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CLASSIFICATION OF EUROPEAN BIOMASS POTENTIAL FOR BIOENERGY USING TERRESTRIAL & EARTH OBSERVATIONS

CONTRACT №:

2 1 3 6 3 4

Funded by:

European Commission
Framework Programme 7
Cooperation

Thematic Area
Energy 3.7
Cross-Cutting Issues

WP4 – COMBINATION AND HARMONIZATION OF EO AND TERRESTRIAL METHODS

DELIVERABLE D 4.2 - *REVISED VERSION* COMPENDIUM ON COMBINED METHODS

Date of preparation: February 2010
Date of preparation of the revised version: August 2010

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SEVENTH FRAMEWORK PROGRAMME

CONTENT

1. Introduction

The aim of this report is to identify different options to combine terrestrial data with remote sensing imagery (satellite EO data).
In this respect, terrestrial data means all data measured 'in-situ', i.e. not by remote sensing. This can be either statistics or ground truth data on biomass, land use/land cover information, etc with coordinates.
However, before starting the review, the basic options for biomass measurement shall be briefly reviewed.

According to [Herold et al., 2008], there are basically four options for biomass monitoring or measurement:

- Destructive sampling (terrestrial)
- Non-destructive sampling (terrestrial)
- Remote sensing
- Modelling

For destructive sampling, the samples are harvested and the collected biomass is measured (weighted). Non-destructive sampling refers to terrestrial measurements on a sample basis without actually harvesting the biomass. The most common non-destructive sampling of biomass is regularly done in the frame of national forest inventories (NFIs).
The third option covers the whole group of remote sensing technologies; the different methods have already been discussed in depth in Deliverable D 2.1 in work package 2. Finally, the use of models is another option to estimate biomass potential.

In addition to these individual methods, different combinations are possible. This report is focused on the assessment of biomass potential from a combined use of terrestrial (mainly non-destructive sampling) and remote sensing data.
A good basic overview of combining terrestrial and satellite data in general terms (not specifically for biomass) is given in [Jennings et al., 2010]. The authors identify the main problems in data integration such as varying definitions, different temporal resolution; incongruent data formats etc. and propose general recommendations to solve these problems.

This report is focused on estimating two biomass types from terrestrial and EO data. The two types considered in CEUBIOM are 'forest biomass' and 'agricultural biomass'. They are defined as follows:

a) Forest biomass is equivalent to 'woody biomass' according to European Norm EN 14961-1
b) Agricultural biomass is equivalent to 'herbaceous biomass' and 'fruit biomass' according to European Norm EN 14961-1.

Within CEUBIOM, specific energy crops will be considered separately. They can fall under either of the above mentioned categories (e. g. short rotation forest is woody biomass; rape is herbaceous biomass).

In this context, the term 'potential' is defined in congruence with the definition given in the partner project BEE.
BEE defined the **theoretical potential** as:
"the overall maximum amount of terrestrial biomass which can be considered theoretically available for bioenergy production within fundamental bio-physical limits"
(from BEE deliverable D3.2).

The ‘potentials’ calculated in the reviewed literature in Chapter 2 are almost exclusively theoretical potentials at a given point in time (time of the analysis) without considering projection into the future and also without considering technical, sustainability, ecological or economical criteria. So mostly, the output of these studies is standing biomass. The criteria on how to come from the standing biomass to a realistic potential for bioenergy will be discussed in Chapters 3 and 4 and in more detail in Deliverable 4.3.

Finally, it should be mentioned that the papers referred herewith represent only a selection, as such a review can never be complete.

2. Method review for the combined use of EO and terrestrial data

In Deliverable D2.1 of WP 2, the difference of direct and indirect biomass assessment from remote sensing is described. None of these methods can be applied relying exclusively on remote sensing data. To some extent ground truth data is always needed, e. g. for direct biomass estimation to build the regression curve.

For direct biomass assessment, it does not matter whether it is a single or multiple linear regression, a partial least squares (PLS) regression or an artificial neural network (ANN) analysis. Ground truth (terrestrial) data is always necessary to build the relation between a remotely sensed signal and the actual biomass on the ground. Using an indirect approach, also terrestrial data is needed: first, training data for the classification of the land cover and second, biomass data for each of the land cover types.

Studies comparing different combination techniques of EO and terrestrial data are of methodological interest. [Chen et al., 2009] report aboveground biomass (woodlands, shrub sites, grass/herbs sites) estimates along the Dempster Highway and around Yellowknife and the Lupin Gold Mine by using Landsat-7/ETM+ and JERS-1/SAR data. For the biomass estimation several analytical techniques such as simple, multiple or stepwise regressions, artificial neural networks and kNN have been used. The combination of JERS backscatter and Landsat TM4/TM5 in multiple regression analysis give the best biomass equation with $r^2=0.72$ when using one-step approach (i.e. using all points) and 0.78 when using a two-step approach (i.e. stratifying data into three classes).
[Roy and Ravan, 1996] developed empirical regression models between satellite measured spectral response and biomass in Madhav National Park (India). [Baffetta et al., 2009] implemented a design-based approach to k-nearest neighbours technique for coupling field and remotely sensed data. [McRoberts, 2009a] presented diagnostic tools for nearest neighbour techniques when used with satellite imagery.

To summarize the comparing studies, there is no clear indication for one best method, however most authors consider kNN methods and multiple regression analysis as the most promising options.

The terrestrial data used in remote sensing studies such as the ones mentioned above is generally acquired for the specific purpose or project. It has to fulfil several requirements which are for example:

- Positional accuracy
- Thematic congruence of classes with classes obtainable from remote sensing
- Size of the observed area on the ground has to fit the resolution of the EO data
- Acquisition times have to be coordinated, etc.

All these requirements make terrestrial data very costly. Much research efforts are thus invested in reducing the efforts for terrestrial data. Approaches include the investigation of options to

- transfer terrestrial data from one time of analysis to another;
- transfer terrestrial data to a different area (given similar conditions);
- use indices rather than the image spectral values to reduce the sensitivity of the regression to e. g. atmospheric effects;
- build libraries of terrestrial data for use in many different projects.

For the CEUBIOM approach, obtaining large amounts of terrestrial data specifically for biomass potential assessment all over Europe is not viable. Therefore the focus is on using terrestrial data, which were collected **anyway** and/or for a **different purpose**. Such data for example can be all types of statistics, general landcover information, and national forest inventories (NFI), etc. The data has to be analysed and the satellite based classification procedures have to be adapted in an appropriate way as explained in [Jennings et al., 2010]. For example the class definitions have to be clear and transferable between terrestrial and satellite data and the used formats must allow data integration.
In addition, also remote sensing data should be used, if already available, such as the GMES data sets 'image2000', image2006', core service products [GEOLAND2, 2009], CORINE land cover products, MARS products, etc. For the full list and details on existing remote sensing products see CEUBIOM Deliverable D2.3.

A review of methods to combine these data sets with remote sensing is given in the following sub-chapters. In addition to the method description, also the achievable accuracies, the size of the study area (local, regional, national, European, global) and possible restrictions are summarized.

2.1. Methods for forest biomass potential assessment

A large variety of methods is currently in use, amongst them two main groups can be distinguished. The difference between these two is the way how terrestrial data is available.

For the first group, <u>terrestrial data has to be available with spatially explicit location</u>. This is for example true for NFI plot data, where each plot has a defined location and extent. Methods of this group generally try to set up a link between the terrestrial measurement and the pixel information in the EO data. These approaches are sometimes also called <u>'bottom up approaches'</u>.

The second group involves all methods, which use <u>terrestrial data on an aggregated basis or general equations</u>, such as from national statistics. These terrestrial data have no more defined location, but are aggregated to a larger area. Examples would be statistics on the total amount of deciduous timber volume in a country or region or the growth and yield tables generated from forest inventories (e. g. for Austria [Hasenauer et al., 1994], [Eckmüllner et al., 2007]). In this case, other parameters such as forest age or density are derived from the EO data and then linked to 'typical' biomass values in this area and with the given parameters. Methods under this group are sometimes summarized under the term <u>'top-down approaches'</u>. In addition, below there are some interesting references given under <u>'other approaches'</u>, which do not clearly fit into either one or the other above mentioned categories.

One could also subdivide the approaches according to the amount of helping variables needed to reach the biomass calculation result. Direct methods (mainly based on LiDAR data) measure the height of the trees or stand directly and then estimate the biomass from existing equations. Indirect methods classify for example in a first step age classes and species from the remote sensing data. In the second step, this information is linked to average height and diameter at breast height (DBH) and finally in a third step biomass is estimated using the parameters gathered in the second step.

2.1.1. Bottom-up approaches for forest biomass

The following papers are sorted in alphabetical order.
[Barth et al., 2009] suggest a method for improving spatial consistency in the estimation of forest stand data. The first step of the method is a k-NN assignment. In the second step an optimization algorithm is applied in order to reach certain spatial variation targets. The method was tested in a case study where tree stem volume data were assigned to each pixel of forest stands, using satellite digital numbers as carrier data. The case study stands were constructed to be 64 hectares squares consisting of 1600 pixels (each 20x20m). The accuracy of the estimated stand level mean volume was used as a target in order to avoid drifts in mean volume during the optimization. The method was successful in three out of four stands. In the fourth case the mean stem volume was slightly overestimated (stem volume of 375 m^3 ha rather than 336 m^3 ha).

[Bauerhansl, 2005] investigated the use of satellite imagery in the frame of the Austrian National Forest Inventory. 13 Landsat scenes and a digital terrain model were used and combined in a kNN approach. No accuracy values are given.

[Blackard et al., 2008] generated a spatially distributed dataset of aboveground live forest biomass from ground measured inventory plots of the conterminous U.S., Alaska and Puerto Rico. The plot data are from the USDA Forest Inventory and Analysis (FIA) program. To scale these plot data to maps, they developed models relating field-measured response variables to plot attributes serving as the predictor variables. The plot attributes came from intersecting plot coordinates with geospatial datasets. First, they developed a forest mask by modeling forest vs. nonforest assignment of field plots as functions of the predictor layers using classification trees in „See5“. Then, forest biomass model were built within the predicted forest areas using tree-based algorithms in „Cubist“. The estimated proportion of correctly classified pixels for the forest mask ranged from 0.79 to 0.94. For biomass it ranged from a high of 0.73 to a low of 0.31.

[Coulibaly et al., 2008] developed a method of aboveground forest biomass mapping from Ikonos high resolution satellite imagery and geospatial data. They assessed a geostatistical method (ordinary kriging) to map the biomass estimated with the neural networks approach trained with inventory plot biomass data. The study area, covering approximately 19720 hectares, is located in the North-West of New Brunswick (Canada). Reference biomass values by group of species (spruce, balsam fir, intolerant hardwood, tolerant hardwood and other conifers) were estimated using the equations of Ker (1980, 1984) and inventory data from permanent sample plots (PEP) of 400 m^2. The results have shown percentages of residual errors ranging between 2.6 and 9.8% (absolute value) and percentages of RMSE (root mean square error) ranging between 17.2 and 61.1%.

[Gallaun et al., 2005] describes several methods for bottom-up approaches in the frame of the CarboInvent project. For the Austrian Alpine test area in Salzburg, a kNN method was applied to Landsat data. It was observed, as in previous studies on kNN that the RMSE is high for the comparison of small areas and decreases for larger regions. The RMSE of the volume of growing stock was between 30 and 60 %.

[Gallaun et al., 2010] used an automatic up-scaling approach making use of satellite remote sensing data and field measurement data for EU-wide mapping of growing stock and above-ground biomass in forests. The validation at the regional level shows a high correlation between the classification results and the field based estimates with correlation coefficient $r = 0.96$ for coniferous, $r = 0.94$ for broadleaved and $r = 0.97$ for total growing stock per hectare. The mapped area is 5 million km^2, of which 2 million km^2 are forests, and covers the whole European Union, the EFTA countries, the Balkans, Belarus, the Ukraine, Moldova, Armenia, Azerbaijan, Georgia and Turkey.

[Gjertsen, 2007] developed a multi-source forest inventory (MSFI) method for use in the Norwegian National Forest Inventory (NFI). The study area is about 60 km x 50 km. The method is based on a k-nearest neighbour rule and uses field plots from the NFI, land cover maps, and satellite image data from Landsat Thematic Mapper. The inventory method is used to produce maps of selected forest variables and to estimate the selected forest variables for large areas such as municipalities. In this study, focus has been on the qualitative variables ‘dominating species group’ and ‘development class’ because these variables are of central interest to forest managers. A mid-summer Landsat 5 TM scene was used as image data, and all NFI plots inside the scene were used as a reference dataset. The relationship between the spectral bands and the forest variables was analysed, and it was found that the levels of association were low. A leave-one-out method based on the reference dataset was used to estimate the pixel-level accuracies. They were found to be relatively low with 63 % agreement for species groups.

[Koukal and Schneider, 2004] describe the use of Remote Sensing data for the inventory of high structured forests in mountainous regions in Austria (Tyrol and Lower Austria: 2 test side with 114.600 ha and 97.600 ha). Input data are: Inventory data (permanent sampling grid with 11.000 plots) and satellite image data (Landsat TM). The kNN-technique was used to combine the Landsat images with inventory data.

[Magnussen et al., 2009] included model-based estimators of the uncertainty of pixel-level and areal k-nearest neighbour predictions of attribute Y from remotely-sensed ancillary data X. The two study areas are in Minnesota and in Finland (three separate contiguous forested areas of the size of 100 ha). Three forest inventory data sets with multivariate attributes of interest and co-located information on a suite of ancillary remotely-sensed attributes (from Landsat ETM+) were used. The RSME was in the range from 2.1 % to 3.7 %.

[McRoberts, 2009b] proposed a two-step algorithm in which the class of a relevant categorical variable such as land cover is predicted in the first step, and continuous variables such as volume are predicted in the second step subject to the constraint that all nearest neighbours must come from the predicted class of the categorical variable. In the first step nearest neighbour multinomial logistic regression and discriminant analysis techniques were investigated and in the second step the kNN technique was used. For this study Landsat imagery were used for a study area in northern Minnesota (6 areas with 15x15 km). The accuracy is about 80%.

[Rauste, 2005] used multi-temporal JERS SAR data to study forest biomass mapping. The study area is in South-eastern Finland. In single-date regression analysis between backscatter amplitude and stem volume, summer scenes from July to October produced correlation coefficients (r) between 0.63 and 0.81. Multivariate regression analysis with 6-date JERS SAR dataset produced correlation coefficient of 0.85. A combined JERS –optical regression analysis improved the correlation coefficient to 0.89.

[Tomppo et al., 2002] developed a multisource and multiresolution method for estimating large area tree stem volume of growing stock and aboveground biomass of trees. Combined Landsat-TM data and IRS-IC WiFS data, together with field data of NFI were applied. Landsat-TM data were used as an intermediate step between the field data and WiFS pixels. A nonparametric kNN estimation method was applied with Landsat-TM data and field plot data from the Swedish NFI. A nonlinear regression analysis was used in deriving models for volume and biomass as a function of WiFS data. The study area is located in the northern part of Sweden and has a size of 1.1 million hectare. The mean relative difference of biomass aggregated to municipality level is 3 % compared to the NFI data.

[Tomppo et al., 2008] provide a review of how NFI (National Forest Inventories) field plot information has been used for parameterization of image data in Sweden and Finland, including pre-processing steps and the optimization of the estimation variables. Therefore Landsat 5 TM or Landsat 7 ETM+ sensors have been used. As a substitute for Landsat images, multi-spectral SPOT or IRS-1 images can also be used. For the combination of field data and satellite images the the k-NN algorithm was applied. Relative RMSE of 5% for mean volume and 12%, 15% and 16% for mean volumes of pine, spruce and birch were obtained in seven test units of 100 km².

[Zheng et al., 2004] bridge the application of remote sensing techniques with various forest management practices in Chequamegon National Forest, Wisconsin by producing a high-resolution stand age map and a spatially explicit aboveground biomass map. Therefore they coupled AGB values, calculated from field measurements of tree DBH, with various vegetation indices derived from Landsat 7 ETM+ data through multiple regression analysis to produce an initial biomass map. This map was overlaid with a land-cover map to generate a stand age map. The final estimated AGB values compared reasonably with the independent field observations (R^2=0.67).

In order to summarize all above mentioned studies, the following table was created. It shows the method, type of EO data, the size of the study area (as an indicator for the operational capability of the method), achieved accuracy and the type of terrestrial data used. It can be observed that several variations of kNN estimators are most popular. Further the type of data belongs in most cases to the group of optical high resolution data (Landsat-type). The size of the study areas varies strongly, but it is clearly shown that lower resolution data is rather used for continental-wide applications ([Blackard et al., 2008], [Gallaun et al., 2010]), while HR data is mainly used for national or sub-national applications. VHR data is basically used for local applications, which was to be expected. Accuracies are very difficult to compare, because different statistical measures are used. Finally, in almost every case, national forest inventory (NFI) data was the source for the terrestrial data.

Table 1: Overview table of bottom-up approaches for forest biomass

Reference	**Method**	**Remote sensing data**	**Approximate size of area**	**Accuracy**	**Type of terrestrial data**
[Barth et al., 2009]	kNN & top down correction	Optical HR (5 – 30m)	2,56 km²	75 % (3 of four correct)	Forest plots
[Bauerhansl, 2005]	kNN	Optical HR (5 – 30m)	Austria (84.0000 km²)	NA	NFI plots
[Blackard et al., 2008]	Modelling, See5 & Cubist	Optical MR (30– 500 m)	Continental U.S., Alaska & Puerto Rico (almost 10.000.000 km²)	Correlation of 0.31 - 0.73	NFI plots
[Coulibaly et al., 2008]	Neural networks	Optical VHR (< 5m)	197,20 km²	RMSE: 17.2 - 61.1%.	NFI plots
[Gallaun et al., 2005]	kNN	Optical HR (5 – 30m)	Province of Salzburg (7.154 km²)	RMSE for volume of growing stock: 30 - 60%.	NFI plots
[Gallaun et al., 2010]	Clustering, fractional cover map calculation, classification with membership functions	Optical MR (30– 500 m)	5.000.000 km²	R = 0.97 for total growing stock per hectare	NFI plots
[Gjertsen, 2007]	kNN	Optical HR (5 – 30m)	3.000 km²	63 % agreement for species groups	NFI plots
[Koukal and Schneider, 2004]	kNN	Optical HR (5 – 30m)	2.122 km²	Total volume aggregated for the two test sites: +/-1%	NFI plots
[Magnussen et al., 2009]	Modelling & kNN	Optical HR (5 – 30m)	3 km²	RMSE: 2.1 % - 3.7 %.	NFI plots
[McRoberts, 2009b]	NN multi-logistic regression and discriminant analysis & kNN	Optical HR (5 – 30m)	1.350 km²	Ca. 80 %	NFI plots
[Rauste, 2005]	Multivariate regression analysis	Optical and SAR HR data (5 – 30m)	1.444 km²	Correlation of 0.63 - 0.89 (depending on input data)	Stand-wise forest inventory map
[Tomppo et al., 2002]	Nonparametric kNN	Optical HR (5 – 30m)	11.000 km²	Mean relative difference of biomass on municipality level: 3%	NFI plots
[Tomppo et al., 2008]	kNN	Optical HR (5 – 30m)	Seven areas à 100 km²	RMSE of 5% for mean volume	NFI plots
[Zheng et al., 2004]	Multiple regression	Optical HR (5 – 30m)	ca. 280 km²	R^2=0.67	NFI plots

2.1.2. Top-down approaches for the estimation of forest biomass

[González-Alonso et al., 2006] and [González-Alonso et al., 2005] show three possible uses of satellite data of various sources and resolutions in the generation of forest biomass cartography. The first one attempts to find statistical relationships between satellite-derived NDVI time series and field measurements from the Spanish National Forest Inventory on a province basis (accuracy: 82-95%). The second one is focused on updating and scaling-up such a relationship using Envisat-MERIS Full Resolution data (accuracy: max. 58%). The third one tries to produce medium resolution biomass maps using information derived from the Envisat-MERIS-FR sensor in combination with finer satellite data from SPOT5-HRG (accuracy: 61%), field data from the Spanish NFIs and forest cartography (accuracy: 94-96%). The study area is the whole Spanish territory. For the combination of satellite data with inventory data they used regression models.

An experiment was performed by [Santos et al., 2004] in the Brazilian Amazon (Tapajós National Forest and surroundings) to provide airborne SAR data at X- and P- bands over tropical rainforest. The best biomass model was established after comprehensive testing of a range of specific allometric equations to achieve statistically high precision in biomass prediction. A final mapping result displays forest biomass, and accounts for different succession stages and primary forest in intervals. The coefficient of determination for tree height as the most important variable to the biomass calculation attained a value of $R^2 = 0.87$ on the regression analysis.

In this study [Quinones and Hoekman, 2002] created biomass maps of two study sites at the Colombian Amazon by using results from polarimetric classification algorithm that combines power, phase and correlation of C, L and P band of AirSAR data. Therefore two different approaches (bottom-up vs. top-down) were used. For one site (dry and flat) the biomass classes selected are related to Land Cover types and an empirical relationship between biomass and the average backscatter is used to create the biomass map (r^2 is 0.94). For the other site (hilly and flooded) a biomass map is created by reclassifying a biophysical forest structural map with biomass values obtained from field available data (overall accuracy for the biomass map: 92%).

In the project CARBO-INVENT (e.g. [Galinski, 2005]), two different top-down approaches to estimate carbon stock changes were employed: 1) by using aggregated data from two different NFIs and 2) by using aggregated data from one NFI and in addition the help of the European forest information scenario model (EFISCEN). The CARBO-INVENT analyses were carried out for Finland, Sweden, Germany, Austria, Ireland and Spain.
The basic input data in both cases is derived from the national forest inventory/ies (aggregated NFI data). This includes forest area, growing stock and increment by age-class and forest type. Most biomass functions, however, use diameter at breast height (DBH) and/or tree height as explaining variables to generate in the first step stem volume. Growth and yield tables were used to get values for DBH and tree height by age class. Biomass Expansion Factors (BEFs) are used to expand from stem volume to whole tree biomass and to carbon contents. Carbon stock changes are calculated in case 1 by simple subtraction (stock 1 – stock 2), while in case 2, stock 2 is defined as stock 1 + gross increment – harvesting – mortality (from EFISCEN).
Within CARBO-INVENT, a comparison of this top-down to the bottom-up approach described [Gallaun et al., 2005] was performed. This comparison revealed that the deviation between the two approaches was highest for the youngest age classes. The bottom-up method resulted in lower uncertainties in the results (of carbon stock and stock changes), but with the

drawback of depending on detailed (plot-level) forest inventory data. In contrast, the top-down approach is much more cost-efficient. It was observed, that modelling is sensitive to the accuracy of the available harvest and increment estimates.

[Dorfinger and Bachhiesl, 2008] calculated the biomass potential from forestry for the province of Salzburg based on a satellite image classification of forest classes (based on SPOT imagery) and yield tables. In addition, they compared the results with average energy demand from households and industries.

In the GSE-FM project, the product 'National and Regional Volume, Biomass and Carbon Statistics'(Code: GSE-FM-VBCS) is a product designed for central Europe to obtain the information required for UNFCCC- and Kyoto reporting in the sector of LULUCF. The products include volume, biomass and carbon stock estimates in table format according to FCCC and Kyoto reporting requirements. These estimates are

1) Area change of the classes forest land, cropland, grassland, wetland, settlements, other land
2) Forest area (with a higher accuracy than 1)
3) Change of stem volume
4) Change of woody biomass
5) Change of carbon stock

The methods are partly top-down and partly bottom-up approaches, all details can be found in [GSE-FM, 2010].

2.1.3. Other combination approaches for forest biomass

The following three papers are mainly using tree or stand height from remote sensing (LiDAR or stereo) in combination with allometric models to estimate biomass, while the other approaches are either based on models or use a different method or method combination.

[Simard et al., 2008] describe a new systematic methodology to measure mangrove height and aboveground biomass by remote sensing. The method is based on SRTM (Shuttle Radar Topography Mission) elevation data, ICEsat/ GLAS waveforms (Ice, Cloud, and Land Elevation Satellite/Geoscience Laser Altimeter System) and field data. The study area is Colombia with an extension of 1280 km². They compared height estimation methods based on waveform centroids and the canopy height profile (CHP). Linear relationships between ICEsat height estimates and SRTM elevation were derived. So they found the centroid of the canopy waveform contribution (CWC) to be the best height estimator. The field data was used to estimate a SRTM canopy height bias (−1.3m) and estimation error (RMS = 1.9m). The relationship was applied to the SRTM elevation data to produce a mangrove canopy height map.

[Koch et al., 2009] describe enhanced processes to delineate stand or sub-stand units and to extract different forest information based only on airborne LIDAR data. For the stand delineation an automatic process was developed which provides a stand or sub-stand unit delineation. With a combined method the stand boundaries as they are established by the mapping units today, as well as sub-stand units which have in common physical characteristics indicating the same management disposition, were assessed. Finally a first validation of the forest stand unit delineation is provided. The process was tested in two different test sites. One in a sub-mountainous area in Rheinland-Pfalz (4 km²) and the other is a mountainous forest in Baden-Württemberg (9 km²), both with a mixture of conifers and broadleaf forests. The correlation coefficient between LIDAR measurements and field inventory averages 78.2 for coniferous trees, 81.6 for deciduous trees and 84.1 for the top height per sample plot.

[St-Onge et al., 2008] assess the accuracy of the forest height and biomass estimates derived from an Ikonos stereo pair and a lidar digital terrain model (DTM). The coefficient of determination reached 0.91 and 0.79 for average height and biomass, respectively. In both cases, the accuracy of the Ikonos-lidar canopy height model (CHM) predictions was slightly lower than that of the all-lidar reference CHM.

In [Chopping et al., 2008] a rapid canopy reflectance model inversion experiment was performed using multi-angle reflectance data from NASA Multi-angle Imaging Spectro-Radiometer on the Earth Observing System Terra satellite. The goal was to obtain measures of forest fractional crown cover, mean canopy height, and aboveground woody biomass for large parts of south-eastern Arizona and southern New Mexico (>200.000 km²). The results showed good matches with maps from the USDA Forest Service, with R^2 values of 0.78, 0.69 and 0.81 and absolute mean errors of 0.1 - 2.2 m.

In response to an announcement of the German Aerospace Center (DLR) for a national Earth observation mission, the Friedrich-Schiller University Jena and the JenaOptronik GmbH proposed the EO-mission CARBON-3D. The data products of this multi sensor mission will for the first time accurately estimate above-ground biomass, one of the most important parameters of the carbon cycle. This mission will simultaneous acquire data with a multi-angle optical instrument and with NASAs Lidar system VCL (Vegetation Canopy Lidar). The second instrument onboard Carbon-3D is a BRDF-imager that extrapolates the laser-retrieved height profiles to biophysical vegetation maps using the horizontal, spectral information as well as multidirectional information. The aim of this mission is to reduce uncertainties about net effects of deforestation and forest re-growth on atmospheric CO2 concentrations. [Hese et al., 2004]

[Haapanen and Tuominen, 2008] evaluated the potential of the combination of Landsat ETM+ multispectral data and aerial photograph spectral and textural features for forest variable estimation. The studied stand variables were mean height, basal area per hectare, and the volume of the growing stock. Several approaches were tested when combining the image data sources: feature selection, feature weighting, satellite image-based stratification, and combination of individual estimates by weighting. The highest accuracies were obtained when both data sources were used. There were several good ways to combine the data sources. Feature selection with generic algorithm and subsequent feature weighting gave the lowest mean volume RMSE (63.7 m³/ha, 65.3 percent of the mean).

[Hu et al., 1996] used an approach to estimating biomass by integrating satellite data and carbon dynamics model. Anural actual net primary productivity (NPP) is first estimated with monthly composite 1-degree AVHRR Normalized Difference Vegetation Index (NDVI) data using the production efficiency approach in which canopy absorbed photo synthetically active radiation is transformed into net primary productivity. NPP estimates are subsequently incorporated into primary production is considered. NPP estimates are subsequently incorporated into a carbon dynamics model, PHYTOMASS model, to simulate biomass accumulation over succession until equilibrium with climate. A global map to terrestrial biomass is finally generated based on the estimation results after their validation with field measurements. The biomass estimates are validated with 98 sites of field measurements with a correlation coefficient of 0.44.

[Thenkabail et al., 2004] developed biomass models to calculate carbon stock levels of the West African oil palms using multi-date wet and dry season IKONOS images. Four IKONOS images, each of about 13 500 ha were selected for the two representative areas. Allometric equations related aboveground palm biomass to their stem heights. Empirical regression models based on field plot data were established to determine wet and dry biomass of oil palm plantations in IKONOS images. The best explained between 63 and 72% of the variability in the data. Model evaluations with independent datasets showed there is 28-36% uncertainty in dry biomass predictions. The best results had an overall accuracy of 74.5% using all four IKONOS bands.

The **FAO Forest Resources Assessments** in 2000 and 2005 ([FAO, 2001], [FAO, 2006]) collected and summarized 229 national reports on forest, including forest biomass. A special working paper [Garzuglia and Saket, 2003] on woody biomass based on the FRA 2000 data states that national reports from the individual countries are not prepared in a harmonized way. Three levels of reliability of the data are defined:
1 – high: computed from NFI data based on field sampling complemented by thematic mapping
2 – medium: mainly based on remote sensing
3 – low: based on secondary sources, general assessments, statistics and expert estimates.
The procedures for the calculation of volume and biomass in tropical areas are adopted from [Brown, 1997]. For industrialized temperate-boreal countries, the technical specifications of [A. Bombelli, 2009] are followed.
In addition to the new ‘standard’ Forest Resources Assessment 2010 (FRA2010), a remote sensing survey (RSS) is currently carried out in the frame of FRA2010. The two main components of this RSS are:

1. Generating a new, validated global tree cover map using time-series imagery from MODIS satellites at 250 m resolution.
2. Gathering and analysing the best existing global imagery (Landsat images at 30 m resolution) from 1975, 1990, 2000 and 2005 for improved estimates of forest area and forest area change. This is done on the basis of a regular sampling grid (a sample every one by one degree longitude/latitude).

2.2. Methods for agricultural biomass potential assessment

Quite some references have been already given in the Deliverable D2.2 on SAR data. Most of these studies are using specifically derived terrestrial data as for example [Karnchanasutham et al., 1995], who evaluated the capabilities of BRS-l SAR data for monitoring of rice planting acreage and its growth reaching an accuracy for the rice mapping of 78% and the overall accuracy of 79%. Another work by [McNairn et al., 2000] postulated that the multi-polarized configuration of RADARSAT-2 is likely to provide more information related to crop structure and crop condition than previously available sensors to address the sensitivity of multi-polarized SAR data to characteristics of corn, wheat and soybean crops. The HH-HV-LL 3-polarization combination had the highest Kappa coefficient (0.92).

Aside from these very specific studies, there is a large variety of studies on crop type classification, where only a selection can be cited below. Although crop type is not the required information, it can be seen as a first step towards biomass assessment. In the second sub-chapter, combined approaches to estimate biomass are reviewed.

2.2.1. Crop type classification (first step towards biomass estimation)

Studies in this section do not assess biomass, but only the crop types as their final mapping result. Therefore, these studies provide only the first step in an indirect approach, which would then need a second calculation of biomass per crop type. The following papers are only a small extract from the large amount of studies in this field.

[Feingersh et al., 2001] tested the use of radar and optical imagery and their synergy for crop mapping, with dependence on the sequence of pre-processing and processing techniques in the mapping procedure. Classification accuracy of crop maps based on synthetic aperture radar (SAR), visible-infrared (VIR) and fused imagery reached 82%, 92% and 76% respectively. Majority based object classification does not improve significantly the overall accuracy.

[Wardlow and Egbert, 2008] evaluated the applicability of time-series MODIS 250 m normalized difference vegetation index (NDVI) data for large-area crop-related LU/LC mapping over the U.S. Central Great Plains. A hierarchical crop mapping protocol, which applied a decision tree classifier to multi-temporal NDVI data collected over the growing season, was tested. The hierarchical classification approach produced a series of four crop-related LULC maps that progressively classified: 1) crop/non-crop, 2) general crop types (alfalfa, summer crops, winter wheat, and fallow), 3) specific summer crop types (corn, sorghum, and soybeans), and 4) irrigated/non-irrigated crops. The series of MODIS NDVI-derived crop maps generally had classification accuracies greater than 80%. Overall accuracies ranged from 94% for the general crop map to 84% for the summer crop map.

A crop map of the Netherlands was created using a methodology that integrates multi-temporal and multi-sensor satellite imagery (Landsat TM, IRS-LISS3, ERS2-SAR), statistical data on crop area and parcel boundaries from a 1:10 000 digital topographic map [DeWit and Clevers, 2004]. In the first phase a crop field database was created by extracting static parcel boundaries from the digital topographic map and by adding dynamic crop boundaries using on-screen digitizing. In the next phase the crop type was determined from the spectral and phenological properties of each field. The resulting crop map has accuracy larger than 80% for most individual crops and an overall accuracy of 90%.

The purpose of this project by [Cook et al., 1996] was to establish a crop specific classification for a group of counties in Southeastern North Dakota. Landsat TM data (from May, June, July, and September 1994) provided 24 bands of multi spectral information (the thermal bands were not used). Extending this crop classification throughout North Dakota using AVHRR data and developing relationships to spring wheat yield are the focus of the North Dakota spring what yield modeling project. Crop information came from both the National Agricultural Statistics Service (NASS) June Agricultural Survey (JAS) and the Farm Services Agency (FSA) for the 1994 growing season. ERDAS IMAGINE2 software was used in the clustering and classification of the four dates of Landsat TM imagery. Mapping accuracy is around 85%.

[González-Alonso and Cuevas, 1997] used regression estimators for crop area estimation. They found out that regression estimators are less prone to errors compared to other methods when using terrestrial data from another year than the satellite imagery. This however is only true if the magnitude of change between the year of satellite data acquisition and ground survey is not too large.

A simple combination approach of terrestrial and EO data is disaggregation of statistical data. This means, if terrestrial data (statistics) are available only on an aggregated level (e.g. for communities or at a low spatial resolution), remote sensing based classifications can be used to disaggregate the information to more spatial detail. This is for example true for IACS data, which is in Austria only available for 100 by 100 m squares due to data confidentiality issues.

2.2.2. Agricultural biomass estimation

The **MARS** project has already been described in the frame of Deliverable D2.3. [Gallego, 1999] explains two different activities of the MARS project in crop area estimation:

1. The regional crop inventories, that combine high resolution satellite images and ground surveys in a classical statistical scheme based on area frame sampling and ground visits providing the main estimation variable.
2. The rapid estimates of crop area change at the EU level based on a more flexible expert procedure combining general information and satellite images on a fixed panel of sites.

The methods were tested on five pilot regions of approximately 20.000 km² each. The accuracy for various crops in the pilot regions was between 49% and 66%.
For yield forecasting, agro-meteorological models (Crop Growth Monitoring System - CGMS) and low resolution remote sensing methods are used in combination with the crop area estimation. The description of the methodology (including use of meteorological data, agro-meteorological processing, use of remote sensing data and statistical data analysis and result validation) is accessible on the website (see http://www.marsop.info).

[Hu et al., 1996] describes a promising approach to estimating biomass by integrating satellite data and carbon dynamics model. Annual actual net primary productivity (NPP) is first estimated with monthly composite 1-degre AVHRR Normalized Difference Vegetation Index (NDIV) data using the production efficiency approach, in which conversion efficiency of canopy absorbed photosynthetically active radiation into primary production is considered. NPP estimates are subsequently incorporated into a carbon dynamics model, PHYTOMASS model, to simulate biomass accumulation over succession until equilibrium with climate. A global map to terrestrial biomass of 1989 is finally generated based on the estimation results after their validation with field measurements. The NPP estimates are validated with only 14 sites of field measurement available; the correlation coefficient is 0.65. The biomass estimates are validated with 98 sites of field measurements; the correction coefficient is 0.44.

The aim of a study by [Butterfield and Malmström, 2009] is to examine the influence of phenological changes on NDVI-biomass relationships in annual grasses to improve the capacity to evaluate grassland dynamics over time. Also relationships between biomass and fAPAR and between biomass and LAI were analysed. To do this, they planted stands of three annual grass species in an agricultural field on the Michigan State University campus in 2003. Accuracy between R^2=0.73 and R^2=0.82.

[Yamamoto et al., 2008] estimated biomass using field measurement data and NOAA AVHRR LAC satellite data, and evaluated the estimated biomass using meteorological station data. The NDVI was calculated from convolved reflectance to NOAA AVHRR spectral resolution. As the result, they found that it is possible to estimate vegetation biomass without influence of clouds and vegetation growth with more than 5 days composite of NOAA AVHRR LAC data. Biomass in the wide area could be estimated with less than 10% error.

[Chen et al., 2009], already described in the introductory part of chapter 2, used biomass measurements of grass (including herbs, lichen and moss) as well as shrubs and correlated them in a bottom-up approach to the remote sensing signals from Landsat TM and JERS data. The results indicate that a transfer of the developed regression model from one site to another is possible without large errors.

[DiBella et al., 2003] combined SPOT VEGETATION medium resolution optical data with the STICS prairie simulation model to improve model predictions and evaluation. Thus, in this case, satellite imagery was used as a kind of 'ground truth' compared to the simulation model.

[Eerens et al., 2001] used medium-resolution NOAA-AVHRR or also SPOT VEGETATION in combination with the terrestrial IACS data to improve the biomass (dry matter) predictions. The main processing steps are: (1) filtering of the multitemporal image data; (2) spectral unmixing of the coarse satellite pixels to the IACS segments; (3) estimation of dry matter production by using solar radiation and temperature; (4) calculation of the cumulative values to reach a quantifyable amount of harvest material; (5) differencing to assess zones of progressed or retarded growth compared t previous years; (6) regionalization including data reduction and finally (7) calibration and integration with the official yield statistics.

The CROPMON project [Suba et al., 2009] was established to support the mapping of different crop types (winter wheat, winter and spring barley, maize, sugar beet, sunflower, alfalfa and maize to ensilage) in the activity area and for yield forecasting covering large areas. In the operational phase partially the subsidies system was based on the estimation.
<u>Methodology</u>
1. Experimental Applications Validations in the Agriculture (1980-1996)

- the development of the baseline crop area mapping and area assessment methods plus the yield models' creation and experiments based on statistics (1980-90) and,
- the final accomplishment of the methodology to prepare and validate them for operational use (1993-96)

2. Operational phase (1997-2003)

- information collection on the area of the major crops
- accompanied by problems areas delineation focusing to drought assessment plus the provision of reliable yield forecast and final yield estimates

The method comprises frequent time (NOAA AVHRR) and accurate spatial (Landsat TM, IRS-1C/D, SPOT) sampling. The model calculated vegetation indexes (NDVI, MGVI) to analyze the spatial distribution and strength of the drought in the actual year. Waterlog and flood mapping and its effects for crop development also helped the forecast method. Quality checks are done by farms ground data analyses and the use of empirical confusion matrices.

3. Usability for the harmonized approach

From the review of forest biomass studies, several conclusions can be drawn:
1) bottom-up approaches are generally more accurate than top-down ones
2) the co-location of NFI plots and remote sensing data and dealing with related uncertainties are not trivial in bottom-up approaches
3) a good predefined stratification improves the results
4) generally tree height information leads to more accurate biomass estimates
5) NFI data (either plot-level or allometric equations) is the most commonly used terrestrial data source

From the review of agricultural biomass studies, the outcome is:
1) direct biomass measurement using SAR technology is a straightforward approach at the cost of high complexity
2) crop area estimation and also yield are often supported by modelling
3) existing terrestrial data (from statistics) are rarely taken into account
4) achievable accuracy and spatial detail are reversely correlated: for low resolution data with spatial resolutions with more than 100 m the errors are small, while for detailed mapping the errors are much higher
5) meteorological data and models play a significant role for short-term forecasting

Generally it has to be mentioned that not necessarily only one approach can be used, but it is also possible to define a set of valuable approaches with clearly specified terms and conditions, which can be used. Such an approach is for example also followed in the post-Kyoto carbon reporting system, where three different 'TIER' levels are defined and the countries can decide according to their situation and data availability which TIER level to choose.

3.1. Considerations regarding the user requirements

In comparison with the user requirements (D 4.1), there are some topics, where methods and requirements fit very well. On the other hand, there are also some significant discrepancies. To recapitulate, the <u>main requirements from D 4.1</u> are:

a) *Generate **one basic potential with well defined boundary conditions** (restrictions) applicable for many users. This basic potential can be further used for individual potential assessments for specific user needs, but not be done in the frame of the harmonized approach.*
b) ***Full update every 3 - 6 years**, whenever spatial data, e.g. core service products, are available. In addition, a **statistical update** of the economical potential (maybe only for **agricultural biomass**) can be done **annually**.*
c) *Existing data should be used in order to keep **costs** as **low** as possible*
d) *The resulting potential should be **suitable for different purposes**, especially for internal information, policy and planning, dissemination, reporting and maybe (lower priority) also for subsidies and subsidy control. Potentials with very specific boundary conditions only important to or available in one country or region cannot be considered.*
e) *The resulting **accuracy** should be in the **range of 80 – 85 %** and the errors should be transparently documented and traceable wherever possible.*
f) *It can be recommended to at least generate the **three main thematic classes** 'forest biomass', 'agricultural biomass', 'other biomass'. Further differentiation should be*

done based on accuracy, time and cost considerations as well as based on the existence of data (e.g. if from core services already hardwood/ softwood and crops/ permanent crops/ grassland is available).

g) *The product should be a continuous GIS map with a* ***scale of 1:75.000 – 1:100.000****. Vector data on NUTS levels can be generated on this base in addition.*

h) *The method should be* ***of intermediate complexity*** *and be accompanied by training. The processing time (without EO data pre-processing) should be around 6 – 9 months.*

Regarding **requirements a) and d)**, there is no objection from the methods point of view. The most important issue will be the availability of boundary conditions information. This topic will be discussed in Deliverable D 4.3.

Regarding **temporal resolution (requirement b)**, there is a main drawback, if we want to consider a bottom-up approach for forest biomass. Such an approach would require NFI plot data available and accessible every 3 – 6 years. This is not possible, since most NFIs are done in 10-years intervals and thus, no information would be available in between. This leads to the recommendation to rather use top-down approaches than bottom-up ones or eventually to a combination of the two in an alternating way. For agricultural biomass estimation, there is quite clear need for a stronger integration of existing statistics, which are to a large extent available on an annual basis. The crop area estimation does not have to be updated so frequently and thus allowing the usage of core service data.

Regarding **costs (requirement c);** there is a mayor contradiction with the requirement e), especially regarding tree height as an important parameter for forest biomass estimation. Tree height is rather expensive to obtain, but it improves the resulting accuracy significantly. Thus, here is a major optimization potential (see chapter 4). For agricultural biomass, there is not much contradiction from the cost point-of-view, if existing data is properly used. In general, not only for terrestrial data, existing data sets should be employed, but the same is true for remote sensing data and products. Thus, existing imagery such as the ‘image2000’ and ‘image2006’ data sets of GMES should be used, if methods require the basic imagery. In case of approaches building on land cover products, core service products from GEOLAND 2, CORINE land cover and similar initiatives are data sources to be exploited in order to keep the costs low.

Regarding **accuracy (e)**, in forestry, the use of LiDAR or stereoscopical methods to derive tree height is recommended to achieve the needed accuracy. For agricultural biomass, accuracy is rather difficult to assess, however, the large amount of production statistics are largely accepted and thus should be used. If projections in the future are needed, the accuracy requirement is very difficult to fulfil. Thus, long term projections should be avoided if the accuracy requirement should be satisfied.

Regarding **requirement f (thematic detail)**, in the forest domain hardwood and softwood can be differentiated; this is done on a regular basis (also in the core service products, [GEOLAND2, 2009]) and is also necessary to reach the needed accuracy. For agricultural biomass the main crops should be treated separately, which is done both in the production statistics and also to a certain degree in the land cover classifications. However, there is one large discrepancy in this: if the crop areas are updated only every 3 -5 years, but crop types change annually (or even two times a year), this is a critical deviation.

The **scale (requirement g)** poses a challenge, since up-to-now, most continent-wide assessments are based on medium resolution data with spatial resolution around 250 – 500m, which would result in a scale of 1:1.000.000. In order to achieve a scale of 1:100.000, HR data would be necessary, which is currently mostly used in national or regional assessments. However, the products of geoland2 [GEOLAND2, 2009] are also in this scale, thus it should be feasible to calculate also biomass based on the GEOLAND core service products.

Regarding **requirement h,** there is again a contradiction with requirement e), because often, more **simple methods** lead to less accurate results. However, it is important to mention that the robustness of methods should be given a higher priority than the complexity of methods. Although many users wanted to implement the assessments themselves, there always is the option of outsourcing part of the work. Regarding complexity in case of equal robustness however, for forest, it is easier to implement a top-down assessment than a highly complex bottom-up kNN analysis. Regarding agricultural biomass, indirect assessments based on optical data are easier to implement than direct assessment based on SAR data and thus should be preferred.

3.2. From theoretical to technical/ecological/economic potential

As already mentioned, most of the techniques reviewed so far consider the theoretical potential, which is the base for further calculations. In order to calculate the technical, ecological or economic potential, several restrictions, often also termed as boundary conditions, are necessary. Some widely accepted general boundary conditions are listed below:

1) utilization of forest biomass for energy cannot interfere with use of forest fibre for industry
2) utilization of agricultural biomass for energy cannot interfere with use of agricultural products for food or livestock feeding
3) land in protection areas cannot (unrestrictedly) be used for biomass production
4) usage has to be sustainable, e.g. in a well managed forest, only the increment of forest biomass can be harvested.

Some studies with respect to boundary conditions are mentioned below, however, this topic and the final definitions regarding the boundary conditions in CEUBIOM will be part of Deliverable D 4.3.

[Asikainen et al., 2008] calculated the biomass potential from forest in the EU-27 using technical and economic boundary conditions. For technical consideration, the percentage of mountain area of each country was used. For economic considerations, hourly labour costs, hourly costs for harvesting machinery and different price scenarios for transport of wood material were used for eight out of the 27 countries. All calculations were done on a country by country basis.

In the RENEW project [Seyfried, 2008], different boundary conditions for forest and agricultural biomass potential assessment for fuel were set in a straightforward manner. Regarding forest biomass, the increment and thinning potential was used and then reduced by the amount of biomass needed for industry (fibre). In the agricultural biomass domain, the amount of cereal straw, oilseed straw and maize straw were estimated and reduced by the amounts needed for animal feed or bedding and other fibre needs.

The European Environment Agency (EEA) published a report on: ‘How much bioenergy can Europe produce without harming the environment?’ [European Environment Agency - EEA, 2006]. In their prediction for 2030, they define the following key environmental (ecological) constraints (which are mainly considering agricultural land):

1) *The present share of 'environmentally orientated' farming would need to increase to about 30 % of the Utilised Agricultural Area (UAA) in most Member States, except for densely populated countries such as Belgium, Netherlands, Luxembourg and Malta where the agricultural land per head ratio is very small. In these countries, the necessary share was set at 20 % of UAA by 2030.*
2) *At least 3 % of currently intensively used farmland should be made available by 2030 for nature conservation purposes in order to re-create ecological 'stepping stones' to increase the survival and/or re-establishment of farmland species in these areas.*
3) *If in future extensive land use categories such as permanent grassland, olive groves and dehesas/montados are released from agriculture, and therefore become potentially available for biomass production, these should not be ploughed for targeted biomass crops. Instead they should be maintained under their current land cover and ecological structure, while biomass from grass cutting or tree pruning could be harvested for bioenergy production.*
4) *Biomass crops chosen for future bioenergy production should be selected carefully with respect to both their environmental pressures and their potential to positively influence the landscape and biodiversity quality of an area. The criteria for prioritising these crops on the basis of their environmental performance should involve effects on water, soil and farmland biodiversity.*

Another EEA publication from 2007 is focussing on the environmentally compatible biomass for bio-energy from European forests [European Environment Agency - EEA, 2007]. They considered protected areas, biodiversity, soil erosion and –compaction, site fertility and nitrogen inputs as parameters for boundary conditions in terms of sustainable and environmentally compatible potential. In addition, also an economic model was applied assuming a fixed price for wood chips and varying costs for extracting wood residues from the forest. More details on the model and model structure are given in [Kallio et al., 2004].

The Austrian Research and Training Centre for Forests, Natural Hazards and Landscape (BFW) carried out a study assessing the forest biomass in Austria commissioned by the Austrian Ministry of Agriculture and Forestry; see [Forschungszentrum Wald - BFW, 2008] and [Forschungszentrum Wald - BFW, 2009]. In this study, different aspects such as sustainability and biodiversity, economic developments (five different scenarios) and four different silvicultural treatment scenarios were used to model the biomass until the year 2020. For more details on the different economic scenarios see [Gschwantner, 2009] and for the silvicultural treatments and their respective restrictions see [Ledermann and Neumann, 2009].

4. Optimization potential

This section identifies two different optimization potentials. The first are methodological/technical shortcomings, e. g. where additional research is needed in order to achieve required accuracies or where additional technological developments are necessary to meet temporal requirements. The second optimization potential is identified in the frame of data coverage. This refers to situations, where the methods are available, but not applied on large areas and thus, the required data base is not available.

Both optimization groups are selected separately for forest and agricultural biomass assessments. For both, forest and agricultural classes, there is a challenge and an optimization potential in terms of producing the requested high resolution map (at a scale of 1:100.000) at adequate costs and in an acceptable time interval. In addition, the already mentioned transfer of terrestrial data in time and space especially with respect to radiometric and atmospheric corrections remains a general challenge in all remote sensing applications.

4.1. Forest biomass

The key parameters to estimate forest biomass in a top-down approach are the following:

- forest area
- tree species (-mixture)
- tree density
- tree height

Except for the last parameter, all other parameters will be available through the GMES core service products for land (see GEOLAND 2 project: [GEOLAND2, 2009]). Forest area will be available, the main tree species (at least three classes: coniferous, deciduous and mixed) and tree density are foreseen parameters. Optimization potential can thus be found in

a) distinguishing more tree species types and,
b) deriving tree height as one of the most important input variables.

The latter would be a product of main interest not only for biomass potential assessments, but also for carbon related applications. In order to generate tree height, a DTM (digital terrain model) and a DSM (digital surface model, i.e. the height of the canopy) are needed. While there are several options to generate a DSM: LiDAR, photogrammetry and interferometric SAR processing (InSAR); LiDAR is the only option to derive a high quality digital terrain model (DTM) also beneath forest.

Thus, LiDAR is the best option to generate tree height, although at high costs. However, LiDAR data is currently used for national or sub-national assessments of forest resources and biomass (digital surface model DSM in combination with the DTM) in many European countries. Thus existing LiDAR data sets (both DTM and DSM) should be used.

For future updates, generally only the DSM has to be updated, because the terrain (DTM) is in most cases stable. Since LiDAR acquisitions are expensive and time consuming, alternative systems might be more suitable for the update of the DSM. For such homogeneous DSM update of whole Europe, satellite image photogrammetry would be a more economic alternative, which has to be further developed to an operational use for such large area application.
An operational InSAR DSM is currently also available for purchase from the company Intermap Technologies (http://www.intermap.com/nextmap-digital-mapping-program), but it is not clear, if there are updates planned for this project.

4.2. Agricultural biomass

One main challenge with agricultural biomass is the fast and frequent change of crop types. This change often happens annually or even two times a year.
In order to realize a high resolution crop type map, quite some time (often more than a year, if the area is large) is needed for data processing. By the time, the classification is done, it may

happen, that situation has already changed. Thus, optimization potential can be found in operational capability and processing speed of crop classifications at the required resolution.

A second topic with optimization potential can be identified in direct biomass assessment with SAR. The methods should be made more easily understandable, preferable employing open source software and accompanied by adequate training material.

Optimization from the legal framework point of view can be found in changing the data confidentiality rights. IACS data is generated every year, but it is not available at the original resolution for further use such as for biomass potential assessment. This makes duplication of efforts necessary.

5. Summary & Outlook

5.1. Suitability of methods for biomass for energy

Forest biomass estimation methods - conclusions
In conclusion, a large variety of algorithms to estimate standing forest biomass from remote sensing and terrestrial data are available. National forest inventory data (either plot-level or allometric equations) is the widest available and most commonly used terrestrial data source. Among the combination approaches, bottom-up approaches are generally more accurate than top-down ones, however top-down approaches are easier to implement and more flexible for frequent updates. In addition, the co-location of NFI plots and remote sensing data and dealing with related uncertainties are not trivial in bottom-up approaches and can thus lead to errors. A good predefined stratification, e.g. into different species classes, elevation classes or density classes typically improve the results for all methods. Tree height as a main information parameter leading to higher accuracy is still missing for large areas and should thus be mapped preferable by LiDAR or for frequent and more economic updates by combining LiDAR DTM and satellite photogrammetry-based DSM.

Total (above-ground) forest biomass versus forest biomass for energy:
Basically all of the methods described in the literature review above aim at calculating either total biomass or above-ground biomass; thus additional steps are necessary to calculate the amount of biomass available for energy purposes. This amount depends on a large variety of boundary conditions or frame parameters such as industry needs; market prices for fuel wood versus industrial wood, ecological and technical considerations. The framework conditions need to be defined for an assessment, which will be part of the deliverable D4.3.
However, at this point, a general suitability of the different methods with regard to estimate the biomass for energy share can be given:

- using bottom-up approaches (like kNN methods) with both optical or RADAR data, the amount of biomass for energy can only be assessed by using an approximated share depending on the area (country or district, wherever this has been assessed). Sources of this information are NFI data or literature.
- using top-down approaches, the other parameters such as crown cover, species and stage of stand development (if available) can be used to better estimate this share.
- Using LiDAR data, the same applies as for the top-down approaches, but with even more spatial detail and higher accuracy, since tree height and stem density are also available. These are two important parameters to assess the potential for energy (thinning of young stands, i.e. stands with limited vegetation height).

Agricultural biomass estimation methods - conclusions
For agricultural biomass (including agricultural energy crops), there are rarely any papers available integrating remote sensing and existing terrestrial data such as statistics. The best operational example is probably [Eerens et al., 2001] combining IACS data, satellite imagery and yield models. However, this method is using low resolution spatial data, which is not detailed enough regarding the user requirements. Most studies use terrestrial data specifically generated for this purpose in order to be temporally compatible with the remote sensing imagery. Among those, direct biomass measurement using SAR or optical data is a straightforward approach at the cost of high complexity. Crop area estimation and yield are often supported by modelling including meteorological, pedological data and phenological information as well. Achievable accuracy and spatial detail are reversely correlated: for low resolution data with spatial resolutions with more than 100 m the errors are small, while for detailed mapping the errors are much higher. For most studies, a two step procedure is performed: First, classifying the area into different crop types and second, correlating biomass with image features individually for each crop type.

Total agricultural biomass versus agricultural biomass for energy:
Basically the same considerations apply to agricultural products as for forestry products. Frame conditions determine the amount expected to be usable for energy purposes rather than the total amount. For agricultural products, this is even a more conflicting issue (‘food versus fuel’). Measurement systems such as remote sensing can only deliver total amounts and indicators for ecological considerations, all additional restrictions have to be defined by legal or expert frameworks. In D4.3 a method will be presented on how to consider the most important frame condition in a common way.

5.2. Consideration regarding the cost of the methods

Regarding costs, two types of costs have to be distinguished: data costs and processing costs.

Data costs
The issue of data costs applies to both forestry and agriculture applications. Regarding basic satellite data costs, a table of remote sensing data costs have been compiled in D2.3. The costs given there are costs for commercial use, thus they have to be considered with care, because different prices might apply if the user is an administration or a research institute. In addition, quite a huge amount of data has been made available in the past through programs such as GMES at no cost. A further option to reduce data costs is coordinated data acquisition across disciplines, e. g. the acquisition of LiDAR data for hydrographic, forest-, spatial planning and energy purposes as already mentioned. For all these reasons, it is not possible to give specific costs for data applicable for all of these options. However, in general it can be said, that lower spatial resolution remote sensing data, also covering larger areas (see Figure 1) is cheaper than higher one and that aggregated terrestrial/statistical data is cheaper (and easier to get) than plot or field level data.

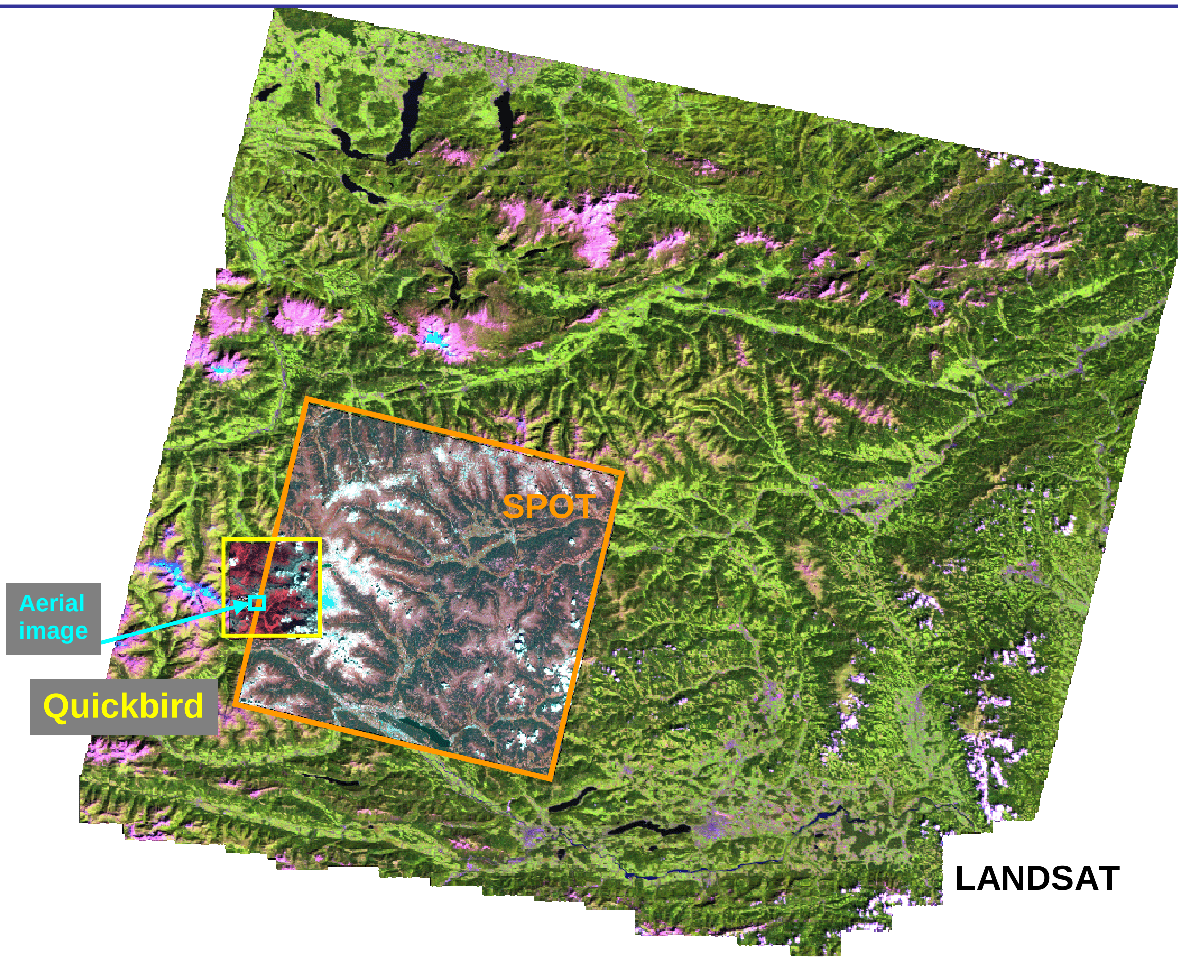

Figure 1: Different optical data sets in comparison showing the relation between spatial resolution and spatial extent of one scene from aerial images to Landsat data sets.

Processing costs
Processing costs again have to be subdivided into pre-processing and the main processing costs themselves. Again, shared use of data can significantly reduce the costs for pre-processing, which has to be done and paid only once. The main processing costs are generally higher for high-resolution data than for low resolution data, because typically fewer images are needed to cover the same area (see Figure 3). Fewer images mean a lesser amount of data leading to both less processing time and also less need for data calibration. Comparing SAR and optical data, processing SAR data needs more knowledge and typically more processing steps and is thus in general more expensive than processing optical data. However, this is a very general statement, which might differ in specific situations.

Considering strictly the methods without the related data requirements, it can be stated that for forestry:

- Top-down are cheaper than bottom-up (plus they allow more additional benefits for other application, which can further reduce the costs).
- LiDAR data processing is nowadays already very much developed towards operational applications. Low manual interaction is needed and thus the related costs are relatively cheap except for long processing times due to the huge amounts of data

when applied on very large areas. Also combination with other data sets, such as optical data to obtain the species typically increases processing costs.

Considering strictly the methods without the related data requirements, it can be stated that for agricultural approaches:

- Regression models are able to capture the relation between field data and image data but the needed close time correlation makes use of existing data difficult. Also the transfer of models is not a straightforward technique, although successful in individual studies. These two factors make this method rather pricy for larger areas.
- Combining IACS data with remote sensing data would be the most economic alternative with expected very accurate results. However, IACS data at the needed full resolution is in most countries not freely available due to data confidentiality issues.
- EUROSTAT and other statistics are another economic alternative, however with the drawback of a very limited spatial disaggregation regarding crop types (see D4.3 – basic approach for details).

Considering the large variety of factors influencing the absolute costs such as the institution carrying out the analysis; the salary system and -level in different countries and on many more employment issues, no absolute values can be given here. However, in the deliverable D4.3, the approaches are compared in a relative manner.

5.3. Next steps

The aim of CEUBIOM was to develop a harmonized approach for biomass for energy assessment in Europe based on terrestrial and remote sensing data. In previous deliverables, the terrestrial methods and data sets have been reviewed (WP 3), remote sensing data has been scrutinized for the usability to achieve this aim (WP 2) and the user requirements have been assessed (WP 4.1). This deliverable is the next step by assessing the methods to combine the terrestrial and earth observation data sets. There are many options available, which have been analysed regarding their suitability in terms of user needs.
One main outcome of this comparison is that one single approach will not suffice to cover all requirements. This is also depicted in Figure 4 for the parameters spatial detail, cost and accuracy, although these relations are not true for everything, as if costs can be exceeded to a maximum, both spatial detail and accuracy can be achieved. Spatial detail and accuracy generally go along with the local implementation possibilities, while costs and harmonization rather tend to limit these possibilities. Thus it was discussed and decided to define a set of valuable approaches with clearly specified terms and conditions instead of offering only one approach. Such an approach is for example also followed in the post-Kyoto carbon reporting system, where three different ‘TIER’ levels are defined and the countries can decide according to their situation and data availability which TIER level to choose.

However, it is important to select a small number of approaches in order not to overload the user and/or increase confusion on the options. Thus still compromises are needed, but not as much as for one single approach.

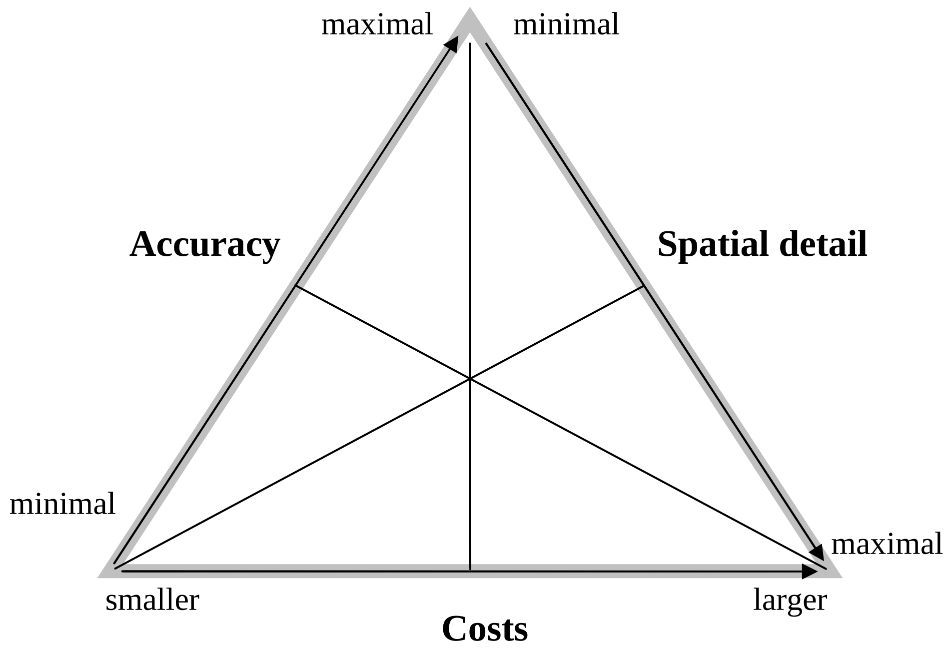

Figure 2: Generalized interplay between spatial detail, costs and accuracy

The next steps in CEUBIOM WP 4 will be

- the detailed analysis of national data sets available in the countries (e.g. specific energy crops – area and yield)
- the analysis of boundary conditions in order to go from the theoretical to a techno-ecological or even an economic potential
- the definition of harmonized approaches taking into account the user requirements, combination methods, available data and applying a set of boundary conditions.

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