetation Index (SAVI) and Bare Soil Index (BSI):

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad (4.1; \text{Hildebrandt, 1996})$$

$$\text{IPVI} = \frac{\text{NIR}}{\text{NIR} + \text{Red}} \quad (4.2; \text{Crippen, 1990})$$

$$\text{DDVI} = 2(\text{NIR} - \text{Red}) - (\text{Green} - \text{Blue}) \quad (4.3; \text{Hildebrandt, 1996})$$

$$\text{SAVI} = (1 + L) \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red} + L} \quad (4.4; \text{Huete, 1988})$$

$$\text{BSI} = 100 \left(\frac{(\text{MIR} + \text{Red}) - (\text{NIR} + \text{Blue})}{(\text{MIR} + \text{Red}) + (\text{NIR} + \text{Blue})} \right) + 100 \quad (4.5; \text{Rikimaru and Miyatake, 1997})$$

where:

NIR = near infrared (band 4 Landsat)

MIR = middle infrared (band 5 Landsat)

L = parameter depending on the vegetation density

Classification of Landsat-ETM data

By classifying the satellite imagery using NFI and ICP plots respectively as reference data it was aimed to produce forest type maps according to national and international standard. The kNN and threshold classification methods were tested for the approach. The kNN method has been successfully applied in numerous studies to classify forest parameters from satellite data in combination with NFI plot data (see for example: Kilkki and Päivinen, 1987; Tokola et al. 1996; Tomppo, E., 1996; Franco-Lopez et al., 2001; Reese et al., 2002; Mäkelä and Pekkarinen, 2004; Haapanen, et al., 2004; Koukal, 2004; Stümer and Köhl, 2005). A classification tool developed by Stümer (2004) was used to run the kNN classification on the Landsat data for all the test areas. Additionally, a threshold method was applied to classify forest types in the Spanish and Rhineland-Palatinate test areas to compare accuracies with those achieved with the kNN approach.

To produce forest type maps, following the national definitions, forest type information of the NFI plots was used as a reference for the kNN classification of the Landsat data, i.e. every Landsat-pixel was classified into a forest type according to national standard. The resulting classified map corresponds to the national forest type definition. NFI reference plots were chosen such that each forest type class was represented by an equal amount of reference plots (if possible). Only those plots which were covered by the forest masks were taken into consideration. For these plots the corresponding multi-spectral pixel and vegetation index values were extracted from the Landsat data.

The kNN method uses the information which corresponds to the k nearest reference pixels (nearest neighbours) in the multi-spectral feature space to classify a pixel with unknown value. For metrical data the value of the pixel is determined by means of a weighted average calculation using the spectral information of the k nearest neighbours. In the case of categorical data the pixel is assigned to that class which is represented with the highest weight among the k nearest neighbours and which thus resembles the smallest spectral distance to the pixel to estimate. To derive weight information for the reference pixels, the kNN uses the Euclidian distance between the pixel to estimate and the reference pixels. Additionally, the Euclidian distance is combined with coefficients that increase or decrease the influence of certain spectral features and characteristics (Stümer, 2004). These coefficients and the value of k – hereinafter referred to as kNN-parameters – are determined and adjusted to represent the characteristics of the image data as best as possible in order to optimize the classification results. This can be done using the values of reference pixels (i.e. at the location of reference plots).

In a first step the optimal parameters for the kNN method were determined. Applying the leave-one-out method the kNN was tested for a set of reference pixels and resulting accuracies were used to adjust and optimize the kNN-parameters based on trial-and-error principle. Once the optimal parameters were found, the classification was extended to all Landsat pixels within the forest mask. When using categorical data (3 classes: coniferous, broadleaved, mixed), no root mean square error (RMSE) could be calculated and thus accuracy estimations were derived via the Leave-One-Out-method from the proportion of reference pixels that were classified to the correct class compared to the total number of reference pixels. In the case of metrical data the RMSE can be calculated for the classification results. The adjustment of the kNN-parameters and subsequent classifications were done for each satellite scene separately due to radiometric differences between the images. Table 4.2 and 4.3 show the applied parameters of the kNN classification for all Landsat

scenes and test sites for the two different NFI data sets (categorical and metrical forest type information).

Table 4.2: Applied parameters for the kNN classification of the test areas when using categorical data.

Test site / scene	k	r	t	Bands used
Saxony North	12	5	2	3,4,5,7,NDVI
Saxony South	9	4	2.3	2,3,4,5,7,IPVI,NDVI,SAVI
Rhineland-Palatinate	10	2	2.4	3,4,3,7,BSI
Molise	4	2	1	1,3,4,5,7,NDVI
Sicily East	7	4	1	1,2,4-7, NDVI
Sicily West	20	4	1	1-7, NDVI
Pyrenees East	3	1	1	2,3,4,5,7,NDVI
Pyrenees West	15	2	2	1-7, NDVI
South Catalonia	10	2	2	4,5,NDVI

Table 4.3: Applied parameters for the kNN classification of the test areas when using metrical data.

Test site / scene	k	r	t	Bands used
Saxony North	20	5	1.3	1-7,BSI,IPVI,NDVI,SAVI
Saxony South	20	6	0.5	1-7,BSI,IPVI,NDVI,SAVI
Sicily East	25	4	1.6	1,2,3,4,5,7, NDVI
Sicily West	25	5	0.8	1-7, NDVI

To compare achieved accuracies to another approach, a threshold classification was applied to some of the test areas. The thresholds to discriminate the three forest type classes were based on the quartile and mean values in the histograms of the reference pixels (NFI plots) per class (similar to Riedel, 2008.). The resulting accuracies for the Rhineland-Palatinate test site were comparable to the kNN method, however for the Spanish test areas the achieved accuracies were significantly lower than those of the kNN. Thus all subsequent analyses were focused on the kNN results. The kNN classification results and accuracies are presented in chapter 4.3.

Conversion between national and international standard

The objective of this approach was the generation of forest type maps according to international standard using Level I data as a sub-sampling. There are two possibilities to achieve data harmonisation:

One option is the classification of Landsat data applying the Level I plots as a reference when adjusting the kNN parameters, and thus producing a forest type map following international standard. To apply this method to the given test areas a high density of Level I plots would be necessary to allow correct classification results.

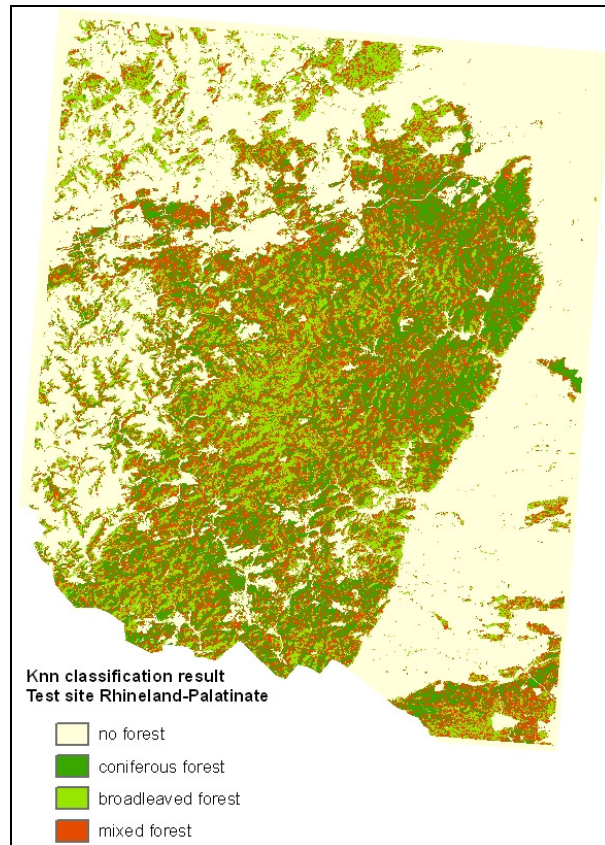
Another option would be using both NFI and Level I plots together as training data for the adjustment of the kNN parameters and optimizing the classification result towards the Level I information, i.e. minimizing the error for Level I. By this the number of samples would be increased and the approach could be applied also at a smaller scale, e.g. at test site level with low number of Level I plots.

Results

Results of the kNN classification based on NFI data

Examples of the kNN classification results representing national standard (using NFI as reference data) are presented below (Fig. 4.3 and 4.4). Classification accuracies and confidence intervals are stated in Table 4.4. For the usage of categorical forest type information the overall classification accuracies vary between 44 % and 84 % for South Catalonia and Molise respectively. The user accuracy relates to the percentage of correctly classified pixels of a class in the classification result, whereas the producer accuracy demonstrates the percentage of correctly classified pixels of a class in the reference data.¹¹ For this project mainly the user accuracy is important as it represents the chance that a pixel in the classification result fits with the ground truth. The given average accuracy is the average of user and producer accuracy.

Fig. 4.3: kNN classification with categorical data based on national forest type definition. Test site: Rhineland-Palatinate.



¹¹ The difference between user and producer accuracy can be explained by means of an example area covered with 50 % coniferous NFI reference plots and 50 % broadleaved reference plots. If in a classification all of these reference plots are classified as coniferous forest then the producer accuracy for the class 'coniferous forest' would be 100 % (as all coniferous reference plots were correctly classified), however the user accuracy for the class 'coniferous forest' would only be 50 % (as only 50 % of those plots specified as coniferous in the classification result were correctly classified).

Fig. 4.4: *k*NN classification with categorical data based on national forest type definition. Test site: Saxony.

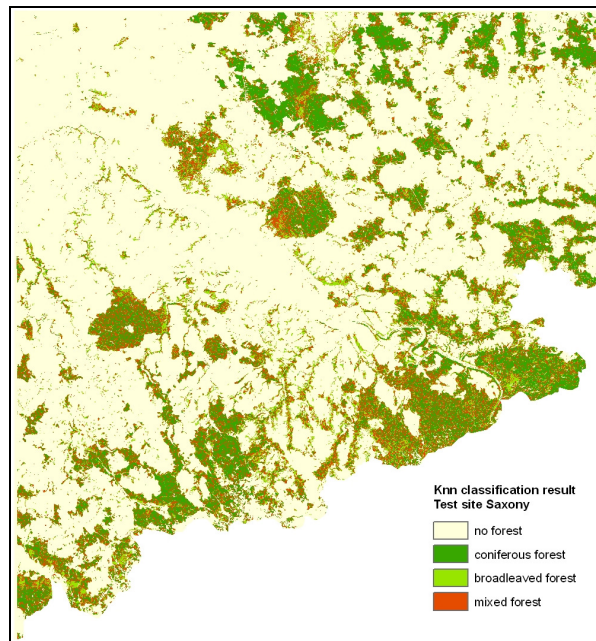


Table 4.4: *k*NN classification accuracies when applying categorical NFI data.

Test site / Scene	User accuracy			Producer accuracy			Average accuracy			Overall accuracy	Confidence interval
	Con	Brd	Mix	Con	Brd	Mix	Con	Brd	Mix		
Saxony North	69,1	69,6	60,0	90,4	68,1	42,0	79,8	68,8	51,0	67,2	+/- 20,9
Saxony South	62,3	75,0	59,3	70,4	66,5	58,1	66,3	70,8	58,7	65,0	+/- 19,3
Rhineland-Palatinate	74,8	72,0	53,4	80,4	67,2	52,8	77,1	70,3	53,0	64,9	+/- 11,9
Molise	66,7	85,5	81,8	50,0	95,9	50,0	58,3	90,7	65,9	84,0	+/- 18,8
Sicily East	63,5	65,7	-	63,5	65,7	-	63,5	65,7	-	64,6	+/- 21,6
Sicily West	72,2	73,8	-	72,2	73,8	-	72,2	73,8	-	73,0	+/- 16,2
Pyrenees East	77,6	63,2	37,5	76,0	72,0	27,3	76,8	67,6	32,4	65,6	+/- 22,2
Pyrenees West	62,0	55,8	54,1	66,9	70,5	35,	64,4	63,2	44,7	58,0	+/- 12,1
South Catalonia	49,7	42,0	39,8	54,6	45,4	32,8	52,2	43,7	36,3	43,3	+/- 12,1

Accuracies were the lowest for South Catalonia and the Western part of the Pyrenees test site and the highest for Molise test area. Due to the low accuracy for the South Catalonian test site as derived from the reference plots the classification was not extended to the entire test area.

Test of metrical NFI forest type data

One option to increase classification accuracies is the usage of metrical NFI forest type information (forest type percentages) instead of categorical data. This was tested for two test sites, namely Saxony (see Fig. 4.5) and Sicily. The results clearly show that by the use of metrical data instead of categorical data the overall classification accuracies will be improved. This method also allows a better assessment of the accuracy as the RMSE can be calculated. The RMSE varied between 26 and 34 and was lower for Saxony in comparison to Sicily. The initial classification result shows the percentage of a forest type (coniferous or broadleaved) per pixel. These results have then been classified back into forest type categories to be comparable to the categorical NFI data. The resulting overall accuracy lies between 78 and 84 % for Sicily West and Saxony North respectively (Table 4.5).

Fig. 4.5: kNN classification with metrical data on percentage of coniferous forest based on national forest type definition. Test site: Saxony.

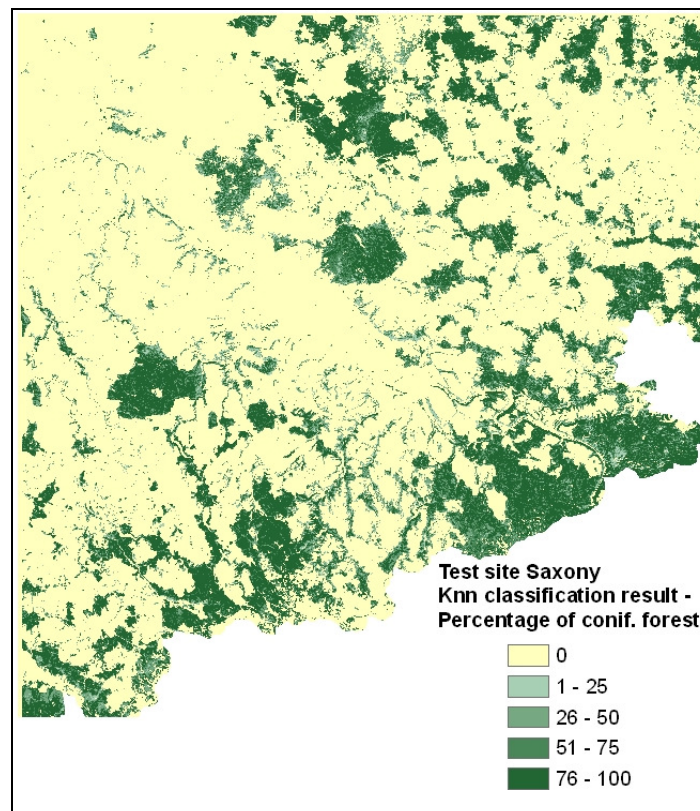


Table 4.5: kNN classification accuracies when applying metrical NFI data.

Test site / Scene	RMSE of forest type percentage	Confidence interval of RMSE		Average accuracies for categorical classes [%] ¹²		
		Low	High	Con	Brd	Overall
Saxony North	25,5	22,7	28,0	89,0	71,4	84,1
Saxony South	29,5	26,8	31,9	86,7	60,6	80,0
Sicily East	33,8	28,6	38,4	53,7	91,2	82,6
Sicily West	34,0	29,4	38,1	38,9	87,8	78,1

Overall, achieved accuracies are comparable to results of other studies of similar spatial scale (e.g. Riedel, 2008; Stümer, 2004; Cho, 2002; Franco-Lopez et al., 2001; Itten, 1992). A review of Holmgren and Thuresson (1998) on the suitability of Landsat data for the derivation of forest parameters indicates that achievable classification accuracies usually lie between 65% and 85% depending on the study area and the parameters to derive. This corresponds well with the accuracies reached with the kNN approach in this study and reflects the uncertainty caused by remote sensing approaches in general. For the harmonisation approach the low classification accuracies for the categorical NFI data imply that the produced maps at national standard need to be evaluated with caution for the test areas. For a comparison to the Level I information and for the derivation of relation factors the classification accuracies need to be higher ($\geq 80\%$).

Factors limiting the classification accuracies for the applied test sites can be summarised as follows:

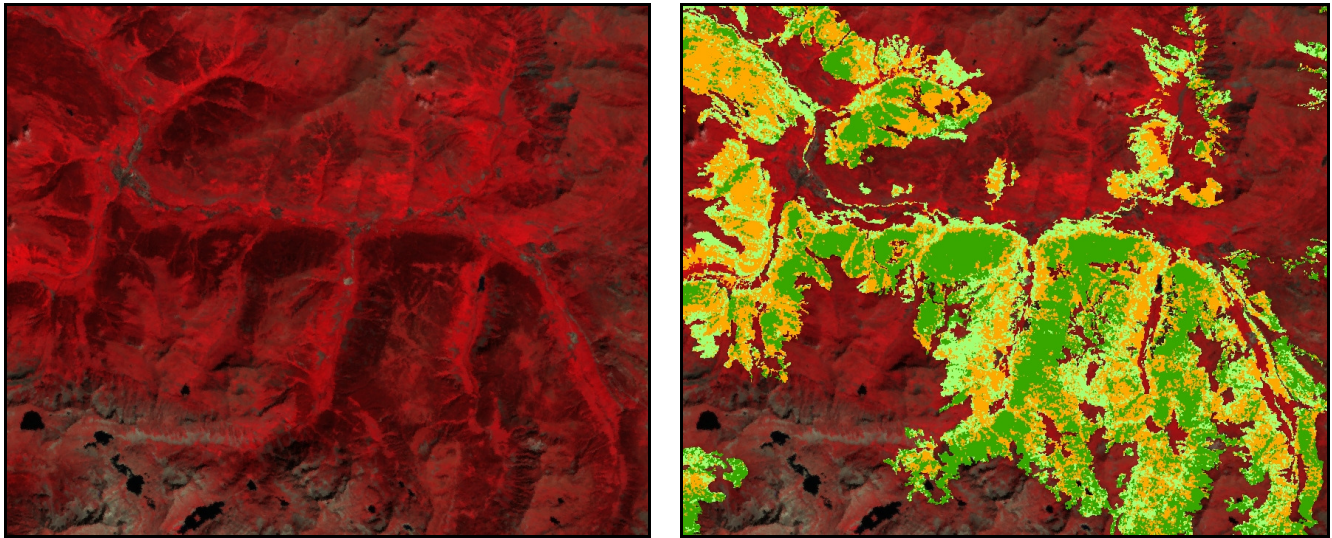
Effect of terrain

Terrain effects are caused by the combination of topography (slope/aspect characteristics) and sun position. They result in shadow and sun areas in the satellite scenes. An object lying in shadow receives and reflects less radiation than the same object on the sunny side. These same objects therefore, despite their equal reflectance, display varying intensity values according to their position to the sun. This fact is a major problem for the classification of satellite imagery (Itten 1992). For a precise and efficient detection of objects, the topographic influence on the illumination has to be eliminated. Terrain effects and possible correction methods are widely discussed in literature (Wu et al. 2004, Orthaber 1999, Leiss et al. 1995, Sandmeier 1995, Itten 1992, Teillet et al. 1982).

Terrain effects are mainly visible in the Pyrenees test site, Rhineland-Palatinate and Saxony. The influence of the terrain is also visible in the two maps (see Fig 4.3 and Fig. 4.4). The occurrence of the forest type classes in the maps is connected to the position of the slopes. Shadow hills are classified as coniferous forest due to their low pixel values while forest areas at sunny hills with high pixel values are classified as broadleaved or mixed forest. Furthermore this bias impacts the reference pixels used to adjust the kNN parameters and thus brings noise into the classification. Fig. 4.6 shows the terrain effect and corresponding classification results for a subset of the Pyrenees test area.

¹² Applied threshold for coniferous and broadleaved forest: 50%

Fig. 4.6: Terrain effect, test site Pyrenees (subset); left: Landsat-ETM data (bands 4, 3, 2); right: Landsat-ETM data with overlaid classification result (dark green: coniferous; light green: broadleaved; orange: mixed).

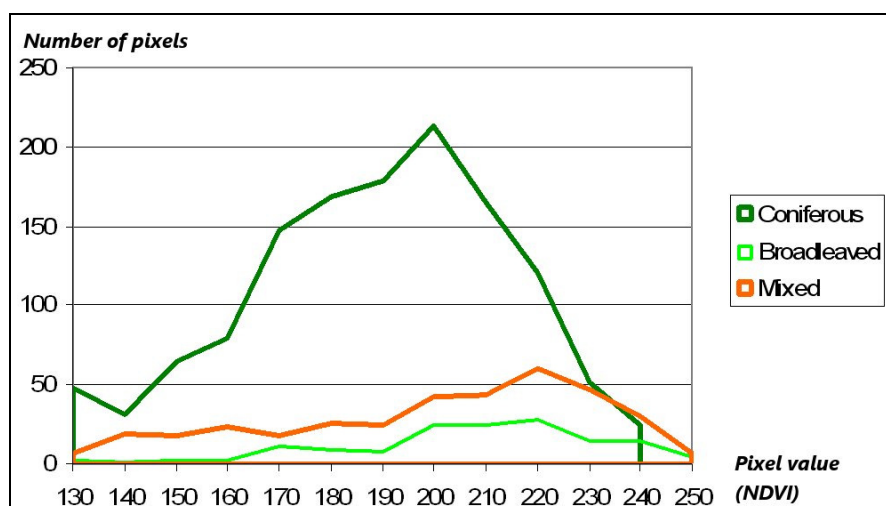


Large spectral overlaps between forest type classes in the Landsat data

Spectral overlap occurs when two pixels that belong to different classes cannot be distinguished spectrally, i.e. contain the same reflection measurements. This does not necessarily mean that those classes cannot be spectrally distinguished at all, but rather that both classes show spectral variation to an extent that the two collections of reflection measurements overlap (Gorte et al., 2003). This problem is very influential during the classification because it reduces the level of discrimination between two classes and leads to uncertainties in the classification results. The spectral separation of forest types is best in the infrared spectrum, but usually overlaps do occur especially for mixed stands and limit the classification accuracies (Cho, 2002).

Analyses of the distribution of the pixel values (reflection) for the different forest types within the reference data of the test sites reveal huge overlaps between the classes. These are partly attributed to terrain effects but also due to other factors such as mixed pixels (mix of spectral signatures), errors in plot locations (mismatch between different data sets) and an overall high variance of the pixel values per forest type class. Fig 4.7 gives an example of the class overlaps between the reference pixels in the NDVI band. It can be seen that in the case of South Catalonia the Landsat data do not allow a proper distinction of the forest types as all three forest type classes show similar pixel value ranges.

Fig. 4.7: Histogram for the NDVI, test site South Catalonia.



Categorical classes

The usage of categorical (nominal) classes as reference data instead of metrical data (which would be e.g. percentage values of a forest type) certainly reduces the reachable accuracies with kNN. Applying different thresholds for class discrimination causes unequal class distributions, makes error analyses fuzzy and thus prevents an optimal adjustment of the kNN-parameters.

Large test areas

For most of the test sites entire Landsat scenes had to be classified. For a small part of a scene the kNN parameters can be adjusted more accurately and will result in higher classification accuracies (which explains good results for Molise area). However for the extent of an entire image scene this is not feasible. Radiometric distortions within the scene resulting e.g. from atmospheric effects reduce reachable accuracies. A possibility to assure better results would be a thorough atmospheric correction of the data (Itten 1992, Teillet et al. 1982). This challenge needs to be taken into consideration especially when extending this harmonisation approach to country level.

Analysing the Feasibility of the Approach

As explained in section 4.2.3 there are two options for producing forest type maps according to international standards by using Level I data as a sub-sampling. The analyses carried out revealed that both options are not applicable in this form for the given test areas. A classification based solely on Level I plots was not possible due to the low sampling density and the corresponding low number of plots per test area. The second option using both NFI and Level I information as input parameters to have more reference plots available does also not result in a satisfying output, as the influence of the Level I plots in the classification is too low due the small number of plots. Therefore, within the given test areas, it was not possible to derive classification parameters for the kNN and threshold method that would properly reflect international standard according to EC Forest Focus/ ICP Forests. Also, it has to be considered that the problems related to the remote sensing part of the approach (as described in section 4.3.1) will occur in similar extent for a classification with Level I as reference. Therefore, a higher density of Level I comparable data as well as higher classification accuracies is essential for a successful implementation of the sub-sampling approach for the variable forest type.

To analyse the feasibility of the approach in more detail, a comparison was made between the classes of the Level I plots and the corresponding estimated class values resulting from the NFI based kNN classification. This overlay of the ICP plots with the kNN classification results (national standard) suggests that differences between national and international standard can not

easily be derived from the given input data. Discrepancies between ICP plot classes and corresponding NFI based classification results are mostly attributed to classification inaccuracies rather than differences between national and international standard. However, the number of ICP plots per test site is too low to draw proper conclusion on a correlation between both data sets. As an example Table 4.6 shows how ICP plots in the Rhineland-Palatinate test area correspond with the NFI based classification result. An overview for the other test sites is given in Table 4.7. For most of the test areas about half of the ICP plots fit with their forest type class to the NFI-based classification results. However, the plots which differ from the classification result do not necessarily indicate a difference between the national and international forest type data assessments. The differences between ICP plots and classification outputs are more likely the result of the low classification accuracies stated in Table 4.4. Table 4.6 demonstrates this problem in more detail: Only very few of the non-fitting ICP plots in Rhineland-Palatinate can be attributed to differences between international and national forest type definitions whereas most discrepancies result from remote sensing based inaccuracies or location errors. This indicates that due to the low density of the ICP grid (connected with low number of available ICP plots per test site) and the uncertainties in the data resulting from the remote sensing approach, it is not possible for the given test sites to derive a conversion factor between national and international Level I information. Also the usage of categorical classes instead of metrical data is a limiting factor for correlation analyses.

Table 4.6: Level I plot overlay with classification results for test site Rhineland-Palatinate based on categorical NFI data.

ICP plot ID	Level I forest type	kNN classification with NFI as reference	Comments
629	coniferous	broadleaved	Edge forest-nonforest (mixed radiometric signatures)
630	mixed	mixed	
655	broadleaved	coniferous	Shadow slope
656	coniferous	mixed	83% coniferous in ICP data – difference in definition for mixed forest between German NFI and ICP data
680	broadleaved	broadleaved	
681	mixed	mixed	
682	broadleaved	mixed	Positioning error (plot outside forest in Landsat data)
705	coniferous	coniferous	
729	mixed	mixed	

Table 4.7: Level I plot overlap with classification results of 5 test areas based on categorical NFI data.

Test area	Number of Level I plots	Number of Level I plots that correspond in their forest type to the NFI-based classification result	Comments
Saxony	6	3	
Rhineland-Palatinate	9	5	
Molise	2	-	Both ICP plots are outside of the forest mask
Sicily	5	2	3 ICP plots are outside of the forest mask
Pyrenees	11	7	1 ICP plots is outside of the forest mask

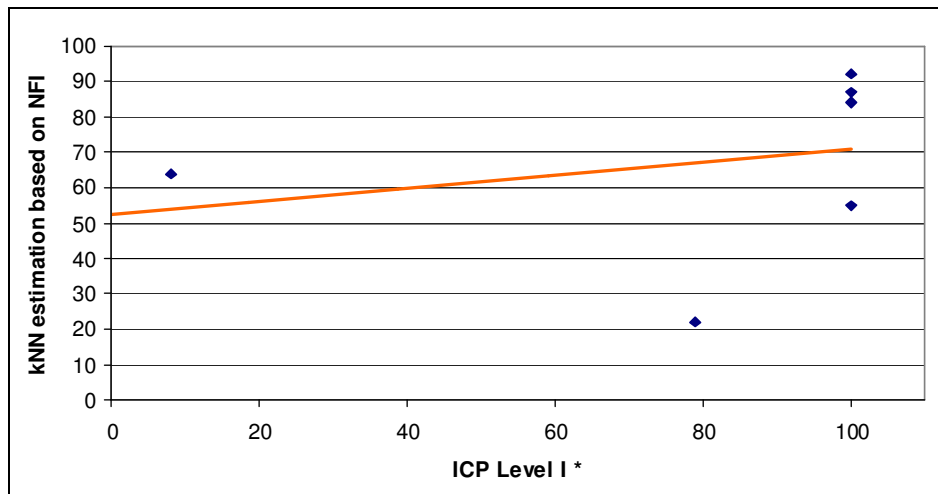
The application of metrical forest type data in combination with a sufficient amount of ICP plots provides a promising method to derive a correlation factor between forest type information based on national and international standard. Based on the proportion of tree species for each ICP plot forest type percentages can be calculated per plot. The ICP forest type percentages can be compared to the kNN estimations for the same forest type according to national standard. This allows for detailed regression analyses between the forest type percentages of both standards and the identification of a transformation function between both standards. Table 4.8 shows such a comparison between ICP data and kNN estimations. Fig. 4.8 demonstrates the principle for deriving a transformation function. However, the low amount of ICP plots per test area hindered the achievement of proper results on the correlation between national and international data.

Table 4.8: ICP plot overlay with classification results for the test site Saxony based on metrical NFI data.

Plot-ID	Forest type	ICP coniferous% *	knn estimate of coniferous%
8312	coniferous	100	55
8334	broadleaved	8	64
8352	coniferous	100	87
8353	coniferous	79	22
8356	coniferous	100	92
8373	coniferous	100	84

* Applied threshold for coniferous forest: $\geq 50\%$ coniferous trees per plot.

Fig. 4.8: Correlation between Level I forest type information and the respective kNN estimations based on metrical NFI data for coniferous forest in test site Saxony. The red line indicates the transformation function between ICP and NFI forest type data.



Discussion

The primary objective of the harmonisation approach was to use Level I as a sub-sampling of NFI to calibrate forest type information according to an international standard and to derive relation factors between the applied national and international standard. In both monitoring systems the information on forest type is derived from the assessment on tree species. The variable “tree species” is – at the moment – the only common variable between both monitoring systems.

The results obtained for all six test sites reveal that Approach 2 has a potential to create some linkage between national and international standard, offering the opportunity for using synergies between NFI and Level I. However, when applying the approach at test site level, different factors limited the feasibility of the proposed approach.

The obstacles which hindered the implementation of the approach most can be summarised as follows:

- low density of Level I plots per test site,
- kNN classification inaccuracies.

Most critical for the applicability of the harmonisation Approach 2 is the low density of Level I plots at test site level. Due to the limited number of reference plots a conversion of the NFI forest type information into an international standard such as of ICP was not possible. Thus, relation factors could not be calculated. Other limiting factors are seen in the forest type classification of Landsat data by using kNN. For successfully harmonising forest type data involving the kNN method, it is essential that the results of the kNN classification applied have a high accuracy (preferably above 80%). Within this project high classification accuracies were not achieved, but it is shown that the accuracies can be considerably improved by applying metrical instead of categorical forest type data (see also below).

Applying a remote sensing approach to assess forest types, it needs to be considered that the assessment of Level I is based on the most dominant trees (Kraft classes 1-3) whereas NFI assessments are based on minimum DBH. Information derivable from satellite imagery mainly relates to the upper canopy layer, which does not necessarily coincide with the data provided by NFIs as these assess also trees below the top crown cover. Mixed stands under a canopy of predominantly broadleaved or coniferous trees might therefore not be assessed.

Suggestions for improvements of Approach 2 comprise a) efforts aimed at increasing the classification accuracies and b) increasing the density of sub-sampling for assessing more representative international reference data.

As mentioned above, higher classification accuracies (at least 80 %) can be achieved by applying metrical forest type information in the kNN classification (percentages instead of categorical classes). In addition, metrical data provide the advantage to be independent from national thresholds for mixed forest. The classification results are flexible and can be classified back into forest type categories applying thresholds as needed. Furthermore, with a sufficient amount of ICP plots the metrical forest type information allows for the identification of a transformation function between national and international standard and thus for a conversion between both standards.

Also a thorough correction of the satellite imagery on atmospheric and topographic effects is likely to increase the classification accuracies. Applying correction methods such as the statistic-empirical, the semi-empirical or the Minnaert correction to remove the effect of terrain, leads to substantial improvements of the classification results (Itten et al. 1992). Itten (1992) shows that a terrain correction can improve the accuracy of a forest type classification by up to 30 %. The reduction of the atmospheric effect is especially important when extending the approach to national level. Such an extension requires the radiometric adjustment of many satellite scenes in order to provide comparable pixel values for the ICP plots at a national scale. Another option for achieving higher classification accuracy is to use high-resolution data such as optical or radar satellite imagery. However, the usage of Landsat data has the advantage of being relatively low in costs, especially for a national or even European level assessment. In this respect it needs to be considered that extending the approach to a wider scale implies surely a challenge for the image classification, not only due to necessary technical capacities but also due to the high heterogeneity of forest landscapes.

The problem of low sub-sampling density could theoretically be solved in two ways. One option is that the approach will be conducted on to a larger scale (e.g. national level), which will automatically increase the number of ICP plots within the area of interest. A higher number of ICP plots would allow a successful implementation of the kNN classification with ICP standard as a reference. The other option is that the number of reference plots could be increased by shifting ICP assessments on a certain number of NFI plots. Options like assessing certain key parameters at Level I and on additional sub-sampling NFI plots are already under discussion in countries like Spain and Italy. However, both options will not be tested within this project due to limited time frame and capacities within this pilot study. For future research it might also be worth to explore alternative harmonised European data sets, which could be used as complementary input. For example, within the frame of the LUCAS project¹³ a harmonised field plot data set has been compiled for the EU15 countries covering the main European land cover and land use classes including the forest types coniferous, broadleaved and mixed forest. The sampling design is based on cluster samples at a regular grid of 18x18 km with each cluster consisting of 12x30 points with a density of 1.5x0.6 km. Such sampling density would allow promising input for the Landsat classification.

Conclusions

It can be concluded that the proposed approach is feasible but on the premise that the additional reference data set (like EC Forest Focus/ ICP Forests Level I) is of a finer resolution with more representative plots. Unfortunately, the approach could not be effectively demonstrated in the framework of this project due to the limited number of Level I plots per test site. Future prospects are seen in either conducting this approach at a larger scale (e.g. national level) or taking

¹³ LUCAS: Land Use/Land Cover Area Frame Survey; see at: <http://circa.europa.eu/irc/dsis/landstat/info/data/context.htm>

into account additional NFI sub-plots as reference sets if their assessment is based on an international standard. Using Level I as a sub-sampling seems very promising for the harmonisation of diameter distributions via extrapolating distribution functions. Information on DBH distributions from Level I BioSoil data for example could be used to calibrate diameter distributions and adjust national information on growing stock, carbon stock etc. (see Approach 4, Chapter 6). However, further research is still needed before implementing the proposed sub-sampling approach at national or even European scale.

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5. Approach 3: Combining NFI data with CLC2000 – Variable: Forest types

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Introduction

The need for a common approach to forest biodiversity reporting at national and international level has increased in last years. Lists of forest biodiversity indicators have been published by international agreement and processes and scientific groups (e.g. MCPFE, CBD, EEA SEBI 2010, COST Action E43), which recognised ‘forest types’ as one of the key variables for assessing and reporting on national and European forest biodiversity (Winter et al., 2008).

Forest type information in terms of *broadleaved*, *coniferous* and *mixed forest* is provided at national level by the National Forest Inventories (NFI) and at European level by the Coordination of Information on the Environment (Corine Land Cover) Programme.

From 1985 to 1990 the European Commission implemented the Corine Land Cover Programme (CLC), which represents a harmonised thematic reference data set within Europe. It provides comparable land cover digital maps for most of European countries. Such information are useful for spatial and environmental analysis as well as for comparisons, policy making and assessment. Satellite images were used as the main source of data to derive land cover information according to a standardised European methodology (CEC, 1994; Bossard et al., 2000; EEA/JRC-IES, 2005). CLC1990 is the first CLC inventory. It was carried out by photointerpretation of hardcopies of Landsat 4-5 TM images (single date). In 2004 the European Environment Agency (EEA) presented the Image2000 and CLC2000 database, which includes data from 1990, 2000 and the land cover changes, which occurred during that decade. The next update of CLC data is scheduled for the reference year 2006 (EEA, 2007). To update the reference year 2000, the computer aided visual interpretation approach was chosen as mapping methodology to analyse Landsat 7 ETM+ images (single data). The CLC map has a scale of 1:100 000, with Minimum Mapping Unit (MMU) of 25 ha and minimum width of linear elements of 100 metres. The standard CLC nomenclature includes 44 land cover classes, which are grouped in a three-level hierarchy. Land cover classes are discriminated mainly by physiognomic attributes (shape, size, colour and pattern) of landscape objects (natural, modified – cultivated and artificial), as recorded on satellite images.

The CLC defines its forest types as follows (Bossard et al., 2000):

- **broadleaved:** vegetation formation composed principally of trees, including shrub and bush under storeys, where broadleaved species predominate. Broadleaved trees represent more than 75%. Tree heights under normal climatic conditions are higher than 5 m;
- **coniferous:** vegetation formation composed principally of trees, including shrub and bush under storeys, where coniferous species predominate. Coniferous trees represent more than 75%. Tree heights under normal climatic conditions are higher than 5 m.
- **mixed:** vegetation formation composed principally of trees, including shrub and bush under storeys, where neither broadleaved nor coniferous species predominate. Crown cover of more than 30% or a 500 subjects/ha density for plantation structure. The share of coniferous or broad-leaved species does not exceed 25% in the canopy closure. Tree heights under normal climatic conditions are higher than 5 m.

At national level NFIs are the main source for assessing and reporting on various forest resources variables. In most cases estimation of forest variables rely on sample-based methods. Although NFIs have common objectives in terms of forest resources assessment, the data they collect and report on are often not comparable, as field measurement and estimation methods are not harmonised. With respect to the variable ‘forest types’, most assessments are based on the basal area of occurring tree species within each sampling plot. Each plot is assigned to that forest type class with the most dominant group of forest species. In some cases instead, the assessment of forest types relies on a visual interpretation method carried out at plot level according to the predominant group of tree species (see for example Italian NFI). Furthermore most of the definitions of forest types are different between countries. The thresholds applied to define ‘predominant broadleaved’, ‘predominant coniferous’ and ‘mixed forests’ are different, for example in Spain 70% and in Italy 75%. Germany uses a threshold of 50% to discriminate ‘predominant broadleaved’ and ‘predominant coniferous’ only. Mixed forests are explicitly not assigned within German NFIs.

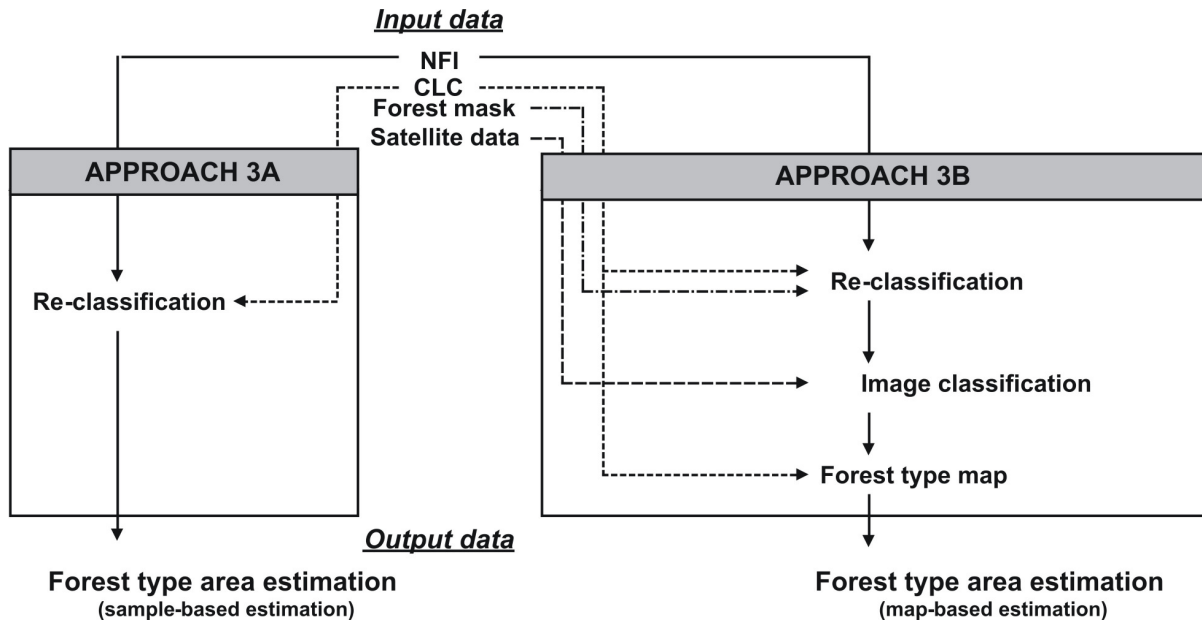
NFIs are an important data source for developing a common approach for forest biodiversity assessment and reporting (Winter et al., 2008). Thus, the development of a NFI based technical approach for harmonising the key variable ‘forest types’ is a relevant issue. The proposed approach in this study focuses only on three ‘classic’ types of forests: broadleaved, coniferous and mixed forests. The new forest type scheme, with 14 main forest categories, developed by the EEA (2006), is not taken into account.

The primary objective of Approach 3 is to develop and test different technical approaches to harmonise NFI data using CLC2000 definitions on forest types as a reference or as a harmonised data input for NFI based forest type mapping. The CLC project was chosen as it represents a harmonised already available European reference data set and methodology for land use/land cover analysis.

Traditionally NFI reports contain tabular estimates, such as forest area classified by forest types. Nowadays, users ask also for maps depicting the spatial distribution and changes of forest resources. Map-based estimations are expected to be one of the major standard products of future forest inventories (see William et al., 2006; Corona and Marchetti, 2007; McRoberts and Tomppo, 2007; Shaw, 2008). As this aspect is of particular relevance in the proposed approach, two different approaches are developed and tested in this study, hereinafter named as **Approach 3A** and **Approach 3B** (see Fig.5.1).

Within **Approach 3A**, NFI data are re-classified according to the CLC standard definition and used for estimating forest type area based on a sample-based procedure. Obtained figures are provided in tabular format only. In **Approach 3B** instead, NFI data are re-classified according to the CLC definition like in Approach 3A, but are also used to produce forest type maps by remote-sensing image classification. In Approach 3B figures on the area of forest types are computed by a map-based estimation method.

Fig. 5.1: Workflow for Approach 3A and Approach 3B.



Approach 3 was implemented in three test sites representing different forest ecosystems with different forest structure and pattern. The Sicilian test site was selected for the Mediterranean region; the Saxony and the Rhineland-Palatinate test sites were chosen to represent the continental region. The two German test sites are taken as they are different in forest spatial pattern, which are more heterogeneous and fragmented in the Saxony test site than in the Rhineland-Palatinate test site.

Input data

Approach 3 was performed by using following data sets:

- NFI plot data;
- CLC data (year 2000);
- Landsat data;
- JRC pan-European forest/non-forest map 2000 (Pekkarinen et al., 2007)¹⁴;
- National forest/non-forest maps.

The NFI plots in vector format and the national forest/non-forest map (NFM), as well as the Landsat 7 ETM+ data were delivered by the project partners responsible for the three selected test sites. The CLC2000 map in vector format was downloaded via internet from the data service of the

¹⁴ Applied forest definition based on CORINE Land Cover (Bossard et al., 2000): “Areas occupied by forest and woodlands with a vegetation pattern compose of native or exotic coniferous and/or deciduous trees and which can be used for the production of timber or other forest products. The forest trees are under normal climatic conditions higher than 5 m with a canopy closure of 30% at least”.

EEA.¹⁵ The pan-European forest/non forest map 2000 was downloaded from the web-portal of the JRC.¹⁶

For the Sicilian test site, data from the 2nd NFI are used. The inventory is based on a non-aligned systematic method with a three-phase sampling for stratification. The first two phases, hereinafter named as NFI Phase 1 and NFI Phase 2, are applied to estimate the forest area and its classification into forest types, while the third, hereinafter named as NFI Phase 3, is applied to collect dendrometric data. The sample (plot) distribution is based on a nationwide 1x1 km quadrangle grid. Inventory plots of Phase 1 are random-distributed: one plot within each grid square. Plots of Phase 1 were photo interpreted and classified by land cover/land use classes according to the first level of the CLC and with the FAO-FRA2000 forest definition. In Phase 2 a sub-sample is selected from the forest stratum. Plots of Phase 2 were surveyed in the field to identify forest types by visual interpretation according to the 75% threshold and to collect other qualitative attributes of forest stands. In Phase 3 a sub-sample is selected from the Phase 2 sample. Plots of Phase 3 were surveyed in the field to collect dendrometric data and other attributes like dead wood, understory vegetation etc. (INFC, 2005; Tabacchi et al., 2007). Within this pilot study, 626 random-distributed inventory plots of Phase 2 with forest type information (broadleaved, coniferous, mixed) were selected. Moreover, 231 inventory plots of Phase 3 with dendrometric data were available. Phase 3 data were used in the Approach 3B only.

For the Saxony and Rhineland-Palatinate test sites, cluster data from the 2nd NFI were provided. The inventory is carried out on permanent sample points. The sample (cluster) distribution is based on a quadrangle grid, which is in most regions 4x4 km. In some German Federal States the sample grid is intensified to 2.83x2.83 km or 2x2 km in order to get more accurate or regionally differentiated information (see BMVEL, 2006). Each cluster consists of 4 inventory plots located at the corner of a square with a side of 150 m. The sides of the cluster are oriented north-south and east-west, respectively. The cluster coordinates give the location of the south-west plot. Clusters, in which at least one plot is located in forest, are defined as forest clusters. As there is no explicit threshold for defining forest types in the German NFI, data of the two test sites were provided with following classifications: *coniferous forest; pure broadleaved forest; coniferous forest with small share of broadleaved trees; broadleaved forest with a small share of coniferous trees; mixed forest with equal share of coniferous and broadleaved trees (50/50%)*. In the Saxony test site, 627 clusters (2.83x2.83 km quadrangle grid) are located, while 901 clusters (2x2 km quadrangle grid) are located in the Rhineland-Palatinate test site (see Table 5.1).

The national forest masks for each test site were produced by Landsat 7 ETM+ classification according to the national definition of forest. For each test site the full coverage of all Landsat multispectral bands was available.

Table 5.1: Number of NFI sampling units per test site. For Sicilian test site the number of NFI plots is listed; for German test sites the number of NFI clusters is listed. For Sicily data refer to the inventory plots of NFI Phase 2, which were selected from the forest stratum.

Test site	Nr. of 'no forest' plots	Nr. of 'forest' plots	Total Nr. of plots
Rhineland-Palatinate	320	581	901
Saxony	371	256	627
Sicily	0	626	626

¹⁵ http://dataservice.eea.europa.eu/map/clc_download/ (last access in April 2008).

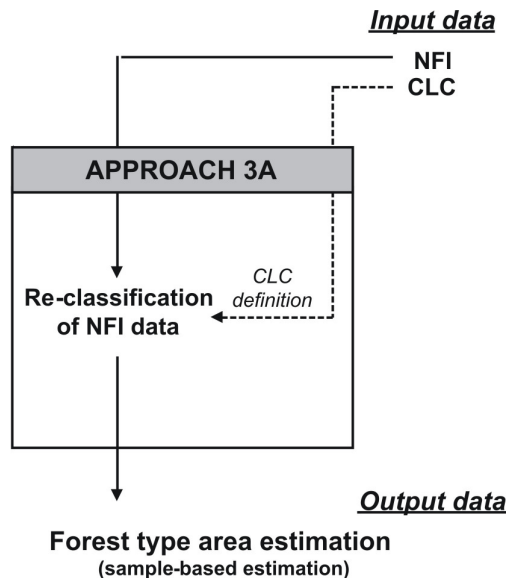
¹⁶ <http://forest.jrc.it/ForestResources/ForestMap/> (last access in April 2007).

Approach 3A

Methodology

In the frame of Approach 3A, the forest type definition of CLC2000 was used as an international reference standard to re-classify NFI plot data into predominant broadleaved, predominant coniferous and mixed forest (see Fig. 5.2).

Fig. 5.2: Workflow for Approach 3A.



As described above, CLC defines its forest types on the basis of the predominant group of tree species according to a threshold of 75%. As most NFIs apply different thresholds for the discrimination of predominant broadleaved, predominant coniferous and mixed forest, forest type classifications of NFI sampling units were basically re-classified according to the international reference threshold of 75%.

Once the re-classification was completed, the area of forest types was assessed by a sample-based procedure. Obtained figures were reported in tabular format. Contrary to Approach 3B no new forest type maps were produced.

A prerequisite for applying Approach 3A is that tree data at plot level are available for re-classification.

In Italy the sampling design adopted for the NFI is a three-phase sampling for stratification in which forest classification into forest types is conducted in the second Phase by visual interpretation using a 75% threshold. NFI plots of Phase 2 are used for forest types area estimation. Tree data are not collected in the second Phase. According to Italian NFI, tree data are available only for Phase 3, covering dendrometric information. As in Sicily tree data are not available for the re-classification of NFI plots of Phase 2, Approach 3A was applied for the two German test sites only.

For Rhineland-Palatinate and Saxony test sites the re-classification was performed into two steps. In a first step the total number of coniferous and broadleaved trees were used to classify forest plots of each forest clusters. In a second step each cluster was classified into 'pure' forest cluster, when the number of 'pure' forest plots of the same type of forest represents more than 75% of the total number of forest plots.

Within this pilot study, the following sample-based estimation method was applied for the two German test sites:

$$A_j = \frac{n_j}{n} A \quad (5.1)$$

where,

A_j = total area of forest type j ;

n_j = number of cluster classified as forest type j ;

n = number of cluster classified as forest;

A = total forest area.

$$A = nl^2k^2 \quad (5.2)$$

where,

A = total forest area;

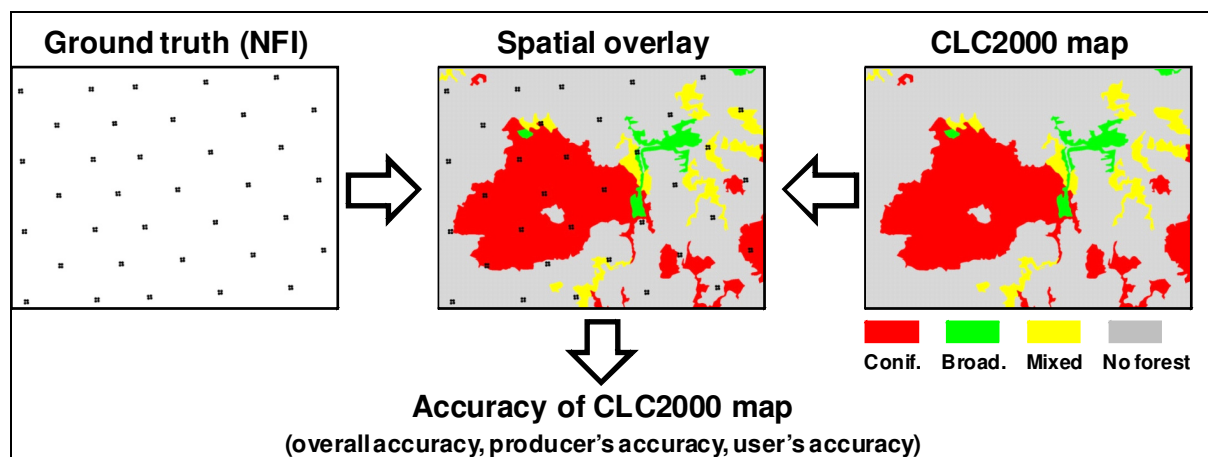
n = number of cluster classified as forest;

l = grid side;

$k = 1$.

In addition, the accuracy of the CLC2000 map in the selected test sites was roughly validated using NFI sampling units as ground truth. Basically, the forest type classification of each NFI plot was compared with the classification of the corresponding CLC2000 polygon by means of spatial overlay (see Fig. 5.3).

Fig. 5.3: Workflow of the additional analysis on CLC accuracy.



The accuracy of CLC2000 map was assessed using a confusion matrix. The overall accuracy (see equation 5.3) as well as the user's and the producer's accuracy was computed for each test site:

$$v = \frac{\sum_{j=1}^C n_j}{n} \quad (5.3)$$

where,

n_j = number of NFI plots belonging to the validation set that were correctly assigned to the j -class of forest type;

n = total size of the validation set;

C = total number of forest type classes.

The variance (equation 5.4) and the confidence intervals given a probability $p=95\%$ (equation 5.5) were also estimated:

$$\text{var}(v) = \frac{v(1-v)}{n-1} \quad (5.4)$$

$$v \pm t\sqrt{\text{var}(v)} \quad (5.5)$$

where,

t = t -student for $n-1$ degrees of freedom with a probability $p=95\%$.

To use NFI data as an independent data set for accuracy validation of thematic maps like CLC, the classification into land use/land cover classes at plot level needs to be revised in order to take into account the MMU of CLC2000 maps. This is usually done by the creation of a buffer zone around each sampling point. The size of the buffer needs to be representative of the MMU. The land use/land cover type of each buffer is classified by visual interpretation of remote sensing data (e.g. using DOPs) (see APAT, 2005; EEA, 2006b). This additional method was not applied in this pilot study, as it is very time consuming and the accuracy assessment of CLC2000 is not an objective of this approach.

Results Approach 3A

Sample-based estimation of forest type

The distribution of forest types according to the number of NFI sampling units fulfilling the threshold of 75% is summarised in Table 5.2.

Table 5.2: Number of NFI sampling units (cluster), classified into forest types with a threshold of 75%.

Test site	Coniferous	Broadleaved	Mixed	Total
Rhineland-Palatinate	115	158	308	581
Saxony	132	55	69	256

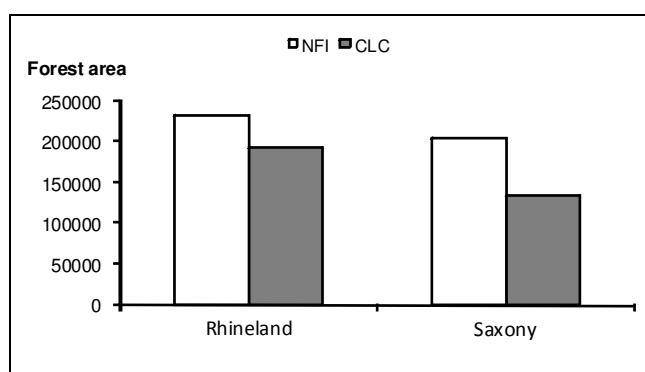
The total forest area assessed by sample-based estimation method is: 232 400 ha in Rhineland-Palatinate and 205 829 ha in Saxony. The partition (in ha) of forest area into forest types is shown in Table 5.3. Mixed forests prevail in Rhineland-Palatinate while coniferous forests mainly occur in Saxony.

Table 5.3: Forest types area by NFI sample-based estimation method.

Test site	Area of coniferous forest [ha]	Area of broadleaved forest [ha]	Area of mixed forest [ha]	Total area of forest [ha]
Rhineland-Palatinate	46 000	63 200	123 200	232 400
Saxony	106 519	44 049	55 261	205 829

Overall, the CLC2000 underestimates forest area compared to German NFI (see Fig. 5.4), mainly due to the fact that CLC does not take into account forest patches smaller than 25 ha (see MMU). Differences between NFI and CLC were greater in Saxony (54%) than in Rhineland-Palatinate (22%). This is mainly due to the fact that in Saxony forests are more fragmented and patches are of smaller size than in Rhineland-Palatinate.

Fig. 5.4: Total forest area estimation (in ha) by NFI and CLC2000.



Despite the different methodologies between NFI and CLC (sample-based estimation method vs map-based estimation method), the estimates on forest types by CLC fit quite well with the estimates by re-classified NFI data (see Fig. 5.5 and Fig. 5.6). Applying the paired comparison t

test (Zar, 1996), it is shown that there are no significant differences between NFI and CLC estimates ($p=0.05$).

Fig. 5.5: Rhineland-palatinate: area of forest types in %.

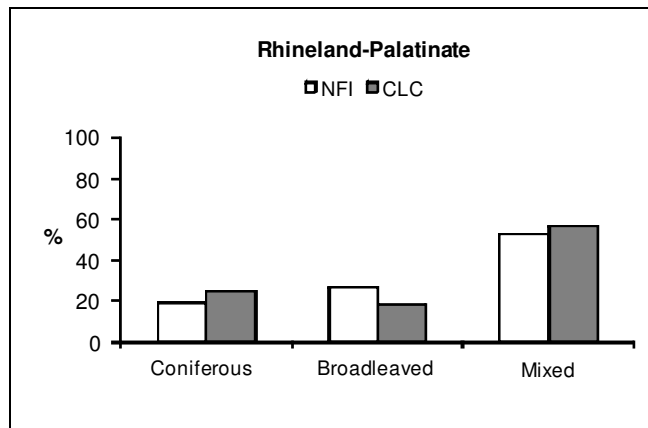
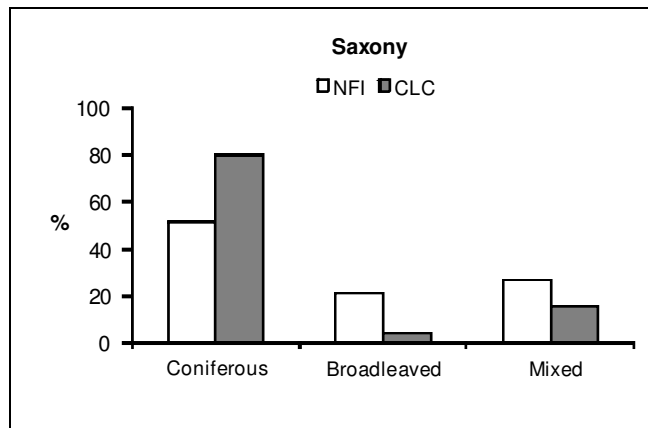


Fig. 5.6: Saxony: area of forest types in %.



Accuracy of CLC2000

For each of the test sites the accuracy of CLC2000 map was estimated with a confusion matrix using NFI sampling units as ground truth. The thematic accuracy of CLC represented by overall accuracy, producer's and user's accuracy are reported in Table 5.4, including confidence intervals. The assessment below includes also the Sicily test site, as NFI data are already available according to the threshold of 75% (see above).

The overall accuracy ranged from 0.56 (± 0.03) in Sicily to 0.80 (± 0.02) in Saxony. The highest class-level accuracy (> 0.75) was obtained for coniferous in Saxony, whereas the lowest (< 0.1) was obtained for broadleaved in the same test site. The accuracies of the most dominant forest type according to the CLC2000 map was 0.39 (± 0.04) in Sicily, 0.76 (± 0.04) in Saxony and 0.57 (± 0.04) in Rhineland-Palatinate.

Table 5.4: Accuracy of CLC2000 map using NFI sampling units as ground truth. The confidence interval of the estimates is in brackets.

Test site	Overall accuracy	Producer's accuracy				User's accuracy			
		Conif.	Broad.	Mixed	No forest	Conif.	Broad.	Mixed	No forest
Rhineland-Palatinate	0.64 (±0.02)	0.41 (±0.04)	0.33 (±0.04)	0.57 (±0.04)	0.88 (±0.02)	0.55 (±0.04)	0.54 (±0.05)	0.33 (±0.03)	0.89 (±0.02)
Saxony	0.80 (±0.02)	0.76 (±0.04)	<0.10 (±0.04)	0.13 (±0.06)	0.91 (±0.01)	0.58 (±0.04)	0.34 (±0.18)	0.15 (±0.07)	0.92 (±0.01)
Sicily	0.56 (±0.03)	0.41 (±0.09)	0.39 (±0.04)	0.16 (±0.09)	-	0.67 (±0.12)	0.72 (±0.06)	0.25 (±0.14)	-

Discussion

The primary objective of the Approach 3A was to provide harmonised information on forest type's area by using a traditional NFI sample-based estimation method.

The method of the proposed approach basically is a re-classification of NFI plot data into forest types according to an international reference definition like of CLC. The 75% reference threshold of CLC was used to discriminate the three main types of forests, namely: broadleaved, coniferous and mixed forests.

The proposed harmonisation approach is relative easy to accomplish. The only prerequisite for conducting the approach is that NFI tree data are available for re-classifying NFI plot information.

In the frame of Approach 3A, the Italian test site represents as a special situation. NFI plots of Phase 2 are already classified according to a 75 % threshold. However, even if the same definition and threshold for discriminating forest types is applied, the Italian classification is based on visual interpretation only. Tree data at plot level are not available, thus making an applicability of the approach to any other reference definition and threshold complicated.

As demonstrated by the two German test sites, the re-classification of NFI plots can be conducted on the number of tree species. Possible would be also to use the basal area of main species (see Approach 3B).

The results obtained in the German test sites show that forest types area obtained by re-classified NFI data are similar to those provided by CLC2000 data. The paired comparison t test clearly shows that there are no significant differences.

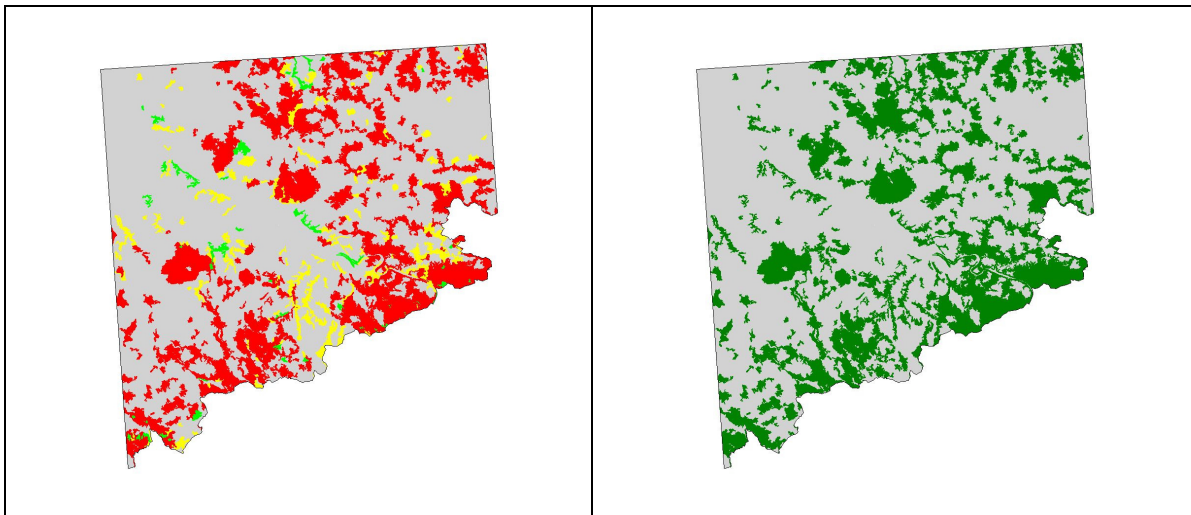
Finally it can be concluded that the proposed methodology offers a relative simple approach to harmonise forest type information to any international reference standard. The only prerequisite for applying the approach is that tree data, like number of tree species or basal area of tree species, are available. As the data processing (re-classification) can be performed with any data base management system, the proposed method can be easily applied to complete NFI data sets, in order to harmonise national forest type information to international reference standards like of CLC.

Approach 3B

Methodology

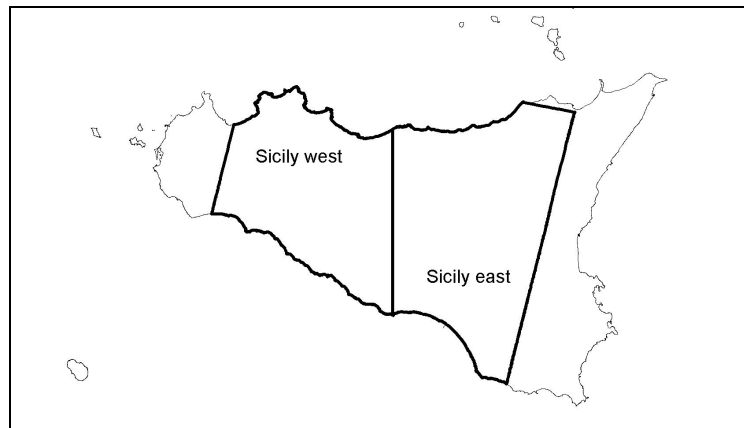
The objective of this approach is to produce harmonised forest type maps, using re-classified NFI sampling units as reference sets for multispectral satellite classification. Like in Approach 3A, NFI plots were re-classified into forest types using the international reference threshold of 75%. Landsat images were used as a basis for the classification of forest/non-forest maps derived from CLC2000 (see Fig. 5.7). Forest patch polygons were drawn by satellite image segmentation techniques. Finally, the area of forest types estimated by a map-based estimation method, were put into relation with CLC2000 assessment and different regression equations were computed for each test site. For the forest patch segmentation process also other sources than CLC were taken into account, like the National forest/non forest map provided by project partners and/or the JRC pan-European forest/non-forest map 2000.

Fig. 5.7: Saxony: Example of forest/non forest map derived from CLC2000. On the left side: CLC2000 map (Green=broadleaved forest, Red=coniferous forest, Yellow=mixed forest, Grey=no forest). On the right side: forest map produced from CLC2000 (Green=forest; Grey=no forest).



For the Sicily test site the analysis was performed on the Landsat scene, which covered the most part of the Sicily administrative region. To reduce data volume and speed up image segmentation processing, the selected scene was divided into two sub-scenes, hereinafter named as Sicily East and Sicily West (see Fig. 5.8).

Fig. 5.8: Location of the Sicily East and Sicily West Landsat scenes and selected test site.



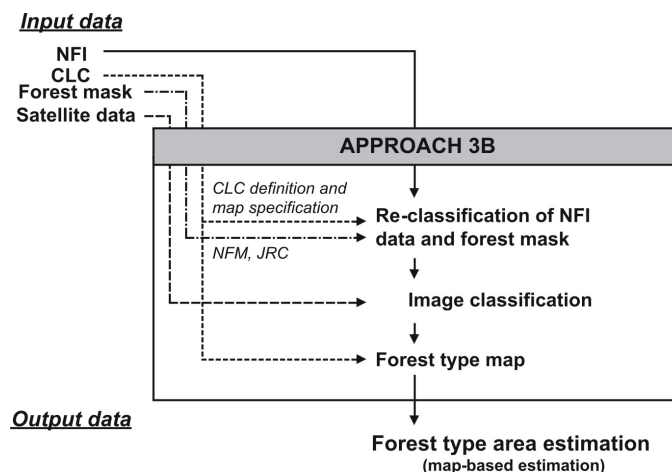
The proposed method consists of five steps as follows:

1. Re-classification;
2. Image segmentation;
3. Satellite classification;
4. Forest type map;
5. Forest type area estimation (map-based estimation).

Step 1 – Re-classification

In Approach 3B the re-classification of NFI data was performed like in Approach 3A, taking into account the definition of the CLC programme. In addition the map specifications applied in CLC programme were used to calibrate forest/non forest maps (see Fig. 5.9).

Fig. 5.9: Workflow for Approach 3B – re-classification.



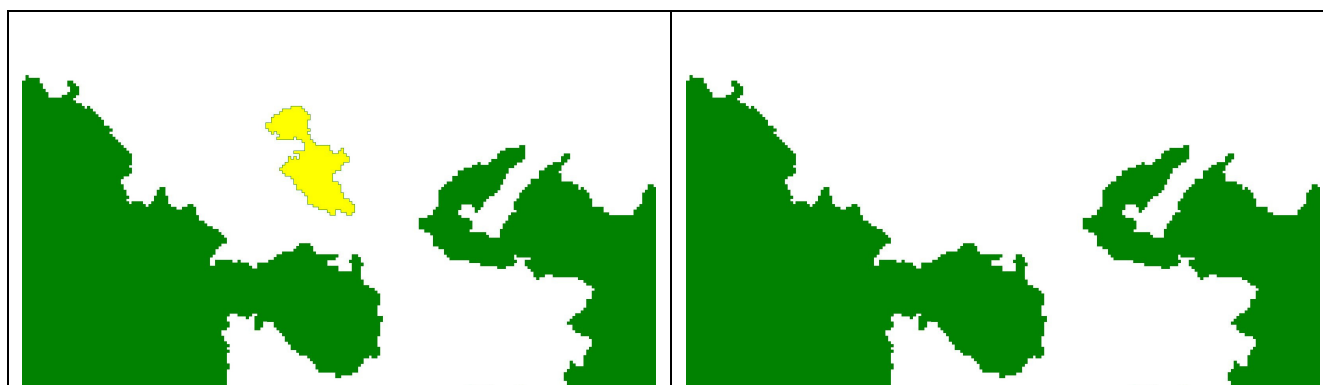
In Germany, the forest type re-classification by number of trees species was performed at plot level. The cluster level was not considered as it represents the mean value of the four plots. Therefore plot information was used, providing a finer detail of information per forest patch. Using forest type information at plot level rather than at cluster level is recommended, when data of cluster-based forest inventories have to be used as reference data for satellite image classification.

This counts especially for satellite bands, which have spatial resolutions smaller than the linear distance among plots and the centre of clusters.

In Sicily, two data sets were used. The first one corresponds to the inventory sampling units of NFI Phase 2 (with information on forest types already classified according to the threshold of 75%). The second data set was composed by inventory sampling units of NFI Phase 3, with tree data measured in the forest. For each plot of NFI Phase 3, basal area of coniferous and broadleaved species was computed in m² per ha, then the classification into coniferous, broadleaved and mixed forest was carried out using the threshold of 75%. Both categorical (broadleaved, coniferous and mixed forests classes) and metrical (basal area per ha) information were used for satellite classification.

To accomplish the calibration of map specifications, the MMU of 25 ha was chosen as it represents the CLC reference standard. Accordingly, forest patches with an extent less than the MMU were not taken into account and removed from the forest/non forest map (see example in Fig. 5.10).

Fig. 5.10: Example of national forest/non forest map before (left side) and after (right side) the calibration. Forest highlighted in yellow has an area less than the MMU of 25 ha.



Step 2 - Image segmentation

CLC2000 discriminates land cover classes mainly by physiognomic attributes of landscape objects. In most countries Landsat 7 ETM+ data were used for image interpretation on screen. National interpreters delineated land use patches and classified them according to the technical guidelines and specifications of the CLC Programme (see CEC, 1994; Bossard et al., 2000).

In Approach 3B an automated image segmentation technique was applied using *Definiens Professional* software. Segmentation is performed by splitting the image into separated areas of different characteristics. The segments are called image objects. Spectral characteristics as well as shape and textural characteristics can be taken into account for creating image objects, which all together form a level of segmentation. Two or more levels of segmentation can be performed with a hierarchy approach. In short, every image object of a lower level is linked to image objects of its upper level (Definiens, 2006).

The automated segmentation technique was applied to delineate image objects representing forest patches. Three hierarchical levels of segmentation were created (see Fig. 5.11):

- Level 1 represents forest coverage within test sites;
- Level 2 represents forest patches of differing multispectral characteristics fulfilling the MMU of 25 ha. Level 2 is the selected level for forest type map production by assigning each segment to one type of forest;
- Level 3 represents different units of feature extraction for satellite classification.

Fig. 5.11: Workflow for Approach 3B – forest segmentation.

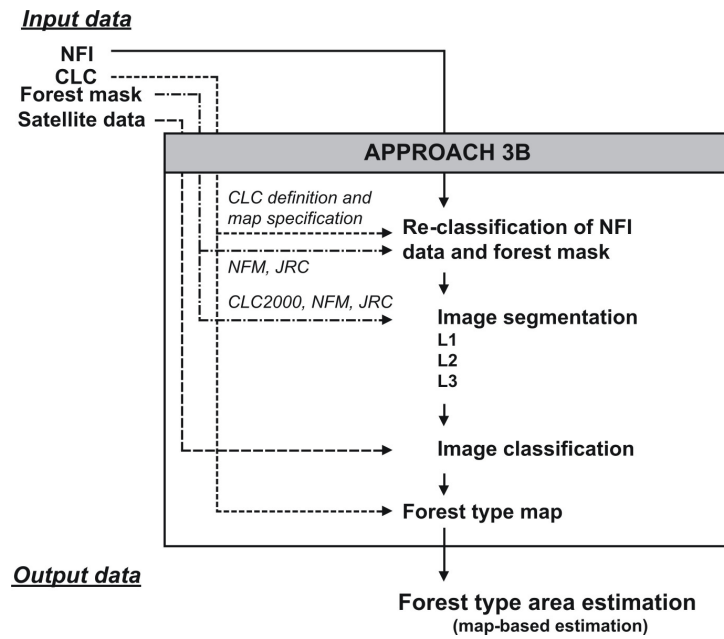


Image segmentation parameters set up with *Definiens Software* refer to (Definiens, 2006):

- Level name: the name of the level of segmentation;
- Scale parameter: it determines the maximum allowed heterogeneity for the resulting image objects. A larger scale parameter value means larger image objects. The object homogeneity to which the scale parameter refers is defined by color and shape criterion;
 - Color: the criterion used by Definiens's multiresolution segmentation is comprised partly by homogeneity concerning the color (*color criterion*) and homogeneity concerning the shape (*shape criterion*) of the image objects. The color criterion minimises the standard deviation calculated from the spectral values of an image object. By decreasing the value assigned to the Color, the decrease of the percentage of the spectral values of the image layers will contribute to the entire homogeneity criterion;
 - Shape: the shape criterion is composed of two parameters, compactness and smoothness. The compactness is used to optimise image objects with regard to compactness. The smoothness is used to optimise image objects with regard to smoothness of borders.

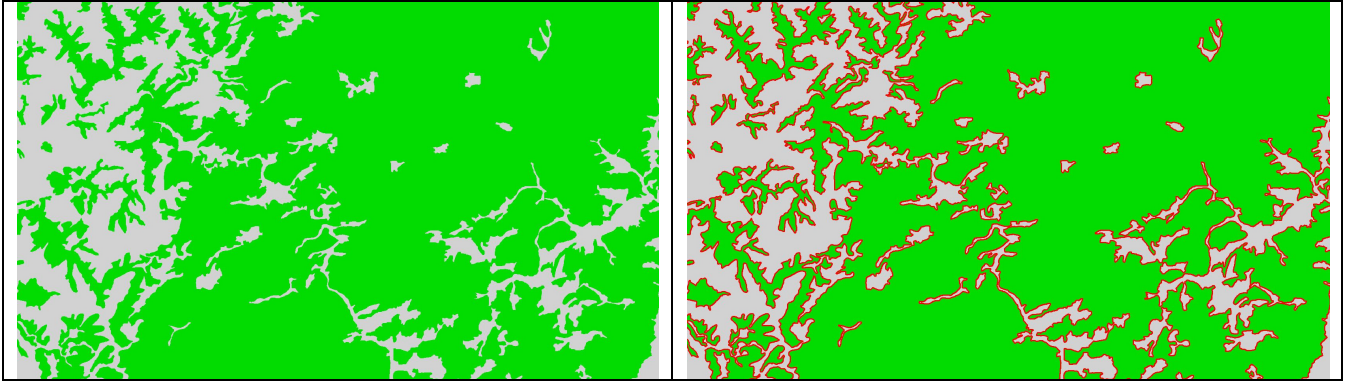
The technical details of image segmentation parameters applied in this study are listed in Table 5.5.

Table 5.5: Image segmentation parameter: scale, color, shape, compactness and smoothness.

Level of segmentation	Segmented image	Scale parameter	Color	Shape	Compactness	Smoothness	Minimum polygon size (ha)
1	Forest mask	10	1.0	0.0	0.5	0.5	25
2	Landsat bands	50	0.9	0.1	0.5	0.5	25
3	Landsat bands	5-10	0.9	0.1	0.5	0.5	0.063

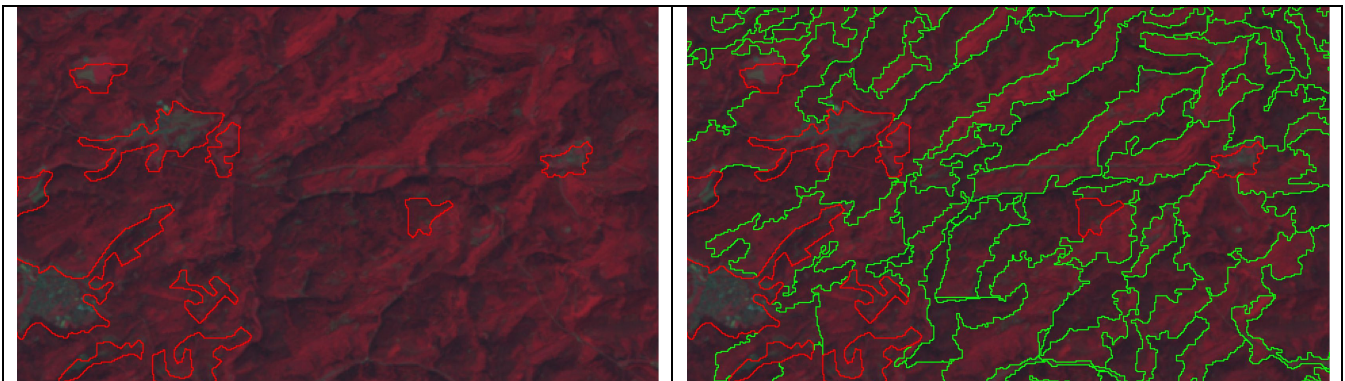
At Level 1 the segments were extracted as polygons in vector format from available forest/non-forest maps: CLC, National, JRC (see Fig. 5.12).

Fig. 5.12: On left side: example of forest/non forest map. On the right side: result of the segmentation at Level 1 (red polygons).



At Level 2 and Level 3 the segments were extracted from Landsat bands, except band 6. At Level 2 a scale parameter equal to 50 was used as it proved to be the best value for generating segments fitting the selected MMU of 25 ha (see Fig. 5.13). Nevertheless, this scale parameter generated a few polygons with an area smaller than the MMU. These smaller polygons were merged with neighbourhood objects using common GIS tools to ensure that all segments fulfil the MMU of 25 ha.

Fig. 5.13: On left side: Level 1 of segmentation, lines in red are the boundary of forest. On the right side: result of the segmentation at Level 2; lines in green are forest polygons with an area equal to or greater than the MMU.



At Level 3, a scale parameter equal to 5 and 10 was taken for the German and the Italian test sites, respectively. The scale parameters were selected in order to generate small segments as homogeneous as possible (see Mäkelä and Pekkarinen, 2001; Pekkarinen, 2002), taking also into account that smaller scale parameters would result in a higher processing workload (see Fig. 5.14). The average area as well as the minimum and maximum area of polygons obtained at Level 3 are listed in Table 5.6.

Fig. 5.14: On left side: second level of segmentation, lines in green are forest polygons with MMU equal to 25 ha. On the right side: result of the segmentation at Level 3 (see white polygons).

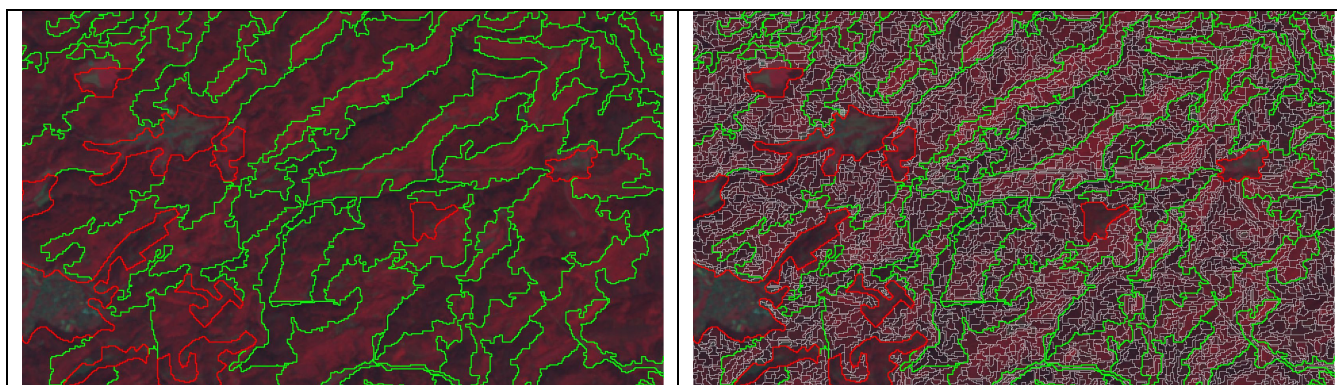


Table 5.6: Minimum, maximum and average area of Level 3 polygons.

* CLC: from Corine Land Cover 2000; NFM: National Forest/Non-forest Map; JRC: Pan-European Forest/Non-forest Map 2000.

Test site	Forest mask*	Area (ha)		
		minimum	maximum	average
Rhineland-Palatinate	CLC	0.063	50.928	2.064
Rhineland-Palatinate	JRC	0.063	30.250	1.885
Saxony	CLC	0.063	45.000	2.081
Saxony	NFM	0.063	33.938	2.436
Saxony	JRC	0.063	34.375	1.739
Sicily east	CLC	0.063	54.814	5.313
Sicily east	NFM	0.063	57.563	6.288
Sicily west	CLC	0.063	40.500	4.158
Sicily west	NFM	0.063	50.375	4.718

Step 3 - Satellite classification

Landsat 7 ETM+ classification was performed using NFI plot as reference data set (Fig. 5.15). For each test site the reference set was divided into two sub sets with a random approach, hereinafter named the *training set* and the *validation set*. The former was set equal to 70 % of total number of NFI plots, the latter was equal to 30 % of total number of plots. The training set was used for feature extraction from Landsat multispectral bands, except band 6. The validation set was used for the accuracy estimation of Landsat classification at pixel level.

Fig. 5.15: Workflow for Approach 3B – satellite classification.

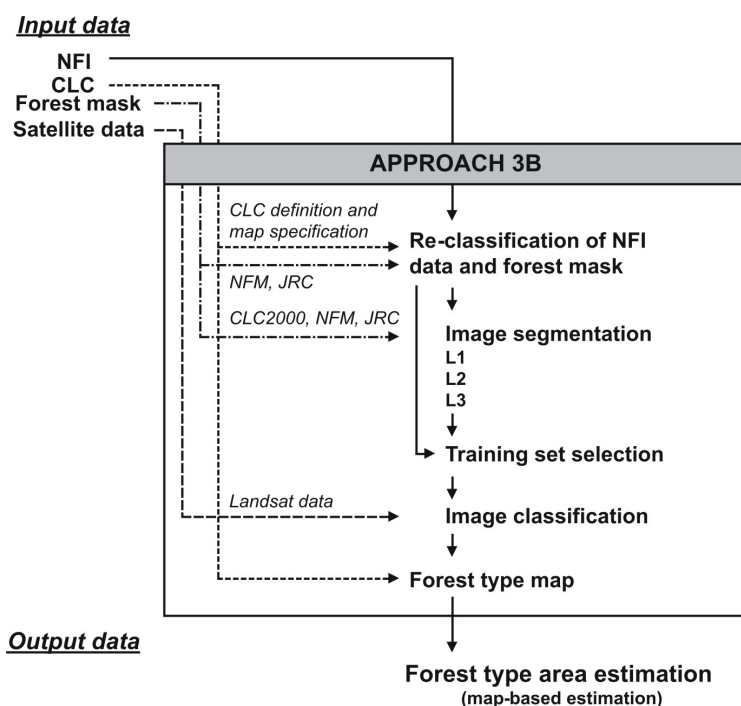


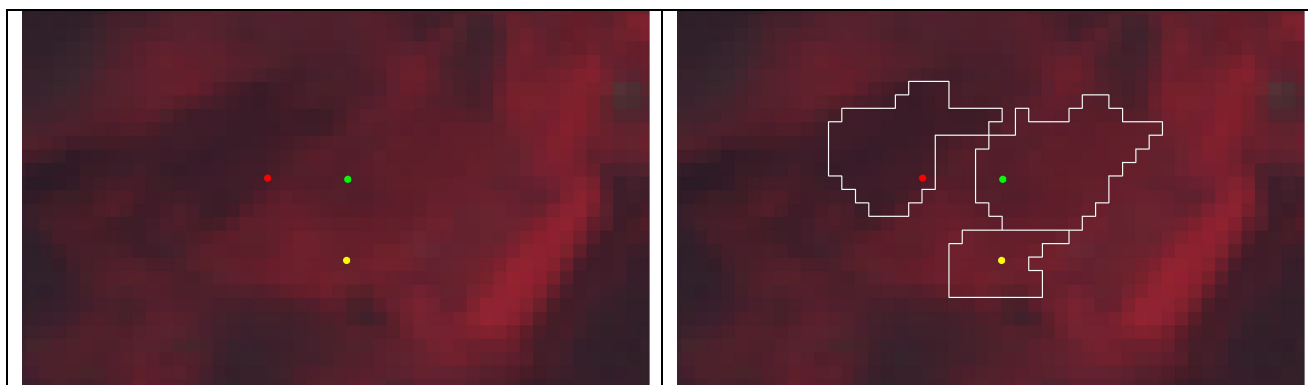
Table 5.7 shows the training and the validation set in each test site.

Table 5.7: Training and validation set of each test site.

Test site	NFI plot classification method	NFI plot	Training set				Validation set			
			Tot.	Con.	Broad.	Mixed	Tot.	Con.	Broad.	Mixed
Rhineland-P.	Number of trees	1674	1172	398	401	373	502	182	157	163
Saxony	Number of trees	640	448	282	105	61	192	126	25	41
Sicily east	Visual interpretation	316	221	19	185	17	95	12	76	7
Sicily east	Basal area	107	75	11	59	5	32	5	23	4
Sicily west	Visual interpretation	123	86	30	46	10	37	15	18	4
Sicily west	Basal area	46	32	7	21	4	14	6	6	2

Concerning the feature extraction method, two alternatives have been usually considered in applications based on satellite images and field data gathered from sample plots (Pekkarinen 2002): a) features have been extracted from a single pixel on which the plot is located, hereinafter named as the ‘*per-pixel*’ method, or b) from its local neighbourhood that fall within square-shaped window or polygon around each field plot, hereinafter named as the ‘*per-polygon*’ method (Fig. 5.16).

Fig. 5.16: Example of the per-pixel and per-polygon feature extraction method. Red, green and yellow dots correspond to NFI plots classified into coniferous, broadleaved and mixed forests, respectively. On the left side, features are extracted from that pixel on which the NFI plots are located. On the right side, features are extracted from that pixel that fall within the polygon (see white polygons) on which the NFI plot area is located.



In many applications, based on relatively small sample plots and Landsat data, the sampling area is usually smaller than the pixel size, which may negatively affect the image analysis. In addition, errors in image registration and/or in the location of sample plot are a possible potential source of error. One solution for this kind of problem is the extraction of spectral feature from polygons which are homogeneous in sense of their spectral characteristics (see Mäkelä and Pekkarinen, 2001).

Concerning the satellite classification method, two main approaches are available: the *pixel-oriented* approach and the *object-oriented* approach (see Dorren et al., 2003; Benz et al., 2004).

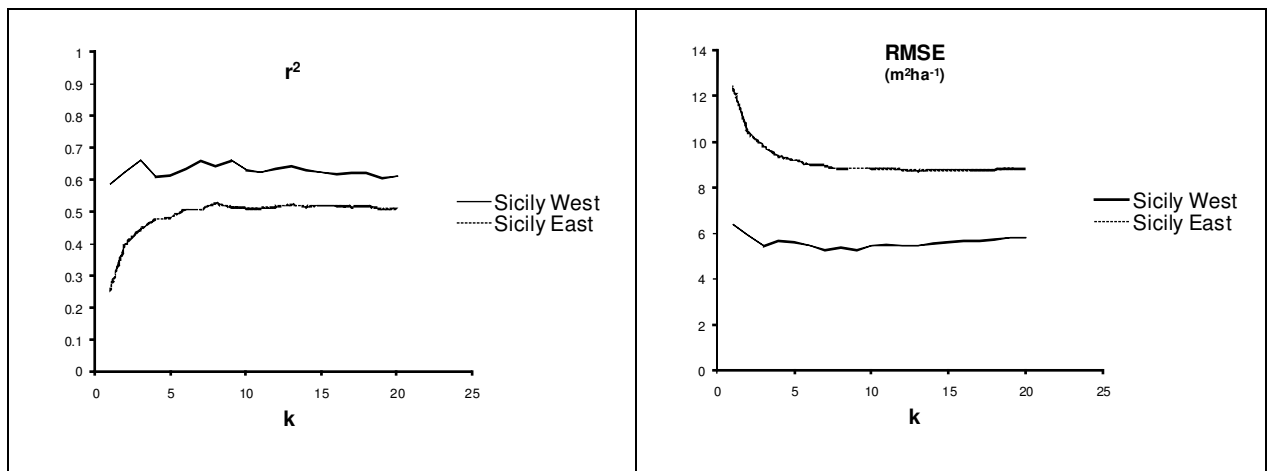
In the preliminary phase of the study, the *per-pixel* and the *per-polygon* method for multispectral feature extraction as well as the *pixel-oriented* and the *object-oriented* approach for satellite classification were applied and effects on the classification were evaluated. The per-polygon method for feature extraction was performed using polygons (segments) from Level 3 of segmentation. Spectral features were computed as the mean of digital number of reference pixels recorded in each satellite band (except band 6). In German test sites, polygons including more than one NFI plot were excluded from the training set if plots were assigned to different types of forests. The pixel-oriented classification was performed using *Idrisi Andes* software with the Maximum Likelihood method, which is a traditional hard classifier used in remote sensing (Lillesand and Kiefer, 2000; Franklin, 2001; Hagner and Reese, 2007). The object-oriented classification was carried out using the *Definiens Professional* software with the Standard Nearest Neighbour classifier. Under the study conditions, achieved results showed that the per-polygon feature extraction method slightly improved the accuracy of the classification and the pixel-oriented classification system proved to be better than the object-oriented approach.

Based on the preliminary results, the per-polygon feature extraction method and the pixel-oriented approach were finally chosen.

The Maximum Likelihood classifier was used for forest type classification using categorical information.

In Sicily the k-Nearest Neighbor (k-NN) estimation method (Tomppo, 1991) was applied and tested for forest type classification using metrical information. Several k-NN configurations were tested by a) changing the type of multidimensional distance measures (Euclidean Distance, Mahalanobis Distance, Fuzzy Distance) and b) the number of nearest neighbours (from 1 to 20) using the Leave-One-Out (LOO) procedure (Chirici et al., 2008). The coefficient of determination (R^2) and RMSE were computed as proposed by Franco-Lopez et al. (2001). The best k-NN configurations (the best configuration in Sicily East was: $k=6$, Euclidean Distance; the best configuration in Sicily West was: $k=3$, Fuzzy Distance) were then used for pixel level estimation (Fig. 5.17). First, the basal area per ha of coniferous and broadleaved species was estimated by k-NN algorithms, then, each pixel was assigned to one type of forest according to the prevailing group of tree species.

Fig. 5.17: Results of the Leave-One-Out procedure. The Euclidean and the Fuzzy distance were used in Sicily East and Sicily West, respectively.



A complete list of configurations applied in Approach 3B for satellite classification is documented in Table 5.8.

Table 5.8: List of configurations for satellite classification.

* ML: Maximum Likelihood.

** CLC: Corine Land Cover 2000; NFM: National Forest/Non-forest Map; JRC: Pan-European Forest/Non-forest Map 2000.

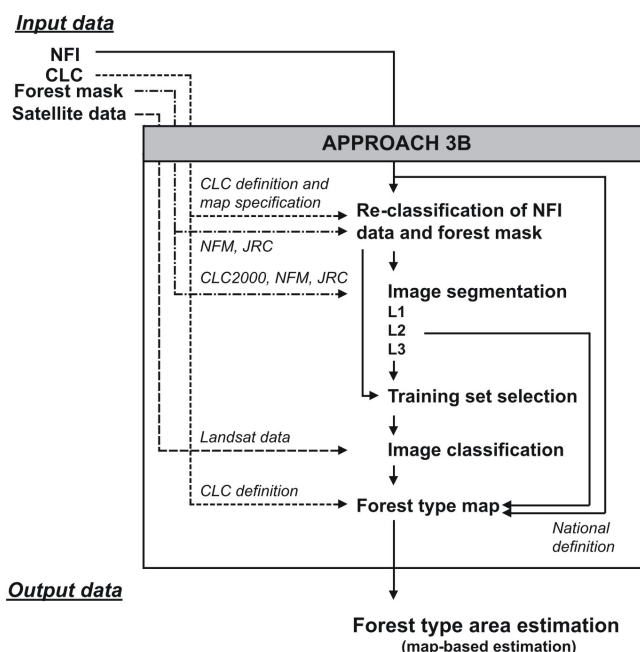
*** Percentage used for forest type classification of Level 2 polygons by means of pixel-oriented Landsat classification.

Test number	Test site	Training set classification method	Training set extraction method	Classifier (*)	Forest mask (**)	Forest type classification threshold (**)
1	Sicily east	Visual interpretation	Pixel	ML	CLC	75
2	Sicily east	Visual interpretation	Polygon	ML	CLC, NFM	75
3	Sicily east	Basal area (categorical)	Polygon	ML	CLC, NFM	70; 75
4	Sicily east	Basal area (metrical)	Polygon	k-NN	CLC, NFM	70; 75
5	Sicily west	Visual interpretation	Pixel	ML	CLC	75
6	Sicily west	Visual interpretation	Polygon	ML	CLC, NFM	75
7	Sicily west	Basal area (categorical)	Polygon	ML	CLC, NFM	70; 75
8	Sicily west	Basal area (metrical)	Polygon	k-NN	CLC, NFM	70; 75
9	Saxony	Number of tree species	Pixel	ML	CLC	75
10	Saxony	Number of tree species	Polygon	ML	CLC, NFM, JRC	75
11	Rhineland	Number of tree species	Pixel	ML	CLC	75
12	Rhineland	Number of tree species	Polygon	ML	CLC, JRC	75

Step 4 - Forest type map

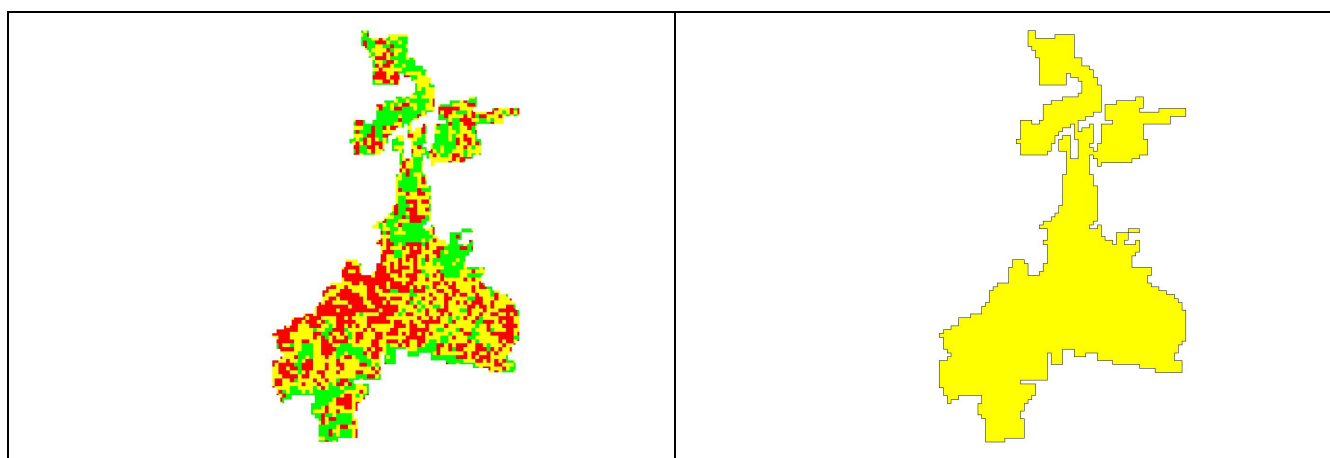
Once the Landsat classification was completed, the pixel-oriented classification was used to classify the forest type of each Level 2 polygon in order to produce forest type maps with a MMU of 25 ha (Fig. 5.18).

Fig. 5.18: Workflow for Approach 3B – forest type map.



The classification of a Level 2 polygon was performed as follows: a) in a first step the area of each forest type was computed using the satellite classification at pixel level; b) in a second step the Level 2 polygon was labelled according to the prevailing forest type according to the threshold of 75% (see example in Fig. 5.19).

Fig. 5.19: Example of forest type classification of a polygon created by Level 2 segmentation. On the left side: result of the satellite classification at pixel level (Red=coniferous; Green=broadleaved; Yellow Mixed). On the right side: Level 2 polygon labelled completely as mixed forest, as no coniferous nor broadleaved coverage reached the 75%.



To demonstrate the use of different thresholds for forest type discrimination, also the threshold of 70% as applied by the Spanish NFI was tested in the Sicilian test site (see results in Table 5.10).

Step 5 - Forest type area estimation (map-based estimation)

Finally, for each test site the total area of forest types was estimated using forest type maps in vector format with a MMU of 25 ha.

Thematic accuracy of Landsat classification

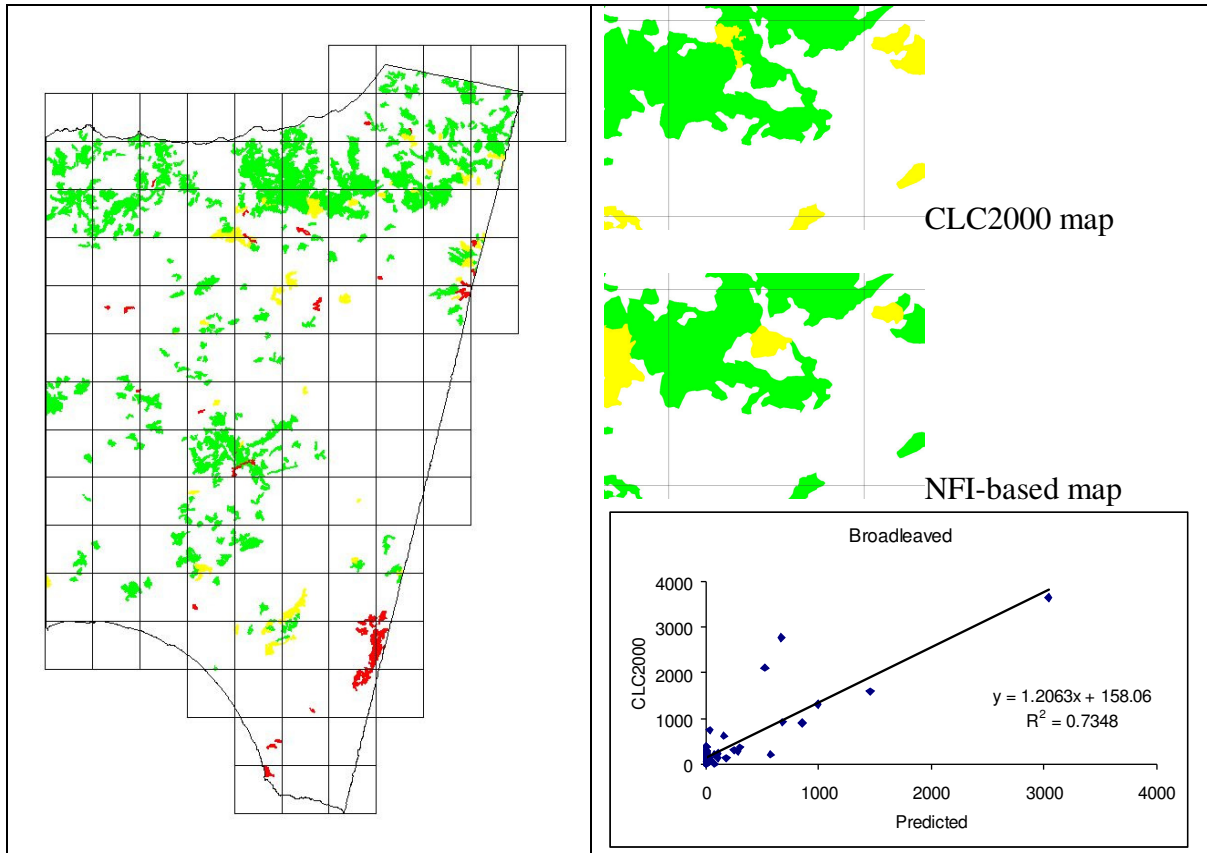
The thematic accuracy of satellite classification was analysed at pixel level with a confusion matrix and using the NFI validation set as ground truth. The overall accuracy as well as the producer's and user's accuracy and their confidence intervals were assessed for each configuration used for satellite classification (see Table 5.8).

Regression analysis

Regression analyses among produced forest type maps and CLC2000 maps were carried out by a window approach. In each test site a systematic quadrangle grid with 10x10 km was created with GIS tools. This grid size was selected in order to have at least 30 windows in each test site.

In each window, the area of broadleaved, coniferous and mixed forests (estimated with the method proposed in the Approach 3B) was compared with the area provided by CLC2000. Finally, results achieved in each window were graphed and regression equations for each type of forest were computed (Fig. 5.20).

Fig. 5.20: Example of systematic grid used for regression analysis. Green=broadleaved; Red=coniferous; Yellow=mixed.



Results

The accuracies of estimates of Landsat classification are shown in Table 5.9. Achieved results are similar to those reported by other studies (see Franco-Lopez et al., 2001; Dorren et al., 2003; Hagner and Reese, 2007). The overall accuracy ranged from 0.60 (± 0.04) to 0.79 (± 0.24). In Sicily the accuracies of the most dominant forest type according to the CLC2000 map varied from 0.71 (± 0.20) to 1.00, while in Saxony and in Rhineland-Palatinate the accuracies were 0.88 (± 0.06) and 0.44 (± 0.08), respectively.

Table 5.9: Thematic accuracy of Landsat classification. The confidence interval is put in brackets. For further details on test number see Table 5.8.

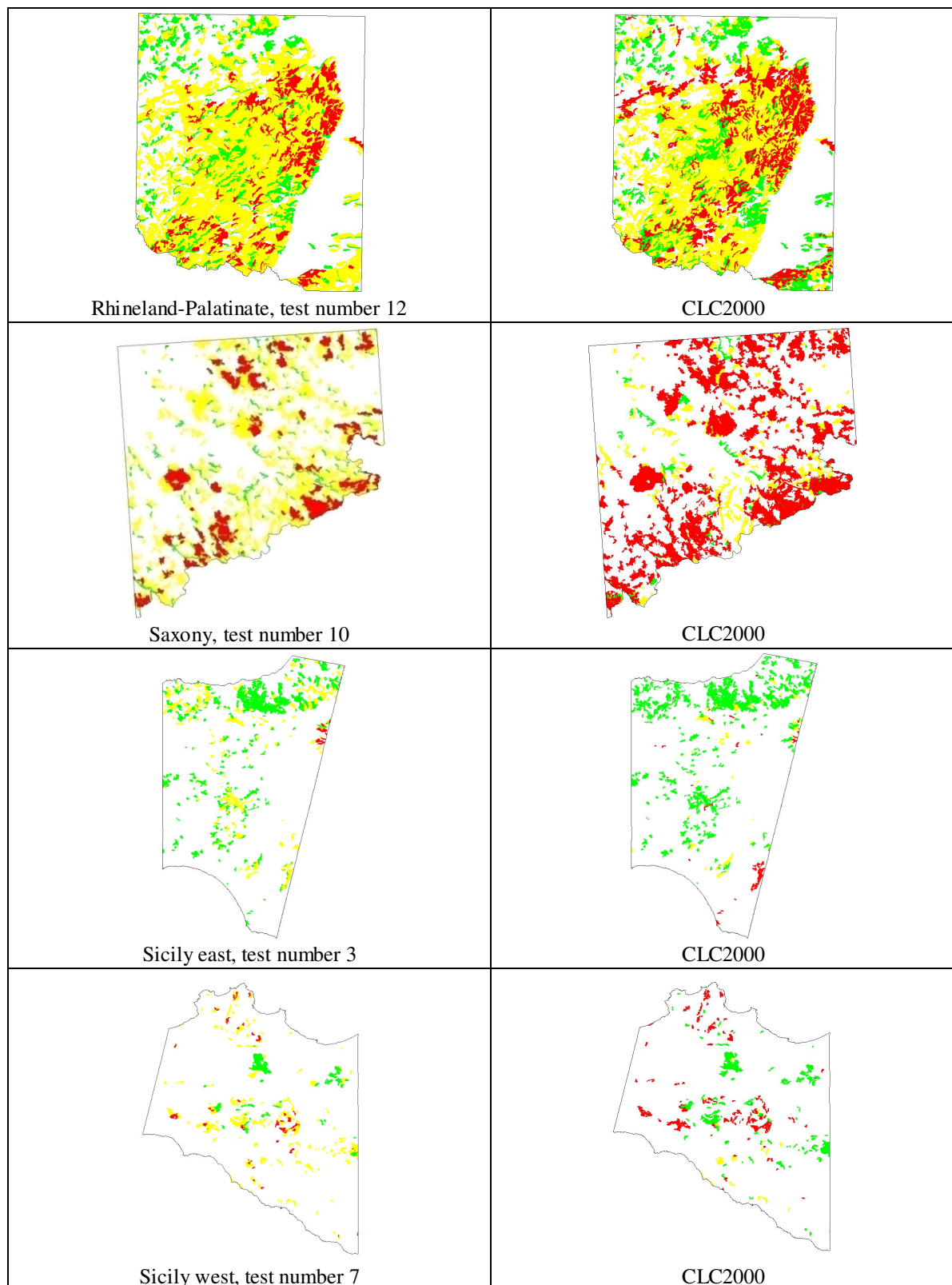
** Test number of configuration for different satellite classification.*

Test number *	Overall accuracy	Producer's accuracy			User's accuracy		
		Coniferous	Broadleaved	Mixed	Coniferous	Broadleaved	Mixed
1	0.76 (± 0.09)	0.55 (± 0.35)	0.93 (± 0.06)	0.19 (± 0.22)	0.50 (± 0.33)	0.83 (± 0.08)	0.43 (± 0.49)
2	0.69 (± 0.09)	0.58 (± 0.33)	0.74 (± 0.10)	0.43 (± 0.49)	0.54 (± 0.31)	0.95 (± 0.06)	0.13 (± 0.15)
3	0.78 (± 0.15)	0.60 (± 0.68)	0.95 (± 0.10)	0.20 (± 0.56)	0.60 (± 0.68)	0.91 (± 0.13)	0.25 (± 0.80)
4	0.78 (± 0.15)	0.60 (± 0.68)	0.87 (± 0.15)	0.50 (± 0.67)	0.50 (± 0.57)	1.00 (± 0.00)	0.33 (± 0.54)
5	0.65 (± 0.16)	0.78 (± 0.34)	0.71 (± 0.20)	0.00 (± 0.00)	0.47 (± 0.29)	0.94 (± 0.12)	0.00 (± 0.00)
6	0.65 (± 0.16)	0.64 (± 0.29)	0.74 (± 0.22)	0.25 (± 0.80)	0.60 (± 0.28)	0.78 (± 0.21)	0.25 (± 0.80)
7	0.79 (± 0.24)	0.71 (± 0.45)	1.00 (± 0.00)	0.00 (± 0.00)	0.83 (± 0.43)	1.00 (± 0.00)	0.00 (± 0.00)
8	0.64 (± 0.29)	0.50 (± 0.57)	1.00 (± 0.00)	0.00 (± 0.00)	0.60 (± 0.68)	1.00 (± 0.00)	0.00 (± 0.00)
9	0.66 (± 0.07)	0.87 (± 0.06)	0.32 (± 0.20)	0.41 (± 0.13)	0.75 (± 0.08)	0.32 (± 0.20)	0.59 (± 0.16)
10	0.76 (± 0.06)	0.88 (± 0.06)	0.57 (± 0.30)	0.54 (± 0.13)	0.85 (± 0.06)	0.32 (± 0.20)	0.73 (± 0.14)
11	0.60 (± 0.04)	0.71 (± 0.06)	0.63 (± 0.08)	0.42 (± 0.07)	0.80 (± 0.06)	0.57 (± 0.08)	0.41 (± 0.08)
12	0.61 (± 0.04)	0.72 (± 0.06)	0.61 (± 0.07)	0.44 (± 0.08)	0.76 (± 0.06)	0.67 (± 0.07)	0.37 (± 0.07)

Overall, the spectral feature extraction by per-polygon method slightly improved the performances of the classification (see test 5-6, 9-10 and 11-12), except in Sicily East. Accuracies increased when NFI plots were classified into forest type by basal area, whereas metrical data did not lead to any improvements (see test 2-3-4 and 6-7-8).

Four different examples of forest type maps produced by Approach 3B are depicted in Fig. 5.21. Table 5.10 list the total area of forest types as well as the regression coefficient for each experimental configuration. The depicted maps were produced according to test number 3, 7, 10 and 12, using the CLC forest/non forest mask and a threshold of 75%. These examples were taken, due to the high overall accuracy of Landsat classification.

Fig. 5.21: On the left side: examples of produced forest type maps of selected test sites. On the right side: CLC2000 forest type maps of selected test sites (Legend: Green=broadleaved, Red=coniferous; Yellow=mixed).



In total, 29 maps were produced with the Approach 3B. The total area of broadleaved, coniferous and mixed forests, estimated by produced forest type maps are listed in Table 5.10. Also listed are the coefficients of determination based on the regression model between NFI and CLC2000 estimates. For each test site, results are shown according to the following three variables:

- the configuration for satellite classification (see test number);
- the forest/non forest map used for image segmentation (see Level 1);
- the reference threshold applied for discriminating forest types within polygons that fulfil the MMU of 25 ha (see Level 2).

Highest coefficients of determination (R^2) were obtained for coniferous (>0.81) and mixed forest (>0.92) in Rhineland-Palatinate (see test 11 and 12). The highest coefficient of determination for broadleaved instead was only 0.66. For the other two test sites, coefficients of determination higher than 0.75 were obtained for coniferous (in Saxony) and broadleaved forests (in Sicily). For mixed forest instead R^2 were very low (<0.34). This is mainly explained by the fact that, especially in Saxony and Sicily, NFI overestimates the area of mixed forests compared to CLC2000 estimates. In general, obtained results clearly show that high correlation coefficients are obtained for the most prevalent forest type within each test site.

Table 5.10: Estimated area of forest types and results of the regression analysis. Tests in bold type are those where the Spanish threshold of 70% was used for forest type classification of Level 2 polygons. For further details on test number see Table 5.8.

* CLC: Corine Land Cover 2000; NFM: National Forest/Non-forest Map; JRC: Pan-European Forest/Non-forest Map 2000.

** Percentage used for forest type classification of Level 2 polygons by means of pixel-oriented Landsat classification.

Test number	Test site	Forest mask (*)	Forest type classification threshold (**)	Coniferous		Broadleaved		Mixed	
				ha	r ²	ha	r ²	ha	r ²
1	Sicily east	CLC	75%	2193	0.70	45446	0.68	53009	<0.10
2	Sicily east	CLC	75%	1408	<0.10	39542	0.65	59698	<0.10
3	Sicily east	CLC	75%	1839	<0.10	59833	0.75	38976	<0.10
3	Sicily east	CLC	70%	2150	<0.10	64599	0.79	33899	<0.10
4	Sicily east	CLC	75%	43	0.16	44356	0.70	56250	<0.10
4	Sicily east	CLC	70%	586	0.38	54364	0.76	45698	<0.10
2	Sicily east	NFM	75%	1976	<0.10	61446	0.56	57218	<0.10
3	Sicily east	NFM	75%	2215	<0.10	76315	0.60	42110	<0.10
3	Sicily east	NFM	70%	2215	<0.10	81808	0.62	36617	<0.10
4	Sicily east	NFM	75%	48	<0.10	64073	0.66	56513	<0.10
4	Sicily east	NFM	70%	494	0.46	76286	0.65	43859	<0.10
5	Sicily west	CLC	75%	855	<0.10	12030	0.14	26049	<0.10
6	Sicily west	CLC	75%	4629	0.41	8191	0.29	26114	<0.10
7	Sicily west	CLC	75%	4999	0.50	9755	0.20	24180	<0.10
7	Sicily west	CLC	70%	6511	0.45	10435	0.73	21988	<0.10
8	Sicily west	CLC	75%	314	<0.10	4912	0.65	33708	<0.10
8	Sicily west	CLC	70%	2891	0.39	8630	0.66	27413	<0.10
6	Sicily west	NFM	75%	5194	0.36	6964	0.29	21874	<0.10
7	Sicily west	NFM	75%	6285	0.59	9145	0.20	18602	<0.10
7	Sicily west	NFM	70%	7930	0.64	9652	0.76	16451	<0.10
8	Sicily west	NFM	75%	619	<0.10	2986	0.60	30428	<0.10
8	Sicily west	NFM	70%	2365	0.23	6357	0.66	25310	<0.10
9	Saxony	CLC	75%	30699	0.53	7006	0.20	95445	0.22
10	Saxony	CLC	75%	40822	0.76	9108	0.14	83220	0.27
10	Saxony	JRC	75%	36387	0.77	18274	<0.10	88132	0.21
10	Saxony	NFM	75%	47421	0.79	69	<0.10	85823	0.33
11	Rhineland	CLC	75%	27298	0.83	14370	0.54	149492	0.93
12	Rhineland	CLC	75%	29077	0.82	24817	0.30	137267	0.94
12	Rhineland	JRC	75%	30924	0.86	25220	0.66	129425	0.94

Discussion

The primary objective of Approach 3B was to develop and test a methodology, which produces harmonised forest type maps using NFI data as training data for satellite image classification.

Basically, the proposed methodology foresees the harmonisation of both NFI data and map specifications according to an international reference standard. In this study NFI plots were re-classified into forest types using the international reference threshold of 75% as applied in the CLC programme. The calibration of the maps with CLC programme specifications was accomplished by an automated image segmentation technique.

The results obtained reveal a high potential of the proposed method to produce harmonised forest types maps by using NFI and satellite data, especially on a larger scale.

The re-classification of sampling units into forest types was relative easy to develop. However, it is important to remind that the re-classification can be applied only when NFI tree data are available (see Approach 3A).

With reference to the calibration of map specification, it can be concluded that the segmentation technique is a suitable method to automatically delineate forest patches according to any selected MMU. In this case, a scale parameter equal to 50 revealed to be suitable, for example to fulfil the MMU of 25 ha as applied by CLC programme.

Satellite classification was performed using Landsat 7 ETM+ data and NFI plot as training set. Different configurations for Landsat image classification were evaluated. Under the examined conditions, obtained results show that:

- the usage of average spectral properties extracted from small homogeneous polygons slightly improved the accuracy of the classification compared to the traditional per-pixel extraction method. This can be explained by the fact that the per-polygon extraction method reduced the effect of some source of error like errors in image registration and/or in the location of the sample plots;
- the pixel-oriented classification method performed better than the object-oriented approach. A similar result was obtained by Dorren et al. (2003) using Landsat images for forest mapping in mountain terrain. The results obtained by Chirici et al. (2006) reveal that the object-oriented classification has its potential especially when applied to very high resolution images like Spot 5 or Quick Bird;
- the usage of metrical forest type information did not improve the accuracy of the classification obtained with categorical information. However, further research is needed to evaluate which information is better for forest type mapping by satellite classification, as the metrical and the categorical data were compared in the Sicilian test site only (see also results of Approach 2, Chapter 4).

Overall, the accuracy of the classification at pixel level was similar to those obtained by other studies based on Landsat data. High accuracy level (producer's accuracy greater than 0.80) were achieved in Sicily and Saxony for broadleaved and coniferous forest only, which are, respectively, the most dominant forest types within the two test sites. Likewise, the results of the regression analysis (between the area of forest types estimated by NFI and CLC2000) show that high coefficient of determination (greater than 0.75) were obtained only for the most dominant forest type within selected test sites.

The main factors limiting the accuracy of the Landsat classification can be summarised as follows:

- overlap between spectral signatures of the forest type classes: such a problem can arise from a variety of sources, but in the case of Landsat data, mixed pixels (pixel containing more than one land cover class) are usually one of the reasons for low accuracy of the classification obtained by hard classifier (Foody, 1996). A hard classifier, like the

Maximum likelihood method which was applied in this study, classifies every pixel (mixed or not) always in one of the target classes. Hard methods are usually suitable when mixed land cover classes are rare. In complex forest environments instead, which are characterised by high spatial heterogeneity and where the area represented by each pixel could contain more than one land cover class, such an approach might be inappropriate. A solution to improve land cover mapping based on remote-sensing imagery is for example offered by soft classification approaches like the fuzzy supervised classification (see Wang, 1990) or the mixture modelling approach (see Sohn and McCoy, 1997; Faraklioti and Petrou 2000);

- the differences in acquisition dates of NFI data and satellite data are surely the main obstacle when combining remote sensing data with field data. For instance, in Sicily the Landsat scene was acquired in 2000, while NFI field data are from 2005.
- the random selection of the training set affect the k-NN classification based on metrical information. The k-NN method provides estimates that are in the range of the values as used as training sets. Accordingly, it is important that the training set is selected in order to cover the variability of the parameter of interest within the study area (Chirici et al., 2008). In Sicily East, the range of the training set was smaller than the full range observed in the field by NFI and the k-NN classification was affected by the random selection of training sets.

In the Approach 3B the area of forest types were computed as figures but also depicted as maps. Especially maps are an important input to policy and decision making processes but also for conducting other spatial and environmental analysis. The examples of mapping mixed forests in selected test sites using NFI and satellite data clearly show that the proposed approach offers new opportunities to detect changes in forest structure and management. As CLC information covers only canopy layer by visual interpretation, understory data, like underplanting or natural regeneration of broadleaves in pure coniferous stands, are not detected (see examples in Fig 5.21). NFIs instead, collect both upper-storey and under-storey data at the sampling unit level. The methodology proposed in Approach 3B offers the opportunity of combining NFI plot data with multispectral data detected by satellite sensors in order to produce harmonised forest type maps at different scales.

Conclusions

In this study two approaches were proposed for the harmonisation of NFI data with the international reference standard applied in CLC programme. In the context of Approach 3A NFI data were used for estimating the area of forest types by applying a sample-based procedure. In the Approach 3B, first forest type maps were produced by NFI data and satellite imagery. In a second step the area of forest types were computed by a map-based estimation method.

The results obtained for the selected test sites show that:

- the methodology developed in Approach 3A is an applicable approach to harmonise the variable forest types according to any reference standard, like CLC. The proposed method is merely a re-classification of NFI data at plot or cluster level and therefore offers a relative simple method applicable at all scales. The only prerequisite for applying the approach is that NFI tree data are available.
- the methodology developed in Approach 3B reveals a solid opportunity to harmonise forest type data and compute forest type maps on a harmonised basis at various scales. Nevertheless, operative applications might be limited due to low classification accuracies of Landsat imagery.

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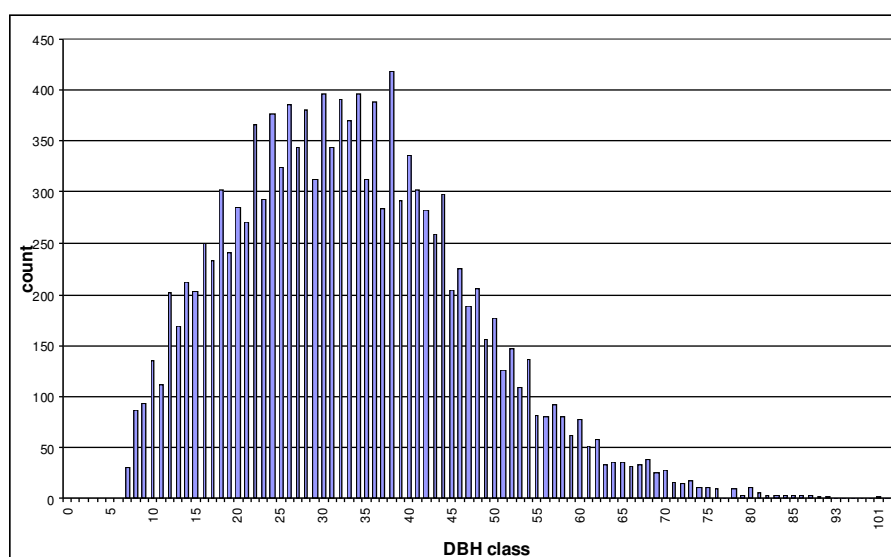
6. Approach 4: Extrapolating stand typical parameter functions – Variable: DBH (Growing stock, Carbon stock)

Main Authors: Anabel Sanchez, Jordi Vayreda, Carlos Gracia

Introduction

Tree populations can be characterised, among other ways, by their DBH distributions (see Fig. 6.1). DBH distribution reflects the forest development stage as well as the effects of forest management practices (e.g. different thinning regimes) and the historical development of the population. DBH is one of the key parameters in assessing growing stock and carbon stock, which are important indicators in forest resources reporting like on MCPFE C&I, FAO FRA and the UNFCCC Kyoto Protocol.

Fig. 6.1: Diameter distribution of Spruce (Picea abies) in Germany. This is one of the simplest ways to represent the tree population structure of a forest. DBH is also one of the key parameters in assessing growing and carbon stocks.



Thus, it is of great interest to have comparable data across the different European NFIs. As most NFIs apply different thresholds for DBH assessment (see below), it is crucial to have harmonised and reliable estimates of the number and size of trees below a certain applied threshold. For the future the most convenient practice would be to standardise the methodologies applied in the different NFIs, setting specific standards for nomenclature and technical criteria applied to NFIs design, or even more, to design a standardised European Forest Inventory System. Nevertheless at present there exists abundant not comparable information from the different NFIs. The context of international reporting obligations like towards the UNFCCC Kyoto Protocol, requires to explore applicable methodologies that are successful in harmonising and making comparable existing NFI information, especially with respect to core variables such as DBH.

Regarding field sampling of DBH, different parameter and threshold values are applied in the different NFIs in Europe (see Table 6.1). For example, trees of all sizes are sampled in Finland and Sweden. In Switzerland and Liechtenstein instead, only trees with a DBH equal to or higher than 12 cm are sampled. Due to these different threshold values, country figures on population density, stem volume, growing stock or carbon stock are not easy to compare unless some harmonisation or

standardisation is applied. The approach of harmonisation requires an estimation of the number and size distribution of trees below a certain applied threshold.

Table 6.1: Diameter thresholds and starting points for volume assessment applied in European NFIs (EFICS, 1997).

	Minimum DBH cm	Minimum top stem diameter, cm	Starting point for volume assessment
Finland, Sweden	0	0	stump
United Kingdom, Iceland	0 (1)	0	ground
Austria, Netherlands, Portugal	5	0	ground
Italy	3	0/3	stump
Norway	5	0	stump
Germany, Ireland	7	7	ground
France	7.5	7	ground
Belgium	7	7	stump
Greece	10	0	stump
Liechtenstein	12	0	ground
Spain	7.5	7.5	stump
Switzerland	12	7	ground

In case that an international standard applies a minimum DBH, which is below the national applied threshold, national authorities are not able to report the full diameter distribution and estimated figures on growing stock and carbon stock. Within the Kyoto Protocol reporting countries have to report on changes in carbon stock including total biomass (see IPCC Good Practice Guidance for LULUCF). Data which are missing and not assessed by an inventory system, like woody biomass below applied DBH threshold, have to be estimated. Therefore it is of great importance having a reliable method that can be applied at national level to estimate missing data and harmonise DBH assessment.

The primary objective of Approach 4 is to derive diameter distribution models for main tree species for each test site, taking into account specific DBH thresholds as they could theoretically be defined by international standards. In addition to these models, differences in percentage are calculated comparing the estimated diameter distribution with observed diameter distribution based on already available data. In addition, the contribution of DBH classes below the defined thresholds to the estimates on total growing stock and total carbon stock are evaluated.

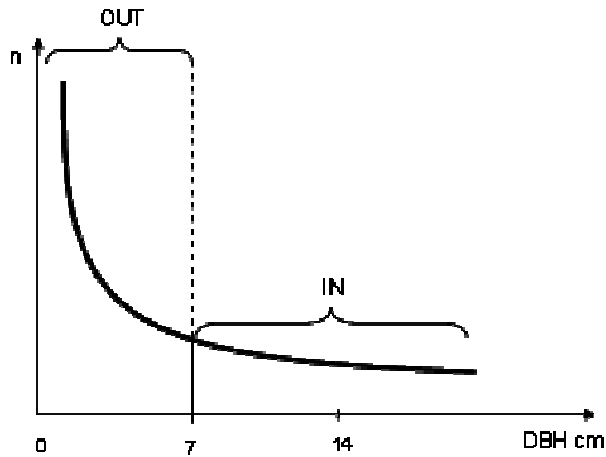
Methodology

The methodology within this approach was developed and tested in four different test sites: Saxony, Rhineland-Palatinate (Germany) and Pyrenees (Spain). Based on available NFI data (observed data), parameters like tree density, growing stock and carbon stock were calculated for each DBH class. As the Good Practice Guidance for LULUCF do not define certain DBH thresholds for biomass and carbon estimation, the threshold of 7.5 and 12 cm are taken as an example to demonstrate the approach. The DBH threshold of Switzerland/Liechtenstein (12cm) was chosen as it represents the highest DBH threshold applied by European NFIs (see Table 6.1). The threshold of 7.5 cm, which is used in the Spanish and French NFI, was selected as it is the highest threshold applied within the three case study countries; Spain, Italy and Germany (see Table 6.1). For the Saxony data only the effect of the 12 cm DBH threshold was tested.

Observed diameter distributions (based on available NFI data) were divided in two parts: the IN part, which describes those data which are available to the applied threshold (see right-hand part

of the distribution in Fig. 6.2), and the OUT part, which describes the missing data below the applied threshold (see left-hand part of the distribution in Fig. 6.2).

Fig. 6.2: Section “IN” and section “OUT” of the DBH distribution defined by applying different thresholds (in this case 7 cm). All the trees with DBH equal or higher than the threshold are considered as “IN”, while all the trees with DBH lower than the threshold are considered as “OUT”.



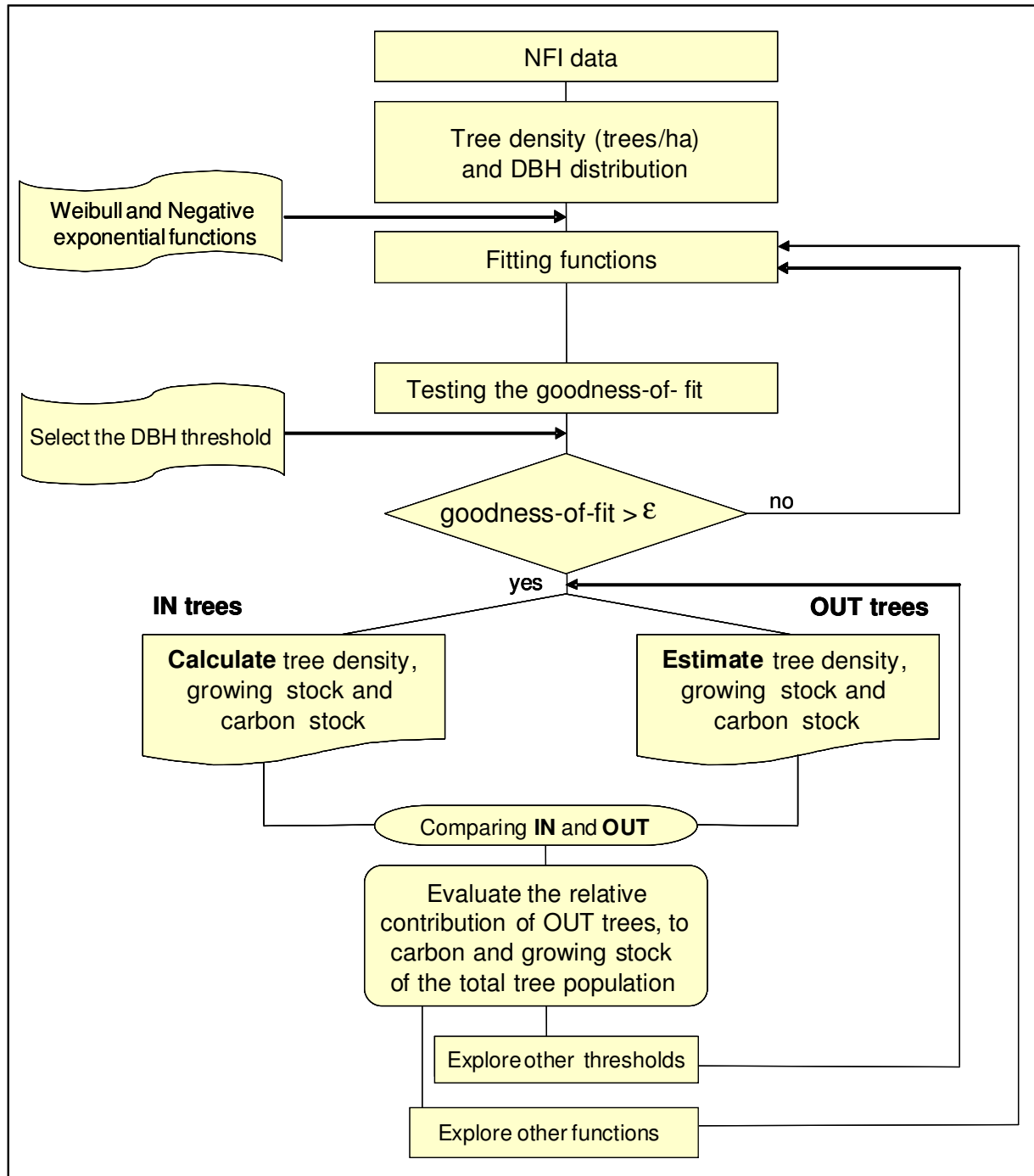
The basic steps of the approach are:

a) to derivate different DBH distributions of available data for main tree species of each test site, applying different regression models/functions with highest goodness-of-fit.

b) to estimate the missing data within the distribution, below the applied threshold (the OUT section).

c) to evaluate the effects of missing data on total tree density and growing stock and carbon stock estimates. See Fig. 6.3.

Fig. 6.3: Flow diagram of the methodological procedure applied in the Approach 4. Tree density and size of trees are the basic variables. Based on these two main variables, other variables like growing stock and carbon stock are estimated. Observed DBH data are fitted using the Weibull and the Negative Exponential function. With the fitted function, the number of trees per DBH class below a certain threshold is estimated and the results compared to the observed NFI data. Finally the contribution of missing data (see section OUT) to the estimates on total tree density, carbon stock and growing stock are evaluated.



In a first approach (Approach 4A), DBH classes of 5 cm were taken to fit the observed values in each DBH class to statistical distributions. The approach was tested with the data of Pyrenees (Spain) and Saxony (Germany).

In a second approach (Approach 4B), DBH classes of 1 cm were taken to get more detailed information and a higher goodness-of-fit of calculated distributions. Results were obtained for

Saxony (Germany) and Pyrenees (Spain). In addition data of Saxony and Rhineland-Palatinate (Germany) test site were merged for common main species, in order to have one bigger data set and test the applicability of the approach on a larger scale.

For each one of the four test sites the following NFI plot level data were used:

- Plot area;
- DBH of individual trees;
- Regeneration data (if available);
- Volume over bark or the volume equation applied;
- Tree species.

Approach 4A

Within the first step of Approach 4A, DBH plot level data were aggregated to obtain the mean number of trees per ha of each test site according to the DBH class of 5 cm. The 5 cm width was chosen, as in the Spanish NFI, regeneration data are available for the DBH classes 2.5 to 7.5 cm. Data on regeneration in the Spanish NFI are collected only by number of trees per hectare. Specifications on the size of regeneration trees are not available. To be able to use the regeneration data as additional reference data for calibrating distribution models, all regeneration data from 2.5 to 7.5 cm were put into the first 5 cm class. For modelling DBH distributions for main species, two thresholds for DBH (7.5 cm and 12 cm) were determinate and applied for the Spanish NFI data.

An important step in the approach was to find that distribution model with highest goodness-of-fit, which is a) most accurate and consistent in describing the diameter distribution of available data and b) can be used to extrapolate the distribution of DBH classes below the defined threshold.

Among the different tested functions, the Weibull and the Negative Exponential function performed best in describing observed NFI data.

Reviewing different literature, the Weibull function is often found to be the most suitable function in estimating diameter distributions (see e.g. Gadov, 1984; Borders et al., 1987). For instance, in Spain, the Weibull function is the most widely used for describing tree diameter distributions (e.g.: Álvarez, 1997; Cómides Ruiz, 1997; Del Rio, 1998; Garcia Güemes et al., 2002; Palahí et al., 2006). The wide use of this function is probably explained due to its simplicity and high flexibility (see Bailey and Dell, 1973).

One of the main characteristics of Weibull function for modelling for example diameter distribution, is that the number of trees goes close to 0 or is 0, when the diameter goes close to 0 or is 0 cm. NFI data in general instead, show that highest number of trees are found in particularly in the smallest DBH classes. Therefore the Negative Exponential function was considered, as it describes very well the lower diameter classes with high number of trees.

The Weibull function

Weibull distribution (Weibull, 1951) is a continuous probability distribution. The probability density function of a Weibull random variable x is:

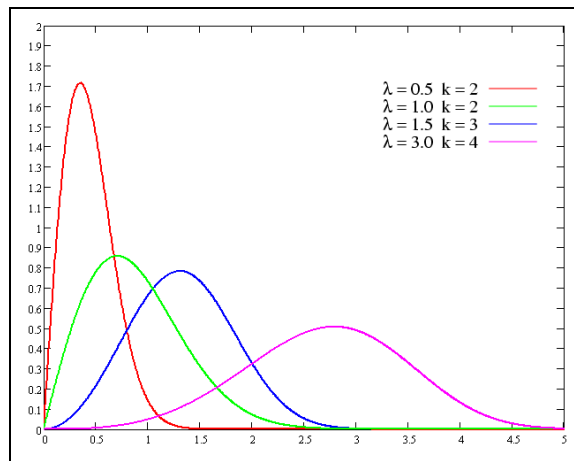
$$f(x, k, \lambda) = m \cdot (k/\lambda)^k \cdot x^{k-1} \cdot e^{-(x/\lambda)^k} \text{ for } x > 0 \quad (4.1)$$

$$\text{and } f(x; k, \lambda) = 0 \text{ for } x \leq 0 \quad (4.2)$$

where, $k > 0$ is the shape parameter, $\lambda > 0$ is the scale parameter of the distribution, and $m > 0$ the value to scale the function to real data.

Fig. 6.4 illustrates different shapes and the flexibility of the Weibull function depending on parameter values.

Fig. 6.4: Weibull 2-parameter probability density functions (pdfs), showing different possible shapes depending on parameter values. Note that in all cases when diameter is 0 also the number of trees is 0.



The Negative Exponential function

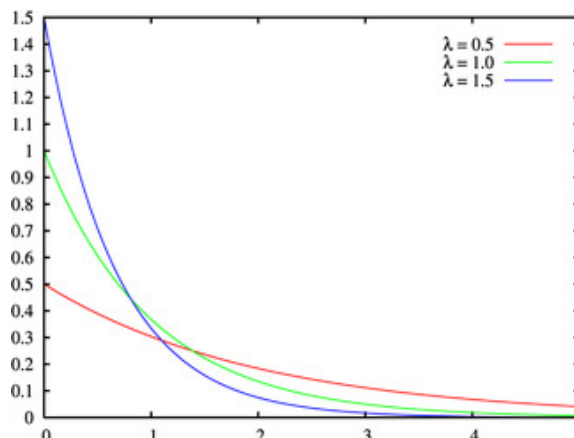
The Negative Exponential distribution is part of a class of continuous probability distributions. The probability density function of a Negative Exponential distribution has the form:

$$f(x) = a \cdot e^{-b \cdot x} \text{ for } x \geq 0 \quad (4.3)$$

$$\text{and } f(x) = 0 \text{ for } x < 0 \quad (4.4)$$

where a and $b > 0$ are constant parameters.

Fig. 6.5: Examples of different Negative Exponential distributions, depending on different parameter values. Note that the Negative Exponential distribution can be used specifically to describe lower diameter classes with high number of trees.



Taking the Weibull and the Negative Exponential function, the fitting of data was performed by using the number of trees/ha per DBH class available above the applied threshold, which is either 7.5 or 12 cm. After the parameters of the fitting functions were obtained, these were applied to extrapolate the distribution of DBH classes below the applied threshold. Finally observed NFI data were compared with estimated/extrapolated data. Differences between observed and estimated data were assessed and expressed as a percentage of the observed values:

$$dif = 100 \cdot \frac{Estimated - Observed}{Observed} \quad (4.5)$$

Approach 4B

Within Approach 4B DBH plot level data of individual tree species were aggregated according to the DBH class of 1 cm. The approach was tested with the data of Pyrenees (Spain), Saxony (Germany) and a merged data set from Saxony and Rhineland-Palatinate (Germany). Within this approach only the DBH threshold of 12 cm was applied for data selection and diameter distribution modelling. Data were taken in 1 cm classes, mainly to a) obtain more detailed information about the goodness-of-fit of applied fitting distributions – specifically of lower diameter classes, b) get more significant statistical results and c) have more detailed data (DBH classes) available for comparing observed data with estimated/extrapolated data.

To assess and validate the performance and goodness-of-fit of different diameter distribution functions (see Weibull and Negative Exponential), the Normality test, Constant Variance test and Kolmogorov-Smirnov test were applied. Statistical tests were performed using *SigmaPlot 9* Software for Windows.

Selected test area and data

From each of the selected test area, single tree data at NFI plot level were taken and the mean number of trees per DBH class calculated for main tree species. Only those NFI plots were taken into account where the selected tree species was most dominant according to basal area. For the Spanish and German test area parameters like mean growing stock per DBH class were calculated. Data on mean carbon stock per DBH class instead were only calculated for the Spanish test site.

In the Pyrenees test area, the main species are *Pinus sylvestris* and *Pinus uncinata*. 562 plots for *Pinus sylvestris* and 473 plots for *Pinus uncinata* were taken into account. DBH class data in the Spanish NFI are available from 7.5 cm onwards. In addition the Spanish NFI records regeneration data of trees between 2.5 to 7.5 cm. Collected are only the number of trees per ha but not the size of regeneration.

In the Saxony and Rhineland-Palatinate test area, the main species are *Pinus sylvestris* and *Picea abies*. For the Saxony test site, 169 plots for *Pinus sylvestris* and 279 plots for *Picea abies* were taken into account. For the Rhineland-Palatinate test area, 354 plots for *Pinus sylvestris* and 122 plots for *Picea abies* were used. DBH class data according to German NFI are available from 7 cm onwards.

Data of the Rhineland-Palatinate test area were not analysed separately, but were merged with Saxony data, in order to evaluate the applicability of the approach on a larger scale.

Results

Results of DBH class 5 cm (Approach 4A)

Fitting the sampled trees (IN data)

Pyrenees test area

NFI data of the two main species, *Pinus sylvestris* and *Pinus uncinata* were fitted to both, the Weibull and the Negative Exponential function, applying the two determined DBH thresholds, 7.5 cm and 12 cm. Figures below show the a) observed data from NFI, b) fitted function and estimated values and c) a comparison of both data sets.

Fig. 6.6: Number of trees/ha per DBH class (cm) of *Pinus uncinata* in the Pyrenees test area. Minimum DBH = 7.5 cm. a) Fitted to Weibull distribution (green = observed data; red = estimated data). Equation parameters: $k = 1.113$, $\lambda = 14.848$, $m = 5408.164$; $r^2 = 0.995$; significance < 0.0001 , 95% confidence interval. b) Scatter plot showing the relationship between observed and estimated data.

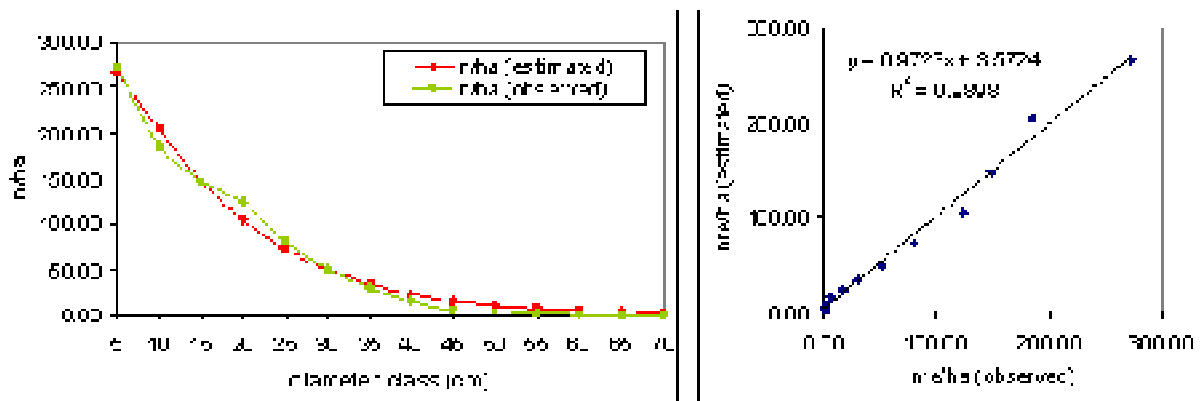
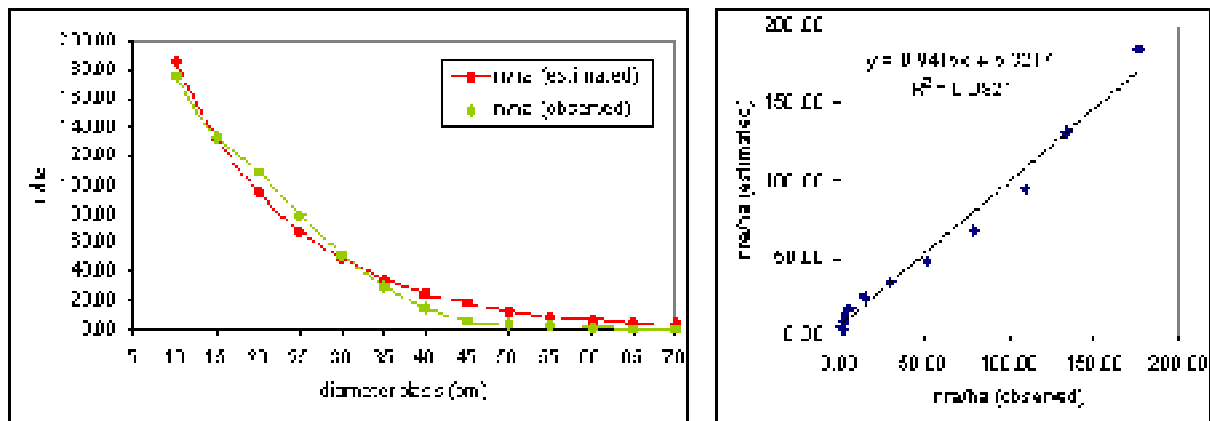


Fig. 6.7: Number of trees/ha per DBH class (cm) of *Pinus sylvestris* in the Pyrenees test area. Minimum DBH = 7.5 cm a) fitted to the Negative Exponential distribution (green = observed data; red = estimated data). Equation parameters: $a = 363.627$, $b = 0.068$; $r^2 = 0.978$; significance < 0.0001 , 95% confidence interval. b) Scatter plot showing the relationship between observed and estimated data.



In all cases the coefficient of determination is above 0.97, meaning that the goodness of prediction fit is relative high. Parameters of the regression model are also significant (at a 95% confidence interval).

Saxony test area

NFI data of the two main species, *Pinus sylvestris* and *Picea abies* were fitted to both, the Weibull and the Negative Exponential function, applying a DBH threshold of 12 cm. Figures below represent a) the observed values from the NFI, b) the fitted function and estimated values and c) a comparison of both data sets.

Fig. 6.8: Number of trees/ha per DBH class (cm) of *Pinus sylvestris* in Saxony test area. Minimum DBH = 12 cm. a) Fitted to Negative Exponential distribution (green = observed data, red = estimated data). Equation parameters: $a = 791.603$, $b = 0.089$; $r^2 = 0.996$; significance < 0.0001, 95% confidence interval. b) Scatter plot showing the relationship between observed and estimated data.

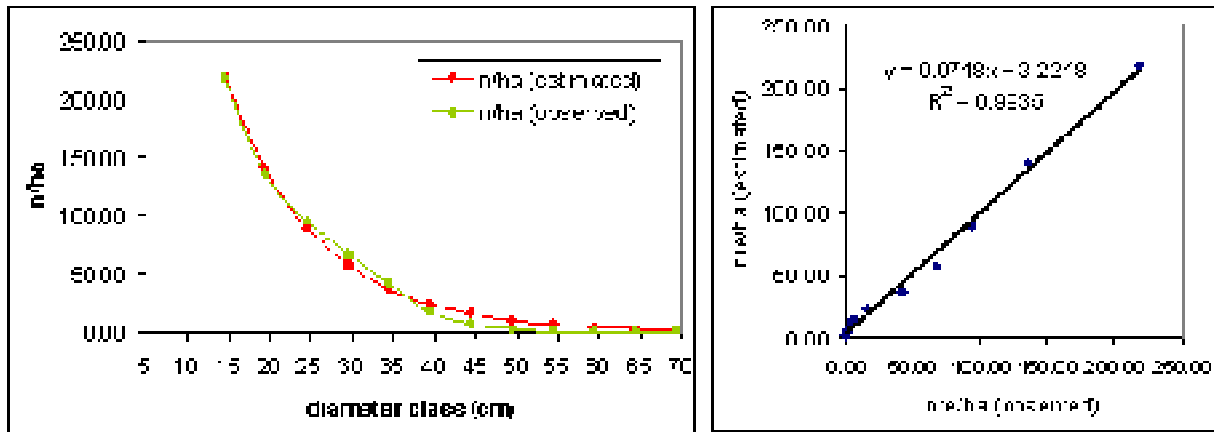
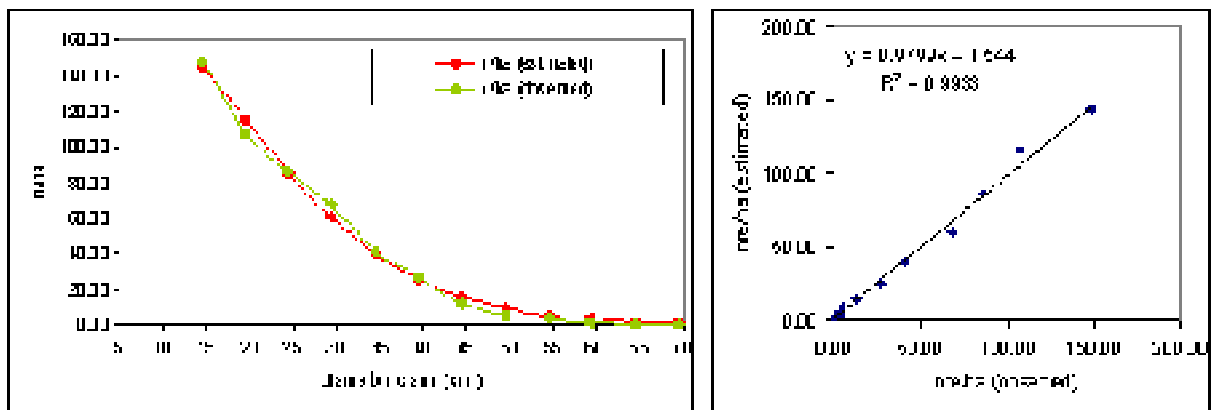


Fig. 6.9: Number of trees/ha per DBH class (cm) of *Picea abies* in Saxony test area. Minimum DBH = 12 cm. a) Fitted to Weibull distribution (green = observed data, red = estimated data). Equation parameters: $k = 1.460$, $\lambda = 19.270$, $m = 4195.711$; $r^2 = 0.993$; significance < 0.0001, 95% confidence interval. b) Scatter plot showing the relationship between observed and estimated data.



In all cases the coefficient of determination is above 0.99 showing that the goodness of prediction fit of both functions is high. Parameters of the regression model are also significant (at a 95% confidence interval).

Based on the results obtained from the two distribution functions applied, it can be concluded that in all cases the goodness of prediction fit of Weibull distribution was higher than the one of the Negative Exponential distribution. This was independent from the different DBH thresholds applied. Furthermore Weibull distribution reaches higher coefficients of determination (R^2). Nevertheless, it can also be concluded that both functions performed well in describing the observed NFI data above the applied threshold.

Estimating the number of trees below applied threshold (OUT data)

The function parameters obtained for Weibull and the Negative Exponential function were taken to extrapolate the distribution and estimate the number of trees below the applied threshold (see section OUT below 7.5 or 12 cm). Finally extrapolated data were compared with observed data and differences in percentage (see equation 4.5) were calculated (see Table 6.2 and 6.3).

Table 6.2: Difference between estimated and observed number of trees per ha (DBH class 5cm) of Pinus sylvestris and Pinus uncinata (test site Pyrenees).

	Threshold (cm)	DBH class OUT (cm)	Observed (n/ha)	Weibull		Observed (n/ha)	Negative Exponential	
				Estimated (n/ha)	Differences %		Estimated (n/ha)	Differences %
<i>Pinus sylvestris</i>	7.5	2.5 – 7.5	292.70	171.68	41.35	292.70	259.46	11.36
		12	2.5 – 7.5	292.70	99.69	144.83	292.70	293.62
		7.5 – 12	153.53	134.31	17.60	153.53	206.27	-34.35
<i>Pinus uncinata</i>	7.5	2.5 – 7.5	273.22	168.11	59.63	273.22	278.77	-2.03
		12	2.5 – 7.5	273.22	118.46	196.17	273.22	343.99
		7.5 – 12	165.79	156.72	17.54	165.79	237.49	-43.25

Table 6.3: Differences between estimated and observed number of trees per ha (DBH class 5 cm) of Pinus sylvestris and Picea abies (test site Saxony).

	Threshold (cm)	DBH class OUT (cm)	Observed (n/ha)	Weibull		Observed (n/ha)	Negative Exponential	
				Estimated (n/ha)	Differences %		Estimated (n/ha)	Differences %
<i>Pinus sylvestris</i>	12	7 – 12	395.40	300.16	24.09	395.40	340.05	14.00
<i>Picea abies</i>	12	7 – 12	244.76	160.81	34.30	244.76	214.10	12.53

In most cases, differences between observed and estimated data were lower for the data predicted by the Negative Exponential distribution, than for the data by the Weibull distribution. As mentioned above, Weibull distribution is forced to cross the origin of xy-coordinates. This specific characteristic obviously fits not to the characteristics of observed data, which show that the highest number of trees per ha are mainly in the lower diameter classes. This explains why Weibull distribution highly underestimates tree density for lower DBH classes (see Table 6.2 and 6.3).

Results of DBH class 1 cm (Approach 4B)

Fitting the sampled trees (IN data)

Pyrenees test area

NFI data of the two main species, *Pinus sylvestris* and *Pinus uncinata* were fitted to both, the Weibull and the Negative Exponential function, according to the applied DBH threshold of 12 cm. In difference to the Approach 4B DBH data were aggregated according to 1 cm classes. Figures below show the a) observed NFI data, b) fitted function and estimated values and c) a comparison of both data sets.

Fig. 6.10: Number of trees/ha per DBH class (cm) of Pinus sylvestris in the Pyrenees test area. Minimum DBH = 12 cm. a) Fitted to Negative Exponential distribution. (green = observed data, red = estimated values). Equation parameters: $a = 82.090$, $b = 0.074$; $r^2 = 0.975$; significance < 0.0001 with confidence interval 95%. b) Scatter plot showing the relationship between observed and estimated data.

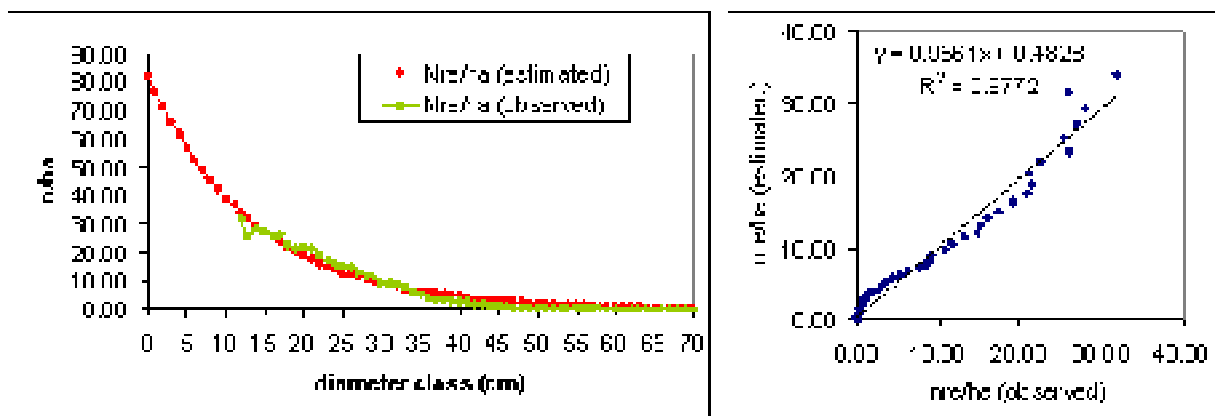


Fig. 6.11: Number of trees/ha per DBH class (cm) of *Pinus sylvestris* in the Pyrenees test area. Minimum DBH = 12 cm. a) Fitted to Weibull distribution. (green = observed data, red = estimated values). Equation parameters: $k = 1.679$, $\lambda = 18.691$, $m = 697.627$; $r^2 = 0.996$; significance < 0.0001 , confidence interval 95%. b) Scatter plot showing the relationship between observed and estimated data.

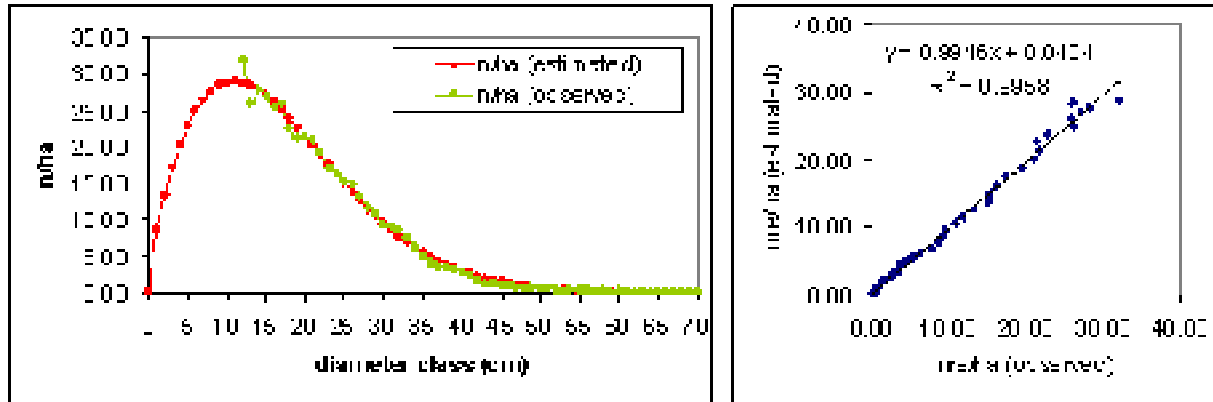


Fig. 6.12: Number of trees/ha per DBH class (cm) of *Pinus uncinata* in the Pyrenees test area. Minimum DBH = 12 cm. a) Fitted to Negative Exponential distribution. (green = observed data, red = estimated values). Equation parameters: $a = 93.694$, $b = 0.077$; $r^2 = 0.976$; significance < 0.0001 , confidence interval 95%. b) Scatter plot showing the relationship between observed and estimated data.

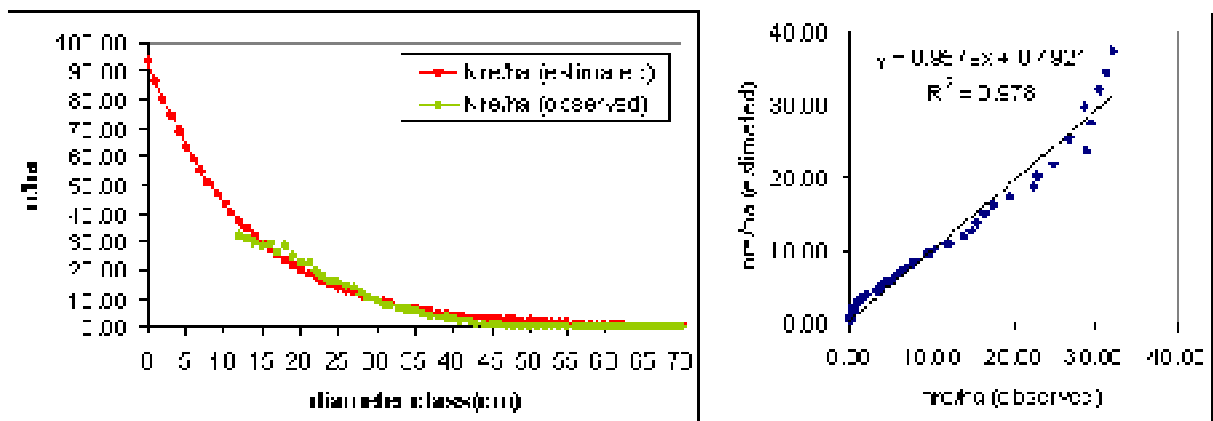
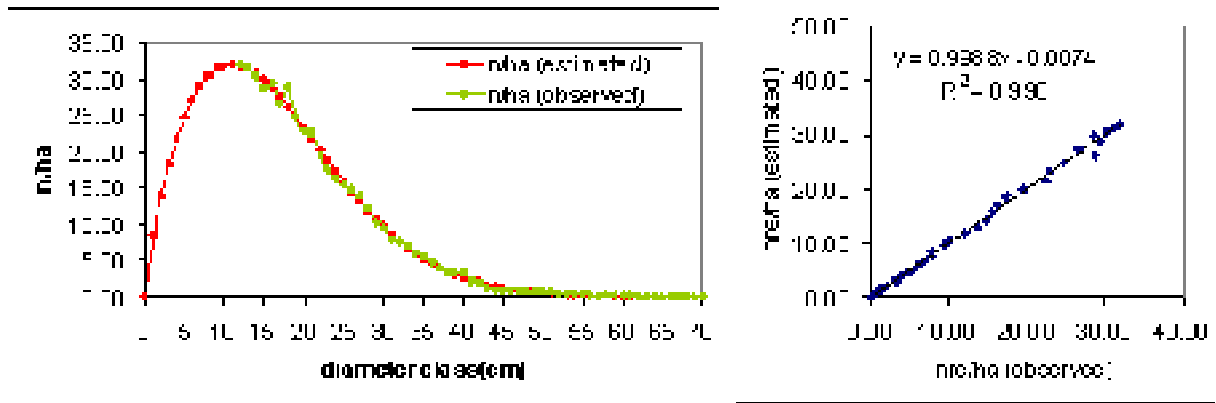


Fig. 6.13: Number of trees/ha per DBH class (cm) of *Pinus uncinata* in the Pyrenees test area. Minimum DBH = 12 cm. a) Fitted to Weibull distribution. (green = observed data, red = estimated values). Equation fitted parameters: $k = 1.724$, $\lambda = 18.243$, $m = 740.090$; $r^2 = 0.998$; significance < 0.0001 , confidence interval 95%. b) Scatter plot showing the relationship between observed and estimated values.



Saxony and merged data of Saxony plus Rhineland-Palatinate test area

In a first step data only for Saxony were analysed, to assess differences between common species in European continental region and Mediterranean region (see results Pyrenees). In a second step NFI data of the two German test sites were merged for main species in order to obtain one bigger data set and test the applicability of the approach on a larger scale. DBH data in 1 cm classes of the two main species, *Pinus sylvestris* and *Picea abies*, were fitted to both, the Weibull and the Negative Exponential function. The DBH threshold applied was 12 cm. Figures below show the a) observed NFI data, b) fitted function and estimated values and c) a comparison of both data sets.

Fig. 6.14: Number of trees/ha per DBH class (cm) for *Picea abies* in Saxony test area. Minimum DBH = 12 cm. a) Fitted to Negative Exponential distribution. (green = observed data, red = estimated data). Equation fitted parameters: $a = 78.740$, $b = 0.068$; $r^2 = 0.961$; significance < 0.0001 , confidence interval 95%. b) Scatter plot showing the relationship between observed and estimated values.

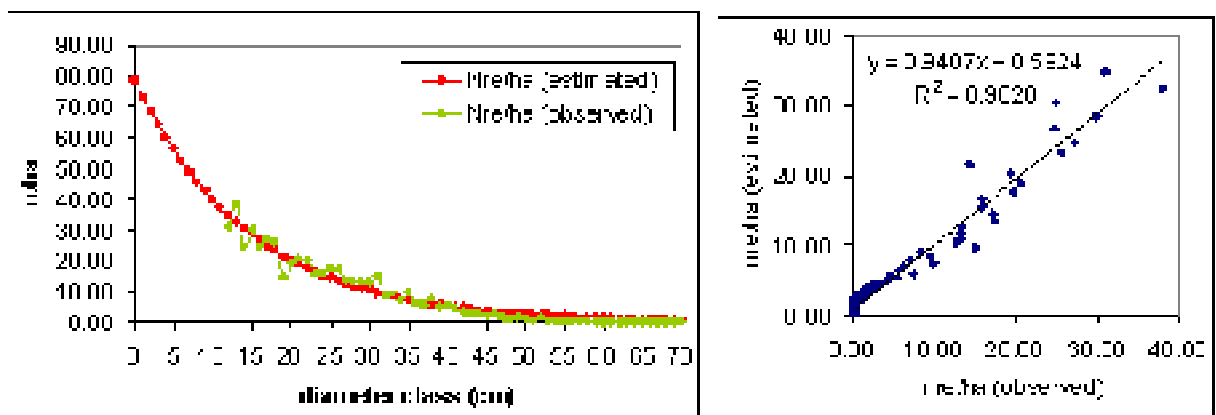


Fig. 6.15: Number of trees/ha per DBH class (cm) of *Picea abies* in Saxony test area. Minimum DBH = 12 cm. a) Fitted to Weibull distribution (green = observed data, red = estimated data). Equation parameters: $k = 1.354$, $\lambda = 18.217$, $m = 872.852$; $r^2 = 0.968$; significance < 0.0001, confidence interval 95%. b) Scatter plot showing the relationship between observed and estimated values.

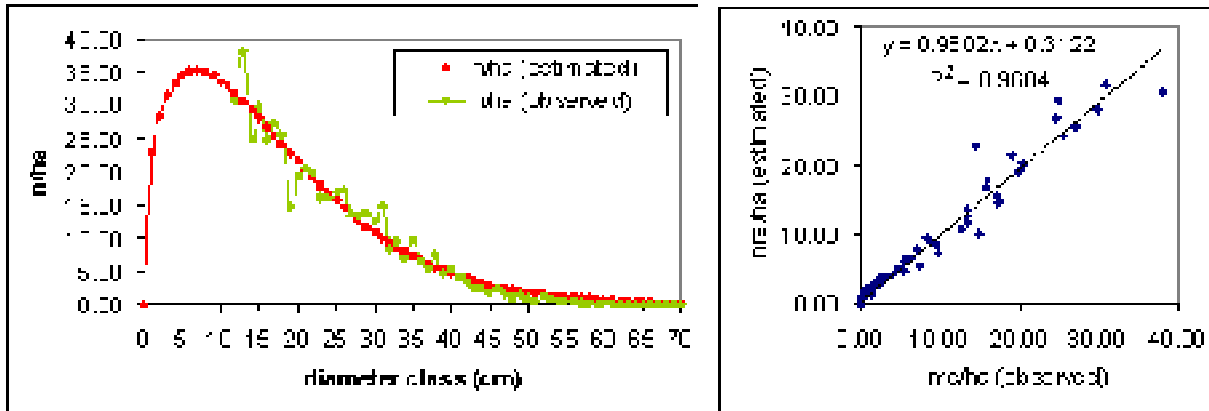


Fig. 6.16: Number of trees/ha per DBH class (cm) of *Pinus sylvestris* in Saxony plus Rhineland-Palatinate test area. Minimum DBH = 12 cm. a) Fitted to Weibull distribution Negative Exponential distribution. (green = observed data, red = estimated data). Equation parameters: $a = 76.387$, $b = 0.069$; $r^2 = 0.976$; significance < 0.0001, confidence interval 95%. b) Scatter plot showing the relationship between observed and estimated values.

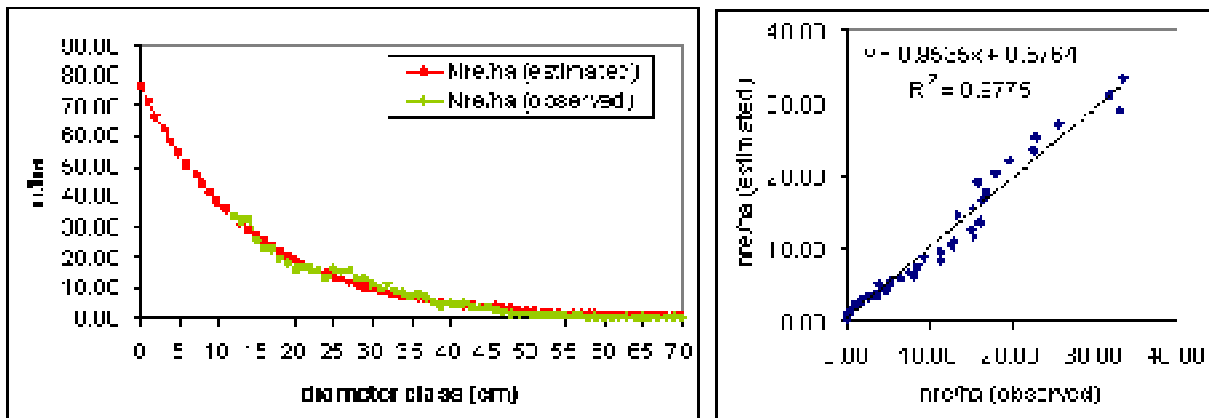
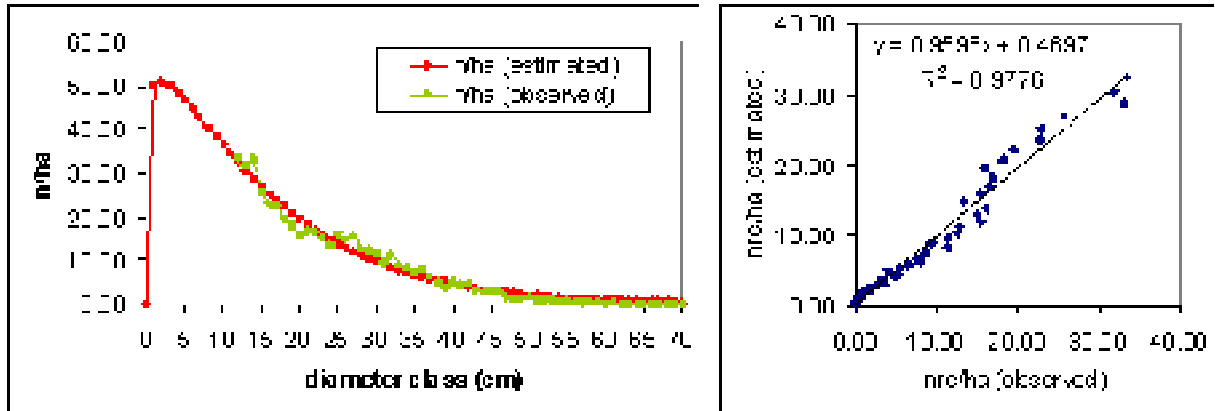


Fig. 6.17: Number of trees/ha per DBH class (cm) of *Pinus sylvestris* in Saxony plus Rhineland-Palatinate test area. Minimum DBH = 12 cm. a) Fitted to Weibull distribution. (green = observed data, red = estimated data). Equation parameters: $k = 1.105$, $\lambda = 15.738$, $m = 995.127$; $r^2 = 0.977$; significance < 0.0001 , confidence interval 95%. b) Scatter plot showing the relationship between observed and estimated values.



In all cases, the coefficient of determination is above 0.97, meaning that the goodness of prediction fit of both functions is high. Like in approach 4B, parameters of the prediction models (equation) are significant (at a 95% confidence interval).

Based on the results obtained for Pyrenees, Saxony and Saxony plus Rhineland-Palatinate test area, it can be concluded that in most cases the goodness of prediction fit of Weibull distribution is higher than of the Negative Exponential distribution. Weibull distribution achieved higher coefficients of determination (R^2). Nevertheless, both functions performed well in describing observed NFI diameter distribution of 1 cm classes above the applied threshold.

The Normality test, Constant Variance test and Kolmogorv-Smirnov test were applied to assess the goodness-of-fit of the estimated distributions and gave significant results on their performance. All tests show that Weibull function performs slightly better in describing observed data than the Negative Exponential function.

Estimating the number of trees below applied threshold (OUT data)

The function parameters obtained from each data set were taken, to extrapolate the distribution and estimate the number of trees below the applied threshold (see section OUT, below applied threshold). Finally extrapolated data were compared to observed data and differences in percentage (see equation 4.5) were calculated (see Table 6.4 and 6.5).

Table 6.4: Difference between estimated and observed number of trees per ha (DBH class 1cm) of Pinus sylvestris and Pinus uncinata (test site Pyrenees).

			Weibull			Negative Exponential		
	Threshold (cm)	DBH class OUT (cm)	Observed (n/ha)	Estimated (n/ha)	Differences %	Observed (n/ha)	Estimated (n/ha)	Differences %
<i>Pinus sylvestris</i>	12 (n=562)	8	41.01	27.69	32.47	41.01	45.60	-11.19
		9	37.83	28.46	24.78	37.83	42.36	-11.97
		10	31.72	28.89	8.93	31.72	39.36	-24.10
		11	29.68	29.00	2.28	29.68	36.57	-23.23
<i>Pinus uncinata</i>	12 (n=473)	8	45.22	30.25	33.12	45.22	50.76	-12.24
		9	39.84	31.20	21.70	39.84	47.02	-18.01
		10	32.30	31.74	1.74	32.30	43.55	-34.82
		11	36.61	31.92	12.81	36.61	40.34	-10.18

Both for *Pinus sylvestris* and *Pinus uncinata* in the Pyrenees test area, differences between observed and estimated data are in most cases quite high, varying between 1.74 and 34.82 %. Differences were in general lower for the Negative Exponential function than for Weibull function. Like in all tests before, Weibull function systematically underestimates observed data while Negative Exponential overestimates them.

Table 6.5: Difference between estimated and observed number of trees per ha (DBH class 1cm) of *Pinus sylvestris* and *Picea abies* (test site Saxony).

			Weibull			Negative Exponential		
	Threshold (cm)	DBH class OUT (cm)	Observed (n/ha)	Estimated (n/ha)	Differences %	Observed (n/ha)	Estimated (n/ha)	Differences %
<i>Pinus sylvestris</i>	12 (n=169)	7	124.01	61.88	50.10	124.01	79.10	36.21
		8	124.38	59.62	52.06	124.38	72.48	41.72
		9	46.60	57.04	-22.40	46.60	66.42	-42.53
		10	57.99	54.25	6.45	57.99	60.86	-4.96
		11	42.42	51.33	-21.00	42.42	55.77	-31.47
<i>Picea abies</i>	12 (n=279)	7	38.77	35.16	9.31	38.77	48.93	-26.20
		8	49.14	34.92	28.94	49.14	45.72	6.96
		9	54.10	34.40	36.42	54.10	42.71	21.05
		10	48.63	33.66	30.79	48.63	39.91	17.94
		11	54.13	32.75	39.50	54.13	37.28	31.12

With respect to the Saxony data and the tree species *Pinus sylvestris* and *Picea abies*, differences are similar to those for the Pyrenees data, varying between 1.42 and 52.06 % (see Table 6.5). Again they are lower for the estimates of Negative Exponential function than for Weibull function.

Table 6.6: Difference between estimated and observed number of trees per ha (DBH class 1cm) of *Pinus sylvestris* and *Picea abies* (merged data set - test site Saxony plus Rhineland-Palatinate).

			Weibull			Negative Exponential		
	Threshold (cm)	DBH class OUT (cm)	Observed (n/ha)	Estimated (n/ha)	Differences %	Observed (n/ha)	Estimated (n/ha)	Differences %
<i>Pinus sylvestris</i>	12 (n=523)	7	65.24	42.66	34.62	65.24	47.03	27.91
		8	56.89	40.54	28.74	56.89	43.88	22.86
		9	35.40	38.43	-8.58	35.40	40.95	-15.68
		10	42.57	36.36	14.59	42.57	38.20	10.24
		11	30.32	34.33	-13.24	30.32	35.65	-17.57
<i>Picea abies</i>	12 (n=401)	7	35.87	40.17	-11.99	35.87	50.83	-41.70
		8	48.07	39.15	18.54	48.07	47.38	1.42
		9	47.51	37.93	20.17	47.51	44.17	7.04
		10	44.51	36.56	17.86	44.51	41.17	7.51
		11	52.38	35.09	33.00	52.38	38.38	26.73

As mentioned before, data of the Rhineland-Palatine test site were not separately analysed. Data were merged instead with Saxony data in order to test the approach on a larger scale. Table 6.6 shows the estimation of tree density for DBH classes below 12 cm for *Pinus sylvestris* and *Picea abies*, of both test sites. The differences between observed data and estimated data are in most cases again high, ranging from 1.42 to 41.70 % (see Table 6.6). Again differences were lower for Negative Exponential function than for Weibull function and Negative Exponential distribution estimated observed data with higher accuracy.

A comparison between observed data (total number of trees per ha below applied threshold) and estimated data of all test sites is depicted in Table 6.7.

Table 6.7: Number of trees/ha and differences in percentage of main species of all studied test areas.

		Observed	Estimated Weibull	differences % W	Estimated Negative Exponential	differences % NE
Pyrenees (8 to 11 cm)	<i>Pinus sylvestris</i>	140.24	114.04	18.68	163.90	-16.87
	<i>Pinus uncinata</i>	153.97	125.10	18.75	181.66	-17.98
Saxony (7 to 11 cm)	<i>Pinus sylvestris</i>	395.40	284.12	28.14	334.64	15.37
	<i>Picea abies</i>	244.76	170.88	30.18	214.55	12.34
Saxony-Rhineland (7 to 11 cm)	<i>Pinus sylvestris</i>	230.41	192.31	16.53	205.71	10.72
	<i>Picea abies</i>	228.34	188.92	17.27	221.93	2.81

Again it is shown that the Negative Exponential distribution gives much better estimations on tree density below applied thresholds than the Weibull function. Weibull instead describes much better observed data above applied thresholds (see results in Chapter 6.3.2.1).

Contribution of DBH classes below applied threshold to the estimates of Growing stock and Carbon stock

After the number of trees per ha for selected DBH classes below 12 cm were estimated (using Weibull and Negative Exponential function), it was of particular interest to evaluate to which extend missing data below applied threshold (see section OUT) effect the estimates on growing stock and carbon stock. Effects on carbon stock were estimated for the test site Pyrenees only. Obtained data are only rough estimates, demonstrating the effect and relevance of lower DBH classes in deriving NFI key variables like growing stock and carbon stock.

To estimate data on growing stock and carbon stock for the Pyrenees, equations from the Spanish NFI were applied (see Gracia et al., 1998-2003). Equation parameters for main species are listed in Table 6.8.

Table 6.8: Volume and Carbon equation parameters (a and b) taken from the Spanish NFI. VOB = Volume over Bark (dm³), C = Carbon (kg), and DBH is in cm.

		VOB or C = a*DBH ^b	
		a	b
Volume equation	<i>Pinus sylvestris</i>	0.080	2.524
	<i>Pinus uncinata</i>	0.066	2.536
Carbon equation	<i>Pinus sylvestris</i>	0.030	2.465
	<i>Pinus uncinata</i>	0.031	2.471

Volume and Carbon equation parameters rely on data measured in Spanish NFIs. Meaning, equations are not necessarily applicable for any other data (like estimated data of lower DBH classes, in this case: 0-11 cm). As mentioned above obtained values are only rough estimates, giving some first hint on the relevance and effects of lower DBH classes and the necessity for harmonisation.

Table 6.9: Effects of trees below 12 cm threshold on the estimates of a) number of trees per ha, b) growing stock and c) carbon stock, (NE = Negative Exponential; W = Weibull), in percentage of the total.

		DBH 7/8 to 11 cm						DBH 0 to 11 cm			
		Pyrenees (8-11 cm)			Saxony (7-11 cm)			Pyrenees		Saxony	
		Observed	NE	W	Observed	NE	W	NE	W	NE	W
% N trees/ha	<i>Pinus sylvestris</i>	23.01	25.48	20.28	36.11	29.50	26.53	58.66	35.63	64.95	52.40
	<i>Pinus uncinata</i>	24.57	26.40	20.98	-	-	-	60.13	36.23	-	-
	<i>Picea abies</i>	-	-	-	25.65	23.83	20.28	-	-	55.80	41.10
% m3/ha	<i>Pinus sylvestris</i>	3.38	2.62	2.83	4.34	3.48	3.40	3.37	3.66	-	-
	<i>Pinus uncinata</i>	4.75	4.08	4.05	-	-	-	4.85	4.84	-	-
	<i>Picea abies</i>	-	-	-	2.68	1.66	1.59	-	-	-	-
% Mg/ha	<i>Pinus sylvestris</i>	3.85	2.92	3.21	-	-	-	3.75	4.06	-	-
	<i>Pinus uncinata</i>	4.96	4.10	4.24	-	-	-	4.95	5.12	-	-

To compare the different effects of lower DBH classes, estimated values were compared with observed data for the DBH classes 7-11 cm (see Table 6.9). The results obtained show the number of trees/ha for *Pinus sylvestris* and *Pinus uncinata* in the Pyrenees make up 20-26 % of the total number of trees. Looking at the variables growing stock and carbon stock instead, the proportion is only about 2-5 % of the total. For *Pinus sylvestris* in Saxony the results were slightly higher than those for the same species in the Pyrenees, 26-36 % regarding number of trees/ha and 3-4 % with respect to growing stock estimates. For *Picea abies* the proportions varied between 20-26 % and 1.5-2.7 % respectively.

For the DBH classes 0 to 11 cm (without any comparison to observed data), the contribution to the total number of trees/ha in both test sites and for all species varied between 35 to 65 %. With respect to the estimates on growing stock and carbon stock the contribution of 0-11 cm is again relative low, varying between 3-5 %.

Looking at the results above, it should be noted that in the equation used for carbon stock estimation, parameters like 'biomass of braches' and 'wood density' are constant parameters with constant values. These constant values surely cause a bias in carbon stock estimation. It is obvious that the proportion between 'biomass of branches' and total biomass is not constant during the life span of a tree; the bigger the tree the lower this proportion is. Moreover, this proportion is not the same for all tree species, as it depends very much on tree architecture and wood density.

Discussion

Looking at the relative high differences between observed and estimated data, two fundamental aspects should be considered. The first aspect concerns the principle of tree population dynamics and competition. Trees with high DBH and more dominant position in the stand can resist adverse conditions and competitions of neighbouring trees much better than smaller trees. Trees with low DBH are fragile and sensitive to various environmental impacts such as caused by

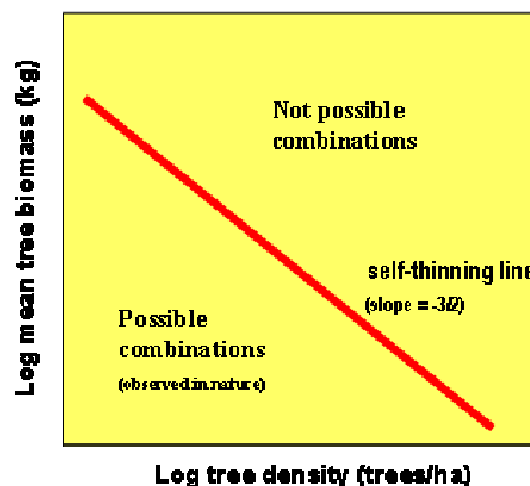
drought, grazing, shading etc. As a result, the number of seedlings and smaller trees is much more variable over time than trees with higher DBH. Population dynamics like these are very difficult to consider in the monitoring of forests, by variables like growing stock and carbon stock.

Another aspect that should be taken into account is that the sampling process affects very much the quality of data. While the big trees are easily recognized and sampled in the NFI, small trees, usually recorded in a different sampling process, are submitted to higher assessment errors. The low data quality for trees with lower DBH, again reinforces the above mentioned challenge to assess variables like growing stock and carbon stock.

Nevertheless, the low significance in modelling DBH distributions of lower DBH classes has only little effects on growing stock and carbon stock estimates. Mainly, as trees with lower DBH make up only 2-5 % of the total growing stock or carbon stock.

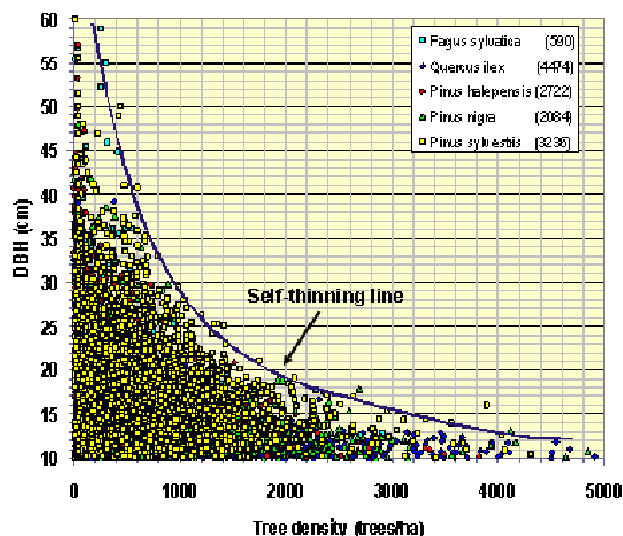
Coming back to the process of population dynamics, the results obtained are clearly in line with the self-thinning law by Yoda et al., 1963. The self-thinning law describes basically the correlation between mean biomass and tree density per ha. Whatever species looking at, the number of trees decreases while the size of trees increases, which is a logic geometrical principle. A determinate area can only bear a determinate amount of biomass. As trees grow, they keep taking up more and more space, which necessarily means that the number of trees per ha decreases. Besides taking up more space, trees use more and more resources such as light, water and nutrients. As a consequence resources competition tree growth slows down and/or individual trees die. This process is described as the self-thinning process. The relationship between mean individual size and population density takes place in such a way that an upper limit of it seems to exist (see Fig. 6.18). A very wide range of species of very diverse morphological and taxonomical groups have been studied in the past and in all of them the self-thinning line tends to present a $-3/2$ slope when representing mean individual biomass logarithm versus density logarithm (Yoda et al., 1963).

Fig. 6.18: The relationship between density and mean tree biomass has an upper limit that can not be passed. This means that a given plant population with many individuals can co-exist at high density but of small size, or on the contrary, at a low density but of big size. Any combination below the upper limit, which describes the so called ‘self-thinning line’, is possible, while any combination above the ‘self-thinning line’ is not possible.



To illustrate this theory, an example of real data is depicted in Fig. 6.19, showing the relationship between tree density and mean DBH and the self-thinning line of different tree species in Catalonia (Gracia et al., 1998-2003).

Fig. 6.19: Relationship between tree density and mean DBH, describing the self-thinning line of different tree species in Catalonia (Gracia et al, 1998-2003).



As mentioned above the results obtained in Approach 4 are in line with the self-thinning law and its effect on total biomass development. DBH classes below the defined threshold, the so called missing data, contribute to a large extend to the total number of trees per ha but only to a minor extend to total growing stock and carbon stock.

As it clearly exposed by the results above, the Weibull distribution performs very well in fitting DBH distributions above the defined thresholds. With respect to DBH classes below the defined thresholds instead, Weibull distribution does not coincide with biological characteristics of forests. Weibull function predicts that when mean DBH gets close to 0, the number of trees per ha also gets close to 0 which disagrees completely with the self-thinning law. Taking this aspect into account, it can be concluded that the Negative Exponential function describes much better the characteristics of young tree populations, predicting a maximum number of trees when the DBH are lowest.

In order to provide a more reliable basis for lower DBH classes, additional reference data are needed to calibrate/correct estimated values. The BioSoil project¹⁷ has been conducted under the Forest Focus scheme¹⁸, which expired in 2006. It demonstrated different options to supplement the Level I monitoring of the EC Forest Focus/ ICP Forests (16x16 km) by new assessments related to forest soils, carbon sequestration, biodiversity, climate change and protective functions of forests. The BioSoil assessment also include DBH measurements applying a threshold of 5 cm. Unfortunately there were only few Level I plots per test site available in this pilot study, and additional reference data were not representative for any assessment. However, using Level I as an additional sub-sampling with standardised DBH assessment would offer opportunities to calibrate NFI assessments and DBH estimates below applied NFI thresholds. Continuing assessments like in the BioSoil project on Level I also in future are regarded as crucial for the harmonisation of NFI variables, like of DBH distributions, growing stock and carbon stock. This is planned to be implemented within the FUTMON project¹⁹, which will be carried out under LIFE+ regulation²⁰ in the years 2009-2010. FUTMON foresees the integration of Level I and NFI plots on national scales and the assessment of core variables, following both, transnational standardised methodologies and national protocols.

¹⁷ <http://forest.jrc.ec.europa.eu/ForestFocus/biosoil.html>

¹⁸ Council Regulation (EC) No 2152/2003, Forest Focus Article 1(b)

¹⁹ See at: http://www.icp-forests.org/DocsTFM/FutMon_12Sept08.pdf

²⁰ Regulation (EC) No 614/2007 of the European Parliament and of the Council of 23 May 2007 concerning the Financial Instrument for the Environment (LIFE+).

Conclusions

Based on the obtained results and above discussion, following conclusions can be made:

- The 1 cm DBH class distribution provides statistically stronger and more clearly interpretable results. Differences between observed data and estimated data were lower than for the 5 cm classes.
- In general, Weibull distribution produced a higher goodness-of-fit than the Negative Exponential distribution. Although both distributions were successful in modelling observed NFI data, the Negative Exponential distribution overestimated DBH classes of bigger trees.
- For the Pyrenees, Saxony and merged data of Saxony plus Rhineland-Palatinate the Negative Exponential distribution produced better results (lower differences in percentage) when extrapolating to the missing values.
- Merged data from the Saxony and Rhineland-Palatinate test area gave very similar results to those of considering Saxony data only. This clearly shows that the proposed approach is applicable on a larger scale. Options of stratification into bio-climatic regions should be considered, when comparing data of one species at a larger scale (e.g. *Pinus Sylvestris* occurs in Saxony but also in the Pyrenees).
- The contribution of missing data varies between 12-50 % regarding tree density (nr. of trees/ha) and only 2-5 % regarding growing stock (m³/ha) and carbon stock (Mg/ha).
- The approach developed can be applied relative easily to any NFI data set. Estimates of missing DBH data below applied threshold can easily be obtained, thus allowing calculating rough estimates on growing stock and carbon stock according to all DBH classes and thresholds.

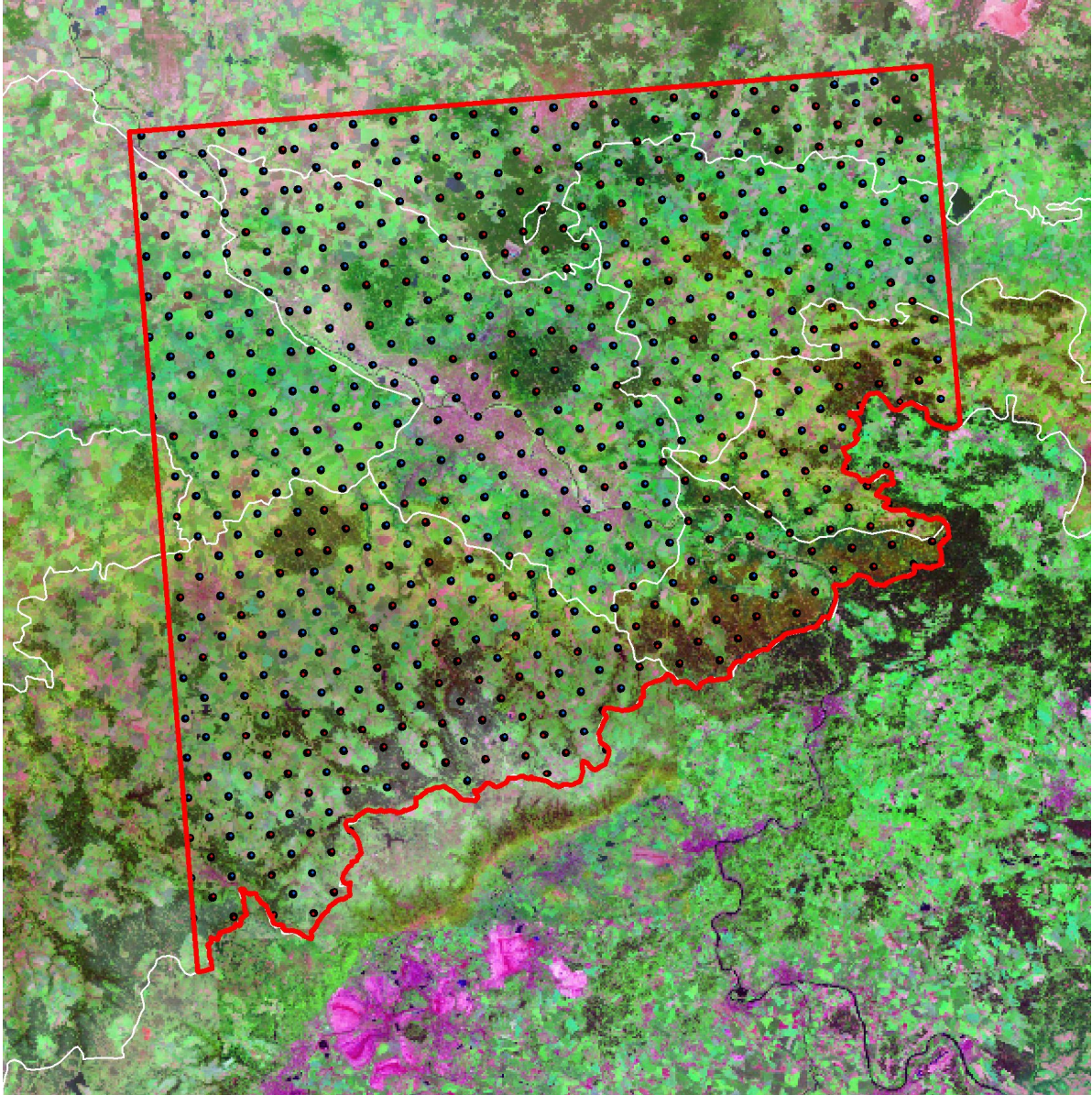
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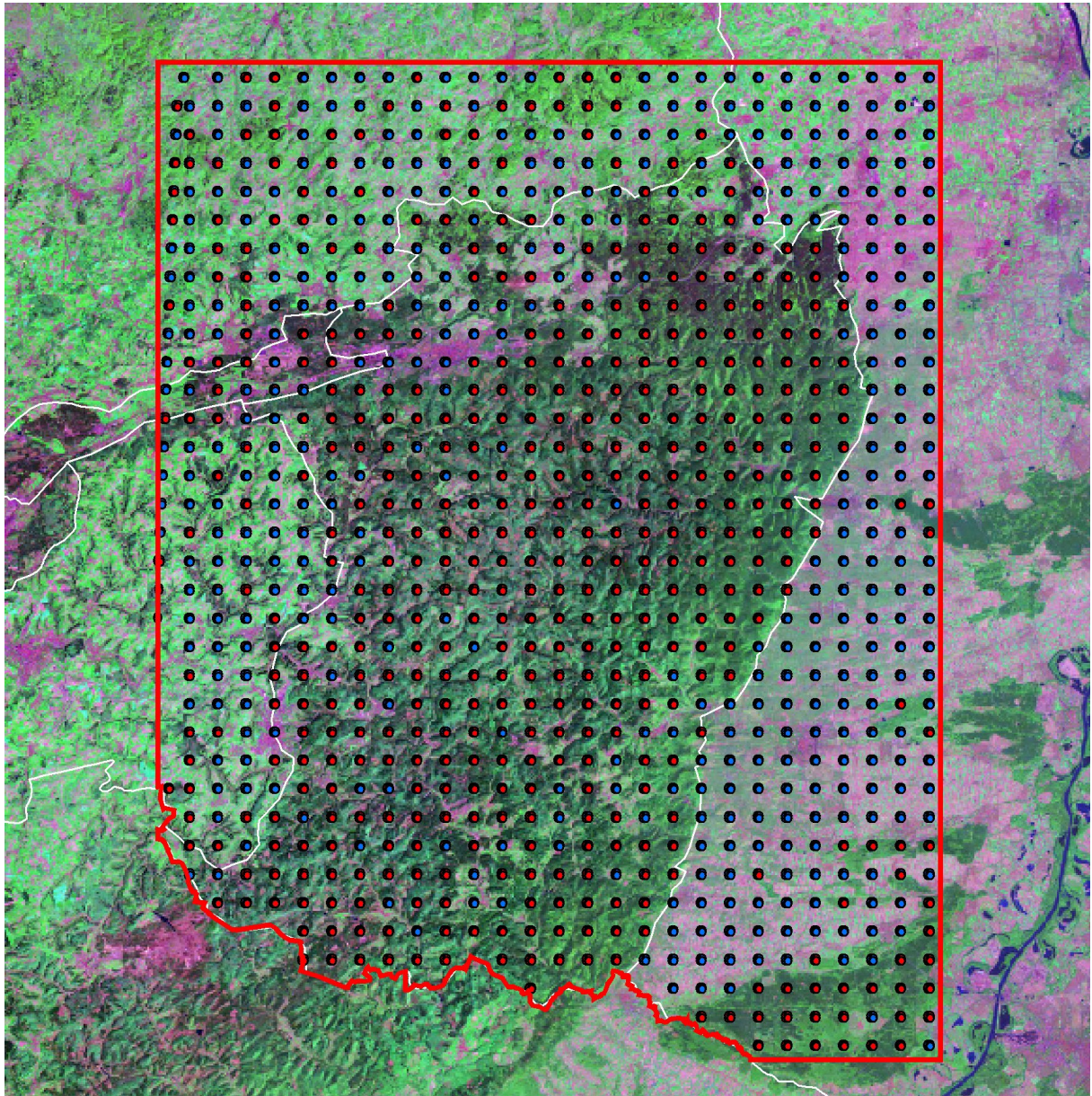
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Annex I – Test Sites

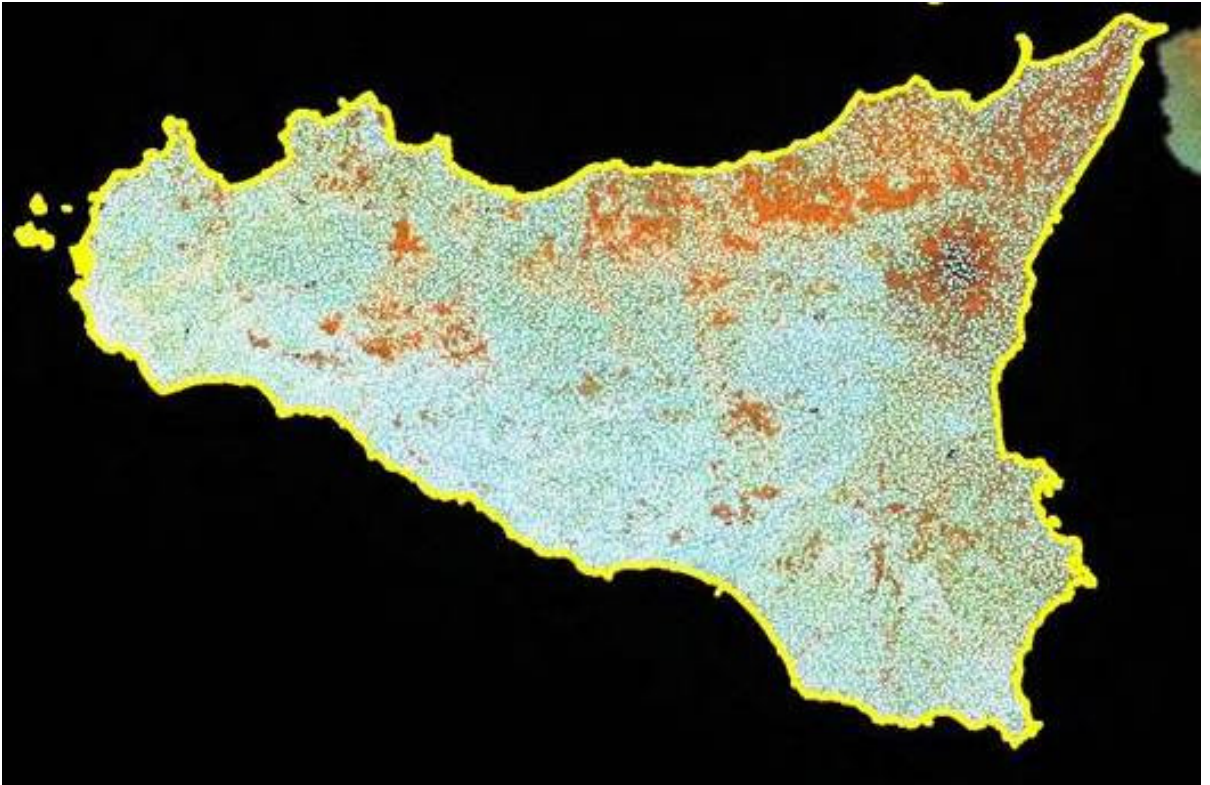
Germany – Saxony (5100 km²)



Germany - Rhineland-Palatinate (3600 km²)

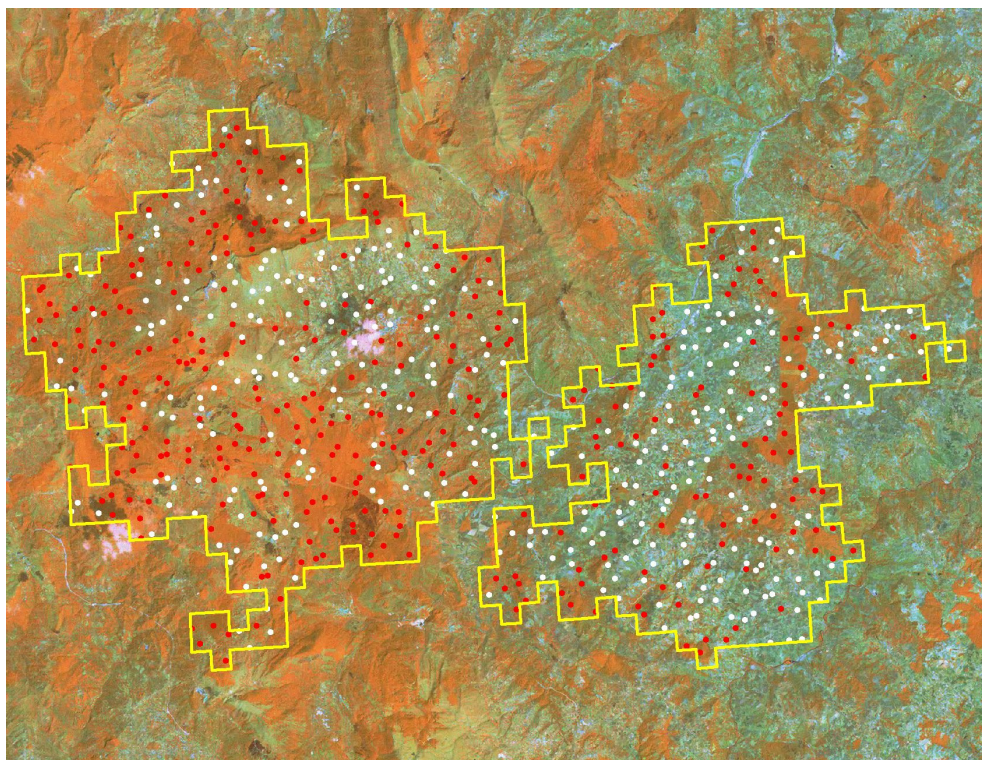


Italy – Sicily (25709 km²)



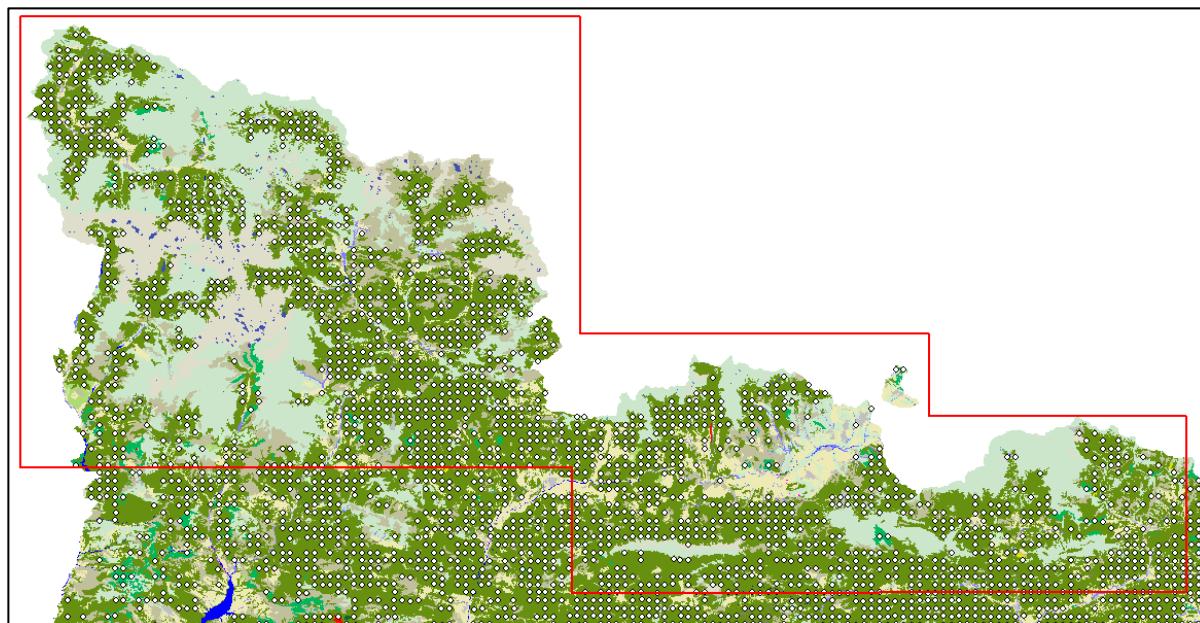
NFI plots location (red dots are forest, white dots are non forest)

Italy – Molise (709 km²)

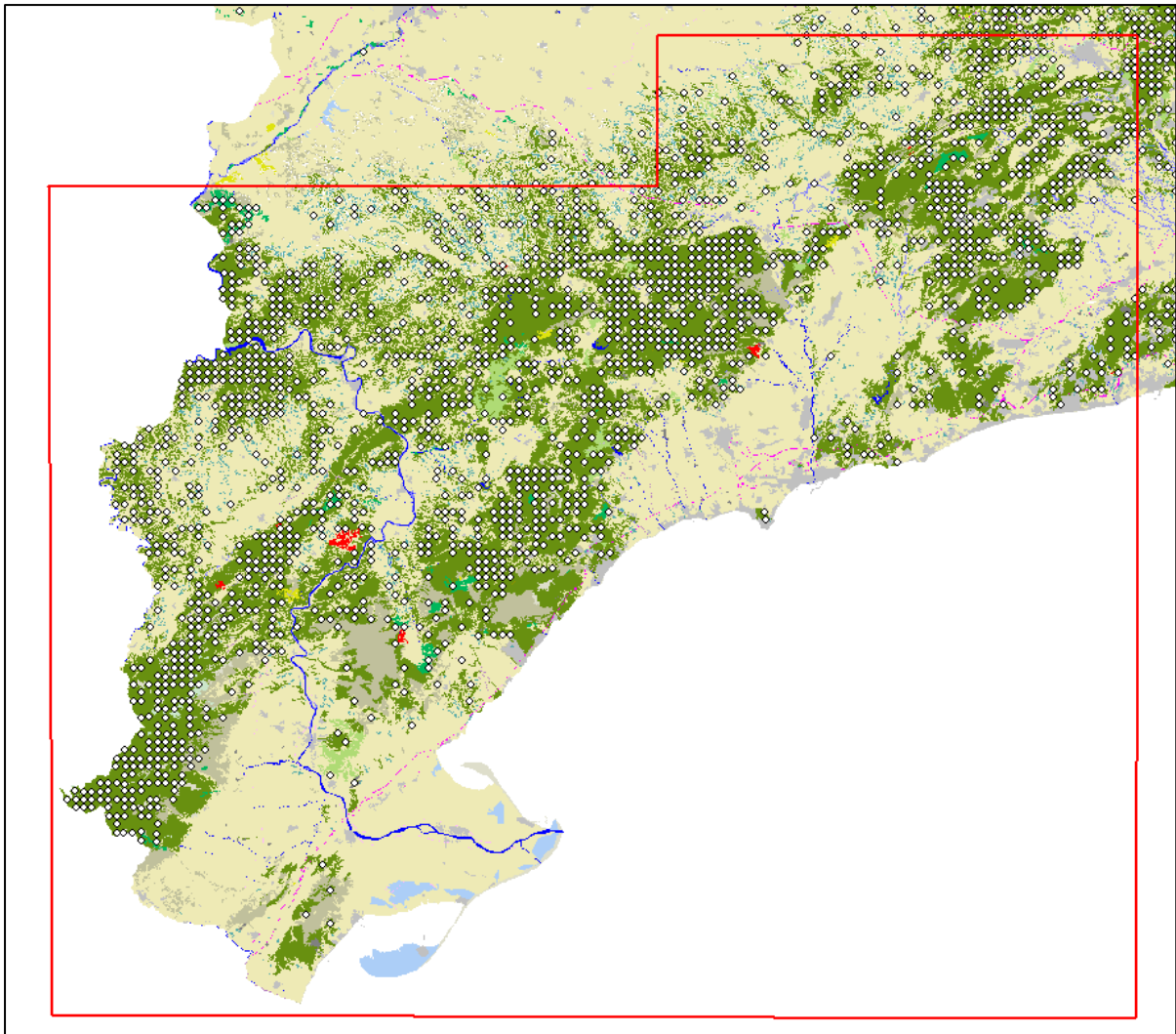


Local inventory plots location (red dots are forest, white dots are non forest)

Spain – Pyrenees (7900 km²)



Spain – Mediterranean area (4400 km²)



Annex II – Data and Database

A work package of the study was dedicated to the development of a project information database, which includes original input data and harmonised output data. Data can be queried according to a) the selected variables, b) the applied approach and c) for each test site. The database mainly includes metadata records, but also input and output data, which can be depicted either in tables, diagrams or maps. There are two versions available: a) one database that contains all input and output data, provided to JRC for internal use and project validation only and b) one public version, which contains only metadata records but no input or output data. Data can only be depicted as tables, graphs etc.

The database is written in HTML. Metadata records were collected according to the INPIRE metadata schema²¹ to assure consistency and interoperability with the European Forest Data Centre (EFDAC) maintained by JRC.²²

The list below provides some overview about the data used and produced in the project. It also lists, which data are available for internal use and validation by JRC.

Basically all data are available: Not available are original NFI plot data and DOPs for the two German test sites Saxony and Rhineland-Palatinate. Short explanations for this are given below the table.

²¹ <http://www.inspire-geoportal.eu/catalogues.htm>

²² <http://efdac.jrc.ec.europa.eu/>

Table 0.1: List of data used and produced in the study

Appr.	Name of Dataset	Data Availability	Type of Dataset	Format	Test site	Acquisition date (for Input data only)	Input / Output data
		= dataset available					
		= dataset available at JRC					
		= dataset not available / restricted access					
1	Forest mask (Landsat)	available	geo data	img	Saxony	2006	input
1	JRC Forest mask	available at JRC	geo data	img	Saxony	2000	input
1	DOP	only examples*	geo data	img	Saxony	2006	input
1	IWs	available	geo data	img	Saxony		output
1	IWs with Delinated Patches	available	shape file	shp	Saxony		output
1	Forest Patch Attribute Table	available	table	dbf/xml	Saxony		output
1	Scatter Plots	available	graphic	jpg	Saxony		output
1	Forest area	available	graphic/table	jpg/xls	Saxony		output
1	Forest mask (Aerial Photogr.)	available	geo data	img	Pyrenees	2000	input
1	JRC Forest mask	available at JRC	geo data	img	Pyrenees	2000	input
1	DOP	available	geo data	img	Pyrenees	2001-2003	input
1	IWs	available	geo data	img	Pyrenees		output
1	IWs with Delinated Patches	available	shape file	shp	Pyrenees		output
1	Forest Patch Attribute Table	available	table	dbf/xml	Pyrenees		output
1	Scatter Plots	available	graphic	jpg	Pyrenees		output
1	Forest area	available	graphic/table	jpg/xls	Pyrenees		output
2	Forest mask (Landsat)	s. Appr1	geo data	img	Saxony	2006	input
2	Landsat multispectral bands (northern part)	available at JRC	geo data	img	Saxony	2000	input
2	Landsat multispectral bands (southern part)	available at JRC	geo data	img	Saxony	2000	input
2	NFI plot data	not available**	table	xls	Saxony	2002	input
2	Level I data	available at JRC	table	xls	Saxony	2006	input

Appr.	Name of Dataset	Data Availability	Type of Dataset	Format	Test site	Acquisition date (for Input data only)	Input / Output data
2	NFI plots (categorical)	available	geo data	shp	Saxony		output
2	NFI plots (metrical)	available	geo data	shp	Saxony		output
2	Level I plots (reclassified)	available	geo data	shp	Saxony		output
2	kNN result (categorical data)	available	geo data	img	Saxony		output
2	kNN result (metrical data)	available	geo data	img	Saxony		output
2	Forest mask (Landsat)	s. Appr1	geo data	img	Rheinland Palatinate	2007	input
2	Landsat multispectral bands	available at JRC	geo data	img	Rheinland Palatinate	1999	input
2	NFI plot data	not available**	table	xls	Rheinland Palatinate	2002	input
2	Level I plot data	available at JRC	table	xls	Rheinland Palatinate	2006	input
2	NFI plots (categorical)	available	geo data	shp	Rheinland Palatinate		output
2	Level I plots (reclassified)	available	geo data	shp	Rheinland Palatinate		output
2	kNN result (categorical data)	available	geo data	img	Rheinland Palatinate		output
2	Forest mask (Landsat)	s. Appr1	geo data	img	Sicily	2000	input
2	Landsat multispectral bands (Eastern part)	available at JRC	geo data	img	Sicily	2000	input
2	Landsat multispectral bands (Western part)	available at JRC	geo data	img	Sicily	2000	input
2	NFI plot data	available	geodata	shp	Sicily	2005	input
2	Level I plot data	available at JRC	table		Sicily	2006	input
2	NFI plots (categorical)	available	geo data	shp	Sicily		output
2	NFI plots (metrical)	available	geo data	shp	Sicily		output
2	Level I plots (reclassified)	available	geo data	shp	Sicily		output
2	kNN result (categorical data)	available	geo data	img	Sicily		output
2	kNN result (metrical data)	available	geo data	img	Sicily		output
2	Forest mask (Landsat)	s. Appr1	geo data	img	Molise	2007	input
2	Landsat multispectral bands (subset of original image)	available at JRC	geo data	img	Molise	2000	input

Appr.	Name of Dataset	Data Availability	Type of Dataset	Format	Test site	Acquisition date (for Input data only)	Input / Output data
2	NFI plot data	available	geodata	shp	Molise	2005	input
2	Level I plot data	available at JRC	table	xls	Molise	2006	input
2	NFI plots (categorical)	available	geo data	shp	Molise		output
2	Level I plots (reclassified)	available	geo data	shp	Molise		output
2	kNN result (categorical data)	available	geo data	img	Molise		output
2	Forest mask (Aerial Phot.)	s. Appr1	geo data	img	South Catalonia	1997	input
2	Landsat multispectral bands	available at JRC	geo data	img	South Catalonia	2002	input
2	NFI plot data	available***	table	xls	South Catalonia	?	input
2	Level I plot data	available at JRC	table	xls	South Catalonia	2006	input
2	NFI plots (categorical)	available	geo data	shp	South Catalonia		output
2	Level I plots (reclassified)	available	geo data	shp	South Catalonia		output
2	Forest mask (Aerial Phot.)	s. Appr1	geo data	img	Pyrenees	1997	input
2	Landsat multispectral bands (Eastern part)	available at JRC	geo data	img	Pyrenees	2002	input
2	Landsat multispectral bands (Western part)	available at JRC	geo data	img	Pyrenees	2002	input
2	NFI plot data	available***	table	xls	Pyrenees	?	input
2	Level I plot data	available at JRC	table	xls	Pyrenees	2006	input
2	NFI plots (categorical)	available	geo data	shp	Pyrenees		ouput
2	Level I plots (reclassified)	available	geo data	shp	Pyrenees		ouput
2	kNN result (categorical data)	available	geo data	img	Pyrenees		output
3	Landsat multispectral bands	available at JRC	geo data	img/tif	Rheinland Palatinate		input
3	NFI plot data	not available**	geo data	shp	Rheinland Palatinate		input
3	Corine Land Cover	available at JRC	geo data	shp	Rheinland Palatinate		input
3	JRC Forest mask	available at JRC	geo data	img/tif	Rheinland Palatinate		input
3	Forest mask (Landsat)	s. Appr1	geo data	img	Rheinland Palatinate		input

Appr.	Name of Dataset	Data Availability	Type of Dataset	Format	Test site	Acquisition date (for Input data only)	Input / Output data
3A	NFI plot reclassified	available	geo data	shp	Rheinland Palatinate		output
3A	Forest type area	available	table	xls	Rheinland Palatinate		output
3A	Confusion matrix	available	table	xls	Rheinland Palatinate		output
3B (test 11, test 12)	Confusion matrix	available	table	xls	Rheinland Palatinate		output
3B (test 11, test 12)	Forest type area	available	table	xls	Rheinland Palatinate		output
3B (test 11, test 12)	Forest type map	available	geo data	shp	Rheinland Palatinate		output
3	Landsat multispectral bands	available at JRC	geo data	img/tif	Saxony		input
3	NFI plot data	not available**	geo data	shp	Saxony		input
3	Corine Land Cover	available at JRC	geo data	shp	Saxony		input
3	JRC Forest mask	available at JRC	geo data	img/tif	Saxony		input
3	Forest mask (only for Germany)	s. Appr1	geo data	img	Saxony		input
3A	NFI plot reclassified	available	geo data	shp	Saxony		output
3A	Forest type area	available	table	xls	Saxony		output
3A	Confusion matrix	available	table	xls	Saxony		output
3B (test 9, test 10)	Confusion matrix	available	table	xls	Saxony		output
3B (test 9, test 10)	Forest type area	available	table	xls	Saxony		output
3B (test 9, test 10)	Forest type map	available	geo data	shp	Saxony		output
3	Landsat multispectral bands	available at JRC	geo data	img/tif	Sicily	2000/2001	input
3	NFI plot data	available	geo data	shp	Sicily	2005	input
3	Corine Land Cover	available at JRC	geo data	shp	Sicily	2000	input
3	Forest mask (Landsat)	s. Appr1	geo data	TIF	Sicily	2000	input
3A	Confusion matrix	available	table	xls	Sicily		output
3B	NFI plot reclassified	available	geo data	shp	Sicily		output
3B (from test 1 to test 8)	Forest type area	available	table	xls	Sicily		output
3B (from test 1 to test 8)	Confusion matrix	available	table	xls	Sicily		output

Appr.	Name of Dataset	Data Availability	Type of Dataset	Format	Test site	Acquisition date (for Input data only)	Input / Output data
3B (from test 1 to test 8)	Forest type map	available	geo data	shp	Sicily		output
4	NFI plot data	available***	table	xls	Pyrenees	2000-2001	input
4	Volume equations	available	table	xls	Pyrenees	1989-1990	input
4	DBH fitted equations	available	table	xls	Pyrenees		output
4	Tree, volume and carbon estimations	available	table	xls	Pyrenees		output
4	NFI plot data	not available**	table	xls	Saxony	2002	input
4	DBH fitted equations	available	table	xls	Saxony		output
4	Tree, volume and carbon estimations	available	table	xls	Saxony		output

* DOP data of the test site Saxony were bought from the Landesvermessungsamt Sachsen in January 2007. Data are only available for internal use within this project and can not be disseminated to any other users. For validation only examples are submitted. For official data request for the total area, please contact: Landesvermessungsamt Sachsen, Postfach 10 02 44, 01072 Dresden, E-Mail: geodaten@lvs.n.smi.sachsen.de

** NFI data were provided by the Institute for Forest Ecology and Forest Inventory (vTI, Eberswalde). Data were provided only for internal use within this project and can not be disseminated to any other users. For data request please contact: Johann Heinrich von Thünen-Institute (vTI), Institute of Forest Ecology and Forest Inventory, Prof. Dr. Andreas Bolte, Alfred-Möller-Straße 1, D-16225 Eberswalde, E-mail: woi@vti.bund.de

*** NFI plot data are available, but with xy-coordinates deleted.

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Abstract

The objectives of the “Pilot study on harmonising National Forest Inventories in Europe” were demonstrating and implementing in real cases the harmonization of forest information using National Forest Inventory (NFI) data. The pilot study is thus a first attempt in Europe to provide harmonized NFI information at the supra-national level. Different technical approaches to harmonise selected NFI variables have been tested and evaluated. Four proposed approaches have been tested with real data for selected test sites in three different countries, namely Germany, Spain and Italy. For each of the three countries two test sites were selected, which represent different forest ecosystems but also most typical forests landscapes of the countries. This pilot project constitutes a first operational attempt to harmonize national datasets in order to derive a unique Forest Information database at European level that should allow the compilation and analysis of European forest datasets.

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