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ORIGINAL PAPER

Satellite-based stand-wise forest cover type mapping using a spatially adaptive classification approach

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Abstract Due to high variation in forest communities, forest structure and the fragmentation of the forested area in Central Europe, satellite-based forest inventory methods have to meet particularly high-quality requirements. This study presents an innovative method to combine official forest inventory information at stand level with multidate satellite imagery using a spatially adaptive classification approach for producing wall-to-wall forest cover maps of important tree species and management classes across multiple ownership regions in a heterogeneous low mountain range in Germany. The classification approach was applied to a 5,200-km^2 area (about 2,080 km^2 of forest land, mostly mixed forests) located in the Eifel mountain range in Central Europe. In comparison with conventional classifiers, our results demonstrate a significant increase in classification accuracy in the order of 12%. The method was tested with ASTER images but holds the potential to be used for regular state forest inventories based on standard and novel earth observation data supplied for instance from the SPOT-5 and RapidEye sensors.

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Introduction

Forest management considering economic and sustainability aspects needs periodic surveys about the state of forest. Modern forest inventory concepts are focused not only on timber production but also on the multiple functions of forests (as reservoirs of biodiversity, carbon sinks or recreation areas; Köhl 2003). Multiple national and international commitments for reporting on forest resources such as the Montréal Process (McRoberts et al. 2004), the Kyoto Protocol (UNFCCC 1998), the Convention on Sustainable Development and the Convention on Biological Diversity (Glowka et al. 1994) are leading to an increase in demand for expanded information on forest resources (McDonald and Lane 2004; Bolte et al. 2009). This is equally true for modified forest inventory objectives like the pan-European indicators for sustainable forest management of the Ministerial Conference on Protection of the Forests (MCPFE 2003). Accordingly, one of the most relevant objectives of satellite remote sensing has been forest cover mapping and the derivation of forest biophysical attributes (Wolter et al. 2009; Boyd and Danson 2005). Since the 1980s, many studies have focused on how remote sensing could support operational forest management (e.g., Bryant et al. 1980; Gemmell 1995; Kilpeläinen and Tokola 1999; Franco-Lopez et al. 2001; Reese et al. 2003; Conese et al. 1993) and contribute to forest ecosystem research (e.g., Ekstrand 1994; He and Mladenoff 1999; Schlerf et al. 2005). Within this international framework, a continuous development of adaptive regional forest management and forest protection strategies is needed.

In Germany, federal state authorities are responsible for information gathering, monitoring tasks, planning and sustainable forest management. According to § 7 of the Rhineland-Palatinate Forestry Act (LWaldG 2000), the duty does exist "to prepare management and economic plans for state, corporative and private forest."

Currently, in the Federal State of Rhineland-Palatinate (Germany), local forest management plans are based on databases comprising attributes of various forest stand characteristics such as detailed species composition, age information, timber volume and further management-relevant features. Traditionally, information is collected at stand level by measuring individual trees and sample plots complemented through the analysis of aerial photographs and expert knowledge (Peerenboom et al. 2003). Inventories so far relied solely on time-consuming field methods and are repeated every 5–10 years. Due to the prohibitive costs of this inventory concept, there is a strong interest in exploring remote sensing as replacement or complementary strategy (Diemer et al. 2000; Vohland et al. 2007). Emphasis is placed on detailed forest cover maps that, beyond their direct information content, can be used as stratification layer for reducing or optimizing field sampling efforts.

Within this context, the federal state forest survey of Rhineland-Palatinate has defined the following requirements:

- Derivation of spatially explicit forest attributes at stand level.
- Spatial discrimination of five primary forest cover classes (oak, European beech, Norway spruce, Douglas fir and Scots pine) and three species development stages (stand qualification, dimensioning and maturing).
- Direct integration of existing forest inventory data as reference information.
- Use of remote-sensing-based mapping and inventory techniques compatible to standard field survey methods currently conducted on a regular 5-year basis in Rhineland-Palatinate.

Remote sensing techniques, parametric and non-parametric classification methods have been widely tested and applied in various studies to derive forest structural attributes such as tree species composition (e.g., Wolter et al. 1995; Reese et al. 2002; Luther et al. 2006; Magnussen et al. 2004) and stand age (e.g., Cohen et al. 1995, 2001; Franklin et al. 2001; Lefsky et al. 2005).

Traditional statistical classifiers, such as the maximum likelihood classifier, are often used in remote sensing and are well described. These statistical classifiers provide optimal or near-optimal decisions on the cover type if suitable reference data are available and if a multivariate normal distribution of spectral values of pixels belonging to a thematic class is a reasonable assumption (Franklin and Wulder 2002; Swain and Davis 1978; Richards and Jia 2006; Sohn and Rebello 2002). If these requirements are met, maximum likelihood technique is a powerful tool for remote sensing data classification. However, because of the regional differences in growing conditions, the spectral variability within the same tree class is often greater than between different species. As a consequence, traditional per-pixel classifiers with constant class parameters must encounter problems in the derivation of forest stand type maps (Hill et al. 2010; Wolter et al. 1995; Dorren et al. 2003). It should be emphasized that spatially inconsistent class descriptors are a general problem of remote sensing mapping approaches and affect parametric and non-parametric classifiers such as support vector machines or artificial neural network classifiers.

Besides the parametric classification methods described above, integration of terrestrial forest plot data and remotely sensed imagery by means of nearest neighbor algorithms, such as the k-nearest neighbor method (k-NN) described by Franco-Lopez et al. (2001), have shown promising results for estimating forest structure information in large and homogeneous forests (McRoberts and Tomppo 2007). Nearest neighbor techniques have been successfully applied in Northern Europe (Katila and Tomppo 2001; Reese et al. 2003) and North America (Franco-Lopez et al. 2001; Lemay et al. 2008; McRoberts 2009) to produce reliable forest resource information at national and province levels. The advantages of kNN approaches are their simplicity, the simultaneous calculation of all variables and the preservation of between-variable consistency (Barth et al. 2009; Tomppo and Halme 2004).

Applying this approach, however, to forests within the German low mountain ranges has proven less successful, mainly because forests in Central Europe are more fragmented (due to diverse management preferences), more tree species of interest occur within widely distributed mixed stands and various silviculture practices are being applied repeatedly (Fig. 1). Studies from North Rhine-Westphalia (Diemer 1999; Diemer et al. 2000) and some small-sized study areas in Germany of around 2,000–6,000 hectares (e.g., Scheuber 2009; Stürmer and Köhl 2005) have shown that the accuracy of the kNN-derived tree cover maps was insufficient for the integration in forest management strategies and plans.

Objectives

The nearest neighbor methods discussed above have been developed for large-area inventories at regional level with a

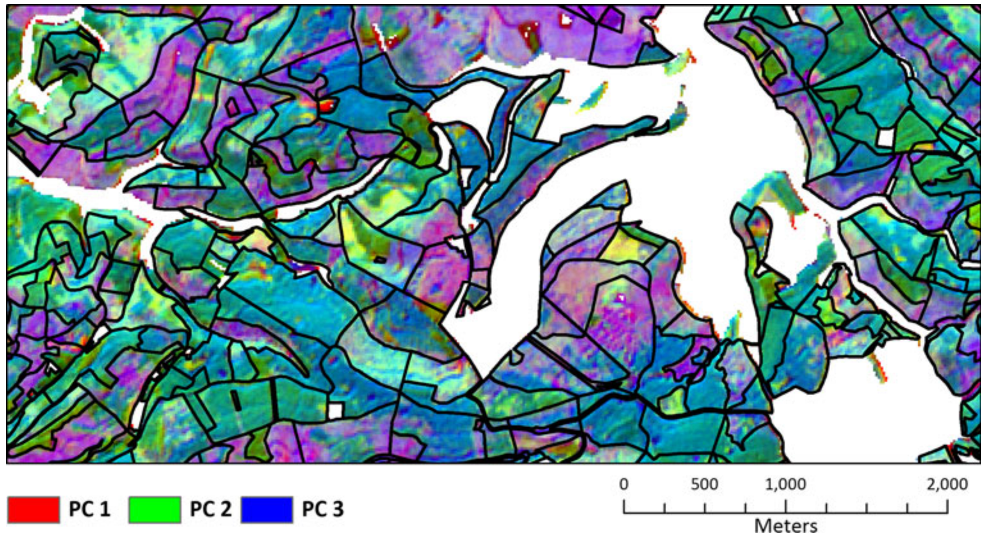

Fig. 1 High variation in forest communities, forest structure and the fragmentation of forested areas in Rhineland-Palatinate. First principal components of multiphenological ASTER data (June 26, 2001, and April 6, 2005) overlaid with stand borders from forest inventory data set

homogeneous forest and ownership structure in mind and are therefore not appropriate to achieve the specific objectives of the state forest survey. On the other hand, also traditional per-pixel classifiers encounter difficulties in consistently separating similar forest cover classes in spatially diverse study areas with varying growth conditions.

Here, we propose a new method for producing spatially explicit tree distribution maps at stand level based on multitemporal satellite observations. The approach is capable of accounting for spectral signature variations within a single tree class which are caused by climatic gradients and gradually changing site characteristics as well as inherited management decisions and silvicultural practices applied in adjacent forests under different ownership or custody. To account for these disturbances, we modified the traditional maximum likelihood classification approach such that it can be operated with spatially adapted and optimized class parameters. Additionally, it can be expected that the required mapping accuracies for operational services can only be achieved by incorporating the discrimination power of phenological dynamics. Therefore, the proposed classification strategy was combined with an optimized processing concept for handling multitemporal satellite observations. This can be broken down into the following objectives:

- Establish an optimized processing chain for handling multitemporal satellite observations (geometric and radiometric corrections).
- Develop a concept for smooth integration of public forest inventory information into a largely automatized classification concept.
- Implement a spatially adaptive training scheme for optimizing the maximum likelihood classifier, which is able to discriminate at least fifteen forest cover classes composed of tree species (Pedunculate and Sessile oak, European beech, Norway spruce, Douglas fir, Scots pine) and their development stages (qualification, dimensioning and maturation) across heterogeneous growth regions.
- Implement an adequate validation strategy.

Materials and methods

Study area

The study area covers important ecological gradients in the southern and eastern parts of the Eifel low mountain range in Central Europe (see Fig. 2). The Eifel, part of the Rhenish Hercynian uplands, is characterized by steep forested hills with elevations up to 700 m above sea level and high plateaus dominated by farmland and pasture. Bounded on the north, east and south by the river valleys of the Ahr, Rhine and Moselle, the study area covers more than 5,200 square kilometers with 2,080 square kilometers of forest and stretches across several bioclimatic growth regions. Although the principal parent material is of devonic origin (mainly slate), vast regions are dominated by Devonian carbonate rocks and Tertiary pyroclastic deposits. Both topography and parent material have resulted in a varied soil development. The sub-Atlantic climate in the investigated area is modified by an altitude-related gradient. Mean annual rainfall ranges from 685 to 914 mm and mean annual temperature from 7.4 to 9.4°C. The growing season, defined as the period when the daily mean temperatures exceed 10°C on consecutive days, varies on average from 146 days in the mountainous parts to about 173 days in the river valleys. According to the variability of climate and the natural environment, the study area is divided into five growing regions with different phenological stages. The current landscape of the Eifel low mountain range is largely forested (>40% forest cover) and shows a mosaic of forest communities. The dominant native trees are European beech (Fagus silvatica L.), Pedunculate and Sessile oak (Quercus robur L. and Quercus petraea (Mattuschka) Liebl.) and Norway spruce (Picea abies (L.) H. Karst.). Forest structure and composition are controlled primarily by physiography, agricultural history and forest management systems. During historical times, the Eifel region had experienced substantial deforestation dynamics with a widespread conversion from mixed deciduous forest to heathlands and moorlands (Kilian 1998). Since the late 18th century, these heathlands and abandoned farmland were reforested primarily with Norway spruce and Scots Pine (Pinus sylvestris L.), while existing beech and oak stands were partially replaced by Norway spruce and, to some extent, by Douglas fir (Pseudotsuga menziesii (Mirbel) Franco). A gradual conversion toward mixed forests began not earlier than in the late 1980s.

Many forest stands in private and municipal ownership were formerly used as coppice forests and nowadays differ in structure and composition from the majority of remaining forests. The medieval system of coppicing existed until the 18th and 19th centuries and secured the availability of wood, charcoal and tanbark. These forests prevail on steep slopes, especially in the valley of the Moselle River and its tributaries. Coppicing is still in practice or has only recently been abandoned (Ostermann and Reif 2000).

Satellite data

Suitable satellite data for the purpose of a study like this need to have a sufficient spectral resolution to ensure a reliable discrimination of different forest cover types (Dymond et al. 2002), while a high spatial resolution is required to accurately depict small forest stands and to adequately characterize forest biophysical parameters (Wolter et al. 2009). Additionally, the system should provide frequent repetition cycles as multitemporal observation is a key asset for separating otherwise spectrally similar species. At present, several satellite systems are

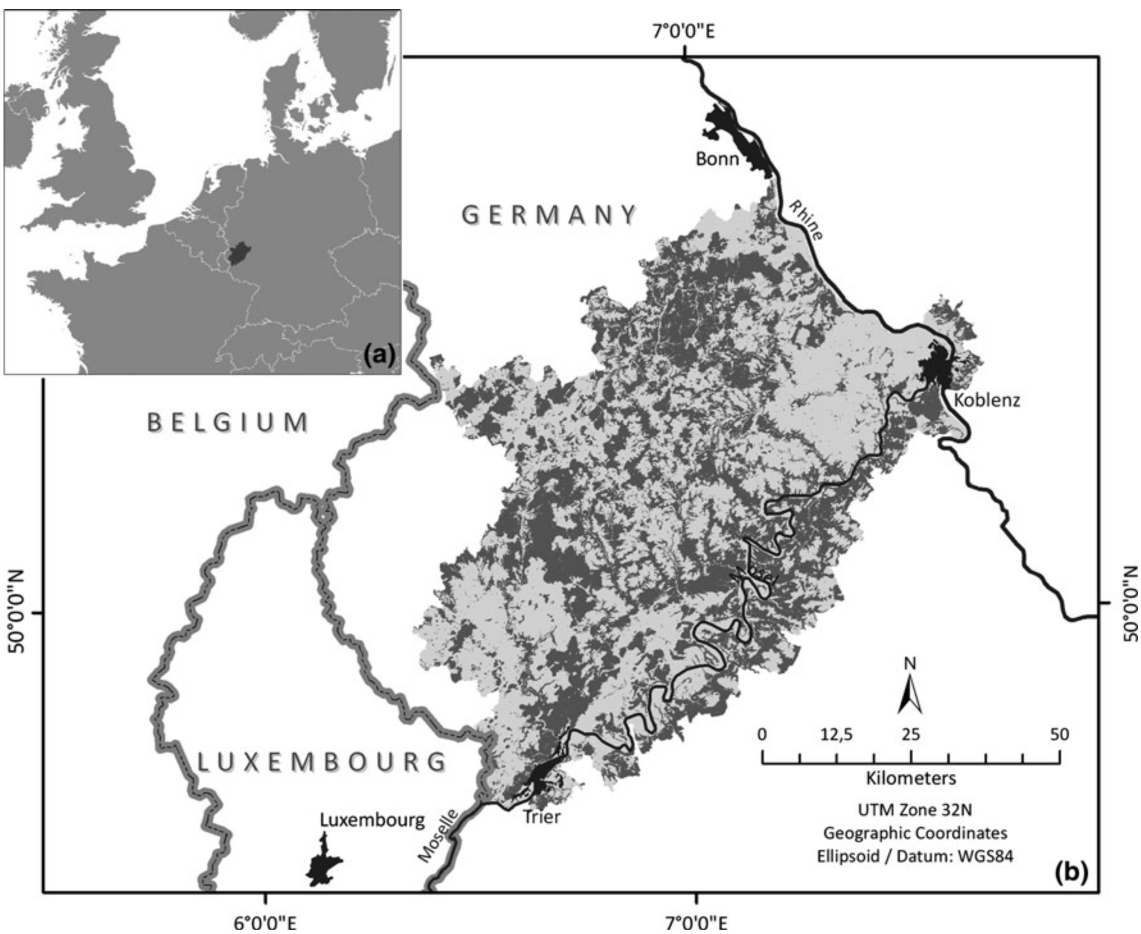

Fig. 2 Study area: **a** Location of the study area in Central Europe and **b** detailed map of the study area (*light grey*) the spatial distribution of forested areas (*dark grey*)

Table 1 ASTER VNIR and SWIR instrument specifications (Abrams 2000)

Subsystem (wavelength region)	VNIR	SWIR
Bandwidth (µm)		Band 4: 1.600–1.700
	Band 1: 0.52–0.60	Band 5: 2.145–2.185
	Band 2: 0.63–0.69	Band 6: 2.185–2.225
	Band 3: 0.76–0.86	Band 7: 2.235–2.285
		Band 8: 2.295–2.365
		Band 9: 2.360–2.430
Spatial resolution (m)	15	30
Swath width (km)	60	60

available, which fulfill these requirements almost perfectly (e.g., SPOT-4/5, RapidEye); the forthcoming Sentinel-2 mission will provide the required data continuity (Martimort et al. 2011).

The ASTER (Advanced Space Borne Thermal Emission and Reflection Radiometer) multispectral imager onboard NASA's Terra satellite is also largely compliant with these requirements; with regard to this explorative study, ASTER offered the advantage that archived data from a suitable time window were available at low cost. ASTER has three separate imaging subsystems (Table 1), which cover the visible and near-infrared (VNIR), the shortwave infrared (SWIR) and the thermal infrared (TIR) spectral ranges with 3, 6 and 5 spectral bands with spatial resolutions of 15, 30 and 90 m, respectively (Abrams 2000).

The selection of ASTER spectral bands for this study included channels 1–3, primarily designed for assessing vegetation properties. Additionally, channel 4 was used since the 1.6 µm spectral range has shown to significantly increase the separability of forest structures (Brockhaus and Khorram 1992; Moore and Bauer 1990). From the especially narrow bands in the 2–2.5 µm range, conceptualized mainly for the purpose of surface soil and mineral mapping (Yamagushi et al. 1998), a single broad bandwidth channel centered at 2.2 µm was synthesized by averaging channel 5–7, thereby prioritizing improved signal-to-noise ratio versus spectral resolution considered less important for our study purpose. No thermal bands were used in the classification process.

To increase species discrimination, two ASTER scenes were used, which represent the most important phenological stages of foliage formation and fully developed foliage (April 6, 2005 and June 26, 2001). Earlier research has confirmed that the spectral separability of deciduous tree species can be substantially increased if the combined satellite observations capture this phenological change (Dymond et al. 2002; Hill et al. 2010; Mickelson 1998; Schriever and Congalton 1995). Ideally, multitemporal satellite observations should be collected within the same year. However, considering the usually limited rate and spatial impact of management interventions and calamities within forest ecosystems, the State Forest Administration suggested that data acquisition windows for this type of inventories may be extended toward several years. Accepting multiannual time lags substantially increases operational flexibilities but should be subject to careful quality checks; in this study, clear cuts incurred between 2001 and 2005 had been removed from the data set when establishing an up-to-date forest/non-forest mask.

Satellite data processing

Several specific processing steps were applied for optimizing the quality of the ASTER data with regard to the subsequent classification process.

Resolution enhancement

Since remote sensing data with medium spatial resolution have only been of limited use for the identification of species compositions (Wulder 1998), the reduced spatial resolution of the ASTER channels in the SWIR range (i.e., 4 and the synthesized channel 5) has been adjusted to match the 15-m pixel size of the visible and near-infrared bands (1–3). The data fusion was performed with a local correlation approach that preserves the spectral characteristics of the low-resolution input and transfers the textural properties of the high-resolution reference to the ASTER–SWIR channels (Hill et al. 1999); the latter contribute essential information on structural canopy properties. The method had proven its suitability in an independent comparison study (de Boissezon and Laporterie-Déjean 2003), and it can be expected that the resulting spatial resolution improvement has a positive impact on the identification of small forest structures.

Geometric registration

Any type of multidate image analysis requires an accurate geometric correction of the data to enable a meaningful analysis. The geometric correction of both ASTER data sets involved the use of a digital elevation model for compensating relief-dependent pixel displacements, which otherwise would negatively impact the classification results (Verbyla and Hammond 1995; Dai and Khorram 1998; Townshend et al. 1992). The resulting ortho-projected data sets were referenced to the Gauss–Krüger coordinate system with subpixel accuracy, thereby fulfilling all requirements for an efficient integration of external database information as well as for executing a classification process that involves two coregistered images.

Atmospheric correction

In principal, parametric classification algorithms do not require image signals to be converted from digital counts to radiance or reflectance values. However, one of the most important problems in mapping forest types in mountainous regions emerges from radiometric distortions of the measured signal due to slope-dependant illumination effects (Hale and Rock 2003; Itten et al. 1992). This effect is particularly strong in our study area where major morphological features extend almost orthogonally to the illumination azimuth. One of the most efficient strategies for compensating the resulting radiometric distortions is to integrate the topographic normalization into an atmospheric correction scheme since explicitly accounting for direct and diffuse irradiance fluxes largely avoids overcorrection effects. The implemented radiometric correction scheme comprises sensor calibration based on ASTER calibration functions (Arai and Tonooka 2005) and full radiative transfer modeling by the AtCPro© code (Hill and Sturm 1991; Hill and Mehl 2003), which is based on the 5S model by Tanré et al. (1990). AtCPro© considers direct and diffuse radiance terms, which are modified according to local elevation, slope and aspect derived from the digital elevation model. This approach has proven to be largely superior to simple cosine corrections which are highly sensitive to overcorrection effects (Hill et al. 1995). Several studies confirm that this type of preprocessing leads to substantial improvements in classification results (Song et al. 2001; Hale and Rock 2003; Meyer et al. 1993).

Stratification

Given the objective to optimize forest mapping, the geometrically and radiometrically preprocessed two-date ASTER data set was stratified into forest and non-forest areas based on an unsupervised classification with the standard ISODATA algorithm (Ball and Hall 1965). The resulting stratum of the total forest area, including forests in private ownership, was validated using an official state GIS including landscape elements in vectorized form. With regard to this reference, an overall accuracy of 97.5% was achieved for the forest/non-forest distinction.

Data transformation

The final processing step before setting up the improved classification and mapping approach involved a principal component transformation of the multidate ASTER data set ($2 \times 5 = 10$ spectral bands) within the area identified as forest stratum. This transformation represents an efficient approach for enhancing the signal-to-noise ratio, reducing data dimensionality and eliminating intercorrelation effects, altogether properties that increase the efficiency of maximum likelihood classifiers (Green et al. 1988; Conese et al. 1988; Richards and Jia 2006). The first four principal components, which explained more than 98% of the variance of the original multidate data set, were retained for the classification process.

Reference data processing

Detailed inventory data at stand level were available for all public (i.e., state and communal) forests through the geo-referenced information system WÖFIS, which is operated by the state forest administration of Rhineland-Palatinate. The database documents approximately 60% of the forested land in this study, and information is collected as part of the regular expert surveys (Forsteinrichtung) carried out at 5–10-year intervals, complemented by Bitterlich sampling and the analysis of aerial photographs (Peerenboom et al. 2003). The position of each stand is stored in a GIS database, associated with numerous attributes (such as species composition, stand structure, development stages, stand density and volume) and additional site characteristics (such as growing conditions, geology, soil, climate and stand history). For each tree species within a forest stand, age class, stand structure and thinning operations are described by a multifunctional definition, which is based on the following distinct development stages:

- establishment (stand foundation and establishment of seedlings)
- qualification (thickets)
- dimensioning (crop tree definition and selective thinning)
- maturation (timber stage)

A forest stand may include several tree species; on average, it comprises two or three main tree species in mixtures. The main tree species Pedunculate and Sessile oak, European beech, Norway spruce, Douglas fir and Scots pine represent more than 92% (1,311 km^2 of 1,414 km^2) of the total forest in public ownership (Table 2). Therefore, the mapping approach is focused on these most important tree species. Stand polygons range in size from 0.05 to 73 ha with an average of 4.5 ha. The forest inventory data provided by the state forest administration is primarily designed for forest management purposes. Accordingly, the within-stand distribution of tree species and development stages are only qualitatively expressed in the form of estimated area proportions but not explicitly localized within the stand. For developing an approach with operational capacities for repeated state forest inventories, it was therefore essential to establish an optimized processing chain for direct integration of forest inventory data in the classification process.

Screening of potential training areas

With the exception of pure stands, the within-stand variability of tree species prevents the immediate integration of inventory information for generating representative training data for the maximum likelihood classifier. Consequently, a preselection of suitable spatial units that represent specific tree species and development stages was necessary.

Based on the GIS layer, forest stands were grouped into 15 thematic classes according to main tree species (European beech; Pedunculate and Sessile oak; Norway spruce; Douglas fir; Scots pine) and development stages (qualification; dimensioning; maturation). It should be noted that the development stage "establishment" was not considered in this work owing to the lack of suitable training areas. Potential training stands for a specific class had to fulfill the following requirements:

- not be part of a multilayer stand architecture,
- not be declared as continuously mixed stand,
- be the dominant species in terms of area within the stand.

For each accepted stand, image subsets of the principal-component-transformed ASTER data set were extracted by intersecting the image with the corresponding stand geometries. Then, each of the extracted image was subset spatially segmented into five spectral subclasses by applying an ISODATA cluster algorithm to identify the largest spectrally homogeneous areas, using an approach similar to the method of guided clustering presented by Bauer et al. (1994) and Reese et al. (2002). Based on transformed divergence values, high-spatial-resolution aerial imagery, forest inventory descriptions and field measurements, clusters were labeled either as representative for one of the 15 thematic classes or as ambiguous. Areas corresponding to the accepted clusters were marked as potential reference areas for the point-sampling process described below. Areas described as ambiguous were assumed to be composed of mixed canopies, e.g., at stand boundaries, shaded areas or other disturbances, therefore considered as unsuitable for training purposes and discarded from further analysis. This procedure led to the elimination of 30% of GIS-selected polygons for the cover classes Norway spruce and Douglas fir and up to 70% for the cover classes beech, oak and Scots pine. Only the most homogeneous and spectrally representative areas were thus retained in the final GIS database for further use.

Selecting training data

The final extraction of spectral reference data for parameterizing the classifier was based on a regular sampling grid superposed on the identified candidate areas. To avoid spatial autocorrelation among reference pixels that are contiguous or close together (Campbell 1981; Gong and Howarth 1990), a 100 × 100 m interval was chosen for systematic sampling. With the restriction of being only selectable from within the admitted areas (resulting from the previously described screening process), spectral reference information was extracted from more than 54,000

Table 2 Forest cover classes and proportion of main tree species of the total forest cover in forests in public ownership as defined by FIS (forest information system) selection

Species	Proportion of forest cover (%)		Forest cover class name
Pedunculate and Sessile oak *(Quercus robur L. and Quercus petraea (Mattuschka) Liebl.)*	26.6	4.2	Oak/qualification
		16.9	Oak/dimensioning
		5.5	Oak/maturation
European Beech *(Fagus silvatica L.)*	20.1	2.4	Beech/qualification
		12.1	Beech/dimensioning
		5.6	Beech/maturation
Norway spruce *(Picea abies (L.) H. Karst.)*	28.3	2.5	Spruce/qualification
		20.1	Spruce/dimensioning
		5.7	Spruce/maturation
Douglas fir (Pseudotsuga menziesii (Mirbel) Franco).	10	0.8	Douglas fir/qualification
		9.1	Douglas fir/dimensioning
		0.1	Douglas fir/maturation
Scots pine *(Pinus sylvestris L.)*	7.7	0.2	Pine/qualification
		6.2	Pine/dimensioning
		1.3	Pine/maturation

reference points (Table 3). The large number of reference data increased the probability that each thematic class is represented by a sufficient number of individuals (Swain and Davis 1978) across each ecoregion.

Visual inspection of histograms for the resulting spectral class signatures confirmed that the prerequisite of low within-class variance and nearly normal (Gaussian) distribution was fulfilled. All appropriate signatures were integrated into a database and used in the classification process.

Spatially adaptive implementation of the maximum likelihood classifier

Supervised classification approaches aim to produce thematic maps derived from multispectral satellite imagery. Based on the principle that different land cover types are characterized by specific reflectance properties, classification algorithms can distinguish these cover types according to their position in the multispectral feature space (Richards and Jia 2006). A number of parametric and nonparametric classification methods have been widely tested and applied in various national forest inventories as well as for the characterization of forest biophysical attributes (e.g., McRoberts and Tomppo 2007; Wulder 1998; Xie et al. 2008; Hall et al. 1995). Among supervised classification methods for multispectral data, the maximum likelihood classifier is one of the most commonly used method. It is a parametric approach that models the statistical distribution of spectral classes in multivariate feature space by class mean vectors and variance–covariance matrices; it assumes a multivariate normal distribution of spectral values describing a given class (Richards and Jia 2006).

The maximum likelihood decision rule

Let the forest cover classes described above be represented by $\omega_i, i = 1, \ldots, K$ where K is the total number of classes. In order to determine the class membership of a pixel with spectral signature $\mathbf{x}$, the conditional probabilities $P(\omega_i|\mathbf{x}), i = 1, \ldots, K$ have to be inferred. The vector $\mathbf{x}$ is a column vector of brightness values for a pixel, and the probabilities stated above give the likelihood that the correct class to be assigned to the pixel is ω_i, given the observed spectral signature $\mathbf{x}$. A maximum likelihood classifier assigns to the pixel the class ω_i for which this probability is largest:

$$\mathbf{x} \in \omega_i \quad \text{if } P(\omega_i|\mathbf{x}) > P(\omega_j|\mathbf{x}) \quad \text{for all } i \neq j$$

Assuming a multivariate normal distribution of the spectral values of N bands in a given class, the conditional probability of observing a specific spectral signature in this class is

$$P(\mathbf{x}|\omega_i) = (2\pi)^{-N/2}|\Sigma_i|^{-1/2} \exp\left[-\frac{1}{2}(\mathbf{x} - \mathbf{m}_i)^T \sum_i^{-1} \mathbf{x} - \mathbf{m}_i\right] \tag{1}$$

where $\mathbf{m}_i$ is the mean spectral signature of class ω_i and Σ_i the variance–covariance matrix. Both $\mathbf{m}_i$ and Σ_i have to be estimated from training data. The quadratic form

$$(\mathbf{x} - \mathbf{m}_i)^T \sum_i^{-1} (\mathbf{x} - \mathbf{m}_i), \tag{2}$$

Table 3 Total number of reference points for each forest cover class as defined by GIS selection

Tree species	Development stage	Number of sample points	Total number of sample points per tree species
Pedunculate and Sessile oak	Stand qualification	142	11,427
	Dimensioning	6,325	
	Maturation	4,960	
European Beech	Stand qualification	1,275	9,493
	Dimensioning	5,328	
	Maturation	2,890	
Norway spruce	Stand qualification	1,706	15,606
	Dimensioning	6,431	
	Maturation	7,496	
Douglas fir	Stand qualification	828	6,768
	Dimensioning	5,823	
	Maturation	117	
Scots pine	Stand qualification	0	7,363
	Dimensioning	374	
	Maturation	1,668	

known as the Mahalanobis distance, measures the distance between $\mathbf{x}$ and the class mean $\mathbf{m}_i$, scaled according to variance and covariance of the class (Swain and Davis 1978; Richards and Jia 2006).

The available $P(\mathbf{x}|\omega_i)$ and the desired $P(\omega_i|\mathbf{x})$ are related by Bayes' Theorem:

$$P(\omega_i|\mathbf{x}) = \frac{P(\mathbf{x}|\omega_i)P(\omega_i)}{\sum_{i=1}^{K} P(\mathbf{x}|\omega_i)P(\omega_i)} \tag{3}$$

The prior probability $P(\omega_i)$ is the probability of occurrence of class ω_i in the study area considered. Ignoring the common divisor

$$\sum_{i=1}^{K} P(\mathbf{x}|\omega_i)P(\omega_i), \tag{4}$$

the maximum likelihood rule can now be stated as

$$\mathbf{x} \in \omega_i \quad \text{if } P(\mathbf{x}|\omega_i)P(\omega_i) > P(\mathbf{x}|\omega_j)P(\omega_j) \quad \text{for all } i \neq j \tag{5}$$

In the absence of any further information about $P(\omega_i)$, a reasonable assumption is that the prior probabilities of occurrence are equal for all classes. In this case, $P(\omega_i)$ can be treated as a constant and the rule simplifies to

$$\mathbf{x} \in \omega_i \quad \text{if } P(\mathbf{x}|\omega_i) > P(\mathbf{x}|\omega_j) \quad \text{for all } i \neq j \tag{6}$$

This rule can be implemented using only Eq. 1. By removing constants that do not contribute to discrimination and noting that the natural logarithm is a monotonous function, Eq. 1 can be simplified to achieve computational efficiency, leaving

$$f_i(\mathbf{x}) = -\mathrm{In}|\Sigma_i| - (\mathbf{x} - \mathbf{m}_i)^T \sum_i^{-1} (\mathbf{x} - \mathbf{m}_i) \tag{7}$$

as a discriminant function. Using logarithms, the probability $P(\mathbf{x}|\omega_i)$ is $f_i(\mathbf{x})$ is minimized. Thus, the final statement

$$\mathbf{x} \in \omega_i \quad \text{if } f_i(\mathbf{x}) < f_j(\mathbf{x}) \quad \text{for all } i \neq j \tag{8}$$

is an efficient implementation of the maximum likelihood rule (Richards and Jia 2006).

Although more advanced classification concepts (such as artificial neural networks, support vector machines, genetic algorithms) have been successfully tested regarding their application to earth observation data (Foody 2004; Foody et al. 2007; Knorn et al. 2009; Waske and Benediktsson 2007), the classical maximum likelihood concept still is considered an efficient classifier as long as the conceptual requirements (consistent training information, sufficient number of training areas, normal distribution of class descriptors) are observed (Swain and Davis 1978; Franklin and Wulder 2002). Most importantly, in comparison with the alternative classifiers listed above, it is computationally less demanding with regard to the training phase, and it offers strategic options for optimized implementation; these are substantial advantages that still qualify the maximum likelihood concept as a prime option.

Limitations to classifier performance emerging from variable terrain conditions and management schemes

The accuracy of multispectral classification in general primarily depends on two conditions:

- the target classes have surface properties that produce sufficiently large differences in terms of the resulting reflectance properties and
- at the time of observation, these reflectance properties are consistent across the complete area to be mapped.

While the first condition is commonly observed and verified, the issue of spatial and temporal consistency usually receives much less attention. However, when addressing large study areas that include ecoregions with different growing conditions and management concepts, it is exactly this part of the process that will determine the rate of success.

Spatially variable growth environments cause the same forest class (e.g., beech in the maturing stage) to exhibit different spectral responses as a function of the local conditions, particularly during early phenological stages. Figure 3 shows schematic maximum likelihood decision boundaries for two distinct thematic classes in the near-infrared band with mean values $\mu 1$ and $\mu 2$ and standard deviations $\sigma 1$ and $\sigma 2$. These may represent for instance two mature beech stands, the first on a low mountain range (Eifel) and the second in an ecologically more favorable region (Moselle valley). Under the more favorable conditions, phenological development is more advanced; thus, reflectance in the near-infrared is slightly higher than for the same beech stand in the Eifel area, both standard deviations being approximately equal. If these effects would be ignored and the class "mature beech" would be parameterized using samples from the entire study site, the maximum likelihood classifier would inappropriately assume a normal distribution with mean μ and standard deviation σ (see Fig. 3), thereby obscuring significant features of the narrower distributions. This is especially important when the variability induced by differences in ecoregions is of the order of the variability between the thematic classes to be distinguished. This is the case in this work, as not only major tree species but also individual development stages and age classes are to be classified.

This type of locally determined spectral variability becomes less relevant during later stages of the season where canopy development is largely terminated. Still management differences and the use of images from early

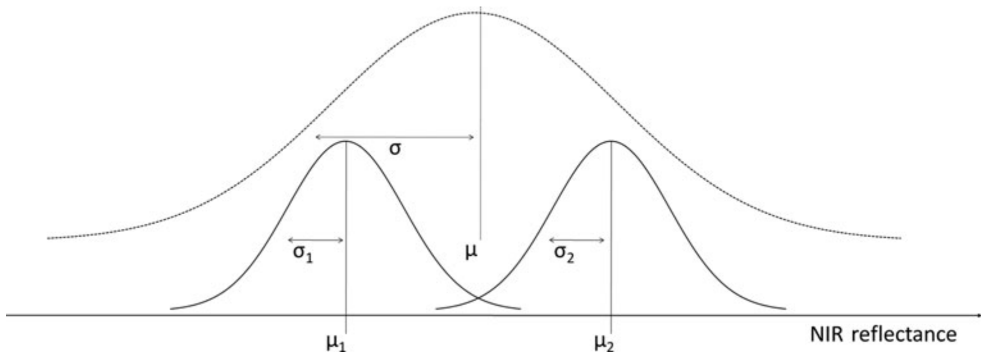

Fig. 3 Maximum likelihood decision boundaries for two distinct thematic classes with mean values $\mu1$ and $\mu2$ and standard deviations $\sigma1$ and $\sigma2$ representing the same type of forest stands in different ecoregions

growth stages necessary to satisfy the first requirement for optimum classification performance impose the need for regionally adapted parameterization schemes. This translates into spatially adaptive adjustments of decision boundaries based on local reference data instead of relying on a reference data set derived from samples spread over the entire study area.

Designing a spatially adaptive classification approach for forest cover mapping

The implementation of the spatial adaptive classification approach requires an efficient organization and flexible access mechanisms regarding the available reference data for parametrizing the classifier. In this study, the training concept was based on a regular 15×15 km^2 raster grid spread over the study area. In principal, each of these quadrants represents a separate spatial unit, within which the parameterization of the classifier is updated, thereby accounting for the existing environmental and management gradients (Fig. 4).

The minimum size of the quadrants was determined through the availability of reference data for each thematic class; smaller areas (e.g., 10×10 or even 5×5 km^2) turned out to frequently provide insufficient amounts of training pixels. If the sampling quadrants become too large, the local character of the classification approach tends to be lost. The amount of reference data needed within each quadrant was defined according to Swain and Davis (1978), who suggest that the number of reference signatures for training a maximum likelihood classifier should not be less than ten times the number of dimensions in the feature space (i.e., 10×4 bands $= 40$ samples).

Starting from these basic considerations, the spatial adaptive classification approach comprises the following steps, as shown in Fig. 4: (a) Identification of the local neighborhood within the unknown forest-pixel will be classified. (b) Verifying whether sufficient reference data per forest cover class are available within this local neighborhood. (c) If yes, direct use of these reference data for the maximum likelihood classification. (d) In case that an insufficient number of training pixels for a class is found within the starting quadrant, the search area for the respective class is expanded by accessing neighboring quadrants (e.g., in this study 45×45 km^2). Only if a class can still not be parameterized within this extended quadrant, the training procedure falls back on a basic parameter set derived from the complete study area. (e) Maximum likelihood classification based on locally optimized training data and derivation of forest cover maps.

It is recalled that for the entire study, more than 50,000 samples are available (see Table 2) to ensure that each forest cover type and development stage is adequately characterized by a sufficient amount of reference data within most quadrants.

Validation

It should be noted that at this time, only validation data from forests in public ownership were available. Strictly speaking, the accuracy assessment is therefore valid only for these forests and cannot be considered representative for private forests that, at least partially, undergo different management concepts. However, the state forest survey is currently collecting inventory data that are within forests in private ownership, such that the accuracy assessment can be extended to the complete forest area as these data become available.

To assess the accuracy of the classification result, a probability sampling design was chosen (Stehman and Czaplewski 1998). According to the relative proportion of the forest cover classes, the number of new reference points was adjusted based on the relative importance of each class (Congalton and Green 1999). A minimum of 80 validation points per forest cover class was used. For classes with high percentage cover, the number of validation points was increased up to 280. The stand delineations of well-defined stands were chosen as sampling unit from the forest inventory GIS-database. Within those stands, about 1,500 reference points were randomly selected. From this sample, points that could not be unambiguously assigned to one stand (e.g., mixed pixels, stand boundaries) were eliminated.

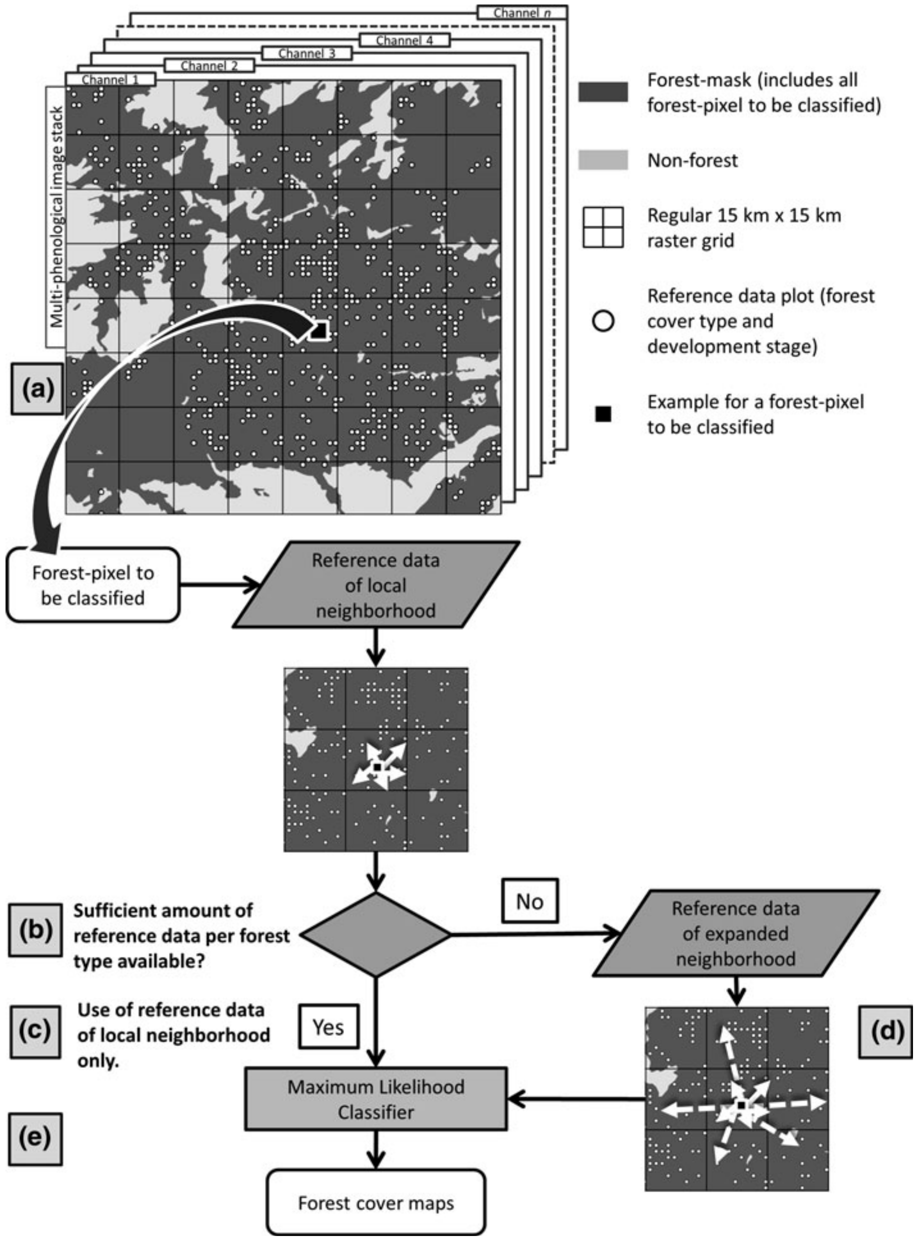

Fig. 4 Schematic representation of the spatially adaptive classification approach

Every validation point was characterized by forest inventory data and verified by visual inspection of high spatial resolution aerial imagery. Finally, 1,461 validation points were chosen for accuracy assessment. The classes "Douglas fir/Maturation" and "Pine/Qualification" were represented by too few validation points and had therefore to be removed from the validation sample. The validation points were used for a comparative analysis of the results obtained from the spatially adaptive as well as from the standard classification procedure.

Comparisons were made by means of confusion matrices (Stehman 1997; Foody 2002). The matrices were used to calculate various accuracy parameters: producer's accuracy (100%—errors of omission), user's accuracy (100%—error of commission), and overall accuracy (ratio of correctly classified validation points to total number of validation points) (Story and Congalton 1986; Congalton 1991). Additionally, Cohen's kappa coefficient (Cohen 1960; Hudson and Ramm 1987) was derived from the error matrices. This more rigorous accuracy assessment identifies the level of agreement actually achieved by the classification with regard to the level that can be expected to occur by mere chance.

Results and discussion

Based on the spatially adaptive maximum likelihood implementation (Fig. 5), a forest cover map at stand level

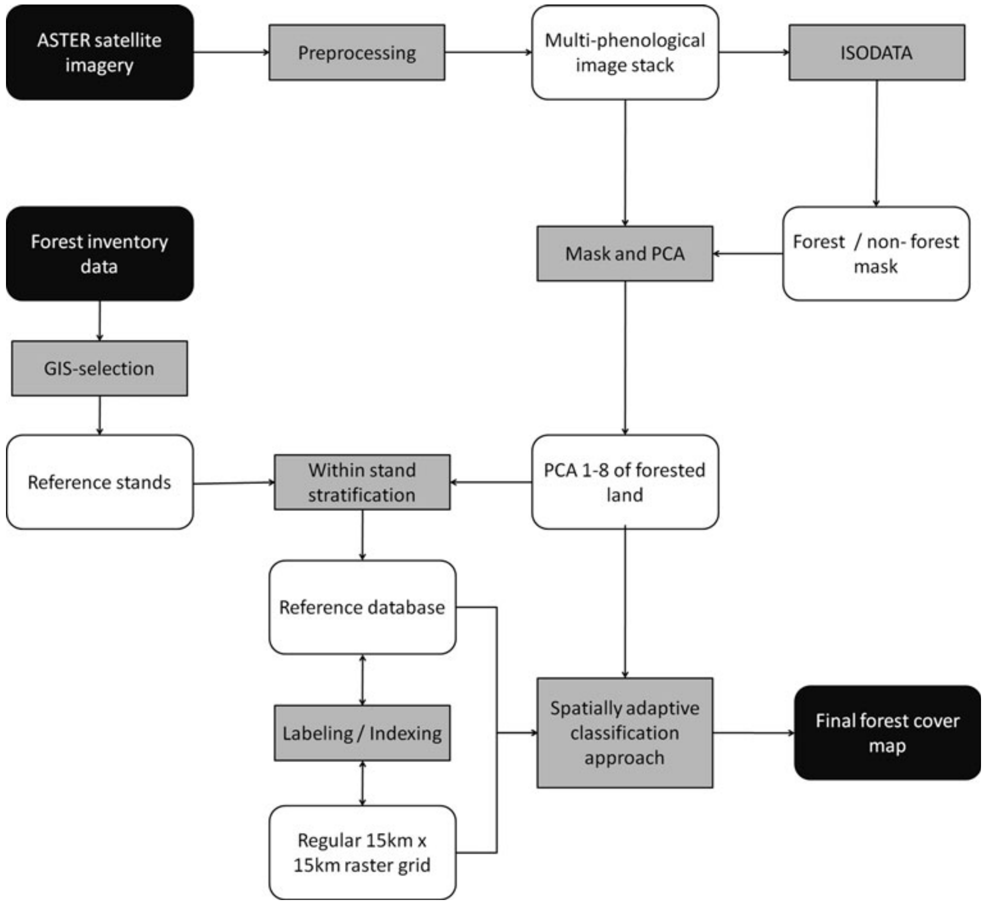

Fig. 5 Classification scheme (PCA = principal component analysis)

was produced for the whole study area including all forests in public and private ownership (Fig. 6). Although no post-classification filtering has been applied, the resulting maps are characterized by a consistent delineation of management units and, as can be verified from aerial photographs, of tree associations inside these compartments. The consistency of these spatial patterns and the general absence of salt-and-pepper noise (Fig. 6, subsets 1–3) are considered positive indicators for the quality of the proposed adaptive classification concept.

Accuracy assessment

Error matrices were used to quantitatively assess the accuracy of the spatially adaptive classification approach in comparison with a standard maximum likelihood classifier which was trained on a global set of reference signatures (i.e., derived from the whole study region without accounting for local phenomena). Tables 4 and 5 summarize the achieved accuracies on two levels of detail, i.e., on tree species level only, and on the combined tree species and development stage level. It should be noted that the accuracy assessment exclusively considers forested areas. As already mentioned earlier, the stratification into forested and non-forested areas was part of the preprocessing and achieved an overall accuracy of 97.5%.

It has been shown in other studies that maximum likelihood classification can achieve high overall accuracies of around 80% within smaller spatial regions (forest district level; Vohland et al. 2007; Hagner and Reese 2007; Bauer et al. 1994). However, in this study on an extended, heterogeneous and bioclimatically diverse study area, the globally trained maximum likelihood approach reached only an overall accuracy of 61.6% (900 from 1,461 validation points were classified correctly), where the accuracies for the individual classes ranged from 33.3% (Pine/Dimensioning) to 88.3% (Spruce/Maturation). This level of accuracy is obviously insufficient for management purposes.

In comparison, the spatially adaptive maximum likelihood implementation produced a substantially improved forest cover map with an overall accuracy of 73.9% and an overall kappa of 0.71 (with regard to the combined tree species and ecological development classes). On tree species level alone, the overall accuracy even reached 87%

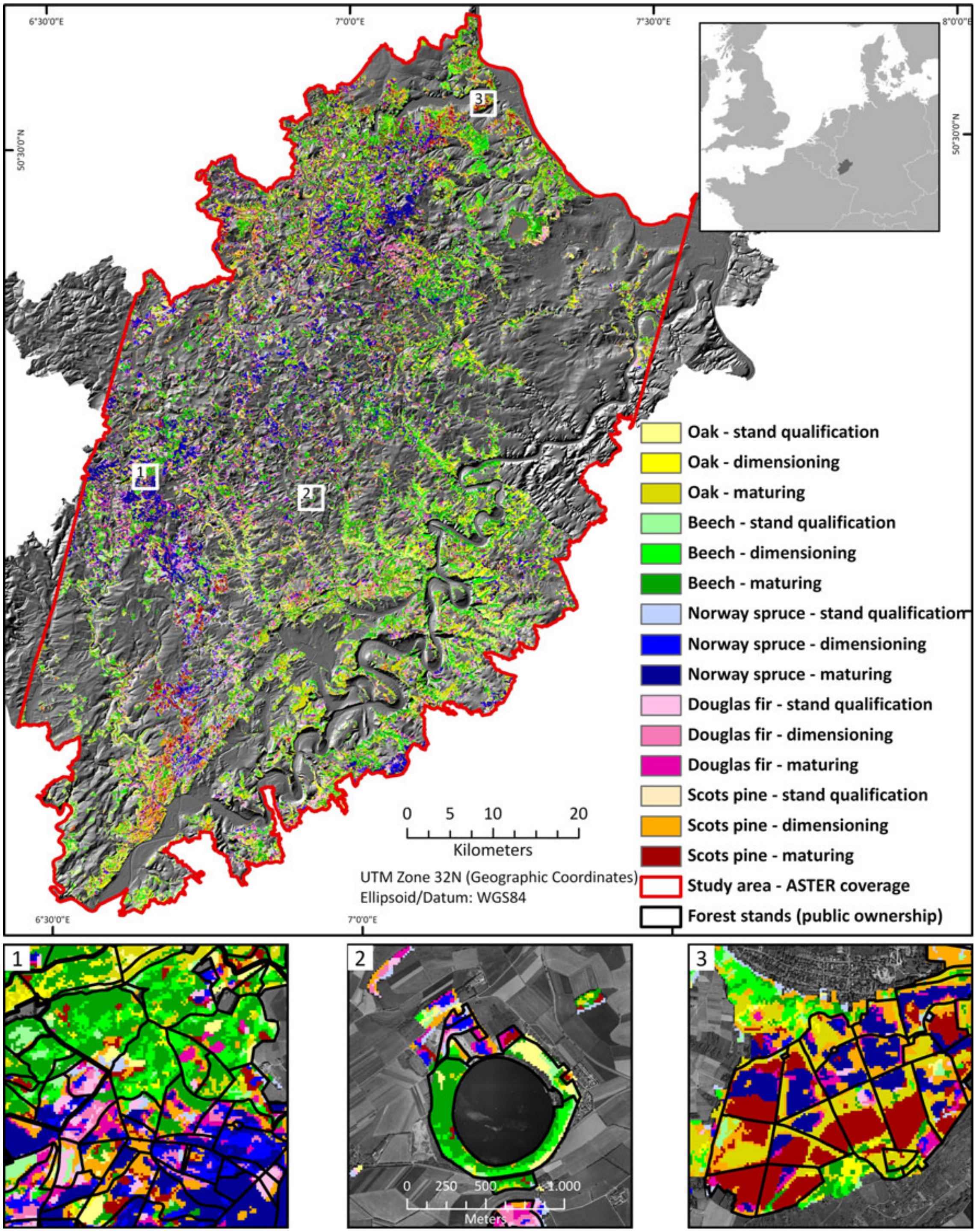

Fig. 6 The final forest cover classification and subsets of the forest cover classification showing typical examples of stand structure and species composition

with an overall kappa of 0.83. Producer's and user's accuracy generally exhibited no strong differences, with the exception of the producer's accuracy of the class "Oak/Dimensioning" where accuracy was 54.1% and user's accuracy for the classes "Oak/Qualification" (41.6%) and "Pine/Dimensioning" (51.2%).

Discussion

In the case of "Pine/Dimensioning", the total amount of reference data is low (374 sampling points in the entire study area). Most of these Scots pine stands are located in the southern part of the study area; other regions are under-represented. A higher amount and a better distribution of reference data for this class, e.g., originating from the new inventory of forests in private ownership, are expected to improve the classification result for this class as well.

The major problems in separating “Oak/Qualification” and “Oak/Dimensioning” are clearly influenced by the specific characteristics of the oak forests on steep slopes in the Moselle valley. Most of these slopes are covered with oak coppice forests, some of them recently abandoned. This forest management system with short rotation cycles has profound impacts on the forest structure and species composition. Additionally, the practice of partible inheritance causes fragmentation of estate through and the resulting characteristic dense pattern of small stands in private forests (Hölscher et al. 2001). Such coppice woods are not captured by the development stages proposed by the state forest service and cannot be adequately characterized by thematic classes based on this concept.

For all other eleven forest cover classes, the classification accuracy is well within the minimum requirements of the forest service. Forest cover maps produced with the spatially adaptive classification approach are currently in use by officials of the forest service in support of preparing their field surveys.

To summarize, the spatially adaptive classification based on a regular grid of sampling units appears well suited for thematic classes whose realizations are spread over the entire study area (e.g., “Oak/Maturation”, all stages of European beech, all stages of Norway spruce) but appear in various modifications according to local climate and topography. In the following discussion, we will refer to these classes as common classes. Oak coppice forests on the steep slopes of the Moselle valley and small tributary valleys as well as pine forests on sandy soils in the southern part of the study area appear only in a distinct local context. In the following discussion, these classes will be referred as classes with limited occurrence.

The validation results indicate that substantial deficits in mapping accuracy are primarily related to classes with limited occurrence. Another problem concerns the consistent assignment of the development phases for the class oak. While the total “Oak class” is assigned with good accuracy (Table 4), its development stage “Oak/Qualification” appears more frequently mislabeled. The reason for this effect is that the adopted sampling scheme does not account for the management system of coppicing. According to the validation table, the forest structure emerging under coppicing may be confused with oak forest in the development stage of “Qualification”. An additional thematic class considering this management system may lead to a higher accuracy rate, but only if it is presented to the classifier in a distinct local context. Otherwise common forest classes could be confused with coppice forest. Thus, the spatial allocation of reference data using a regular raster grid to account for gradually changing growth conditions is only

Table 4 Summary of the standard maximum likelihood classification accuracies (%)

Species level			Species and development stage level		
	Producer’s accuracy	User’s accuracy		Producer’s accuracy	User’s accuracy
Pedunculate and Sessile oak	82.2	80.6	Oak/qualification	64.3	35.0
			Oak/dimensioning	38.8	57.8
			Oak/maturation	66.2	61.9
European Beech	79.7	80.8	Beech/qualification	70.3	65.8
			Beech/dimensioning	45.2	62.2
			Beech/maturation	71.1	61.4
Norway Spruce	80.1	90.6	Spruce/qualification	59.3	75.0
			Spruce/dimensioning	50.6	76.7
			Spruce/maturation	88.3	73.5
Douglas Fir	90.4	67.1	Douglas fir/qualification	83.8	60.8
			Douglas fir/dimensioning	56.6	74.4
			Douglas fir/maturation	No data	No data
Scots Pine	81.2	92.4	Pine/qualification	No data	No data
			Pine/dimensioning	33.3	29.1
			Pine/maturation	64.8	79.0
Overall accuracy = 81.9			Overall accuracy = 61.6		
Kappa statistic = 0.77			Kappa statistic = 0.58		

Table 5 Summary of the spatially adaptive classification approach accuracies (%)

Species level			Species and development stage level		
	Producer's accuracy	User's accuracy		Producer's accuracy	User's accuracy
Pedunculate and Sessile oak	85.3	85.3	Oak/qualification	75.0	41.6
			Oak/dimensioning	54.1	74.6
			Oak/maturation	71.1	72.5
European Beech	85.7	85.7	Beech/qualification	77.1	82.6
			Beech/dimensioning	66.1	71.3
			Beech/maturation	80.9	74.1
Norway Spruce	87.2	92.5	Spruce/qualification	68.6	86.8
			Spruce/dimensioning	67.0	85.3
			Spruce/maturation	94.8	78.1
Douglas Fir	94.7	78.0	Douglas fir/qualification	89.2	70.2
			Douglas fir/dimensioning	77.9	72.1
			Douglas fir/maturation	No data	No data
Scots Pine	85.2	95.5	Pine/qualification	No data	No data
			Pine/dimensioning	81.5	51.2
			Pine/maturation	71.3	96.7
Overall accuracy = 87.1			Overall accuracy = 73.9		
Kappa statistic = 0.83			Kappa statistic = 0.71		

partly valid for classes with limited occurrence. Instead, further extensions of the presented approach are required such as the integration of stratification layers which can delineate areas with different forest management systems or with similar topographic and climatic conditions (in the case that forest types appear only in a local context) on the basis of digital elevation models, topographic and thematic maps as well as expert knowledge. Additionally, the classes with limited occurrence should be offered as a choice to the classifier only within the context of their occurrence.

In summary, the use of satellite observations for producing tree distribution maps in terms of classes defined by species and development stages with an accuracy acceptable for management purposes is feasible under three important conditions:

- use of multitemporal observations that represent the phenological stages of foliage formation and full foliage development, i.e., one spring and one summer observation,
- efficient compensation of terrain-induced illumination effects in the satellite observations (radiometric preprocessing) and
- optimization of classifier performance by introducing spatially adaptive class parameterization (training) mechanisms.

The latter is mandatory to account for the variability in bioclimatic growth conditions, terrain/site characteristic as well as differences in silvicultural practices and forest management. Furthermore, the approach discussed in this paper is designed around the smooth integration of official forest management/inventory data from existing spatial databases. This ensures that any updates and new survey data can be integrated as long as the existing system is maintained.

The ASTER satellite system used in this study of course represents an experimental satellite program with limited lifetime and data availability, quite obviously not a system on which to build an operational mapping program. The crucial point is that the approach developed for this feasibility study based on ASTER data can be transferred to at least one, preferably more satellite systems whose future availability is ensured. Based on the results and processing experiences from this work, suitable candidate systems must offer the following:

- spatial resolution of the order of 5×5–15×15 m^2 to retain mapping capabilities even in a small fragmented landscapes,
- spectral bands in the visible, near-infrared and, possibly, in at least one of the SWIR ranges (preferably around 1.6 μm),
- as frequent as possible revisit cycles, which increase the availability of cloud-free satellite imagery during the required phenological phases and
- swath width suitable for medium to large area coverage (from around 60 to 300 km).

Nowadays, a number of systems exist, which meet most of these requirements and, to some extent, may even be combined in multisensor approaches: the SPOT-4 and SPOT-5 satellites are still operated jointly; the German RapidEye observation system involves a constellation of five identical satellites which dramatically increases the probability of acquiring cloud-free imagery not only during summer but in particular during the crucial time of foliage formation. Especially in tree distribution mapping, the higher spatial resolution of these sensor systems provides additional advantages in comparison with ASTER (Salajanu and Olson 2001). As an extension of this feasibility study, work on the integration of SPOT-5 and RapidEye data into a statewide forest cover classification for Rhineland-Palatinate is already underway. The results are also expected to provide clarity on the issue whether the absence of an SWIR channel on the current RapidEye satellites can be compensated by the additional spectral band available in the red edge region (Marx 2010).

In the perspective of future improvements, the Sentinel program of the European Space Agency (ESA) is of major importance. Within the framework of GMES (Global Monitoring for Environment and Security), the planned Sentinel-2 system (planned to launch in 2013) ensures the continuity of high-to-medium-resolution satellite systems. The combination of high spatial resolution (VNIR: 10×10 m^2; SWIR: 20×20 and 30×30 m^2), increased spectral resolution (13 relatively narrow spectral bands) and short revisit times (5 days at the equator) is considered highly promising sensor characteristics for tree cover mapping (Martimor et al. 2007).

Currently, the mapping results presented in this paper are already tested in the context of ongoing terrestrial inventories. Conceived as “prognostic” map documents, they combine the spatial distribution of tree species and development classes, topographic information, forest management boundaries and further useful annotations. Available as printout or digital GIS layers, they supplement other forest survey data and have proven particularly useful for preparing terrestrial survey missions. In cooperation with the state forest survey of Rhineland-Palatinate, further work will be focused on the integration of the classification results into advanced GIS workflows. The prime focus is on the automatic GIS database comparison between classification result and GIS-based forest inventory data to identify areas with major changes in the forest cover and thereby prioritize field surveys.

Conclusions

Improved satellite-derived forest inventory information, especially stand structure and species diversity within stands, has become increasingly important (Lemay et al. 2008). Acknowledging the fact that high variability in growing conditions, terrain characteristics and differences in silvicultural practice and forest management are a major reason for poor classifier performance a new approach has been tested, which is based on a spatially adaptive parameterization of a maximum likelihood classifier. The method produced an accurate forest cover map with 15 primary classes (defined by tree species and development stage). Compared to a traditional maximum likelihood classification, our results demonstrate that a significant increase in classification accuracy in the order of 12% was achieved. The explicit integration of local reference information which account for site-specific ecoregional and phenological gradients has been identified as the main reason for the improved mapping accuracies. The spatially adaptive classification approach is robust and therefore suited to be implemented in regular state forest inventory concepts.

The strategy of applying a regular raster grid is considered a first approximation toward characterizing the ecological variabilities along regional gradients. Future development will be focused on a more sophisticated and flexible organisation of the reference data by spatial data indexing methods (e.g., quadtrees).

The approach was successfully tested with ASTER satellite imagery but holds the potential to be used for regular state forest inventories based on standard and novel earth observation data supplied for instance from the SPOT-5 and RapidEye sensor. However, different sensor characteristics (e.g., spectral and spatial resolution, revisit time and swath width) may still necessitate further studies on sensor sensitivity and comparability.

It is again emphasized that the tested method is largely driven by terrestrial survey data routinely available in the existing forest management databases. This fact underlines that future inventory designs may substantially benefit from an optimized combination of satellite and field data. These integrated approaches are capable to substantially increase update frequencies of conventional inventories and might thereby assist in closing information gaps that are expected due to the reduction in staff resources.

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