2. Methods and materials

LAND COVER AND LAND USE

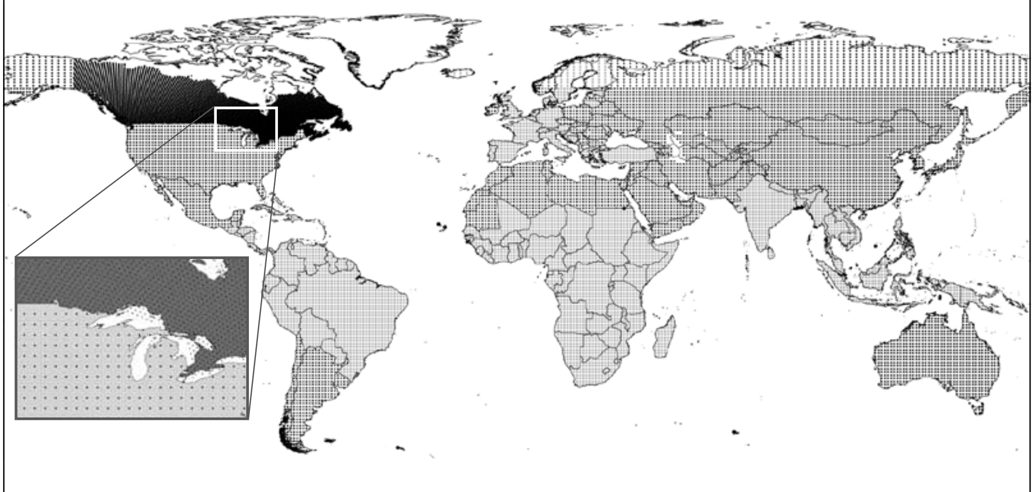
This report includes global statistics on forest land use derived from a land-cover classification and expert image interpretation. Land cover refers to the biophysical attributes of the Earth's surface and can be detected directly from aerial imagery or satellite-borne sensors. Land use implies a human dimension or purpose for which the land is used (Lambin *et al*., 2001). Land use can be inferred from remotely sensed data but typically must be verified by local expert knowledge or data collected in the field. Accurate information on land use is critical for understanding the causes of forest-cover change and for developing effective policies and strategies to slow and reverse forest loss.

SYSTEMATIC SAMPLE DESIGN

The survey used a systematic sample of 10 km x 10 km satellite image extracts at each 1-degree intersection of latitude and longitude (Mayaux *et al.*, 2005; Ridder, 2007). Globally, this is equivalent to a 1 percent sample of the Earth's land surface. Sampling intensity was reduced above 60 degrees latitude, north and south, to include only even degrees of longitude. This was done to avoid an increasing "weight" of samples in the high latitudes due to the curvature of the Earth. No sites were located higher than 75 degrees latitude, north or south. For Canada, the 1-degree grid was modified to use the Canadian National Forest Inventory's 20-km grid of smaller 4-km^2 photo points (Gillis, Omule and Brierley, 2005). The final sample grid consisted of 15 779 samples worldwide (Figure 1).

In a number of national, regional and global studies (e.g. Hansen *et al*., 2008; Stehman, Sohl and Loveland, 2005; Potapov *et al*., 2008; Eva *et al*., 2010), sampling approaches have proved successful in producing results for forest area change with acceptable and known precision. In previous remote sensing surveys, an approach

FIGURE 1
The 15 779 1-degree grid sample site locations used in the survey, with reduced intensity above 60° latitude north and south



Note: Canada samples were spaced on a 20-km grid to match the Canadian National Forest Inventory (inset; see Annex 1 and Annex 2). Sites processed by the JRC are in grey and sites processed by FAO are in black.

using a large sample of satellite imagery over broad geographic regions has been shown to suitably capture parameter estimates at the regional (i.e. > 100 000 hectares (ha)) and continental scales (Czaplewski, 2002).

A systematic sample was chosen for four main reasons (Ridder, 2007): land cover exhibits trends at the regional and continental scales and no *a priori* assumptions of forest area change intensity were considered; the layout of the latitude–longitude grid is not politically biased and is easy to understand; sample locations can easily be identified on maps; and FAO-supported national forest assessments are typically constructed based on the same grid.

IMAGERY DATA SOURCES

Imagery from the United States Geological Survey's Landsat Global Land Survey (GLS) provided the majority of data for classification and interpretation (Gutman *et al*., 2008). The Landsat sensor provides global coverage, a long time-series of acquisitions, and spatial and spectral characteristics suitable for the detection of changes in tree cover. Landsat acquisitions are referenced to the Earth's surface by a grid of paths and rows, called the Worldwide Reference System (WRS). The GLS is a spatially consistent, multi-epoch dataset composed of the best Landsat images for each WRS path/row covering most of the Earth's land surface and centred on the years 1975, 1990, 2000 and 2005.

For each sample site, Landsat optical bands 1–5 and 7 from the GLS1990, GLS2000 and GLS2005 datasets were compiled. These were clipped to a 20 km × 20 km box centred on each 1-degree latitude and longitude intersection to create imagery subsets. The central 10 km × 10 km of each image subset was used for area calculations and statistical analysis. In areas where the GLS acquisitions were cloudy or not seasonally matched, effort was made to obtain additional scenes from the Landsat data archive or directly from regional ground stations (for more detail see Beuchle *et al*., 2011; Potapov *et al.*, 2010; Seebach *et al.*, 2010).

For boreal, temperate and subtropical climatic domains, the GLS data were assumed to be the best available. If more than one GLS acquisition was available for a given site and date, the GLS acquisition with the lowest cloud cover was selected for classification (Lindquist *et al.*, submitted).

IMAGE PREPROCESSING

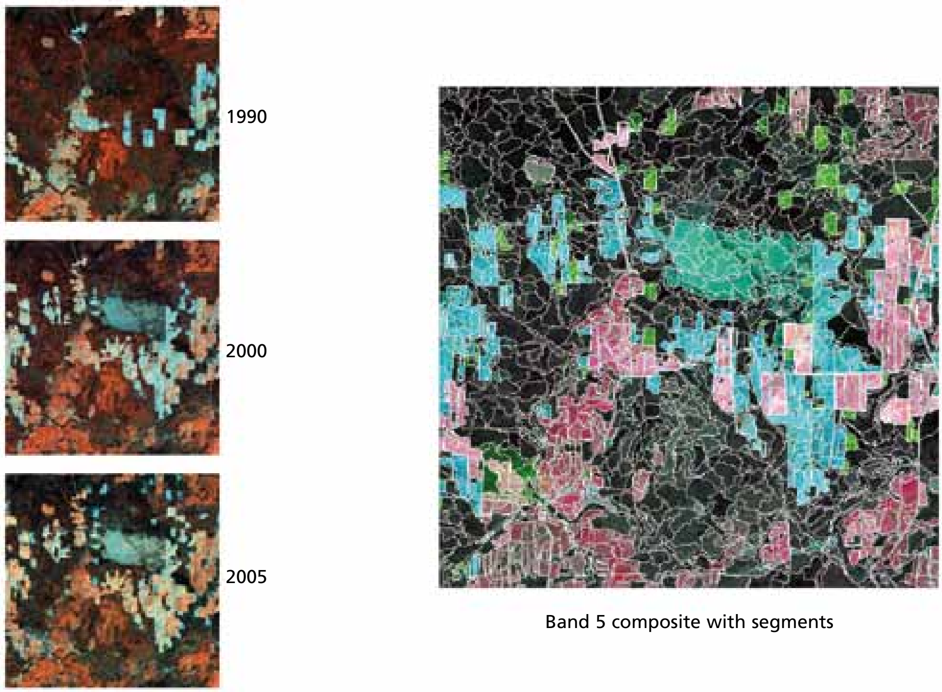
Images were preprocessed to correct for radiometric differences caused by changes in atmospheric quality or sensor characteristics between scene acquisition dates for the same site. Image normalization has the effect of standardizing digital number values relative to dense tree cover on a per-site basis and enables the more efficient application of automated classification algorithms (Toivonen *et al.*, 2006; Potapov *et al.*, 2010; Hansen *et al*., 2008). Potapov *et al.* (2010) describe the preprocessing methods used by the FAO team for areas outside the tropics. Bodart *et al.* (2011) describe the preprocessing methods used by the JRC team for the tropical and sub-Saharan Africa sites.

AUTOMATED LAND-COVER CLASSIFICATION

FAO and JRC both carried out automated land-cover classifications of preprocessed imagery. The JRC team processed sites within the tropics, sub-Saharan Africa (Beuchle *et al.*, 2011) and western Europe (Seebach *et al.*, 2010) as part of its ongoing TREES-3, MONDE and FOREST projects (JRC 2010; see Raši *et al.*, 2011 for details of the JRC land-cover classification processing chain). The FAO team processed all other sites (Figure 1). Although there were differences in the processing methods used by the two teams, the overall processing and importantly the output classifications are comparable. The processing methods consisted of the following common components:

- data acquisition;
- data preprocessing and image normalization;

FIGURE 2
Example of three imagery dates combined to make a single composite image with segments that capture reflectance changes in each period



- image segmentation;
- image classification.

The automated segmentation of land-cover polygons and preclassification of land-cover types had two main goals: to create a spatially and temporally consistent dataset; and to avoid manual delineation, thus reducing the effort involved in the visual review and revision of land-cover and land-use labels.

The FAO–JRC land-cover classification methodology consisted of four main steps:
- image segmentation at level 1 (no minimum mapping unit – MMU) and level 2 (MMU approximately 5 ha in size);
- training data collection of representative sites for supervised classification;
- model construction and land-cover classification of level-1 objects;
- assignment of land-cover classification of level-2 objects.

All functions of segmentation and supervised classification were carried out using eCognition® image segmentation and processing software.[1]

Image segmentation is the process of partitioning an image by grouping similar pixels into patches called objects (regularly referred to as segments or polygons) based on spectral similarity and spatial distinctiveness. The criteria for creating image objects from individual pixels in eCognition can be controlled by the operator by specifying values for a series of parameters such as size, shape and the degree of similarity to be achieved in the segmentation. These values affect clustering and control the overall shape and size of the objects created (Baatz and Schappe, 2000).

A multi-date segmentation routine used Landsat image bands from all three survey periods to create a single layer containing objects based on the spectral information in each period (Figure 2). Image segmentation was implemented in two parts. The FAO

[1] www.ecognition.com/products/ecognition-developer.

method was similar to the segmentation routines described by Raši *et al.* (2011), using parameters that allowed the creation of small, irregular-shaped objects based on the spectral reflectance values of Landsat bands 3, 4 and 5 (0.63–1.75 µm). These bands were chosen for their ability to discriminate differences in surface reflectance caused by changes in vegetation type (Desclée, Bogaert and Defourny, 2006; Duveiller *et al*., 2008). The first (i.e. level-1) segmentation created very small objects that ranged in size from a single Landsat pixel to greater than 100 ha and varied inversely with the spectral heterogeneity of the underlying Landsat image.

The most recent image (i.e. 2005) was segmented first. The objects created during this process were used to constrain the segmentation of the image for 2000 and, in turn, those objects constrained the segmentation of the 1990 image. For the tropics, the segmentation was first applied to the pair of 1990 and 2000 images, then the dissolved objects for 2000 were used to constrain the segmentation of the image for 2005.

The target MMU of the level-2 segments was 5 ha (Ridder, 2007). The desired MMU was achieved by aggregating level-1 segments smaller than 5 ha with adjacent objects with the most similar average Landsat band 5 reflectance. Short-wave infrared reflectance was used due to its effectiveness in forest mapping applications (Horler and Ahern, 1986; Hoffhine and Sader, 2002). Land-cover classification was carried out on the spectrally homogenous level-1 segments. The level-2 segments were assigned class labels according to the underlying percent composition defined by the level-1 segments (Table 1).

Given the large number of samples and the complexity involved in classifying each site, a supervised automated classification approach was selected as the best processing option. The overall classification methodology (depicted as a generalized flowchart in Figure 3) was as follows:

- For each site and date, a land-cover classification was produced with the following main classes – *tree cover*, *shrub cover*, *other land* (comprising herbaceous cover and bare ground/non-vegetated, which were grouped and not shown separately), *water* and *no data*. These classes were broadly in line with the IPCC land-use good-practice guidelines (Paustian, Ravindranath and van Amstel, 2006) when ultimately converted to land-use labels.
- Imagery from 2000 was classified first. When there was a low likelihood of detecting change between surveys, the class label for objects in the image object layer for 2000 was transferred to the 1990 and 2005 image object layers.
- The objects determined to have a relatively high likelihood of change between 1990 and 2000 and between 2000 and 2005 were classified separately using training data automatically selected from non-changing objects in the same period.
- The 5-ha MMU objects were assigned class labels according to the proportion of labelled level-1 objects they contained.

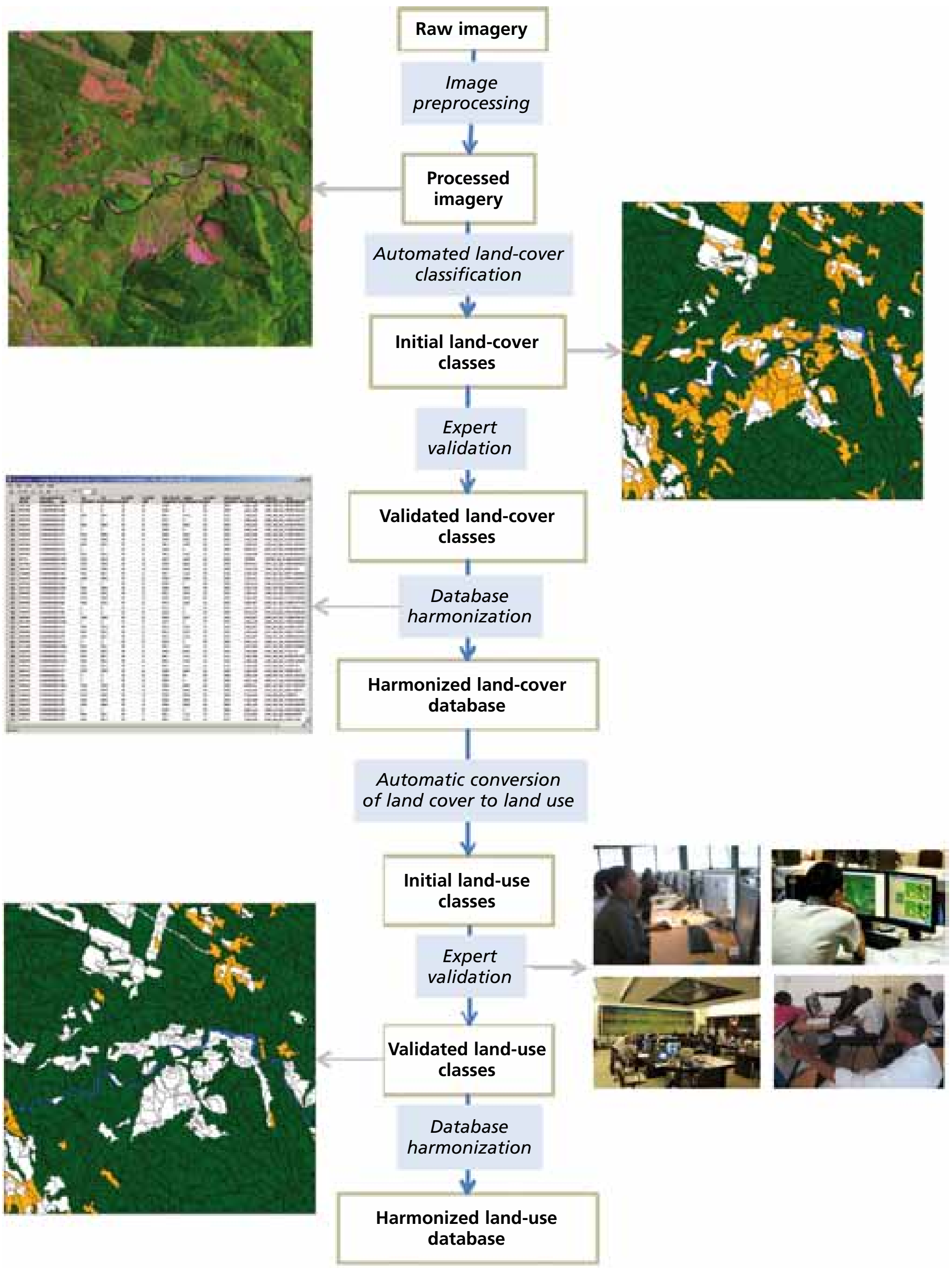
TRAINING THE CLASSIFICATION

The broad range of biophysical traits exhibited globally by tree cover presented a challenge for training data collection. For example, dense, dark, evergreen conifers have different characteristics to broad-leaved evergreens, which differ, in turn, from

TABLE 1
Level-2, 5-ha MMU land-cover labelling scheme based on the percent composition of underlying level-1 segments, listed in descending order of priority

Level-1 segment	% composition	Level-2 land-cover label
Tree cover	≥ 30	Tree cover
Other wooded land	≥ 70	Other wooded land
Other land cover	≥ 70	Other land cover
Water	≥ 70	Water

FIGURE 3
Generalized flowchart of the FAO processing chain



the characteristics of broad-leaved deciduous trees. The variations in biophysical features, changing seasonality and illumination conditions due to sun angle and slope position combine to affect the spectral reflectance properties of tree cover and make it difficult to create reflectance-based models that can accurately classify tree cover in its myriad forms globally. The FAO classification methodology attempted to account for this variation by applying a single method for creating tree-cover classification models globally to each sample site and period. At each sample site, therefore, three separate models of land-cover classification were created and applied, one for each period.

For sites in the boreal, temperate and subtropical domains, training labels for each land-cover class were assigned to level-1 image objects using temporally coincident year 2000 Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Continuous Fields (VCF) (Hansen *et al*., 2003) and 2005 GlobCover (Arino *et al.,* 2008) land-cover products. Training class labels for water bodies were assigned based on the proportion of MODIS global water mask pixels (Carroll *et al.*, 2009) falling within an individual image object. Data from GlobCover were used to assist with the classification of shrub-dominated land cover.

Artificial neural network classifiers were used to produce land-cover classifications for the FAO-processed sample sites. For each site, the network was trained and then applied to all year 2000 image objects. Objects with the same or similar spectral characteristics in 1990 and 2005 as in 2000 were automatically assigned the land-cover label from the 2000 image object. Where a large spectral change was detected between 1990 and 2000 or between 2000 and 2005, the 1990 and 2005 image objects were assigned labels based on individually created 1990 and 2005 classification models. The methods are detailed in Lindquist *et al.* (submitted).

For the tropics, the object-based land-cover classification at level 1 was based on a supervised spectral library (Raši *et al.*, 2011). Spectral signatures were collected from a common set of training areas representing the main land-cover classes within the tropics. For this purpose, the preprocessed Landsat ETM+ data for the year 2000 of all sample sites in a subregion were used. For each main land-cover class, several subclasses were identified, representing spectral variations due to site condition or land-cover subtype. For *tree cover*, for example, identified subclasses were dense evergreen forests, degraded evergreen forests, dry deciduous forests, mangroves and swamp forest. For each subclass, several training areas were selected. The number of pixels ultimately used for establishing the spectral signature of a subclass was generally higher than 1 000. Spectral signature statistics (means and standard deviations) were calculated at the level of subclasses. For South and Southeast Asia, for example, 73 spectral signatures were established as inputs to the digital classification of the four main land-cover categories. A generic supervised classification of the level-1 segmentation objects was performed uniformly for all sample sites, based on membership functions established from the spectral signature of each subclass for the Landsat spectral bands 3, 4 and 5. The membership functions were defined as an approximation of the class probability distribution. These membership functions were then applied to the imagery of the three years, i.e. extending the spectral signatures to 1990 and 2005. The subclasses resulting from supervised classification were not mapped as separate thematic land-cover categories but contributed to the mapping of the four main land-cover classes.

The supervised classification result obtained for the level-1 objects served as direct input to the thematic aggregation done at the level-2 segmentation (with a 5-ha MMU). The labelling of the level-2 objects was performed by passing them though a sequential list of classification criteria (Table 1). For the purpose of forest monitoring, the main emphasis was on tree cover and tree-cover proportions within level-2 objects. For tropical sites, a *tree cover mosaic* class was introduced for objects containing partial tree cover at level 2: for example, a mapping unit containing 40 percent tree cover (= total area of aggregated tree-cover objects at level 1) was still labelled *tree cover mosaic*. Level-2 objects were the only image object labels considered for the expert review-and-revision process described in later sections.

LAND-USE CLASSES

Land-use classifications were based on FAO forest definitions (FAO, 2010), as follows:

- *Forest* – land spanning more than 0.5 ha with trees higher than 5 metres and canopy cover of more than 10 percent, or trees able to reach these thresholds *in situ*. It does not include land that is predominantly under agricultural or urban land use.
- *Other wooded land* – land not classified as *forest*, spanning more than 0.5 ha; with trees higher than 5 metres and canopy cover of 5–10 percent, or trees able to reach

these thresholds *in situ*, or with a combined cover of shrubs, bushes and trees above 10 percent. It does not include land that is predominantly under agricultural or urban land use.
- *Other land* – all land that is not classified as forest or other wooded land.

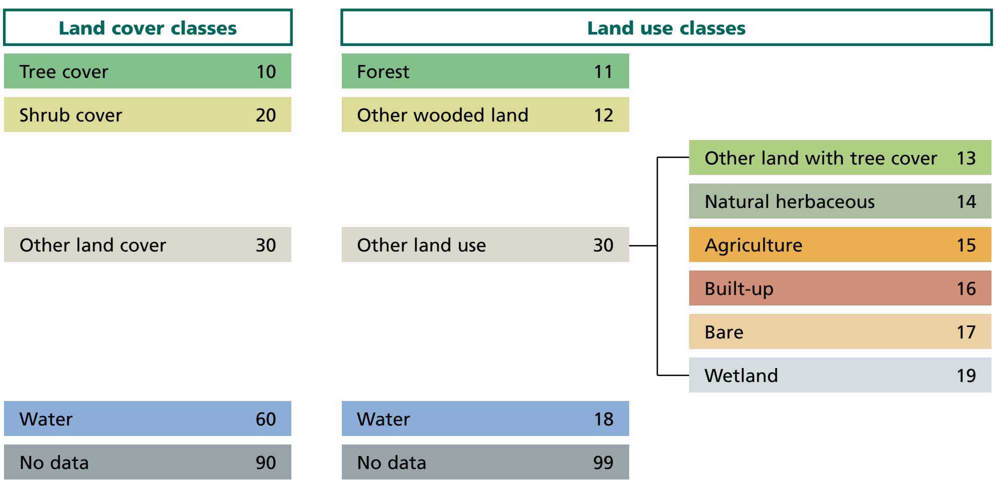
CONVERSION OF LAND COVER TO LAND USE

The conversion of land-cover class to land-use class was a two-step process. The first involved the automated conversion of land-cover classes to preliminary land-use labels (Figure 4). This conversion was presumed to account for the majority of polygons in the dataset. However, the accurate quantification of true land-use changes is complicated. The true land use of a given area must be examined in an ecological context that includes determining not only the vegetation present at the time of satellite image acquisition but also how the land will respond in the future (e.g. through regeneration, afforestation or deforestation) (Kurz, 2010).

Operationally, FAO definitions required expert human interpretation to provide the context necessary for the accurate categorization of land use, especially where exceptions to the automated rules existed. The exceptions were as follows (see also Figure 4):

- The *tree cover* and *tree-cover mosaic* land-cover classes were converted to the *forest* land-use class. Experts looked for exceptions where the land uses were either urban (e.g. trees in parks or gardens around houses) or agricultural (e.g. orchards). Urban areas with trees, orchards, oil-palm plantations, agricultural land with trees, and areas under agroforestry were identified and manually re-coded as *other land use with tree cover.*
- *Shrub cover* was converted to the *other wooded land* land-use class. Experts looked for exceptions, such as forest re-growth where trees were likely to grow taller than 5 metres, and re-coded those areas as *forest.*
- *Other land cover* was converted to *other land use*. Experts looked for exceptions such as temporarily un-stocked areas that may have had no trees at the time of the image but were likely to regenerate or be replanted, in which case they were re-coded as *forest.*

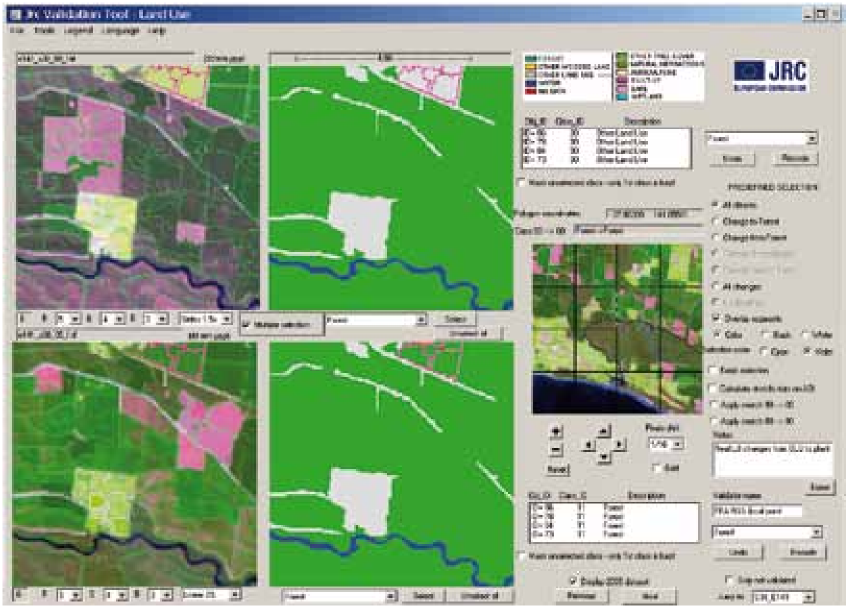
FIGURE 4
Land-cover and land-use classes and their associated numeric codes



Note: In the conversion from land cover to land use, tree cover was converted to forest, shrub cover was converted to other wooded land, other land cover was converted to other land and water stayed as water. Ideally, where there was a change in land use either to or from forest, the subclasses of other land use were to be used to identify the cause of the change.

FIGURE 5

JRC validation tool user interface showing Landsat imagery from each survey period (left) and FAO land-use classes (centre)



EXPERT INTERPRETATION, VALIDATION AND CORRECTION OF LAND COVER AND LAND USE

The final assignment of land-cover and land-use labels was carried out by selected national forestry or remote sensing experts. The visual checks were conducted on all the imagery of three survey periods to review and revise the automatically assigned land-cover and land-use labels. The JRC developed a dedicated stand-alone computer application for this purpose (Simonetti, Beuchle and Eva, 2011). The aim of this tool was to provide a user-friendly interface, with an easy-to-use set of functions for navigating and assessing a given dataset of satellite imagery and land-cover/land-use maps, and to efficiently re-code areas where, according to expert judgement, changes were required (Figure 5).

Visual control and refinement of the digital classification results at object level 2 were implemented in three steps:

- Obvious errors from the automatic classification were corrected.
- At regional workshops, a revision of the mapping results was carried out by national experts, who contributed local forest knowledge to improve the interpretation. Nineteen regional workshops were held between September 2009 and July 2011, involving 204 national experts from 107 countries (Annex 3).
- In a final phase of regional harmonization, experienced image interpreters performed a final screening for errors overlooked or mistakenly re-introduced and controlled for interpretation consistency across the region, applying final corrections where necessary.

The review and revision of the classification was aided by very-high-resolution satellite imagery, Google Earth™, images from the Degree Confluence Project[2], Panoramio™, and existing vegetation maps, where available. Specific expert field knowledge was also important. The phase of visual control and refinement was designed as a crucial component for correcting classification errors and for implementing the change assessment.

[2] www.confluence.org.