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Mapping organic carbon stocks in eucalyptus plantations of the central highlands of Madagascar: A multiple regression approach

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A B S T R A C T

Recent concerns about global warming have resulted in more concerted studies on quantification and modeling of carbon (C) storage in different ecosystems. The aim of this study was to assess and map the carbon stocks in above (ABG), below-ground (BLG) biomass and soil organic carbon contained in the 30 centimeter top-layer (SOC) in coppices of eucalyptus plantations in the central highlands of Madagascar in an area of 1590 ha. Relationships between C stock and various biophysical (stool or shoot stockings and ages, circumferences) and spatial (elevation, slope, and soil type) factors that may affect C storage within each pool were investigated. Three different modeling techniques were tested and compared for various factor sets: (i) simple linear regression (SLM), (ii) multiple linear (MLM) models and, (iii) boosted regression tree (BRT) models. Weights of the factors in the respective model were analyzed for the three pool-specific models that produced the highest accuracy measurement. A regional spatial prediction of carbon stocks was performed using spatial layers derived from a digital elevation model, remote sensing imagery and expert knowledge. Results showed that BRT had the best predictive capacity for C stocks compared with the linear regression models. Elevation and slope were found to be the most relevant predictors for modeling C stock in each pool, and mainly for the SOC. A factor representing circumferences of stools and their stocking ($stools \cdot ha^{-1}$) largely influenced BLG. Shoot circumference at breast height and shoot age were the best factors for ABG fitting. Accuracy assessment carried out using coefficient of determination (R^2) and ratio of standard deviation to prediction error (RPD) showed satisfactory results, with 0.74 and 1.95 for AGB, 0.85 and 2.59 for BLG, and 0.61 and 1.6 for SOC respectively. Application of the best fitted models with spatial explanatory factors allowed to map and estimate C contained within each pool : 32 ± 13 Gg C for ABG, 67 ± 15 Gg C for BLG and, 139 ± 36 Gg C for SOC ($1\ Gg = 10^9$ g). A total of 238 ± 40 Gg C was obtained for the entire study area by combining the three C maps. Despite their relatively low predictive quality, models and C maps produced herein provided relevant reference values of C storage under plantation ecosystems in Madagascar. This study contributed to the reducing of uncertainty related to C monitoring and baseline definition in managed terrestrial ecosystem.

1. Introduction

Terrestrial ecosystems, as potential sinks for atmospheric CO_2, have received considerable attention due to the Kyoto Protocol to the United Nation Framework Convention on Climate Change (UNFCCC). At global scale, carbon (C) stocks are important either in biomass (near 650 Gt C) or in the top first meter of soils (1500 to 2000 Gt C) compared with the atmospheric CO_2 stock (750 Gt C) (IPCC, 2007; Robert and Saugier, 2003; Malhi et al., 1999). Changes in land uses may causes important variation in carbon stocks and quality which has in turn consequences on both CO_2 emissions to the atmosphere and C sequestration potential (Fearnside, 2001; Post et al., 2001; Post and Known, 2002; Guo and Gifford, 2002; Houghton and Goodale, 2004). UNFCCC requires reporting on a regular basis and in a transparent manner of C forest sinks. Tropical ecosystems represent a substantial share of the global C pools, and this needs particular attention to remedy the lack of accurate C accounting. Numerous studies at scales ranging from global to local (Batjes, 1996, Eswaran et al., 1993), aimed in quantifying organic C contained in natural pools

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of the terrestrial ecosystems including the living biomass above (ABG) and below-ground (BLG), the litter (L) and the soil organic matter (SOC) (IPCC, 2003; IPCC, 2006).

ABG carbon stocks have received much attention for years as this pool is visible and easily quantified either by direct ground observations such as the establishment of field allometric equations, or by remote sensing and derived products such as vegetation index maps. In comparison, studies on BLG and soil pools are scarce even if they are required for complete C storage estimation. Few works focused on the root system due to (i) tedious and time-consuming labor to measure this biomass pool and (ii) the lack of adequate method to study its dynamics and functions (Santantonio et al., 1977; Cairns et al., 1997; Robinson, 2007). Therefore, BLG was generally indirectly estimated from ABG by using default root/shoot ratio. This is a source of uncertainties considering the wide range of species and their specific root systems. BLG determination remains a major issue that deserves attention in order to provide complete terrestrial carbon estimates. Soil carbon pool has been put forward in climate change studies for its high storage capacity of C. However the variability of the soil properties and complexity of their interactions remain the main issues that limit the production of accurate and precise estimation (Bernoux et al., 2002; Lal, 2005). Soil carbon estimation is derived mostly from either calculation of average SOC by soil types (e.g. Batjes, 1996) or soil-vegetation units (e.g. Bernoux et al., 2002), either using the whole range of geostatistics methods (e.g. Phachomphon et al., 2010), either by fitting statistical models relating controlling factors to SOC stocks (Yang et al. 2008) and either by the use of mechanistic models based on soil carbon turnover rates, such as RothC and Century (e.g. Cerri et al., 2007; Tornquist et al., 2009). Besides carbon budget purposes, knowledge on SOC and its distribution over the landscape is essential for effective use, management and conservation of this resource (Gray et al., 2009).

Identification and understanding of factors controlling C variability in forests are of prime interest in C quantification and modeling. Those determinants and their relative importance may vary depending on the forest type and location. However, it has long been recognized that temperature, rainfall, soil texture, pH, type of vegetation and previous land use are the major factors controlling the amount of SOC (Jenny, 1941; Lugo and Brown, 1993; Bourgeon et al., 1999; Post and Known, 2002; Guo and Gifford, 2002; Krishnan et al., 2007). Regarding forest biomass pools, carbon stocks are mainly determined by climate, age of the stand, structure of plantation and sylvicultural cares (Locatelli and Lescuyer, 1999, Guo and Gifford, 2002). Thus, applying global method on a specific area is highly prone to uncertainties; site-specific method based on local relevant factors has to be developed when possible. Policies based on a C mapping approach showed to have more benefits relative to the ones that focused only on field sampling and inventories mainly in ABG estimation (Goetz et al., 2009). This is true not only to provide estimates of forest C-storage capacity at any location of the study area, but also to take into account the spatial variability and related uncertainties (Houghton and Goetz, 2008). The development of remote and imagery technologies made available a broad range of data (e.g. terrain or land use information) from which spatially explicit information can be derived and used as predictors. Remote-sensing based methods and models are still less developed for BLG and SOC than for ABG (Havemann, 2009). However, recent advances in statistics applied to ecology associated with increasing computer performance (McBratney et al., 2003) allow a better use of the numerous available spatial datasets to provide accurate estimates in natural ecosystem, even with few data.

For Madagascar, due to mainly the lack of available data and basic knowledge, C pools are still poorly estimated. Few attempts on biomass or soil C storage have been achieved at global and national scales (FAO, 2002; Grinand et al., 2009). *Eucalyptus* is the major planted tree species in Madagascar, with stands covering about 150,000 ha which represent half of the afforested area (Randrianjafy, 1999). Such dominance was attributed by eucalyptus importance in providing goods and services for local people in the highlands where agriculture activities are limited by soil fertility. Among the different planted species, *Eucalyptus robusta* is the most widespread in Madagascar, mostly for its ability to develop on stony soil, to bear with fire conditions and to sprout easily (Randrianjafy, 1999).

In this context, the objective of this study was to estimate the spatial C stocks in above- and below-ground biomass and soil of *E. robusta* plantations in the central highlands of Madagascar at the county scale. More precisely, this study aimed to (i) compare different regression methods that are usually found in the literature to determine the best models that can predict C stocks for the three main C pools of forest land cover (ABG, BLG, and SOC), (ii) identify the relevant factor sets that explain C stock variation for each of the pools, and (iii) produce carbon maps based on the best fitted models. This approach is thought to provide an accurate insight into the carbon accountancy of the studied area, its spatial distribution and variability.

2. Materials and methods

2.1. Study area

The study area is located in Sambaina-Manjakandriana, a county of 3000 ha in Malagasy Highlands ranging from 1350 to 1750 m elevation above sea level, at 47°45′–47°50′ East and 18°50′–18°56′ South (Fig. 1). Mean annual precipitation and mean annual temperature are 1600 mm and 16 °C respectively. The land cover is mainly composed of *E. robusta* plantations, covering for more than half of the studied area (54%). The remaining land cover is non-irrigated crop land (31%), irrigated rice land (11%), natural grassland (2%), and other land use including village or rock outcrop (2%). Species of natural grassland are *Philippia* sp. and *Aristida* sp. This county has a long history of tree planting and offers a great opportunity to sample eucalyptus plantations of various ages so as to establish a chronosequence. The first plantation, dated towards 1890, was used for engine fuel wood supply. Nowadays, eucalyptus plantations are used for landed property and mainly for energy purposes until now (Carriere and Randriambanona, 2007). Stands are all privately managed, and coppices are usually harvested at the age of 3–5 years and stumps, cut on ground level are left to resprout stool, and are not renewed. No sylvicultural treatments are practiced and all stems (shoots) are left after coppicing for natural thinning.

The parental material is composed of intrusive igneous rock mainly leucogranite and porphyry granite. Dominant soil types are Ferralsols (86%) according to the FAO classification (FAO, 2006), They represent low-activity clay, mainly kaolinite (1:1) with mean clay content of 52.7%; average pH and cation exchange capacity (CEC) values are 5.23 and 2.8 me 100 g^{-1} clay. Further description of soils and morphological units realized during a soil survey and mapping process is presented below.

2.2. Carbon inventory

The carbon inventory carried out included determination on above and below ground biomass and soil organic carbon. The surveyed plots were located with a global positional system (GPS) and data were integrated onto a Soil and Biomass Database linked with a Geographical Information System (GIS). They were used as a reference dataset for spatial analysis (Section 2.3) and carbon modeling (Section 2.4).

2.2.1. Biomass data

Data on vegetation biomass were obtained from several field works including inventory and measurements on 41 different eucalyptus stands (Fig. 2) with size coppice ranging from a few hundred square-meters to less than 10 ha. These plots were selected

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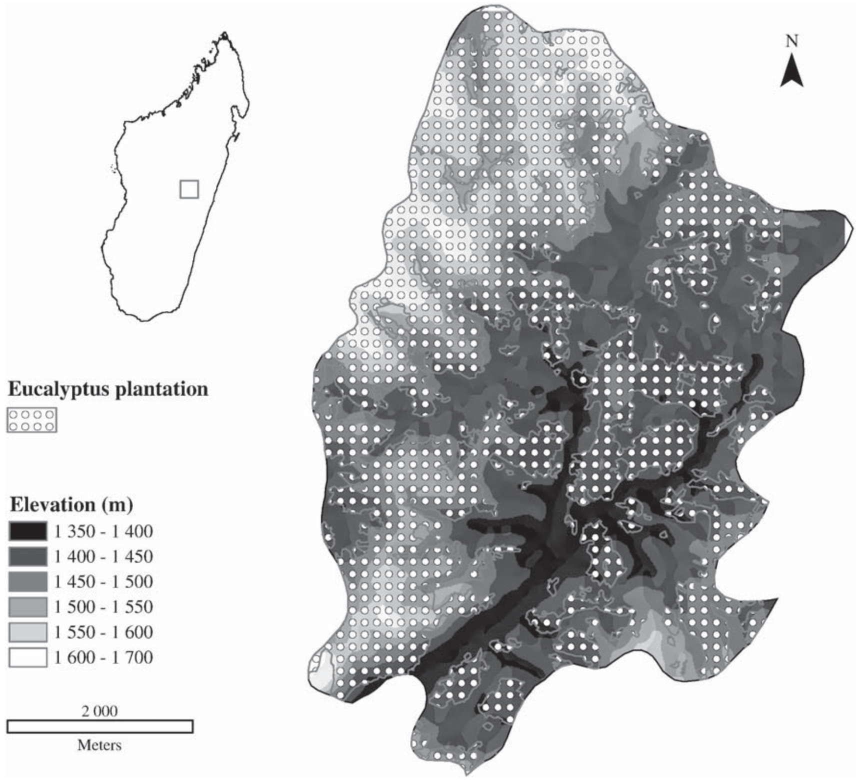

Fig. 1. Map of the study area showing location relative to the map of Madagascar.

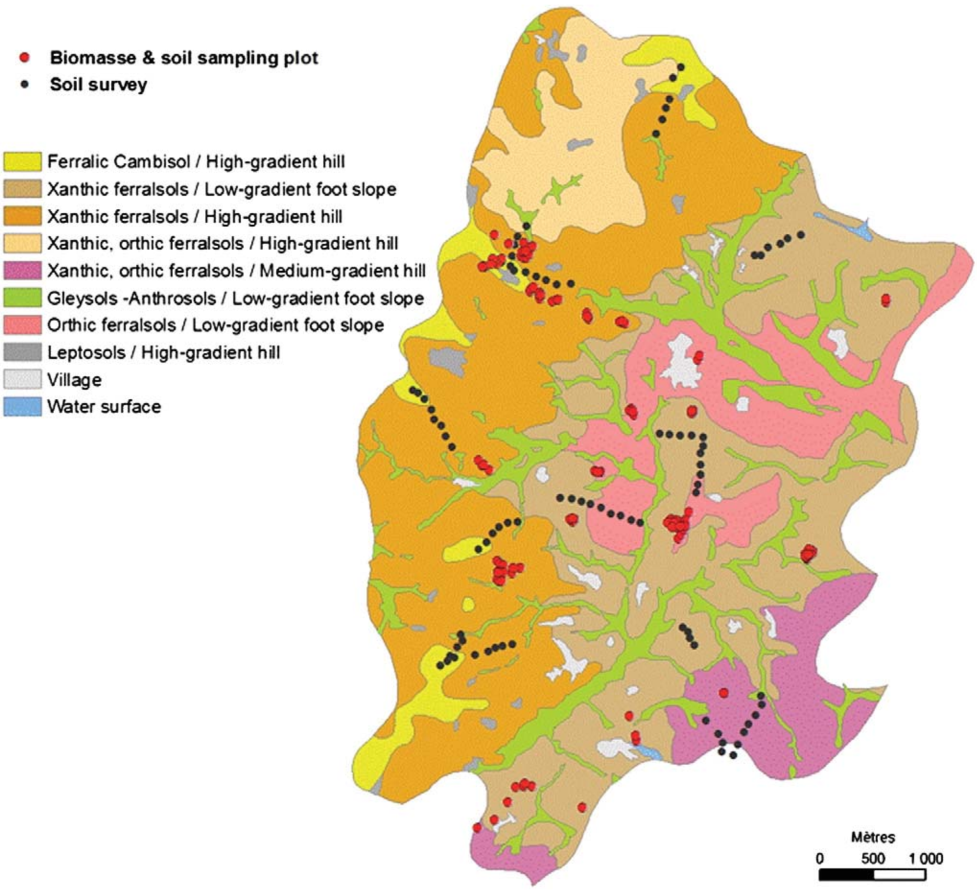

Fig. 2. Digital soil map with plots and transects location.

Table 1
Characteristics and statistics of predictor variables.

Type	Name (code name)	Type	Unit	Min	Max	Mean	SD
Site specific	Mean circumference of stumps (Cir)	Quantitative	cm	98.5	196.6	141.8	25.5
	Mean circumference at breast height of shoots (CBH)	Quantitative	cm	4	14.3	7.1	2.5
	Stump density (Stocking1)	Quantitative	Nb stump ha^{-1}	700	5200	2838	1000
	Shoot density (Stocking2)	Quantitative	Nb shoot ha^{-1}	7933	24,800	15,485	3495
	Interaction of tree density and their circumference (NhaCir)	Quantitative	_	111,500	683,100	388,200	114,320
	Clay content (Clay)	Quantitative	%	29.8	64.2	52.73	8.4
Spatially derived	Elevation (Elevation)	Quantitative	m	1382	1655	1487	73.6
	Slope (slope)	Quantitative	Degree	1	40.7	19.4	9.8
	Plantation duration (age 1)	Quantitative	Year	17	111	67.1	21
	Coppice age (age 2)	Quantitative	Year	3	5	4	0.72
	Soil unit (UCsoil)	Categoric	3 classes				
	Morphological Unit (UCmod)	Categoric	3 classes				

according to the age of the plantation and their location. The first criterion was fulfilled thanks to field investigation that allowed establishing a chronosequence of eucalyptus plants over a century. The second criterion was achieved by choosing plot location representative of the various landscapes and covering as much as possible the study area (see Section 2.3.3). Due to the small size of the stands, three plots of 10 m × 10 m were randomly set up within each stand for counting of stools and shoots. Direct measurements of dendrometric parameters such as circumference of stump and stool were carried out as used in other studies on short rotation forestry such as coppices of eucalyptus (Senelwa and Sims, 1998; Verwijst and Telenius, 1999; Heinsoo et al., 2002; Zewdie et al., 2009). Table 1 presented a summary of main descriptive statistics of these field measurements.

Allometric equations for ABG assessment were pre-established by carrying out destructive sampling on 27 selected trees covering the full range of stump circumference variation. Likewise, BLG component (stump, coarse root with diameter ≥10 mm and medium root with diameter ≤2 mm) of each sampled tree was assessed using allometry equations and based on a sampling unit known as “Voronoï polygon”. The Voronoï polygon is the area of occupancy of a tree, delimited by the intersection of the perpendicular lines that pass through the midpoints of the lines connecting the center of the sampled tree to the center of the nearest neighboring trees (Santantonio et al., 1977; Saint-André et al., 2005). After a manual excavation to 1 m depth of all fresh BLG within this polygon, corresponding dry weight of this BLG was related to the stump circumference as dry weight of ABG was related to the basal area of shoots per tree. Allometric equations were then applied on inventory data for each site in order to calculate the biomass density per ha. A mean biomass conversion factor of 0.5 was applied on these biomass densities to derive C density in biomass pools (Table 2).

2.2.2. Soil data

Soil sampling was carried out in the same eucalyptus stands used for biomass assessment ($n=41$). Soils were sampled using soil core sampler (Cobra TT Hammer, 8.6 cm of diameter) in four replicates for each stand and at four different depths (0–10 cm, 10–20 cm, 20–30 cm and 30–40 cm). Soil bulk density was determined after oven-drying for 48 h at 105 °C and carbon content was measured after dry combustion with an elemental microanalyzer (Carlo Erba 2000) after air drying and sieving to 2 mm. SOC stock was then calculated as follows:

$$\mathbf{SOC} = \sum(\mathbf{BD_i} \times \mathbf{C_i} \times (1 - \%\,\mathbf{stoniness_i}) \times \mathbf{t_i}) / 10 \quad (1)$$

where **SOC**: C stock in soil to 30 cm depth (Mg ha^{-1}), $\mathbf{BD_i}$: bulk density of the soil (Mg m^{-3}) in i layer, Ci: C content of the soil (mg C g^{-1} soil) in layer i,% stoniness$_i$: percentage of rock fragment >2 mm in the sampled soil and $\mathbf{t_i}$: thickness of the corresponding layer i ($i=0$–10 cm, 10–20 cm, …).

This formula (Eq. (1)) calculated the C stocks contained in a fixed depth or volume of soil. Nevertheless, comparison of SOC changes at fixed depth might be compromised whether soil compaction took place (Ellert and Bethany, 1995; Gifford and Roderick, 2003). Correction was then applied in order to get an identical soil mass for each SOC stocks. SOC were calculated for a fixed equivalent mass of soil of 400 Mg ha^{-1} which corresponds roughly to a 30 cm depth (Table 2) (Turner and Lambert, 1999; Paul et al., 2002).

2.3. Spatial analysis

2.3.1. Land use mapping

The combined use of detailed field base vegetation data, environmental data and satellite imagery is a promising approach for accurate predictive mapping of vegetation (Poulos et al., 2007; Ordőñez et al., 2008; Goetz, et al., 2009). In this study, land use mapping was focused on eucalyptus plantation and more precisely on the mapping of plantation age and coppice age. These two plantation characteristics were thought to be important predictors for biomass and soil carbon pool. Both data issued from 2006 map was used as a reference. Spatial analysis and remote sensing processing were performed using ArcGIS 8.3 (ESRI®, 1994–2008) and ENVI 4.0 (ITT, 2009) respectively.

Photo-interpretation was performed on aerial photographs obtained from the Malagasy National Geographic Institute taken at three different dates, 1949, 1965 and 1995 and at 1:40,000, 1:25,000, 1:20,000 scales respectively. A supplementary QuickBird image (DigitalGlobe, 2006) at 2.5 m resolution from 2006 was also used as base map for photo-interpretation. Aerial photographs were scanned

Table 2
Descriptions and statistics of carbon pools.

Carbon pool	Components	C stocks (kg m^{-2})				
		n	Min	Max	Mean	SD
Above ground biomass (ABG)	Leaves, branches, shoots	29	5.8	38.5	16.4	6.7
Below ground biomass (BLG)	Coarse root, Medium root	41	11.2	54.1	39.1	10.0
Soil organic carbon (SOC)	Calculated for a fixed equivalent mass of soil (400 kg m^{-2})	41	63.0	143.8	85.5	18.7
Total carbon stock (TCS)		29	112.9	210.2	145.4	24.5

Components of ABG pool were separated as practiced locally; Coarse root have diameter ≥ 10 mm; 10 cm < diameter Medium root < 2 mm.

at 300 dpi, georeferenced in the national spatial reference system called Laborde (IGN, 1995). Orthorectification was impossible due to either the lack of camera information or fiducial marks on the photographs. At each date, resulting image was interpreted according to five land cover classes: plantation of eucalyptus, slope crop land ("*tanety*"), rice crop land, village and rocks. The four land cover maps were overlaid and areas with eucalyptus in 2006 were kept for further processing. Considering the date at which eucalyptus appeared for each corresponding polygon, it was possible to establish a map representing the following four periods of plantation: more than 57 years, between 41 and 57 years, between 11 and 41 years and less than 11 years. Field validations, including sociological survey with interviews of the elders' members in the county, were performed for classification validation.

A supervised maximum likelihood classification was performed on 20-m resolution SPOT 4 images (CNES©, 2006) acquired at three different years: 1999, 2003 and 2006. Images were coregistered on 2006 SPOT image and normalized difference vegetation index (NDVI) was derived for each date. All these images were stacked together and areas without eucalyptus plantation were masked using the 2006 photo-interpretation. Training sites were digitally delineated using a visual recognition of eucalyptus cuts, easily detectable on vegetation index images, and a comparison between dates. This allowed identifying coppice plot cut in 2006, coppice plot cut in 2003 but not in 2006, coppice cut only in 1999 and coppice plot that does not show any clearance area for all these dates. Considering that cuts are detectable after a few years, we ended with four coppice age classes: less than one year coppice, one to three years, three to seven years and more than seven years. Classification accuracy was tested using a random selection of several sites (145 tests pixels) for each class that was not used for model calibration. According to Landis and Koch (1977), classification accuracy is considered satisfactory when global accuracy coefficient is superior to 0.84 and Cohen's kappa coefficient superior to 0.81.

2.3.2. Terrain proxies

Digital Elevation Model (DEM) is among the most widely used spatial data source as it can serve as a basis for multiple purpose study and because accurate and high resolution DEM are less and less expensive. In this study the freely available Shuttle Radar topographic Mission DEM (SRTM 2009) at 90 meter resolution was used. Slope expressed in percentage was derived using a GIS and tested together with elevation as potential carbon predictors in modeling and soil mapping process as presented below.

2.3.3. Digital soil mapping

Soil type diversity may greatly affect eucalyptus growth and production. As such information was not available on the studied area, a soil survey was carried out in order to produce a georeferenced soil map (Fig. 2). The traditional exploratory soil survey procedure described by Legros (2006) was followed. The process was collecting existing knowledge and survey maps, sketch mapping using aerial photograph, field trip and sampling with an auger, data synthesis and soil unit delineation.

Two national scale soil maps, including a morphological map at 1:1,000,000 (Delenne and Pelletier, 1981) and a soil map at 1:1,000,000 (Riquier, 1968) showed a uniform granite parental material and the dominance of Ferralsols. Previous soil studies showed the high influence of landform and elevation on soil differentiation, in the highlands of Madagascar (Bourgeat and Zebrowski, 1973; Randriamboavonjy, 1996). Field observation of soil profiles along 12 topographic transects, from the top to the bottom of the hill at 100 m interval, confirmed the landform–soil type relationship. A landform map was produced using elevation and slope cutoff values. Three morphologic units were defined: high-gradient hill characterized by high elevation (1450 to 1750 m of elevation) with sloping sites (14 to 29% or more), medium-gradient hill characterized by intermediate elevation (1450 to 1600 m) with moderate to high slope (8 to 29% or more) and low-gradient foot slope with low elevation (1350 to 1450 m) and gently slope (<8%).

Thirty two soil profiles to 1 m depth were described and sampled for complementary laboratory analysis. Field soil description was focused on criteria to differentiate Ferralsol sub-types (FAO, 2006): color of the horizon, stoniness or weathered minerals, soil compaction, texture and depth of appearance of the C horizon. Soil laboratory analysis included: determination of carbon and nitrogen contents by dry combustion (use of CHN microanalyser), pH measurement, analysis of the texture with the pipette method, determination of cation exchange capacity and acidity with the method of cobaltihexammine chloride ($(Co(NH_3)_6\ Cl_3$. Three soil types were identified following the FAO classification, namely: ferralic cambisol (CEC = 4.97 me 100 g^{-1} clay and about 35.6% of clay content to 1 m depth and C horizon appearance at less than 60 cm depth,), xanthic ferralsol (CEC = 2.87 me 100 g^{-1} clay to clay content is around 52% to 1 m depth, with yellow horizon and C horizon appearance between 60 and 100 cm depth) and orthic ferralsol (deep weathered, with red and yellow B horizon, CEC = 1.33 me 100 g^{-1} clay and 51.3% of clay content to 1 m depth and no C horizon beyond 100 cm depth or deeper). A soil map (Fig. 2) was then delineated on the 2006 image, according to the profile location, field knowledge and the morphological map.

2.4. Carbon modeling

2.4.1. Factor sets

From the data collection and spatial analysis of land use and digital soil, various factors (Table 4) were identified and further used in the modeling. The first set of variables represented those that were measured on field and referred more to eucalyptus stand biophysical variables. The second set of variables represented spatially derived variables which cover the whole county. Several combinations of variable were tested in order to select the most relevant factors related to the considered pool.

2.4.2. Regression

Regression models were used in this study in order to (i) predict C stocks using various factor sets and to (ii) evaluate influences of the relevant predictors in the modeling. Three different regression methods were tested: a simple linear regression (SLM) that expressed the relationship between C stock and a single quantitative predictor, a multiple linear model (MLM) and a boosted regression tree model (BRT) that both involved several factors into the modeling. The MLM is a linear regression for different quantitative factors. It is commonly used in environmental studies for testing the interaction between quantitative factors from the b-coefficients indicated on the linear model expression (Bourgeon et al., 1999). BRT is considered as a "machine learning" algorithm that combines the strength of regression tree algorithm known as CART (Classification and Regression Tree; Friedman, 2001; Poulos et al., 2007) and boosting which is an adaptive method for combining many simple models to improve the predictive performance (Elith et al., 2008). The BRT algorithm generated small decision trees of recursive binary splits from a set of learning case focusing iteratively on the less well-predicted case. The final model is a linear combination of many sub-tree models. BRT inherited several advantages from CART say the ability to deal with numeric or categorical factors, nonlinearity and to its robustness to outliers, irrelevant factors and missing data. Boosting tended to increase predictive performance compared to CART and to better handle over-fitting (McBratney et al., 2003; Brown et al., 1999; Krishnan et al., 2007). BRT was previously used in C stock mapping (Krishnan et al., 2007) and other soil property estimation (Brown et al., 1999; Tittonell et al., 2008; Martin et al., 2009) and soil landscape prediction (Grinand et al., 2008). A thorough description of BRT is provided in Elith et al. (2008). Prior to analyze the predictive performance, BRT model has to be optimized by setting up three parameters: the learning rate, tree complexity and number of trees. Elith et al. (2008) recommend fitting models with at least 1000 trees. From various tests (data not shown) a tree complexity of 3 and a learning rate of 0.005 were found to provide the lowest predictive deviance between 1000 and 3000 trees. They were retained for further processing and the optimal number of trees was determined by a leave-one-out cross-validation. This procedure prevented over-fitting by calibrating the model on n-1 sample and validating on the sample excluded from calibration, each sample being excluded once in turn. The final optimal number of tree was thus determined by the minimum predictive deviance obtained. All data regression and mining tasks were performed with an R-stat software (R Development Core Team, 2009), using *glm* package for linear regression (Hastie and Pregibon, 1992) and *gbm* package (Ridgeway, 2007) for BRT modeling.

2.5. Relative importance of factors

Relative importance of factors can be measured differently according to the model used. For MLM models this might be achieved by comparing b-coefficients on the linear fitted formula. For BRT, the contribution of the factor into the model was a measure of “the number of times a factor is selected for splitting, weighted by the squared improvement to the model as a result of each split, an averaged over all trees” (Elith et al., 2008). In our study, the importance of factors was evaluated at two levels: by changing the set of factors used in the modeling and by looking at the measurements provided by the models presented above.

2.6. Carbon mapping and quantification

Carbon mapping of natural biosphere component is under considerable studies that aim to find out easy-to-use, accurate and reproducible method. These methods include a range of approaches from small-scale simple method to fine-scale more complex method, without intermediary options. For instance, in biomass mapping using remote sensing data, Goetz et al. (2009) identified three main approaches: Stratify & Multiply (SM), Combine & Assign (CA) and Direct Remote Sensing (DR). SM is the simplest approach which estimates total C values by multiplying an assigned single value (or a range of values) for thematic map class with the area of this thematic class. CA is an extension of SM approach which essentially uses a multiple spatial dataset to produce smaller spatial units of aggregation. DR consists in deriving C stocks directly from satellite measurements, by calibrating them to field estimates using statistical technique such as regression models.

A modified DR technique was used in this study as it involved regression model and a set of spatial and non-spatial predictors. The models that provided the most accurate results from the modeling were selected to produce C stock map for each pool (ABG, BLG, and SOC). The first step involved a standardization of the spatial predictors. Vectors explanatory variables (soil and landforms units) were converted into raster. All corresponding grids were adjusted to the same map extent and resampled with the same 30 meter grid cell size. This value was considered suitable for a 1:25,000 output mapping as suggested by McBratney et al. (2003) for pedometric application. For the numeric dataset, a bilinear resampling method was used in order to give a more suitable continuous surface. Secondly, these variables were then imported in R (R Development Core Team, 2009) for modeling. The retained pool-specific model was applied on each of the relevant factors set so that to predict carbon within each pool. Finally, predicted values of C stock in each C pool calculated per pixel were exported back into a GIS. This method produced three pool-specific carbon maps of the studied area.

The total C stocks map per pixel was afterwards estimated as follows (Ordonez et al., 2008):

$$\mathbf{C_{total}} = \mathbf{SOC} + \mathbf{C_{blg}} + \mathbf{C_{abg}} \tag{3}$$

where C_{total}: total C stocks; SOC:C stocks in fixed equivalent mass of soil in 0–30 cm depth; and Cblg: C stocks in belowground component; all expressed in Mg C ha^{-1}.

The total C stock in Gg (10^9 g) over the entire county, for each pool and for total C, was finally estimated by multiplying C values of pixels by 0.09, i.e. the surface in ha of a 30-m cell-size and summing the results. The C stock mean error resulting from the modeling was estimated using the mean stock multiplied by the coefficient of variation.

2.7. Validation procedure

Model performances were evaluated using the root mean square error (RMSE), the coefficient of determination (R^2) and the bias (measured − predicted values). They were calculated using a leave-one-out cross validation procedure as described in Section 2.4.2. Due to the low number of sample for the AGB dataset and the willingness to get a unique accuracy measurement method, a more comprehensive validation framework using a 10 fold cross validation and a test set could not be carried out. We thus considered our results as an internal validation. Coefficient of variation (CV) associated with the mean C stock for each component was calculated to show the variation of C stock for each pool. The ratio of performance to deviation (RPD) was also computed in order to interpret the prediction ability of each model (Chang and Laird, 2002; Gomez et al., 2008). RPD corresponded to the ratio between the standard deviations of the variable to predict over RMSE. Quality of the model was interpreted according to the three classes of RPD proposed by most authors (Chang et al., 2001; Pirie et al., 2005; Du et al., 2009; Du, and Zhou, 2009): RPD>2 corresponded to models that can accurately predict the tested property, RPD between 1.4 and 2 gathered models with a possible improvement, and models of RPD<1.4 indicated no prediction ability of the model.

3. Results and discussions

3.1. Correlation between variables

Relationships between variables including quantitative predictors and C stocks are given in Table 3. About field variables, the following was observed: (i) a positive correlation (R = 0.59) between elevation and the slope close to the delimitation of morphology units, (ii) a negative correlation (R = −0.55) between elevation and soil clay content in relation with soil type distribution, (iii) a negative correlation between the mean circumference at breast height (CBH) and both density of shoots (Stocking2, R = −0.53) and elevation (R = −0.45) but a positive one with coppice age (Age2, R = 0.58) and (iv) a negative correlation between the mean circumference of stumps per plot (Cir) and both the plantation age (Age1, R = −0.45) and density of plantation (Stocking1, R = −0.58) which may have resulted from management practice or natural regeneration (sucker development).

For the C stock variables, (v) SOC stock was positively correlated with elevation (R = 0.56) and slope (R = 0.72), (vi) Cblg was correlated with Cir (R = 0.48), interaction of density of stumps and their circumference (NhaCir, R = 0.49) and elevation (R = 0.4) and (vii) Cabg showed relationships with CBH (R = 0.53), coppice age (R = 0.65), density of shoots (R = −0.6) and slope (R = 0.48).

Field variables seemed to be well correlated with C stocks in all compartments. Based on these correlations between variables, several

Table 3
Correlation matrix between carbon pools and predictor variables.

	SOC	Cblg	Cabg	Cir	CBH	Age1	Age2	Stocking1	Stocking2	NhaCir	Altitude	Slope	Clay
SOC	1.00												
Cblg	0.21	1.00											
Cabg	0.21	0.14	1.00										
Cir	0.32	**0.48**	0.15	1.00									
CBH	−0.35	−0.24	**0.53**	−0.01	1.00								
Age1	0.02	0.13	−0.09	**−0.45**	−0.11	1.00							
Age2	−0.03	0.19	**0.65**	−0.06	**0.58**	0.18	1.00						
Stocking1	−0.17	0.17	−0.14	**−0.58**	−0.23	**0.43**	−0.02	1.00					
Stocking2	−0.21	0.17	**−0.60**	−0.10	**−0.53**	0.11	**−0.44**	0.16	1.00				
NhaCir	−0.05	**0.49**	−0.09	−0.10	−0.25	0.25	−0.06	**0.86**	0.15	1.00			
Altitude	**0.56**	**0.40**	0.12	0.24	**−0.45**	−0.07	0.08	−0.10	−0.11	−0.01	1.00		
Slope	**0.72**	0.27	**0.48**	0.10	−0.28	0.12	0.19	0.11	−0.28	0.15	**0.59**	1.00	
Clay	−0.09	−0.32	0.00	0.20	0.33	−0.31	−0.25	−0.30	−0.14	−0.25	**−0.55**	−0.31	1.00

Value in bold represent significant relationship between two variables with $p<0.05$.

model structures have been established in order to determine and compare their predictive ability for C stock estimations within each pool.

3.2. Results of modeling

Table 4 summarized the results from the modeling trials where, for each compartment, all model approaches (SM, MLM and BRT) were tested. For predictive performance (comparison of observed and predicted values of C stock), BRT model offered the highest values of coefficient of determination (R^2) and RPD and the lowest error values (RMSE).

For the ABG component, the range of values for R^2, RMSE and RPD were respectively 0.12–0.74, 7.42–3.47 and 0.92 to 1.95. Single predictor as coppice age was not enough to explain variability of Cabg (always below 42%) and MLM and BRT presented similar performance when considering Age2, Stocking2, Slope and CBH as predictors.

For the BLG component, R^2, RMSE and RPD varied in the ranges 0.02–0.85, 10.23–3.89 and 0.66–2.59 respectively and NhaCir (interaction between stump stocking and circumference) should be a good predictor of Cblg. Actually, NhaCir could explain more than 80% of Cblg variability, even with SM. Concerning SOC prediction, values of R^2, RMSE and RPD ranged 0.04–0.68, 18.6–11.38 and 1.06–1.72, respectively. Plantation duration alone was not enough to explain evolution of SOC stocks and considering all possible relevant predictors allowed to account for less than 70% of SOC variability.

BRT models which considered the higher number of relevant predictors offered the best performance; they correspond to Eqs. (16), (22) and (31) in Table 4 for ABG, BLG and SOC respectively. The

Table 4
Characteristics of models tested for each pool.

Pool	Approach	Variables	R2	RMSE	RPD	Bias	n
Cabg	SLM						
		Age2	0.33	5.53	1.23	−2.86	29
		Stocking2	0.32	7.42	0.92	−0.5	29
		CBH	0.15	6.27	1.09	−3.39	29
		Slope	0.12	6.24	1.06	−1.57	29
	MLM						
		Age2, Slope, CBH	0.4	5.3	1.29	−2	29
		Age2, Stocking2, Slope	0.25	5.8	1.17	−1.2	29
		Age2, Stocking2, Slope, CBH	0.6	4.29	1.59	0.02	29
	BRT						
		Age2, Slope, CBH	0.68	3.84	1.76	−0.65	29
		Age2, Stocking2, Slope	0.58	4.37	1.55	−0.54	29
		Age2, Stocking2, Slope, CBH	**0.74**	**3.47**	**1.95**	**−0.09**	**29**
Cblg	SLM						
		Age1	0.02	10.23	0.66	10.55	41
		NhaCir	0.52	7.05	0.96	8.8	41
		Altitude	0.09	9.68	0.7	1.28	41
	MLM						
		Age1, NhaCrir, Altitude	0.48	7.37	1.36	14.45	
	BRT						
		Age1, NhaCrir, Altitude	**0.85**	**3.89**	**2.59**	**−1.34**	**41**
SOC	SLM						
		Age1	0.041	18.6	1.06	−3.13	41
		Altitude	0.28	16.86	1.19	−2.55	41
		Slope	0.18	17.19	1.18	−7.6	41
	MLM						
		Age1, Altitude, Slope	0.49	14.6	1.29	−5.05	41
		Age1, Altitude, Slope, Cabg, Cblg	0.327	16.8	0.4	−5.06	29
	BRT						
		Age1, Altitude, Slope	**0.61**	**11.82**	**1.59**	**−0.5**	**41**
		Age1, Altitude, Slope, Cabg, Cblg	**0.66**	**11.68**	**1.682**	−1.83	29
		Age1, Altitude, Slope, Cabg, Cblg, UCsoil, Ucmod	0.68	11.38	1.72	0.51	29

(i) Models tested are SLM for simple linear regression, MLM for multiple linear regression and BRT for boosted regression tree and (ii) C pool modeled are Cabg for aerial biomass, Cblg for belowground biomass and SOC for soil organic. Values in bold represent the best criteria for the choosen fitted models, using the T Student test $p<0.05$.

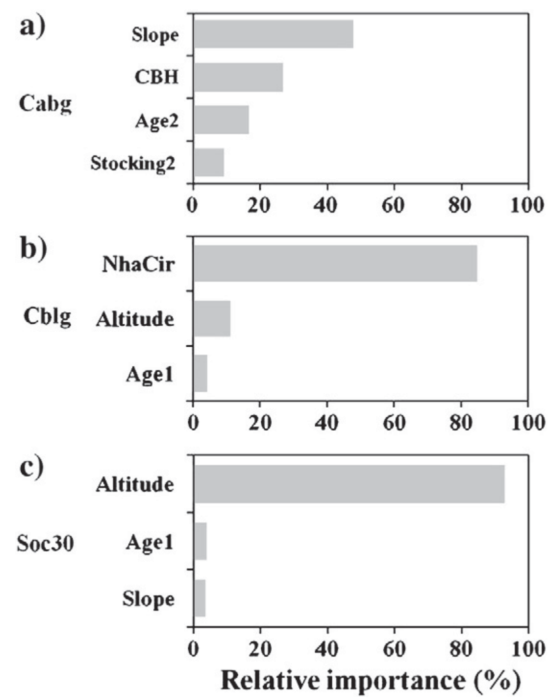

Fig. 3. Bar charts giving the relative importance of predictor variables determined by BRT approach and used for estimation of C stock in (a) ABG pool, (b) BLG pool and (c) SOC pool.

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relative importance of predictor variables in each compartment model is represented in bar charts (Fig. 3). For Cabg, slope and mean circumference of shoots mainly contributed in the model (45 and 28% respectively); the contribution of coppice age and density of shoots were less important (about 18 and 10% respectively). ABG density was affected by topographic aspect (Leuschner et al., 2007), CBH and coppice age as they are concerned by establishment of allometry equations (Telenius and Verwijst, 1995; Senelwa and Sims, 1998, Heinsoo et al., 2002; Zewdie et al., 2009) and density (Proe et al., 1999; Proe et al., 2002). Concerning Cblg, density was an effective predictor but only when values were below 10^4 stools ha^{-1} in Tomé and Verwijst (1996) and, presumably, BLG became more important once trees had a given size (Sumanta, 2007). These reasons may explain the large contribution (more than 80%) of NhaCir in model construction, this variable reflecting interaction between Cir and density of stumps. Besides, elevation and plantation age were also found to affect Cblg by increasing it as observed in other studies (Paul et al., 2002; Guo and Gifford, 2002; Leuschner et al., 2007). For SOC, the largest contribution in model was from elevation (about 85%), followed by slope and plantation duration (Age1). Soil classes are markedly related to landform in the highlands of Madagascar (Bourgeat and Zebrowski, 1973; Randriamboavonjy, 1996). Concomitantly increased elevation could induce microclimate patterns, mainly in moisture regime; with soil acidity and eucalyptus residue recalcitrancy to microbial activity, that would explain the observed SOC accumulation (Guo and Gifford, 2002; Chen et al., 2005; Yimer et al., 2006; Leuschner et al., 2007).

In summary, cross validation from retained BRT models confirmed the performance of selected models, as shown in Fig. 4. General forms of the models were as follows: *Cabg-f (Slope, CBH, Age2,* and *Stocking2), Cblg-f (NhaCir, Altitude,* and *Age1)* and, *SOC-f (Altitude, Slope,* and *Age1)*.Values of R^2 and RPD between measured and predicted C stocks ranged from 0.61 to 0.85 and 1.6 to 2.59 respectively. Based on RPD thresholds mentioned in the statistic analysis section, the C stock models have good prediction ability and could be improved (mainly for SOC).

4. Mapping of C stocks and their variability

The combination of selected BRT models within a GIS produced C stock maps for each compartment (Fig. 5). C stock values over the study area varied from 9 to 27 Mg ha^{-1} in ABG, 22 to 47 Mg ha^{-1} in BLG and 61 to 109 Mg ha^{-1} in SOC. The total C stocks ranged from 104 to 183 Mg ha^{-1}, and ABG, BLG and SOC compartments represented respectively 13.5%, 28% and 58.5% of the total C stock.

Comparing with published data and regarding the particularity of the ecosystem studied herein (old coppice of eucalyptus plantation), it was noticed that, for each component: (i) the values of C stock concerning ABG were close to that obtained in other coppiced eucalyptus study (Zewdie et al., 2009), (ii) C stocks in the BLG were by far higher (reaching more than six times) than those mentioned in other studies where the stands corresponded to high forest of eucalyptus (Harmand et al., 2004; Saint-André et al., 2005), and (iii) SOC values were in the same range of value obtained by Maquere et al. (2008) under coppice and high forests of eucalyptus plantations in Brazil.

5. Carbon accountancy at county scale

C-pool variability within studied plots expressed by the coefficient of variation was used to provide a first estimate of the C variation over the entire study area. We obtained values of 41.5% for ABG ($n=29$), 22.1% for BLG ($n=41$), 25.7% for SOC ($n=41$) and 17%, for total-C ($n=29$). The moderately high values observed here reflected the complexity of the studied ecosystem and mainly the high variability of intrinsic biomass and soil properties. For the county, C stocks were

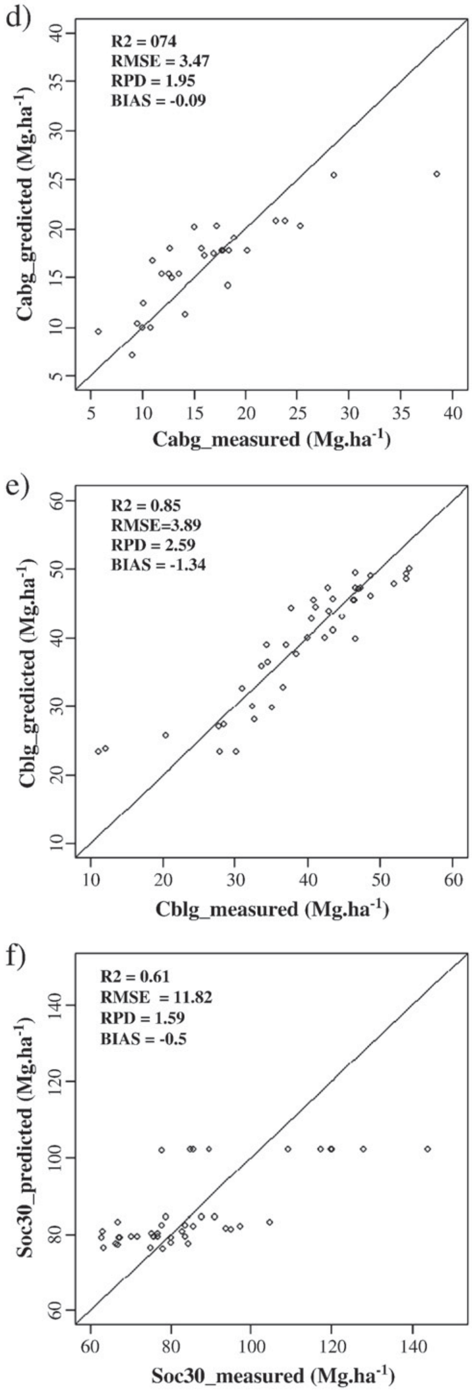

Fig. 4. Graphs of predicted vs measured C stocks for each model retained in (d) ABG pool, (e) BLG pool and (f) SOC pool.

32.25 ± 13.28 Gg C for ABG, 66.63 ± 14.72 Gg C for BLG and, 139.36 ± 35.88 Gg C for SOC, contributing to a total stock of 238.26 ± 40.5 Gg C (1 Gg$=10^9$ g). When considering the morpho-pedology map (Fig. 2), higher C stocks occurred mainly in the west part of the studied area where landforms were characterized by high elevations and important slopes. Higher stocks might be related mainly to elevation variations as found in other studied mountainous area (Schwartz and Namri, 2002; Chen et al., 2005; Yimer et al., 2006; Lemma et al., 2007; Leuschner et al., 2007; Zhang et al., 2008). Explanations proposed by these authors were: i) the particular bio-functioning of roots in a coppice ecosystem where stump recovered by cambium were added to the remaining root system in each new resprouting (Wildy and Pate, 2002), ii) an investment in BLG component for C allocation due

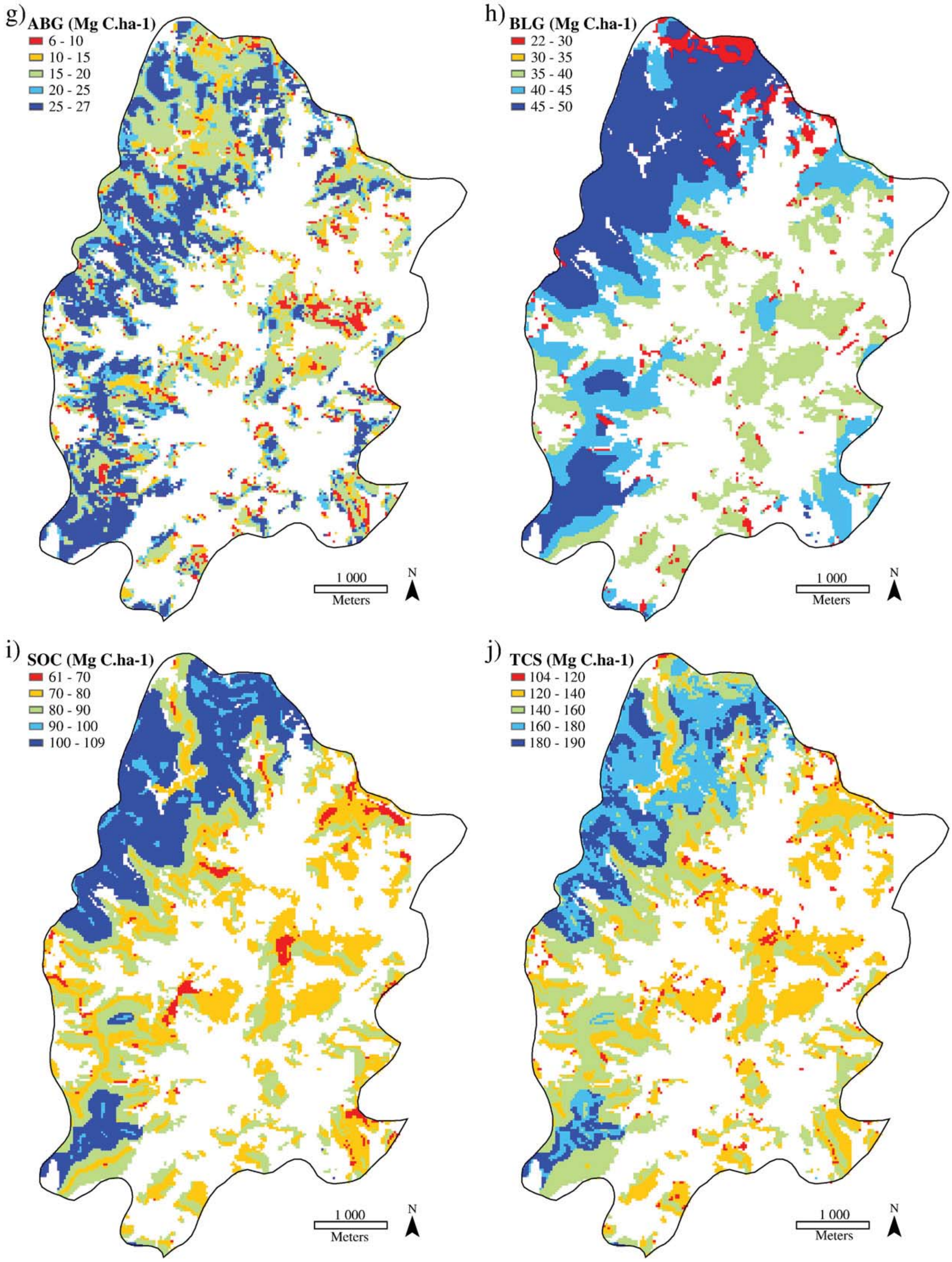

Fig. 5. C stock (kg m^{-2}) distribution maps in the deferent pools of the study area based on predicted C stocks obtained by the use of boosted regression tree models, in (g) the ABG pool, (h) the BLG pool (i) the SOC pool and (j) all pools. The scale is in 1:25,000. * 1 Gg = 10^3 Mg = 10^9 g.

to reduced nitrogen supply in low temperature, and iii) the influence of litter production and quality associated with microclimate at high altitude which favored SOC accumulation through plantation duration (Lal, 2005; Su et al., 2006).

The ecosystem studied herein is a wood fuel coppice system where after each cutting cycle only BLG and SOC remain in the site, and these stocks of C might constitute carbon-neutral and carbon-negative compartments as described by Mathews (2008). Actually, regarding mainly CO_2 as the main greenhouse gas concerned by this ecosystem, ABG pool is first a C-neutral fuel because it absorbs CO_2 as it grows and releases the same C back into the atmosphere when burnt, but constitutes a fuel switching by avoiding C fossil consumption. BLG and SOC compartments are effective C negative compartments as they absorb CO_2 as they grow and release less than this amount into atmosphere through carbon capture and storage.

6. Accuracy considerations

Measurement of estimation accuracies resulting from modeling was achieved using correlation between observed and predicted values and determination of the RMSE and RPD.

Theses values provide insight at sampling location but one cannot extrapolate theses measurement to the entire study area. Thus detailed accounting of all sources of error is required using an error propagation process estimated for instance with Monte Carlo simulations. So far, in C budget accounting studies, accuracy has been little reported as many sources of errors have to be investigated (Brown et al., 1999; Phillips et al., 2000; IPCC, 2003; Peltoniemi et al., 2006; Krishnan et al., 2007; Zhang et al., 2008; Heim et al., 2009). They include: sample plot location and representativeness, laboratory analysis error, land cover mapping error from remote sensing, measurement precision in the field, regression error from modeling, tree based biomass error derived from allometric regression. Although deeper accuracy assessment is required, this study provided first references values for C budget at a local scale (1:25,000). Considering the emerging C market regarding forested lands or terrestrial ecosystem in general, focus on accuracy is recommended to provide credible C gain or loss estimates.

7. Conclusions

This study presented a full integrated evaluation of evaluation of C stocks on eucalyptus plantation at the sub-regional scale including field sampling, digital soil mapping, land cover mapping using remote sensing, carbon stock calculation of all the pools, multivariate modeling and production of carbon maps. Results demonstrated that there were different relevant factor sets which controlled C storage in each pool. Slope, coppice age, mean circumference at breast height and density of shoots were the best predictors for the ABG; for BLG, they were predictors that considered the interaction between the mean circumference and density of stools, elevation and plantation duration and; for soil organic carbon pool, they were elevation, slope and plantation duration. This work showed that multiple linear regression (MLM) and boosted regression tree (BRT) were efficient tools to estimate C stocks in the different compartments over the studied area, with more improvement using BRT. Accuracy assessment carried out using coefficient of determination (R^2) and ratio of standard deviation to prediction error (RPD) showed satisfactory results, respectively 0.74 and 1.95 for AGB, 0.85 and 2.59 for BLG, and 0.61 and 1.59 for SOC.

In terms of C quantity, BLG and SOC compartments, with their contribution of 28% and 58.5% to the total C that amounted 238.26 ± 40.5 Gg (1 Gg $= 10^9$ g) were pointed out to constitute major components for C storage in these coppices of *E. robusta* in the highlands of Madagascar. Hence, we suggested that future studies on carbon accounting on natural ecosystem especially forest land cover should better consider these two main C pools. They may greatly influence or counteract the increasing trend of atmospheric CO_2 concentration.

Nevertheless, these assessments considered only spatial variability between studied eucalyptus stands as uncertainty assessment. Coefficient of variation ranged from 17 to 41.15% depending on the pool. They need to be computed accurately at each step of the C stock estimation; they could be also reduced by improving sampling designs.

Finally, this work allowed a better understanding of the spatial and temporal distributions of C stock in Malagasy Highlands. This study provides new insight into the development or improvement of methodologies that reliably define the baseline of C stock in natural C pool at Madagascar national scale. Presently, this is an essential need for Madagascar as a nation which is setting up climate change policies that rule and generate activities such as Clean Development Mechanism and Reducing Emissions from Deforestation and Degradation.

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