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Use of Wall-to-Wall Moderate- and High-Resolution Satellite Imagery to Monitor Forest Cover across Europe

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11.1 Introduction

Forest resources are very relevant in the political agenda of the European Union, as forestry influences many sectorial policies dealing with environmental protection, renewable energy, and biodiversity, to name some. The design, implementation, monitoring and evaluation, and impact assessment of environmental policies at the European level require reliable, consistent, and updated information of forest resources.

Although several countries in Europe collect a considerable amount of forest-related information, this is often not spatially continuous and frequently not accessible, nonharmonized, scattered in remote databases, and encapsulated in diverse data formats. One critical aspect regarding forest information in Europe is the different forest definitions used by countries, which hampers the comparability of nationally collected forest information.

Remote sensing–based products are thus the most suitable source of consistent and up-to-date forest information over large areas. Remote sensing techniques have been widely used for mapping forest resources at local and national levels. Working over large areas poses additional logistic, technical, and managerial challenges that have limited the number of existing pan-European products. Large-area projects usually require a considerable data management capacity. They also require carefully planned processing chains, including consistent preprocessing of satellite and ancillary information and mapping methodologies to produce large-area products. In addition, these methodologies must be robust, reliable, and flexible to handle suboptimal data sets of images from several sensors.

Several remote sensing–based products exist that include forest information and have pan-European coverage. However, these products were derived from coarse-resolution satellite images (Bartholomé and Belward 2005; DeFries et al. 2000; Friedl et al. 2002; Häme 2001; Hansen et al. 2000; Schuck 2003) or are labor intensive (Corine Land Cover [CLC]). Furthermore, the lack of comprehensive validation schemes of these products limits their utility in a number of applications.

The recent availability of a wider selection of remote sensing data allows an improvement in spatial resolution over the existing products. It also allows exploiting the temporal domain of remote sensing data. This scenario enables the development of products with higher spatial detail and increased thematic information content.

In this context, the Joint Research Centre (JRC) of the European Commission has been working on the production of enhanced remote sensing–based forest products. Two pan-European forest maps with a ground sampling distance (GSD) of 25 m have been produced based on Landsat ETM+ imagery (Pekkarinen et al. 2009) and IRS LISS-III, SPOT 4-5, and Moderate Resolution Imaging Spectroradiometer (MODIS) remote sensing data

(Kempeneers et al. 2011). Besides these high-resolution products, the JRC is carrying out research to improve forest monitoring capabilities at 250 and 500 m GSD based on time-series analysis of remote sensing data. This chapter presents the methodologies used in the production of these maps and their accuracies and discusses future potential developments in forest monitoring at the pan-European level.

11.2 Materials and Methods

This section describes the materials used in the production of the forest maps for the years 2000 and 2006 (Figures 11.1 and 11.2).

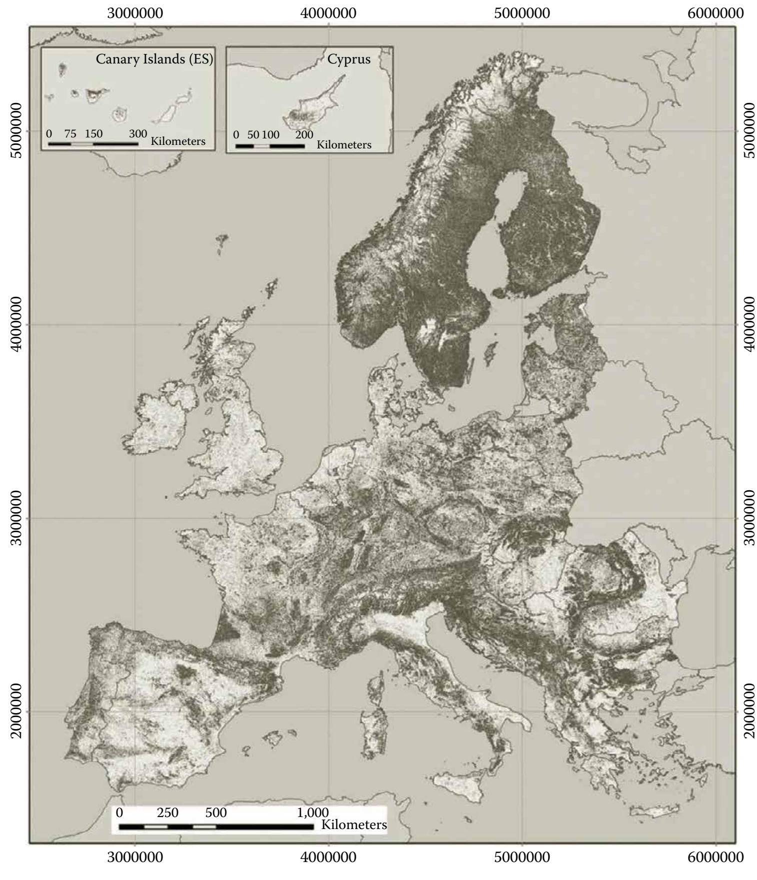

FIGURE 11.1
(See color insert.) JRC forest map 2000.

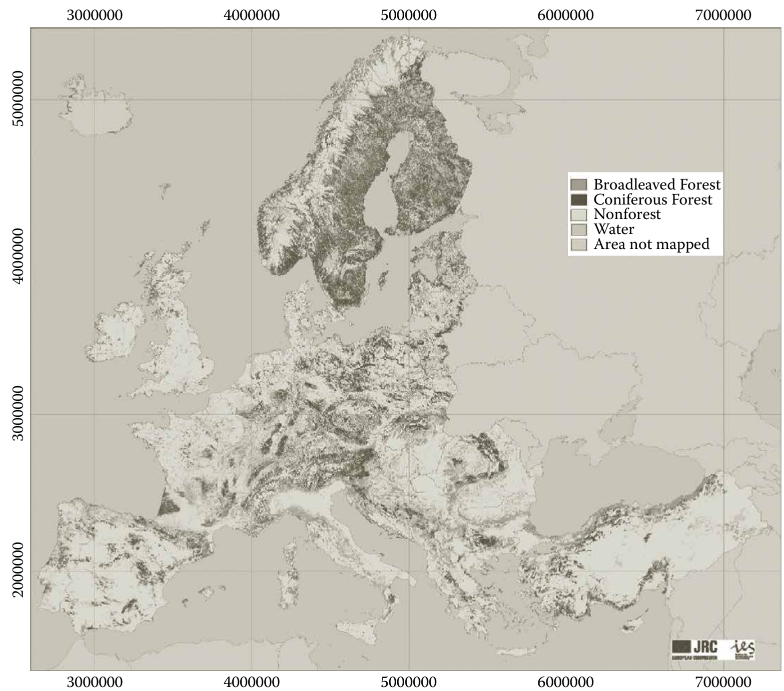

FIGURE 11.2
(See color insert.) JRC forest map 2006.

11.2.1 Materials

The forest/nonforest map for the year 2000 (FMAP2000) was derived from Landsat-7 ETM+ imagery. Scenes belonged to two different image datasets: the NASA Orthorectified Landsat Dataset (Tucker et al. 2004) available from the Global Land Cover Facility (GLCF) and the IMAGE2000 data set (JRC 2005). The two data sources were mixed in order to optimize cloud freeness and acquisition date. The target year for the scenes was 2000, but the acquisition window covered years from 1999 to 2002. The full data set included 415 scenes available as top of atmosphere (TOA) radiance: 285 of them from the GLCF and 130 from the IMAGE2000 data set. All images in the full data set were reprojected to the European Terrestrial Reference system 1989 and the Lambert Azimuthal Equal Area (ETRS89-LAEA) projection and resampled to 25 m rasters. In order to ensure consistent geometrical quality between scenes coming from the two different data sets, IMAGE2000 scenes were orthorectified taking GLCF scenes as a reference.

The forest/nonforest map for the year 2006 (FMAP2006) and the forest type map (FTYP2006) were derived from the IMAGE2006 data set. This data set includes TOA radiance IRS-LISS-3 scenes and additional SPOT 4 and

5 scenes for those regions in which cloud-free IRS-LISS-3 were not available. The scenes were orthorectified and geometrically corrected. As in the year 2000, all images were reprojected to ETRS89-LAEA projection and resampled to 25 m rasters.

In addition to the IMAGE2006 data set, the production of FTYP2006 required 12 (one per month) MODIS 16-day composites at 250 m spatial resolution. These composites were reprojected and resampled to 25 m to match the IMAGE 2006 data set.

11.2.2 Ancillary Data

11.2.2.1 Training Data

The CLC data set was used as training data. CLC includes 44 land cover (LC) and land use classes from which three correspond to forest classes (broadleaved, coniferous, and mixed forests). The CLC covers all EIONET countries, which includes the EU-27 Member States and neighboring countries. The CLC is available for the reference years 1990, 2000, and 2006. The corresponding data set was used for the production of each pan-European forest map.

11.2.2.2 Reference Data

The validation of the FMAP2000 was performed using two data sets. The first included field plot data from the land use/cover area frame statistical survey that was carried out in 2001 (LUCAS2001). LUCAS2001 is based on 94,984 sampling units, which consist of a circle with a 20 m radius. It is based on a seven LC classification nomenclature, with the forest class subdivided into broadleaved, coniferous, and mixed, but it also includes a land use component. The second data set was derived from the visual interpretation of sample points overlaid on very high-resolution satellite imagery from Google Earth. In total, 5,193 forest and nonforest points were collected from the interpretation of this data set and classified into forest and nonforest classes.

The FMAP2006 was validated using ground reference data that were derived from European National Forest Inventories (NFIs). NFI data are frequently collected by national authorities for the production and planning of forest resources at national and regional levels, but they are also needed to meet international reporting requirements to the FAO's Forest Resource Assessment (FAO 2010) and other requirements.

The NFI data used in this validation were managed in the so-called eForest platform. The eForest platform, established for the provision of data and services to the European Forest Data Center (EFDAC) of the European Commission, is the first step to produce a harmonized database of all European NFIs. It emerged from the work carried out by the COST Action E-43 that sought to develop methods, concepts, and definitions that would harmonize NFIs between countries (Tomppo et al. 2010). Of particular importance within

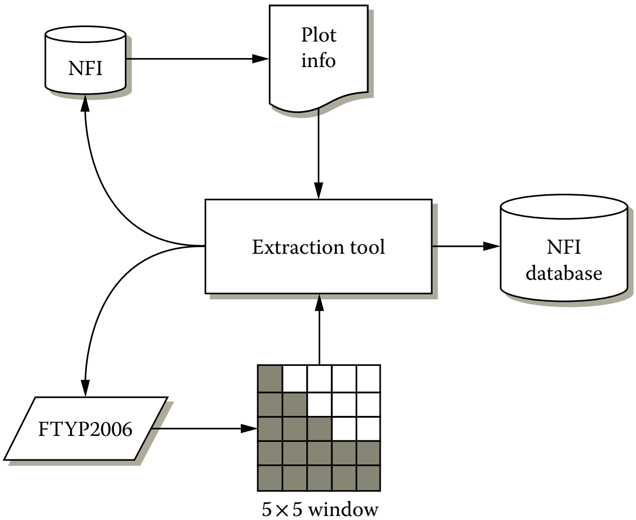

FIGURE 11.3
Pixel extraction tool.

this process was the harmonization of the definition of forest, which varies between NFIs.

The platform consisted of 1,080,829 NFI plots, distributed across 21 countries. However, the exact plot locations were not disclosed by the NFIs. For the validation, it was necessary to build a pixel extraction tool that was used by the data owners to extract the forest map data within a 5 × 5 window around the NFI plot coordinates (Figure 11.3). These data were used to compute the overall, producer, and user accuracies for the FMAP2006 at country and regional scales. Plots that were labeled as young stands or unstocked were removed from the eForest validation data set so that the accuracy assessment of the FMAP2006 focused on forest cover and nonforest use. It should be noted that unstocked forest areas are considered forests from a land use perspective, although they are not forests from an LC (remote sensing) perspective.

Additionally, the LUCAS2001 data were used to validate the FMAP2006 data set. The results of this validation process are described hereafter.

11.3 Methods

11.3.1 Data Preprocessing

The high spatial resolution scenes from IRS LISS-3 and SPOT4/5 were preprocessed by the German Aerospace Center (DLR). The scenes were orthorectified using rational polynomial functions (Lehner et al. 2005) and geometrically corrected using ground control points (GCPs) and a digital elevation model (DEM). The orthoimages were resampled to 25 m in the standard projection for Europe, using the ETRS89/LAEA projection (Annoni et al. 2003). The reported root mean square errors in both horizontal directions were less than a pixel. The images were only available as TOA radiances (not atmospherically corrected).

In the case of the MODIS, daily images were also preprocessed by DLR in the standard European projection. However, a geometric and atmospheric correction was performed to obtain ground reflectances for bands 1–7 at 250 and 500 m GSD.

A 16-day MODIS composite was created from the daily images. By not using the MOD13Q1 product (Huete 2002), a reprojection from sinusoidal to the standard European projection was not needed, avoiding an extra interpolation step. Unlike the MOD13Q1 product, our 16-day composite was not corrected for BRDF effects. Nevertheless, by selecting the median pixel value in the NIR band of all cloud-free observations within the 16-day window, some of the effects due to undetected clouds and extreme observation angles were alleviated.

11.3.2 Forest Mapping Approaches

A nonparametric supervised classification algorithm was used to obtain the forest maps FMAP2000 and FTYP2006. Supervised classification methods are preferable in cases where *a priori* information is available for the desired output classes and their spatial distribution (Cihlar 2000). With the CLC map, training data for forests (types) and nonforests were available in a consistent way for the entire area of interest (Europe).

Given the large geographic extent of the pan-European map, the interclass variance was expected to be high. For example, broadleaved forests in northern Europe have different spectral characteristics than those in southern Europe. Moreover, the digital numbers stored in the multispectral image bands represented TOA radiance and thus were not corrected for atmospheric effects. Consequently, image data were processed on a scene-by-scene basis, allowing the classifier to be trained for the specific conditions within each scene. The final output, the pan-European forest map, was then obtained by mosaicing the different scenes, using a composite rule where pixels did overlap. In the case of the FMAP2000, the composite rule was based on uncertainty information derived during the classification process. The number of overlapping scenes in the case of the FMAP2006 was larger (every pixel was observed at least twice but often three to four times). This allowed for a (weighted) maximum voting of the classified scenes. Weights were introduced based on seasonality. Summer scenes were weighted in favor of early spring or late autumn scenes.

The main requirements for the classification method were:

1. Consistency: The wall-to-wall pan-European forest map had to be produced in a homogeneous way.
2. Performance: Algorithms had to be fully automatic.
3. Robustness for deficiencies in the training and input data: The methods for the FMAP2000 and FTYP2006 showed some important differences in how this was achieved. This is explained in the following overview.

The FMAP2000 was mapped using a *k*-nearest-neighbor (*k*-NN) classifier (Tomppo et al. 2008). Instead of extracting spectral information for each Corine Land Use Land Cover patch, two key improvements in the classification approach were implemented to improve the performance (Pekkarinen et al. 2009): first, a segmentation prior to the classification step and second, an adaptive spectral representivity analysis (ASRA) (Pekkarinen et al. 2009). ASRA was developed to improve the training process and to minimize errors resulting from the relatively large minimum mapping unit of Corine. The segmentation was merely used to speed up the *k*-NN classification, which is known to be inefficient for processing large data sets. The ASRA was introduced after clustering the segments into spectral classes. It seeks to identify representative combinations of spectral and informational classes using a contingency table, derived from the cluster labels and CLC classes. For more details of the algorithm, the reader is referred to Pekkarinen et al. (2009).

The classification method for the FTYP2006 was based on an artificial neural network (ANN) (Rumelhart and McClelland 1986) that has been shown to combine two excellent classification properties: high accuracy (Chini et al. 2008; Licciardi et al. 2009) and robustness to training site heterogeneity (Paola and Schowengerdt 1995). Also important for the selection of the classifier was that the ANN, once trained, is very fast. Unlike for the production of the FMAP2000 method, a segmentation step was therefore not needed.

Another difference with the FMAP2000 is that forest types were introduced in the FTYP2006. To increase the potential of the classifier, multitemporal information was added to the multispectral information (data fusion). The multitemporal data were obtained from the MODIS sensor, using a 16-day composite for each month in 2006 at 250 m spatial resolution. The temporal aspect of the spectral reflectance can describe phenology, which is a potential indicator for LC types (DeFries et al. 1994; Hansen et al. 2005). The data fusion with this additional information source also increased the robustness of the classification process (Kempeneers et al. 2011).

However, fusing data from sensors at different spatial resolutions posed a challenge to retain the fine spatial resolution in the final LC map. A new data fusion method was therefore proposed, based on a two-step approach (Kempeneers et al. 2011). In step one, the classifier created a forest map, classifying forests and nonforests only. In step two, a new classifier refined forest into forest types, excluding the nonforested pixels from the classification process. The multitemporal data at medium spatial resolution were introduced only in step two.

The idea is that, as the classes are refined, the complexity of the classification increases. At this point, the classifier can benefit most from the added information obtained from data fusion. The forest/nonforest map was mapped using only the spectral information at fine spatial resolution and therefore retained the finest spatial resolution possible.

11.4 Results

The accuracy assessment of the forest cover maps was performed using three reference data sets that were previously described in Section 11.2.2. The overall accuracy (OA) of the FMAP2000 was 88.6% and 90.8% respectively for the VISVAL and LUCAS data sets, while the OA for the FMAP2006 was 88.0% and 84.0% based on the eForest and the LUCAS2001 data sets. The results for eForest and LUCAS2001 cannot really be compared due to a different coverage in both space and time (where LUCAS2001 can be regarded as outdated).

The calculation of the producer and user accuracies provided information on the performance of both maps for the forest and nonforest classes (Table 11.1). The producer's accuracy of the forest class was lowest for the FMAP2006 (75%) with respect to the eForest database, while it was slightly higher than FMAP2000 at 85.5% and 83.9% when compared to the VISVAL and LUCAS data sets. When compared to official statistics, the results demonstrated an overall underestimation of forest area in both forest maps, which was particularly emphasized in Ireland, Spain, Portugal, and Greece. This underestimation can be explained by the high rate of recent afforestation in Ireland, while in the Mediterranean countries, the forests typically have a very low percentage forest cover (e.g., 5% in Spain).

TABLE 11.1

FMAP2000 and FMAP2006 Accuracies with Respect to Validation Data Sets

	FMAP2000		FMAP2006	
Accuracies	**VISVAL**	**LUCAS**	**eForest**	**LUCAS2001**
OA%	88.6	90.8	88.0	84
Forest PA%	85.5	83.9	75	66
Forest UA%	77.66	85.8	87	85
Nonforest PA%	89.58	NA	94	94
Nonforest UA%	93.59	NA	88	84

The individual accuracies for the forest and nonforest classes were computed for the 3 × 3 window, and it was found that the producer accuracies improved by 1% for the eForest database (from 75% to 76%) and by 3% for the LUCAS data set (from 66% to 69%).

11.5 Applications

Harmonized spatial information on forest area is an important basis for environmental modeling and policy making at both national and international levels. Even if a majority of these data have been supplied by NFI statistics, detailed spatial distribution needed for modeling or further applications can mainly be provided by remote sensing–based products. Yet, reliability, consistency, and a high level of harmonization are important aspects to ensure comparability and enable the development of forest scenarios at an international level. The pan-European forest cover maps (FMAP2000 and FMAP2006) have the advantage to be produced under these prerequisites due to their harmonized approaches and, therefore, guarantee spatial consistency for further applications. Besides that, the medium resolution of the maps offers higher spatial details as previous pan-European LC products such as the CLC maps.

Most of the applications of the forest cover maps (FMAP2000 and FMAP2006) are related to the need for accurate and up-to-date estimates on the spatial distribution of forests as inputs into various models. Baritz et al. (2010) investigated the carbon concentrations and stocks in forest soils of Europe and located forested areas with the help of FMAP2000. Similarly, information on forest distribution was needed for a vulnerability study in the Alps and the Carpathian mountains (Casalegno et al. 2011). As the forest definition of the forest cover maps includes also urban parks in contrast to CLC, FMAP2000 could have been applied in a pan-European urban greening study, where growth of urban forest was investigated. In some of aforementioned studies, the initial medium resolution (25 m) was degraded down to 1 km resolution to speed up the process of the models, yet even with the degraded resolution of 1 km, FMAP2000 was found to be preserving the detailed forest spatial pattern of the original map (Seebach et al. 2011a). Besides applications at the pan-European level, the forest cover maps have been used in local or regional studies as the high resolution allows for detailed studies at that level. The large extent of Europe further enables potential reproducibility of regional studies using these maps as proposed by Lasserre et al. (2011) or Casalegno (2011). Another example of the same kind is the study of Chirici et al. (2011) that used FMAP2000 for a regional study in central Italy (Molise) as an initial forest mask for subsequent delineation of clearcuts based on very high-resolution imagery.

Another application of these maps apart from their indirect use as forest masks is, for example, the estimation of forest area at different units. Seebach et al. (2011b) investigated the applicability of FMAP2000 for reporting harmonized forest estimates for European countries. The comparison with official statistics derived from NFIs indicated an overall good agreement if uncertainties of both sources were taken into account; yet, discrepancies were found in areas with very low and fragmented forests or in mountainous regions. Another major driver of the remaining disagreements between official statistics and map-derived estimates originates from the common issue of land use versus LC. While official statistics reports are based on forest use definitions, estimates based on remote sensing products like FMAP2000/2006 will report land coverage with forest-like vegetation. The latter might become forest use maps only if extensive auxiliary data are available for their manipulation. A further direct application of the forest cover maps are their use for assessing change using postclassification comparison as both maps have been produced by a comparable and consistent approach. This was done for the European part of the FAO FRA 2010 Remote Sensing Survey (RSS), where both forest maps were used to detect reliable forest cover changes based on an enhanced postclassification approach. This approach accounts for potential misregistration errors and reduces the uncertainty of erroneous change detection due to classification errors (Seebach et al. 2010).

All in all, FMAP2000 has proved its ability to serve as a multipurpose product from direct use to downstream services. FMAP2006 and the associated FTYPE2006 have been recently released and are foreseen to be used in upcoming studies, where the differentiation of forest types is of high importance, for example, pan-European forest biomass estimation. Yet, care must be exercised for any application of these maps as every map inherits uncertainties, which need to be addressed depending on the intended use.

11.6 Conclusions and Future Aspects

The pan-European forest maps have been produced for the reference years 2000 and 2006 using optical satellite imagery and standardized methodologies with respect to preprocessing and classification. These maps have provided a baseline assessment of the spatial distribution and composition of forest resources in Europe and demonstrated improvements in terms of quality and production with respect to the CLC Project. In the frame of the Global Monitoring for Environment and Security (GMES) Initial Operations, the production of a new set of so-called high-resolution layers (HRLs) is foreseen, which will be coordinated by the European Environment Agency. Among these, HRLs will be a forest layer designed to closely resemble the JRC FMAP2000 and FMAP2006, but with a target reference year of 2012.

The mapping methods presented within this chapter were based on at-sensor radiances of the remote sensing sensors. Despite the fact that the applied methods are scientifically sound and practical, future mapping applications should be based on well-calibrated image data, from which the effects of the atmosphere have been removed. That would allow for the development of well-defined algorithms that could be applied to a range of different optical sensors, since these algorithms would be based on registered spectral responses of real-world objects. Recent advances in preprocessing algorithms and new European optical imaging sensors, such as RapidEye and ESA's Sentinel II, will hopefully facilitate future development of such mapping approaches.

It is evident that the demand for European level information on forest resources will increase in the future. We need to better understand the integrated role of forests in the protection of the environment, biodiversity, well being and recreation, timber and bioenergy production, as well as mitigation of climate change and monitoring compliance to international climate change agreements. In the future, other sources of Earth observation data should be further studied and used in large-scale mapping projects. For instance, interferometric SAR and space-borne LiDAR could be used to map land use and LC as well as being used to estimate other forest parameters, particularly by their combined use with field measurements and/or high-density airborne LiDAR data.

About the Contributors

Jesús San-Miguel-Ayanz is a senior researcher at the Institute for Environment and Sustainability of the European Commission's Joint Research Centre and leads the forest research activities of the JRC in Europe. He has a PhD and MSc in remote sensing and GIS from the University of California, Berkeley (1993 and 1989, respectively) and a degree in forest engineering (1987) from the Polytechnic University of Madrid.

Pieter Kempeneers received his MS in electronic engineering from Ghent University, Belgium, in 1994, and a PhD in physics from Antwerp University, Belgium, in 2007. He was a researcher with the Department of Telecommunications and Information Processing, Ghent University, and with Siemens (mobile communication systems). In 1999, he was with the Centre for Remote Sensing and Earth Observation Processes (TAP), Flemish Institute for Technological Research (VITO), as a scientist. From 2008 to 2011, he was a scientist with the Joint Research Centre, European Commission, Ispra, Italy. His research focus is on image processing, pattern recognition, and multi- and hyperspectral image analyses.

Daniel McInerney graduated from University College Dublin in 2002 with an honors degree in forestry; he also holds an MSc in geoinformation science and remote sensing from the University of Edinburgh (2004) and a PhD in remote sensing applied to forest inventories from University College Dublin. He is currently a postdoctoral researcher at the Institute for Environment and Sustainability at the European Commission's Joint Research Centre. His research interests include NFIs, forest mapping, and Web-based geoinformation systems.

Fernando Sedano holds a PhD from the University of California, Berkeley. He was a NASA Earth Science Fellow from 2005 to 2008 and a postdoctoral researcher with the Institute for Environment and Sustainability of the JRC. Previously, he also worked as a forest consultant in several tropical countries. Fernando Sedano's research focuses on the development of remote sensing methods and applications to monitor and understand forest dynamics.

Anssi Pekkarinen studied forest inventory, remote sensing, and GIS at the University of Helsinki, Finland, and holds a Dr Sc in agriculture and forestry. He worked at the Institute for Environment and Sustainability of the JRC-EC during the period 2005–2009 and is currently with the Food and Agriculture Organization of the United Nations. He has more than 15 years of experience in operational mapping and monitoring of forest resources with space and airborne remote sensing. His fields of specialty are forest inventory, remote sensing aided land use and LC mapping applications, and image processing.

Lucia Seebach received her diploma (masters equiv.) in geoecology from the University of Bayreuth, Germany, in September 2003. After her graduation, she worked until 2010 as a scientific officer at the Institute for Environment and Sustainability of Joint Research Centre of the European Commission in Ispra, Italy. Currently, she is a PhD fellow at the Department of Forest and Landscape, University of Copenhagen, Denmark. Her main areas of scientific interest are monitoring and modeling of forest resources, uncertainty analysis, and assessment of applicability of remote sensing–derived maps.

Peter Strobl graduated in geophysics from the University of Munich in 1991 and obtained a PhD in geosciences from the University of Potsdam, Germany, in 2000. His career history includes the University of Munich, the German Aerospace Centre (DLR), and the Joint Research Centre of the European Commission. He has worked on a wide range of remote sensing–related issues and currently focuses on preprocessing, analysis, and quality aspects of large multisensor, multitemporal data sets.

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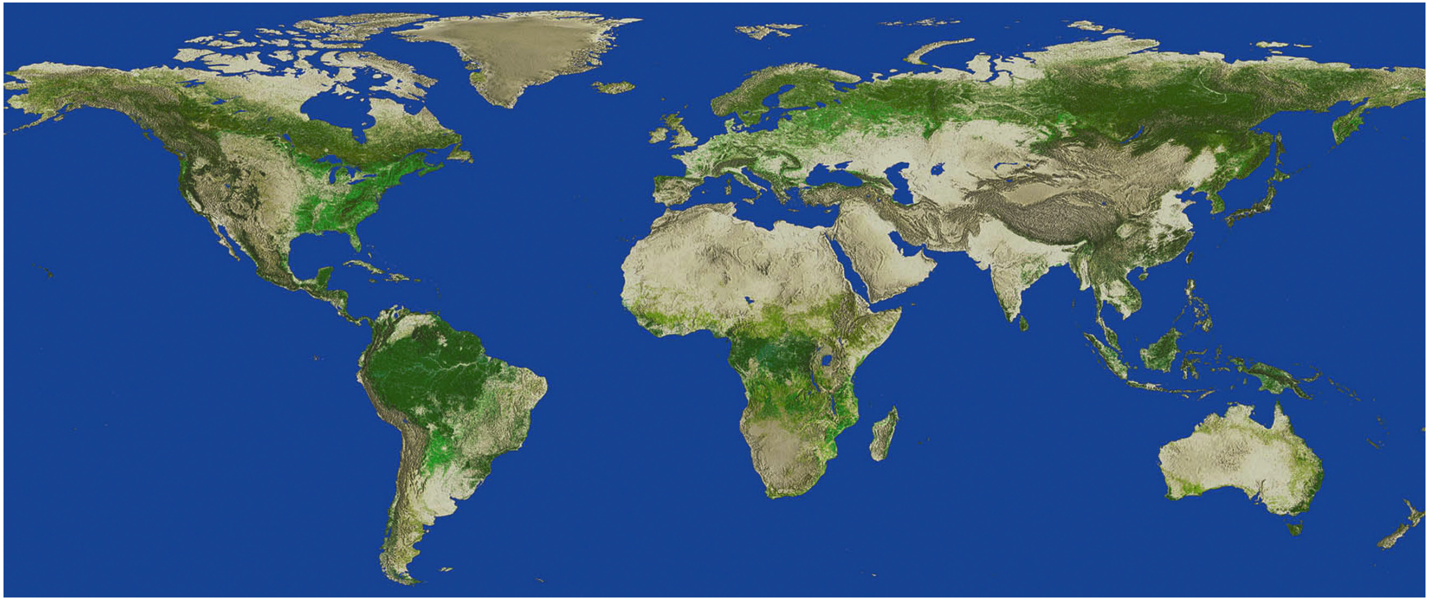


FIGURE 3.1
Global forest cover map derived from the GlobCover Land Cover map at 300 m resolution. Forested areas appear in green. (From Arino, O. et al., *ESA Bull.*, 136, 24, 2008; The GlobCover Land Cover map is available from the European Space Agency website at http://ionia1.esrin.esa.int/.)

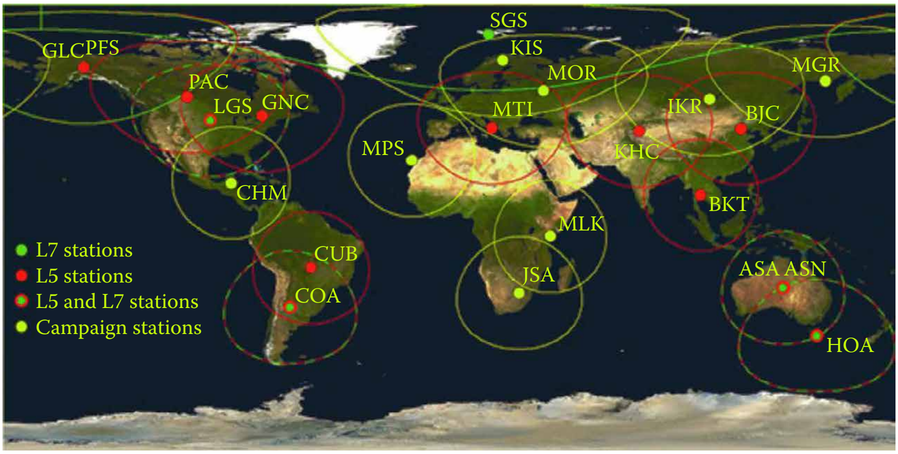


FIGURE 4.1
Active Landsat ground stations. (More details are available at http://landsat.usgs.gov/about_ground_stations.php.)

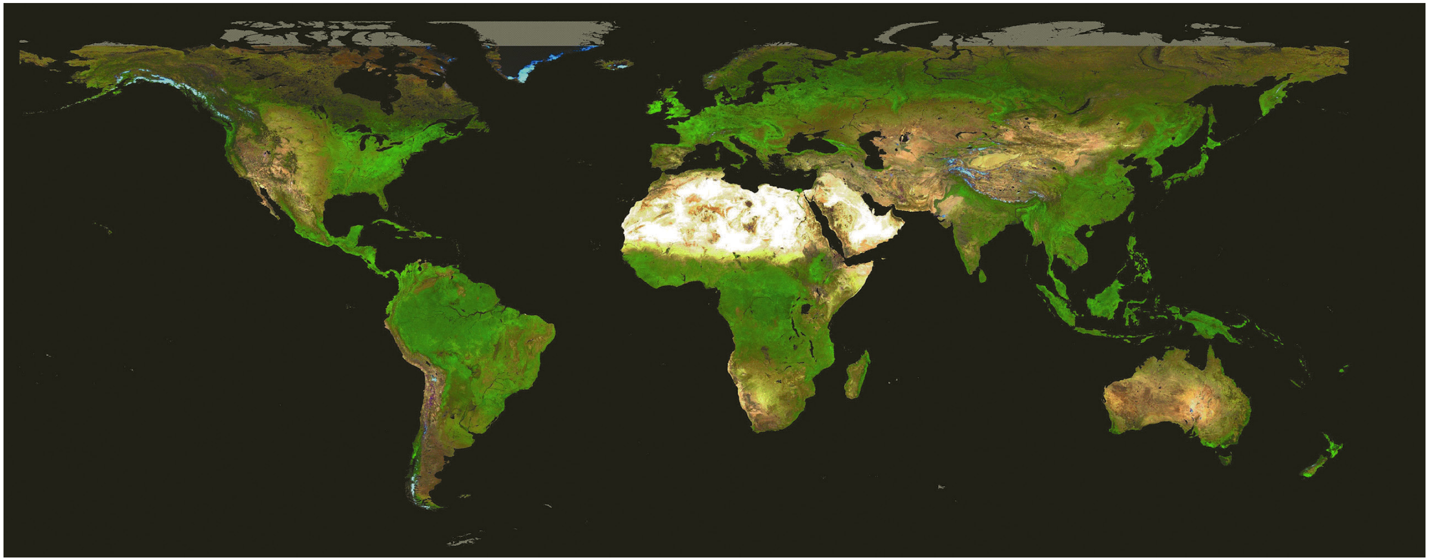


FIGURE 6.1
MODIS annual growing season image composite of shortwave, near-infrared, and red band, enhanced to appear as true color.

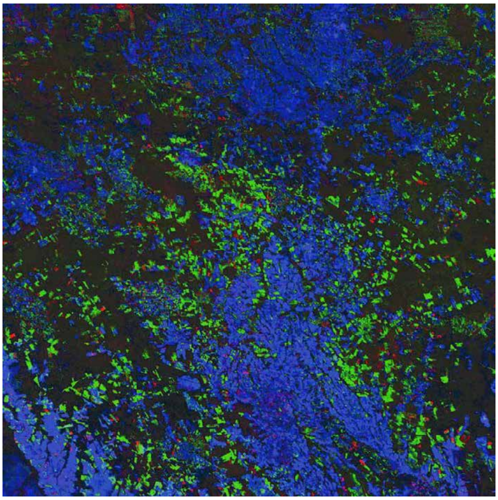


FIGURE 6.2
400 km × 400 km subset centered on 12° 4′ S, 55° 59′ W in Mato Grosso, Brazil. False-color composite of MODIS band 7 growing season metrics—*blue*: 2000 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods, *green*: difference in the 2000 and 2005 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods, and *red*: difference in the 2005 and 2010 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods.

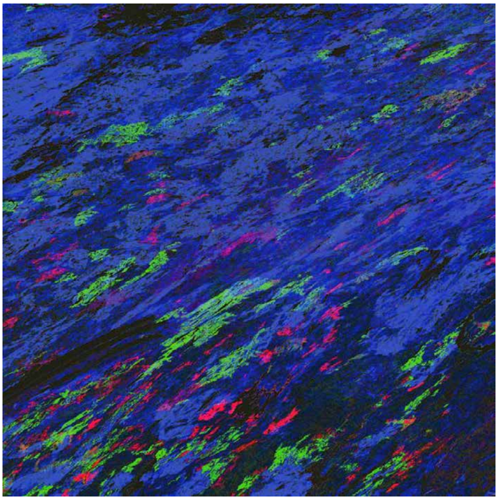


FIGURE 6.3
400 km × 400 km subset centered on 51° 45′ N, 72° 8′ W in Quebec, Canada. False-color composite of MODIS band 7 growing season metrics—*blue*: 2000 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods, *green*: difference in the 2000 and 2005 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods, and *red*: difference in the 2005 and 2010 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods.

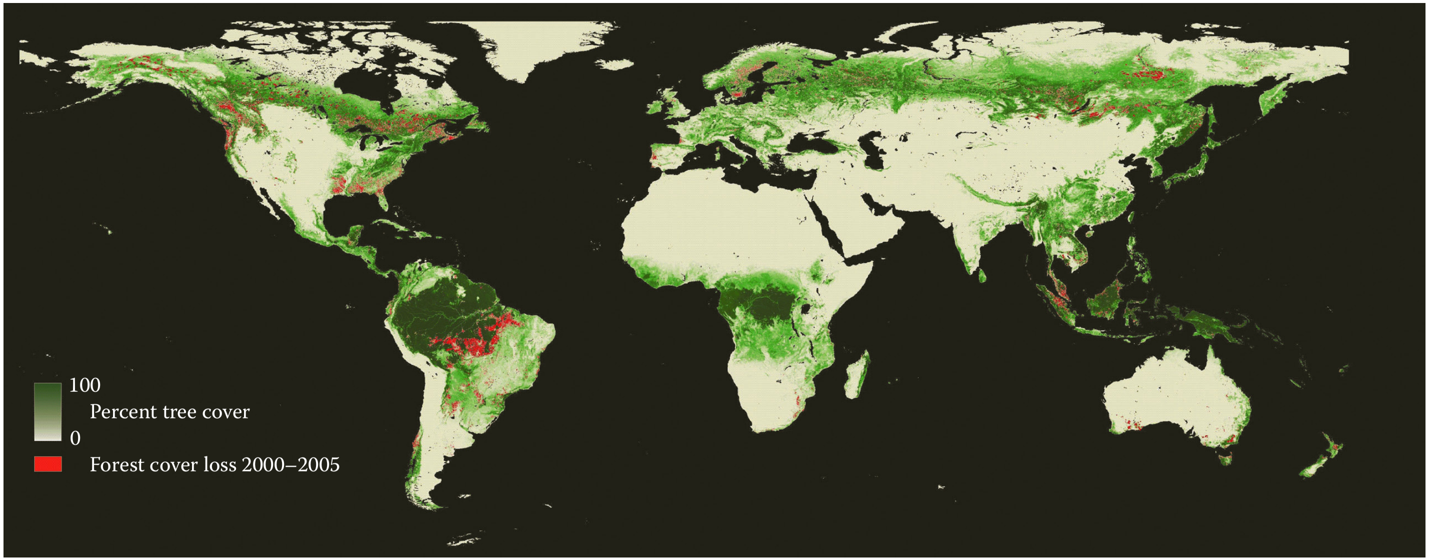


FIGURE 6.5
MODIS percent tree cover 2000 and indicated forest cover loss from 2000 to 2005.

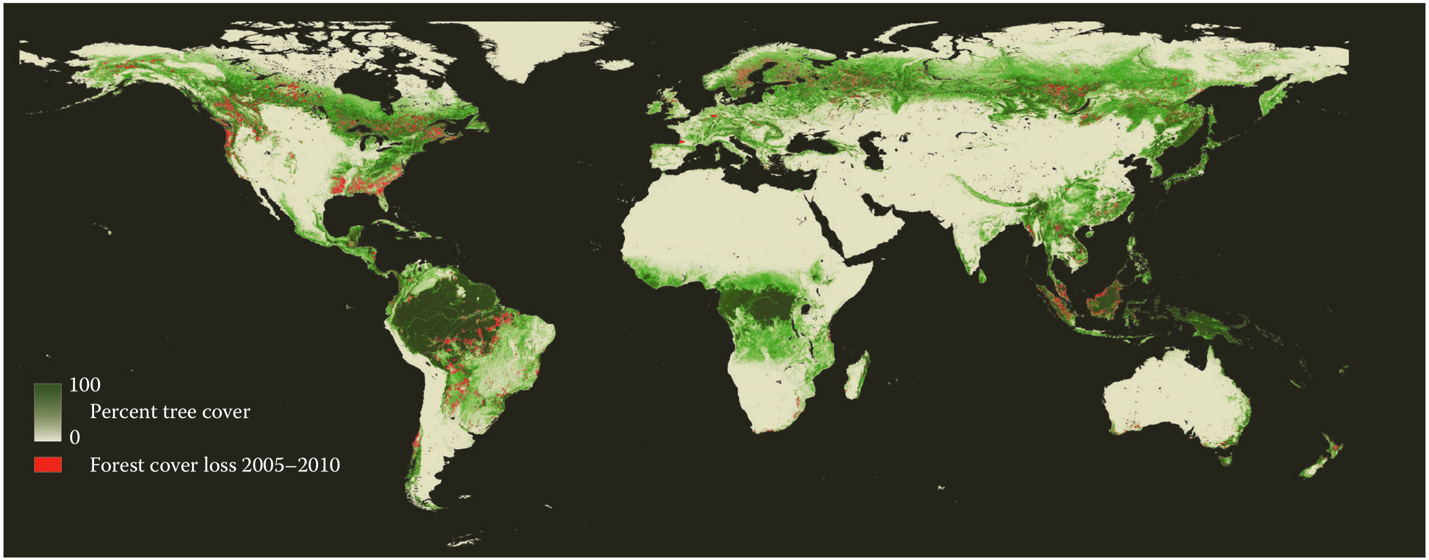


FIGURE 6.6
MODIS percent tree cover 2000 and indicated forest cover loss from 2005 to 2010.

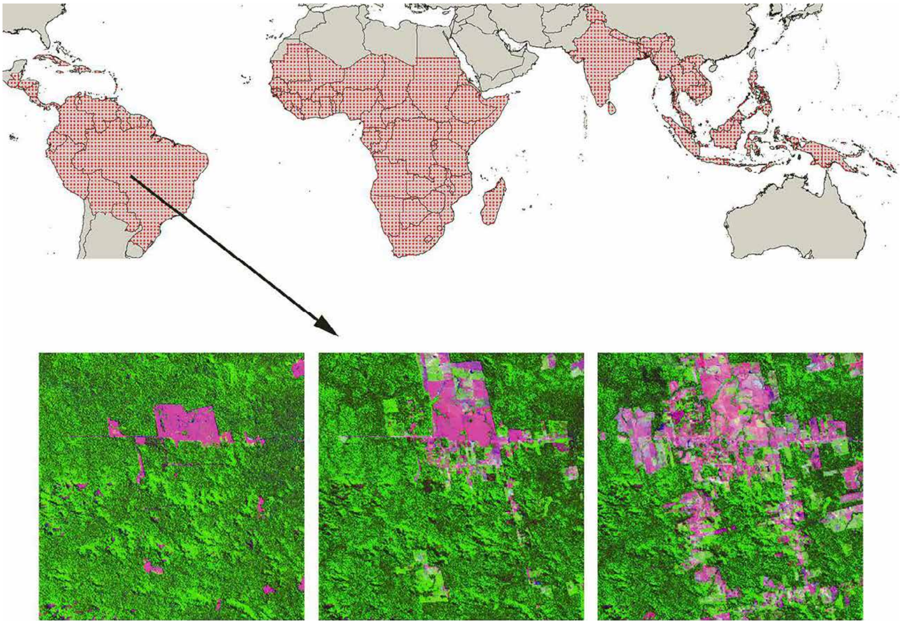


FIGURE 7.1
Example of time series (for years 1990, 2000, and 2005) of Landsat satellite imagery over one sample site in the Amazon Basin (20 km × 20 km size). Forests appear in dark green, deforested areas (agriculture and pastures) appear in light green or pink.

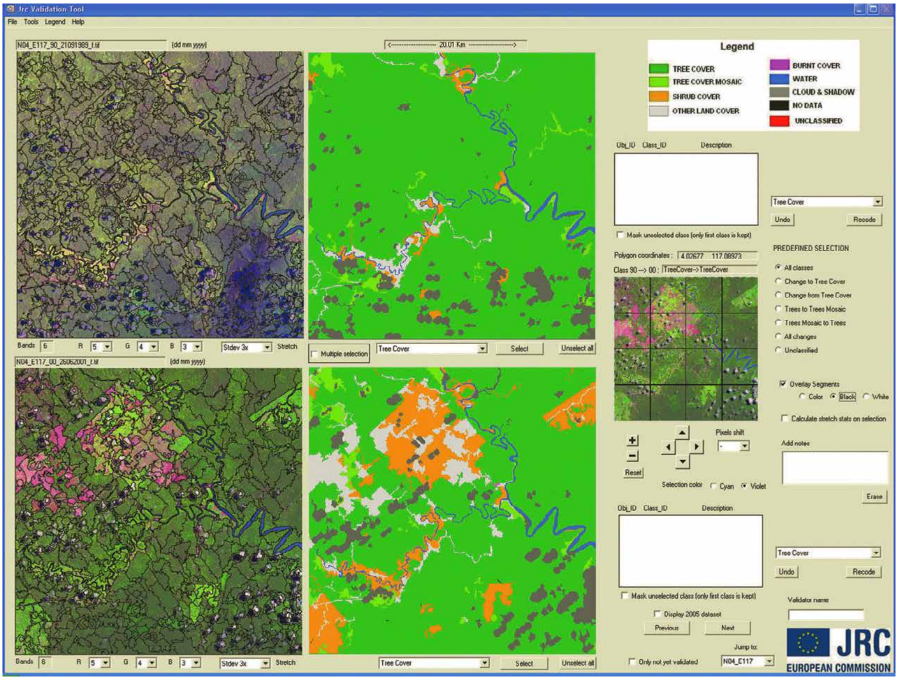


FIGURE 7.2
Visualization tool used for the process of verification and correction of multitemporal classifications. *Left column*: Segmented Landsat imagery displayed (top: year 1990, bottom: year 2000). *Right column*: Land cover maps produced from satellite imagery.

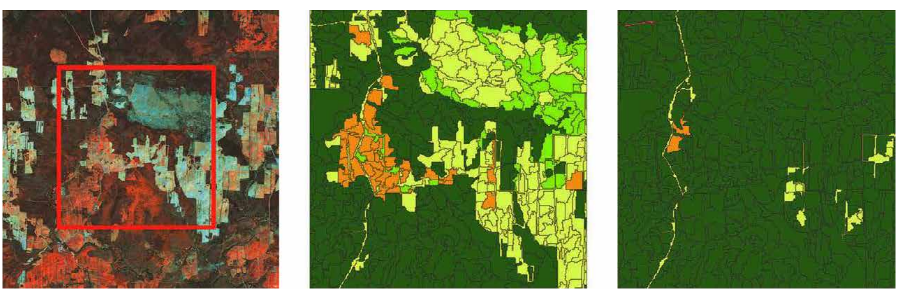


FIGURE 7.3
The 20 km × 20 km multi-spectral Landsat image (left) for a sample site in the boreal forest showing, for the central 10 km × 10 km portion (red box), the classification of land cover (center) and land use (right). Land cover is classified as TC (green), tree cover mosaic (light green), OWL (orange), and other land cover (yellow). Land use is classified as forest (green), OWL (orange), and other land use (yellow).

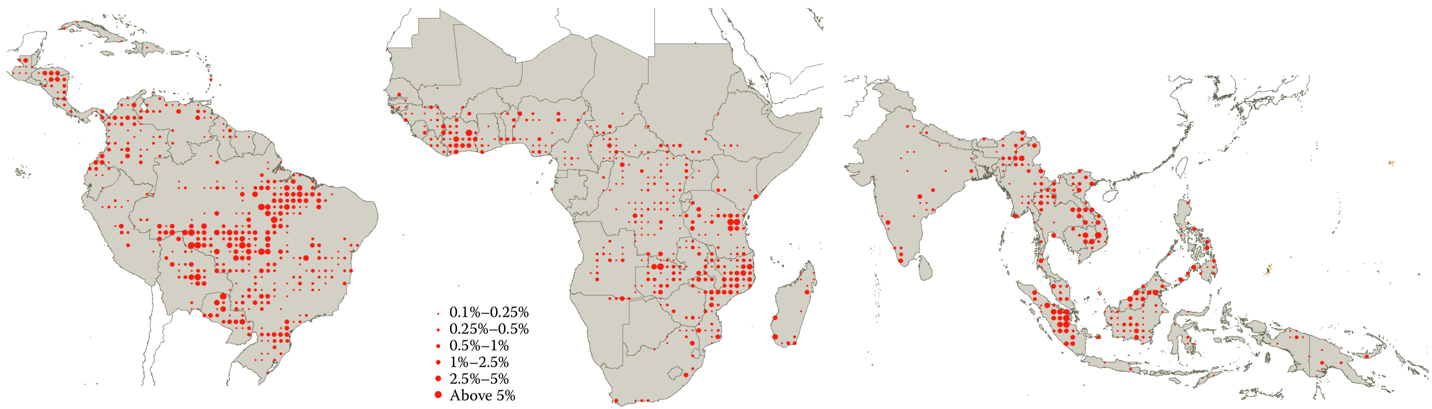


FIGURE 7.4
Annual rate of gross forest cover loss during the period 2000–2005 for the tropical sample units of the global systematic sample.

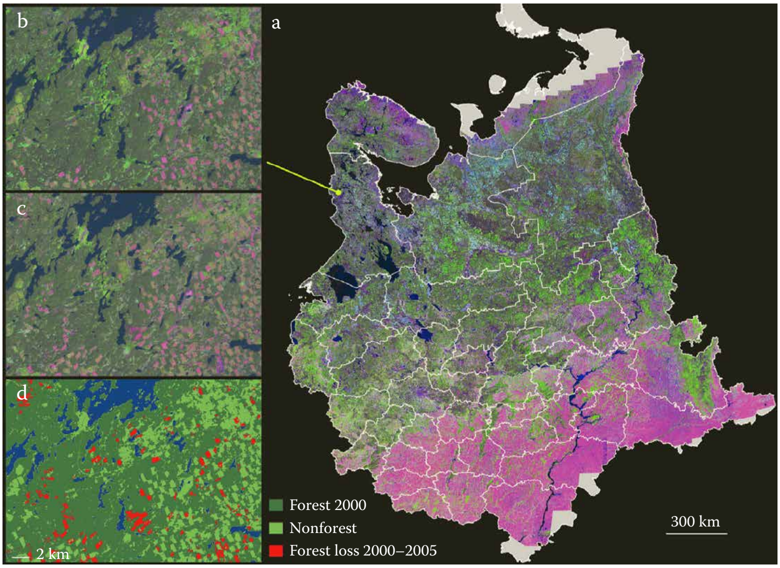


FIGURE 8.2
Forest cover loss monitoring in European Russia. (a) The ca. 2000 region-wide Landsat ETM+ image composite. (b–d) Zoom-in example of forest cover and change mapping in the Republic of Karelia: b—the ca. year 2000 image composite; c—the ca. year 2005 image composite; d—classification result.

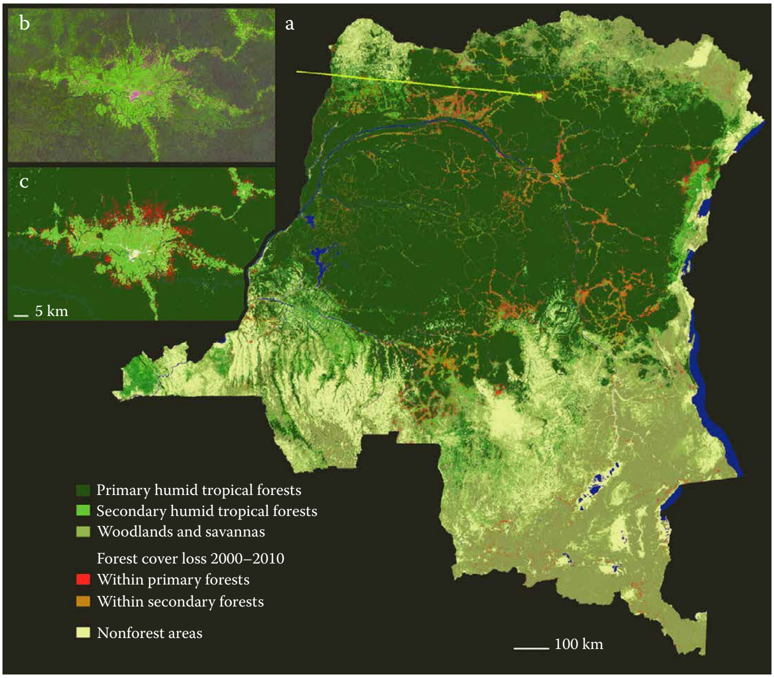


FIGURE 8.4
Forest cover loss monitoring in the DRC. (a) Nation-wide forest cover and change mapping result. (b–c) Zoom-in example of forest cover and change mapping around Buta: b—ca. year 2010 image composite; c—classification result.

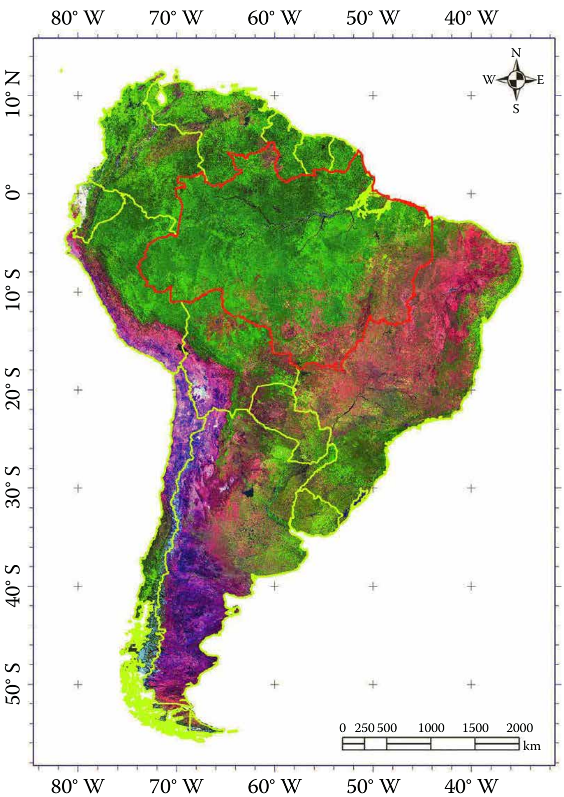


FIGURE 9.1
The BLA (*red*) located in the South American continent.

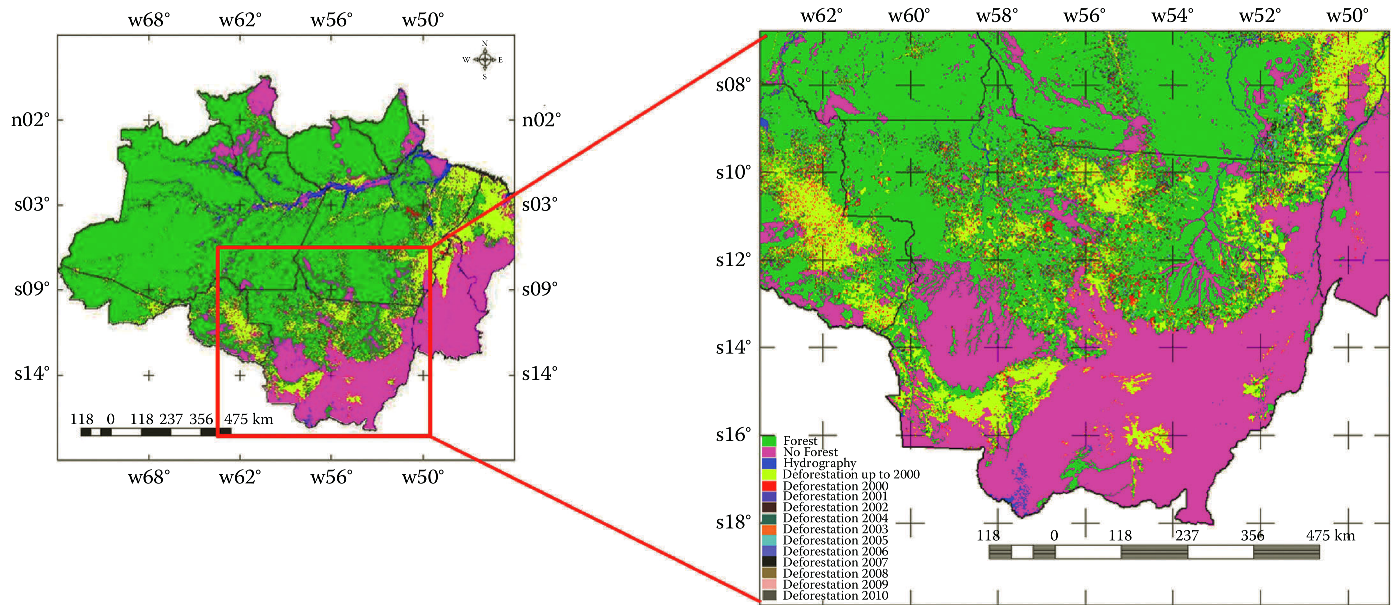


FIGURE 9.4
Mosaic of digital PRODES mapping over the period 2000–2010.

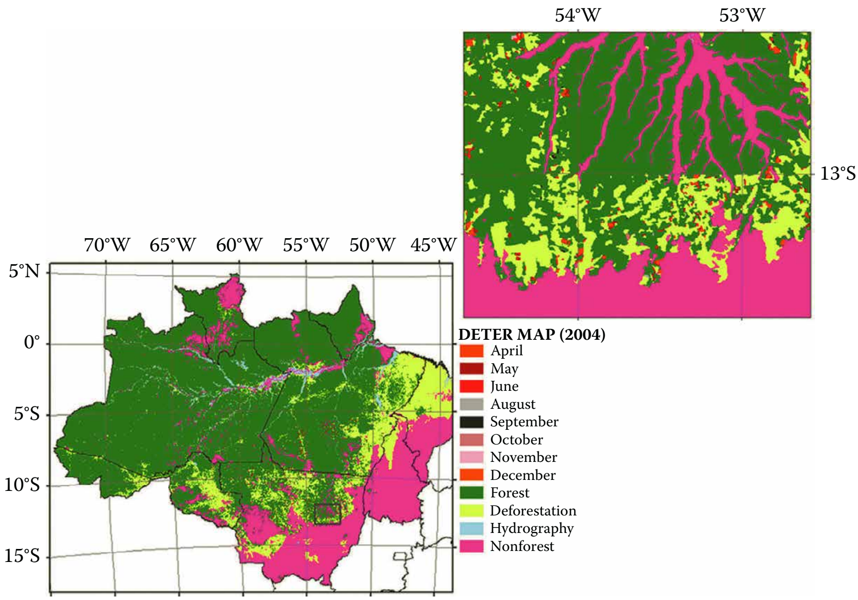


FIGURE 9.5
Illustration of the example of DETER project results, showing the deforested areas detected during the year 2004.

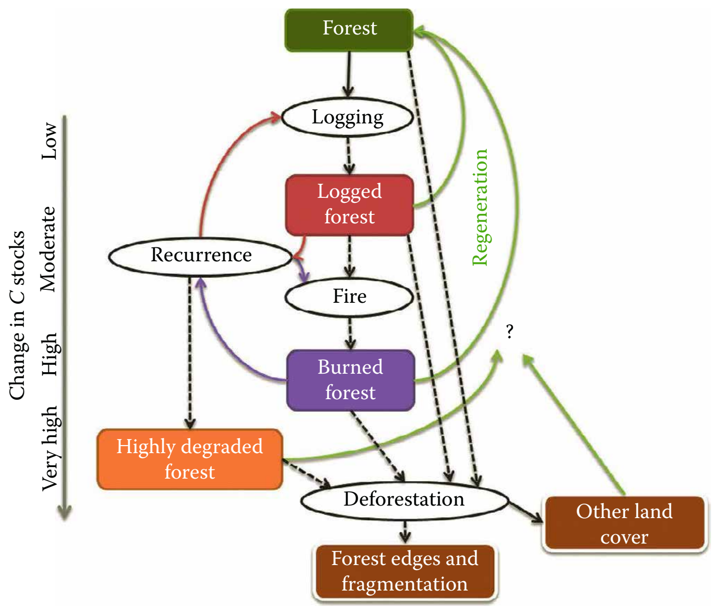


FIGURE 10.1
Forest degradation processes and interactions commonly found in the Brazilian Amazon. Pristine forests can be subject to selective logging, creating favorable conditions for burning when fires from adjacent agriculture fields unintentionally escape. Logging and fires can be recurrent, creating highly degraded forests. Eventually, degraded forests can be converted by deforestation, increasing forest edges and landscape fragmentation. If degraded forests are not cleared, vegetation regeneration processes can prevail given the high resiliency of forests.

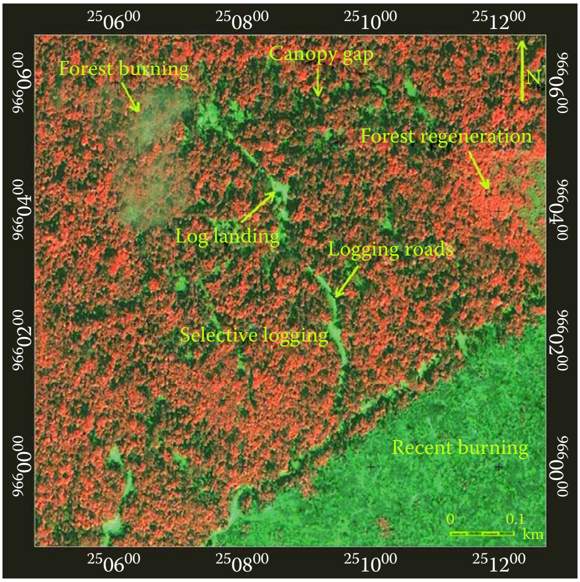


FIGURE 10.2
Very high spatial resolution false-color infrared IKONOS image showing the different environments commonly found in logged and burned (LB) forests in the eastern Brazilian Amazon. At 1 m spatial resolution, log landings, logging roads, tree fall canopy gaps, and forest edges can be identified as well as "islands" of UFs and signs of regeneration. Signs of forest erosion along the edges between the LB forest and the recently slashed-and-burned forest can also be observed. (From Souza, C.M. and Roberts, D., *Int. J. Remote Sens.*, 26, 425, 2005.)

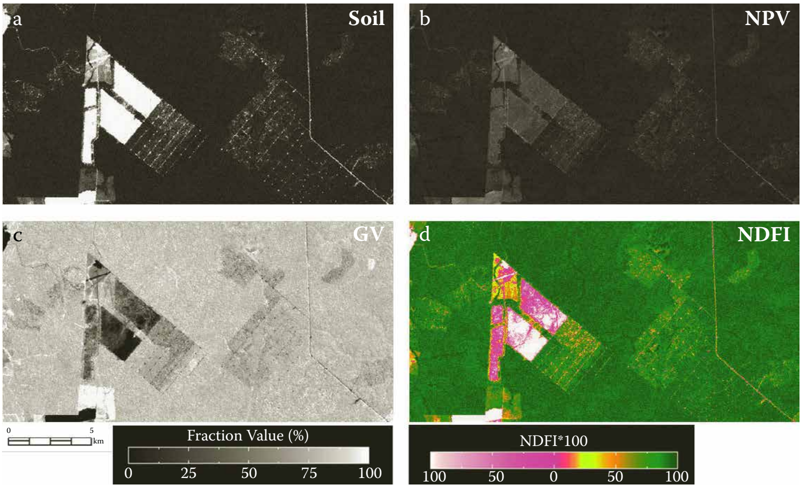


FIGURE 10.4
Subset of a Landsat TM image showing fractions obtained from SMA and NDFI. (a) High soil fraction shows logging infrastructure (log landings and roads); (b) NPV shows higher fraction values for canopy-damaged areas along infrastructure relative to the surrounding intact forest; (c) canopy damage is also identified with lower GV fraction values (dark colors); and (d) all the fraction information are combined to enhance the detection of logged forest.

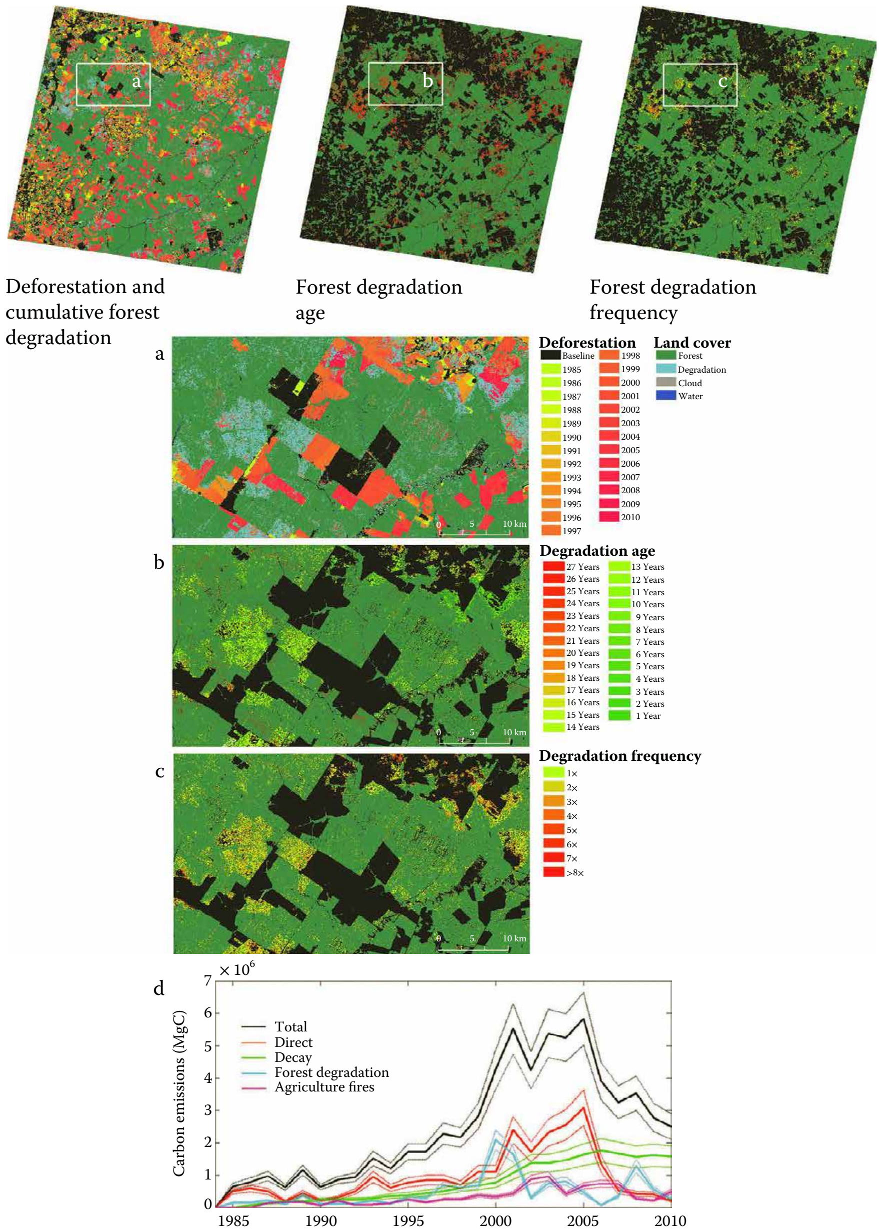


FIGURE 10.5
In this example, a long time series (i.e., >25 years) of Landsat TM/ETM+ data from Sinop, Mato Grosso state, was used to track deforestation and forest degradation. Forest degradation age and frequency maps are obtained from the annual maps and used together with the forest degradation and deforestation maps in a CES model to estimate carbon emissions associated with these processes. More reliable and consistent baseline scenarios for REDD+ can be obtained with this type of model because information about forest degradation is included and associated uncertainty estimated.

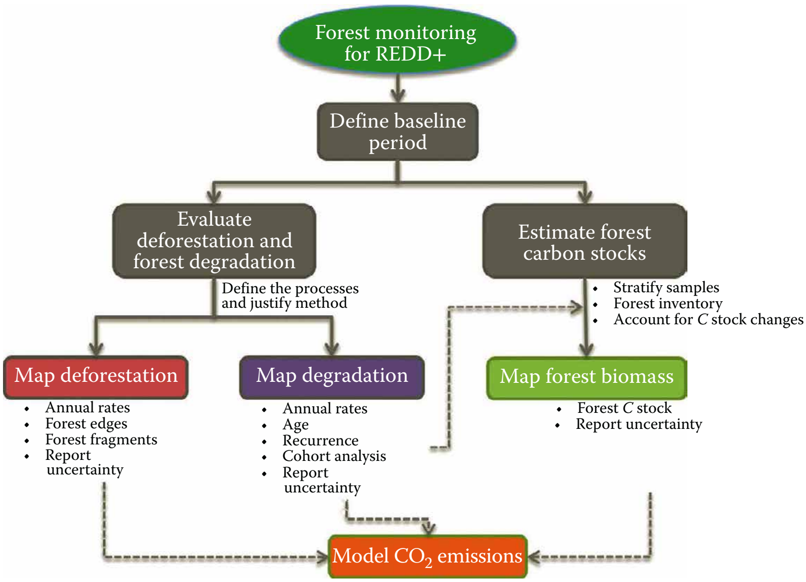


FIGURE 10.6
Integrating deforestation and forest degradation information to estimate forest carbon stock changes for REDD+ projects.

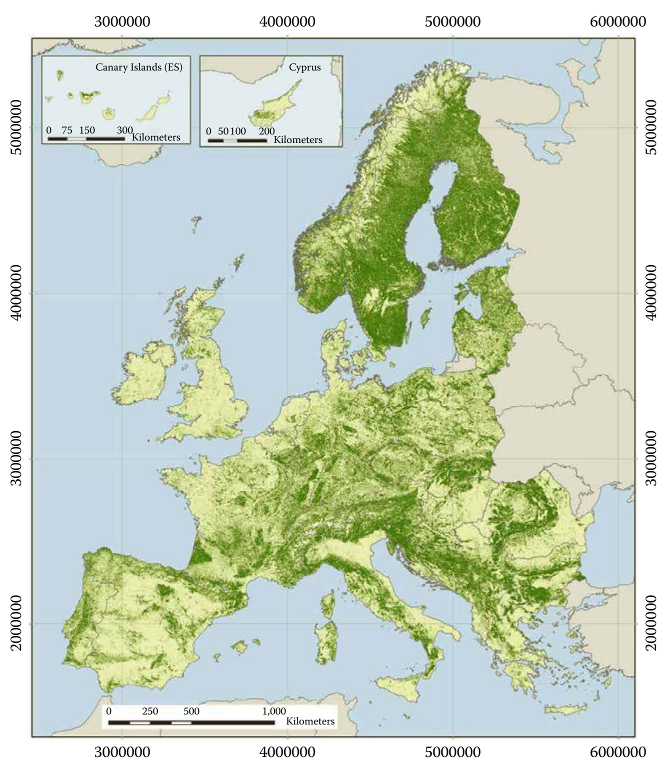


FIGURE 11.1
JRC forest map 2000.

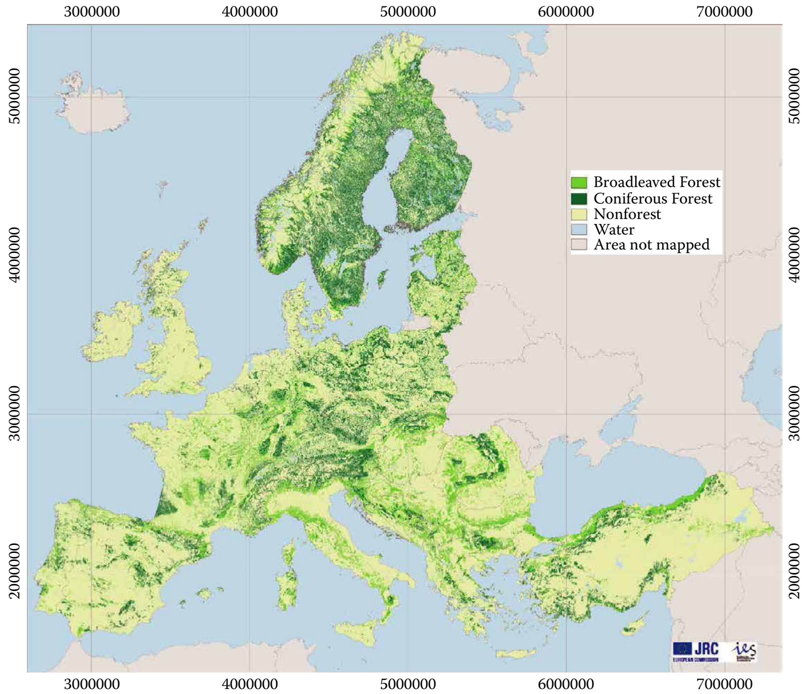


FIGURE 11.2
JRC forest map 2006.

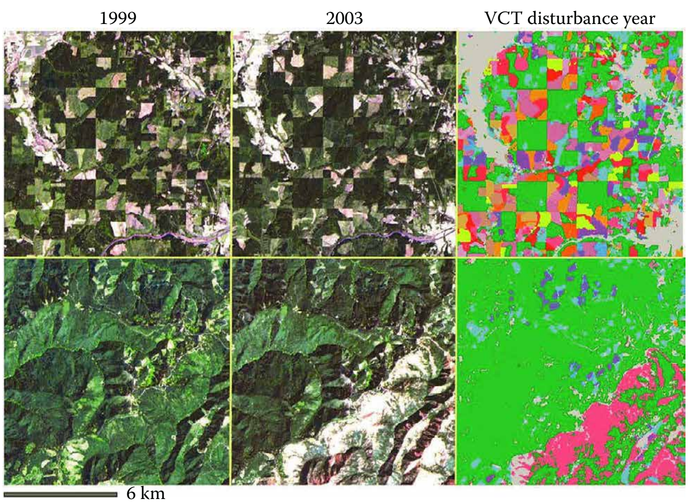
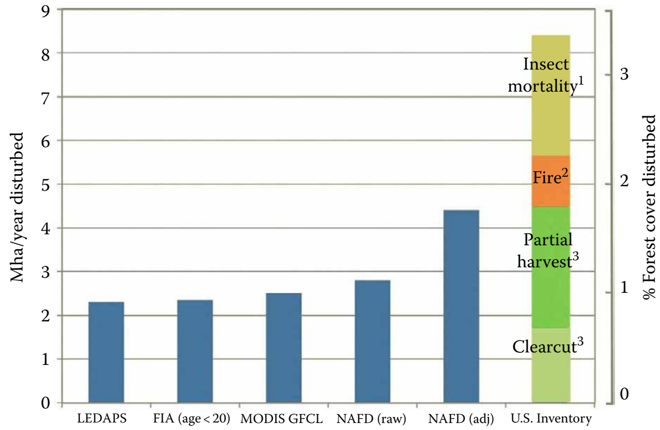


FIGURE 12.2
Examples of NAFD disturbance mapping from southern Oregon (Landsat path 46, row 30). Top row: RGB imagery (bands 7, 5, 3) and VCT disturbance maps for an area of active harvest; bottom row: RGB imagery and disturbance map for the northern edge of the 2002 Biscuit Fire. The VCT maps shows permanent forest (green), permanent nonforest (gray), and the year of mapped disturbance from 1985 to 2009 (other colors).



1. USDA Forest Service (2010) for USA—includes areas of mortality only, excluding defoliation without mortality.
2. U.S. EPA (2010)—includes Alaska fires.
3. Smith et al. (2009).

FIGURE 12.3
Comparison of disturbance rates among satellite-based and inventory-based studies. LEDAPS (Masek et al. 2008) and NAFD (Kennedy et al. in preparation) are based on Landsat change detection. NAFD (adj) reflects compensation for net omission errors based on visual validation. MODIS GFCL is based on MODIS gross forest cover loss (GFCL) (Hansen et al. 2010). The FIA (age < 20) is based on equating the area of young forestland from the FIA with an annualized turnover rate. The percent forest cover values are based on the area of forest land in the "lower 48" conterminous United States (~250 Mha).

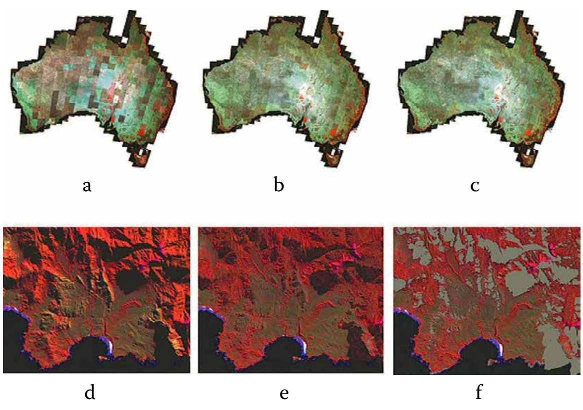


FIGURE 13.1
Image calibration (top) and normalization (bottom). Calibration: Landsat mosaic of Australia showing (a) uncalibrated, (b) TOA correction, and (c) TOA + BRDF correction. Normalization (From Wu et. al., 2004.): (d) uncorrected, (e) terrain illumination correction, and (f) estimated occlusion mask overlaid and shown in gray. (From Wu, X., et al., An approach for terrain illumination correction. Australasian Remote Sensing and Photogrammetry Conference, Fremantle, Western Australia, 2004.)

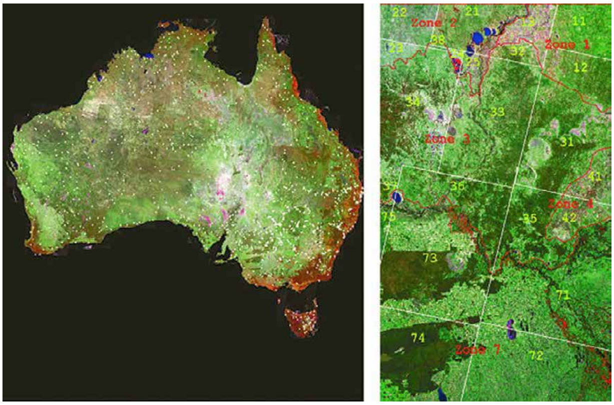


FIGURE 13.3
(Left) Graphical depiction of the location of high-resolution IKONOS data used in the derivation of classifier training information. (Right) Typically, samples are required by intersection of zone and image, though well-calibrated data can reduce this requirement by allowing extrapolation across scene boundaries in many cases.

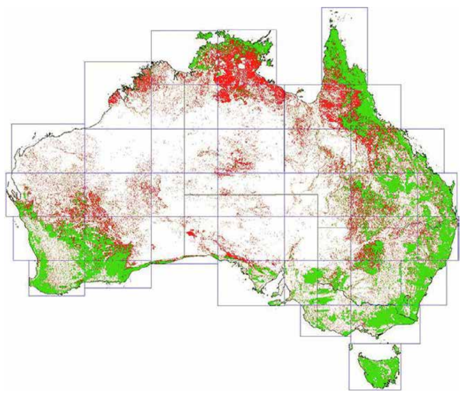


FIGURE 13.5
Map of Australia showing NCAS forest extent (green) and sparse extent (red).

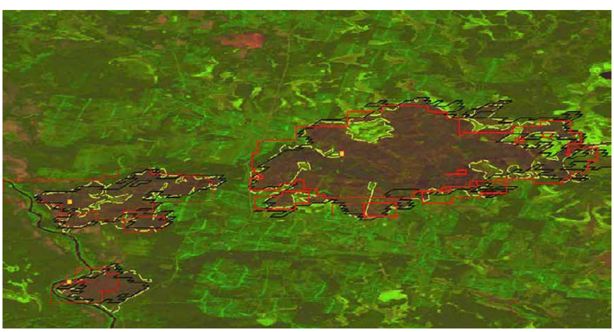


FIGURE 14.8
Example of burned area polygons derived from the three methods: red polygon, AFBA product; black polygon, SRBA product; yellow polygon, HRBA product. The results are displayed in the Web-service user interface with the Landsat-TM scene used for the HRBA product as a background image.

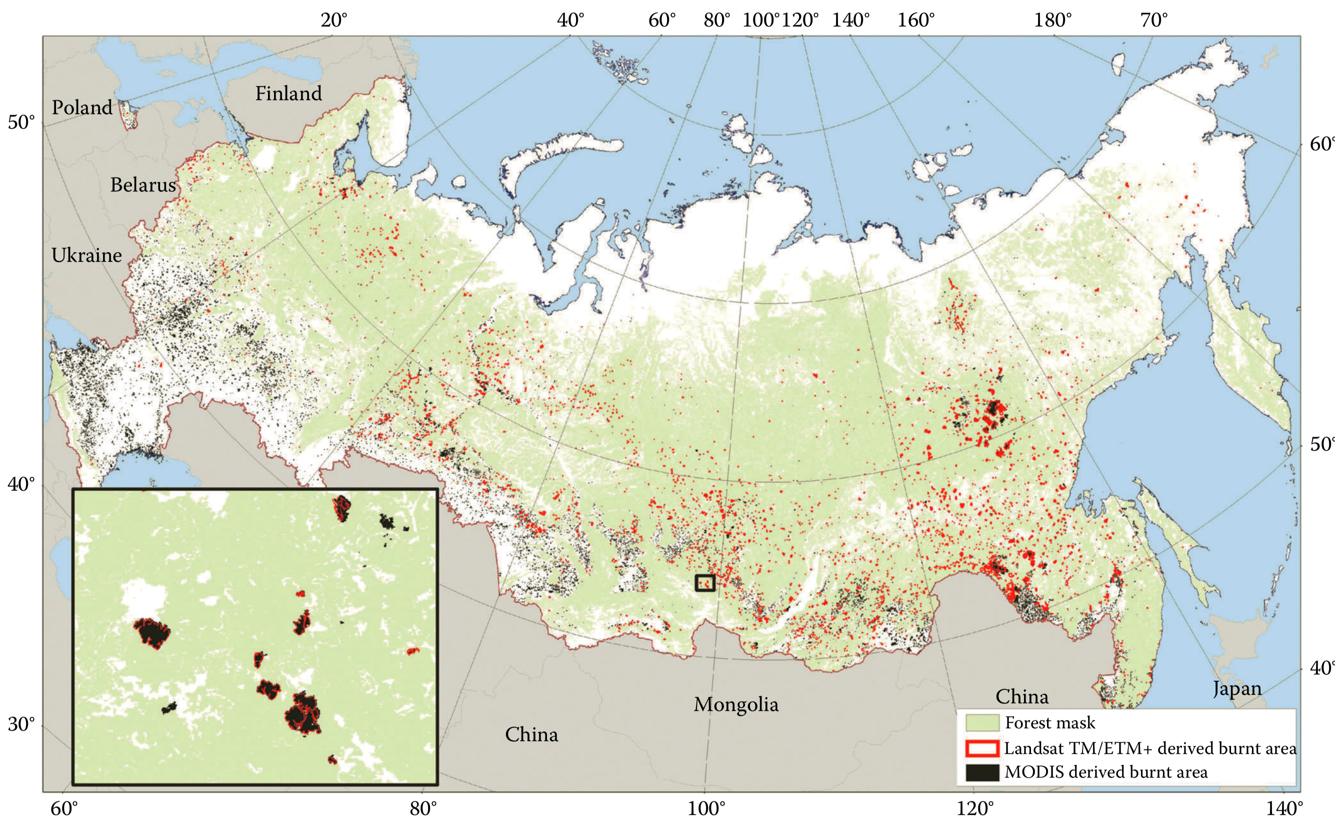


FIGURE 14.14
Burned areas for the year 2011 over Russian Federation as depicted by the SRBA product (black areas) and the HRBA product (red polygons).

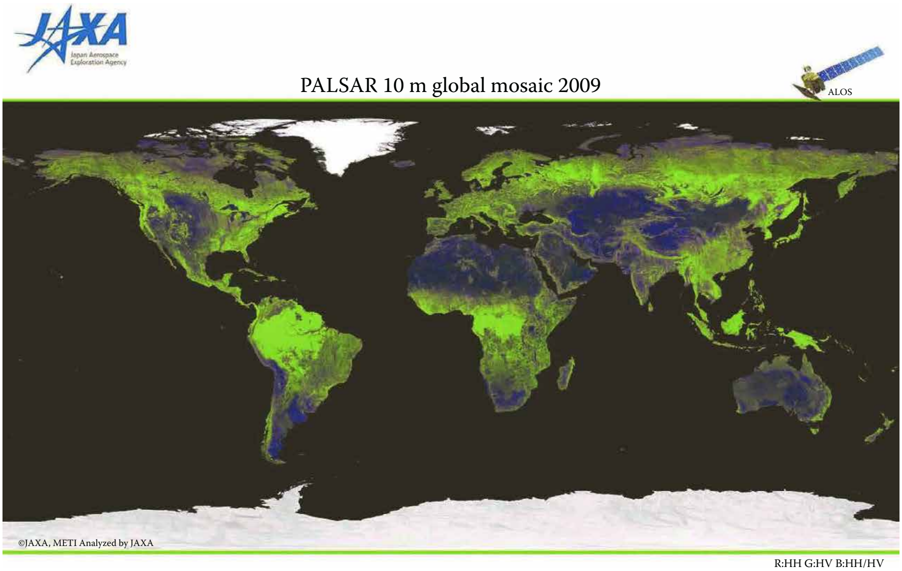


FIGURE 15.1
Global ALOS PALSAR color composite mosaic at 10 m pixel spacing (R: HH, G: HV, B: HH/HV). 95% of the data—a total of approximately 70,000 scenes—were acquired within the time period June–October 2009. (Courtesy of JAXA EORC, Tsukuba, Japan.)

FIGURE 15.2
(d) A composite of HH data from two dates (September 12 and 15, 2011) and coherence (in RGB respectively; blue areas indicate deforested areas).

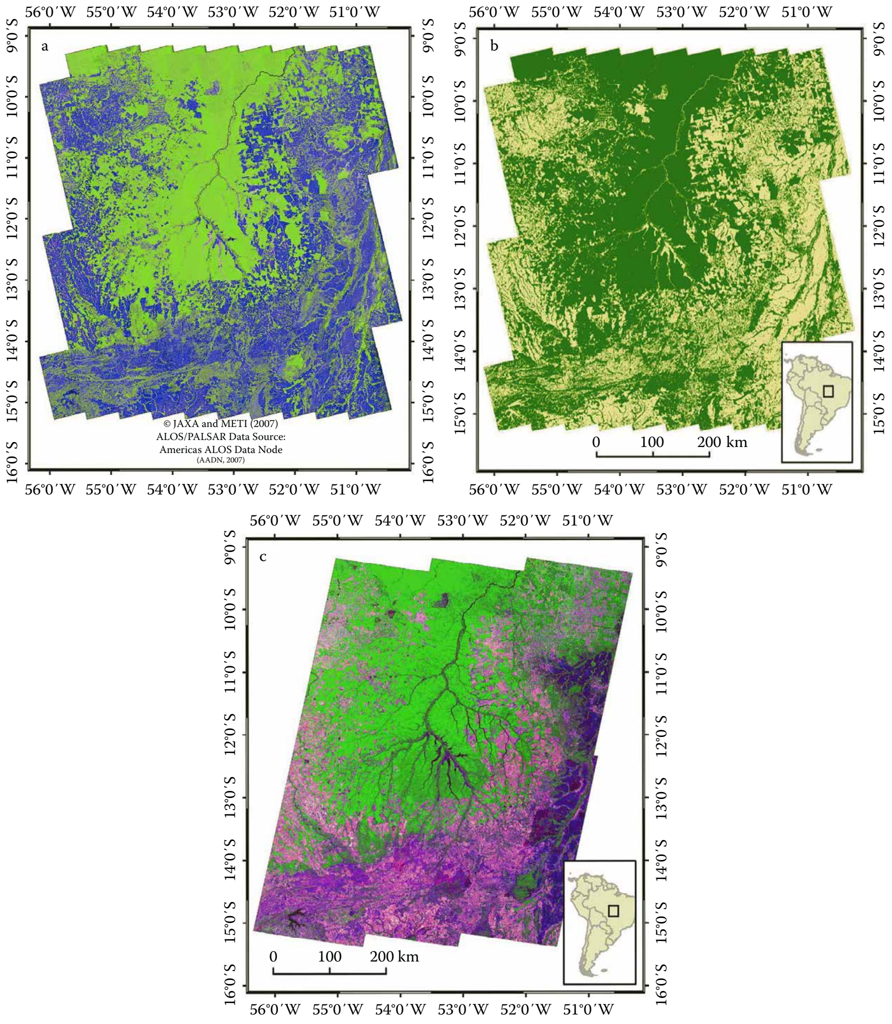


FIGURE 15.4
Satellite image mosaics produced for the Xingu River headwaters region. (a) ALOS PALSAR mosaic consisting of 116 individual Level 1.1 (single-look complex) fine beam, dual-polarimetric scenes (R/G/B = polarizations HH/HV/HH-HV difference). (b) Map of forest (green) and nonforest (beige) generated with an overall classification accuracy of 92.4% ± 1.8%. (c) Landsat 5 mosaic consisting of 12 individual Level 1G (Geocover) scenes (R/G/B = bands 5/4/3).

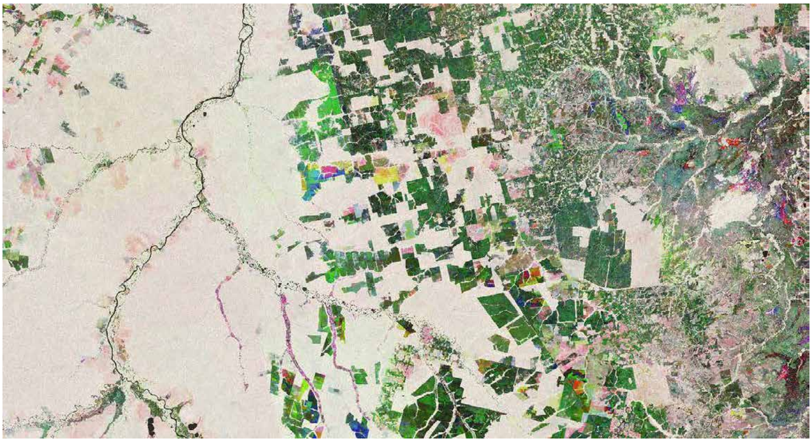


FIGURE 15.5
Multitemporal ALOS PALSAR L-band HV image generated from data acquired in 2007 (red), 2008 (green), and 2009 (blue) for a part of the Xingu watershed. Closed forest (white) is interspersed with fire scars (red tones) along the main stem of the Xingu River and tributaries (black).

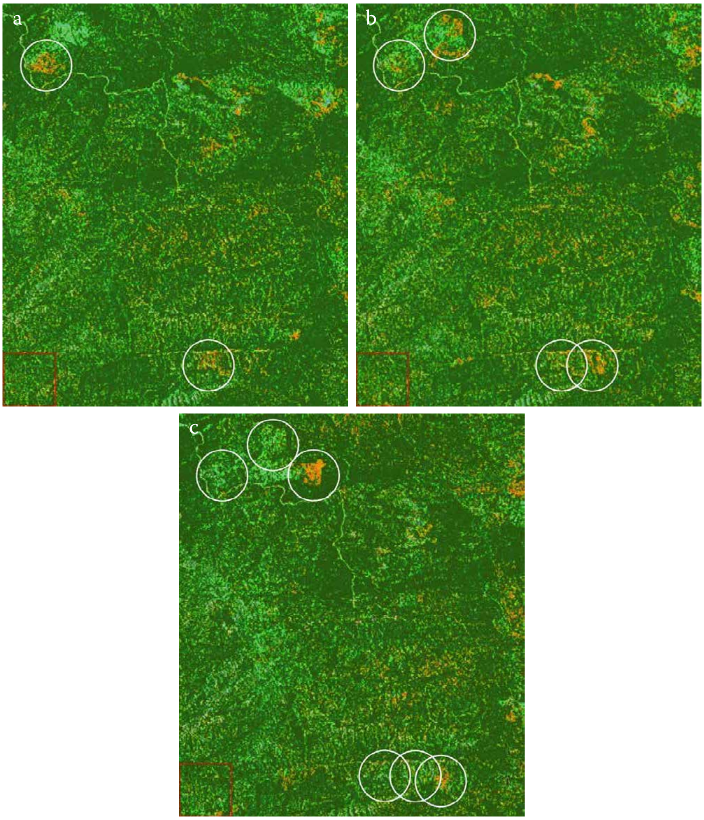


FIGURE 15.6
Forest degradation in Sarawak through selective logging observed through comparison of forest maps generated using ALOS PALSAR data for the years (a–c) 2007 through to 2009.

11.1 Introduction

Forest resources are very relevant in the political agenda of the European Union, as forestry influences many sectorial policies dealing with environmental protection, renewable energy, and biodiversity, to name some. The design, implementation, monitoring and evaluation, and impact assessment of environmental policies at the European level require reliable, consistent, and updated information of forest resources.

Although several countries in Europe collect a considerable amount of forest-related information, this is often not spatially continuous and frequently not accessible, nonharmonized, scattered in remote databases, and encapsulated in diverse data formats. One critical aspect regarding forest information in Europe is the different forest definitions used by countries, which hampers the comparability of nationally collected forest information.

Remote sensing–based products are thus the most suitable source of consistent and up-to-date forest information over large areas. Remote sensing techniques have been widely used for mapping forest resources at local and national levels. Working over large areas poses additional logistic, technical, and managerial challenges that have limited the number of existing pan-European products. Large-area projects usually require a considerable data management capacity. They also require carefully planned processing chains, including consistent preprocessing of satellite and ancillary information and mapping methodologies to produce large-area products. In addition, these methodologies must be robust, reliable, and flexible to handle suboptimal data sets of images from several sensors.

Several remote sensing–based products exist that include forest information and have pan-European coverage. However, these products were derived from coarse-resolution satellite images (Bartholomé and Belward 2005; DeFries et al. 2000; Friedl et al. 2002; Häme 2001; Hansen et al. 2000; Schuck 2003) or are labor intensive (Corine Land Cover [CLC]). Furthermore, the lack of comprehensive validation schemes of these products limits their utility in a number of applications.

The recent availability of a wider selection of remote sensing data allows an improvement in spatial resolution over the existing products. It also allows exploiting the temporal domain of remote sensing data. This scenario enables the development of products with higher spatial detail and increased thematic information content.

In this context, the Joint Research Centre (JRC) of the European Commission has been working on the production of enhanced remote sensing–based forest products. Two pan-European forest maps with a ground sampling distance (GSD) of 25 m have been produced based on Landsat ETM+ imagery (Pekkarinen et al. 2009) and IRS LISS-III, SPOT 4-5, and Moderate Resolution Imaging Spectroradiometer (MODIS) remote sensing data

(Kempeneers et al. 2011). Besides these high-resolution products, the JRC is carrying out research to improve forest monitoring capabilities at 250 and 500 m GSD based on time-series analysis of remote sensing data. This chapter presents the methodologies used in the production of these maps and their accuracies and discusses future potential developments in forest monitoring at the pan-European level.

11.2 Materials and Methods

This section describes the materials used in the production of the forest maps for the years 2000 and 2006 (Figures 11.1 and 11.2).

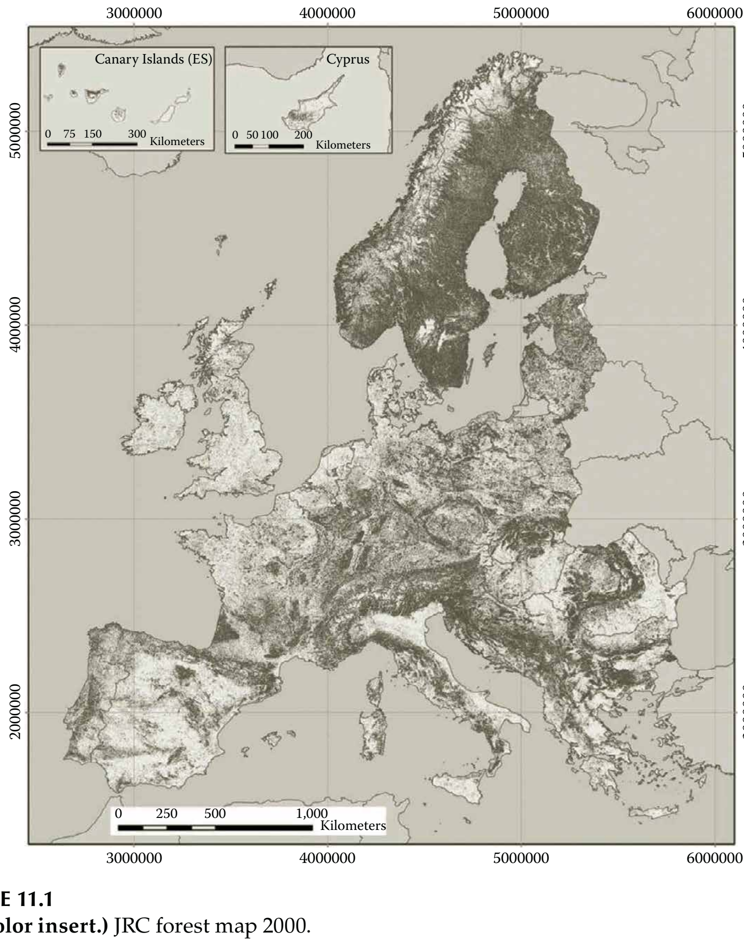


FIGURE 11.1
(See color insert.) JRC forest map 2000.

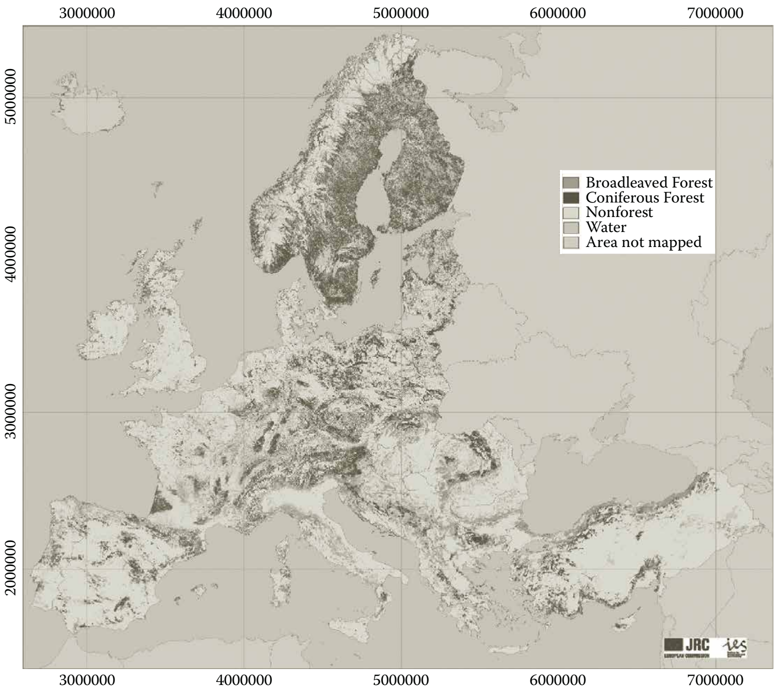


FIGURE 11.2
(See color insert.) JRC forest map 2006.

11.2.1 Materials

The forest/nonforest map for the year 2000 (FMAP2000) was derived from Landsat-7 ETM+ imagery. Scenes belonged to two different image datasets: the NASA Orthorectified Landsat Dataset (Tucker et al. 2004) available from the Global Land Cover Facility (GLCF) and the IMAGE2000 data set (JRC 2005). The two data sources were mixed in order to optimize cloud freeness and acquisition date. The target year for the scenes was 2000, but the acquisition window covered years from 1999 to 2002. The full data set included 415 scenes available as top of atmosphere (TOA) radiance: 285 of them from the GLCF and 130 from the IMAGE2000 data set. All images in the full data set were reprojected to the European Terrestrial Reference system 1989 and the Lambert Azimuthal Equal Area (ETRS89-LAEA) projection and resampled to 25 m rasters. In order to ensure consistent geometrical quality between scenes coming from the two different data sets, IMAGE2000 scenes were orthorectified taking GLCF scenes as a reference.

The forest/nonforest map for the year 2006 (FMAP2006) and the forest type map (FTYP2006) were derived from the IMAGE2006 data set. This data set includes TOA radiance IRS-LISS-3 scenes and additional SPOT 4 and

5 scenes for those regions in which cloud-free IRS-LISS-3 were not available. The scenes were orthorectified and geometrically corrected. As in the year 2000, all images were reprojected to ETRS89-LAEA projection and resampled to 25 m rasters.

In addition to the IMAGE2006 data set, the production of FTYP2006 required 12 (one per month) MODIS 16-day composites at 250 m spatial resolution. These composites were reprojected and resampled to 25 m to match the IMAGE 2006 data set.

11.2.2 Ancillary Data

11.2.2.1 Training Data

The CLC data set was used as training data. CLC includes 44 land cover (LC) and land use classes from which three correspond to forest classes (broadleaved, coniferous, and mixed forests). The CLC covers all EIONET countries, which includes the EU-27 Member States and neighboring countries. The CLC is available for the reference years 1990, 2000, and 2006. The corresponding data set was used for the production of each pan-European forest map.

11.2.2.2 Reference Data

The validation of the FMAP2000 was performed using two data sets. The first included field plot data from the land use/cover area frame statistical survey that was carried out in 2001 (LUCAS2001). LUCAS2001 is based on 94,984 sampling units, which consist of a circle with a 20 m radius. It is based on a seven LC classification nomenclature, with the forest class subdivided into broadleaved, coniferous, and mixed, but it also includes a land use component. The second data set was derived from the visual interpretation of sample points overlaid on very high-resolution satellite imagery from Google Earth. In total, 5,193 forest and nonforest points were collected from the interpretation of this data set and classified into forest and nonforest classes.

The FMAP2006 was validated using ground reference data that were derived from European National Forest Inventories (NFIs). NFI data are frequently collected by national authorities for the production and planning of forest resources at national and regional levels, but they are also needed to meet international reporting requirements to the FAO's Forest Resource Assessment (FAO 2010) and other requirements.

The NFI data used in this validation were managed in the so-called eForest platform. The eForest platform, established for the provision of data and services to the European Forest Data Center (EFDAC) of the European Commission, is the first step to produce a harmonized database of all European NFIs. It emerged from the work carried out by the COST Action E-43 that sought to develop methods, concepts, and definitions that would harmonize NFIs between countries (Tomppo et al. 2010). Of particular importance within

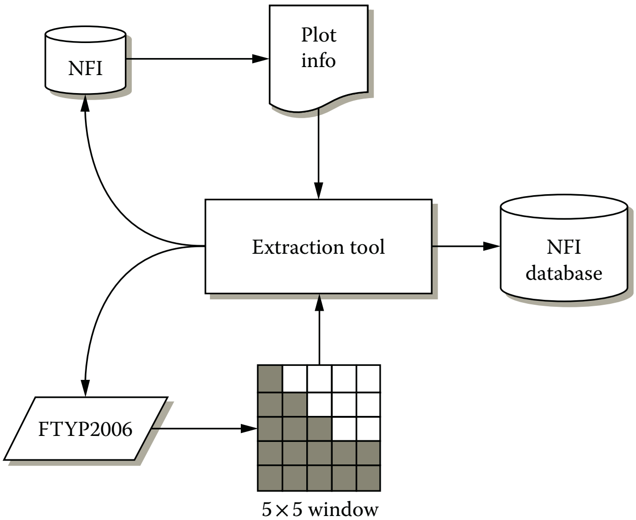


FIGURE 11.3
Pixel extraction tool.

this process was the harmonization of the definition of forest, which varies between NFIs.

The platform consisted of 1,080,829 NFI plots, distributed across 21 countries. However, the exact plot locations were not disclosed by the NFIs. For the validation, it was necessary to build a pixel extraction tool that was used by the data owners to extract the forest map data within a 5 × 5 window around the NFI plot coordinates (Figure 11.3). These data were used to compute the overall, producer, and user accuracies for the FMAP2006 at country and regional scales. Plots that were labeled as young stands or unstocked were removed from the eForest validation data set so that the accuracy assessment of the FMAP2006 focused on forest cover and nonforest use. It should be noted that unstocked forest areas are considered forests from a land use perspective, although they are not forests from an LC (remote sensing) perspective.

Additionally, the LUCAS2001 data were used to validate the FMAP2006 data set. The results of this validation process are described hereafter.

11.3 Methods

11.3.1 Data Preprocessing

The high spatial resolution scenes from IRS LISS-3 and SPOT4/5 were preprocessed by the German Aerospace Center (DLR). The scenes were orthorectified using rational polynomial functions (Lehner et al. 2005) and geometrically corrected using ground control points (GCPs) and a digital elevation model (DEM). The orthoimages were resampled to 25 m in the standard projection for Europe, using the ETRS89/LAEA projection (Annoni et al. 2003). The reported root mean square errors in both horizontal directions were less than a pixel. The images were only available as TOA radiances (not atmospherically corrected).

In the case of the MODIS, daily images were also preprocessed by DLR in the standard European projection. However, a geometric and atmospheric correction was performed to obtain ground reflectances for bands 1–7 at 250 and 500 m GSD.

A 16-day MODIS composite was created from the daily images. By not using the MOD13Q1 product (Huete 2002), a reprojection from sinusoidal to the standard European projection was not needed, avoiding an extra interpolation step. Unlike the MOD13Q1 product, our 16-day composite was not corrected for BRDF effects. Nevertheless, by selecting the median pixel value in the NIR band of all cloud-free observations within the 16-day window, some of the effects due to undetected clouds and extreme observation angles were alleviated.

11.3.2 Forest Mapping Approaches

A nonparametric supervised classification algorithm was used to obtain the forest maps FMAP2000 and FTYP2006. Supervised classification methods are preferable in cases where *a priori* information is available for the desired output classes and their spatial distribution (Cihlar 2000). With the CLC map, training data for forests (types) and nonforests were available in a consistent way for the entire area of interest (Europe).

Given the large geographic extent of the pan-European map, the interclass variance was expected to be high. For example, broadleaved forests in northern Europe have different spectral characteristics than those in southern Europe. Moreover, the digital numbers stored in the multispectral image bands represented TOA radiance and thus were not corrected for atmospheric effects. Consequently, image data were processed on a scene-by-scene basis, allowing the classifier to be trained for the specific conditions within each scene. The final output, the pan-European forest map, was then obtained by mosaicing the different scenes, using a composite rule where pixels did overlap. In the case of the FMAP2000, the composite rule was based on uncertainty information derived during the classification process. The number of overlapping scenes in the case of the FMAP2006 was larger (every pixel was observed at least twice but often three to four times). This allowed for a (weighted) maximum voting of the classified scenes. Weights were introduced based on seasonality. Summer scenes were weighted in favor of early spring or late autumn scenes.

The main requirements for the classification method were:

1. Consistency: The wall-to-wall pan-European forest map had to be produced in a homogeneous way.
2. Performance: Algorithms had to be fully automatic.
3. Robustness for deficiencies in the training and input data: The methods for the FMAP2000 and FTYP2006 showed some important differences in how this was achieved. This is explained in the following overview.

The FMAP2000 was mapped using a *k*-nearest-neighbor (*k*-NN) classifier (Tomppo et al. 2008). Instead of extracting spectral information for each Corine Land Use Land Cover patch, two key improvements in the classification approach were implemented to improve the performance (Pekkarinen et al. 2009): first, a segmentation prior to the classification step and second, an adaptive spectral representivity analysis (ASRA) (Pekkarinen et al. 2009). ASRA was developed to improve the training process and to minimize errors resulting from the relatively large minimum mapping unit of Corine. The segmentation was merely used to speed up the *k*-NN classification, which is known to be inefficient for processing large data sets. The ASRA was introduced after clustering the segments into spectral classes. It seeks to identify representative combinations of spectral and informational classes using a contingency table, derived from the cluster labels and CLC classes. For more details of the algorithm, the reader is referred to Pekkarinen et al. (2009).

The classification method for the FTYP2006 was based on an artificial neural network (ANN) (Rumelhart and McClelland 1986) that has been shown to combine two excellent classification properties: high accuracy (Chini et al. 2008; Licciardi et al. 2009) and robustness to training site heterogeneity (Paola and Schowengerdt 1995). Also important for the selection of the classifier was that the ANN, once trained, is very fast. Unlike for the production of the FMAP2000 method, a segmentation step was therefore not needed.

Another difference with the FMAP2000 is that forest types were introduced in the FTYP2006. To increase the potential of the classifier, multitemporal information was added to the multispectral information (data fusion). The multitemporal data were obtained from the MODIS sensor, using a 16-day composite for each month in 2006 at 250 m spatial resolution. The temporal aspect of the spectral reflectance can describe phenology, which is a potential indicator for LC types (DeFries et al. 1994; Hansen et al. 2005). The data fusion with this additional information source also increased the robustness of the classification process (Kempeneers et al. 2011).

However, fusing data from sensors at different spatial resolutions posed a challenge to retain the fine spatial resolution in the final LC map. A new data fusion method was therefore proposed, based on a two-step approach (Kempeneers et al. 2011). In step one, the classifier created a forest map, classifying forests and nonforests only. In step two, a new classifier refined forest into forest types, excluding the nonforested pixels from the classification process. The multitemporal data at medium spatial resolution were introduced only in step two.

The idea is that, as the classes are refined, the complexity of the classification increases. At this point, the classifier can benefit most from the added information obtained from data fusion. The forest/nonforest map was mapped using only the spectral information at fine spatial resolution and therefore retained the finest spatial resolution possible.

11.4 Results

The accuracy assessment of the forest cover maps was performed using three reference data sets that were previously described in Section 11.2.2. The overall accuracy (OA) of the FMAP2000 was 88.6% and 90.8% respectively for the VISVAL and LUCAS data sets, while the OA for the FMAP2006 was 88.0% and 84.0% based on the eForest and the LUCAS2001 data sets. The results for eForest and LUCAS2001 cannot really be compared due to a different coverage in both space and time (where LUCAS2001 can be regarded as outdated).

The calculation of the producer and user accuracies provided information on the performance of both maps for the forest and nonforest classes (Table 11.1). The producer's accuracy of the forest class was lowest for the FMAP2006 (75%) with respect to the eForest database, while it was slightly higher than FMAP2000 at 85.5% and 83.9% when compared to the VISVAL and LUCAS data sets. When compared to official statistics, the results demonstrated an overall underestimation of forest area in both forest maps, which was particularly emphasized in Ireland, Spain, Portugal, and Greece. This underestimation can be explained by the high rate of recent afforestation in Ireland, while in the Mediterranean countries, the forests typically have a very low percentage forest cover (e.g., 5% in Spain).

TABLE 11.1

FMAP2000 and FMAP2006 Accuracies with Respect to Validation Data Sets

	FMAP2000		FMAP2006	
Accuracies	**VISVAL**	**LUCAS**	**eForest**	**LUCAS2001**
OA%	88.6	90.8	88.0	84
Forest PA%	85.5	83.9	75	66
Forest UA%	77.66	85.8	87	85
Nonforest PA%	89.58	NA	94	94
Nonforest UA%	93.59	NA	88	84

The individual accuracies for the forest and nonforest classes were computed for the 3 × 3 window, and it was found that the producer accuracies improved by 1% for the eForest database (from 75% to 76%) and by 3% for the LUCAS data set (from 66% to 69%).

11.5 Applications

Harmonized spatial information on forest area is an important basis for environmental modeling and policy making at both national and international levels. Even if a majority of these data have been supplied by NFI statistics, detailed spatial distribution needed for modeling or further applications can mainly be provided by remote sensing–based products. Yet, reliability, consistency, and a high level of harmonization are important aspects to ensure comparability and enable the development of forest scenarios at an international level. The pan-European forest cover maps (FMAP2000 and FMAP2006) have the advantage to be produced under these prerequisites due to their harmonized approaches and, therefore, guarantee spatial consistency for further applications. Besides that, the medium resolution of the maps offers higher spatial details as previous pan-European LC products such as the CLC maps.

Most of the applications of the forest cover maps (FMAP2000 and FMAP2006) are related to the need for accurate and up-to-date estimates on the spatial distribution of forests as inputs into various models. Baritz et al. (2010) investigated the carbon concentrations and stocks in forest soils of Europe and located forested areas with the help of FMAP2000. Similarly, information on forest distribution was needed for a vulnerability study in the Alps and the Carpathian mountains (Casalegno et al. 2011). As the forest definition of the forest cover maps includes also urban parks in contrast to CLC, FMAP2000 could have been applied in a pan-European urban greening study, where growth of urban forest was investigated. In some of aforementioned studies, the initial medium resolution (25 m) was degraded down to 1 km resolution to speed up the process of the models, yet even with the degraded resolution of 1 km, FMAP2000 was found to be preserving the detailed forest spatial pattern of the original map (Seebach et al. 2011a). Besides applications at the pan-European level, the forest cover maps have been used in local or regional studies as the high resolution allows for detailed studies at that level. The large extent of Europe further enables potential reproducibility of regional studies using these maps as proposed by Lasserre et al. (2011) or Casalegno (2011). Another example of the same kind is the study of Chirici et al. (2011) that used FMAP2000 for a regional study in central Italy (Molise) as an initial forest mask for subsequent delineation of clearcuts based on very high-resolution imagery.

Another application of these maps apart from their indirect use as forest masks is, for example, the estimation of forest area at different units. Seebach et al. (2011b) investigated the applicability of FMAP2000 for reporting harmonized forest estimates for European countries. The comparison with official statistics derived from NFIs indicated an overall good agreement if uncertainties of both sources were taken into account; yet, discrepancies were found in areas with very low and fragmented forests or in mountainous regions. Another major driver of the remaining disagreements between official statistics and map-derived estimates originates from the common issue of land use versus LC. While official statistics reports are based on forest use definitions, estimates based on remote sensing products like FMAP2000/2006 will report land coverage with forest-like vegetation. The latter might become forest use maps only if extensive auxiliary data are available for their manipulation. A further direct application of the forest cover maps are their use for assessing change using postclassification comparison as both maps have been produced by a comparable and consistent approach. This was done for the European part of the FAO FRA 2010 Remote Sensing Survey (RSS), where both forest maps were used to detect reliable forest cover changes based on an enhanced postclassification approach. This approach accounts for potential misregistration errors and reduces the uncertainty of erroneous change detection due to classification errors (Seebach et al. 2010).

All in all, FMAP2000 has proved its ability to serve as a multipurpose product from direct use to downstream services. FMAP2006 and the associated FTYPE2006 have been recently released and are foreseen to be used in upcoming studies, where the differentiation of forest types is of high importance, for example, pan-European forest biomass estimation. Yet, care must be exercised for any application of these maps as every map inherits uncertainties, which need to be addressed depending on the intended use.

11.6 Conclusions and Future Aspects

The pan-European forest maps have been produced for the reference years 2000 and 2006 using optical satellite imagery and standardized methodologies with respect to preprocessing and classification. These maps have provided a baseline assessment of the spatial distribution and composition of forest resources in Europe and demonstrated improvements in terms of quality and production with respect to the CLC Project. In the frame of the Global Monitoring for Environment and Security (GMES) Initial Operations, the production of a new set of so-called high-resolution layers (HRLs) is foreseen, which will be coordinated by the European Environment Agency. Among these, HRLs will be a forest layer designed to closely resemble the JRC FMAP2000 and FMAP2006, but with a target reference year of 2012.

The mapping methods presented within this chapter were based on at-sensor radiances of the remote sensing sensors. Despite the fact that the applied methods are scientifically sound and practical, future mapping applications should be based on well-calibrated image data, from which the effects of the atmosphere have been removed. That would allow for the development of well-defined algorithms that could be applied to a range of different optical sensors, since these algorithms would be based on registered spectral responses of real-world objects. Recent advances in preprocessing algorithms and new European optical imaging sensors, such as RapidEye and ESA's Sentinel II, will hopefully facilitate future development of such mapping approaches.

It is evident that the demand for European level information on forest resources will increase in the future. We need to better understand the integrated role of forests in the protection of the environment, biodiversity, well being and recreation, timber and bioenergy production, as well as mitigation of climate change and monitoring compliance to international climate change agreements. In the future, other sources of Earth observation data should be further studied and used in large-scale mapping projects. For instance, interferometric SAR and space-borne LiDAR could be used to map land use and LC as well as being used to estimate other forest parameters, particularly by their combined use with field measurements and/or high-density airborne LiDAR data.

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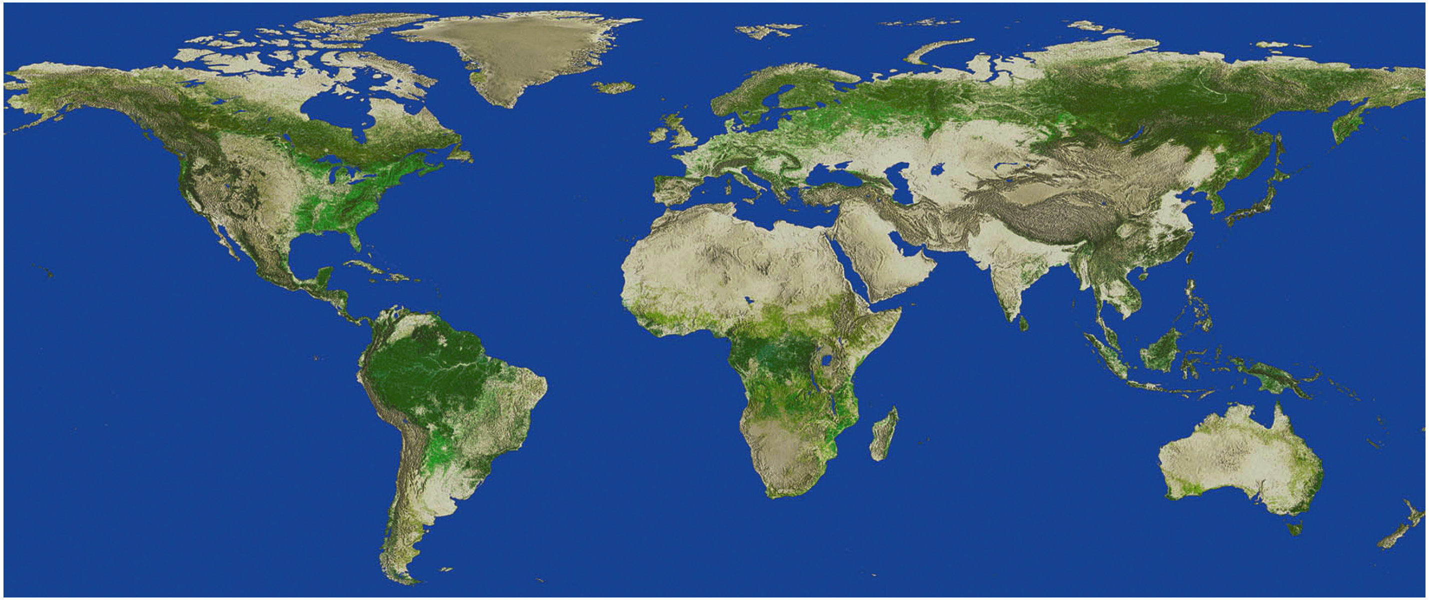


FIGURE 3.1
Global forest cover map derived from the GlobCover Land Cover map at 300 m resolution. Forested areas appear in green. (From Arino, O. et al., *ESA Bull.*, 136, 24, 2008; The GlobCover Land Cover map is available from the European Space Agency website at http://ionia1.esrin.esa.int/.)

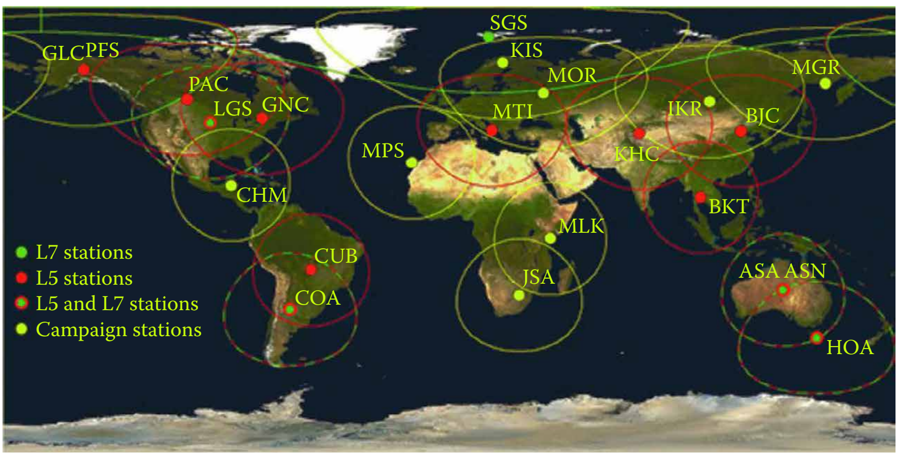


FIGURE 4.1
Active Landsat ground stations. (More details are available at http://landsat.usgs.gov/about_ground_stations.php.)

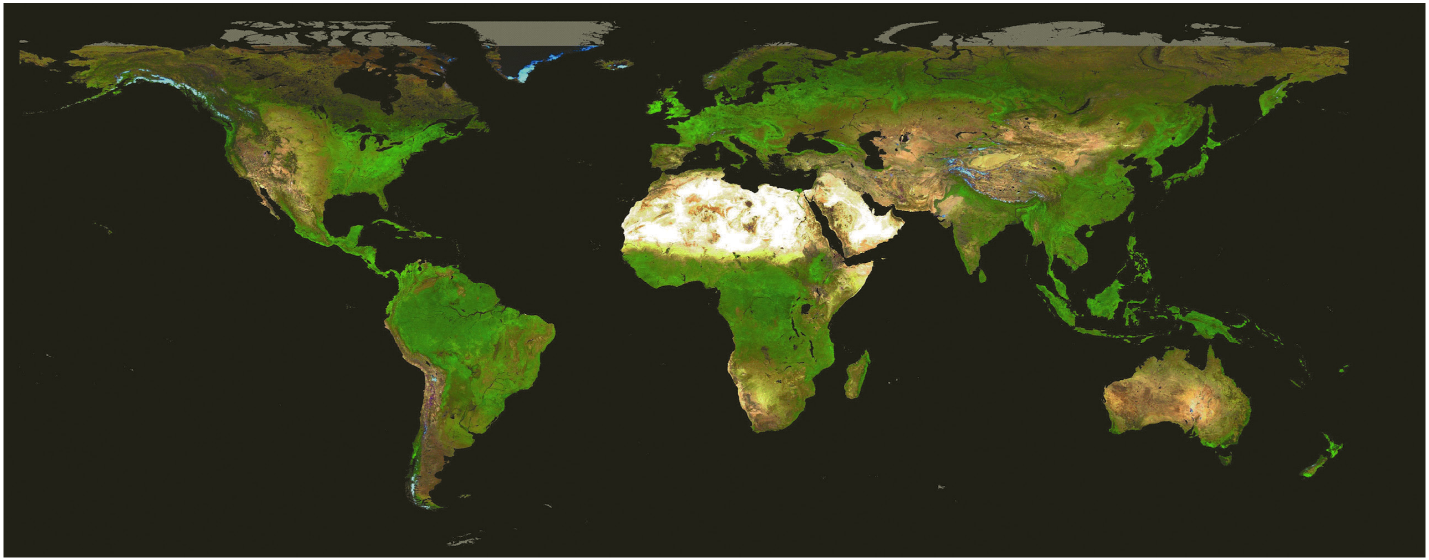


FIGURE 6.1
MODIS annual growing season image composite of shortwave, near-infrared, and red band, enhanced to appear as true color.

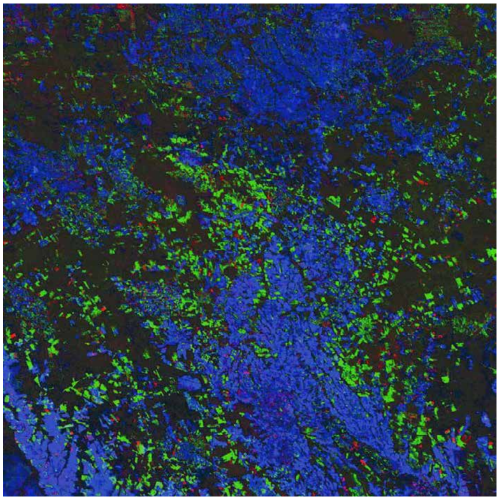


FIGURE 6.2
400 km × 400 km subset centered on 12° 4′ S, 55° 59′ W in Mato Grosso, Brazil. False-color composite of MODIS band 7 growing season metrics—*blue*: 2000 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods, *green*: difference in the 2000 and 2005 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods, and *red*: difference in the 2005 and 2010 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods.

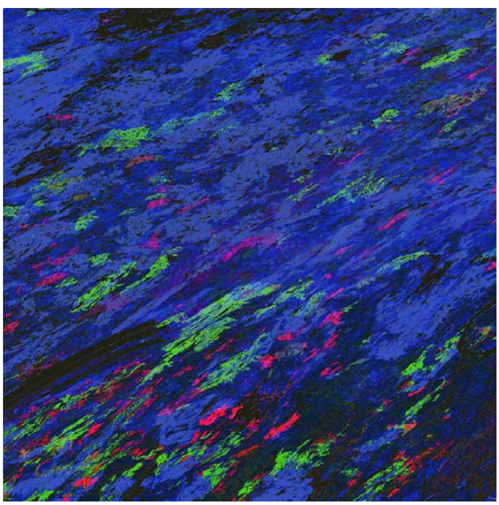


FIGURE 6.3
400 km × 400 km subset centered on 51° 45′ N, 72° 8′ W in Quebec, Canada. False-color composite of MODIS band 7 growing season metrics—*blue*: 2000 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods, *green*: difference in the 2000 and 2005 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods, and *red*: difference in the 2005 and 2010 mean band 7 shortwave infrared reflectance from the three greenest 16-day composite periods.

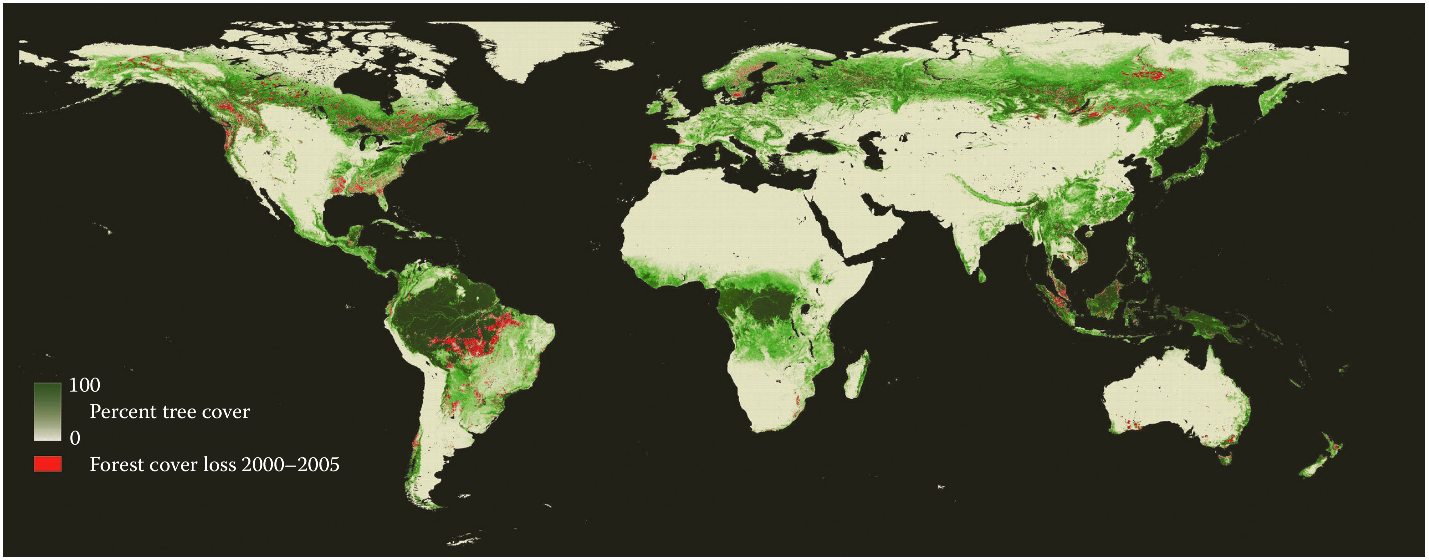


FIGURE 6.5
MODIS percent tree cover 2000 and indicated forest cover loss from 2000 to 2005.

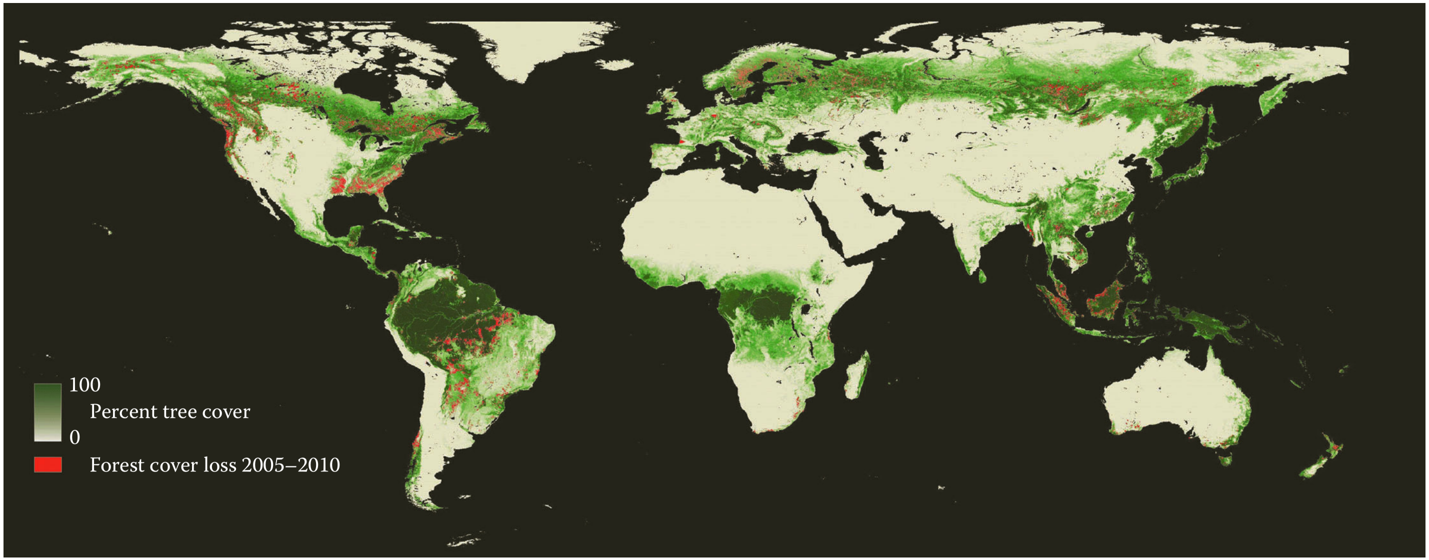


FIGURE 6.6
MODIS percent tree cover 2000 and indicated forest cover loss from 2005 to 2010.

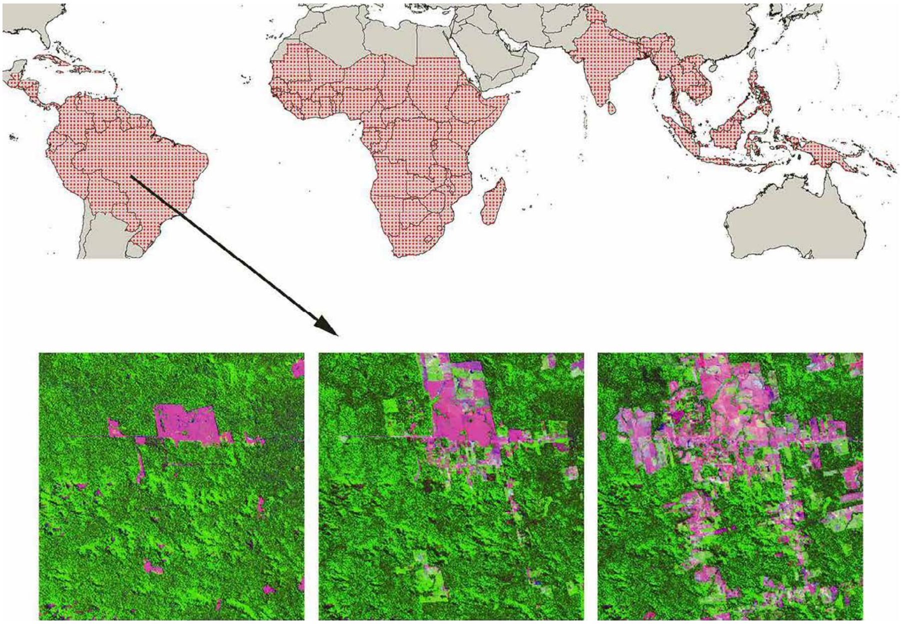


FIGURE 7.1
Example of time series (for years 1990, 2000, and 2005) of Landsat satellite imagery over one sample site in the Amazon Basin (20 km × 20 km size). Forests appear in dark green, deforested areas (agriculture and pastures) appear in light green or pink.

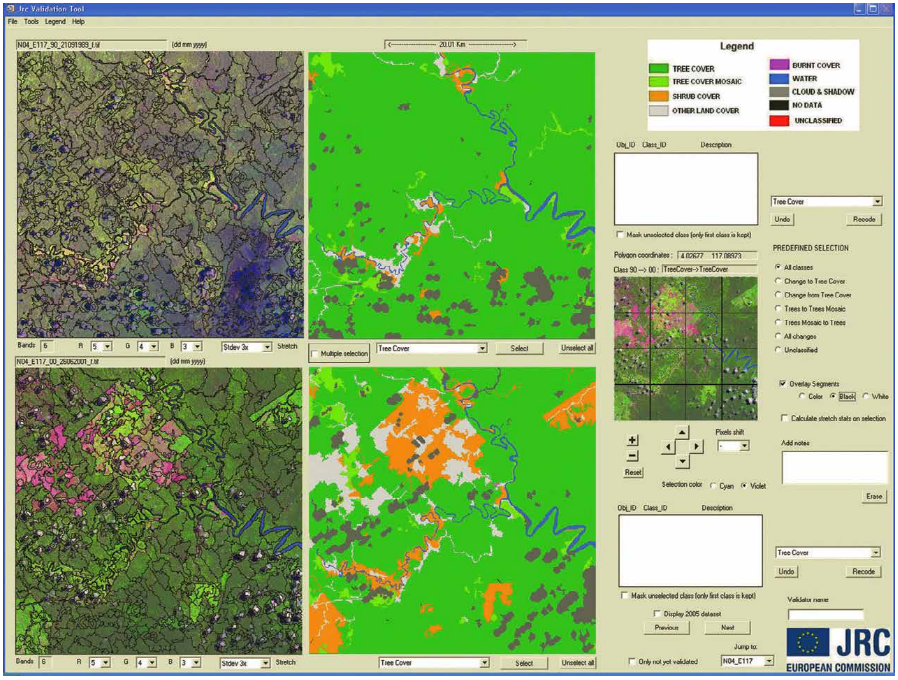


FIGURE 7.2
Visualization tool used for the process of verification and correction of multitemporal classifications. *Left column*: Segmented Landsat imagery displayed (top: year 1990, bottom: year 2000). *Right column*: Land cover maps produced from satellite imagery.

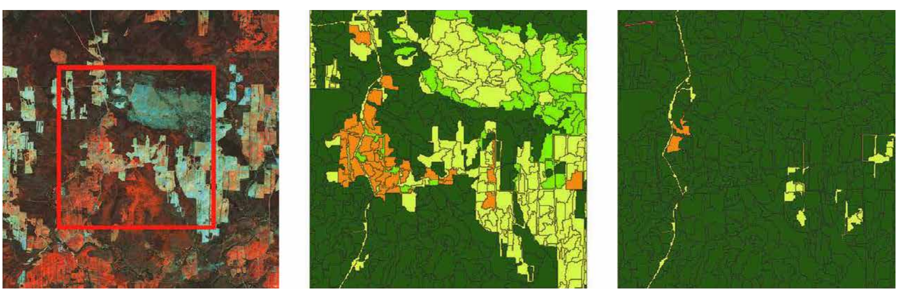


FIGURE 7.3
The 20 km × 20 km multi-spectral Landsat image (left) for a sample site in the boreal forest showing, for the central 10 km × 10 km portion (red box), the classification of land cover (center) and land use (right). Land cover is classified as TC (green), tree cover mosaic (light green), OWL (orange), and other land cover (yellow). Land use is classified as forest (green), OWL (orange), and other land use (yellow).

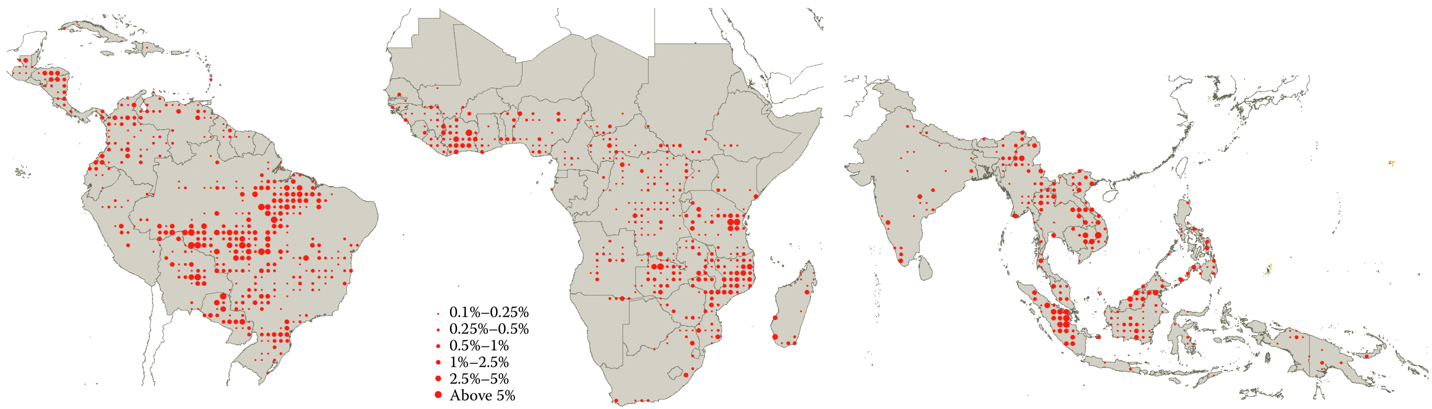


FIGURE 7.4
Annual rate of gross forest cover loss during the period 2000–2005 for the tropical sample units of the global systematic sample.

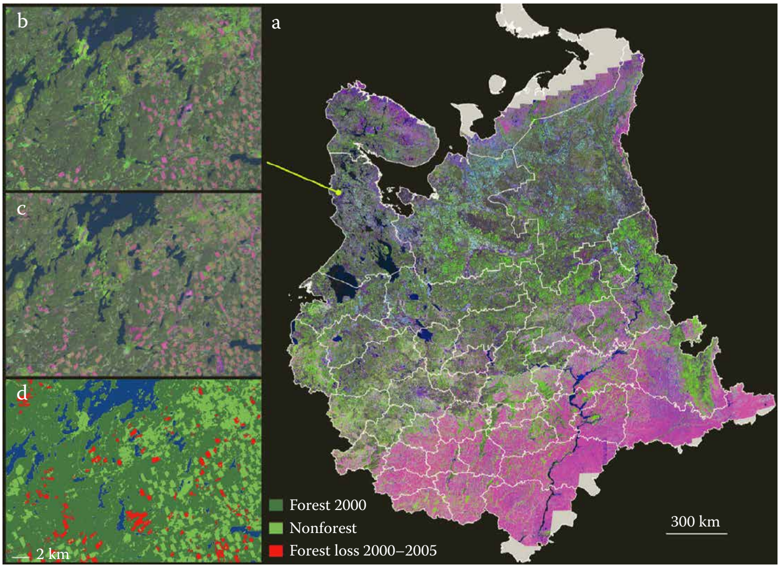


FIGURE 8.2
Forest cover loss monitoring in European Russia. (a) The ca. 2000 region-wide Landsat ETM+ image composite. (b–d) Zoom-in example of forest cover and change mapping in the Republic of Karelia: b—the ca. year 2000 image composite; c—the ca. year 2005 image composite; d—classification result.

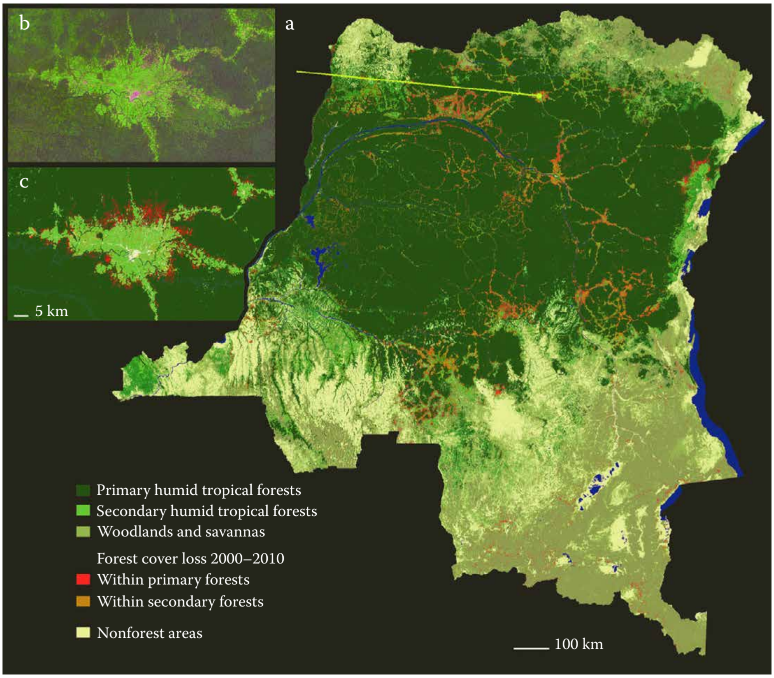


FIGURE 8.4
Forest cover loss monitoring in the DRC. (a) Nation-wide forest cover and change mapping result. (b–c) Zoom-in example of forest cover and change mapping around Buta: b—ca. year 2010 image composite; c—classification result.

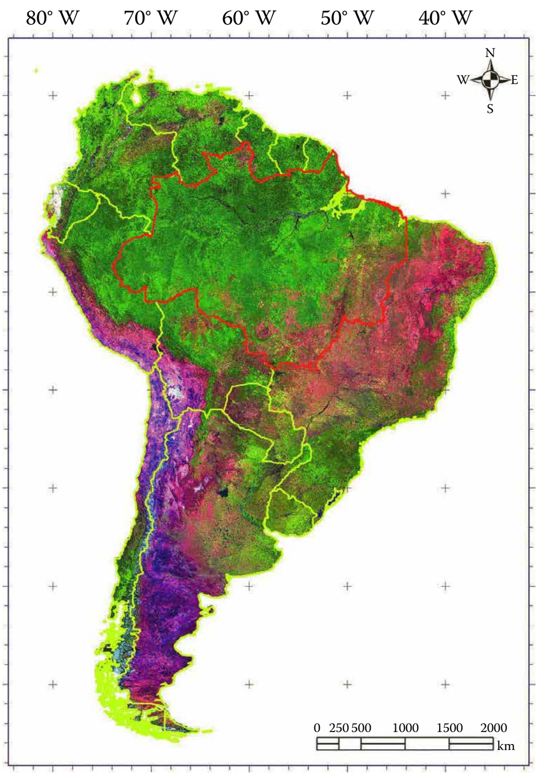


FIGURE 9.1
The BLA (*red*) located in the South American continent.

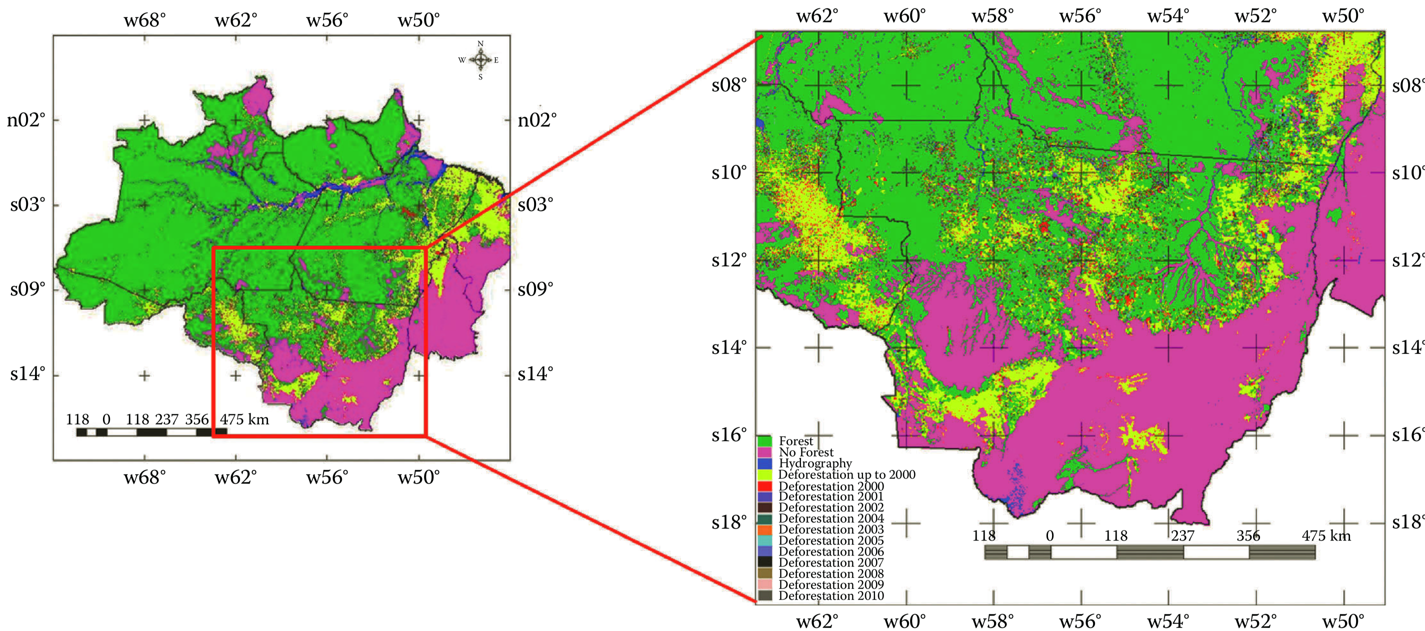


FIGURE 9.4
Mosaic of digital PRODES mapping over the period 2000–2010.

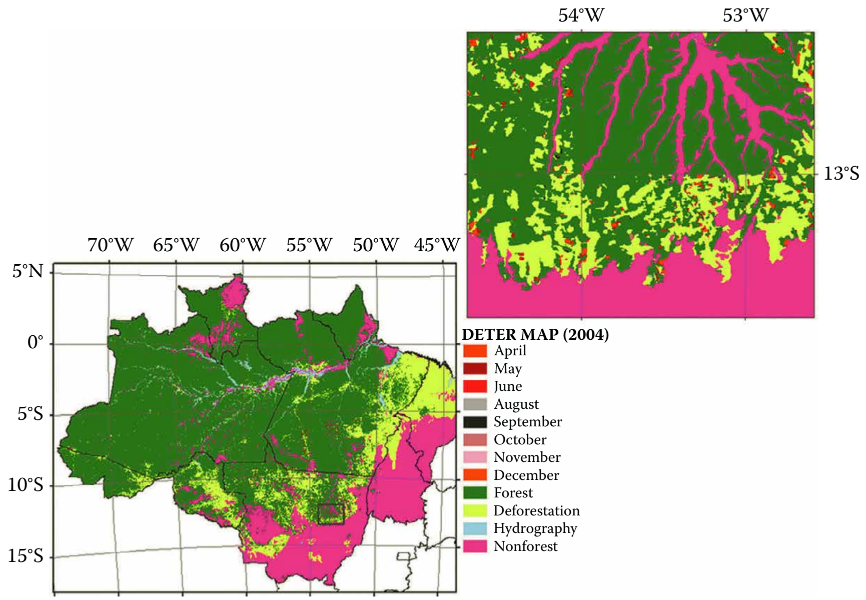


FIGURE 9.5
Illustration of the example of DETER project results, showing the deforested areas detected during the year 2004.

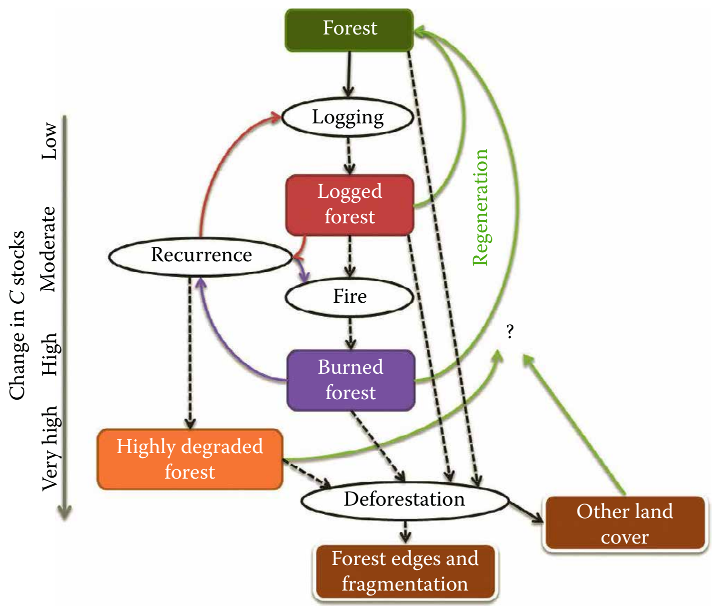


FIGURE 10.1
Forest degradation processes and interactions commonly found in the Brazilian Amazon. Pristine forests can be subject to selective logging, creating favorable conditions for burning when fires from adjacent agriculture fields unintentionally escape. Logging and fires can be recurrent, creating highly degraded forests. Eventually, degraded forests can be converted by deforestation, increasing forest edges and landscape fragmentation. If degraded forests are not cleared, vegetation regeneration processes can prevail given the high resiliency of forests.

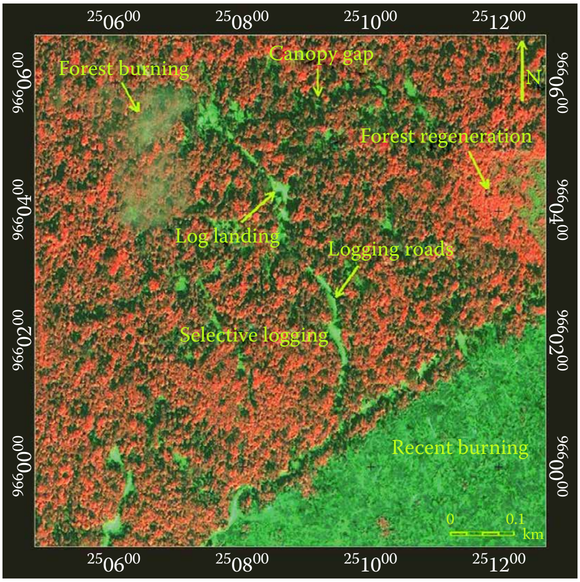


FIGURE 10.2
Very high spatial resolution false-color infrared IKONOS image showing the different environments commonly found in logged and burned (LB) forests in the eastern Brazilian Amazon. At 1 m spatial resolution, log landings, logging roads, tree fall canopy gaps, and forest edges can be identified as well as "islands" of UFs and signs of regeneration. Signs of forest erosion along the edges between the LB forest and the recently slashed-and-burned forest can also be observed. (From Souza, C.M. and Roberts, D., *Int. J. Remote Sens.*, 26, 425, 2005.)

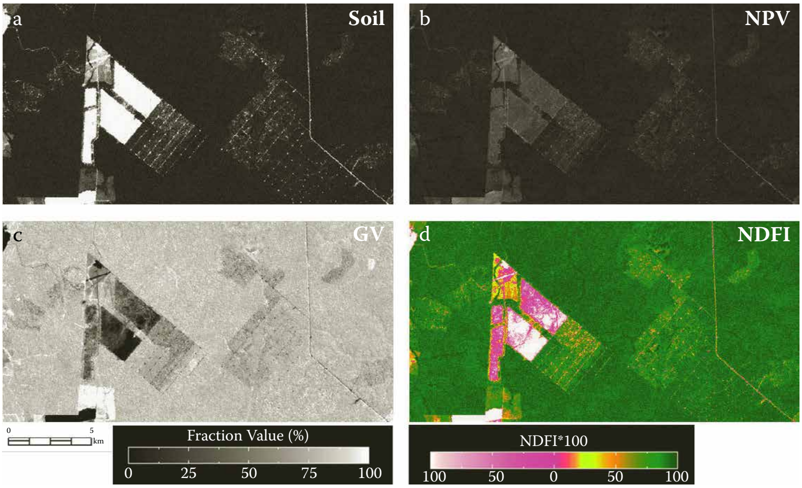


FIGURE 10.4
Subset of a Landsat TM image showing fractions obtained from SMA and NDFI. (a) High soil fraction shows logging infrastructure (log landings and roads); (b) NPV shows higher fraction values for canopy-damaged areas along infrastructure relative to the surrounding intact forest; (c) canopy damage is also identified with lower GV fraction values (dark colors); and (d) all the fraction information are combined to enhance the detection of logged forest.

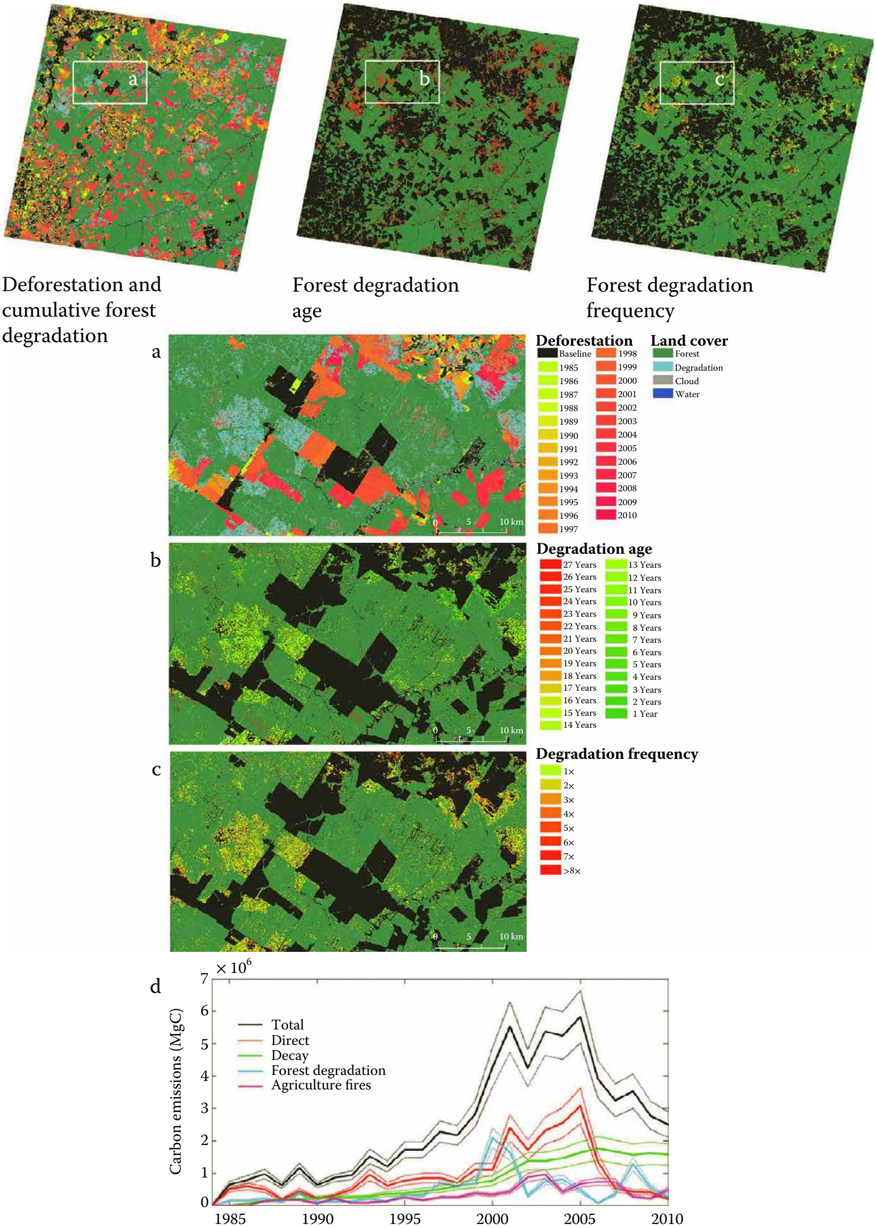


FIGURE 10.5
In this example, a long time series (i.e., >25 years) of Landsat TM/ETM+ data from Sinop, Mato Grosso state, was used to track deforestation and forest degradation. Forest degradation age and frequency maps are obtained from the annual maps and used together with the forest degradation and deforestation maps in a CES model to estimate carbon emissions associated with these processes. More reliable and consistent baseline scenarios for REDD+ can be obtained with this type of model because information about forest degradation is included and associated uncertainty estimated.

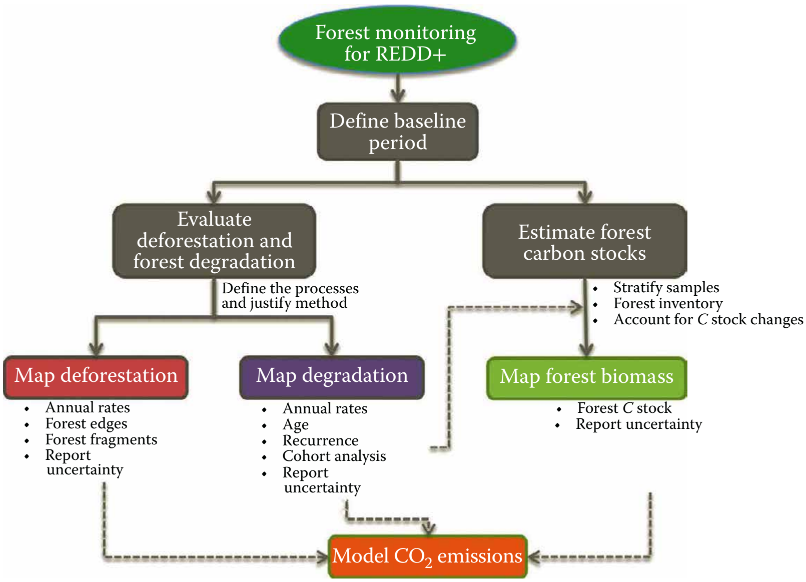


FIGURE 10.6
Integrating deforestation and forest degradation information to estimate forest carbon stock changes for REDD+ projects.

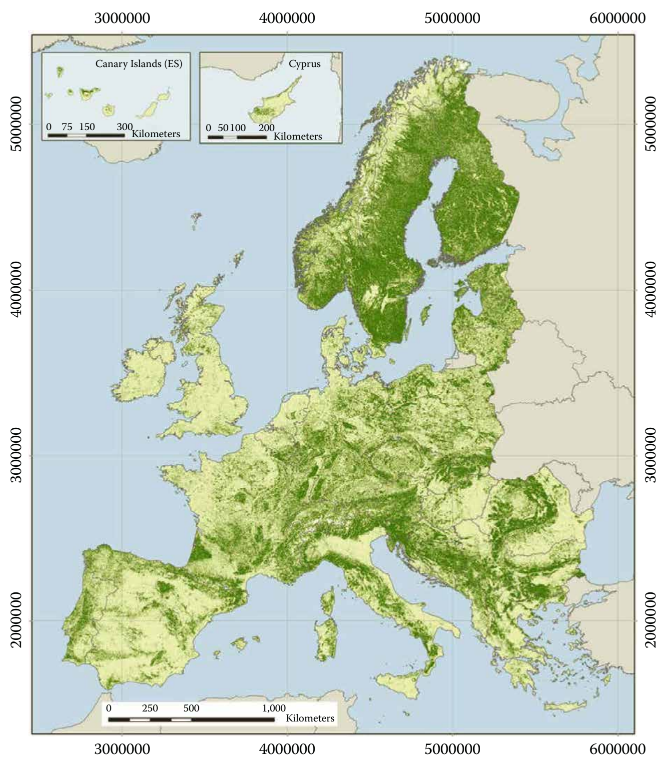


FIGURE 11.1
JRC forest map 2000.

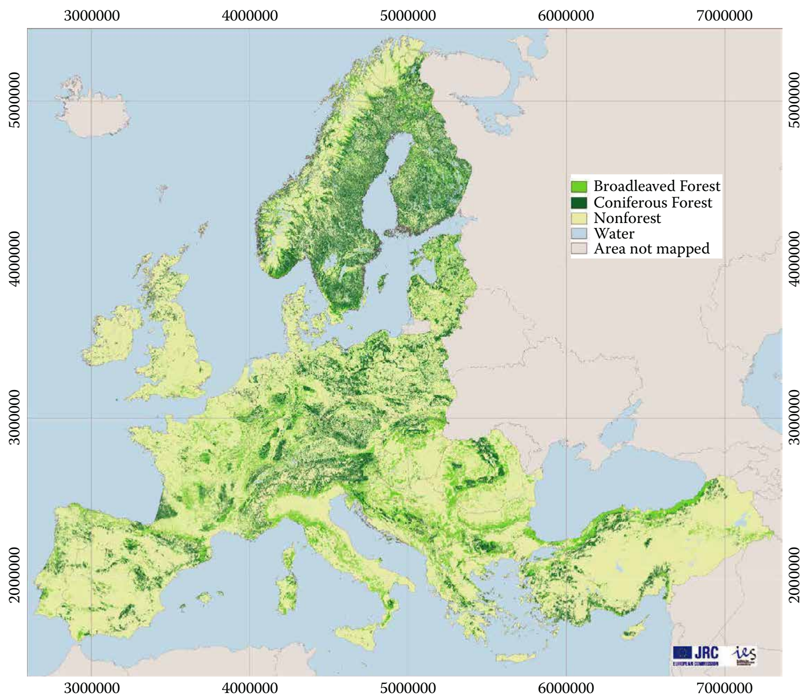


FIGURE 11.2
JRC forest map 2006.

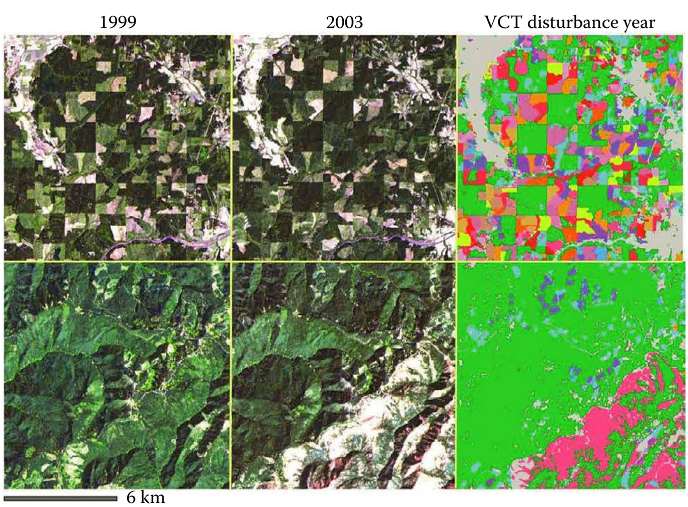
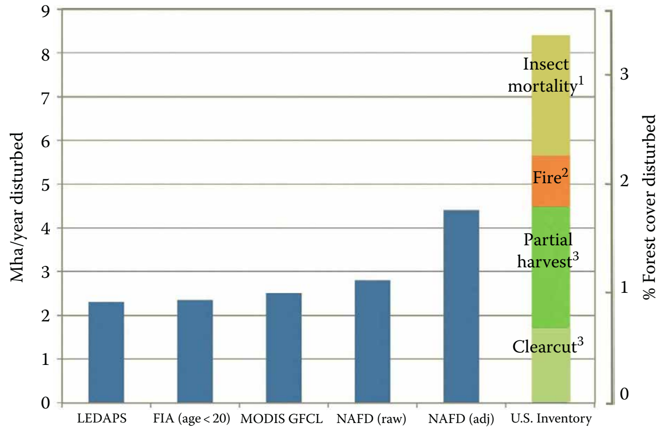


FIGURE 12.2
Examples of NAFD disturbance mapping from southern Oregon (Landsat path 46, row 30). Top row: RGB imagery (bands 7, 5, 3) and VCT disturbance maps for an area of active harvest; bottom row: RGB imagery and disturbance map for the northern edge of the 2002 Biscuit Fire. The VCT maps shows permanent forest (green), permanent nonforest (gray), and the year of mapped disturbance from 1985 to 2009 (other colors).



1. USDA Forest Service (2010) for USA—includes areas of mortality only, excluding defoliation without mortality.
2. U.S. EPA (2010)—includes Alaska fires.
3. Smith et al. (2009).

FIGURE 12.3
Comparison of disturbance rates among satellite-based and inventory-based studies. LEDAPS (Masek et al. 2008) and NAFD (Kennedy et al. in preparation) are based on Landsat change detection. NAFD (adj) reflects compensation for net omission errors based on visual validation. MODIS GFCL is based on MODIS gross forest cover loss (GFCL) (Hansen et al. 2010). The FIA (age < 20) is based on equating the area of young forestland from the FIA with an annualized turnover rate. The percent forest cover values are based on the area of forest land in the "lower 48" conterminous United States (~250 Mha).

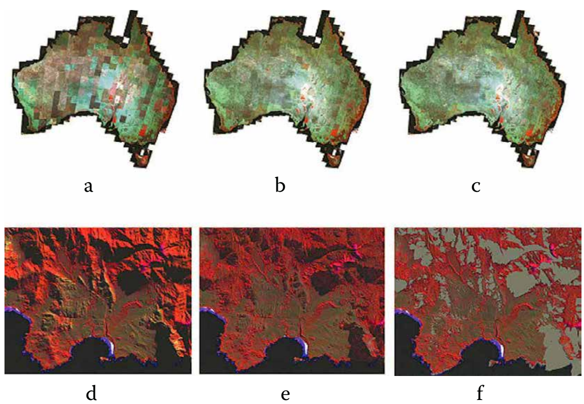


FIGURE 13.1
Image calibration (top) and normalization (bottom). Calibration: Landsat mosaic of Australia showing (a) uncalibrated, (b) TOA correction, and (c) TOA + BRDF correction. Normalization (From Wu et. al., 2004.): (d) uncorrected, (e) terrain illumination correction, and (f) estimated occlusion mask overlaid and shown in gray. (From Wu, X., et al., An approach for terrain illumination correction. Australasian Remote Sensing and Photogrammetry Conference, Fremantle, Western Australia, 2004.)

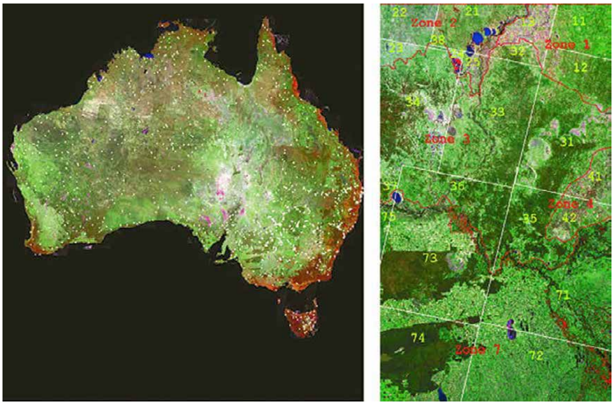


FIGURE 13.3
(Left) Graphical depiction of the location of high-resolution IKONOS data used in the derivation of classifier training information. (Right) Typically, samples are required by intersection of zone and image, though well-calibrated data can reduce this requirement by allowing extrapolation across scene boundaries in many cases.

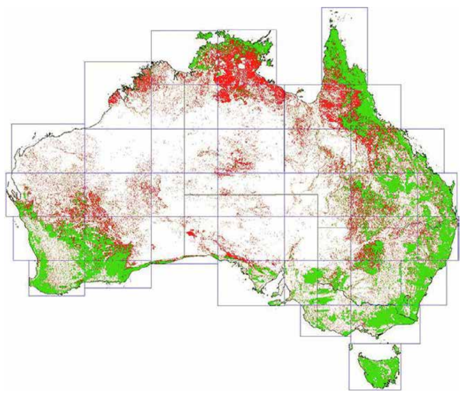


FIGURE 13.5
Map of Australia showing NCAS forest extent (green) and sparse extent (red).

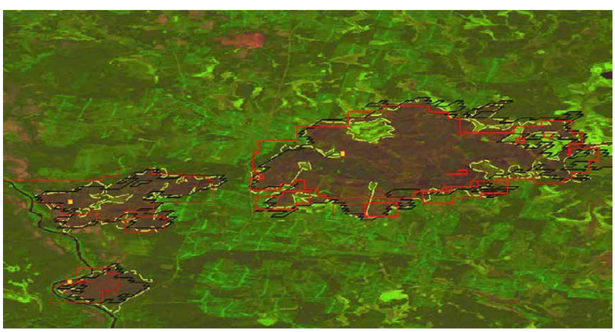


FIGURE 14.8
Example of burned area polygons derived from the three methods: red polygon, AFBA product; black polygon, SRBA product; yellow polygon, HRBA product. The results are displayed in the Web-service user interface with the Landsat-TM scene used for the HRBA product as a background image.

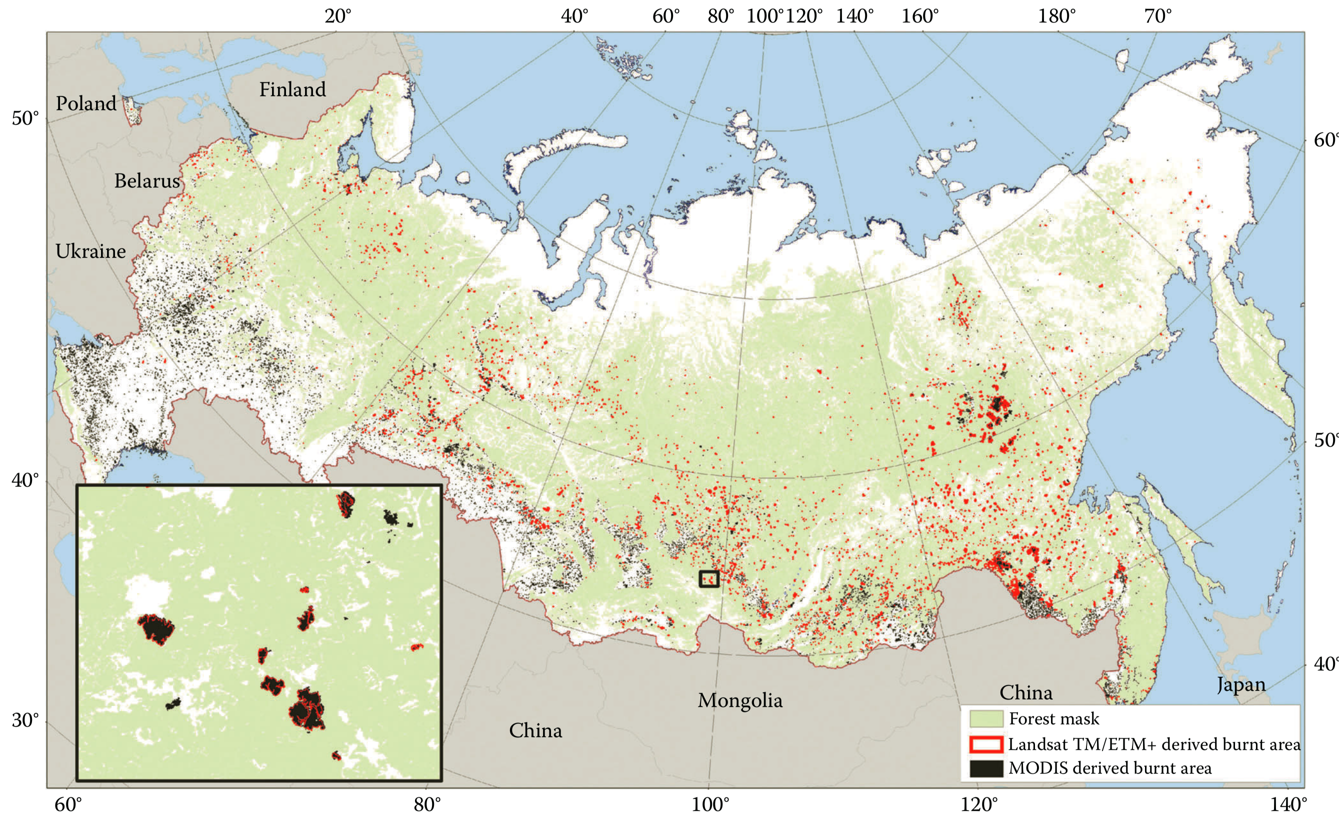


FIGURE 14.14
Burned areas for the year 2011 over Russian Federation as depicted by the SRBA product (black areas) and the HRBA product (red polygons).

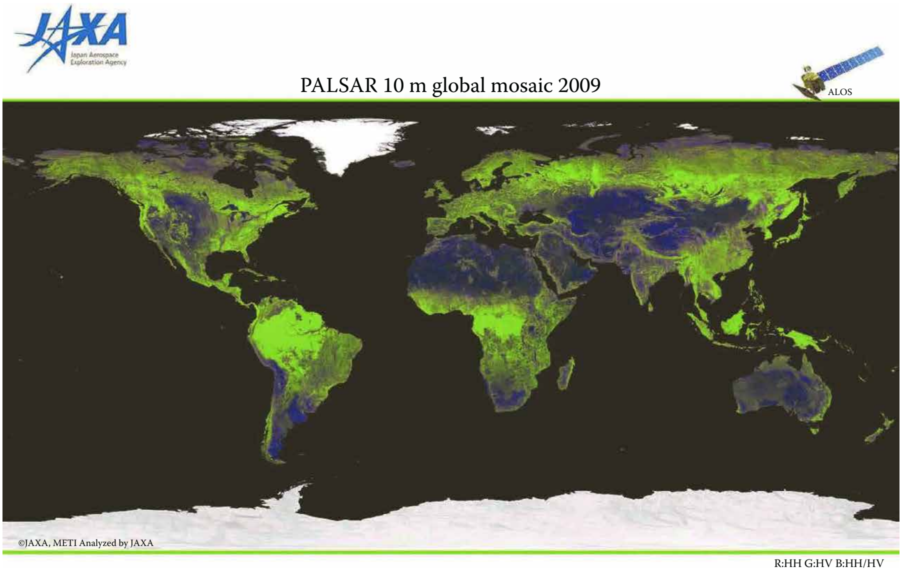


FIGURE 15.1
Global ALOS PALSAR color composite mosaic at 10 m pixel spacing (R: HH, G: HV, B: HH/HV). 95% of the data—a total of approximately 70,000 scenes—were acquired within the time period June–October 2009. (Courtesy of JAXA EORC, Tsukuba, Japan.)

FIGURE 15.2
(d) A composite of HH data from two dates (September 12 and 15, 2011) and coherence (in RGB respectively; blue areas indicate deforested areas).

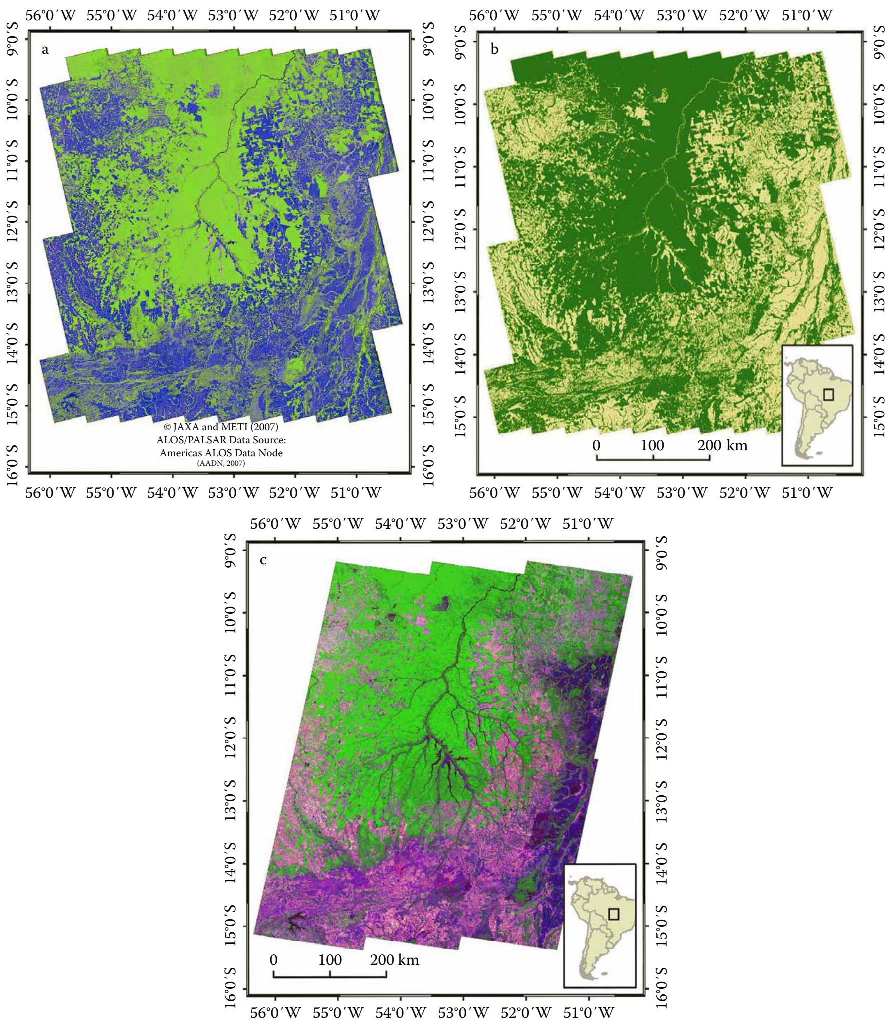


FIGURE 15.4
Satellite image mosaics produced for the Xingu River headwaters region. (a) ALOS PALSAR mosaic consisting of 116 individual Level 1.1 (single-look complex) fine beam, dual-polarimetric scenes (R/G/B = polarizations HH/HV/HH-HV difference). (b) Map of forest (green) and nonforest (beige) generated with an overall classification accuracy of 92.4% ± 1.8%. (c) Landsat 5 mosaic consisting of 12 individual Level 1G (Geocover) scenes (R/G/B = bands 5/4/3).

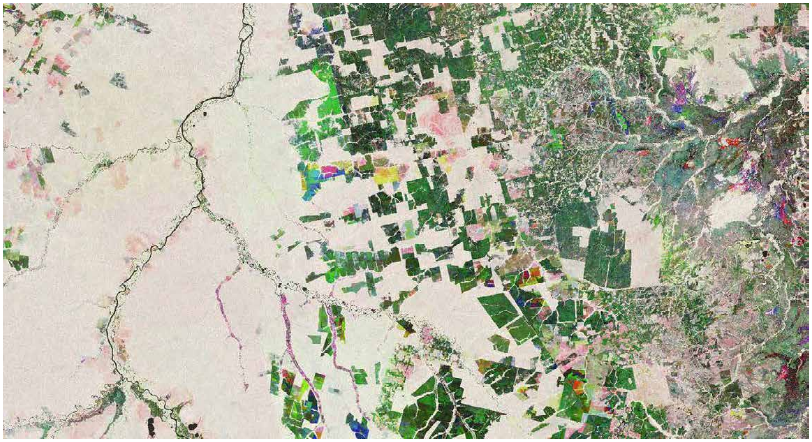


FIGURE 15.5
Multitemporal ALOS PALSAR L-band HV image generated from data acquired in 2007 (red), 2008 (green), and 2009 (blue) for a part of the Xingu watershed. Closed forest (white) is interspersed with fire scars (red tones) along the main stem of the Xingu River and tributaries (black).

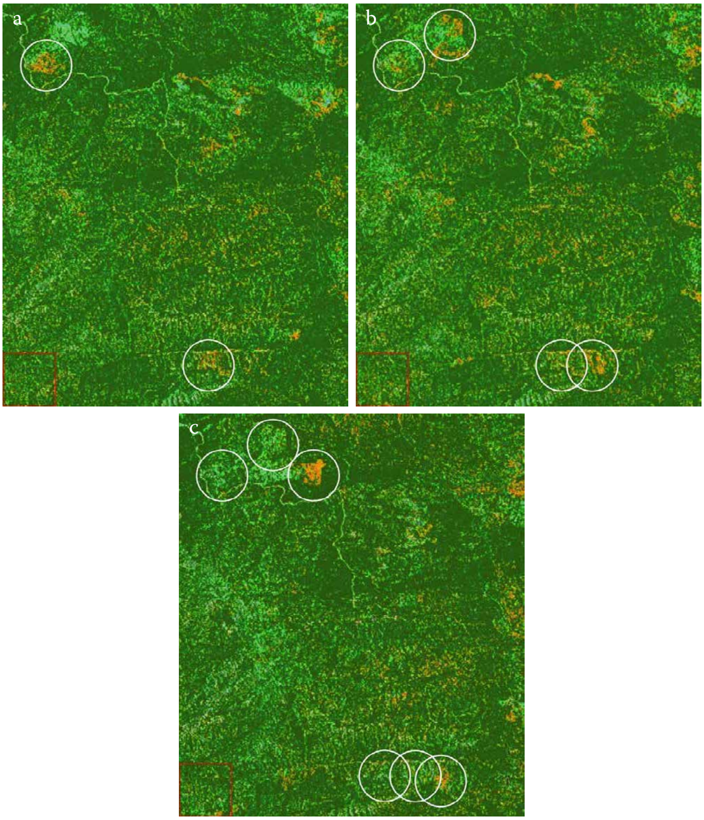


FIGURE 15.6
Forest degradation in Sarawak through selective logging observed through comparison of forest maps generated using ALOS PALSAR data for the years (a–c) 2007 through to 2009.