Working sites and soil sampling environmental sciences essay

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Introduction

Soils play a vital role as being a medium for plant growth and providing essential ecosystem services. In addition, soils contain the largest pool of the global carbon. Though subject to regular change, the global amount of carbon in the worldwide soils (2500 Gt) has been reported to be 3. 3 times the size of the atmospheric pool (760 Gt) and 4. 5 times the size of the biotic pool (560 Gt) (Lal, 2004). It has been estimated that soil organic carbon (SOC) constitutes the largest pool of the global soil carbon with about 1550 Gt of SOC and 950 Gt of soil inorganic carbon (SIC) (Lal, 2004). In fact, SOC contributes heavily to most soil functions such as nutrient and water storage, soil biological activity and structural stability. Consequently, soil fertility and productivity are closely related to the level of SOC. Maintaining SOC is thus necessary for a soil to fulfil primary ecosystem services, especially in West Africa which is characterized by structurally degraded and nutrient depleted soils (Soler et al., 2011) and where natural soil fertility and fertilizer input are low (Doraiswamy et al., 2007). However, the SOC pool is subject to a dynamic balance severely affected by different factors. Different factors such as environmental elements (climate with mean annual precipitation and temperature, slope), land use, soil characteristics (texture, lithology), and microbal biomass are reported to have an impact on the processes of gain and losses of SOC (Jorbbágy et al., 2000; Albaladejo et al., 2012). Though establishing the SOC stocks is the first step in studying C sequestration in an

environment, it is also relevant to investigate factors affecting its dynamics for optimal strategies for land management (Chaplot et al., 2010). The sensitivity of SOC to climate variability is receiving full interest because of its feedback on climate change at local and global scale. As the major terrestrial biosphere's carbon reservoir (Batjes and Sombroek 1997; Smith, 2008), SOC is a crucial component in climate change mitigation. Slight changes in the processes driving C cycling in soil have the potential to increase the release of CO_2 into the atmosphere. Terrestrial ecosystems taking up carbon have largely buffered the atmospheric carbon increase until now, yet their buffering capacity is projected to decrease as a reaction to climate change in the future (Friedlingstein et al., 2006). Certain models even predict that soils will convert from carbon sinks to carbon sources in the future as a result of increased soil respiration with increased temperature (Cox et al., 2000), although overall prediction uncertainty is still large and requires deeper insight into the response of soil respiration to a warming environment (Cox et al., 2000; Smith, 2008). Since soil atmospheric CO_2 production is temperature-sensitive, global warming will probably exacerbate the rise of atmospheric CO_2 concentration especially in the semi-arid West African context. Thus, maintaining or enhancing SOC is necessary not only for soil fertility and productivity but also for atmospheric CO_2 mitigation. Apart from climate, land use changes and associated management practices also have a strong impact on SOC stock variation (Vaccari et al., 2012). Land use changes like expanding or intensifying agricultural production (i. e. change from pasture or native forest to plantation or cropland) typically cause a decline of SOC stocks (Guo and Gifford, 2002) and thus a decline of soil fertility. The reverse processes (e. g. reforestation) may rebuild SOC stocks

(Guo and Gifford, 2002), yet rates are slow and properties may not reach former values (Preger et al., 2010). Land use and agricultural practice may furthermore foster soil erosion, which involves a preferential depletion of SOC (Lal, 2003). In the 1990s, land use change thus contributed about one third of the carbon emitted due to fossil fuel burning to global carbon emissions (Smith, 2008). Most land use change nowadays occurs as tropical deforestation primarily in Africa (Nieder and Benbi, 2008) and regional climate models indicate that land use changes and land degradation are predominantly causing the simulated climate response in West Africa (Paeth et al., 2009). The latter projects a strong warming and an overall drier tendency for West Africa, resulting in reductions of agricultural yields by up to 50% for some West African countries by 2020 and thereby threatening West African livelihoods (as e. g. modeled for Mali by Butt et al., 2005). Land use changes as an adaptation strategy to reduced yields might fuel climate change and reduce soil productivity and thereby additionally aggravate food shortages. In addition to climate and land use, many studies report the interplay of different factors on SOC dynamics. In diverse arrays of soil and ecosystems, regional SOC and soil texture were found to be positively associated with mean annual precipitation and clay content and were negatively correlated with mean annual temperature (Burke et al., 1989; Percival et al., 2000; Jobbággy and Jackson, 2000; Azlan et al., 2011). Clay content related poorly to SOC accumulation which was rather correlated with chemical stabilization of organic matter in a range of grassland soils in New Zealand (Percival, 2000). In Malawi (South central Africa) however, the clay content was significantly correlated with the SOC of the Miombo woodlands´ soils. The SOC and its status in the soil was closely associated with clay and

silt contents and clay type in a review carried out by Bationo et al. (2012) for West African agrosystems. The same trend was established by Azlan et al. (2011) in Kota Bharu district in Malaysia. Saiz et al. (2012), studying the variation in soil carbon stocks and their determinants across a precipitation gradient in West Africa (from Ghana to Mali), found out that available water and sand content explain much of the total variability in SOC stocks observed. Moreover, Chaplot et al. (2010) correlated SOC content and lithology in Laos and recorded higher SOC content under intrusive rocks than under sedimentary ones with larger SOC contents measured on steep slopes. The preceding results indicate potential relationship between SOC and factors such as soil texture, precipitation, temperature, lithology and slope. Most of the studies focusing on SOC stock distribution as well as its controlling factors are mainly carried on the surface soil layer. In fact, subsoil carbon, although equaling atmospheric carbon in amount is typically neglected in models of soil fertility and carbon balances. However, Fontaine et al. (2007) showed that subsoil carbon is readily decomposable upon addition of a fresh C-source, suggesting that excluding subsoil carbon from our studies on SOC dynamics might have been overhasty. Moreover, some results suggest that subsurface SOC is significantly more sensitive to increases in temperature or nutrient availability than surface SOC (Fierer et al., 2003) whereas others point out that surface SOC is more sensitive to climate and texture than subsurface SOC (Jobbággy and Jackson, 2000; Liu et al., 2011). Albaladejo et al. (2012) found out that with increasing depth, texture is the main controlling factor no matter the land use with the decrease of the influence of the climatic factors. Though these results show that there is no consensus, there is evidence that the controlling factors of

subsoil SOC dynamics vary along the vertical soil profile and more studies are needed especially for tropical soils. When monitoring changes in SOC, analyses should include pools of different SOC stability, since overall response rates may be slow and thus ignored when based on bulk SOC analyses only (e. g., Powlson et al., 1987; Skjemstad et al., 2004). Analysis of various SOC pools is furthermore required to initialize SOC models when data from long-term experimentations are not available (Skjemstad et al., 2004). Classically, the identification of such pools involved the fractionation of SOC according to particle size, density or a combination thereof. Recent evidence, however, suggests that the workload may be substantially reduced when the analyses are based upon rapid screening techniques, such as minimum-invasive mid-infrared spectroscopy (MIRS, Bornemann et al., 2010). These techniques have, to my knowledge, not yet been adapted for tropical and subtropical environments.

1. 1 Objectives

Increased climate variability and land use change are most likely to affect SOC in West African soils, an area still struggling to provide food security for its ever rising population in a low input agricultural system. Therefore, knowledge on the impact of climate change and land use on SOC will contribute to a better soil resources management towards mitigating greenhouses gas while guaranteeing the maintenance of the soil's production potential. Thus, this study aims at analyzing the SOC stocks of WASCAL's focal watersheds and their feedbacks to land use and climate change in West Africa.

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Specifically, it will focus on: estimating the surface and subsurface SOC stocks in different land use and soil type and capitalizing these results into SOC stock maps for the studied areasdetermining the factors affecting SOC stock in different land use and depthassessing the effectiveness of the use of rapid screening techniques such as MIRS to establish soil organic carbon stocks and pools for the tropical environmentevaluate a soil carbon dynamics model (Roth C model) performance by comparing modeled and measured results.

Methodology

Data collection

Working Sites and soil sampling

The study will be conducted in two catchments located respectively in Burkina-Faso (Dano catchment) and Benin (Tetonga catchment). Different maps (soil, topographic, land use) of the watersheds will be used to identify representative soil units based on elements of landform analysis (such as soil type, slope gradient, relief type, drainage) and land use / land cover (Brabyn, 1998, Chopra and Sharma, 1993). All major soil groups present in the different watersheds will be investigated, with transects covering the different soil units. For this purpose, preliminary field works will be carried out. It will consist in checking map data and to specifically set the transects and choose the sampling points.

Sampling approach

Soil maps with relevant soil information are a valuable tool which may be used for specific purposes. In fact, such information systems on soil types and possibly SOC stocks are necessary for policy and decision makers as well as for the scientific community for the evaluation of the productive capacity of the land and its degradation (Oldeman and Engelen, 1993). This section discusses the approach considered for the soil mapping of the present study as well as the scale and sampling intensity. Different approaches are used for soil mapping and soil sampling schemes are different accordingly. In West Africa, which is dominated by former French colonies, the ORSTOM (now called IRD) approach is mainly used for soil mapping. French scientists from ORSTOM established maps following the French soil classification (CPCS), which is a hierarchical approach consisting of the elements class, subclass, group, subgroup, family, series and phase (Bossa et al., 2012). The scale mostly used for these soil maps is 1: 200 000. This way, maps represent the dominant type of soil in a given area but differences in topography do not change its fundamental characteristics (Durbroeucq, 1977). Consequently, the variability of soils along the hillslopes as well as the hydromorphic soils in inland valleys are not considered. A more recent approach, the Soil and Terrain Digital Database (SOTER) has been developed (van Engelen and Wen, 1995; van Engelen, 2000) and it has the advantage of relating soil information to its landscape context. SOTER is a computerized information system on soil and terrain attributes. The SOTER approach tackles the mapping of areas by focusing on some typical patterns of landform, morphology, slope, parent material and soils (Oldeman and Engelen, 1993). The main difference between SOTER and the ORSTOM

approach is that the latter gives only the most common soil types and oversees the variability in soil due to differences in topography (Durbroeucq, 1977). Consequently, the soil sampling in this study will follow the SOTER approach with sampling based on main slope positions.

Sampling intensity for mapping

In general, the conventional soil survey follows the discrete model of spatial variation resulting in a polygon type or entity map (Heuvelink in Vargas and Alim, 2007). There are specific standards for scale and sampling intensity for conventional soil survey. According to Avery (in Vargas and Alim, 2007) and Dent (in Vargas and Alim, 2007), a map at 1: 50 000 and 1: 100 000 should respect the following rules: At 1: 50 000 scaleAt 1: 100 000 scaleInspection density according to Avery and Dent: 1 per 0. 2 km2 (20 ha) to 1 km² (100 ha)Inspection density according to Avery and Dent: 1 per 1 km² (100 ha) to 4 km² (400 ha)Considering the optimum and the area characteristics: Considering the optimum and the area characteristics:

Dano: 1 sample – 0. 2 km²Dano: 1 sample – 1 km²Area: 155 km²Area: 155 km²Number of samples = 775 samplesNumber of samples = 155 samples

Tetonga : 1 sample – 0. 2 km²Tetonga : 1 sample – 1 km²Area: 195 km²Area: 195 km²Number of samples = 975 samplesNumber of samples = 195 samples

The preceding calculation shows that a production of a map at a scale of 1: 50 000 requires a high amount of soil samples ranging from 975 to 775 soil samples per watershed. By taking in this study one sample every 0. 5 km², 310 samples will be required for the Dano catchment, and 390 for the

Tetonga catchment. However, the latter catchment might be subdivided into smaller sub-catchments and only some can then be selected for investigation instead of the whole area. Transects will be set based on the Digital Elevation Model, land use maps, parent material maps and soil type maps to cover the watershed's variability. As soil properties vary along the slope, the sampling will be carried out following the toposequence along preselected transects. Soil samples will be taken from soil profiles (down to 1 m where possible) which will be excavated along transects and sampling will be carried out per horizon. For each sampling point (soil profile), soil cores will be collected per horizon to a depth of 1 m using a standardized hammering head (100 cm3). Three cores will be bulked per horizon to form a composite sample. Further soil cores (4) will be used to determine bulk density (BD) with the core method (Blake and Hartge, 1986). In addition to the soil profile, auger soil sampling will be carried out following a regular grid to refine the sampling for soil mapping. A soil collection form is designed (Appendix 1) to collect site information, soil attributes and soil profile/auger description data. Soil classification and soil horizon description will be based on the World Reference Base for soil resources (IUSS, Working Group WRB 2006). Moreover, some laboratory analysis will be carried out to corroborate field diagnostic. Soil cores for bulk density will be oven dried at 110°C for 24 hours and then weighed for bulk density. The other samples will be oven dried (40° C), weighed and sieved through a 2-mm sieve. The samples with diameter < 2 mm will be analyzed for the soil texture, pH, cation exchange capacity (CEC), C/N, total organic carbon, acid oxalate (pH 3) extractable Fe and Al and citrate-dithionite extractable Fe.

2. 2 Modeling Carbon Dynamics

The capacity of purely empirical methods for projecting future trends in SOC stocks is limited as the latter is prone to change over time as a consequence of the interplay of dynamic factors such as soil, climate and land use. Estimating the soil C stock under widely varying conditions therefore is complicated and requires the use of simulation models (Paustian et al., 1997, Soler et al., 2011).

2. 2. 1 Model

The existing SOC models may be classified into (1) process-oriented, (multi-) compartment models, (2) organism-oriented models (food web-models), and (3) cohort models describing decomposition as a continuum, combining the first and the second model approaches. However, only the process-oriented models consider different fractions of Soil Organic Matter (SOM) with similar chemical and physical characteristics as a pool or compartment based on biological stability, decomposition rate and turnover time (Post et al., 2007; Adams et al., 2011). The appendix 2 gives an overview of the main characteristics of six process oriented models (CENTURY, RothC, DNDC, DAISY, NCSOIL, CANDY) recognised as the most used in literature with CENTURY and RothC mentioned as having the highest frequency (Davidson and Janssens, 2006; Viaud et al., 2010). CENTURY and RothC are built on the same basic idea and the latter will be considered for the present study. RothC (Jenkinson and Rayner, 1977) was originally developed and parameterised to model the turnover of organic C in arable topsoils from the Rothamsted long-term field experiments. It has been extensively used (Jenkinson and Rayner, 1977; Falloon, 1998; Cerri et al., 2007; Kamoni et al.,

2007; Nieto et al., 2010; Carta, 2012) at different spatial scales (plot, field, regional, national, and global), in different ecosystem (natural vegetation, rangeland ecosystem, arable ecosystem, forestry ecosystem) and in various climate zones (temperate, tropical, and subtropical).

2. 2. 2 Structure of the RothC model and limitation

As indicated in the manual (Coleman and Jenkinson, 1999), the model can be used in two modes: a forward mode to simulate SOM based on known inputs and an inverse mode to calculate required plant inputs to reach the measured SOC content. The model distinguishes five basic compartments (Figure 1) based on the biological properties and mean residence times (MRTs) of the different pools. Incoming plant material is partitioned into decomposable plant material (DPM) and resistant plant material (RPM) depending on the DPM/RPM ratio of the incoming plant material. This ratio is 1. 44 for arable land and grassland soil with 59% of the plant material being DPM and 41% RPM. For shrubland and savannah, a ratio of 0. 67 is used and a ratio of 0. 25 is considered for tropical woodland. For the mineral soil, three pools are considered. The plant material decomposes to form: CO_2, an active pool called microbial biomass (BIO), a slow pool named humified organic matter (HUM) and a passive pool which is the inert organic natter (IOM). The proportion affected to CO_2, BIO and HUM is based on the soil clay content. BIO and HUM are further decomposed to form more CO_2, BIO and HUM. Except the IOM, each pool decomposes by first order kinetics and each has a maximum decomposition rate (year-1) of 10 for DPM, 0. 3 for RPM, 0. 66 for BIO and 0. 02 for HUM. These decompositions rates are affected by a factor modifier based on temperature, moisture and the degree of soil cover. Figure

1: Structure of RothC (Coleman & Jenkinson, 1999)RPM: Resistant Plant Material, DPM: Decomposable Plant Material, BIO: Microbial Biomass, HUM: Humified OM, IOM: Inert Organic Matter. As most of the process oriented models, RothC possess some limitations common to most process-oriented models. First of all, their testing and validation is difficult to carry out as the theoretical compartments related to the structure of multi-compartment process-oriented models are difficult to compare with the different SOM fractions measurements (Batlle-Aguilar et al., 2010). In addition, most models neither account for decreasing SOM contents with depth nor for changes in pH which potentially influence decomposition rates. Furthermore, they only take into account the topsoil (RothC models only the first 30 cm) in modelling SOC dynamics as this depth is affected by most changes (Viaud et al., 2010, Adams et al., 2011) while quantifying or simulating the processes of soil C in the subsoil level could shed more light in the soil C dynamics (Adams et al., 2011, Trumbore, 2009). Furthermore, the absence of a plant growth sub-module in RothC leads to an independent estimation of plant C-input or recovering this input by inverse modelling (Carta, 2012).

2. 2. 3 Data requirement for RothC

The data required to run the RothC are as follows: Monthly rainfall (mm). Monthly potential evapotranspiration (mm)Average monthly mean air temperature (oC). Clay content of the soil (%): clay content is used tocalculate how much plant available water the topsoil can hold; it also affects the wayorganic matter decomposes. An estimate of the decomposability of the incoming plant material i. e. theDPM/RPM ratio. Soil cover. Is the soil bare or vegetated in a particular month ? Monthly input of

plant residues (t C ha-1). The plant residue input is the amount of C that is put into the soil per month (t C ha-1), including C released from roots during crop growth. As this input is rarely known, the model is most often run in' inverse' mode, generating input from known soil, site and weather data. Monthly input of farmyard manure (FYM) (t C ha-1), if any. The amount of FYM (t C ha-1) put on the soil, if any, is inputted separately, because FYM is treated slightly differently from inputs of fresh plant residues. Depth of soil layer sampled (cm) (Coleman and Jenkinson, 1999)

2. 2. 4 Application of RothC to the present Study

The five conceptual compartments developed in RothC are to be related to measured pools for the model initiation, parameterization and validation. Denef et al. (2009) presented a review of the techniques used to fractionate and characterize SOM present in literature ranging from biological fractionation to physical and chemical fractionation. Though these methods could identify different functional SOC pools with similar turnover times, there still remain practical issues as how to relate them to the conceptual pools developed in SOC models. However, recent studies suggest possibilities either by fractionating soil samples by physical and chemical methods or by using MIRS to identify carbon pool which can be linked to the RothC model compartments.

Physical and chemical fractionation

Some studies carried out by Skjemstad (2004) in croplands in a subtropical area in Australia and by Zimmerman et al. (2007a) in different agricultural sites (arable land, grassland and alpine pasture) in Switzerland revealed strong correlations between SOC in measured fractions and modeled pools

using a method of fractionation of SOC which could be linked to the RothC pools. The same fractionation procedure tested with RothC by Xu et al. (2010) in temperate grassland in Ireland and by Poeplau and Don (2013) in different land use (cropland, grassland, forest) using data from ten (10) European countries showed no significant difference between measured and modeled values. Figure 2 presents an overview of the fractionation procedure according to Zimmerman et al. (2007a) which consists of a combination of physical and chemical procedures. Figure 2: Diagram of the fractionation procedure; s + c = silt and clay, rSOC = resistant soilorganic carbon, DOC = dissolved organic carbon, S + A = sand and stableaggregates, and POM = particulate organic matter (Zimmerman et al., 2007a). According to Zimmermann et al. (2007a), the sum of POM and DOC corresponds to the modeled sum of DPM and RPM. The sum of POM and DOC could be separated into DPM and RPM using the ratio of DPM: RPM from the modeled DPM and RPM pools obtained by RothC for equilibrium conditions for each site. Furthermore, the measured fractions S + A and s + c − rSOC as a sum correspond to the modeled sum of BIO and HUM, and could be separated into BIO and HUM by the ratio of BIO: HUM from the modeled BIO and HUM pools for each site. The recalcitrant silt and clay fraction (rSOC) could be associated with IOM.

Mid Infra-Red Spectroscopy (MIRS)

MIR spectroscopy enables the identification of specific soil minerals and of organic matter functional groups such as alkyl or carboxyl groups, carbohydrates, amides, amines, and aromatic functional groups (Janik et al., 2007). The estimation of soil properties is generated by calibrating spectral

information against conventionally obtained data using multivariate statistical procedures such as partial least-squares regression (PLSR) (Janik et al., 2007; Denef et al., 2009). In contrary to physical and chemical methods, no fractionation or chemical reagent is required and MIRS thus offers a simple, rapid, and low-cost alternative especially when dealing with huge amounts of sample. Some studies have shown the ability of the MIRS for determining several soil properties. Bornemann et al. (2010) reached a good prediction out of a set of 186 soil samples when investigating different POM pools ranging from coarse to medium sand (POM1: 2000–250 μm), fine sand to coarse silt (POM2: 250–53 μm) and coarse silt to fine silt (POM3: 53–20 μm) as well as the lignin contents. However, these fractions cannot be related to RothCs pools which also requires the evaluation of SOC in the clay fraction. Zimmermann et al. (2007b) and Yanik (2012) differentiated both, POM and carbon contents in different soil fractions including clay using MIRS, making it possible to reconstruct the different pools matching with Roth C's theoretical compartments as in the physical and chemical method (TOC, POM, S + A and s + c − rSOC and rSOC). In the present study, a set of 100 soil samples (including surface and subsoil samples) will undergo both the MIRS techniques and the physical and chemical fractionation. The results from the latter will be used for the calibration of the MIRS. In both cases, the following soil properties will be determined: TOC, POM, DOC, S + A, s + c, rSOC. As a high amount of soil samples is expected, the fractionation of the remaining soil samples will be carried out using MIRS. The results from this preliminary fractionation will serve as input for the RothC initialization. As long term data cannot be established within the timeframe of the present study to validate the model, the concept of " false chronosequence" will be

used. Sampling will be carried out within several land use units with similar characteristics (lithology, soil type, land use, elevation, slope, etc.) and with known conversion time (e. g. years of conversion into agricultural fields or afforested land...). Each sampling set will potentially include agricultural fields, reconverted areas, natural vegetation and pasture (if distinctly identified). For the calibration, the following site specific information is required: Climate data: As climate input, the RothC model requires monthly air temperature (maximum and minimum), precipitation and evapotranspiration. Monthly data covering the different sites will be collected from national meteorological office in each country or from other relevant sources. Land use data: For the present study, current land use will be recorded during the field work. Land use history will combine remote sensing data at low resolution and statistics from historical reports (annual reports etc.) via collaboration with the remote sensing group. Clay content: The soil samples collected from the field will undergo laboratory analysis to determine the clay content. Monthly input of plant residues (t C ha-1) and monthly input of farmyard manure (FYM) (t C ha-1): An extensive literature research focusing on the sudano-sahelian ecosystem will be conducted to determine the monthly amount of plant residues and farmyard manure.

2. 2. 5 Limitation in present study and possible alternatives

Most studies use long data for modelling carbon dynamics, especially for prediction. In fact, carbon modelling requires long term data on soil, land uses and climate. Failing to provide these data (not finding reliable false chronosequence for example) might affect the running of the model. In addition, a high correlation between modelled and measured data at the

calibration stage of the model should be recorded for it to be run with the remaining soil data. Moreover, data for carbon modelling in the present case study might suffer from the availability of reliable data, especially on land use history as well as from gaps in climatic data or from the fact that different theoretical carbon pool might not correlate properly with the measured ones. In that case, a different topic will be chosen to replace the modelling activitiesInterest might be directed towards exploring the variability of black carbon (BC) in semi-arid tropical soils. It is reported that BC represents 30 to 45 % of the total soil organic carbon (Skjemstad et al., 1996). Because its decomposition cycle is very slow, it is seen to be an important element of carbon sequestration in soil (Simpson et al., 2004; Major et al., 2010). Consequently, data on BC are needed for predicting the response of the soil organic carbon (SOC) pool to the projection of climate change. A current issue related to black carbon is its physical and chemical heterogeneity making it difficult to be isolated from the SOM (Denef et al., 2009). However, spectroscopic methods such as the nuclear magnetic resonance (NMR) (Skjemstad et al., 2004) and the MIRS (Bornemann et al., 2008) hold the greatest ability in quantifying the large range of BC material. To my knowledge, the latter method is yet to be applied to semi-arid tropical soils. The following topic could then focus on: " Characterization of black carbon in tropical semi-arid soils using infrared-spectroscopy".

2. 4 Timeline for the research

ActivitiesYear I (May 2012-Apr 2013)May 2012Jun 2012Jul 2012Aug 2012Sept 2012Oct 2012Nov 2012Dec 2012Jan 2013Feb 2013Mar 2013Apr 2013Literature research and preparation of field workTrip to Dano (Burkina-

Faso)Preliminary field workField work in Dano (Burkina-Faso)Coming back from field work to Bonn, GermanyLaboratory soil sample analysisYear II (May 2013-Apr 2014)ActivitiesMay 2013Jun 2013Jul 2013Aug 2013Sept 2013Oct 2013Nov 2013Dec 2013Jan 2014Feb 2014Mar 2014Apr 2014Laboratory soil sample analysisMap of soil types and soil carbon stocksTrip to Tetonga (Benin)Field workComing back from field work to Bonn, GermanyLaboratory soil sample analysisMap of soil types and soil carbon stocks establishment / Writing first paperYear III (May 2014-Dec 2015)ActivitiesMay 2014Jun 2014Jul 2014Aug 2014Sept 2014Oct 2014Nov 2014Dec 2014Jan 2015Feb 2015Mar 2015Apr 2015Map of soil types and soil carbon stocks establishment / Writing first paperwriting second paper / Setting RothC SOC model and model runningModeling SOC model with RothCWriting PhD Dissertation / writing third paperWriting PhD DissertationYear III (May 2014-Dec 2015)ActivitiesMay 2015Jun 2015Jul 2015Aug 2015Sept 2015Oct 2015Nov 2015Dec 2015Writing PhD Dissertation / Conferences participationEditing and final draftPhD Defense

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