Models in Country Scale Carbon Accounting of Forest Soils

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Countries need to assess changes in the carbon stocks of forest soils as a part of national greenhouse gas (GHG) inventories under the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol (KP). Since measuring these changes is expensive, it is likely that many countries will use alternative methods to prepare these estimates. We reviewed seven well-known soil carbon models from the point of view of preparing country-scale soil C change estimates. We first introduced the models and explained how they incorporated the most important input variables. Second, we evaluated their applicability at regional scale considering commonly available data sources. Third, we compiled references to data that exist for evaluation of model performance in forest soils. A range of process-based soil carbon models differing in input data requirements exist, allowing some flexibility to forest soil C accounting. Simple models may be the only reasonable option to estimate soil C changes if available resources are limited. More complex models may be used as integral parts of sophisticated inventories assimilating several data sources. Currently, measurement data for model evaluation are common for agricultural soils, but less data have been collected in forest soils. Definitions of model and measured soil pools often differ, ancillary model inputs require scaling of data, and soil C measurements are uncertain. These issues complicate the preparation of model estimates and their evaluation with empirical data, at large scale. Assessment of uncertainties that accounts for the effect of model choice is important part of inventories estimating large-scale soil C changes. Joint development of models and large-scale soil measurement campaigns could reduce the inconsistencies between models and empirical data, and eventually also the uncertainties of model predictions.

Keywords decomposition, greenhouse gas inventory, IPCC, national forest inventory, regional and national modeling, soil carbon, soil model
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1 Introduction

According to the UN Framework Convention on Climate Change and the Kyoto Protocol, countries need to include changes in soil and litter carbon pools in their annual greenhouse gas inventory submissions (UNFCCC 1992, UNFCCC 1997). Reliable methods to estimate soil carbon stock changes are needed for reporting, and for the assessment of soil response to changing climate.

The Intergovernmental Panel on Climate Change provides guidelines for conducting these inventories and has ranked approaches from Tier 1 to Tier 3 (IPCC 2003). The Tier 1 approach is the simplest for estimating changes and soil C stocks, requiring only country-specific data on forest land use. For forest lands, this method assumes no change in soil C stocks due to management. If there are changes in soil C stocks associated with other activities in forest lands than only land use, either a Tier 2 or Tier 3 approach is needed. Tier 2 also uses simple empirical relationships that are derived from country-specific data. Tier 3 approaches are completely country-specific, and presumably the most accurate.

The most straightforward way of preparing Tier 3 estimates would be repeated sampling of changes in soil C. However, presently, only a few countries, the UK (Bellamy et al. 2005), Belgium (Lettens et al. 2005a), and Sweden (Ståhl et al. 2004), have soil measurements providing nationwide estimates of soil C stock changes. Establishing such surveys in all countries is unrealistic because of high costs and extensive effort needed to collect the data for nationwide sampling. Costs increase greatly with increasing variation in soil properties, as is often the case in forest soils.

Flux-based measurements of ecosystems provide information on changes in carbon stocks as a whole (see e.g. Baldocchi 2003), but partitioning fluxes into vegetation and soil components requires either modelling of soil carbon dynamics or measuring plant detritus inputs and heterotrophic soil respiration. The present grid of measurement stations is also too sparse for reliable national estimates with flux measurements alone. Regional scaling has been made with satellite measured photosynthetically active radiation (PAR) and models of net ecosystem exchange (NEE), and in conjunction with measurements made from research aircraft (Miglietta et al. 2007).

Changes in soil C stocks can also be estimated across a country by combining input data with process-based models (Ogle and Paustian 2005). This approach is another example of a Tier 3 method, and is the focus of this review paper. The details of this approach vary. For example, Liski et al. (2006) presented a calculation based on aggregated forest inventory data and a dynamic soil model. Post et al. (2001) proposed a combination of process-based models and multiple data sources such as eddy-covariance measurements, forest inventory data, and soil measurements. Lagergren et al. (2006) calibrated ecosystem model Biome-BGC with eddy covariance measurements, and used it in conjunction with forest inventory data to estimate the carbon balance of Swedish forests. Several countries have chosen, and are already using, either a fully or partly process-based modelling approach for the nationwide reporting of changes of carbon in forest soils (UNFCCC 2006).

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A few comprehensive soil model reviews have been published in recent years. McGill (1996) assessed the structure of 10 soil models, and found that the trend was toward kinetic compartmentalization of SOM. Smith et al. (1997) compared performance of nine SOM models against repeated long-term measurement from agricultural, grassland and woodland soils, including some models discussed in this review. Rodrigo et al. (1997) compared temperature and moisture functions of selected models, but only one of those models is included in this study (*SOILN*). Izaurralde et al. (2001) was the only review that compared models for the purpose of selecting the best performing model for a regional application.

All previous model comparisons were done for land-uses other than forests except for two woodland / forestry sites used in Smith et al. (1997). Therefore, our goal was to review existing soil models that are available for the estimation of carbon stock changes in forest soils, providing an overview to scientists and officials involved with national GHG inventories.

The objective of this study is to analyze how different soil carbon models can be applied to estimate short-term changes in soil carbon over large spatial scales. Specifically, 1) we review 7 soil models used for estimating forest soil C stock changes (*Century*, *Forest-DNDC*, *ROMUL*, *RothC*, *SOILN*, *Yasso*, and a statistical model *Forcarb*), 2) we evaluate their applicability at regional scale considering commonly available data sources, and 3) compile references to relevant datasets that could be used for their evaluation.

2 Models Estimating Soil Carbon Fluxes

2.1 Decomposition Process

Forest and agricultural soils differ in many respects; they experience different management/ disturbance regime, and there are differences in their vegetation and biota. Some authors have suggested that different model structures might be needed for forest and agricultural soils (Li et al. 2000, Chertov et al. 2001) but many models have been applied to both types of soil, although some with modified parameterization (Peng et al. 1998, Eckersten et al. 1999, Kätterer et al. 1999, Falloon and Smith 2002, Falloon et al. 2002, Peng et al. 2002, Smith et al. 2006).

Decomposition is mediated mainly by the activity of soil microbes, fungi and fauna, but their specific population dynamics and explicit contribution to decomposition is rarely described in soil models (McGill 1996). A few models provide a very coarse scale description of biological control: *ROMUL* regulates the translocation of SOM between soil layers with soil biota (Chertov et al. 2001), and decomposition in *SOILN* (Eckersten and Beier 1998) and *Q-model* (Rolff and Ågren 1999, Ågren and Hyvönen 2003) is controlled by microbial biomass. Most models assume that the size of the microbial pool does not explicitly restrict decomposition, but rather that decomposition is limited by variables known to be correlated with microbial activity. Smith (2001, 2002) reviews the representation of decomposition processes in different SOM models.

In most models, microbial activity is expressed in the decomposition rates of model pools, which are typically first-order rate constants regulated by variables describing ambient conditions and properties of the soil matrix. Compounds belonging to more stable fractions of SOM require higher activation energies to decompose (Davidson and Janssens 2006). The complexity of degrading compounds creates a continuum of activation energies, which is usually approximated with several pools differing in turnover time. Empirical data and modelling studies also imply that the temperature effect on decomposition cannot be adequately approximated with only one soil pool (Kätterer et al. 1998, Davidson et al. 2000, Knorr et al. 2005, Davidson and Janssens 2006). All of the models included in this review describe decomposition of SOM with a multi-pool approach (Table 3).

Besides temperature, decomposition of litter or SOM can be affected by several variables, such as topography (mostly via moisture and temperature), parent material and management (Jenny 1941), litter quality, nitrogen or other macronutrients (Melillo et al. 1982, Prescott 1995, Berg 2000), heavy metals (Berg and McClaugherty 2003), and chemical weathering (Sverdrup 1990, Sverdrup et al. 1995). SOM decomposition may also be influenced by chemical or physical protection through occlusion of SOM in complexes with clay mineral or encapsulation within soil aggregates (Oades 1988, Christensen 1996, Elliot et al. 1996, Six et al. 2002), or influenced by drought, flooding or freeze/thaw cycles (Davidson and Janssens 2006).

The complexity of the decomposition process and large uncertainties in empirical data make it difficult to develop a completely accurate model as well as to parameterize exceedingly sophisticated models.

2.2 Process-based Models - Key Factors Affecting Decomposition

Below we describe how the most typical input variables (i.e. temperature, moisture, soil texture and nitrogen) influence the decomposition process as represented in six common models, including *SOILN* (Eckersten and Beier 1998), *RothC* (Coleman and Jenkinson 1996), *ROMUL* (Chertov et al. 2001, Bykhovets and Komarov 2002), *Century* (Parton et al. 1987, Parton et al. 1994), *Yasso* (Liski et al. 2005) and *Forest-DNDC* (Li et al. 2000, Stange et al. 2000). The minimum required input information needed by the model users is presented in Table 1, and the model-specific influences on the decomposition process are described in Table 2. Model initialization is also discussed due to its importance for estimating accurate trends.

2.2.1 Temperature

In all revieved models, temperature affects a rate modifier that multiplies the decomposition rates of one or several compartments. Main differences among the models arise from use of air or soil temperature as the input data, exact formulation of the temperature models, and their time steps.

In *SOILN*, daily soil temperature of each soil layer is simulated with the water and heat model *CoupModel* (Jansson and Karlberg 2002) using information of daily air temperature and global radiation. The simulated soil temperatures are used as driving variables to calculate decomposition rates. In *SOILN* there are three alternative functions to describe the effect of soil temperature on decomposition, i) the Q_{10}, ii) the Q_{10} after threshold, and iii) the Ratkowsky functions (Ratkowsky et al. 1982). The Q_{10} function, originally introduced by van 't Hoff and Arrhenius in late 19th century, implies that for each 10 degree increase in temperature, decomposition rates increase with the Q_{10} factor (Lloyd and Taylor 1994). The Q_{10} after threshold means that the Q_{10} relationship is applied at temperatures higher than a certain threshold, commonly 0 to 5 ˚C.

Forest-DNDC uses daily minimum and maximum air temperature as inputs and implements an O'Neill response function to describe the effect of temperature on decomposition (Stange 2007). This function yields an exponential increase in decomposition at lower temperatures ranges, but it has a distinct temperature optimum and a sharp decrease at higher temperatures. The effects of moisture and temperature on decomposition are combined by multiplication in many decomposition models response functions, including *Forest-DNDC* (see e.g. review by Rodrigo et al. 1997). Moreover, in the *Forest -DNDC* model, the advantage of using a multiplier for moisture and temperature effects on decomposition (i.e., continuity) is combined in a framework to evaluate the most limiting factor for microbial activity (Liebig´s law). This is achieved by adding reciprocal values of the respective response functions for moisture and temperature. Using this approach, the factor most limiting for decomposition (temperature or soil moisture) dominates the relationship (Li et al. 2000, Stange et al. 2000).

In *RothC* (Coleman and Jenkinson 1996), mean monthly air temperature (ºC) is used. Temperature effects are represented as a multiplicative rate modifier on the decomposition of active compartments. The relationship is close to linear between temperatures 10 and 35ºC.

In *ROMUL* (Chertov et al. 2001), forest floor and soil temperatures are used to calculate non-linear rate modifiers for decomposition rates of aboveground and belowground litter portions correspondingly. These soil temperatures can be simulated by the SCLISS generator (Bykhovets and Komarov 2002), which uses monthly air temperature and soil texture parameters as input information. Temperature corrections that depend

Table 1. Minimum required input data according to variables and temporal resolution.

	Yasso	*ROMUL*	*SOILN*	*RothC*	*Forest-DNDC*	*CENTURY*
Time-step	Year	Month, other time-steps also possible	Day	Month	Day, part of the routines hourly or even sub-hourly	Month (daily version exists)
Litter input data	Amount of non-woody, fine woody and coarse woody litter	Amount of leaves, branches, stem, coarse and fine roots	C and N content of fine litter, course litter, humus and optionally those of microbes	Amount of decomposable and resistant plant material	Plant material transferred during senescence to above and below-ground structural and metabolic litter pools	Similarly to *Forest-DNDC*
Temperature (T) input	Annual average air T or effective T sum, monthly mean T (MMT) to calculate PET (May-Sep)	Mean monthly soil T in organic layer and in mineral layer or mean monthly air T given to SCLISS	Daily soil temperature of each layer as simulated with *CoupModel*	Mean monthly air T	Daily min, max or alternatively average daily temperature	Monthly min and max T, (canopy biomass to calculate soil T)
Moisture input	Monthly precipitation (PPT) May-Sep	Monthly PPT and hydrological soil parameters (Bykhovets and Komarov 2002)	Soil moisture content, and soil water flows into and from the different soil layers (i.e. also infiltration and percolation flow). AET/PET as simulated with *CoupModel*	Monthly PPT and PET or open pan evaporation (Smith et al. 2005b, Smith et al. 2006)	Daily PPT, in case of the wetland model (Cui et al. 2005)	Monthly PPT from rainfall and snow, as well as irrigation inputs of water and losses from evapotranspiration, runoff and ground-water flow
Texture input	–	Clay content (ROMUL). Loam and sand (SCLISS soil weather generator)	Hydraulic properties either measured or from a database (Jansson and Karlberg 2002)	Clay content	Clay content	Sand, silt and clay content
N input	–	N deposition data	N deposition and fertilization, initial N content of different plant parts	–	N deposition and fertilization	N deposition and fertilization, organic amendment N inputs
Nutrients (excl. N)	–	–	–	–	–	P,S
Initialization	Spin-up with steady state assumption or by allocating measured values with some assumptions	Measured or compiled data on SOM and N pools in organic layer and mineral topsoil	Measured C and N content of a mature forest in combination with steady state assumption	Either initialised to measured SOC (Smith et al. 2005b, Smith et al. 2006) or run to equilibrium using estimated inputs	Can be initialised with measured SOC values (Li et al. 2000, Kesik et al. 2005)	Typically initialized with spin-up (several 1000 years) under native vegetation, measured soil characteristics and mean climate for the site

Table 2. Effect of environmental factors on modeled decomposition.

	Yasso	*ROMUL*	*SOILN*	*RothC*	*Forest-DNDC*	*CENTURY*
Effect of T and moisture on modelled decomposition (D)	D-rates adjusted by empirical regression models based on litter bag experiment (Liski et al. 2003)	Empirical regression models based on laboratory data (Chertov et al. 2001)	D-rates calculated using empirical functions and simulated values of daily soil temperature and moisture content	Soil moisture deficit and T affects rate modifier that multiplies the D-rates of active compartments (Coleman and Jenkinson 1996)	Combined moisture and temperature factor used to modify potential D, nitrification or denitrification rates (Li et al. 2000, Stange et al. 2000)	Soil moisture and temperature effects on D modeled with DEFAC relationship (multiplier combining temperature and moisture effects)
Effects of texture on modeled decomposition	–	Affects stable humus mineralization rate and soil moisture in SCLISS	Affects decom position rate, N leaching, denitrification	Affects SOM stabilisation and soil water retention (Coleman and Jenkinson 1996)	Affects aeration, ammonium absorption, water movement and soil moisture, decomposition etc.	Affects moisture availability (Metherell et al. 1993) and decomposition rates (Parton et al. 1987, Parton et al. 1994)
Effect of N on modeled decomposition	–	N dynamics calculated in close interaction with SOM (soil C) dynamics	Dynamically coupled C and N model	–	Explicit N model, algorithm partly derived from *DNDC* (Li et al. 1992, Li et al. 2000)	Dynamically coupled C and N model
Nutrients (excl. N)	–	–	–	–	–	P,S optional sub-models

on forest type are used in some cases due to difference between standard meteorological data and the temperature of forest floor and soil.

In *Century*, soil temperature is modelled as a function of daily maximum and minimum air temperatures, along with the influence of canopy cover on the radiation budget (Metherell et al. 1993). Temperature effects on decomposition vary across a range of temperatures according to empirically-derived relationships from decomposition studies (Parton et al. 1987). The influence of temperature on decomposition is combined with moisture into a single multiplicative factor (Parton et al. 1994).

In *Yasso* (Liski et al. 2005), the effect of temperature on decomposition is described with linear regression models that modify decomposition rates (Liski et al. 2003). The description of the effect of climate on decomposition in *Yasso* is based on geographically derived litterbag data. These regressions are scaled with decomposition rates at the reference location to estimate rate modifiers for decomposition in each model compartment. Temperature variables used in the regression models are mean annual temperature (MAT) or effective temperature sum (DD0).

2.2.2 Soil Moisture

The effect of soil moisture on decomposition in the models is closely related or similar to the effect of temperature on decomposition.

In *SOILN*, daily soil moisture content of each soil layer is simulated with the water and heat model *CoupModel* (Jansson and Karlberg 2002) and they are used as driving variables to calculate decomposition rates. *CoupModel* includes the main processes influencing soil water balance for high latitudes such as precipitation (rain, snow), evaporation (transpiration, interception and soil evaporation) and losses as surface run-off, percolation and drainage. Decomposition rates are assumed to be optimal for a defined soil moisture range. The user defines this range by two threshold values. The first threshold value is around the wilting point (i.e, minimum water content for optimal decomposition rate), while the second threshold is close to saturation (i.e., maximum water content for optimal decomposition rate). The relationship used to estimate the range of limiting water contents can be described with a linear, concave or convex function. The user may also define specific relationships for different processes, such as decomposition and nitrification.

Forest-DNDC uses total daily rainfall as input to calculate soil moisture values (Li et al. 1992, Li et al. 2000, Stange et al. 2000). The modelled amount of rainfall reaching the soil surface is influenced by interception (depending on LAI and rainfall history). Furthermore, winter storage of precipitation as snow is considered. Newer versions also account for surface runoff during heavy rainfall events. Actual soil moisture is calculated using a cascade model with determination of evapotranspiration losses. The agricultural version of *DNDC* uses a linear function to describe the effect of soil moisture on decomposition, but the *Forest-DNDC* version uses a Weibull function, which is allowed to vary from 0–1. These values are combined with a temperature factor to modify decomposition.

In *ROMUL* the monthly weight of moisture of organic horizons and mineral top soil are used to determine the influence or moisture availability on decomposition. If these data are missing, then a statistical soil weather generator SCLISS (Bykhovets and Komarov 2002) can be used to calculate the moisture content based on the total monthly precipitation and hydrological soil characteristics. The calculation of potential evapotranspiration is based on the model that allows one to evaluate potential evapotranspiration using air temperature only (Blaney and Criddle 1950). Moisture of organic horizons affects a non-linear rate modifier for decomposition rates of aboveground litter portions. These dependencies are evaluated from various experiments (Chertov et al. 2001). For belowground litter portions (root litter), the moisture of mineral topsoil is used to modify decomposition rates.

In *RothC* total monthly rainfall (mm) and monthly open pan evaporation (mm) (or PET, mm) (Smith et al. 2005b, Smith et al. 2006) are used to calculate topsoil moisture deficit (TSMD), as it is easier to obtain rainfall and pan evaporation data, from which the TSMD is calculated, than monthly measurements of the actual topsoil water deficit. Decomposition constants of active compartments are multiplied by a rate modifier that depends on cumulative monthly TSMD using a linear function within the typical range of TSMD. Outside the typical range, fixed minimum and maximum values are used.

In *Century*, soil moisture availability is simulated based on input data for rainfall, snow and irrigation, after adjusting for interception within the canopy, and taking into account water losses from simulated storm runoff, groundwater flow, and evapotranspiration (Metherell et al. 1993). Decomposition rates in *Century* are influenced by moisture availability according to a calculation based on the moisture left over from the previous monthly time step and current rainfall divided by PET. This estimation is combined with the temperature influence on decomposition to form a single multiplicative factor (Parton et al. 1994). The factor ranges from 0 to 1, with simulated values below 1 reducing decomposition rates.

In *Yasso*, the effects of moisture on decomposition are included in the same regression models that describe the effect of temperature on decomposition (Liski et al. 2003). These models are used to adjust the decomposition rates of model compartments. Moisture is estimated from a summer drought index calculated by subtracting potential evapotranspiration from precipitation.

2.2.3 Soil Texture

Soil texture has two main impacts on decomposition in the *ROMUL*, *RothC*, *Forest-DNDC* and *CENTURY* models. Texture influences decomposition both by affecting soil moisture through soil water holding capacity and by affecting stabilization of soil organic matter at higher clay contents.

SOILN model doesn't use texture as an input parameter; instead the hydraulic properties like water retention curves, hydraulic conductivity and porosity are explicitly defined for each soil layer in the water and heat model *CoupModel*. The relationships between hydraulic properties and simulated soil moisture content, water flow and soil temperature are described in the *CoupModel* documentation (Jansson and Karlberg 2002). *SOILN* does not take into account the stabilizing effect of soil texture on SOM.

Unlike the other models, *Yasso* does not account for the effects of texture on decomposition. In *Yasso*, it is assumed that most of the short-term changes occur in organic layer where texture is not important, and that the effects of soil texture on soil C dynamics are mostly the result of influences on productivity litter production, rather than from the direct effect on decomposition (Liski et al. 2005).

2.2.4 Nitrogen

The group of the models selected in this study is very diverse with respect to nitrogen modeling. *SOILN*, *Forest-DNDC*, *ROMUL* and *CENTURY* explicitly include nitrogen in their framework coupled with soil C dynamics. These models require nitrogen input data such as atmospheric N deposition and N additions in fertilizers (Table 1). By contrast, nitrogen is ignored in *Yasso* and *RothC*.

In *SOILN*, plant N uptake is controlled by the plant C:N ratios and plant biomass, and growth is limited by N availability. N availability depends on litter quality, decomposition rates, immobilization and external inputs of nitrogen from fertilization, atmospheric deposition and nitrogen fixation. In addition, processes are included that determine losses of N, such as nitrate leaching, and gas emissions of CO_2 and NO_2 (Johnsson et al. 1987, Eckersten and Beier 1998, Eckersten et al. 1998).

In *Forest-DNDC* decomposition of SOM leads to the formation of inorganic ammonium, which can be processed by microbial activity into various reactive forms (e.g., NO_3^-, NO_2^-, N_2O, NO) and also to N_2, volatilized as NH_3 (depended on soil pH), chemo-denitrified (NO_2^-)(depended on soil pH) or leached (depending on soil water flux, texture and plant N uptake). The algorithms used for simulating soil N transformations are described in Li et al. (2000).

In *ROMUL*, the various litter cohorts and soil organic matter pools have different nitrogen contents, which influence the rates of their decomposition. The equations for nitrogen, being a principal limiting factor of plant nutrition in forest ecosystems, are similar to the equations for carbon, but have some additional kinetic parameters, reflecting nitrogen retention in the soil system (Chertov 1990). The total amount of nitrogen available for plants is determined at the ecosystem level and it defines the forest growth. Nitrogen leaching and deposition, as well as gas emissions of CO_2 are included.

In *Century*, carbon uptake is simulated through plant production, and this process is limited by nitrogen availability according to a maximum C:N ratio (Metherell et al. 1993). Thus, nitrogen availability affects the amount of nitrogen taken up by the plant and its subsequent litter quality, as well as decomposition. In turn, nitrogen availability is affected by the rate of decomposition, the amount of nitrogen immobilized, and the external inputs of nitrogen to the model, including atmospheric deposition, biological nitrogen fixation and fertilization events. Parton et al. (1987) and Metherell et al. (1993) provide additional details.

Nitrogen is omitted in *RothC*, but is included in the Rothamsted Nitrogen Model (Bradbury et al. 1993), which has been further developed into the SUNDIAL model (Smith et al. 1996, Smith 2002) and currently being extended for use in organic soils as the ECOSSE model (Smith et al. 2005a).

2.2.5 Model Initialization

For each time step, the values for the state variables of any process model are dependent on parameterization of the processes, inputs to the model, and previous values of the state variables. Consequently, initialisation of model pools is a potentially critical step during the parameterization of a process-based model. The overall importance of initialisation will depend on the question being addressed, the time frame of the study, and the model structure.

The initialisation of model pools with measured data is not straightforward, since model pools do not necessarily represent fractions measurable in the field (Table 4). Initialisation based upon measurements or on a subjective basis can lead to values for state variables that deviate considerably from those that would be achieved by running the model with any plausible combination of input parameters and data for estimating current trends. This can lead to simulations with excessively high loss or gain in carbon (in some models the trajectory can even be chaotic). In many model applications, this behaviour is avoided with a spin-up to a steady-state under native vegetation and mean climate, followed by simulations of the historical land use and management according to survey records and expert knowledge. The assumption of a soil being in a steady state equilibrium with respect to current inputs is likely to be violated in most applications; therefore, historical data is crucial to produce a more realistic initialisation of state variables, and quantify the current trends and short-term changes in soil carbon (Foster et al. 2003). Similarly, this assumption can be violated during the model calibration. The soil C pool of a calibration site(s) may be far from equilibrium, but still the model parameters are calibrated so that the modelled equilibrium state matches the measured C pool. Therefore, a further correction of the parameters and the pools is necessary to avoid the underestimation of century-term soil C accumulation (Wutzler and Reichstein 2007)

RothC can be initialized with spin-up runs and litter input data. In contrast to some of the other models, however, *RothC* can incorporate measurements in this initialisation process. For example, the size of the inert pool can be determined by ^{14}C measurements or using an almost linear relationship between the size of the inert pool and bulk soil carbon stocks (Falloon et al. 1998a). The remaining amount of the measured SOM forms the active pools in the model, which are assumed to be in steady state equilibrium. The *RothC* is run to steady state using an approximate litter input, and is then adjusted to achieve a perfect match with initial bulk soil C using the proportional difference between the measured carbon and that estimated using the first, approximate litter C inputs. The litter input corresponding to measurements (and past conditions) can be used to scale future litter input. *RothC* can also be run in 'reverse mode' to deduct the required input corresponding to measured bulk soil content (Coleman et al. 1997). There are also promising results to determine initial sizes of all carbon pools of the Roth-C model from soil samples using soil fractionation (Zimmermann et al. 2006a) or infrared-spectroscopy (Zimmermann et al. 2006b). However, these procedures have only been tested for agricultural soils at this time.

The most common procedure for initialisation of the *Yasso* model is using spin-up runs with historical litter input. On national level analyses, *Yasso*'s initialization dominated the uncertainty of soil C balance but the use of longer spin-up period clearly reduced its effect (de Wit et al. 2006, Peltoniemi et al. 2006). Other options for the initialisation of the model are to allocate the measured values to model pools with some additional assumptions, or to calculate steady-state values analytically.

For *SOILN*, carbon or nitrogen for the different pools is often initialised by running the model several times for mature forests with stable fluxes (several spin-up runs). As a starting point for the spin-up runs, the sum of C and N of all pools in each layer equals the in-situ measured total sum of C and N. Total C and N is split into fine litter, coarse litter (i.e. woody litter), humus and microbes. Litter dominates in the surface layer(s), while in the mineral soil, litter is assumed to be proportional to root biomass distribution.

For the *Century* model, equations have been developed that provide a first approximation of initial pool sizes based on relationships derived from Burke et al. (1989). However, many applications begin with a spin-up to prevent chaotic behaviour.

The *Forest-DNDC* model is initialised with fixed proportions for each of the pools. These proportions will change over time based on litter input and its C:N ratio. Use of spin-up runs for pool initialisation is also an alternative.

Although the *ROMUL* model can be initialised with spin-up runs and the steady state assumption, the model developers recommend using measured or compiled data on SOM and N pools in organic layer and mineral topsoil (Chertov, personal communication 2006). This is preferred because the pools correspond to soil layers that can be determined in the field. Model developers have compiled a database of initial values by forest site/type, tree species, age class, and area of consideration (Komarov and Chertov 2007). Initial SOM and nitrogen pools of disturbed sites with unknown history can be initialised using forest successional series marked by vegetation composition.

2.3 Statistical Models of Soil Carbon

Another option for estimating changes in soil carbon stocks is to use common forest inventory variables and statistical methods. According the UNFCCC, this is also considered a Tier 3 approach. An example of such a statistical approach to monitor soil carbon stocks is the U.S. *Forcarb* model, described by Smith and Heath (2002). Estimates for soil organic carbon are derived with statistical models from the STATSGO database and forest inventory data using the methodology described by Johnson and Kern (2002) and more recently by Amichev and Galbraith (2004). Fundamentally, soil organic carbon stock changes at the national level are then estimated as a function of change in land cover and forest resources, including forest type and land use (US-EPA 2006).

At the regional scale, many parameters included in process-based soil models (e.g., soil moisture and temperature) co-vary with more general explanatory variables such as forest type, time since disturbance and location (Smith and Heath 2002). Therefore, this approach is likely to provide parallel trends as the process-based models.

3 Regional Soil Carbon Modeling

3.1 Overview on Data Sources

Information on land management, anthropogenic and natural disturbances are key inputs for the models. Small land-use changes may lead to large changes in soil carbon, e.g. land use change from cropland production to forest causes a relatively large increase in soil C stocks compared to many land use and management activities (Post and Kwon 2000). Frequent disturbances induced by forest management (harvests, tillage), and natural disturbances (such as fire, pests) have an important effect on litter input subsequent years after the event (Gärdenäs 1998, Liski et al. 2002, Peltoniemi et al. 2004, Thürig et al. 2005). However, the direct effect of some disturbances on SOM is still controversial (Johnson and Curtis 2001).

National forest inventories (NFI) are carried in several countries over the world to provide representative data on e.g., forest (and other land) area, stand structure, soil type and timber resources (Tokola 2006). Together with land use surveys, and forest management records they provide the underlying input data on anthropogenic activity in forested lands (e.g. USDA 2005). Thus, they provide a valuable source of input data as well as a framework for scaling model results (Vetter et al. 2005). Advantages of NFI data are that typically they cover a large area, in some cases the records span several decades. Temporal resolution, however, is often limited (1–10 years). Changes in the forests resulting from changes in growing conditions (e.g. climate change), harvesting or other disturbances, are measured but the information on the causes remains often limited. Inventory data (with appropriate biomass and biomass turnover models) constitute a representative nation-wide data source for independent soil modules, such as *Yasso* or *RothC*, that are not able to simulate plant production and litter input (see e.g. de Wit et al. 2006, Liski et al. 2006, Smith et al. 2006).

Field measurements of forest inventories may not capture land-use changes or disturbances (thinnings, harvests, fire, etc) with sufficient precision and accuracy. Inventory grids are typically too coarse in comparison with what would be required to detect rare events occurring on limited area. Additional forest management records may be used to supplement NFI data, such as reported harvests or timber purchase statistics.

Remotely-sensed data provide spatial information to improve, for example, inventory estimates on growing stocks and land-use, or to produce information on vegetation cover to derive biomass estimates (Rosenqvist et al. 2003, Tomppo 2006). For example CORINE land cover data or the PELCOM database have been used as a basis for model input data on land use and for up-scaling of measured soil carbon pools (e.g. Vleeshouwers and Verhagen 2002, Lettens et al. 2005a, Lettens et al. 2005b, Schmit et al. 2006) (Meesenburg et al. 1999). Digital elevation models (DEM) could also be used to provide information on topographic position, aspect and slope, which influence temperature and thermal regimes. In addition, edaphic characteristics are required by several models, including soil texture. The use of these data sources is important when plot level data are scaled over larger areas.

3.2 Scaling Model Functions and Input Data

Scaling decisions are a critical component of the inventory development. The resulting operational scale of the process-based model and associated input data will determine the spatio-temporal resolution of a model application, which could range from finely resolved scales such as m^2 and minutes to coarser scales such as 10s of km^2 and decades. In turn, the model application will determine the scale at which soil C stock trends can be interpreted. Interpreting trends at an inappropriate scale can introduce large biases, referred to as ecological fallacies (Clark 2003). Thus, scaling decisions will determine the level of detail available for reporting soil C trends as well as its uncertainty, which will be the basis for informing policy decisions.

Much of the experimental research used to generate models is conducted at relatively small spatial resolutions, such as a forest stand, and short time periods of weeks to a few years. Consequently, models developed from this information can be 1) applied repeatedly at a finer scale (e.g., a stand with daily time step), or 2) the model can be scaled to meet the spatio-temporal domain of the input data (Rastetter et al. 1992, Rastetter et al. 2003).

Repeated application of a model on finer scale often requires scaling of the input data to meet the operational scale of the model. For example, monthly mean temperature may need to be estimated for a daily time step. If scaling is not done, non-linear relationships between input and modeled output may cause biased estimates for the spatio-temporal domain of analysis.

Scaling models to a larger resolution can also create biases. For example, Ogle et al. (2006) demonstrated how increasing the spatial resolution of a model application by using coarser-scale parameters introduced significant bias into estimates of soil C change. Essentially, coarser scale parameters did not adequately represent the underlying regional heterogeneity in their analysis. Consequently, rescaling the model input or the model functions needs to be done with careful consideration of the uncertainties.

In many cases, input data sets are incomplete in time or space, for example, data may be collected only from a small number of plots for short period of time, which are subsequently scaled to a larger region. In these cases, interpolation and extrapolation can be used to estimate input values for missing data with techniques such as geostatistics (Kyriakidis 2001). Errors will inevitably be generated through these scaling exercises, and need to be quantified as part of the uncertainty in model results.

All models are developed for a certain spatio-temporal domain, and subsequently they neglect processes operating on a coarser domain. Increasing the spatio-temporal domain of a model application (e.g., from forest stand to a watershed or larger region) will impose additional processes on a model analysis. Ecosystems are structured in a hierarchical manner and different processes tend to operate and shape the structural patterns found within each level of the hierarchy (O'Neill et al. 1986, Holling 1992). Large scale processes may be considered invariant at a finer scale and treated as a constant if the system is relatively stable (Wessman 1992). For example, erosional processes or leaching are not likely to create significant heterogeneity for soil C stocks in a forest stand, over a short time period, but they will have a significant effect at a larger spatial scale where soil or dissolved organic C is redistributed by wind or water from the original positions to depositional sites (Harden et al. 1999, Liu et al. 2003, Kortelainen et al. 2006). Therefore, results from the models included in this review will likely have additional uncertainties unless they have been further developed or linked with another model representing the larger scale processes.

3.3 Model Selection: Influence of Data Availability

Model selection and development is the first step when developing forest inventories for soil C; this process has been documented thoroughly by Ogle and Paustian (2005). While any of the models included in this review could potentially be used for a national scale analysis, selection is constrained by the availability of model input and evaluation data.

Input data provide detail on spatial heterogeneity in initial conditions as well as associated change over time. These data characterize abiotic and biotic conditions as well as anthropogenic activity, and are fundamental to simulate variation in ecosystem process rates in a large-scale analysis. Although some of the variables affecting litter and SOM dynamics (such as soil texture, proportion of rocks) can be treated as static on each site, their inclusion in a regional analysis is often viewed as critical to extend the application range of the model (McGill 1996).

Fully process-based modeling approaches for ecosystems (see e.g. Chen et al. 2000), which simulate plant production, microbial decomposition and associated processes to provide estimates of changes in all C pools [typical application approach for *Century*, *Forest-DNDC*, *ROMUL* with forest process-based model of growth and element cycling *EFIMOD* (Komarov et al. 2003), and *SOILN*] have a tendency to require more input data than if soil pools are only modelled. For the latter, soil models are used in connection with measured inventory data (typical approach for *RothC* and *Yasso*), and appropriate biomass and biomass turnover models. Ultimately, availability of data dictates the selection between these two approaches.

With detailed forest inventory data, statistical models, such as *Forcarb* in US, may be used to estimate change in soil C stocks. However, this method is not transferable to new conditions without a large measurement effort, and is not typically used for forecasting soil C stock changes because it is predicated on measurements from the past that may not represent future conditions.

3.4 Model Input Data Requirements and Sources of Data

Climatic data from weather monitoring stations are available in most countries. Assuming that microclimatic conditions in (a sample of) forests can be estimated with sufficient precision and that the soil or air temperatures can be adequately estimated by ancillary models, availability of climate data is not likely to limit model selection. The exceptions, however, may be the very detailed information required for several soil layers in *SOILN* and the fine time resolution of the models *SOILN* and *Forest-DNDC*.

Input data on soil texture and nitrogen are more likely to become limitations for model use than climatic data. These data are typically collected in soil surveys and in experimental studies (which may also provide data on soil C). Experimental soil studies at plot level may not provide sufficient coverage, or a link to other input data required by the models.

Soil texture (e.g., clay content) is needed in *Century*, *Forest-DNDC*, *ROMUL*, and *RothC*, and it is most often collected in surveys. However, in forest soils, this property varies widely, and plot averages may be consisted of very few samples. The input soil data requirements are greatest for *SOILN*, including hydraulic properties of each soil layer, but a database of hydraulic properties is provided for various soil textural compositions and land uses (Jansson and Karlberg 2002). If data on soil texture is missing, quality or coverage is limited, or its effect on soil C dynamics is assumed to be negligible, *Yasso* or a similar model can be used that does not require these input data.

The other potential limitation is the availability of nitrogen input data. Surveys usually provide information on average N concentration or C:N ratio in the upper soil layers, which may be used as an input parameter to initialize model nitrogen pools (in *Century*, *Forest-DNDC*, *ROMUL*, *SOILN*). If N data are not directly available, correlation between site fertility and N could allow an approximate estimation of initial N status of soil (Komarov and Chertov 2007). The predictions of C and N with *Century*, *Forest-DNDC*, *ROMUL*, *SOILN* also require information on nitrogen inputs such as atmospheric deposition and fertilization.

Nitrogen fertilization is less common in forest, and data may be available from timber companies to the extent that fertilizers are used. Atmospheric N deposition is reported as NO_3^- and NH_4^+, and these data are typically collected on large scales that could be used as inputs to the models requiring this information (see e.g., on-line data set from Holland et al. 2005).

4 Soil Model Evaluation

Besides availability of input data, the performance of the model can affect the model selection (Ogle and Paustian 2005). Evaluation data are used to test a model's performance, which along with an assessment of composition and sensitivity determine the adequacy of a model for reporting C stock changes (Prisley and Mortimer 2004). Specifically, the performance of soil models is evaluated by comparing simulation results to field measurements of stocks (see e.g. Smith et al. 1997) or fluxes of carbon.

An example of soil model evaluation for regional application is given by (Izaurralde et al. 2001). They selected the model that performed best among six candidates by comparing model simulations to measurements in 7 long-term experiments. They used the selected model for a regional analysis of SOC changes in agricultural soils for two ecodistricts in Alberta, Canada. Besides, for model selection, evaluation of model performance can also be included as a component of the uncertainty, providing information on model error (Falloon and Smith 2003, Ogle et al. 2007).

4.1 Comparability of Simulations and Empirical Data

Soil models vary in their definitions of carbon pools (Table 3) and the depth in the profile that is included in the model estimation of carbon stocks (Table 4). Similarly, soil inventories apply no consistent definitions for sampled soil pools, layers, and depth (Table 5). Testing model predictions will clearly be influenced by varying definitions of measurable depth in soil inventories, which limits the usefulness of data for comparisons with model results (Table 5 and Table 6). Some of the models (*ROMUL*, *SOILN*, *RothC*, *Forest-DNDC*) facilitate comparisons to data of varying depths by allowing for an adjustable simulation depth during parameterization (Table 3).

Simulating distinctive pools of litter, an organic layer, and mineral soil layers could allow for more detailed comparisons with measurements. Some models (*Forest-DNDC*, *ROMUL*, *SOILN*) split decomposing matter to individual pools (litter, organic, and mineral), which also loosely correspond to vertical distribution of SOM. A newer model which was developed from *Century* also includes a separate humified litter pool (Nalder and Wein 2006). In *Forest-DNDC*, distinction has been made due to its importance for soil hydrology, aeration and mineralization: the organic layer is simulated separately from the mineral soil (Li et al., 2000). In *ROMUL* and *Forest-DNDC*, the simulated organic layer pools are equivalent to a measurable pool. Simulating separate pools that are measurable for the litter and organic layer are especially relevant in boreal forests where the forest floor is distinctive and thick. Moreover, turnover rates of organic matter decrease with depth, which means that litter and organic layer contribute the most to the short term changes (Gaudinski et al. 2000). The changes of C in different soil layers may be even in opposite directions (e.g. Bashkin and Binkley 1998, Heidmann et al. 2002, Vesterdal et al. 2002). Even with a model that simulates measurable pools, comparing model results with existing measured data is often complicated because definitions of pools are not consistent, or are not even reported. For instance, among the soil inventories referred in this study, only Bellamy et al. (2005) explicitly mention that they separated the litter from the organic layer.

Attempts have also been made to characterize kinetic pools of SOM by chemical (Berg et al. 1991, Henriksen and Breland 1999), physical fractionation (Oades 1989, Elliot and Cambardella 1991, Cambardella and Elliot 1993, Oades 1993), and infrared spectroscopy (Zimmermann et al. 2006b, Zimmermann et al. 2006a). If these methods prove to be useful in future, they will most likely be model-specific. This may limit their usefulness in evaluating several

Table 3. List of pools in soil models.

	Yasso	*ROMUL*	*SOILN*	*RothC*	*Forest-DNDC*	*CENTURY*
Stand	–	–	Plant: roots, stem, leaves (current year and older) and grains	–	3 vegetation layers (upper-story, understory, ground growth)	Plant production submodel with leaves, fine roots, fine branches, large wood, and coarse roots
Litter	2 (fine woody litter and coarse woody litter)	2 or more: Pools for both above-ground and belowground litter for different compartments of different tree species. Division of senescent plant material into litter pools based on nitrogen and ash contents	1 or 2 per soil layer, 10 to 15 soil layers	2 [resistant and decomposable plant material; RPM & DPM (Coleman and Jenkinson 1996)]	3 per soil layer (very labile litter, labile litter and resistant litter) per layer (Li et al. 2000)	Metabolic and structural pools for both aboveground and belowground litter. Division of senescent plant material into litter pools based on lignin/N ratio
SOM	5 (extractives, celluloses, lignin-like compounds, 2 humus)	6 (or more if litter specified for different tree species)	1 humus pool and optional 1 microbe pool per soil layer (10–15 layers)	3 SOM pools: BIO, HUM & IOM	2 humads and humus per layer	3 SOM pools: active, slow and passive SOM
Pools divided between organic and mineral soil layers?	No	Yes	Yes	No	Yes, 2 layers in organic soil and 2 in mineral soil	No

models as potential candidates for a regional analysis. Fractionation techniques may also be useful for model parameterization (Skjemstad et al. 2004), and initialisation of carbon pools (see also Section 2.2.5).

Overall, soil surveys should provide high quality data and include error assessments of measured stocks and changes (Falloon and Smith 2003). Thus, ideally, all parameters needed to determine soil carbon stocks (C concentration, bulk density and stone content) should be measured to a sufficient soil depth, including the organic layer at forest sites, and with enough repetitions per unit area to represent the spatial variability of soil carbon stocks. As can be seen from in Table 5 and Table 6, parameters like bulk density or stone content are often not directly determined when soil samples have been taken in the past. As a consequence, changes in soil carbon are often only expressed as changes in C concentrations (e.g. Bellamy et al. 2005, Kelly and Mays 2005).

Since models usually predict total amounts of carbon in the soil, C concentrations first have to be converted into stocks before they can be applied for model evaluation. This can be done by using various available pedotransfer functions to estimate bulk densities, which are often based on parameters such as soil texture (usually also only estimated in the field) and C concentrations (Tamminen and Starr 1994). This technique has been applied in a number of large-scale studies on soil C changes in agricultural soils (e.g. Heidmann et al. 2002, Sleutel et al. 2003). The stone content can only be determined in the field although direct measurements are difficult and estimates often erroneous (Eriksson and Holmgren 1996, Wirth

Table 4. Specific model assumptions, limitations and planned improvements.

	Yasso	*ROMUL*	*SOILN*	*RothC*	*Forest-DNDC*	*CENTURY*
Simulation depth	Organic layer + 1 m mineral soil	Organic layer and 1 m mineral soils	Any depth, commonly 1.5–3 meters	Any depth to 1m	Routinely 50 cm, but can be modified to go down to e.g. 1.5 m	20 cm
Limitations	Only for upland forest soils	Only for well or excessively drained mineral soils	Needs a lot of input information, never been applied to peat soils	Only for upland forest soils	Needs a lot of input information	Only for top 20 cm, no peatlands, does not separate the humified portion of the litter from mineral soils (Kelly et al. 1997)
Planned improvements	Modifications to model structure and further development of the climatic dependency	Model for organic soils under development	*CoupModel*: new plant pool coarse roots, new harvest regimes modules	Model for organic soils under development (Smith et al. 2005a)	Version for Mediterranean forest under development	New model using *Century*-based algorithms with humified litter pool separate from mineral soil (Nalder and Wein 2006)
Measurability of pools	Only extractives, celluloses and sums of other pools measurable	Yes, pools or their sums are measurable	No, conceptual pool approach which cannot directly be measured. Total sum of N and C can be compared with measured ones	Yes (Skjemstad et al. 2004, Shirato and Yokozawa 2006, Zimmermann et al. 2006a)	No, conceptional pool approach, cannot directly be measured	Comparison of modeled SOC and measured C in SOM, as well as modeled and measured litter pools possible. Conceptual subpools for litter and soil organic C not directly measurable
Model application / evaluation	(Kaipainen et al. 2004, Peltoniemi et al. 2004, Palosuo et al. 2005, Thürig 2005, de Wit et al. 2006, Liski et al. 2006)	(Smith et al. 1997, Chertov et al. 1999, Chertov et al. 2002, Chertov et al. 2003, Mikhailov et al. 2004, Chertov et al. 2006)	Forest sites (Eckersten et al. 1995, Eckersten and Beier 1998, Beier et al. 2001, Gärdenäs et al. 2003) Evaluation (Tiktak and van Grinsven 1995, Wolf et al. 1996)	Forest sites (Coleman et al. 1997, Smith et al. 1997, Romanya et al. 2000) Regional / continental application (Falloon et al. 1998b, Falloon et al. 2002, Smith et al. 2006)	Upland forest soils (Li et al. 2000, Stange et al. 2000, Butterbach-Bahl et al. 2001). Update for forested wetlands (Zhang et al. 2002, Cui et al. 2005) Tropical forests (Kiese et al. 2005). Model evaluation (Kesik et al. 2005, Miehle et al. 2006)	(Kelly et al. 1997, Smith et al. 1997, Peng et al. 1998)
Uncertainty or sensitivity analysis	(Liski et al. 2005, Peltoniemi et al. 2006, Monni et al. 2007)	Komarov and Chertov 2007)	(Eckersten et al. 2001)	In unpublished reports – available from P. Smith	Most sensitive factor method or Monte Carlo approach (Li et al. 2004), applications (Kesik et al. 2005, Kiese et al. 2005)	None have been published
Transferability of model to new country	Yes (Palosuo et al. 2005, Thürig et al. 2005, de Wit et al. 2006)	Yes (Nadporozhskaya et al. 2006, Shaw et al. 2006)	Yes, see (Eckersten et al. 1995, Eckersten and Beier 1998)	Yes, applied regionally and globally (Post et al. 1982, Jenkinson et al. 1991, Wang and Polglase 1995, Falloon et al. 1998a, Tate et al. 2000, Falloon and Smith 2002, Smith et al. 2005b, Smith et al. 2006)	Yes (Stange et al. 2000, Zhang et al. 2002, Kesik et al. 2005, Kiese et al. 2005)	Yes

Table 5. Repeated soil inventories at regional or country scale and information on data quality. (St: sampling time, Sd: soil depth sampled, Snp: Sample number per Plot, Pn: plot number, Pr: paired resampling, Bd: bulk density, Sc: stone content, Si: soil information as concentration only [g C kg^{-1}] or per area [C ha^{-1}]).

Country/ region	Land use	St	Sd [m]	Snp	Pn	Pr	Bd, Sc	Si
Great Britain[1] England, Wales	forest, grassland cropland	1978, 1994, 1995, 2003*	0.15	25+ per 400 m^2	5662	Y	n	g C kg^{-1}
Denmark[2]	cropland	1987, 1998	0.5	1	336	Y	e	t C ha^{-1}
Belgium[3]	forest, grassland cropland	1990, 2000#	<0.3–>1.0	differs LSU	289 LSU	N	m, e	t C ha^{-1}
Belgium[4]	forest, grassland cropland	1960, 1990, 2000	ca. 0.3	differs per LSU	289 LSU	N	m,e	t C ha^{-1}
Belgium[5] Flanders	cropland	1989–91, 1992–95, 1996–99	0.24 (1.0)	total of 210000 samples	7 APU	N	e	t C ha^{-1}
Belgium[6] West Flanders	cropland	1952,1990, 2003	ca. 0.3	6+ per 50 m^2	116	Y	m,e	t C ha^{-1}
Ireland[7] southeastern part	grassland	1964,1996	0.1	15, 25 per 400 m^2	191, 220	N	n	g C kg^{-1}
Finland southern part[8]	forest	1965–1993	0.1 / 0.3	8–25	54	N	Sc m	g C kg^{-1}
Sweden[9]	forest	1983–1987, 1993–2002 2003–2012	0–0.05, 0.45–0.55, 0.60–0.65	min. soil layers 1, humus 1–5	23100	Y	e,e	t C ha^{-1}

[1] Bellamy et al. 2005, [2] Heidmann et al. 2002, [3] Lettens et al. 2005a, [4] Lettens et al. 2005b, [5] Sleutel et al. 2003, [6] Sleutel et al. 2006, [7] Zhang & McGrath 2004, [8] Tamminen & Derome 2005, [9] (Olsson 1999, Olsson et al. personal communication)
* dependant on land-use, + bulked for C analyses, # for forests only 2000 data available
e: estimated from pedotransfer functions; m: measured; n: no / not determined; y: yes
LSU: landscape units derived from soil and land-cover data; APU: agropedological units

et al. 2004). A practical approach that is easy to apply in inventories is to measure the steel rod penetration depth at several points in a plot and convert it to average stone content with empirical equations (Viro 1952, Tamminen 1991). Since the stone content influences total carbon stocks in the soil by reducing the available fine-soil volume (Leifeld et al. 2005), its exclusion from analyses will lead to erroneous results, especially in stone-rich forest sites (Jia and Akiyama 2005).

4.2 Large-scale Datasets of Soil Carbon Changes

Traditionally, long-term soil C studies focused on agricultural sites, where the soil organic matter content was important as a measure for soil fertility. Many of these studies pre-date the global change debate. The need for monitoring soil C contents across land-uses and large spatial scales only became important during the last few decades with rising interest in quantifying terrestrial carbon sources and sinks (Houghton et al. 1983).

The existing field experiments evaluating changes in European soil C at regional or coun-

Table 6. Repeated forest soil inventories at plot/ecosystem scale (St: sampling time, Sds: soil depth sampled, Snp: Sample number per Plot, Pn: plot number, Bd: bulk density, Sc: stone content, Ol: organic layer, Si: soil information as concentration only [g C kg^{-1}] or per area [C ha^{-1}], Da: at least average temperature and rainfall data available, L: data on annual small litterfall available).

Country/ region	Forest type	St	Ol	Sds [m]	Snp	Pn	Bd, Sc	Si	Da	L
New Zealand[1] Central North Island	*Pinus radiata*, replanted 1997	before and after harvest in 1995/6 and 2000	ni	≤ 2.0	5–30+ per 400m^2	30	m	t C ha^{-1}	ni	ni
Germany[2] Solling	*Fagus sylvatica* and *Picea abies*	1966–1995	y	0.5	3–6+	2–6	ni	t C ha^{-1}	y	y#
United States[3] Camp Branch Watershed	mixed oak	1976, 2002	n	0.5	1	11	ni	g C kg^{-1}	ni	ni
United States[4] southeast	deciduous and pine, regrowth after different harvest techniques	before and ca. 16 years after harvest	y, n	0.3–1.0	varying	4 forest sites, varying plot numbers	m,e	t C ha^{-1}	y/ni	ni◊
United States[5] Lower Michigan	mixed oak, mixed oak-maple, mixed oak-basswood	11 times between 2001–2003	n	0.2	8+ per 450 m^2	3 fertilized/ unfertilized per forest	N	g C kg^{-1}	ni	y

[1] Oliver et al. 2004, [2] Meesenburg et al. 1999, [3] Kelly & Mays 2005, [4] Johnson et al. 2002, [5] Waldrop et al. 2004
* dependant on land-use, + bulked for C analyses, # available from other studies in the same forests, ◊ data on biomass available
e: estimated from pedotransfer functions; m: measured; n: no; y: yes; ni: no information

try scales is scarce overall and forested areas are less represented in these studies than agricultural land. Currently, four regional or country scale studies with repeated measurements for changes in forest soil properties have been reported (Table 5). Large scale surveys are valuable for model evaluation because they provide measurements made with coherent methods over large spatial coverage, which may constitute notable climatic gradients or other variables of importance, which are included in the models.

Although sample numbers per plot are generally limited in these experiments, average changes in subsets of data may be significant allowing for meaningful comparison of model predictions and measurements. Generally, paired re-sampling is necessary to detect change, and it allows smaller sets of data to be compared to simulations. Unpaired sampling with no control plot can lead to a large amount of unexplained variation due to differences in historical management and other factors influencing soil C stocks (Garten and Wullschleger 1999).

A regional study in southern Finland evaluated changes in soil properties based on repeated unpaired sampling of 54 plots during 12–28 years (Tamminen and Derome 2005). The changes in organic layer content (%) were assessed down to 30 cm but changes in carbon (%) were analysed only for organic layer, which decreases the usability of data in evaluation of models that cannot simulate organic layer explicitly. Changes in organic matter content of organic layer ($n_{\text{plots}} = 54$) and 0–30 cm mineral soil ($n_{\text{plots}} = 32$) were significant, as were the changes of N and C:N in organic layer.

Nationwide soil data from Belgium (Lettens et al. 2005a, Lettens et al. 2005b) have been used to report soil C changes with unpaired repeated sampling. The change assessment was based on datasets of a number of individual soil surveys that represented specified landscape unit (LSU). For each LSU the average carbon content was then obtained from all soil profiles within this LSU and compared among different years of data collection (Lettens et al. 2005a, Lettens et al. 2005b). Significant changes in soil C in forested LSUs were rare due to large variability (Lettens et al. 2005a).

In England and Wales, Bellamy et al. (2005) used a repeated paired soil sampling along a grid covering the entire region. However, only the top 15 cm was collected, and most of the land was not forested. Average of changes of soil C in groups of both coniferous and deciduous woodland were significant; group sizes were not reported (Bellamy et al. 2005).

Swedish soil survey provides representative and repeated samples from a grid covering the whole nation (Olsson 1999, Ståhl et al. 2004). Measurements are conducted in conjunction of NFI, and they are concentrated on forest soils where stand growth exceeds 1 m^3a^{-1}; soils under other land-uses are not measured. Third inventory cycle has started in 2003, and is scheduled to end in 2012 (Olsson, M. personal communication 2007).

4.3 Stand-scale Studies

Most studies evaluating changes in soil carbon are on the plot scale, and again forests are less represented than agricultural sites. The meta-database EuroSOMNET, (http://www.rothamsted.bbsrc.ac.uk/aen/eusomnet/expts/eurodb.htm) summarizes information about 110 long-term soil organic matter studies (Powlson et al. 1998, Smith et al. 2002) of which only two were located on forested land: a coniferous forest stand in Russia (started in 1965) and a stand of natural forest regeneration in UK (started in 1883). These data have already been used for comparison with model results of *RothC* and *Century* (Falloon and Smith 2002).

Long-term studies in unmanaged old growth forests are scarce and based on a review of recently published studies, we are only aware of the long-term study at Hubbard Brook experimental forest (Fahey et al. 2005). Fahey et al. (2005) did not detect a significant change in SOM.

Other studies on forest soil carbon mainly focus on afforestation and on other disturbances like harvest, windthrow or fire followed by forest re-growth. It is likely that recently disturbed systems have the largest changes in soil C, and thus they may provide interesting test cases for models. Potential studies providing data for comparison have been summarized in recent literature (Johnson and Curtis 2001, Paul et al. 2002, Waldrop et al. 2004), while some additional experiments are included in Table 6.

4.4 Chronosequences in Model Evaluation

Since it can take decades before changes in soil carbon stocks are detectable (Johnson et al. 2002, Paul et al. 2002), chronosequence studies have often been used instead of time series data to assess management effects across time (Johnson and Curtis 2001). The assumption underlying chronosequence studies is that all sites are comparable and differences among sites are due to the parameter of interest (e.g., stand age, management). Since this assumption cannot be validated, chronosequence studies are associated with an unpredictable error due to site selection.

Chronosequences are likely to be valuable for model comparisons in future, providing that they are successful in isolating the variable of interest as the main determinant of differences between the sites. Johnson and Curtis (2001) and Paul et al. (2002) summarised a number of available chronosequence studies, and more recent studies analyzing the effects of afforestation and management on soil carbon stocks include Vesterdal et al. (2002), Thuille and Schulze (2006), and Mund and Schulze (2006).

4.5 Future Prospects

A number of monitoring programs have started in recent years at various spatial scales and are now waiting for the first re-sampling. CarboEurope IP and NitroEurope IP may provide data for model comparison at the plot scale in the near future. A variety of model input parameters are being measured and intensive soil analyses conducted at six European forest sites (http://www.carboeurope.org/, http://www.neu.ceh.ac.uk/). Depending upon the extent, suitability and quality of plot level data (Table 3), these results may be used either for model calibration or testing. The combination of knowledge on the process and calibration in several representative sites from these studies may lead to enhanced predictive power of the models included in this review.

At the European scale, the soil inventory of the International Co-operative Programme (ICP) based on sampling with a grid density of 16 x 16 km^2 has been repeated after ten years following the first sampling. After processing samples collected in 2006, these results will provide a unique large-scale dataset that will likely be useful for model evaluation (BioSoil 2006).

5 Discussion

Development of forest carbon inventories is largely dependent on available data. We reviewed six process-based and one statistical model for estimating soil C stock changes, assessed how they incorporate input data, and listed references to studies that could potentially be used for model evaluation.

The models included in this review have been calibrated and applied in different regions, have been developed to simulate only certain ecosystem types, and require varying level of detail for input data (Table 1 and Table 4). Consequently, the methodology for applying these models in national GHG inventories will be somewhat unique. For example, models incorporating a module for ecosystem production may be used to prepare simultaneous estimates of biomass and litter production, which are dynamically linked to soil processes. Models restricted to simulation of soil processes only, require input data on litter production.

The models with fewer requirements in respect to input data, such as *Yasso* or *RothC*, may be the only option for some countries given their resource availability. Models such as *Century*, *ROMUL*, *Forest-DNDC*, and *SOILN*, may be more accurate due to a greater level of detail represented in their structure. However, the input data requirements may be too great for their application. Regardless, it is recommended that inventory compilers consider and even test multiple models for which the necessary input data are available for their country.

Most of the models in this review are applicable on upland forest soils, while only the wetlands version of *DNDC* has been applied on peat lands (Zhang et al. 2002, Li et al. 2004). In the future, it is anticipated that versions of *RothC* and *ROMUL* will also be available for wetlands (Table 4). If model that is used in the soil C inventory is not applicable on peat soils, an alternative is to use IPCC Tier 1 method with default factors, or possibly the Tier 2 approach with habitat specific emission factors that are obtained with the flux measurements. However, use of same model across all land use categories, would increase the coherency of inventory. For example, change in land-use would not require changing the model, and re-calculating the time series (IPCC 2006).

At present, the number of published data sets that could be used for soil model evaluation is scarce (Table 5 and Table 6), but more measurements will become available in near future. Besides for measurements of soil carbon, evaluation of soil models requires comprehensive data on factors that influence SOM, as well as input and parameterization data. It seems that most of the existing studies provide sufficient information to evaluate only the simplest soil models without the need to use average or assumed values for some input variables. Hopefully, in future, more soil studies and inventories will collect and publish data on ancillary variables such as data on site history, stand description, climate, texture, and nitrogen inputs.

Process-based modelling of soil carbon dynamics can be used to produce soil C change estimates for countries with different resources and levels of input data, since a wide range of models with differing input data requirements exists. Large uncertainties are involved in predicted soil C change estimates, comparisons of predictions between different countries, estimates prepared with different methodologies, and in comparisons to empirical data. Therefore, uncertainties of predicted soil C change estimates should be always assessed. Whenever possible, models and other methods should be developed in parallel.

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