Quantification of topsoil organic carbon in Europe

A statistical approach combining harmonised soil and land cover point data with spatial layers

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LIST OF ABBREVIATIONS

AIC: Akaike Information Criterion

AAT: Annual Accumulated Temperature

BD: Bulk Density

CO_2: Carbon dioxide

CORINE: CORdinate INformation on the Environment

DEM: Digital Elevation Model

DG-ENV: European Commission's Directorate General for the Environment

DG-JRC: European Commission's Directorate General Joint Research Centre

DSM: Digital Soil Mapping

ENVASSO: Environmental Assessment of Soil for Monitoring

ESDB: European Soil DataBase

ESGDB: European Soil Geographical DataBase

EU: European Union

EVI: Enhanced Vegetation Index

FAO: Food and Agriculture Organisation (of the United Nations)

GAM: Generalised Additive Model

GLM: Generalised Linear Model

LUCAS: Land Use/Cover Area frame Statistical survey

MARS: Monitoring Agriculture with Remote Sensing

MODIS: Moderate Resolution Imaging Spectroradiometer

NASA: National Aeronautics and Space Administration

NDVI: Normalised Difference Vegetation index

NPP: Net Primary Productivity

NRMSE: Normalised Root Mean Squared Error

NUTS: Nomenclature of the Territorial Units for Statistics

OC: Organic Carbon

OCTOP: map of TOPsoil Organic Carbon in Europe (Jones *et al.,* 2005)

OM: Organic Matter

PESERA: Pan European Soil Erosion Risk Assessment

PTR: Pedo-Transfer Rule

RK: Regression Kriging

RMSE: Root Mean Squared Error

SMU: Soil Mapping Unit

SRTM: Shuttle Radar Topography Mission

STU: Soil Typological Unit

UNESCO: United Nations Educational, Scientific and Cultural Organisation

UNFCCC: United Nations Framework Convention on Climate Change

WRB: World Reference Base

INTRODUCTION

GENERAL INTRODUCTION

Soil is an exhaustible natural resource and it is non-renewable on a human time scale. Soil is a complex porous environment, consisting of mineral and organic particles, interspersed with water and gases. It is home to a myriad of living organisms, with size ranging from the micro- to the macro scale; it provides the basis for food, fibre and biomass production; it stores and filters water and regulates the release of various gases in the atmosphere. As such, soil is recognised as a major contributor to sustain life on earth.

Historically, soil scientists focussed on understanding the processes responsible for soil formation and on controlling the factors ensuring productive agricultural systems (Montanarella *et al.*, 2004). In the late 1980's, on-going degradation of soils was widely observed by experts in Europe and the prevention of irreversible consequences of these processes on the environment and living organisms became a priority.

Intensive agricultural practices such as the use of heavy machinery; water management systems (drainage, irrigation); the use of chemical fertilisers and pesticides; the shortening or ceasation of rotation cycles eventually lead to the obvious degradation of soils (Oldeman *et al.*, 1990). These degradation processes translate into soil compaction; soil erosion; salinisation; removal of soil nutrients; soil contamination and decline in soil biodiversity which in turn jeopardise soil's ability to carry out essential functions (Lal, 2010). Man-made activities such as soil sealing (Huber *et al.*, 2008) or land use change for agriculture or urban development purposes also greatly affect soil conditions.

In particular, there is a growing interest to address the decline in soil organic matter as the latter directly affects soil fertility and soil resilience to further degradation. Furthermore, the potential of soils to sequester organic carbon (which is the principal component of soil organic matter) or to release it as atmospheric carbon dioxide is of major importance to address the global issue of climate change. Also, organic carbon is recognised as an essential property for soils to function properly and to deliver ecosystem services (Banwart *et al.*, 2014). Through these effects, soil organic carbon has been defined as an important contributor to soil quality (Doran & Parkin, 1994), as an indicator of global soil conditions (Koch *et al.*, 2013) and of environmental quality (Ogle & Paustian, 2005). In this context, soil organic carbon has gained the attention of policy-makers and has triggered a growing interest in the science community, over the last two decades.

PROBLEM STATEMENT

As soil carbon receives a global recognition of its major role in ensuring key ecosystem services and in mitigating climate change, the need for up-to-date data is expanding from field to global scale (McBratney *et al.*, 2003; Sanchez *et al.*, 2009).

A significant challenge in the assessment of the status of soil organic carbon (OC) is its high spatial and temporal variability. Moreover, the lack of standard protocols for soil sampling and for the analysis of OC in soils results in heterogeneous datasets that prove difficult to be combined for large-scale assessments. The design of monitoring networks that are able to detect changes in OC levels in soils, taking into account the uncertainties caused by spatial and temporal heterogeneity, sampling methods and analytical errors is therefore of critical importance (Saby *et al.*, 2008).

To date, and because soil is recognised to be the largest terrestrial pool of carbon (Batjes, 1996), climate change negotiations are the main driver of soil OC research (McBratney *et al.*, 2014). As a result, estimates of the size of soil OC pools have been produced all over the world, at various spatial scales. However, estimates of OC pools are crucially affected by the spatial variability in OC content as well as by the large uncertainties resulting from inaccurate data on soil depth, rock fragment content and bulk density (Minasny *et al.*, 2013). Estimates of those uncertainties are rarely calculated, which greatly jeopardises the reliability of the provided figures for decision making-processes. OC stock predictions with associated uncertainties are rare, especially at large scale. An example for Australia is given by Viscara-Rossel *et al.* (2014) that recently estimated the current stock of OC in the upper 30 cm of Australian soils, together with the uncertainty of these estimates, using data on OC content and bulk density from different sources which they harmonised. The Rapid Assessment of Soil Carbon performed in the United States (West *et al.*, 2013) is an exemplary project that provides reliable estimates of the amount and distribution of mean soil carbon stocks at large scale. A stratified random sampling was designed for the selection of 1m deep soil profiles for which measurements of OC and bulk density were made at different depths. The samples were taken and analysed according to standard methodologies and the uncertainty of the stock predictions, associated to OC variability and bulk density measurements, were calculated. Moreover, the project made sure to create a database that was easily accessible to others in order to support model simulations.

In fact, it is clear that the need for soil OC data for global environmental modelling, and in turn to support sound policy-making processes, requires the accessibility to and communication of soil data in an easily comprehendable form to a wide range of stakeholders. Whilst global environmental studies still rely on the FAO-UNESCO Soil Map of the World (1974), published at 1:5,000,000 scale, fine-resolution maps of soil properties are needed.

Conventional soil maps often lack detailed information on soil properties, crucial for the assessment of soil conditions (Sanchez *et al.*, 2009). Digital soil mapping (DSM) (Lagacherie & McBratney, 2007) proposes the use of computer and remote-sensing technologies, together with a wide range of statistical techniques, to spatially predict soil properties, also providing the uncertainties associated with those predictions. Besides the production of maps, which are powerful communication tools, applying DSM methods to geo-referenced field data results in the creation of a spatial database that can always be refined and up-dated as more data are collected. Minasny et al. (2013) reviewed the challenges of digital soil carbon mapping and showed that, notwithstanding the usual lack of geo-referenced, harmonised and comparable soil data, the difficulty to map soil OC mostly relates to its large spatial variability across landscapes. Addressing this issue requires the collection of sufficient representative soil samples and of environmental covariates which information quality and resolution will help explaining such variation. Moreover, if soil OC maps have to be used for global environmental modelling, the integration of the time dimension is essential.

OBJECTIVES OF THE THESIS

The overarching goal of this thesis is to produce the most up-to-date distribution of topsoil OC content and estimates of OC stocks for 25 Member States of the European Union. The specific objectives of this research are the following:

1. **Build a harmonised spatial database at European scale, consisting of soil data and environmental covariates relevant to the study of OC levels in soils**. With the development of technologies and the increase in demand for input data for environmental modelling, the creation of soil spatial information systems has become a necessity. During the land use/cover area frame

statistical survey (LUCAS) implemented in 2009 across Europe, approximately 20,000 topsoil samples were collected for further physico-chemical analyses and 200,000 observations of land use/cover status were recorded in the field. The creation of a spatial database, resulting from the compilation of these geo-referenced data with a set of spatially continuous environmental data layers, is essential to build quantitative relationship between soil OC data and their "environment" (McBratney *et al.*, 2003). The function established can in turn be used to predict soil OC at unsampled locations.

2. **Predict and represent the spatial distribution of topsoil OC content in Europe, together with its associated uncertainties.** In 2006, a proposed Soil Framework Directive (European Commission, 2006a) called for the delineation of the areas in Europe threatened by six main degradation processes, of which soil organic matter decline, requires the implementation of appropriate measures to reverse this negative trend. Before this could be done, baseline levels of OC in soils had to be established, and the monitoring of their changes planned. Although a map of topsoil OC content already existed in Europe (Jones *et al.*, 2005), it was based on heterogeneous soil data and suffered from the lack of geo-referenced soil OC measurements. The OC measurements carried out on the LUCAS topsoil samples comprised the first existing harmonised and geo-referenced data of such kind and therefore offered a unique opportunity to produce the baseline required by the Directive. In this thesis, we therefore produced the first pixel-based map of topsoil OC content for Europe, by applying digital soil mapping techniques. The ability to produce a map of uncertainties associated with our predictions should support a careful use and interpretation of the spatial values by the end-users, whether they be policy-makers, land owners or scientists.

3. **Propose a method for the quantification of the size of OC pools in Europe.** Current discussions and negotiations on food security, agri-environmental issues and climate change require the detection of changes in soil OC pools over time. Before these changes can be assessed, baseline values of OC stocks need to be calculated and the development of soil monitoring networks for the collection of comparable data in the future is crucial. As opposed to traditional methods that used to derive OC stocks from existing soil maps (e.g. Jones *et al.,* 2005), the method proposed in this thesis uses point – based statistics. OC measurements of the LUCAS 20,000 topsoil samples and the land cover observed on the 200,000 locations of the master grid of the LUCAS survey are used and the calculation of OC stocks, with a confidence interval accounting for part of the uncertainty, for any given spatial unit, is performed. The scheduled repetition of the LUCAS soil survey in 2015 will mark the establishment of the first soil monitoring network in Europe and the use of the method proposed here will allow to checking consistently for changes in OC stocks, using precise land cover and OC data.

OUTLINE OF THE THESIS

This introduction sets the frame of the research, identifies the challenges to be addressed and states the overarching goal and specific objectives of the thesis. The main body (chapter 1, chapter 3 – 5) consists of four research articles published or ready for submission to international peer-reviewed scientific journals. Each article is presented in a separate chapter (Figure 0-1).

Chapter 1 gives an overview of soil carbon data and maps available in Europe, from 1950 to the present. It first explains why research on soil organic carbon became of interest to scientists and policy-makers, and secondly it defines soil organic carbon and soil organic matter. Thereafter, the first map of topsoil

organic carbon is presented and the need for, and complexity of, soil monitoring networks is explained. Finally, the LUCAS survey and its soil component are presented.

Chapter 2 explains how the land use/cover observations from the LUCAS survey and the laboratory analysis of the topsoil samples taken at the same location were merged. The collection of spatially continuous data layers of environmental data and their compilation into a comprehensive geo-referenced database, together with the data resulting from the LUCAS survey, is explained.

Chapter 3 and chapter 4 relate the application of DSM techniques to the comprehensive spatial database compiled beforehand, and lead to the creation of two maps of topsoil OC content and associated uncertainties. The selection of (statistically) significant covariates for the prediction of OC content; followed by the calibration and validation of statistical models that illustrate the relationship between dependent and independent variables are also explained. An interpretation of the spatial distribution of OC content, once plotted as a map, is given in terms of the observed global trends across Europe. Prediction uncertainties were also plotted and an interpretation of their absolute value and spatial distribution is given. In these chapters, an attempt is made to address the issues of spatial correlation between regression residuals and of the bi-modality of the frequency distribution of OC in the soils of Europe.

Chapter 5 proposes a methodology to calculate OC stocks in Europe that is applicable to spatial units of any size or areas covered by a specific land cover type, and to regions or countries. The different approaches followed for the predictions of OC in mineral and organic soils are presented, and the calculation of a confidence interval of those predictions is explained. The results are then aggregated at EU, country and land cover scale, and compared with predictions made by other researchers. The chapter concludes with a reflection on the limitations to soil OC stock calculations.

The general conclusion summarises the main findings and presents them in parallel with the thesis' specific objectives. The limitations encountered during the research are discussed and recommendations for the future monitoring of topsoil organic carbon in the European Union are given.

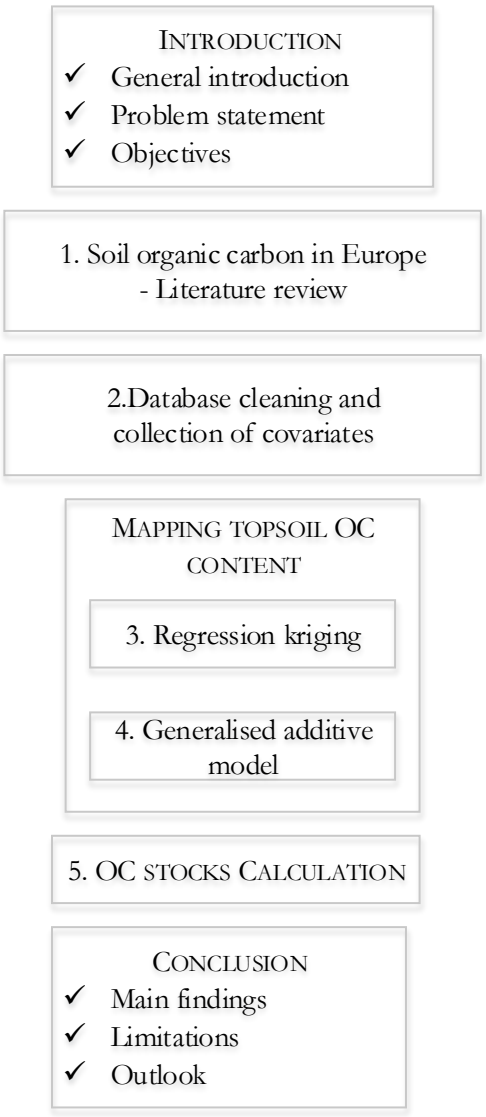

Figure 0-1 Chapters of the thesis.

CHAPTER 1. SOIL ORGANIC CARBON IN EUROPE

In the early 20th century the idea, pioneered in Russia, to make maps depicting different types of soil spread to other European countries. However, most soil science research at this time focused on understanding the processes of soil formation and how basic soil properties developed. After the First World War, in addition to gaining more knowledge about soil processes, the importance of harmonising spatial information on soils across regions and continents was recognised.

1.1. SOIL MAP OF EUROPE

Work began to construct a unified soil map of Europe in the late 1920s (Stremme, 1929) following earlier discussions between soil scientists in Europe under the chairmanship of Professor Murgoci (1924). Those discussions started in response to concerns about food security and the need to improve the efficiency of agricultural systems if the expanding populations in Europe were to be fed after the First World War. After the Second World War, attention re-focused on building a Soil Map of Europe, in response to the need to rebuild agricultural production systems that had become dysfunctional if not destroyed during the conflict. Following the compilation of the FAO-UNESCO Soil Map of the World at 1:5,000,000 scale (FAO-UNESCO, 1974), the production of a Soil Map of Europe at 1:1,000,000 scale (Commission of the European

This chapter is based on: de Brogniez D., Jones R.J.A., van Wesemael B. (in preparation). Soil organic carbon in Europe. To be submitted.

Communities, 1995) was seen as a logical next step. The compilation of the first Soil Map of Europe at 1:1,000,000 scale, by contributors from all the countries

of Europe, marked a key stage in the development process. The soil information was harmonised according to a comprehensive legend (FAO-UNESCO, 1974) that defined 106 Soil Mapping Units (SMU) for the continent (King *et al.*, 1994). These SMUs consisted in the grouping of several Soil Typological Units (STU), each of which represented soil types and associated properties. The proportion of each STU in the SMU is known, yet the exact location of STUs within SMUs is not defined.

In the mid- to late 1980s, due to the unprecedented intensification of agricultural systems after the Second World War, a number of European countries became self-sufficient in staple agricultural products and large food surpluses, of cereals for example, were produced (Montanarella *et al.*, 2004). Soils in Europe were coming under increasing environmental pressure with the added concern that degradation processes, exacerbated by human activity (e.g. physical damage and pollution), were likely to reduce the capacity of soils to perform their key functions in the future. Furthermore, there was concern at the European Commission in Brussels that some aspects of the Common Agricultural Policy were contributing disproportionally to soil degradation in some Member States.

Policy makers recognised that protection of soil against degradation processes would require an enhanced digital information base for the European Union (EU) and consequently digitisation of the Soil Map of Europe at 1:1,000,000 scale was commissioned in 1986 (Platou *et al.*, 1989) by the European Commission's Directorate-General for the Environment (DG-ENV). Independently in 1988, the Coordination of Information on the Environment (CORINE) Programme produced a database of land cover of the continent at 100 m resolution (Corine Land Cover, 1992). The digitised Soil Map of Europe became the main component of the European Soil Database (King *et al.*, 1995)

with accompanying data sets of soil property attributes (Madsen & Jones, 1995) and a knowledge database that translated basic soil data into data needed for environmental purposes at SMU level (Van Ranst *et al.*, 1995). The work throughout this phase of development was supported by the MARS - Monitoring Agriculture by Remote Sensing - Project of the European Commission's Directorate-General Joint Research Centre (DG-JRC) (Vossen & Meyer-Roux, 1995).

1.2. THE DECLINE IN SOIL ORGANIC MATTER: A THREAT TO EUROPEAN SOILS

The period 1950-1990 was the most productive for soil science in Europe because the understanding of soil processes and the knowledge of the status of soils were seen as essential for having productive agricultural systems. In the late 1990s, attention began to focus on the degradation of soil conditions, which in most cases was the result of expansion of arable cultivation and the intensification of most agricultural systems during the second half of 20th century (Sleutel *et al.*, 2003; Bellamy *et al.*, 2005; Jones *et al.*, 2005). This led to the development in Europe of a Thematic Strategy for the protection and sustainable use of soil in the future (European Commission, 2002, 2006a).

In particular, the decline in soil organic matter (OM) observed in the soils of Europe was identified as a key threat. As a result, the maintenance of adequate OM levels in agricultural soils was recognised as one of the cross-compliance criteria for Good Agricultural and Environmental Conditions within the revised Common Agricultural Policy (CAP). These criteria are still mandatory for farms receiving direct payments (subsidies) from the CAP. The main driver of the political attention to soil OM was nevertheless related to the recognition of soil as a major carbon pool and therefore of great relevance to climate change discussions and negotiations.

1.3. SOIL ORGANIC MATTER AND SOIL ORGANIC CARBON

From the early stages of the development of soil science, soil OM has been regarded as a fundamental property underpinning structure and fertility. Organic carbon is the main component of the soil OM.

Soil **organic matter** consists of plant and animal residues, in various stages of decomposition. The mineralisation of OM in soils is carried out by microorganisms, under the influence of climatic and ambient soil conditions (Jones *et al.*, 2004). Soil OM represents the total sum of all substances in soil containing organic carbon. The organic matter content in soils ranges from < 10 g C kg^{-1} in dry arid areas to almost 1000 g C kg^{-1} in peat soils (Schnitzer, 1991). Most mineral topsoils (0-15 cm) nevertheless have organic matter contents in the range 10-100 g C kg^{-1}. Soil OM is a complex system that can be subdivided into humic and non-humic substances (Schnitzer & Khan, 1972). The bulk of OM consists of humic substances that are amorphous, dark-coloured partly aromatic, mainly hydrophilic, chemically complex and resistant to chemical and biological degradation.

The OM in soils contributes significantly to, many soil functions that are vital for ecosystems and life on Earth. Soil OM influences plant growth through its effect on the physical, chemical and biological properties of soils (Stevenson, 1982). It promotes good soil structure, improving tilth, aeration and movement and retention of moisture (Hallett *et al.*, 2012; Robinson *et al.*, 2012). The chemical function of soil OM takes place through its ability to interact with metals, metal oxides and hydroxides, and clay minerals that form metal-organic complexes, which act as ion exchangers and a storehouse of nitrogen, phosphorus and sulphur. It's the biological function of soil OM that provides carbon as an energy source for microorganisms, thus enhancing root initiation, nutrient uptake, chlorophyll synthesis, seed germination and yield (Prakash & MacGregor, 1988).

Soil carbon was described by Yang (2014) as the motherhood of life, as it provides energy, food, fibre and shelter. **Soil organic carbon,** which is generally agreed to make up 58% of the soil OM by weight, is traditionally used as a proxy for soil OM because it is more easily analysed in the laboratory and then converted to OM content. Throughout this work, the following terms will be used to define OC levels in soil:

OC content in soils: given in grams of OC per kilograms of soil (g C kg^{-1}).

OC stock is the amount of OC in a total volume of soil. It can either be given in unit of mass (e.g. Megagrams - Mg) for a specified area, or in unit of mass per unit of surface area (e.g. Mg per hectare) for a specified depth of soil. For instance, OC stock in Belgium, in the upper 20 cm of soil, can be expressed as approximately equal to 0.26 Pg (Petagram), considering a surface area of ca. 31,000 km^2, or as equal to 84 Mg ha^{-1}. Calculation of OC stock requires data on OC content, bulk density and rock fragment (stone) content for a specified depth of soil.

Hence, the equation to calculate OC stock is:

Equation 1-1

$$Organic\ carbon\ stock = SOC \cdot BD \cdot d \cdot (1 - R_m) \cdot 10^{-3}$$

where OC stock is in Tg km^{-2}, SOC is the OC content (g kg^{-1}), BD is the bulk density of the soil sample (g cm^{-3}), d is the sample depth (m), R_m is the rock fragment content by mass (-).

Oades (1988) found that the decomposition of soil OM depends on the nature and quantity of the added fresh organic materials, as well as ambient temperature and moisture conditions. The paradigm that OC turn-over in soils is governed mostly by the chemical composition of organic compounds was dominating among the soil scientific community in the last decades (Schmidt *et*

al., 2011). In recent years however, efforts have focused on identifying soil OM fractions that are directly dependent on specific stabilisation mechanisms. Of these, selective preservation, spatial inaccessibility and interaction with surfaces and minerals (Christensen, 2001; Six *et al.*, 2002; Lützow *et al.*, 2006) are commonly recognised as important processes for regulating OC turn-over. Lavelle *et al.* (1993) presented a general model in which the dynamics of soil OM decomposition are determined by a set of hierarchically organised factors which regulate microbial activity at decreasing scales of time and space in the following order: climate (particularly temperature and moisture regimes), clay mineralogy and soil nutrient status, chemical constraints (quality of decomposing resources), and at the lower scale, biological systems of regulation based on mutualistic interactions between microorganisms and macroorganisms.

Climatic conditions indisputably exert a dominant influence on the C cycle in soils because temperature, rainfall and the resulting soil moisture content affect microbial community's dynamics. Davidson and Janssens (2006) showed that the temperature sensitivity of soil carbon decomposition by microorganisms can be altered by several environmental constraints; namely the physical protection of organic substrates by soil aggregates; their chemical protection created by strong bounds with mineral surfaces; drought which inhibits the diffusion of enzymes responsible for decomposition and which reduces the availability of C-substrates in solution; flooding which results in anaerobic conditions; and freezing which slows down decomposition processes due to the absence of solutions in soils. In particular, Davidson and Janssens (2006) stressed that understanding the effects of climate on peatlands, wetlands and permafrost C decomposition is of critical importance as they store enormous amounts of C globally.

Land use and land cover have also been demonstrated to have a major influence on the levels of organic materials in soils (IPCC, 2000). More

importantly, the **management practices** associated with certain land uses greatly affect the condition of soils. For instance, ploughing or drainage of agricultural soils triggers OC mineralisation by bringing oxygen into the system. Also, ploughing repeatedly disturbs the structure of soil aggregates and by this fact exposes more soil components to the microbial communities. Changes in land use and land cover, mostly due to the need to increase the size of agricultural land globally or for urban development, greatly affect soil OM (Guo & Gifford, 2002), generally by either removing fresh organic materials (ie. removal of plant residues by crop harvesting) and/or by causing the rapid oxidation of stored OM present in the soil. Although the intensive use and management of agricultural lands lead to the loss of C in soils, mitigation options exist to reverse the current trend. Lal (2004) and Smith *et al.* (2008) showed that better management of agricultural ecosystems, through the adoption of mechanisms such as the set-aside, no-till agriculture, improved grazing, cover crop, restoration of former wetlands now used for agriculture can both reduce the loss of C in soils and improve its sequestration.

1.4. First map of topsoil organic carbon content for Europe

After the decline in soil OM was recognised as a threat to European agricultural production systems and to the environment (European Commission, 2002), there was a growing interest in quantifying and studying the geographical distribution of OC contents in soils (Jones *et al.*, 2005).

1.4.1. Pedo-transfer rule

The digital Soil Map of Europe (King *et al.*, 1995), which constitutes an assemblage of polygons representing the main soil types (Soil Typological Units – STU) of Europe, was accompanied by a Soil Profile Analytical Database that attempted to provide representative soil profile data for the dominant SMUs on

the Soil Map of Europe (Madsen & Jones, 1995). Van Ranst *et al.* (1995) had developed the first procedures to derive soil properties at SMU level from a combination of pedo-transfer rules (PTR), using expert knowledge, a method based on the concept of pedo-transfer functions (Bouma & Van Lanen, 1987).

A PTR was defined to infer four classes of topsoil (25 cm) OC content, using soil type, topsoil textural class, land use class and accumulated annual mean temperature as input data (Jones & Hollis, 1996). In a further stage, OC levels could be converted to organic matter content, considering the commonly agreed 58% (in weight) of C in OM.

1.4.2. OCTOP map

The first map of topsoil organic carbon in Europe was produced by Van Ranst *et al.* (1995) and presented to the European Commission by Rusco *et al.* (2001). The pedo-transfer approach was significantly modified by Jones *et al.* (2005) who applied a revised PTR directly on spatial data layers, instead of polygons, in order to create the first pan-European map of topsoil organic carbon content. The spatial data layers comprised the soil type and dominant surface textural class, extracted from the European soil database, together with CORINE land cover class, as input to the revised PTR. The influence of temperature on OC content was removed as a fixed input parameter and replaced by a mathematical function (Jones *et al.*, 2005). The input data were applied on a 1 km x 1 km raster data set, output being the continuous prediction of topsoil OC content for Europe (so-called OCTOP).

The predicted (modelled) organic carbon contents from OCTOP compared closely with measured OC levels from ground surveys in Italy (Rusco, per comm) and in the United Kingdom (McGrath & Loveland, 1992). This was an important validation of the OCTOP map, but it was not possible to repeat this validation procedure for other EU Member States at that time because of data confidentiality and/or lack of ground measurements (field sampling). Moreover, Jones and co-authors (2005) stressed the lack of comprehensive geo-

referenced, harmonised (in sampling and analysis methodologies) soil OC data to test the reliability of their map. Whilst the OM status of Europe's soils was comprehensively reviewed by Robert *et al.* (2004) and by Huber *et al.* (2008), a reliable harmonised spatial data set of soil organic matter contents, based on sampling across the whole continent, has remained elusive.

1.5. SOIL ORGANIC CARBON VARIABILITY IN SPACE AND TIME – A NEED FOR MONITORING NETWORKS

Whilst the need for soil carbon data in the second-half of the 20th century was inextricably linked to agricultural productivity, the new driving forces for soil C research are related to climate change and to the known benefits of OC for the functioning of soils and the environment (McBratney *et al.*, 2014). In particular, as soil is recognised to be the largest terrestrial carbon pool, the quantification of its potential to sequester C has gained the attention of policy-makers globally.

1.5.1. Quantification of OC pools

Extensive literature has been addressing the problem of the quantification of OC pools and their variability over space and time (Smith, 2004; Morvan *et al.*, 2008; Saby *et al.*, 2008; Schrumpf *et al.*, 2011; Jandl *et al.*, 2014). The main challenges highlighted by these studies to detect changes in OC pools in a cost effective and reliable manner are listed below:

- The intrinsic high spatial variability of carbon (at multiple scales) requires high density sampling schemes, coupled with the necessity to take composite samples in order to reduce the standard error of the estimates;
- Verification of the reported estimates requires periodic re-sampling, preferably at the same location, which is costly and logistically demanding, and therefore rarely implemented;

- Bulk density and rock fragment content, which are in addition to OC content required for the quantification of OC stocks (Equation 1-1), are very rarely measured *in-situ*. Values derived from pedo-transfer rules based on texture, structure and organic matter content or set as default are generally used to fill this data gap;
- Uncertainties of the OC stock estimates are difficult to quantify as they cumulate the errors associated with the measurement or estimation of OC content, bulk density and rock fragment content (Equation 1-1);
- If soil OC stock changes are studied following a change in land use or land cover, an additional source of uncertainty is related to the reliability of the geographical extent of the land under scrutiny, usually estimated by ortho-photo interpretation or by remote sensing;
- Long-term experiments have demonstrated that OC levels in soils change relatively slowly over short periods of time under changing management practices and a 10-year interval was seen as meaningful for the cycle of soil OC inventories (Arrouays *et al.*, 2008b). It is worth noting that the relatively long period of time needed to detect these changes has been one of the main reasons for excluding OC from the mandatory accounting for carbon within binding agreements, e.g. UNFCCC and the related Kyoto Protocol (Smith, 2004).

Another limitation to the detection of changes in OC pools is related to the sampling design of the soil surveys and, to a broader extent, to the implementation of a monitoring scheme. Specific statistical methodologies exist and should be employed to design surveys aiming at the estimation of a parameter, such as the mean OC stock of a country, over time (de Gruijter *et al.*, 2006). However, in practice, the incomplete knowledge of these statistical tools by the scientists involved in the preparation of the soil survey result in the design of sampling schemes that lack coherence. Also, inconsistencies in the reconduction of the sampling, often result in the compilation of heterogeneous datasets whose recorded OC values are not comparable, in a statistically-sound

manner. Moreover, the lack of documentation on the sampling strategies followed in previous soil surveys generally leads to the limited value of legacy data for calculating OC stocks.

In addition to the many challenges listed above, the depth of reporting is an important question to address. Jandl *et al.* (2014) stated that the purpose of the monitoring programme should guide decisions as to whether to sample (and report) at shallow (typically 20 to 30 cm) or to greater depth. The authors suggested that if a baseline estimate of the total soil OC pool is to be produced, both the topsoil and the subsoil should be sampled. On the contrary, if the monitoring of OC pool dynamics is targeted, restricting the survey to the upper part of the soil might be sufficient. In fact, topsoil usually contains the majority of the active microbial community, which is responsible for the mineralisation of C, whereas the deeper horizons are rather inert and therefore have a slower turn-over. However, the applicability of these last rules depends on the local conditions, soil types, vegetation (root system), etc.

It is clear that even in cases where good data are available, the uncertainties of the OC stock estimates are likely to be large, and difficult to quantify. Whilst OC content data are usually sufficient to assess the quality of soil and its ability to fulfill its several functions, the reporting on OC pools dynamics for the sake of climate change negotiations requires the calculation of OC stocks. Efforts should therefore be focussing on the improvement of OC content or stocks estimates, depending on the purpose of the studies of interest.

1.5.2. Soil monitoring networks in Europe

To answer the increasing demand for data on global soil resources in relation to climate change or to ecosystem services, the establishment of effective soil monitoring networks for reporting of soil conditions, particularly of soil OC pools over time, has become a priority. This can only be achieved through an effective system implemented at national and EU level. In 2008, the Environmental Assessment of Soil for Monitoring project (ENVASSO), which

reviewed existing soil monitoring networks across Europe, showed that although topsoil OC content was one of the most widely measured indicators of soil threats, the data were highly dispersed and not harmonised (Arrouays *et al.*, 2008a; Kibblewhite *et al.*, 2008; Saby *et al.*, 2008). Differences in sampling design (random vs. stratified, sampling density), soil surveying (sampling depth, composite vs. non-composite sample), and laboratory analytical methods for OC measurements, together with discrepancies in dates of the surveys, were highlighted as impediments to combining the national data sets that currently existed. In addition, bulk density was measured only in half of the EU Member States and there was no mention of rock fragment content in the ENVASSO report (Arrouays *et al.*, 2008a). Furthermore, Jones *et al.* (2005) noted that sample data from national field surveys in Europe often lacked precise geo-references and accessibility to data has traditionally been restricted by confidentiality issues, or the lack of standards on data dissemination.

Because regulations on climate and environmental management are agreed upon globally, the need for comparable data at national and supra-national scale is becoming of pressing concern. The adoption of, and compliance to, a standard procedure for soil sampling and laboratory analysis should be a priority as it would ensure the comparability of data across scales in the future. However, this might prove complicated in practice because most countries (in the EU) already have their soil monitoring network in place and changing procedures would impede the comparison of the new results with the previous data (Jandl *et al.*, 2014). For instance, France has launched its soil quality monitoring network in 2002. The so-called "Réseau de Mesure de la Qualité des Sols" (RMQS) is based on 16 km x 16 km regular grid, covering the entire French territory. Every ten years, the 2200 sites located at the centre of the grid cells are visited to observe land use and land cover and soil samples are taken at a depth of 30 cm. At each site, 25 core samples are taken with a hand auger, within an area of 20 m x 20 m around the central point, and bulked to form a composite sample. Moreover, a soil pit is dug and a detailed description

of soil horizons is performed, at every sampling site (Arrouays *et al.*, 2003). The composite samples are analysed in a central laboratory, for among other parameters, total C content, carbonates content, bulk density and rock fragment are measured.

At the international scale, a group of experts has been recently formed, under the 5th Pillar of action defined by the Global Soil Partnership (www.fao.org/globalsoilpartnership), to address the issue of the harmonisation of methods, measurements and indicators for the sustainable management and protection of soil resources. Moreover, the group aims to provide the mechanisms for exchanging comparable soil information, globally.

Under the framework of the Thematic Strategy for Soil Protection in Europe a consultation process (Montanarella *et al.,* 2004) found that although most EU Member States have their own soil inventory or monitoring systems, there is no common approach. Data harmonisation procedures can consist in fitting a pedo-transfer rule or a regression model to transform legacy data so that they become comparable with the new data. Louis *et al.* (2014), however, highlighted the necessity to take samples at the same site, and according to the different methodologies, in order to meaningfully calibrate a harmonisation function that would link data from different networks. Unfortunately, resampling is generally prohibitively expensive and in most cases, not implemented. The authors also warned that functions developed locally should not be extrapolated to other cases regardless of their assumptions (type of models tested, variables measured, etc.) but that local functions could provide guidance for similar work.

The ENVASSO project reinforced the conclusion of the consultation process (Montanarella *et al.*, 2004) recommending that an EU-wide soil inventory be established in order to build a harmonised digital soil information system. The systematic adoption of standard sampling methodology and analytical procedures for the measurement of selected soil properties would lead to the

establishment of a common baseline. The monitoring (through re-sampling and measurement) of these soil properties over-time would allow detecting changes. It was suggested that the land use/land cover area frame statistical survey (LUCAS), which was in a pilot phase since the early 2000s, be used as a basis to stratify the soil survey. The LUCAS survey had demonstrated that it could consistently apply a harmonised methodology across the EU, following a systematic sampling approach (regular grid). The possibility to collect soil samples as part of a fully operational monitoring system, that had already proved its reliability in providing harmonised and comparable data, was seen as an opportunity to seize. Furthermore, the land use and land cover data collected during the LUCAS survey were judged highly relevant for the monitoring of soil degradation. This led to the first harmonised topsoil sampling campaign in the EU, as an additional module to the collection of land use and land cover data during the LUCAS survey, in 2009.

1.6. THE LUCAS SURVEY

The LUCAS survey is a project that aims at collecting data on the state and the dynamics of land use and land cover across Europe. The survey provides essential information to statisticians and decision makers, as well as to the general public, on changes in land management and land coverage in Europe. Land use and land cover are very well distinguished in the LUCAS survey, with the former referring to the socio-economic use of land (e.g. agriculture, forestry, recreation) and the latter referring to the bio-physical coverage of the land (e.g. crops, grass, broad-leaved forest). After a pilot project tested the methodology in 15 countries from 2000 to 2005, the survey has been carried out on the whole EU territory every three years since 2006. The LUCAS master sample is a 2 km x 2 km grid which consists of more than 1,000,000 points. In the first stage of the survey, these points are photo-interpreted using the most recent ortho-photos, in order to classify the sample into eight strata (arable

land, permanent crops, permanent grassland, wooded areas and shrubland, bare land, low or rare vegetation, artificial land, water bodies). The second phase selects a sub-sample of the master sample, in order to visit points in the field and to classify them according to the full land cover and land use nomenclature (Eurostat, 2009a). As an approximate budget of 10 million € is allocated for the observation of these points, ca. 250,000 points are visited during the second phase. In 2009, a topsoil survey was simultaneously carried out at approximately ten percent of these sites.

1.6.1. Topsoil sampling

In 2009, 19,967 topsoil samples were taken in 25 EU countries, namely Austria, Belgium, Czech Republic, Denmark, Estonia, France, Finland, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, the United Kingdom, Malta and Cyprus (Figure 1-1). A survey was done in Romania and Bulgaria in spring and summer 2012 (data not available at the beginning of this research). Iceland, a candidate for adhesion to the EU, was surveyed in the summer 2012 and 2013. The country has since then withdrawn its candidacy.

As a 2.2 million € budget was allocated for the analysis of the LUCAS soil samples, it was calculated that a total amount of 22,000 topsoil samples across the EU could be afforded. The amount of samples to be taken in every Member State was calculated proportionally to surface areas. The topsoil sampling locations were selected from the LUCAS sites on the 2 km x 2 km original grid (= minimum sampling distance) with the aim of being representative of European land use and topographic features, excluding areas above 1,000 m elevation above sea level. The sampling locations were chosen in every country separately, following a latin hypercube-based stratified random sampling design (Minasny & McBratney, 2006) having as variables CORINE land cover 2000 (Commission of the European Communities, 1995), NASA Shuttle Radar Topography Mission (SRTM) digital elevation model (Farr *et al.*,

2007) as well as its derived slope, curvature and aspect. The latin hypercube technique each time selected a triplet of points with equal properties in the feature hyperspace (Montanarella *et al.*, 2011). This way, surveyors were given two alternative locations when a point was not accessible in the field. Using a spade, a V-shaped hole was dug to a depth of 20 cm, at the exact sampling location. A 3 cm thick layer was sliced off, of which the surveyors removed vegetation residues and litter. Some fine roots and brownish organic material could however remain. The 0-20cm depth range was chosen for the LUCAS survey as it targets the topsoil most affected, and most important, for agriculture. The first subsample taken was put in a bucket. Following the same procedure, and after having cleaned the soil in excess from the spade, four other subsamples were taken successively at a distance of 2 m from the central hole, at the cardinal points. The five subsamples were thereafter bulked to create a 500 g composite sample and put in a labelled plastic bag (Eurostat, 2009b). The samples were air-dried and then shipped to a central laboratory. The LUCAS topsoil module is scheduled to be repeated in spring-summer 2015 (Eurostat, 2014).

1.6.2. Laboratory analysis

In the laboratory, any extraneous matter (e.g. stones, fragments of glass, rests of plants) was removed from the samples prior to crushing and sieving (< 2 mm). The portion of the soil samples sieved finer than 2 mm was used for the analysis of 13 physico-chemical parameters. For each parameter, about 200 local reference soil samples were analysed in between the batches of LUCAS soil samples, in order to identify pre-treatment (drying, sieving) and measurement errors. If the values of these quality control (QC) samples were different from the average measured in the 30 previous QC samples by $\pm 2\sigma$ (two times the standard deviation), the equipment and sampling sequence were controlled and the entire analysis re run. The quality control was strengthened by repeating the full analysis of 28 randomly selected LUCAS soil samples (SGS Hungary Ltd, 2011).

The rock fragment, sometimes referred to as coarse fragment, of the soil samples was calculated as the difference between the total mass of dried soil (m_t) and the portion of soil with particle size smaller than 2 mm ($m_{<2}$), following Equation 1-2:

Equation 1-2

$$Rock\ fragment\ = \frac{m_t\ -\ m_{<2}}{m_t}$$

Organic carbon content was traditionally determined by wet oxidation in potassium dichromate, also known as the Walkley & Black method (1934). However, the technique was proved inaccurate because of an incomplete oxidation (OC is underestimated in most cases) and requires the use of a correction factor for comparative purposes. OC content values obtained by dry-combustion of the soil sample are considered as the most accurate and are therefore often used as a reference to calibrate other methods (Bisutti *et al.,* 2004; Meersmans *et al.,* 2009). In the context of the LUCAS survey, total carbon was determined by dry-combustion in a CN analyser (VarioMax, Elementar Gmbh, Hanau, Germany). The carbonates present in the sample were then determined volumetrically by addition of hydrochloric acid and measuring the volume of CO_2 emitted (Sherrod *et al.*, 2002). Soil organic carbon content was determined by subtracting the carbonate C content from the total carbon content.

The present study uses the results provided for the 25 countries surveyed in 2009 (Figure 1-1). These results showed a minimum OC content of 2.0 g kg^{-1} and a maximum of 589 g kg^{-1}, with 90% of the samples containing less than 100 g C kg^{-1}. The mean content is 50 g kg^{-1} and the median is equal to 20 g kg^{-1}. The distribution of topsoil OC content in the LUCAS samples is positively skewed, with most samples being mineral (Figure 1-2).

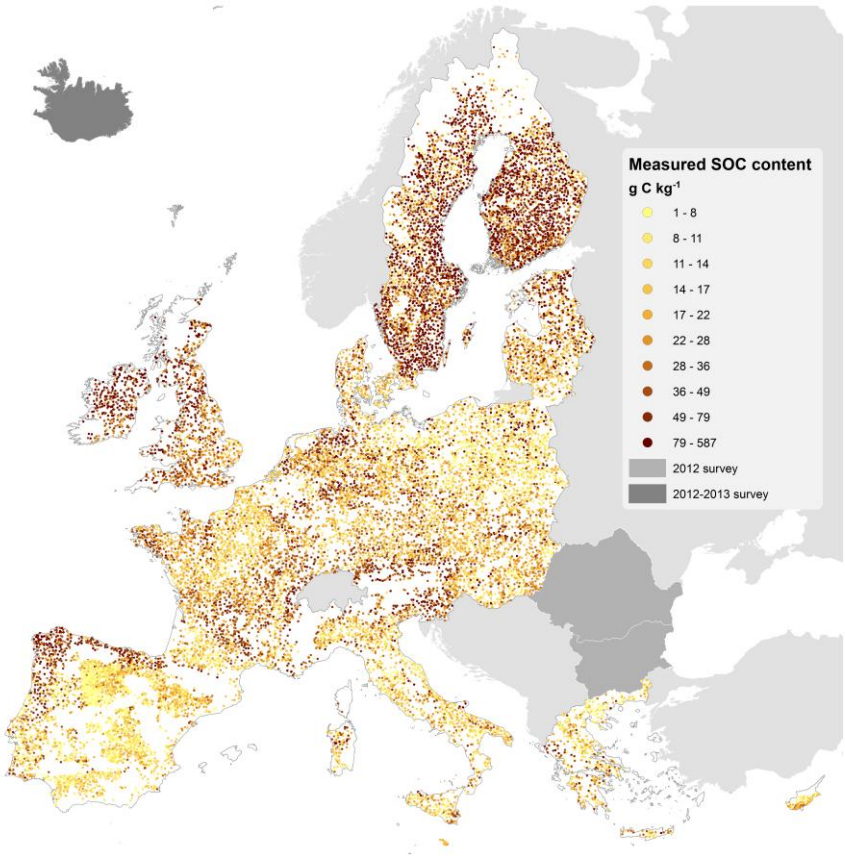

Figure 1-1 Measured organic carbon content at LUCAS topsoil survey (2009) sampling locations.

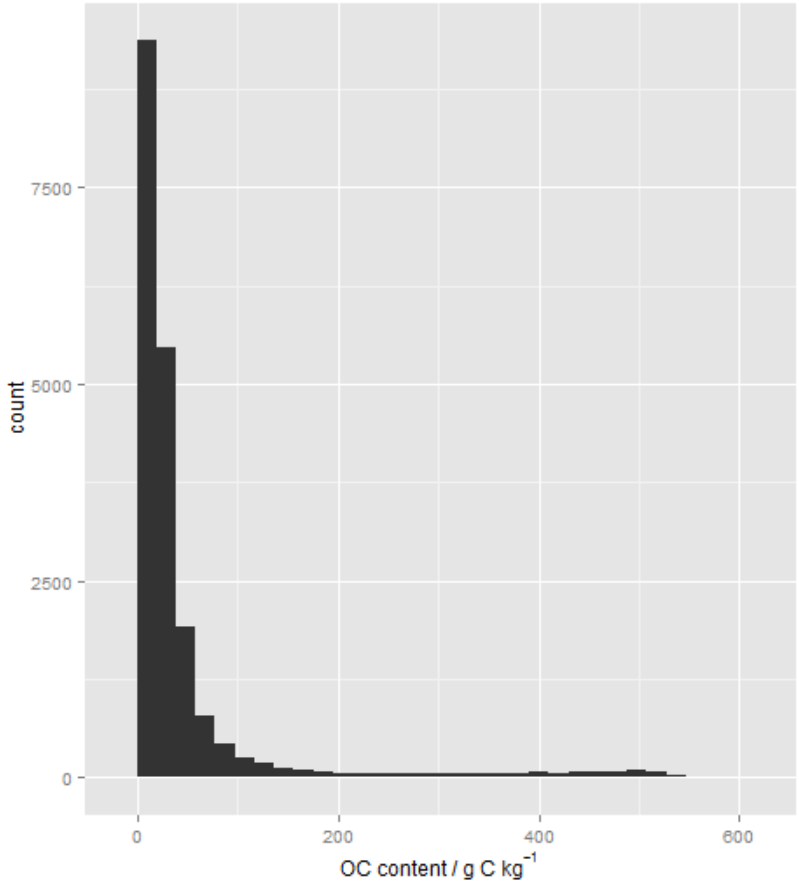

Figure 1-2 Histogram of OC content in LUCAS topsoil samples.

1.7. EVOLUTION OF SPATIAL MODELS

Soil mapping has historically been the main activity of national soil surveys (Montanarella *et al.*, 2004). In the last decades, the demand for soil maps at a range of scales from very detailed (1:5,000) to global (1:5,000,000) soared (Sanchez *et al.*, 2009) and the techniques/technologies used to produce them underwent dramatic changes.

1.7.1. Soil survey and soil mapping

The objective of a soil survey is to identify and classify soils and map their distribution. The basic unit of study is the soil profile, which is a vertical section through the soil in which horizontal layers called soil horizons are distinguished by their colour, texture, structure and organic matter content (Jones, 1983). Classification is based on combinations of horizons within the upper 1.5 m. In classifying soils, emphasis is placed on gley morphology (greyish and ferruginous colouring), texture, calcium carbonate, organic matter, parent material, argillic horizons (subsurface layers of clay accumulation) and podzolic horizons (layers of iron accumulation). The basic unit of classification in detailed surveys is the soil series, defined as a group of soils similar in character and arrangement of horizons developed under similar conditions and from similar parent materials.

Because of the inherent variability of soils, both laterally and vertically, it is rarely possible to map the distribution of soil series. The soil map shows the distribution of map units, each of which contains mainly soils of one series but has small inclusions of additional profile classes. Small-scale reconnaissance maps show only associations of soil series, which are synonymous with the Soil Typological Units (STU) on the Soil Map of Europe, together with a legend that defines dominant soils series (STU) and the proportions of subsidiary series within the Soil Mapping Units (SMU) as defined by King *et al.* (1994).

Detailed soil maps are the result of extensive field work, during which soil surveyors gained knowledge on the soils by digging profiles and describing them horizon by horizon. Soil samples from every horizon were taken and analysed in the laboratory for various properties. Soil experts tried to understand the effect of local environmental conditions on pedogenesis by developing models explaining the variability of soils across landscapes. Traditionally these models encompassed precious information that until recently remained in the minds and/or the field notebooks of the experts.

These landscape models were rarely communicated beyond the survey group to which the field experts were assigned. Consequently, the soil information available to the end-users (farmers, land managers, policy-makers) was restricted to hand-drawn maps that typically depicted qualitative data on texture, structure, drainage status and parent material. Variability was seldom documented.

In the last two to three decades, there was a strong development in the technologies and data (at different spatial and temporal scales) available to soil scientists, which came simultaneously with the demand for up-to-date soil data from various types of audiences (McBratney *et al.*, 2003). As a result, the development of computerised soil information systems with incorporated metadata became critical, which created an opportunity for 'modernisation' that soil scientists had to seize. However, most of the soil maps that had been produced around the world in the past were in paper format, and the related metadata mostly on field forms (if not lost) were difficult if not impossible for non-specialists to interpret. Consequently, the conversion of this huge wealth of data to digital format was identified as an urgent task, which still exists today.

1.7.2. The theory of digital soil mapping

As soil is now recognised as a multi-functional environment that provides a wide range of ecosystem services, it is clear that traditional soil maps which were focussed on agricultural productivity could no longer respond to the wider needs of the society. The development of information systems, which stored date of sampling, geo-referenced field and laboratory soil data, together with information extracted from remote sensing images triggered new research. Complex models illustrating the relationship between soil properties and environmental parameters were generated.

McBratney *et al.* (2003) introduced the *scorpan* model (Equation 1-3) as an empirical equation aiming at the spatial prediction of a soil property/class by the establishment of a relationship with spatially referenced soil forming

factors. The model requires every factor to be spatially referenced and located in time.

Equation 1-3

$$S = f(s, co, r, p, a, n)$$

where S is the soil attribute or class to predict; s refers to available information on other soil properties; c refers to the climatic properties of the environment; o refers to the organisms, vegetation, fauna or human activity; r is the topography or landscape attributes; p is the parent material; a is the time factor (age) and n refers to the spatial position.

The *scorpan* model, although based on the one proposed by Jenny in his book 'Factors of Soil Formation' (1941), differs in that it allows the geographical distribution of soil classes and properties and their evolution to be modelled over time. Also, the *scorpan* model includes other soil properties as possible independent variables.

In the 2000s, budgets for conventional soil surveys were being cut or reallocated to other activities because these surveys were considered slow, relatively expensive and, more importantly, increasingly hampered by a widespread scarcity of scientists with the necessary training and opportunities for field employment. Furthermore, the policy-makers responsible for funding such work had become increasingly desk-bound and isolated from the need for field experimentation. As it became clear that less data were likely to be collected in the field in the future, the limits of conventional soil information systems had been reached. Lagacherie & McBratney (2007) saw a great potential in the use of the data stored in soil information systems to produce a new generation of maps. They defined digital soil mapping (DSM) as the "creation and population of spatial soil information systems by numerical models inferring spatial and temporal variations of soil properties from soil observation and knowledge and from related environmental variables". Digital

soil maps differ from conventional maps in that they are pixel-based and that a quantitative estimate of the uncertainty of the predicted parameter can be produced (McBratney *et al.*, 2003). Therefore DSM offers a useful cost effective replacement for conventional soil survey, although validation should not be overlooked.

1.7.3. Recent OC digital mapping studies

In a recent review, Grunwald (2009) showed that DSM studies generally focus on the spatial prediction of basic soil properties. In particular, the author showed that due to the growing concern in addressing climate change and global warming issues, the majority of those studies focus on soil OC and OM. Minasny *et al.* (2013) reviewed recent studies in digital mapping of soil OC and demonstrated the challenges of such efforts. They showed that soil OC is being mapped all over the world at different spatial scales and resolutions – with a general focus on topsoil (down to 10 cm to 30 cm depth), using mostly terrain attributes and land use/cover data as covariates, sometimes combining them with legacy data. Furthermore, Minasny *et al.* (2013) observed that most studies do not present estimates of the uncertainty of their OC predictions and that those predictions are rarely validated. We refer the reader to the literature for various examples of DSM studies at subnational scale (Grimm *et al.*, 2008; Rawlins *et al.*, 2009; Mishra *et al.*, 2010; Lacoste *et al.*, 2014) ; and at national scale (Martin *et al.*, 2011; Li *et al.*, 2013; Poggio *et al.*, 2013; Viscarra Rossel *et al.*, 2014). At the global scale, the GlobalSoilMap (www.globalsoilmap.net) initiative aims at producing maps of soil properties at a spatial resolution of 100 m, by applying DSM techniques. Preliminary results of OC predictions following the project' standardised specifications were presented for the United States, Canada and South Korea by Hempel *et al.* (2014).

CHAPTER 2. LUCAS DATABASE CLEANING AND COLLECTION OF COVARIATES

In order to study and illustrate the spatial distribution of OC content with DSM techniques (Chapter 3; Chapter 4), and to quantify OC stocks in the soils of Europe (Chapter 5), topsoil OC measurements from the LUCAS survey were used as the dependent variable and several environmental covariates were tested as independent variables. The preparation of a comprehensive geo-referenced data set (projection: ETRS 89 Lambert Azimuthal Equal Area) compiling these data is explained here.

2.1. LUCAS DATABASE CLEANING

The work consisted in merging two components of the 2009-LUCAS survey; namely the land use/land cover data and the topsoil data. The land use/land cover database, owned and prepared by the European Commission's DG-ESTAT, consisted of an Excel spreadsheet with 234,710 rows and 125 columns. Each row represents one location visited for land use/cover observations and each column gave an information about that point, whether it be the observed land use or land cover class, the geographical coordinates, the date of the survey, the country etc. 20,226 out of the total 234,710 rows had a SOIL LABEL, corresponding to a topsoil sample taken at that location. The topsoil database, owned by DG-JRC, consisted of another Excel spreadsheet, presenting the results of the physico-chemical analyses performed by the laboratory. To protect the privacy of landowners, the laboratory did not have access to the geographical coordinates of the location at which the samples were taken. The country of sampling was nevertheless communicated. The

topsoil samples therefore had, as unique tracking system, a SAMPLE ID that matched the SOIL LABEL from the land use/land cover database. Through these two fields, that were the only common attribute to both tables, we could append the information of the land use/cover data to the topsoil database and more importantly match the laboratory analyses of a sample with its geographical coordinates.

Before the two databases could be merged, 335 rows from the land use/cover table showed duplicated SOIL LABELS and were deleted. As it was attempted to merge the two databases, three types of problems were identified. Firstly, when the country indicated by both databases for a same sample did not match. Secondly, when a SAMPLE ID was composed of numbers and letters. For instance, the lab communicated different results for sample "476A" and sample "476B", although the land use/land cover database only had one sample with the SOIL LABEL "476". Thirdly, when a SAMPLE ID was duplicated, that is when several lab analyses results were provided for the apparently same sample. Altogether, 376 rows presented problems and had to be deleted during that second phase of database cleaning.

As problems were identified, data deletion was always used as a last resort. In the hope to recover some data or to obtain information that would help solving the issues faced, we tried to retrieve the field forms of the problematic points. As the survey was managed by five main contractors across Europe, who themselves sub-contracted to national or regional offices, it took several months before we could get hold of the people actually in charge of data management. Field forms were usually kept unsorted in their paper form, and scanned versions were in most cases not available. Moreover, some teams had simply burnt the field forms as they were not bound by contract to archive them. Nevertheless, 723 field forms, originating from 18 countries, were retrieved. Overall, 19,858 topsoil samples with complete data were used in this study.

2.2. ENVIRONMENTAL COVARIATES

Various spatially continuous data layers were extracted from different sources and stacked in a raster data set of 500 m spatial resolution. The maps of the covariates are available in Appendix A.

2.2.1. Land cover

CORINE (CORdinate INformation on the Environment) land cover is an inventory in 44 classes coordinated by the European Environment Agency and is presented as a raster data set at 1:1,000,000 scale. The method used consists of a computer-aided photointerpretation of aerial photographs followed by manual digitisation of land cover areas. A ground truth survey was conducted for validation (Commission of the European Communities, 1995). The 2006 version of CORINE was used, except for Greece which has not started the production of up-dated products (European Environment Agency, 2012). The Greek data were therefore extracted from CORINE2000 and was simply attached to the rest as the nomenclature remained unchanged between 2000 and 2006. In the present study, we re-classified CORINE data in 16 classes (Appendix A 1; Appendix B).

2.2.2. Pre-Quaternary geology

The 1:5,000,000 International Geological Map of Europe and Adjacent Areas (Asch, 2003) proposed by the German federal institute for geosciences and natural resources (Bundesanstalt für Geowissenschaften und Rohstoffe – BGR) was used (Appendix A 2).

2.2.3. Soil reference group and qualifier

The European soil database (ESDB) at scale 1:1,000,000 derives from the harmonisation of national soil surveys from EU countries (King *et al.*, 1994). It consists of two main databases: the European soil geographical database (ESGDB) (King *et al.*, 1995) and the pedo-transfer rule database (Van Ranst *et al.*, 1995). The ESGDB consists of both a semantic and a geometrical dataset.

The former contains a list of soil typological units (STUs) that represent soil types and associated properties (e.g. water regime, texture) defined by experts for very specific areas. In order to allow the geographical representation of the data at 1:1,000,000, the STUs were grouped into soil mapping units (SMUs), to form soil associations that illustrated the functioning of pedological systems at landscape scale.

The soil type of the dominant STU in SMUs was extracted from the ESGDB and split into two covariates: the World Reference Base (IUSS Working Group WRB, 2007) Reference soil group (e.g. Podzol, Cambisol) and the qualifier (e.g. Umbric, Mollic, Eutric).

2.2.4. Terrain attributes

The digital elevation model from the United States National Aeronautics and Space Administration (NASA) – Shuttle Radar Topography Mission (SRTM) was used, as well as its derived slope (Farr *et al.*, 2007). The data were extracted at 30 arc second resolution, equivalent to 100 m at European latitudes (Appendix A 3; Appendix A 4).

2.2.5. Climatic data

Temperature

Accumulated annual temperature (AAT) was generated using the air temperature data collected on a daily basis across all of Europe and subsequently collated by the MARS (Monitoring Agriculture by Remote Sensing) Project (Vossen & Meyer-Roux, 1995). The computed monthly mean values were interpolated to a resolution of 1 km x 1 km, using an inverse-spline function and the adiabatic lapse rate (6 °C decline in temperature for every 1000 m rise in altitude) operating on a 1 km digital elevation model (Daroussin, 2003), for the Pan European Soil Erosion Risk Assessment (PESERA) project (Kirkby *et al.*, 2008) (Appendix A 5).

Rainfall

The mean annual rainfall was calculated by summing the mean monthly rainfall available on the WorldClim data set for the period 1950-2000 (Hijmans *et al.*, 2005). The data set was available at a spatial resolution of 1 km (Appendix A 6).

Potential evapotranspiration

Annual potential evapotranspiration data were also obtained from the MARS Project, at 50 km x 50 km resolution. These data were then interpolated to a resolution of 1 km x 1 km, using the same inverse-spline function (Daroussin, 2003) as that used in the PESERA erosion project (Kirkby *et al.*, 2008) for interpolating temperature, but not in combination with the adiabatic lapse rate (Appendix A 7).

Aridity index

The aridity index (UNEP, 1997), is widely used in land evaluation studies as a better index of aridity and/or humidity than annual rainfall or evapotranspiration alone. It was calculated as the ratio of mean annual rainfall and annual potential evapotranspiration. An index > 0.75 characterises the humid and wet zones, whereas an index < 0.65 identifies dry sub-humid, arid conditions (Kosmas *et al.*, 1999) (Appendix A 8).

2.2.6. Net primary productivity

Plants' gross primary productivity is the amount of energy they capture through photosynthesis and that they transform into organic compounds. Part of this chemical energy produced is respired by the plant, whilst the rest, referred to as net primary productivity (NPP), is used for growth and reproduction. In other words, NPP is the net production of organic matter by plants in an ecosystem (IPCC, 2000). The Moderate Resolution Imaging Spectroradiometer (MODIS) annual NPP products, available at 1 km spatial resolution, were averaged between 2000 and 2009 and used to produce a unique raster layer. The MODIS algorithm uses the fraction of absorbed photosynthetically active radiation and

the leaf area index both computed daily from MODIS spectral reflectances, which are used in turn to estimate the daily gross primary productivity, the daily photosynthesis and finally the annual net primary productivity (Appendix A 9).

2.2.7. Soil texture

Particle size distribution of the LUCAS topsoil samples was determined by wet sieving and sedimentation (< 2 mm), according to ISO 11277:1998 standards. Soil texture was extrapolated to the full extent of Europe by mean of Multivariate Adaptive Regression Splines (

Appendix A 10; Appendix A 11). This technique is an adaptive procedure for regression using basis expansion through piecewise linear functions (Hastie *et al.*, 2009). The approach was to model soil texture as a dependent variable, whereas the seasonal variation of vegetation cover was taken as an independent descriptor.

Besides the climatic effect that substantially controls vegetation dynamics, plant growth and senescence cycle are mostly influenced by the soil available water content, which in turn is controlled by soil texture and soil organic matter content. The regression model was therefore fitted using climatic data from the WorldClim global climate database, SRTM-derived geomorphometric variables (elevation and slope) and vegetation indices. Soil vegetation dynamics over several years (2000-2008) was derived from the MODIS 16-days vegetation indices (NDVI and EVI) and modelled using strictly concave splines to generate a prototype yearly cycle. The model was tested by cross-validation, performed on 5000 random samples and by k-fold cross-validation (k=5, 500 repeated random split). The model fitting resulted in the following performance metrics: $R^2_{cv\text{-}clay} = 0.50$, $R^2_{cv\text{-}sand} = 0.49$, $R^2_{kcv\text{-}clay} = 0.65$, $R^2_{kcv\text{-}sand} = 0.60$. The root mean squared error (RMSE) of the clay and sand content predictions were also calculated in cross-validation, and were $CV\text{-}RMSE_{clay} = 7.70$ and $CV\text{-}RMSE_{sand} = 17.30$. The work described in this section was performed by C.

Ballabio (personal communication) and is undergoing a peer-review process for publication.

2.2.8. Spatial resolution of the covariates

A spatial resolution of 500 m was chosen as a compromise between the different original resolutions of the covariates. Continuous variables were rescaled by bi-linear interpolation, which determined the output value of a cell based on a weighted distance average of the four nearest input cell centres. Land cover (discrete variable) was re-scaled by following the majority rule, that is by assigning the most popular cell value within the filter window to the re-scaled, output cell. Slope was derived from the DEM at the original resolution (about 100 m) and then re-scaled to 500 m, by doing this, we avoided the generation of artefacts by downscaling. Climatic data and NPP had a resolution of 1 km and were thus downscaled. Bilinear re-sampling was considered feasible because the climatic gradients are necessarily smooth as these maps capture the effect of meteorological processes at meso (2 – 2000 km) and synoptic (> 2000 km) scales. This choice was also supported by the fact that the variograms of climatic variables show gentle increment and ranges around 700 km.

CHAPTER 3. MAPPING TOPSOIL ORGANIC CARBON CONTENT WITH REGRESSION KRIGING

3.1. ABSTRACT

Within the framework of the European Land Use/Cover Area frame statistical Survey (LUCAS), a soil sampling campaign was implemented in 25 countries in the year 2009. Altogether, about 22,000 composite topsoil samples were collected following a standardised sampling methodology and analysed in one laboratory. In this study, we present the first map of topsoil organic carbon (OC) content estimates for part of the European Union based on that comprehensive sampling programme. A digital soil mapping (DSM) by regression kriging (RK) approach was followed, and the covariates selected by the model were: land cover, elevation and slope, accumulated annual temperature and the rainfall over potential evapotranspiration ratio, lithology, net primary productivity, and sand content. The results show high OC contents in northern latitudes and low contents in southern European countries which corroborates current expert knowledge. The overall model-fitting performance (R^2) is 0.52 and the root mean squared error of the RK predictions equals 77 g C kg^{-1}. Kriging of the regression residuals create hot-spots of OC content predictions on the map which are not believed to be realistic. It was concluded that different DSM techniques should be tested on the OC measurements data from the LUCAS database to try and improve the predictions and that validation against national data sets should be performed.

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3.2. INTRODUCTION

Soil organic carbon pools have received increasing attention from policy-makers at national and sub-national levels because of their relevance to agriculture and food security, climate change, air and water pollution and biodiversity. In its proposal for a Soil Framework Directive (European Commission, 2006a), the European Commission called for the delineation of the areas in Europe threatened by soil organic matter decline and for the establishment of appropriate measures to reverse this negative trend. A first step to achieve these goals is to establish a baseline OC level on which management decisions can be taken. When they produced the OCTOP map, Jones and co-authors (2005) considered that the amount of data was insufficient to generate a spatial distribution at an acceptable scale and therefore excluded to apply a point-based extrapolation procedure. Although the map was recognised to provide realistic OC content estimates, it does not provide the baseline requested by the Soil Framework Directive since covariates from various periods were used. The application of the Digital Soil Mapping techniques to geo-referenced soil data and the large amount of remotely sensed data available today has allowed soil scientists to provide the broader scientific community with spatially continuous quantitative estimates of OC content, and their associated uncertainty (Lagacherie & McBratney, 2007). The topsoil component of the LUCAS survey (Montanarella *et al.*, 2011) offers the opportunity to replace the OCTOP data set (Jones *et al.,* 2005), providing a spatial database for environmental and climatic modelling with a baseline for monitoring OC content in Europe's soils. The objective of this chapter is to produce the first map of OC content in Europe based on an annual comprehensive database of topsoil samples, by applying regression kriging on the LUCAS topsoil samples OC data.

3.3. MATERIALS AND METHODS

3.3.1. Soil Data

The measured OC content of the LUCAS topsoil samples was used.

3.3.2. Environmental Covariates

In order to predict the OC content, a database of environmental covariates with full spatial coverage was compiled, including CORINE land cover; SRTM-derived elevation and slope ; accumulated annual net primary productivity (NPP); main lithological units of the pre-Quaternary geology; accumulated annual temperature; annual rainfall over potential evapotranspiration ratio (P/P0); sand and clay content and latitude. We refer the reader to Chapter 2 for more information on the covariates.

3.3.3. Spatial Prediction

The spatial distribution of topsoil OC content was mapped by using regression kriging (RK) (Matheron, 1969), a technique that combines the result of a regression between a dependent variable (OC content in this case) and selected covariates, with the kriged residuals of this regression.

A multiple linear regression was fitted between the log transformed OC measurements and the independent variables by the ordinary least squares method. A forward/backward-stepwise regression was carried out to derive the best subset of predictors, using the Akaike information criterion (Akaike, 1974) and the importance of the selected covariates was evaluated by calculating the t-statistics from tests with the null hypotheses that each regression coefficient equals zero. The performance of the prediction model was assessed by leave-one-out cross- validation (Hastie *et al.*, 2009).

3.4. Results and Discussion

3.4.1. Environmental Covariates Selection and Linear Regression

High collinearity was found between sand and clay (−0.70), latitude and temperature (−0.89), latitude and clay (−0.70) (results not shown). Clay and latitude were therefore excluded from the regression analysis. Their influence on OC content will however be discussed (with sand and temperature respectively) since the dismissal of one between two correlated covariates is random. The stepwise regression kept the remaining independent variables. The screening of variable importance by t-test gave in descending order of relevance: temperature, elevation, inland wetlands and sand content as the most significant independent variables (Table 3-1). Although the regression is empirical and the data were collected all over Europe, most of the observed trends can be explained by biophysical processes. Temperature (|t-value| = 30.2) is one of the main drivers of biochemical reactions and therefore has a major importance in the dynamics of soil carbon decomposition and respiration (Davidson & Janssens, 2006). Latitude illustrates the climatic variations across Europe and highlights the influence that both temperature and water regimes have on OC dynamics (Post *et al.*, 1982; Raich & Schlesinger, 1992). OC content is generally expected to vary with elevation (|t-value| = 17.4), as a response to changes in the abiotic (temperature) and biotic (quality and quantity of organic matter inputs) environment (Garten & Hanson, 2006). The land cover classification ($|\text{t-value}|_{\text{inland wetlands}}$ = 16.4) includes peat bogs (organic soils) whose high water content decreases organic matter decay. As for the sand content effect on OC levels (|t-value| = 14.3), it can be explained by the higher mineralisation rate in well-aerated sandy soils. In addition, OC is associated with soil mineral components, and particularly with clay and silt size particles (Cheshire *et al.*, 2000), which are indirectly expressed by sand content. The sorption of organic molecules to clay minerals is assumed to stabilise OM (Oades, 1988; Lützow *et al.*, 2006) and therefore plays a crucial role in OC

dynamics. The coefficient of determination (R^2) of the linear regression performed, adjusted for the amount of independent variables, equals 0.38.

Table 3-1 Relative importance of the independent variables in the multiple linear regression model, expressed by the absolute value of the t-statistic.

Independent variables	Variable type	|t-value|
intercept	-	58.4
Temperature	Climate	30.2
Elevation	Topography	17.4
Inland wetlands	Land cover	16.4
Sand content	Soil texture	14.3
Acid magmatic and metamorphic rocks	Geology	13.8
P/P_0	Climate	13.0
NPP	Vegetation	12.9
Mixed forest	Land cover	11.9
Coniferous forest		11.7
Other rocks	Geology	9.4
Transitional woodland - shrub	Land cover	8.4
Moors and heathland		7.4
Natural grassland		6.7
Arable land		5.7
Pastures		5.4
Basic magmatic and metamorphic rocks	Geology	4.5
Broad-leaved forest	Land cover	4.2
Sclerophyllous vegetation		4.1
Water bodies		2.7
Limestones	Geology	2.5
Slope	Topography	2.5
Basic to ultra-basic rocks	Geology	2.1
Open spaces with little or no vegetation	Land cover	1.1
Permanent crops		0.6
Acid to intermediate rocks	Geology	0.6
Intermediate to basic igneous and metamorphic rocks		0.5
Intermediate magmatic and metamorphic rocks		0.4
Maritime wetlands	Land cover	0.3
Ultra-basic magmatic and metamorphic rocks	Geology	0.3
Heterogeneous agricultural area	Land cover	0.2

3.4.2. Kriging and Variogram Modelling

In order to observe the effect of the regression at different ranges, 150 km and 3,000 km cut-off were used to plot the empirical variograms of the original OC measurements and of the regression residuals (Figure 3-1). The two variograms show similar trends, with the variogram of the residuals showing a lower semi-variance, especially at large distances. This could be interpreted as the regression model being able to capture long distance trends likely due to climatic conditions rather than short distance trends, such as due to topography. Furthermore, as the two variograms run relatively parallel, the mostly constant difference between them can be explained by the linear model being unable to account for complex relations among covariates. Another interpretation is that the covariates show some degree of random noise that cannot be explained. When the variograms are calculated for distances up to 150 km, both of them reach stationarity at ca. 40 km range. At this scale, the difference between the variogram of measured OC and of regression residuals is relatively small and accounts for 10% of the semi-variance. This can be explained by either the linear regression model being too simple to capture the relationship between OC content and the covariates selected and/or by the fact that we might be missing relevant covariates.

At long distances (cut-off = 3,000 km), stationarity isn't reached. This is probably due to the fact that the residuals are large in high latitudes, and low in low latitudes, which inevitably leads to an increase in variance with distance between points. Since stationarity was only reached at short scale, we fitted a variogram calculated for distances up to 150 km, using an exponential function, with a nugget to sill ratio of 0.7. The map of the kriged residuals shows hotspots (in Slovenia and most northern European countries) resulting from the presence of statistical outliers in the OC data, namely organic soils (Figure 3-2). The centre of each spot corresponds to the location of a LUCAS sample where high OC content was measured and which value accounts for a great part of the kriging estimates of the surrounding pixels.

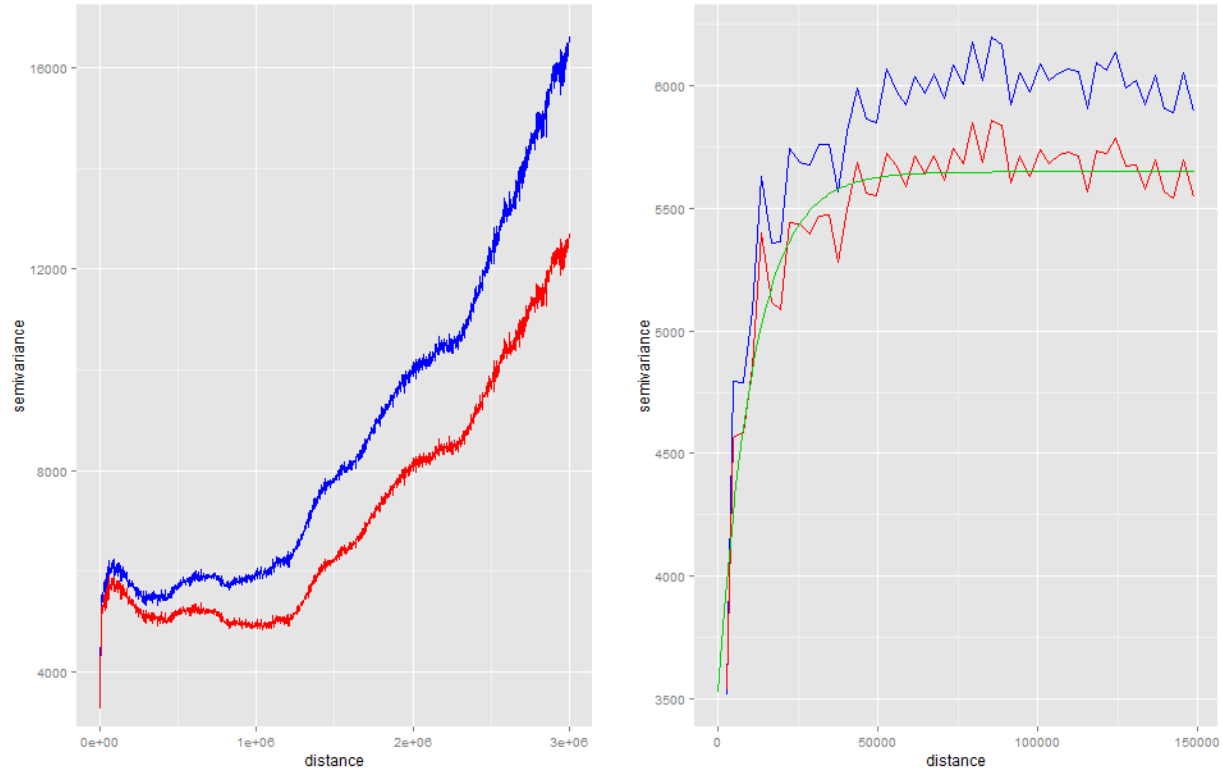

Figure 3-1 Empirical variograms of OC measurements (blue) and regression residuals (red) with 3,000 km (left) and 150 km (right) cut-off. The green line represents the variogram model fitted on the regression residuals.

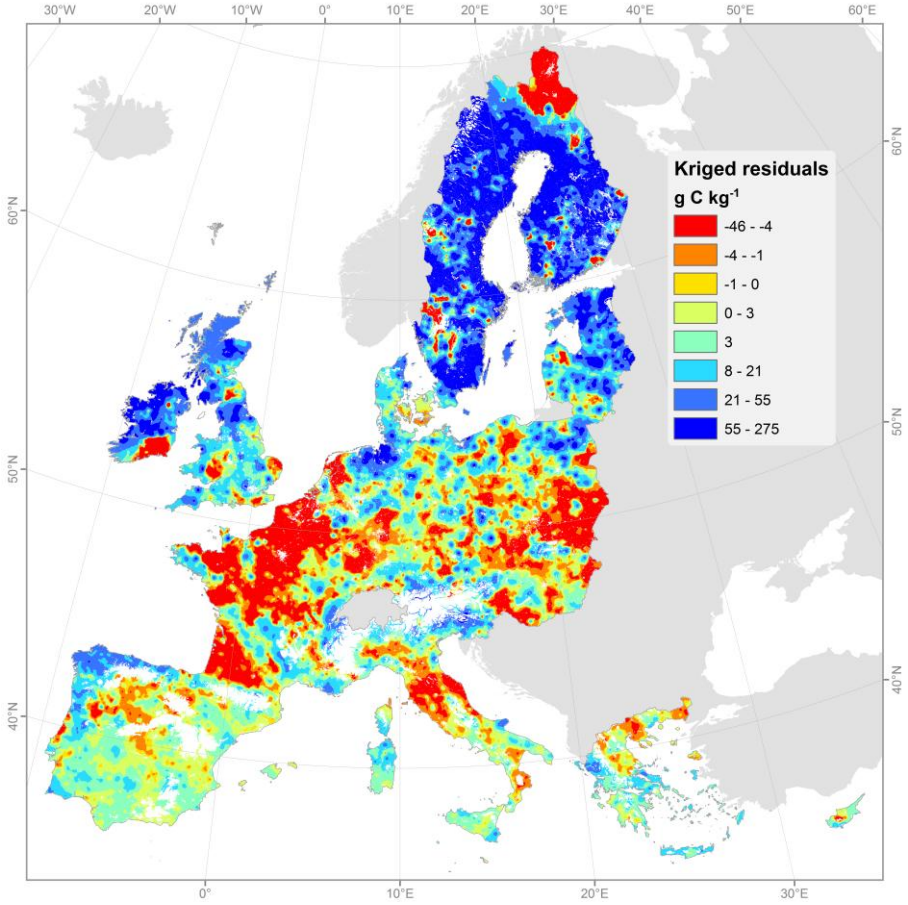

Figure 3-2 Kriged regression residuals.

3.4.3. OC Content Prediction and Model Accuracy

The predictions of OC content produced by regression kriging (RK) (Figure 3-3) show values ranging from 10 to 450 g C kg^{-1}, with a mean of 49 g C kg^{-1} and a median of 28 g C kg^{-1}. The topsoils (percentile 0.20) that have OC content lower than 15 g C kg^{-1} are found in Mediterranean countries but also in Belgium, the Netherlands, France, Germany, Poland, Czech Republic, Slovakia, Hungary and Denmark. When overlaying the land cover data, we observed that the areas with low OC content correspond mostly to arable land. The topsoils

(percentile 0.80 and beyond) with OC content greater than 77 g C kg^{-1} are predominantly found in Northern Europe but also in Belgium, Austria and Slovenia. They mostly correspond to moors, heathlands and coniferous forests. The presence of spots on the map indicating high level of OC is not believed to give a realistic picture of the OC status in topsoils. The model prediction accuracy was assessed, at the sampling locations, by comparing the measured OC content with the value predicted by the RK interpolation.

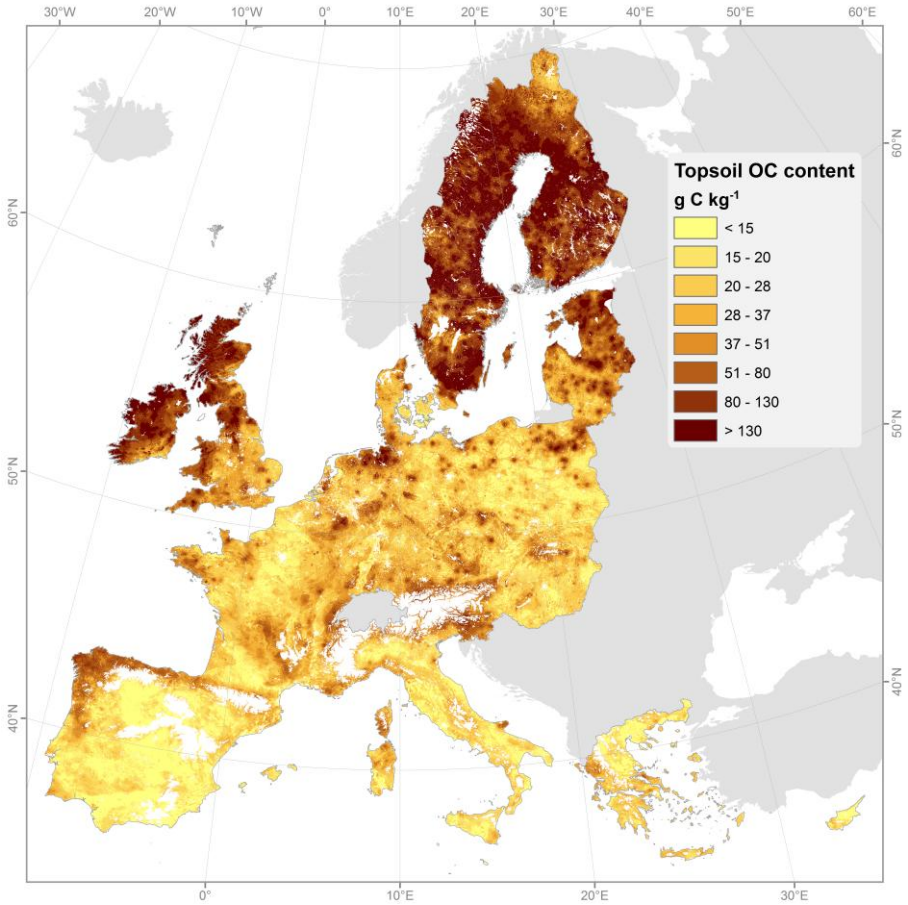

Figure 3-3 Topsoil organic carbon content estimates.

The root mean squared error (RMSE) of the RK predictions equals 77 g C kg^{-1}. The cumulative density function of the residuals calculated by subtracting the RK predictions from the observed OC content (Figure 3-4) shows that most residuals are negative, demonstrating a general over estimation of OC content y the RK model fitted, at sampling locations

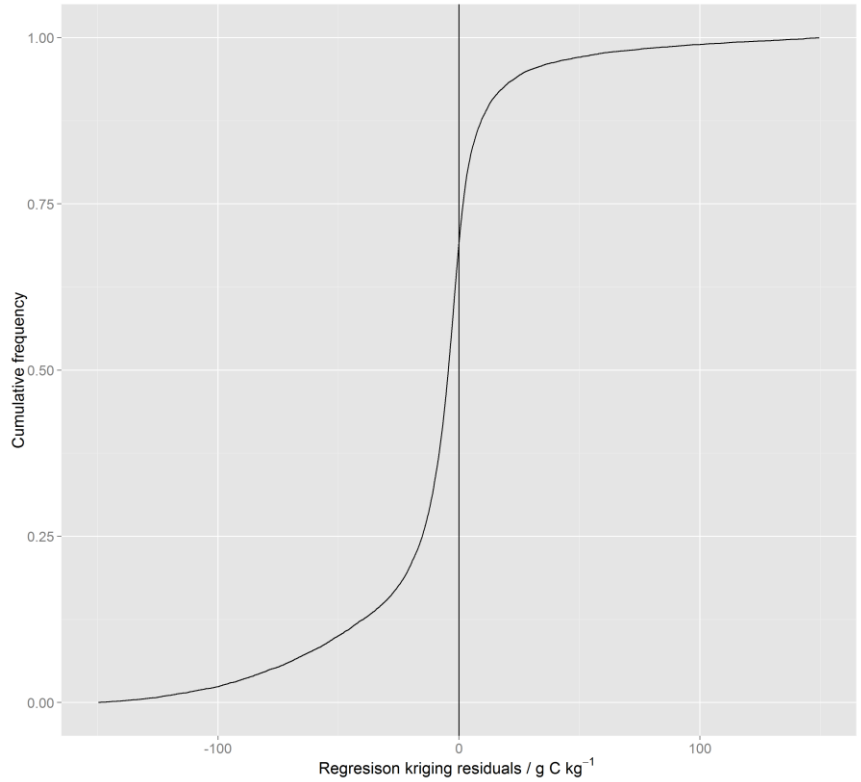

Figure 3-4 Cumulative density function of the regression kriging residuals. The vertical line drawn for x = 0 marks the split between positive and negative residuals and their frequency.

The spatial distribution of prediction residuals (Figure 3-5) shows that large residuals (in absolute value) mostly occur in northern Europe. The highly positive values occur in areas where there are organic soils for which OC content was underestimated by the model whereas the negative values probably correspond to areas close to peat bogs for which the kriged residuals pull the estimation up.

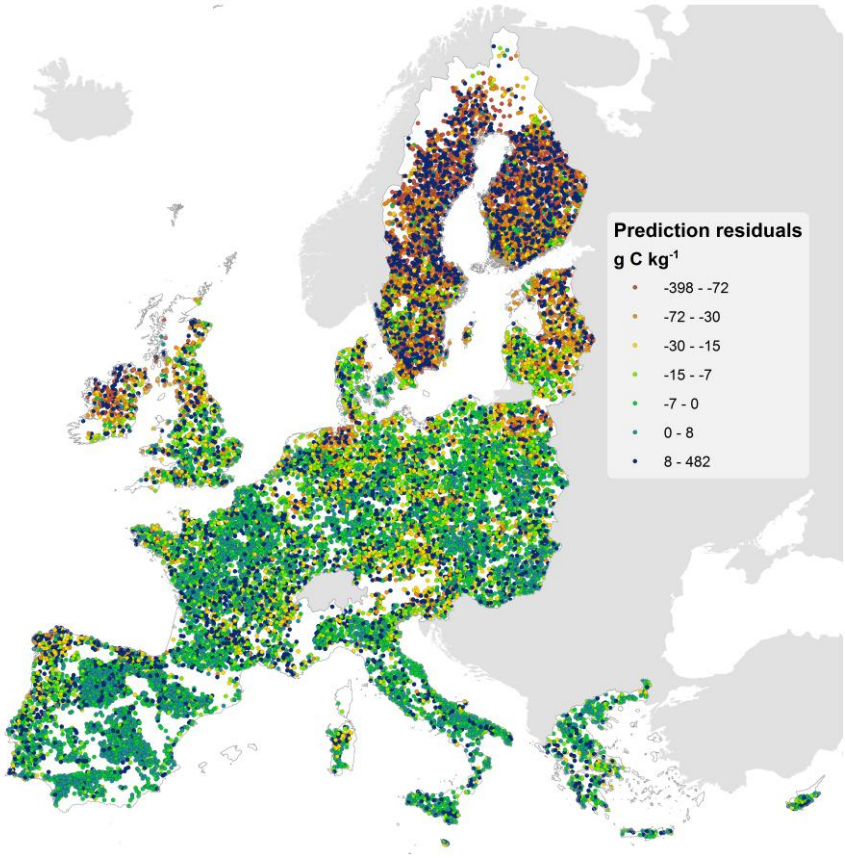

Figure 3-5 Regression kriging residuals at sampling locations.

The concentration of large residuals in northern latitudes can be explained by the difficulty to model the presence of microtopography and consequent highly variable water regimes that influence mineralisation rate and therefore OC dynamics. Low residuals (in absolute value) mostly occur in areas with the most common (i.e. less variable) features of European landscapes (arable land, low elevation and slope) that were better modelled by the regression. The R^2 of the regression kriging model equals to 0.52 which means that kriging increased the fitting by 0.14. The leave-one out cross-validation gave an R^2 of 0.12.

3.4.4. Comparison with the OCTOP map

The two maps show a similar gradient of OC content decreasing from North to South, with OCTOP predicting higher contents in Scandinavia and Scotland. High contents in mountainous areas are presented by both maps, yet with lower estimates in the Alps and Dolomites on the map presented in this chapter. In addition, there is a clear difference in prediction in Eastern Europe where our map predicts lower values. Even though the prediction methods were extremely different (expert knowledge-based pedo-transfer rule vs. regression kriging), the use of land cover and temperature as common covariates to both maps explains the overall similarity in the patterns presented. An in-depth comparison of the two maps was not in the scope of this work.

3.5. CONCLUSIONS

The study has constructed the first map of topsoil organic carbon content for parts of Europe based on a comprehensive sampling programme, the LUCAS-soil survey. For 25 countries of the European Union, our map provides the baseline topsoil OC estimates for the year 2009 and is seen as the first attempt to answer the questions of the proposed Soil Framework Directive regarding the decline in soil organic matter in Europe. The predictions obtained by regression kriging mostly corroborate the current expert knowledge of the

range of OC contents and their variability across Europe, yet with some differences observed in northern and Eastern Europe. The high OC values are outliers in the database that are responsible for a large proportion of the prediction error. Modelling the mineral soil data separately from the organic soil data should be examined in the future as a means to improve the accuracy of the predictions. Also, interpolation techniques that do not treat regression residuals separately, as in RK, could be tested and their performance compared. A full validation would require a resampling campaign to provide a random validation sample. The resampling should target areas where we obtained high prediction error and cover the full range of values taken by the covariates. In the meantime there is scope for comparing our OC predictions with OC data available from other European and national sources (Howard *et al.*, 1995; Arrouays *et al.*, 2001; Lettens *et al.*, 2004; Baritz *et al.*, 2011)

CHAPTER 4. MAPPING TOPSOIL ORGANIC CARBON CONTENT BY APPLYING A GENERALISED ADDITIVE MODEL

4.1. ABSTRACT

The aim of this study was to create a map of topsoil OC content at the European scale by applying digital soil mapping techniques to the first European harmonised geo-referenced topsoil (0–20 cm) database, which arises from the Land use/Cover Area frame statistical Survey (LUCAS). A map of the associated uncertainty was also produced to support careful use of the predicted OC contents. A generalised additive model (GAM) was fitted on 85% of the data set (R^2 =0.29), using OC content as dependent variable; a backward stepwise approach selected slope, land cover, temperature, net primary productivity, latitude and longitude as suitable covariates. The validation of the model (performed on 15% of the data-set) gave an overall R^2 of 0.27 and an R^2 of 0.21 for mineral soils and 0.06 for organic soils. Organic C content in most organic soils was under-predicted, probably because of the imposed unimodal distribution of our model, whose mean is tilted towards the prevalent mineral soils. This was also confirmed by the poor prediction in Scandinavia (where organic soils are more frequent), which gave an R^2 of 0.09, whilst the prediction performance (R^2) in non-Scandinavian countries was 0.28. The map of predicted OC content had the smallest values in Mediterranean countries and in croplands across Europe, whereas largest OC contents were predicted in wetlands, woodlands and mountainous areas. The map of the predictions' standard error had large uncertainty in northern latitudes, wetlands, moors and

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heathlands, whereas small uncertainty was mostly found in croplands. The map produced gives the most updated general picture of topsoil OC content at the European Union scale.

4.2. INTRODUCTION

Building on the results of Chapter 3, the aim of the present work was to improve the map of predicted topsoil OC content, with associated uncertainty, according to DSM principles. The kriging of the regression residuals in Chapter 3 showed that the low sampling density of the LUCAS survey did not allow capturing the spatial correlation at short range. Another technique will therefore be proposed in this chapter to take into account the potential effect of longitude/latitude, directly in the model. Moreover, in order to obtain a smoother result than when applying a strictly linear regression model, the use of a semi-parametric model is tested.

4.3. MATERIALS AND METHODS

4.3.1. Soil data

The measured OC content of the LUCAS topsoil samples was used.

4.3.2. Environmental covariates

The DSM approach adopted fitted a statistical regression model between the soil property to predict and the independent variables at the same location. The soil property values are then predicted at unsampled locations by applying the fitted model to the covariates, collected as spatially continuous data layers. The environmental covariates used to predict OC content, at a 500 m spatial resolution, were SRTM-derived elevation and slope; CORINE data re-classified into 16 classes; accumulated annual temperature (AAT); the ratio of annual

rainfall and annual potential evapotranspiration totals and NPP. We refer the reader to Chapter 2 for more information on the covariates.

4.3.3. OC prediction model

The initial data set was split into a calibration (85%) and a validation (15%) set by Latin hypercube sampling (Minasny & McBratney, 2006). The stratification was conditioned by the following variables: elevation, slope, net primary productivity, temperature, PP0, latitude, longitude, measured OC content and CORINE land cover. Knowing that land cover has a large impact on OC content, we developed the model on samples for which observed land cover (from the LUCAS survey) and CORINE land cover inventory were in agreement to avoid using wrong land-cover classes to calibrate the model. However, using observed land cover (LUCAS) instead of mapped/predicted (CORINE) land cover has potentially the consequence of under-estimating the prediction error variance (Kempen *et al.*, 2010). To check this, we fitted a model on the entire data set and found no differences in cross-validation results. A generalised additive model (GAM) was fitted on the calibration set: GAMs are a generalisation of linear regression models in which the coefficients can be expanded as smooth functions of covariates (Hastie & Tibshirani, 1986). They are semi-parametric and can account for non-linear relationships between dependent variables and covariates (Equation 4-1):

Equation 4-1

$$E(Y|X_1, X_2, \ldots, X_p) = \alpha + f_1(X_1) + f_2(X_2) + \cdots f_p(X_p)$$

where X_1, X_2, …, X_p represent the predictors, Y is the response variable and f_i's are the smooth functions.

As for generalised linear models, GAMs specify a distribution for the response variable Y and use a link function g relating the conditional mean $\mu(Y)$ of the

response variable to an additive function of the predictors as follows (Equation 4-2):

Equation 4-2

$$g[\mu(Y)] = \alpha + f_1(X_1) + f_2(X_2) + \cdots f_p(X_p)$$

To prevent an 'over-fit', thin plate regression splines were fitted by maximum penalised likelihood (Wood, 2006a). A backward stepwise approach was then followed to select the best set of covariates and to determine the relative influence of each of the covariates on the overall prediction capabilities of the model (Poggio *et al.*, 2013). The Akaike Information Criterion (AIC) and the deviances explained were calculated and compared for each of the models created (Akaike, 1974).

The selected model was then applied to the points of the validation set. Predicted and measured OC content were compared and both root mean square errors (RMSE) and normalised root mean square error (RMSE divided by the observed data range; NRMSE) were calculated. The coefficient of determination was calculated for the validation procedure.

4.3.4. Mapping

We refitted a model with the same covariates on all available samples by using the set of covariates identified by the methodology presented above and applied it to the stack of EU-wide spatially continuous covariates. Maps of predicted OC contents and model standard error were prepared, with urban areas, large water bodies and areas above 1000m altitude masked out (because no topsoil samples were taken above that altitude and mapping these areas would have been pure unconstrained extrapolation). The standard error, which shows the theoretical range of deviation in the prediction made by the model, was calculated for every pixel of the created map, and was based on the sampling from the posterior covariance matrix of the fitted parameters. In order to validate the standard error map, the z-score for the observations in the

validation set was calculated. This was performed by simulating coefficient vectors from the posterior distribution of the GAM coefficients, by drawing samples from a multivariate normal distribution. The samples drawn from the posterior distribution of the coefficients were then used to generate samples from the posterior distribution for the observations in the validation set upon which the standard error was calculated. Finally the z-score was calculated as the ratio between the observed error and the standard error. The distribution of the z-score should be normal, with μ close to 0 and σ_2 close to 1.

4.4. RESULTS AND DISCUSSION

4.4.1. Data exploratory analysis

Prior to regression analysis, the measured OC values, the environmental covariates and the relationship between them were studied. OC content ranged from 1.0 g to 586.4 g kg^{-1} (mean value = 48.5 g kg^{-1}) in the calibration set and from 1.0 to 586.8 g kg^{-1} (mean=53.7 g kg^{-1}) in the validation set (Figure 4-1). The histograms reveal a positively-skewed bimodal distribution with the two modes observed around 20 and 500 g kg^{-1}. The first local maximum highlights the predominance of mineral soils in Europe and the second indicates the presence of organic soils. Organic soils are classified as Histosols by the World Reference Base for Soil Resources (IUSS Working Group WRB, 2007), which are characterised by the presence of a histic or a folic horizon. The former has a lower limit of OC content of between 12 and 18%, depending on the clay content of the mineral fraction. The latter contains more than 20% OC content. The threshold of 20% (200 g kg^{-1}) OC content will be taken in this work as the reference limit for the presence of organic soils. The histograms show that at least 75% (up to the third quartile) of the samples are mineral (Figure 4-1).

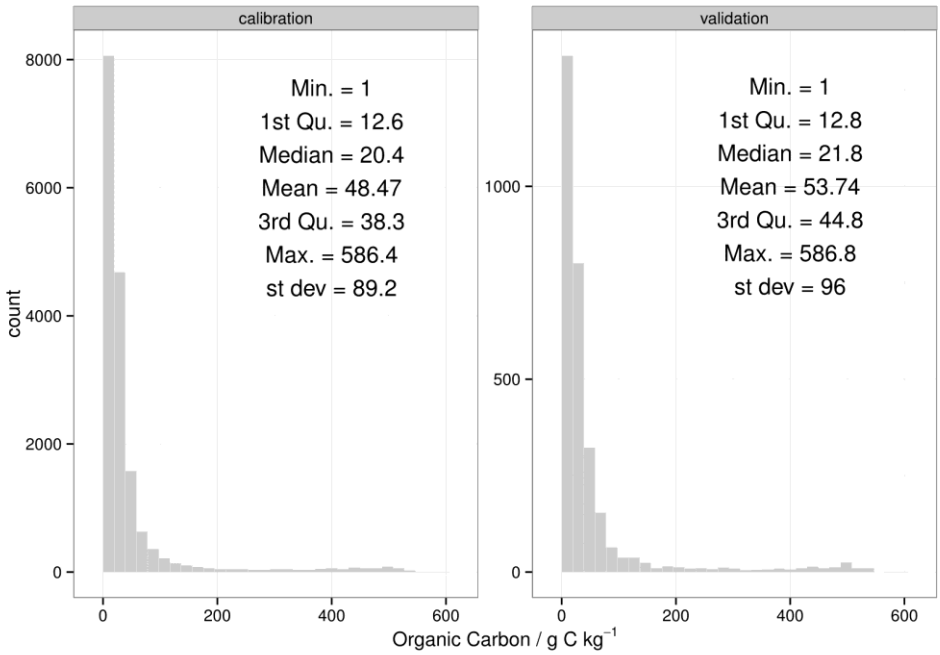


Figure 4-1 Histogram and summary descriptive statistics of measured OC content in calibration (a) and validation (b) sets.

Looking at the OC content for each land cover class, we observed that, unsurprisingly, wetlands have the largest OC content in Europe, with a mean value of 365.1 g kg^{-1} (median = 452.5 g kg^{-1}) (Figure 4-2). According to the LUCAS survey nomenclature, wetlands encompass marshes and peat bogs, which explains the large OC content. Woodlands had the second largest OC content (mean=99.7 g kg^{-1}, median=41.9 g kg^{-1}), followed by shrub lands and grasslands, which have similar values (mean=59.1 and 42.0 g kg^{-1}, median=30.1 and 27.3 g kg^{-1}, respectively). Croplands have the smallest average OC content (mean= 18.7 g kg^{-1}, median=14.5 g kg^{-1}), although the middle 50% of data samples in uncropped land have smaller values than croplands (mean=23.7 g kg^{-1}, median=10.5 g kg^{-1}). A correlation matrix between the dependent and independent variables of our model was computed firstly to study the linear relationship between OC and the covariates and secondly to prevent the

presence of collinear covariates in the regression model (Table 4-1). Covariates that correlated most with OC content were latitude (0.4) and temperature (−0.34).

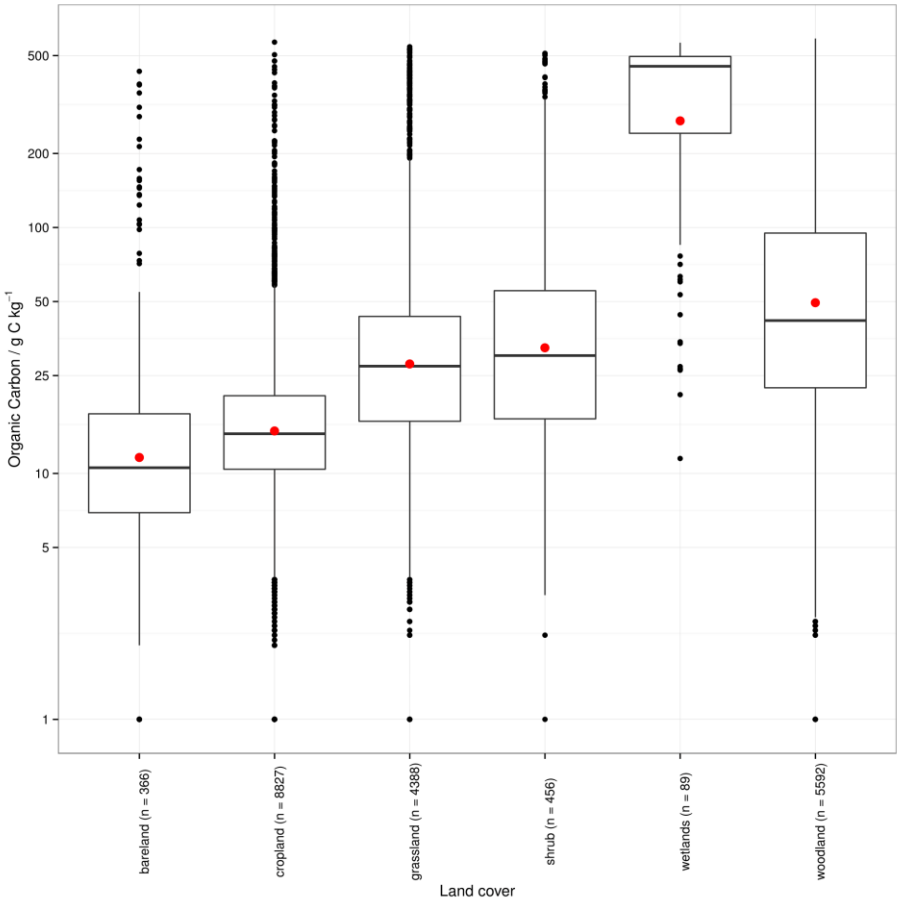


Figure 4-2 Boxplot of OC content (logarithmic scale) for each land-cover class, as defined in the LUCAS survey nomenclature. The dot in the boxes is the mean, the horizontal line in the middle of the boxes is the median, while their lower and upper limits correspond to the first and third quartiles (the 25th and the 75th percentiles). The number of soil samples taken in each class is indicated along the X axis (n).

Table 4-1 Correlation matrix of measured OC content and covariates used in the regression model. "elev" stands for elevation and "temp" for temperature.

	Elev	Slope	NPP	Temp	PP0	y	x	OC
Elev	1.00	0.39	-0.06	0.13	-0.20	-0.42	-0.32	-0.09
Slope		1.00	0.27	0.10	0.11	-0.25	-0.07	-0.02
NPP			1.00	0.08	0.32	-0.15	-0.16	-0.01
Temp				1.00	-0.52	-0.89	-0.43	-0.34
PP0					1.00	0.44	0.08	0.22
y						1.00	0.50	0.40
x							1.00	0.16
OC								1.00

As for the independent variables, the correlation matrix reveals large negative correlations between temperature and latitude (−0.89) as well as between temperature and PP_0 (−0.52). Latitude and longitude also have relatively large correlation values with several covariates. Scatterplots of the measured OC content within the different feature spaces of covariates were plotted for mineral and organic soils (Figure 4-3). The former appear ubiquitously in the feature spaces whereas the latter only occur along a very limited range of covariate values. Moreover, the variation of mineral soils' OC content with the different covariates seemed to follow a trend whereas organic soils showed no specific response to the range of covariate values.

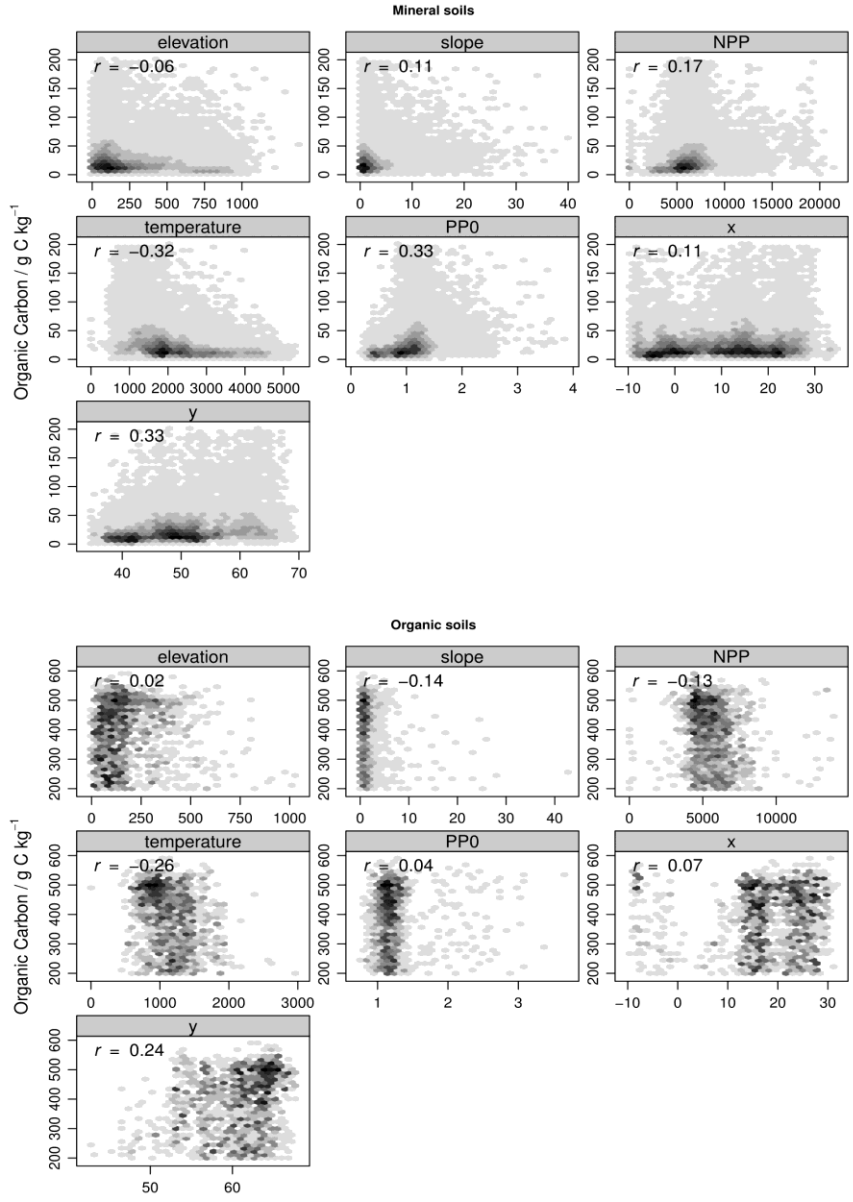


Figure 4-3 Scatterplot between measured OC content and covariates in mineral (a) and organic (b) soils. The colour gradient indicates the density of points, with darker colours representing high density. X-axes units are elevation (m), slope (%), NPP (gCm^{-2} $year^{-1}$), temperature (∘C $year^{-1}$), PP0 (-), x (degrees) and y (degrees). The correlation coefficient (r) is shown.

4.4.2. OC model

Calibration of the model.

A Gamma distribution was chosen for the GAM as OC content was continuous and strictly positive. Identity and log-link function were tested. The analysis of the residuals' Quantile-Quantile (Q-Q) plot showed better results with the log-link function which was therefore chosen for the model fitting (results not shown). The more-or-less straight line observed on the Q-Q plot of the calibration residuals suggests an approximate Gamma distribution of the regression residuals (Figure 4-4). The curved pattern with slope increasing from left to right suggests that the distribution is skewed to the right. The plot highlights the potential weakness of the chosen distribution towards large OC values. The backward stepwise selection of the covariates showed that elevation and PP0 were influencing the prediction model the least (Table 4-2). Slope, temperature, NPP, land cover, longitude and latitude were selected as covariates for the final regression model.

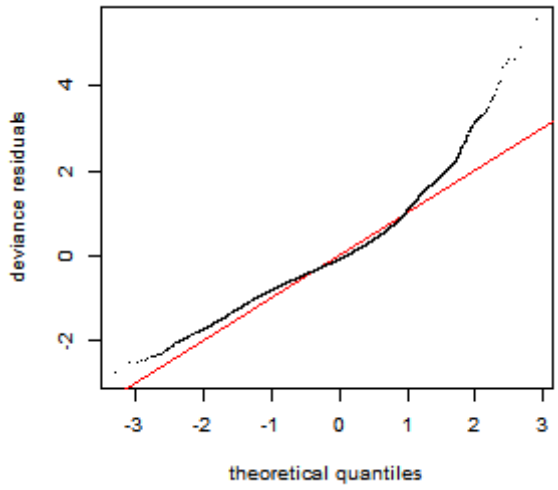


Figure 4-4 QQplot of the calibration residuals. The straight line represents the case where the residuals would strictly follow a Gamma distribution.

The interaction between latitude and longitude was included in the model using a non-parametric function in two features using smooth interaction as scale-invariant tensor products (Wood, 2006b). The interaction accounts for the fact that the two variables belong to the same physical feature space. Elevation is often interpretable as a proxy for climatic variables in regression models predicting soil properties. The presence of temperature data in our model probably justifies the removal of elevation by the stepwise selection procedure. The correlation of −0.52 observed between temperature and PP0 explains the loss of the latter variable during the selection (Table 4-1). The variation in AIC scores calculated after the removal of each covariate from the model revealed that land cover is by far the most influential covariate in the model (Table 4-2).

Table 4-2 Summary table of the GAM models tested by backward step-wise removal of the covariates. The difference in Akaike Information Criterion (AIC) scores and deviance explained were calculated.

xy	Corine	Elev	Slope	Temp	PP0	NPP	ΔAIC	Δdev explained
x	x	x	x	x	x	x	0	0
	x	x	x	x	x	x	178	0.7
x		x	x	x	x	x	1976	6.6
x	x		x	x	x	x	16	0.1
x	x	x		x	x	x	49	0.2
x	x	x	x		x	x	63	0.2
x	x	x	x	x		x	19	0.1
x	x	x	x	x	x		126	0.4

Several authors have also recognised the important influence of land use and land cover on a soil's organic carbon pool (Jones *et al.*, 2005; Meersmans *et al.*, 2011). The combination of longitude and latitude was the second most influencing variable, followed by net primary productivity. The 'fitting performance' (R^2) was 0.29, which is similar to values found by Meersmans *et*

al. (2011). As well as the model performance, the smooth function presented in Figure 4-5 illustrates the estimated effects of the annual accumulated temperature (AAT) on OC content. The y-axis is the centered value (log scale) of the regression coefficients.

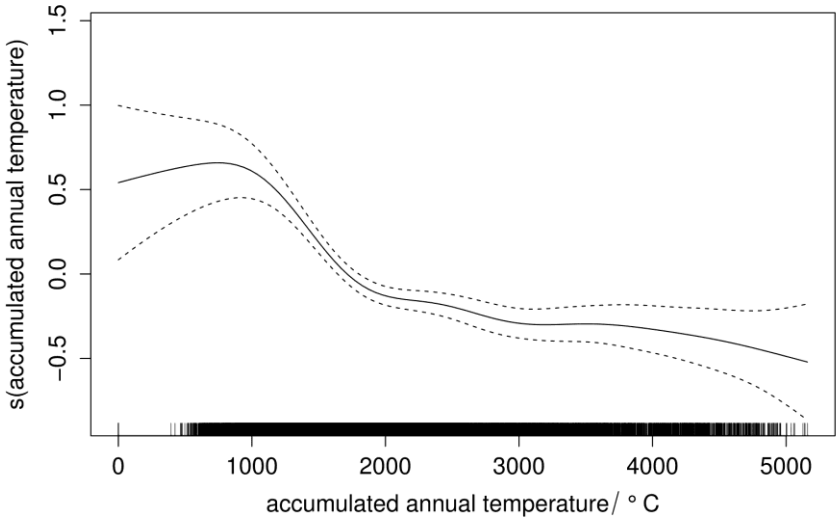


Figure 4-5 Smooth function of temperature as produced by the GAM model. The solid line is the predicted value of OC content as a function of temperature. The upper and lower dashed lines are the 95% confidence interval. The bar at the bottom of the graph indicates the presence or absence of a sample.

Overall, OC content decreases as AAT increases, with a rapid decline observed between 1000 and 2000 °C year^{-1} and then a slower decline for AAT greater than 2000 °C year^{-1}. The decrease in decomposition rate with increasing temperature has been explained by Arrhenius (1889). Below 1000 °C year^{-1}, however, we observed an opposite trend as OC content increases with temperature. Areas where these low temperatures were recorded include the north of Scotland, Finland and Sweden, where the smallest values of NPP were also observed. The increase in OC content as AAT increases in these cold

regions is related to the increase in vegetation cover that contributes to OC input. The small number of samples taken in these temperature conditions (shown on the bottom bar) and the large confidence interval observed encouraged us to regard this last trend with caution.

Model validation.

The validation of the model gave an R^2 value of 0.27, which is comparable to coefficients obtained in similar studies (Meersmans *et al.*, 2011; Kumar *et al.*, 2012). We believe that the relatively poor model fitting that we obtained was because of the complexity of the processes of OC accretion and mineralisation operating at different spatial scales and the great variety of landscapes and soil types found across Europe (Arrouays *et al.*, 2012). Also, the covariates, having a resolution of 500 m, may not be able to explain the exact conditions encountered at the validation profile. For instance, CORINE gives the dominant land cover, but mixed pixels are common and hence the observed land cover for the validation profile might not correspond to the CORINE class. More generally, OC variations occurring at scales smaller than the grid size of the map cannot be captured by the model and will not be depicted in the map. Predicted values plotted against observed OC contents had poor results for Scandinavia (R^2 = 0.09), but the remaining countries had better results (R^2=0.28). In those northern latitudes, the model performance was poor for the prediction of both mineral and organic soils (Figure 4-6). Olsson *et al.* (2009) and Heikkinen *et al.* (2013) showed that, in Sweden and Finland, OC contents in mineral soils tend to decrease as latitude increases, contrary to what is observed in other parts of Europe. Although the results of temperature smoothing indicate an increase in OC content with temperature in those regions (Figure 4-5), the north to south increase in OC content in mineral soils of Scandinavia is not well predicted (Figure 4-6b). The presence of organic soils at those latitudes is probably partly responsible for that, by putting a bias on the model towards large OC contents. As for the difficulty in predicting OC content larger than 200 g kg^{-1}, we observe that most organic soils in Europe are

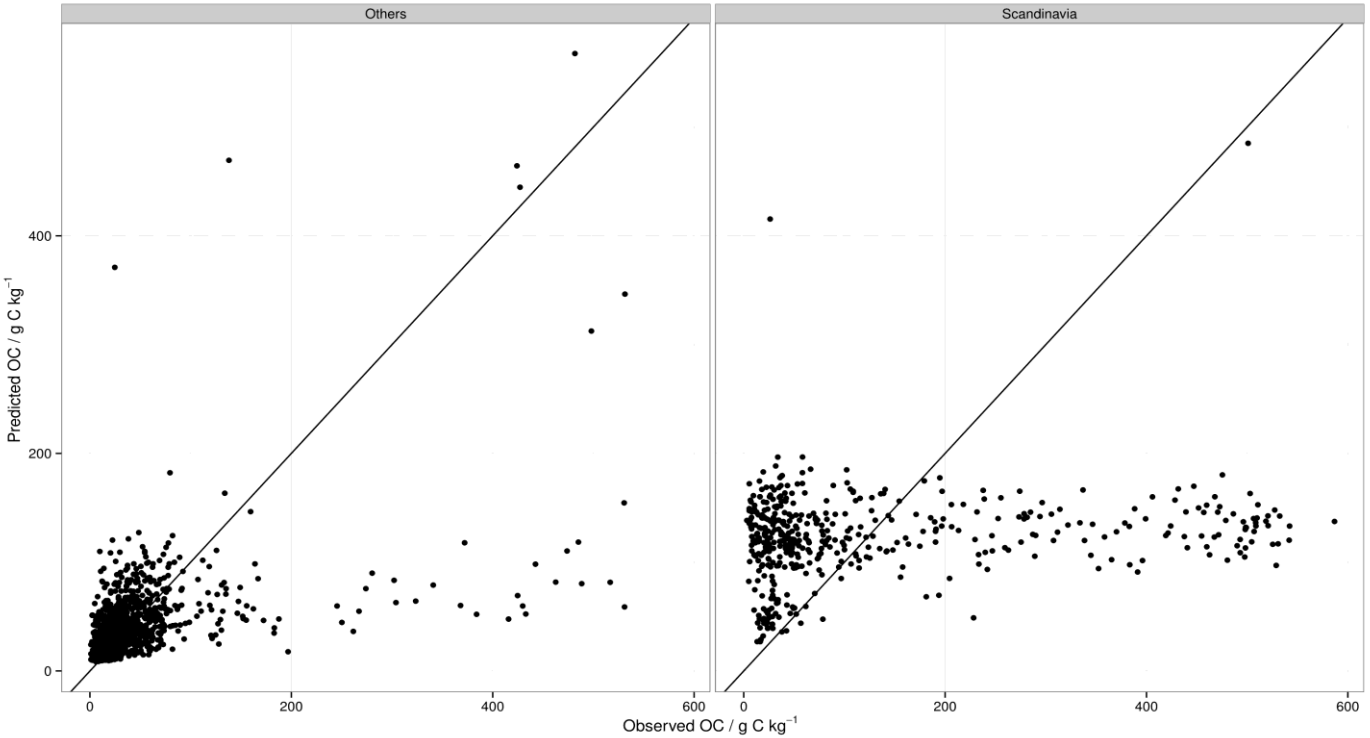


Figure 4-6 Predicted values plotted against observed OC contents in the validation set. Other countries (a) and Scandinavia (b).

in fact under-predicted (Figure 4-6 a, b). This can be explained by the unimodal distribution used by the model, whose mean value is tilted towards the vast majority of residuals coming from mineral soils, therefore leaving residuals from the organic part of the population in the tail of the distribution. Rawlins *et al.* (2009) encountered similar problems in their study in Northern Ireland and concluded that mineral and peat soils should be modelled separately. This could be achieved using for instance the methods developed in Poggio *et al.* (2013). Overall, the model had an RMSE of 79 g kg^{-1} (NRMSE=85%). The model had an RMSE of 42 g kg^{-1} and an R^2 of 0.21 for the prediction of mineral soils, as well as an RMSE of 287 g kg^{-1} and an R^2 of 0.06 for organic soils. These results indicate that the use of a unimodal distribution results in a better prediction of the mineral soils for which the OC values are in the centre of this distribution. When considering the land cover classes separately, predictions for croplands on mineral soils are the most accurate (Table 4-3). Croplands represent the second main land cover type in Europe (after woodlands) by occupying nearly a quarter of the area and they are distributed evenly across the EU (Eurostat, 2011a). Within the organic soils, the model performs better in woodland, which is the most common land cover type in Europe, with a 39% share of the total surface area. Most of the organic soil samples in the calibration set were taken in woodlands, which may explain the better performance of the model for that land cover type. Conversely, in mineral soils, the model performed the worst at predicting OC content in woodlands. A reason for this might be the great heterogeneity observed in forest soils, with measured OC contents ranging from 1 to 586 g kg^{-1}. Even slight differences in sampling depth and removal of the ectorganic horizons can induce large variation in OC content because of the strong vertical gradient in OC contents of forest soils.

Table 4-3 Model accuracy (RMSE, root mean square error, g kg^{-1}) and normalised root mean squared error (NRMSE, %) calculated for mineral and organic soils (OC content > 200 g kg^{-1}) and for each LUCAS land-cover class.

Soils	Land cover	RMSE / g kg^{-1}	NRMSE / %	n
Mineral	Bareland	31	161	54
Mineral	Cropland	12	96	965
Mineral	Grassland	37	126	653
Mineral	Shrub	44	119	68
Mineral	Wetlands	245	-	1
Mineral	Woodland	74	192	443
Organic	Cropland	412	-	1
Organic	Grassland	290	320	20
Organic	Shrub	289	319	7
Organic	Wetlands	183	295	4
Organic	Woodland	290	282	108

The normalised root mean square error is calculated as the ratio of the root mean square error and the range of observed values.

4.4.3. OC predictions and standard error maps

The largest OC contents were observed in Ireland, the United Kingdom, Sweden, Finland, Estonia and Latvia, mostly in wetlands (peat lands), woodlands and in mountainous areas (Figure 4-7). These findings are in line with current knowledge on spatial distribution of topsoil OC content in Europe (Jones *et al.*, 2005).

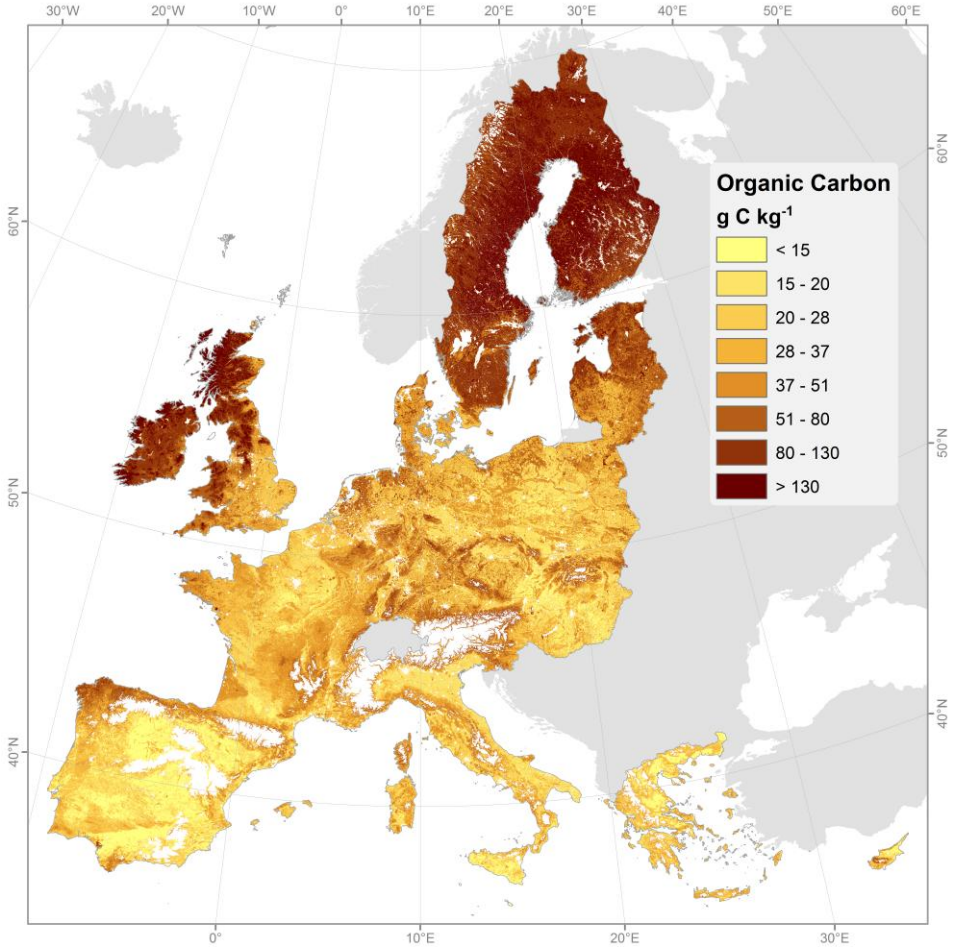


Figure 4-7 Map of predicted topsoil organic carbon content (g kg^{-1}).

The smallest OC concentrations were predicted to be mostly in the Mediterranean countries and also parts of France, Germany, Poland, the Czech Republic, Slovakia and Hungary, where the land cover is defined as croplands or permanent crops. Intensive management practices, as implemented on much agricultural land in Europe, increase the mineralisation of soil organic matter and therefore reduce OC contents (Lal, 2002). The visual comparison of the spatial distribution of organic soils proposed by our model and by Montanarella et al. (2006) indicates good agreement in Ireland, the United Kingdom,

Scandinavia and Baltic countries. However, our model seems to predict fewer organic soils in the Netherlands and in Poland. The reason for the observed discrepancies might be the differences in the methods used to produce both maps. The distribution of organic soils in Europe (Montanarella *et al.*, 2006) was inferred by using a polygon-based approach, following the identification of different key soil types within the European Soil Map and data-base (King *et al.*, 1994; Heineke *et al.*, 1998). Large standard errors are observed in northern latitudes but also in inland wetlands or moors and heathlands (Figure 4-8). Few samples were taken in the highlands of Scotland, in Wales, in south-western Ireland or in northern Sweden and Finland, where OC variation tends, moreover, to be very large (Figure 1-1). In all these areas, OC predictions have large standard errors. Mountain ranges such as the Alps (Italy, France and Austria), the Carpathians (the Czech Republic, Slovakia and Poland), the Apennines (Italy), the Central Massif and the Vosges (France) and the Pindus (Greece) had large standard errors in their areas below 1000m altitude (areas above 1000m altitude were masked out in Figure 4-8). The model, whose weakness at larger OC contents we understand, failed to predict the generally large OC content measured in these mountain ranges. Areas where a large standard error is estimated should be considered with caution. In contrast, areas where a small standard error is calculated (mostly corresponding to the croplands of Europe) give predictions of OC content that more accurately approximate the real values. These areas are therefore the most reliable predictions in Figure 4-7. The standard error map gave a z-score distribution with μ =0.043 and σ^2 =2.01. These values are, however, biased because of the skewness of the distribution of residuals and when the right tail values are excluded μ =0.013 and σ^2 =0.91.

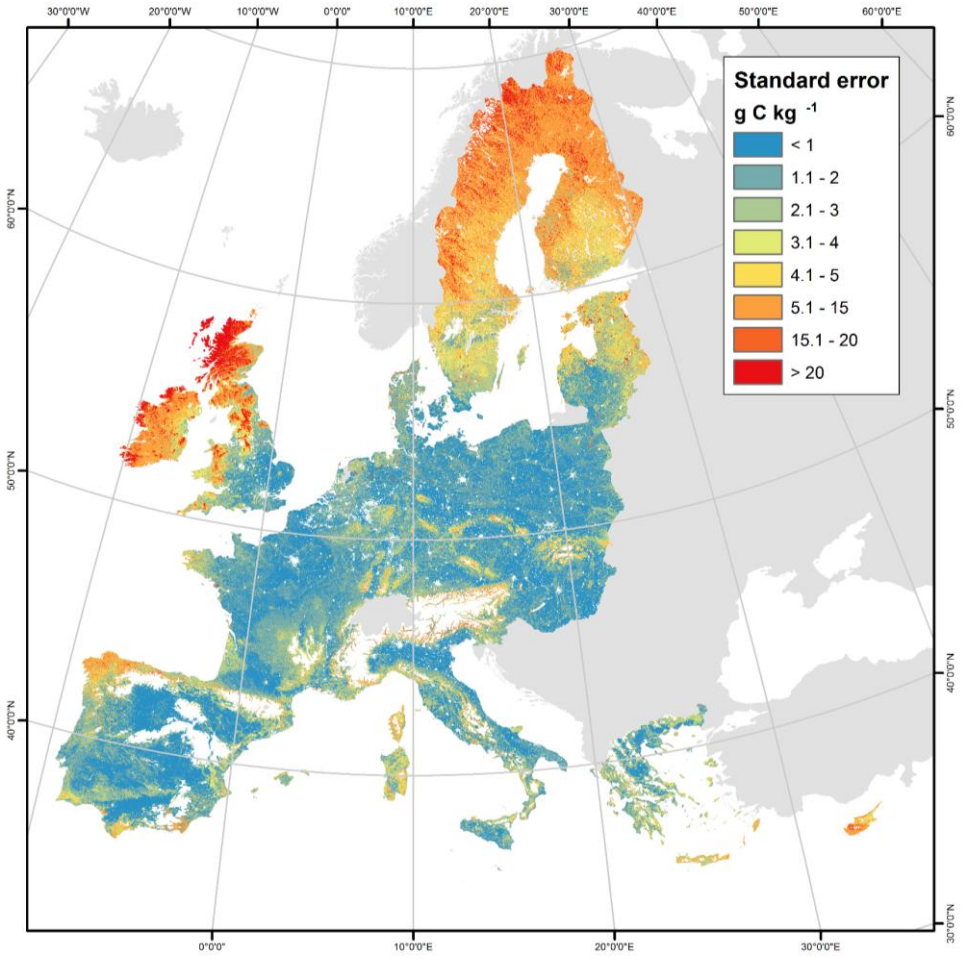


Figure 4-8 Map of standard error of the OC model predictions (g C kg^{-1}).

4.4.4. Comparison with existing OC map

Here, we compare the values predicted on the validation set of our model with those predicted by Jones *et al.* (2005) for the same pixel. Because the validation procedure showed a tendency of our model to poorly predict the OC content of Scandinavian soils (Figure 4-6), we chose to compare the two models for Scandinavi and the other countries separately. Figure 4-9 shows that the prediction models generally agree on the prediction of OC content of mineral

soils in 'other countries'. Although the two models were substantially built in different ways (pedo-transfer rule or regression model), the logic behind their prediction of OC content is quite similar. Jones *et al.* (2005) and we recognised the large influence of land cover and temperature on OC dynamics in soils and fed the respective models with such information, which led to similar outcomes. In addition, whilst our input data were actual measured OC values, OCTOP predicts OC content from measurements from representative soil profiles synthesised by expert soil scientists from across Europe (King *et al.*, 1994; Van Ranst *et al.*, 1995). Areas of disagreement are mostly where our model predicts the OC content for mineral soils whilst the OCTOP model predicts OC content greater than 200 g kg^{-1}, in Scandinavia, there is not any clear pattern of agreement or disagreement. The two models can also be compared on mean OC estimates by land-cover class (Figure 4-10). As the validation set used for the GAM did not encompass enough points in every land-cover class to allow for such comparison, we extracted predictions from the map. Globally, we can see that the average predictions compare well, except for the inland wetlands class for which the GAM estimates a larger OC content. The observed match is probably through the use of a common layer in the prediction models, namely land cover. Also, the error bars are always smaller in the case of the GAM. Because in OCTOP soil variation is expressed by discrete soil classes, a mismatch between the large soil units and land cover classes at larger scales can occur. This creates a more heterogeneous range of predicted values per land cover class, resulting in wider standard deviations. The latter supports our initial assumption that OCTOP could be improved by using more detailed soil spatial information layers or by modelling soil properties at a finer resolution using DSM techniques.

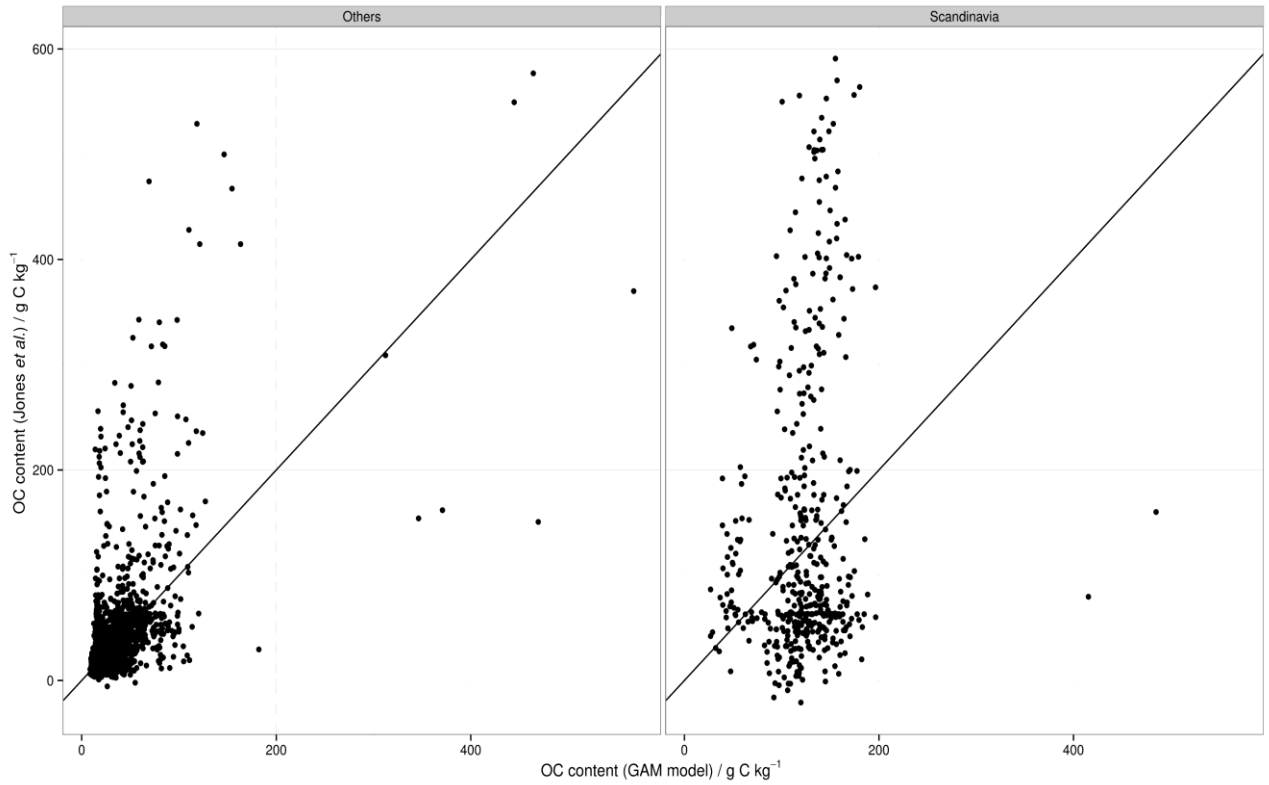


Figure 4-9 Scatterplot of OC content predictions proposed by Jones et al. (2005) and by our model in Scandinavia (b) and other countries (a).

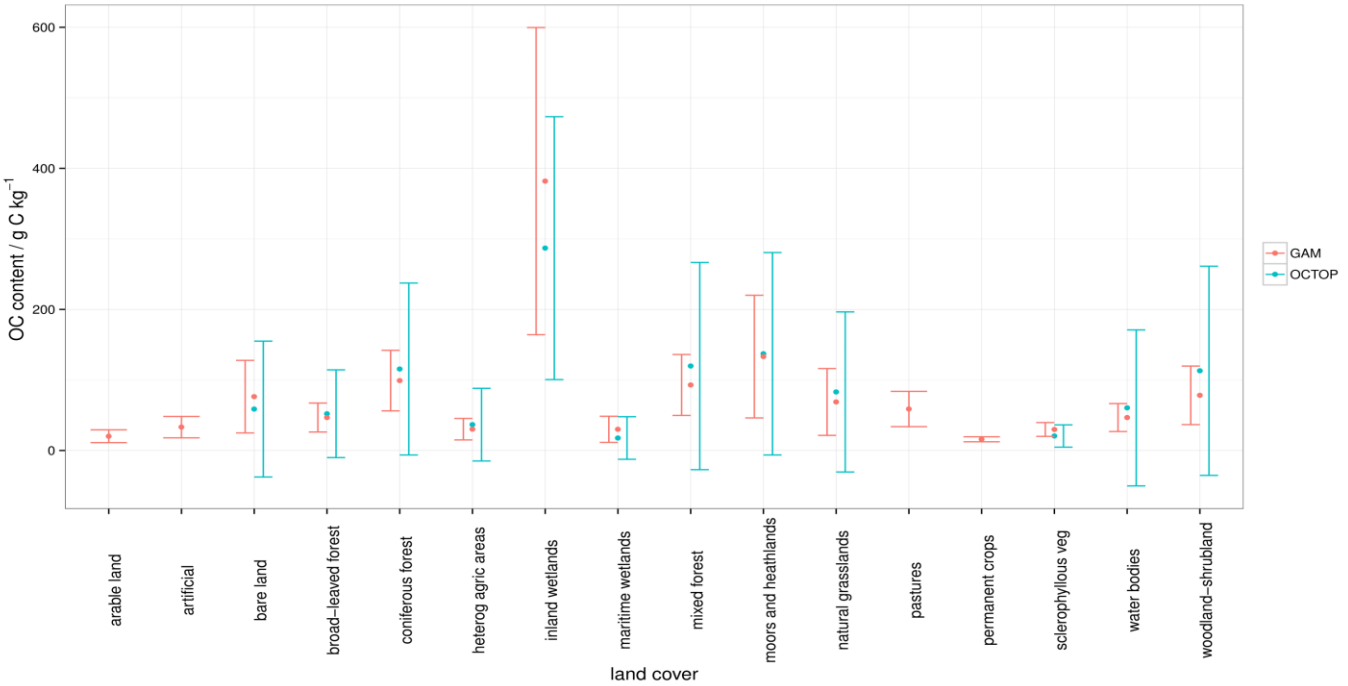


Figure 4-10 Comparison of mean OC content predictions (g kg^{-1}) per land-cover class, for OCTOP and for the GAM model (this study). Dots are mean OC values and the error bars represent two standard deviations (2σ).

4.5. CONCLUSION

Our study has proposed the first topsoil OC content map of Europe which is based on direct harmonised measurements stored in a soil database, produced using DSM techniques. The model shows a fairly good accuracy for most of the EU (R^2 =0.28), except for Scandinavia (R^2 =0.09) where organic topsoils predominate. This was also indicated by the validation procedure, which revealed that the unimodal distribution imposed by the fitted model was not suited to accurately predicting the bimodal distribution of OC content of all soils in Europe. Hence modelling mineral and organic soils separately might give better results. However, if the final output is to be spatial, the lack of an accurate spatial data layer predicting the localisation of organic soils in Europe will remain a limitation for producing a continuous map using both models. The comparison of our map with OCTOP underlined the influence of land cover on OC content in soils and it showed that the use of (discrete) soil classes instead of continuous fields to express soil OC variation is a major source of uncertainty. The map produced gives the most up-to-date general picture of topsoil OC content at the European Union scale and is not intended to be a substitute for national-scale or local maps that are based on more detailed spatial information. Moreover, it is important that the uncertainty associated with the predicted values from this study is understood by the end-users and should encourage careful use and interpretation of the spatial values.

CHAPTER 5. ESTIMATING TOPSOIL ORGANIC CARBON STOCKS IN EUROPE USING GEO-REFERENCED HARMONISED TOPSOIL AND LAND COVER DATA

5.1. ABSTRACT

The quantification of soil organic carbon (OC) stocks, and the assessment of their variability in space and time, have become a common request for soil scientists, globally. As a consequence to soil being the largest terrestrial carbon pool, and to the understanding of soil OC major role in the provision of vital ecosystem services, baseline estimates of soil organic carbon are needed. At the European Union scale, the only stock estimates available were derived from harmonised national soil surveys data on OC content estimates (Jones *et al.,* 2005) combined with bulk density and rock fragment data. In this study, we proposed baseline estimates of topsoil (0-20 cm) OC stocks in Europe for the year 2009. Predictions for 23 countries and seven main land cover classes were generated using 20,000 topsoil OC measurements and 200,000 land cover observations from the land use/cover area frame statistical survey (LUCAS), which is the first harmonised topsoil and land cover survey in the European Union. Several regression models were tested to predict OC content in mineral soils; whilst average OC measurement values were used for organic soils. A logistic regression model was built to predict the probability of a soil to be

mineral or organic, and to thereafter classify an unknown location as organic or mineral topsoil. Whilst measurements of gravimetric proportion of rock fragment were available, bulk density values had to be derived by pedo-transfer rule. Values of stocks were calculated at 200,000 locations where land cover observations were available and then extrapolated to countries and land cover classes. A 95% confidence interval was calculated by bootstrap. The total estimate, for a 0-20 cm reference depth, is 38.3 Gt with a $CI_{95\%}$ ranging between 34.9 and 42.4 Gt. Our results showed that 35% of Europe's total OC stock are stored in Sweden and Finland. In addition, as far as land cover classes were concerned, woodlands were given as the largest topsoil OC pool in Europe, with a total of 20.6 Gt ($CI_{95\%}$ = ± 7%). The baseline OC stocks presented here for the year 2009 are the first estimates derived from a harmonised soil and land cover database at EU scale. The re-conduction of the LUCAS survey in 2015 and the re-sampling of more than 20,000 topsoil will allow up-dating the estimates and assessing the effect of a potential land cover change on topsoil carbon pools.

5.2. INTRODUCTION

Because it consists in the largest terrestrial organic carbon reservoir, which can sequester (sink function) or release (source function) atmospheric CO_2, soil is recognised as having a potential to help mitigate and adapt to climate change (Batjes, 1996). There is an evident need for data on the status of organic carbon pools in world soils, whether it be at local scale for agri-environmental management, at national scale for the reporting of greenhouse gas inventories to the United Nations Convention on Climate Change or at global scale for

providing soil inputs to climatic and environmental models that address crucial societal challenges. Yet, reliable estimates are lacking.

The quantification of the size of carbon pools requires data on soil OC content, bulk density and proportion of rock fragments at sampling location. The reliability of the estimates therefore depends on the accuracy of this input data and on the sampling density (Martin *et al.*, 2011). The lack of agreement, at any scale, on harmonised sampling and analytical procedures, in addition to the rarity of sampling programmes that systematically include measurements of the necessary parameters, lead to incomplete and inconsistent soil databases that make accurate OC stocks difficult to estimate. Moreover, the high spatial variability of OC content requires soil monitoring networks with a high sampling density, which are expensive and rarely implemented (Saby *et al.*, 2008).

Traditionally, OC stocks were derived from existing soil maps by attributing OC values to polygons derived from pedo-transfer rules combining the soil maps with data layers such as topography, land cover and climate. The OC values, originating from surveys carried out at different times and following different methodologies, were used despite the absence of standard method for combining data and for up- or down scaling it (Krogh *et al.*, 2003). To date, digital soil mapping techniques (McBratney *et al.*, 2003) have become very popular to produce estimates of OC stocks and the most recent studies have been reviewed by Minasny *et al.* (2013). Digital mapping techniques allow the production of the uncertainty of estimates and differ from traditional polygon-based maps in that they are pixel-based (Sanchez *et al.*, 2009). Alternatively, soil OC dynamics models such as RothC (Coleman & Jenkinson, 1996) or Century (Parton *et al.*, 1987) have been applied to simulate OC changes for areas with

similar climate, soil type and management. Lugato *et al.* (2014) defined units with a homogeneous soil and climate throughout Europe and ran the Century model to estimate the baseline soil OC in these units given the current land management practice. Furthermore, they simulated the soil OC dynamics under different land cover scenarios, for time periods going from decades to centuries.

In Europe, the ENVASSO project which reviewed existing soil monitoring networks across the EU, defined topsoil OC content and soil OC stocks as indicators of soil organic matter decline (Arrouays *et al.*, 2008a; Kibblewhite *et al.*, 2008). The project showed that, although topsoil OC content was one of the most widely available indicator across the monitoring sites under scrutiny (Saby *et al.*, 2008), the data was dispersed and not harmonised. Differences in soil surveying and laboratory analytical methods, together with discrepancies in dates of the surveys were highlighted as impediment to a joined use of the national data sets. In addition, bulk density was measured in half of the countries only. Hiederer (2010) provided the first OC stocks estimates for Europe, by combining a map of OC content realised during a previous study (Jones *et al.*, 2005) with bulk density and rock fragments data from the European Soil Database (ESDB) (King *et al.*, 1994). The data used by Hiederer (2010) originated from national soil profile surveys, which were heterogeneous in terms of sampling scheme, analytical procedures and date of collection. The lack of a harmonised soil database at continental scale was stressed at the same period as the work of Hiederer (2010), which led to the implementation of the first European Union (EU)-wide topsoil sampling campaign as a part of the LUCAS survey. The scheduled repetition of this survey in 2015 (Eurostat, 2014) will mark the establishment of the first harmonised topsoil monitoring network at European scale.

Here we aim at creating a baseline of topsoil OC stocks at the EU scale for the year 2009, using both the land cover observations and the OC measurements from the LUCAS survey. As the land cover was recorded in the field during the LUCAS survey, this information was preferred to data extracted from CORINE, which unavoidably contains error caused by the spatial interpolation of point observations to mapping units. As suggested by de Brogniez *et al.* (2014), the OC content of mineral and organic soils was modeled separately, as the bi-modal distribution of the OC data hampered accurate predictions using a single regression model. Following the definition of histic (organic) soil horizon, a threshold of 180 g kg^{-1} OC content will be used as the reference limit for the presence of organic soils (IUSS Working Group WRB, 2007). Several regression techniques were then tested to best predict OC content and a bootstrap approach was implemented to derive confidence intervals and estimate the uncertainty. Finally, bulk density and rock fragment data were derived from the LUCAS and ESDB databases and representative surface areas for each combination of organic/mineral soil and land cover were defined for the calculation of stocks at national level. We analysed our results and compared them with those obtained in similar studies. We propose to calculate OC stocks based on geo-referenced land cover observations and topsoil OC measurements that originate from a single harmonised database at continental scale. The method proposed, based on the use of combined land cover and topsoil sampling networks, allows the calculation of stocks for various types of spatial units (whether they are continuous or discontinuous in the landscape) ranging from country level, to land cover class to regional units such as the European Nomenclature of the Territorial Units for Statistics (NUTS) (Eurostat, 2011b). The repetition of the LUCAS survey in 2015 will allow calculation of new stock estimates and therefore offer an over-view of the state

and evolution of topsoil carbon pools in Europe, through comparison with the 2009 values.

5.3. MATERIALS AND METHODS

In order to calculate topsoil OC stocks we propose different approaches for mineral and organic soils. A previous study showed that the bi-modal distribution of the OC data hampered accurate predictions if a single regression model only was used for all soils (de Brogniez *et al.*, 2014). In addition, the lack of availability of a harmonised spatial layer that locates organic soils in Europe was highlighted as a limitation. As opposed to working with a set of continuous spatial data layers and in order to address the above-mentioned issues, the work has focussed on point data from the LUCAS and other databases. Figure 5-1 illustrates the methodology followed to predict OC stocks and guides the reader through the text.

5.3.1. Input data

LUCAS survey

The topsoil OC measurements were used as dependent variable. Land cover observations for the 200,000 points from the master grid were used as covariates. Sub-class of land cover was also tested as a covariate where present. Hence, cropland was sub-classified as cereals, fodder crops, root crops or other crops; grassland as grassland with sparse tree/shrub cover, grassland without sparse tree/shrub cover and spontaneously re-vegetated surfaces; woodland as broadleaved and evergreen woodland, coniferous woodland or mixed woodland; shrubland as shrubland with sparse tree cover and shrubland without sparse tree cover.

Covariates

Elevation and slope, net primary productivity (NPP), annual accumulated temperature (AAT), mean annual rainfall were used. We also included in our set of covariates the World Reference Base (IUSS Working Group WRB, 2007) reference soil group (e.g. Podzol, Cambisol) and the qualifier (e.g. Umbric, Mollic, Eutric), extracted from the 1:1,000,000 European soil geographical database (ESGDB). The reference soil group and the qualifier allocated to every soil sample correspond to the dominant soil typological unit (STU) in each soil mapping unit (SMU) corresponding to the polygon where the soil sample is located. As the ESDB does not cover the islands of Malta and Cyprus, this study was realised only for the 23 other countries that were sampled in 2009, during the LUCAS campaign. We refer the reader to Chapter 2 for more details on the covariates.

Rock fragment

In order to calculate the OC stock from a core sample of a known volume, the rock fragment content by mass (R_m) (that is the gravimetric proportion of gravels in a sample) must be known. This parameter was measured for the 20,000 topsoil samples of the LUCAS survey.

Bulk density

Bulk density of soils is needed to calculate carbon stocks, but it was not measured during the LUCAS survey. As clay content (particle size < 2 μm) and packing density data were available, we calculated bulk density applying the following equation proposed by Jones et al. (2003) (Figure 5-1, letter A):

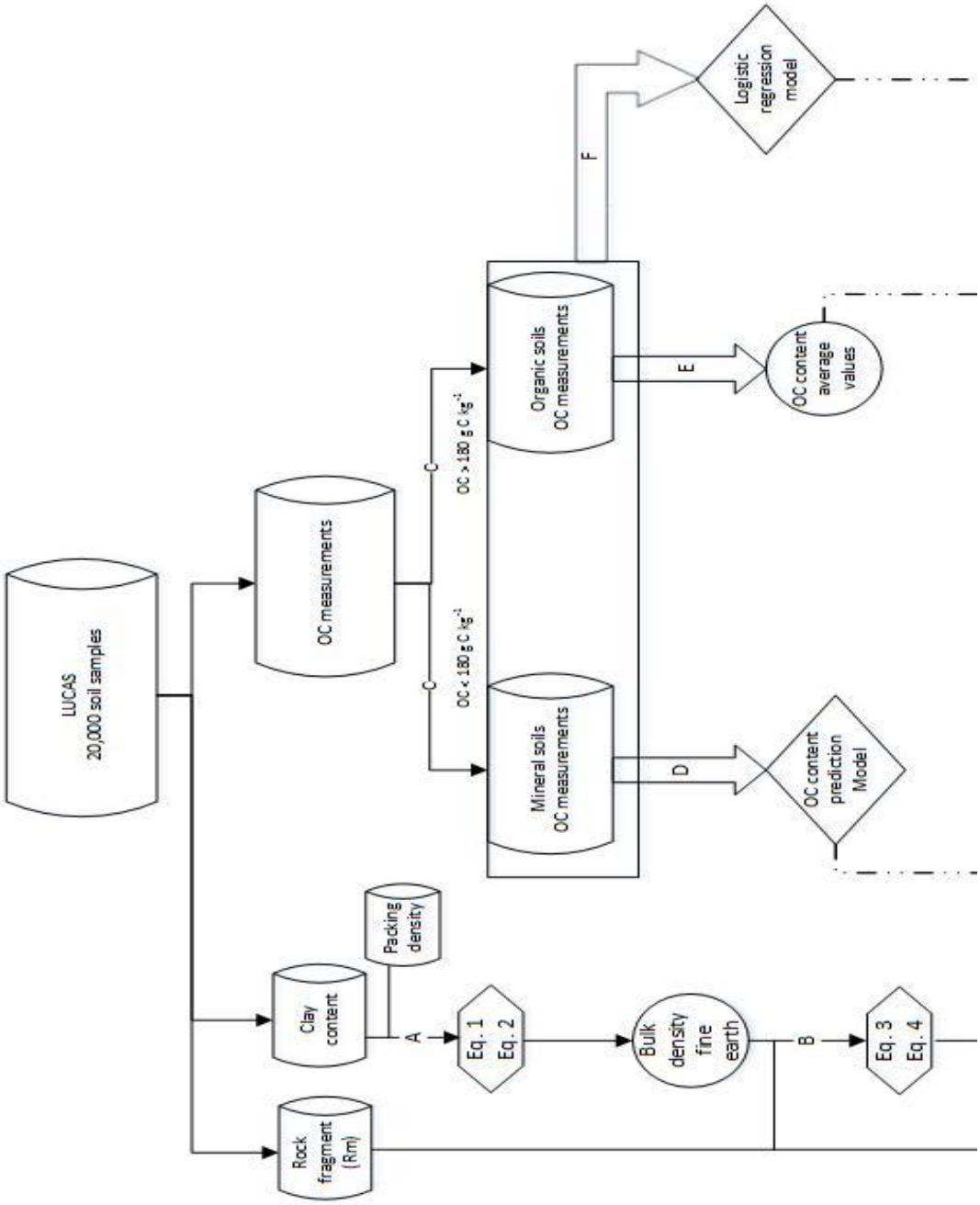
Equation 5-1

$$BD_{fe} = \rho_P - 0.009\ C$$

where BD_{fe} is the bulk density of the fine earth (g cm^{-3}), ρ_P is the packing density (g cm^{-3}) and C is the clay content (in % mass of the fine earth).

The packing density is a parameter that gives a measure of the apparent compactness of a soil and was formerly derived in the European soil database, by applying a pedo-transfer rule (Van Ranst *et al.*, 1995). The packing density thus obtained for the dominant STU of an SMU was used for the calculations, together with the clay content which was measured for the LUCAS topsoil samples and then extrapolated to the 200,000 locations as explained in de Brogniez *et al.* (2014).

The bulk density values obtained were judged unsatisfying for the organic soils, where values ranged between 1.15 and 1.50 g cm^{-3}. The bulk density of peat depends on the class and type of peat (degree of humification). In Northern Europe, ombrotrophic peat accumulates as raised moss/bog and blanket bog because of excess precipitation and slow drainage, whereas mineraotrophic peat accumulates in hollows, depressions and basins which receive water draining from surrounding land which does not drain away. Blanket peat forms in the hills and mountains where decomposition of organic material is slowed by cold conditions and raised bog form in the lowlands. Analysis of almost 100 measurements of bulk density in the full range of peat types across Ireland revealed significant differences between the bulk density in the surface horizons (topsoil) compared to the subsurface (subsoil) horizons. A working average of 0.25 g cm^{-3} for the former and of 0.12 g cm^{-3} for the latter were deemed meaningful for Ireland (R. Jones, personal communication). Another review of the literature reports an average bulk density of around 0.1 g cm^{-3} for peat soils


LUCAS
20,000 soil samples
OC measurements
OC < 180 g C kg-1
OC > 180 g C kg-1
C
C
Organic soils
OC measurements
Mineral soils
OC measurements
F
E
D
Logistic
regression
model
OC content
average
values
OC content
prediction
Model
Packing
density
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Rock
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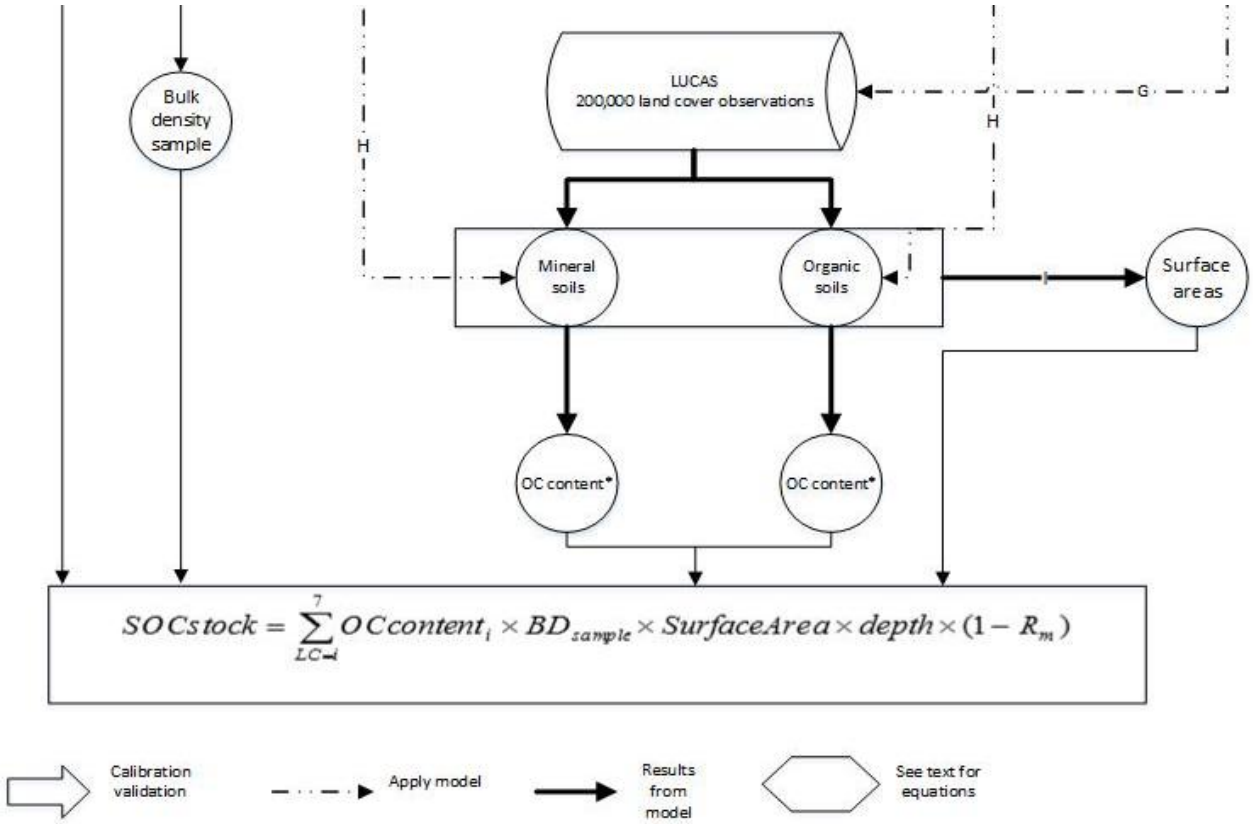

Figure 5-1 Methodology for the calculation of OC stocks, with logical flow indicated by capital letters (A-I).

with minima of 0.062 g cm^{-3} (Tomlinson, 2005). From the conclusions of both above-mentioned studies, it seemed obvious that our predictions were greatly overestimating the bulk density in organic-rich soils and that they had to be modified. It was decided to transform the bulk density of the organic soil samples (OC content > 180 g kg^{-1}) by applying an equation fitted by Hollis *et al.* (2012) (Figure 5-1, letter A):

Equation 5-2

$$BD_{fe} = 1.4903 - 0.33293 * \ln(OC)$$

where OC is the OC content (%).

As the bulk density of the total soil sample (fine earth + rock fragment) is needed to calculate carbon stocks, a last equation was applied (Figure 5-1, letter B):

Equation 5-3

$$BD_{sample} = \frac{1}{\frac{R_m}{BD_r} + \frac{1 - R_m}{BD_{fe}}}$$

where BD_{sample} is the bulk density of the total sample (g cm^{-3}), R_m is the rock fragment content by mass (-), BD_r is the bulk density of the rock fragment (g cm^{-3}) and BD_{fe} is the bulk density of the fine earth (g cm^{-3}).

A value of 2.65 g cm^{-3} was used as an approximation for BD_r as it was not measured. This value corresponds to the bulk density of quartz and is commonly used to substitute BD_r.

Hence,

Equation 5-4

$$BD_{sample} = \frac{1}{\frac{R_m}{2.65} + \frac{1 - R_m}{BD_{fe}}}$$

5.3.2. Prediction models

Topsoil organic carbon content

Firstly, we labelled the LUCAS topsoil samples as mineral (measured OC content < 180 g kg^{-1}) or organic (measured OC content ≥ 180 g kg^{-1}) and created two subsets based on that criterium (Figure 5-1, letter C). The topsoil OC content of mineral and organic soils was then predicted following two different approaches. In the case of *minerals soils*, the subset was split between a calibration set (70%) and a validation set (30%). For every land cover class, three regression models were tested and the best model was selected based on its coefficient of determination (R^2) and root mean squared error (RMSE) (Figure 5-1, letter D). The three models, namely generalised linear model (McCullagh & Nelder, 1989), Cubist (Quinlan, 1992) and generalised additive model (Hastie & Tibshirani, 1986) were tested as they can account for non-linear relationship between the variable to predict and the covariates, and also because they can handle non-normal distributions. This latter fact was of major interest as topsoil OC content does not follow a normal distribution be it in mineral soils or in organic soils. In addition, Cubist and GAM models have been recently used by several authors to predict soil OC content (Bui *et al.*, 2006; Yang *et al.*, 2008; Mayr *et al.*, 2010; Poggio *et al.*, 2013; Roudier *et al.*, 2014).

The covariates were selected by backward stepwise regression, based on the Akaike Information Criterion (AIC) (Akaike, 1974) of the tested models. As for *organic soils,* we decided to use the average measured OC content of the land cover class where the sample falls as prediction (Figure 5-1, letter E). Hence, as many estimators of OC content as the combination of two measured soil classes (mineral vs. organic) and seven land cover classes (cropland, grassland, bareland, woodland, shrubland, permanent crops, wetlands), that is in total fourteen models, were produced.

Occurrence of mineral vs. organic soils

A binary logistic regression model was built to predict the probability of a soil to be organic, as opposed to it being mineral (Figure 5-1, letter F). The probabilities were estimated by maximum likelihood (ML) as a function of the covariates and taking an OC content of 180 g kg^{-1} as a threshold to classify the observed soils as mineral or organic. It is known that the ML estimation of logistic models can suffer from unbalanced populations that is from population where one of the events is rare (King & Zeng, 2001). Because our initial data set encompassed 18,491 mineral soils and only 1,195 organic soils, we decided to fit the model on a sample composed of an even amount of mineral and organic soils. Whilst all the organic samples were kept in the "pool of data", 1,195 mineral samples were randomly selected. The calibration of the logistic regression was performed on 70% of those 2390 samples and 30% were kept aside for the validation procedure. The covariates were selected by backward stepwise procedure based on the AIC of the different models generated. The probabilities generated were used to classify a soil as organic or mineral (hereafter referred to as "soil classes"), choosing a probability of 0.5 as a threshold for the prediction of one or the other class. Predictions on the whole data set were made by re-fitting the model, using only the covariates selected by

the stepwise procedure. It should be underlined here that the OC content prediction models were built on the samples classified as mineral or organic, based on the OC measurements. The results of the logistic regression model were used in a further stage, when predictions at unknown locations were done (Figure 5-1, letter G).

A summary of the observed vs. predicted soil classes was obtained by generating a confusion matrix (Table 5-1). The latter gives a detailed analysis of the classification by reporting the number of true positives (organic soils correctly classified as such), false positives (mineral soils incorrectly classified as organic), true negatives (mineral soils correctly classified as such) and false negatives (organic soils incorrectly classified as mineral).

Table 5-1 Theoretical confusion matrix, as generated in this study.

		OBSERVED	
		Mineral	Organic
PREDICTED	Mineral	True negative (TN)	False negative (FN)
	Organic	False positive (FP)	True positive (TP)

The performance of the model was assessed by calculating the following parameters, directly derived from the results of the confusion matrix (Equation 5-5; Equation 5-6; Equation 5-7):

Equation 5-5

$$Error\ rate = \frac{False\ positives\ (FP) + False\ negatives\ (FN)}{Total}$$

Equation 5-6

$$\boldsymbol{S}ensitivity = \frac{True\ positives\ (TP)}{TP+FN}$$

Equation 5-7

$$\boldsymbol{S}pecificity = \frac{True\ negatives\ (TN)}{TN+FP}$$

The performance of the model was assessed on the full data set, on the entire validation set, and for every land cover class within the validation set.

5.3.3. Soil organic carbon stocks

Samples labeling

To calculate the stocks, we assumed that the LUCAS survey gave a representative picture of the land cover at country scale on the one hand and at EU scale on the other hand. By applying the logistic regression model on the 200,000 locations of the survey, we obtained predictions of soil classes (Figure 5-1, letter G). We then labeled the samples with a combination of their predicted soil class (mineral or organic) and the observed land cover class at that location. Hence, fourteen different labels were created, namely organic*cropland, organic*grassland, organic*bareland, organic*woodland, organic*shrubland, organic*permanent crops, mineral*wetlands, mineral*cropland, mineral*grassland, mineral*bareland, mineral*woodland, mineral*shrubland, mineral*permanent crops, mineral*wetlands.

OC stocks calculation

After having predicted OC content on the predicted mineral or organic soils, by applying the selected models (Figure 5-1, letter H), we could finally calculate the total OC stock in the upper 0-20 cm layer of European soils.

To calculate the OC stock, we firstly had to transform the points (of a support size equals to approximately 12 m^2 as the composite sample was taken on 2m radius around a central point) on which we had worked so far to meaningful spatial units. To do so, we derived from the points' statistics the percentage of the total surface area of every country occupied by each of the fourteen combinations of soil class*land cover (Figure 5-1, letter I). For instance, if country A counted 45,000 observations of which 5000 were labeled as mineral*woodland, we considered that one ninth (5000/45,000) of the national territory was occupied by mineral*woodland soils. These proportions were used to calculate the surface area, in km^2, occupied by the fourteen classes in every country. Taking the example of country A, if its total surface area was of 63000 km^2, mineral*woodland soils were considered to cover 1/9 of it, that is 7000 km^2.

Averages of both predicted OC content and bulk density were calculated for each of the soil class*land cover combinations at national scale. National OC stocks were eventually calculated as follows (Equation 5-8):

Equation 5-8

$$OC\ stock = \sum_{i=1}^{14} SOC_i \cdot BD_{sample} \cdot S_i \cdot d \cdot (1 - R_m) \cdot 10^{-3}$$

where i is the soil class*land cover combination, SOC is the OC content (%), BD_{sample} is the bulk density of the sample (fine earth and rock fragment) (g cm^{-3}), S is the surface area (km^2), d is the sample depth (20 cm) equal to 0.2 m, R_m is the rock fragment content by mass (-).

It should be noted that for these calculations, we considered every country to be fully covered by the soil class*land cover combinations, and we ignored the presence of urban areas, water bodies, and areas above 1,000 m altitude. These assumptions introduce an error in the estimation of the total stocks, expressed in unit of mass (Equation 5-8). However, estimates of stocks expressed as a mass per unit of surface area, are not affected by these assumptions as the surface area is not a factor in the equation.

Stocks per land cover class (expressed in unit of mass), at EU scale, were calculated by summing up national estimates.

Confidence interval

Given the approach followed to derive the soil class (mineral vs/ organic) and to calculate OC estimates for each combination of soil class*land cover, and in order to derive confidence intervals for the mean of estimated OC content for each stratum, a two-stages percentile bootstrap approach was implemented.

The first stage involves the repeated fitting of *n* logistic models using random sampling with replacement of the original population of observations for each stratum. The n models are then used to create a series of classification vectors where the original population observations are classified as, either organic or mineral soils. For each of these vectors the subpopulation of mineral soils is then used in the second stage using it as a sample from which the random sampling with replacement is applied again, this time to fit the regression model

(Cubist, GAM, GLM) predicting the OC content for each observation. The procedure is then repeated m times to gather a final sample of dimension $n \cdot m$. Upon this sample the confidence intervals were calculated using the empirical distribution percentiles.

For organic soils, the procedure is similar but diverges at stage two, as instead of fitting a regression model, distribution statistics are calculated directly from the bootstrapped sampling from the re-classified population.

Mapping OC stocks

OC stocks figures (and their confidence interval) obtained at national scale are reported on a map to illustrate the trends across the European Member States. A map of OC stocks per land cover class could however not be generated as the point-based approach followed for the estimation of the surface areas covered by every land cover class, did not allow the delineation of areas of same land cover. The decision to use land cover data coming from field observations (LUCAS) was motivated by their increased reliability compared to spatially interpolated data (e.g. CORINE).

5.4. RESULTS AND DISCUSSION

5.4.1. Models calibration and validation

GAM, GLM and Cubist regression models were fitted for the prediction of OC content in mineral soils under every land cover type and the most performant models were selected (Table 5-2). Because only 20 topsoil samples were collected in mineral wetlands (Table 5-3), it was decided to calculate an average value of the measured OC content as its predictor. Results showed that the Cubist rule-based regression method outperformed the other models in croplands, that a GLM was selected for predictions in bareland and shrubland whilst a GAM performed the best for predictions in grassland and woodland.

The comparison of the performance of these selected models (Table 5-2) with the performance (on the validation set) of the GAM model used in the previous chapter (Table 4-3) shows a clear advantage in creating a different model for each land cover class for the prediction of OC content in mineral soils. RMSEs obtained by fitting a different model for each land cover class are always lower than with the GAM model. Moreover, the overall R^2 for mineral soils with the GAM is 0.21 (see section 4.4.2) whilst it is 0.59 with the approach followed in the present chapter. The differences in performance observed can easily be explained by two facts. Firstly, the fitting of the GAM model on the whole sample (mineral and organic soils taken together) generated issues for the prediction of mineral soils in Scandinavia (Figure 4-6) and thereby decreased the overall performance of the model for these soils. Secondly, the use of land cover as a discrete covariate in the GAM model allowed accounting for land cover influence on OC content, only in the intercept of the regression curve whilst the fitting of separate models for the different land cover classes allowed

different slopes (and different intercepts) for the regression curves, which led to a better accuracy of the predictions.

The covariates selection procedure retained NPP, temperature and rainfall for all the above-mentioned models (Table 5-4). Moreover, prediction models for cropland, woodland, grassland and permanent crops selected all the covariates as of significant influence,

Table 5-2 Summary table for the goodness-of fit and error of the selected best prediction models for OC content (in mineral soils).

		Calibration		Validation	
Land cover	Model	R^2	RMSE (g C kg^{-1})	R^2	RMSE (g C kg^{-1})
Bareland	GLM	0.26	19.8	0.36	22.8
Cropland	Cubist	0.27	12.1	0.29	10.4
Permanent crops	GAM	0.25	10.1	0.16	9.4
Grassland	GAM	0.25	21.7	0.22	22.7
Shrubland	GLM	0.16	28.1	0.10	28.5
Woodland	GAM	0.17	32.7	0.13	32.3
Overall $R^2 = 0.59$					

Table 5-3 Number of samples and summary statistics of measured and predicted OC content for each soil class*land cover type combination. The soil class has to be understood as "measured" for the LUCAS topsoil survey and "predicted" for the LUCAS general survey (200,000 points).

Soil class	Land cover	n (LUCAS topsoil)	n (LUCAS general survey)	SUMMARY STATISTICS							
				Measured OC (g C kg^{-1})				Predicted OC (g C kg^{-1})			
				Min	mean	Max	St.dev	Min	mean	Max	St.dev
Mineral	Bareland	350	3208	1	17	172	24.6	13	32	47	8.8
Mineral	Cropland	7768	51056	1	17	179	13.2	11	17	29	4.5
Mineral	Permanent crops	1014	9005	1	16	143	11.3	10	23	80	14.6
Mineral	Grassland	4249	39923	1	33	178	25.2	20	33	59	10.8
Mineral	Shrubland	423	10065	1	37	176	31.2	24	41	60	8.5
Mineral	Woodland	4667	40565	1	45	179	35.6	22	46	111	18.4
Mineral	Wetlands	20	134	11	60	156	40.1	-			
Organic	Bareland	8	948	213	322	431	77.6			322	
Organic	Cropland	37	175	181	306	567	103.1			306	
Organic	Permanent crops	0	0	-	-	-	-			-	
Organic	Grassland	131	7928	180	335	543	98.2			335	
Organic	Shrubland	32	5653	182	349	510	108.2			349	
Organic	Woodland	918	41491	180	378	587	109.4			378	
Organic	Wetlands	69	3820	210	453	564	80.8			453	

Table 5-4 Selected covariates for every model. (nr) means not relevant, when no sub-classification of land cover class was available for a particular class.

Covariates	MIN vs. ORG	Mineral bareland	Mineral cropland	Mineral Permanent crops	Mineral grassland	Mineral shrubland	Mineral woodland
Elevation	X		X	X	X		X
Slope		X	X	X	X		X
NPP	X	X	X	X	X	X	X
Rainfall	X		X	X	X	X	X
Temperature	X		X	X	X	X	X
Latitude		X	X	X	X		X
Longitude	X		X	X	X		X
Land cover	X	-	-	-	-	-	-
Sub-levels of Land cover		nr	X	nr	X		X
Soil type Qualifier			X		X		X

whereas shrubland showed a different selection. Soil qualifiers were dismissed for all the models. An overall $R^2 = 0.59$ was obtained for observed mineral soils, whilst in a previous study, we found an overall $R^2_{calibration} = 0.29$ and $R^2_{validation} = 0.27$, whilst an $R^2 = 0.21$ was obtained for mineral soils only (de Brogniez *et al.*, 2014). The methodology followed in this study therefore offers a clear improvement in terms of OC content prediction (Table 5-2).

The logistic regression model was calibrated on 1672 soil samples (836 mineral and 836 organic) and the stepwise procedure selected elevation, NPP, rainfall, temperature, longitude and land cover as predictors (Table 5-4). The validation procedure gave an error rate of 0.20, a sensitivity of 0.87 and a specificity of 0.80. Predictions on the whole data set after re-fitting the model gave similar results, with an error rate of 0.19, a sensibility of 0.88 and a specificity of 0.80 (Table 5-5). These figures demonstrate the overall capability of the logistic regression model to predict the occurrence of both soil classes. The validation procedure also showed that soil classes are best predicted in croplands and permanent crops, where the error rate is equal to zero (Table 5-2). Cultivated topsoils tend to have very low OC content, which resulted in the model to predict, correctly in most cases, a high probability for soil covered by crops to be mineral. The largest error rate (0.58) was observed in woodlands, for which 55% of the soil samples (3029) were taken in Sweden and Finland. Within this land cover class, organic soils were well predicted by the logistic regression model (sensitivity = 0.96), whereas mineral soils' occurrence was poorly predicted (specificity = 0.39). Our analysis of the results for the two Scandinavian countries revealed that although 75% of the samples in woodlands were mineral, all of them were classified as organic. This large amount of misclassified mineral soils can be explained by the fact that 75% of the organic soil samples of the LUCAS survey were taken in Finland and

Table 5-5 Confusion matrices and performance tests parameters. TP= true positives, FN = false negatives, FP = false positives, TN = true negatives.

Data set	TP	FN	FP	TN	Error rate	Sensitivity	Specificity	n
Validation	313	46	3481	14174	0.20	0.87	0.80	18014
Full data set	1040	155	3631	14860	0.19	0.87	0.80	19686
Bareland	0	2	33	302	0.10	0	0.90	337
Cropland	0	7	15	7391	0	0	1.00	7413
Permanent crops	0	0	0	966	0	-	1.00	966
Grassland	16	25	575	3465	0.15	0.39	0.86	4081
Shrubland	9	1	91	318	0.22	0.90	0.78	419
Woodland	271	11	2750	1730	0.58	0.96	0.39	4762
Wetlands	17	0	17	2	0.47	1.00	0.11	36

Sweden. The logistic regression model therefore saw the values taken by the explanatory covariates, such as NPP, temperature and rainfall, in these regions as an "ideal" environment for organic soils and tended to classify most soils in such conditions as organic. Nevertheless, it should be kept in mind that this study aims at proposing a harmonised method for predicting OC stocks at EU scale and the overall performance of the model should therefore take precedence over localised weaknesses. Further work could focus on the creation of a local model for Scandinavia, and thereby on the possibility to obtain a refined logistic regression model for the other countries, as the "bias" towards the Northern latitude would no longer be present.

It is noteworthy that NPP, temperature and rainfall were selected as meaningful covariates for all the models. Climate, usually expressed as temperature and rainfall, has long been recognised as a major soil forming factor (Jenny, 1941) and more specifically as having an effect on soil OC dynamics (Post *et al.*, 1982). NPP is the net production of organic matter by plants in an ecosystem (IPCC, 2000) and is by definition one of the most important component of the carbon cycle in soils. The selection of those three variables in all models is therefore not surprising. On the other hand, the dismissal of the data from the ESDB as covariates is a surprise, as we expected soil reference groups such as Podzols or Histosols and qualifiers such as Histic or Humic to be deemed relevant for our classification. An explanation might be that the (unknown) location within an SMU of the dominant STU, whose properties were extracted, does not necessarily match with the location where the LUCAS sample was taken. Traditional soil mapping used to delineate large areas whose properties were defined by a reference profile. SMUs were delineated by hand, based on expert local knowledge of soil properties and soil forming factors such as topography and the underlying geology. The use of such "units" as

covariates for a point-based digital soil mapping analysis at European scale might therefore not be recommended. In addition, the shallow sampling depth (20 cm) used during the LUCAS survey, and the fact that only one depth was sampled might have failed to highlight differences in OC content between horizons, which are characteristic of some soil types (e.g. Podzols). This probably led to a heterogeneous "picture" of the samples in terms of OC content within SMUs that hampered the model to use the ESDB data.

5.4.2. Predictions

OC content

Table 5-3 presents a summary of the statistical distribution of measured and predicted topsoil OC content. Overall, mean observed and predicted values are similar for all land cover classes, except for bareland. However, the narrower range (higher minima and lower maxima) and smaller standard deviation of predicted OC content as compared to the observations within the different land cover classes stand out. The results of the logistic regression revealed that 75 % of the actual mineral soils predicted as mineral had OC content lower than 28 g C · kg^{-1} (results not shown). We can therefore assume that the points of the LUCAS survey predicted as mineral by the logistic regression model were in environmental conditions (combination of covariates value) that referred to "low" OC content values for the fitted model, which would explain the low maxima. The overall R^2 of predicted OC content on predicted mineral soils is 0.43.

OC stocks

Results at European scale

We computed the descriptive statistics of OC stocks for Europe' soils in tonnes of OC per hectare, taking as spatial unit the combination of land cover*soil

class within countries. The results ranged between 25 t C ha^{-1} (predicted in Greek mineral cropland) and 230 t C ha^{-1} (predicted in Irish mineral woodland). The minimum value we obtain is comparable to the minimum OC stock Doblas-Miranda *et al.* (2013) observed in dry Mediterranean areas (23 t C ha^{-1}). In a study carried out in Ireland, Tomlinson (2005) predicted OC stocks reaching 3000 t C ha^{-1} in peat bogs, which greatly contrasts with our last result. The latter study thoroughly assessed the contribution of peat soil to national stocks and concluded that peat accounts for 53% of Ireland's soil OC stocks. As the full depth of peat bogs, which ranged between 60 cm and 750 cm depending on the peat type, was considered for the assessment, the large difference between the figure we obtained and the Irish one can be explained. However, the mean OC stocks we predicted for Irish organic soils (= 185 t C ha^{-1}) is very similar to the value we can extract from the Irish study, which is approximately 150 t C ha^{-1}. Our national estimates of OC stocks in Ireland are in agreement with the findings of Tomlinson (2005), despite the great difference in depths accounted for in peat soils. At a 20 cm depth, the mean OC stock for Europe was 119 t C ha^{-1} and its median was 105 t C ha^{-1}, whilst 25% (1st quartile) of the areas defined had a stock lower than 64 t C ha^{-1} and 25% (3^{d} quartile) had a stock higher than 185 t C ha^{-1}.

The total OC stocks in the upper 20 cm of European soils were estimated to be equal to 38.3 Gt, with a 95% confidence interval (CI_{95}) ranging between 34.9 and 42.4 Gt (Table 5-6). If we rescale (by simple rule of three) those estimates to the most commonly used 0-30 cm depth for stock calculations, we obtain a global stock of 57.4 Gt (CI_{95} = 52.4-63.6 Gt) (Table 5-6). This stock, calculated for 23 EU countries which occupy 2.7% of the total land area on earth, correspond to 8 % of the global terrestrial carbon stocks as estimated by Batjes (1996) for the upper 30 cm of soils. Similarly, other authors compared their

results with the estimates of Batjes (1996); Tarnocai *et al.* (2009) estimated carbon pools of the northern circumpolar permafrost region to be 191.29 Gt (27% of total stock on 16% of global land area) whilst Viscarra Rossel *et al.* (2014) estimated as stock of 25 Gt for the Australian continent (3.5% of total stock on 5.2% of global land area).

At European scale, the combined work of Jones *et al.* (2005) and Hiederer (2010) is the only other study that estimated OC stocks by country, following a harmonised methodology. Jones *et al.* (2005) applied a pedo-transfer rule on a set of spatial data layers, inferring topsoil OC from the combination of soil properties, land cover and temperature. The calculations were processed on harmonised spatial data layers on a 1 km x 1 km grid. Hiederer (2010) used these OC content estimates combined with bulk density and stone content data extracted from the European soil database to in turn predict national OC stocks for Europe. The authors estimated the total OC stock in the upper layer (0-30 cm) of European soils (23 countries of our study) to be equal to 68.2 Gt, which exceeds by 7.2% the upper limit of our CI_{95} (= 63.6 Gt). Table 5-6 presents, country by country, the national OC stocks from Hiederer (2010) together with our own OC stock estimates and the lower and upper limit of their CI_{95}, all of them adjusted (by rule of three) to a 0-30 cm depth. For the stocks from Hiederer (2010) beyond our CI_{95}, the importance of the under/over estimation as compared to our data was calculated as a percentage of the lower/upper CI_{95} respectively. The results concurred only for Austria and Spain, whilst Poland and Luxembourg showed the worst results with Hiederer (2010) estimating respectively 65% and 50% bigger OC stocks than the upper limit of our CI_{95}. Overall, the average difference between predictions of both studies is 11%, where in most cases we predict lower OC stock values than Hiederer (2010). The coefficient of determination (R^2) for the values

Table 5-6 Summary table presenting OC stocks for the 23 countries of the study. The columns present, from left to right: the predicted OC stocks for the sampling depth (20 cm) with the lower and upper limits of the 95% confidence interval and the uncertainties (calculated as half the CI95 divided by the mean stock); the predicted OC stocks adjusted to a standard 0-30 cm depth with the lower and upper limits of the 95% confidence interval; the OC stocks calculated by Hiederer (2010).

	Stocks (0-20 cm)					Stocks (adjusted to 0-30 cm)			Hiederer	Standardised difference between the estimates of Hiederer and ours
Country	Lower limit CI_{95} (Gt C)	Mean stock (Gt C)	Upper limit CI_{95} (Gt C)	Uncer-tainty (%)	Stock (t ha^{-1})	Lower limit CI_{95}	Mean stock	Upper limit CI_{95}		
AT	0.69	0.82	1.03	20.4	97	1.04	1.24	1.54	1.20	0.0
BE	0.24	0.26	0.29	9.9	84	0.35	0.39	0.43	0.30	-14.9
CZ	0.48	0.54	0.61	12.3	68	0.71	0.81	0.91	1.10	20.5
DE	2.68	2.96	3.29	10.3	83	4.02	4.44	4.94	5.80	17.4
DK	0.42	0.45	0.48	7.6	103	0.63	0.67	0.73	0.60	-4.0
EE	0.66	0.68	0.71	3.4	150	0.99	1.02	1.06	1.50	41.7
ES	1.90	2.33	2.84	20.1	45	2.85	3.49	4.25	3.50	0.0
FI	5.54	5.74	5.94	3.4	169	8.32	8.60	8.90	12.50	40.4
FR	3.72	4.24	4.88	13.6	66	5.59	6.36	7.32	5.00	-10.5
GR	0.51	0.64	0.84	25.2	48	0.77	0.97	1.25	0.60	-21.7
HU	0.39	0.43	0.49	11.7	47	0.58	0.65	0.73	1.00	36.7
IE	1.07	1.14	1.22	6.5	162	1.60	1.71	1.82	1.60	-0.1
IT	1.37	1.70	2.20	24.5	56	2.05	2.55	3.30	2.00	-2.5

LT	0.60	0.64	0.68	5.8	98	0.91	0.96	1.02	1.10	8.2
LU	0.018	0.020	0.022	10.4	76	0.027	0.03	0.033	0.05	50.4
LV	0.83	0.87	0.90	4.3	134	1.25	1.30	1.36	1.80	32.7
NL	0.35	0.38	0.41	8.2	101	0.52	0.56	0.61	0.80	30.1
PL	1.88	2.06	2.26	9.1	66	2.82	3.09	3.39	5.60	65.4
PT	0.44	0.53	0.64	18.8	56	0.66	0.79	0.95	0.50	-23.8
SE	7.59	7.84	8.09	3.2	174	11.39	11.76	12.13	13.80	13.7
SI	0.19	0.22	0.26	14.1	108	0.29	0.33	0.38	0.20	-47.8
SK	0.27	0.31	0.35	13.4	62	0.40	0.46	0.53	0.60	13.6
UK	3.16	3.48	4.00	12.2	142	4.74	5.22	6.00	7.10	18.3
TOTAL	34.9	38.3	42.4			52.5	57.4	63.6	68.25	

predicted by each study equals 0.94 for the national predictions (Figure 5-2). The potential source of discrepancies between the two studies are manifold: the origin and type of soil data, the methods applied to calculate OC content and bulk density, the resolution of spatial data layers do all contribute to the differences observed. Hiederer (2010) used a pedo-transfer rule developed by expert knowledge to predict OC content by harmonising measurements stored in national soil databases, whilst we developed regression models. The OC contents had been validated (Jones *et al.*, 2005) against soil profile data originating from an inventory at 5 km interval across England and Wales (> 5500 points) and a survey of agricultural soils in Italy (6779 points), whereas we calibrated and validated our model on ca. 20,000 soil samples taken across Europe.

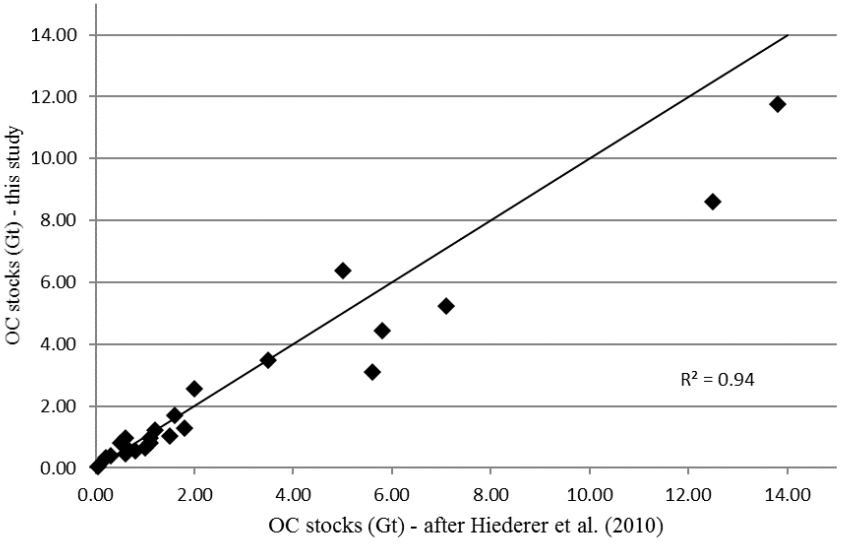

Figure 5-2 Comparison of the national OC stocks (Gt) at a 0-30 cm depth, as predicted in the present study and by Hiederer (2010). The line with equation y = x shows that our analysis underestimates the larger OC stocks as compared to Hiederer. R^2 is the coefficient of determination.

Results at country scale

Table 5-6, Figure 5-3 and Figure 5-4 summarise the predictions obtained at country scale and reveal that the country with the largest predicted OC stock was Sweden, with about 20% of Europe's total OC stock stored in its topsoil (174 t C ha^{-1} and 7.8 Gt, with CI_{95} = 7.6-8.1 Gt). Sweden is followed by Finland with 15% (169 t C ha^{-1} and 5.7 Gt, with CI_{95} = 5.5-5.9 Gt) of the EU total OC stocks. These are situated in the most Northern latitudes of Europe, where climate is cold. These climatic conditions lead to slow rates of C mineralisation and therefore boost C sequestration in soils. With a total surface area of almost 450,000 km^2, Sweden is the third biggest country in the 23 participating countries, coming after France (ca. 552, 000 km^2) and Spain (ca. 506,000 km^2). We estimated that 92% of the Swedish territory is occupied by organic soils, whereas national experts (Berglund & Berglund, 2010) stated that about 25% of the territory is covered by peat. Although not all organic soils are necessarily classed peat soils, we should assume that our study largely overestimates the area of organic soils in Sweden and that, as already exposed, this is a result of the logistic regression model we fitted (see section "Models calibration and validation"). We consequently should assume that national OC stocks for Sweden are also largely overestimated in our study. However, no values of stocks estimated with national OC stocks data for Sweden could be found in the literature to compare with our results. As the present study aims at proposing a harmonised method for predicting OC stocks at EU scale, it appears that it will inevitably result in national totals being different from estimated OC stocks based on national data sets.

Countries with the smallest OC stocks (Table 5-6; Figure 5-4) were Luxembourg (20 Mt), Slovenia (221 Mt) and Belgium (259 Mt). These countries are the smallest of the 23 participating to our study, and they are not known for

having large areas of organic soils, which explains their small OC stocks. In terms of stocks expressed per unit of surface area, Spain (45 t C ha^{-1}), Hungary (47 t C ha^{-1}), Greece (48 t C ha^{-1}) and Italy (56 t C ha^{-1}) showed the lowest values for the upper 20 cm of soils (Table 5-6; Figure 5-3). The low ranking of Mediterranean countries is explained by the high rock fragment content predicted in the soils of these regions, as well as by their low OC content (de Brogniez *et al.*, 2014). However, it is important to underline that areas above 1,000m altitude were not sampled during the LUCAS survey. Low OC stocks in Spain, Greece and Italy therefore result from calculations made regardless of their vast areas of mountain ranges (Pyrenees, Pindos, Alps and Apennines) which are known to store a lot of carbon in their soils. The absence of data from the main European mountain ranges such as the Alps, the Pyrenees, the Pindos and the Carpathians is therefore to be born in mind as a source of underestimation of the total OC stocks in this study.

The uncertainties of our estimates at national scale (Table 5-6; Figure 5-4) calculated as half of the CI_{95} divided by the mean OC stock, were small for northern European countries and large for Mediterranean countries. Because we can see the outcome of the bootstrap as the overlapping of two different continuous distributions, a difference in their frequencies will affect the estimation of the confidence interval. If for instance we were to classify every sample as mineral, we would have a distribution with a range from 1 to 180 g C kg^{-1}. Elsewise, if the model predicts an even number of organic and mineral soils, the potential range of the data goes from 1 to 600 g C kg^{-1}. Hence, the largest uncertainty will be observed if we obtain an even population, made of similar amounts of organic and mineral soils. So, in the case of northern European countries were we showed (see section "Models calibration and validation") that most soils were misclassified as organic, we obtain a narrow

confidence interval. In addition, since the uncertainty was standardised by the mean predicted value (high in Scandinavia), the range observed is even lower. In contrast, in Mediterranean countries where we know that soils were mostly classified correctly, the uncertainty comes from the wide range of OC content generated by the higher variability in land cover and environmental conditions encountered.

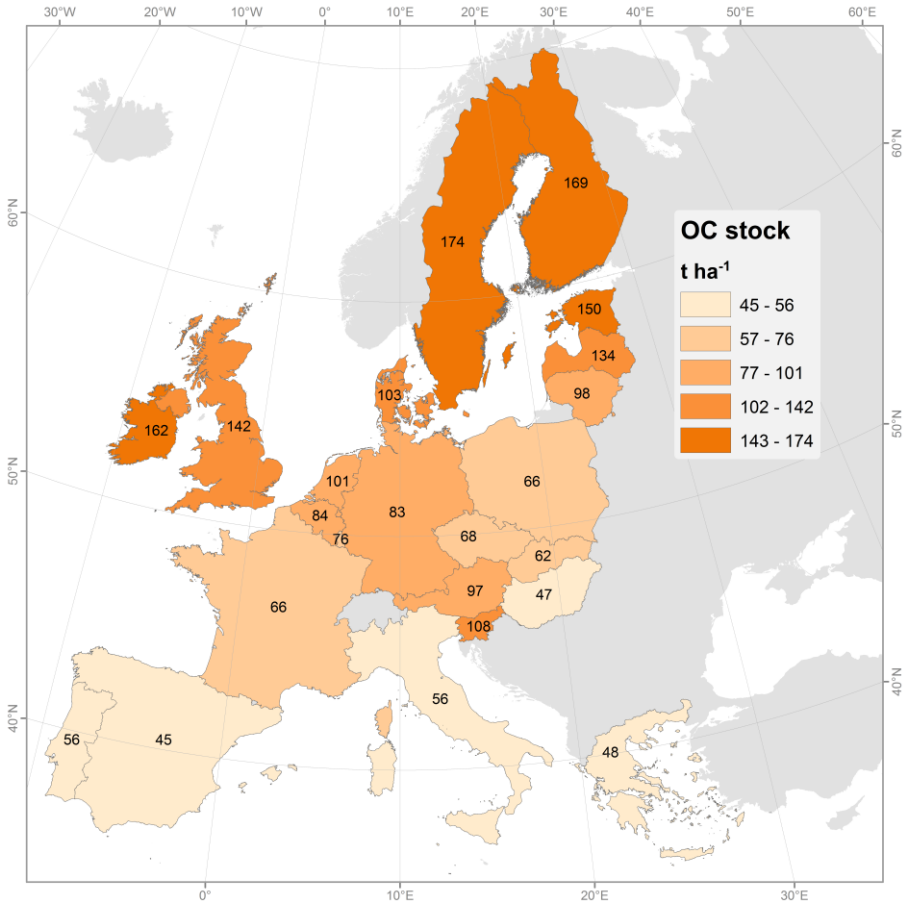

Figure 5-3 National OC stocks in t C ha^{-1}.

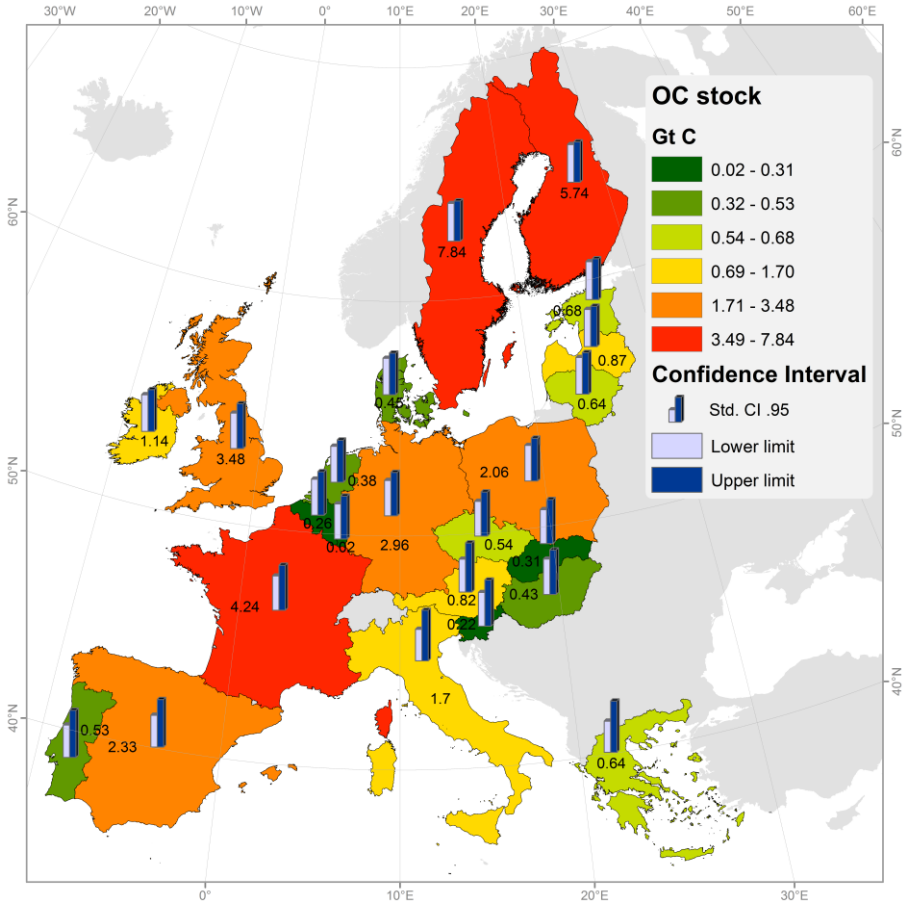

Figure 5-4 National OC stocks in Gt C with bars showing the lower and upper limit of the 95% standardised confidence interval.

On average, the uncertainty of the estimates at national scale were ± 11.7% and ranged between ± 3.4% and ± 25.2% of the mean OC stock. In similar studies, Martin *et al.* (2011) and Viscara-Rossel *et al.* (2014) found uncertainties equal to ± 25% of their estimates, whilst Krogh *et al.* (2003) and Lettens *et al.* (2005) found an uncertainty of ± 4% and ± 0.9% respectively. In contrast, the studies

realised by Hiederer (2010) and Tomlinson (2005) did not provide any confidence interval or estimator of predictions' reliability. Most studies aiming at the prediction of soil OC stocks face the challenge of validating results because soil measurements of OC stocks are rarely (if ever) available. Consequently, the researchers are left to either assess the uncertainty of their estimates based on the quality of the input data to their models (Lugato *et al.*, 2014), or to simply not estimate the uncertainty.

Although most countries in Europe carry out research projects aiming at predicting national soil OC stocks, notably within the context of the national inventory report for greenhouse gas emission, only a few of them are published in scientific literature (Krogh *et al.*, 2003; Tomlinson, 2005; Bradley *et al.*, 2005; Lettens *et al.*, 2005; Martin *et al.*, 2011). An in-depth comparison of published national findings with our results was considered outside the scope of this study.

Results per land cover type

Land use and land cover are widely recognised as amongst the main factors influencing OC content and stocks in soils. Whilst the former can be defined as the socioeconomic use made of land (for example, agriculture, commerce, residential use or recreation), the latter is generally understood as the bio-physical coverage of land (for example, crops, forest, buildings or roads). Both factors are connected as a change in land use generally implies a change in land cover, which in turn affects the plant community as well as soil conditions and therefore the C cycle in soils (Batjes, 1996; Bolin & Sukumar, 2000). Land management practices, associated with a certain land use/land cover combination, have also been demonstrated to greatly influence OC stocks (van Wesemael *et al.*, 2010). Several agro-ecosystem models such as Century (Parton

et al., 1987) and RothC (Coleman & Jenkinson, 1996) were developed to simulate C dynamics in different land use and in different ecosystems. These models are able to account for land use change and produce long-term prediction scenarios of OC stocks. Regression-based techniques, as applied in this study, have also been widely used in the literature (Smith *et al.*, 2000; Grimm *et al.*, 2008; Martin *et al.*, 2011; Viscarra Rossel *et al.*, 2014).

Our results gave woodlands as the largest topsoil OC pool in the EU, with a total of 20.6 Gt (CI_{95} = ± 7%), which correspond to 54% of the total estimated stock in Europe (Table 5-7). Woodlands, which occupy 38% of the European territory ($1.56*10^6$ km^2), are consequently the primary store of OC stocks in Europe. Baritz *et al.* (2010) also highlighted the major importance of forest soils for the terrestrial carbon pool in Europe, as compared to agricultural soils with much lower OC contents. These authors analysed the data from the ICP-Forests soil condition inventory which is, to date, the only project that attempted to build a harmonised database for forest soils in Europe.

Despite the availability of a manual with recommended procedures for soil sampling and laboratory analysis, various national modifications of the scheme proposed by the ICP – Forests inventory were implemented and introduced systematic errors in the data reported. This again, demonstrated how challenging it is to establish a harmonised soil-monitoring scheme at large scale. Nevertheless, Baritz *et al.* (2010) developed several techniques to render the heterogeneous data provided by the countries comparable. One of their main findings was that the investigation of topsoil only was not sufficient to understand regional patterns of OC (in forests) as some soils, such as Podzols and Luvisols that accumulate carbon in the subsoil, may appear poorer in carbon than shallow soils with an organic-rich topsoil. Also, the authors

Table 5-7 Summary table of the OC stocks predictions (Gt) per land cover at 20 cm depth. The lower and upper limit of the 95% confidence interval (Gt), the calculated uncertainty, the occupied surface area (km2) and the OC stock (t ha^{-1}) are also presented.

	Lower limit CI_{95} (Gt)	Mean stock (Gt)	Upper limit CI_{95} (Gt)	Uncer-tainty (%)	Occupied surface area (km^2)	Stock (t ha^{-1})
Bareland	0,50	0,650	0,80	22,66	77019	84,26
Cropland	3,40	3,82	4,34	12,32	971466	39,35
Grassland	7,58	8,42	9,48	11,24	908453	92,74
Permanent crops	0,49	0,62	0,91	33,70	166398	37,38
Shrubland	2,83	3,16	3,51	10,79	294837	107,26
Wetlands	0,97	1,00	1,03	3,41	73045	137,17
Woodland	19,22	20,59	22,33	7,55	1561702	131,84
Total		38.3				

concluded that large C terrestrial pools are located in the European mountain ranges. These two aspects are important because LUCAS soil samples were taken down only to a depth of 20 cm and at altitudes lower than 1,000 m. Whilst the lowest stocks were predicted in permanent croplands with 0.62 Gt ± 34%, woodlands are followed by grasslands and croplands, which account for 22% (8.4 Gt ± 11%) and 10% (3.8 Gt ± 12%) of EU OC stocks respectively (Table 5-7). In the literature, analysis of OC stocks for agricultural soils (van Wesemael *et al.*, 2010; Romanyà & Rovira, 2011; Lugato *et al.*, 2014) usually combines stocks calculated for grasslands (agricultural grasslands only), croplands and permanent croplands (orchards, vineyards and olive groves). In the context of the LUCAS survey, grasslands encompass pastures, grassland under permanent-crops, temporary and artificial grassland, as well as natural grasslands and fallows; comparison of our results with studies for agricultural

soils should be viewed, keeping in mind the more extensive "grassland" pool in our calculations. If we adjust our results for a 0-30 cm depth, we obtain OC stock of 59 t C ha^{-1}, 56 t C ha^{-1} and 139 t C ha^{-1} for cropland, permanent crops and grasslands respectively. These values are very similar to those simulated by Lugato *et al.* (2014), who ran the agro-ecosystem model Century on almost 164,000 soil-climate-land use combinations to produce OC stocks estimates for agricultural land in Europe. They obtained a total OC stock of 15.48 Gt for the same 23 countries as in our study, which is approximately 25% lower than the total agricultural stock of 19.31 Gt we found. Figure 5-5 (top-graph) shows that our national estimates are mostly similar to those of Lugato *et al.* (2014) but that in a few cases, we indeed predict higher stocks. Those values could probably be explained by the wider definition of grasslands we adopted, which artificially increases the agricultural carbon pool. Also, as Lugato *et al.* (2014) carried out their study using CORINE land cover which has a specific class for moors and heathlands, we can hypothesise that very few, if any, organic soils were accounted for whilst we considered agricultural land covers, regardless of the soils.

Lugato *et al.* (2014) estimated the European agricultural land to be of 138 Mha, whilst we found 189 Mha of agricultural land on mineral soils, and 16 Mha on organic soils. The latter figures show that a comparison of both studies using our results for mineral soils only might be a good thing. Indeed, we obtained a total agricultural soils' stock of 14.65 Gt on mineral soils, which is much more similar to what Lugato *et al.* (2014) found (Table 5-6). Coefficients of determination (R^2) between both studies were calculated to be 0.96 when all soils are considered and 0.85 for mineral soils only (Figure 5-5). The complete removal of grasslands in our study leads to a drastic drop of the coefficient of determination ($R^2 = 0.67$) observed.

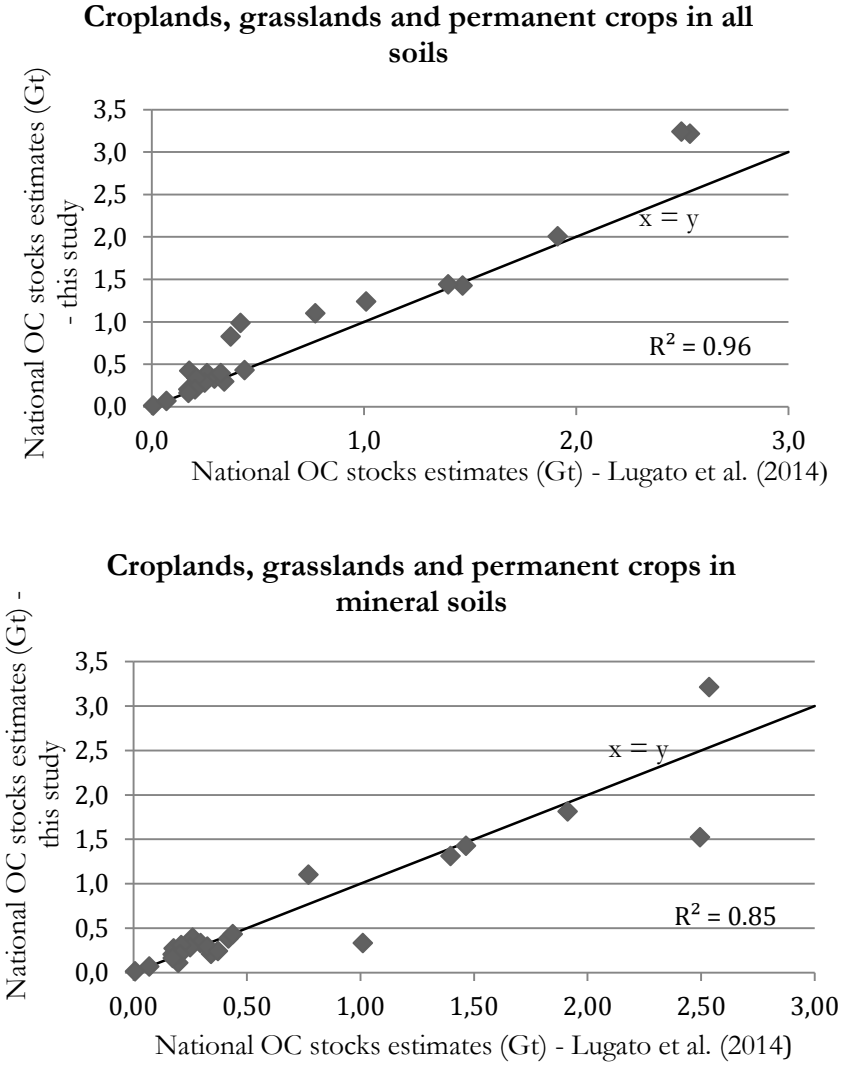

Figure 5-5 Comparison of the OC stocks (Gt) predictions for a 30 cm depth made by Lugato et al. (2014) for the agricultural soils of Europe and the predictions made in this study. The graph at the top illustrates our stocks estimates in croplands, grasslands and permanent crops on all soils; whilst the bottom-graph shows our results in mineral soils only. R^2 is the coefficient of determination.

Soils under permanent crops and bareland have the highest uncertainties (Table 5-7). The former encompass orchards, berries, olive groves, vineyards and nurseries according to the LUCAS survey nomenclature. Such crops are usually managed by leaving strips of bare ground between and around the rows of trees, which can cause a rather great variety of OC content measured in the soils, whether the sample is taken under the tree, or in between rows. As far as bareland is concerned, it has no dominant vegetation on at least 50% of its area and includes "ecosystems' as diverse as surfaces covered by mosses and lichens, bare arable land, temporarily unstocked areas within forests, tidal areas, etc. The wide range of land use "history" that possibly relates to a bare land explains how difficult it is to predict its OC level with accuracy. A fallow land with crop residues or a bare arable land ploughed and ready for seeding will certainly have different OC content than a tidal surface or a clear-cut on a previously forested soil.

For more detailed results, we refer the reader to Appendix C, where predictions per country, land cover type and soil class are given.

5.5. CONCLUSION

In this study, we proposed a baseline estimate of soil OC stocks in Europe for the year 2009, which we generated by following a different approach for mineral and organic soils. For the first time in the EU, a harmonised topsoil and land cover database was used to produce OC stocks estimates, which allowed a meaningful comparison of our results across countries and land cover classes. Also, as we compared our results with those of other EU studies, we saw that orders of magnitudes and "contributions" of countries/land cover classes to the total carbon pool were generally very similar, despite the different

approaches followed. Our methodology however showed some limitations in Northern Europe where the majority of the organic samples of the EU-wide survey were taken. This most likely led to a great overestimation of the OC stocks in those latitudes. The lack of availability of a very detailed map locating organic soils remains a major constraint for the spatial study of soil OC (ESDB map was tested but gave no significant result). For our predictions, we were able to define a 95% confidence interval which gives an indication on the uncertainty of our estimates. Overall, the approach we followed for mineral soils, using a different model for each land cover class, gave good results in the validation procedure and we would encourage its application in studies focussing on mineral soils only.

The calculation of OC stocks crucially depends on bulk density, soil depth and stone content. These parameters are however rarely measured consistently (if ever) in soil surveys and they have to be estimated, which introduces significant uncertainty in the estimation of OC stocks for large areas (e.g, at regional and national level). Bulk density is ephemeral as it changes significantly with management and climatic pressures, and accurate estimates should ideally be revised frequently. Soil depth is key to calculating stocks and, although there have been debates on whether to work on topsoil or surface soil depth, a fixed topsoil depth (e.g. 20 cm or 30 cm) is traditionally chosen for comparative purposes. However, the dynamic nature of surface bulk density has triggered another debate on whether to use the soil surface as a datum for the monitoring of OC stocks over space and time. Ellert *et al.* (2002) demonstrated that the assessment of OC stock changes on the basis of equivalent soil mass, by an adjustment of the soil thickness, might be more accurate. Measurements of stone content for areas of land are even scarcer than for bulk density and soil depth and their estimates, rarely validated against measurements, are usually

considered even more inaccurate than those of bulk density and soil depth. To these limitations, we should add the lack of precise data on the extent and depth of organic soils (peat and peaty topped soils), which show different OC dynamics than mineral soils and should therefore be approached differently for stock estimates. It seems reasonable to assume that the organic material at depth is likely to be subject to more change than mineral soil material at the same depth. Furthermore, the bulk density of peat soil material (0.04 to 0.50 g cm^{-3}) is much smaller and the range much less than in mineral soils (1.1 to 1.8 g cm^{-3}) (B. Jones, personal communication). Thus with a much smaller bulk density, heat transfer is much faster in peat than in mineral material which influences greatly C mineralisation rate and therefore emissions. Taking all the above-mentioned considerations into account, there seems to be some merit in either following the equivalent mass method of soil sampling when possible, or in restricting the calculation of OC stocks present in a fixed depth of soil, which we did in the present study (0 - 20 cm). In general, we would consider that topsoil OC only is worth monitoring because the amount of carbon per unit depth is much less in the subsoil than in topsoil and because likelihood of changes in subsoil OC content is much less than in topsoil (except in organic soils). Moreover, the topsoil layer is after all the soil material most prone to the effects of climate change. In addition, when accurate *in-situ* measurements of bulk density are lacking, it may be expedient to use average bulk densities for mineral (e.g. 1.3 g cm^{-3}) and organic (e.g. 0.25 g cm^{-3}) topsoils rather than use complex pedo-transfer functions to estimate bulk density which can have large uncertainty. Nevertheless, no matter what technique is implemented for the calculations of stocks, these generally highly uncertain estimates should be interpreted carefully, keeping the various sources of uncertainties in mind.

At a time when mitigation and adaptation strategies to climate change are sought by policy-makers around the globe, values of soil OC stocks should be regarded as indicators of the status of soil carbon pools and their potential to sequester carbon. Given the large sources of uncertainties to stocks estimates, what is important is not particularly their value per se but the possibility to produce comparable estimates across countries and over time. The creation of soil monitoring networks where measures of OC content (at a constant depth) are recorded to consistently account for the spatial and temporal variability of those parameters is therefore of major importance for the assessment of terrestrial carbon pools. In the European context, the re-conduction of the LUCAS survey scheduled for 2015 will allow updating the baseline we've produced here for the year 2009, and the differences observed will help assessing the effect of land cover change on soils carbon pools.

CONCLUSION

MAIN FINDINGS

As the importance of soil OC for ecosystem services and for mitigating climate change is now clear, the establishment of baseline values to support strategic environmental management through sound decision making at national and international level is needed. However, the large spatial variability of soil OC, together with its slow turn-over, which requires long-term planning of monitoring systems, make cost-effective and reliable evaluations of soil OC difficult. Both mapping and accounting help gaining knowledge on the status of OC in soils; whilst mapping attempts to give a representation of the spatial distribution of OC in soils, accounting aims at estimating the total amount of OC in soils, for a particular depth and over a defined area (Minasny *et al.*, 2013). Knowing the spatial distribution of soil OC can help delineate areas, on the verge of or undergoing degradation, whereas the quantification of OC stored in soils relates to the potential of soils to sequester OC and thereby plays a crucial role in greenhouse gases balance.

In the EU, the absence of a geo-referenced and harmonised data set on soil OC has hampered a comprehensive assessment of the status of OC in European soils during the past 40 years. We aimed at producing the most up-to-date estimates of topsoil OC content and stocks for 25 countries of the European Union. The following sections explain how the three specific objectives defined at the beginning of the thesis were met.

1. BUILD A HARMONISED SPATIAL DATABASE AT EUROPEAN SCALE

The study of the spatial distribution and the prediction of a soil property requires the creation of a spatial soil information system. This consists in a geo-referenced soil database, linked to an attribute database containing measured values of the particular soil property together with predictive environmental covariates, relevant to the predictive process and available for the area of interest (Lagacherie & McBratney, 2007). This study used a combination of geo-referenced point data (lab analyses of the topsoil samples) collected during the LUCAS survey and 11 spatially continuous environmental data layers (covariates) relevant for the prediction of topsoil OC. Regression models were based on the extracted values of the covariates at the topsoil sampling locations, while the spatially exhaustive rasters were only used for the creation of maps. The selection of covariates was restricted by the need to have data layers that fully covered the study area and were relevant to the year of topsoil sampling (2009). The creation of such a spatial information system is an asset for future work as it will allow the addition of new data and it thereby forms the basis of a dynamic soil information system for Europe. Moreover, as the system is built as a simple matrix whose rows correspond to a specific location, the data set can be passed on to scientists from other fields to carry out their own research.

2. PREDICT AND REPRESENT THE SPATIAL DISTRIBUTION OF TOPSOIL OC CONTENT IN EUROPE, TOGETHER WITH ASSOCIATED UNCERTAINTIES

The first attempt (chapter 3) to represent the spatial distribution of topsoil OC content (and the uncertainties associated with the predictions) was made by applying a multiple linear regression between measured soil OC and the environmental covariates and by kriging the residuals of that regression, with the OC content predictions resulting from the addition of both models' results.

The second attempt (chapter 4) was made by applying a Generalised Additive Model (GAM) to the same set of soil and environmental data.

In both chapters, topography (elevation and slope), land cover and temperature were selected as the most significant covariates. This corroborates the findings of Minasny *et al.* (2013) who showed that land use/cover and topographic features were generally preferred for mapping of topsoil OC. The relevance of these variables for explaining the variability of soil OC across Europe has been extensively explained in the different chapters, and references to reviews are given. However, it is appropriate to highlight the particular relevance of temperature and land cover in the context of future climatic and demographic conditions. Davidson & Janssens (2006) showed that the importance of temperature on soil OC dynamics, an effect that is likely to increase with global warming; soils that are under current climatic conditions either waterlogged (peat) or frozen (permafrost) will release substantial amounts of CO_2 as their upper layers dry out or thaw. Moreover, growing world population will undoubtedly result in increasing conversions of natural or semi-natural land to arable land or urbanised areas, which in turn will translate into inevitable losses of soil OC.

The amount of topsoil OC content was shown to increase with latitude in Europe on both prediction maps, which corroborated the findings of Jones *et al.* (2005) and the current knowledge on soil OC status across Europe. Low OC content was consistently observed in croplands whilst high OC content was unsurprisingly predicted in woodlands and wetlands. Intensive agricultural systems that are widespread across Europe, and the potential effect of land conversion to cropland, are clearly identified here as a cause of low OC content in soils. On the other hand, the results suggest that the preservation of moors and heathlands, as well as of forests, would encourage the sequestration of C in soils.

Results showed that the GAM performed better ($R^2_{validation}$ = 0.27) than the regression kriging technique ($R^2_{validation}$ = 0.12) and this is most probably due to the fact that GAM can capture the non-linear relationship between soil OC and covariates, which are most likely to occur in nature. Moreover, the bi-modality of the frequency distribution of OC content in the topsoils of Europe, with the majority of samples being taken in mineral soils, resulted in the underestimation the OC content of organic soils by both models and in the generation of large uncertainties in areas where organic soils mostly occur (Scandinavia, UK, Ireland). Low uncertainties were found in croplands. This latest finding suggested that the study of mineral and organic soils should be done separately.

3. PROPOSE A METHOD FOR THE QUANTIFICATION OF THE SIZE OF OC POOLS IN EUROPE.

Chapter 5 proposes a methodology for the calculation of OC stocks (Figure 5-1) in Europe, with a confidence interval associated with the predictions. The method, based on soil and land cover statistics of data collected at geo-referenced locations, is flexible and applicable to any spatial unit of interest. The OC stocks were calculated for countries and for land cover classes throughout Europe, but they could have been obtained just as easily for NUTS areas or for other delineated areas of particular interest such as national parks, as long as at least one sample was taken there.

Net Primary Productivity (NPP), temperature and rainfall were selected as meaningful covariates for all models, whilst data extracted from the European Soil Database (ESDB) were excluded because the use of relatively large spatial units such as SMUs (which represent a group of soil associations) might not be relevant for point-based statistical analyses. The total OC stock in Europe of 38.3 Gt (CI_{95}: 34.9 – 42.4) was predicted for the reference topsoil depth (0-20 cm). One third of that stock was found to be stored in Finland and Sweden, and woodlands were identified as the land cover storing the largest OC pool of 20.6 Gt (CI_{95} ± 7%). Overall, the predictions and their confidence intervals

obtained for the 23 countries and for main land cover classes were of similar order of magnitude to those found in studies conducted at national or EU scale. The use of a logistic regression model to predict the occurrence of mineral or organic soils gave good results except in woodlands where mineral soils were most of the time misclassified as organic. This was explained by the high frequency of organic soils sampled in woodlands which "biased" the logistic regression model. Building separate models for land cover classes in mineral soils allowed the prediction performance to increase and therefore this practice is to be recommended.

LIMITATIONS

A series of constraints beset the objectives of this study and these are outlined below.

Most constraints were related to the use of topsoil data originating from the LUCAS survey 2009. First of all, no topsoil samples were taken above 1,000 m altitude, mostly corresponding to extensive areas in the Alps, Apennines, Pyrenees, Pyndus, Central Massif and Sierra Nevada. Mountain soils are likely to accumulate substantial amounts of OC because cold temperatures limit mineralisation of carbon (Sjögersten *et al.*, 2011). It can therefore be expected that the accounting of soils above 1,000 m altitude in the Alps would have led to higher total estimates of OC stocks for Europe. Moreover, as climate change predictions suggest that European mountains will experience increasing warming in the next century (Nogués-Bravo *et al.*, 2007), the monitoring of the OC status of their soils should be encouraged.

Secondly, the absence of measurements of bulk density for the LUCAS topsoil samples was seen as a major impediment to the calculations of OC stocks. This issue is discussed in the conclusion of chapter 5. Thirdly, the fact that no resampling campaign of the LUCAS survey was conducted (in 2009) prevented

us from performing an independent validation of our predictions. Finally, the low density of soil sampling based on the 2 km x 2 km LUCAS original grid, coupled with the relatively coarse resolution of the covariates (500m) jeopardised our ability to model, understand and therefore explain the spatial variability of soil OC at short range. Any variation arising from the intrinsic variability of soil OC (random variability) or from environmental factors whose effects operate at distances shorter than the spatial resolution and minimum sampling distance cannot be captured by the spatial model and is therefore excluded from the assessment (Lagacherie & McBratney, 2007). Whilst McBratney & Pringle (1999) found that the spatial correlation of soil OC within a field is between 20 and 300 m, Minasny *et al.* (2013) showed that the spatial variation of soil OC, as observed on a variogram, depends on the extent of the study area. At large scale, it seems likely that the theoretical variogram of soil OC never reaches a steady-stationarity, but is instead made of a series of "plateaus". Each of these plateaus illustrates the consistent influence of an environmental factor on OC levels at a certain scale.

Besides all the constraints related to the LUCAS survey itself, our investigation was often limited by the lack of a detailed map delineating organic soils in Europe. The use of dominant soil types and soil qualifiers extracted from the European Soil DataBase (ESDB) did not give significant results and no other data layer at EU scale was found in the literature. As organic soils show different OC dynamics than mineral soils, which was clearly highlighted in this research, their study should be approached differently. The selection of covariates and most importantly, the design of soil sampling strategies targeting the assessment of OC conditions in either mineral or organic soils is essential.

Last but not least, a broader limitation concerns the use of this thesis' outputs and is related to the interpretation of the models accuracy and uncertainty by a broad range of end-users (policy-makers, land planners, farmers, scientists with a different expertise, etc.). Because scientific literature (including this work)

generally targets an audience of peers, an in-depth discussion of the meaning of values such as RMSEs or standard errors is often overlooked. The RMSEs tell us how well the predicted values match the measured values, i.e. the accuracy of the prediction model. A graph plotting predicted vs. observed values should always be provided with the results as it illustrates what part of the sample is well predicted and whether some part of it is under- or over-predicted. As for the standard error, it relates the variability of the input data with the variability of the predicted mean output value (OC content in our case), i.e. the uncertainty of the model. A thorough understanding of these model evaluation parameters is crucial for a careful use and interpretation of the model outputs.

OUTLOOK

This study has produced estimates of topsoil OC stocks and has illustrated the spatial distribution of topsoil OC content based on laboratory measurements in 25 Member States of the European Union, establishing a baseline for the year 2009. Trends at continental and national scale were highlighted and they are deemed relevant for policy areas, particularly agriculture and environment. Moreover, the use of the spatial database resulting from this research as an input for large scale studies focussing on environmental management and food security should be promoted. The maps produced may allow the delineation of vulnerable areas, typically those with low OC content, where "good" management should be implemented in order to prevent further degradation going past a point of no return. The management of areas with high OC content should also be a priority in the context of climate change mitigation strategies, but also for the benefit of the environment as a whole.

This research has highlighted the importance of sampling soils in the field using standard protocols and methods of analysis. Land above 1000 m in altitude must be sampled in the next LUCAS survey if the distribution of the OC content in soils of the whole of Europe is to be determined. This is essential to

obtain more accurate estimates of OC stocks in Europe. Likewise, the measurement of bulk density and subsoil sampling should enhance our ability to accurately and comprehensively estimate total OC stocks in Europe, although this would be impractical in the context of a rapid and large-scale survey such as the LUCAS.

This research also highlights the importance of establishing a comprehensive soil monitoring system for Europe. When the repetition of the soil component of the LUCAS survey is planned, special emphasis should be put on the use of the same sampling and analytical protocols in order to obtain the first time series of comparable soil data across Europe. Moreover, to make sure that the next sample is as equally representative of EU soils as the LUCAS 2009 data, re-sampling as close as possible to the same locations is essential. Research has already shown that a sampling interval of 10 years is appropriate for soil OC (Arrouays *et al.*, 2008b) and this should be kept in mind when the analyses of the LUCAS 2015 topsoil samples will be made available. If no better resolution of covariates and if no new data relevant for the study of OC are available, the reproduction of maps and the re-calculation of OC stocks using spatial interpolation techniques at EU scale will most probably show similar, if not identical, results as those produced in this thesis. However, this assumption should be verified by comparing the distribution of the OC content data from 2009 and 2015. The use of cumulative distribution functions or histograms, together with basic descriptive statistics will allow this comparison and should determine the next step of the study. If the distributions of measured OC content data are identical, and if the same covariates as in 2009 are available, the creation of new models and maps of OC content will most probably be a waste of time. In this case, we'd advise a second-round of soil sampling, which should occur in areas where large uncertainties were predicted in 2009. By doing so, a refined understanding of the distribution of OC content will be acquired and new predictions should therefore be informative. If the distributions of 2009 and 2015 differ, then a similar study to the one presented

in this thesis could be performed. Moreover, the difference between measured values in 2009 and 2015 could be used as a new variable of which the spatial variability could be studied.

Last but not least, increasing the sampling density (on more than 10% of the LUCAS original sites) should be considered. Areas where the frequency of organic soils (in the LUCAS 2009) is high should be given priority for denser sampling, to better estimate the statistical distribution of OC content in such soils. Moreover, having sub-samples of closely spaced point-pairs (< 2 km) across Europe would allow the calculation of OC content variogram at short scale and the estimation of its nugget. Such variogram would in principle improve the understanding of the spatial variability of OC in soils by differentiating the intrinsic soil OC variability from the variation caused by environmental features (such as topography) at short scale.

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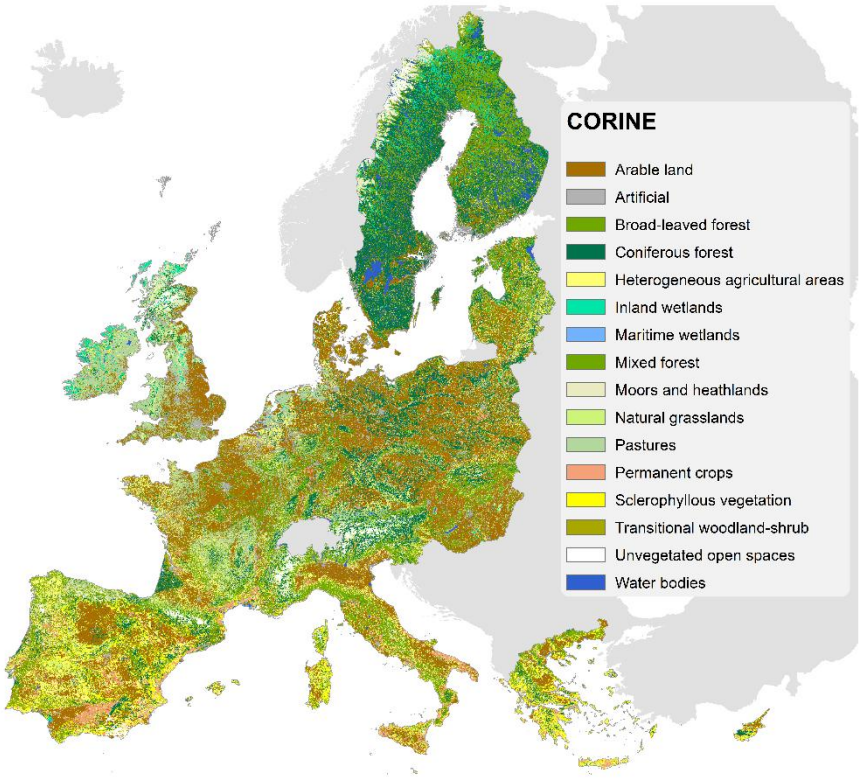
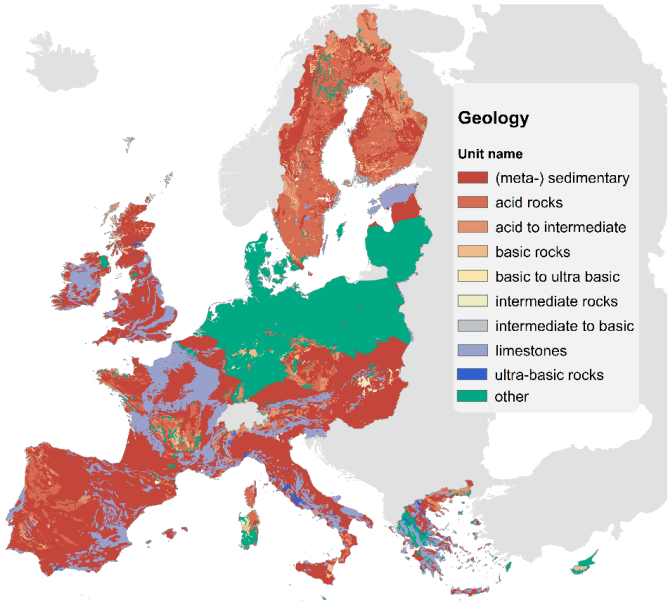
APPENDICES

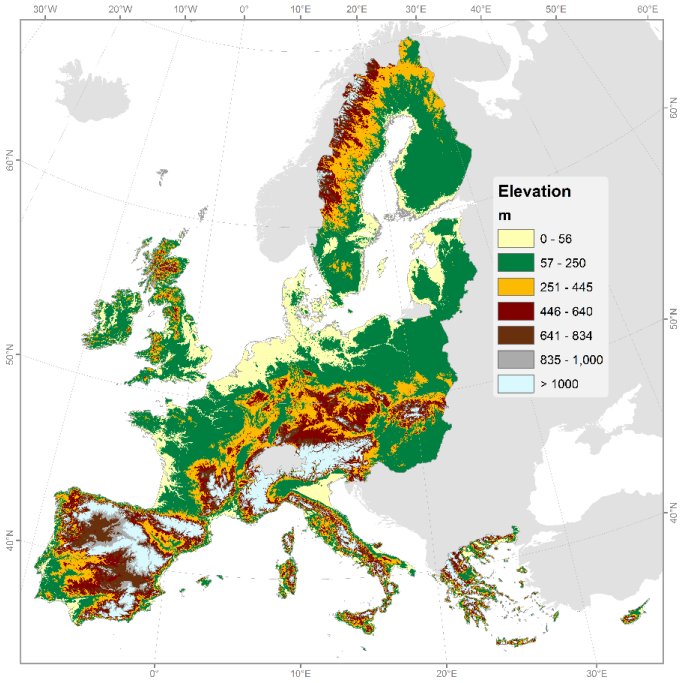
APPENDIX A MAPS OF COVARIATES



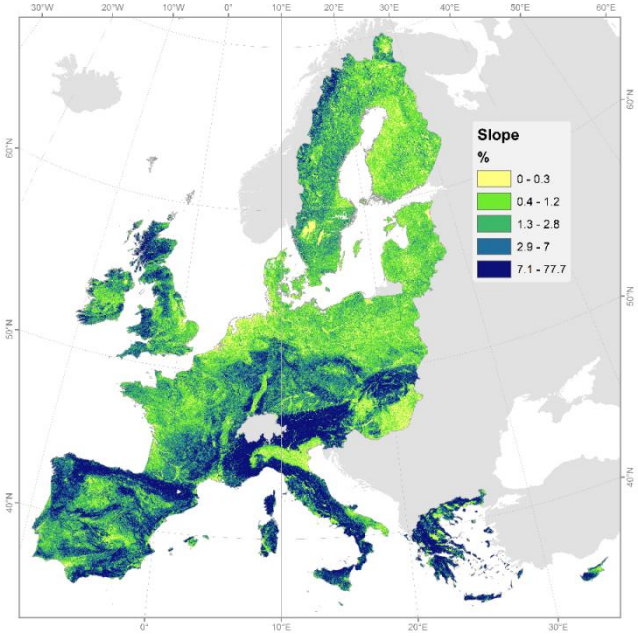
Appendix A 1 CORINE land cover as re-classified in 16 classes.



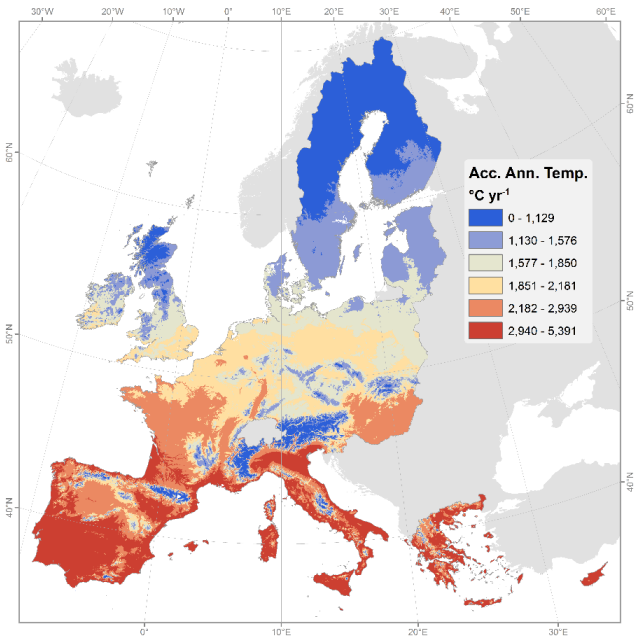
Appendix A 2 Pre-Quaternary geology (source: BGR).



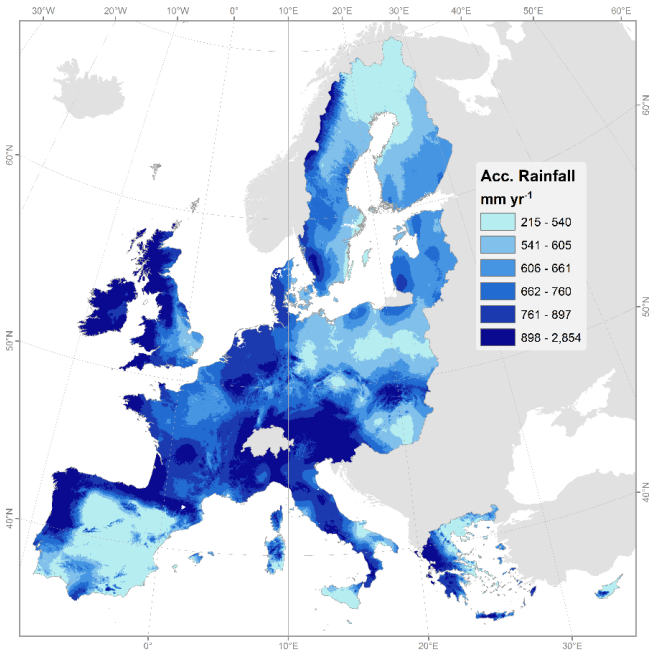
Appendix A 3 Elevation (source: NASA-SRTM).



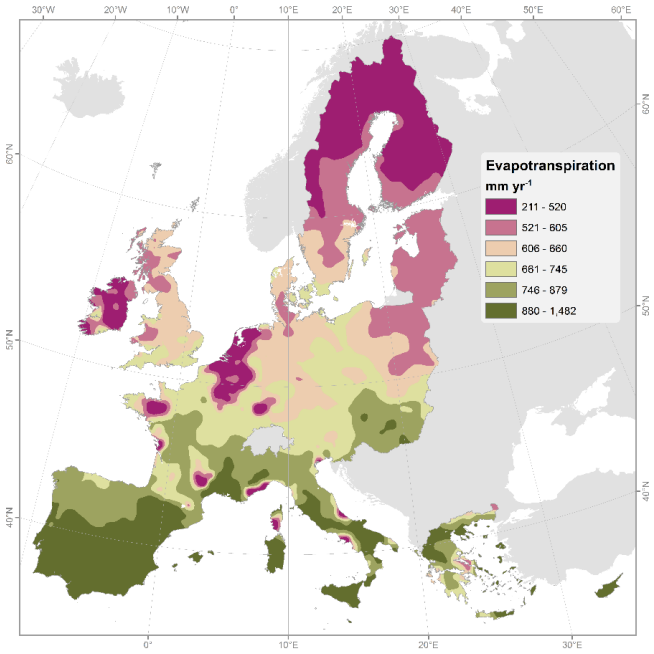
Appendix A 4 Slope (source: derived from NASA-SRTM).



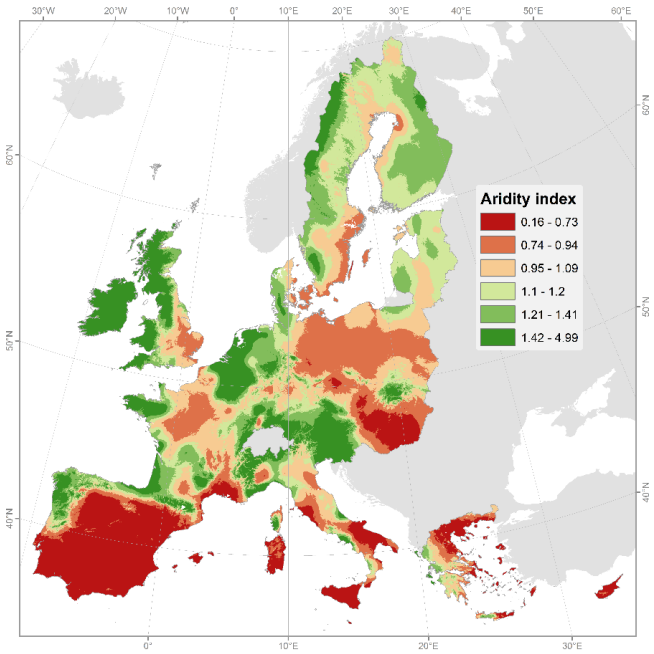
Appendix A 5 Accumulated annual temperature (source: PESERA erosion project).



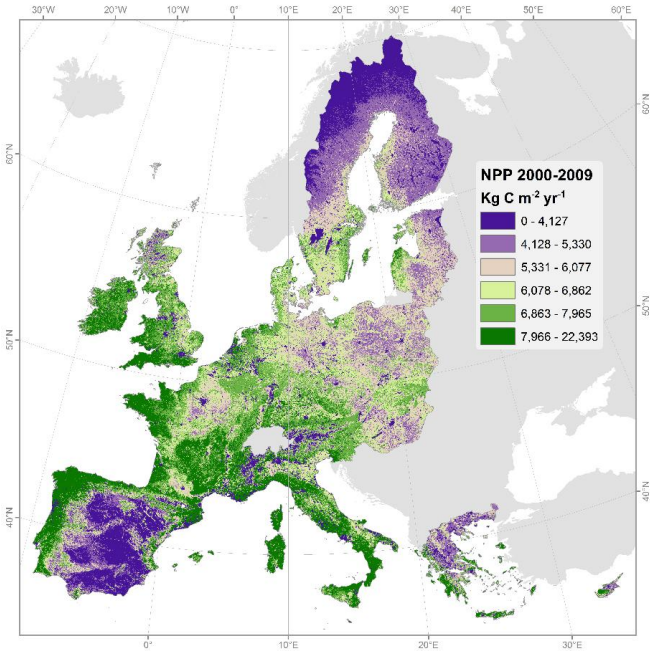
Appendix A 6 Mean annual rainfall (source: WorldClim dataset).



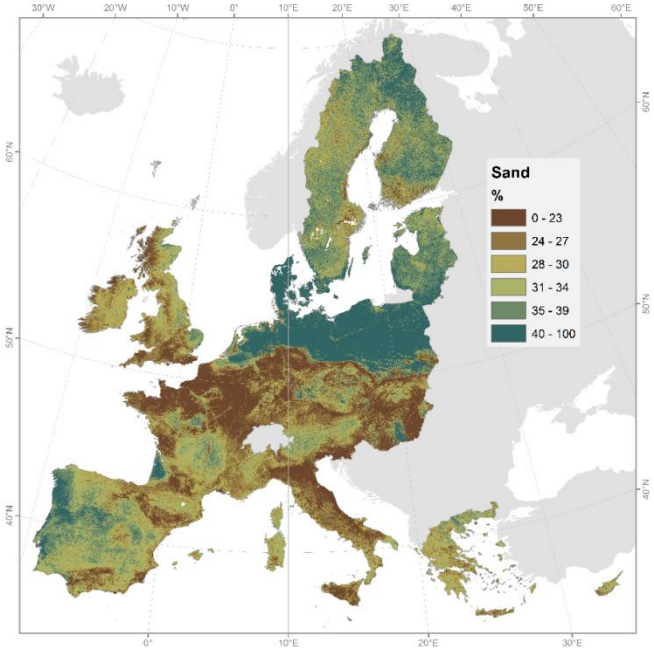
Appendix A 7 Annual potential evapotranspiration (source: PESERA erosion project).



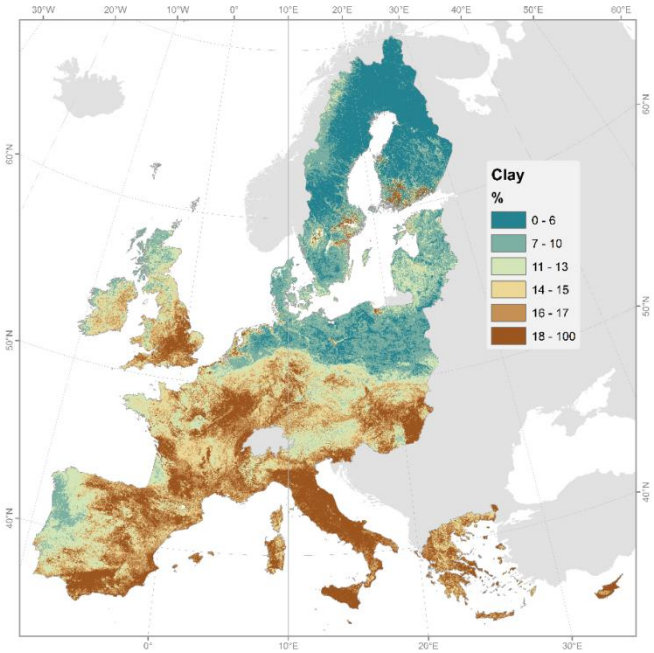
Appendix A 8 Aridity index.



Appendix A 9 Net primary productivity (source: MODIS).



Appendix A 10 Sand content.



Appendix A 11 Clay content.

APPENDIX B RE-CLASSIFICATION OF CORINE LAND COVER

Class	CLC code	LABEL1	LABEL 2	LABEL 3	Re-classification	New class
1	111	Artificial surfaces	Urban fabric	Continuous urban fabric	Artificial	1
2	112	Artificial surfaces	Urban fabric	Discontinuous urban fabric		
3	121	Artificial surfaces	Industrial, commercial and transport units	Industrial or commercial units		
4	122	Artificial surfaces	Industrial, commercial and transport units	Road and rail networks and associated land		
5	123	Artificial surfaces	Industrial, commercial and transport units	Port areas		
6	124	Artificial surfaces	Industrial, commercial and transport units	Airports		
7	131	Artificial surfaces	Mine, dump and construction sites	Mineral extraction sites		
8	132	Artificial surfaces	Mine, dump and construction sites	Dump sites		
9	133	Artificial surfaces	Mine, dump and construction sites	Construction sites		
10	141	Artificial surfaces	Artificial, non-agricultural vegetated areas	Green urban areas		
11	142	Artificial surfaces	Artificial, non-agricultural vegetated areas	Sport and leisure facilities		
12	211	Agricultural areas	Arable land	Non-irrigated arable land	Arable land	2
13	212	Agricultural areas	Arable land	Permanently irrigated land		
14	213	Agricultural areas	Arable land	Rice fields		
15	221	Agricultural areas	Permanent crops	Vineyards	Permanent crops	3
16	222	Agricultural areas	Permanent crops	Fruit trees and berry plantations		
17	223	Agricultural areas	Permanent crops	Olive groves		
18	231	Agricultural areas	Pastures	Pastures	Pastures	4
19	241	Agricultural areas	Heterogeneous agricultural areas	Annual crops associated with permanent crops	Heterogeneous agricultural areas	5
20	242	Agricultural areas	Heterogeneous agricultural areas	Complex cultivation patterns		
21	243	Agricultural areas	Heterogeneous agricultural areas	Land principally occupied by agriculture, with significant areas of natural vegetation		

22	244	Agricultural areas	Heterogeneous agricultural areas	Agro-forestry areas		
23	311	Forest and semi natural areas	Forests	Broad-leaved forest	Broad-leaved forest	6
24	312	Forest and semi natural areas	Forests	Coniferous forest	Coniferous forest	7
25	313	Forest and semi natural areas	Forests	Mixed forest	Mixed forest	8
26	321	Forest and semi natural areas	Scrub and/or herbaceous vegetation associations	Natural grasslands	Natural grasslands	9
27	322	Forest and semi natural areas	Scrub and/or herbaceous vegetation associations	Moors and heathland	Moors and heathland	10
28	323	Forest and semi natural areas	Scrub and/or herbaceous vegetation associations	Sclerophyllous vegetation	Sclerophyllous vegetation	11
29	324	Forest and semi natural areas	Scrub and/or herbaceous vegetation associations	Transitional woodland-shrub	Transitional woodland-shrub	12
30	331	Forest and semi natural areas	Open spaces with little or no vegetation	Beaches, dunes, sands	Open spaces with little or no vegetation	13
31	332	Forest and semi natural areas	Open spaces with little or no vegetation	Bare rocks		
32	333	Forest and semi natural areas	Open spaces with little or no vegetation	Sparsely vegetated areas		
33	334	Forest and semi natural areas	Open spaces with little or no vegetation	Burnt areas		
34	335	Forest and semi natural areas	Open spaces with little or no vegetation	Glaciers and perpetual snow		
35	411	Wetlands	Inland wetlands	Inland marshes	Inland wetlands	14
36	412	Wetlands	Inland wetlands	Peat bogs		
37	421	Wetlands	Maritime wetlands	Salt marshes	Maritime wetlands	15
38	422	Wetlands	Maritime wetlands	Salines		
39	423	Wetlands	Maritime wetlands	Intertidal flats		
40	511	Water bodies	Inland waters	Water courses	Water bodies	16
41	512	Water bodies	Inland waters	Water bodies		
42	521	Water bodies	Marine waters	Coastal lagoons		
43	522	Water bodies	Marine waters	Estuaries		
44	523	Water bodies	Marine waters	Sea and ocean		

APPENDIX C SUMMARY TABLE OF THE MEAN PREDICTED OC STOCKS FOR THE SAMPLING DEPTH (20CM) WITH THE LOWER AND UPPER LIMITS OF THE 95% CONFIDENCE INTERVAL. PREDICTIONS ARE GIVEN FOR MINERAL VS. ORGANIC SOILS PER LAND COVER CLASS AND WITHIN COUNTRIES

Country	Land cover	Soil	Lower limit CI_{95}	Mean stock	Upper limit CI_{95}
AT	bareland	MIN	3.391	5.901	8.782
AT	bareland	ORG	0.643	0.733	0.832
AT	cropland	MIN	58.364	63.971	70.961
AT	perm. crops	MIN	6.814	8.793	11.767
AT	grassland	MIN	157.877	187.187	237.039
AT	grassland	ORG	2.071	2.152	2.243
AT	shrubland	MIN	21.739	23.751	25.897
AT	shrubland	ORG	0.314	0.344	0.375
AT	woodland	MIN	329.302	417.233	551.920
AT	woodland	ORG	100.804	102.450	103.959
AT	wetlands	ORG	4.368	4.529	4.676
BE	bareland	MIN	1.980	2.504	3.087
BE	cropland	MIN	30.960	34.601	38.790
BE	perm. crops	MIN	2.086	2.827	3.794
BE	grassland	MIN	89.664	99.070	109.738
BE	grassland	ORG	0.357	0.371	0.387
BE	shrubland	MIN	2.238	2.518	2.828
BE	woodland	MIN	58.749	67.611	77.141
BE	woodland	ORG	47.698	48.494	49.217
BE	wetlands	ORG	0.516	0.535	0.553
CZ	bareland	MIN	3.113	3.867	4.725
CZ	cropland	MIN	96.345	104.540	114.309
CZ	perm. crops	MIN	8.900	11.152	14.135
CZ	grassland	MIN	93.707	104.541	116.521
CZ	shrubland	MIN	4.064	4.565	5.141
CZ	woodland	MIN	260.959	298.194	343.406
CZ	woodland	ORG	3.210	3.260	3.309
CZ	wetlands	ORG	2.838	2.944	3.041

DE	bareland	MIN	11.593	15.041	18.971
DE	bareland	ORG	5.298	6.089	6.922
DE	cropland	MIN	450.517	498.986	559.029
DE	cropland	ORG	1.773	1.928	2.094
DE	perm. crops	MIN	29.541	36.965	46.373
DE	grassland	MIN	603.469	669.807	744.383
DE	grassland	ORG	123.006	128.101	133.590
DE	shrubland	MIN	23.366	25.966	28.799
DE	shrubland	ORG	2.346	2.572	2.806
DE	woodland	MIN	979.523	1116.115	1279.741
DE	woodland	ORG	423.511	430.458	436.918
DE	wetlands	ORG	19.875	20.615	21.285
DK	bareland	MIN	1.245	1.525	1.861
DK	bareland	ORG	2.214	2.550	2.890
DK	cropland	MIN	109.715	122.746	140.553
DK	cropland	ORG	2.369	2.581	2.807
DK	perm. crops	MIN	0.276	0.427	0.689
DK	grassland	MIN	49.743	58.114	67.046
DK	grassland	ORG	95.036	98.911	103.125
DK	shrubland	MIN	2.029	2.269	2.522
DK	shrubland	ORG	9.355	10.271	11.200
DK	woodland	MIN	8.002	9.111	10.530
DK	woodland	ORG	131.964	134.162	136.179
DK	wetlands	ORG	4.442	4.607	4.756
EE	bareland	MIN	0.915	1.157	1.446
EE	bareland	ORG	4.701	5.421	6.140
EE	cropland	MIN	27.573	30.282	33.672
EE	cropland	ORG	5.724	6.267	6.827
EE	perm. crops	MIN	0.059	0.255	0.483
EE	grassland	MIN	38.192	42.992	48.402
EE	grassland	ORG	71.855	74.767	77.944
EE	shrubland	MIN	6.016	6.817	7.755
EE	shrubland	ORG	7.179	7.885	8.603
EE	woodland	MIN	0.737	0.811	0.893
EE	woodland	ORG	460.075	467.679	474.710
EE	wetlands	ORG	35.619	36.940	38.134
ES	bareland	MIN	50.859	84.520	120.771

ES	cropland	MIN	283.815	335.323	393.096
ES	perm. crops	MIN	152.342	185.749	230.142
ES	grassland	MIN	352.092	421.706	509.978
ES	grassland	ORG	1.022	1.063	1.110
ES	shrubland	MIN	355.272	422.690	496.622
ES	shrubland	ORG	0.954	1.044	1.135
ES	woodland	MIN	610.163	774.564	974.778
ES	woodland	ORG	70.600	71.751	72.837
ES	wetlands	ORG	0.238	0.246	0.254
FI	bareland	MIN	1.093	1.450	1.872
FI	bareland	ORG	78.271	90.082	101.917
FI	cropland	MIN	211.998	251.011	302.629
FI	cropland	ORG	74.308	81.322	88.632
FI	perm. crops	MIN	0.074	0.413	0.857
FI	grassland	MIN	3.060	3.839	4.914
FI	grassland	ORG	308.539	320.983	334.640
FI	shrubland	MIN	0.149	0.179	0.215
FI	shrubland	ORG	408.446	448.388	488.499
FI	woodland	ORG	4178.990	4248.013	4311.878
FI	wetlands	ORG	270.926	280.975	290.061
FR	bareland	MIN	24.112	37.153	51.553
FR	cropland	MIN	663.319	735.057	819.554
FR	perm. crops	MIN	55.789	70.734	97.919
FR	grassland	MIN	1186.318	1325.263	1488.549
FR	grassland	ORG	2.860	2.976	3.106
FR	shrubland	MIN	207.480	231.262	255.432
FR	shrubland	ORG	0.372	0.408	0.444
FR	woodland	MIN	1476.284	1727.480	2041.793
FR	woodland	ORG	73.882	75.070	76.206
FR	wetlands	ORG	9.070	9.407	9.715
GR	bareland	MIN	6.622	12.795	19.614
GR	cropland	MIN	48.121	56.438	65.712
GR	perm. crops	MIN	41.667	52.383	67.394
GR	grassland	MIN	62.215	79.687	105.805
GR	shrubland	MIN	151.087	171.844	192.247
GR	woodland	MIN	193.937	262.037	373.826
GR	woodland	ORG	0.683	0.694	0.704

GR	wetlands	ORG	0.252	0.260	0.270
HU	bareland	MIN	2.028	2.518	3.062
HU	cropland	MIN	153.782	171.572	188.874
HU	perm. crops	MIN	6.856	8.846	11.082
HU	grassland	MIN	95.813	107.726	122.659
HU	shrubland	MIN	13.902	15.375	16.996
HU	woodland	MIN	99.155	113.351	129.470
HU	woodland	ORG	3.277	3.321	3.374
HU	wetlands	ORG	10.502	10.886	11.254
IE	bareland	MIN	0.966	1.326	1.740
IE	bareland	ORG	5.943	6.831	7.731
IE	cropland	MIN	15.081	18.086	21.719
IE	cropland	ORG	1.742	1.900	2.067
IE	grassland	MIN	172.820	201.784	235.260
IE	grassland	ORG	577.566	601.133	626.822
IE	shrubland	MIN	3.207	3.537	3.900
IE	shrubland	ORG	78.856	86.565	94.248
IE	woodland	MIN	0.622	0.872	1.370
IE	woodland	ORG	148.841	151.302	153.576
IE	wetlands	ORG	56.725	58.830	60.733
IT	bareland	MIN	16.568	27.228	38.741
IT	bareland	ORG	0.329	0.371	0.424
IT	cropland	MIN	230.943	263.238	303.535
IT	perm. crops	MIN	131.564	165.183	208.492
IT	grassland	MIN	248.727	301.504	383.066
IT	shrubland	MIN	122.616	141.043	159.631
IT	woodland	MIN	560.700	741.961	1042.326
IT	woodland	ORG	41.334	41.999	42.623
IT	wetlands	ORG	1.774	1.839	1.901
LT	bareland	MIN	2.967	3.637	4.449
LT	bareland	ORG	0.319	0.366	0.414
LT	cropland	MIN	68.986	75.510	83.860
LT	cropland	ORG	0.337	0.367	0.399
LT	perm. crops	MIN	0.440	0.968	1.361
LT	grassland	MIN	115.980	129.537	143.371
LT	grassland	ORG	19.538	20.336	21.187
LT	shrubland	MIN	7.367	8.264	9.242

LT	shrubland	ORG	3.821	4.190	4.576
LT	woodland	MIN	38.880	45.022	52.098
LT	woodland	ORG	340.110	345.827	350.993
LT	wetlands	ORG	4.490	4.657	4.808
LU	bareland	MIN	0.218	0.265	0.318
LU	cropland	MIN	1.989	2.301	2.561
LU	perm. crops	MIN	0.298	0.347	0.417
LU	grassland	MIN	6.334	6.954	7.675
LU	shrubland	MIN	0.158	0.172	0.185
LU	woodland	MIN	7.511	8.444	9.453
LU	woodland	ORG	1.354	1.375	1.397
LV	bareland	MIN	3.243	4.021	4.958
LV	bareland	ORG	3.793	4.353	4.935
LV	cropland	MIN	36.925	40.512	45.540
LV	cropland	ORG	0.674	0.736	0.801
LV	perm. crops	MIN	0.326	0.968	1.542
LV	grassland	MIN	87.871	98.771	110.757
LV	grassland	ORG	55.339	57.585	60.016
LV	shrubland	MIN	16.854	18.855	21.189
LV	shrubland	ORG	16.026	17.595	19.203
LV	woodland	MIN	21.668	24.632	27.861
LV	woodland	ORG	560.272	569.537	578.093
LV	wetlands	ORG	26.472	27.455	28.343
NL	bareland	MIN	2.159	2.810	3.514
NL	bareland	ORG	0.726	0.833	0.947
NL	cropland	MIN	40.943	47.391	55.509
NL	perm. crops	MIN	3.250	4.599	6.333
NL	grassland	MIN	129.443	142.895	158.923
NL	grassland	ORG	66.870	69.692	72.695
NL	shrubland	MIN	5.927	6.587	7.251
NL	shrubland	ORG	1.094	1.199	1.311
NL	woodland	MIN	7.893	9.070	10.358
NL	woodland	ORG	86.756	88.217	89.547
NL	wetlands	ORG	2.963	3.073	3.173
PL	bareland	MIN	15.307	18.807	22.930
PL	bareland	ORG	1.259	1.442	1.634
PL	cropland	MIN	338.396	373.496	413.352

PL	perm. crops	MIN	13.109	17.090	21.286
PL	grassland	MIN	430.838	483.028	540.288
PL	grassland	ORG	83.824	87.446	91.054
PL	shrubland	MIN	25.069	28.302	31.907
PL	shrubland	ORG	5.153	5.635	6.168
PL	woodland	MIN	496.481	560.741	638.536
PL	woodland	ORG	453.255	460.703	467.675
PL	wetlands	ORG	17.778	18.440	19.039
PT	bareland	MIN	12.353	19.095	26.522
PT	cropland	MIN	21.214	26.646	33.493
PT	perm. crops	MIN	26.652	36.204	49.283
PT	grassland	MIN	58.410	72.084	87.801
PT	shrubland	MIN	109.028	125.426	141.615
PT	shrubland	ORG	0.317	0.347	0.378
PT	woodland	MIN	197.836	235.637	281.845
PT	woodland	ORG	1.648	1.675	1.700
PT	wetlands	ORG	0.482	0.505	0.519
SE	bareland	MIN	9.045	12.145	15.770
SE	bareland	ORG	170.391	195.515	221.573
SE	cropland	MIN	96.568	109.663	127.772
SE	cropland	ORG	5.396	5.895	6.416
SE	perm. crops	MIN	0.206	0.326	0.483
SE	grassland	MIN	42.662	51.310	62.102
SE	grassland	ORG	369.147	384.140	400.485
SE	shrubland	MIN	22.918	27.320	32.078
SE	shrubland	ORG	678.877	745.072	812.209
SE	woodland	MIN	1.989	2.236	2.515
SE	woodland	ORG	5747.807	5842.140	5929.863
SE	wetlands	ORG	430.284	446.245	460.676
SI	bareland	MIN	0.819	1.460	2.202
SI	bareland	ORG	0.316	0.359	0.408
SI	cropland	MIN	6.371	7.252	8.283
SI	perm. crops	MIN	1.998	2.763	4.089
SI	grassland	MIN	30.862	35.411	41.099
SI	grassland	ORG	0.340	0.353	0.368
SI	shrubland	MIN	5.889	6.443	7.039
SI	woodland	MIN	98.948	118.684	142.577

SI	woodland	ORG	45.582	46.338	47.016
SI	wetlands	ORG	0.477	0.495	0.511
SK	bareland	MIN	1.133	1.521	1.955
SK	cropland	MIN	45.113	49.694	54.569
SK	perm. crops	MIN	3.099	3.778	4.640
SK	grassland	MIN	48.810	55.693	64.372
SK	shrubland	MIN	15.752	17.326	18.979
SK	woodland	MIN	131.087	153.768	181.728
SK	woodland	ORG	22.611	22.967	23.313
SK	wetlands	ORG	0.468	0.485	0.501
UK	bareland	MIN	8.746	12.031	15.881
UK	bareland	ORG	49.829	57.344	64.803
UK	cropland	MIN	248.645	283.458	327.460
UK	cropland	ORG	4.647	5.073	5.520
UK	perm. crops	MIN	1.573	6.668	120.773
UK	grassland	MIN	574.955	719.223	928.014
UK	grassland	ORG	1092.634	1136.970	1185.518
UK	shrubland	MIN	40.486	45.142	49.924
UK	shrubland	ORG	429.861	471.861	513.732
UK	woodland	MIN	84.899	108.326	143.822
UK	woodland	ORG	542.462	551.438	559.737
UK	wetlands	ORG	64.502	66.895	69.058