Changes in soil organic carbon

at regional scales:

Strategies to cope with spatial variability

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List of abbreviations

AHS: Airborne Hyperspectral Sensor
ASD: Analytical Spectral Device
ASD_d: ASD data in 'dry' conditions
BD: Bulk Density
BRDF: Bidirectional Reflectance Distribution Function
C: Carbon
CASI: Compact Airborne Spectrographic Imager
CN ratio: Carbon-to-Nitrogen ratio
CV: Coefficient of Variation
GHG: Greenhouse Gases
GLM: Global Linear Model
GPS: Global Positioning System
Gt: Gigaton (10^9 t)
IGN: Institut Géographique National
INS Inertial Navigation System
IS: Imaging Spectroscopy
LS: Laboratory Spectroscopy
LOI: Loss-on-Ingnition
LUC: Land Use Change
LUCH: Land Use Change History
LULUCF: Land Use, Land Use Change and Forestry
LV: Latent Variable
MDD: Minimal Detectable Difference
MIR: Mid InfraRed
Mt : Megaton (10^6 t)
NDVI: Normalized Difference Vegetation Index
NIR: Near InfraRed
PLS: Partial Least Square

PRESS: Predicted Residual Sum of Squares
PS: Portable Spectroscopy
RMSE: Root Mean Square Error
RMSEC: Root Mean Square Error of Calibration
RMSECV: Root Mean Square Error of Cross-Validation
RMSEL: Root Mean Square Error of Laboratory
RMSEP: Root Mean Square Error of Prediction
RPD: Ratio of Performance to Deviation
SASI: Shortwave Infrared Airborne Spectrographic Imager
SD: Standard Deviation
SNR: Signal-to-Noise Ratio
SOC: Soil Organic Carbon
SOM: Soil Organic Matter
SWIR: Short Wave InfraRed
UNFCCC: United Nations Framework Convention on Climate Change
UV: Ultaviolet
VIS: Visible
VNIR : Visible and Near InfraRed

List of publications

[1] Stevens et al. (2006) Detection of Carbon Stock Change in Agricultural Soils Using Spectroscopic Techniques. Soil Science Society of America Journal 70, 844-850. doi:10.2136/sssaj2005.0025

[2] Stevens et al. (2008). Laboratory, field and airborne spectroscopy for monitoring organic carbon content in agricultural soils. Geoderma, in press. doi:10.1016/j.geoderma.2007.12.009

[3] Stevens A. and van Wesemael B. (2008). Soil organic carbon dynamics at the regional scale as influenced by land use history: a case study in forest soils from southern Belgium. Soil Use and Management, in press. doi: 10.1111/j.1475-2743.2007.00135.x

[4] Stevens A. and van Wesemael B. (2008). Soil organic carbon stock in the Belgian Ardennes as affected by afforestation and deforestation from 1868 to 2005, Forest Ecology and Management, submitted

Chapter 1

Introduction

1.1 General introduction

Human activities have directly or indirectly altered the natural carbon (C) cycle in such a way that atmospheric carbon, in the form of carbon dioxide (CO_2) and methane (CH_4), has dramatically increased at levels that have never been attained at least since 650,000 BP as inferred from EPICA[1] ice cores (Siegenthaler *et al*., 2005; Spahni *et al*., 2005). These gases, along with nitrous oxide (N_2O) are the major greenhouse gases (GHG) released by human activities in the atmosphere. The identification of terrestrial C sources and sinks is not only important in the framework of international agreements such as the Kyoto Protocol but also for the development of climate models, the understanding of feedback mechanisms and the prediction of actual and future response of ecosystems to global warming.

The present carbon cycle is shown in Figure 1.1 (reproduced from Houghton, 2007). About 8.3 Gt C yr^{-1} (1 Gt = 10^9 tons) have been released to the atmosphere in the 1990's due to fossil fuel combustion, cement production and land use changes. Only 3.2 Gt C yr^{-1} is actually accumulating in the atmospheric pool, the rest being absorbed back by the oceans and terrestrial ecosystems (see Figure 1.1). Producing an accurate estimation of global carbon budget of the atmosphere is a difficult task. For instance, current state of knowledge still indicates an imbalance between estimates of net terrestrial fluxes of carbon based on land use changes (LUC) and esti-

[1] European Project for Ice Coring in Antarctica.

mates determined by inverse calculations[2], leaving an unexplained residual C sink (Houghton, 2007). This apparent difference may be caused by errors in modelling of the impact of LUC on terrestrial ecosystems or by processes not related to LUC (e.g. forest growth, Houghton, 2007).

Fluxes of C due to LUC are known with an uncertainty of ± 30 % while the uncertainty in the emissions from fossil fuel and cement production are only ± 5 % (Canadell et al., 2007a). Also, in the assessments of fluxes of C, the soil compartment is the pool showing the largest uncertainties (Malhi *et al.*, 1999; Heath and Smith, 2000; Goodale *et al.*, 2002; Nabuurs *et al.*, 2003; Lindner and Karjalainen, 2007). Monitoring fluxes of C between soils and the atmosphere is essential for the evaluation of the role of soils in the global carbon budget and its contribution to global environmental change.

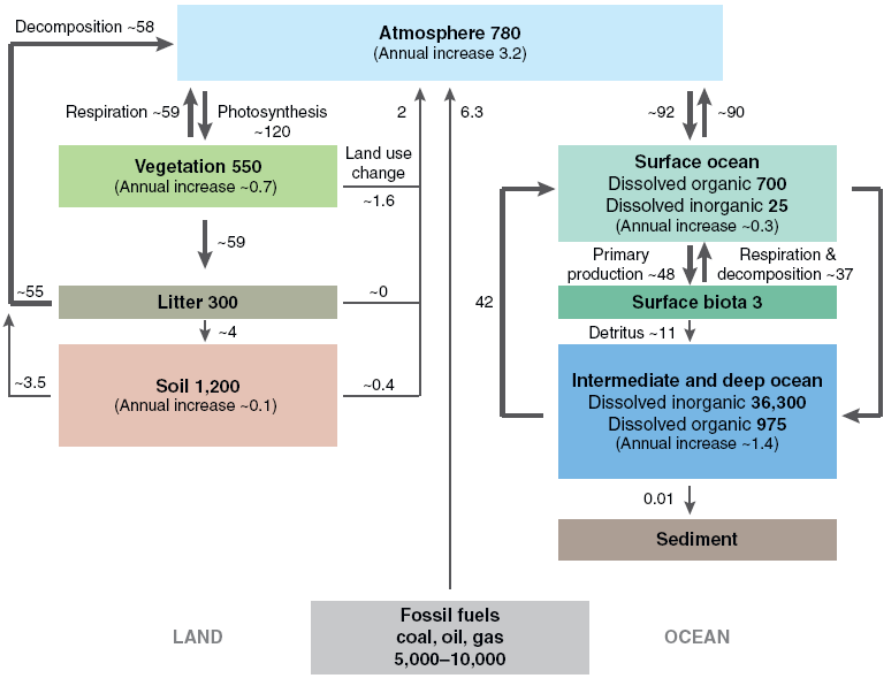

Figure 1.1. The global carbon cycle in the 1990's. Units are in Gt C or Gt C yr^{-1} (Houghton, 2007[3]).

[2] With this method, changes in C in terrestrial ecosystems are assessed by the computing the difference between (i) C emissions by fossil fuel combustion and cement production and (ii) atmospheric increase and oceanic uptake (Houghton, 2007).

[3] Reprinted, with permission, from the Annual Review of Earth and Planetary Sciences, Volume 35 ©2007 by Annual Reviews www.annualreviews.org

Recently, the concern about the role of the soil in the global carbon budget and the effects of Soil Organic Carbon (SOC) decline on soil quality has been incorporated in international treaties. The United Nations have adopted the Kyoto Protocol that allows taking into account, under some constraints, sequestration of carbon into the soil. European Commission has proposed in September 2006 a Framework Directive[4] for protecting soils across the EU. The decline of soil organic matter as one of the 8 threats to soil degradation identified must be tracked in order to delineate risk areas and set up operational measures to mitigate and prevent further problems.

1.2 Setting the problem

There is thus a need in the development of efficient and accurate method to assess SOC stocks and stock changes at various scales: plot/local ($< 10^3$ km^2), regional/national (10^3-10^6 km^2) and continental/global scales ($> 10^6$ km^2). Increasingly, **inventories of SOC stocks and CO_2 fluxes as a result of LUC are requested at the regional/national level** for countries involved in the Kyoto protocol and as input in biogeochemical and regional climate models. The impact of LUC on SOC stocks has been extensively studied at the plot scale (see Post and Kwon, 2000; Guo and Gifford, 2002; Murty *et al*., 2002; Paul *et al*., 2002a). These studies demonstrated that **the capacity to detect and explain temporal changes in SOC is limited by (i) the large spatial variability of SOC content, (ii) the small changes in SOC relative to large baseline SOC quantities and (iii) the slow dynamic of SOC.** While the last two problems can only be tackled by increasing the observation period, the spatial variability is a practical and methodological issue that can be handled with appropriate strategies. **Two possible approaches can be identified to reduce the effects of spatial variability: (i) increasing sampling density and (ii) stratify soil samples based on (similar) initial conditions.**

The first strategy is based on the idea that the area that a sample represents depends on the degree of variability of the soil property of interest. Increasing the number of samples in a given area decreases the confidence limit around the estimate. Usually, long data series must be analysed to detect significant changes. Since analytical methods, such as Loss On Ignition (LOI), wet oxidation (Walkley and Black, 1934) or dry combustion (CN analysers), are generally slow and labour intensive, they may be not appropriate for SOC studies at such scales. The material needs to be first dried, crushed and sieved before analysis. Moreover, these methods may not be reliable. For instance, the Walkley-Black method does not measure all the carbon present in a sample. A correction factor must be applied, which may vary

[4] COM(2006)232

with land use, soil type, sampling depth and climate (Lettens *et al*., 2007). Predicting SOC from LOI may be also challenging because there is no universal calibration equation (Konen *et al*., 2002). **Thus, an efficient alternative to conventional sampling method is needed. Current methods of soil analysis are too expensive and time consuming to meet the amount of quantitative data required for statistical inference in soil monitoring or modelling.**

Modelling (e.g. Falloon *et al*., 2006), inventories (e.g. Lettens *et al*., 2004) intensive re-sampling (e.g. Goidts and van Wesemael, 2007) have been privileged so far to try to capture SOC dynamics at regional scales. Spatial variability in SOC contents is the result of edaphic factors, land use history and management practices. This variability may express itself at various scales and therefore the way to cope with it depends on the scale of the study. At local scale, these factors may be kept constant and the effects of one factor relative to another may be easily extracted. At regional scale, databases generally lack in reproducing biogeochemical trends observed at the local scale (Holmes *et al*., 2004). This is due to the fact that the variability in soil properties observed at the local scale is likely to be small in comparison with the spatial heterogeneity generated by processes acting at broader scales (e.g. climate, geology). Therefore, the correlations between biological, chemical and physical properties of the soil are usually weaker due e.g. to variations in climate and cropping practices (Stenberg *et al*., 1998). Moreover, even if regional soil studies can demonstrate a significant trend in SOC stocks (e.g. Bellamy *et al*., 2005; Lettens *et al*. 2005a), they have often some difficulties to explain observed trends due to a lack in ancillary explicative variables. **We hypothesize that variation in initial soil conditions - specifically differences in land use change history - between parcels preclude the detection of temporal changes in SOC stocks. Moreover, land use change history is one of the key factors that could permit to better explain and predict dynamics of SOC at regional scales**.

1.3 Objectives

The overall aim of this thesis is to investigate strategies to cope with spatial variability of SOC content at regional scales. These strategies will potentially enhance the detection of changes in SOC content and elucidate some of the processes driving SOC dynamics at regional scale.

We propose to evaluate the potential of reflectance spectroscopy in the Visible-Near Infrared (VNIR) and Short Wave Infrared (SWIR) spectral regions as an alternative to conventional methods to determine SOC concentration in agricultural soils. Numerous applications of reflectance spectroscopy have been de-

veloped so far in soil science and particularly for soil carbon measurements (see e.g. McCarty *et al.*, 2002). While it has been demonstrated that SOC can be detected with reasonable accuracy under laboratory conditions, only few studies have investigated the ability of reflectance spectroscopy to produce accurate measurements outside of the laboratory. Hence, several questions about their relevance and accuracy remain open. First, what is the predictive ability of remote- and ground-based spectroscopy (both in the field and in the laboratory) compared to a 'reference' method? Secondly, to which extent the accuracy and stability of the method is influenced by the measurement conditions (soil surface conditions, spectral calibration)? Finally, how VNIR-SWIR reflectance spectroscopy (especially, remote spectroscopy) may improve soil monitoring at regional scales.

Our second objective will be to detect if changes in SOC stocks can be related to land use change history (LUCH) at regional scales. This thesis will further model the dynamic of SOC stocks as influenced by LUC during the last 150 years in a pilot area. It will allow to assess the contribution of soils to past and recent sources and sinks of carbon. We will focus on forest soils since their SOC stocks are known to respond more slowly than agricultural lands to land conversion and hence, LUCH is likely to have a greater impact.

1.4 Outline of the thesis

This thesis is based on articles published or submitted to international peer-reviewed journals.

The institutional and scientific context of the thesis is presented in Chapter 2 ('state of the art'). The most recent literature will be used to demonstrate how and to which extent spatial variability in SOC contents is an issue for regional scales studies. The impact of LUCH on SOC stocks will be addressed together with reflectance spectroscopy (principles, field of applications and methods), as a fast technique to measure SOC.

Chapter 3 and 4 will present the capabilities of VNIR-SWIR reflectance spectroscopy for SOC determination by using several spectral datasets recorded during 2 campaigns in 2003 and 2005 in 3 different study areas. SOC concentrations are predicted from VNIR-SWIR spectra using Partial Least Square Regressions (PLSR). Chapter 3 will describe the methodology and study areas. Then, laboratory, field and remote spectral sensors will be compared. Finally, the potential of reflectance spectroscopy for SOC monitoring will be assessed using the concept of Minimal Detectable Difference. In Chapter 4, the stability of non-laboratory spectroscopic methods

will be explored. This question will be addressed by using a spectral dataset collected under different measurement conditions and study areas.

Chapter 5 and 6 propose to evaluate and model the impact of LUCH on SOC stocks and changes in SOC stocks at regional scales. A study area, known for its complex LUCH since the end of the 18th century, has been chosen as a case study. In chapter 5, a regional soil database is first improved by the reconstruction based on historical maps of the LUCH of each soil profiles. Then, part of this database is resampled to support the view that LUCH may explain an important part of SOC variability at regional scale. Based on the results of chapter 5, chapter 6 will adopt a bookkeeping modelling strategy to assess the contribution of soils to carbon fluxes using well-documented historical records of land use for the period 1868-2005.

Chapter 7 ('Conclusion') gives an overview of the main findings of the thesis. Building on this, research needs will be stressed and some perspectives for further research will be presented.

Chapter 2

Soil organic carbon stocks and fluxes at regional scales: a literature review

Outline

After a brief outline of the institutional context, this chapter will look at the global C cycle, the impact of land use changes and the magnitude and fluxes associated to the carbon stored in the soil pool. Then, the chapter will focus on more specific matters regarding the subject of the thesis. First, the different approaches used to evaluate stocks and fluxes of soil carbon at regional scales will be presented. The chapter will also introduce the concept of soil spatial variability, its extent and how it is reducing our ability to produce accurate regional estimates of stocks and explain fluxes of carbon. Then, two possible strategies to tackle this problem will be discussed: (i) the development of more efficient analysis technique (i.e. reflectance spectroscopy) and (ii) taking into account land use change history.

2.1 The United Nations Framework Convention on Climate Change and the Kyoto Protocol

The United Nations Framework Convention on Climate Change (UNFCCC), one of the milestones in the fight to reduce the effects of climate changes, was formulated during the UN conference known as the "Earth Summit", in June 1992. Its principal objective was to stabilize Greenhouse Gas (GHG) concentration to a level "that would prevent dangerous anthropic interference with the climate system"[5]. During the next fifteen years, 13 "Conference of the Parties" (CoP) were organized and allowed, step by step, to precise the countries' commitments and to put in legal texts the objectives of the Convention. Particularly, the Kyoto Protocol (CoP 3) fixed specific GHG[6] emission reduction targets to industrialized countries ('Annex I Parties'[7]) and finally entered into force on 16 February 2005 after Russia ratified the Protocol[8].

All in all, Annex I Parties must reduce their GHG emissions by 5 % within the commitment period 2008-2012, the reference 'baseline' year being 1990 (art 3.1). The European Union has committed itself to reduce its GHG emissions by 8 %. This objective is shared unevenly between all the Member States (EU-15) according to a *burden sharing agreement*[9]. The Parties must provide data on carbon stocks and emissions that will be used to establish their reference level (art. 3.4) and emissions measures will be realised on the basis of the methodologies developed by the Intergovernmental Panel on Climate Change (IPCC, art. 5).

Despite this international willingness to decrease the anthropogenic impact on climate, it seems that countries' efforts to reduce their emission have been not sufficient. For instance, Belgium has increased its CO_2 emission by ± 6% between the 1990-2003 period while the country was committed to a reduction of 7.5%. In the mean time, CO_2 concentrations in the atmosphere grew at a faster rate from 1.1% yr^{-1} for 1990-1999 to >3% yr^{-1} for 2000-2004 (Raupach *et al.*, 2007).

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[5] Article 2 UNFCCC.
Web page accessed on 01/09/2007. URL: [http://unfccc.int/resource/docs/convkp/conveng.pdf]

[6] The six GHG by the Protocol are the followings: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFC), perfluorocarbons (PFC) and sulphur hexafluoride (SF_6). See Annex A of the Kyoto Protocol [http://unfccc.int/resource/docs/convkp/kpeng.pdf].

[7] The list of the countries involved is in Annex I of the Convention. There are no emission targets for developed countries.

[8] Ensuring that no less than 55 Parties to the Convention, representing 55% of the industrial world's CO_2 emissions in 1990, ratified the Protocol. See Article 25 of the Kyoto Protocol.

[9] See Article 4. Commitments of each country are indexed in Annexe B of the Kyoto Protocol.

2.2 Land Use, Land Use Change and Forestry

Two human-induced sources of carbon emission dominate fluxes to the atmosphere, respectively (i) CO_2 releases from fossil fuel burning (7.9 Gt C yr^{-1} in 2005) and (ii) CO_2 fluxes from land use changes (1.5 Gt C yr^{-1} in 2005; Raupach *et al*., 2007). Recognizing that this latter flux represent a significant part of the global carbon budget, the Kyoto Protocol allowed to include terrestrial sinks[10] of carbon in order to fulfil part of the reduction commitments of the Parties (Article 3.3[11]). Article 3.4[12] mentions the possibility for the Parties to account for the influence of anthropogenic activities on sources and sinks of carbon. Activities reported by Article 3.3 and 3.4 are regrouped under the term Land Use, Land Use Change and Forestry (LULUCF)[13]. These activities may be a cost-effective way to offset emissions. LULUCF have been the object of an IPCC Special Report (Bolin *et al*., 2000) and several methods of measurements have been established (Houghton *et al*., 1996; Penamn *et al*., 2000; Eggleston *et al*., 2006). Annex 1 Parties reported a total net sequestration of 371 Mt C yr^{-1} due to LULUCF in 1990 and 344 Mt C yr^{-1} in 2004, i.e. a decrease of ± 7 % over the period[14].

One of the greatest scientific problem concerning LULUCF activities is related to the accuracy of measurement methods and their verifiability. For some reasons that will be evoked in next sections, it is still difficult to calculate with precision quantities of carbon sequestered or emitted by terrestrial ecosystems (either by soils or vegetation).

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[10] Article 1 UNFCCC " Sink *means any process, activity or mechanism which removes a greenhouse gas, an aerosol or a precursor of a greenhouse gas from the atmosphere.* Source *means any process or activity which releases a greenhouse gas, an aerosol or a precursor of a greenhouse gas into the atmosphere"*

[11] "*The net changes in greenhouse gas emissions by sources and removals by sinks resulting from direct human-induced land-use change and forestry activities, limited to* afforestation, reforestation and deforestation *since 1990, measured as verifiable changes in carbon stocks in each commitment period, shall be used to meet the commitments under this Article of each Party included in Annex I. The greenhouse gas emissions by sources and removals by sinks associated with those activities shall be reported in a transparent and verifiable manner* […]". Even if changes in the soil pool are not explicitly included in Article 3.3 of the Kyoto Protocol, IPCC Good Practice Guidance for Land Use, Land Use Change and Forestry (LULUCF) recommend to include in the assessment of fluxes the contribution of soils (Eggleston *et al*., 2006).

[12] Art 3.4 "*The Conference of the Parties serving as the meeting of the Parties to this Protocol shall, at its first session or as soon as practicable thereafter, decide upon modalities, rules and guidelines as to how, and which, additional human-induced activities related to changes in greenhouse gas emissions by sources and removals by sinks in the agricultural soils and the land-use change and forestry categories shall be added to, or subtracted from, the assigned amounts for Parties included in Annex I*"

[13] Several issues regarding the precise definition of these activities and rules for accounting were not addressed at the time of the Kyoto Protocol and were resolved in the Marrakech Accords (CoP 7).

[14] Data from the UNFCC website
[http://unfccc.int/ghg_emissions_data/predefined_queries/items/3854.php]

2.3 The global C cycle and climate change

Carbon is stored in the Earth in different pools distributed across land, atmosphere and oceans. These pools are closely inter-related and carbon fluxes are continuous between these pools. As stated earlier, human activity has principally altered the global C cycle through fossil fuel burning and land use change (LUC). The radiative forcing[15] of climate between 1750 and 2005 due to increase in GHG concentrations in the atmosphere is estimated at 2.63 W m^{-2}, of which 1.66 W m^{-2} is attributed to CO_2 and 0.48 W m^{-2} to CH_4 and 0.16 W m^{-2} to N_2O (Forster *et al.*, 2007). The concentration in CO_2 increased from 280 ppm in 1750 to 379 ppm in 2005, i.e. 100 times faster than during the last 20.000 years. Compared to the size of those natural reservoirs, the average annual fluxes of CO_2 from land and oceans to atmosphere and the reverse are rather low. However, a small variation in carbon stocks and fluxes can have important climatic consequences. According to IPCC SRES[16], mean temperature would increase by 0.3-6.4 °C and see level rise by 0.18-0.59 m at the end of the current century (Meehl *et al.*, 2007).

2.4 The global C cycle and land use changes

From 8000 BP to the industrial era (1800 AC), deforestation and agriculture use (rice cultivation and livestock breeding) may have been the main drivers of increases in atmospheric CO_2 and CH_4 concentrations (Ruddiman, 2003). Land use changes from 1850 to 2000 added 156 Gt C in the atmosphere, essentially due to deforestation in temperate regions until the mid-20th century and in the tropics thereafter (Houghton, 2003a). Most of the CO_2 emissions (87%) originated from forestland (Houghton, 2003a). If the total emitted carbon in the atmosphere by LUC is sequestered again in the terrestrial biosphere, the atmospheric CO_2 concentration would drop by 40-70 ppm (House *et al.*, 2002). Inversely, a global deforestation scenario would increase CO_2 concentration of 130-290 ppm. In comparison, different scenarios of increase of CO_2 concentration in the atmosphere forecast a concentration of 600-1550 ppm in 2100 (Nakicenovic *et al.*, 2000).

Over the past 150 years, the net terrestrial sink (estimated by inverse methods) has increased while changes in land use have been thought to be a growing source of carbon, leaving an increasing unexplained 'residual' carbon sink of c. 3 Gt C yr^{-1} by the mid-1990s (Houghton, 2007). Recently, a net carbon sink established in Western Europe and North America. In Europe, LUC through 1980-2000 were responsible

[15] The radiative forcing is defined as the "*rate of energy change per unit area of the globe as measured at the top of the atmosphere*" (Forster et al., 2007).
[16] Refers to the IPCC Special Report on Emission Scenarios (Nakicenovic *et al.*, 2000).

for a sink of 200 Mt C yr^{-1} (Houghton, 2003a). According to De Vries *et al*. (2006), the net uptake of carbon by European forest is in the range of 100 to 150 Mt C yr^{-1}, due to a net increase in forest growth. Janssens *et al*. (2003) estimated that European terrestrial ecosystems absorb 135 to 205 Mt C yr^{-1}, i.e. 7-12 % of European anthropogenic emissions. The same net carbon sink was also observed at the country scale (Janssens *et al*., 2005). Cropland-dominated countries tend to be a carbon source in the 1990s while forest/grassland-dominated countries were terrestrial carbon sinks (Janssen *et al*., 2005).

There are two main reasons for the net sink observed in the Northern hemisphere: (i) an enhanced vegetation growth due to factors not related to land use (CO_2 fertilization, nitrogen deposition, climatic variability and interactions between these factors) and (ii) regrowth from past disturbances, changes in land use (e.g. land abandonment) and management as well as forests age structure (Houghton, 2007). European forests are currently intensively managed, rather young, and experiencing a vegetation rebound (Nabuurs *et al*., 1997). According to Heath *et al*. (2005), temperate forests generate a net sink of 205 Mt C yr^{-1} mainly due to forest regrowth. Based on forest inventories, Goodale *et al*. (2002) calculated that 80 % of the Northern hemisphere sink (i.e. 600 to 700 Mt C yr^{-1}) was due to temperate regions affected by fire suppression, agricultural abandonment, and plantation forestry. Similarly, forest regrowth after agricultural abandonment during the late 19^{th} and early 20^{th} century in USA is pointed out as the main drivers explaining the Eastern US carbon sink (Caspersen *et al*., 2000; Albani *et al*., 2006). Although often controversial, nitrogen deposition may have also played an important role in the sequestration of carbon by northern ecosystems (see De Vries *et al*., 2006; Magnani *et al*., 2007). In the future, the terrestrial biosphere in the Northern hemisphere will continue to act as a net carbon sink (Zaehle *et al*., 2007) although its strength is likely to be reduced (for a review of the processes responsible for the current C sink and its dynamic in the future, see Canadell *et al*., 2007b).

2.5 The soil pool

Global SOC stocks are evaluated at 1500-2000 Gt C to a depth of 1m depending on the estimates (Janzen, 2005) and 2344 Gt C in the top 3 m (Jobbágy and Jackson, 2000). Compared to the carbon in the vegetation (550 Gt C) and in the atmosphere (780 Gt C; Houghton, 2007), the soil pool is the largest biospheric pool on which human activities can have a significant impact. Historically, soils have lost between 40 and 90 Gt C (Lal and Bruce, 1999). In the context of global environmental change, the estimation of carbon fluxes between soils and the atmosphere has been the object of a growing number of studies (Ryan and Law, 2005). The contribution of soils to the global C fluxes is uncertain but is generally considered to be less im-

portant than C fluxes due to changes in vegetation cover (Post and Kwon, 2000; Houghton, 2007).

Inventories of SOC stocks have been realized at various scales for Belgium (Lettens *et al.*, 2004), France (Arrouays *et al.*, 1999), Denmark (Krogh *et al.*, 2003), Great Britain (Howard *et al.*, 1995), United Kingdom (Bradley *et al.*, 2005), Brazil (Bernoux *et al.*, 2002), Conterminous United States (Guo *et al.*, 2006), China (Wang *et al.*, 2003; Li *et al.*, 2007) and New Zealand (Scott *et al.*, 2002), Central and Eastern Europe (Batjes, 2002). SOC stocks estimates are also available specifically for forest soils at country scale (e.g. Dupouey *et al.*, 1999; Liski *et al.*, 1997).

2.5.1 Soil Organic Matter

Within any terrestrial ecosystem, the annual gain of energy and matter by the vegetation (NPP[17]) is further distributed in three ways (Swift et al., 1979): (i) a variable portion of the NPP contributes to the net growth of the plant subsystem, depending on the type of ecosystem (mature or immature), (ii) a small part is consumed by herbivores, and (iii) the rest – usually the largest part – enters the decomposition subsystem where micro-organisms (bacteria and fungi) and invertebrate of the soil use dead organic matter (plant and animal residues) as energy (C) and nutrients supply for their own growth. Plant residues are made of several organic compounds such as cellulose, hemicellulose, lignin, protein, sugars, starches, fats and waxes. These compounds are broken down by soil fauna activity into simpler compounds, which can be transformed again through the metabolism of micro-organisms.

The soil organic matter (SOM) represents all organic components in the soil excluding undecayed plant and animal tissues. The bulk of SOM is composed of carbon. According to Schnitzer (1991), SOM can be defined as "*a mixture of plant and animal residues in various stage of decomposition, of substances synthesized microbiologically and/or chemically from the breakdown products, and of the bodies of live and dead micro-organisms and small animals and their decomposing remains*". SOM is thus made of several organic C components (or pools), which differ in nature and origin. These SOM pools may be described according to their chemical properties (humic *vs.* non-humic substances), by their residence time (labile *vs.* stable fraction) or by means of fractionation (Particulate Organic Matter, Free/Occluded fractions, etc…). A review of the different methods available to analyse and characterize the different SOM pools can be found in Cheng and Kimble (2001). SOM can be used in the assessment of soil quality due to its influence on soil physical, chemical and biological properties (e.g. structure, fertility, hydrology,

[17]Net Primary Production, the net flux of carbon from the atmosphere to vegetation per unit of time.

Tiessen *et al.*, 1994; Lal, 2002) and as a generic indicator of ecosystems response (Janzen, 2005).

The rate at which SOM increases or decreases is controlled by the balance between plant input into the soil and the losses through decomposition. The first is function of the NPP, which, in turn, depends mainly on climate (temperature and precipitation). For instance, NPP of tropical forests is twenty times greater than NPP of the tundra (Swift *et al.*, 1979). However, in the meantime, turnover time of soil carbon follows the inverse trend. According to Raich and Schlesinger (1992), carbon in tundra soils is characterized by turnover times of 490 yr and tropical forest show much lower turnover times of 38 yr due to enhanced soil respiration. Decomposition by micro-organisms increases with increasing temperature[18] and precipitation (Raich and Schlessinger, 1992) although an excess of water in the soil may diminish microbial activity due to lower levels of oxygen concentration in the soil (anaerobic conditions). The net effect of climate on SOM stocks depends thus on the relative response of the different processes of SOM production *vs.* SOM destruction (e.g. plant growth *vs.* decomposition). In general, SOM stocks increase with increasing precipitation and for any given level of precipitation, decrease with increasing temperature (Post *et al.*, 1982).

Not only the quantity, but also the quality of plant residues affects the rates of SOM decomposition. Plant residue compounds are characterized by different decomposition rate: sugars and starch are easily decomposed while lignin is very resistant. Moreover, the C:N ratio of plant residues influences strongly SOM turnover rates because the availability of nitrogen in the soil limits decomposition by microorganisms (see e.g. Knops and Tilman, 2000). The processes of C stabilisation are also important factors controlling SOM turnover rates. Indeed, part of the SOM can be protected from rapid degradation through different physical (e.g. occlusion within stable aggregates) or chemical (e.g. adsorption of OM on the surface of clay minerals) mechanisms (see e.g. Oades, 1988; Balesdent *et al.*, 2000; Lutzow *et al.*, 2006). To this regard, clays are well known to promote SOM accumulation for their key role in these mechanisms of SOM protection. Moreover, fine-textured soils contain more SOM due to their greater nutrient and water-holding capacities, which favour plant growth and reduce decomposition.

2.5.2 Factors affecting SOC stocks

At global scale, the distribution of SOC stocks follows broad climatic zone (Post *et al.*, 1982). At local level, carbon stocks depend on the vegetation type, topography,

[18] The temperature sensitivity of soil carbon decomposition is still subject to debate (see Davidson and Janssens, 2007).

soil type (texture, structure, mineralogy) and the local climate and are strongly influenced by human activities (Hendrickson, 2003). The anthropogenic perturbation can be divided in two main impacts: (i) direct impacts comprising LUC and management practices, and (ii) indirect impacts comprising climate change, increasing fertilization by CO_2 and N deposition.

Changes in land use and/or management lead to changes in SOC stocks generally tending towards a new equilibrium status reflecting environmental conditions of a given location (e.g. climate, land use, management, topography and physico-chemical properties of the soil). The effects of land conversion have been reviewed at the plot scale by Post and Kwon (2000), Guo and Gifford (2002) and Murty *et al*. (2002). On average, LUC are responsible for a decrease of the stocks of 9 % (Guo and Gifford, 2002). Stocks increased significantly after the conversion of forests to pasture (+8%), cropland to plantation (+ 18%), cropland to secondary forest (+ 53%), cropland to pasture (+19%). Stocks declined after the conversion from pasture to plantation (-10%), forests to plantation (-13%), forest to cropland (-13%) and pasture to cropland (-59%). One can notice that conversion processes are often not symmetrical, i.e. the carbon lost or gained during a particular conversion will not be exactly balanced by the inverse conversion. This is due to the time scale over which the studies are conducted: in general, processes of C accumulation into the soil are much slower than processes of degradation. Paul *et al*. (2002a) reviewed change in soil carbon following afforestation. They concluded that previous land use, climate and forest type have an important impact on soil C accumulation. To a lesser extent, long-term management regime like stocking, thinning, fertilizer application, fire management and rotation length can modify the rate of C accumulation following afforestation.

It is considered that variations in SOC stocks due to management are greater than variations induced by disturbances linked to climate or atmospheric CO_2 concentration changes (Paustian *et al*., 1996). Forest and agricultural soil management affect SOC stocks by modifying rates of SOM decomposition (e.g. no- or reduced-tillage) and rates of carbon incorporation into the soil (e.g. rotation length) or a combination of both (e.g. fertilizer application). These practices may induce a C sequestration in soils as high as 1.9 t C ha^{-1} yr^{-1} (Freibauer *et al*., 2004). The CESAR model predict a sequestration of 0.15 to 1.5 t C ha^{-1} yr^{-1} in European croplands by the commitment period 2008-2012 after adopting management activities aiming at carbon sequestration, compared to a release of 0.84 t C ha^{-1} yr^{-1} under the business as usual scenario (Vleeshouwer and Verhagen, 2002).

Climate changes are also often invoked as a driver of SOC changes. For instance, Bellamy *et al*. (2005) noted, after re-sampling in England and Wales more than 2000 locations from their National Soil Inventory, consistent carbon losses across land

uses, which suggested a link with climate changes[19]. Zaehle *et al*. (2007) calculated that soil carbon losses in European forests due to global warming could reduce or even offset the benefit of a warmer climate and increasing concentration of CO_2 for NPP. The response of SOC to further environmental changes is also to some extent related to the global N cycle since several terrestrial ecosystems (mostly forest lands) are limited by N availability. However, the study of Hagedorn *et al*. (2001) suggests a negligible impact of CO_2 enrichment and N deposition on C sequestration in forest soils.

2.5.3 The potential of soils to sequester carbon

Considering the historical release of soil carbon, there is a potential of sequestration in forest soils through better management practices, afforestation and reforestation schemes (Johnson, 1992; Lal, 2001; Lal, 2005). Huntington (1995) demonstrated that soil carbon sequestration rates following conversion of abandoned cropland continue at their maximum rates at least for 70 years. In temperate forest, the accumulation of C on former agricultural fields may last until 40-115 years (McLauchlan, 2006). However, sequestration of carbon into the soil is obviously not unlimited and the impact of these practices lasts in general max. 100-150 years in forest soils and 20-50 years in agricultural soils. The global SOC sequestration potential is 0.9 ± 0.3 Mt C yr^{-1}, giving a cumulative potential of 30-60 Gt C over 25-50 years (Lal, 2004).

2.5.3.1 Forest soils

Smith *et al*. (2006) presented an evaluation of future changes in SOC stocks in EU forests (1990-2100) using the RothC model and different scenarios of change in climate, land use and litter input. Over the next 100 years, carbon fluxes of European forest soils are thought to range from 0.3 to – 4.6 Gt C, depending on climate scenarios (Smith *et al*., 2006). Showing a slight increase in SOC stocks over the 21st century for three of the four climate scenarios, the simulations demonstrated the greater role of age-class structure and future LUC than climate change in the projected stock changes. Using optimistic estimates of afforested/reforested areas in the Northern hemisphere through the 80-90's, Post and Kwon (2000) calculate a rate of SOC accumulation of 110 Mt C yr^{-1}. Overall, the potential of sequestration of atmospheric C in forest soils is small in comparison with the increasing anthropogenic emissions of CO_2

[19] Although this view has been contested, see e.g. Smith *et al*. (2007).

2.5.3.2 Agricultural soils

The potential of SOC sequestration in croplands seems higher than in forests since SOC stocks have been depleted after centuries of agricultural use. Historical carbon losses in cultivated soils are estimated to amount to 40-60 Gt C (Paustian *et al.*, 1997). Globally, agricultural lands have the capacity to absorb 450-600 Mt C yr^{-1} (Lal and Bruce, 1999). The maximum rate of sequestration after adopting improved management practices would be 0.4-0.8 t C ha^{-1} yr^{-1} in humid and cold climates and 0.2-0.4 t C ha^{-1} yr^{-1} in warm and dry climates (Lal *et al.*, 1998). In Europe, a combination of management measures could sequester 2-9 % of annual CO_2 emissions (Smith *et al.*, 1997) although this estimated *potential* would probably not be realized by 2010 (Smith *et al.*, 2005). European Union (EU-15) agricultural soils could realistically sequester 0.16 to 0.19 Mt C yr^{-1} (Freibauer *et al.*, 2004). Sperow *et al.* (2003) calculated that U.S agricultural soils could sequester under better management practices 15 % of the reduction target fixed by the Kyoto Protocol.

2.6 Measuring SOC stocks and fluxes at regional scales

2.6.1 Methods of measurements

2.6.1.1 Accounting methods

This first group of methods is based on average SOC response functions upon LUC and local rates of LUC. These accounting or bookkeeping approaches have been notably applied to estimate changes in SOC stocks of Austria (Gringrich *et al.*, 2006), France (Arrouays *et al.*, 2002) and southern United States (Woodbury *et al.*, 2006) and the entire world (Houghton, 2003a). Global average functions may not be pertinent in a region where substantial climate, texture and management gradients exist.

2.6.1.2 Chronosequence/paired-plot/re-sampling

Chronosequence studies (*e.g.* Vesterdal *et al.*, 2002; Cerri *et al.*, 2003) and paired-plot studies (*e.g.* Martens *et al.*, 2003) operate a time to space substitution assuming similar initial conditions (soil type, topography, climate, land use history) to assess the impact of land use or management changes. Paired studies use adjacent plots of different land use while chronosequences use adjacent plots of different ages. Re-

peated sampling over the same location - or re-sampling - has the main advantage that paired designs are more likely to achieve greater statistical power than those in which independent sampling units are compared (Yanai *et al*., 2003). A wide range in SOC response is generally observed in chronosequence and paired-site studies (Paul *et al*., 2002a; Post and Kwon, 2000; Guo and Gifford, 2002). This variation is attributed to variation in climate, soil type and land use and management history. Lack in consistent initial conditions generates large variability when comparing different studies (Post and Kwon, 2000). Scaling-up SOC stocks and fluxes measured at the plot scale ('bottom up' approaches) may be thus largely inadequate to produce a regional estimate.

Re-sampling at regional scales has been attempted by Bellamy *et al*. (2005) in England and Wales as well as by Van Meirvenne *et al*. (1996) and Goidts and van Wesemael (2007) in Belgium[20]. Due to spatial variability, these studies often collect a large number of samples to observe significant changes in SOC stocks (e.g. Goidts and van Wesemael, 2007).

2.6.1.3 Inventories

Inventory-based approaches have also been used to predict SOC evolution after land use conversion at regional/national scale (Lettens *et al*., 2004 2005ab; Wu *et al*., 2003). Geo-referenced soil profiles are spatially extrapolated to a map with predefined soil/land use combinations. Alternatively, when the number of sample is too small, the approach seeks for relationships between easily identifiable soil and environmental variables and SOC and then distributes the calculated SOC stocks throughout the region (e.g. Leifeld *et al*., 2005). In this kind of studies, the comparison of different land use types under the same soil type forms the basis of the prediction of future SOC change following LUC.

The general applicability of this 'scaling-up' approach is limited by the two following assumptions (Lettens *et al*., 2004): (i) the comparisons must only consider SOC stocks that are in equilibrium and (ii) the estimates reflect current management and climate conditions implying that it is not possible to make dynamic extrapolation and account for future environmental changes (e.g. climate, atmospheric CO_2 concentration, N deposition). The problem associated with assumption (i) is that the information needed to assess whether a particular parcel is at equilibrium or not (among others, land use history) is rarely known. The history of the plots is unknown so that such studies have some difficulties to link observed changes with processes (e.g. Sleutel *et al*., 2007). This results in an underestimation or overestimation of the true effect of LUC on carbon stocks. The error is particularly impor-

[20] A list of all the efforts to monitor soils at national scales throughout Europe can be found in Montanarella *et al*. (2004).

tant if recent LUC occurred and if the system tends towards an increase in SOC stocks (e.g. cropland to forest), a process that is known to be slower than a decrease of SOC (e.g. grassland to cropland). Hence, estimates often show a large uncertainty due to variability in initial conditions, so that the SOC stocks of most soil/land use combinations are not significantly different (Lettens *et al*., 2005a).

2.6.1.4 Modelling

Paustian *et al*. (1997) and Peltoniemi *et al*. (2007a) reviewed the use of models to predict SOC changes and understand SOC dynamics at regional/national scales. Modelling approach and extrapolation based on experimental data may produce different estimates of SOC changes but they are of the same order of magnitude (Falloon *et al*., 2002). They usually integrate SOC measurements at the regional level by linking SOM models with spatial databases. Taking into consideration local conditions in a spatially explicit way has proven to be useful to (i) understand the dynamics of SOC estimates, (ii) make projection of C change under different scenarios (changes in climate, CO_2 fertilisation effect, future pattern of land use) and (iii) locate areas with large change in soil C stocks. For example, Falloon *et al*. (2006) modelled the impact of LUC on SOC stocks in the UK between 1990 and 2000 with an integrated SOM model working with 1 km resolution input datasets (RothCUK).

Models at coarse spatial and temporal resolutions are subject to aggregation errors associated to non-linear responses of SOC to input variables (texture, climate; Paustian *et al*., 1997). Errors between modelled and measured value (% RMSE) using regional default model inputs can be as high as 12-34% compared to 6.8-8.5 % when using locally calibrated inputs (Falloon and Smith, 2003). Falloon *et al*. (2006) evaluated the uncertainty surrounding their estimates to 50-100 % with the largest source of error residing in the estimation of the size and the quality of C input. One of the major sources of error in the prediction of C inputs pointed out by Falloon *et al*. (2006) is the fact that several soils sampled could not be at equilibrium state (as it is assumed in model runs).

Using the FORCARB inventory-based model, Heath and Smith (2000) showed that uncertainties in forest carbon stocks and to a lesser extent uncertainties in carbon fluxes were mainly driven by uncertainties in the soil compartment. Errors in the soil pool are related to uncertainties in initial SOC stocks and their response upon land use, management and other environmental changes (climate, etc…).

2.6.1.5 Uncertainties in the estimates

From the different examples above, one can conclude that the different methods to measure SOC stocks and fluxes at regional scales still show several limitations. On

the one hand, uncertainties surround 'scaling-up' approaches, raising questions whether processes observed at the local scale by field studies applies to other areas or if the carbon content measured at one location can be unequivocally attributed to other land units due to differences in initial conditions. On the other hand, the use of global averages does not take into account spatial variations in SOC fluxes generated by differences in land use history or management practises. This spatial heterogeneity is likely to increase the uncertainties associated with this latter approach. Spatial variability in SOC content is thus clearly limiting our ability to make reliable estimates of SOC stocks and explain SOC fluxes at regional scales.

2.6.2 Spatial variability

Soil spatial variability can be separated into a systematic part for which causal factors can be attributed and a random part for which no causes have been yet established (Wilding and Drees, 1983). Random variability arises also from measurement errors. Systematic spatial variability in soils arises primarily from (i) pedogenetic factors and (ii) land use and management practices. Pedogenetic factors are summarized in the classical equation of Jenny (1941; Eq. 2.1):

$$S = f(CL, O, R, P, T, ...) \qquad \text{(Eq 2.1)}$$

where S is a soil property, function of the climate (CL), organisms (O), relief (R), parent material (P), and time (T). According to this view, soil formation and therefore spatial variability results from a complex combination of these factors (or 'state variables'). Among sites on the same soil, land use, disturbance history and management practices generate also variations in soil properties, as suggested notably by the results of Robertson *et al*. (1993).

Spatial variability is scale-dependent (Conen *et al*., 2004; Lin *et al*., 2005) because soil properties are influenced by driving factors acting at different levels[21]. It must therefore always be compared to the size of the spatial unit for which it is estimated (Burrough *et al*., 1994). Variability affects not only the lateral distribution of soil properties but also its vertical distribution through the profile (e.g. Mollitor *et al*, 1980; Wilding *et al*., 2000). Spatial variability in soils can be quantified and modelled notably by means of multivariate statistics and geostatistics (McBratney *et al*.,

[21] See for instance section 2.5.2

2000). This has lead to the emergence of a relatively recent field in soil science known as pedometrics (Burrough *et al*., 1994).

2.6.2.1 Spatial variability of SOC content

Spatial variability affects stocks as well as fluxes of carbon in the soils. According to the classification of Wilding (1985), SOC has a moderate to high spatial variability (Coefficient of Variation – CV – of 21-41 %; Mulla and McBratney, 2000). The range of the semivariogram[22] of organic matter is on average 112-250 m, i.e. rather long in comparison to other soil properties (Mulla and McBratney, 2000). Similarly to other soil properties, variation in SOC is scale-dependent. For instance, Conen *et al*. (2004) found a logarithmic relationship between relative plot size and relative plot variance in soils carbon stocks. Similarly, Conant and Paustian (2002) found an increasing CV in grassland soils from 39 % at the county scale (Dundy County) to 63 % at the national scale (USA). At the field level, their results indicate CV varying from 13 to 24 %, depending on the sampling design.

Variation in SOC stocks is the product of a combination of environmental factors that have already been mentioned in section 2.5.2. Coefficients of variation are therefore also function of these drivers. For instance, Conant *et al*. (2003), showed that SOC variability was greater in less disturbed sites than in more disturbed sites. Cultivation may induce also a decrease in spatial variability (Paz-Gonzales *et al*., 2000). Shaw and Carter (2002) demonstrated that timber harvesting might increase spatial variability of some properties of southeastern U.S. Piedmont forest soils. Another example comes from the study of Mollitor *et al*. (1980), which found that the properties of 'vertical accretion' soils were less variable than those of 'lateral accretion' soils[23].

Spatial variability in forest soils

A large part of the spatial variability in SOC stocks can be found at the stand level. For example, Homann *et al*. (2001) reported in soils of US Pacific Northwest forest a CV of 27 % among points within plots *vs.* a 31 % CV among all points in the 0-15 cm layer. Conant *et al*. (2003) also found a high micro-plot CV varying from 4.6 to 23.4%. Conen *et al* (2004) reviewed studies reporting CV of carbon in forest soils (23 sites, from 0.001 to 578 ha). CV ranged from 10 to 112 %. As shown by Schöning *et al*. (2006) in a temperate deciduous forest, spatial dependence can be found at a very short distance (< 5 m).

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[22] The semivariogram gives the variance between pairs of sample points as a function of the distance. The range of the semivariogram expresses the length over which spatial dependence exists.

[23] According to Mollitor *et al*. (1980), "*lateral accretion deposits are formed primarily by redistribution of bedload materials during flood flows. Vertical accretion deposits are built up from repeated additions of sediment from overbank flows*".

Carbon spatial variability in forest soils can be attributed to several origins such as soil type (Tan *et al*., 2004), management practices (e.g. Johnson and Curtis, 2001), site history (Koerner *et al*., 1997), topography-related factors (e.g. Thompson and Kolka, 2005) or other environmental gradients (e.g. flooding events, Gallardo, 2003).

Spatial variability in agricultural lands

Spatial variability in SOC contents of croplands was found to be related to tillage (*vs.* no-till; Bricklemyer *et al*., 2005), tillage-induced erosion (Van Oost *et al*., 2005), nitrogen inputs (Bahri and Berndtsson., 1996), plant cover distribution and soil structure (Hook *et al*., 1991; Chevallier *et al*., 2000) or topography (Burke, 1999). Plant species seem to have little influence (Burke, 1999).

Shi *et al*. (2002) estimated the range of the semi-variogram of SOC concentration to be 113-169 m in a temperate grassland. In similar environment, Don *et al*. (2007) found equivalent results i.e. a range of 47-131 m while Cerri *et al*. (2004) estimated the semi-variogram range to be 500+ m in Brazil Amazon pastures. Coefficient of Variation in fields of a single farm in Sweden may be half (23 %) of the variation found over 26 fields spread across Sweden (54 %, Stenberg *et al*., 1998). Van Meirvenne *et al*. (1996) were able to show distinct spatial structures between a region and its sub-regions by looking at semi-variograms of SOC concentrations in Flemish croplands. Fine-scale spatial heterogeneity (< 1m) can occur as well (Solie *et al*., 1999; Amador *et al*., 2001; Stark *et al*., 2004). Bricklemyer *et al*. (2005) discovered that micro-site (10 m^2) variability was greater than within-micro-site variability in wheat fields of Montana. In spite of this, they were able to demonstrate differences among micro-sites showing that SOC varies significantly across an agricultural field. Other authors found little variability in SOC contents in croplands. Lopez-Granados *et al*. (2002) observed for instance a lack of spatial dependence of organic matter in fields of southern Spain. Röver and Kaiser (1999) found a low variability in carbon concentration (CV < 10%) in agricultural field in Germany reflecting homogeneous incorporation of plant residues within the parcel.

2.6.2.2 The Minimal Detectable Difference (MDD)

The measurements of SOC stocks and fluxes must be robust, verifiable and cost-effective, notably in the context of the Kyoto Protocol (Smith, 2004a). Spatial variability has important consequences for the monitoring of SOC over time. For instance, Paul *et al*. (2002a) calculated that the average rate of SOC sequestration following afforestation in the 0-30 cm soil layer equalled 0.86% yr^{-1} after 30 years. Detecting such small variation over a short period time span[24] and extract the signal

[24] As required for instance for the Kyoto Protocol.

of change from the background noise induced by spatial variability require a high sampling density.

Numerous authors paid attention to the detection of SOC changes in forest (e.g. Homann *et al.*, 2001; Conant *et al.*, 2003; Yanai *et al.*, 2003; Schöning *et al.*, 2006), grassland (e.g. Conant and Paustian, 2002), cropland soils (e.g. Wilding *et al.*, 2000; Garten and Wullschleger, 2002; Bowman *et al.*, 2002; Kucharik *et al.*, 2003) and how long it would take to detect a change in SOC stocks (Smith, 2004b). These studies are based on a methodology called 'Power Analysis' and often use the concept of Minimal Detectable Difference (MDD). MDD can be defined as the smallest difference that can be detected between two treatments (Conen *et al.*, 2005, Eq. 2.2):

$$MDD = \sqrt{\frac{s^2 \cdot \Phi^2}{n}} \qquad \text{(Eq 2.2)}$$

where s^2 is the estimate of the variance in the population, n is the sample size, Φ is a tabulated critical value depending on the statistical power desired (Eq 2.3.).

$$\Phi = t_{\alpha,n-1} + t_{\beta,n-1} \qquad \text{(Eq 2.3)}$$

with t the critical value of the student's table, with n-1 degree of freedom, α the type I error rate and β the type II error rate. Since n is not known *a priori*, an iterative method to estimate MDD can be used (Skopp *et al.*, 1995). MDD is based on classical ANOVA design, so that normality is required. When normality is not met, bootstrap methods are privileged (Johnson *et al.*, 1990; Poussart *et al.*, 2004). The number of samples required to detect a given change in SOC stocks can be computed by reverting Eq. 2.2.

Sampling densities depend on the size of the area considered since variability generally increases with scale[25]. Schöning *et al.* (2006) showed that one would need more than 300 samples to detect a change of 10 % in SOC stocks in the 0-0.12 m layer of a 1 ha forested area in Germany. Conen *et al.* (2004) estimated that up to 2415 samples would be needed to detect a change of 5 t C ha^{-1} in a forest plot as small as 0.03 ha. The sampling density required in agricultural lands may be lower because of a smaller variability. Kucharik *et al.* (2003) estimated that 42 paired samples are needed to verify a SOC stock change between degraded soils of a conservation program and benchmark cropland sites. Garten and Wullschleger (2002) calculated that only 16 samples are required to detect a change of 5 t C ha^{-1} in a bioenergy crop plantation (i.e. 10-15% of total SOC stocks). Accuracy and thus the

[25] See section 2.6.2.1.

chance to detect a change are also proportional to the quantity of SOC because there is a general relationship between mean soil carbon stocks and estimated variance (Conen *et al.*, 2004).

From Eq. 2.2, it can be deduced that there are two possible ways to reduce MDD: (i) reduce observed standard deviation and (ii) increase the number of samples. The first solution can be achieved through the definition of efficient sampling designs (e.g. Conant and Paustian, 2002; Ellert *et al.*, 2002) and stratification (e.g. Bricklemyer *et al.*, 2005; Peltoniemi *et al.*, 2007b) or the use of analyses that are able to measure different SOC fractions responding to land use changes (Six *et al.*, 2002; Leifeld and Kögel-Knabner, 2005). The second solution, i.e. an increase in sampling size, may be more problematic. Indeed, MDD between two treatments decreases with the square root of the number of samples, so that for instance decreasing the MDD by a factor 2 requires multiplying sampling size by 4. Therefore, the sampling effort required to achieve a given level of accuracy in the estimates at regional scales is often time consuming and rather expensive. Fast sampling techniques are therefore required to detect significant changes in soil properties. In particular, diffuse reflectance spectroscopy can be a suitable alternative method to rapidly quantify various soil characteristics (see section 2.6.3). Remote spectrometers are able to produce maps of soil properties and therefore it may also constitute an alternative to geostatistics.

2.6.3 Diffuse reflectance spectroscopy

2.6.3.1 Principles

The study of the light reflected by an object to determine its properties is the subject of a discipline named diffuse reflectance spectroscopy. This technique relies on the analysis of spectral reflectance, which can be described as the reflectance as a function of wavelengths. Reflectance is the "radiant power […] reflected from the surface of a system divided by the incident radiant power" (Sheppard *et al.*, 1985). In other words, it expresses the percentage of incident light that is reflected from a surface. Near-InfraRed (NIR) spectroscopy was applied – since its first developments in the 1960's – to various fields of science like food and animal sciences, pharmaceuticals, chemicals, agronomy, textile, etc. (Davis, 1998). To a lesser extent, Visible (VIS) and Mid-InfraRed (MIR) parts of the spectrum have been used as well. The different regions of the electromagnetic spectrum and their spectral ranges are presented in Table 2.1. Several classifications of the spectral regions exist, depending on the field of science (e.g. laboratory spectroscopy or imaging spectroscopy). The classification as defined in Table 2.1 is often used in remote sensing literature.

Every substance possesses its own characteristic spectrum that can be detected by a sensor. This spectrum constitutes a unique 'fingerprint', which is determined by the composition of the object in question. The form of the spectrum in a particular wavelength region depends on the selective absorption of radiations of given frequencies by molecular bonds. The VNIR and Short-Wave Infrared (SWIR) regions are characterised by absorption bands due to overtones and combinations of the fundamental vibrations of bonds C-H, N-H and O-H in the Mid InfraRed (MIR) (Pasquini, 2003).

Table 2.1. Regions of the electromagnetic spectrum

Wavelength	Region	Abbreviation
250 nm		
	Ultraviolet	**UV**
400 nm		
	Visible	**VIS**
700 nm		
	Near-Infrared	**NIR**
1.1 µm		
	Short-Wave-Infrared	**SWIR**
2.5 µm		
	Mid-Infrared	**MIR**
25 µm		

2.6.3.2 Soil reflectance

Ben-Dor *et al*. (1999) and Malley *et al*. (2004) reviewed soil reflectance issues and applications. Only a brief overview on soil reflectance is given here.

Two typical soil spectra are given in Figure 2.1. Soil reflectance in the VNIR range is characterized by absorption bands around 1.4 µm, 1.9 µm and 2.2 µm due to molecules known as 'chromophores' (Ben-Dor *et al*., 1997). If the shape of soil reflectance is relatively homogeneous across soil types in the 400-1000 nm region, the 1000-2400 nm region shows more pronounced differences in spectral shape (Ben-Dor *et al*., 1999). Stoner and Baumgardner (1981) were able to show marked difference in spectral shape between 5 types of soils. In general, soil reflectance decreases with organic matter concentration (Stoner and Baumgardner, 1981; Galvão *et al*., 2001; Kooistra *et al*., 2003).

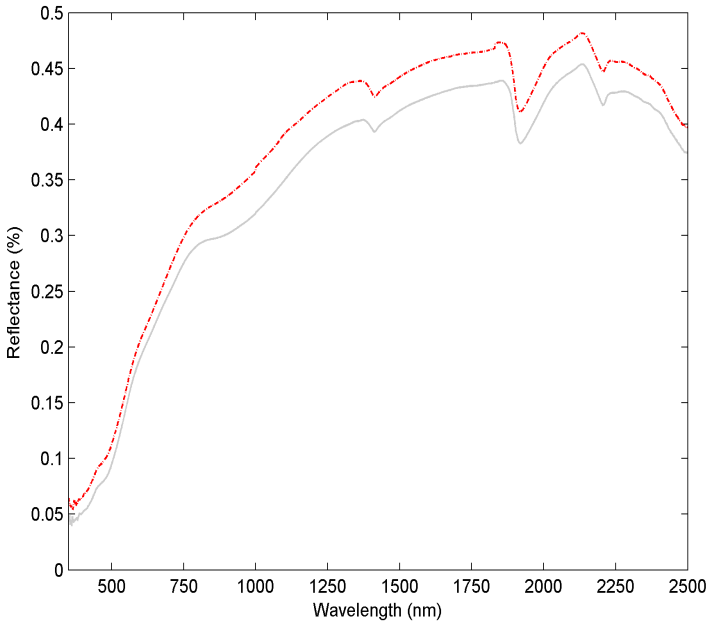

Figure 2.1. Spectral Reflectance of two soils of the same series, with ± 1 % of organic matter (dash-dotted line) and ± 4.5 % of organic matter (plain line).

Although mineralogy (clay, iron oxides), organic matter and water constitute the main soil chromophores (Malley *et al*., 2004), other soil properties such as carbonate concentrations (Ben-Dor and Banin, 1990a), CEC (Kariuki *et al*., 2003), dielectric properties (Middleton *et al*., 2004), soil texture (Sørensen and Dalsgaard, 2005), soil structural crusts (Ben-Dor *et al*., 2003), heavy metal contamination (Kemper *et al*., 2002), salt concentration (Farifteh *et al*., 2007), and soil nutrients (Na, P, K, S, Mg, Fe, Mn, etc.; e.g. Islam *et al*., 2003) have been studied as well. Therefore, reflectance Spectroscopy is often used to measure numerous soil properties simultaneously (Ben-Dor and Banin, 1995; Viscarra-Rossel *et al*., 2006, Cohen *et al*., 2007).

2.6.3.3 Applications

Several applications of reflectance spectroscopy have been developed in soil science. The determination of soil properties is the most evident one but other fields of research have been investigated as well. Fields of application in soil science include:

- *Routine soil analysis*. Reflectance spectroscopy is often invoked to be a viable solution/alternative for several routine agronomic soil analysis (e.g. Cohen *et al*., 2007).

- *Soil mapping.* Along with other new technologies, reflectance spectroscopy can be used to measure soil properties *in-situ* (Gehl and Rice, 2007). Using laboratory (Odlare *et al*., 2005), on-line (Mouazen *et al*., 2007) or remote sensors (Ben-Dor *et al*. 2002; Selige *et al*., 2006), numerous studies focused already on soil mapping. Possible applications included precision agriculture (Thomasson *et al*., 2001; Adamchuk *et al*., 2004; Uno *et al*., 2005) and digital soil mapping (McBratney *et al*., 2003).

- *Soil monitoring.* The potential of reflectance spectroscopy for carbon inventories and the monitoring of changes in carbon concentration in agricultural soils have been investigated by McCarty *et al*. (2002) and Reeves *et al*. (2002).

- *Soil fertility/quality.* Due to its capability to measure several soil properties simultaneously, reflectance spectroscopy has been used to develop soil fertility/quality indices (Cohen *et al*., 2005; McCarty and Reeves, 2006; Vågen *et al*., 2006).

- *Other soil/environmental-related studies.* Reflectance spectroscopy has been applied to several others domains in soil science. Demattê *et al*. (2004) explored soil classification based on reflectance, while Coûteaux *et al*. (2003), Cozzolino and Morón (2006) and Zimmerman *et al*. (2007) attempted to quantify soil organic matter fractions by means of spectroscopic techniques. Shirshova *et al*. (2006) characterized different soil humic acid fractions based on different spectroscopic techniques and Ben-Dor *et al*. (1997) assessed the decomposition process of organic matter using VNIR-SWIR spectra. McMorrow *et al*., (2004) were able to derive physical properties (degree of humification, moisture content) of exposed peatland from remote sensing data. Chabrillat *et al*. (2003) tried to relate reflectance data to erosion modelling in order to construct a global land degradation index.

2.6.3.4 Measurement methods

Spatial variability and the need for a large amount of spatial data for modelling or prediction favoured the appearance in reflectance spectroscopy of new portable solutions. Spectra can now be recorded either in the laboratory or in the field, under uncontrolled environmental conditions. Spectra can also be collected one point at a time (point spectroscopy, e.g. with a contact probe in the laboratory), as an array of measurements (on-line spectroscopy, e.g. the sensor is mounted on a tractor and its position is recorded by a GPS receiver) or as a two-dimensional array of measure-

ments (imaging spectroscopy; e.g. a whiskbroom or pushbroom scanner[26] records the surface aboard a plane or satellite[27]).

In principle, any object reflects the same proportion of light independently of the light source or its environment. Unfortunately, some factors like atmosphere absorption and scattering, surface scattering, illumination geometry and shadowing influence and disturb the measurements in such a way that the reflectance recorded by the sensor differs from the real spectrum despite available correction techniques. Moreover, all things being equal, each sensor will produce different spectra for the same object due to internal characteristics of the instrument (*e.g.* spectral sampling interval, spectral calibration, Signal-to-Noise Ratio[28]), system options (*e.g.* number of scans) or user manipulation. For the purpose of this thesis, we distinguish three different methods of measurement although other classifications are possible: (i) laboratory spectroscopy, (ii) field spectroscopy and (iii) imaging spectroscopy.

Laboratory spectroscopy

Laboratory spectroscopy is the most widely developed technique at the moment. The perspective to replace several routine laboratory analysis by a cheep, non-destructive, non-chemical and fast technique has promoted numerous studies (e.g. Chang *et al.*, 2001; Van Waes *et al.*, 2005; Nanni and Demattê, 2006; Cohen *et al.* 2007). Laboratory spectroscopy does not resolve all problems of classical techniques, as sample collection and preparation are still required. Moreover, the accuracy of the technique may vary with different sampling preparation techniques (Russel, 2003). Questions about calibration/validation requirements remain still open (Brown *et al.*, 2005).

At the plot scale, Udelhoven *et al.* (2003) were not able to develop a satisfactory model for organic carbon and nitrogen. However, at the regional scale, the estimation of SOC was significantly better due to a wider range in the observed concentrations. On the other hand, a large variation in SOC concentration may also be problematic. For instance, Ben-Dor and Banin (1995) used samples with a large variation in organic matter (3-132 g C kg^{-1}) and noticed that, above 40 g C kg^{-1}, the agreement between predicted and observed values was weak. They assumed that soil samples were divided into two groups having different spectral properties: soils with highly decomposed soil organic matter (0-40 g C kg^{-1}) and those with less decomposed organic matter (40-132 g C kg^{-1}). Calibration of spectral data over heterogeneous areas in terms of geology or soil type may also diminish the predictive ability of the

[26] A whiskbroom scanner consists of a single sensor using rotating mirrors to scan the surface. A pushbroom consists of a 2-dimensional sensor array, scanning the landscape directly for the entire width of the image.
[27] Although imaging spectroscopy has now also applications in the laboratory (see Geladi *et al.*, 2004)
[28] In reflectance spectroscopy, a signal to noise ratio (SNR) can be computed for every wavelength as the mean spectrum of several spectra of the same object divided by their standard deviation.

technique (Udelhoven *et al*., 2003). Van Waes *et al*. (2005) showed that dividing samples into groups according to agricultural practices or texture may improve the prediction of soil organic carbon in grassland soils.

Field spectroscopy

Field spectroscopy allows collecting spectra *in-situ*. For this reason, the quality of the spectral measurements depends on environmental conditions at the time of the measurement. Light conditions (quality and stability) and soil surface conditions (roughness, vegetation cover) must be optimal in order to enable measurement replication. Many authors report the development of spectral sensors mounted on tractors, allowing the mapping of soil properties (e.g. Shonk *et al*., 1991; Sudduth and Hummel, 1993; Mouazen *et al*., 2006, 2007). These systems are generally used in precision agriculture to manage the quantity of nutrients inputs into soils (Adamchuk *et al*., 2004. Shonk *et al*. (1991) described a prototype able to produce strong calibration models (R^2 = 0.84-0.95) for soil organic matter sensing in the field. While laboratory tests showed good calibration results for the prediction of soil organic matter (R^2 = 0.89; RMSE in the prediction[29] = 2.3 g C kg^{-1}), Sudduth and Hummel (1993) reported poor results in the field due to the movement of soil under the sensor during data acquisition. Mouazen *et al*. (2007) showed moderate correspondence between maps of C, pH, P and moisture content as measured with an online sensor and ground-truth maps calculated from a dense network of samples analysed with the reference method. Contrary to these authors, Kooistra *et al*. (2003) and Udelhoven *et al*. (2003) use field (point) spectroscopy as a fast tool to monitor several soil properties *in-situ*. Both studies notice a degradation of the accuracy of the method in the field compared to laboratory tests. For instance, Kooistra *et al*. (2003) observed a decrease of the R^2 in the prediction of organic matter from 0.69 under laboratory conditions to 0.45 in the field. Udelhoven *et al*. (2003) explained this decrease in predictive ability by the variability induced by shadowing of the soil surface.

It should be noted that such method of data acquisition measures the reflectance of the first few millimetres of the surface and therefore does not represent the entire soil profile. To this regard, a significant progress has been realized by Ben-Dor et al. (2008) who described a sensing device allowing to collect spectral data through the profile.

Imaging spectroscopy

Remote sensing of soil properties has been attempted using aerial photographs (Chen *et al*., 2000a; Fox and Sabbagh, 2002), multispectral (Galvão *et al*., 2001; Chen *et al*., 2005a; Sullivan *et al*., 2005) or hyperspectral images (Ben-Dor *et al*.,

[29] See Eq. 2.5.

2002; Uno *et al*., 2005; Selige *et al*., 2006). Hyperspectral sensors differ from multispectral instruments in the greater number of wavebands, enabling a precise recording of the spectrum and a detailed analysis of spectral properties of the soil surface. Each pixel provides the full spectrum of the surface in the sensor range, giving the possibility to study spatial distribution of soil properties with a high spatial resolution. The same restrictions as those mentioned for field spectroscopy apply *a fortiori* to imaging spectroscopy. Atmospheric perturbations and geometric problems (geo-referencing and BRDF[30] effects) may challenge the retrieval of the true spectral information. Signal to noise ratios of remote sensors are still much lower than those achieved in the laboratory, so that reliable prediction may be impossible. Lagacherie *et al*. (2007) identified up to nine intermediate stages between the laboratory and airborne measurement during which there is a possible degradation of the performance of the prediction. In their assessment, the factors significantly degrading the performance of the airborne sensor were stoniness, atmospheric attenuation and radiometric calibration.

2.6.3.5 Multivariate analysis

The analysis of chemical data by means of statistical or mathematical models is the subject of the discipline named Chemometrics. A recent review on the use of chemometrics in spectroscopy, its history and main concepts has been published by Geladi (2003). The quantification of the property of interest is usually done with multivariate models. Numerous multivariate techniques such as Multiple Linear Regression (MLR, e.g. Dalal and Henry, 1982; Ben-Dor *et al*., 2002), Artificial Neural Networks (ANN, e.g. Fidêncio *et al*., 2002a; Daniel *et al*., 2003), Regression Trees (RT, e.g. Cohen *et al*., 2005) Principal Component Regressions (PCR, e.g. Chang *et al*., 2001; Islam *et al*., 2003) Partial Least Square Regressions (PLS, e.g. Fidêncio *et al*. 2002b, Reeves and Delwiche, 2003) have been used to relate spectral measures to soil properties. An overview of the standard procedure applied in this thesis to predict SOC concentration is given in next sections.

Spectral pre-treatments

Before the statistical analysis of spectral dataset, several mathematical pretreatments are necessary. These operations transform the spectrum to correct for two problems: (i) change in the signal intensity (or non-linearity) due to scattering and absorbance by the soil surface (Beer's law) and (ii) noise in the signal. Reflectance is converted into absorbance in order to reduce the non-linearity problem (Eq.2.4):

[30] Bidirectional Reflectance Density Functions (BRDF) give the reflectance as a function of viewing and illumination geometry.

$$A = \log_{10}(1/R) = -\log_{10} R \qquad \text{(Eq 2.4)}$$

with A the absorbance and R, the reflectance.

Noise reduction is achieved through standard pre-treatments like differentiation and smoothing. Smoothing is used to diminish random noise around the signal and differentiation to increase the difference between spectral bands. Standard spectral pre-treatments consists of the following steps:

- *First and second derivatives.* Computing 1st and 2nd derivative may be useful to enhance subtle changes in spectral shape and highlight absorption peaks. Moreover, it allows removing the effects of differences in absolute reflectance induced by variation not related to changes in soil properties (e.g. shadowing).

- *Gap derivatives.* First and second derivatives may increase spectral noise. This problem may be partially overcome by the computation of 1st and 2nd *gap* derivatives with different window size. The gap derivative implies that the differentiation is not done between two adjacent points x_{i+1} and x_i but between points x_{i-n} and x_{i+n} with $2n+1$, the window size.

- *Savitzky-Golay's smoothing and derivatives.* Savitzky-Golay's algorithms are widely used in signal pre-processing when the distance between spectral bands is constant. They are similar to a moving window averaging method but have the property to better preserve local peaks in the spectrum. The principle is that, for any window $[x_{i-n} ; x_{i+n}]$ centred on a point in position *i* on the spectrum, a polynomial with a given degree is fitted through the points by least square. The fitted value for the point *i* replaces the measured value. The algorithms involve the use of tabulated coefficient, published by Savitzky and Golay (1964) and further corrected by Steiner *et al.* (1972), instead of computing each time the polynomial. An example of the effect of Savitzky-Golay algorithms is shown in Figure 2.2.

- *Mean centering and variance scaling (normalization).* Their purpose is to normalize spectral data and give the same variance to all the predictors (Bro and Smilde, 2003). Mean centering is obtained by subtraction of the mean spectrum from each spectrum and variance scaling by dividing spectra with the spectral variance. If mean centering is applied, differences in mean values between spectra are not considered in the model. Variance scaling allows emphasizing small variation in the data and to process different spectral dataset jointly by making them comparable. When mean centering is combined with variance scaling, the procedure is called *autoscaling*. Then, each wavelength has a mean value of zero and unit variance, so that they have equal chances to contribute to the model.

- *Scatter corrections.* Difference in particle size between samples may induce different spectral responses due to light scattering. The effects of light scattering are usually minimized by using the Multiplicative Scatter Correction (MSC; Geladi *et al*., 1985), the Standard Normal Variate Transformation and detrending (SNV and DT; Barnes *et al*., 1989).

Partial Least Square Regressions

Partial Least Square (PLS) Regressions is a multivariate method often employed in VNIR spectroscopy. This technique has the advantage to avoid co-linearity problems common in multiple linear regressions when the number of explaining variables (i.e. the spectral bands) is high. A description of the PLS algorithm is given by Geladi and Kowalski (1986a) and an example of its use by Geladi and Kowalski (1986b). PLS regression is a generalization of the concept of Principal Component Regression (PCR; Abdi, 2007). In PCR, a set on Principal Components is extracted from explaining variables (X) and used as regressors of the response (Y). However, no information on Y was exploited to calculate these PC. Therefore, there is no guarantee that they are relevant to explain most of the variation in Y. The PLS approach seeks linear combinations of the predictors, that explain *both* response and predictor variation. The general PLS model has the form (Geladi and Kowalski, 1986a, Eq. 2.5):

$$\begin{aligned} X &= TP' + E \\ Y &= UQ' + F \end{aligned} \qquad \text{(Eq 2.5)}$$

with Y, the matrix of responses, X, the matrix of predictors, T, X-scores, P, X-loadings, E, X-residuals, U, Y-scores, Q, Y-loadings, and F, Y-residuals. The PLS algorithm construct components from X (TP') and Y (UQ') that maximize the covariance between X-scores and Y-scores (Abdi, 2007). These components are called Latent Variables or Latent Vectors (LV). The optimal number of LV in a model is usually determined by minimizing the value of the Predicted Residual Sum of Squares (PRESS) based on *leave-one-out* cross-validation. This procedure is critical as it permits to circumvent the problem of overfitting. When overfitting occurs, the model will produce a very good calibration but will fail to predict samples belonging to the validation set. This is due to the fact that an increase in the number of LV results in a decrease in the variability not accounted for by the model (Pasquini, 2003).

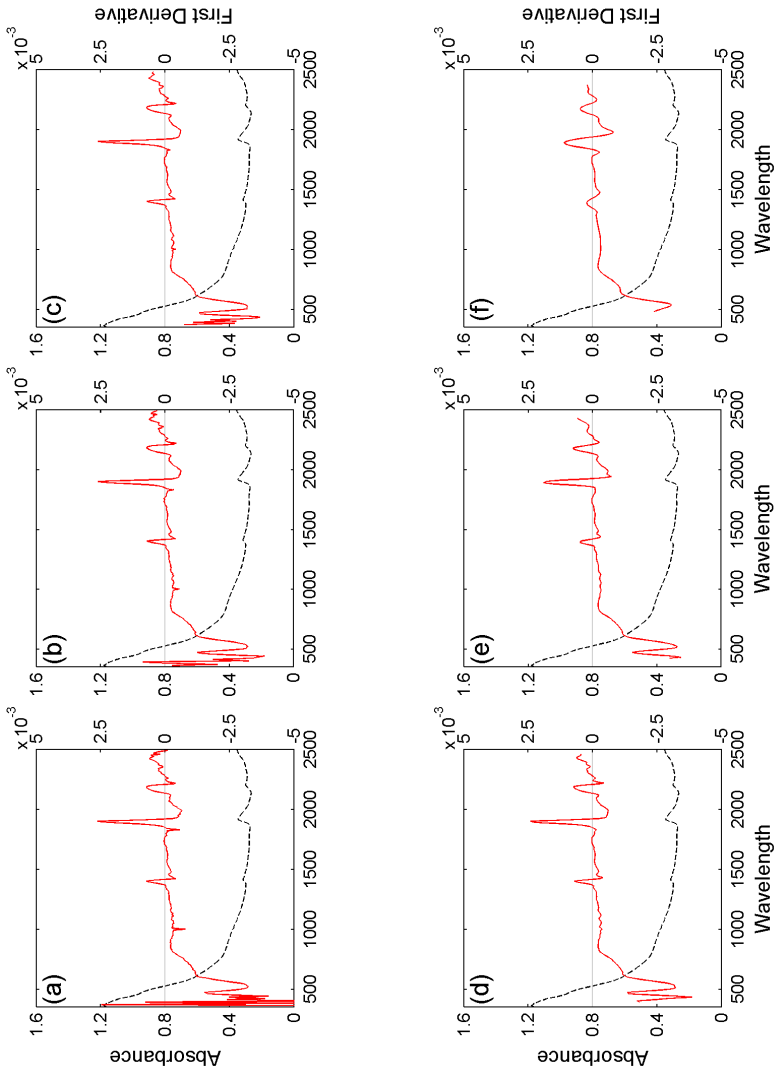

Figure 2.2. Examples of the effect of different pre-treatments on a laboratory spectrum. Absorbance (black, left scale) is converted to the Savitzky-Golay first derivative (red, right scale) with a window size of (a) 5, (b) 9, (c) 17, (d) 33, (e) 65 and (f) 129 points

Outlier detection

In spectroscopic statistical analysis, the detection of outliers during the calibration is an important part of the procedure. An outlier is a sample that appears to be unusual in relation to the remainder of the dataset. Several reasons can explain this incompatibility such as an inaccuracy in the concentration value as measured by the reference method, an error in the manipulation of the spectrometer, a variation in environmental conditions between spectral measurements (angle and height of measurement, level of solar radiation, etc...) or a difference in the sample properties (soil

moisture and roughness, particle size, presence of vegetation, etc...). These samples should be removed in order to construct a robust calibration model accurately describing the population. A calibration model can only predict samples that fall within the same population as the one used during the calibration. It results that the efficiency of a calibration depends on the extent of the calibration set in terms of diversity or spectral characteristics. The detection of outliers in multivariate models may be done either visually by examining X- and Y-scores and residuals plots or automatically. Several strategies have been developed (e.g. Koshoubu *et al.*, 2001; Forina *et al.*, 2004; Chen *et al.*, 2005b; Lillhonga and Geladi, 2005). For instance, the method called "Iterative Predictors and Objects Weighting PLS" (IPOW-PLS) runs the PLS algorithm and calculates samples weights on the basis of prediction residuals in a loop until steady state is attained (Forina *et al.*, 2004).

Validation quality metrics

Two different approaches can be used to validate the model and evaluate its prediction error. Either, a random part of the dataset is selected before the analysis and used to validate the model by confronting measured and predicted values. This approach is called test set validation and the performance of the model is measured by the Root Mean Square Error of Prediction (RMSEP, Eq. 2.6):

$$RMSEP = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \qquad \text{(Eq 2.6)}$$

where $\hat{y}_i$ and y_i are the predicted and the observed values of the sample i in the test set of n samples. The RMSEP is an average prediction error estimate and can be used as an approximation of the Standard Deviation (SD) of the prediction error for all future prediction samples. The RMSEP constitutes a limit beyond which it is impossible to reliably differentiate two samples having a smaller difference in concentration of the substance being analysed. The average error in the calibration set (RMSEC) can be calculated with the same formula.

Alternatively, the cross-validation procedure involves the division of the dataset in several groups, each one being estimated from a calibration on the basis of the remaining samples. In the *leave-one-out* cross-validation procedure, each sample is checked individually against the remaining dataset. The difference between predicted and observed value of each individual pass is determined to calculate the Root Mean Square Error of Cross-Validation (RMSECV). For a small dataset, this method has the advantage to estimate the "true" prediction error more accurately (Ben-Dor and Banin, 1990; Martens and Dardenne, 1998). Accuracy of reflectance spectroscopy depends partly on the accuracy of the reference method (e.g. Morón

and Cozzolino, 2007). The RMSEP overestimates the true prediction uncertainty since it includes measurement errors in the reference values. Therefore, a simple correction for this error leads to the corrected RMSEP ($RMSEP_{corr,}$; Faber *et al.*, 2004; Eq. 2.7).

$$RMSEP_{corr} = \sqrt{RMSEP^2 - RMSEL^2} \qquad (\text{Eq } 2.7)$$

where RMSEL is the Standard Error of Laboratory analyses i.e. the Standard Deviation (SD) of differences between duplicate samples of the reference method. A corrected RMSECV ($RMSECV_{corr}$) can be calculated according to the same rule. RMSEL of the Walkley and Black method (Walkley and Black, 1934) reach maximum values of 1-2 g C kg^{-1} (Colinet, 2005). This latter value is only a rough estimate because RMSEL can vary with the range of SOC concentration measured (usually lower for lower SOC concentration).

A greater variability in the calibration set may increase the ability of the model to characterize diverse samples but, in turn, it may also result in a decrease of the prediction accuracy of the PLS model (McCarty *et al.*, 2002). Therefore, RMSEP depends on the Standard Deviation (SD) of the dataset. The Ratio of Performance to Deviation (RPD) may be computed to interpret and compare the prediction ability of each model. RPD is defined as the ratio between the standard deviation of the reference method against that of the RMSEP or RMSECV. Chang *et al.* (2001) defined three classes of RPD: category A (RPD > 2) are models that can predict accurately the property in question, category B (RPD = 1.4~2) is an intermediate class which regroups models that can be possibly improved, and models falling in category C (RPD < 1.4) have no predictive ability.

2.6.3.6 Prediction of soil organic carbon

Malley *et al* (2004) reviewed the predictive ability of reflectance spectroscopy in the VNIR-SWIR regions in determining different soil properties. Viscarra-Rossel *et al.* (2006) also reviewed the accuracy of reflectance spectroscopy and extended their analysis to the MIR region. No simple generalisation can be drawn from these studies because the accuracy of the method depends on several factors of which sampling preparation (Fystro, 2002; Russel, 2003; Brunet *et al.*, 2007), particle size (due to light scattering, Geladi *et al.*, 1985; Reeves *et al.* 2002), concentration range (Sørensen *et al.*, 2005), measuring conditions, spectral pre-treatments and sensor type[31]. However, it seems that soil organic matter concentration can be determined with a good accuracy compared to other soil properties. As a soil spectrum is the

[31] See Chapter 4.

result of the overlapping of absorption features of several soil components, the relationship between single chemical properties and soil spectra may not be straightforward. Therefore, the prediction of SOC can depend partly on the correlation of SOC with other soil properties. In the study of 11 different soil properties by Cohen *et al*. (2007), soil organic matter was one of the two properties showing RPD greater than 2. Similarly, based on RPD, soil organic matter was ranked in category A by Coûteaux *et al*. (2003) and Chang *et al*. (2001). Table 2.2 gives a summary of the predictive power of VNIR-SWIR-MIR spectroscopy in the determination of SOC concentration. RMSEP varies between 0.09 and 14.3 g C kg^{-1}, with a median of 2.53 g C kg^{-1}. RPD are generally above 2, indicating that spectroscopy can produce reliable models for soil organic carbon (see Table 2.2).

Several problems in the determination of soil organic carbon by means of spectroscopic techniques can be pointed out. Soil organic matter can, in some circumstances, mask the effect of other soil properties on soil reflectance (e.g. Galvão and Vitorello, 1998) because it represents a strong chromophore. However, in other cases, some soil properties may have the inverse effect. For instance, Palacios Orueta (1999) showed that the detection of iron concentration and organic matter depend on the relative proportion of one property to the other and on the sand fraction. Water content may also have an influence on predictions. For instance, Chang *et al*. (2005) produced better predictions when analysing air-dried samples rather than moist samples while Fystro (2002) concluded the inverse. In the study of Kooistra *et al*. (2003), soil moisture and vegetation cover were identified as the main causes of the loss of accuracy between field and laboratory spectra. Soil moisture affects predictions of carbon in two possible ways:

(i) There is a strong negative exponential relationship between moisture content and soil reflectance at each wavelength (Lobel and Asner, 2002). Thus, variability in water content within samples is likely to induce a spectral variability.

(ii) The deep absorption peak that may be related to C and N at 2200 nm is reduced as water content increases (Lobel and Asner, 2002; Whiting et al., 2004).

Clays also play a role in the accuracy of the predictions. Sørensen et al. (2005) noticed for instance that SOC predictions improved when samples in the calibration were split up into two classes of clay contents. Clay minerals may produce different absorption features near 2200 and 2300 nm, the form of which depends on clay type (Chabrillat et al., 2002). Calibrations based on samples having different clay mineralogy may thus produce poor predictions due to spectral variability possibly not related to variation in SOC concentrations.

Table 2.2. Review of the literature on the quantitive prediction of soil organic carbon by means of reflectance spectroscopy. Only studies reporting RMSE in the prediction are included in the table.

Type	Statistical method[a]	Spectral region[b]	Spectral range	RMSE[c]	RPD[d]	Reference
Laboratory Spectroscopy			nm	g C kg^{-1}		
	MLR	NIR-SWIR	1000-2500	0.76	n.a.	Ben Dor and Banin, 1995
	PLS	SWIR	1100-2500	0.38-3.94	2-4.2	Brunet et al., 2007
	PLS	VNIR-SWIR	350-2500	1.4-1.5	1.73-2.62	Brown et al., 2005
	BST	VNIR-SWIR	350-2500	7.90	n.a.	Brown et al., 2006
	PCR	VNIR-SWIR	400-2498	7.9*	2.79	Chang et al., 2001
	PLS	SWIR	1100-2498	6.20	4.2	Chang and Laird, 2002
	PLS	VNIR-SWIR	400-2498	2.53-3.81	1.29-3.16	Chang et al., 2005
	PLS	VNIR-SWIR	400-2500	5.50	n.a.	Chodak et al., 2003
	PLS	VNIR-SWIR	350-2500	2.76	2.12	Cohen et al., 2007
	BRT	VNIR-SWIR	350-2500	3.53	1.65	
	PLS	VNIR-SWIR	400-2500	1.6*	n.a.	Couteaux et al., 2003
	MLR			1.6-2.2	n.a.	Dalal and Henry, 1986
	PLS	NIR-SWIR	1000-2500	0.12	n.a.	Fidêncio et al., 2002a
	ANN	NIR-SWIR	1000-2500	1.45	n.a.	Fidêncio et al., 2002b
	PLS	VIS-NIR	400-2500	5.7-7.4	1.7-2.7	Fystro, 2002
	MLR	SWIR	1603-2598	4.50	2.11	Hummel et al., 2001
	PCR	UV-VNIR-SWIR	250-2500	4.40	1.7	Islam et al., 2003
	PCR	UV-VNIR-SWIR	250-2500	2.20	1.8	Islam et al., 2004
	PLS - GA	VNIR-SWIR	400-2500	10.50	n.a.	Kooistra et al., 2003
	PLS	VNIR-SWIR	400-2500	14.5*	n.a.	Ludwig et al., 2002
	PLS	SWIR	1100-2500	0.721*	n.a.	Madari et al., 2006
		MIR	2500-25000	1.73*	n.a.	
	PCR - PLS	SWIR	1100-2500	3.30	1.97	Martin et al., 2002
	PLS	SWIR	1100-2498	1-2.6	n.a.	McCarty and Reeves, 2001
	PLS	VNIR-SWIR	400-2498	5.50	n.a.	McCarty et al., 2002
		MIR	2500-25000	3.20	n.a.	
	PLS	SWIR	1100-2498	5.4*	n.a.	McCarty et al., 2002
	PLS	MIR	2500-25000	3.4*	n.a.	
	PLS	VNIR-SWIR	400-2500	1.40	n.a.	McCarty and Reeves, 2006
		MIR	2500-25000	0.84	n.a.	
	PLS	VNIR-SWIR	306-1711	4.80	1.97	Mouazen et al., 2007

Table 2.2 (continued)

Type	Statistical method[a]	Spectral region[b]	Spectral range	RMSE[c]	RPD[d]	Reference
	PCR	UV-VNIR-SWIR	250-2500	5.00	2	Pirie et al., 2005
		MIR	2500-22222	5.50	2.6	
		UV-VNIR-SWIR-MIR	250-22222	6.20	2.2	
	PLS	SWIR	1100-2498	1.02*	n.a.	Reeves et al., 1999
	PLS	VNIR-SWIR	400-2500	0.82-2.04	n.a.	Reeves et al., 2002
		MIR	2500-25000	0.71-0.79	n.a.	
	MLR - PLS	SWIR	1100-2500	1.70	n.a.	Salgó et al., 1998
	MARS	VNIR-SWIR	350-2500	2.20	n.a.	Shepherd and Walsh, 2002
	PLS	VNIR-SWIR	400-2500	4.2*	2.4	Sørensen and Dalsgaard, 2005
	PLS	SWIR	1630-2650	2.30	n.a.	Sudduth and Hummel, 1993
	PLS	VNIR-SWIR	400-2500	1.40	1.57	Udelhoven et al., 2003
	PLS	VNIR-SWIR	350-2500	8.40	n.a.	Vagen et al., 2006
	PLS	VIS	400-700	1.80	n.a.	Viscarra Rossel et al., 2006
		NIR-SWIR	700-2500	1.80	n.a.	
		MIR	2500-25000	1.50	n.a.	
		VNIR-SWIR-MIR	400-25000	1.50	n.a.	
	PLS	VNIR-SWIR	1100-2500	3.95	2.9	Van Waes et al., 2005
Field Spectroscopy						
	PCR	NIR-SWIR	780-2500	5.00	n.a.	Christy et al., 2003
	PLS - GA	VNIR-SWIR	400-2500	14.30	n.a.	Kooistra et al., 2003
	PLS	SWIR	1630-2650	4.00	n.a.	Sudduth and Hummel, 1993
Imaging Spectroscopy						
DAIS	MLR	VNIR-SWIR	400-2500	0.09	n.a.	Ben-Dor et al., 2002
Hyperion	MLR	VNIR-SWIR	400-2500	1.45	n.a.	Jaber and Lant, 2007
HyMap	PLS	VNIR-SWIR	330-2500	1.70	n.a.	Selige et al., 2003
HyMap	PLS	VNIR-SWIR	420-2480	2.90	n.a.	Selige et al., 2006
	MLR			2.20	n.a.	
ATLAS	PLS	VNIR-SWIR	400-1250	1.4-2	n.a.	Sullivan et al., 2005
	SI			1.2-2.5	n.a.	
CASI	SMLR	VNIR	408-947	2.85	n.a.	Uno et al., 2005
	ANN			3.43	n.a.	

[a] Statistical method used . PLS = Partial Least Square regression; PCR = Principal components regression; (S)MLR = (Stepwise) Multiple Linear Regression; GA = Genetic algorithms, ANN = Artificial Neural Networks; BRT = Bootstrap Regression Tree, MARS = Multivariate Adaptive Regression Spline.

[b] VIS = visible; NIR = near infrared; VNIR = Visible and Near-Infrared; SWIR = Short Wave Infrared; MIR = mid-infrared.

[c] Root mean square error in the prediction. When applicable, soil organic matter (SOM) concentration in the original study was transformed into carbon concentration (SOM/1.72= SOC). The asterisk (*) indicates that the RMSE refers to Total Carbon, not Organic Carbon.

[d] Ratio of Performance to Deviation (see text for definition)

2.6.4 Land use change history (LUCH)

Studies about the impact of LUCH on SOC stocks are generally based on (i) chronosequences (e.g. Compton *et al*., 1998; Latty *et al*., 2004), (ii) detailed records of land use history of some selected forest stands (*e.g.* Koerner *et al*, 1997; Verheyen *et al*., 1999; Kasel and Bennett, 2007), and (iii) modelling approaches (e.g. Liu *et al*. 2004; Parton *et al*., 2004; Tan *et al*., 2005). Sonneveld *et al*. (2002) were able to show that differences in land use history within soil series had a significant impact on soil organic carbon and its dynamics. Poulton (2003) showed that soils were still accumulating carbon 120 yr after reversion to woodland. Flinn and Marks (2007) observed a recovery within 100 yr of most soil chemical and physical properties in secondary forests compared to less disturbed forests. However, soil organic matter, carbon, and phosphorus presented still lower levels. Latty *et al*. (2004) and Koerner *et al*. (1997) found that the influence of disturbance and previous land use on chemical properties of Northern hemisphere forests soils could still be detected some 100 years later. Verheyen *et al*. (1999) arrive at the same conclusion by showing a negative correlation between SOC concentration and the length of cultivation since the 19th century in a mixed hardwood forest in Belgium. Knops and Tilman (2000) predicted that the recovery of 95% of primitive levels would take some 230 yr following abandonment of agricultural fields. According to Sun *et al*. (2004), soil carbon storage in a temperate coniferous forest following disturbance reached an asymptote after 150-200 yr. The effects of land use changes on SOC stocks are thus long-lasting and differences in land use history between sites is one of the factors that may induce spatial variability. For instance, Kasel and Bennett (2007) were able to establish a strong predictive model of SOC concentration by combining edaphic and land use history variables at some locations. Stratifying samples by their land use change history (LUCH) may reduce the variability of SOC concentration within spatial units, so that significant changes could be detected. Also, the observed dynamic of SOC stocks may be better interpreted.

2.7 Conclusion

The main factual background and concepts of the thesis were presented in this chapter. First, the institutional context of the thesis and the importance of the soil pool in

the global carbon cycle were outlined. In doing this, one of the main challenges pointed out appeared to be the reduction of the uncertainties in the estimation of carbon fluxes from soils at regional scale. Uncertainties originated mainly from the spatial variability of soil carbon content at various scales. At the global scale and the local scale, the problem of spatial variability can be handled more easily because processes driving the quantity and fluxes of SOC are dissociated. Indeed at global scale, climate and geology are much more important than management, land use or topography in explaining SOC variability. The inverse is true at local scale. However, at regional scale, both kinds of factors are likely to interact in a complex way and generate high uncertainties around the estimates.

Therefore, we have identified two promising strategies to achieve significance in the detection of changes in SOC stocks and better explain their dynamic: (i) increase sampling density and (ii) decrease spatial variability using stratification based on initial conditions. The latter approach specifically focused on a stratification based on land use change history. While this factor has been recognized to be determinant in the reliability of several methodologies, it has often been neglected in previous studies. A better understanding of the role of land use change history may help to predict the future evolution of SOC stocks at regional/national scales. The problem with the first approach, i.e. increasing sampling size, is that the number of samples required to achieve a certain level of accuracy increases non-linearly with the accuracy desired. Considering the large number of sample required, reflectance spectroscopy might be a convenient and fast technique to sense various soil properties. Its principles, field of applications and methods of measurements and analysis have been briefly reviewed. We presented the three measuring methods used in this thesis: laboratory, portable and imaging spectroscopy. Compared to laboratory spectroscopy, portable and imaging spectroscopy are able to collect spectra in-situ but, on the other hand, these sensors can only determine properties of the soil surface and the retrieval of the true spectral information may be problematic. Although the technique reveals a great potential in the determination of SOC, for the time being, spectroscopy has not been yet much used for direct applications in soil science. This raises some questions about the accuracy and stability of the method. They are the followings: (i) what is the accuracy of reflectance spectroscopy relative to that of a standard 'reference' method, (ii) what is the accuracy of field and imaging spectroscopy relative to that of laboratory spectroscopy, (iii) what are the factors that may change its ability to predict SOC and how to handle them, (iv) what is the stability of the calibrations and most importantly, (iv) to which extent can we use the different spectroscopic techniques as a routine and viable soil analysis technique.

The strategies identified here to cope with SOC spatial variability at regional scales will be explored in the next chapters.

Chapter 3

The potential of VNIR-SWIR reflectance spectroscopy for SOC monitoring and mapping

Outline

Soil organic carbon (SOC) represents one of the major pools in the global carbon cycle. Therefore, even small changes in SOC stocks cause important CO_2 fluxes between terrestrial ecosystems and the atmosphere. However, SOC stocks are difficult to quantify accurately due to their high spatial variability. The aim of this chapter is to evaluate the predictive ability and potential of Portable Spectroscopy (PS) and Imaging Spectroscopy (IS) to measure SOC concentration in agricultural soils. Partial Least Square regression analysis was used to relate spectral measurements to SOC concentrations. Standard Error of Prediction (RMSEP) of PS ranged from 2.4 to 3.3 g C kg^{-1} depending on soil moisture content of the surface layer. Imaging spectroscopy performed poorly, mainly due to the narrow spectral range of the CASI. RMSEP can possibly be reduced by taking into account factors that degrade the spectral response of SOC like soil moisture. These factors preclude a regional calibration. Applications of spectroscopy for SOC stock inventories

and for soil mapping are discussed. A detailed SOC maps produced by IS reflected the patterns in SOC concentrations due to the recent conversion from grassland to cropland.[32]

3.1 Introduction

Soils play an important role in the global carbon cycle and small relative changes in this pool can lead to large fluxes of CO_2 towards or from the atmosphere. Considering the important historic SOC loss upon conversion from forest to agricultural land, SOC stocks in agricultural land are generally low and there is a potential of carbon sequestration (Lal, 2004; section 2.5.3.2). Even if a number of studies have already demonstrated the impact of specific management practices or land use changes on SOC stocks (*e.g.* Johnson and Curtis, 2001, Guo and Gifford, 2002; West and Post, 2002), several difficulties in estimating SOC stocks and their temporal evolution remain (Post *et al.*, 2001; Chapter 2).

The 'stock changes' method is often applied to monitor the fluxes between land and atmosphere. It implies sampling before and after the change in land use or management. One solution to reduce the uncertainty due to spatial variability consists in increasing the number of samples. Conventional measurement campaigns result often in under-sampling, because of the time consuming and costly sampling and analysis. Even at the field scale, the sampling density required to detect a change in SOC stocks can be very high (section 2.6.2.2).

Reflectance spectroscopy is one of these techniques that can produce the large number of samples needed and can thus improve the accuracy of SOC stocks for individual fields. Moreover, this technique allows analysing soil properties *in situ*. It is fast, cost effective, non-destructive and does not use chemical reagents. There are three types of spectroscopic techniques operating at different spatial scales and in different environments: (1) Laboratory Spectroscopy (LS), (2) Portable field Spectroscopy (PS) and (3) Imaging Spectroscopy (IS). LS and PS rely on ground-based sensors (usually point spectrometry) and IS on air- or space- borne sensors (usually image spectrometry). These techniques are promising in the context of SOC stock inventories (McCarty and Reeves III, 2001; Martin *et al.*, 2002; McCarty *et al.*, 2002; Reeves III *et al.*, 2002) because they offer an instant analysis of SOC concentration and in the case of IS provide a full regional cover.

Organic matter is a soil property showing important chromophores in the NIR-SWIR region so that the measurement of SOC at the LS level is well developed (Ta-

[32] The two following chapters are based on articles by Stevens *et al.* (2006) Soil Science Society of America Journal 70, 844-850 and Stevens et al. (2008). Geoderma, in press.

ble 2.2). However, relatively few studies have investigated the use of PS or IS for the analysis of SOC (Table 2.2). This chapter aims to evaluate the prediction ability of VNIR-SWIR spectroscopic techniques – PS and IS – to measure SOC concentration in agricultural soils. In addition, the potential of the technique for SOC monitoring and mapping will be explored using the collected spectral dataset.

3.2 Materials and methods

3.2.1 Study sites

Two different test sites were monitored (Figure 3.1). They cover the localities of Ortho and Attert in Belgium (Walloon region) and provide a range of soil types. In general, the soils are poorly developed except for the clay soils. Soils are classified as Eutric Cambisols and Haplic Luvisols and occasionally Gleyic Cambisols and Luvisols in case of poor drainage (FAO-ISRIC-ISSS classification; Table 3.1).

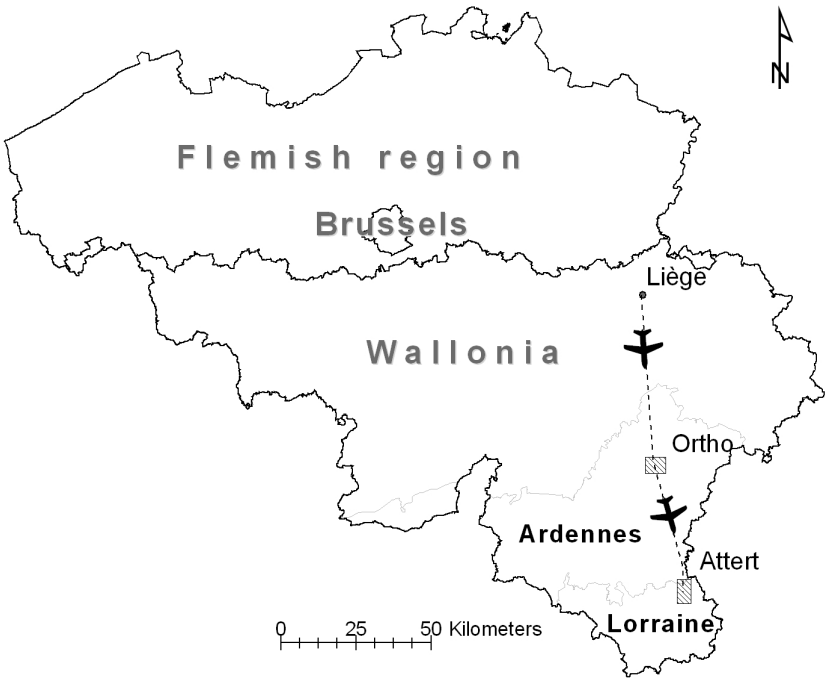

Figure 3.1. Location of the two study areas (Ortho: 50°8'N 5°36'E;Attert: 5°44'N 49°45'E).

The first study area (Ortho) is located in the Belgian Ardennes (50°8'N 5°36'E). Cropland (60 % cereal and 30 % silage corn) represents ± 8% of this hilly area. Agricultural lands are generally located on high plateaus covered by silty and shallow soils. Rotations consist mainly of 3 years of silage corn/cereal and 3 years of pasture. The second study area (Attert) is located in Belgian Lorraine (5°44'N 49°45'E). This area is characterized by a heterogeneous land use of meadows and fodder maize with cereal crops. The zone was selected because of its variation in soil texture over a short distance (sandy to clayey soils; Table 3.1).

Table 3.1. Properties of the soil associations occurring in Ortho and Attert test sites.

Dominant soil series[a]	N	SOC content[b]				Clay content[b]			
		Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
		g kg^{-1}							
Well drained stony loam soils (Eutric Cambisols[c])	95	30	11	10	58	196	58	36	433
Well drained slightly stony loam soils (Eutric Cambisols[c])	35	29	9	11	42	167	44	50	265
Well drained sandy to sandy loam soils (Eutric Cambisols[c])	20	14	3	11	24	146	50	63	264
Moderately drained clay soils (Haplic Luvisols[c])	20	17	4	8	24	221	68	106	415

[a] Calculated for the soil associations in the Ap horizon from a geo referenced soil data base (Aardewerk, Van Orshoven *et al*., 1988).

[b] Soil series covering more than 65% of the soil association. The soil associations are broad zones with homogenous texture and drainage (Tavernier and Maréchal, 1958).

[c] FAO-ISRIC-ISSS (1998) classification.

3.2.2 Spectral measurements

3.2.2.1 Imaging Spectroscopy

Airborne hyperspectral data was acquired from the Compact Airborne Spectrographic Imager (CASI-2, Itres Research Ltd, Alberta, Canada) mounted on a Dornier 228 aircraft from the NERC (Natural Environment Research Council). The CASI-2 is a pushbroom scanner that operates in the VNIR region (405-950 nm) with a spec-

tral resolution of 96 bands (every 6 nm). The flight took place on a clear and windy day, 15 October 2003, when cereal fields and a part of the corn fields had been ploughed, harrowed and re-seeded. The aircraft flew over Ortho at an altitude of ± 2700 m with a spatial resolution of 6x6 m and over Attert at an altitude of ± 1500 m, providing a pixel size smaller than 2.5x2.5 m. The acquired data cube was first ortho-rectified with PARGE (ReSe Applications Schäpfler & RSL, University of Zurich[33]) using the Inertial Navigation System data (pitch, yaw and roll) of the aircraft and the GPS data (lat, long, height) recorded in the aircraft and differentially corrected using the base station GPS data. Then, the CASI image was corrected for atmospheric interferences by using the MODTRAN-4 radiative transfer code (Berk *et al*., 1999) embedded in a modified version of ATCOR-4 (The, 2000; Richter, 2005) using ground reflectance and sunphotometer measurements (optical depth) achieved during the flight. BRDF effects were not taken into account. These corrections were not applied to the image by the author but by a third-party (Vlaamse Instelling for Technologische Onderzoek, VITO) so that a precise assessment of the outcome of these operations cannot be presented. Nevertheless, we verified the quality of these operations by performing the following post-hoc tests: (i) the image is overlaid with the 1:10,000 topographic map of the area to visually estimate the accuracy of the georeferencing and (ii) spectral data of the image is compared with ground-based spectra (see section 3.2.2.2) to assess the spectral calibration.

Spectra were extracted from the data cube using ENVI (Research Systems Inc., Boulder, CO). A window of 3x3 pixels was used to extract spectral signatures of all the plots at the Attert test site in order to make comparable spectral signatures of the two study areas. Eight plots, located near parcels borders, showed in their spectra an influence of the vegetation and were removed from the analysis. These samples present typically a steep slope in the spectral signature due to chlorophyll content at wavelengths between 690-740 nm, known as the "red edge" (Curran *et al*., 1990).

Another data set from a previous IS campaign in Belgian Lorraine (Touré and Tychon, 2003), using both the CASI and the Shortwave Infrared Airborne Spectrographic Imager (SASI, Itres Research Ltd, Alberta, Canada) will also be analysed. The SASI is a pushbroom scanner providing 160 spectral bands from 850 to 2500 nm. This dataset, hereafter called CASI+SASI, contains thus soil spectra in the VNIR-SWIR region ranging from 444 nm to 2500 nm.

[33] PARGE is an orthorectification and geocoding software dedicated to airborne imaging spectroscopy. See [http://www.rese.ch/parge/]

3.2.2.2 Portable spectroscopy

One hundred twenty two soil spectra were taken at Ortho and 40 at Attert with a field spectrometer Fieldspec Pro FR (ASD - Analytical Spectral Devices Inc., Boulder, CO). This instrument is characterized by a Full Width Half Maximum of 3 nm for the 350-1000 nm region and 10 nm for the 1000-2500 nm region and by Field Of View of 25° that from a measurement height of 1 m gave a spot size of 0.45 m at nadir. Soil spectra were obtained by averaging repeated scans - approx. 6 ASD measurements - taken around the marked sampling site within a square corresponding to the pixel size of the airborne instrument. Several PS spectra (n = 11) with very low Signal-to-Noise Ratio (mean SNR < 3) were also removed from the analysis. Here, SNR is defined as the ratio between the average signal reflectance and the standard deviation of the repeated measurements. One range of the signature corresponding to water vapour band (1815-1940 nm) was removed. Beyond 2385 nm, the signal tends to be noisy due to a low level of incoming radiation (Kooistra *et al.*, 2003) and was eliminated.

3.2.3 Soil analyses

A total of 23 freshly tilled fields (13 in Ortho and 10 in Attert) were selected for soil sampling. During three days of field measurements (14-16 October 2003), approximately 10 sampling sites per field were marked and geo-referenced, leading to 138 sampling sites in Ortho and 100 in Attert. Each soil sample consisted of ± 20 subsamples collected around the marked sampling site to a depth of 5 cm across an area corresponding to the pixel size of the airborne instrument. Moreover, 3 samples per field were also collected for the determination of bulk density using 100 cm³ steel cylinders. Soil samples were stored in plastic bags. Gravimetric soil moisture content was determined on a sub-sample and surface moisture conditions of the fields were assessed visually (some fields presented a dry layer of 1-2 cm at the surface contrasting with the rest of the soil, Figure 3.2). The remainder of the sample was air dried (30 °C) and sieved (2 mm) to remove small rocks and coarse residues. Then, the soil carbon concentration was analysed by means of wet oxidation in potassium dichromate and sulphuric acid, the so-called Walkley and Black method (Walkley and Black, 1934). SOC stocks of the plough layer were calculated as follows (Eq. 3.1):

$$S_{ij} = C_{ij} \cdot BD_j \cdot z \quad /10 \qquad \text{(Eq 3.1)}$$

where S_{ij} is the SOC stock (t C ha^{-1}) of sample i in parcel j, C_{ij} is the SOC concentration (g C kg^{-1}), BD is the mean bulk density of parcel j (g cm^{-3}) and z is the mean depth of the plough layer (22 cm) as measured during the field survey (1 measure-

ment per field). Although SOC samples have been collected from the topsoil, Meersmans et al. (2008) have shown that the distribution of OC in several cropland soil profiles of Belgium (Flanders) is constant in the plough layer. As a consequence, SOC samples are considered to be representative of the whole plough layer and bulk density, which is known to depend on SOC concentration, is also considered constant.

Figure 3.2. Picture showing the strong vertical gradient in soil moisture in the field.

3.2.4 Pre-treatments and statistical analysis

First, spectral data were converted into absorbance (Eq.2.4). In order to eliminate the noise, soil spectra were pre-processed using *MATLAB* (The MathWorks Inc., Natick, MA) with combinations of pre-treatments (see section 2.6.3.5): (i) Savitzky-Golay smoothing and derivative algorithm (Savitzky and Golay, 1964), (ii) gap derivative, (iii) moving average and (iv) skipping every n data points. The latter pre-treatment allows reducing the number of spectral bands. Ben-Dor and Banin (1995) showed that reducing the spectral resolution might improve validation results. After autoscaling (see section 2.6.3.5), datasets were randomly split into two sets for calibration and validation purposes. One quarter of the soil samples was used as the validation set. Calibrations of SOC from spectral data were developed for each pre-

treatment using Partial Least Square Regression (PLSR) using the *SAS* statistical package (*SAS* Institute Inc., Cary, NC). The maximum number of PLS factors was set to 10 and determined using the Predicted Residual Sum of Squares (PRESS) statistic and *leave-one-out* cross validation (see section 2.6.3.5). The best treatment was considered to be the one with the highest RPD (see section 2.6.3.5). We also used the ratio between the RMSEC and the SD of the samples involved in the calibration phase was used to measure the quality of the calibration (Coûteaux *et al.*, 2003). The Bias and r^2 were also computed to assess the predictive ability of the model. To assess the relative efficiency of the technique to measure SOC concentration, the RMSEP (Eq.2.6) will be compared with the Standard Error of Laboratory analysis (RMSEL) i.e. SD of differences between duplicate samples of the reference method (see section 2.6.3.5).

During the calibration procedure, samples having *t-statistic* ≥ 2.5 were considered as spectral outliers and removed. The expression for *t* is (Eq.3.2):

$$t = \left| \frac{X_{pred} - X_{obs}}{RMSEC} \right| \qquad \text{(Eq 3.2)}$$

where X_{pred} is carbon predicted by spectroscopy and X_{obs} is carbon analysed by the Walkley-Black method.

3.2.5 SOC monitoring and mapping

The number of samples needed for monitoring and the detection of significant change in SOC stocks depends on the variability within the study area. The Minimal Detectable Difference (MDD; Eq.2.2-2.3) was used here to assess the benefits of spectroscopic techniques. MDD has been calculated for each field on the basis of the variability in SOC and the number of samples collected during the field campaigns. When spatial correlation is present within a spatial unit, the information included in correlated samples (N) is decreased. The number of equivalent independent observation (N') may be assessed by (Eq. 3.3.; Mulla and McBratney, 2000):

$$N' = N \Big/ \left[1 + 2\{\rho/(1-\rho)\}\{1-(1/N)\} - 2\{\rho/(1-\rho)\}^2 \{1-\rho^N\}/N \right] \qquad \text{(Eq 3.3)}$$

with ρ, the autocorrelation[34].

[34] The autocorrelation parameter may be estimated from a pure spatial autoregressive model (SAR).

Maps of SOC concentration in agricultural parcels were produced as follows. First, a mask of the parcels on the hyperspectral cube is created from polygons digitalized based on orthophotoplans. Then, the pixels of the mask are extracted and their SOC concentration is predicted using the best PLS model found for the CASI dataset – which was build on a limited number of SOC samples (calibration set).

3.3 Results and discussion

3.3.1 Quality of the CASI (IS) dataset

Figure 3.3 shows a subset of the ortho-rectified image of the Ortho test site, overlaid with the 1:10,000 topographic map. It can be seen that the accuracy of the georeferencing is satisfactory: roads and parcel borders correspond well with information in the topographical map. However, on other part of the image (not shown), one can distinguish in some places a divergence of 2-3 pixels between the image and the reference map. This positioning error may result in inaccuracies when relating spectral data with SOC concentrations, depending on the spatial variation of SOC within an agricultural field.

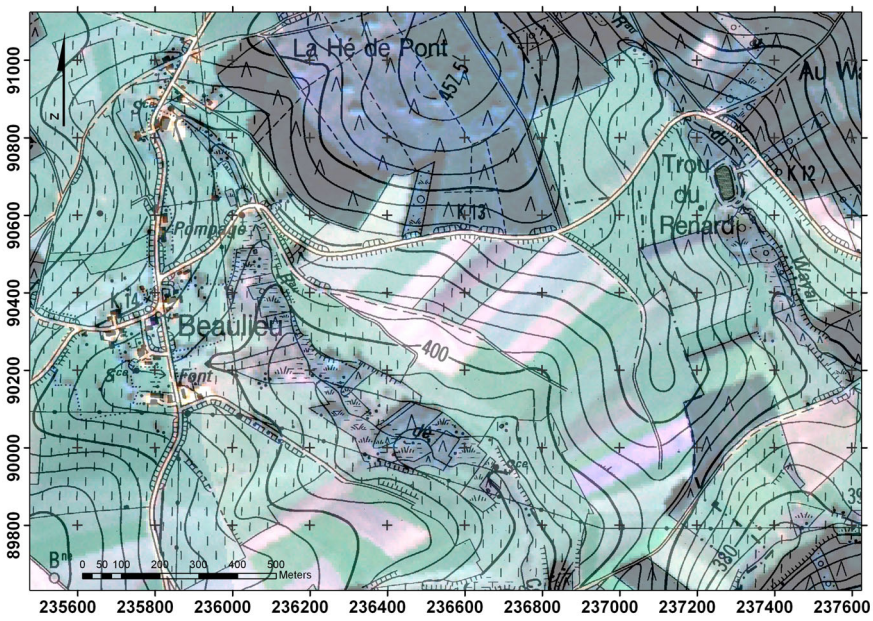

Figure 3.3. Ortho-rectified image of the CASI, overlaid with the 1:10000 topographical map. Map projection: Belgian Lambert 72. Units: meter.

We assessed the quality of the atmospheric correction by comparing several airborne (IS) and ground-based (PS) spectra of the same soil surface. An example – representative of most of the comparisons – is shown in Figure 3.4. Overall the spectrum of the airborne instrument closely follows the one measured on the ground. However, one can notice that the spectrum from the image deviates strongly from the reference at 405-420 nm and 940-950 nm, i.e. at the beginning and the end of its spectral range. In addition, the imaging spectrometer seems to produce noisier spectra than the portable spectrometer in the field. These two problems are only partly fixed with the use of pre-treatments.

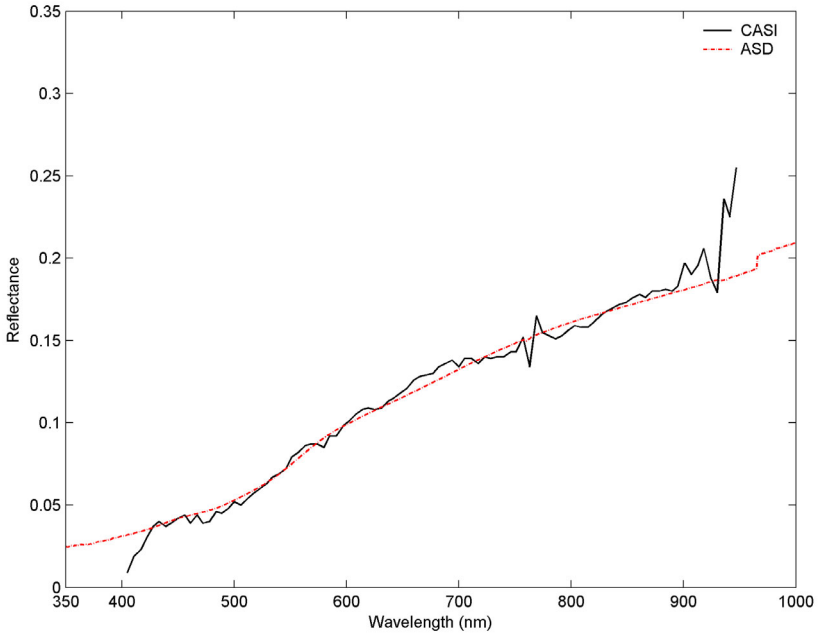

Figure 3.4. Comparison between two spectra of the same soil surface, as produced by the CASI (IS) and ASD (PS) sensors

3.3.2 Calibration and validation

During the 3 days of field campaign, variations in soil moisture conditions were noticed. The moisture content of the soil surface was not measured, but rather the moisture content of the 0-6 cm topsoil was determined by drying sealed soil samples (gravimetric soil moisture content). Due to the strong vertical gradient, the method does not represent the soil moisture at the surface, for which the reflectance is measured. This problem emphasizes a clear weakness of field spectroscopy (PS or IS),

which is only able to measure reflectance of the soil surface. As a consequence, these techniques may be of little interest when vertical gradients in soil properties occur. During the first day of measurement (14th October), the soil surface was visibly wet and progressively dried during the day while part of the field spectra was collected (mean temperature[35]: 8.3 °C). The soil was moist after small precipitation events that occurred the 10-11th October (4 mm in total[36]). In order to take into account the effect of moisture, a subset of the PS dataset was created with measurements taken only on a dry soil surface. The first day of measurement was considered to represent 'wet' conditions and the two following days of measurements 'dry' conditions. IS data, collected on the 2nd day, were considered to be representative for a dry surface. This discrimination between wet and dry days is not based on measured moisture data. However, Figure 3.5 shows that spectra taken the first day have lower average reflectance values and higher standard deviation than spectra in 'dry' conditions, a pattern to be expected (see section 2.6.3.6). Also, as observed by Viscarra-Rossel *et al*. (1998), the average spectrum of moist soils shows more pronounced absorption peaks at 1.4 and 1.9 μm and a less developed one at 2.2 μm. Hence, four different data sets were processed: PS spectra (hereafter called ASD), PS spectra in 'dry' conditions (ASD_d), IS data from the CASI and IS data from the CASI+SASI. Table 3.2 gives the combinations of pre-treatments yielding the best model for each dataset.

The RMSEC ranged from 1.7 g C kg^{-1} for ASD_d to 2.8 g C kg^{-1} for ASD. The SEC-to-SD ratio of ASD_d was quite low (0.25) and ASD has a higher value (0.45), indicating that quantitative prediction should be treated with caution. The RMSEP varies between 2.4 g C kg^{-1} for ASD_d and 3.3 g C kg^{-1} for ASD (Figure 3.6; Table 3.3). The r^2 of ASD was greater than 0.8 and the r^2 of ASD_d as high as 0.9 denoting reliable models (Coûteaux *et al*., 2003). According to the classification of Chang *et al*. (2001), the RPD of the best model for ASD_d (2.33) falls in the highest category meaning that SOC concentration of dry soils can be well predicted by a field spectrometer. The predictive ability of ASD based on its RPD (1.79) falls in the intermediate category. Bias, which is a measure of the difference between reference and predicted means, were low (ranging from -0.12 to 0.08 g C kg^{-1}). This implies that models using the data from the portable spectrometer do not systematically under- or overestimate carbon concentrations determined by the classic Walkley and Black method. These results suggest overall that soil moisture decreases the predictive ability of the method by ± 30 %, probably by inducing a greater spectral variability.

[35] Neder-Over-Heembeek weather station, Brussels, 46 m, from [http://www.meteobelgique.be/]
[36] *Cf. supra*

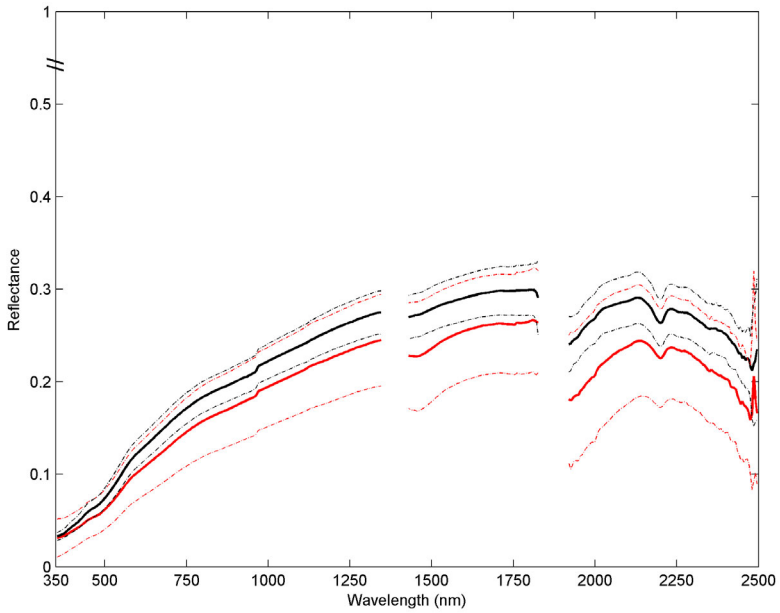

Figure 3.5. Mean spectrum of 'dry' (black, n = 64) and 'wet' (n = 44) samples with standard deviations (dash-dotted lines).

The PLS regressions on CASI data were run separately for the two study area. Problems encountered when joining IS data from different study areas will be addressed in the next chapter. Overall, IS yielded less satisfying results than on PS data (Figure 3.7; Table 3.3). SEC-to-SD ratios are higher than 0.5 and the RMSEPs are 3-3.4 g C kg^{-1}. Biases are much greater than for the PS dataset. In the case of the Ortho site, bias represents a large part of the total error. A relatively high RPD value (1.97) is found for CASI in the Attert test site.

The Ortho site shows much lower validation results. This can be attributed to the higher SD. However, Figure 3.7c-d shows that the PLSR did not produce a good model because the correlation between observed and predicted values is weak (r^2 = 0.44). The CASI+SASI data performed better than the CASI alone, reaching a RMSEP of 1.7 g C kg^{-1}. This may be due to the lower range of SOC concentration found within the study area. However, the high RPD (2.5) indicates rather that it is most probably due to the wider spectral range of the CASI+SASI (444 to 2500 nm) compared to the CASI (405-950 nm) sensor.

Table 3.2. Combinations of pre-treatments yielding the best model for each dataset

Data type	Mathematical pre-treatment type
ASD_d	derivative with a gap of 4 bands, keep one band every 10 nm
ASD	Savitsky-Golay smoothing with a 3rd polynomial covering 40 nm, keep one band every 5 nm
CASI (ORTHO)	1st derivative with a gap of 1 band
CASI (ATTERT)	Savitsky-Golay 1st derivative with a 3rd polynomial covering 40 nm
CASI+SASI	Moving average with a window size of 9 bands, 1st derivative with a gap of 3 bands

RMSEP in this study are in the lower part of the range of RMSEP found in the literature. Model predictive accuracy indexes in this study are within the range of those found in the literature (Table 3.3). Some studies show much lower RMSEPs, but this is often caused by a low variation in SOC concentration. Predictive statistics of ASD_d and CASI+SASI are relatively good, suggesting that those field spectrometer and hyperspectral remote sensors could efficiently predict SOC. However, RMSEP values of ASD_d and CASI+SASI are at least 2-3 times higher than the RMSEL (1 g C kg^{-1})[37]. This difference could be due to the diversity of soils found in our two study areas, giving a large variation in soil texture and SOC concentration (Table 3.1). Although one needs some variability in soil properties to detect a trend and obtain a good relationship between carbon concentration and spectral characteristics of the soil, the variation can be too large. The relationship between SOC and spectral properties can be non linear, so that a universal calibration is difficult to obtain (Sørensen *et al.*, 2005). Previous efforts have shown that this problem could be partially solved by neural networks (Fidêncio *et al.*, 2002b). Likewise, a good relationship can hardly be found if soil texture varies too widely (Hill and Schütt, 2000).

In the next sections, the benefits that such techniques can offer in different applications such as determining CO_2 fluxes induced by SOC stock change or detecting the spatial pattern of SOC concentrations caused by land use history or natural factors are discussed.

[37] Since the correction for errors in the reference method (Eq.2.7) would improve the RMSEP negligibly, the $RMSEP_{corr}$ was not computed .

Table 3.3. PLSR output statistics of the best model for each dataset.

	Calibration						Validation					
DATA	N	RMSEC[a]	SD[b]	RMSEC-to-SD	t-outliers	Number of PLS factor	N	RMSEP[c]	SD[b]	RPD[c]	Bias	r^2
		g C kg^{-1}						g C kg^{-1}			g C kg^{-1}	
ASD	108	2.8	6.2	0.45	3	9	37	3.3	5.9	1.79	-0.12	0.82
ASD_d	77	1.7	6.8	0.25	2	3	24	2.4	5.6	2.33	0.08	0.9
CASI (ORTHO)	94	3.0	4.8	0.93	1	1	32	4.4	4.0	1.08	-1.02	0.44
CASI (LORRAINE)	75	3.4	7.5	0.51	1	3	24	3.8	6.7	1.97	-0.42	0.87
CASI+SASI	73	2.9	4.8	0.60	3	7	26	1.9	4.9	2.50	0.52	0.92

[a] Root Mean Square Error of Calibration (see Eq.2.6)

[b] Standard Deviation

[c] Root Mean Square Error of Prediction (see Eq.2.6). It must be compared to the Root Mean Square Error of Laboratory (RMSEL, see section 2.6.3.5) of the Walkley and Black method, fixed at 1 g C kg^{-1} (Colinet *et al*., 2005)

[d] Ratio of Performance to Deviation

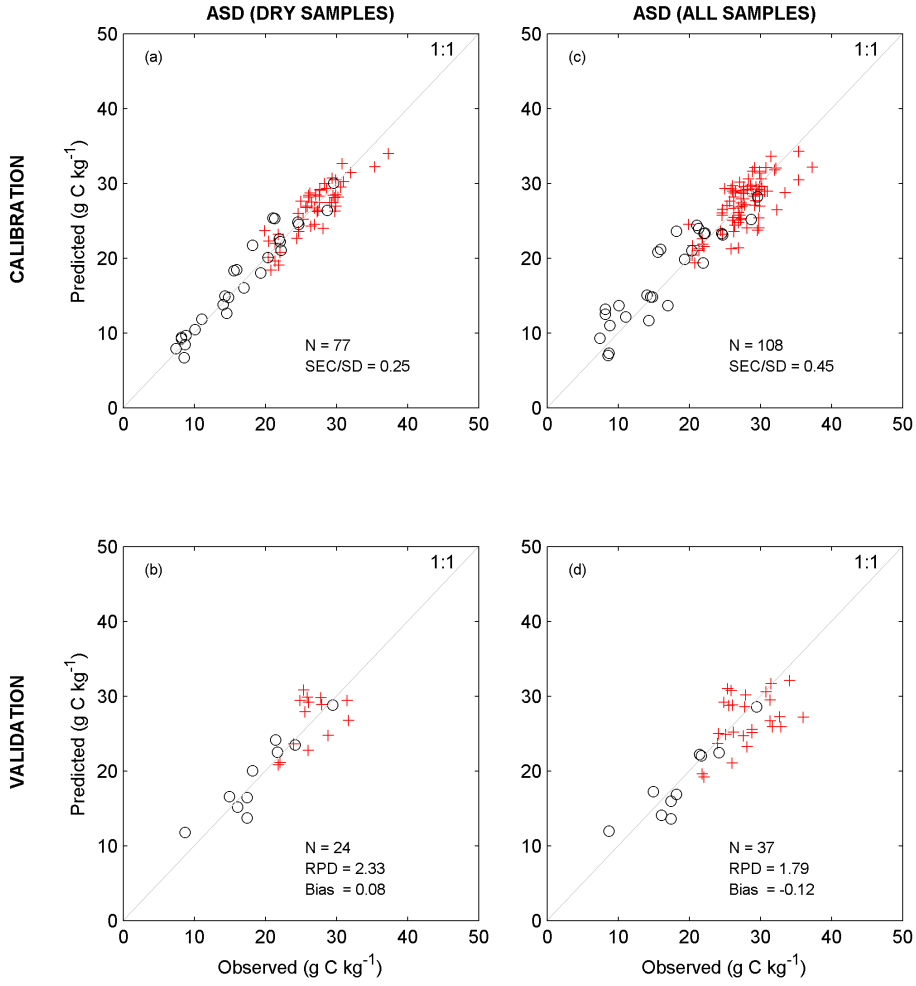

Figure 3.6. Graphs of predicted vs. *observed C concentration (g kg^{-1}), respectively in the calibration and validation set of ASD$_d$ (a-b) and ASD (c-d). Circles are samples from the Attert test site and crosses are samples from the Ortho test site.*

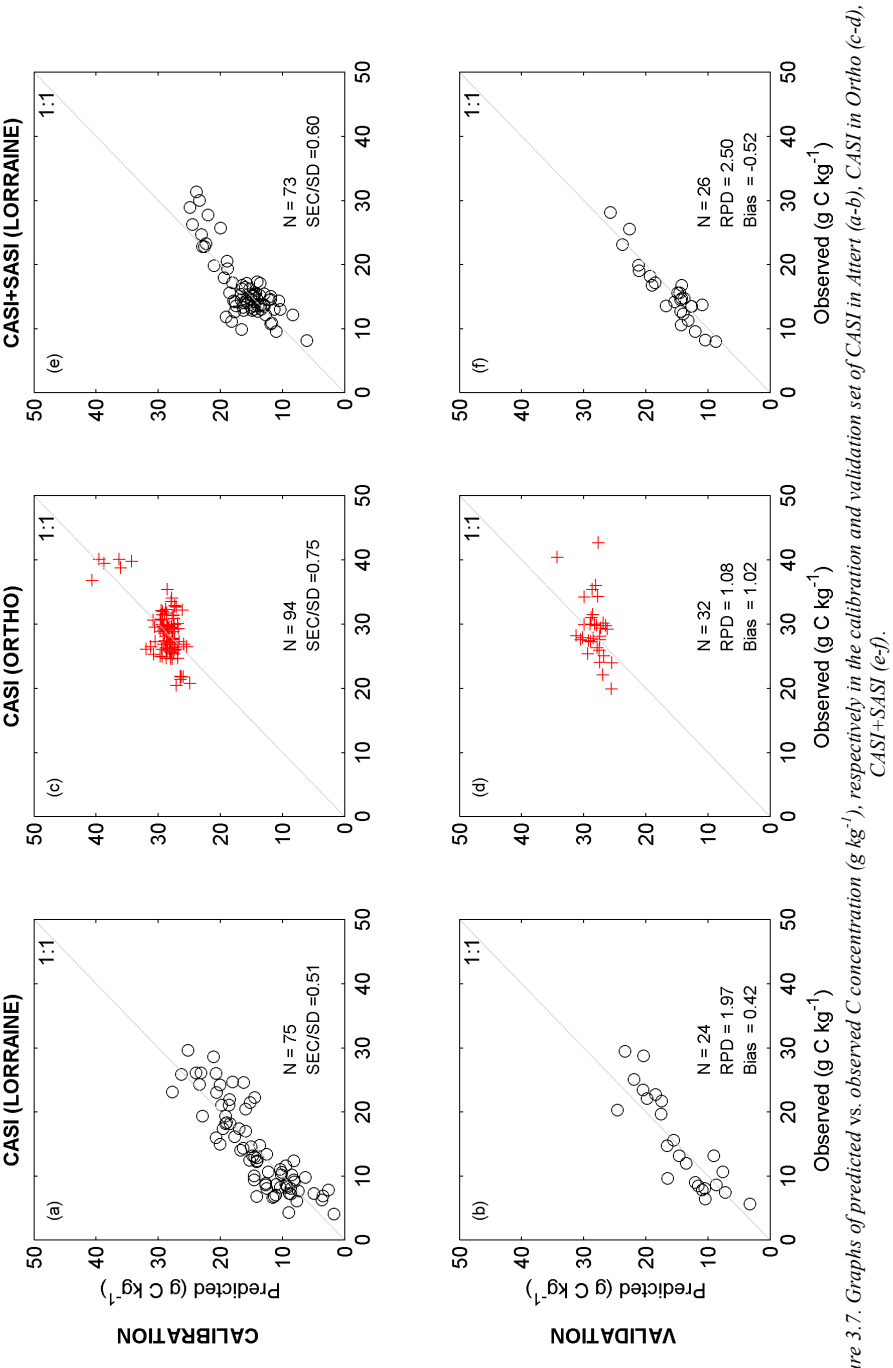

Figure 3.7. Graphs of predicted vs. observed C concentration (g kg^{-1}), respectively in the calibration and validation set of CASI in Attert (a-b), CASI in Ortho (c-d), CASI+SASI (e-f).

3.3.3 Monitoring SOC changes and SOC inventories

The intra-field variability of SOC stocks in the Ortho study area may be in the same order of magnitude as the variability across all fields (Table 3.4) and therefore, the detection of significant changes is difficult. Most carbon sequestration options in soils range from about 0.3 to 0.8 t C ha^{-1} yr^{-1} (Smith, 2004c). Such small rates will be hardly detected e.g. in a 5 years commitment period for the Kyoto Protocol. The maximum change in SOC stock to be expected would not be higher than 1.5-4 t C ha^{-1}. This corresponds to a concentration of 0.67-1.8 g C kg^{-1} (considering a mean bulk density of 1.01 g cm^{-3} – see Table 3.4 – and a depth of 22 cm). In the Ortho test site, the number of samples required to detect such a change, assuming normality, is 15-187 samples if the difference to be detected is 1.5 t C ha^{-1} and 2-28 samples if the difference is 4 t C ha^{-1} (Table 3.4). With the number of samples collected in each field during the measuring campaigns, one can detect changes (MDD, Eq.2.2-2.3) varying between 4.1 and 12.2 t C ha^{-1} (Table 3.4). MDD of the entire study area (considered as a homogeneous spatial unit) is lower (3.2 t C ha^{-1}) because of the larger sample size and comparable variance. However, MDD decreases non-linearly with sample size and for a given sample size increases with the variance. Hence, to detect 1.5-4 t C ha^{-1} in mean SOC stocks in the study area, the number of samples required would be relatively high (29-196; Table 3.4).

These calculations show the need for high sampling densities, at the field and regional scale. Increasing the sampling density will result in a smaller detection limit of SOC stock change. Such sampling intensity can only be achieved when studies are carried out for larger spatial units keeping the sample density to a reasonable level. Conventional sampling strategies are often too time consuming and expensive to provide such large amounts of samples. PS and IS may be an attractive alternative to estimate SOC changes with higher confidence at various scale. PS can be used to rapidly scan the soil surface of individual fields and estimate with confidence their mean SOC concentration. The main advantage of IS in comparison to PS lies in its ability to monitor large area at once.

Converted to SOC stock in the plough layer (0-22 cm with an average BD of 1.01 g cm^{-3}), the RMSEP of PS corresponds to 5.3-7.3 t C ha^{-1} and those of IS to 4.2-9.7 t C ha^{-1}. The precision of the method is still high in comparison to rates of SOC stock changes after land conversion or change in management of agricultural soils found in the literature (see section 2.5.2). However, the fact that biases are generally low is critical (PS: 0.17-0.26 t C ha^{-1}; IS: 1.15-2.26 t C ha^{-1}). Indeed, contrary to RMSEP, such biases are not reduced by increasing the sampling size and would greatly influence the estimation of SOC stocks. Hence, low bias enable one to use

VNIR-SWIR spectral data to estimate population means with confidence using a large number of samples. IS can provide a large amount of samples. Assuming 1600 samples/ha (pixel resolution of 2.5 m) and no biases, the field with the highest variance in the Ortho test site (field B Table 3.4) would see its MDD decreases from 12.2 t C ha^{-1} to 0.9 t C ha^{-1}, i.e. a value falling within the range of SOC stock changes observed after 5 years of management changes.

Table 3.4. SOC stocks statistics per field in the Ortho test site, and Minimal Detectable Difference

ID	Surface	N	BD[a]	Mean[b]	Var[c]	CV	MDD	MDD_{IS}[d]	n_1[e]	n_2[f]
	ha		g cm^{-3}	— t C ha^{-1}—		%	— t C ha^{-1}—			
A	0.12	7	0.92	79.9	6.4	3	4.2	0.7	15	2
B	0.83	10	1.01	69.7	89.5	14	12.2	0.9	187	28
C	0.91	11	0.84	56.3	11.4	6	4.1	0.3	25	5
L	5.01	11	1.10	71.8	80.3	12	10.9	0.4	168	25
M	2.42	11	1.00	66.8	28.1	8	6.5	0.3	60	10
N	3.01	11	1.03	67.8	66.7	12	10.0	0.4	140	21
O	1.41	11	0.86	51.7	11.3	7	4.1	0.3	25	5
P	2.73	11	1.03	52.6	54.4	14	9.0	0.4	114	18
Q	0.91	11	1.10	67.1	56.8	11	9.2	0.7	119	18
R	1.12	11	1.18	66.2	60.8	12	9.5	0.7	128	19
S	2.10	11	1.00	59.6	13.5	6	4.5	0.2	30	6
T	3.22	11	0.97	60.1	49.1	12	8.5	0.4	103	16
U	2.04	11	1.09	65.7	36.9	9	7.4	0.4	78	13
ALL	25.82	121	1.01	63.8	93.9	15	3.2	0.2	196	29

[a] Bulk density

[b] Mean SOC stocks, see Eq.3.1.

[c] Variance of SOC stocks.

[d] MDD reachable with IS, assuming 1600 samples/ha (see text)

[e] The number of samples required to detect 1.5 t C ha^{-1}. See text for explanations and Eq.2.2-2.3

[f] The number of samples required to detect 4 t C ha^{-1}. See text for explanations and Eq.2.2-2.3

This MDD is based on classical ANOVA and confidence limits. ANOVA, and thus MDD, must be applied on distributions that respect hypothesis of normality and sample independence. When the number of samples is large enough, normality can be reasonably hypothesized (Central Limit Theorem). Independence must be respected because statistical significance is decreased when observations have close values as a result of spatial proximity (loss of degrees of freedom). However, in the case of IS samples, independence cannot be assumed. Indeed, it is known that SOC in agricultural soils may show spatial dependence at short distances (see section

2.6.2.1 and Solie *et al*., 1999). The increase in the number of samples required to detect a given change may be assessed by computing the equivalent number of independent samples giving the same variance (Eq 3.3; Mulla and McBratney, 2000; Griffith, 2005). For instance, assuming an average autocorrelation of 0.5, the MDD of field B, as expected from IS measurements, would increase from 0.9 to 1.6 t C ha^{-1} (other results not shown).

3.3.4 Mapping Spatial Variability of SOC

Despite the lack of precision in the estimation of SOC with the IS instrument (CASI alone), a SOC map of fields was produced (see section 3.2.5). They may be used e.g. to detect spatial patterns induced by land use or land management change and precision farming. Figure 3.8 shows an agricultural field extracted from the SOC map. According to recent aerial photographs dating from 1998, this large field was originally made up of smaller parcels of both grassland and cropland. We can clearly see the effect of land use change. Arable parcels to the west were permanent grassland one year before the flight. The new arable parcel in the eastern part of the field (grassland tilled one day before the flight) has higher carbon concentration (mean: 30.2 g C kg^{-1}) than surrounding cropland parcels (mean: 27.9 g C kg^{-1}). Converted to SOC stocks in the 0-22 cm topsoil (plough layer), this results in a difference of 5 t C ha^{-1} in one year or a decrease of about 7 % in SOC stock. The decline in SOC concentration upon conversion from grassland to cropland is often observed (e.g. Burke *et al*., 1989; Bowman *et al*., 1990) and is mainly due to increased erosion and agricultural practices such as tillage and residue removal. The difference observed here is far greater than the value of -0.95 ± 0.3 t C ha^{-1} yr^{-1} by converting permanent grassland to cropland found by Soussana *et al*. (2004). The maps show some differences between sampling points and predicted values but the overall variation is respected. Moreover, the range of SOC predicted by IS is consistent with the SOC concentration measured, suggesting that the two fields can be well differentiated according to their spectral response. However, it seems likely that there are also some artefacts in this image. For instance, some pixels at the eastern border of the field have a higher SOC concentration than surrounding pixels. The inspection of their spectral characteristics revealed that they present a steeper slope between 600 and 700 nm than other pixels of the field, indicating a response of the vegetation. These pixels are thus probably composite pixels, which include surfaces of the adjacent parcels.

Spatial variability of SOC is often too detailed to be captured by a coarse sampling grid. The presence in agricultural fields of complex patterns of SOC due to land use or management history may cause significant errors in scaling-up ap-

proaches (Venteris *et al*., 2004). This is a problem that IS can effectively address. The well-defined pattern of SOC concentration observed in Figure 3.8 would have been difficult to detect with classical sampling technique. Likewise, geostatistical techniques rely also on the density of the sampling grid. Hence, IS may be the sole approach able to identify fine-scale patterns of SOC with minimal sampling sites.

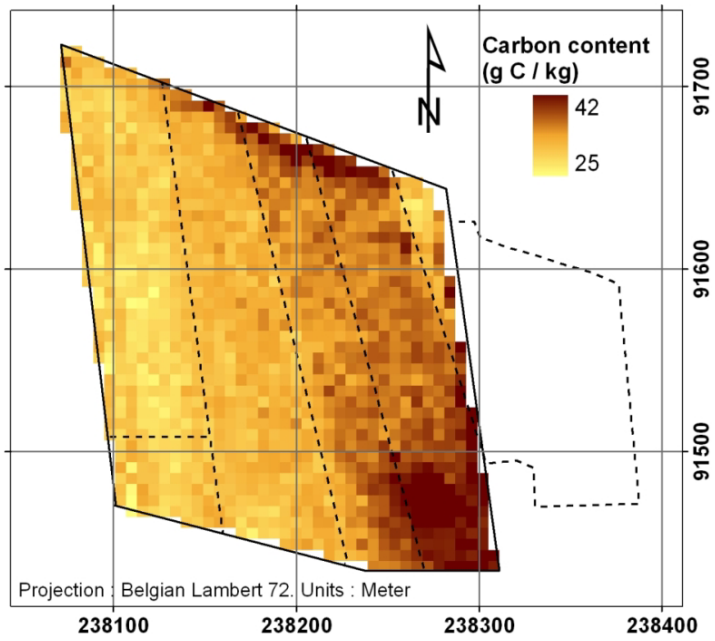

Figure 3.8. Map of soil organic C concentration in a freshly ploughed field after land consolidation. The borders of the original fields that were joined are indicated with dashed lines.

3.4 Conclusions

This chapter evaluated the possibility to use VNIR-SWIR Portable Spectroscopy (PS) and Imaging Spectroscopy (IS) to estimate SOC concentration in agricultural soils. The field spectrometer produced more precise estimates of SOC than imaging spectroscopy. PS performed better when moist surface samples were removed from the analysis. Results from the airborne CASI sensor (405-950 nm) could not be used for accurate quantitative prediction. The airborne CASI+SASI sensor (444-2500 nm) showed improved results, probably due to its wider spectral range. A SOC map was produced with the CASI. Despite the low precision of the data, some significant differences corresponding to recent conversion from grassland to arable land have

been distinguished. Variability in soil surface conditions decreases the predictive power of spectroscopic techniques. Calibration should be carried out simultaneously with ground measurements to include disturbing factors in the regressions. There is thus no universal calibration. Examining the stability of the calibrations through space and time is needed to evaluate the possibility to apply these techniques at the regional scale within operational SOC monitoring systems.

The large amount of samples provided by these techniques can sensibly reduce the minimum detectable difference (MDD) in SOC stocks between different dates. These differences can then be used to assess sequestration or emission of CO_2. The precision of these techniques is still rather low but the low bias allows to use them for SOC stock change studies. In order to make these techniques fully operative, some additional efforts have to be done to increase their predictive ability and stability. In this respect, a better monitoring of disturbing factors and management practices and the use of a sensor covering a wider spectral range might help.

Chapter 4

Performance and stability of Partial Least Square Models for SOC determination by means of VNIR-SWIR reflectance spectroscopy

Outline

The performance of three different instrumental settings (laboratory, field and airborne spectroscopy) is assessed. Carbon concentrations are predicted from spectra through Partial Least Square Regressions (PLSR) It appears that ground-based spectrometers give Root Mean Square Errors of Cross-Validation similar to the limit of repeatability of a routine SOC analytical technique such as the Walkley and Black method (± 1 g C kg^{-1}). The airborne spectrometer has some difficulties to reach such values due to a lower signal to noise ratio. Because of its statistical nature, the method and its potential rely on the stability of the calibrations obtained. It appears that calibrations

are currently site-specific due to variation in soil type and surface condition. However, it is shown that PLSR can take into account both soil and spectral variation caused by different measuring campaigns and study areas.

4.1 Introduction

A cost effective monitoring system is needed to calculate the emissions of CO_2 from individual fields and follow the evolution of SOC concentration in the topsoil as an indicator of Good Agri-Environmental Conditions. In this context, Chapter 3 showed that reflectance spectroscopy can be useful in studies where a large number of samples and spatial information are required like in precision agriculture (SOC mapping) and soil monitoring. However, it also showed that variation in soil moisture content degrades the spectral response to SOC concentrations as measured in the field by Portable Spectroscopy (PS) or Imaging Spectroscopy (IS). Within a given study area, a large variability in soil surface conditions can occur. Some of the properties that are subject to variation both in time and in space are: the degree of soil crusting as a result of rain drop impact, soil texture, soil moisture, roughness and vegetation or crop residue cover. This variation in surface conditions may induce changes in soil reflectance that approach or exceed the spectral response of organic matter (Barnes *et al.*, 2003).

These factors generate a spatial variability in soil surface conditions limiting the regional-scale application of the technique. Also, these factors may change rapidly through time. Since the methodology relies on calibrations based on samples having specific surface conditions, LS and PS measurements may not be stable through time and the accuracy of these techniques may vary. Despite their potential outlined in Chapter 3, this may preclude the use of such techniques to address real problems. Before their implementation within regional-scale monitoring systems, PS and IS must demonstrate robust and replicable results.

The first objective of this chapter is to evaluate the loss of accuracy by using spectroscopic techniques outside the controlled conditions of the laboratory. The second objective is to investigate calibration stability. This question is poorly addressed by other studies and we will use SOC as an indicator for that purpose. Spectral measurements from LS, PS and IS were collected during a field campaign in 2005 and SOC concentrations were predicted using Partial Least Square Regressions (PLSR). The problem of the stability of the calibration will be addressed by means of (i) IS spectral dataset from a flight in 2003 covering 2 contrasted study areas and (ii) PS datasets from 2 field campaigns (in 2003 and 2005) and 3 study areas.

4.2 Materials and Methods

4.2.1 Study Sites

The area selected for the 2005 campaign, from which LS, PS and RS data were collected, is located in the Belgian Lorraine (Tintigny; 49°43' N 5°27' E and 49°39' N 5°32' E, Walloon region). This site has a mean altitude of 350 m.a.s.l with a rather flat topography and a mean temperature of 8.5 °C and an annual precipitation of 1013 mm. Grassland is the dominant agricultural land use (± 75 %), while fodder maize and some cereal crops occupy the remaining 25 %. The southern part is mainly composed of sandstones while marls are found under the alluvial deposits of the Semois River in the north. The Tintigny area (52.5 km²) is thus characterized by diverse soil types, from sandy to clayey and overall the Fe_2O_3 concentration ranges from 8.8 to 16.4 g kg^{-1} (based on analysis of 13 field samples, with dithionite extraction). Most of the selected fields are on sandy-loam or loamy-sand soils (Haplic and Gleyic Luvisol, FAO-ISRIC-ISSS, 1998). The two other study areas in the Belgian Ardennes (Ortho) and the Belgian Lorraine (Attert), from which additional PS spectra have been measured in September 2003, are fully described in section 3.2.1. Soils in the Ortho area site are mainly loamy acid brown soils (Cambisols, FAO-ISRIC-ISSS, 1998) and contain from 13 to 24.2 g Fe_2O_3 kg^{-1} (based on analysis of 16 field samples). The Attert test site shares similar pedological characteristics with the Tintigny area.

4.2.2 Spectral Measurements

All ground truth spectral measurements (apart from those planned in the laboratory) were collected on the day of the overpass. The time window dedicated to spectral measurements (end of spring), constrained by other projects[38] using the same remote sensor, introduced non-ideal circumstances since bare fields, needed for soil sensing, are extremely rare in the region during spring. In order to circumvent the problem, we cleared 81 areas of 7.5 by 7.5 m in 8 maize fields. The size of these bare plots corresponds to an area of 3 by 3 pixels of the sensor. Furthermore, two fields of approx. 0.25 ha each were ploughed and left bare by the farmers within which 36 similar plots have been delimited, resulting in a total of 117 plots.

[38]Projects from the Program for Earth observation research (STEREO I) financed by the Belgian Science Policy (BELSPO).

4.2.2.1 Remote Spectroscopy

The remote sensor AHS-160 was mounted onboard a CASA aircraft and flown on June 20, 2005, at an altitude of 1000 m.a.s.l., and covered 7 south-north flight lines. The sensor is a whiskbroom scanner, which provides a total of 80 bands covering the spectrum in the VNIR-SWIR (400-2500 nm) and MIR (3300-5400 nm and 8200-12700 nm) region, with a Instantaneous Field Of View of 2.5 mrad and a Field Of View of 90° enabling pixel size of 2.6 m and swath of 2000 m. Images were atmospherically, radiometrically and geometrically corrected using the same methodology as in Chapter 3. The quality of spectral calibration was assessed by comparison with ground-based measurements. The geometrical correction was verified by comparing the measured geographical position of the cleared plots with their corresponding position clearly visible on the image. It was indeed possible to discriminate vegetated and non-vegetated areas within each field due to the strong response of vegetation in the NIR region.

For each plot, 9 pixels centred on the middle of the plot were extracted using the ENVI software (ITT Visual Information Solutions, Boulder, CO) and averaged to give the plot representative spectrum that was further used for the statistical analysis. Some pixels, especially those located at the edge of the plot, were influenced by the surrounding vegetation and were omitted from this averaging. This was done by removing those pixels with NDVI values greater than 0.3.

In order to evaluate the quality of RS spectra, a Signal-to-Noise Ratio (SNR) was estimated similarly to the one in Ben-Dor and Levin (2000; Eq. 4.1).

$$SNR = AV / SD \qquad \text{(Eq 4.1)}$$

where AV is the mean signal of an homogeneous target and SD is the Standard Deviation of the same pixels values.

4.2.2.2 Portable Spectroscopy

PS measurements were taken with a FieldSpec Pro FR spectrometer (Analytical Spectral Devices Inc., Boulder Co) during two field campaigns in 2003 and 2005 using a similar measurement protocol. Since measurements were taken the same day as the flight (under perfectly clear sky and between 11 am and 5 pm), light conditions (stability and intensity) were optimal. Each spectrum consisted of 9 individual spectra taken across each experimental plot and measured against Spectralon white reference under similar geometry and level of radiation. The 9 spectra were averaged to give a plot representative spectrum. The plot of the reflectance at 780 nm

against the reflectance at 670 nm of the mean spectra revealed that 7 mean spectra were influenced by the presence of residual vegetation (Figure 4.1). These spectra are not a part of the "soil line" and were therefore removed from the analysis. A strong atmospheric noise due to water vapour affected wavelengths between 1340-1430 nm, 1810-1970 nm and beyond 2400 nm. These were removed.

4.2.2.3 Laboratory Spectroscopy

Air-dried and sieved soil samples in small cups were measured with a FieldSpec Pro FR spectrometer that was hooked to a contact probe with a built in halogen bulb for illumination and Spectralon as a white reference. Nine spectra were produced per sample from which the mean spectrum of the plot in question was calculated. As the measurement conditions of the contact probe are ideal, the entire spectral range (350-2500 nm) was further used.

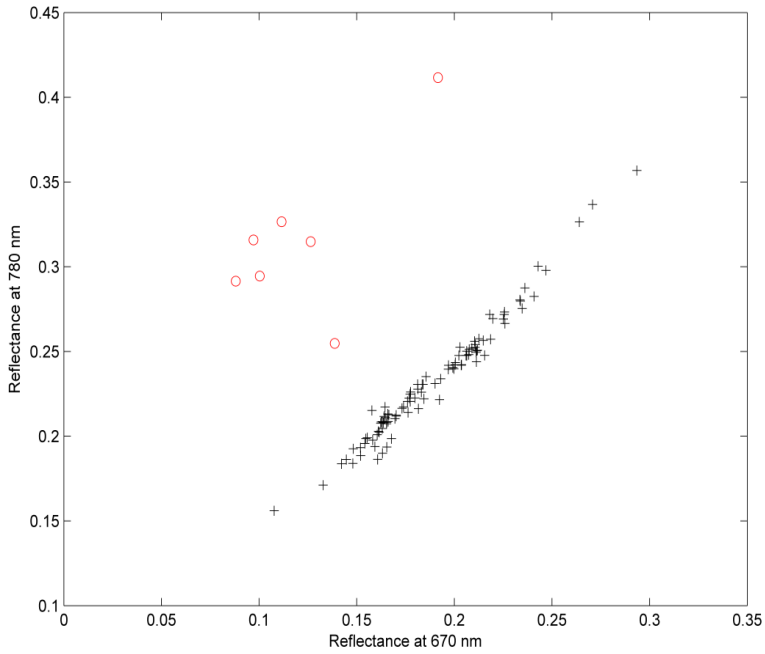

Figure 4.1. Plot of the reflectance of PS measurements at 780 nm vs. *reflectance at 670 nm with vegetation outliers (circles).*

4.2.3 Soil Analysis

In each plot, 9 sub-samples were collected to a depth of 5 cm, mixed and a representative sample was taken for carbon and spectral analysis in the laboratory. These samples can be considered to represent the SOC concentration of both the soil surface (with which spectral data must be theoretically related) and the entire plough layer because a uniform distribution of SOC with depth is often observed in the plough layer (Meersmans et al., 2008). All soil samples were air dried (30 °C) and sieved to pass a 2 mm mesh. The SOC concentration was determined using the Walkley and Black method (Walkley and Black, 1934). Moreover, 15 soil samples were taken randomly in all of the selected plots, up to a maximum depth of 1 cm and put into a hermetic plastic bag in order to determine the soil moisture content upon drying the sample at 105°C for 24 hours. SOC and soil moisture statistics of each field of the Tintigny area are given in Table 4.1. Several soil samples were also measured for iron (Fe_2O_3) concentration by dithionite extraction.

4.2.4 Statistical Analysis

Before the quantitative statistical analysis, a series of pre-treatments were applied to each spectrum (LS, PS and IS) using *MATLAB* (The Matworks Inc., Natick, MA). Reflectance is converted into absorbance. Other pre-treatments consisted of: (i) 1st and 2nd derivatives, (ii) 1st and 2nd gap derivatives, (iii) Savitzky-Golay smoothing and differentiation algorithms (Savitzky and Golay, 1964), (iv) mean centering and variance scaling, and (v) skipping (Reeves and Delwiche, 2003; see section 2.6.3.5). Each pre-treatment or combination of pre-treatments was related separately to carbon concentration with PLSR as implemented in *SAS* (*SAS* Institute Inc., Cary, NC). The maximum number of Latent Variables (LV) was set to 10. The optimal number of LV was determined by *leave-one-out* cross-validation (see section 2.6.3.5).

In order to construct a robust calibration model (see section 2.6.3.5), an automatic outlier removal procedure was implemented in *SAS*, which is close to the procedure developed by Koshoubu *et al*. (2001). Sample outliers are detected after each PLSR on the basis of their prediction error. Then, this PLSR macro is run in a loop until the number of outliers reaches zero. Our procedure is recapitulated below (Figure 4.2):

- PLSR is applied on the pre-treatment. The optimal number of LV is determined by cross-validation, using the PRESS statistics implemented in the *SAS* PLS algorithm (see section 2.6.3.5).

- Residuals are calculated and inserted in the calculation of the *t*-statistics. The expression for *t* is given by (Eq.4.2):

$$t = \frac{|e_i|}{RMSECV} \qquad (\text{Eq } 4.2)$$

where e_i is the residual for sample *i* in the calibration set. If *t* is greater than 2.5, the sample is considered as an outlier. The optimal number of LV is fixed during this step.

- The PLS macro is run in a loop until the number of outliers reaches zero, then the final PLS macro is run with the optimal number of factor determined earlier. This rerun of the PLS is necessary to get the predicted values linked with the optimal model because the *SAS* algorithm calculates values from the PLS model that produce the minimum PRESS (Reeves and Delwiche, 2003).

- A summary table with all the statistical parameters of the model is created for each pre-treatment. This table is sorted according to the RPD and the best model is selected.

Two different approaches, depending on the number of samples available, were used to validate the model and evaluate its prediction error: (i) test set validation and (ii) cross-validation. In the test set validation procedure a third of the data was randomly selected and used to validate the model by confronting measured and predicted values. The performance of the models was measured by the RMSEP and RMSECV (Eq.2.6). A $RMSEP_{corr}$ was calculated as well (Eq.2.7). RMSEL of the Walkley and Black method has been fixed to 0.1 g C kg^{-1} (Colinet *et al.*, 2005). RPD was computed in order to interpret the prediction ability of each pre-treatment (Chang and Laird, 2002). The quality of the calibration was also evaluated by checking the shape of the X-weights of the LV's. Noisy features may indicate overfitting and thus that the calibration may not be suitable for future prediction. If so, the PLS model was rejected. The best pre-treatment able to predict un-sampled sites with the highest precision was selected on the basis of its RPD value and the percentage of X (wavelengths) and Y (carbon concentration) variation explained by the model.

Table 4.1. Summary statistics of field samples in the Tintigny area

	N	SOC content (g C kg^{-1})				Moisture content (g kg^{-1})				Main texture[a]
Field		Mean	SD	Min	Max	Mean	SD	Min	Max	
G1	21	11.2	1.3	9.2	14.6	16.3	9.8	6.7	44.0	Loamy-sand
G2	15	15.6	1.2	13.3	17.7	5.3	2.5	3.0	12.2	silt/silt-loam
P1	15	13.6	1.1	11.5	15.9	6.1	2.6	3.4	12.7	sandy-loam
P2	15	16.6	2.3	13.0	22.1	17.4	6.5	8.7	28.3	sandy-loam
P3	9	13.3	1.8	10.7	15.9	21.8	7.5	12.1	35.8	silt-loam/silt
P4	6	9.8	2.1	5.9	11.9	22.4	9.8	6.2	35.5	Loamy-sand/sandy-loam
P5	8	13.3	3.7	10.5	22.1	30.4	39.1	10.1	126.8	Loamy-sand/sandy-loam
P6	9	15.6	2.1	13.3	19.8	19.7	10.8	5.5	38.9	silt-loam/loam/sandy-loam
P7	10	12.6	1.2	11.3	15.5	14.1	5.4	5.7	23.0	Loam/clay-loam/silt-loam
P8	9	10.8	1.5	8.6	12.7	12.8	5.8	4.7	21.8	Loamy-sand/sandy-loam
TOTAL	**117**	**13.4**	**2.7**	**5.9**	**22.1**	**15.2**	**13.6**	**3.0**	**126.8**	-

[a] USDA textural class, translated from the Belgian soil map

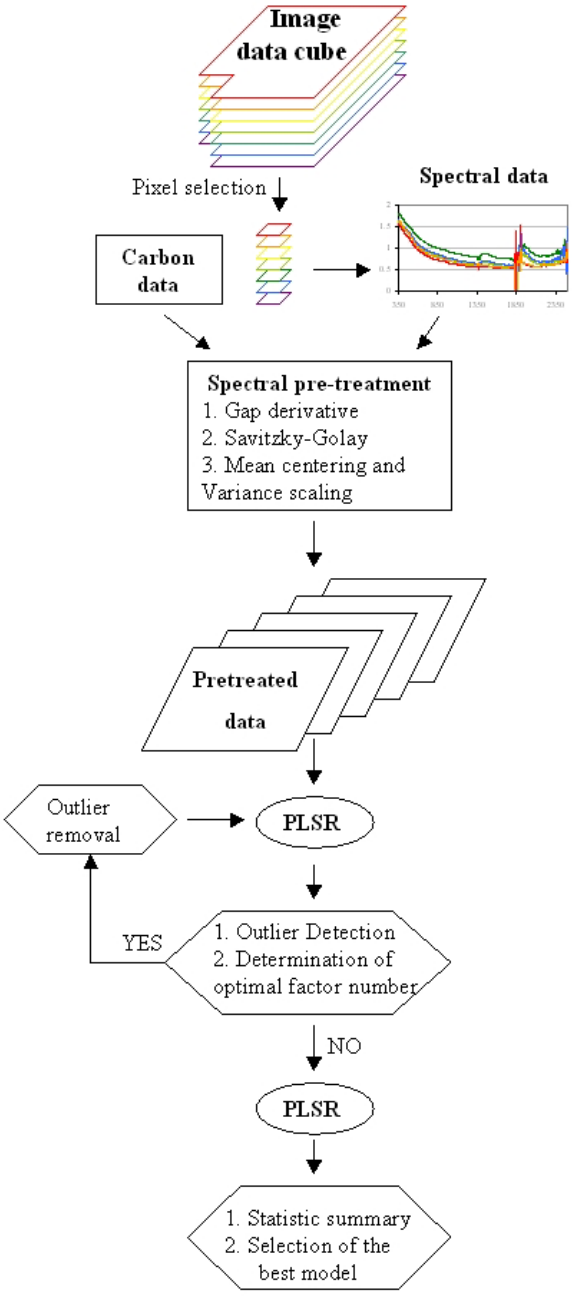

Figure 4.2. PLSR flow chart and outlier removal procedure.

4.2.5 Assessing the stability of calibrations

The problem of calibration stability can be described as the shifting, warping and scaling of the spectral predictors arising from using spectra measured under conditions/instruments different from the ones used during the model calibration (Marx and Eilers, 2002). Two spectral datasets were used to test the stability over time and across different physiographic zones of the calibrations obtained by PLSR. Firstly, spectral data from 2 study areas overflow by the CASI sensor in 2003 (see Chapter 3) will be analysed simultaneously. Secondly, the PS dataset of the 2005 field campaign is joined with PS spectra collected in 2003 in the Ardennes and Lorraine regions. The resulting dataset contained 201 samples with a range of carbon concentrations, texture and field surface conditions. Three different tests using this dataset will be carried out: (i) predict samples of the Lorraine region taken during the 2003 field campaign using the regression obtained from samples of the same area but from a different field campaign (2005), (ii) validate the entire PS dataset using a random validation set and (iii) cross-validate the entire PS dataset.

4.3 Results

4.3.1 Spectral Data Quality and Comparison

The geometrical correction of the hyperspectral image is of good quality, as shown in Figure 4.3. There is indeed a good correspondence between the positioning of the bare experimental plots on the image (clearly visible as light green area surrounded by vegetation in red) and their geographical positions as measured with the differentially corrected GPS signal.

Several pixels of homogeneous light (gravel quarry), grey (parking) and dark (roof) areas were used to calculate a mean Signal to Noise Ratio (SNR) of the IS sensor, according to Eq.4.1. Generally, the SNR of the IS sensor was low in the 1900-2500 nm region (mean: 6.3) where its spectral resolution is high while the SNR was high in the 430-1030 nm region (mean: 30.3) where its spectral resolution is low (Figure 4.4). The low SNR in the 1900-2500 nm region is probably due to a technical problem in the SWIR detector. Mean SNR was 64.8 for LS and 16.7 for PS (data not shown). The difference between LS and PS is probably due to a lower stability of incoming light and variation in viewing/illumination geometry under field conditions.

In principle, any object reflects the same proportion of light independently of the light source or its environment. Atmospheric absorption and scattering, surface scat-

tering, illumination geometry and shadowing influence and disturb the measurements in such a way that the reflectance recorded by the sensor differs from the real spectrum. LS and PS spectra were resampled to fit the resolution of the IS sensor and plotted in order to visually compare the spectra retrieved by the three techniques (Figure 4.5). Maximum reflectance varied from 15 % to 55 %. Figure 4.5a shows spectra of the same experimental plot as measured by the three sensors. Small absorption features can be seen around 500 nm, 700 nm and 2300 nm with a more distinct one at 2200 nm associated with combination mode of OH ($\nu_{OH} + \delta_{OH}$) in the clay lattice (Ben-Dor and Banin, 1990b). Classical absorption at 1400 nm and 1900 nm due to the soil water are masked by the poor spectral resolution of the IS sensor at these wavelengths.

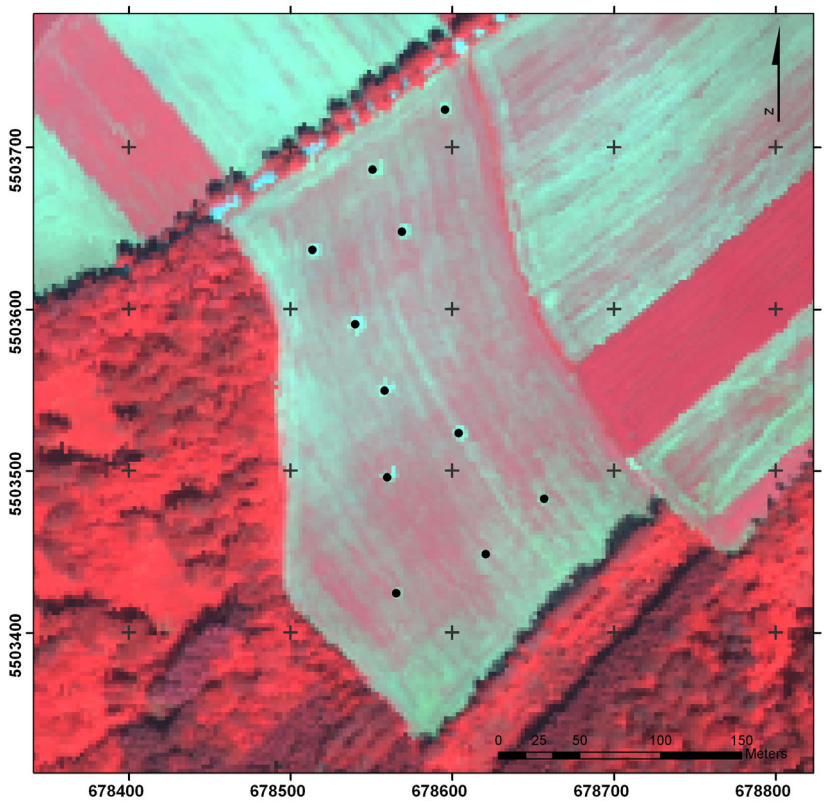

Figure 4.3. Colour composite image of the AHS of a field showing bare (light green) and vegetated area (red) as well as the position of the experimental plots (black dots). Map projection: Belgian Lambert 72. Units: meter.

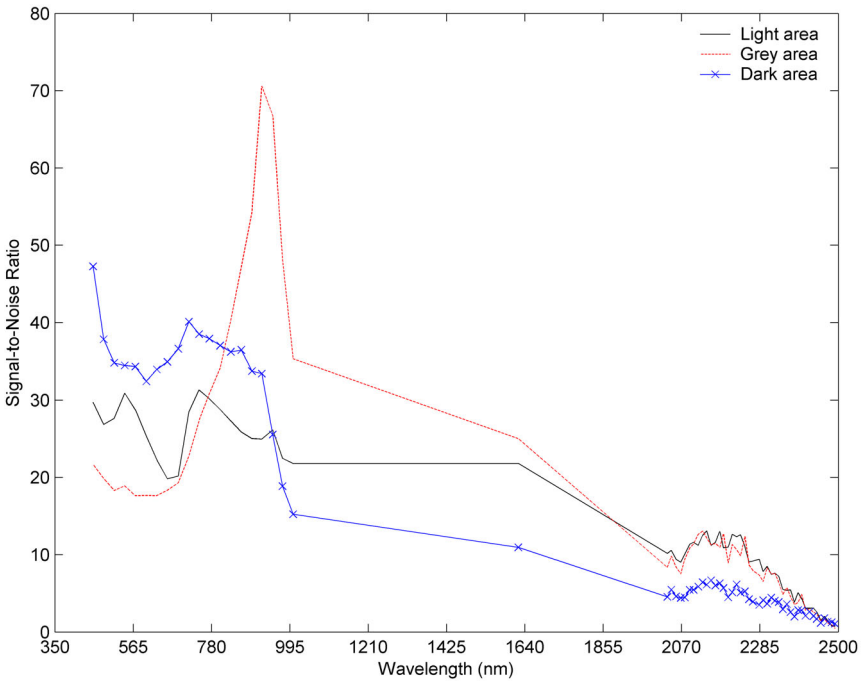

Figure 4.4. Signal-to-Noise Ratio of the AHS-160 sensor as a function of wavelength for a light, grey and dark area.

Above all, LS, PS and IS spectra showed large difference in absolute reflectance (Figure 4.5a). The mean reflectance of the PS is much lower than LS. This is probably caused by shadowing due to soil roughness that adds a micro shade domain to the measured reflectance. This reduction seems not linear across the spectrum since the visible part is less affected by this reduction than the NIR-SWIR region. Nevertheless, the shape of the spectrum obtained by PS is similar to the shape of the spectrum of LS and, when looking at the first derivative of the reflectance, the LS and PS yield more or less the same spectrum (Figure 4.5b). The IS differs strongly from LS and PS in the 1900-2500 nm, while having a closer match in the 430-1400 nm region. The strong divergence as well as the low SNR in the 1900-2500 nm region indicate that the atmospheric correction of the IS sensor was not adequate or the radiometric calibration of this instrument is questionable. The MIR window of the IS sensor suffered the same problem. The 1900-2500 nm and the MIR region were thus considered useless and, as such, removed from the analysis.

4.3.2 Model Calibration and Validation

4.3.2.1 Comparing the predictive ability of LS, PS and IS

Spectral data collected during the 2005 field campaign were used to compare the performance of the different spectroscopic techniques (LS, PS and IS). These three datasets contain more or less 100 samples each, so that cross-validation was considered more appropriate to estimate future predictive ability than test set validation (see section 2.6.3.5). The statistical routine developed in the *SAS* code selected pretreatment able to predict unsampled sites with the highest precision on the basis of its RPD value and the percentage of X (wavelengths) and Y (carbon concentration) variation explained by the model (see section 2.6.3.5).

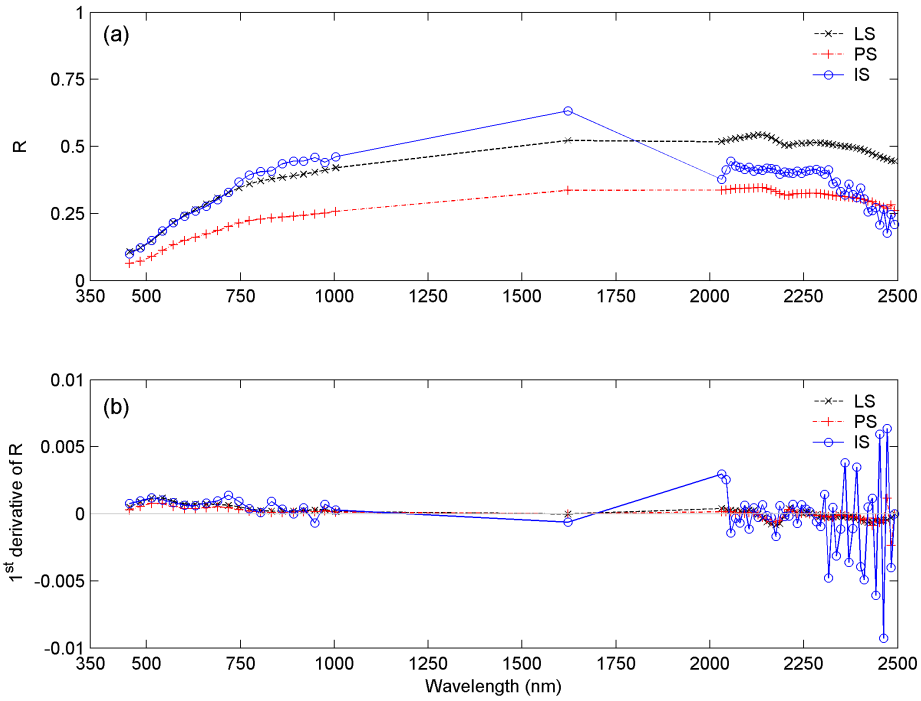

Figure 4.5. Comparison between (a) the reflectance and (b) the 1st derivative of the reflectance, for three spectra of the same plot, as measured by IS, PS and LS. PS and LS spectra have been resampled to the AHS (IS) configuration.

The percentage of X (wavelengths) and Y (carbon concentration) variation explained by the models is high for LS and PS (X-var and Y-var in Table 4.2), sug-

gesting that the models are well constructed. The results show that RPD decreased from ground-based (LS and PS) to remote measurements (IS; Table 4.2; Figure 4.6). This decrease of predictive ability is undoubtedly due to difference in sensor characteristics, an increase in environment-induced variation and in uncontrolled measuring/experimental conditions (*e.g.* SNR, light source quality etc.). RPD values ranged from 1.47 (IS) to a maximum of 2.08 (PS). Ground-based spectroscopy (either LS and PS) shows RPD values greater than 2, indicating that these techniques are reliable estimators of SOC concentration (Chang and Laird, 2002).

While PS and LS have similar RMSECV (1.2 g C kg^{-1}), PS has a better RPD than LS due to a slightly higher standard deviation in the calibration set. This result is counter-intuitive, since LS is measuring spectra under optimal conditions and thus is supposed to produce more accurate predictions. Two reasons can potentially explain the slightly higher performance for PS. First, one can assume that a large part of the noise has been successfully removed by pre-treatments. Secondly, we presume that spectral variation caused by disturbing factors not encountered in the laboratory was effectively handled. These disturbing factors can be: (i) soil moisture content, (ii) soil roughness and (iii) vegetation cover. Soil moisture has been highlighted in section 3.3.2 as a factor degrading the prediction of SOC. However, the field campaign took place under different weather conditions than the ones encountered in 2003: the last shower occurred 16 days before the campaign and mean temperature of the 5 preceding days was 22°C [39]. These particular conditions resulted in very low soil moisture of the first few centimeters and little variation across samples (Table 4.1). Therefore, no preliminary signal processing was necessary to remove the moisture effect. Similarly, soil roughness was generally low because measurements were taken on fields in seedbed conditions. The problem of vegetation cover was resolved by removing samples different from the "soil line" (Figure 4.1). In summary, the performance of PS is equivalent to LS when measuring SOC under specific surface conditions and subject to appropriate signal pre-treatments.

Compared to ground-based sensors, IS has a RPD value close to the one of a very bad model (RPD close to 1.4), according to the classification of Chang and Laird (2002) and thus produces less accurate measurements. However, the removal of the 1900-2500 nm region before the PLSR may cause some discrepancies when comparing the results of IS (430-1400 nm) with LS and PS (350-2500 nm). The RMSECV of IS is 1.7 g C kg^{-1}, yielding a $RMSECV_{corr}$ of 1.4 g C kg^{-1} twice as high as the one of ground-based spectroscopy (0.7 g C kg^{-1}).

$RMSECV_{corr}$ values of LS and PS are smaller to the limit of repeatability (RMSE of replicate samples) of 1 g C kg^{-1} of the Walkley-Black method (Colinet *et al.*,

[39] Neder-Over-Heembeek weather station, Brussels, 46 m, from [http://www.meteobelgique.be/]

2005). They are also in the lower range of values found in Table 2.2. This would mean that ground-based spectroscopy approaches the quality of a standard analytical method. However, it should be noted that the samples have a relatively low mean (13.4 g C kg^{-1}) and standard deviation (2.7 g C kg^{-1}) so that this is only true for this particular type of soils and range of SOC concentration.

4.3.2.2 Testing calibration stability with an IS dataset

During the 2003 flight campaign, two study areas (Ortho in the Ardennes and Attert in Lorraine) were overflow the same day with the same sensor (CASI; see Chapter 3). Ground measurements were equivalent and therefore it gives us the opportunity to join spectral data from the two study areas in order to assess the stability of the calibrations through space. In this regard, the question to be answered is the following: what is the spatial extent of the calibration obtained and, as an auxiliary, is it possible to find a single calibration for various soil types and conditions?

Figure 4.7 shows that PLSR can reasonably take into account the large variability in SOC concentration in the two study areas. RPD in the validation set reaches a value of 1.84, which lies between the values found for the Ortho and Attert sites treated separately (Table 3.3). Thus, the application of the technique to contrasted soil types (from clayey to sandy-loam soils; see Table 3.1) does not degrade significantly its predictive ability. Nevertheless, the precision of IS seems not sufficient to use the technique for the prediction of the SOC concentration of a given pixel or location. Overall, correlations between observed and predicted values in the calibration and validation sets are high. However, a careful examination of Figure 4.7 reveals that, taken individually, the study areas shows weak correlations between their predicted and observed data points. There are still some doubts whether part of SOC predictions are based on indirect correlations with other soil constituents (clay minerals, iron oxides; see Brown et al., 2005). We observed a positive correlation ($r = 0.72$, $p < 0.001$) between iron (Fe_2O_3) and carbon concentrations in the three study areas (based on analysis of 31 samples). This correlation is much weaker if we consider the study areas separately (Ortho: $r = 0.41$, $p > 0.1$; Tintigny: $r = 0.20$, $p > 0.5$). Iron concentration has a masking effect on OM spectral response and inversely (Palacios-Orueta and Ustin, 1999). If the model builds its predictions partially on this correlation, it is likely that a model with an acceptable accuracy will be found at large scale. On the other hand, this model will poorly predict SOC samples of each study area taken individually due to a weaker correlation between SOC and iron concentrations at smaller scale.

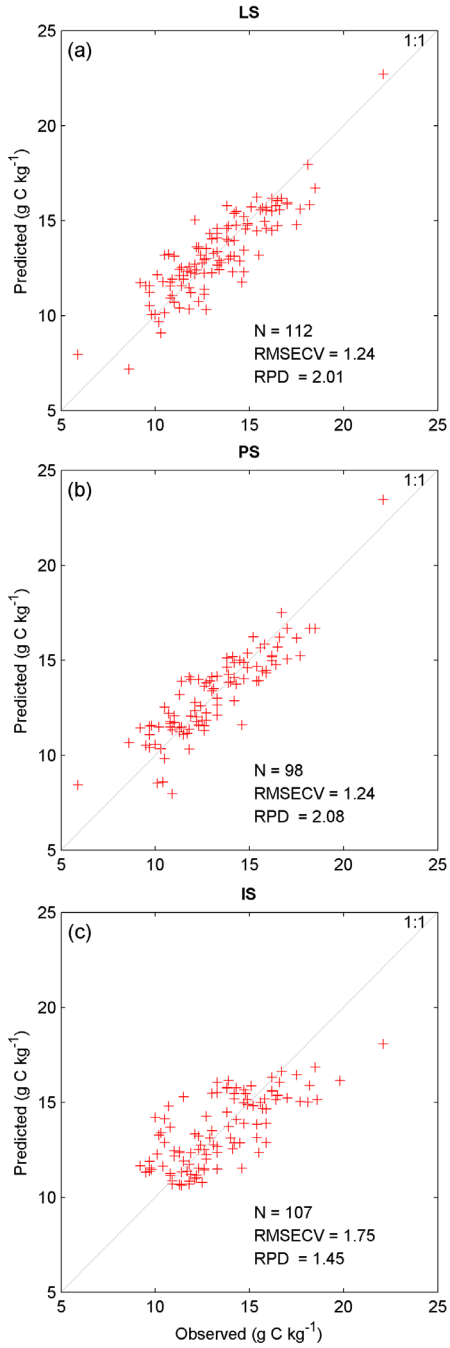

Figure 4.6. Predicted vs. observed C concentration (g C kg^{-1}) for (a) LS, (b) PS and (c) IS spectral data-sets of the Tintigny test site (collected during the field campaign in 2005).

Table 4.2. Predictive statistics of the best model for each sensing technique (Tintigny, 2005).

Sensor type	X var[a]	Y var[a]	LV number[b]	N	SD	RMSECV[c]	Corrected RMSECV[c]	RPD[d]	Outlier	Treatment	Window size[e]
					———	g C kg^{-1}	———				
IS	98.36	52.74	2	110	2.5	1.7	1.4	1.47	3	No treatment	0
PS	72.68	76.97	3	99	2.6	1.2	0.7	2.08	1	Savitzky-Golay 1st derivative 2th order polynomial	65
LS	99.96	75.30	8	117	2.5	1.2	0.7	2.01	5	Savitzky-Golay smoothing 5th order polynomial	65

[a] Total predictor (X) or response (Y) variation (%) explained by the model

[b] Smallest number of PLS factors determined by the cross-validation procedure

[c] Root Mean Square Error of Cross-Validation (see Eq.2.7)

[d] Ratio of Performance to Deviation

[e] Window size of the best pre-treatment in number of spectral bands.

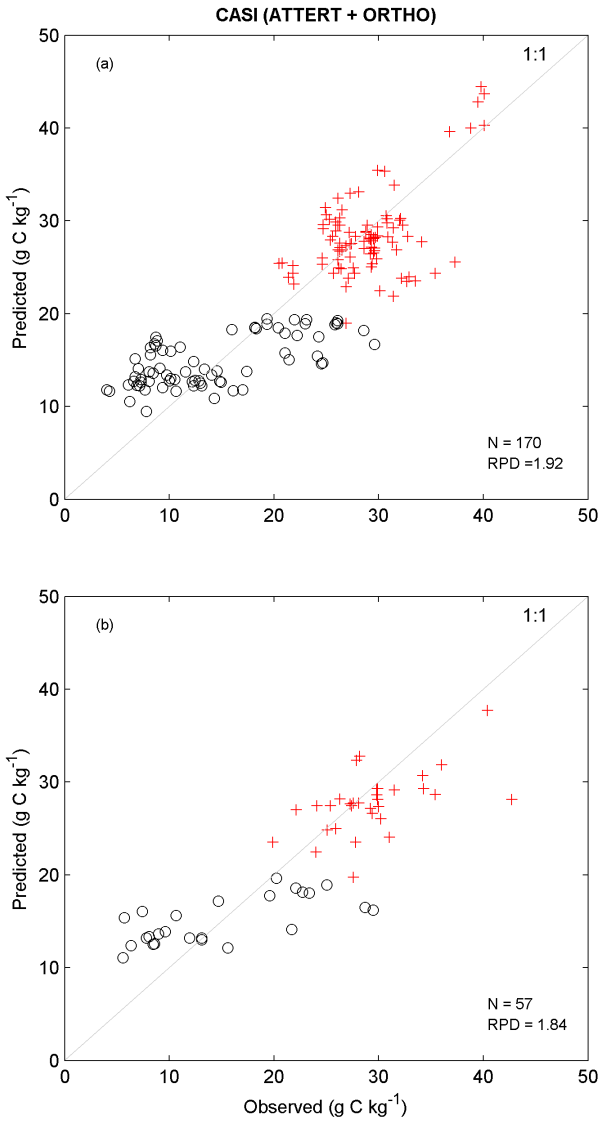

Figure 4.7. Predicted vs. *observed C concentration (g C kg^{-1}) in (a) the calibration and (b) validation set of the CASI sensor (see Chapter 3). Circles are samples from the Attert (2003) test site and crosses are samples from the Ortho test site (2003).*

Therefore, other authors developed a different strategy based on spectral indices (e.g. 1/ 'slope 400-600 nm'), which can be more easily related to the biochemical

composition of OM and may show a greater stability (Bartholomeus et al., 2008). Bartholomeus et al. (2008) were able to demonstrate good correlations between these spectral indices and SOC concentrations over nine soil types and a range of mineral compositions.

These observations indicate that the relationship between SOC and spectral data may be different in the two study areas. Therefore, even with (supposed) similar light and soil surface conditions, obtaining a good regional calibration equation is challenging. The spatial extent of the calibration seems thus restricted to homogeneous area in terms of soils type or geology. Also, differences in spectral calibration (atmospheric corrections) between the two study areas may explain this problem. For the time being, local calibrations are thus probably more appropriate than a regional one. We showed that the chemometric approach applied to our spectral data was very flexible and able to produce an acceptable model over a wide range of soil types. However, this can be misleading due to difference in spectrum-SOC relationships between study areas. This is clearly a drawback of the chemometric approach when applied to data subject to varying conditions.

4.3.2.3 Testing calibration stability with a PS dataset

We have seen in section 4.3.2.1 that the accuracy of PS and LS are similar. This was attributed to the fact that our measurements were limited to one particular study area and therefore soil surface conditions were similar: fields were all in seedbed conditions with a low roughness and moisture content of the soil surface, and the effect of vegetation cover has been removed with a simple rule. Then, what would be the predictive ability of such technique if we transfer it to broader areas with a range of soil surface conditions and soil type? For instance, in the 2005 campaign soil crusts have been observed in several fields. Others fields were covered with some vegetation residues. Also, during the 2003 field campaign, some fields were in perfect seedbed conditions while others were freshly ploughed and thus affected by greater soil self shadow due to roughness. Another factor that may induce a variation is the decomposition level of organic matter (see e.g. Ben-Dor *et al.*, 1997). However, in our case, all samples, with the exception of one (clear-cut forest), were collected in ploughed agricultural fields with presumably low and comparable C:N ratio. Therefore the effect is considered to be negligible.

The different areas we covered in 2003-2005 represent an occasion to explore the quantitative effect of surface condition variability on the predictions. This question is important because unstable calibrations through time compel to re-calibrate each measuring campaign. The PS measurements taken during the 2003 and 2005 field campaigns were analysed simultaneously to evaluate if there is a temporal

variation in PLS calibrations due to environmental factors. Since the PS dataset contained 201 samples, a true test set validation could be used rather than a cross-validation. Location of the field campaigns and SOC statistics of the combined dataset are given in Table 4.3.

As a preliminary approach, we tried to build a stable calibration curve for the same physiographic region. Samples taken during the 2005 field campaign in Lorraine were used to calibrate a model, which was validated with spectral data measured in 2003 in the same region. RPD in the calibration set is high (4.26) while RPD in the validation set is low reaching a value of 1.09 (Table 4.4). Other statistics tell us the same story: high bias and high RMSECV. The graph of the loadings of the LV's (not shown) displays an extremely noisy shape, suggesting that the noise, rather than the true signal, has been modelled. It indicates a very bad model and poor replication of a calibration through time for the same area.

Table 4.3. Summary statistics of SOC (g C kg^{-1}) for the different field campaigns in the PS dataset

		SOC content				
Field campaign	N	Mean	SD	Min	Max	Region
		g C kg^{-1}				
Attert 2003	37	13.3	4.9	5.7	22.8	Lorraine
Ortho 2003	65	26.9	3.5	19.9	37.3	Ardennes
Tintigny 2005	99	13.2	2.7	5.9	22.1	Lorraine
All campaigns	201	17.7	7.3	5.7	37.3	-

The calibration made on 2005 samples was obviously not representative of spectra measured in 2003. Nevertheless, the range of SOC concentration measured in 2005 was within the range of SOC concentration measured in 2003 (Table 4.3) and soil types were similar. Moreover, even if light conditions were different between the two campaigns, spectral calibration through white reference measurements should ensure a constant spectral shape. This first test shows that the methodology is very sensitive to small changes in the predictors and that a calibration is needed before each measurement campaign.

In a second experiment, a calibration was carried out using the dataset from the different campaigns randomly leaving out a portion (1/3) that was used for validation (Table 4.4, second line). RPD in the calibration set was considered satisfactory since it reached a value of 2.70. However, in the validation set, RPD is falling to 1.21 with a $RMSEP_{corr}$ of 6.96 g C kg^{-1}. This decrease is due to a few outliers, clearly visible in Figure 4.8 and increasing the latter statistic. For the same reason,

the bias in the validation set was unexpectedly large (1.21 g C kg^{-1}). If we remove these outliers, the RPD increases to 2.55. Either these samples are spectral outliers and are influenced by other factors than the dependent variable (like roughness), or they are not comparable to the group of samples used in the calibration in terms of SOC concentration. In our case, the five outliers are samples from one particular field, for which all other samples in the calibration set have been removed during the outlier detection phase (see section 4.2.4). The processing of all the pre-treatments by PLSR confirmed that spectra from this field were systematically removed from the calibration set during the outlier detection phase (results not shown). A preliminary Discriminant Analysis could help to identify these kinds of problematic spectra. As a matter of fact, PLSR was unable to predict samples falling outside of the calibration set.

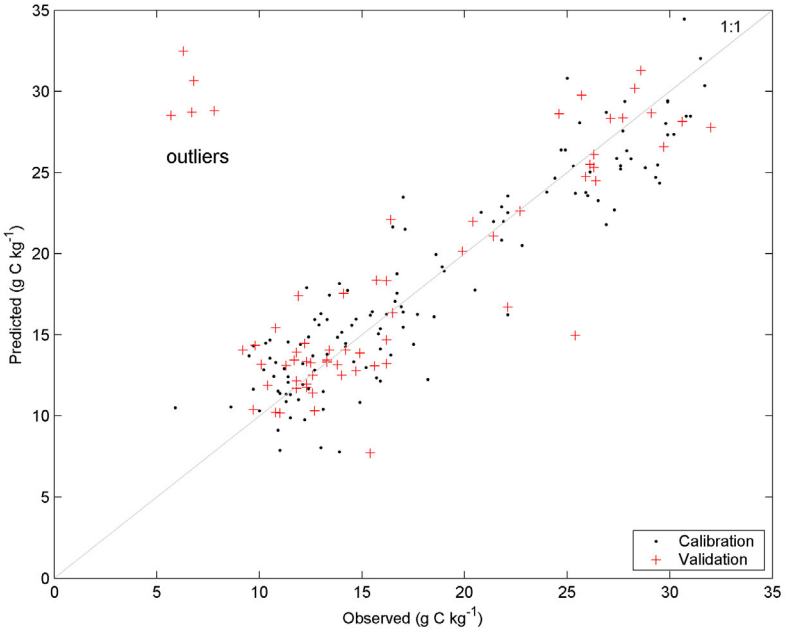

Figure 4.8. Plot of predicted vs. *observed organic carbon as obtained after a random test set validation on field spectroscopic spectra from Ortho and Attert 2003 (see Chapter 3) and Tintigny 2005*

In a third experiment, we analysed the entire PS dataset using cross-validation. This gave better results (RPD = 2.84, $RMSECV_{corr}$ = 2.29 g C kg^{-1} , 17 outliers) indicating that the statistical procedure can effectively predict samples when they are within the same range as the calibration set. Scores are linear combinations of the predictors (X-scores) or response (Y-scores). Plotting X-scores by Y-scores can be

used to visualize samples that are similar in spectral shape (X-score axis) and SOC concentration range (Y-score axis). It appears that spectra of the three study areas (Tintigny (A), Attert (B), Ortho (C); Table 4.3) can be roughly discriminated on the basis of their scores, defining groups of similar characteristics (Figure 4.9). Tintigny spectra generally have low X-scores while Attert and Ortho spectra generally have high X-scores, this pattern corresponds to the two field campaigns (A: 2005 and B+C: 2003). Along the Y-axis, there are two groups again (A+B with low Y-scores and C with high Y-scores) differing in their carbon concentration range (see Table 4.3).

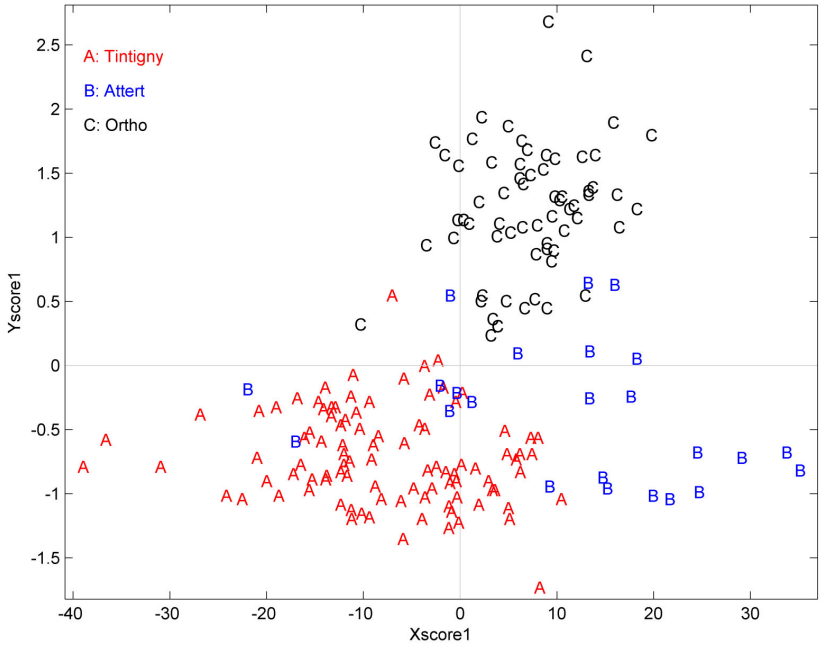

Figure 4.9. Plot of Y-Score vs. *X-Score of the first Latent Variable as obtained after a cross-validation on the joined PS dataset. Samples are labelled according to their origin: "A" for Tintigny 2005, "B" for Attert 2003, and "C" for Ortho 2003.*

These observations are encouraging because the model constructed by PLSR, reaching relatively high RPD, appears to be able to take into account this double variation in spectral shape and carbon concentration. This fact is particularly important when assessing the stability of the calibration at the regional scale and between measurement campaigns. Still, $RMSECV_{corr}$ is higher than the one obtained by the model restricted to only one study area (Table 4.2). This difference can be due to a

larger range of SOC concentrations but also possibly to the variability in field conditions across study areas. Unfortunately, the monitoring of soil surface conditions was not done properly so that it was not possible to relate spectral data with particular surface conditions (e.g. soil crusting). Only the quantitative effect of surface variability on the predictions was addressed. We need thus to define surface conditions characteristics required to measure SOC in the field with acceptable accuracy (like low variation in moisture content of the soil surface, low roughness and absence of vegetation).

Currently, attempts to predict samples from different locations and studies have shown relatively low validation results (*e.g.* Brown *et al*., 2005) due to varying soil types or soil surface conditions. Brown *et al*. (2006) produced a generic model for several thousands of soils from all over the world but failed to predict C at an acceptable accuracy for most applications (RMSE: 9 g C kg^{-1}). However, such a global spectral library can be used to classify measured spectra (e.g. based on scores). Then, only a portion of the library may be used for prediction.

4.4 Discussion

LS has the advantage to allow stable calibrations through time and is, therefore, currently implemented in some laboratories as a routine soil analysis technique (e.g. Genot, *pers comm*., 2007). Although LS allows a much quicker and cheaper analysis compared to traditional techniques, it still requires sample preparation (collecting sample, sieving, crushing, etc…). This study shows that PS can reach precision comparable to LS but it still needs a calibration before each measurement campaign. Outside of the laboratory, some factors, differing in each study area, like soil moisture, soil types and vegetation residues can disturb the signal and alter the calibration. Airborne sensors give also non-comparable spectra between two campaigns because of surface conditions or atmospheric absorption interfering with the measurements. Furthermore, imaging spectroscopy and to a lesser extent field spectroscopy only measure the reflectance of the soil surface and therefore are not able to detect vertical gradients in SOC within the topsoil.

In SOC monitoring studies, changes in SOC stocks rather than changes in SOC concentrations are generally considered. However, when applied to croplands, the plough layer can be considered to be homogenous as a result of frequent mixing by tillage. Therefore, SOC concentrations determined at the soil surface can be transformed into SOC concentrations and SOC stocks of the entire plough layer, which reacts most quickly to changes in management or land use.

Table 4.4. Predictive statistics of the best model for PS under different validation settings.

				Calibration							Validation							
Validation[a]	X var[b]	Y var[b]	LV[c]	N	SD[d]	RMSECV[e]	Corrected RMSECV[e]	RPD[f]	Outlier	Bias	N	SD[e]	RMSEP[e]	Corrected RMSEP[e]	RPD[e]	Bias	Treatment	Window size[g]
(A)	79.55	79.30	4	99	2.59	1.17	0.61	4.26	5	-0.26	37	4.85	4.56	4.45	1.09	-0.45	Savitzky-Golay 1st derivative 5th order polynomial	129
(B)	99.74	84.81	5	134	6.90	2.67	2.48	2.70	7	0.26	67	7.79	7.03	6.96	1.21	1.21	Savitzky-Golay smoothing 5th order polynomial	5
(C)	99.75	87.50	5	201	7.12	2.50	2.29	2.84	17	0.00	-	-	-	-	-	-	No treatment	0

[a] Validation type: (A) Validation of Tintigny (2005) samples against Attert (2003) samples (both study areas are located in Lorraine); (B) Random test set validation of all field spectral data (Ortho and Attert 2003, Tintigny 2005); (C) Cross-validation of all field spectral data (Ortho and Attert 2003, Tintigny 2005)

[b] Total predictor (X) or response (Y) variation (%) explained by the model

[c] Smallest number of PLS factors determined by the cross-validation procedure

[d] Standard Deviation in the calibration or validation set

[e] Root Mean Square Error of Cross-validation or Validation (see Eq.2.7)

[f] Ratio of Performance to Deviation in the calibration or validation set

[g] Window size of the best pre-treatment in spectral bands unit..

Although it is clear that IS has for the moment poor detection levels, its capability to cover large surfaces in a single campaign and thus producing a complete picture of surface SOC concentrations of bare soils in a given area represents an opportunity for SOC monitoring. Since local calibrations increase the workload, imaging spectroscopy appears to be more efficient than field spectroscopy given the large number of measurements that the former technique can provide. In this respect, users willing to choose one of these techniques for a particular application have to weigh the accuracy against the area to be covered.

The development of a regional calibration would significantly reduce the costly sampling and calibration phases. This can be fixed through the establishment of spectral libraries regrouping soil spectra from the same region that could be recalibrated at fixed time intervals (*e.g.* Shepherd and Walsh, 2002). Such spectral libraries should be constructed by setting the precise conditions in which the measurements are recorded (soil surface status, number of scans per samples, etc...).

Also, further research should concentrate on the determination of the spatial extent of the calibrations in relation to the precision obtained. A greater variation in a training set may increase the ability of the statistical model to characterize diverse samples but it may results in a decrease of the prediction accuracy of the PLSR. Then, the extent of the spectral library and thus the region that it covers would be a trade-off between these two constraints, depending on the level of precision that a given application requires.

4.5 Conclusions

Spatial variability and slow temporal change in SOC stocks at various scales reduce our capacity to detect changes within a short time span. This problem can be resolved by using a high sampling density that can only be achieved by means of more rapid analytical methods like reflectance spectroscopy. Soil spectra can be measured with different instruments and settings (laboratory, field, airborne), each having its comparative advantages and limitations.

The accuracy of field spectroscopy is equivalent to laboratory spectroscopy when measuring SOC under specific surface conditions (low variation in moisture content of the soil surface, low roughness, absence of vegetation) and appropriate pre-treatments able to extract information from noisy spectra. The potential of this technique is high, since it requires very little prior sample manipulation. Our calibrations showed that it is possible to reach accuracies comparable to standard analytical method (Walkley-Black). These two techniques can thus be potentially used for monitoring studies where their speed is a valuable advantage. Airborne techniques,

such as IS, appear, for the time being, not able to predict SOC with an acceptable accuracy due to their low SNR and problem to achieve true spectral information. Nevertheless, the greater potential lies in this technique and more efforts have to be put in spectrum calibration.

The use of different datasets from different study areas and field campaigns showed that calibrations are currently site-specific and partly fail to predict, under a proper test set validation procedure, samples belonging to another study area or falling outside of the range of the calibration set. The development of a regional calibration, valid for soils of the same physiographic region is thus one of the first research priorities.

Chapter 5

Soil organic carbon dynamics at regional scale as influenced by land use history

Outline

Land Use Change (LUC) is known to have a large impact on Soil Organic Carbon (SOC) stocks. However, at a regional scale, our ability to explain SOC dynamics is limited due to the variability generated by inconsistent initial conditions between sample points, poor spatial information on previous land use/land management history and scarce SOC inventories. This chapter combines the re-sampling in 2003-2006 of an extensive soil survey in 1950-1960 with exhaustive historical data on land use change (1868-2006) to explain observed changes in the SOC stocks of temperate forest soils in the Belgian Ardennes. Results from re-sampling showed a significant loss of SOC between the two surveys, associated with a decrease in variability. The mean carbon concentration decreased from 40.4 to 34.5 g C kg^{-1} (106 to 96 t C ha^{-1}), with a mean rate of C change (ΔSOC) of -0.15 g C $kg^{-1}yr^{-1}$ (-0.23 t C ha^{-1} yr^{-1}). Soils with high SOC concentration tended to loose carbon while conversely soils with low SOC tended to gain carbon. Land Use Change His-

tory (LUCH) explained a significant part of past and current SOC stocks as well as ΔSOC during the last fifty years. We show that the use of spatially-explicit historic data can help to quantitatively explain changes in SOC concentration at the regional scale.[40]

5.1 Introduction

The current sink of the European biosphere (forest, cropland, grassland, peatland) is estimated to range from 7 to 12 % of the anthropogenic CO_2 emissions of 1995. This corresponds to a net sequestration of 0.135 to 0.205 Gt C yr^{-1} (Janssens *et al*., 2003). The role of forest soils is a particular matter of interest because of the large quantity of carbon stored in forest soils[41] and large areas covered by forest in the world. In temperate forests, 60 % of the total C stocks are found in soils (Dixon *et al*., 1994). Therefore, forests represent a large part of this carbon sequestration while croplands and peatlands constitute a source of CO_2 (Janssens *et al*., 2003). A major reason for this sink can be found in the management and disturbance history of European forests that are recovering from the 18th century onwards after a long period of deforestation that began some 8,000 yr ago (Williams, 2003). According to some authors, soils would only account for 5-15 % of the total forest sink (Gaudinski *et al*., 2000; Baldocchi *et al*., 1988; De Vries *et al*., 2006). Woodbury *et al*. (2006) estimated that land use changes caused a carbon sequestration in the trees 6-7 times greater than carbon sequestration into the soil for the period 1990-2004 in southern United States. Others assume a much bigger role for forest soils. Nabuurs *et al*. (2003) calculated with a bookkeeping model that the soil C sink of European forest during the 1950-1999 period was similar to that of the tree biomass during the first two decades. Liski *et al*. (2002) estimated the soil carbon sink of western European forest to be 32-48 % of the one of the tree biomass in 1990 and 61-69% by 2040. According to De Vries *et al*. (2006), the net sequestration by European forest was estimated at 0.117 Gt C y^{-1} in 2000, of which 20 % (0.023 Gt C y^{-1}) came from the soil pool.

In forest, the observed variations of SOC stocks can be explained by several factors, such as: stand age (Grigal and Ohman, 1992; Vesterdal *et al*., 2002), litter quantity during the growth of the forest (Wilde, 1964; Covington, 1981; Wigginton *et al*., 2000), management practices (Johnson, 1992; Jandl *et al*. 2007), harvesting (Johnson and Curtis, 2001), dominant species and humus type (Grigal and Ohman, 1992; Dupouey *et al*., 1999; Giardina *et al*., 2001). Carbon stocks in forest soils are more or less equivalent to those found in grasslands but sensibly higher than those

[40] This chapter is based on an article by Stevens A. and van Wesemael B. (2008) Soil Use and Management, in press

[41] ± 50 % of world SOC stocks according to Jobbágy and Jackson (2000).

found in cropland (Arrouays *et al*., 2001). Based on an extensive Belgian soil survey made in 1950-1970, Lettens *et al*. (2004) calculated the SOC stock to a depth of 30 cm. Sock stocks range from 70 t C ha^{-1} under coniferous forest to 58 t C ha^{-1} under broadleaf and 65 t C ha^{-1} under mixed forest. It is well-known that differences in allocation of carbon in woody and non-woody tissues, above and below ground biomass and lignin content in the leaves between vegetation types will have a strong impact on decomposition rates of organic matter and consequently on the size of the SOC pools. Difference between SOC pools in deciduous and coniferous forests are generally explained by the influence of litter quality on decomposition rates. However, Arrouays *et al*. (2001) did not observe a significant difference in SOC stocks between deciduous and coniferous forests of France. Taking into account the area covered by forest in Belgium in 2000, the total amount of carbon in forest soils reached 57 Mt C (Lettens *et al*., 2005b). For a global overview of SOC stocks in forest soils, the factors affecting its dynamics (global change, management, land use) and a description of the main challenges and methodological issues, see Hendrickson (2003) and Lal (2005).

The monitoring of SOC through time and the assessment of LUC impact are essential to the evaluation of the role of soils in the global carbon budget and their contribution to climate change. Often, a wide range in responses (or spatial variability) is observed in estimates of SOC stocks and their evolution, which can be attributed to variation in initial conditions (climate, soil, topography and land use history; Guo and Gifford, 2002; Paul *et al*., 2002a). Specifically, land use change history (LUCH) is one of the key factors that could better explain the dynamics of SOC at regional scales. The knowledge of site history at the regional scale could be used to distinguish soils that are in an equilibrium, recovery or degradation phase. While LUCH is frequently reported as a major driver of SOC change at the regional/national scales (e.g. Tan *et al*., 2005; Sleutel *et al*., 2007), few studies (Holmes *et al*., 2004; Kasel and Bennett, 2007) *quantitatively* investigate the effect of land use history on SOC stocks, due to an absence of accurate historical data at such scale. The objective of this chapter is to estimate the effect of LUCH on carbon concentration dynamics of forest topsoils (0-30 cm depth[42]) at a regional scale.

[42]While in some particular cases (e.g. tropical soils), changes in soil carbon can occur over the whole profile, it is also commonly admitted that this layer respond quicker and stronger to changes in land use, climate or management than deeper horizons. For instance, Guo and Gifford (2002) calculated that forest to crop conversions are on average responsible for a soil C stocks decrease of 50-60 % if sampling depth is less than 30 cm. Horizons deeper than 60 cm did not changed significantly. In temperate humid forest, the proportion of SOC in the top 20 cm reaches on average 50 % of the SOC pool (Jobbágy and Jackson, 2000). This depth increment has been used among others in national- or continental-scale estimates of SOC stocks (Arrouays *et al*., 2001, Jones *et al*., 2005), in a study of future SOC stock change in European forest (Smith *et al*., 2006) and at the plot scale in a review of SOC changes following afforestation (Paul *et al*., 2002).

Fieldwork consisted of a partial re-sampling of an historical soil inventory some fifty years later along with analysis of historical maps.

5.2 Material and methods

5.2.1 Study area

The study area in the Walloon region, covers 1280 km² of the northern part of the Belgian Ardennes (5°35'E 50°11'N). The landscape consists of plateaus and valleys incised by the Ourthe River and its tributaries with a mean altitude of 300 - 652 m.a.s.l. Soils are mainly loamy and may contain a high rock fragment content (shale and sandstone). Cambisols, Eutric Cambisols and occasionally Haplic Luvisols (FAO-ISRIC-ISSS, 1998) are found on the slopes and shoulders of the plateau while hydromorphic soils (Gleyic Cambisols, FAO-ISRIC-ISSS, 1998) are found in flat positions on the plateau and in the valley bottoms. Peat bogs can be found in the northern part of the study area (Plateau des Tailles) and developed since the last glaciation (12,000 BP) on the flat parts overlying impermeable shales favouring waterlogging in a cold and wet climate (1200 mm of precipitation and mean annual temperature of 7°C, De Sloover *et al*., 1980). Soil organic carbon stocks are generally high in this part of Belgium due to a wetter and colder climate (mean temperature of 8 °C and precipitation of 1100 mm) than in the rest of the country (Lettens *et al*., 2004).

5.2.2 Land use history

The physical environment and land use history of the region have been described extensively in Petit and Lambin (2002) and are summarized below. Until the 13th century, a deciduous forest consisting mainly of oak, beech and birch covered the area. From the 14th to 18th century, the Walloon forest was progressively degraded due to agricultural and pre-industrial environmental pressures including agricultural clearing, extensive grazing and charcoal production. Heathlands developed but starting in the 19th century, agricultural intensification and a decrease in the rural population pressure reversed this process of degradation. From the 19th century onwards, the area of forest has constantly increased, reaching 30 % of the total surface of the Walloon region (DGRNE, 1997). This increase has been concomitant with a decline in deciduous forest, drainage of peatlands and an increase in coniferous plantations. During the 20th century, the largest part of the arable land was converted to grassland as a result of specialization in breeding of dairy and beef cattle. This general

pattern of land use change in the Belgian Ardennes has been confirmed in the study area by the analysis of historical maps (Figure 5.2).

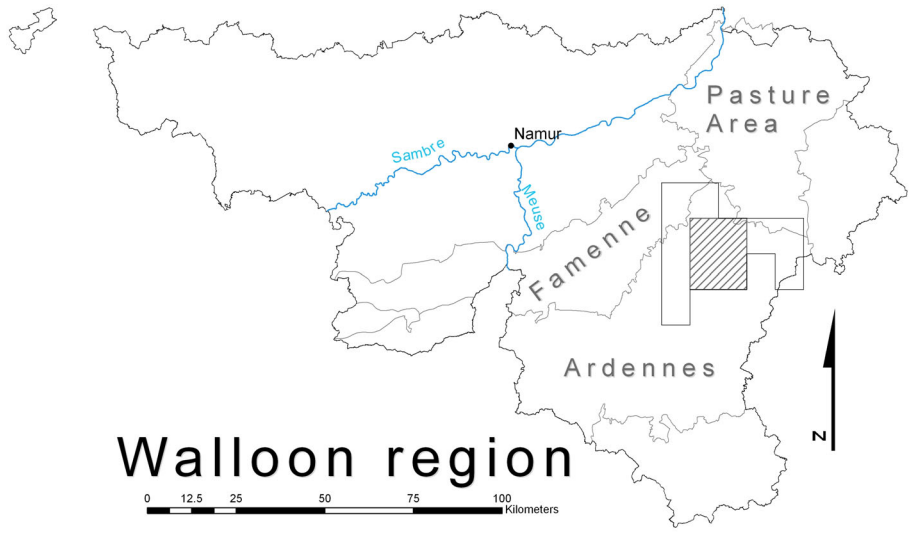

Figure 5.1. Location of the study area within the Walloon territory. Geo-referenced and digitised maps are hatched, while the rest are only geo-referenced and scanned historical maps

5.2.3 Soil database

The soil profiles resampled during this study were initially analysed (each profile was sampled in a single pit) during the Belgian National Soil Survey between 1947 and 1962, and compiled in a geo-referenced database, referred to as 'Aardewerk' (Van Orshoven *et al.*, 1988). This database[43], hereafter 'survey 1', contains for the area south of the Sambre and Meuse rivers ca. 3,800 soil profiles with data on each horizon on thickness, textural class, drainage, rock fragment content, and organic and inorganic carbon concentration. Some anomalies in the database (overlapping horizons, redundant samples, etc.) were corrected and inconsistent soil profiles were deleted. The coordinates of each profile were checked against the original location maps from the time of the survey and their coordinates were corrected when necessary.

[43] This database has been already used several times in SOC-related studies, for instance in the quantification of SOC and SIC content of landscape units in Belgium (Lettens *et al.*, 2004), the evaluation of the accuracy of the estimation of SOC stocks in Flemish grasslands (Mestdagh *et al.*, 2004) or the study of the temporal evolution of SOC in Flemish croplands (Van Meirvenne *et al.*, 1996; Sleutel *et al.*, 2003a). To our best knowledge, it has never been used for forest soils.

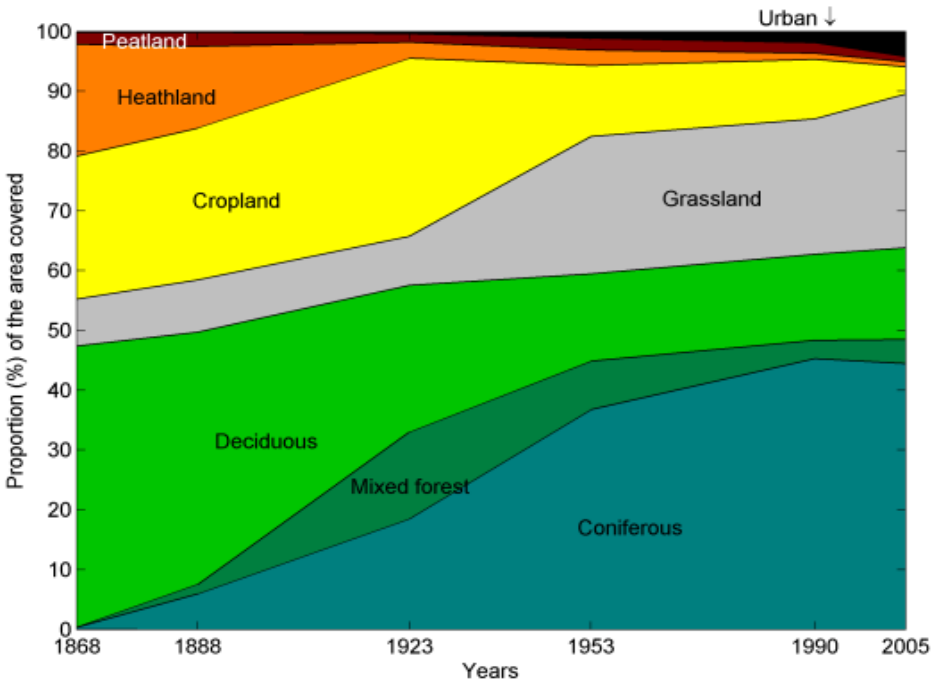

Figure 5.2. Evolution of land cover change between 1868 and 2005 in the study area, based on geo-referencing and digitising of historical maps.

5.2.4 Historical maps geo-referencing and digitising

In order to reconstruct the land use history at each soil profile in the study area, 12 sheets of the 1:10,000 topographical maps published by National Geographical Institute in 1868, 1888, 1923, 1953 and 1990 were geo-referenced. The residual mean square error of the geo-referencing ranged from 10 to 20 m. On these maps, the following land use classes corresponding to the ones of the 'Aardewerk' database, were identified: coniferous (*co*), deciduous (*de*) and mixed (*mx*) forest, grassland (*gr*), cropland (*cr*), heath (*he*), peat bogs (*pb*) and urban areas. For each date, these classes were given as attributes to each soil profile. In addition to the geo-referencing, 1/3 of the study area was digitised using ArcGis 8.3 (ESRI Redlands CA) from these historical maps in order to accurately quantify the conversions in time and space between the land use classes.

5.2.5 Sampling and SOC analysis

There were 365 forest soil profiles in the original soil inventory of the study area. From these, 127 (34 %) sites were resampled during 2003-2006 on the basis of history[44] and accessibility, and the results were collated in a database called "survey 2". The location error in re-sampling of survey 1 in croplands was estimated at ca. 10 m (Van Meirvenne *et al*., 1996). In the forest, the accuracy was likely to be lower due to the effect of the vegetation on the GPS signal. The majority of the soil profiles sampled (82 %) were classified as stony loam soils with a favourable to moderate drainage (Gb-c in the Belgian soil classification system). The remainder was classified as stony loam with poor drainage (Gd-i, 9%), loam (A, 3%), light clay (E, 4 %) and heavy clay (U, 2 %) soils.

Soil samples were taken at the selected sites[45] by an auger at five random locations within a radius of 5 m and to a depth of 30 cm. Only the organo-mineral part of the soil was sampled with the O horizon being removed before augering. The subsamples were mixed to make a bulk soil sample part of which was collected in a plastic bag for analysis in the laboratory. Composite sampling is used to encompass the high spatial variability of SOC (Wilding *et al*., 2000). By doing only one sample per stand thus visiting a great number of different locations**,** we have deliberately chosen to 'sacrifice' *within-site* variability to *between-site* variability in order to concentrate our analysis on regional SOC variation in relation to LUCH. This strategy is presumably the most efficient to increase the power of the design to detect land use effects on SOC concentration (Kasel and Bennett, 2007). In addition, the core technique, rather than the pit excavation technique, was chosen for sampling. Although the technique may be less accurate when the rock fragment content is high, it allows collecting more samples and therefore has proven to be more efficient to estimate soil nutrient storage in rocky forest soils (Kumaltiski *et al.*, 2003).

Three samples per plot were taken to estimate bulk densities using steel cylinders (100 cm^3, height 5 cm). Bulk densities were taken only in the first cm of the soil due to the difficulty in stony soils of taking samples using the volumetric ring method. Hence these samples represented soil on average between 1 and 6 cm. Soil samples were air-dried, crushed to pass a 2 mm sieve and analysed for carbon using the Walkley-Black method (Walkley and Black, 1934), the same as used for the National Soil Survey. Bulk density samples were weighed, oven-dried (105 °C during 24h), weighed again, then gently crushed and sieved (2 mm) to calculate the weight of coarse fragments.

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[44] Profiles having a simple land use history (no or one land use conversion since the mid-19th century) were visited in priority.

[45] Positioning errors mentioned by the GPS ranged from 1 to 10 m

5.2.6 Calculation of bulk density and SOC concentration

Survey 1. Due to the lack of bulk density values in the Aardewerk database, these were estimated using the pedotransfer function (PTF) of Rawls (1983) and adapted for Belgian conditions (Lettens *et al.*, 2004; Eq. 5.1):

$$BD = \frac{100}{\{(OM/VOM)+(100-OM)/VMF\}} \qquad \text{(Eq 5.1)}$$

with OM the percentage of organic matter[46], VOM the bulk density of organic matter (0.224 g cm^{-3}; see Lettens *et al.*, 2004) and VMF the bulk density of the mineral fraction (g cm^{-3}; Table 5.1). SOC concentration (g C kg^{-1}) of the profiles was estimated to a depth of 30 cm (Eq. 5.2):

$$SOC = \frac{\sum_{i=1}^{k} C_i \cdot D_i}{30} \cdot (1-S) \qquad \text{(Eq 5.2)}$$

with k the number of horizons, C_i the carbon concentration[47] of horizon i (g C kg^{-1}), D_i the thickness of horizon i (cm) and S the proportion of rock fragments in bulk density samples. The rock fragment content was available in the National Soil Survey database. However, this parameter was generally nil or very low for the profiles selected in the study area, contrary to what was observed during survey 2, and therefore was not considered reliable. Instead, we used a proxy, i.e. the proportion of rock fragment in the bulk density samples, which varies from 0 to 21 % with a mean of 6.6 % (in volume). These are likely to underestimate on average the true rock fragment content since only small rock fragment can be incorporated in these samples[48]. However, the rock fragments consisted mainly of slate, which are often made of small fragmented pieces in the soil matrix. In addition, the same correction for the coarse fraction was applied to SOC in survey 1 and survey 2 so that a possible error will affect only absolute estimates of SOC1 and SOC2 and not the rates of SOC change.

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[46] In survey 1 database, OM has been calculated as follows:

$$\begin{cases} t_{survey} < 1961 \Rightarrow OM = OC \cdot 1{,}724 \\ t_{survey} \geq 1961 \Rightarrow OM = OC \cdot 2 \end{cases}$$

[47] Due to the incomplete recovery of the Walkley-Black method, total C content is obtained by multiplying measured concentration by 4/3.

[48] In the Belgian soil series classification system, these soils would be classified as slightly stony (5-15% of rock fragment).

Table 5.1. Bulk density of the mineral soil fraction (VMF) as a function of soil textural classes from the Belgian soil map (Goidts and van Wesemael, 2007, from Boon, personal communication).

Soil textural class[a]	Clay	Loam	Sand	VMF
	———	%	———	g cm^{-3}
Z	2	7	89	1.54
S	6	18	75	1.55
P	7	33	59	1.41
L	11	52	35	1.3
A	14	76	9	1.4
E	25	43	31	1.41
U	41	12	15	1.35
G[b]	15	61	22	1.22
G[c]	25	51	22	1.28

[a] Soil textural classes of the Belgian soil map. Z = (loamy) sand; S = sandy loam to loamy sand; P = sandy loam: L = (silt) loam; A = silt (loam); E = (sandy) clay loam, loam, silt, (clay) loam; U = sandy clay, clay (loam), silty clay; G = loose stony sediment (within A, L, E) (see Table 2 in Goidts and van Wesemael, 2007)

[b] G soils with low clay content (< 20 %)

[c] G soils with high clay content (≥ 20 %)

Survey 2. The rock fragment content was often high in the forest soils of the study area and therefore the measured bulk density had to be corrected (Curtis and Post, 1964; Eq. 5.3):

$$BD = \frac{W_t - W_c}{V_t - \left(W_c / SG_c \right)} \qquad \text{(Eq 5.3)}$$

with W_t (g) the total weight of the sample core; W_c (g) the weight of coarse fragment (> 2 mm), V_t the total volume of the core (100 cm^3) and SG_c (g cm^{-3}) the specific gravity of the coarse fraction (mainly slate, with a SG_c of 2.691 [49]). Since bulk density samples were taken only within the topsoil that usually contains more carbon than in lower layers, these measurements are likely to underestimate the true bulk density of the 0-30 cm layer. Therefore, the Rawls' PTF (Eq. 5.1) was preferred for estimating bulk densities of survey 2 samples. We used the bulk density from the

[49] Walker, R. *Mass, weight and specific gravity of bulk materials* see [http://www.simetric.co.uk/si_materials]

field measurements to assess the precision and the accuracy of the PTF in the estimation of bulk densities of survey 2. First, we calculated the theoretical SOC concentration in the 0-6 cm topsoil. Then, the result was used in the Rawls' formula and this estimate of bulk density was compared with the bulk density as measured in the field.

The SOC concentration between two fixed depths was calculated by fitting a negative exponential function on the profiles in the Aardewerk database. The general form of this equation as given by Sleutel *et al.* (2003b) is (Eq. 5.4):

$$C(z) = C_b + (C_0 - C_b)e^{-kz} \qquad \text{(Eq 5.4)}$$

with $C_{(z)}$, the carbon concentration in g kg^{-1} at depth z, C_0 the carbon concentration at the top of the profile, C_b the carbon concentration at the bottom of the profile (100 cm) and k an unknown constant to be estimated. By integration of Equation 5.4, we can obtain the mean carbon concentration between depth *a* and *b* (cm, Eq. 5.5).

$$C_{mean} = \int_a^b C(z)/(b-a) \qquad \text{(Eq 5.5)}$$

Some sites with very stony soils were not dug to the desired depth (c. 25 % of the profiles, with a mean depth of 22 cm) and their SOC concentration was extrapolated to a depth of 30 cm according to Eq. 5.4. SOC concentration was also corrected for the percentage of rock fragments (> 2 mm) by using the proportion of rock fragments from the bulk density samples.

5.2.7 Calculation of SOC stocks

SOC stocks (t C ha^{-1}) in survey 1 and 2 were computed as follows (Eq. 5.6):

$$STOCK = \frac{SOC \cdot BD \cdot z}{10} \qquad \text{(Eq 5.6)}$$

with SOC the mean SOC concentration in the top 30 cm (g C kg^{-1}; Equation 2), BD the bulk density calculated by the PTF (g cm^{-3}) and z the depth of the layer (30 cm). This methodology is based on the assumption that no compaction due to increasing mechanisation occurred in the study area and that the only factor influencing bulk density was the soil organic matter concentration. The difference in SOC stocks between survey 1 and 2 was calculated on an equivalent soil mass basis (Ellert *et al.*,

2001) so that there are no bulk density effects on the change of stocks. For each profile of survey 1, an equivalent depth with reference to survey 2 was computed as (Eq. 5.7):

$$z_{eq} = BD_2 \cdot z_2 / BD_1 \qquad \text{(Eq 5.7)}$$

with $BD_{1,2}$ bulk density of survey 1 and 2 (Equation 1) and z_2 is the reference depth of sampling for survey 2 (30 cm). Then z_{eq} was used to calculate SOC stocks of survey 1 (Equation 5) on a soil equivalent mass basis with reference to survey 2.

5.2.8 Statistical analyses

Relationships between variables. The relationships in the database were explored with ANCOVA using the GLM procedure in *SAS* (*SAS* Institute, Cary, NC). When the design was unbalanced, the Type III Sum of Squares was used in the computation of the *F*-ratio to assess the significance of the difference between treatments ($\alpha = 0.05$). Dependent variables were (i) the rate of SOC change (ΔSOC), (ii) SOC concentrations in 1951-1962 (SOC1) and (iii) SOC concentrations in 2003-2006 (SOC2). The description and origin of the explanatory variables used in the modelling are summarized in Table 5.2. The forest land use history variable was created by different combinations of land use classes identified for the years 1868, 1888, 1923, 1953, 1990, 2003-2006. As most of the groups showed a normal or log-normal distribution, pairwise comparisons between group means were performed with the Tukey's HSD test ($\alpha = 0.05$). Groups having a sample size below 3 were suppressed from the ANCOVA analysis. It resulted in a small loss of information regarding the original database as this suppression concerned generally 25-30 observations. Homogeneity of variance between land use history groups was checked using the Levene's test. This test revealed no violations of the assumption for ANCOVA. Finally, SOC concentrations of different combinations of land use history groups were compared (CONTRAST option in the GLM procedure). Adjusted means of land use history groups (corrected for the effect of the covariate) were compared using the pdiff option in *SAS*.

Relating SOC change with original SOC concentration. The rate of SOC change (ΔSOC) may depend on the initial SOC concentration (first order kinetics; Lark *et al*., 2006). For example, Bellamy *et al*. (2005) showed that soils across England and Wales are currently loosing carbon, irrespective to land use and soil type, at a rate depending on the initial carbon concentration measured during the first inventory, so that soils with high OC concentration experienced a high rate of loss and inversely. However, when relating an observed change (y-x) with its baseline value (x), one

methodological problem needs to be addressed and must be corrected with appropriate statistical tools (Tu *et al.*, 2005), namely: the regression to the mean. This phenomenon arises with any variable subject to measurements errors. It can be shown that, assuming equal variance between x and y, the Pearson correlation coefficient between (y-x) and original value x is (Tu *et al.*, 2005; Eq. 5.8):

$$r_{x-y,x} = \sqrt{\left(1 - r_{xy}\right)/2} \qquad \text{(Eq 5.8)}$$

with $r_{x\text{-}y,x}$ the correlation between observed change and baseline, so that even without any relationship between the two variables ($r_{xy} = 0$), the correlation between (y-x) and x is close to 0.71. The spurious correlation introduced by those two phenomenons can be corrected by using the method of Oldham (Oldham, 1962) and Blomqvist (Blomqvist, 1977). The two methods try to answer two different research questions and are complementary (Tu *et al.*, 2005). Blomqvist formula seeks for an unbiased estimate of the regression slope and thus allows predicting without bias the expected SOC change, given the original SOC concentration. It is given as (Eq. 5.9):

$$\hat{\beta} = \frac{\hat{\beta}' + \left(1 - \hat{\nu}\right)}{\hat{\nu}} \qquad \text{(Eq 5.9)}$$

where $\hat{\beta}$ is an estimate of the regression coefficient, $\hat{\beta}'$ is the regression coefficient of y-x on x, and $\hat{\nu}$ is (Eq. 5.10)

$$\hat{\nu} = 1 - \frac{s_u^2}{s_x^2} \qquad \text{(Eq 5.10)}$$

where s_x^2 is the sample variance of x and s_u^2 is the variance of the measurement error. In the case of SOC, the sources of uncertainty in the measurements are due to relocation errors, analytical errors and spatial variability within the sampling unit (Lark *et al.*, 2006). The magnitude of these measurement errors can be estimated by re-sampling the same sampling units sufficiently close in time.

Oldham's approach checks if there is a true baseline effect or not. In other words, Oldham tests the null hypothesis of no relationship between change and the original value. He proposed to plot the change (x-y) against the average of the two measurements (x+y)/2 instead of the baseline values. The Pearson correlation becomes (Eq. 5.11):

$$Corr[x-y,(x+y)/2]=\frac{s_x^2-s_y^2}{\sqrt{\left(s_x^2+s_y^2\right)-4r_{xy}s_x s_y}} \quad (\text{Eq } 5.11)$$

where s_x^2 is the variance of x, s_y^2 is the variance of y. As Odlham's method tests the null hypothesis, it gives thus the correct P-value (Tu *et al.*, 2005). Eq. 5.11 shows that the method tests the difference in variance between the two campaigns of measurements. Intuitively, one can imagine that, if there is a differential baseline effect (e.g. soils with greater carbon concentration undergo higher rates of change than those with lower carbon concentration), the values measured during the second survey will get closer to each other and this will result in a difference in the variance between the two sampling campaigns.

5.3 Results and discussion

5.3.1 Bulk density in survey 1 and 2

The mean bulk density as measured in the field was 0.79 g cm^{-3}, with a mean rock fragment content of 6.6 %. This bulk density is low because it represents only the first centimetres of the soil. Therefore, using a PTF is more appropriate for estimating bulk densities of the 0-30 cm topsoil than using measured values. The comparison between measured bulk densities and the ones calculated from the carbon concentration in the 1-6 cm layer (Eq. 5.1 and 5.4) demonstrated fair accuracy (RMSE = 0.14 g cm^{-3}) compared to the standard deviation of the measured bulk density (SD = 0.16 g cm^{-3}) but good precision (Bias: 0.015 g cm^{-3}, Figure 5.3). Using the PTF the mean bulk densities of survey 1 and survey 2 at 30 cm depth were 0.92 g cm^{-3} and 0.96 g cm^{-3} respectively (Table 5.3). Given the low accuracy of the PTF as used and the general poor performance of published PTF for forest soils (RMSE ranging from 0.16 to 0.23 g cm^{-3} after local calibration; De Vos *et al.*, 2005), SOC concentrations rather than SOC stocks were used in further statistical analysis. This was to avoid introducing additional variability as required for the detection of land use effects. This is a reasonable assumption only if bulk density did not change too much through time. Indeed, biogeochemical processes are directly acting on SOC stocks and not on SOC concentrations. We are not aware of any data on the historical evolution of bulk densities in Belgium. However, Ardennes forests have always suffered disturbance, in particular compaction by local people collecting fuel wood and livestock trampling during grazing in forest.

Table 5.2. Description and origin of explaining variables used in the GLM

Variable Name	Description	Code	Type
Present Land Use	Land use type at the time of the resampling	LU2006	Categorical
Previous Land Use	Previous Land use recorded on the basis of historical maps (1868, 1888, 1923, 1953, 1990)	LU+YR	Categorical
Land Use History	Concatenation of different combinations of variables Previous Land Use	LUCH(X_1,...,X_n) with X_1,...,X_n = LU1868-LU2006	Categorical
Texture	Belgian soil textural groups	TEXT	Categorical
Drainage	Reclass of drainage classes in the belgian classification: well drained (a-c), moderatly drained (d) and poorly drained (e-i)	DRAIN	Categorical
Soil Organic Carbon	SOC content in survey 1 (g C kg^{-1})	SOC1	Continuous
Mean Soil Organic Carbon	Mean carbon content between survey 1 and survey 2 (g C kg^{-1})	MEAN SOC	Continuous

Heavy mechanisation already began just after World War II with the use of vehicles from the US army surplus (Lecomte, *pers. comm.*.). Logging traffic has dramatic effects on soil physical and mechanical parameters, including an increase in bulk density. Ampoorter *et al.* (2007) showed that most of the compaction was accomplished after only one pass. Therefore we assumed no over-compaction due to mechanisation after 1950-1960.

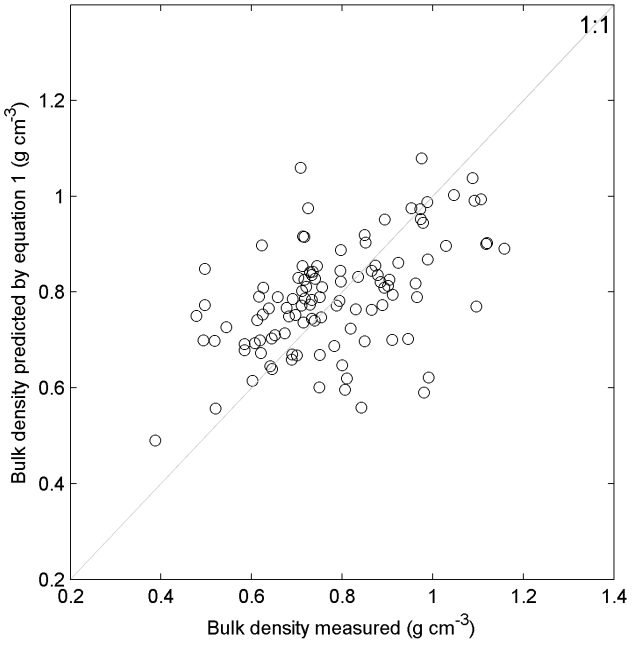


Figure 5.3. Comparison between measured and predicted values of bulk density (Eq. 5.1).

5.3.2 SOC concentrations in the original soil survey (survey 1) and re-sampling (survey 2)

Mean carbon concentration of forest soils in the study area decreased from 40.4 to 34.5 g C kg^{-1} with a mean ΔSOC over the time period equal to -0.15 g C $kg^{-1}yr^{-1}$ (Table 5.4). In SOC stocks this corresponds to a decline from 106 to 96 t C ha^{-1} at a rate of -0.23 t C ha^{-1} yr^{-1}. SOC values from survey 1 (SOC1) have high positive skewness and kurtosis while carbon concentrations of survey 2 (SOC2) show a normal distribution (Kolmogorov-Smirnov p-value > 0.15) and half of the standard deviation compared to SOC1 (Figure 5.4a and Figure 5.4b). A paired *t*-test indicated that the decrease in SOC concentration between the two surveys was highly significant.

Table 5.3. Descriptive statistics of characteristics of the topsoil sampled in survey 1 and 2

Statistic	SOC1	SOC2	ΔSOC	BD1[a]	BD2[a]	S[b]	STOCK1	STOCK2	ΔSTOCK
	g C kg^{-1}		g C kg^{-1} yr^{-1}	g cm^{-3}		%	t C ha^{-1}		t C ha^{-1} yr^{-1}
Mean	40.4	34.5	-0.151	0.92	0.96	6.6	105.7	95.6	-0.228
Standard Deviation	17.7	10.9	0.434	0.11	0.08	4.9	32.0	22.3	0.740
Minimum	12.3	11.2	-2.493	0.50	0.75	0.1	41.9	36.6	-2.057
Maximum	100.7	82.3	0.703	1.15	1.20	21.2	194.8	186.0	1.466
Kurtosis	7.36	2.51	7.47	0.73	0.28	0.5	1.59	0.19	-0.21
Skweness	2.10	0.91	-1.97	-0.65	0.35	0.87	0.44	0.64	-0.32
Kolmo *p* -value[c]	< 0.01	> 0.15	0.04	-	-	< 0.01	0.15	> 0.15	> 0.15
Kolmo *p* -value[c] on log transformed data	> 0.15	-	> 0.15	-	> 0.15	< 0.01	-	-	-

[a] Bulk-density (g cm^{-3}) calculated from Rawls' PTF (Eq. 5.1).

[b] Rock fragment concentration (%) in bulk density samples

[c] *p*-value of Kolmogorov-Smirnov test for normality

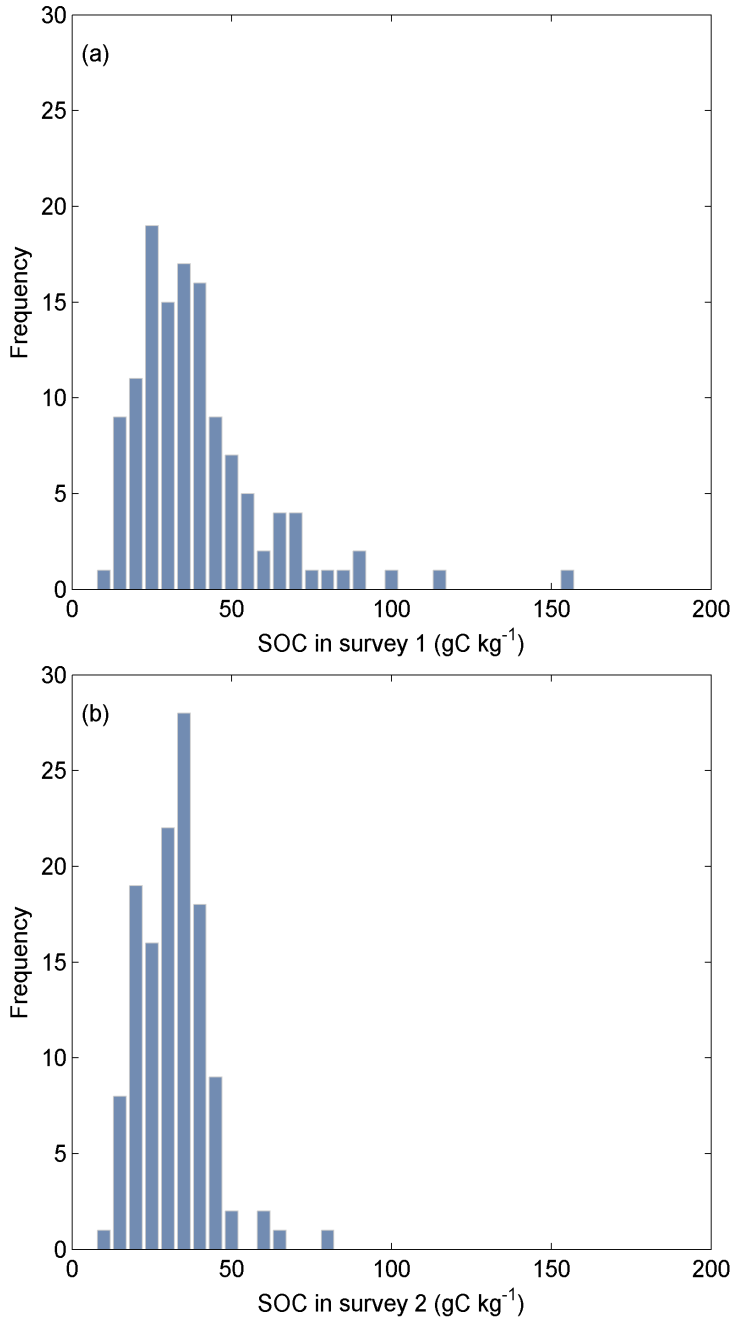


Figure 5.4. Histogram of SOC concentration (g C kg^{-1}) in forest soils (0-30 cm) as measured in (a) survey 1 (1952-1961) and (b) survey 2 (2003-2006).

5.3.3 Predictors of SOC concentration in survey 1 (SOC1)

A one-way ANOVA revealed a significant effect of land use history on log-transformed SOC1 concentrations (Table 5.4). The combination of land use classes in 1868, 1923 and 1953 gave the best fit (r^2=0.31). One could argue that LUCH has a significant influence on SOC1 due to a correlation between LU variables and soil or topographical variables (e.g. clay content, CEC, altitude), reflecting the physical suitability of a land use for a particular geographical location compared to another. However, these variables were included in the modelling exercise and none of these variables were significant at the 0.05 probability level. This lack of significance can be due to the relative homogeneity in soil conditions within the study area. Individual comparisons between land use groups can be made by examining the 95 % confidence limit in Figure 5.5a. Coniferous plots that had been cropland in 1868 or both in 1868 and 1923 generally had significantly lower SOC1 values than coniferous plots with other former land use classes (grassland, heath or deciduous; Figure 5.5a). Comparisons of the different groups of land use classes also clearly illustrate the effect of previous arable land use (Table 5.5). The difference between coniferous parcels planted on former cropland (*cr-co*) and coniferous parcels on former heath, grassland and deciduous forest were significant and were 22.1, 42.4 and 25.5 g C kg^{-1} (respectively 42, 72 and 49 t C ha^{-1}). There were no significant differences in SOC between deciduous and coniferous stands at the time of survey 1 (data not shown). Former grasslands had higher SOC1 concentrations than former heath and heath more than former deciduous forests (Figure 5.5a). However, only former grassland parcels showed a significant difference with former deciduous forests (data not shown).

5.3.4 Predictors of SOC concentration in survey 2 (SOC2)

The model incorporated for SOC2 an integrated land use history variable (LUCH), an interaction term between the texture and drainage and SOC1 concentrations as covariate (Table 5.4). LUCH and SOC1 shared more or less the same proportion of explained variance (r^2=0.60). The variable LUCH included the land use classes of the parcels in 1888, 1923, 1953 and 1990. A large part of the variability is explained by LUCH (Table 5.4) to indicate that land use 100-150 years ago still has an influence on present SOC under forest. Figure 5.5b shows the different LUCH groups and their 95% confidence limits. Contrary to SOC1, coniferous stands in survey 2 had significantly higher SOC values than under deciduous stands (mean difference of 9.85 g C kg^{-1} or 21.3 t C ha^{-1}) at the time of the survey (p = 0.001). Compared to survey 1, the detection of this higher level of SOC concentration in coniferous forest can be the result of two factors: (i) a lower variability in SOC2 compared to SOC1

(Table 5.3) and (ii) the progressive recovery of SOC in coniferous stands after land use change. Most land use conversions in the study area occurred before the mid-20th-century, i.e. before the first survey (Figure 5.2). The highest conversion rate to coniferous plantations occurred between 1923 and 1953 (nearly 15 % of the study area was converted over the entire time period, corresponding to a rate of 146 ha yr^{-1}). This means that on average the converted ecosystems have had 21 years to adjust to the changes in soil carbon balance. Hence it is unlikely that the SOC concentrations determined during survey 1 had already reached values that could be expected for an old coniferous plantation.

The impact of past agricultural use was still apparent for SOC2, as indicated by significant differences upon conversion of type *cr-co* versus *he-co*, *de-co* or 'no change' groups (Table 5.5). The group 'no change' consists of old coniferous plantations (since 1888). The difference between *cr-co* and 'no change' reached -10 g C kg^{-1} (- 19 t C ha^{-1}). Parcels that have always been forest contain on average 4.12 g C kg^{-1} (9 t C ha^{-1}) more than parcels that had at least one non-forest land use since 1888, but the difference was found to be not significant (p = 0.055). Incomplete recovery since the end of agricultural use and grazing (heathland or grassland) can explain these lower SOC stocks. Stands growing on former peat bogs (*pb-co*) contained the highest SOC concentration in survey 2 (53 g C kg^{-1}, or 132 t C ha^{-1}; Figure 5.5b), showing the inheritance of SOC stocks accumulated in peat bogs even after drainage and afforestation with coniferous trees. No significant differences between *he-co* and 'no change' were detected. However, these conversions are relatively old compared to conversions of arable land to coniferous, and therefore their SOC concentrations reach the levels of coniferous stands that have not undergone conversions ('no change'). No conclusions can be drawn from the comparison between *de-co* parcels and 'no change' (a non significant difference of 1.18 g C kg^{-1} or 2 t C ha^{-1}). These results suggest a positive impact of the conversion from broadleaf to coniferous plantation on SOC stocks[50].

5.3.5 Modelling changes in SOC concentration between survey 1 and survey 2 (ΔSOC)

There is a strong negative correlation between ΔSOC and SOC1 (R = -0.79). This means that soils with high SOC1 concentration tend to loose carbon while soils with low SOC1 concentration tend to increase their stocks, resulting in an overall decrease in the variability of SOC2 in comparison to SOC1 (Table 5.3).

[50] However, it should be noted that this type of conversion could provoke a concomitant reduction of the CH_4 sink (Borken *et al*., 2003).

Table 5.4. ANCOVA results

Independent variable	Explaining variable[a]	df	Type III SS	*F*-value	*Pr* > F	N	Total r^2
Log(SOC1)	LUCH(1868,1923,1953)	10	5.55	3.83	0.0003	98	0.31
SOC2	LUCH(1888,1923,1953,1973)	12	5241	6.48	< .0001	106	0.60
	SOC1	1	510	7.05	0.0095		
	TEXT*DRAIN	10	1370	2.03	0.0399		
ΔSOC	MEAN_SOC	1	3.086	42.57	< .0001	94	0.51
	LUCH(1868,1888,1953)	9	2.598	3.98	0.0003		

[a] For the meaning of the explaining variables, refer to Table 5.2

Table 5.5. Comparisons between land use history groups.

Variable	Contrast[a]	cr-co	he-co	gr-co	de-co	pb-co
SOC1	he-co	-22.13***				
	gr-co	-42.44***	-20.3			
	de-co	-25.56***	-3.43	16.87		
	pb-co	n.d.	n.d.	n.d.	n.d.	
SOC2	he-co	-7.14*				
	gr-co	-1.48	5.67			
	de-co	-11.19**	-4.05	9.71		
	pb-co	-24.2***	-17.05**	-22.72***	-13.01*	
	no change	-10.01**	-2.87	-8.53	1.18	14.18**

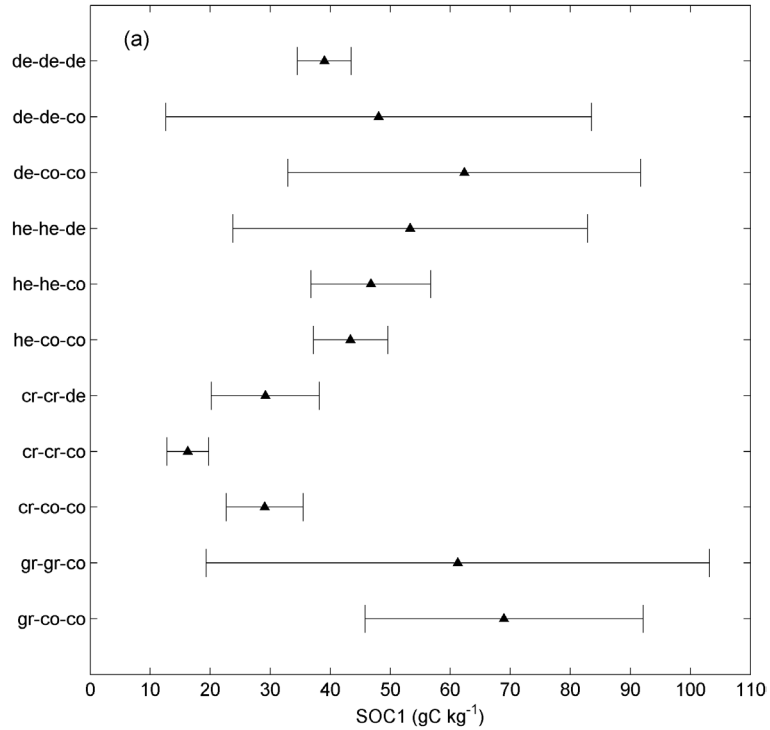
[a] Differences between land use history groups are expressed in g C kg^{-1}. For SOC1, differences are shown in original units (not log-transformed). *co*: coniferous, *de*: deciduous , *gr*: grassland, *cr*: cropland, *he*: heath, *pb*: peat bogs. *, significant at p <0.05. **, significant at p <0.01. ***, significant at p <0.001. N.d. stands for no data.

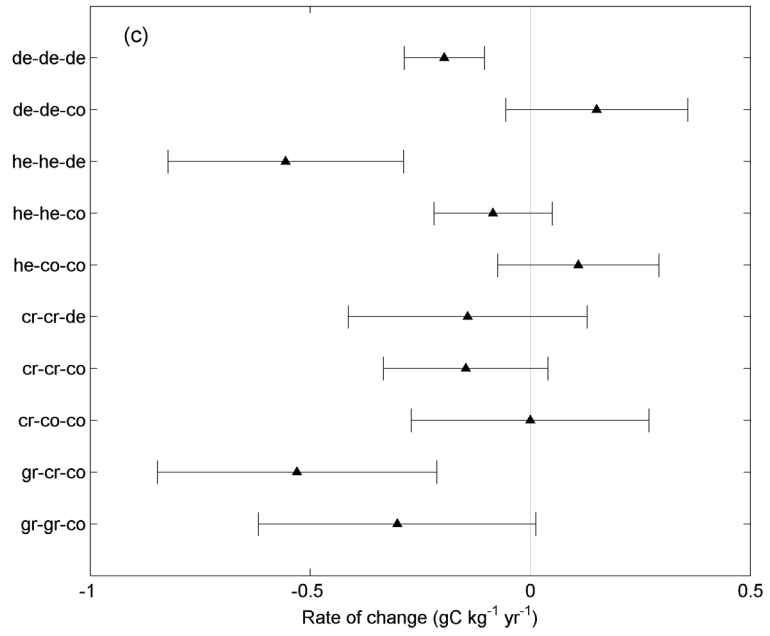
In order to correct for the bias generated by the regression to the mean (see section 5.2.8), the Oldham (1962) approach has been implemented. Oldham tested the null hypothesis of no relationship between change and the original value by plotting the change (x-y) against the average of the two measurements (x+y)/2. This latter variable, hereafter called MEAN SOC, was adjusted to take into account the fact that samples have non-equivalent time intervals between measurements in survey 1 and 2 (Lark *et al*., 2006). As Oldham's method tests the null hypothesis, it gives thus the correct p-value (Tu *et al*., 2005), so that MEAN SOC can be used in the modelling of ΔSOC by ANCOVA.

The best prediction model of ΔSOC included LUCH and MEAN SOC as covariates, producing a r^2 of 0.51 (Table 5.4). The interaction term between LUCH and MEAN SOC was not significant. This means that the relationship between ΔSOC and MEAN SOC is not affected by the history of the parcels. The combination of historical land use classes explaining the greater part of the variation was LU1868, LU1888 and LU1953 indicating that ΔSOC was mainly governed by land use conversions that occurred before 1950. We previously showed that overall the difference between SOC1 and SOC2 is negative and highly significant. However, only three types of land use history presented the same pattern with negative ΔSOC significantly different from zero (Figure 5.5c).

Deciduous stands lost carbon at a faster rate than coniferous between the studied period (p = 0.026). During the 19th century, the traditional form of woodland management was, for economical reasons, coppice or coppice-with-standards. Since the 20th century, these secondary forests are in decline (294.000 ha in 1895 to 92.000 ha nowadays), mainly at the advantage of high broadleaf forest and coniferous plantations (DGRNE, 1997). This management change may explain part of the losses in deciduous forests. Little information was found in the literature to support this assumption. While coppice forests contain typically less C ha^{-1} than high forests in their tree biomass, coppice-with-standards exhibit similar amounts of C ha^{-1} (St André and Pignard, 2004). In addition, one could presume that such practice may promote SOC sequestration due to a continuous vegetation cover and litter input.

Also, parcels that are supposed not to have changed (*de-de-de*) showed a significant decrease in SOC (-0.19 g C kg^{-1} yr^{-1} or -0.40 t C ha^{-1} yr^{-1}). This is in disagreement with most studies arguing that eventually plant inputs to the soil are counterbalanced by the decomposition rate of organic matter and SOC stocks reach steady state. Our result is thus counter-intuitive since those forest stands should either accumulate carbon or at least reach a steady state. Hence, processes other than LUCH should also be active in the study area (e.g. forest management, climate change).


(a)
de-de-de
de-de-co
de-co-co
he-he-de
he-he-co
he-co-co
cr-cr-de
cr-cr-co
cr-co-co
gr-gr-co
gr-co-co
0
10
20
30
40
50
60
70
80
90
100
110
SOC1 (gC kg-1)


(c)
de-de-de
de-de-co
he-he-de
he-he-co
he-co-co
cr-cr-de
cr-cr-co
cr-co-co
gr-cr-co
gr-gr-co
-1
-0.5
0
0.5
Rate of change (gC kg-1 yr-1)

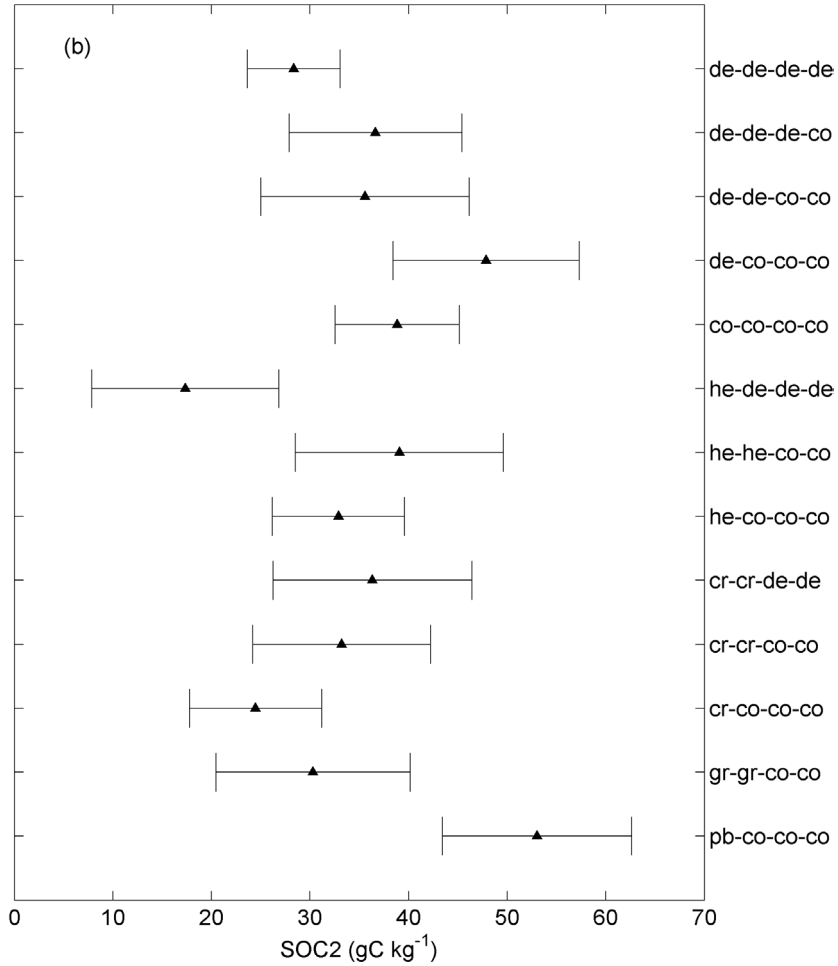


*Figure 5.5. (a) Mean of SOC1, (b) adjusted mean of SOC2 and (c) adjusted mean ΔSOC for different land use history groups, with 95 % confidence limits. Groups are labelled in the X-axis using the following symbols: X_1-X_2...-X_n, with X_n the land use (*co*: coniferous,* de*: deciduous ,* gr*: grassland,* cr*: cropland,* he*: heath,* pb*: peat bogs) observed at each time period, in chronological order, used to construct the land use history variable in the model. E.g.: for ΔSOC,* gr-co-co *stands for grassland (*gr*) in 1868 and coniferous (*co*) in 1923 and 1953.*

Conversions *gr-cr-co* and *gr-gr-co* are characterised by high SOC1 concentration and are decreasing in carbon as well (Figure 5.5c). This may be due to the fact that a part of such forests was established on wet meadows located in valley bottoms and

probably once contained a high SOC concentration but has been lost following land use change. However, this hypothesis could not explain all the points. A straightforward explanation can neither be found to account for the strong decrease in SOC for the group *he-he-de* (Figure 5.5c). Some parcels of this small group were later converted to coniferous forest which may have induced a disturbance and hence a decrease in SOC concentration, others were characterised by a high rock fragment content which may have caused errors during sampling. Parcels of the group *de-de-co* have a positive ΔSOC, which proved to be almost significant (Figure 5.5c).

Parcels that have been cropland in the past presented non-significant ΔSOC (Figure 5.5c) while an increase in SOC stocks following afforestation of cropland was expected (Paul *et al.*, 2002a). This may be due to several reasons, of which we can cite:

- The accumulation of carbon following coniferous plantation may be limited to the litter layer. Richter *et al.* (1999) found that, after the afforestation of cultivated soil in South Carolina, mineral soil was responsible only for less than 1 % of the increase observed, almost all the carbon accretion in soil being restricted to the litter layer (20 %).

- There is a large variation in the longevity and the rate of C accumulation in soil, depending on the vegetation NPP, soil conditions, past history of SOC inputs and management (Post and Kwon, 2000; Paul *et al.*, 2002a), which may preclude the detection of significant changes. Moreover, agricultural activities can, under some conditions, increase SOC relative to natural systems (McLauchlan, 2006). Particularly, organic amendments can have a significant long lasting effect on carbon stocks as demonstrated by the experiment of Johnston (1986) at Rothamsted, which showed that after 20 yr of manure application in an agricultural field, soils contained still larger SOC stocks 100 yr later.

- There could have been confusion by soil surveyors in 1950-1960 and cartographers between permanent and temporary grassland within a cultivation rotation. The latter land use has been included in the land use class ‘cropland’. If temporary grassland does not have been correctly assigned to the land use ‘cropland’, this may have as a consequence a lowering of the negative effect of cropland on SOC stocks (or inversely, the positive effect of pasture).

5.3.6 Uncertainty assessment

Several errors associated with differences in sampling protocols between the two surveys and with assumptions used in the computation of both SOC concentrations and SOC stocks may have affected the range of observed values and rates of change.

Bulk density. The PTF used in the prediction of bulk densities showed a rather low accuracy. This is likely to influence the observed levels and changes in SOC stocks. The error made on bulk densities (in standard deviation units) can be approximated by the Root Mean Square Error (RMSE = 0.14 g cm^{-3}, see Figure 5.3). Then, assuming no errors in SOC concentration and sampling depth, one can propagate this uncertainty in the calculation of the stocks. Using simplified propagation formulae[51], errors due to the use of the PTF would be on average 18 t C ha^{-1} on STOCK1, 15 t C ha^{-1} on STOCK2 and 0.3 t C ha^{-1} yr^{-1} on ΔSTOCK. It shows that calculations of SOC stocks are subject to high uncertainties and this confirms our cautious approach i.e. analysing concentrations rather than stocks.

Compositing vs. non-compositing. Composite samples were taken during survey 2, contrary to survey 1 in which only one sample per plot was extracted. The process of bulking induces a 'dilution' effect on minimum and maximum values and may possibly explain the decrease in the variability observed in survey 2 compared to survey 1. Obviously, this will also have affected the rates of change presented above. Using geostatistics, Schöning *et al*., (2006) showed in German beech forest Luvisols that the relative semivariance[52] of SOC stocks at a lag distance of 5 m is in the order of 15 %. We assume here that the error made by averaging can be approximated by the unknown standard deviation of the samples that we used to make each composite sample. Then, applying the figure of Schöning *et al*., (2006) to our data, the potential error would be 14.3 t C ha^{-1} for STOCK2 and 0.27 t C ha^{-1} yr^{-1} for ΔSTOCK (using standard uncertainties propagation formulae). Between 89 out of a total of 125 samples have higher absolute rates of change so that this error is unlikely to radically change the results.

Sampling with an auger vs. pit excavation. Soil profiles were examined during survey 1 whilst soil cores were extracted with an auger in survey 2. Since it is difficult to distinguish between organo-mineral and O horizons with an auger, part of the

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[51] $\sigma^2_{STOCK} = STOCK^2 \cdot (\sigma_{BD}/BD)^2$

$\sigma^2_{\Delta STOCK} = \frac{1}{y^2} \cdot \left[\sigma^2_{STOCK1} + \sigma^2_{STOCK2} - 2 \cdot \mathrm{cov}_{STOCK1,STOCK2}\right]$

with σ the standard deviation; cov, the covariance and y, the mean elapsed time between survey 1 and survey 2 (52 yr)

[52] The relative semivariance can be computed as the semivariance at lag *h* divided by the square of the mean of the values at lag *h*.

former may have also been removed from the core. On the other hand including part of the O horizons during augering might also have occurred. To assess the effect of such sampling error, we calculated the impact of having unintentionally (i) added 1 cm of litter in the bulk sample and (ii) removed 1 cm of the top of the mineral soil using the survey 1 dataset in which the full soil profile is described (including O horizons). We computed for each profile the C concentration of 1 cm of the litter layer and the C concentration of the 0-1 cm layer of the mineral soil (using Eq. 5.4 and 5.5). These calculations were done separately for deciduous and coniferous forests because the latter contain on average more C than deciduous forests. The first test – i.e. adding 1 cm of litter – showed that we might overestimate on average the true SOC concentration by 20 % in coniferous and 4.5 % in deciduous forests. The second test yielded smaller errors: an underestimation of up to 8 % for coniferous and 10 % for deciduous forests. These situations are considered to be two extreme cases because it supposes that the same error occurred five times during survey 2 at each location (composite sample = 5 sub-samples). Moreover, it is likely that these two errors have to some extent cancelled each other out.

5.3.7 SOC stocks and dynamics at regional scale

Our estimates of forest SOC stocks (106 t C ha^{-1} in 1950-1960 and 96 t C ha^{-1} in 2006) are a bit higher than SOC stocks found in bordering countries like France (70 t C ha^{-1}; Arrouays *et al*., 1999) or Germany (65 t C ha^{-1}; Baritz and Strich, 2000) and is due to the specific climate conditions of the study area compared to country wide average estimates. Both deciduous (104 t C ha^{-1} in 1950-1960 and 88 t C ha^{-1} in 2003-2006) and coniferous forests (111 t C ha^{-1} in 1950-1960 and 99 t C ha^{-1} in 2003-2006) in the study area contained on average more SOC than the national average in 1950-1960 i.e. 58 t C ha^{-1} for deciduous and 70 t C ha^{-1} for coniferous forests (Lettens *et al*., 2004) and roughly similar stocks in 2000 i.e. 87 t C ha^{-1} for deciduous and 92 t C ha^{-1} coniferous forests (Lettens *et al*., 2005b). In contrast to our study, Lettens *et al*. (2005a) observed an average increase in SOC stocks in Belgian forests between 1950-1960 and 2000 based on the 'Aardewerk' database for 1960 and an independent sampling survey for 2000. Vande Walle *et al*. (2007) also found an increase in total carbon stocks in Belgian forest soils of 412.3 kt C yr^{-1} between 1990 and 2000, which corresponded to approx. 30 % of the C sink during the time period. This increase was mainly attributed to an increase in Belgian forest biomass (Lettens *et al*., 2005a).

A simple empirical model can resolve this apparent disagreement between the two studies. On the basis of the relationship between ΔSOC and SOC1 (Table 5.4), the following regression can be constructed (Figure 5.6; Eq. 5.12):

$$\Delta SOC = 0.513 - 0.015 \cdot SOC1 \qquad \text{(Eq 5.12)}$$

Two samples (SOC1 > 100 g C kg^{-1}) influencing excessively the relationship and showing moderate to high residuals were removed from further analysis. The regression slope was modified through Blomqvist's formula (Blomqvist, 1977) to correct the regression for the mean effect. This allows calculation of an unbiased estimate of the regression between rate of change and the baseline value by taking into account measurement error variance[53]. While the relationship between ΔSOC and SOC1 is strong ($r^2 = 0.62$), the plot of ΔSOC versus MEAN SOC (Odlham's method) reveals a much weaker but significant correlation (Figure 5.6b, R = -0.44), suggesting larger errors in the measurements than previously estimated. By integration[54], Eq. 5.12 can be used to predict carbon concentration at any given time in the study area if the initial carbon concentration is known. No corrections were made to adjust for the autocorrelation arising from spatial dependence between samples. The analysis of semi-variograms did not identify a spatial component within the overall variability (Appendix 1). Using Eq. 5.12 with estimates of Lettens *et al*. (2005a) as inputs and assuming a constant bulk density of 0.95 g cm^{-3}, mean carbon stocks would increase from 58 to 74 t C ha^{-1} in deciduous and from 70 to 84 t C ha^{-1} in coniferous forest soils. Thus, it appears that the difference in the direction of change between the two studies can be explained by the difference in initial conditions. Our study area in the Belgian Ardennes is well-known for its higher SOC stocks within Belgium (Lettens *et al*., 2004) and thus shows a decline rather than an accumulation of SOC stocks. However, the relationship is not able to account for the larger accumulation observed by Lettens *et al*. (2005a) between the two dates, indicating that the parameters of Eq. 5.12 are site-dependent. At least, this relationship can be extended to areas with similar climate and soils (e.g. Belgian Ardennes). The comparison between the two studies only shows that SOC stocks in 1960 were not in steady state and that the system tended towards an equalization of forest SOC stocks across Belgium during the last decades.

The equilibrium SOC concentration in forests of the study area can be derived from Eq. 5.12 and is (Eq. 5.13):

$$\lim_{t \to \infty} C(t) = \frac{0.57}{0.016} = 35.6 \ gC \ kg^{-1} \qquad \text{(Eq 5.13)}$$

[53] We assumed an error variance of 14 g C kg^{-1} on the basis of two repeated samplings of three plots by two different teams of surveyors.

[54] Assuming that the rate of change is constant through the studied period.

Converted in SOC stocks, it corresponds to an average of 82 t C ha^{-1}. Soils that are below this figure tend to gain carbon while those that are above tend to loose carbon. This dynamic seems to generate a carbon sink in Belgium forest soils. Following the calculations of Lettens *et al*. (2005a), forest carbon stocks in the Walloon region are assumed to increase on average from 64 t C ha^{-1} in 1960 to 96 t C ha^{-1} in 2000. Multiplied by the total forest area in the Walloon region (496 482 ha) in 2005 – i.e. without taking into account land use changes since 1960-, these estimations would have generated a sink of more or less 1 Mt CO_2 yr^{-1} (Lettens *et al*., 2005a).

When plant inputs to soil are counterbalanced by the decomposition of organic matter, SOC stocks are supposed to reach equilibrium, the level of which depend on several factors such as soil type, land use, management and climate. Based on experimental data or modelling studies (e.g. Jenkinson, 1990; Paul *et al*., 2002b; Sun *et al*., 2004), it is commonly assumed that SOC stocks evolve after any disturbance (land use, management or climate change) from a steady state to another after a sufficiently long period of time (50-200 yr depending on the land use conversions type). Nevertheless, simple calculations above showed that most forest soils in the study area and in the remainder of Belgium did not reach equilibrium nor in 1960 nor in 2000-2006 and that a re-balancing would still continue for some times in the future. This is illustrated by the fact that deciduous parcels under forest since at least 1868 have been loosing carbon since the 1950-1960 sampling. This is in disagreement with the view that SOC stocks in European forest are growing mainly as a result of tree age structure (Janssens *et al*., 2005). Other driving factors in our study area may thus explain why there is locally a reversal of the general increase in SOC stocks in Belgian forests.

Soils with high SOC concentration are more likely to loose carbon and soils with low SOC concentration are more likely to gain carbon through time, patterns to be expected and also shown by Bellamy *et al*. (2005) who for all land uses found an intercept of 0.6 and a rate of change of - 0.0187 g C kg^{-1} yr^{-1}. This trend was attributed to climate change given the lack of relationship to land use and soil type. In our case, several possible explanations for this pattern of change in SOC can be put forward:

- *Land use change history*. Results from statistical analysis showed that LUCH explained more or less 25 % of the variance of ΔSOC at the regional level. The mean time since the last conversion in the study area is 100-120 yr. Several local studies demonstrated that the impact of land use conversions on SOC stocks can be measured even after a longer time period (e.g. Knops and Tilman, 2000).

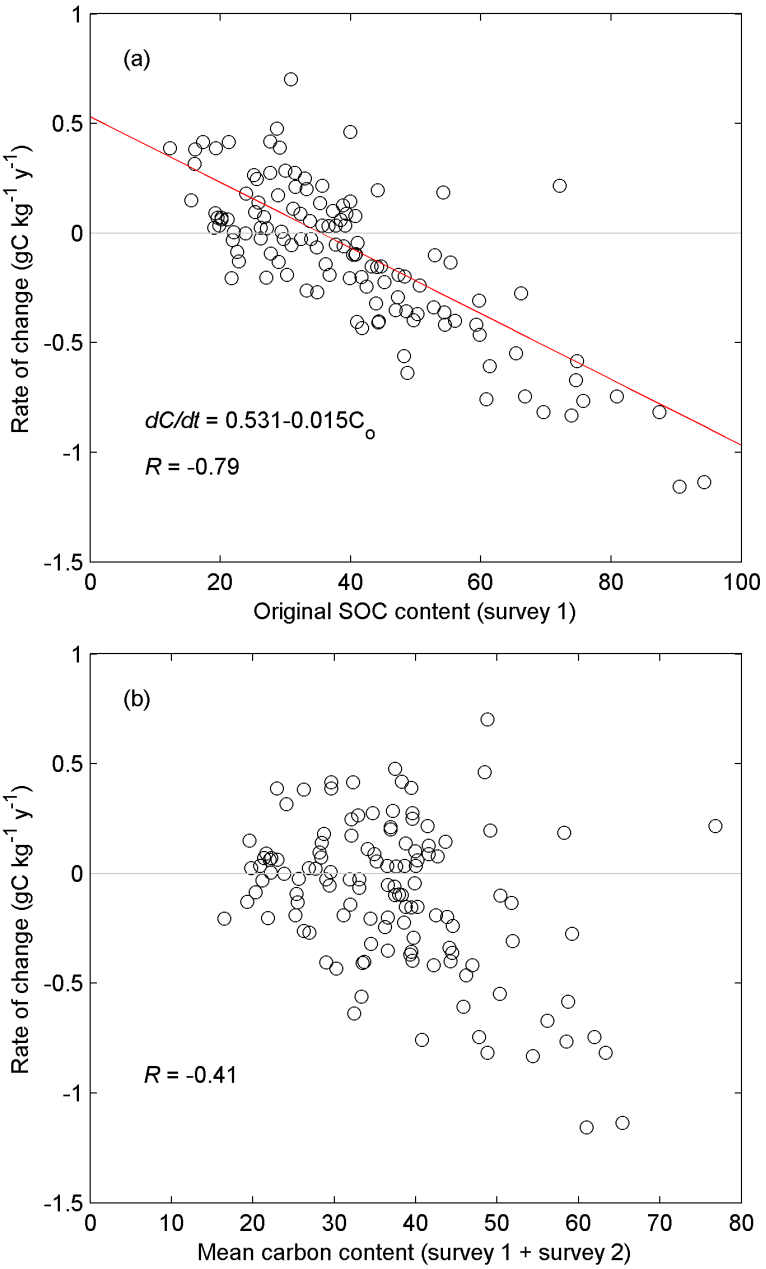

Figure 5.6. Plot of ΔSOC in g C kg^{-1} y^{-1} against (a) original SOC concentration in survey 1 and (b) mean carbon concentration of survey 1 and survey 2. The solid line in (a) is the slope corrected for the regression to the mean effect by the Blomqvist formula.

- *Forest management history*. As previously demonstrated, there was a decrease in the variability of SOC values between the two surveys and an equalization of C concentration over the study area (Figure 5.4). This phenomenon might be due to a standardization of forest practices (rotation length, conversion of coppice to high stands, drainage[55]). However, in the absence of spatial data on forest management, it is difficult to propose explanations of observed change in SOC concentration.

- *Climate change*. In order to isolate the effect of climate, we simulated the SOC evolution of an old deciduous forest parcel with climate data for the period 1900-2000 (ATEAM project; Mitchell *et al*., 2004) using the RothC model (Jenkinson, 1990) and assuming steady state conditions in 1950-1960. Following the methodology of Smith *et al*. (2006), the model was run to equilibrium with an average climate for 1900 to 1952 (time of the original sampling) in order to estimate the total plant input. Then, knowing initial SOC concentration of the forest parcel and its plant input, the model simulated the changes in SOC concentration using the actual monthly climate data from 1952 to 2000. Plant input was assumed to remain unchanged during this period. Only the effect of climate change on decomposition was studied since an increase in plant input due to climate change is supposed to have the opposing effect (increase rather than decrease SOC concentrations). In 2000, the modelled soil showed only a 3% loss in SOC stock compared to the reference year while the observed mean relative decrease in SOC stocks between survey 1 and survey 2 was 14 % (Table 5.3). Similarly, Smith *et al*. (2007) demonstrated that climate change could be responsible for only 10-20 % of the soil carbon losses reported by Bellamy *et al*. (2005) in England and Wales. It is thus very unlikely that climate explains a large part of the observed ΔSOC in the study area.

A large part of the variance remains thus unexplained. Sleutel *et al*. (2007) estimated that SOC losses in croplands in Flanders during the last decade could be attributed to an extent of (i) 33 % to shifts in OM-input management, (ii) 10-45% to land use changes, and (iii) 10% to temperature increase. Proportions associated with the two latter explaining factors (i.e. land use and climate) were based only on rough estimations. The remaining proportion was still unexplained. Nevertheless, it suggests that no single factor can explain unambiguously the ΔSOC observed. Our current analysis of SOC dynamic in the study area, based on spatially explicit historic data, tends to indicate LUCH and management history as the main driving factors of SOC change.

[55] The drainage of coniferous stands that have been planted on former peatlands and hydromorphous soils was a common practice in high Ardennes plateaus. It has been now prohibited but this phenomenon could be involved in in the observed loss in several coniferous stands of the study area.

5.4 Conclusion

Several recent studies (e.g. Bellamy *et al*., 2005; Sleutel *et al*., 2007) failed to assess quantitatively the impact of former land use on SOC dynamic at regional scale due to a lack of spatial data at such scale. Our study shows the need for spatially-explicit historic data to explain ΔSOC and that would allow to better predict regional response to future environmental changes. Our approach showed that Land Use Change History (LUCH) clearly influences past and current OC stock levels of mineral soils (0-30 cm depth) of southern Belgian forests. Previous land use still has an impact on present SOC stocks more than 100 yr after conversion suggesting that recovery after disturbance was only partial. The long-term legacy of past agricultural use has been highlighted. However, the total variability cannot be accounted for by LUCH. There was strong evidence that the SOC concentration in part of our profiles was not in steady-state conditions as often assumed for estimating the impact of LUC on SOC stocks. While SOC may respond quickly to environmental changes, a part of this stock can be characterised by slow turnover times and experience either aggrading or degrading processes centuries after disturbance.

The effects of LUCH on C pools in deeper layers (> 30 cm) have not currently been studied. The understanding of their dynamic is of great interest because a large portion of total SOC stocks in temperate forests is stored in deep layers (e.g. Arrouays and Pélissier, 1994a). We focused on surface soil layers because they are likely to react faster to environmental changes and therefore may be easier detected with the implemented *modus operandi*. SOC of deep soil layers are characterized by higher residence times (> 1000 yr, see e.g. Fontaine *et al.*, 2007) and thus must be analysed with more sensitive tools (e.g. soil fractionation).

In the IPCC guidelines, steady-state SOC stocks are attributed to soil/land use combinations allowing the calculation of national carbon budgets (Eggleston *et al*., 2006). Geo-referenced soil databases are often used to assign steady state SOC stocks without taking into account variation in initial conditions induced by previous land use (e.g. Lettens *et al*., 2005a; Tate *et al*., 2005). As a consequence, despite the large sample size, it is generally difficult to detect significant land use effects. Moreover, comparison between two types of land use to assess the effect of LUC may lead to erroneous conclusions due to differences in LUCH between samples.

The use of simulation models to infer SOC evolution at a regional scale and based on soil databases as input may also be challenging since soils are supposed to be at equilibrium at the beginning of the simulation. The decay rate of the slower pools is often difficult to estimate. It has been shown in this study that steady state

conditions are rare and thus caution has to be paid to results from model runs, which assume an initial equilibrium.

Chapter 6

Changes in soil organic carbon stocks after afforestation and deforestation in the Belgian Ardennes, 1868-2005

Outline

The effects of historical land use changes on the global C cycle have mainly been studied by means of bookkeeping models. These models are subject to several sources of errors, of which the rates of land use conversion and predicted rates of carbon decay or recovery following land use changes. Moreover, the soil pool is often the one associated to the largest uncertainties. Here, we investigate with such models the impact of afforestation and deforestation on soil organic carbon (SOC) over one and a half century (1868-2005) in a pilot area in the Belgian Ardennes using a spatially explicit database of land use changes and field-based estimates of the response of SOC upon land use changes. After a small initial decline during the 1868-1888 period due to deforestation for agricultural use, mean SOC stocks increased steadily up to 1990, due essentially to the conversion of deciduous forests to

coniferous and the reclamation of heathland at the turn of the 19th and 20th centuries. The last period (1990-2005) shows a low positive rate of SOC changes (i.e. an emission to the atmosphere) because of the slow down of sequestration in coniferous and the beginning of a process of reversion of coniferous plantations to deciduous forests. Over the whole period, afforestation activities generated a net sequestration of carbon (0.16 t C ha^{-1} yr^{-1} on average), the soil C sink being only limited by the afforestation of peatland within the study area. Monte Carlo simulations demonstrated that the model was highly sensitive to its inputs (initial SOC stocks for each land use) both in term of predicted SOC stocks and rates of SOC stocks change. However, the sensitivity of the model was not large enough to revert the main tendencies of changes in SOC stocks observed through the studied period. Compared to the amount of carbon sequestered in biomass, the contribution of soils to the C sink in forest is low. Despite several sources of errors, a detailed reconstruction of land use changes combined with realistic SOC response curves upon land use conversion are determinant to be able to quantify the contribution of soils to terrestrial carbon fluxes.[56]

6.1 Introduction

Land use change and management history is often invoked to explain broad-scale processes, notably the recent increase in the strength of terrestrial carbon sinks (e.g. Nabuurs *et al*., 1997, Bradforst *et al*., 2001; Schimel *et al*., 2001; Nabuurs *et al*., 2003), the residual sink (Caspersen *et al*., 2000) or the observed large variability in the rate of sequestration of soil organic carbon (SOC) stocks after land use change (Post and Kwon, 2000). While soils represent a large pool of carbon within terrestrial ecosystems, estimates of their contribution to terrestrial carbon fluxes are highly variable (see section 5.1).

When assessing the effect of land use and land use changes on soil carbon at national/global scales, modelling approaches is usually preferred (Houghton, 2007; Lindner and Karjalainen, 2007). Re-sampling of regional-scale soil inventories occurs, but examples are rare (e.g. Bellamy *et al*., 2005; Goidts and van Wesemael, 2007). Soil inventories that have been repeated so far generally point out the difficulty to explain observed trends due to the lack of spatial quantitative explaining factors (Bellamy *et al*., 2005; see Chapter 5).

[56] This article is based on an article by Stevens, A. and van Wesemael, B. (2008). Forest Ecology and Management, submitted

Two distinct modelling approaches have been developed to explicitly take into account the effect of land use change on carbon stocks. First, steady-state stocks calculated from geo-referenced soil profiles are assigned to soil/climate/land use combinations and the impact of land use changes is estimated by comparison (Eggleston *et al*., 2006). Alternatively, *bookkeeping* or *accounting* models construct time-dependent functions of carbon changes upon specific land use changes, which are combined with rates of land use changes from multiple databases (e.g. census from FAO, 2006). While the first approach has been applied essentially at regional/national scales (Tate *et al*., 2003; Lettens, 2005), the second approach has been applied at various scales from the region (Woodbury *et al*., 2006), to the nation (Austria: Gringrich *et al*., 2007, France: Arrouays, 2002), the continent (USA: Houghton and Hacker, 2000; China: Houghton and Hackler, 2003) and global scales (Houghton, 2003a). The major problem with the first approach is the validity of the steady state assumption in SOC densities. Steady state SOC concentration cannot be derived by averaging data from soil profiles that underwent prior land use conversion and for which land use history is not known (see Chapter 5). This may result in wrong estimates of changes in SOC after land use change. For instance, recent conversions of cropland to grasslands may induce a decrease of equilibrium SOC stocks of grasslands (Lettens, 2005).

In bookkeeping models, the errors in the estimation of carbon fluxes are mainly due to uncertainties in land use change rates (Houghton, 2003b). For instance, using net rather than gross rates of land use transitions may not capture the precise dynamic of C fluxes because absolute changes in carbon stocks due to afforestation (quantity and time-scale) are likely to be different than those induced by deforestation (Woodbury *et al*., 2006). A detailed reconstruction of land use changes is thus necessary to make reliable estimates.

Building on the conclusions of the previous chapter (i.e. LUCH has a significant impact on forest SOC stocks), this chapter aims to assess temporal changes in SOC stocks and fluxes due to land use changes using well-documented gross rates of land use change for a pilot region in Belgian Ardennes. This chapter will adopt a bookkeeping modelling strategy, by combining (i) a spatially-explicit land use database over the period 1868-2005 with (ii) changes in SOC stocks after conversion and (iii) pre-conversion SOC stocks. The last two components will be determined mainly from a local soil database and will be supplemented by data from peer-reviewed studies in temperate ecosystems. Since Belgian forests were at their historical minimum surface in the mid-19th century (Tallier, 2004), the period from 1868 to 2005 allows to encompass 150 years of forest re-growth. Only changes related to afforestation and deforestation activities will be considered in this chapter. This methodology will be compared with a “lumped” approach in which equilibrium C stocks are

attributed to land use units for each time frame and stock changes are evaluated by difference between SOC maps (e.g. Gingrich *et al.*, 2007). The last step, using Monte Carlo simulations, will assess the sensitivity of the model to changes in initial SOC stocks.

6.2 Materials and method

6.2.1 Study area

The study area covers 320 km^2 on 4 sheets of the 1:10 000 topographical maps of southern Belgium (Ardennes; 5°40'E 50°11'N) and is included within the area described in Chapter 5 (see Figure 5.1). The geographical setting and land use history of the study area from the 13^{th} century onwards can be found in section 5.2.1 and 5.2.2. Land use is dominated by coniferous and deciduous forest (62 %) and the rest of the area is mainly agricultural land (grassland : ±22 %, cropland: ±10 %) surrounding small villages.

6.2.2 Datasets

6.2.2.1 Land use change data

Land use change data are based on the georeferencing and digitising of a time series of land use maps of the National Geographic Institute (IGN) dating from 1868, 1888, 1923, 1953, 1990 and 2005. Each polygon was assigned to a particular land use according to the following simple classification: coniferous, mixed forest, deciduous, grassland, cropland, heathland, peatland, urban/undefined and rivers. Polygons were then rasterised with a pixel size of 50 by 50 m (majority method, ArcGis 9.1, ESRI Redland CA). Using map algebra, rasters were combined to give for each pixel a code representing its land use transition history. Pixels with the same code were regrouped and their total area was calculated.

6.2.2.2 Soil data

Changes in soil carbon stock following land use conversions were estimated with two different sources of data: (i) a local soil database, (ii) a literature review. The local soil database consisted of samples located within the study area collected during the National Soil Survey (1947-1962) and resampled during a field campaign in 2003-2006. The land use history of each sample was determined by checking the

geo-referenced historical land use maps. The re-sampling methodology and the way SOC stocks were computed from the database is described in Chapter 5. SOC stocks were estimated to a depth of 30 cm, considering that this layer is the most exposed to natural/human disturbances (Eggleston *et al.*, 2006). Only forest soils were present in this database so that only afforestation sequences can be assessed. The literature review focused on land use conversions for which there were not enough samples in the local database in a particular conversion type or that were simply absent in the database (i.e. deforestation). Only studies located in temperate regions and giving the precise age of the land use change were taken into consideration in the literature review. SOC stocks per unit area were extracted from these studies and when possible, calculated only for the 0-30 cm layer. If SOC concentration rather than SOC stocks was reported, bulk densities (BD) were estimated with the Rawl's formula (Eq. 5.1) with VOM = 0.244 and VMF = 1.64 to calculate SOC stocks to a depth of 30 cm. OM, the concentration of organic matter (g C kg^{-1}) was converted to OC assuming a conversion factor of 58 %. Eq. 5.1 is commonly used in review studies or meta-analysis (e.g. Mann *et al.*, 1986; Post and Kwon, 2000; Guo and Gifford, 2002; Paul *et al.*, 2002a) but may show a low accuracy, notably in forest soils (Kaur *et al*, 2002; De Vos *et al.*, 2005). Thirty percent of the studies used in the review did not report BD.

6.2.2.3 Conversions type

Only afforestation and deforestation activities were taken into account in the modelling exercise i.e. conversion between forest types (coniferous, deciduous), conversions from forest to non-forest land use (grassland, cropland, heathland, peatland) and inversely (Figure 6.1). This scheme gives a total of 18 different conversion types for which response curves have to be assigned. SOC changes in forest that did not experience land use changes since 1868 (mainly old deciduous forest) were excluded from the modelling exercise although processes other than land use changes may have had an impact on SOC stocks in these forests (see Chapter 5). Conversion between urban/undefined and forest and conversions involving mixed forests were also excluded due to the scarcity of data in these categories. Mixed forests in the land use database were alternatively considered as coniferous or deciduous forest based on simple rules respecting the history of each pixel. For instance, if a pixel shows through time a deciduous – mixed forest – cropland transition, then the mixed land use is replaced by deciduous. If we consider a deciduous – mixed forest – coniferous transition, then mixed forest is replaced by coniferous and inversely because we assume that the land use change is occurring at the time of the conversion from deciduous to mixed forest. In the absence of such clear transition type, a majority rule was applied on each pixel.

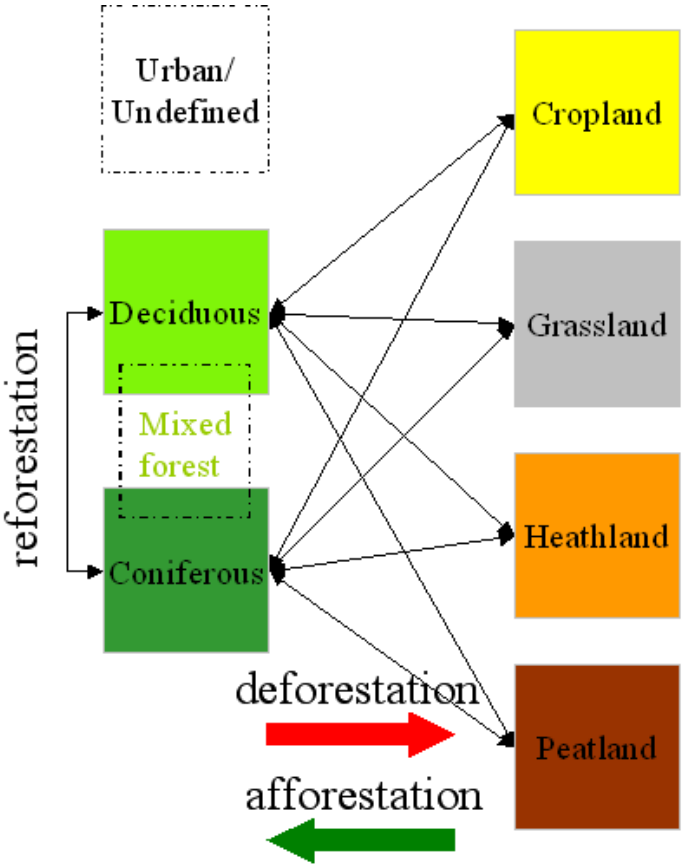

Figure 6.1. Land use conversions taken into account in the modelling exercise.

6.2.2.4 Building response curves

Change in soil carbon as a result of land use conversion was integrated in the model by means of standard response curves. These curves represent the response ratio i.e. the SOC stock under the new land use divided by the original SOC stock as a function of time for a particular conversion. These ratios allow a comparison with data from different studies and they are often used in reviews (e.g. Murty *et al*. 2002; Guo and Gifford, 2002).

In the case of the local soil database, data points in the response curves were calculated by constructing chronosequences. A particular conversion type and approximate time after land use change were assigned to each sample in the database

based on land use maps. Only samples having the dominant soil texture (stony loam soils,) and having a good to moderate drainage (apart for those involving conversions from or to peatland) were taken into consideration. For conversions where the initial land use involves deciduous or coniferous forest, the pre-conversion SOC stock was calculated as the mean of samples under forest since 1868. In other cases, since no reference 'equilibrium' SOC stocks were available, the pre-conversion SOC stock was calculated as the mean of samples of the National Soil Survey (South of Sambre and Meuse rivers) for the same land use and dominant texture. Data points obtained by the literature review were extracted from selected chronosequences, paired sites and long-term studies, which are listed in Appendix 2. The response curves were fitted through the data points using non-linear regression in *SAS* 9.1 with the Marquardt method (PROC NLIN, *SAS* Institute, Cary NC). The forms of the equations used are (Eq. 6.1, Eq. 6.2):

$$\text{Exponential: } \Delta(t) = C_0 \cdot e^{-k_1 t} + C_{ss} \cdot \left(1 - e^{-k_2 t}\right) \quad (\text{Eq } 6.1)$$

$$\text{Logarithmic: } \Delta(t) = 1 + k \cdot \log t \quad (\text{Eq } 6.2)$$

with $\Delta(t)$, the relative change in SOC stocks, k, k_1, k_2, a kinetic constant, C_0 the relative change in carbon stocks at $t = 0$ (by definition, $C_0 = 1$) and C_{ss}, the relative change in carbon stocks at steady state (%). An approximate R^2 was calculated as follows (*SAS* sample library, Eq. 6.3).

$$R^2 = 1 - (SSE/CSS) \quad (\text{Eq } 6.3)$$

with SSE, the error sum of square and CSS, the corrected total sum of square for the dependent variable. Eq. 6.1 is flexible and allows to model processes in two phases, with a initial decline driven by the k_1 constant, followed by a period of accumulation driven by the k_2 constant. This kind of carbon dynamic in the soil is often observed after afforestation (see Romanyà *et al*., 2000; Guo and Gifford, 2002; Paul *et al*., 2002a). Furthermore, if $k_1 = 0$ and $C_{ss} < 0$, the response will follow a exponential decrease towards an equilibrium state, which can be useful for instance to describe the dynamic of soil carbon after deforestation (see e.g. Woodbury *et al*., 2006).

For some response curves, there were very few or virtually no data points available either in the local soil database due to the limited surface it represents (e.g. coniferous-heathland, coniferous-deciduous) or from the literature review (e.g. coniferous-grassland). In that case, we used a simple linear relationship and a reasonable

assumption about the time (t_{ss}) to evolve from one equilibrium state to another (Eq. 6.4).

$$\begin{cases} t < t_{ss} \Rightarrow \Delta(t) = 1 + \alpha \cdot t \\ t \geq t_{ss} \Rightarrow \Delta(t) = 1 + \alpha \cdot t_{ss} \end{cases} \quad \text{(Eq 6.4)}$$

We decided also to treat both forest types (deciduous and coniferous) together for deforestation activities, due to a lack of data in temperate ecosystems. Similarly, the conversion grassland-deciduous was considered equivalent to the conversion grassland-coniferous.

6.2.3 Approach and model description

The bookkeeping model was developed using arrays and macro language in *SAS* 9.1. This kind of model, as described by Houghton (2003), needs a matrix of response curves, a matrix of land use change data and initial SOC stocks for each land use to assess stocks and net fluxes of soil carbon through time.

6.2.3.1 Combining datasets

Since the type of conversion, the time at which the conversion occurred and the time since conversion can vary for each pixel, each pixel is treated separately. First, an initial SOC stock is assigned to each pixel. Then, the model proceeds through time to determine, if a conversion occurred, which response curve should be applied to the pixel and it calculates new SOC stocks knowing the time since conversion and initial SOC stocks at the time of the conversion. Total SOC stocks and total changes in SOC stocks (ΔSOC) for each time period were calculated as (Eq 6.5, Eq 6.6):

$$SOC_j = \sum_{i=1}^{n} area_{ij} \times SOC_{ij} \times 10^{-6} \quad \text{(Eq 6.5)}$$

$$\Delta SOC_k = \frac{SOC_j - SOC_{j+1}}{t_{j+1} - t_j} \quad \text{(Eq 6.6)}$$

where SOC_j is the total SOC stocks (Mt C) in the study area for time *j,* ΔSOC (Mt C yr^{-1}) is the change in total SOC stocks between *j* and *j+1,* $area_{ij}$, SOC_{ij} denotes respectively the surface area (ha) and SOC stocks (t C ha^{-1}) of cell *i* at time *j* (t_j). By convention, negative ΔSOC (i.e. negative emission or removal from the atmosphere) represents an increase in C stocks while positive ΔSOC (i.e. positive emission to the atmosphere) represents a decrease in C stocks (Eggleston *et al*., 2006). To make the estimates comparable between time period, a SOC density at time *j* is computed by dividing SOC_j by the total area that has at least been once under forest at time *j*. ΔSOC was calculated individually for each conversion type in order to identify which conversions represent the main contributions to total changes through time. Only changes in SOC stocks due to afforestation and deforestation are included in the computation of ΔSOC. The model excludes changes in soil carbon due to conversion involving two non-forest land uses. However, if such a transition is present, the model automatically assigns equilibrium SOC stock of the following land use to keep estimates consistent if further conversions to forest occur. These changes are not taken into account in the computation of ΔSOC (contrary to total SOC stocks). Only 20 % of the surface area that have been at least one time under forest land use is concerned by such cases. If this kind of conversion happens after a conversion from forest to non-forest land use, then this correspond to a kind of carbon leakage and further changes will not be considered in the calculation of the total. The approach is also based on several other assumptions that are listed below:

- Changes in soil carbon due to land use changes can be represented by an equation. Parameters as well as the form of equation are assumed to remain stable through time.
- Every pixel having the same land use change history undergoes the same changes in soil carbon within the study area.
- When a conversion is recorded between two time periods, the conversion is supposed to occur at the middle of the interval.
- Since only land use conversion is taken into account and only time since conversion is known, the model assumes in the case of a transition to forest no effect of rotation, rotation length and possible harvesting. This is a reasonable hypothesis considering the length of the studied period.
- Pixels are evolving from one equilibrium state to another, unless another land use change happens before.
- Only surfaces that have been at least one period of time under forest land (deciduous, mixed or coniferous forest) within the study area are included in the model.

- All soil carbon is assumed to be lost in the atmosphere. There is no increase or decrease in erosion rates with land conversion.
- There are neither changes in bulk density after conversion although it is implicitly taken into account in the response curves since they are calculated in terms of SOC stocks.

The approach implemented here allows taking into account the dynamic of SOC within a spatially-explicit scheme. In this way, the evolution of each landscape unit may be tracked and related to its LUCH. In order to assess its relevance, we will compare this method with a lumped approach. In this approach, equilibrium SOC stocks are affected to each land use for each time period based on average data from the National Soil Survey (see Table 6.1). Then, an average SOC stock weighted by the area of each land use is computed. Changes in SOC stocks are calculated simply as the differences in SOC stocks between two time periods. The same surfaces as the ones in the non-lumped approach will be included in this exercise, except that their spatial location will not be taken into account, so that not only stocks but also fluxes are likely to differ between the two methods.

6.2.3.2 Uncertainty estimates

The estimates produced by a bookkeeping models are subject to several errors, which may degrade their accuracy. These errors are linked to the three components of such models (see Table 1 in Powers *et al*., 2004), namely, pre-conversion SOC stocks, land use conversion rates and response curves. In our study, errors in land use conversion rates are small and will thus be considered negligible but the two other sources of errors remain. It is thus necessary to evaluate the sensitivity of the model to these two components. Two tests were implemented.

First, in order to estimate upper and lower bounds for our estimates, 95 % confidence limits of the mean for each response curve were calculated. When no data were available (see section 6.2.2.4), a standard 20 % error was applied to the assumed response curve. Then, best/worst cases were calculated for total SOC stocks by using upper/lower confidence limits in the model rather than the mean response. Secondly, a Monte Carlo simulation (n = 10.000) was run to assess the sensitivity of the model to variation in initial SOC stocks. Probability distribution functions of the inputs (i.e. mean SOC stocks and standard deviations) were determined from the National Soil Survey (Table 6.1). Normal distributions of initial SOC stocks were assumed. Then, histograms of the model outputs (SOC density and ΔSOC) were produced.

Table 6.1. Initial SOC stocks and standard deviation for each land use calculated from the National Soil Survey, as used in Monte Carlo simulations.

Land use[a]	Mean[b]	SD[b]
	t C ha^{-1}	
Coniferous	75.9	31.6
Grassland	68.6	25.9
Cropland	52.5	21.1
Heathland	48.6	30.2
Deciduous	66.9	33.9

[a] Peatlands are assumed to contain a constant stock of 240 t C ha-1 in the first 30 cm (based on estimations of Cannell *et al*., 1993)

[b] Calculated with stony-loam samples and good to moderate drainage (Ga-c).

6.3 Results

6.3.1 Response curves

The parameters, type (linear or bi-exponential) and origin of data points for each response curve are given in Table 6.2.

6.3.1.1 Afforestation

Deciduous to coniferous

The conversion of deciduous stands to coniferous follows a bi-exponential curve (Table 6.2, Figure 6.2a). All data points (n = 42) were extracted from the local soil database. The response curve predicts a loss of carbon of c. 30 % during the first 10 years, a recovery to the value of the initial SOC stocks after c. 30 years and equilibrium stocks (+ 30 % relative to pre-conversion time) to be reached after 80-90 years. Lettens *et al*. (2005a) observed a 20 % difference between deciduous (58 t C ha^{-1}) and coniferous (70 t C ha^{-1}) forest in Belgium. However, this difference may partly reflect differences in climate and soil conditions under which they are planted. The initial decline seems rather high compared to the 6 % decrease after harvesting reported by Johnsson and Curtis (2001).

Table 6.2. Parameters, type and origin of the response curves describing the effect of land use conversion on SOC stocks.

Conversion			Parameters								
From	To	Equation type	Exponential[a]			Linear[b]		Log[c]	$r^{2,d}$	Origin[e]
	Afforestation		C_{ss}	k_1	k_2	α	t_{ss}	k		
Deciduous	Coniferous	bi-exponential	1.30	0.119	0.048	-	-	-	0.35	LD
Grassland	Coniferous/deciduous	bi-exponential	1.45	0.063	0.031	-	-	-	0.45	LD + LR
Cropland	Coniferous	bi-exponential	1.71	0.1	0.042	-	-	-	0.35	LD
Heathland	Coniferous	logarithmic	-	-	-	-	-	0.084	0.06	LD
Peatland	Coniferous/deciduous	negative exponential	-0.50	0	0.036	-	-	-	0.19	LD
Coniferous	Deciduous	linear	-	-	-	-0.003	90	-	-	no data
Cropland	Deciduous	bi-exponential	1.73	0.072	0.038	-	-	-	0.3	LD + LR
Heathland	Deciduous	linear	-	-	-	0.003	150	-	-	no data
	Deforestation									
Coniferous/deciduous	grassland	linear	-	-	-	-0.006	50	-	-	no data
Coniferous/deciduous	cropland	negative exponential	-0.39	0	0.5	-	-	-	0.012	LR
Coniferous/deciduous	heathland	linear	-	-	-	-0.010	40	-	-	no data

[a] Parameters of exponential equation given by Eq.6.3

[b] Parameters of the linear equation given by Eq.6.6

[c] Parameter of the logarithmic equation given by Eq.6.5

[d] Coefficient of determination, as calculated by equation Eq.6.4

[e] Origin of data points included in the regression. 'LD' stands for Local soil Database and 'RL' for Literature Review

Coniferous to deciduous

Since no data were obtained for this conversion, a linear relationship was used and it is assumed that soil carbon follows an opposite trend to the one described above i.e. a loss of 30 % over 90 years.

Grassland to coniferous/deciduous

The conversion of grassland to coniferous has extensively been studied, particularly in New Zealand (Annex 1). There are fewer studies on the conversion from grassland to deciduous but they generally concern longer-term changes (> 50 years, Annex I). The response upon conversion of grassland to forest greatly varies according to sampling depth and climate (Davis and Condron, 2002; Jackson *et al*., 2002). On average, SOC stock tends to decrease (Paul *et al*., 2002a). According to Guo and Gifford (2002), planting deciduous trees on pasture will not significantly affect SOC stocks, while planting coniferous tress would result in a stock decrease of 12 %. Davis and Condron (2002) found that after an initial mean decrease of 9.5 %, SOC is recovering to its level before the conversion. Our literature review along with some data points from the local soil database suggests a long term increase in SOC stocks of 30 % during the first 75 years levelling off thereafter (Figure 6.2b).

Cropland to coniferous

The effect of afforestation of cropland on SOC stocks is well documented (see Post and Kwon, 2000, Guo and Gifford, 2002; Paul *et al*., 2002a). Guo and Gifford (2002) calculated an average increase of 53 %. However, a large, climate-dependent, range of responses may be observed, ranging from a small loss in the temperate-zone to large gains in subtropical wet forest plantations, with an average accumulation rate of 33.8 g C m^{-2} yr^{-1} (Post and Kwon, 2000). Sampling depth may also be important (Degryze, *et al*., 2004). Richter *et al*. (1999) found in a long term experiment of pine afforestation over 35 years an increase in SOC concentration at 0-7.5 cm depth while the 35-60 cm layer lost SOC, suggesting a carbon redistribution within the soil profile rather than a net accumulation. Our response curve using the local soil database, suggest an initial loss of 6 %, followed by a net gain of 60 % after 70 years (Figure 6.2c).

Cropland to deciduous

According to our response curve (composed of data from the literature and from the soil database), SOC stocks do not show an initial decline and the time to reach equilibrium (+ 70 % relative to pre-conversion stocks), is somewhat longer compared to the conversion cropland – coniferous (Figure 6.2d). This is in agreement with the results of Balesdent (1995), who stated that the equilibrium SOC stocks of a decidu-

ous forest might be 1.5-2 times greater than those of a cropland. Robertson and Vitousek (1981) indicated a rate of 0.1 t C $ha^{-1}yr^{-1}$ over 250 years. Poulton *et al*. (2003) observed a constant rate of 2-3.39 t C $ha^{-1}yr^{-1}$ over 118-120 years after reversion of croplands to deciduous at Broadbalk and Geescroft experimental site (Rothamsted, UK).

Heathland to coniferous

While the conversion of heathland to coniferous is a wide-spread phenomenon within the study area throughout the last 150 years, no relevant quantitative data was found in the literature to construct the response curve. Our own estimation reveals no temporal trend, the response curve depending highly on pre-conversion estimates of initial SOC stocks in heathland (Figure 6.2e). The SOC density of 48 t C ha^{-1} calculated from the National Soil Survey is rather low. Low SOC values in such systems can be expected as a result of decreased input of organic matter and acidification of the soils (Duchaufour, 1977; pp 296-297). A logarithmic curve was fitted through the data, giving an equilibrium state 40 % above pre-conversion time.

Heathland to deciduous

No data were collected for this conversion. The process was assumed to be linear, with a net gain 40 % after 150 years (maximum similar to heathland – coniferous conversion).

Peatland to coniferous/deciduous

The afforestation of peatland has been the object of several studies, notably in Canada (Cleary *et al*., 2005), U.K. (Cannell *et al*., 1993) and Scandinavian countries (Braekke, 1987). Peatland is usually drained before planting and hence the topsoil (60-70 cm) dries out. Once the trees establish, the drying of the topsoil is enhanced by the increased water consumption of the growing trees (Cannell *et al*., 1999). Rates of carbon loss from a decomposing peat are highly variable. A reasonable range is between 0.5-3 t C ha^{-1} yr^{-1} (Cannell *et al*., 1993). A lower estimate of < 1 t C $ha^{-1}yr^{-1}$ is given by Hargreaves *et al*. (2003). Based on few data points in the study area and assuming an initial carbon stocks of 240 t C ha^{-1} in the first 30 cm (8 t C ha^{-1} cm^{-1} of peat; Cannell *et al*., 1993), we estimate a rapid decline of 50 % during the first 50 years (Figure 6.2f). No distinction is made between coniferous and deciduous plantations, since the latter conversion is almost absent in the study area.

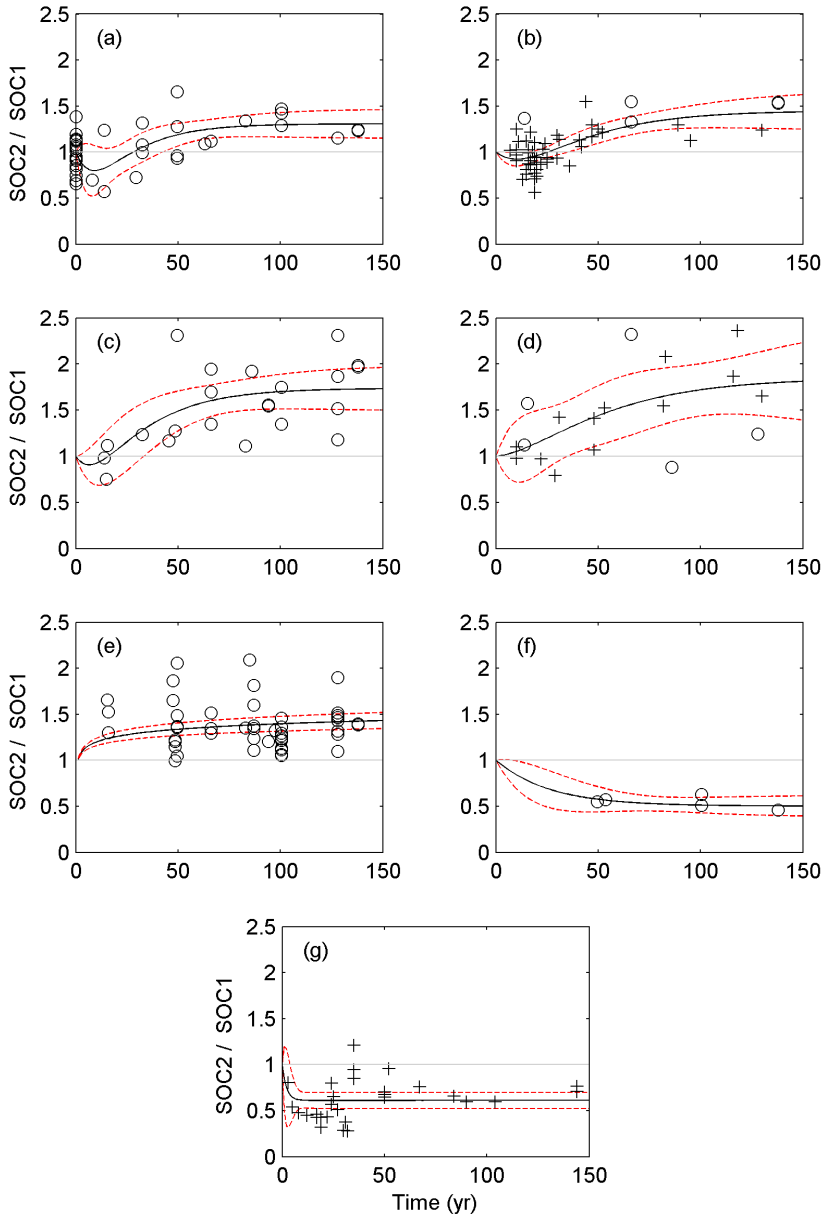

Figure 6.2. Response curves of SOC associated to afforestation/deforestation activities (black line: fitted equation, 95 % confidence limits : dashed lines): conversions from (a) deciduous to coniferous forest, (b) grassland to coniferous/deciduous, (c) cropland to coniferous, (d) cropland to deciduous, (e) heathland to coniferous, (f), peatland to coniferous/deciduous (g) coniferous/deciduous to cropland. Data points from the local soil database are indicated with circles and those from the literature review with crosses.

6.3.1.2 Deforestation

Coniferous/deciduous to grasslands

Conant *et al*. (2001) reviewed the impact of grassland management and the conversion to grassland on SOC stocks. They found a carbon gain of 15 % after conversion of natural vegetation to grassland. In their review, Murty *et al*. (2002) noted that changes in soil C after forest to grassland conversion were highly variable, with a response ranging from –50 % to + 60 %, with a mean of 6.4%. However, most of the studies included in these two reviews are from tropical regions, and hardly relevant to our study. Therefore, we propose a linear relation modelling a loss of 30 % (to be consistent with the reverse conversion, i.e. grassland-coniferous) over 40 years.

Coniferous/deciduous to cropland

Clearing forests for agricultural use may cause on average a depletion of SOC stocks of 42 % (Guo and Gifford, 2002). Forest soils contain generally a high concentration of Particulate Organic carbon (POC). This fraction is rapidly decomposed following the first years of cultivation while other fractions may show more refractory behaviours (Chan, 1997; Arrouays and Pélissier, 1994a). Turnover of SOC in forests may be more than 8 times slower than under cropland (Balesdent *et al*., 1998). Hence, forest clearing induces a rapid decline of SOC stocks. In south-west France, the clearing of coniferous forest (Pinus maritimus) for maize cultivation led to a 40-50 % decrease in SOC stocks (Arrouays and Pélissier, 1994b; Jolivet *et al*., 1997). A loss of 0-60% of initial SOC stocks is very common (Murty *et al*., 2002). Murty *et al*. (2002) calculated, after reviewing 75 different studies, a mean loss of 30 % after 10 years of cultivation. Earlier reviews found similar results (Mann, 1986; Post and Mann, 1990; Davidson and Ackerman, 1993). The extent of the decline may depend on several factors, of which climate and soil type (e.g. Lugo *et al*., 1986), initial SOC stocks (e.g. Mann, 1986), management practices (e.g. Pug*et al*., 2005), and sampling depth[57] (e.g. Davidson and Ackerman, 1993) can be highlighted. The literature review in temperate climate reveals a decrease of 39 % after 10 years (Figure 6.2g).

Coniferous/deciduous to heathland

No data were available for this type of conversion. A linear relationship was constructed symmetrically to the inverse conversion (i.e. a decrease of 40 %). However, the time to reach equilibrium was lower (40 years) due to the difference between the

[57] Due to the strong gradient in SOC in forest soils compared to more homogeneous distribution in the plough layer.

dynamic of soil carbon gain (slow accumulation) and loss (rapid mineralisation after disturbance; Johnson *et al.*, 1995).

Coniferous/deciduous to peatland

There are very few pixels showing the inverse trend of the afforestation of peatlands i.e. reversion of forest to peatland. There are some restoration projects in the study area (LIFE projects under Natura 2000 European Directive) but they are recent (since 2003), and it is too early to detect changes in SOC stocks. Furthermore, it is assumed that at the regional scale such conversions are artefacts (due to errors in the land use attribution of the polygons or errors caused by GIS manipulations). Therefore, this conversion will not be taken into account in further estimations of the impact of land use change on SOC stocks.

6.3.2 Land use changes history

Important changes in land use occurred especially between 1888 and 1953, with a steady decline of peatland, heathland and deciduous area and an increase of coniferous plantations along with an increase in landscape fragmentation (Figure 6.3). The surface area of agricultural land remained more or less constant through this period, but a large part of cropland was converted to grassland. In the Ardennes, establishment of coniferous plantations is mainly the consequence of the enforcement of the law, in 1847, on the clearing and exploitation of uncultivated land for forestry or agricultural purposes (Tallier, 2004). During the 19th century, afforestation and deforestation may have occurred simultaneously according to local interests, so that there is no clear period of afforestation or deforestation (Tallier, 2004). This produced a complex land use change history. Petit and Lambin (2002) showed for a study area just a few km to the north that at least 50 % of the surface underwent one major land use change since the mid 18th century. Since 1868, between 100 and 275 ha yr^{-1} (0.31% - 0.86% of the area yr^{-1}) were converted from or to forest. The process of land use change is still ongoing, since the surface converted from or to forest during the 1990-2005 period is c. 4000 ha, and is slightly higher than in the period 1953-1990. Between 1868 and 1888, the land use change history is complex, numerous conversions being equally distributed within the study area (Figure 6.4a). Afforestation of heathland and cropland occurred at the same time as deforestation to grassland, cropland and heathland. The process of conversion from deciduous forest to coniferous (19% of all conversions) started during this period.

From 1888 onwards (Figure 6.4b-e), the conversion from deciduous to coniferous forest is the main type of land use change, representing 28-48% of all conversions, with a peak between 1888 and 1923. However, the inverse trend, i.e. conifer-

ous to deciduous forest, played an increasing role since 1923 with 26% of the surface area being reverted back to deciduous trees between 1990 and 2005 (Figure 6.4e). The conversion of heathland to coniferous and cropland to coniferous are also important processes of land use change. Both conversions represented systematically more than 5% of all conversions until 1990 (Figure 6.4a-d). The highest rates of conversion from peatland to coniferous occurred during the 1888-1923 and 1990-2005 period, concerning respectively a total of 184 and 93 ha. While peatland afforestation represents only a small portion of the conversions (0-2%), this process should be mentioned due to the large quantities of carbon contained within these ecosystems.

6.3.3 Evolution of SOC stocks

The model predicts a constant increase in SOC stocks for the total area converted from or to forest from 0.791 Mt C in 1868 to 1.36 Mt C in 2005, mainly due to the increase in the surface having been at least once within the study period under forest (from 11 818 ha to 17 844 ha). However, SOC density shows an initial decrease from 67 t C ha^{-1} to 64 t C ha^{-1} between 1868 and 1888 followed by an increase cumulating at 76 t C ha^{-1} in 1990 and 2005 (Figure 6.5a). From 1990 to 2005, a slight decrease of 0.26 t C ha^{-1} was observed. The uncertainty around these estimates is large and gradually increases to reach c. 20 t C ha^{-1} in 2005 (Figure 6.5a). The lower bound of the mean estimate ('worst case') indicates a longer initial decline of 7 t C ha^{-1} lasting until 1923 and then a recovery so that SOC stocks in 2005 are similar to the initial levels (65 t C ha^{-1}). The upper bound ('best case') predicts an increase up to 88 t C ha^{-1} in 2005.

The analysis of changes in total SOC stocks per year (ΔSOC; Figure 6.5b) reveals also a first period of decline in SOC stocks, then a net increase through 1888 to 1990 and again a decrease in the last period. The largest emission occurred between 1868 and 1888 (0.68 kt C yr^{-1}) while the largest sequestration between 1923 and 1953 (2.13 kt C yr^{-1}). The last period (1990-2005) corresponds to the UNFCCC reporting period for which countries involved in the Kyoto Protocol are required to calculate carbon sequestration/emission due to LULUCF activities. Using a "net-net" approach a net loss of 2.35 kt C yr^{-1} might have to be accounted for 1990-2005 compared to the previous period.

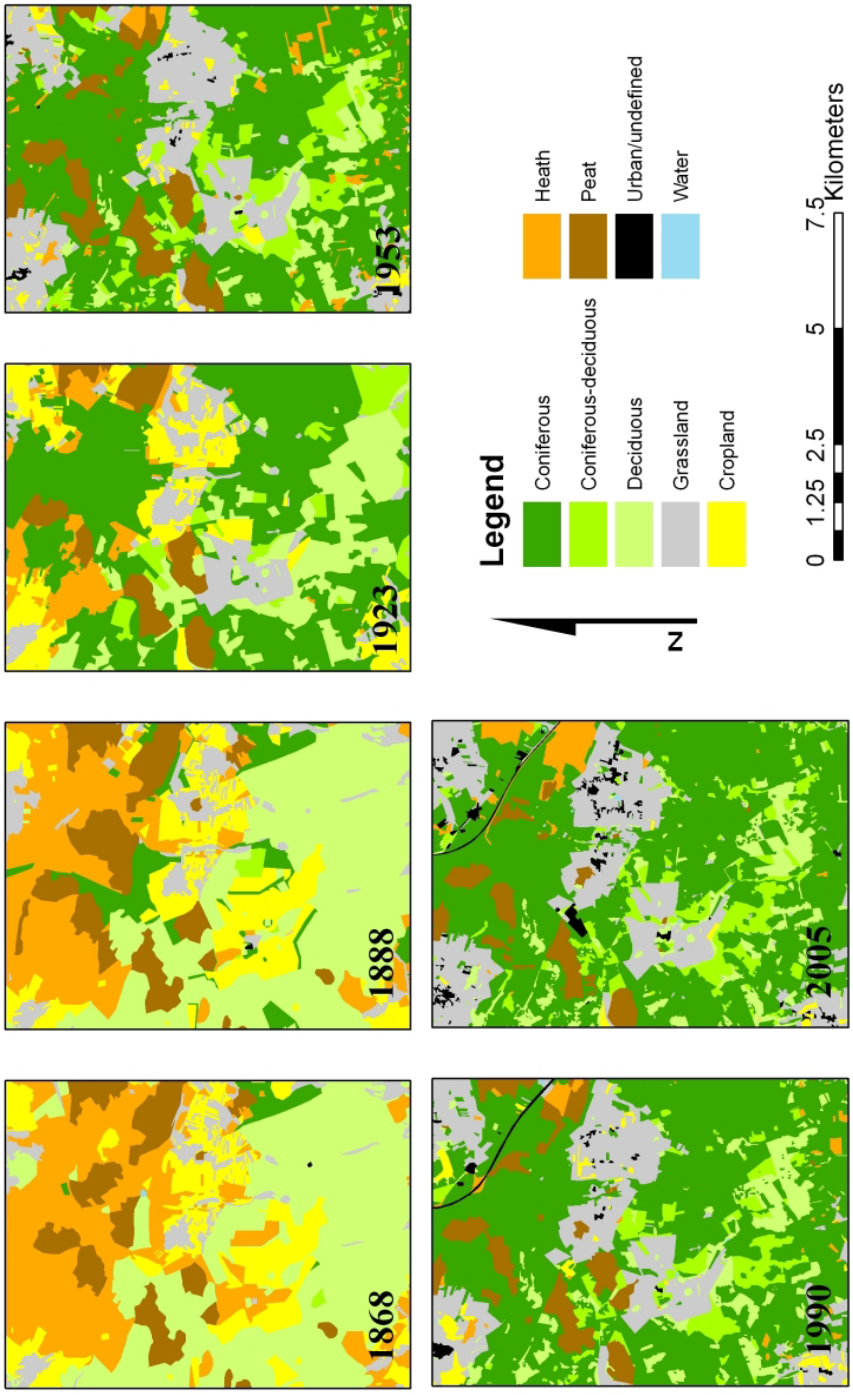

Figure 6.3. Land use history (1868-2005) of a portion of the study area.

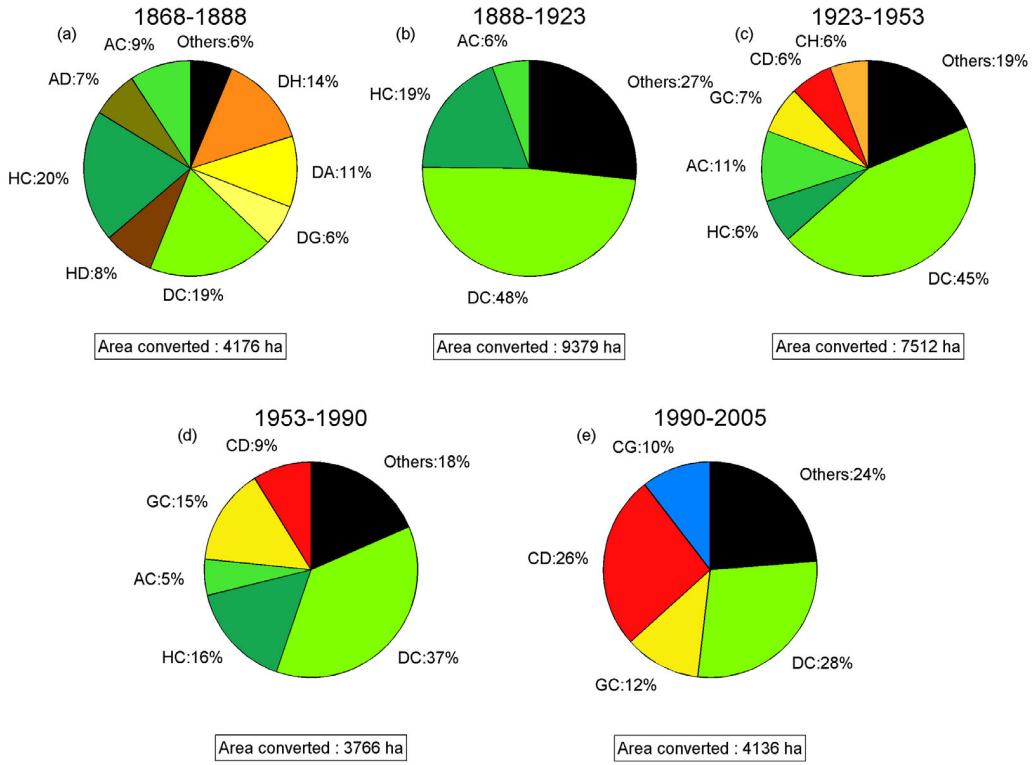

Figure 6.4. Percentage each conversion represents on the total area converted from or to forest during the period (a) 1868-1888, (b) 1888-1923, (c) 1923-1953, (d) 1953-1990, (e) 1990-2005. Legend: 'AC', Cropland to Coniferous; 'AD', Cropland to Deciduous; 'HC', Heathland to Coniferous; 'HD', Heathland to Deciduous; 'DC', Deciduous to Coniferous; 'DG', Deciduous to Grassland; 'DA', Deciduous to Cropland; 'DH', Deciduous to Heathland; 'GC', Grassland to Coniferous; 'CD', Coniferous to Deciduous; 'CH', Coniferous to Heathland; 'CG', Cropland to Grassland; 'Others', sum of all conversions representing less than 5% of the total.

These figures mask the effects of individual conversions on the global response of afforested/deforested ecosystems. While deforestation caused greater absolute changes in soil carbon per unit area and per unit of time (Figure 6.6a), afforested areas generally dominated the carbon fluxes (Figure 6.6b), due to the larger areas involved (Figure 6.4). All in all, afforestation activities over the entire period caused a storage about 2.5 times greater than losses to the atmosphere due to deforestation (results not shown). In order to point out areas of carbon sequestration vs. carbon emission, SOC stock changes per unit area and unit of time were mapped (Figure 6.7).

During the first period (1868-1888), deforestation of deciduous stands to heathland and cropland drives SOC fluxes (Figure 6.6b and Figure 6.7, Southeast of the study area). Only the afforestation of heathland to coniferous is dampening this phenomenon. While deforestation for agriculture is a major process of SOC changes at the turn of the 20th century, its influence progressively diminished (Figure 6.6b). During the second period (1888-1923), afforestation activities were the main causes of SOC fluxes and conversions of heathland, cropland and deciduous to coniferous sequestered more or less the same quantity. During this period, peatland afforestation released carbon at a rate of 2 t C ha^{-1}yr^{-1}. The surfaces concerned by this process are small. They are clearly visible on Figure 6.7 in the Northeast. Their influence on SOC fluxes is significant since peatland afforestation caused a reduction of SOC sequestration by afforestation activities of 11 % during the entire period (results not shown). Afforestation activities caused a peak rate of sequestration into the soil of 3 kt C yr^{-1} during the 1923-1953 period. At least since the second quarter of the 20th century, the land use class 'Coniferous remaining Coniferous' is the main contributor to total SOC changes (Figure 6.6b). SOC sequestration in this land use class is due to the lag-effect of previous conversions to coniferous. Mean SOC stock change in this land use class is not high (Figure 6.5a) but the area concerned by a conversion to coniferous is large (Figure 6.4).

Since 1888, the major part of the study area is experiencing a slow accumulation of SOC stocks mainly due to the conversion to coniferous (Figure 6.7). However, the contribution of these types of conversions diminishes after a rapid increase from 1868 to 1953 (Figure 6.6b). Hence, the SOC sequestration for this class decreases gradually from the beginning of the 20th century onwards. This is due to the fact that the period 1888-1923 was characterised by one of the highest rates of land use changes during the studied period (268 ha yr^{-1}), almost all areas being converted to coniferous (78 % of all conversions). Hence, these coniferous stands, converted c. 100 yr ago, are supposed to arrive at a steady state so that their contribution to SOC fluxes is diminishing. Balesdent and Arrouays (1999) observed a similar decrease in

rates of carbon sequestration in French forest soils during the last decade of their study period (1900-1999).

To a lesser extent, CO_2 in 1990-2005 is also due to the conversion from deciduous to coniferous, coniferous to cropland, peatland to coniferous and deciduous to cropland (Figure 6.6b). For the last period, the model predicts high rates of CO_2 emission for these conversions (0.5-2 t C $ha^{-1}yr^{-1}$; Figure 6.6a) because of the non-linear nature of the response curves used and the relatively short time separating 1990 and 2005 years. In the future, due to recovery of coniferous stands planted on former deciduous parcels, mean SOC stocks are assumed to slightly increase rather than decrease, *ceteris paribus*

6.3.4 Comparison with the lumped approach

The results we obtained here are, to a certain extent, different from the ones we would get from a lumped approach. Figure 6.5a shows that the estimates of average SOC stocks at the beginning and the end of the period analysed are more or less equivalent but the dynamic of SOC between these periods is not captured by the lumped approach. This approach predicts higher SOC stocks over most of the time period and lower stocks at the end. Several phenomenon combine to produce this divergence. First, at the beginning of the period, the gain in SOC due to the conversion of heathland, deciduous and cropland to coniferous between the two first periods (48 % of the conversions, Figure 6.4) is predicted to be small with the book-keeping model while the lumped method attribute large SOC gains over a short period (see Table 6.1; 20 yr). On the other hand, the loss of carbon due to the conversion of deciduous to cropland and heathland (25 % of the conversions, Figure 6.4) is predicted to be much more rapid and therefore corresponds better with estimates of the lumped approach. Throughout the entire period, this initial difference is progressively dampened because of the equivalence of the approaches when integrated over the long term. At the end of the period, a small difference of 3 t C ha^{-1} is observed (Figure 6.5a). As a matter of fact, the lumped approach predicts SOC stocks disregarding the previous land use. It results among other things that (i) coniferous planted on peatlands contain lower SOC stocks in comparison with the ones which would have been obtained if former land use is take into account and (ii) coniferous planted on former deciduous parcels are underestimated in comparison with our method because SOC stocks represent in this case only average stocks over a range of LUCH (while we showed that coniferous planted on deciduous contain more C than the ones planted e.g. on former cropland, see Chapter 5).

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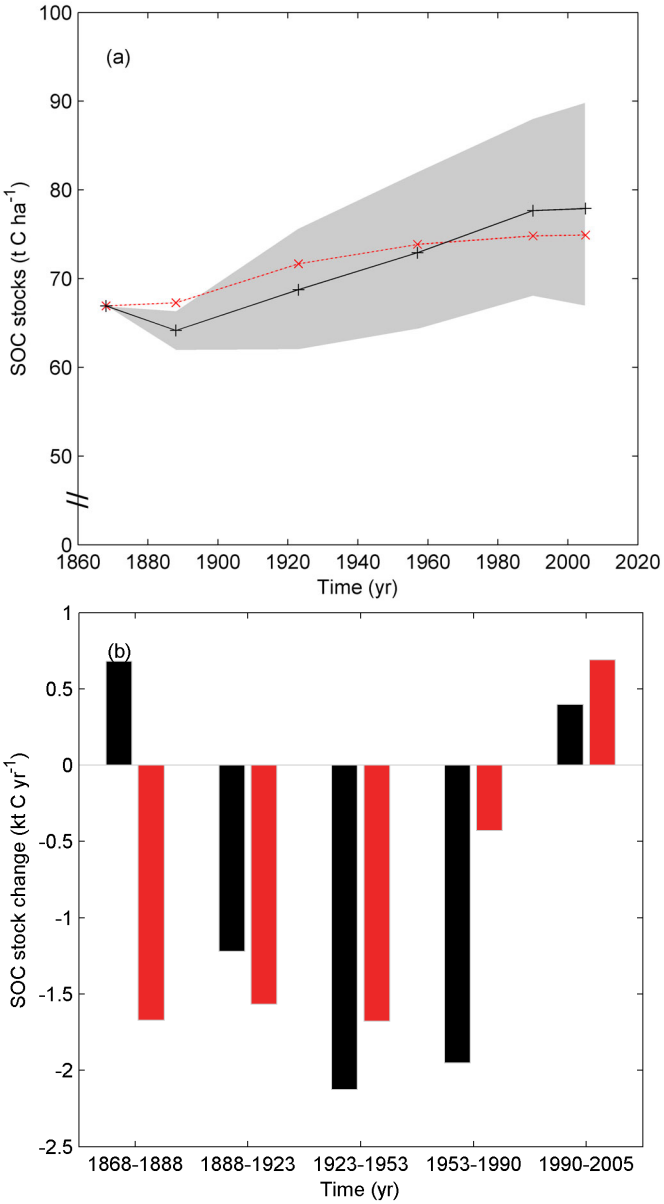


*Figure 6.5. Plot of (a) mean SOC stocks in surfaces having been at least once forest in the study area through time (black line), with upper ('best case') and lower ('worst case') bounds in grey, and mean SOC stocks as estimated with the lumped approach (red line). (b) Changes in SOC stocks per year in the area due to afforestation/deforestation (*ΔTSOC) with the standard (black bar*) and with the lumped approach (red bar). By convention, positive* ΔTSOC *represent carbon emissions to the atmosphere and negative* ΔTSOC *represent a removal of carbon from the atmosphere (i.e. soil sequestration).*

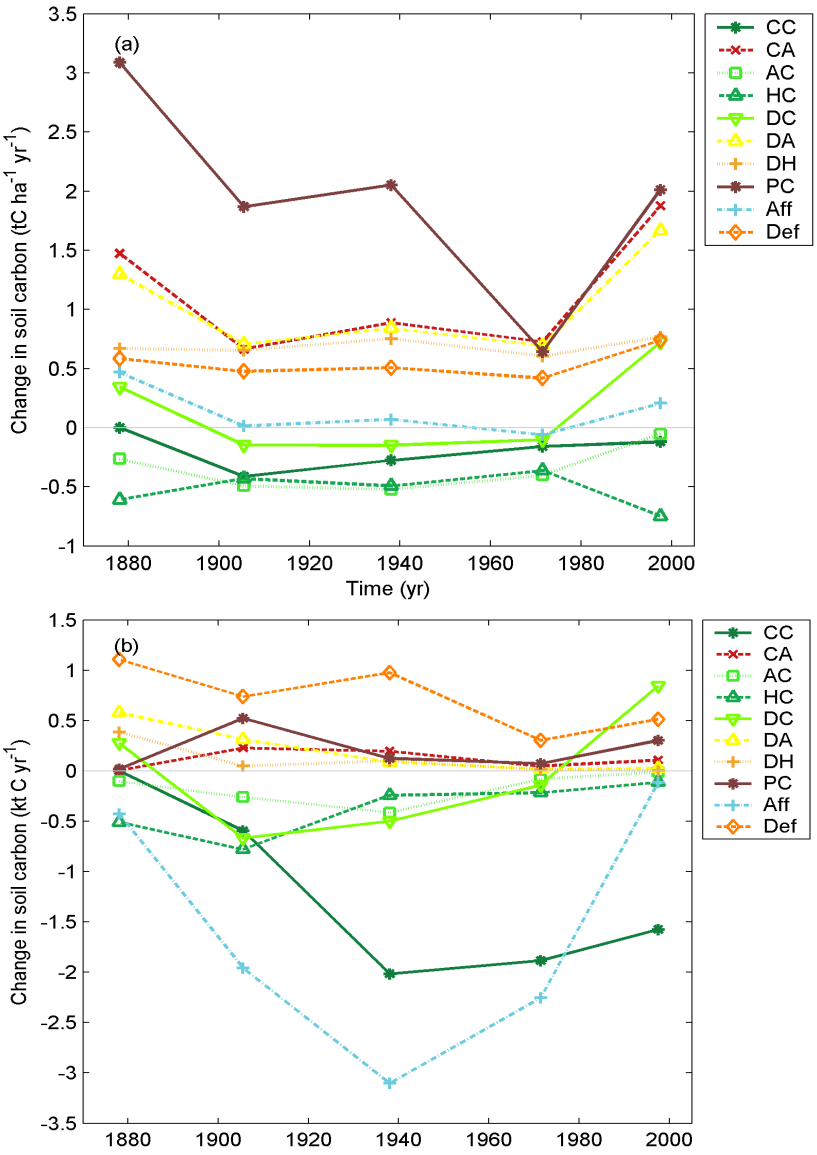


Figure 6.6. Contribution of each land use conversion to changes in SOC stocks in the study area to (a) mean changes in SOC stocks per unit area and unit of time and (b) the total change in SOC stocks per unit of time through time. Only important contributions to changes are shown. Legend: 'CC', Coniferous remaining Coniferous; 'CG', Coniferous to Grassland; 'CA', Coniferous to Cropland; 'CH', Coniferous to Heathland; 'AC', Cropland to Coniferous ; 'DC', Deciduous to Coniferous; 'DA', Deciduous to Cropland; DH, Deciduous to Heathland; 'PC', Peatland to Coniferous, 'Aff', Afforestation activities (conversion from 'CD' and 'DC', included); 'Def', Deforestation activities.

The difference between the two approaches is even more dramatic when comparing SOC stock changes (Figure 6.5b). This is due to the fact that the lumped approach is not spatially-explicit (fluxes of C are computed in an aggregated way). For instance, in the first period (1868-1888), the lumped approach predicts a high SOC sequestration because the surface of forests, which contain higher SOC stocks, has increased significantly (see Figure 6.4). Our bookkeeping model predicted rather a loss of C during the same period mainly due to deforestation of deciduous parcels converted to cropland and heathland (rapid decline of SOC) and a small effect of afforestation activities (slow accumulation of SOC). Similar assertions can be established for the next periods. Thus, the lumped approach is not able to catch the dynamic of SOC changes at short term. However, the divergence is less marked when looking over a longer time period. Indeed, the difference between the lumped approach and the methodology we developed is, for the entire period, only 43 kt C (0.31 kt C yr^{-1}). All these observations indicate that both approaches are comparable when longer time periods are taken into consideration.

6.3.5 Monte Carlo Simulation

The analysis of the histograms of the Monte Carlo simulations reveals that predicted SOC stocks are highly variable (Figure 6.8). The interquartile range varies between 32-45 t C ha^{-1} and decreases throughout the study period. The interquartile range represents 42-67% of the mean response of the model. It means that the model is highly sensitive to changes in the input variables. These variables affect the model in two ways. First, they are used to initialise the model. Secondly, in the model, changes in SOC stocks are proportional to SOC stocks at pre-conversion time. The variability in the response of changes in SOC stocks through time is also large with an interquartile range varying from 0.003 to 0.232 t C $ha^{-1}yr^{-1}$ (13-150% of the mean response; Figure 6.9). Again, the first period of time is more affected by changes in the input variables than the later periods. However, the histograms show that interquartile ranges do not intersect zero, indicating that variation in the input variables is not able to reverse the main trends, i.e. an emission of CO_2 from 1868 to 1888, followed by sequestration during about a century and again a small emission of CO_2 to the atmosphere from 1990 to 2005. Hence, the model appears to be able to predict consistent changes in SOC stocks that can be used to estimate the ecosystem response to past and contemporary land use changes in the study area. However, Monte Carlo simulations showed that the variability in SOC stocks is too large for useful predictions.

6.4 Discussion

6.4.1 Carbon fluxes and land use changes

Our findings are in line with broader scale studies showing that forest soils in the northern hemisphere have been sequestering carbon during the last century (e.g. Liski *et al.*, 2002). Gingrich *et al.* (2007) showed how this dynamic may be related to the forest transition that occurred in industrialized societies at the turn of the last century, which rapidly shifted from area-dependent energy sources (biomass) to area-independent energy sources (fossil fuels). However, the intensity of the sequestration, driven by past land use changes, is currently decreasing. For the study area, this trend is not likely to be reverted in the future since most of the surface has already contributed to the soil C sink in the past and, particularly, coniferous forest soils are approaching steady state (see Figure 6.7).

Considering the population density and the limited surface available for afforestation in Belgium (Dendoncker *et al.*, 2004), options to further increase or even stabilize the current soil C sink are limited. In the Walloon region (South part of Belgium), only 167-340 ha yr^{-1} have been afforested between 1990 and 2000 (EEW, 2000). Thus, the only possibility to maintain the C sink may be through enhanced management practices in forest (see e.g. Johnson and Curtis, 2001; Lal, 2005). Subsidies for the regeneration of forest land adopting sustainable forestry practices exist in the Walloon region and may be favourable to soil carbon sequestration. Such measures cover a total area of 2321 ha in 1995-1999 (EEW, 2000). Those guidelines for sustainable management include (i) obligation to leave more deadwood in forests, (ii) interdiction of drainage on hydromorphous and peatland soils, (iii) maintenance, restoration and expansion of copse forest or coppice under high forest and mixed stands, (iv) obligation to leave residues after clear cutting and (v) recommendations to reduce mechanical soil disturbance by machines during the exploitation of the forest (Branquart and Liégeois, 1997).

Liski *et al.* (2002) predicted a soil sink of 0.24 t C $ha^{-1}yr^{-1}$ in Belgian forests for 1990. De Vries *et al.* (2006) found an average soil C sequestration rate of 0.14 t C $ha^{-1}y^{-1}$ between 1960 and 2000 due to forest growth in Europe. Falloon *et al.* (2002) obtained an increase in SOC stocks of 0.15 t C ha^{-1} yr^{-1} when they simulated the reforestation of all agricultural land in Hungary using the RothC model. Our own predictions are comparable, with a mean carbon sink in forest soils (thus disregarding deforested areas) of 0.16 t C $ha^{-1}yr^{-1}$ for the entire period, 0.14 t C $ha^{-1}yr^{-1}$ from 1953 to 1990 and 0.005 t C $ha^{-1}yr^{-1}$ from 1990 to 2005.

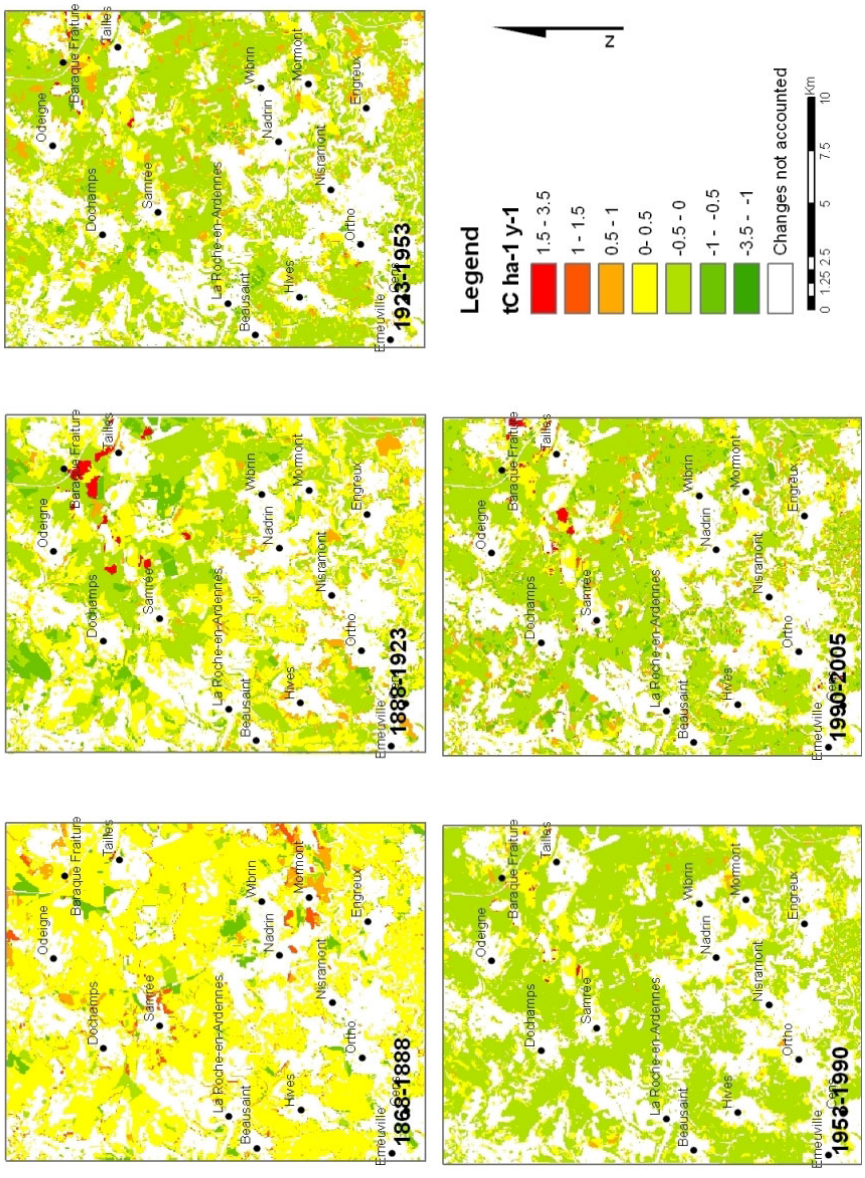


Figure 6.7. Maps of changes in mean SOC stocks per unit area per unit of time (t C ha^{-1} yr^{-1})

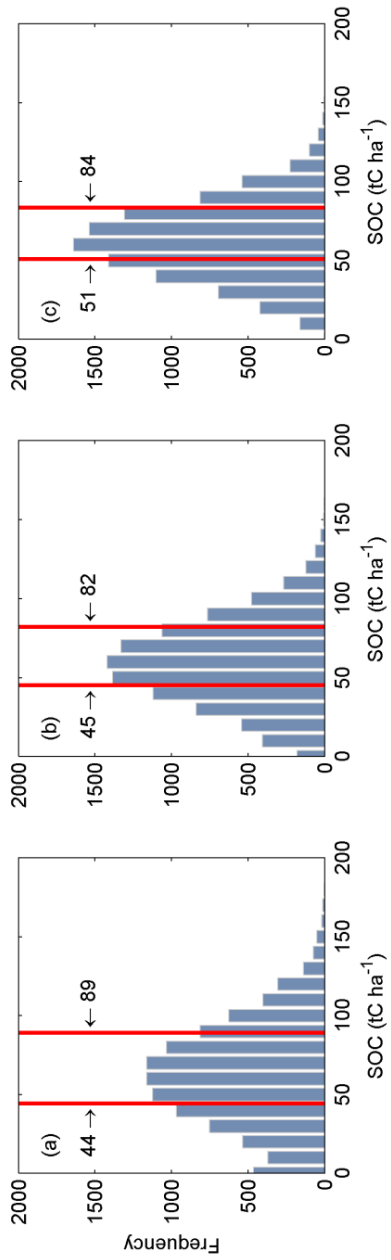


Figure 6.8. Histogram of Monte Carlo Simulation results for SOC stocks (t C ha^{-1}) in (a) 1868, (b) 1888, (c) 1923, (d) 1953, (e) 1990 and (f) 2005. Vertical red lines show the 1st and 3rd quartile of the histograms.

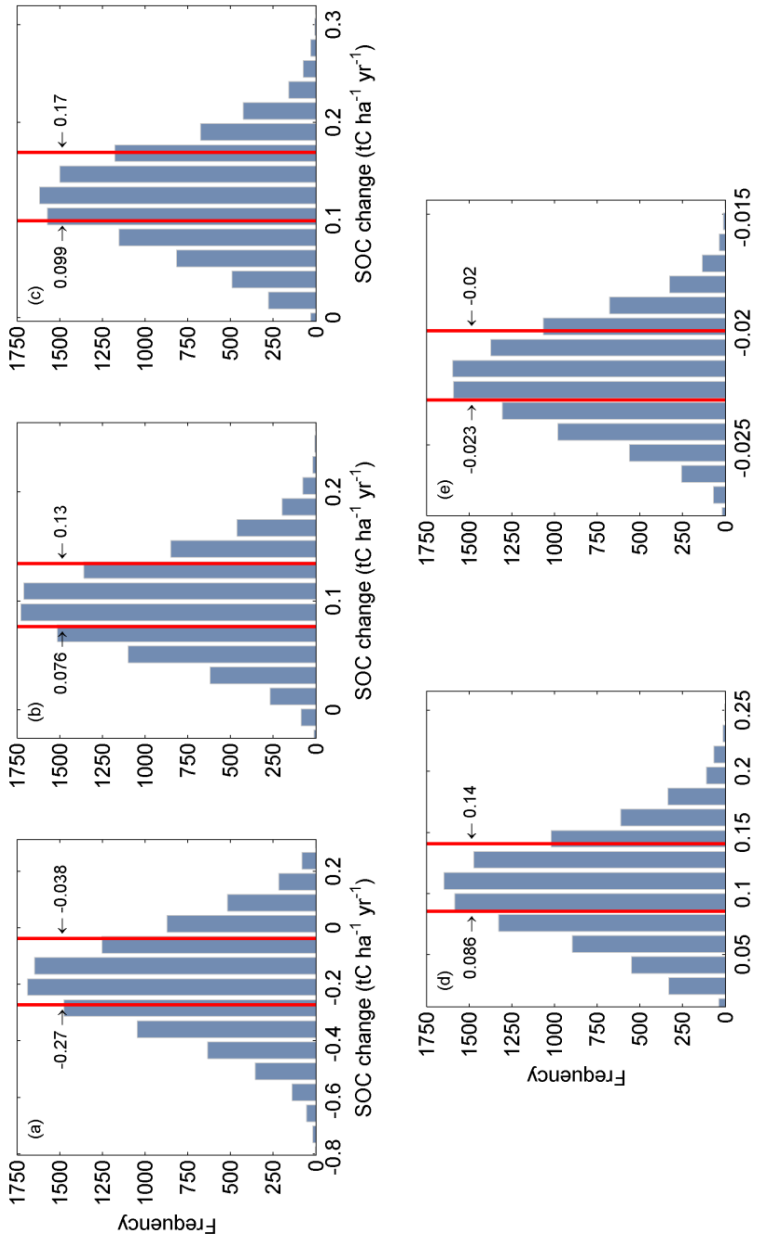


Figure 6.9. Histogram of Monte Carlo Simulation results for changes in SOC stocks (t C ha^{-1} yr^{-1}) during (a) 1868-1888, (b) 1888-1923, (c) 1923-1953, (d) 1953-1990 and (e) 1990-2005. Vertical red lines show the 1st and 3rd quartile of the histograms.

These values are similar to the average C accumulation after forest establishment found by Post and Kwon (2000) at 0.33 t C $ha^{-1}yr^{-1}$ and Paul *et al.* (2002a) at 0.14 t C $ha^{-1}yr^{-1}$. However, Balesdent and Arrouays (1999) predicted much lower rates of C sequestration due to the abandonment and regrowth of forest on agricultural land in France at 0.023 to 0.050 t C ha^{-1} yr^{-1} (1900 to 1999). The carbon sequestration in the soil, calculated above, is limited compared to sequestration in forest biomass: 0.92 t C $ha^{-1}yr^{-1}$ for forests in the Ardennes (calculated from Perrin *et al.*, 2000) and 0.45 t C $ha^{-1}yr^{-1}$ for US forests (Houghton and Hackler, 2000). Janssens *et al.* (2005) evaluated the total carbon sink in European forest to be 1.24 t C $ha^{-1}yr^{-1}$ during the 1990s. In the Walloon region, terrestrial ecosystems sequestered 724 to 1174 kt C yr^{-1} in 1990-2004 (Perrin, 2005). This confirms the estimations of Lettens *et al.* (2005a), which predicted a low potential of sequestration from land use changes in Belgian soils.

6.4.2 Are estimates representative?

Estimates produced by the model do not intend to represent actual changes in SOC stocks but rather changes in SOC stocks due to land use conversions (afforestation/deforestation), so that a validation of the modelling exercise with real data is of limited use. They do not take into account changes in carbon stored in biomass or changes in SOC due to changes in climate or increased atmospheric nitrogen deposition (see e.g. Pregitzer *et al.*, 2007). One of the stronger hypotheses of the model is the fact that response curves remain constant through time. It is obviously not the case as stressed notably by Balesdent and Arrouays (1999) and this is linked with changes in management regime that can occur through time. While our model predict an overall increase in SOC stocks in forests of the study area, field evidence indicates an average decline in SOC stocks between 1950-60 and 2006 (Chapter 5). Chapter 5 showed that land use change history explained only part of observed changes in SOC stocks. Management practices may have played an important role in these observed processes of change. For instance, artificial drainage to establish coniferous plantations was a common practice on hydromorphous soils in the study area at the end of the 19th and beginning of the 20th century[58]. It is known that impeded drainage results in greater carbon stocks in forest soils (e.g. Weimin *et al.*, 2006). It is now recommended to abandon these practices in Walloon forests (Branquart and Liégeois, 2005).

By expressing response ratio of SOC as a function of time, the approach may not be able to catch the fact that fractional loss or gain of SOC can also be related to

[58] This practice was made possible notably by the large pool of workforce available (Dufrêne, *pers. comm.*).

initial or current SOC stock. For instance, Mann (1986) showed that the fraction of soil C loss after cultivation is correlated to the amount of C initially present in the soil. Similarly, Knops and Tilman (2000) found that the carbon accumulation rate in forest after agricultural abandonment was significantly and negatively related to carbon concentration at the time of the last sampling. These studies suggest that soil carbon dynamic after land use changes would follow first-order kinetics tending towards an equilibrium state (exponential or logistic equation). However, other studies have challenged these views and did not found any evidence of such processes (e.g. Davidson and Ackerman, 1993).

Another source of error in the model is the shape of the response curves. First, these response curves rely on data points from various studies, locations and soil textures. Secondly, errors associated to these studies apply *a fortiori* to the modelling exercise. For instance, Yanai *et al.* (2003), stressed the difficulty in chronosequence studies to distinguish between the effect of change in the nature of the treatment over time and change in time since treatment. Chronosequences consider stand age as the only explaining factor, assuming other sources of variability fixed (e.g. initial soil conditions, forestry practices over time).

6.5 Conclusion

Based on historical land use maps and SOC response curves upon changes in land use, our modelling approach has tempted to evaluate the effect of afforestation and deforestation on SOC stocks in the Belgian Ardennes over most of the industrialized period (1868-2005). Reclamation of heathland and establishment of coniferous plantations has resulted in a net increase in SOC densities in the study area. Afforestation dominated carbon fluxes but deforestation also played an important role and reduced the carbon sink to nearly 40 % of the initial value. Although afforestation of peatland was limited in area, its impact on SOC fluxed was significant. The increase in carbon stocks gained over the entire period is large (on average 9 t C ha^{-1}). However, the annual sequestration of SOC due to afforestation/deforestation is rather low (0.16 t C ha^{-1} yr^{-1}) compared to changes in carbon stocks in forest biomass. The largest rates of sequestration occurred between 1923 and 1953 due to land use changes at the end of the 19th century and beginning of the 20th century. After this peak, rates of sequestration decreased and the soil carbon sink turned to a small carbon source at the end of the study period (1990-2005). A small carbon sink is expected in the future. The effects of the recovery of forested areas since the mid-19th century are nowadays mostly reabsorbed and management options are required to at least maintain the historical carbon sink.

The comparison of the bookkeeping model we developed with a lumped approach demonstrated that such kind of spatially-explicit modelling exercise is relevant and essential for the understanding of the dynamic of SOC over time. We observed several discrepancies between the two approaches at a local/regional scale. These errors arising from a coarse modelling approach might be of great importance when assessing SOC fluxes at larger scales. Monte Carlo simulations showed that the bookkeeping model was highly sensitive to changes in initial carbon stocks both in predicted mean SOC stocks and rates of changes. However, this variability was not sufficient to revert the observed trends. By comparing our results with estimates of biomass fluxes, our approach allowed to better evaluate the contribution of soils to carbon fluxes in a temperate forest.

Chapter 7

General conclusion

7.1 Main findings

Inherent characteristics of soil organic matter (high spatial variability at various scales) and methodological problems regarding its monitoring (lack in consistent initial conditions in soil type, climate, land use change and management history) lead to difficulties in the detection of significant Soil Organic Carbon (SOC) stock changes. The latter is particularly important in the assessment of soil C response to environmental changes and in the implementation of Land Use, Land Use Change and Forestry projects in the context of the Kyoto protocol (Chapter 2). This thesis represents an effort in assessing and explaining SOC changes at the regional scale. Two different strategies have been adopted: (i) exploring the potential of Visible, Near-Infrared and Short-Wave Infrared (VNIR-SWIR) reflectance spectroscopy as a rapid SOC analysis technique in croplands (Chapter 3 and 4) and (ii) combining a SOC inventory with spatial data on LUCH to explain and model changes SOC stocks in forests (Chapter 5 and 6).

Regional estimates of SOC changes can only be obtained by analysing very large number of samples over large areas. Current methods of soil analysis are too expensive and time consuming to meet the amount of data required for statistical inference in soil monitoring. VNIR-SWIR reflectance spectroscopy provides an alternative to chemical analyses. The benefits of this technique include a reduction of the sampling processing time, an increase of the number of samples that can be analysed

within time and budget constraints and hence an improvement of the detection of changes in SOC stocks for a given area.

Using a chemometric approach (Partial Least Square – PLS – Regressions), SOC concentration in the plough layer of bare agricultural fields have been related to spectral data (Chapter 3 and 4). It was found that ground-based spectroscopy (i.e. Laboratory and Portable Spectroscopy – LS and PS) may be able to estimate SOC concentrations with a precision equivalent to the classical chemical Walkley and Black method. Imaging Spectroscopy (IS) fails, for the time being, to reach an acceptable precision for a point-to-point estimation. However, this thesis has shown, using the concept of the minimum detectable difference (MDD) that, even with somewhat lower precision levels, such technique can enhance the estimation of changes in SOC stocks at the field and regional scales, provided that the bias is low (Chapter 3). The large number of samples that can be processed could improve estimates of mean SOC stocks compared to more precise chemical analyses of an inherently smaller number of samples.

SOC mapping capabilities of IS were also outlined (Chapter 3). Despite the low precision achieved by the airborne sensor (CASI), the SOC concentration of bare fields were predicted pixel-by-pixel. Overall, the range of SOC predicted by IS is consistent with the SOC concentration measured in the field. Spatial patterns of SOC concentration at a very fine resolution were distinguished. It suggests that intra- and inter-field SOC variability can be detected according to the spectral response of the soil. In one field, a sharp and geometrical pattern of SOC concentrations corresponding to old field boundaries was observed. While geostatistics have been widely exploited to assess the spatial distribution of SOC concentration in agricultural fields (e.g. Zhang and McGrath, 2003; Liu *et al*., 2005), it may be not able to detect such detailed and well-defined footprint of past land use or management history without resorting to a very high sampling density.

In a second step, this thesis was concerned with the stability of the calibrations retrieved by the chemometric approach (Chapter 4). In the case of PS and IS techniques, changes in the measurement environment (light and soil surface conditions) may generate problems for the spectral calibration (i.e. the rendering of the true spectral information) and the statistical calibration (i.e. changes in spectral predictors). Also, spatial variation in soil chemical and physical properties (e.g. iron concentration, clay concentration) across the landscape reduces the precision of the SOC predictions as the spatial extent of the calibration increases.

Under laboratory conditions, reflectance spectroscopy yields stable calibrations (Genot, 2007, pers. comm.) but it presents little improvement in the context of soil SOC monitoring – with the exception of the costs – in comparison with reference

methods since the workload (e.g. sample collection and preparation) is equivalent. Our results show that PS calibrations depend mainly on uncontrollable factors affecting the reflectance of the soil surface: moisture, vegetation residues and roughness (Chapter 3 and 4). These factors vary through time and inconsistent measures between the field campaigns lead to non-repeatable results. Nevertheless, PS presents good validation results over two (Chapter 3) or three contrasted study areas (Chapter 4) and, when restricted to a single area, it may be able to increase its precision to levels comparable to the one of LS and the reference analytical method (Chapter 4). IS presents similar problems as those found for PS. In addition, spectral calibrations of IS (e.g. atmospheric corrections) may also induce a spectral variation (Chapter 4) so that calibrations from IS data are limited to continuous and homogeneous areas. However, since local calibrations are still required for both techniques, imaging spectroscopy seems definitely the best alternative to traditional analytical methods for regional SOC monitoring, considering the efficiency of the method to measure the soil surface.

The second part of the thesis addressed the problem of detecting, explaining and modelling the evolution of SOC concentration at the regional scale (Chapter 5 and 6). Complex land use change history and lack in uniform initial conditions between measurements may obscure the detection of SOC changes. Systems characterized by transient dynamics are difficult to apprehend because slow and fast SOC pools may react in different ways to changing conditions. Particularly, the slow SOC pools may not be at equilibrium. A study area in the Belgian Ardennes that has experienced a forest re-growth since the middle of the 19th century has been selected for its capacity to illustrate the problem.

Chapter 5 looked into the relationship linking SOC stocks and SOC stock changes with Land Use Change History (LUCH) at the regional scale. An historical soil C inventory (1950-1960) was partially resampled in 2003-2005 and land use history variables (1868-1990) were collated and put in a global linear model. A significant decrease in SOC concentration along with a decrease in the variability between sampling points during the last 50 years was observed. It was also found that old deciduous stands (planted at least in 1868) were not at equilibrium in 1950-1960 and were losing carbon. Coniferous parcels planted on former agricultural fields generally had lower SOC concentrations than coniferous plots with other former land use classes (e.g. grassland, heathland). Large decreases in SOC concentrations were reported in former peatland soils. However, not all variability can be accounted for by LUCH variables. In the absence of spatial data in other environmental factors able to explain SOC changes (climate, forest management), no quantitative estimations of their impact were produced. However, similarly to another study in England and Wales (Smith *et al.*, 2007), climate change has been eliminated as a driving fac-

tor using a simple experiment with the RothC model. The decrease in SOC variability between the two sampling dates may be related to a standardization of management practices (among others, artificial drainage). A simple predictive model allowed to explain why a general decline in SOC concentration is observed in the study area, whereas other studies observe rather an increase of SOC stocks in Belgian forest (e.g. Lettens *et al.*, 2005a; Vande Walle *et al.*, 2007).

These findings have implications for SOC stocks changes studies based either on broad-scale inventories or modelling. If, as observed in this thesis, steady state conditions are rarely observed, regional-scale estimations of the impact of land use changes on SOC stocks based only on geo-referenced soil profiles (e.g. Lettens *et al.*, 2005b) may be erroneous or, at least, flawed. Modelling strategies assume also that soils at the beginning of an experiment are at equilibrium, corresponding to the environmental setting (climate, plant inputs,…) in which they are evolving. If this condition is not met, Wutzler and Reichstein (2007) showed that only small accumulation rate in slow C pools of disturbed sites can lead in large underestimation of theoretical equilibrium stocks.

Chapter 6 focuses on the modelling of SOC changes as a result of afforestation and deforestation activities that occurred during the last 150 years (1868-2005) in a pilot area of the Belgian Ardennes. The aim was not to evaluate actual SOC changes during the study period but rather model SOC changes due to LUCH, in the absence of other driving factors. We adopted a bookkeeping strategy by combining spatially explicit data of land use changes with empirically- and theoretically-based response functions modelling SOC changes upon land use conversion.

Our model predicted an average increase in SOC stocks due to the reclamation of heathland and establishment of coniferous plantations in the late 20^{th} century. This phenomenon tended to slow down i.e. the soil carbon sink observed during the period 1888-1990 turned to a small carbon source in 1990-2005. Since afforestation was more widespread than deforestation in the study area, the latter was generally driving the predicted carbon fluxes. The average SOC sequestration rate due to land use changes in the study area is low (0.16 t C ha^{-1} yr^{-1}) compared to the increase in carbon stocks in forest biomass (0.92 t C ha^{-1} yr^{-1}, Perrin *et al.*, 2000). Simple Monte Carlo simulations showed that bookkeeping models are highly sensitive to initial conditions but that main tendencies observed remain pertinent.

Detailed historical records of land use and field-based response curves are necessary to realistically represent SOC changes in areas having complex land use history. Although our bookkeeping model was only applied to a small area, we have demonstrated the importance of using a spatially explicit database of land use changes to calculate soil carbon fluxes. Reproduced in other terrestrial ecosystems

where such records are available, we think that such studies may help to estimate the contribution of land use changes to the global C cycle and be one of the solutions to elucidate processes that are observed at global scales.

7.2 Limitations and perspectives of further research

Outside of the controlled conditions of a laboratory, one of the severe limitations of VNIR-SWIR spectroscopy is that calibrations generated from spectral data acquired during a given field campaign cannot be extrapolated to spectral data from another field campaign. Therefore, our thesis – like numerous other studies (e.g. Reeves *et al*., 2002) – failed so far to demonstrate more than the *potential* of VNIR-SWIR spectroscopy for determining the SOC concentration and its spatial variation. We should therefore wonder why such a promising technique is still not largely widespread in soil analysis practice and how it may become a robust and routine analytical technique for applications e.g. in soil monitoring. Further research is obviously needed to develop regional-scale calibrations.

An important progress in the search for a regional calibration would be accomplished if the calibrations obtained by PLS regressions can be related to identifiable chromophores linked with molecular bonds present in the soil. This would demonstrate that the statistical nature of the methodology relies also on true chemical soil properties and soil organic matter in particular. If this may be possible under laboratory conditions, there is still a long way to go to demonstrate such a link with field and airborne measurements. Elaborate a practical solution to this problem is complicated and requires to eliminate the factors affecting the measured reflectance across space and time. In spite of this, several approaches to resolve these difficulties can be envisaged.

Vegetation cover, soil moisture and roughness are the three main factors disturbing the spectral response of soil. The effect of fractional vegetation cover on the accuracy of the SOC predictive capacity of our models has not been extensively studied yet, but all fractionally covered pixels show a clear influence of vegetation on the spectral signature. This usually leads to large deviations in the estimation of soil parameters (Bartholomeus *et al*, 2007). Our approach was simply to remove these spectra from predictions but, in the future, spectral unmixing techniques could offer a possible solution to estimate SOC in partially vegetated areas. The removal of soil moisture and roughness effects on the calibrations may be accomplished firstly by studying more precisely their impact on soil reflectance under controlled experimental conditions. Then, based either on absorption features or Principal

Component analysis, spectral data collected in the field would be classified into several groups representing defined surface conditions. Predictions of SOC concentrations would be limited to specific classes, others classes being simply rejected before their processing by the model. Another solution is to model the effect of the disturbing factor (e.g. Cierniewski, 1987; Lobel and Asner, 2002; Whiting et al., 2004) and apply a correction to the spectrum before the calibration. Similarly, we may use in the future multivariate regression techniques allowing to include the effects of a covariant (e.g. Eilers and Marx, 2003). In practice, this method requests to spatially measure the disturbing factor over the entire study area (e.g. soil moisture). However, the recent convergence of several new measuring technologies aiming to map soil properties (e.g. SAR imagery, see Dubois *et al.*, 1995; Kelly *et al.*, 2003) enables the investigation of such strategies in the short term.

The stability of the calibrations may also be improved by using more efficient chemometric approaches. For instance, Marx and Eilers (2002) have developed a multivariate technique – called Penalized signal regressions – that forces the regression coefficients to vary smoothly across wavelengths. It allows removing the effects on calibrations of noisy features in the spectral data and yields in general more robust calibrations. Also, at regional scale, the range of SOC concentration may be large, producing a possible non linear relationship between spectral data and SOC concentration. This is a problem that PLS regressions cannot address since they are based on linear models. Non-linearity may be effectively fixed with more sophisticated statistical techniques such as Neural Networks (e.g. Fidêncio *et al.*, 2002a) and Boosted Regression Trees (e.g. Cohen *et al.*, 2005).

When assessing the potential of imaging spectroscopy for SOC monitoring, this thesis has not fully considered the effects on sample size requirements when autocorrelation between neighbouring pixels occurs. Such matter could be explored in more details using for instance the methods proposed by Griffith (2005), which proposes several model-informed solutions to find the number of equivalent independent observation equal to the sample size of an autocorrelated dataset (i.e. the effective sample size).

Our study on the changes in SOC concentrations in the forests of the Belgian Ardennes showed that an important part of the variability was not attributed to land use history. Management drivers were evoked but their real impact was not quantified. However, a preliminary study demonstrated that such data can be collected and that, adopting the same strategy as the one presented in this thesis, forest management history can be related to SOC changes at regional scales. We should also further investigate the factors affecting the evolution of SOC concentrations observed in several old deciduous forests (> 150 yr) of the study area.

SOC concentrations, rather than SOC stocks, have been related to land use history variables. A systematic sampling of soil bulk density through the experimental plot and the profile would be the more obvious solution to assess with more precision SOC stocks in forest. However, this is laborious and, in the presence of high rock fragments content, inaccurate or complicated. Therefore, we used a pedotransfer function and assumed no soil compaction between the two surveys due to other factors than SOC changes. This is a strong assumption and an evident limitation of our thesis. Thus, we suggest for a further research to try to collect data on forest soil compaction in Belgium (e.g. Rohand *et al.*, 2000) and find out if there is any evidences of historical changes in soil compaction due e.g. to mechanisation.

Chapter 6 employed a modelling strategy in which soils are evolving from one steady state to another. Chapter 5 showed that SOC pools in forests might be affected by slow and long-term processes of aggradation/degradation, which may be not correctly represented by the simple model developed in Chapter 6. Process-based models may be also not suitable since they require generally steady state conditions at the beginning of the experiment. However, using the Yasso model (Liski *et al.*, 2005), Wutzler and Reichstein (2007) proposed an interesting alternative by excluding the slowest pool from the equilibrium assumption.

7.3 Final remarks

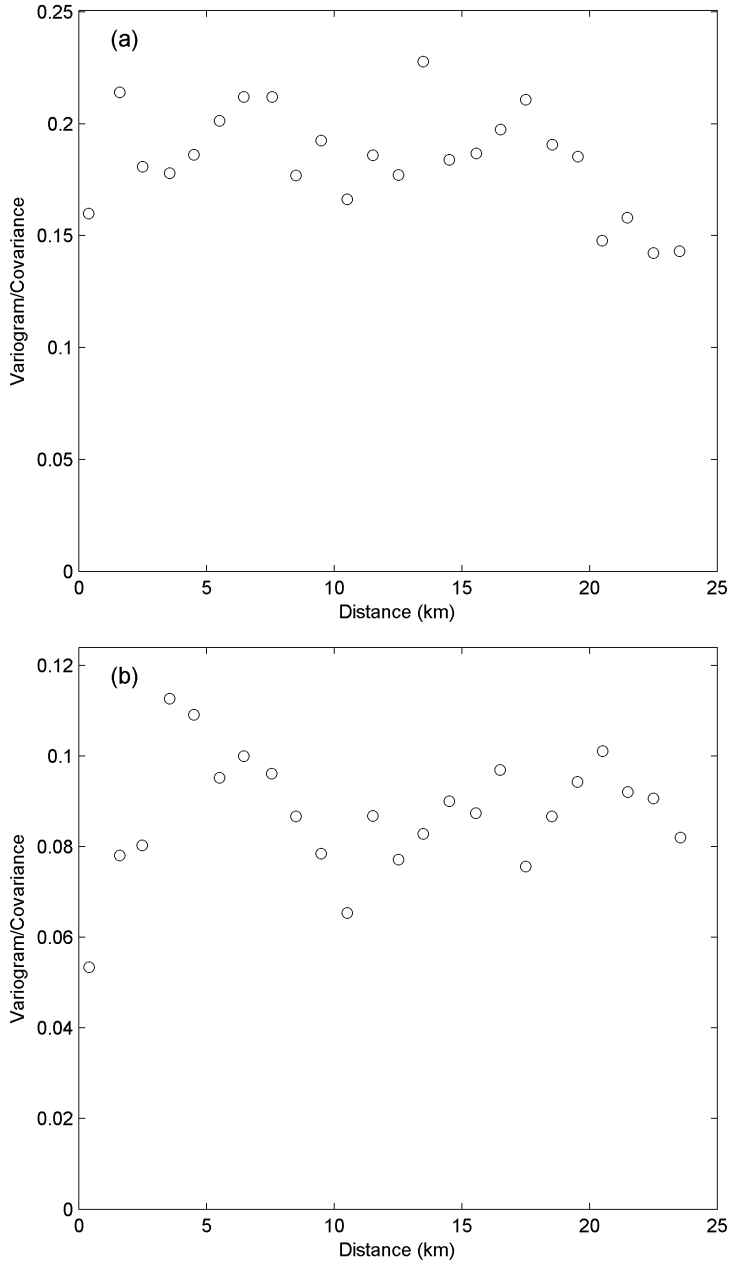
The structure of this work came up naturally during the thesis when we tried to detect and explain SOC changes at the regional scale. The objective was to tackle scientific and societal questions arising from the rapid global environmental changes. Considering the large quantity of carbon stored in the soil, are SOC stocks increasing or decreasing and if so, what are the main drivers of SOC changes? Does it have a significant impact on CO_2 fluxes at national/global scales? To respond to these recent concerns, soil science has progressively switched its focus from the plot to the region or the continent.

However, at these scales, spatial variability in soil properties blurs the signal of change and observed trends cannot be assigned to a single causal factor. New challenges in soil science call for new analytical techniques as well as innovative and broad-scale data acquisition/spatialisation methods. To this regard, two ongoing projects – "MOnitoring soil organic CArbon in croplands using Imaging Spectroscopy (MOCA)" and "Integrated system of data collection technologies for mapping soil properties (DIGISOIL)" – have been set up to develop Imaging Spectroscopy as a practical and functional tool for SOC monitoring. The MOCA project will analyse a hyperspectral image covering ca. 350 km^2 in Grand Duchy of Luxembourg. More

than 300 soil samples have been collected that will allow testing the stability of the method across 4 different geological units. Part of the DIGISOIL project will focus on a better characterization of the soil surface conditions in order to remove the influence of the disturbing factors on the spectral response.

Appendix 1

Semi-variograms of SOC concentrations (Chapter 5)



Appendix 1. Semivariogram of (a) SOC concentration in survey 1 and (b) change in SOC concentration between survey 1 and 2

Appendix 2

Studies included in the literature review (Chapter 6)

Landuse1	Landuse2	Depth1	Depth2	Age[a]	Stock1	Stock2	Response ratio[b]	Location	Type	Main texture	Reference
From	*to*		*cm*	*yr*	*t C ha^{-1}*						
Conversions of cropland to deciduous											
Cropland	Sugar Maple, white oak, tulip poplar	23	31	53	29.2	44.4	0.52	Michigan, USA	Paired site	Loamy	Morris et al., 2007
Field beans	Oak	69	69	82	90.0	139.0	0.54	Geescroft, Rothamsted, UK	Long term experiment	Silty clay loam	Poulton et al., 2003
		69	69	116	90.0	168.0	0.87				
Wheat	Mixed deciduous	69	69	82	85.0	177.0	1.08	Broadbalk, Rothamsted, UK	Long term experiment	Silty clay loam	
		69	69	116	85.0	201.0	1.36				
Alfalfa, corn rotation	Maple	41	41	22	78.9	76.5	-0.03	Ontario, USA	Paired site	Sandy loam	Paul et al., 2003
Corn, soybean rotation	Oak	100	10	48	68.1	95.9	0.41	Ohio, USA	Paired site	Fine sand	
Corn, soybean rotation	Maple	100	10	48	106.0	113.8	0.07	Ohio, USA	Paired site	Silt loam	
Cropland	Oak, Norway Spruce	25	25	31	83.9	119.2	0.42	Sellingen, Netherlands	Chronosequence	Sandy	Vesterdal et al., 2007
Cropland	Oak, Norway Spruce	25	25	29	66.6	52.7	-0.21	Vestskoven, Danemark	Chronosequence	Loam	
Arable land	Balsam poplar, aspen and willow clone	30	30	10	38.0	41.8	0.10	Upper Palatia, South Germany	Resampling	Sandy-clayey	Jug et al., 1999
Arable land	Balsam poplar, aspen and willow clone	30	30	10	42.0	41.0	-0.02	Central Germany	Resampling	Sandy loam and loamy sands	
Ragweed, though wild radish and lamb's-quarters	Whit, black and red oak	15	15	250	25.3	48.8	0.92	New Jersey Piedmont, USA	Paired site	Silty loam	Robertson and Vitousek, 1981

Soybean-corn-wheat rotation	Black cherry, black locust, ash, american basswood, eastern redcedar, hackberry, oak and black walnut	38	33	130	89.5	147.7	0.65	Nebraska, USA	Paired site	Silty clay loam	Martens et al. 2003
Conversions of grassland to forest											
Tall tussock , brown top, Yorkshire fog, browntop, some white clover and various weeds	Douglas Fir	30	30	17	174.6	158.5	-0.09	New Zealand	Paired site	n.d.	Alfredsson et al., 1998
	Pinus radiata	30	30	15	132.5	100.5	-0.24	New Zealand	Paired site	n.d.	
Snow tussock, lightly grazed	Pinus radiata	10	10	10	71.3	69.1	-0.03	Otago, New Zealand	Paired site	Silt loam	Davis, 1994
Unimproved grassland	Pinus con	10	10	10	63.0	57.2	-0.09	New Zealand	Paired site	n.d.	Davis and Lang, 1991 in Davis and Condron, 2002
Unimproved grassland	Pinus Radiata	10	10	15	61.7	50.1	-0.19	New Zealand	Paired site	n.d.	
Unimproved grassland	Pinus sylvestris	10	10	23	66.8	68.7	0.03	New Zealand	Paired site	n.d.	
Unimproved grassland	Pinus radiata	10	10	30	56.1	52.5	-0.07	New Zealand	Paired site	n.d.	
Unimproved grassland	Pinus nig	10	10	31	32.3	36.7	0.14	New Zealand	Paired site	n.d.	
Unimproved grassland	Pinus nig	10	10	47	33.8	39.5	0.17	New Zealand	Paired site	n.d.	
Unimproved grassland	Pinus nig	10	10	52	32.5	39.5	0.22	New Zealand	Paired site	n.d.	
Improved grassland	Pinus Radiata	10	10	19	42.2	39.8	-0.06	New Zealand	Paired site	n.d.	Giddens et al 1997 in Davis and Condron, 2002
Improved grassland	Pinus Radiata	10	10	20	44.1	35.8	-0.19	New Zealand	Paired site	n.d.	
Improved grassland	Pinus Radiata	10	10	20	82.5	77.7	-0.06	New Zealand	Paired site	n.d.	

Improved grassland	Pinus Radiata	10	10	22	61.0	52.8	-0.13	New Zealand	Paired site	n.d.	Sparling et al., 2002 in Davis and Condron, 2002
Low fertility grasses with some white clover, lotus, and suckling clover.	Pinus Radiata	20	20	20	75.0	55.2	-0.26	Palmerston North, New Zealand	Paired site	Silt loam	Parfitt et al., 1997
Cocksfoot, Yorkshire fog, ryegrass, sweet vernal, Poa spp. and white clover	Pinus Radiata	20	20	19	101.3	71.5	-0.29		Paired site	Sandy loam	Ross et al. 1999
Ryegrass /white clover	Pinus Radiata	30	30	25	103.8	97.5	-0.06		Long term experiment	Loam Sand	Yeates et al., 2000
Ryegrass /white clover	Pinus Radiata	20	20	25	94.6	84.2	-0.11		Long term experiment	Loam Sand	Saggar et al., 2001
Pasture	Australian Pine	30	30	10	47.5	48.6	0.02	Ohio, USA	Paired site	Silty clay loam	- Ussiri et al., 2006
Unimproved grassland	Pinus ponderosa	30	30	19	124.2	136.8	0.10	New Zealand	Paired site	n.d.	Chen et al., 2000b
Mixture of cool- and warm-season	Black cherry, black locust, ash,	33	33	130	119.1	147.7	0.24	Nebraska, USA	Paired site	Silty clay loam	Martens et al. 2003
Pasture	Black Locust	30	30	10	47.5	59.4	0.25	Ohio, USA	Paired site	Silty clay loam	- Ussiri et al., 2006
Pasture	Balsam poplar, aspen and willow clone	30	30	7	51.0	52.0	0.02	Lower Saxony, Germany	Resampling	Gravelly and sa	Jug et al., 1999
Pampa	Eucalyptus camaldulensis	20	20	50	74.0	92.4	0.25	Pampa, Argentina	Paired site	n.d.	Jobbaggy and Jackson, 2003
Pampa	Eucalyptus camaldulensis	20	20	95	65.8	74.0	0.12	Pampa, Argentina			
Pampa	Eucalyptus camaldulensis	20	20	36	70.0	59.3	-0.15	Pampa, Argentina			
Pampa	Eucalyptus camaldulensis	20	20	47	65.8	85.4	0.30	Pampa, Argentina			
Pampa	Eucalyptus viminalis	20	20	11	57.1	63.7	0.12	Pampa, Argentina			
Pampa	Eucalyptus camaldulensis	20	20	44	47.8	74.0	0.55	Pampa, Argentina			
Pampa	Eucalyptus camaldulensis	20	20	89	52.5	67.9	0.29	Pampa, Argentina			

Pampa	Eucalyptus camaldulensis	20	20	41	37.8	42.9	0.13	Pampa, Argentina			
Pampa	Eucalyptus camaldulensis/viminalis	20	20	42	90.7	95.8	0.06	Pampa, Argentina			
Conversions of forest to cropland											
Mature Maritime Pine	Maize	30	27	17	209.6	89.5	2.06	Pyrenean Piedmont, France	Chronosequence	Clay-loam	Arrouays and Pelissier, 1994b
		30	25	19	209.6	66.3	1.27				
		30	23	30	209.6	59.9	1.05				
		30	28	17	209.6	96.5	2.31				
		30	25	8	209.6	100.5	2.44				
		30	24	5	209.6	112.5	2.85				
		26	28	24	154.9	87.8	-0.43				
		26	24	27	154.9	79.2	-0.49				
		26	25	3	154.9	124.5	-0.20				
		28	27	22	177.1	76.1	-0.57				
		28	24	32	177.1	49.7	-0.72				
		28	27	19	177.1	75.7	-0.57				
		28	22	31	177.1	66.5	-0.62				
		28	26	12	177.1	79.7	-0.55				
Mature trees	Corn	30	30	35	81.5	98.5	0.21	Ottawa,Ontario, Canada	Paired site	Silt	Coote and Ramsey, 1983
Mature trees	Corn	30	30	35	75.0	70.8	-0.06			Sandy-loam	in Davidson and Ackerman, 2003
Mature trees	Small grains	30	30	35	244.7	207.4	-0.15			Clay	
Forest	1 yr cereal, 4 yr hay rotation	38	33	50	176.3	118.8	-0.33	Quebec, Canada	Paired site	Clay-loam	Martel and MacKenzie, 1980
Forest	1 yr cereal, 4 yr hay rotation	30	30	50	176.3	82.8	-0.30	Quebec, Canada	Paired site	Silt	in Davidson and Ackerman, 2003
Forest	1 yr cereal, 4 yr hay rotation	30	28	50	90.2	58.2	-0.35	Quebec, Canada	Paired site	Silt	

Red Pine, white pine	Cereal, forage, bean		Equivalent mass	67	90.1	68.6	-0.24	Ontario, Canada	Paired site	Silt	Ellert and Gregorich, 1996
White Pine	Corn, forage		(350 kg m^{-2})	24	136.7	109.0	-0.20	Ontario, Canada	Paired site	Sand	
Pine, black spruce	Forage, cereals			52	79.4	76.1	-0.04	Ontario, Canada	Paired site	Silty clay loam	
Jack pine	Forage, cereals, corn			144	84.8	64.7	-0.24	Ontario, Canada	Paired site	Sandy-loam	
Maple, hemlock, beech	Forage, cereals, corn			90	105.3	62.9	-0.40	Ontario, Canada	Paired site	Silty clay loam	
Sugar maple	Forage, corn, cereals			84	108.1	71.1	-0.34	Ontario, Canada	Paired site	Silt loam	
Cherry orchard	Peaches, annual ryegrass			144	56.5	40.1	-0.29	Ontario, Canada	Paired site	Sandy-loam	
Maple, beech, white oak	Corn, forage, soybeans			104	127.3	76.1	-0.40	Ontario, Canada	Paired site	Silty clay loam	
Maple	Maize	30	30	25	122.3	79.7	-0.35	Ontario, Canada	Paired site	Clay-loam	Gregorich et al., 1995

[a] Time since land use change

[b] Relative change in SOC stocks (STOCK2/STOCK1)

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