Quantifying Tree Biomass Carbon Stocks, Their Changes and Uncertainties Using Routine Stand Taxation Inventory Data

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For carbon (C) trading or any other verifiable C reports, it would be reasonable to identify and quantify continuous changes in carbon stocks at regional scales without high investments into additional C-specific, time- and labor-intensive inventories. Our study demonstrates the potential of using routine stand taxation data from large scale forestry inventories for verifiable quantification of tree biomass C stocks, C stock change rates, and associated uncertainties. Empirical models, parameters, and equations of uncertainty propagation have been assembled and applied to data from a forest management unit in Central Germany (550 000 ha), using stand taxation inventories collected between 1993 and 2006. The study showed: 1) The use of stand taxation data resulted in a verifiable and sufficiently precise (cv = 7%) quantification of tree biomass carbon stocks and their changes at the level of growth-regions (1700 to 140 000 ha). 2) The forest of the test region accumulated carbon in tree biomass at a mean annual rate of 1.8 (–0.9 to 4.5) tC/ha/yr over the studied period. 3) The taxation inventory data can reveal spatial patterns of rates of C stock changes, specifically low rates of 0.4 tC/ha/yr in the northwest and high rates of 3.0 tC/ha/yr in the south of the study region.

1   Introduction

The quantification of carbon stocks in managed forest ecosystems, their changes over time and the quantification of associated uncertainties is a prerequisite for studying forest carbon sequestration (Nabuurs et al. 1997), for reporting removals and sinks to the UNFCCC (Eggleston et al. 2006), and for forest carbon sink accounting under the Kyoto protocol (UNFCCC 1997) and/or potential following agreements and protocols. Furthermore, such studies are necessary to assess the effect of forestry management options on carbon dynamics and to guide management decisions that deal with enhancing carbon sequestration potential of forest ecosystems.

There are numerous studies that analyzed carbon stocks in forest ecosystems using forest inventory data (Cannell et al. 1992, Kauppi et al. 1992, Liski et al. 2000, Nabuurs et al. 2001, Liski et al. 2003, Janssens et al. 2003). These studies use data directly from national inventories (e.g. Baritz and Strich 2000), or from data reported to the FAO (TBFRA 2000), which are originally based on national inventories. At regional and larger scales, changes in carbon stocks are commonly assessed by comparing the stocks from several inventories over time. Studies that include analyses on the uncertainties of carbon stock estimates and their changes are less abundant (Heath and Smith 2000, Phillips et al. 2000, Brown 2002).

All studies mentioned above are based on repeated large-scale, sample-based inventories. Such inventories refer to a grid of sampling plots or randomized plots that are assumed to represent the entire studied forest area (Loetsch et al. 1973, Kurth et al. 1994). These measurements have a high precision per plot because all trees within the plot are measured. However, the disadvantage is that a high number of plots is required to calculate precise and representative results for small forest management units, such as forest districts or many private land ownerships in Central Europe. It is also difficult to assess the spatial heterogeneity within distinct sub-regions. Last, but not least, it is a time-consuming and cost-intensive method. Therefore, many forest administrations prefer the so called "forest taxation" method – a method in which the basal area of each stand or each cohort within a stand is solely estimated by relascope-sampling (Hartig 1804, Bitterlich 1952, Kuusela 1966). This method is associated with comparably high uncertainties (Kurth et al. 1994) at stand scale, but allows the forest owners and managers to get reliable estimates for small forestry units at lower costs compared to the usual sample-based inventory approach. This type of inventory method is used in several federal states of Germany and Eastern European countries, e.g., Czech Republic, Slovakia, and Poland. However, a question arose: Are the large and usually easier available data sets of forest stand taxations suitable for a reliable and verifiable quantification of regional tree biomass carbon stocks and their changes?

In order to demonstrate the potentials and limitations of this methodological approach, we tackled the following sub-questions:

1) How large are the uncertainties of the quantified carbon stocks and their changes?
2) Is it possible to detect spatial patterns at smaller spatial scales than the entire administrative management unit (e.g. at forest districts)?
3) How do the stand taxation based results compare to those results that use data from sample-based inventories.

As a test case area, we used stand taxation data of the public forests of the federal state Thuringia in Central Germany. Since the mid of the 19th century, the forest area has been divided into forest stands of a few hectares, characterized by similar age and management history. Carbon stocks and their uncertainties were quantified at this stand scale. For further analyses the results of the single stands were aggregated to larger spatial units of similar growth conditions and then aggregated to the entire forest area of the test region (540 000 ha total forest area). We assembled empirical models and parameters for carbon stock quantification in all tree compartments (stem, branches, foliage, and roots) and calculated the total tree biomass carbon stocks for two inventory cycles. In addition, we accounted for uncertainties in carbon quantification, for error propagation during aggregation to larger spatial units, and for inconsistencies in forest area between subsequent inventories. Finally, we compared the stand taxation approach to the sample-based approach.

2 Methods

2.1 Study Region

The test region of this study is the managed forest in Thuringia, a federal state in Central Germany (Fig. 1). It encompasses almost the entire forest area, excluding only several nature reserves. The test region was already selected for a study on the implementation of the Kyoto protocol in Germany (Wirth et al. 2004, Mund et al. 2005), as a test region for the European Carbo-Invent project (Baritz 2005), and as a reference region in the DEMO project of the European research cluster CarboEurope-IP (Dolman et al. 2008). The largest parts of the forest area are located in the southern low mountain ranges and in the east and west of Thuringia. The dominating bedrock of the southern low mountain ranges is slate and the soils are mostly dystric cambisols. The eastern and western areas are dominated by limestone and eutric cambisols. The central Thuringian basin is characterized by soils with a relatively thick loess layer. These fertile soils are mainly used for agriculture, such that only 4% of the area is forested.

The temperate climate of Thuringia represents a transition between the maritime climate of Western Europe and the continental climate of Eastern Europe. Due to the lower mountain ranges, there are strong differences in the local climate, ranging from more maritime conditions in the south to a more continental climate in the central Thuringian basin.

After the last glaciations, the entire area was initially populated by early successional species (poplar, birch, willow, spruce). The naturally dominating species of later states of succession are spruce (*Picea abies*) at higher elevations, beech (*Fagus sylvatica*) at lower elevations that have relatively high precipitation, and pine (*Pinus sylvestris*) and oak (*Quercus* spp.*)* at sites where the competitiveness of beech is reduced due to low precipitation. Since the beginning of the 19th century the forests have been regularly managed, with management preference given to coniferous trees. As a result, about 70% of the forest area is currently dominated by conifers, mainly mono-specific even-aged spruce stands. The management is guided by yield tables, which list expected
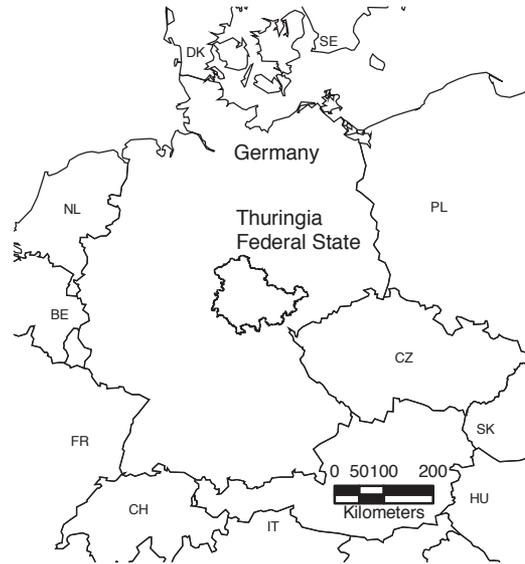

Fig. 1. Map locating the study area.

timber diameter, height, and volume of stands for different site qualities and distinct management regimes. The aim of present forest management is to foster mixed and multi-cohort stands.

2.2 Inventory Data

The stand taxation forest inventory data used in this study is based on an assessment of basal area and tree height of each stand of a forest area with a relascope (Bitterlich 1952). The data provides information on cohorts, which are trees of the same species group, the same crown layer, and similar age. The relascope sampling is based on circular plots where the plot size increases with the increasing diameter of the tree. The relationship between, the sizes of trees and the plot area is such that each tallied tree on a plot gives 1 m²/ha of the basal area, or a multiple of it to the estimate of cohort basal area (Kuusela 1966). Timber volume is calculated by multiplying the basal area by a form factor that depends on stand characteristics such as species and tree height of basal area mean tree. The data used in this study is already a summary of several relascope plot measurements at different positions within each

stand. It reports species, age (years) known from year of establishment, quadratic mean of diameter at breast height (dbh) (cm), tree height (m) (calculated from stand height curves), calculated timber volume (m³/ha), and basal area (m²/ha). The inventory does not include the variance of the tree parameters, timber volume of trees with a dbh smaller than 7cm, nor the number of trees within a cohort.

The number of relascope sample plots per forest stand varies depending on species, stocking density and homogeneity of the stand in order to achieve precision of basal area of 12% in stands near time of harvesting or 18% in younger stands respectively (VEB Forstprojektierung 1978, VEB Forstprojektierung 1988). In each sample plot tree height of about 8 trees or dominant trees are measured, depending on vertical structure of the stand yielding a precision of height of the mean basal area tree of 10%. Ulbricht (1984) reviews amongst others several Eastern-German studies that compare taxation based estimates to detailed inventories (Kangas et al. 2004). He reports relative random errors of timber volume of 34% of a single sample plot yielding relative errors at stand scale of 23% in forest stands near harvesting and 27% in plots with trees of younger age. In addition there are systematic errors in a big part due to subjective parts of the estimates of the staff of up to 19% that differ by species and forest district (Kurth and Ott 1980, Ulbricht 1984).

Because of several administrative changes after 1989, inventory data before 1993 were not available anymore. The available data from 1993 (Kurzfassung… 1989) was based on stand taxations of the previous 10 years, which had been projected to the year 1993 using regional yield tables (Nicke 1997). Due to data privacy restrictions, we were only allowed to use cohorts in public forests for our analysis. In total, these comprised about 145 000 cohorts, representing about 90 000 stands.

The first subsequent taxation after 1993 was done between 1998 and 2006 for the entire reestablished federal state Thuringia (LAWUF 1999). Below we refer to data from this time period as "post 1997 inventories". In each year the taxation process covered about 1/10 of the forested area. Therefore, the date of the post 1997 inventories in single stands varied across the test region between less than one year and 9 years after 1997. The interpolation of the carbon stocks to the reference year 2001 is described below.

2.3 Growth Regions As Aggregation Units

The aggregation and spatial analysis of carbon stocks was performed for areas with comparable growth conditions, mainly climatic and topographic characteristics (Fig. 2). In this study we call these areas "growth regions" (in German: *Wuchsgebiete*). The main advantage of using growth regions instead of administrative units is that their boundaries do not change substantially over time. In contrast, the administrative boundaries were changed several times at the test region, especially within the last two decades. In addition, the use of growth regions allowed interpreting the resulting carbon stocks and their changes in relation to environmental conditions. However, the disadvantage of this approach was that several administrative units with differing taxation dates often intersected one growth region. We denoted forest area A_s of the same inventory year for each growth region as a "growth sub-region". The growth sub-regions conceptually corresponded to the spatial units defined by intersections of districts and ecozones in the Canadian CBM-CFS 3 forest carbon accounting model (Kurz et al. 2009). In the 1993 inventory, all data referred to same date. Thus, in 1993 there was only one sub-region per growth region.

2.4 Calculation of Cohort Carbon Contents

We used the term "carbon content" to refer to the mass of carbon in a distinct carbon reservoir (e.g. tree compartment or tree cohort) of variable spatial size. We used the term "carbon stock" to refer to the carbon content normalized to one hectare (Eggleston et al. 2006) (Annex 4.A.1). Cohort carbon contents were calculated by multiplying the timber volume reported in the inventory database with an age- and site index-specific factor (Eq. 1).

$$C = kV$$
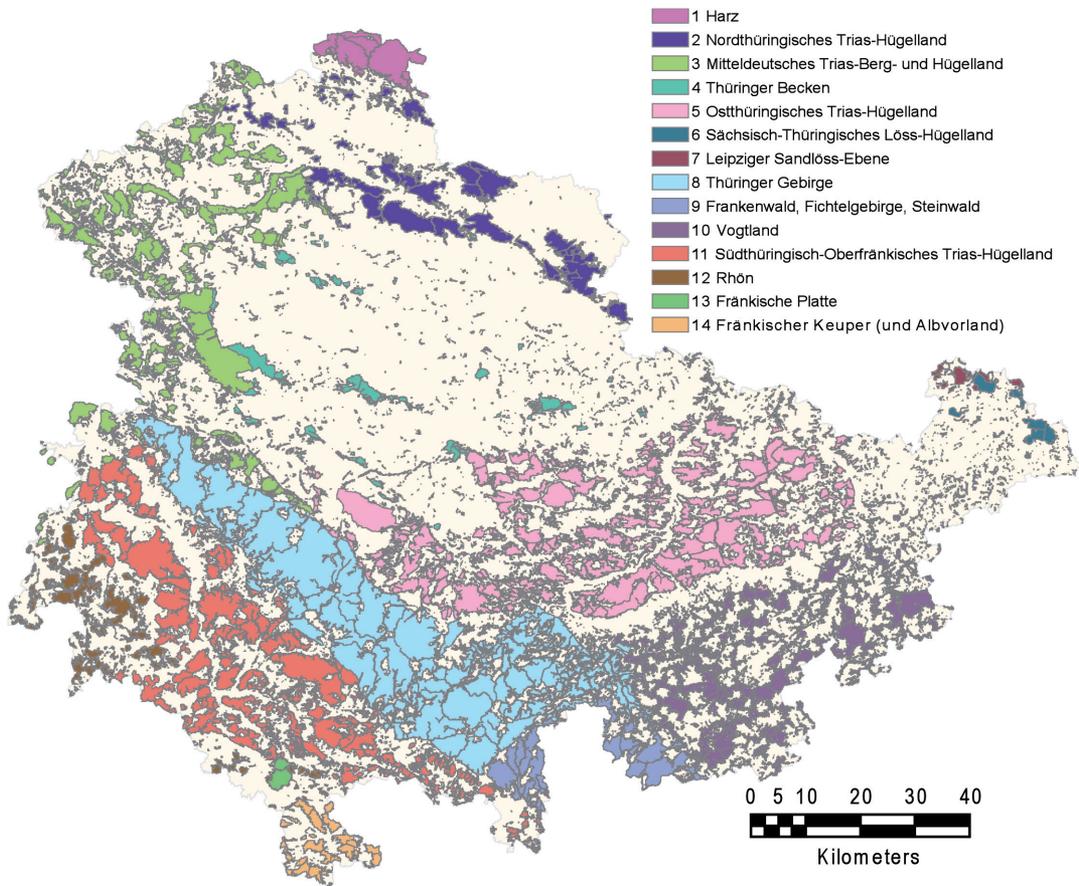$$k = k_V \rho \; c_C = f(species, age, siteindex)$$

(1)

Fig. 2. Map of the forest area by growth regions of Thuringia.

where C is the carbon content, k is the conversion-expansion factor and V is the absolute timber volume of a tree cohort. The conversion-expansion factor, k, is the product of an expansion factor, k_V, from timber to whole tree biomass, wood density, ρ, and the carbon fraction, c_C. Note that k substantially differs from the biomass conversion and expansion factor (BCEF) of the IPCC guidelines (Eggleston et al. 2006). Factor k already includes the carbon fraction, and second, it is a continuous function of stand age and depends on site index. For the dominant species, Norway spruce (*Picea abies*) and European beech (*Fagus sylvatica*), conversion-expansion factor functions were taken from Wirth et al. (2004) and Wutzler and Mund (2007), respectively. For pine (*Pinus sylvestris*), we used factors from Lehtonen et al. (2004a). Table 1 lists some k-function values for

combinations of species, site index, and stand age. Tree biomass carbon contents of broadleaved species other than beech were calculated using the factor k of beech, and that of coniferous species other than spruce and pine by using the factor k of spruce, corrected for species-specific wood densities, carbon fraction, and site index groups (Table 2). Wood density and carbon fraction of the tree compartments of the dominant species were taken from Weiss et al. (2000) (Table 3).

In case of missing values in the inventory database (in total less than 5% of basal area), we estimated them from relationships given in yield tables that were commonly used in Thuringian forestry (Wutzler and Mund 2007, Nicke 1997). When data, for tree cohorts with a diameter smaller than 7 cm, were missing then the carbon stocks of these small trees were set to zero. The

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Table 1. Conversion-expansion factors calculated from exponential functions of tree age. The specific function was selected based on tree compartment, species, and site index. Last four columns list the conversion-expansion factors for exemplary tree ages.

Compartment	Species	Site index	30yr	50yr	70yr	100yr
Stem	Spruce	Unspecific	0.42	0.39	0.38	0.37
		High	0.41	0.41	0.4	0.4
		Intermediate	0.41	0.39	0.38	0.38
		Low	0.43	0.38	0.36	0.34
	Beech	Unspecific	0.69	0.62	0.57	0.53
		High	0.85	0.71	0.62	0.54
		Intermediate	0.65	0.61	0.57	0.54
		Low	0.64	0.57	0.54	0.53
	Pine	Unspecific	0.4	0.41	0.42	0.42
Branches	Spruce	Unspecific	0.115	0.096	0.095	0.094
		High	0.079	0.079	0.079	0.079
		Intermediate	0.107	0.088	0.086	0.086
		Low	0.2	0.14	0.12	0.12
	Beech	Unspecific	0.21	0.17	0.15	0.14
		High	0.32	0.26	0.22	0.19
		Intermediate	0.23	0.16	0.14	0.14
		Low	0.16	0.13	0.11	0.11
	Pine	Unspecific	0.101	0.097	0.094	0.091
Leaves	Spruce	Unspecific	0.082	0.046	0.038	0.035
		High	0.044	0.04	0.04	0.04
		Intermediate	0.075	0.043	0.037	0.035
		Low	0.119	0.06	0.043	0.038
	Beech	Unspecific	0.0354	0.0181	0.0107	0.0066
		High	0.055	0.03	0.018	0.009
		Intermediate	0.0361	0.0127	0.0075	0.0062
		Low	0.0249	0.0109	0.0073	0.0062
	Pine	Unspecific	0.055	0.048	0.042	0.036
Root	Spruce	Unspecific	0.11	0.11	0.1	0.1
		High	0.094	0.091	0.089	0.086
		Intermediate	0.11	0.11	0.1	0.1
		Low	0.12	0.12	0.11	0.11
	Beech	Unspecific	0.17	0.17	0.16	0.15
		High	0.23	0.21	0.19	0.17
		Intermediate	0.18	0.17	0.16	0.15
		Low	0.13	0.14	0.16	0.18
	Pine	Unspecific	0.2	0.19	0.19	0.18

relative error of the calculated carbon stocks of each cohort and tree compartment was estimated assuming that the relative errors of timber volume, the expansion factor, and the carbon fraction were independent of each other (Eq. 2).

$$cv_C = \sqrt{cv_V^2 + cv_k^2} = \sqrt{cv_V^2 + cv_{kV}^2 + cv_\rho^2 + cv_{Cc}^2} \qquad (2)$$

For the timber volume reported in the database,

we used a relative error of 27% (Kurth et al. 1994). For the calculation of relative errors of the conversion-expansion factors depending on tree species, tree compartments, and site index groups and the associated parameters, we refer to the original publications (Lehtonen et al. 2004, Wirth et al. 2004, Wutzler and Mund 2007). The relative errors, used for the carbon fraction of the dominant species, are listed in Table 3. For the non-dominant coniferous species, we assumed a

Table 2. Parameters for the conversion of timber volume to tree biomass carbon stock. The last two columns report site indices above which a different equation for the biomass conversion-expansion factor was used.

Species group	Wood density (g/cm³)	cv of wooddensity	Carbon fraction of stem wood (g C/g dry mass)	Min high site index (m)	Min intermediate site index (m)
Spruce	0.38	16%	0.501	34	25
Larch	0.49	15%	0.521	34	29
Pine	0.43	23%	0.51	No regard of site index	
Beech	0.56	12%	0.486	28	20
Oak	0.57	17%	0.495	25	20
Ash	0.56	13%	0.49	28	24
Maple	0.52	9%	0.49		
Birch	0.53	11%	0.485	28	20
Poplar	0.37	8%	0.49		
Douglas fir	0.412	10%	0.51		
Other conifers	0.37	25%	0.51		
Other broadleaved	0.49	25%	0.49		

Table 3. Carbon fractions for major tree species and compartments (g C/g dry mass). Percentage values denote the coefficient of variation of the values listed in the previous column.

Compartments	Spruce	cv_spruce	Beech	cv_beech	Pine	cv_pine
Stem	0.501	1%	0.486	1%	0.511	1%
Foliage	0.5	4%	0.463	4%	0.5	4%
Fineroots	0.5	4%	0.5	4%	0.5	4%
Roots	0.5	5%	0.5	5%	0.5	5%
Branches	0.5	2%	0.497	2%	0.5	2%

relative error of the stem carbon fraction of 10%, and for non-dominant broadleaved species a relative error of 20%.

2.5 Aggregation to Growth Sub-Region Area

Within each growth sub-region, the sum of the carbon contents of all cohorts was calculated (Eq. 3).

$$\hat{z} = \sum_{i \in A_s} \hat{y}_i \qquad (3)$$

where z is the aggregated carbon contents of all cohort carbon contents y_i of cohorts i within sub-region A_s.

The variance of the aggregated carbon contents was assessed with several scenarios of correlations among calculated cohort carbon contents. Usually, the cohort carbon contents are assumed to be independent, i.e. the correlations between two different cohorts are zero and the variances of the cohort carbon contents sum up. However, we hypothesized that this convenient assumption results in an underestimation of the variance at the aggregated level (Heath and Smith 2000) and explicitly included correlations in the uncertainty estimate (Eq. 4).

$$Var(\hat{z} - z) = \sigma_{\hat{z}}^2 = \sum_{j \in A_s} \sum_{l \in A_s} \mathrm{Cov}(y_j - \hat{y}_j, y_l - \hat{y}_l) \qquad (4)$$

The covariance of two cohort carbon contents is given by Eq. 5, which is derived in general form in Appendix A. There were three components

of uncertainty: 1) due to random error in timber volume, 2) due to uncertainty in model parameters

of the conversion expansion factor and, 3) due to systematic errors in timber volume.

$$Cov(y_j - \hat{y}_j, y_l - \hat{y}_l) = \hat{k}_j \sigma_{Vjl}^2 \hat{k}_l + \hat{V}_j \sigma_{kjl}^2 \hat{V}_l + \hat{k}_j \sigma_{bjl}^2 \hat{k}_l$$

$$\sigma_{Vjl}^2 = \begin{cases} \sigma_V^2 & \text{for } j = l \\ 0 & \text{otherwise} \end{cases}$$

$$\sigma_{kjl}^2 = \begin{cases} cv_{kj}\hat{k}_j \cdot cv_{kl}\hat{k}_l & \text{for same species group (same model)} \\ 0 & \text{otherwise} \end{cases}$$

$$\sigma_{bjl}^2 = (r_B^2 \hat{V}_j \hat{V}_l) p_B \begin{cases} 1 & \text{for same species and same district} \\ p_S & \text{for same species and different district} \\ (1 - p_S) & \text{for different species and same district} \\ 0 & \text{otherwise} \end{cases}$$

(5)

where j and l denote cohorts within forest area of a growth sub-region A_s, V is the timber volume from inventory, σ_V^2 its variance, k is the conversion-expansion factor, and σ_k^2 its variance, r_B is the systematic error of about 27% in measured timber volumes at stand scale (Kurth and Ott 1980, Ulbricht 1984), P_B is the proportion of this systematic error that varies with species group or forest district and P_S is the proportion of this varying systematic error that is attributed to different species groups.

The systematic error in timber volume was partitioned into a component that is constant bias across species group and growth sub-region area A_s and a part P_B that varies with species and forest district, i.e. different staff performing the inventory. The varying part can be regarded as a random variable across species groups and forest districts and contributes to the random uncertainty of the sum of carbon contents. We calculated different scenarios of increasing amount of the varying part of the systematic error ($P_B = 0.3, 0.5, 0.7$, and 0.9) and attributed half of this variance to differences in systematic error by species and half by forest district respectively ($P_S = 0.5$).

Finally, the sum of carbon contents z (Eq. 3), expressed in tons of carbon, was divided by the public forest area, A_s, to obtain growth sub-region estimates of carbon stocks, c, expressed in tons of carbon per hectare.

2.6 Aggregation to the Same Year and Growth Region

As mentioned above, all calculated carbon stocks for the 1993 inventory database referred to the same year. The sub-growth region carbon stocks for the post 1997 inventories, however, had to be projected to the common reference year 2001 (Eq. 6).

$$c_{01i} = c_{98i} + \delta_C \Delta t_i$$

(6)

where c_{01i} is the sub-region carbon stock projected to 1.1.2001; c_{98i} are the post 1997 inventory carbon stocks; Δt_i is the difference in years between the date of the post 1997 inventory date and 1.1.2001; and δ_C is the mean annual rate of C-stock change of a growth region.

In order to determine the mean annual rate of C-stock change, δ_C, we assumed the rate to be equal among sub-regions of a growth region (equal slopes in Fig. 3). Next, we used the constraint that growth region carbon stock in 2001, c_{01}, which was derived by projecting 1993 growth region carbon stocks to 2001 using δ_C, was equal to the area-weighted mean of sub-region carbon stocks in 2001 (Eq. 7).

$$c_{01} = c_{93} + \delta_C \Delta t_{93} = \sum_i r_i c_{01i} = \sum_i r_i \left(c_{98i} + \delta_C \Delta t_i \right)$$

$$\delta_C = \frac{\sum_i r_i c_{98i} - c_{93}}{\Delta t_{93} - \sum_i r_i \Delta t_i}$$
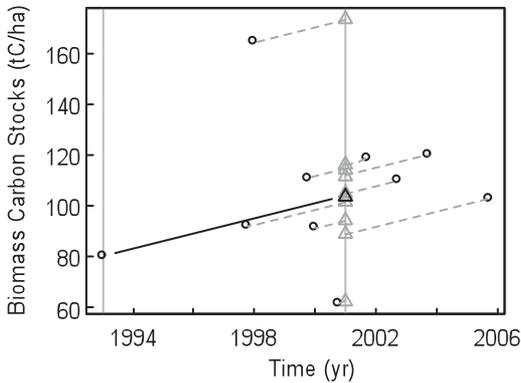
(7)

Fig. 3. Carbon stocks in public forests of the sub-regions of growth region 8, Thüringer Gebirge. Dots represent inventory-based carbon stocks and triangles represent stocks that have been estimated by a common change rate. The grey sloped lines connect points of the same sub-region. The black line connects growth-region aggregated C-stocks. The vertical lines guide to the reference dates 1.1.1993 and 1.1.2001 of the two inventories.

where c_{93} is the growth region carbon stock based on the 1993 inventory database; Δt_{93} is the time difference between 1.1.2001 and 1.1.1993; r_i is public forest area of growth sub-region i, relative to the entire public forest area of the growth region; c_{01i}, c_{98i}, and Δt_i are the same as in Eq. 6. After calculating the rate of change, we replaced a single unreasonable outlier of 7.4 tC/ha/yr from growth region 14 by the value of 2.5 tC/ha/yr from a similar growth region 12. The reason for this is discussed below in the discussion section.

When aggregating the uncertainty from several growth sub-regions to the growth region, we assumed uncorrelated carbon stocks and added the variances. With a mean of n = 3.8 sub-regions per growth regions, this assumption resulted in only a moderate decrease of uncertainty from growth sub-region to growth region level.

2.7 Resampling Analysis of Uncertainty Due to Area Mismatch

The proportion of the public forest area to total forest area differed markedly between the 1993

inventory database and the post 1997 inventories (Table 4). In the 1993 database, the exact location of many stands could not be reconstructed, because ownerships changed between the two inventory periods. Therefore, the growth region level carbon stocks represent slightly different areas. Because of the large spatial variability of the carbon stocks within a growth region (e.g. within region 8, Fig. 3) this contributed to the uncertainty of the estimated rate of carbon stock changes. In order to get an estimate of the magnitude of this uncertainty component, we performed a resampling analysis (Eggleston et al. 2006) (Vol 1, p3.25). The resampling technique simulates the uncertainty within a population by generating many subsamples of an existing sample (Efron and Tibshirani 1986, Davison and Hinkley 1997). The existing sample consisted of all the growth sub-regions within one growth-region. We generated $n = 1000$ subsamples of areas that represent a part, p_{Area}, of the post 1997 inventory area of one growth region. The area of each subsample was chosen randomly among the growth sub-regions (details given in Appendix B). Next, we repeated the calculation of the mean annual rate of C-stock change (Eq. 7) and the 2001 carbon stocks (Eq. 6) for each of the subsamples. Additionally, we included the uncertainties at sub-growth region level by adding to each growth sub-region carbon stock a random component, which differed among the subsamples. The random component was drawn from a normal distribution with variance according to Eq. 4. The resulting sample of the mean annual rate of C-stock change and the 2001 carbon stocks provided empirical estimates of statistical parameters, such as the 95% uncertainty bounds or the coefficient of variation. We performed the resampling analysis with several scenarios of matching area, p_{Area}. The reported numbers refer to the case when $p_{Area} = 80\%$ and $p_b = 50\%$.

2.8 Aggregating to the Total Forest Area of the Test Region

We assumed that the carbon stocks in the public forests within a growth region were representative of those from the total forested area of that growth region. Hence, to aggregate growth region

Table 4. Overview of calculated total carbon stocks for years 1993 and 2001 and the mean annual rate of C stock change by growth region. Last two columns report the proportion of forest area of public forest, i.e. owned by the federal state Thuringia, for which data was available for the 1993 and the post 1997 inventories, relative to total forest area. Values in parentheses represent the rounded 2.5% and 97.5% quantiles of the empirical distribution of the value. cv is the coefficient of variation.

Region	C stock 1993	cv C stock 1993	C stock 2001	cv C stock 2001	Mean annual rate of C stock change	cv rate of C stock change	Forest area	Public forest area 1993	Public forest area 1998–2006
	tC/ha	%	tC/ha	%	tC/ha/yr	%	ha	%	%
1	97 (73,121)	12	106 (71,141)	17	1.0 (–4.5, 6.8)	280	10933	40	41
2	117 (90,145)	12	122 (102,141)	8.1	0.6 (–2.6, 3.8)	280	35596	33	36
3	126 (98,154)	12	129 (110,147)	7.4	0.4 (–3.7, 4.6)	500	67541	8	19
4	104 (85,124)	9.5	117 (104,130)	6	1.6 (–1.0, 4.0)	81	16140	12	20
5	98 (84,112)	7.5	111 (99,123)	5.5	1.6 (–0.6, 3.9)	73	103639	21	21
6	94 (72,115)	11	123 (99,148)	10	3.7 (0.3,7.0)	47	5544	38	53
7	65 (49,82)	13	82 (65,99)	11	2.0 (–0.4, 4.5)	61	1945	27	57
8	80 (67,94)	8.6	104 (93,115)	5.3	3.0 (1.1,4.8)	31	137047	49	18
9	82 (63,100)	12	104 (81,126)	11	2.8 (–0.4, 5.9)	58	17960	38	32
10	93 (78,108)	8.3	99 (81,116)	9	0.7 (–1.6, 3.0)	170	50640	18	11
11	98 (81,113)	8.4	113 (102,125)	5.2	2.0 (–0.4, 4.4)	62	79992	34	22
12	115 (86,146)	13	135 (109,161)	9.8	2.5 (–1.8, 6.8)	86	15877	29	29
13	102 (77,127)	12	120 (78,164)	18	2.2 (–4.5, 9.0)	150	1677	53	49
14	83 (63,102)	12	131 (106,156)	9.8	2.5 (–1.8, 6.8)	86	7270	16	17
Total	97 (79,116)	9.5	112 (97,127)	6.9	1.8 (–0.9, 4.5)	77	551801	30	22

C stocks to the test region, we used an area-weighted mean of total forest area instead of public forest area only. This procedure assured that larger forest areas contributed more to the aggregated value, despite the possibly lower proportion of publically owned forests. Similarly, we calculated an area-weighted mean of the lower and upper uncertainty bounds across growth regions. The coefficient of variation at test region level was inferred from the confidence range, assuming a normal distribution.

2.9 Carbon Stocks and Changes Derived from Sample-Based Forest Inventory

The stand taxation based approach above uses inventory data of many comparably cheap and uncertain measurements. As an alternative we quantified C stocks using a subset of data for Thuringia from the sample-based second German national forest inventory performed between 2001 and 2002 (BMVEL 2005). There are fewer but more precise measurements. We converted aggregated timber volume, which has been reported by species groups and age classes, to carbon stocks using the conversion expansion factors reported by Wirth et al. (2004). The error for carbon stocks of 13.1% was calculated using Eq. 2, assuming uncorrelated errors of conversion-expansion factors and timber volume. We assumed a value of 12.7% for the error in conversion expansion factors, which corresponded to the value reported by Wirth et al. (2004) for spruce across site indices and age classes. The error of the aggregated timber volume at federal state level was reported to be 3.4%.

3 Results and Discussion

3.1 Carbon Stocks and Their Changes of the Test Region

The quantified total tree biomass carbon stocks,

for the entire Thuringian public managed forest, were 97 tC/ha for the year 1993 and 112 tC/ha for 2001 (Table 4). The carbon stocks quantified in this study for 1993 were about 15 tC/ha higher than those previously quantified for Thuringian forests (Wirth et al. 2004) and 9 tC/ha higher than those calculated for 1993 for the Tharandt forest, a smaller forest similar to those east of the test region (Wutzler et al. 2006). In comparison, the carbon stock of the entire German forest was quantified to be about 104 tC/ha (Dieter and Elsasser 2002). The differences between our results and the study by Wirth et al. (2004) can be explained mainly by the fact that, in this study, we calculated carbon stocks for each cohort within each stand separately, while in the previous study, the timber volume of each stand was converted to carbon stocks by factors representing only the dominant cohort. In Wirth's approach many interspersed broadleaved cohorts were calculated with the factors of the dominant coniferous cohort, with a lower conversion-expansion factor. These findings underline the importance of considering all cohorts in a stand. The findings also show that there is a potentially significant model selection error, in addition to the propagation of errors in the data.

When looking beyond the total tree biomass carbon stocks to their distribution in different tree compartments, the results were as expected. Most of the carbon stock was sequestered in stem biomass (60%), but significant amounts are also sequestered in roots and branches (17% and 19% respectively).

From the carbon stocks at different times we inferred the mean annual rate of C-stock change, i.e. the rate at which carbon was accumulated or released from the tree biomass pool. For the total Thuringian forest area, we quantified a mean accumulation rate of 1.8 tC/ha/yr between years 1993 and 2001 although with wide confidence interval (–0.9 to 4.5 tC/ha/yr). This rate was higher than the rates reported formerly for the test region (1.15 tC/ha/yr) (Vetter et al. 2005) and for the entire German forest (1.43 tC/ha/yr) (Dieter and Elsasser 2002). The rates in the past two studies were based on estimates of timber volume increment as recorded in yield tables, which are known to underestimate current growth rates (Mund et al. 2002, Jandl et al. 2007). In contrast, the rate of C stock change, based on repeated national inventory for the larger region of the eastern part of Germany, reported in a more recent study was higher, at 2.52 tC/ha/yr, between years 1988 and 2001 (Dunger et al. 2009).

There are three main reasons for the observed trend of net carbon accumulation in tree biomass, which were revealed by detailed analyses of several long-term silvicultural study plots, forestry planning, and stand age distribution in Thuringia (DEMO project of the European research cluster CarboEurope IP (Schulze 2008)). First, the realized timber harvest was only 77% of the potential yield. Second, the real growth of beech forests was up to 30% higher than reported in yield table data used for forestry planning. A third reason for the relatively high carbon sequestration in Thuringia's forests can be a surplus of middle aged stands (40–100 years old, covering 54% of the forested area) that have relatively high growth rates, but that are too young (not mature) for final timber harvesting.

3.2 Uncertainties of Carbon Stocks and Their Changes

Uncertainty estimates are important to judge the significance of quantified stocks and sequestration rates. At stand scale, uncertainties of tree biomass carbon stocks were high (coefficient of variation, cv = 30–50%). However, the aggregation across many stands (n ≈ 1e5) had a similar effect as a repeated measurement. Hence, at growth region level, the uncertainty for total tree biomass carbon stocks decreased to 0.5% to 2.5% depending on the number of cohorts when neglecting systematic components.

However, systematic error due to uncertainty in conversion expansion factors and timber volume do not decrease this strongly with population size. In addition to the random error in timber volume, there were uncertainties in the model coefficients for the conversion expansion factor that cause deviations of same direction for similar trees. Moreover, there were systematic errors in timber volume at stand scale that only partially average out when aggregating results across larger groups such species or forest districts. Random and systematic uncertainties of relascope based inven-
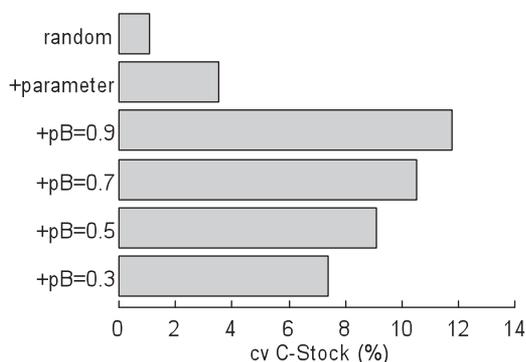
Fig. 4. Relative error of carbon stocks in stem biomass at sub-growth region 5 in 1997 by different error components and bias scenarios. First bar only accounts for random error in timber volume, second bar accounts in addition for uncertainty in parameters for the conversion-expansion factor, and remaining bars in addition account for a portion p_B of systematic error of timber volume that varies by species and forest district.

Fig. 5. Empirical upper and lower 95% confidence bounds of the mean annual rate of tree biomass carbon stock change for different scenarios of mismatches in forest area between 1993 and post 1997 inventories.

tory data are a topic of long debate (Kurth and Ott 1980, Ulbricht 1984, Seltzer 1977, Kangas et al. 2004, Haara and Leskinen 2009, Piqué et al. 2010). Fig. 4 shows an example of how uncertainty increases up to 12% with accounting for additional error components. The largest increase was due to systematic errors in timber volume and increased with the proportion p_B of the systematic error that varied by species and forest district. Note that in addition to the random error of carbon contents there was bias of sum carbon contents of size $(1-p_B)$ of the systematic error at stand scale, i.e. 1.9%, 5.7%, 9.5% or 13.5% respectively for the different p_B bias scenarios.

Another source of uncertainty that we accounted for was the difference in reference area between the inventories. The exact spatial location was not known for many records in the 1993 inventory, and in addition, there were large changes in forest ownership. Hence, the public forest area had a net decrease of about 44 200 ha, i.e. 27%, between the 1993 and post 1997 inventories, and we could not trace down all the changes. If we assumed in the resampling analysis scenario that at least 80% of the post 1997 forest area was in accordance with
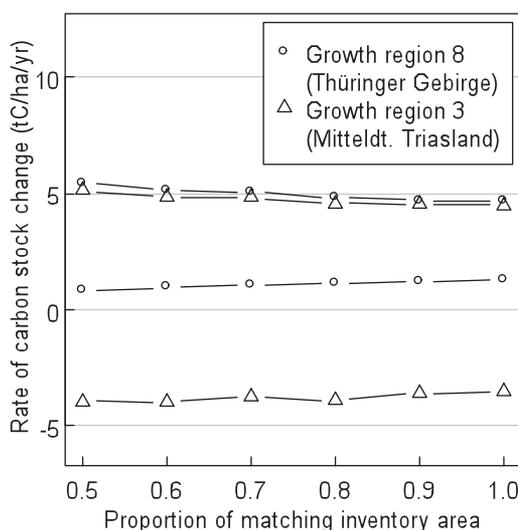
the 1993 inventory area, then the 95% confidence range of the rate of C stock change increased by 0.24 tC/ha/yr, as compared to the scenario where the two inventories referred to the identical forest area (Fig. 5). While this increase was only about 1/10 of the magnitude of uncertainty, it can be avoided by keeping track of the administrative changes and comparing the same areas.

There were at least three more potential sources of error that we could not take into account. First we were restricted to public forest area. We expect a slight negative bias in both quantified C stocks and rate of mean annual C stock change, because the amount of harvest in public forests was greater than in small (< 100 ha) private forests (BMVEL 2005). Second, there was systematic bias in the 1993 baseline timber volumes that differed by forest district. As mentioned above, the timber volume of the 1993 dataset was based on projections of the timber volume from previous inventories by yield tables. This likely underestimated the true timber volume, because it did not take into account the effects of increased stem growth over the last decades (Mund et al. 2002). The magnitude of the resulting negative bias depends

on species composition, the used yield tables, and the length of the projection period to 1993 that varied among the forest districts. If this effect was accounted for, the uncertainty of the calculated change rate would slightly increase and its absolute value would decrease because of higher carbon stocks in 1993. For future studies, based on repeated stand taxations, this unaccounted source of uncertainty will be irrelevant. Third, we had to assume that rates of mean annual carbon stock change were equal among sub-regions of a growth region (Eq. 6). Neglecting the variability of the rates among sub-regions does underestimate the uncertainty of 2001 growth carbon stocks and the uncertainty of the mean rate of C-stock change of the growth region. However, we suppose that those effects are much smaller than the uncertainty caused by systematic errors in timber volume.

The overall uncertainty estimates of mean annual rates of C stock change for growth regions or the entire test region are of reasonable magnitude (cv = 7% to 10%, Table 4). Thus, the results support the hypothesis that stand-based taxation forestry inventories are viable for quantifications of tree biomass carbon stocks at the level of growth regions.

3.3 Spatial Patterns of Carbon Stocks and Sequestration Rates

One advantage of the stand taxation-based approach is an increased spatial resolution. For the test region we found high variability in total tree biomass carbon stocks among growth regions (Table 4). In the year 1993, the highest carbon stocks of 124 to 127 tC/ha/yr were in the northwest of the Thuringian basin, in growth region 3. That growth region is characterized by a large proportion of beech and other broadleaved species growing on nutrient-rich soils on limestone. At the mountain ranges in the south (growth regions 8 and 9), with less favorable growth conditions, there were lower carbon stocks of about 80 to 83 tC/ha. In 2001 this distribution changed only slightly.

Tree biomass carbon stocks increased throughout the entire Thuringian forest area. However, the increase in carbon stocks was higher in growth regions with low carbon stocks in 1993, and differences among growth regions in 2001 were not as large as in 1993.

The strongest increase of tree biomass carbon stocks was calculated for the south of the mountain range "Thüringer Wald" and at the mountain range itself (Fig. 6). The increasing trend was significant in only two of the 14 growth regions (Table 4, regions 6 and 8). The calculated mean annual rates of carbon stock change varied between 0.4 and 3.7 tC/ha/yr across growth regions. The lowest increase of 0.4 tC/ha was calculated for the northwest of the study region, and the higher increases of 2.8–3.0 tC/ha/yr for the high elevation areas in the south of the test region. The extremely high outlier rate of carbon stock change of 7.4 tC/ha/yr at growth region 14 can be explained by the short time period between years 1993 and 1998 when the only inventory of the post 1997 inventory took place in that growth region. We suppose that in this short period less timber was harvested than it would be on average over longer time periods. The spatial patterns in the rates of C stock change are likely caused by differences in age-distribution between regions dominated by spruce compared to regions dominated by broadleaved species.

3.4 Comparison to Sample-Based Approaches

The stand taxation-based approach was compared to results using data from the German national forest inventories in years 2001 to 2002 that represented a sample-based approach. The stocks of 106 (79 to 133) tC/ha calculated by converting aggregated timber volume to carbon units were not significantly different from the stand-taxation based results for 2001 (97 to 127 tC/ha). The quantified uncertainty in 2001 C stocks (cv = 13.1%) was similar to the uncertainty resulting from the stand taxation-based approach of cv = 6.9% plus a systematic error of $(1 - p_B) \, r_B \approx$ 10%. We note, however, that the uncertainty of the sample-based approach could be decreased if the non-aggregated original tree measurement data had been converted to carbon and detailed error propagation to the study area had been performed. From the sample-based approach, only the aggre-
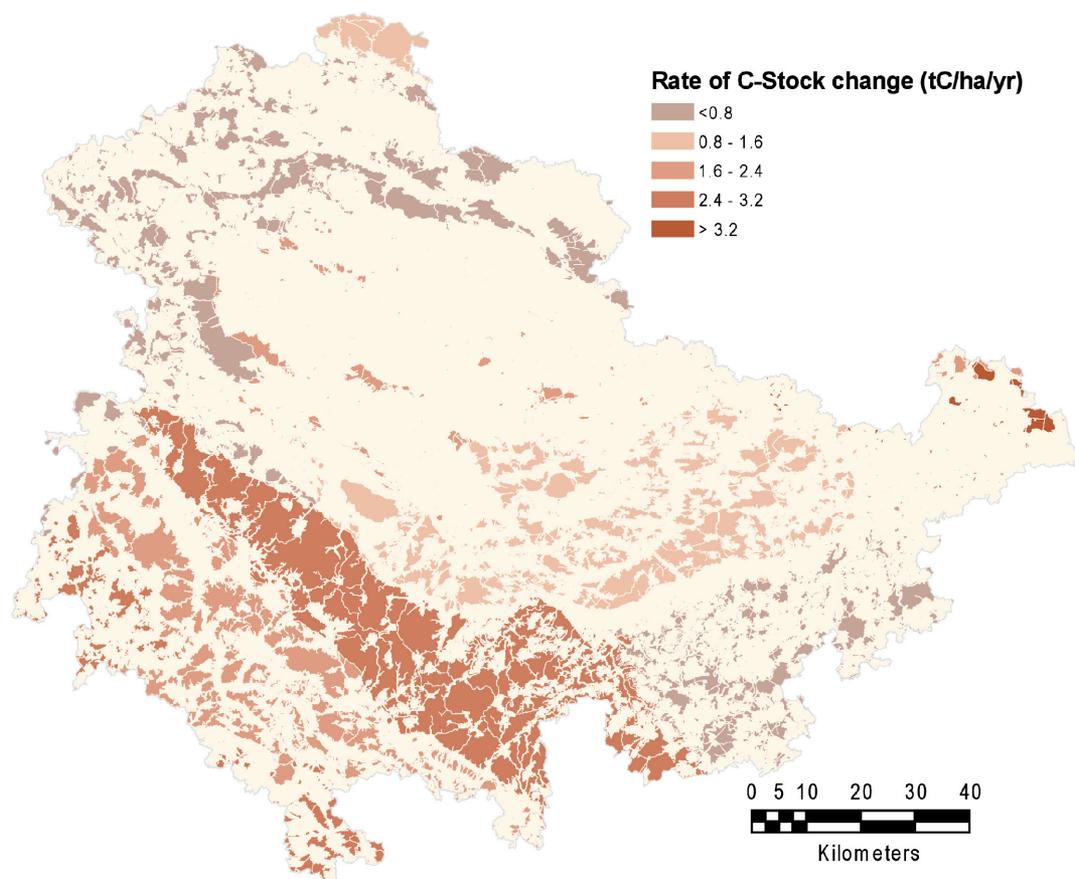
Fig. 6. Map of the mean annual rate of biomass carbon stock change for Thuringian forest area, by growth region estimated for the period 1993 to 2001.

gated timber volume was used in this study, such that many details of the cohorts were neglected. In addition, the classes of species groups and age classes of the sample-based approach were coarser (age classes of 20 years).

We could not directly compare rates of C-stock change between stand taxation-based and sample-based approach for the study area because the preceding national inventory covered only the western part of Germany. Uncertainty of the rate of carbon stocks change between 1987 and 2002 for the total forest area of the entire western part of Germany was cv = 7.1% (UBA 2010 Table 170). We roughly extrapolate this uncertainty to the study area by assuming that the number of sampling points of a future national inventory that are located in Thuringia is about 1/10 of

number of sampling points for the entire western part of Germany. The resulting estimate of 7.1% * sqrt(10) = 22.5% is smaller than the uncertainty of cv = 77% when using the stand taxation based approach. The sample based inventory yields a better precision because it can make use of paired sampling, whereas the stand taxation based approach compares stocks at aggregated level.

4   Conclusions

This study demonstrates the potentials of using routine stand taxation forest inventory data for quantifying tree biomass carbon stocks. The assembling of empirical models and param-

eters for converting timber volume of single tree cohorts to carbon stocks, together with a detailed accounting of the aggregation of uncertainties in the data and the model parameters, showed satisfying results. For the test region, the tree biomass carbon stock estimates of 97 and 112 tC/ha during years 1993 and 2001, respectively, were determined with a precision of cv = 9.5 and 6.9% respectively. The largest contribution to the uncertainty originated from systematic errors in timber volume within species groups and forest districts. The presented approach could quantify a spatial pattern of carbon sequestration rates ranging between 0.4 tC/ha yr and 3.0 tC/ha/yr. Altogether, the presented stand taxation-based approach resulted in a higher spatial resolution, a similar precision of carbon stocks, and a higher uncertainty in the rate of carbon stocks changes compared to an aggregated sample plot-based approach.

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Appendix A: Covariance between Two Predictions

Consider the linear model (Eq. A1) with prediction y depending on predictor vector $\mathbf{x}$ and parameter vector $\boldsymbol{\beta}$ and random component ε_y.

$$y_{\text{obs}} = y + \varepsilon_y$$
$$y = \boldsymbol{\beta}^T \mathbf{x}$$

(A1)

The covariance between two predictions y_j and y_k based on predictors $\mathbf{x_j}$ and $\mathbf{x_k}$ is given by Eq. A2. Symbols with hats indicate estimates and symbols without hats, the population values.

$$
\begin{aligned}
&\text{Cov}(y_{obs,j} - \hat{y}_j, y_{obs,l} - \hat{y}_l) \\
&= \text{Cov}(\boldsymbol{\beta}^T \mathbf{x}_j + \varepsilon_{yl} - \hat{\boldsymbol{\beta}}^T \hat{\mathbf{x}}_j, \boldsymbol{\beta}^T \mathbf{x}_l + \varepsilon_{yl} - \hat{\boldsymbol{\beta}}^T \hat{\mathbf{x}}_l) \\
&= \text{Cov}(\boldsymbol{\beta}^T \mathbf{x}_j - \hat{\boldsymbol{\beta}}^T \hat{\mathbf{x}}_j, \boldsymbol{\beta}^T \mathbf{x}_l - \hat{\boldsymbol{\beta}}^T \hat{\mathbf{x}}_l) + \text{Cov}(\varepsilon_{yj}, \varepsilon_{yl}) \\
&= \text{Cov}(y_j - \hat{y}_j, y_l - \hat{y}_l) + \text{Cov}(\varepsilon_{yj}, \varepsilon_{yl})
\end{aligned}
$$

(A2)

The covariance between the residuals can be assumed to be zero for $j \neq l$ in accordance with regression analysis, which estimated the model parameters.

We first examine two special cases and combine the results afterwards to a conservative estimate for the covariance between two predictions. For the first case we assume fixed predictors $\hat{x}_i = x_i$. Then covariance of two predictions simplifies to Eq. A3.

$$
\begin{aligned}
&\mathrm{Cov}(y_j - \hat{y}_j, y_l - \hat{y}_l) \\
&= \mathrm{Cov}((\boldsymbol{\beta} - \hat{\boldsymbol{\beta}})^T \hat{\mathbf{x}}_j, (\boldsymbol{\beta} - \hat{\boldsymbol{\beta}})^T \hat{\mathbf{x}}_l) \\
&= \hat{\mathbf{x}}_j^T \mathrm{Var}(\boldsymbol{\beta} - \hat{\boldsymbol{\beta}}) \hat{\mathbf{x}}_l \\
&= \hat{\mathbf{x}}_j^T \mathrm{Var}(\hat{\boldsymbol{\beta}}) \hat{\mathbf{x}}_l
\end{aligned}
\tag{A3}
$$

With $\mathrm{Var}(\hat{\beta})$ is the variance-covariance matrix representing the uncertainty of model parameters, which is estimated during model fitting.

Similarly, for the second special case of fixed model parameters $\hat{\boldsymbol{\beta}}_i = \boldsymbol{\beta}_i$ covariance of two predictions further simplifies to Eq. A4.

$$
\begin{aligned}
&\mathrm{Cov}\left(y_j - \hat{y}_j, y_l - \hat{y}_l\right) \\
&= \mathrm{Cov}(\hat{\boldsymbol{\beta}}^T (\mathbf{x}_j - \hat{\mathbf{x}}_j), \hat{\boldsymbol{\beta}}^T (\mathbf{x}_l - \hat{\mathbf{x}}_l)) \\
&= \hat{\boldsymbol{\beta}}^T \mathrm{Cov}(\mathbf{x}_j - \hat{\mathbf{x}}_j, \mathbf{x}_l - \hat{\mathbf{x}}_l) \hat{\boldsymbol{\beta}}
\end{aligned}
\tag{A4}
$$

If the predictor value $\hat{\mathbf{x}}_i = \mathbf{x}_i + \mathbf{b} + \mathbf{b}_d + \boldsymbol{\varepsilon}_i$ is composed of the true value plus bias $\mathbf{b}$ plus a systematic error $\mathbf{b}_d$ that varies by group d and independent random error $\boldsymbol{\varepsilon}_i$ then we have Eq. A5. Note that the constant bias does not contribute to the covariance.

$$
\begin{aligned}
&\mathrm{Cov}\left(y_j - \hat{y}_j, y_l - \hat{y}_l\right) \\
&= \hat{\boldsymbol{\beta}}^T \mathrm{Cov}\left(\mathbf{x}_j - \left(\mathbf{x}_j + \mathbf{b} + \mathbf{b}_{d(j)} + \boldsymbol{\varepsilon}_j\right), \quad \mathbf{x}_l - \left(\mathbf{x}_l + \mathbf{b} + \mathbf{b}_{d(l)} + \boldsymbol{\varepsilon}_l\right)\right) \hat{\boldsymbol{\beta}} \\
&= \hat{\boldsymbol{\beta}}^T \left(\mathrm{Cov}(\mathbf{b}_{d(j)}, \mathbf{b}_{d(l)}) + \mathrm{Cov}(\boldsymbol{\varepsilon}_j, \boldsymbol{\varepsilon}_l)\right) \hat{\boldsymbol{\beta}} \\
&\mathrm{Cov}(\boldsymbol{\varepsilon}_j, \boldsymbol{\varepsilon}_l) = \begin{cases} \mathrm{Var}(\boldsymbol{\varepsilon}) & \text{for } j = l \\ 0 & \text{otherwise} \end{cases} \\
&\mathrm{Cov}(\mathbf{b}_{d(j)}, \mathbf{b}_{d(l)}) = \begin{cases} \mathrm{Var}(\mathbf{b}) & \text{for } d(j) = d(l) \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
\tag{A5}
$$

For the general case of uncertainty in both inputs, i.e. the predictors and the model parameters, we assume that those components are independent. Then the sum of the two above cases represents the Covariance between two predictions (Eq. A6).

$$
\begin{aligned}
&\mathrm{Cov}(y_j - \hat{y}_j, y_l - \hat{y}_l) \\
&= \hat{\boldsymbol{\beta}}^T \mathrm{Cov}(\boldsymbol{\varepsilon}_j, \boldsymbol{\varepsilon}_l) \hat{\boldsymbol{\beta}} + \hat{\mathbf{x}}_j^T \mathrm{Var}(\hat{\beta}) \hat{\mathbf{x}}_l + \hat{\boldsymbol{\beta}}^T \mathrm{Cov}(\mathbf{b}_{d(j)}, \mathbf{b}_{d(l)}) \hat{\boldsymbol{\beta}}
\end{aligned}
\tag{A6}
$$

The three terms in Eq. A6 represent error due to random uncertainty in predictors, error due to uncertainty in parameters and error due to systematic deviations in predictors.

The generalization to nonlinear models can be done by approximating the non-linear model by a Taylor series at the given predictor values and estimated parameters as in (Wutzler et al. 2008).

Appendix B: Details of the Subsampling Analysis

The individuals of sub-region C-stocks within a growth region were permutated randomly. The subsample contained only the first m individuals of the permutated dataset, with the least m yielding a cumulated area greater or equal the inventories of p_{Area} times the cumulated post 1997 inventory area. The area of the individual at the end of the permutation was decreased so that the cumulated area matched $p_{Area} = 80\%$ of the cumulated post 1997 inventory area.

The resampling analysis was applied only to the growth regions where at least 3 growth sub-regions were present. In addition, we performed a resampling analysis for all growth regions using $p_{Area} = 100\%$. The comparison of the 100% and the 80% scenarios showed that area mismatch added about 0.5 tC/ha/yr to the 95% confidence range of the mean annual rate of C-stock change for the growth region. Similarly, the increase of coefficient of variation (cv) of 2001 carbon stocks between the 80% and 100% scenario was linearly related to the growth regions public forest area. These finding were used to estimate the confidence range also for the growth regions with less than three growth sub-region.